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Induced travel demand in Spanish regions: a dynamic panel data model

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ABSTRACT

Distinguishing between traffic generated exclusively from the expansion of the road network (induced demand) and that resulting from other demand factors is of crucial importance to properly designed transport policies. This paper analyzes and quantifies the induced demand for road transport for Spain's main regions from 1998 to 2006, years that saw mobility in Spain attain its highest growth rate. The lack of research in this area involving Spain and the key role played by the sector, given its high level of energy consumption and the negative externalities associated with it (accidents, noise, traffic congestion, emissions, etc.), endow greater relevance to this type of study. Based on a Dynamic Panel Data (DPD) reduced form model, we apply alternative approaches (fixed and random effects and GMM-based methods) for measuring the induced demand. The results obtained provide evidence for the existence of an induced demand for transport in Spain, though said results vary based on the estimating method employed.

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1. INTRODUCTION

The demand for transport in Spain in recent decades has been characterized by a strong rise of road traffic.[2] According to the theory on transport economics, one of the reasons that could cause an increase in road traffic is the growth of the road network.[3] The road network growth would favor decongestion and the productivity of existing transport (i.e., reduce the time for each trip), as well as it may also have a beneficial initial effect on fuel consumption and emissions. However, because of the decreased congestion and reduction in generalized travel costs, it would generate more transport demand, which could offset the initial effect and lead to similar or even greater overall levels of vehicle traffic, congestion, fuel consumption and emissions. This indirect effect on demand stemming from the expansion of the road network is known as *induced demand*.

In general, the push for new infrastructure must be preceded by qualitative and quantitative studies to evaluate its benefits and opportunities.[4] One of the costs that an expansion of the road network can trigger, at least in the long-run and on a macroeconomic level, is to generate induced demand. Thus, testing its existence is very important not only for properly assessing the impact of public infrastructure on mobility and traffic congestion, but also for designing infrastructure and energy policies. Also, distinguishing between the traffic generated exclusively from the expansion of the road network and that stemming from other demand factors is of prime importance in terms of properly designed transport policies. This is because the origins behind these two types of mobility (induced and the rest) are very different (stemming from supply and demand factors, respectively). Therefore, policy measures for managing them must also be different: pricing (introduction of tolls) and tax policies, as opposed to policies to manage mobility and/or invest in infrastructure.

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[2] The road transport participation rate in domestic transport has been over 80%. Between 1990 and 2007, the road passenger per km has increased in Spain by 94% (almost 4% per year), and the freight transport (tm. per km) has increased by 159% (5.8% per year) in the same period. These growth rates have been notably higher than those of the population (0.83% per year) and real GDP (3.1% per year). Moreover, these figures doubled and even tripled in some cases the growth rates of most OECD countries.

[3] See Galindo et al. (2006); Cervero and Hansen (2002); Noland (2001) and Noland and Lem (2002).

[4] Investment in transport infrastructure has traditionally been regarded as an indicator of development. The European White Paper on Transport (2001) is clear in this regard in considering transport policy as essential to the economic and social cohesion of EU countries. And yet, we must bear in mind that specific modes of transport, such as road transport, necessitate a high usage of land area. This led, in the mid 1990s, to the introduction of economic and environmental sustainability in the planning of road

For the case of Spain, despite having one of the highest growth rates in road traffic within EU countries in recent years, little works are found that attempt to measure the induced demand at an aggregate or regional level. Thus, the main goal of this paper is to test the hypothesis of induced transport demand at the regional level in Spain. To this end, we estimate a Dynamic Panel Data (DPD) model for the transport demand, as measured by vehicles-kilometers traveled, as a function of the road network, the real regional Gross Domestic Product (GDP), the real fuel price and the vehicle fleet. For homogeneity and availability reasons, the database used relies on information from 1998 to 2006 for 16 Spanish regions. The combination of cross-sectional data and of time series allows us to work with panel data, with the attendant gains in terms of heterogeneity and degrees of freedom (Hsiao, 1986).

The second contribution of the paper involves the estimation methods used for this type of model. Traditional fixed or random effect panel data methods are unsuitable for estimating a DPD model like the one proposed here (Hsiao, 1986; Anderson and Hsiao, 1982). As detailed in Section 3, procedures based on the generalized method of moments proposed by Arellano and Bover (1995) and developed by Blundell and Bond (1998), referred to in the literature as GMM-SYS, address many of the econometric problems in DPD models posed by traditional procedures.[5] A comparison of our results using alternative estimating methods is very revealing in two aspects. First, the dynamic term is highly significant, which reaffirms the importance of considering dynamic models instead of static models.[6] Moreover, it would allow us to estimate simultaneously short- and long-term effects. Second, the results are sensitive to the estimating method utilized, hence the importance of adopting the proper method. Specifically, while the (biased) estimates of traditional methods show little or no evidence to prove the existence of an induced demand, estimates using the GMM-SYS

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networks which has resulted in promoting more rational and balanced modes of transport as planners look to the future.

[5] The work by Forbes (2005) on inequality and growth, by Huang et al. (2008) on energy consumption and growth, by Marrero (2009) on emissions and growth and by González et al. (2009) on energy consumption in the road transport sector point to the relevance of using this methodology when working with DPD models.

[6] The results shown in this paper confirm the importance of the specifications of the model used and back the arguments made by some authors, such as Oum, Water and Yong (1992), who note that one way to improve the models is to conduct an in-depth analysis of the functional form that is adopted for addressing simultaneity and introducing delays.

method offer strong proof in favor of this hypothesis. Moreover, for the remaining variables as a whole, this procedure yields the most consistent estimates with the theory on transport economics.

This paper is structured as follows. Section 2 presents the theoretical framework on which the induced demand hypothesis is based. Section 3 specifies the DPD model to be estimated. Section 4 features a descriptive analysis of the data series utilized. The results are presented in Section 5 and, finally, Section 6 highlights the main conclusions drawn from the work.

2. Theoretical framework

The economic theory of supply and demand explains the presence of induced traffic when an expanded road network decreases the generalized cost of a trip, especially the travel time, and as a consequence increases the distances traveled (Goodwin, 1992).[7] Thus, induced traffic in road transport is typically defined as the rise in kilometers traveled resulting from an increase in the capacity of the road network (SACTRA, 1994). It is important to distinguish between this traffic, generated by a supply factor, and the traffic resulting from demand factors, such as increased per capita income, population, economic activity, changes to tax regimes, etc. These differences are illustrated using the typical travel supply and demand graph (Figure 1).

Let us suppose that for a given initial demand D1, there is an expansion of the road network that shifts the supply from S1 to S2. This causes an increase in the amount of trips demanded from Q1 to Q2, resulting from a reduction in generalized travel costs (i.e., less time due to lower congestion).[8] The shift from Q1 to Q2 measures induced

[7] The induced demand theory is consistent with the "triple convergence" theory by Downs (1992), developed to explain the difficulties that must be overcome to eliminate rush hour congestion. The theory states that in response to increased road capacity, which leads to reduced travel time, three effects occur: passengers shift from existing routes to new ones, users shift from off-peak times to rush hour, and users shift from public to private transport. This idea was expanded upon by Mogridge et al. (1987), who established the Downs-Thomson paradox, according to which increasing the capacity of roads can cause traffic congestion to worsen. In fact, there is evidence to support the finding that expanding highway capacity could be detrimental to reducing congestion (see Arnott and Small, 1994).

[8] One of the main components of travel cost is time and its inclusion as an explanatory variable in the demand for transport is a determining factor. See González (1997) for an overview of time allocation models and time values. Goodwin (1996) and SACTRA (1994), among others, maintain that about half of the time saved as a result of the higher travel speed permitted by the increased capacity of the road network will be devoted to additional trips.

traffic. If, however, a simultaneous increase in demand were to take place due to other factors, the resulting increase in trips would be from Q1 to Q3, where the change from Q2 to Q3 does not correspond to induced traffic. This complexity at the empirical level lies in identifying the difference between Q1 and Q2 from that between Q2 and Q3, since what we are actually observing in the data is the overall change from Q1 to Q3. At any rate, it is obvious that the absence of induced traffic only occurs when transport demand is perfectly inelastic with respect to the generalized cost of the trip, a highly unrealistic assumption.

INSERT FIGURE 1 ABOUT HERE

Although the theoretical approach serves to clearly establish the behavior of the induced demand, contradictory results have nonetheless been found at an empirical level. Some authors note that supply and demand in transport are independent (Mackie, 1996), while others, like Mokhtarian et al. (2002) and Prakash et al. (2001), view induced demand as statistically negligible. Nevertheless, the results obtained by the latter have been criticized by authors like Goodwin and Noland (2003), who showed how the model employed was inadequate. Indeed, there is a clear consensus nowadays regarding the existence of induced demand.[9] The consensus on the estimated elasticity values, however, is not as strong. This is due in part to the occasional difficulty in obtaining statistical information on all the factors that affect traffic, to the problems in specifying the causal relationship that exists between the variables and to the different estimating methods. This paper provides empirical evidence on the sensitivity of the estimates to the various methods considered when using panel data.

[9]There is a great deal of empirical work with both individual and aggregate data and short- and long-term analyses to support the induced demand hypothesis (Pells, 1989; Goodwin, 1996; Hansen and Huang, 1997; Heanue, 1998; Fulton et al., 2000; Marshall, 2000; Galindo et al., 2005; Cervero and Hansen, 2002; Noland, 2001 a) and b); Noland and Coward, 2000; Noland and Lem, 2002). Moreover, because long-run effects on energy consumption and emissions might be important, there is even an emphasis on the importance of measuring even small amounts of induced demand in actual traffic congestion situations (SACTRA, 1994).

3. A DYNAMIC PANEL DATA MODEL FOR INDUCED DEMAND IN ROAD TRANSPORT

In this section we present the DPD model for studying the induced demand in road transport for Spanish regions. The specification is in line with the models put forth by the majority of authors, such as Hansen and Huang (1997), Noland (2001), Cervero and Hansen (2001) or Noland and Lem (2002), which relate the traffic volume (Traffic) - measured in vehicle kilometers of travel, as suggested by Noland and Cowart (2000) - with the road network (Network), the Gross Domestic Product (GDP), the average real price of fuel (Price) and the vehicle fleet (Fleet). All variables are expressed in natural logs and, with the exception of the fuel price, in per capital terms.[10] In our case, the dynamic nature of the model requires introducing a lag for the Traffic variable. The time period spans from 1998 to 2006 and considers a total of 16 regions.[11]

$$\begin{aligned} &Trafic_{it} = \alpha_i + \beta \cdot Trafic_{it-1} + \lambda_1 \cdot Network_{it} + \lambda_2 \cdot GDP_{it} + \lambda_3 \cdot \mathrm{Pr}ice_{it} + \lambda_3 \cdot Fleet_{it} + \varepsilon_{it} \\ &t = 1998, \ldots, 2006; \; i = 1,2,\ldots,16. \end{aligned} \qquad \textbf{(1)}$$

The lag term controls the short-term dynamic and the conditional convergence among Spanish regions in relation to the per capita traffic.[12] The constants α_i account for those fixed and inherent factors in each region that are not explicitly considered in the model, such as geographic and social characteristics, local policies and other initial conditions,[13] while ε_{it} includes effects of a random nature that are not considered in the model and which are assumed to have a standard error component structure (Arellano and Bond, 1991; Arellano and Bover, 1995),

A1) $E(\varepsilon_{it}) = 0; \; E(\alpha_i \varepsilon_{it}) = 0; E(\varepsilon_{it}\varepsilon_{is}) = 0, \; i = 1,\ldots, N; t = 1,\ldots, N; s \neq t$.

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[10] We follow Noland and Lem (2002) and express the variables in per capita terms, which is alternative to that used by other authors, such as Cervero and Hansen (2002), Fulton et al. (2000) and Hansen and Huang (1997), who express the variables in absolute terms and introduce the population as an explanatory variable.

[11] Ceuta, Melilla and the Canary Islands were omitted from the sample due to the numerous anomalies present in the traffic volume series.

[12] A significant β coefficient between 0 and 1 would be indicative of this variable's conditional convergence. The larger the coefficient, the greater the effect of the inertia as an explanatory factor of its own evolution, as well as the slower the convergence speed among the regions.

[13] From a theoretical standpoint, we would expect most of the fixed factors to be heterogeneous among regions and correlated with at least some of the specific initial conditions of the regions. Thus, from an empirical standpoint, when these fixed differences are not considered, biased estimates would result. For example, the fixed effects are not included in the ordinary least squares regression, resulting in estimators that are biased downward (Hsiao, 1986).

A2) $E(y_{i1}\varepsilon_{it}) = 0,\ i = 1,..., N; t = 2,..., T$.

Thus, with the remaining factors conditioned, λ_1 reflects the short-term elasticity between traffic and the road network (i.e. the induced demand measure). As for the accumulated, or long-term, elasticity, this can be easily obtained by dividing the short-term elasticity by $1-\beta$, $\lambda_1/(1-\beta)$.

Since the lagged endogenous term is not independent of the error term, traditional methods for estimating a panel data model (fixed or random effects) are not suited to a dynamic model like (1) (Hsiao, 1986). To solve this endogeneity problem, Holtz-Eakin et al. (1988) and Arellano and Bond (1991) transformed model (1) into a first-difference model that obviated the fixed effects. This transformation allowed them to characterize certain orthogonality conditions among the endogenous lagged variable and the model residuals, which they then used to identify a set of valid instruments, enabling them to build an estimator of the generalized method of moments type, which they denote GMM-DIF. The GMM-DIF approach, however, poses serious bias problems when the series used in the model exhibit significant persistence, as is the case of the variables considered in (1). This persistence results in weak instruments, meaning that the correlation between the instrument and the variable to be instrumentalized is small, leading to the bias problems noted above. Arellano and Bover (1995) and Blundell and Bond (1998) offer an alternative to solving the *weak instrument* problem for this type of model. Specifically, they propose estimating a system of equations (GMM-SYS) by combining the conditions of the first-difference estimator with those of a level estimator. They thus suggest using, in addition to level instruments for first-difference equations, the first differences of the variables as instruments for level equations.[14]

The most widely used tests for validating the assumptions involved in the generalized moment methods are the *m1* and *m2* tests, which are first- and second-order serial correlation tests of the estimated residuals, respectively, and the Sargan test, which checks the validity of the instruments used. If the error component ε_{it} in (1) is not serially correlated (which we would want to check), there should be evidence of negative first-order serial correlation and no evidence of second-order serial correlation

[14] See Blundell et al. (2000), Bond et al. (2001) or Marrero (2009) for a more detailed description of these GMM-based procedures. Moreover, a technical appendix would be available upon request.

in the first differences of the errors ε_{it}-ε_{it-1}. Thus, the value of the statistic *m1* must be negative and its associated p-value should be small (less than 0.05, for example), while the p-value associated with the *m2* test should be high (greater than 0.05, for example). The absence of serial correlation in these errors also suggests that the effects of the economic cycle do not significantly bias our results (Caselli et al., 1996).[15]

4. DATA

In this section we describe the data series used to estimate the model described in the previous section, and which involved panel data from 144 observations corresponding to 16 Spanish regions, with the exception of Ceuta, Melilla and the Canary Islands, which exhibited problems with the data. The time period spans from 1998 to 2006. Based on the variables specified in model (1), the following data were considered:

- Vehicle kilometers of travel (VKT) in road transport for the Spanish regions considered, compiled from Ministry of Development statistics.

- Vehicle fleet measured as the total number of vehicles for every region, compiled from Spain's Department of Motor Vehicles (DGT).

- Road network, measured in kms, for every region, extracted from Ministry of Development information.

- Real gasoline and diesel prices, measured in euros, obtained from the Ministry of Development.

- Gasoline and diesel used in road transport, measured in kilotons (kt), for every region and obtained from the Statistical Bulletin on Hydrocarbons (CORES,

[15] The *m1* and *m2* tests are based on the standardized residual covariance matrix and are asymptotically N(0,1) under the null hypothesis of no autocorrelation. The Sargan test is distributed chi-squared with the degrees of freedom equal to the number of instruments minus the number of parameters to be estimated under the null hypothesis that the instruments are valid. The Sargan test is less reliable (and used) in cases like ours, since it requires that the errors be independent and identically distributed, an unreasonable assumption in our case. Thus, our reliance is only on the m1 and m2 tests.

Ministry of Industry, Tourism and Commerce). These data series are used to calculate the average fuel price.[16]

- Real Gross Domestic Product (GDP) for every region, obtained from the National Statistics Institute (INE).

- Population for every region, obtained from INE statistics.

Table 1 shows the average growth rates of the endogenous variable (vehicle kilometers of travel per inhabitant) and of the explanatory variables considered for each Spanish region for the period in question. As noted in the previous section, all of the data are expressed in per capita terms except for fuel price. First, we note that per capita traffic grew in every Spanish region.[17] Among the different regions, Cantabria was the one that exhibited the highest per capita growth rate for the period considered (7.39%), while the Basque Country recorded the lowest growth for this variable, at just 0.63% on average. As for the per capita road network, this grew only in the regions of Aragón, Asturias, Castilla-León, Extremadura and Galicia, with average annual growth rates of between 0.08% and 0.73%. In the remaining regions, although the road network grew in absolute terms, it decreased in per capita terms due to the strong relative growth in population experienced between 1998 and 2006. For example, in the Balearic Islands, population growth was in excess of 3% while the road network expansion was minimal, resulting in a 3.01% drop in this variable in per capita terms. Thus, a simple aggregate comparison of the time dimension in both series (traffic and road network) does not appear to support the hypothesis for the existence of induced demand among Spanish regions, since large increases in per capita traffic are accompanied by small or even negative growth in the road network variable.

INSERT TABLE 1 ABOUT HERE

[16] The real price of fuel was calculated as a Laspeyres index, using the prices of gasoline and diesel and the weights corresponding to the amounts consumed of each.

[17] Spain is, along with perhaps Ireland, the European country with the highest growth in mobility in the last decade.

If we analyze these variation rates in the cross section we see how regions like Extremadura and Galicia are among those with the largest gains in both traffic and road network. At the other extreme are regions like Madrid and Catalonia, which have seen the least growth in terms of traffic and road network. In this sense, these cases would seem to support a positive correlation between traffic and the network, but the evidence from the cross section is inconclusive, yielding cases like that of Aragón (small increase in traffic and one of the largest increases in the network) and of Castilla La Mancha (large traffic increases and one of the most significant drops in road network), which imply a negative correlation between the variables of interest.

Therefore, a simple glance at the data reveals nothing conclusive regarding the presence or absence of induced demand. This comparison only involves a cursory analysis for simple correlation, one which omits many factors (such as activity levels, price trends, motorization rates or simple fixed regional effects) that, if considered, could alter the direct impact the road network has on traffic, which is what we in fact want to measure. Hence, in order to properly contrast the induced demand hypothesis, we need to use a properly specified model (such as model (1)), which simultaneously consider the time variable and the cross section, omit the least number of variables possible and use an estimating procedure that is consistent with and efficient for the statistical information available (panel data) and the model specified (dynamic).

As for the remaining explanatory variables considered, we should note that the motorization rate increased in all Spanish regions, with growth rates averaging a maximum of 4.5% in Extremadura and a minimum of 0.68% for the Balearic Islands. In reference to per capita GDP growth rates, we noted an average national growth rate of 2.6%, ranging from 0.11% in the Balearic Islands to 3.7% in Extremadura. In general, the per capita GDP series exhibit notable synchrony, of note being the deceleration between 2001 and 2003-2004 and the subsequent recovery until 2006 in most cases. Lastly, the real price of fuel increased in all regions at rates of between 1.45% and 4.5%, though notable differences in growth rates were noted over the period analyzed. The high volatility in fuel prices stemmed from Spain's enormous dependence on foreign oil, from the sharp fluctuations in the price of this oil in dollars from 1999 to 2006 and from changes to fuel taxes and their effect on the final price of fuel.[18]

5. RESULTS

In this section we estimate equation (1) using different panel data methods. A comparison of the results obtained with the different estimating procedures will allow us to discuss the utility of the estimates for each of the methods considered, which are: OLS using the entire data pool (OLS-POOL); the Within method with fixed and random effects;[19] and lastly, the two procedures discussed in Section 3: GMM-DIF and GMM-SYS. Table 2 shows the estimates for model (1) using these methods, along with the t-statistic of the individual significance test and its associated p-value.

Based on the above discussion, greater importance will be given to the results of the GMM-SYS method, though its comparison with other procedures is of great interest. In terms of the estimate of the parameter associated with the Traffic delay, the theory (Hsiao, 1989) says that the OLS-POOL method and the random effect method bias the parameter upward, while the fixed effect method biases it downward. Likewise, if there are *weak instrument* problems with the GMM-DIF procedure, the simulation results presented in Blundell and Bond (1998), Bond et al. (2001) and Blundell et al. (2000) show that its estimate will be biased toward the fixed effect method.

Based on the estimates shown in Table 2 for the β coefficient of model (1), the results indicate that this type of bias is in fact taking place. While the estimates for β are clearly in excess of 0.5 and close to 1 for the OLS-POOL and random effect cases, they are not significantly different from zero for the fixed effect and GMM-DIF cases. The estimate for β with the GMM-SYS method is between that for OLS-POOL and the fixed effects, with the estimate being 0.50 and significantly different from zero, as suggested by the simulations in the references mentioned earlier.[20] The consistency in the comparison between our estimates and the results of the Blundell and Bond simulations seems to

[18] For example, the dollar price of a barrel of Brent crude fell 14% in 2001, while in 2004 and 2005 it went up 33 and 42%, respectively.

[19] The results of the random effect method are shown for illustrative purposes only, since the Haussman test, which discriminates between fixed and random effects, clearly favors the former.

favor the GMM-SYS procedure when estimating equation (1). Moreover, as regards the *m1* and *m2* contrasts for the GMM method, we note that these are consistent with the absence of correlation between the residuals of model (1), in that the p-value of *m1* is small (i.e. less than 0.05) and its coefficient is negative, while the p-value associated with *m2* is considerably greater than 0.05.

INSERT TABLE 2 ABOUT HERE

The contrast of the induced traffic hypothesis involves the coefficient associated with the road network variable. A positive and significant coefficient would be indicative of evidence in favor of the existence of induced demand. We must first note that in our case, this coefficient depends on the estimation method considered. This is a relevant result, since it highlights the importance of considering the correct estimation method when contrasting this type of hypothesis, whose effect on the proper design of transport policies could be very relevant. In our study, the coefficient is not significant in the fixed effect and GMM-DIF methods. Recall that these procedures, as discussed earlier, generate biased estimates. The coefficient is positive and significant in the remaining procedures. Two of these procedures (OLS-POOL and random effects) also exhibit serious bias problems in theory. Their coefficients (short-term elasticities) are significant, but have an order of magnitude below 0.1, an uncommon finding in the literature. The GMM-SYS procedure, on the other hand, yields a higher magnitude and a significant coefficient. The estimate is 0.1232, with a very low associated p-value (0.0013), meaning the coefficient is significant even at the 1% level. As noted in Section 3, this elasticity refers to the short-term impact, which is similar to that obtained by Reuter et al. (1979) (cited in Cervero and Hansen, 2002). The long-term, or accumulated, elasticity for these types of models is given by 0.1232/(1-0.5025), which is equal to 0.2476, values that are slightly below those obtained by Cervero and Hansen (2001), which spanned from 0.3 to 0.5, and those obtained by Fulton et al. (2000), who expanded the range to between 0.2 and 0.6.

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[20] The evidence for conditional convergence is significant and the estimate obtained indicates a 50% annual reduction in the convergence ratio for the per capita traffic, conditioned to its long-term

The elasticity value obtained in this paper for the road network is in line with the aggregate nature of the data utilized since, as reported by Noland (2001), in general, the greater the level of disintegration considered, as differentiated by road type, the greater the resulting elasticities. A similar argument is made by Boarnet (1997), who noted that the induced demand derived from a project tends to be small when analyzed from a regional standpoint, and larger if referenced to a specific area or corridor. This is because on a regional level some areas could experience traffic gains at the expense of other areas from which traffic may be diverted.

As for the coefficients for the remaining regressors, and focusing now on the results of the GMM-SYS procedure, we note the following results.[21] The per capita GDP coefficient is not significant. This result is similar to that found by Fulton et al. (2000) for some regions, and suggests that there is no significance effect of an increase in per capita GDP on an increase in vehicle-kilometers traveled. This could be a reflection, as argued in Fulton et al. (2000), of the fact that greater distances are often traveled in rural areas (Castilla Leon, Castila la Mancha or Extremadura in our case), which generally have lower income levels. As for energy prices, these have a negative and highly significant incidence on road traffic mobility, as indicated by the theory. The estimated elasticity is -0.311 and its coefficient is significant at the 1% level. These values are in concert with the values found in other studies. Authors like Oum et al. (1992) found a value of between -0.1 and -0.5 for the price elasticity of travel. Their research also revealed an effect between price policies and road mobility. Lastly, the estimated elasticity for the motorization rate in the region (vehicles per inhabitant) is 0.478 and also significant at the 1% level. This result likewise serves to highlight how policies that encourage vehicle ownership result in, among other things, greater road mobility, with the consequent increases in traffic congestion and energy consumption.

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equilibrium level for each region.

[21] As for the results from the other estimation procedures, and on a final note, we should point out that only with the GMM-SYS procedure are the signs and significance of the various regressors consistent with transport theory.

6. CONCLUSIONS

While there is currently a broad consensus on the existence of induced traffic, there is greater disagreement over the values of traffic elasticities with respect to the road network. The main goal of this paper was to quantify the induced traffic for Spanish regions and to check whether the results obtained are sensitive to the estimation method employed. To this end, we estimated dynamic panel models for 16 Spanish regions from 1998 to 2006 and used traditional methods for estimating panel data with fixed and random effects, as well as the first-differenced Generalized Method of Moments (GMM-DIF) and its system version (GMM-SYS). The results obtained provide evidence for the existence of induced transport demand in Spain and show the relevance of applying proper estimating methods when working with dynamic panel models (the GMM-SYS method in our case). This last result is noteworthy since obtaining accurate estimates for the existence and magnitude of induced demand has important implications for the proper design of transport policies.

Focusing on the estimates yielded by the GMM-SYS method, the induced demand hypothesis is not rejected at the 1% significance level. The estimated short-term elasticity is .012, while the accumulated, or long-term, elasticity is almost 0.25. These values are similar to those obtained in other studies and are in keeping with the nature of the data used in our research. This allows us to conclude that the time saved by expanding the road network translates into an increase - though less than proportional - in the amount of kilometers traveled. Thus, even if the expanded road infrastructure does translate into improved services for some segments of the population, this effect will tend to exhaust itself in the long term.

Finally, we note that the estimates for other elasticities output by the GMM-SYS method are also consistent with transport theory. The per capita GDP is not significant once other explanatory variables are taken into account (as was shown in Fulton et al., 2000). Moreover, energy prices have a negative and very significant effect on road traffic mobility, yielding an elasticity estimate of -0.311. This highlights the importance of price policies on road mobility. Lastly, the estimated elasticity for the motorization rate is 0.478, which indicates that any policy encouraging vehicle ownership would lead to, among other things, greater road mobility, with the consequent increases in congestion, energy consumption and pollution emissions.

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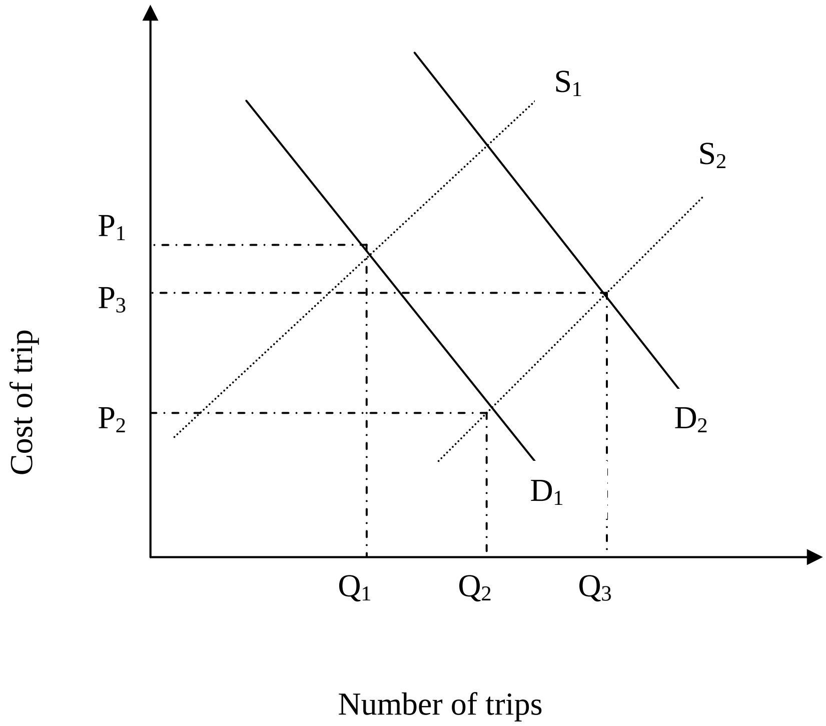
APPENDIX: FIGURES

FIGURE 1: Travel Supply and Demand



APPENDIX: TABLES

TABLE 1: VARIABLES USED PER REGION.

Average annual growth rate 1998-2006

REGIONS	Per capite VKT	Per capite Road Network	Per capite Vehicle fleet	Per capite GDP	Real Fuel Price
ANDALUCÍA	4,61	-1,04	3,81	3,01	4,13
ARAGÓN	1,82	0,73	3,01	2,73	4,01
ASTURIAS	4,09	0,74	3,15	3,12	4,38
BALEARIC ISL.	3,49	-3,01	0,68	0,11	3,21
CANTABRIA	7,39	-0,54	3,78	3,24	1,39
CASTILLA - LA MANCHA	6,31	-0,70	4,01	2,30	4,18
CASTILLA- LEÓN	3,66	0,08	3,63	3,18	4,21
CATALONIA	1,11	-1,39	1,56	2,17	4,51
VALENCIA	3,87	-1,72	2,11	2,02	3,95
EXTREMADURA	5,21	0,38	4,45	3,72	4,22
GALICIA	5,54	0,20	3,49	2,95	4,25
MADRID	1,28	-1,58	1,68	2,62	4,29
MURCIA	3,63	-1,86	3,08	2,27	3,38
NAVARRE	3,66	-0,40	2,32	2,82	3,78
BASQUW COUNTRY	0,63	-0,58	2,46	3,53	4,07
LA RIOJA	4,10	-0,95	2,39	1,90	3,89

TABLE 2: ESTIMATIONS OF THE TRAVEL DEMAND WITH DIFFERENTS PANEL DATA METHODS

		OLS_POOL	
Variables	Parameters	t-statistic	p-value
Traffic -1	0,7426	12,4853	0
Network	0,0699	3,6221	0,0004
GDP	0,0313	0,6988	0,486
Price	0,0309	0,2836	0,7772
Fleet	0,1375	1,634	0,1048
R^2	0.9072		
		Fixed effects	
Variables	Parameters	t-statistic	p-value
Traffic -1	0,0178	0,2006	0,8413
Network	-0,1237	-0,6969	0,4872
GDP	1,1101	3,1207	0,0022
Price	-0,0262	-0,2623	0,7935
Fleet	-0,2613	-0,815	0,4167
R^2	0.5027		
Haussman, test	124,708	--	0
		Random Effects	
Variables	Parameters	t-statistic	p-value
Traffic -1	0,9448	35,5838	0
Network	0,0188	2,2699	0,025
GDP	0,0002	0,0085	0,9932
Price	0,0054	0,0499	0,9603
Fleet	0,0096	0,2675	0,7896
R^2	0.9772		
		GMM-DIF	
Variables	Parameters	t-statistic	p-value
Traffic -1	-0,0257	-0,3064	0,7593
Network	-0,1535	-0,7832	0,4335
GDP	1,5406	2,3396	0,0193
Price	-0,0616	-0,5131	0,6079
Fleet	-0,6171	-1,0674	0,2858
m1	-2,264	--	0,024
m2	-1,113	--	0,2666
		GMM-SYS	
	Parameters	t-statistic	p-value
Traffic -1	0,5025	3,2237	0,0013
Network	0,1232	2,6865	0,0072
GDP	-0,0793	-0,7007	0,4835
Price	-0,3115	-2,793	0,0052
Fleet	0,4785	2,6695	0,0076
m1	-4,116	--	0
m2	-0,67	--	0,503