Demand Elasticity on Tolled Motorways

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ABSTRACT

This paper analyzes the elasticities of demand on tolled motorways in Spain. We use a panel dataset covering an 18-year period, where the cross-section observations correspond to various Spanish tolled motorway sections. A dynamic model is estimated, which allows us to identify short-term and long-term responses to changes in the independent variables. The results show that demand is elastic with respect to the level of economic activity, whereas average elasticity with respect to gasoline price is in line with that estimated in previous studies. For the main variable of interest, the results indicate that demand is relatively sensitive to toll changes, although a wide variation is observed across motorway sections. A statistical analysis reveals that the main factors explaining such differences are related to variables that reflect the quality of alternative and free roads.

INTRODUCTION

In recent years, there has been renewed interest in using tolls to finance road investment, in order to avoid public budget constraints and at the same time to involve the private sector in the provision of infrastructure. In this new context, it is vital to have accu-

KEYWORDS: demand elasticities, toll motorways, intercity road traffic.

rate knowledge of demand behavior for forecasting and evaluation purposes. More precisely, it is necessary to know the elasticity of demand with respect to price, quality, or income, in order to obtain traffic and revenue forecasts or to evaluate potential negative effects such as the misallocation of traffic between tolled roads and parallel untolled roads.

Empirical evidence on demand elasticity on tolled motorways is limited due to the relative scarcity of tolled roads in the world.[1] Furthermore, most of the studies provide average elasticities for specific short road sections, tunnels, or bridges, which are highly dependent on site-specific factors such as the degree of congestion or the availability of alternatives. Because of this, it is difficult to transfer the results to other contexts.

This paper aims to provide new and robust evidence on demand elasticity on tolled motorways with respect to its main determinants, placing special emphasis on toll elasticities. We address this issue by estimating a dynamic demand function using a panel dataset consisting of observations of the Spanish tolled motorway network over the period 1981 to 1998. The results show that the sensitivity of demand to price depends both on the characteristics of the tolled motorways and on those of the alternative free road.

The next section provides a review of demand elasticity with respect to tolls followed by a brief summary of the toll policy in Spain. The model specification and certain relevant econometric issues are discussed next. In the following section, we present the data we used, and then we turn to the model estimation and results. We next carry out a statistical analysis in order to identify the factors that explain the differences in toll elasticities across motorway sections. Finally, the main conclusions of the paper are summarized.

REVIEW OF THE LITERATURE

There is a general consensus that, on average, transportation demand is fairly inelastic with respect to price. The empirical evidence gathered on toll elasticities (table 1) seems to confirm this. The most frequent values fall around −0.2 and −0.3 with a range of −0.03 to −0.50. These values correspond to average demand elasticities. Unfortunately, the potential sources of variation are not taken into account in a formal manner. Nevertheless, some authors do identify the characteristics that will have an impact on the elasticity value.

The lowest values of toll elasticities are usually observed for bridges in highly congested metropolitan areas in the United States. This result can be explained by the low level of the toll fee compared with other components of private car cost, such as parking fees (Harvey 1994). Wuestefeld and Regan (1981) found that response varies according to the purpose of the trips, trip frequency, the existence of a toll-free alternative, and journey length. Hirschman et al. (1995) state that demand is more sensitive in the case of those infrastructures with a good alternative untolled road.

Finally, some authors argue that traffic is sensitive to time-varying pricing schemes. Gifford and Talkington (1996) found evidence that day-of-the-week cross-elasticities are complementary; that is, an increase in toll rates on one day results in a reduction of traffic not only on that day but on other days of the week as well. Burris et al. (2001) showed that travelers responded to the off-peak toll discount implemented on two county bridges in Florida. They also showed that demand elasticities calculated across different off-peak periods varied considerably. These results suggest that the implementation of time-varying pricing schemes can encourage a more efficient use of motorways compared with a uniform toll throughout the day.

TOLL POLICY IN SPAIN

In the early 1970s, tolls were introduced on the road network in Spain mainly to raise revenue to finance construction, operation, and maintenance.[2] According to this objective, each motorway had to cover its own costs, and cross-subsidies between different motorways were not allowed. Initial toll rates were specific to each motorway concession and subsequently increased according to a cost

[1] According to the World Bank (2004), most countries have no toll roads and, where there are such roads, the tolled network typically comprises less than 5% of the entire road network.

[2] Appendix A provides a brief summary of the development of toll roads in Spain.

TABLE 1 Elasticity of Traffic Level with Respect to Tolls

Authors	Results	Context
Wuestefeld and Regan (1981)	Roads between −0.03 and −0.31 Bridges between −0.15 and −0.31 Average value = −0.21	16 tolled infrastructures in the U.S. (roads, bridges, and tunnels)
White (1984), quoted in Oum et al. (1992)	Peak-hours between −0.21 and −0.36 Off-peak hours between −0.14 and −0.29	Bridge in Southampton, UK
Goodwin (1988), quoted in May (1992)	Average value = −0.45	Literature review of a number of previous studies
Ribas, Raymond, and Matas (1988)	Between −0.15 and −0.48	Three intercity motorways in Spain
Jones and Hervik (1992)	Oslo −0.22 Alesund −0.45	Toll ring schemes in Norway
Harvey (1994)	Bridges between −0.05 and −0.15 Roads −0.10	Golden Gate Bridge, San Francisco Bay Bridge, and Everett Turnpike in New Hampshire (U.S.).
Hirschman, McNight, Paaswell, Pucher, and Berechman (1995)	Between −0.09 and −0.50 Average value −0.25 (only significant values quoted)	Six bridges and two tunnels in the New York City area, U.S.
Mauchan and Bonsall (1995)	Whole motorway network −0.40 Intercity motorways −0.25	Simulation model of motorway charging in West Yorkshire, UK
Gifford and Talkington (1996)	Own-elasticity of Friday–Saturday traffic −0.18 Cross-elasticity of Monday–Thursday traffic with respect to Friday toll −0.09	Golden Gate Bridge, San Francisco, U.S.
INRETS (1997), quoted in TRACE (1998)	Between −0.22 and −0.35	French motorways for trips longer than 100 kilometers
Lawley Publications (2000)	−0.20	New Jersey Turnpike, U.S.
Burris, Cain, and Pendyala (2001)	Off-peak period elasticity with respect to off-peak toll discount between −0.03 and −0.36	Lee County, Florida, U.S.

index based on the rate of inflation for the three main factors of production: labor, fuel, and steel. This resulted in a substantial variation in toll rates across the country, with higher tolls per kilometer on those motorways with larger construction costs or lower traffic volume.

However, for various reasons, the toll policy was modified over time and toll rates were not increased as planned. First, the severe economic crisis that the Spanish economy suffered from 1974 to 1984 revealed that certain concessionaires could not break even at initial toll rates. Three of the concessionaires with financial difficulties were taken over by the government, while others were merged with stronger companies. In both cases, the terms of the concession agreements were modified, leading to an increase in the initial toll rates in real terms. Moreover, explicit financial support from the government was allowed for a small share in the motorway network and cross-subsidies appeared among the merged concessionaires.[3] Furthermore, the formula approved for toll revisions was not systematically applied to all the motorways, and, as a consequence, toll rates for different motorways varied over time. Thus, in the 1980s, tolls increased in real terms on 8 of the 10 motorways, although at varying rates, whereas a decrease was observed in the other 2.

[3] It is important to note that the Spanish government assumed a very high level of risk as a consequence of the foreign rate assurance and the loan guarantees offered. The exchange rate losses over the period 1976–1996 were up to 65% of the total investment (Bel 1999).

In 1990, when most of the motorways had already been constructed, the toll revision formula was changed. Since then the new formula has been linked to the consumer price index (CPI) and allows for toll increases equal to 95% of annual CPI growth. This new approach to price regulation should have resulted in a slight decrease in toll rates in real terms over time for all the motorways. However, in practice, this formula was only systematically applied for a short period of time (1990 to 1996) and even then not to all motorways. The reasons again are manifold.

First, in the 1990s, there was renewed interest in the construction of tolled motorways from both central and some regional governments. In the first case, some concession agreements were renegotiated and existing toll rates reduced (even halved) to compensate for the introduction of tolls on upgraded toll-free motorways. Second, toll rates on regional motorways increased well above the average. Finally, the growing political pressure against tolls resulted in a renegotiation of most of the agreements with a reduction of toll rates in exchange for compensating the concessionaires with an extension of the concession period.

Since 1997, those motorways with higher tolls per kilometer have progressively reduced their rates; in some cases, the tolls decreased as much as 40% nominally in one year. Additionally, the rate of value-added tax was lowered from 16% to 7% on all the motorways.

The criterion used to set initial toll rates and changes in the toll policy during the 1990s have resulted in a wide range of variation of rates across the country and over time, which greatly facilitates the econometric estimation of toll elasticities.

MODEL SPECIFICATION

The Demand Equation

The methodology used to estimate the demand function was the panel data approach, where the cross-section observations correspond to motorway sections. This approach has two types of advantages. First, the temporal dimension allows the modeling of the dynamic adjustment of demand resulting from changes in transportation policy and the socioeconomic environment over time. Moreover, the cross-section observations provide more variation in the data, because toll rates vary more between motorway sections than they do over time. It thus solves the problem of insufficient variation in tolls per kilometer that appears in pure time series studies.[4] As a result, the estimated elasticity value captures the rich variation of prices across the different sections, as well as its temporal variation in a given section. Furthermore, by using a panel dataset, the number of observations is increased, which improves the precision of the estimated parameters.

We assumed that the volume of traffic on a motorway section is a function of the monetary and time costs of using the motorway, the monetary and time costs of using the alternative parallel free road or modes, the level of economic activity, and the generation and attraction factors at the origins and destinations. Monetary cost is defined as the sum of three components: toll, gasoline cost, and other vehicle operating costs. All the monetary variables were deflated by the CPI. The level of economic activity was measured as real gross domestic product (GDP); given that trips on motorways are undertaken for both leisure and business purposes, we used real GDP rather than disposable income in order to better capture the level of economic activity. Finally, the amount of traffic on a motorway section depends on the size of the potential market for each of them, which was determined by generation capacity and attraction of the origins and destinations, such as population and employment.

The model can therefore be expressed as follows:

$$Y_{it} = f\Big(GDP_t, GP_t, MT_{it}^m, OC_{it}^m, TC_{it}^m, OC_{it}^o, TC_{it}^o, O_i, D_i, u_{it}\Big) \tag{1}$$

where

m = motorway,

o = alternative (other) routes or modes,

Y_{it} = traffic volume on motorway section i in period t,

[4] When using a panel dataset, the total variability of a measure has two components: the within component (variability of the sample through time within each section) and the between component (variability of the sample across motorway sections). The panel dataset takes advantage of both sources of variability.

GDP_t = real national GDP in period t,
GP_t = gasoline price in period t deflated by the CPI,
MT_{it}^m = motorway toll on section i in period t deflated by the CPI,
OC_{it}^j = other vehicle operating costs (i.e., other than tolls and gasoline), $j = m, o$,
TC_{it}^j = time costs on section i in period t, $j = m, o$,
O_i = generation factors on section i,
D_i = attraction factors on section i,
u_{it} = error term, normally distributed with mean 0 and variance σ^2.

However, this is an ideal model. The empirical specification we finally estimated was limited by some data issues. Unfortunately, no data were available on other vehicle operating costs or time costs for the whole sample period. An analysis of the transportation costs in Spain allowed us to assume that vehicle operating costs and time costs have remained approximately constant over time on most of the motorway sections although this hypothesis did not hold for some of them. This was the case for seven sections, located around urban areas where both an increase in congestion and changes in the road network have affected the quality of service. These observations were excluded from the sample. The rest of the sections corresponded to interurban motorways where congestion was not a problem on most days. Hence, it can be assumed that time costs have remained relatively constant over time.

In order to take into account the most significant changes in the road network, a set of dummy variables was introduced. For example, the improvement of a parallel free road was captured by a dummy variable that takes the unit value since the opening year. Finally, the generation and attraction factors showed that the difference in traffic volume across motorway sections related mainly to population and the level of economic activity. Given that the dependent variable was observed for very short sections of the motorway and given also the difficulty in identifying how these factors should be measured, we assumed that these factors were captured by the specific fixed effects.[5]

[5] See Voith (1991) for a similar assumption.

Hence, under the assumption that $OC_{it}^j = OC_i^j$ and $TC_{it}^j = TC_i^j$ for $j = m$ and o, the equation can be rewritten as

$$Y_{it} = f\left\{\left(OC_i^m, TC_i^m, OC_i^o, TC_i^o, O_i, D_i\right), GDP_t, GP_t, MT_{it}^m, Z_{it}, u_{it}\right\} \quad (2)$$

where Z_{it} is the vector of dummy variables accounting for major changes in the network. These variables are defined in table 2.

One of the advantages of using a panel dataset is that this methodology allows us to explain the differences between cross-section observations not captured by the variables included in the model through the individual fixed effects, α_i. These individual fixed effects are represented by specific intercepts for each motorway section in the sample, and they capture the effect of factors not included in the equation that can be considered fixed over time but vary among motorway sections.

Thus, the demand equation can be rewritten as

$$Y_{it} = f(\alpha_i, GDP_t, GP_t, MT_{it}^m, Z_{it}, u_{it}) \quad (3)$$

where α_i captures the variables in parentheses in equation (2).

From a statistical point of view we have validated the assumed hypothesis that certain factors remain relatively constant over time by the application of recursive least squares.[6] This methodology allows us to prove the constancy of the estimated coefficients over time, so the null hypothesis of the structural constancy of the model is not rejected by the data.

Given the low number of temporal observations available for some of the motorway sections, the demand elasticities with respect to GDP and gasoline price are assumed to be the same across all motorway sections. According to the statistical test

[6] The recursive least squares technique estimates the model by adding new temporal observations in a progressive way, thus making it possible to test the stability of the coefficient vector. If the coefficient displays significant variation as more data are added to the estimated equation, it is an indication of instability. In our case, using the standard approach, the calculation of confidence intervals for the estimated recursive coefficients verifies the structural constancy hypothesis.

TABLE 2 Definition of the Dummy Variables Included in the Estimated Demand Equation

Dummy variables	Period	Comment	Expected sign
Z1–Z4	1994–1998	They reflect the negative impact on traffic on the 4 A(2) motorway sections, derived from capacity and quality improvements on the alternative free road.	–
Z5–Z7	1992	They account for the positive impact on the 3 A(4) motorway sections, derived from the Seville World Exhibition in 1992.	+
Z8–Z11	1995–1998	They reflect the negative impact on traffic on 4 A(7) motorway sections as a consequence of the extension of an alternative tollway.	–
Z12, Z14, and Z16	1993–1998	They reflect the negative impact on traffic on 3 A(7) motorway sections, derived from the opening of an alternative free motorway.	–
Z13, Z15, and Z17–Z24	1990–1998	They account for the positive impact on traffic on 10 A(7) motorway sections, due to the extension of this motorway.	+
Z25	1996–1998	It reflects improvements in the free alternative motorway network for the first of the A(19) motorway sections.	–
Z26, Z27, and Z28	1994–1998	They account for the positive impact on traffic on the 3 A(66) sections as a consequence of the improvement and extension of the motorway.	+

Notes: In Spain, the motorways (autopistas) are identified by the letter "A" followed by a number in parentheses. These variables take the value 1 in the reported period; otherwise they are 0.

applied, these constraints were not rejected by the data.[7] The advantage of estimating a constrained model is that it allows efficiency gains in the estimation of the main parameter of interest, which in our case is toll elasticity. The coefficients of the toll variable, and hence the toll elasticities, are specific for each motorway section. We will, therefore, estimate different toll coefficients for each cross-section unit, which will depend on the characteristics of the motorway and the alternative routes.

To sum up, the traffic volume on motorway section i in period t depends on the individual fixed effects, the level of economic activity, the price of gasoline, and the level of toll. The individual fixed effects capture the effects of factors not included in the equation that remain relatively constant over time but vary among the different motorway sections. As previously mentioned, even for this more parsimonious version of the model, the use of recursive estimation techniques does not reject the temporal stability of the coefficients.

[7] The calculated F statistic for the hypothesis of equal elasticity with respect to gasoline price in all the sections of the motorway included in the sample is 0.944; for the hypothesis of equal elasticity with respect to GDP it is 1.082, while the critical value at a significance level of 5% is 1.22.

Some Econometric Issues

The next step in the model specification process is to decide on the functional form for the demand equation. The first issue we considered is whether the series are stationary or integrated[8] and, in the case of integrated series, whether they are cointegrated or not. The available econometric literature does not offer a clear guide on how to deal with this issue when panel data are used.

In this study, in spite of the short time span for the series (a maximum of 18 years), the traditional unit root tests (Augmented Dickey Fuller and Phillips Perron) were used to test whether the variables were stationary or integrated. The tests were applied to each motorway section. The null hypothesis of unit root was always nonrejected at the usual significance levels of the tests. However, the same tests showed the stationarity of the variables in first differences.

[8] Using integrated series (unit root series) is not a problem if the considered variables are cointegrated, given that in this case the cointegration property guarantees that the estimates are both consistent and efficient. However, if the variables are not cointegrated, this may give rise to the spurious regression problem. For a standard reference to unit root and cointegration tests, see Hamilton (1994). All results from the applied test are available on request.

The following step is an analysis of the series' cointegration. We carried this out using the Engle-Granger and the Cointegration Equation Durbin-Watson tests.[9] In this case, in almost all regressions estimated in levels, the null hypothesis of no cointegration was also nonrejected. Based on this evidence, and following standard econometric practice, all the estimations were carried out using first differences of the variables.

Second, in order to allow for dynamic effects, the starting specification included lags of the dependent and explanatory variables. The search for the final specification followed a general-to-specific process. After simplifying the model with restrictions that were not rejected by the data, a partial adjustment equation was selected. Therefore, both exogenous and lagged dependent variables appear as explanatory variables in the final model.

Finally, given that there are no theoretical arguments that can contribute to the choice of the functional form for the demand equation, we proceeded to select the most appropriate one on the basis of the goodness of fit of the models. We considered three alternatives—the linear model, the semi-log model, and the log-linear model—which are three of the most widely used in estimating aggregate demand models. The criterion used to select among these alternative specifications is based on the comparison of the values of the log of the likelihood function from the three competing models.[10] According to this criterion the log-linear specification was preferred as it showed the highest value for the log of the likelihood function.[11]

According to the three issues previously discussed, the equation to be estimated corresponds to a partial adjustment model where the variables are in first differences of the logarithms. The equation can be written as follows:[12]

$$\begin{aligned}\Delta \ln(Y_{it}) &= \beta_1 \Delta \ln(GDP_t) + \beta_2 \Delta \ln(GP_t) \\ &\quad + \beta_{3i} \Delta \ln(MT_{it}^{m}) + \varphi \Delta \ln(Y_{it-1}) \\ &\quad + \gamma' \Delta Z_{it} + \varepsilon_{it} \qquad (4)\end{aligned}$$

It must be stressed that in equation (4) using first differences of the variables eliminates the fixed effects from the estimated equation. In other words, the section-specific intercepts appearing in the model expressed in levels vanish from the finally estimated equation.

The presence of the lagged dependent variable as a regressor implies a dynamic structure for the response of the dependent variable to changes in the explanatory variable. That is, individuals do not adjust their behavior in one period, but with a delay. The underlying hypothesis for this specification is that present behavior is also determined by the values of the explanatory variables in the past. Therefore, the estimation of a dynamic model makes it possible to distinguish between short-term and long term effects. In our study, short term refers to the effect on demand occurring within one year of a change in the relevant variable, whereas long-term measures the total response to a change in the independent variable over time.

According to equation (4), the coefficients of the independent variables (β) should be interpreted as short-term elasticities. The long-term elasticities are

[9] The Johansen test was not applied to test cointegration, because this test assumes the existence of feedback between all the variables. In our case, variables such as gasoline price, toll, and GDP must be considered as weakly exogenous in a model trying to explain motorway traffic volume.

[10] The log of the likelihood functions for the linear, semi-log, and log-linear specifications are, respectively:

$$L_0 = C - \frac{T}{2}\ln(SSR_0), L_1 = C - \frac{T}{2}\ln(SSR_1) - \sum_1^T \ln(Y_t),$$
$$L_2 = C - \frac{T}{2}\ln(SSR_2) - \sum_1^T \ln(Y_t)$$

where the constant C is the same for each specification, SSR is the residual sum of squares, Y is the dependent variable and T is the sample size (see Davidson and MacKinnon 1993). The calculated values for these functions are, respectively, –9,768.5, –9,201.8, and –9,183.6

[11] The log-linear functional form is one of the most widely used functional forms in aggregate demand models. In spite of its simplicity, the log-linear specification offers an adequate approximation to the demand curve, at least in the neighborhood of the actual data. This is the usual procedure for selecting among alternative functional forms when estimating aggregate transportation demand equations. For an application of similar procedures see, for example, Oum (1989) and Dargay and Hanley (2002).

[12] This is a standard specification for aggregate demand functions. See, for instance, Dargay and Goodwin (1995), Dargay and Hanley (2002).

$\frac{\beta}{1-\varphi}$, where $1-\varphi$ is the adjustment factor measuring the speed of adjustment. The greater the value of φ the slower the speed of adjustment and the greater the difference between short-term and long-term elasticities.

The concept of mean lag is useful to characterize the dynamic structure of the model. The mean lag is defined as a weighted average of the lag structure of the model, where the weighting coefficient for period *j* is the ratio between the coefficient with lag *j* and the long-term coefficient. The mean lag can be calculated as $\frac{\varphi}{1-\varphi}$.

THE DATA

The data cover all Spanish tolled motorways sections for 18 observation years between 1981 and 1998 (see Ministerio de Fomento Annual). The cross-section observations correspond to the shortest motorway section allowed by data-collection processes, with an average length of 14.7 kilometers. The use of these short sections guarantees that the observed traffic mix is homogeneous.

We eliminated 11 sections: those that experienced significant changes in congestion (either on the motorway or on the alternative routes), those that partially admit toll-free traffic, and those that have open tolls. Not all the motorways sections were observed for all the years in the sample. Only sections for which data were available for at least eight periods were used. Furthermore, those sections belonging to motorways not completely constructed during the observation period were also eliminated to avoid changes in traffic volume that may be due to the progressive extension of the motorway. The final sample was a panel dataset of 72 road sections for 1981 through 1998, although this temporal span was not available for all cross-section units. The total number of observations was 1,135.[13]

The dependent variable is the annual average daily traffic volume in each section, defined as the number of vehicle-kilometers run per year, divided by section length and number of days.[14] The explanatory variables are real GDP, gasoline price, and toll per kilometer, the last two deflated by the CPI. Working with short sections of the motorway made it possible to calculate in a fairly precise way the toll paid per kilometer. GDP and gasoline prices are defined at the national level and take the same value for all sections in the sample, but, as we are working with a panel dataset, these have different values for each year of the sample. Finally, a set of 28 dummy variables captures the most important changes in the road network. These variables, defined in table 2 (page 6), take the value 1 in the reported period and 0 otherwise. The main descriptive statistics for the explanatory variables are defined in table 3.

Before estimating the demand equation, we present two of the main features of the relevant variables in the study: traffic volume and toll paid per kilometer. First, as figure 1 shows, there seems to be a clear relationship between the level of economic activity—measured as GDP—and traffic volume over time. Using aggregate data for all the motorway sections for 1981 through 1998, figure 1 shows the synchronism between the rates of growth of GDP and traffic volume with a correlation coefficient equal to 0.796.[15] This preliminary result is in line with previous studies showing that automobile use is elastic with respect to income.[16] It is also interesting to compare the cycles of GDP and traffic volume.[17] As can be seen in figure 2, the traffic cycle clearly overreacts to the GDP cycle. Therefore, in periods of economic expansion, the cyclical components of

[13] Given that the equation is estimated in first differences of the logarithms and includes the lagged dependent variable, the final number of observations is reduced to 990.

[14] It should be noted that the dependent variable is an aggregate of different types of traffic, of different length and purpose. Therefore, estimated elasticity for each section must be understood as an average value.

[15] The *t* statistic is equal to 5.27 and for 18 observations the null hypothesis of independence will be rejected at a *P*-value of 0.0001. This confirms the narrow relationship that exists between both variables.

[16] For a recent review on this subject, see Graham and Glaister (2002).

[17] Cycles for both variables were obtained through the application of the Hodrick-Prescott filter to the log of the series and by calculating the difference between the observed and trend values. This filter is a standard technique that allowed us to smooth the series in order to obtain an adaptive long-term trend for the variable. It is usual to consider that the difference between the observed series and smoothed series approximates the cycle.

TABLE 3 Descriptive Statistics

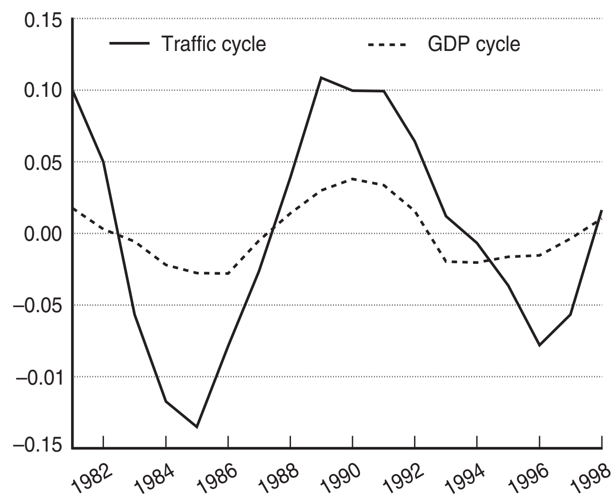
Variables	Mean	Median	Maximum	Minimum	Std. dev.	Observations
Daily traffic volume	11,490	9,460	63,741	1,689	8,821	1,135
Toll (euros per km)[1]	0.091	0.086	0.224	0.037	0.035	1,135
Gasoline price (euros per liter)[1]	0.619	0.533	0.867	0.486	0.139	18
GDP (millions of euros)[1]	219,311	230,277	275,869	174,149	33,619	18
Section length (kms)	14.7	13.9	43.0	2.0	8.2	72

[1] The base year for variables expressed in monetary units is 1992.

traffic volume exceed the corresponding components of GDP, while the opposite occurs during recession.

Second, at the cross-section level, a substantial difference is observed in traffic volume among the different motorways as well as among sections of the same motorway. The daily average traffic volume ranges from 1,689 automobiles per day in the section and year having the lowest volume to 63,741 automobiles per day in the section and year with the highest. Finally, as we explained earlier, we found an extensive price range for initial toll rates. For the whole period, at 1992 prices, the lowest price paid per kilometer was about 0.037 euros, whereas the highest was about 0.22 euros.

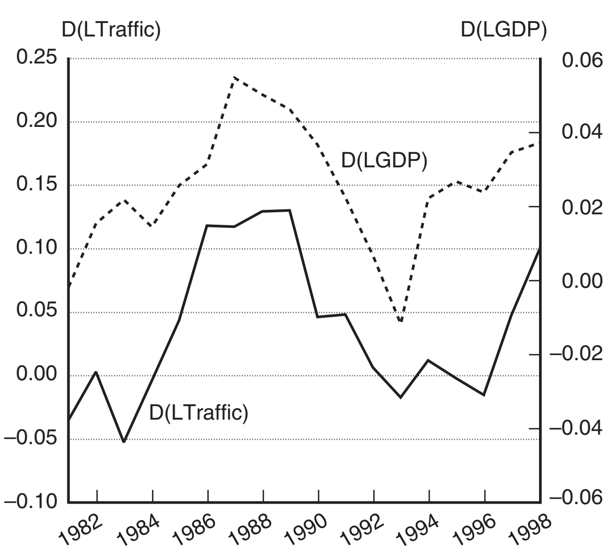
FIGURE 2 Traffic Cycle and GDP Cycle



RESULTS

The results of the estimated model—equation (4)—show that all the estimated coefficients have the expected signs and most of these were estimated with a high degree of precision, as measured by the standard error of the coefficients (see appendix B). Given that heteroscedasticity was observed in the variance of the random term between sections, the model was estimated using weighted least squares (WLS). Comparing ordinary least squares with WLS, the latter procedure results in similar estimates while the standard errors decrease. In relation to the toll coefficients, a significant variation across motorway sections was observed.

FIGURE 1 Rate of Growth of GDP and Traffic Volume



A Chi-square test allowed us to clearly reject the null hypothesis of equality of toll coefficients across all sections.[18] On the other hand, the differences in the value of the toll coefficient (which, given the model specification, correspond to short-term elasticity) could be explained by certain motorway characteristics. First, adjacent sections in the same motorway present very similar elasticities. Second,

[18] The calculated Chi-square statistic was 113.12, while the critical value for 71 degrees of freedom (d.f.) at a significance level of 5% is 52.0.

the more inelastic sections are located on corridors with a high volume of traffic—mainly the motorways along the Mediterranean coast. Third, demand is seen to be more elastic where a good alternative free road exists.

The observed results suggest the possibility of re-estimating the model introducing the hypothesis of equality of toll elasticities across those motorway sections that showed similar coefficients in the initial general model. The introduction of equality constraints among coefficients, not rejected by the data (see below), makes it possible to obtain more precise estimates of the coefficients by reducing both the number of coefficients to be estimated and the multicollinearity. In fact, we followed standard econometric methodology that recommends going from the general to more parsimonious model. These constraints were introduced by classifying the motorway sections into the following groups according to the toll coefficient estimated in the general model:

1. Low short-term elasticity: sections with toll coefficients between 0 and −0.3.
2. Middle-low short-term elasticity: sections with toll coefficients between −0.3 and −0.4.
3. Middle-high short-term elasticity: sections with toll coefficients between −0.4 and −0.6.
4. High short-term elasticity: sections with toll coefficients larger than −0.6 in absolute value.

Thus, four different coefficients for toll elasticities are now estimated. Detailed results of this final model are reported in table 4 and correspond to the WLS estimation. The application of a Chi-square test did not reject the hypothesis of classifying the motorway sections into four groups according to their estimated toll elasticity.[19] The model fits the data well and all estimated coefficients are highly significant. The level of economic activity has a positive effect on traffic volume, whereas gasoline price and the toll have a negative influence. With respect to toll coefficients, significant differences among them can be observed, according to the grouping by sections mentioned above. All dummy variables take the expected signs described earlier in table 2. It should be noted that the inclusion of these variables increased the statistical significance of toll variable estimates without modifying their value in any noticeable way.

The short-term and long-term elasticities are summarized in table 5. As can be seen from the *t*-statistics, all the estimated coefficients are significant at *P*-values clearly lower than the conventional 0.05 or 0.01 levels. A lag parameter equal to 0.366 implies a long-term effect of about 1.58 times the short-term effect. This result reflects a wider range of opportunities and available options open to individuals over a longer time span. However, the period of adjustment is relatively short, with 87% of total adjustment taking place within the first two years.

Traffic on tolled motorways is shown to be elastic in relation to GDP, with elasticity values equal to 0.89 and 1.41 for the short- and long-term, respectively. This result confirms what is intuitively obvious in figures 1 and 2. Elasticity with respect to gasoline price equals –0.34 in the short term and –0.53 in the long term. Our results are consistent with those reported in the literature,[20] although they are closer to the maximum reported values. In the context of this paper, relatively high value for gasoline price elasticity can be expected, compared with other estimates carried out for freeways, given that when the gasoline price is increased tolled motorway users can shift to a parallel free road.

The estimated coefficients on the toll variables provide evidence that demand is sensitive to toll variations. This conclusion is supported by the high precision, measured by the standard error, with which the elasticities have been estimated. Nonetheless, significant differences were observed among groups of motorways. For the first group, demand is shown to be rather inelastic. Short-term and long-term elasticities are equal to –0.21 and –0.33, respectively. However, for the remaining groups, demand becomes more price elastic. For those

[19] The calculated Chi-square statistic was 13.27, while the critical value for 68 d.f. at a significance level of 5% was 49.0.

[20] For a literature review of such findings, see Goodwin (1992), Oum et al. (1992), Johansson and Schipper (1997), Espey (1998), and de Jong and Gunn (2001). Graham and Glaister (2002) provide an extensive international review of demand elasticity with respect to fuel price.

TABLE 4 Estimated Demand Equation
Dependent variable: D(LTRAFFIC)
Estimation method: weighted least squares
Total system (unbalanced) observations: 990

Variable	Coefficient	Std. error	*t*-statistic	*P*-value
D(LGDP)	0.8901	0.0409	21.7605	0.0000
D(LPGAS)	–0.3367	0.0153	–22.0050	0.0000
D(LTRAFFIC(–1))	0.3659	0.0158	23.1470	0.0000
D(LTOLL1)	–0.2092	0.0177	–11.813	0.0000
D(LTOLL2)	–0.3707	0.0147	–25.248	0.0000
D(LTOLL3)	–0.4449	0.0225	–19.801	0.0000
D(LTOLL4)	–0.8286	0.0844	–9.8179	0.0000
D(Z1)	–0.0517	0.0260	–1.9919	0.0467
D(Z2)	–0.0689	0.0239	–2.8782	0.0041
D(Z3)	–0.0718	0.0246	–2.9179	0.0036
D(Z4)	–0.0519	0.0263	–1.9745	0.0486
D(Z5)	0.1549	0.0396	3.9136	0.0001
D(Z6)	0.1690	0.0364	4.6466	0.0000
D(Z7)	0.1196	0.0583	2.0507	0.0406
D(Z8)	–0.0679	0.0219	–3.1035	0.0020
D(Z9)	–0.0623	0.0201	–3.1029	0.0020
D(Z10)	–0.0656	0.0286	–2.2911	0.0222
D(Z11)	–0.0425	0.0227	–1.8689	0.0619
D(Z12)	–0.0550	0.0250	–2.2015	0.0279
D(Z13)	0.0746	0.0251	2.9698	0.0031
D(Z14)	–0.0337	0.0201	–1.6798	0.0933
D(Z15)	0.0626	0.0202	3.0952	0.0020
D(Z16)	–0.0360	0.0188	–1.9175	0.0555
D(Z17)	0.0498	0.0188	2.6367	0.0085
D(Z18)	0.0445	0.0192	2.3154	0.0208
D(Z19)	0.0404	0.0153	2.6397	0.0084
D(Z20)	0.0529	0.0134	3.9563	0.0001
D(Z21)	0.1698	0.0433	3.9163	0.0001
D(Z22)	0.0812	0.0163	4.9712	0.0000
D(Z23)	0.0822	0.0207	3.9686	0.0001
D(Z24)	0.1379	0.0187	7.3903	0.0000
D(Z25)	–0.1366	0.0488	–2.7992	0.0052
D(Z26)	0.0864	0.0177	4.8746	0.0000
D(Z27)	0.0751	0.0175	4.2902	0.0000
D(Z28)	0.0451	0.0206	2.1897	0.0288
R^2 (average for the motorway sections)	0.74			
First order autocorrelation coefficient (pooling estimation for the motorway sections)	0.019			

Note: All variables are defined in first differences (D) of the logarithm (L). GDP = gross domestic product; PGAS = gasoline price; TRAFFIC = average daily traffic volume; TOLL1 = low toll elasticity group; TOLL2 = low-medium toll elasticity group, TOLL3 = medium-high toll elasticity group; TOLL4 = high toll elasticity group; D(Z1) to D(Z28) = first differences of the dummy variables to account for changes in the road network.

TABLE 5 Estimated Short-Term and Long-Term Elasticities[1]

Variable	Short-term elasticity	*t*-statistic	Long-term elasticity	*t*-statistic
GDP elasticity	0.890	21.76	1.405	27.85
Gasoline price elasticity	–0.337	–22.01	–0.531	–18.50
Toll elasticity group 1	–0.209	–11.81	–0.330	–11.42
Toll elasticity group 2	–0.371	–25.25	–0.585	–21.71
Toll elasticity group 3	–0.445	–19.80	–0.702	–17.66
Toll elasticity group 4	–0.828	–9.82	–1.307	–9.81

[1] Group 1 includes 21 sections; group 2, 25 sections; group 3, 21 sections; and group 4, 5 sections.

motorway sections classified in group 4, elasticities are over –0.8 in the short term and well above unity in the long term. These differences prove that the demand response to toll variations depends on the particular characteristics of the motorway and alternative routes. In the next section, we provide some evidence of these characteristics.

VARIATION OF TOLL ELASTICITIES ACROSS MOTORWAYS

Once it has been proved that toll elasticities vary across motorway sections, it is interesting to consider which are the main variables that explain such differences. With this purpose in mind, we estimated an ordered probit model[21] where the dependent variable is the category in which the tolled section falls, ranging from 1 to 4 (low, middle-low, middle-high, and high categories of toll elasticities).

The set of explanatory variables is limited by data availability. First, we were able to gather information on average speed and the percentage of heavy vehicles with respect to total traffic on the parallel free road; these variables reflect the quality of the alternative road. Second, two characteristics of the motorway have been included: section length and a dummy for sections in tourist areas. There are a priori reasons to expect that traffic in tourist areas will be less sensitive to price. It might well be that foreign visitors, due to a lack of information given that they are occasional users, have more inelastic demands than frequent motorway users. Moreover, congestion in these areas on the free alternative roads is rather high during summer months due to their low capacity and the high volume of short-distance traffic for which tolled motorways are not a feasible option. This increased congestion can further reduce demand elasticity.

The number of observations in this model falls from 72 to 52, as we could not gather all the required information for all sections. Table 6 shows the results of the estimated equation. Because the interpretation of the coefficients of the model was not straightforward, we calculated the change in the estimated frequencies (probabilities) after a change in the explanatory variable. Baseline frequencies were calculated for the mean value of the variables in the sample, and the tourism dummy takes value 1. In order to simulate the change in probabilities a 10% increase in each variable was assumed. Results are presented in table 7.

The estimated frequencies show that demand is more sensitive to price when the alternative free road is of better quality. That is, the higher the speed on the alternative road the more elastic demand is with respect to tolls. On the contrary, when the percentage of heavy vehicles on the alternative road increases, the roadway segment shifts into a more inelastic demand category. Additionally, demand is slightly more elastic on longer motorway sections. This can be explained by the fact that demand is more sensitive to price when the total amount to be paid is larger. Finally, as could be expected, motorway demand in tourist areas is more inelastic.

CONCLUSIONS

The estimation of a dynamic demand function on tolled motorways has made it possible to identify the behavioral responses of users to changes in the

[21] Alternatively, a logit ordered model was estimated with very similar results.

TABLE 6 Estimation Results of the Ordered Probit Model
Dependent variable: category of toll elasticity (from 1 to 4)
Robust t-statistics

Variable	Coefficient	Std. error	t-statistic	P-value
Speed on the alternative road	0.032	0.010	3.298	0.001
Percentage of heavy vehicles on the alternative road	–0.053	0.017	–4.233	0.000
Motorway section length	0.024	0.010	4.268	0.000
Tourist dummy	–1.227	0.358	–3.340	0.001
Limit_1	0.919	0.862	1.214	0.226
Limit_2	2.393	0.920	3.014	0.003
Limit_3	3.666	0.962	3.814	0.000
Observations	52			
Likelihood ratio-statistic	25.60 (critical value at 5% = 9.49)			

Notes: The limit points are the estimates of the threshold coefficients of the distribution function. That is, if $F(X'\beta)$ is the distribution function of the unobserved continuous latent variable, the ordered probit model implies that:

If $F(X'\beta) \leq$ Limit_1, then the dependent variable falls into category 1 (low elasticity).

If Limit_1< $F(X'\beta) \leq$ Limit_2, then the dependent variable falls into category 2 (middle-low elasticity).

If Limit_2 < $F(X'\beta) \leq$ Limit_3, then the dependent variable falls into category 3 (middle-high elasticity).

If $F(X'\beta) >$ Limit_3, then the dependent variable falls into category 4 (high elasticity).

TABLE 7 Estimated Probabilities

Motorway group elasticity	Baseline	10% increase in speed on alternative road	10% increase in heavy vehicles on alternative road	10% increase in section length	Tourism dummy = 0
Low	0.522	0.410	0.574	0.500	0.121
Middle-low	0.415	0.484	0.377	0.430	0.498
Middle-high	0.060	0.100	0.047	0.067	0.323
High	0.003	0.006	0.002	0.003	0.058

Note: The baseline values taken by the explanatory variables are: speed = 88.9 km/hr; percentage of heavy vehicles = 24.9%; section length = 23.4 km; and tourism dummy = 1.

explanatory variables. First, traffic on the tolled motorways is shown to be strongly correlated with the level of economic activity in such a way that, during periods of growth, traffic increases clearly exceed GDP growth, with the opposite occurring during recessions.

Travel demand is shown to be less sensitive to gasoline prices and tolls than it is to GDP. Elasticity with respect to gasoline price is about – 0.3, whereas a wide range of variation appears in toll elasticities across motorway sections. The model results prove that an average aggregate toll elasticity cannot be used for forecasting or evaluation purposes. According to individual estimates, the sections were classified into four categories for which short-term elasticity ranged from – 0.21 in the most inelastic sections to – 0.83 in the most elastic. This range of variation can be explained by those variables related to the quality of the alternative roads, the length of the motorway section, and the location of the motorway in a tourist area. The more congested the alternative roads are, the higher the time benefits of using the tolled motorway will be, with demand consequently being more inelastic.

The finding that the sensitivity of demand to tolls can be higher than the average values found in the literature confirms that tolling motorways can have a significant impact on traffic. Setting a toll on a motorway can result in a misallocation of traffic between the tolled motorway and the parallel free road. There are several examples in Spain of underused motorway sections while the alternative road is severely congested, with a consequent increase in maintenance and environmental costs. In such cases, decreasing the toll may improve traffic allocation and, hence, reduce the total costs of using the infrastructure. Moreover, it should be noted that investment in alternative roads or transportation modes would imply a more elastic demand for motorway users, because they can take advantage of a wider range of choices in traveling to their destinations. Thus, decisions about toll levels on the motorways are not independent of investment policy for transportation infrastructure.

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APPENDIX A

In Spain, the tolled motorway construction policy of the 1960s granted concessions to private companies both for their construction and operation. As a result of this policy, 1,800 kilometers of tolled motorways, called *autopistas*, were completed by the end of the 1970s, serving demand along two main traffic corridors.

Once the main traffic corridors had been concessioned and, simultaneously, with the Spanish economy suffering the effects of the energy crisis, private capital was no longer interested in the construction of autopistas. In the mid-1970s, the concession of planned motorways was increasingly difficult, and some were postponed. By the end of that decade, the policy was abandoned.

In the 1980s, the need for significant expansion of the road network was evident, and the government decided to finance this with national tax revenue. Approximately 5,500 kilometers of untolled motorways were constructed by 1998, covering most of the national network. The main exceptions were the concessions granted by the regional government of Catalonia to construct and operate some tolled motorways. By 1998, the Spanish national highway network consisted of 9,637 kilometers, of which 2,072 kilometers were tolled motorways, 6,185 kilometers were untolled motorways, and 1,380 kilometers were two-lane freeways.

More recently, and due to severe public budget constraints, a new program of private tolled motorways was initiated. Nevertheless, the scope of private tolled roads in Spain is currently limited. For a review of the development of Spain's motorways, see Gómez-Ibañez and Meyer (1993), and for an analysis of the present situation, see Ministerio de Fomento (2003).

APPENDIX B

TABLE B1 Estimated General Model
Dependent variable: D(LTRAFFIC)
Estimation method: weighted least squares
Total system (unbalanced) observations: 990

	Coefficient	Std. error	*t*-statistic	*P*-value
D(LGDP)	0.8942	0.0410	21.8117	0.0000
D(LPGAS)	–0.3369	0.0157	–21.4261	0.0000
D(LTRAFFIC(–1))	0.3642	0.0160	22.6942	0.0000
D(LTOLL1)	–0.0371	0.2279	–0.1626	0.8709
D(LTOLL2)	–0.2754	0.2630	–1.0471	0.2954
D(LTOLL3)	–0.2338	0.2631	–0.8886	0.3745
D(LTOLL4)	–0.3237	0.2548	–1.2704	0.2043
D(LTOLL5)	–0.1799	0.2101	–0.8565	0.3920
D(LTOLL6)	–0.4766	0.1451	–3.2853	0.0011
D(LTOLL7)	–0.4758	0.1274	–3.7354	0.0002
D(LTOLL8)	–0.4630	0.1362	–3.3982	0.0007
D(LTOLL9)	–0.2811	0.1296	–2.1689	0.0304
D(LTOLL10)	–0.4903	0.1258	–3.8977	0.0001
D(LTOLL11)	–0.4512	0.1157	–3.9003	0.0001
D(LTOLL12)	–0.5876	0.1893	–3.1042	0.0020
D(LTOLL13)	–0.3588	0.1705	–2.1048	0.0356
D(LTOLL14)	–0.3555	0.2371	–1.4994	0.1341
D(LTOLL15)	–0.1118	0.1281	–0.8725	0.3832
D(LTOLL16)	–0.3144	0.1504	–2.0901	0.0369
D(LTOLL17)	–0.0580	0.1998	–0.2902	0.7717
D(LTOLL18)	–0.1894	0.1477	–1.2828	0.1999
D(LTOLL19)	–0.3475	0.2299	–1.5118	0.1309
D(LTOLL20)	–0.3417	0.1964	–1.7398	0.0822
D(LTOLL21)	–0.4309	0.2585	–1.6672	0.0958
D(LTOLL22)	–0.3609	0.4125	–0.8748	0.3819
D(LTOLL23)	–0.1517	0.0422	–3.5972	0.0003
D(LTOLL24)	–0.1716	0.0390	–4.4061	0.0000
D(LTOLL25)	–0.1815	0.0456	–3.9764	0.0001
D(LTOLL26)	–0.2204	0.0629	–3.5052	0.0005
D(LTOLL27)	–0.2831	0.0827	–3.4209	0.0007
D(LTOLL28)	–0.2653	0.0608	–4.3657	0.0000
D(LTOLL29)	–0.3136	0.0413	–7.5963	0.0000
D(LTOLL30)	–0.4182	0.0646	–6.4717	0.0000
D(LTOLL31)	–0.4387	0.0534	–8.2101	0.0000
D(LTOLL32)	–0.4062	0.0465	–8.7398	0.0000
D(LTOLL33)	–0.3620	0.0537	–6.7361	0.0000
D(LTOLL34)	–0.3915	0.0414	–9.4648	0.0000
D(LTOLL35)	–0.3447	0.0342	–10.0812	0.0000
D(LTOLL36)	–0.3582	0.1184	–3.0254	0.0026

TABLE B1 Estimated General Model (continued)
Dependent variable: D(LTRAFFIC)
Estimation method: weighted least squares
Total system (unbalanced) observations: 990

	Coefficient	Std. error	*t*-statistic	*P*-value
D(LTOLL37)	–0.3701	0.0445	–8.3134	0.0000
D(LTOLL38)	–0.3904	0.0512	–7.6203	0.0000
D(LTOLL39)	–0.3992	0.0489	–8.1651	0.0000
D(LTOLL40)	–0.5231	0.2504	–2.0892	0.0370
D(LTOLL41)	–0.4556	0.2466	–1.8476	0.0650
D(LTOLL42)	–0.4489	0.1657	–2.7082	0.0069
D(LTOLL43)	–0.4662	0.2451	–1.9018	0.0575
D(LTOLL44)	–0.3729	0.1515	–2.4614	0.0140
D(LTOLL45)	–0.4115	0.1619	–2.5420	0.0112
D(LTOLL46)	–0.4045	0.2312	–1.7495	0.0806
D(LTOLL47)	–0.5029	0.1554	–3.2366	0.0013
D(LTOLL48)	–0.0931	0.2265	–0.4108	0.6813
D(LTOLL49)	–0.2227	0.1657	–1.3439	0.1793
D(LTOLL50)	–0.1935	0.0913	–2.1199	0.0343
D(LTOLL51)	–0.3617	0.0650	–5.5628	0.0000
D(LTOLL52)	–0.4411	0.0647	–6.8186	0.0000
D(LTOLL53)	–0.8415	0.1494	–5.6340	0.0000
D(LTOLL54)	–0.8140	0.1435	–5.6730	0.0000
D(LTOLL55)	–0.8301	0.1714	–4.8438	0.0000
D(LTOLL56)	–0.3729	0.1065	–3.5004	0.0005
D(LTOLL57)	–0.3294	0.0839	–3.9255	0.0001
D(LTOLL58)	–0.3569	0.1728	–2.0648	0.0392
D(LTOLL59)	–0.3863	0.0936	–4.1281	0.0000
D(LTOLL60)	–0.5015	0.0830	–6.0381	0.0000
D(LTOLL61)	–0.5248	0.1946	–2.6970	0.0071
D(LTOLL62)	–0.4816	0.1138	–4.2314	0.0000
D(LTOLL63)	–0.3233	0.1335	–2.4213	0.0157
D(LTOLL64)	–0.3922	0.0990	–3.9625	0.0001
D(LTOLL65)	–0.4431	0.1168	–3.7933	0.0002
D(LTOLL66)	–0.3706	0.1427	–2.5963	0.0096
D(LTOLL67)	–0.3451	0.0534	–6.4635	0.0000
D(LTOLL68)	–0.3692	0.0562	–6.5701	0.0000
D(LTOLL69)	–0.4417	0.1117	–3.9532	0.0001
D(LTOLL70)	–0.8108	0.2983	–2.7182	0.0067
D(LTOLL71)	–0.8798	0.3854	–2.2825	0.0227
D(LTOLL72)	–0.2516	0.3066	–0.8208	0.4120
D(Z1)	–0.0517	0.0259	–1.9918	0.0467
D(Z2)	–0.0688	0.0240	–2.8680	0.0042
D(Z3)	–0.0720	0.0246	–2.9222	0.0036
D(Z4)	–0.0518	0.0259	–1.9971	0.0461

(*continues on next page*)

TABLE B1 Estimated General Model (continued)
Dependent variable: D(LTRAFFIC)
Estimation method: weighted least squares
Total system (unbalanced) observations: 990

	Coefficient	Std. error	*t*-statistic	*P*-value
D(Z5)	0.1548	0.0395	3.9192	0.0001
D(Z6)	0.1689	0.0363	4.6490	0.0000
D(Z7)	0.1197	0.0577	2.0755	0.0382
D(Z8)	–0.0687	0.0214	–3.2092	0.0014
D(Z9)	–0.0621	0.0198	–3.1309	0.0018
D(Z10)	–0.0689	0.0283	–2.4343	0.0151
D(Z11)	–0.0428	0.0228	–1.8769	0.0609
D(Z12)	–0.0554	0.0242	–2.2876	0.0224
D(Z13)	0.0726	0.0248	2.9326	0.0034
D(Z14)	–0.0337	0.0198	–1.7058	0.0884
D(Z15)	0.0622	0.0202	3.0823	0.0021
D(Z16)	–0.0365	0.0172	–2.1197	0.0343
D(Z17)	0.0474	0.0175	2.7040	0.0070
D(Z18)	0.0439	0.0194	2.2611	0.0240
D(Z19)	0.0419	0.0155	2.7086	0.0069
D(Z20)	0.0515	0.0130	3.9495	0.0001
D(Z21)	0.1690	0.0440	3.8452	0.0001
D(Z22)	0.0812	0.0168	4.8386	0.0000
D(Z23)	0.0836	0.0209	4.0077	0.0001
D(Z24)	0.1399	0.0187	7.4758	0.0000
D(Z25)	–0.1377	0.0492	–2.7967	0.0053
D(Z26)	0.0863	0.0178	4.8569	0.0000
D(Z27)	0.0749	0.0175	4.2714	0.0000
D(Z28)	0.0449	0.0206	2.1811	0.0294

Notes: All the variables are defined in first differences (D) of the logarithm (L). GDP = gross domestic product; PGAS = gasoline price; TRAFFIC = average daily traffic volume; TOLL = toll paid per km for the 72 motorway sections; D(Z1)–D(Z28) = the first differences of dummy variables to account for changes in the road network.