Modelling Fuel Demand of Passenger Cars in Spain

A Dynamic Panel Data Analysis Using the Generalised Method of Moments

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Abstract

This paper identifies the main determinants of fuel consumption by households in the passenger transport sector in Spain (private cars). We estimate a Generalised Method of Moments model using quarterly (panel) data on automotive fuel consumption by 8,000 households between 1998 and 2005. The paper shows a clear persistence of habit in fuel consumption and a strong, statistically significant relationship between household transport fuel consumption and income, price of public transport and fuel prices. In addition, consumption is significantly related to household size, the geographical location of the household, and whether the breadwinner is an employer and an employee.

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1.0 Introduction

The aim of this paper is to analyse the determinants of fuel consumption in the passenger road transport sector in Spain with the help of an econometric model. Fuel consumption per household is explained by several socio-economic variables, including price and income.

Many papers on the determinants of fuel consumption in the transport sector have been published in the specialised literature (see Bohi and Zimmermann, 1984; Dahl and Sterner, 1991; Graham and Glaister, 2002; and Goodwin *et al.*, 2004 for surveys). More recent papers include Pock (2010), Wadud *et al.* (2009, 2010) and Karathodorou *et al.* (2010), among others.

With respect to the existing literature, this paper has several aspects making it a relevant contribution. First, to our best knowledge, most studies that analyse fuel demand with dynamic models use aggregated data of countries or regions (Baltagi and Griffin, 1997; Q1
Baltagi *et al.*, 2003; Pock, 2010; Sene, 2011; Danessin, 2011). They show a strong persist- Q2
ence of habit, with the relevant parameter being closer to one (Pock, 2010). In this article, we use quarterly microdata on fuel expenditures by Spanish households, allowing us to test habit persistence within a shorter time frame. Second, we apply alternative methods for the correction of the infrequency of purchase: the Keen (1986) and the Meghir and Robin (1991) methods. This is a problem that has to be taken into account when estimating fuel demand with microdata. Additionally, we use both traditional estimation techniques (fixed and random effects) and techniques specifically developed for dynamic models Generalised Method of Moments ((GMM)-based estimators). Finally, we pay attention to the degree of complementarity/substitution between public and private transport.

The paper is structured as follows. Section 2 provides a discussion of the econometric model. Section 3 describes the data used, provides the main results from the econometric study and discusses the results of the econometric estimates. The paper closes with some conclusions.

2.0 Methods

2.1 Model specification

Following the approach used in the partial adjustment models (see, among others, Houthakker *et al.*, 1974; Abdul-razak, 1997; Baltagi and Griffin, 1997; Baltagi *et al.*, 2003; and, more recently, Pock, 2010; Sene, 2011), we define a dynamic log linear model where the desired total consumption of fuel (litres) related to the use of passenger cars per household is defined as:

$$F^*_{ht} = C_h Y^{\delta}_{ht} p^{\gamma}_t q^{\omega}_t, \tag{1}$$

where C is the constant, Y is the household income, p is the fuel price, and q is the public transport price. Variable F^*_{ht} is non-observable, in contrast to current demand, F_{ht}, which is observable. The relationship between F^*_{ht} and F_{ht}, is defined through the partial adjustment behaviour model as follows:

$$\frac{F_{ht}}{F_{ht-1}} = \left(\frac{F^*_{ht}}{F_{ht-1}}\right)^{\theta} \qquad 0 < \theta < 1, \tag{2}$$

where θ represents the speed of adjustment towards the desired consumption level. Flow models such as equation (2) are particularly attractive for two reasons. First, the inclusion of a lag in the dependent variable allows us to capture sequentially correlated behaviour (habit persistence). Second, the specification itself allows us to calculate short- and long-term price and income elasticities. If we insert equation (2) into equation (1), take logs, and include a set of socio-economic variables and a random error, then the equation to be estimated is:

$$\mathrm{Ln}\, F_{ht} = c_h + \lambda\, \mathrm{Ln}\, F_{ht-1} + \beta_1\, \mathrm{Ln}\, Y_{ht} + \beta_2\, \mathrm{Ln}\, p_t + \beta_3\, \mathrm{Ln}\, q_t + \sum_{k=1}^{6} d_k + \varepsilon_{ht}, \tag{3}$$

where the error term has been specified as a one-way error component model $\varepsilon_{ht} = (\eta_h + v_{ht})$. Unobservable heterogeneity (consumer tastes or household preferences) is captured through the parameter η_h which represents the specific individual effect of each household (see Deaton (1985) for a discussion). In addition, the idiosyncratic error term is $v_{\boldsymbol{ht}}$. Under this formulation, short run elasticities are $\lambda = (1-\theta)$, $\beta_1 = \theta\delta$, $\beta_2 = \theta\gamma$, $\beta_3 = \theta\omega \ldots v_{\boldsymbol{ht}}$ where λ captures the habit in fuel consumptions, β_1 is the income elasticity of fuel demand, β_2 is the price elasticity of fuel, and finally β_3 is the elasticity of fuel demand to changes in public transport prices.[1]

The consumption patterns of economic agents are determined by their characteristics, both observable and unobservable (see Deaton *et al.*, 1989; Deaton, 1997; Calvet and Common, 2000; and Christensen, 2002). Following Pollack and Wales (1981), observable heterogeneity is captured through a set of six dummy variables which reflect household socio-economic characteristics. The geographical location of households (rural/urban), the occupational category of the breadwinner (whether they are an employer or an employee),[2] their employment status (whether they are employed or unemployed),[3] and the number of children in the household (household size). A trend variable is included in order to control for unobservable time effects in the survey (see Section 2.2). In addition, with the aim to capture the potential effects of summer vacation on fuel consumption, a dummy variable for the third quarter has been included. Q3

2.2 Expected relationship between the dependent and the explanatory variables

Table 1 describes the variables, identifies the expected sign of the relationship between the dependent and the explanatory variables, and provides some empirical evidence on such a relationship.

The *fuel and income variable*s are expected to have a negative and a positive sign, respectively. The literature shows a low degree of responsiveness of fuel demand to fuel price changes. The price-elasticity of fuel demand is low, especially in the short-term. Whereas short-run price elasticities normally range between −0.2 and −0.3, long-run price-elasticities typically fall in the −0.6 to −0.8 range (Goodwin *et al.*, 2004). How

[1] As it is well known, the short-run effect of gasoline price works primarily through adjustments of car utilisation, while in the long-run consumers adapt their car fleet to long-run changes in gasoline prices (Pock, 2010).

[2] This variable takes the value of one if the breadwinner is an employer and zero otherwise.

[3] This variable takes the value of one if the breadwinner is employed and zero if they are unemployed.

Table 1
Description of Variables and Expected Relation Between Dependent and Explanatory Variables

Variable	*Description*	*Expected sign**	*Empirical evidence in the literature (selected papers)*
Fuel demand	Total fuel consumption per household over the period related to the use of passenger cars (litres, quarterly data)	Dependent variable	–
Fuel prices	Fuel prices (weighted average of gasoline and diesel prices)	(−)	Goodwin (1992), Oum *et al*. (1992), Sterner *et al*. (1992), Espey (1998), Brons *et al*. (2008), Graham and Glaister (2002), Goodwin *et al*. (2004).
Lagged dependent variable	Fuel consumption in the previous quarter (habit persistence).	(+)	Abdul-razak (1997), Baltagi and Griffin (1997), Pock (2010), Sene (2011).
Income	Household income in constant prices (weighted by household size)	(+)	Goodwin (1992), Oum *et al*. (1992), Sterner *et al*. (1992), Espey (1998), Graham and Glaister (2002), Goodwin *et al*. (2004), IPCC (2007), Brons *et al*. (2008), Wadud *et al*. (2009).
Trend	Trend variable capturing non-observable time effects	(?)	Karathodorou *et al*. (2010), Wadud *et al*. (2010).
Summer	Third quarter of the year (dummy)	(?)	Non-available.
Rural	Rural or urban household (dummy)	(+)	Blow and Crawford (1997), Santos and Catchesides (2004), Wadud *et al*. (2009, 2010), Romero-Jordán *et al*. (2010).
Employer	The household breadwinner is an employer or an employee (dummy)	(+)	–
Children	Households with children (dummy)	(?)	Kayser (2000), Pucher and Renne (2003), West and Williams (2004), Wadud *et al*. (2010).
Employed	The household breadwinner is employed (versus unemployed) (dummy)	(+)	Kayser (2000).
Price of public transport	(dummy)	(+)	Karathodorou *et al*. (2010).

Note: *Where (+) means positive sign; (−) means negative sign; and (?) means unclear sign.

inelastic the demand response is varies according to the dataset, time period, and absolute level of fuel prices.

On the other hand, the greater the household income, the more it can spend on fuel, the greater the use of the car, and the greater its financial capacity to buy more powerful (fuel-intensive) cars.[4] The absolute values of income elasticities are generally higher than those for price elasticities. They generally lie between 0.38 and 0.52 in the short term and 1.04 and 1.28 in the long term (Goodwin *et al.*, 2004).

Habit persistence has been a well-researched issue in the general economic literature (see, for example, Abel, 1990; Boldrin *et al.*, 1997; or Carrasco *et al.*, 2005), but its Q4
analysis has not been so common in the analysis of fuel demand. Some studies of travel behaviour point to the possibility that car use can become so routine that 'choice' is not an issue as people act automatically without considering alternatives (Gross *et al.*, 2009).[5] We could expect a positive relationship between fuel consumption in successive quarters.

The *trend variable* captures non-observable time effects — that is, the joint impact of the evolution of different factors, notably regulatory changes and technological improvements. Since transport-fuel demand has increased over the years, a time trend is more appropriate to account for the effect of time (Wadud *et al.*, 2010). The relationship between this and the dependent variable may be positive regarding some factors (the increase in the number of cars per household, distances travelled, and urban sprawl) and negative regarding others (technological changes).[6] Again, which factor dominates is an empirical issue.

There is also an ambiguous relationship between the dependent and the *summer variable*. Fuel expenditures may be greater or lower during vacation, depending on whether the greater use of the car for long-distance trips offsets car use during the rest of the year either for leisure or work-related reasons. Furthermore, vacation-related trips may be made by other transport modes. Finally, anybody is unlikely to be on vacation during the whole third semester.

Compared to households in urban areas, *rural* households will tend to consume more fuel because there are fewer alternatives to the private car in rural areas. Rural households generally have lower income levels than urban households (Wadud *et al.*, 2009).

An ambiguous relationship can be expected in the case of *children* (or household size). Their presence may increase the requirement for mobility to meet their needs. In addition, the use of public transport loses interest in this context for economy and comfortability reasons. But the greater the size of the household, the lower the disposable income of the breadwinner to spend on car use and fuel. Existing empirical research shows ambiguous conclusions. Whereas Kayser (2000) and Wadud *et al.* (2010) report lower fuel consumption for the presence of several children, West and Williams (2004) and Pucher and Renne (2003) find that household size increases the share of gasoline in a household's budget.

The relationship between the *employer* and *employed* variables and the dependent variable would be positive. Work-related trips induce fuel consumption. Kayser (2000) found that less gasoline is consumed in households where the head does not work.

[4]Mendiluce and del Río (2010) have shown that there is a strong correlation between the increase in income and the number of vehicle registrations in Spain.

[5]See Anable *et al.* (2006) for a review of this literature.

[6]According to the IEA (2010), thanks to technological improvements, the energy-intensity of passenger cars has been reduced in the last decade and is expected to continue to do so in the following decades.

Finally, the higher the *price of public transport*, the greater the use of private cars. In their literature review, Gross *et al.* (2009, p. 28) found that pricing, service, and infrastructural changes to public transport systems result in modal shift and efficiency gains, leading to positive effects on fuel consumption. Storchmann (2001) found that changes in the price of public transport affect work-related trips by car and, much less, leisure-related trips.

3.0 Data

We use quarterly data on automotive fuel consumption by 8,000 households for the 1998–2005 period (thirty-two quarters per household), provided by the Spanish Expenditure Household Survey Data (SEHSD). The SEHSD contains detailed information on the expenditures on goods and services by households with different sizes and income levels, the place of residence, employment status of the principal breadwinner, level of education of the breadwiner, and so on. This information is very useful to estimate the fuel demand equation (3).

Since the income level declared in the interviews tends to be below the real income level, we use total household expenditures as a proxy of household income, following Poterba (1990), Wadud *et al.* (2009), Romero-Jordán *et al.* (2010), and Sterner (2012). Notwithstanding, the total expenditures cannot fully capture the real purchase capacity of households if they are not corrected by household size. In order to overcome this problem, we adjust total annual expenditures by an equivalence scale (West and Williams, 2004; Wadud *et al.*, 2010). We have used the OECD square root scale (OECD, 2008), which divides household annual expenditures by the square root of household size. Household annual expenditures had been deflated with the Stone index (Stone, 1953):

$$\mathrm{Ln}\,\tilde{P}_{ht} = \sum_{i} w_{iht}\,\mathrm{Ln}\,p_{it}, \tag{4}$$

where the subindex i refers to the different goods that make up the household consumption basket, w is the share of the different goods in total household expenditure, and p is the price index of each good (available from the Spanish National Statistical Agency — INE, 2010).

4.0 Estimations and Results

Panel microdata are very useful to analyse household fuel demand but they have a major drawback: the econometric problems caused by the existence of zero expenditures.[7]

[7]Once per quarter and during a whole week, households were asked about the composition of their consumption basket. For this reason, some goods (such as transport fuels) were consumed by households one or several weeks before they were interviewed. Consequently, the expenditure allocated to this good was zero during the whole quarter.

Infrequency of purchase leads to a measurement error regarding fuel expenditure and the amount of fuel consumed. In turn, the lagged dependent variable would be correlated with the error term, leading to inconsistent OLS estimations. To overcome this problem, Keen (1986) suggested the use of instrumental variables that provide consistent estimators (see Nichele and Robin, 1995 and Romero *et al.*, 2009, 2010, among others). In Q5 addition, Meghir and Robin (1992) proposed a more refined procedure than Keen's, Q6 recommending a previous correction of the observed expenditures in order to reduce the measurement error of those households with a positive fuel expenditure. This would reduce the gap between the observed expenditure, F_{ht}, and the *true* consumption of households, $\tilde{F}_{ht}$:

$$\begin{aligned} F_{ht} &= \frac{\tilde{F}_{ht}}{P_{ih}} \quad \text{if } n_i > 0, \\ F_{ht} &= 0 \quad \text{if } n_i = 0, \end{aligned} \tag{5}$$

where n_i is the number of observations with a positive expenditure and P_{ih} is the probability of purchase.[8] Inserting equation (5) into equation (3) leads to equation (6), which is the equation to be estimated once the infrequency of purchase has been corrected with the Meghir–Robin procedure:

$$\mathrm{Ln}\,\tilde{F}_{ht} = c_h + \lambda\,\mathrm{Ln}\,\tilde{F}_{ht-1} + \beta_1\,\mathrm{Ln}\,\tilde{Y}_{ht} + \beta_2\,\mathrm{Ln}\,p_t + \beta_3\,\mathrm{Ln}\,q_t + \sum_{k=1}^{6} d_k + \varepsilon_{ht}. \tag{6}$$

Tables 2 and 3 show the results of the estimation with instrumental variables, using the aforementioned methods. For illustrative purposes, we show the results of the OLS estimations first. Then, for each infrequency of purchase correction method, we use the following traditional estimation methods: a standard 2SLS estimator (2SLS), the Within 2SLS estimator (Within-2SLS), which allows for individual fixed effects, and the GLS estimator (GLS-2SLS) which assumes the household-specific effects to be random. We have used the lagged income and the lagged dependent variables as instrumental variables. We have also used two other instrumental variables. One captures how the household breadwinner perceives their own economic situation.[9] The other is the educational level of the breadwinner, given its relationship with the income variable.[10] The share of fuel expenditures on total household expenditures has been used as an instrumental variable of the lag of the dependent variable.

The Hausman test rejects the null hypothesis of no systematic difference between the Within-2SLS and the GSLS-2SLS coefficient estimates.[11] Therefore we accept the existence of fixed effects. The dynamic structure of equations (3) and (6) leads to upward

[8]This is defined as the number of positive expenditures of the household multiplied by the number of observations in the year in which the household has collaborated in the survey.

[9]This variable takes the value of one if the breadwinner perceives that the household will 'run out of money by the end of the month' and zero otherwise.

[10]The educational level of the breadwinner takes the value of one if they have university studies and zero otherwise).

[11]The value of the Hausman test for equation (3) is $\chi^2 = 73.33$ and its p-value is 0.000. For equation (6) the value of the test is $\chi^2 = 22.03$ and its p-value is 0.015.

biased and inconsistent OLS estimators, since the lagged fuel expenditure is correlated with the error term. Unfortunately, this problem cannot be avoided by using the within transformation, because this would result in correlation between the lagged dependent variable and the time averaged idiosyncratic error term (see Bond, 2002).

To overcome this problem, we employ the more efficient two-step GMM estimator (DIF-GMM) proposed by Arellano and Bond (1991) and the two step GMM estimator (SYS-GMM) developed by Arellano and Bover (1995) and Blundell and Bond (1998). The reported two-step standard errors tend to be downward biased, although the Windmeijer (2005) correction is used to avoid this problem (see Roodman, 2009a). These two estimators are more appropriate for the estimation of dynamic models, such as equations (3) and (6). In the DIF-GMM, the dependent variable with first differences and suitable lags is used as an instrumental variable of the endogenous variable. In this way, we remove the impact of non-observable individual effects $\eta_{h,}$ and, consequently, the correlation between η_h and f_{ht-1}. Notwithstanding, DIF-GMM may have poor finite sample properties when the series are persistent (as is the case with fuel demand) and, consequently, it could be downwards biased. In order to avoid this problem, Arellano and Bover (1995) and Blundell and Bond (1998) proposed the SYS-GMM estimator, which uses first-differenced instruments for the equation in levels and instruments in levels for the differenced equation. In the case of the variables in first- differences, the lagged variables at level are used as instruments. The SYS-GMM has dramatic efficiency gains over the DIF-GMM (see Baltagi, 2005).

The use of SYS-GMM has increased substantially in the last years because it is preferable to other procedures which use instrumental variables, including the DIF-GMM estimator (see Blundell and Bond, 1998 and Blundell *et al.*, 2000), and because it is available in standard econometric software. However, it has limitations when applied in empirical analysis. Bruno (2005) and Bun and Kiviet (2006) argue that dynamic estimators can be biased and inefficient when the number of cross-sectional units is not very high. Fortunately, the T value used in this study is relatively large, with thirty-two quarters. Álvarez and Arellano (2003) have shown that GMM estimators are consistent if, as in our Q7
case, $0 < T/N \leqslant 2$, where T stands for the number of quarters and N is sample size.

Another criticism is that the excessive number of instrumental variables being used may lead to bias in the estimated parameters (see Roodman, 2009a). In the case of SYS-GMM, a bias exists when the parameter falls between the values obtained with OLS and Within Groups. Furthermore, the excessive number of instrumental variables being used may weaken the Hansen test. Following Roodman (2009b), when this occurs, a test to assess the robustness of the estimations is not available. Roodman (2009b) proposes two alternatives: to use some lags instead of all available lags for the instrumental variables, and to combine instruments through addition into smaller sets using a collapsing in the matrix of instruments. We have used both alternatives together in Tables 2 and 3, limiting the number of lags of the instrumental variables to two periods. The null hypothesis of joint statistical significance is accepted in all regressions.

Tables 4 and 5 provide a diagnosis of the estimations shown in Tables 2 and 3. In the estimation with traditional models, we have computed the over-identification Hansen test, asymptotically distributed as χ^2, to test the null hypothesis that our instrumental variables are not significantly correlated with the error term. The null hypothesis is rejected in the Within estimations, but accepted in the rest of traditional estimations. In

Table 2
Results of the Estimation Using Keen Procedure

Variables		Keen procedure						
	OLS (1)	2SLS (2)	Within 2SLS (3)	GLS 2SLS (4)	DIF-GMM up to 2 lags (5)	DIF-GMM up to 2 lags Collapsing (6)	SYS-GMM Up to 2 lags (7)	SYS-GMM Up to 2 lags Collapsing (8)
Ln fuel-lag	0.0279* (0.027)	0.0328* (0.0082)	0.2853* (0.0923)	0.0309* (0.0082)	0.0180 (0.0250)	0.0497 (0.0360)	0.044 (0.0212)	0.04712** (0.02063)
Ln fuel-price	−0.3204* (0.1015)	−0.2873* (0.1062)	0.3106 (0.5212)	−0.2885* (0.1063)	−0.4847 (0.4522)	−0.6279 (0.4507)	−0.2819** (0.1103)	−0.3128* (0.1157)
Ln pub-trans	0.3192)** (0.1448)	0.3285** (0.1515)	−0.1451 (0.9510)	0.3288** (0.1516)	1.5894 (1.4236)	1.942 (1.4388)	0.3312** (0.1536)	0.3717** (0.1543)
Ln income	0.7531* (0.0152)	0.5508* (0.0418)	0.6352* (0.0923)	0.5523* (0.0418)	0.5390* (0.0992)	0.5824* (0.1074)	0.5443* (0.0504)	0.5566* (0.0523)
Trend	−0.0254 (0.2422)	−0.2007 (0.0253)	−0.0240 (0.1712)	−0.0200 (0.0253)	−0.1489 (0.1393)	−0.1261 (0.1413)	−0.0218 (0.0258)	−0.0238 (0.0264)
Summer	−0.013 (0.0151)	0.0004** (0.0158)	−0.0379 (0.0586)	0.0003 (0.0158)	0.0008 (0.0300)	−0.0072 (0.0300)	0.0070 (0.0160)	−0.0025 (0.0186)
Rural	0.1300* (0.0141)	0.1106* (0.0156)	0.0886 (0.0634)	0.1108* (0.0156)	0.1293* (0.0354)	0.1268* (0.0383)	0.1138* (0.0184)	0.1149* (0.0185)
Employer	0.0371** (0.0155)	0.0435* (0.0163)	0.1815* (0.0626)	0.0436* (0.0163)	0.0339 (0.0354)	0.0505 (0.0357)	0.0449** (0.0193)	0.0459** (0.0194)
Children	−0.1736* (0.0142)	−0.1532* (0.0153)	−0.2083* (0.0583)	−0.1535* (0.0153)	−0.1683* (0.0334)	−0.1563* (0.333)	−0.1596* (0.0181)	−0.1541* (0.0181)
Employed	0.1640* (0.1640)	0.2101* (0.1734)	0.17825* (0.0676)	0.2093* (0.0173)	0.2191* (0.0381)	0.2089* (0.0377)	0.2185* (0.0207)	0.2103* (0.0205)
Intercept	2.1516* (0.7660)	4.0269* (0.8095)	– –	4.0393* (0.8098)	– –	– –	3.9458* (0.8447)	3.8412* (0.8670)
Joint-test-significance	$F(10, 14225) = 319.95$	$F(10, 14225) = 83.80$	$F(10, 1252) = 4.16$	$F(11, 14225) = 81883.73$	$\chi^2(10) = 186.46$	$\chi^2(10) = 174.99$	$\chi^2(10) = 628.86$	$\chi^2(10) = 608.05$

Notes: *Significant at the 99% confidence level; **95% confidence level. Robust standard errors are reported in parentheses.

Table 3

Results of the Estimation Using Meghir and Robin Procedure

	Meghir–Robin						
Variables	*2SLS (9)*	*Within 2SLS (10)*	*GLS 2SLS (11)*	*DIF-GMM up to 2 lags (12)*	*DIF-GMM up to 2 lags Collapsing (13)*	*SYS-GMM Up to 2 lags (14)*	*SYS-GMM Up to 2 lags Collapsing (15)*
Ln fuel-lag	0.0321* (0.0083)	0.2062* (0.0766)	0.0312* (0.0083)	0.0227 (0.0235)	0.0417 (0.0285)	0.0440** (0.0192)	0.0446** (0.0186)
Ln fuel-price	−0.2295** (0.1080)	0.4162 (0.5446)	−0.2299** (0.1080)	−0.4501 (0.4323)	−0.6336 (0.4297)	−0.3068* (0.1058)	−0.3439* (0.1110)
Ln pub – trans	0.4473* (0.1531)	−0.1336 (0.9947)	0.4470* (0.1532)	1.3460 (1.353)	1.8631 (0.1355)	0.3186** (0.1477)	0.3746** (0.1483)
Ln income	0.5574* (0.0438)	0.6305* (0.1605)	0.5579* (0.0438)	0.6112* (0.1002)	0.5999* (0.1054)	0.5888* (0.0501)	0.5727* (0.0517)
Trend	−0.4051 (0.02524)	−0.0327 (0.5929)	−0.0404 (0.0252)	−0.1336 (0.1350)	−0.0612 (0.1355)	−0.0210 (0.0248)	−0.0229 (0.0254)
Summer	−0.0085 (0.01611)	−0.0423 (0.0592)	−0.0085 (0.0161)	−0.0001 (0.0290)	−0.0061 (0.1355)	0.0063 (0.0154)	−0.0022 (0.0179)
Rural	0.1111* (0.0162)	0.1076 (0.0650)	0.1111* (0.0162)	0.1285* (0.0370)	0.1218* (0.03645)	0.1120* (0.0175)	0.1111* (0.0176)
Employer	0.0323 (0.0169)	0.1648* (0.0625)	0.0324 (0.0169)	0.0318 (0.0340)	0.0521 (0.0340)	0.0426** (0.0186)	0.0469** (0.0186)
Children	−0.1563* (0.1570)	−0.2233* (0.0590)	−0.1564* (0.0157)	−0.1712* (0.0320)	−0.1601* (0.0318)	−0.1656* (0.0174)	−0.1580* (0.0175)
Employed	0.2098* (0.0179)	0.18105* (0.0699)	0.2095* (0.1798)	0.1990 (0.03745)	0.1995* (0.0368)	0.2032* (0.0203)	0.2030* (0.0201)
Intercept	1.8406** (0.8073)	– –	1.8463* (0.8075)	– –	– –	2.5874* (0.8066)	2.554* (0.8279)
Joint-test-significance	$F(10, 12{,}427) = 80.24$	$F(10, 12{,}427) = 7.76$	$F(11, 12{,}427) = 48430.31$	$\chi^2(10) = 203.75$	$\chi^2(10) = 191.35$	$\chi^2(10) = 690.00$	$\chi^2(10) = 659.68$

Notes: *Significant at the 99% confidence level; **95% confidence level. Robust standard errors are reported in parentheses.

Table 4
Diagnosis of the Estimations in Table 2

Variables	*OLS* *(1)*	*Keen procedure* *2SLS* *(2)*	*Within-2SLS* *(3)*	*GLS-2SLS* *(4)*	*DIF-GMM up to 2 lags* *(5)*	*DIF-GMM up to 2 lags Collapsing* *(6)*	*SYS-GMM Up to 2 lags* *(7)*	*SYS-GMM Up to 2 lags Collapsing* *(8)*
Over-identification Hansen test	–	$\chi^2(2) = 0.433$ *p*-value = 0.8054	$\chi^2(2) = 4.859$ *p*-value = 0.0881	$\chi^2(2) = 0.493$ *p*-value = 0.7814	$\chi^2(60) = 89.40$ *p*-value = 0.008	$\chi^2(2) = 2.73$ *p*-value = 0.256	$\chi^2(120) = 151.09$ *p*-value = 0.029	$\chi^2(4) = 2.14$ *p*-value = 0.710
Under-identification Kleibergen–Paap Wald test	–	$\chi^2(3) = 1648.34$ *p*-value = 0.000	$\chi^2(3) = 93{,}19$ *p*-value = 0.000	$\chi^2(3) = 1.642{,}97$ *p*-value = 0.000	–	–	–	–
Weak identification test: Kleibergen–Paap rk statistic	–	411.708 IV relative bias CV (11.04) IV size CV (16.87)	23.077 IV relative bias CV (11.04) IV size CV (16.87)	410.366 IV relative bias CV (11.04) IV size CV (16.87)	–	–	–	–
$m1$	–	–	–	–	−8.07 *p*-value = 0.000	−8.00 *p*-value = 0.000	−8.50 *p*-value = 0.000	−879 *p*-value = 0.000
$m2$	–	–	–	–	−0.69 *p*-value = 0.490	−0.44 *p*-value = 0.661	−0.51 *p*-value = 0.611	−0.49 *p*-value = 0.623
Number of instruments	–	13	12	13	70	12	131	15

Note: The Hansen J statistic is consistent in the presence of heteroskedasticity and autocorrelation.

Table 5
Diagnosis of the Estimations in Table 3

Variables				*Meghir–Robin procedure*			
	2SLS (9)	*Within 2SLS (10)*	*GLS 2SLS (11)*	*DIF-GMM up to 2 lags (12)*	*DIF-GMM up to 2 lags Collapsing (13)*	*SYS-GMM Up to 2 lags (14)*	*SYS-GMM Up to 2 lags Collapsing (15)*
Over-identification Hansen test	$\chi^2(2) = 0.295$ p-value $= 0.862$	$\chi^2(2) = 6.798$ p-value $= 0.0334$	$\chi^2(2) = 0.329$ p-value $= 0.8482$	$\chi^2(60) = 90.98$ p-value $= 0.006$	$\chi^2(2) = 2.73$ p-value $= 0.255$	$\chi^2(120) = 155.65$ p-value $= 0.016$	$\chi^2(4) = 2.23$ p-value $= 0.693$
Under-identification Kleibergen–Paap Wald test	$\chi^2(3) = 1.513,44$ p-value $= 0.000$	$\chi^2(3) = 101,66$ p-value $= 0.000$	$\chi^2(3) = 1.511,58$ p-value $= 0.000$	–	–	–	–
Weak identification test: Kleibergen–Paap rk statistic	377.96 IV relative bias CV (11.04) IV size CV (16.87)	25.138 IV relative bias CV (11.04) IV size CV (16.87)	377.96 IV relative bias CV (11.04) IV size CV (16.87)	–	–	–	–
*m*1	–	–	–	−8.07 p-value $= 0.000$	−8.23 p-value $= 0.000$	−8.31 p-value $= 0.000$	−8.53 p-value $= 0.000$
*m*2	–	–	–	−0.64 p-value $= 0.522$	−0.48 p-value $= 0.630$	−0.48 p-value $= 0.631$	−0.48 p-value $= 0.630$
Number of instruments	13	12	13	70	12	131	15

Note: The Hansen *J* statistic is consistent in the presence of heteroskedasticity and autocorrelation.

addition, the instruments should be sufficiently correlated with the included endogenous regressors. For this purpose, we use the under-identification Kleibergen–Paap Wald test (see Kleibergen and Paap, 2006) and reject the null hypothesis (Table 3) — that is, the instrumental variables are correlated with the instrumented variable. Finally, we apply a weak identification test for the instrumental variables based on Stock and Yogo (2005). This problem arises when the correlations between the endogenous regressors and the excluded instrumental variables are non-zero but small (Baum and Schaffer, 2007). In Q8 this context, a rejection of the null of the under-identification test may not be sufficient to verify that the used instrumental variables are the appropriate ones. The tables show the critical value (CV) tabulated by Stock and Yogo (2005). The weak identification test uses a Wald *F* statistic test based on the Kleibergen–Paap *rk* statistic (Kleibergen and Paap, 2006). The hypothesis of weak instrumental variables is rejected in all estimations.

The tests generally used to assess the validity of the GMM-based estimators are $m1$, $m2$, and the Hansen test. The $m1$ and $m2$ test the null hypothesis of first- and second-order serial correlation in first-differenced residuals $(\varepsilon_1 it - \epsilon_1(it - 1))$. Following Arellano and Bond (1991), GMM-based estimators are consistent if first-order serial correlation is ruled out but there is second-order serial correlation. The $m2$ test is important because the consistency of the GMM estimator relies upon the fact that $E(\Delta v_{it}\Delta v_{it-2}) = 0$ (see Baltagi, 2005). The results of the DIF-GMM and SYS-GMM estimations for $m1$ and $m2$ are as expected (Tables 4 and 5).

The Hansen test allows us to test the validity of the instrumental variables. The test is only accepted in those DIF-GMM and SYS-GMM estimations in which the number of lags is reduced to two and, simultaneously, the matrix of instrumental variables is collapsed. Note that, in these cases, the number of instrumental variables is significantly reduced. Therefore, the best estimates of equations (3) and (6) are those included in columns 6 and 8 when the Keen correction method is used and those included in columns 13 and 15 when the Meghir–Robin method is used. A first look at Table 2 Q9 shows that the estimated parameters generally have the expected sign: they are negative with respect to prices and positive with respect to habit persistence, income, and public transport prices. In some cases the expected sign is unclear (see Table 1), and thus the sign of our estimates clarifies the sign of the relationship between the variables. Most variables are statistically significant in most estimations. The results also show that the econometric technique used and the method used to correct for the infrequency of purchase matter. Instrumental variables combined with the Meghir–Robin correction provides lower parameter values than the rest of estimations.

The economic relevance of the variables can be directly compared between each other, since all parameters are interpreted as elasticities. The variables with the greatest economic importance are, in descending order, price of public transport, income, and fuel prices. They are followed by 'employed', 'children', and 'rural'. The rest of the variables have a small or very small relevance. Section 5 discusses these results further.

5.0 Discussion of Results

Both the income and fuel price variables have the expected sign and are statistically significant. Overall, the relevance of the income variable is in line with the results of the literature, which shows large income elasticities and lower price elasticities (in absolute value) (see Section 2.2). Income elasticities are slightly above the ranges found in the literature and price elasticities are within the range for short-run elasticities reported by Brons *et al*. (2008).[12]

The positive sign, statistical significance, and high relevance of the price of public transport suggests that, as expected, the higher this price, the more attractive is the use of private cars.

Regarding habit persistence, the coefficient of the lagged dependent variable is positive and statistically significant. These findings are consistent with the standard assumption for partial adjustment models. The Within-2SLS estimations show the greatest λ values (0.28 and 0.20), which are within the range of available evidence, showing that λ is generally above 0.15 (see Baltagi and Griffin (1997) for OECD countries, Abdul-razak (1997) for GCC countries and Pock (2010) for the EU). The rest of the estimations for λ are within the 0.03–0.05 range. Since the literature generally uses annual aggregated data, in contrast to the microdata used in this paper, this may explain the lower λ values. The existence of adjustments in habits is probably more visible year after year than quarter after quarter. Furthermore, following Pollack and Wales (1981), λ could also pick up the impact of other factors in addition to habit, such as technological changes.

The negative sign, intermediate relevance, and statistical significance of children suggest that factors inhibiting a greater mobility (lower disposable income and lower comfort to move) dominate (see Section 2.2).

Rurality shows a positive sign and is statistically significant. Therefore, rural households use private cars more intensively than urban ones due to the greater availability of public transport in urban areas and (possibly) the greater distances travelled by members of rural households to access public services.

Employed and employer have a positive sign, and are statistically significant, suggesting that workers have a higher fuel consumption than non-workers, due to the need to travel to work and the availability of income to spend on fuel, and that employers have higher fuel consumption levels than employees, possibly due to higher income levels.

Finally, the trend and summer variables show a positive sign in several estimations and a negative one in others, but they are not statistically significant. This erratic relationship might be explained by the positive and negative effects discussed in Section 2.2 cancelling each other.

[12]As it's usual, we have calculated long-run price and income elasticities by adjusting short-run price and income elasticities by the speed of adjustment (see, for example, Baltagi *et al*., 2003; Pock 2010): $\beta_1^L = \beta_1/(1-\lambda)$, $\beta_2^L = \beta_2/(1-\lambda)$ and $\beta_3^L = \beta_3/(1-\lambda)$, where λ stands for the coefficient of the lagged dependent variable. However, we only report short-run elasticities here, given that the estimated values for λ in our models are generally very low (see below) and, thus, there is a very small difference between short-run and long-run price and income elasticities. This is in contrast to the literature, which finds strong habit persistence, with long-run responses as much as 4.7 times the short-run response (see, for example, Baltagi *et al*., 2003).

6.0 Concluding Remarks

This paper has empirically assessed the determinants of fuel consumption by Spanish households related to private car use. The paper shows a strong and statistically significant relationship between household transport fuel consumption and key explanatory variables (income, price of public transport, and fuel prices). Our results show a clear persistence of habit (inertia) in fuel consumption. In addition, consumption is significantly related to household size, the location of the household, and whether the household breadwinner is an employer or an employee.

The results suggest that, while fuel pricing policies might have significant effects on fuel consumption by households related to private car use, they are only part of the story. The strong income effect indicates that, while those policies are necessary, they may not be sufficient to significantly reduce fuel consumption and they may need to be combined with other regulatory, economic, and information instruments. The significance and economic relevance of the variable price of public transport suggests that it may have an important role to play in reducing private car use.

Furthermore, our results suggest that increasing fuel prices in order to reduce fuel consumption would have important equity impacts on different types of households (with/without children and rural/urban areas). Different households can have different responses to the same stimuli depending on the household characteristics (Wadud *et al.*, 2010). For reasons of equity and policy effectiveness, it is useful to know how an increase in fuel prices will affect different households and from which groups the demand response will be most pronounced.

Finally, several shortcomings of this paper should be mentioned. First, the available data does not allow us to estimate a fuel demand function by distinguishing between gasoline and diesel. Second, data on the number of cars and the number of kilometres travelled per household and important features of the cars (size) affecting fuel consumption are not available in the SEHSD, which prevents us from identifying the effect of those variables on fuel consumption. The total cost of car use and availability and convenience of alternatives is an important variable affecting fuel demand which has not been included in the estimation, although the cost (price) of public transport has been included. Finally, several demographic variables affecting household gasoline consumption, such as household composition, number of wage earners, age, and race and gender of household members have not been included in our study due to unavailability of data (see, among others, Kayser, 2000; West and Williams, 2004; and Wadud *et al.*, 2010).

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07 **Álvarez:** Alvarez in references (no accent).

08 **Baum and Schaffer, 2007:** Baum *et al.* in references.

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