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# Is demand for polluting goods manageable? An econometric study of car ownership and use in Mexico

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## Abstract

Our motivation for estimating a demand system for gasoline and cars is its strategic relevance to policy objectives such as pollution control: if demand is responsive to pricing, demand reductions for polluting goods will provide an important share of the pollution reductions; otherwise, cleaner technologies will have to do most of the job. We estimate a model of gasoline demand and car ownership in Mexico, using a panel of annual observations by state. Key features that we introduce include instrumental variables on differenced data and the treatment of possible dynamics, measurement errors in the data, and unobserved individual state characteristics. We use tests of serial correlation in the residuals to model the dynamics properly. The resulting demand system is quite responsive to pricing even in the short term (−0.6 for the own-price elasticity of gasoline), but we emphasize a medium- to long-term perspective of 5–10 years as most relevant for policy. Five- to ten-year elasticity estimates are in the range of −1.25 to −1.13. Applying these elasticity estimates to data on pollution control options for the vehicle fleet in Mexico City, the costs of reaching a target for pollution reductions would be 45% more expensive if one

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were not willing to use a demand management instrument such a gasoline tax in the control program. 

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## 1. Introduction and background

Empirical studies of energy demand systems received a wave of attention in the 1970s. Oil price shocks provided the experiments and a perception of national management priorities. This spurted an interest in empirical magnitudes and thus, development in techniques. More recently the topic has had its renaissance due to awareness of environmental externalities and its close association to energy consumption [1]. Our motivation is the relevance of demand relations for pollution control policies: a management challenge high on the agenda in Mexico. We engage in an empirical investigation because existing studies are outdated in terms of data, and could be improved in terms of methodology. The study should be of interest also for those interested in empirical methods, or demand for energy and transport energy and transport for other reasons.

This introductory section first explains the relevance of demand parameters when policy makers have a management objective such as pollution control, and first-best policy instruments are not available. We then review briefly the capital of relevant empirical studies, and explain how the present investigation contributes. Section 2 introduces the economic model and presents the treatment of dynamics. Section 3 discusses data and econometric issues, and Section 4 presents the empirical findings. Summary and conclusions are found in a brief Section 5.

### *1.1. Demand management in pollution control*

A control strategy can deliver pollution reductions either by making each activity 'cleaner' per unit of input or output (illustratively, we may call this 'cleaner cars and fuels', or technical controls), or by scaling down the level of polluting activities (we may call this 'fewer polluting trips'). A least cost program could, theoretically at least, be induced by 'first-best' instruments such as tradeable emission permits or emission taxes, based on monitoring of individual emissions. However, obstacles such as monitoring and enforcement costs often will make it costly to use first-best instruments. Then, the policy maker may need

[1] See, for instance, Pindyck (1979) and Sterner (1990) who review the developments and report results. For Mexico, see Berndt and Samaniego (1984) and Berndt and Botero (1985). For the more recent interest, see Jorgenson and Wilcoxen (1990) and Viscusi et al. (1994).

to evaluate the various ways by which emission reductions can be provided, to stimulate them separately [2]. For instance, fees or sanctions associated with initial certification and/or periodic tests of emission rates can stimulate cars and fuels to be cleaner (these instruments also reduce demand, but in a rather costly way if used alone). In contrast, gasoline and road taxes, mass transport policies and parking fees can manage the demand for polluting trips [3].

Most of these instruments change the effective price of cars and their services. Empirical estimates of demand elasticities can inform the policy maker of the role of demand management in a cost-effective control strategy. For example, a low gasoline price elasticity would signal that a gasoline tax would not deliver much of a reduction in gasoline consumption; thus, in pollution. As in the tradition in the recent literature, we introduce a structure that decomposes changes in total demand into changes in demand for vehicles and demand for fuel per car [4].

### *1.2. The empirical literature*

There is a rich body of econometric studies of demand for vehicles and fuels. General studies of demand for energy, and specific fuels among them, bloomed in the years following the first oil price shock in 1973. Among studies focusing on demand for energy, the study of Fuss (1977) on energy use in Canadian manufacturing and the book of Pindyck (1979), 'The structure of world energy demand' probably are the most important: Fuss (1977), for demonstrating methodological breakthroughs concerning interfuel substitution; and Pindyck (1979), for a broad inquiry based on data from many countries, including developing countries.

Pindyck (1979) compares results he obtained from a developing country subsample (Mexico and Brazil) with those from developed countries. For gasoline, he finds the results to be consistent with his expectations of lower price elasticities and higher income elasticities in developing countries: ''The estimated price elasticity of demand is −0.55 as compared to the estimate of about −1.3 obtained

[2] In Eskeland and Jimenez (1992), this point is elaborated in their distinction between direct instruments (based on monitoring of individual emissions) and indirect instruments (based on indicators of emissions, such as emission test results or the characteristics of cars and other machinery as a proxies for 'dirtiness', and fuel use or other measures as proxies for the output). Eskeland and Devarajan (1996), in 'Taxing Bads by Taxing Goods: Pollution Control with Presumptive Charges' synthesizes findings on taxation of goods and inputs used in polluting activities.

[3] The optimal stimulus to cleaner cars and fewer trips is examined in detail in Eskeland (1994) using a simple model with no other distortions and no revenue premium. (Hau, 1992a,b, and Newbery et al. (1988) discuss charging road users, to discourage road wear and congestion. McConnell and Harrington (1992), Hahn (1995), Anderson (1990) and Faiz et al. (1990) are examples of detailed studies of technical control options and costs.

[4] Related issues that could be analyzed with more disaggregate data are effects on the composition of the car stock, and effects by household income groups. While such issues are of great interest to us, we do not pursue them in this study, which is based on aggregate data. Dissaggregate data are used in an analysis of car usage restrictions applied in Mexico City: Eskeland and Feyzioğlu (1995).

for the developed countries... the income elasticity is 1.22 as compared to 0.8 for the developed countries''. Comparing his results with those of many others, Pindyck (1979) notes to have found higher elasticities in general. Arguing for data sets pooling cross-section and time series, he notes ''use of data for a single country is more likely to elicit short-run or intermediate-run elasticities'' (p. 233).

Another, not entirely independent development of the 1970s was regulatory changes to enhance environmental quality and fuel efficiency. Of relevance to our topic, these developments gave emphasis to the distinction between fuel efficiency, measured for instance by liters consumed per vehicle kilometer and kilometers traveled by the average household. Manski (1983) proposed an elegant model of vehicle scrappage, and Berkovec (1985) estimated a model of vehicle demand by type including such scrappage model. Using this model, he could estimate the likely effect of vehicle regulations and the associated price increases for new vehicles on the turnover and properties of the vehicle stock. Broader studies of the behavior of auto ownership and use are found in, inter alia, Winston et al. (1987), Crandall et al. (1986), and Grad et al. (1975). General equilibrium treatments of the effects of energy price increases and environmental regulations, with less emphasis on transportation and a particular fuel, are found in Jorgenson and Wilcoxen (1990), and in Hazilla and Kopp (1990).

There is also a literature of empirical studies based on discrete choice models and microdata, emphasizing the sensitivity of mode choice for individual trips to, inter alia, pricing and travel times (see, for instance, Ben-Akiva and Lerman (1985)). Results from this literature are not generally comparable to those from aggregate data — one of the most obvious reasons for this is that the mode-choice models usually assume many variables as given in the outset (residential location, workplace location, car ownership). Due to these and other important differences between the two empirical bodies of literature, one should not be surprised that estimates of such parameters as the elasticity of car use to car operating costs will usually be much lower in these models than in aggregate models.

Two recent reviews that highlight findings in empirical models are Oum et al. (1990) and Krupnick (1992). Another recent study with both a review of results and empirical estimates is Sterner (1990). Sterner (1990) surveyed close to a hundred different papers with 360 different estimated demand equations, and reestimated the models using a larger data base than those used in the studies he summarized. He points to differences in results, but concludes that there is consistency in the results and that demand does ''adapt to changes in both income and prices''. For OECD countries, the short-run elasticities from the dynamic models ''appear to be around $-0.2$ to $-0.3$ and 0.35 to 0.55 for price and income respectively''. The long-run elasticities were around $-1.0$ to $-1.4$, and 0.6 to 1.6 for price and income, respectively. For OECD countries, the results on price elasticities are consistent with those obtained by Pindyck (1979), but the wide range for income elasticities cast a doubt on the claim that they should be systematically higher for developing countries.

Of special interest is, of course, Berndt and Botero (1985), who obtain elasticities for Mexico close to those reported for developed countries by Sterner. They present a model of vehicle stock and gasoline demand from Mexico, very similar to the objective of our study. They utilize a pooled cross-section time series data set and use the dynamic gasoline demand model discussed in Drollas (1984). For the short-run, their estimates are −0.23 for the price elasticity and 0.31 for the income elasticity. Long-run price and income elasticities are −0.96 and 1.25, respectively.

There are several key issues that Berndt and Botero, 1985 do not address. First, they use pooled cross-section time series data, aggregated to 14 regions; however, they do not make allowance for possible differences among these regions (say geographical, institutional, infrastructural). If these differences across states are correllated with income and gasoline consumption the estimates of the elasticities will be biased and inconsistent [5]. Second, they do not test whether the dynamics are adequately modeled. As a consequence, there could still be important dynamics left as residuals in their model. Such omitted dynamics would result in biased estimates for the short-term and long-term elasticities. In fact, long-term elasticities in this study turned out to be lower than what we would have predicted in the absence of proper tests of dynamics of consumption. Third, they do not consider the effect of gasoline prices on new car sales. This results in the omission of the indirect effect of gasoline prices on total gasoline consumption, thus ignores an empirical effect of policy relevance.

We address these and other issues that arise due to the nature of the data. We utilize a pooled cross-section time series data set with annual observations from the 31 states and the federal district in the Mexican Federation. We address the problem of unobservability in the state specific characteristics by differentiating the data. We explicitly take into account the possible dynamics in behavior by incorporating it into the model and testing the residuals. We also deal with measurement error problems, specifically in income by state, by using instrumental variable techniques.

## 2. Economic model and elasticities

### 2.1. The model

To understand how the total demand for gasoline responds to income and price changes, we decompose it into gasoline consumption per car and number of cars.

[5] For example, if the presence of mountains are negatively correlated with income and positively correlated with gasoline consumption, lower income levels will be correlated with higher gasoline consumption. So, even if in each state consumption may increase as income increases, if we lump all states together, we will include the negative correlation between consumption and income, and the income elasticities estimated from the full sample will be biased downwards.

This decomposition lets us analyze the role of the car stock and the average utilization rate separately [6]. The model is a per capita model, so that all quantities are divided by population (except for consumption per car, for which population cancels out). We start with the identity that the average gasoline consumption per car is equal to the total consumption divided by the number of vehicles registered, for each state and time period [7]. Elementary calculations show that for total gasoline consumption, the elasticities will be the sum of the respective elasticities of gasoline consumption per car and elasticities of the car stock. As an example, for the income elasticity,

$$\eta_y = \eta_{c,y} + \eta_{s,y} \tag{1}$$

where, $\eta_{t,y}$ is the income elasticity of total gasoline consumption, $\eta_{c,y}$ is the income elasticity of gasoline consumption per car, and $\eta_{s,y}$ is the income elasticity of the car stock.

First, we model gasoline consumption per vehicle, which we can view as a short-term utilization decision. We assume a representative consumer with a utility function separable in services rendered by a car and other goods and services. We assume that the services from the car are proportional to gasoline usage. We also assume that consumers estimate their relevant income via their current and past incomes and use this measure to determine their consumption level.

In addition to prices and income, there may be differences between states, due to geography and infrastructure that affect gasoline consumption. More specifically, more roads per car may encourage more travel and more per car gasoline usage, or may decrease per car gasoline consumption due to less congestion. We capture such effects by including miles of highway per car. There may be additional differences among states, like mountains, that affect usage per car. These additional effects are not observable to us, but we can summarize them in a state-specific variable, $\alpha_i$, that is constant throughout years, but differs across states. We also incorporate such effects as habit persistence by considering the lagged values of the dependent variable, and write the consumption function in the following form:

$$C_{it} = f(\mathrm{LagC}_{it}, \mathrm{GASPR}_t, \mathrm{CARPR}_t, \mathrm{PY}_{it}, \mathrm{HW}_{it}, \alpha_i) \tag{2}$$

where, $C_{it}$ is the average gasoline consumption, $\mathrm{GASPR}_t$ is the gasoline price, $\mathrm{CARPR}_t$ is a price index for new cars, $\mathrm{PY}_{it}$ is the relevant income vector, $\mathrm{LagC}_{it}$ is the vector of past consumption rates, $\mathrm{HW}_{it}$ is miles of highway per car, $\alpha_i$ is a scalar that allows for the state-specific characteristics.

[6] Throughout we shall work with three market goods and their prices; gasoline, cars and other goods and services. We normalize each price by the price of other goods and services, thus reducing the analysis to two prices only.

[7] Average consumption per car is for each year, and for each state, but we do not have data on the vintage (or other) characteristics of cars in each state.

Second, we model the car stock. Current car stock is equal to depreciated car stock that remained from the previous year plus the new car purchases:

$$S_{it} = (1 - \delta) S_{it-1} + I_{it} \tag{3}$$

where, $S_{it}$ is the stock of cars, $I_{it}$ is the new car purchases, and $\delta$ is the depreciation factor. New car purchases depend on the current optimal stock [8]. By optimal stock, we mean the optimal level of cars that consumers in each state would prefer to hold, given prices, incomes and infrastructure. The reason why we include gasoline prices is that consumers may take operating costs into account in their purchasing decisions. They may calculate the total discounted cost of gasoline consumption into the car price. This implies that as gasoline prices increase, we should expect a decrease in the car stock. However, since new cars are more fuel-efficient, an increase in gasoline prices may induce more new car sales, and perhaps an increase in the depreciation of the stock (scrappage). Considering these potential effects, we do not know a priori which direction the gas prices may affect new purchases and the stock. We capture the differences across the states by miles of highway per car and an unobserved state specific constant.

We can summarize these in the following optimal stock equation:

$$S_{it}^{*} = s(\mathrm{CARPR}_t, \mathrm{GASPR}_t, \mathrm{PY}_{it}, \mathrm{HW}_{it}, \alpha_i) \tag{4}$$

where $S_{it}^{*}$ is the optimal car stock level.

Investment in car stock should be a function of the optimal stock and the depreciated stock from the previous year. With stock adjustment costs, when the optimal stock changes due to a lasting shift in income, investment changes permanently to a level that builds up the car stock continually, until depreciation level catches up [9]. This can be captured in the following investment equation (where, instead of the optimal stock, we use its determinants):

$$I_{it} = I(\mathrm{CARPR}_t, \mathrm{GASPR}_t, \mathrm{PY}_{it}, \mathrm{HW}_{it}, \mathrm{S}_{it-1}, \alpha_i). \tag{5}$$

For depreciation, we consider two alternatives. One is a constant depreciation rate, which is independent of explanatory variables. While this is a commonly used assumption, we believe it should be tested. It can be argued that the higher the new car prices, the higher the value of the used cars would be, and the lower the number of cars to be scrapped. An elegant model is given by Manski (1983),

[8] Berndt and Botero (1985), among others, use a partial adjustment model. A linear partial adjustment model implies a negative, close to unity relationship between the new car purchases and the previous year's stock, simply because replacement needs are equal to a given fraction the stock. We do not use such a model, as we, Pindyck (1979) and Berndt and Botero (1985) find evidence against these models.

[9] This type of investment behavior is based on investment models with adjustment costs. See Auerbach and Hassett (1992) for fixed investment with adjustment costs in the United States.

and applied successfully to the US market by Berkovec (1985). In addition, as gas prices go up, if older cars have lower fuel efficiency, scrappage should increase. Similar reasoning goes for an income increase: the higher incomes are, the less one would be willing to use and repair old cars (the result could go the other way if households in income ranges to buy used cars experienced much of the income growth). We test a model allowing the depreciation rate to depend on these factors:

$$\delta_{it} = d(\mathrm{CARPR}_t, \mathrm{GASPR}_t, \mathrm{PY}_{it}). \tag{6}$$

This completes our model.

Several caveats are in order. First, we should emphasize that we assume that gasoline prices and car prices are exogenously determined. Apart from believing that these assumptions are plausible, testing them would require more supply side information, and is outside the scope of this study.

Second, since we are using aggregate data at the state level in this study, we are not able to study heterogeneity in the consumption and investment behavior at a lower (individual or household) level. We characterize each state by a state-specific unobserved variable that does not change through time, its highway system and its income. But we are unable to analyze phenomena such as the importance of variation of within-state income distribution, household size, age distribution, etc.

Third, when assuming separability between car services and other consumption, we cannot consider particular changes in prices among other goods and services, such as changes in the availability or price of alternative transportation modes. A substantial change in public transportation capacity and price would likely change the pattern of new car purchases and average gasoline consumption in a particular way, but is only captured through its effect on the overall price of other goods and services in our model. Consider, for example, a decrease in the price of public transportation coupled with a capacity increase. Some consumers would then be induced to use public transportation, and the demand curve for car services would shift inwards. In consequence, the average income of the people who have cars would appear to have risen. If such an incidence occurred simultaneously with income growth, our analysis would only capture the fact that the incomes at which cars are bought was shifted upward, and that the cross price effect to other goods and services was substantial. In consequence, our estimates would be too low for the income elasticity and too high for the price elasticity, should the separability assumption be inappropriate [10].

### 2.2. Elasticities

We assume constant income and price elasticities of gasoline consumption and investment in cars by estimating functions linear in logarithms. We also assume

[10] The opposite would be true, of course, if price changes for other goods and services occurred predominantly among goods and services of little relevance to car and gasoline demand.

that consumers consider their current and previous incomes, and therefore include as many lagged incomes as are statistically significant. We differentiate between the short-run and the long-run elasticities by formulating the equations in a dynamic form. This is done by including lagged dependent and independent variables as explanatory variables.

From the consumption behavior defined in Eq. (2) we obtain the following utilization equation (or gasoline consumption per car):

$$\ln C_{\mathrm{it}} = \beta_0 + \alpha_{\mathrm{i}} + \Sigma_{j=1}^{m} \beta_j \ln C_{\mathrm{it}-j} + \theta_1 \ln \mathrm{GASPR}_{\mathrm{t}} + \theta_2 \ln \mathrm{CARPR}_{\mathrm{t}} + \theta_3 \ln \mathrm{HW}_{\mathrm{it}} + \Sigma_{j=0}^{l} \lambda_j \ln Y_{\mathrm{it}-j} + \epsilon_{\mathrm{it}} \quad (7)$$

where $C_{\mathrm{it}}$ is gasoline consumption, $m$ is the lag length for the dependent variable, $\mathrm{GASPR}_{\mathrm{t}}$ is the gasoline price, $\mathrm{CARPR}_{\mathrm{t}}$ is the car price index, $Y_{\mathrm{it}}$ is income, $l$ is the lag length for adjustment in income, $\alpha_{\mathrm{i}}$ are the individual state effects, and $\epsilon_{\mathrm{it}}$ is the idiosyncratic error term that is assumed to be uncorrelated through time and across states. The parameters $\theta_1$, $\theta_2$ and $\lambda_0$ can be interpreted as short-run price and income elasticities, respectively. The lag length of the dependent variable, $m$, is determined by the minimum number of lags that are necessary to obtain an error term that does not have any serial correlation (see Arellano and Bond, 1991). The number of lagged income values, $l$, is also determined by statistical tests.

Similarly, we assume that the investment equation for new car purchases is linear in logarithms:

$$\ln I_{\mathrm{it}} = \gamma_0 + \omega_i + \Sigma_{j=1}^{k} \gamma_j \ln I_{\mathrm{it}-j} + \phi_1 \ln \mathrm{GASPR}_{\mathrm{t}} + \phi_2 \ln \mathrm{CARPR}_{\mathrm{t}} + \phi_3 \ln S_{\mathrm{it}-1} + \phi_4 \ln \mathrm{HW}_{\mathrm{it}} + \Sigma_{j=0}^{n} \tau_j \ln Y_{\mathrm{it}} + v_{\mathrm{it}} \quad (8)$$

where $I_{\mathrm{it}}$ is the investment variable, $\mathrm{CARPR}_{\mathrm{t}}$ is the car price index, $k$ and $n$ are the appropriate lag lengths, $\omega_{\mathrm{i}}$ are the individual state effects, and $v_{\mathrm{it}}$ is the idiosyncratic error term that is assumed to be uncorrelated through time and across states. Arguments similar to those for the utilization Eq. (7) also follow. The parameters $\phi_1$, $\phi_2$ and $\tau_{\mathrm{o}}$ are interpreted as short-run price and income elasticities for new car sales.

Depreciation may also be responsive to changes in prices and income, and therefore can affect the elasticity calculations for the total stock. We let

$$S_{\mathrm{it}} = (1 - \delta_{\mathrm{it}}) S_{\mathrm{it}-1} + I_{\mathrm{it}} + \eta_{\mathrm{it}} \quad (9)$$

where

$$\delta_{\mathrm{it}} = \delta_0 + \delta_1 \ln \mathrm{GASPR}_{\mathrm{t}} + \delta_2 \ln \mathrm{CARPR}_{\mathrm{t}} + \delta_3 \ln Y_{\mathrm{it}}.$$

Elasticities for depreciation would be the coefficients $\delta_1$, $\delta_2$ and $\delta_3$ divided by depreciation rate.

While short-run elasticities for gasoline consumption per car are readily seen as the coefficients of the price and income variables, the long-run elasticities have to be calculated from the dynamics of the utilization equation. We calculate the implied long-run elasticities for gasoline consumption per car by adding the coefficients of the income variable and solving the difference equations defined by setting the errors to zero.

It is trickier to calculate the elasticities for the car stock. For the short run, the elasticities are the price and current income elasticities of investment times the ratio of investment to car stock, plus elasticities for depreciation multiplied with depreciation rate and ratio of previous to current stock. In steady state, stocks should be equal to the desired stock level $S^*$, and depreciation level should be equal to the investment level. If we assume that depreciation rate is not responsive to changes in prices and income, the magnitude of the rate itself does not affect the elasticities. Since lasting shifts in prices or income change the investment levels permanently, Eq. (3) implies that a percentage change in investment, accumulated, leads to the same percentage change in the stock level [11]. For the steady state, the relevant investment elasticity of income, of course, is the sum of all the coefficients of the current and lagged income variables. If the depreciation rate is responsive to changes in prices and income, we should subtract its elasticities from the investment elasticities to obtain the long-run elasticities for the car stock.

Elasticities for total gasoline consumption, which are given by Eq. (1), are the sums of the elasticities of gasoline consumption per car and number of cars. While sums are trivial for the short run, we should be cautious in adding the long-run elasticities. The reason is that stocks tend to converge at a much slower rate than consumption; it would be informative to explicitly spell out how long it would take for these components to converge.

## 3. Data and econometric issues

### 3.1. Data

The data is collected across 31 states and the Federal District in Mexico from 1982 through 1988. National income data is available annually but disaggregated income for each state is published only every fifth year. The disaggregated data on

[11] When we solve Eq. (3) for long-run stock, stock is equal to the long-run investment divided by the depreciation rate. Another way of looking at the same result is that, in the long run, depreciation rate is equal to the ratio of investment to stocks, since investment level is equal to the depreciation level: $S = I/\delta$. This, in turn, implies that (assuming depreciation is constant), $\partial S/\partial Y = (1/\delta)\partial I/\partial Y$. But since $\delta = I/S$, adding income to both sides show that income elasticity of stock is equal to income elasticity of investment.

income is obtained from a publication of the Bureau of Statistics (Escudero and Rivas, 1989, INEGI), which uses the Chow and Lin (1971) method to model income levels by state for the years not published. The Chow and Lin (1971) method lets us form unbiased estimates of the income levels for each state for each year by using other variables such as bank deposits that change over time and across the states, as well as aggregate income for the nation and the disaggregated figures for each fifth year. By utilizing data generated by this process, we increase our sample, and obtain data on consecutive years. We treat this data as data with measurement errors, and use instruments to obtain consistent coefficient estimates [12].

Gasoline consumption per car is calculated by dividing the total gasoline consumption for each state by the corresponding number of vehicles in stock. Vehicle stock data is based on registration data from INEGI, the national bureau of statistics. Throughout this study, only cars are considered [13]. The gasoline price GASPR is the price of 'nova', and does not include 'extra' or diesel [14]. New car sales is from the association of automobile manufacturers, which publishes sales by state. The index for new car prices is published by Banco de Mexico, and kilometers of roads by Secretaria de Comunicación y Transporte. Imports of cars were zero.

Whenever an 'ln' precedes a variable name, it means that variable is used in logarithmic form. We use population figures by state to estimate a 'per capita' model.

### 3.2. Econometric issues

Simple application of the ordinary least squares (OLS) method would result in parameters that are biased and inconsistent. This is due to the combination of three econometric issues: (i) the unobservability of the state specific individual effects; (ii) the dynamic specification that allows for habit persistence; and (iii) measurement errors in the data set. A method that is capable of remedying these three problems is the instrumental variable (IV) estimation method. In the rest of this section, we discuss these issues and remedies in detail.

The first issue is the possibility of individual, unobservable characteristics that influence a state's demand, given prices and income. Ideally, variables represent-

[12] Without the state-specific annual data, we would have only two years of data, five years apart, and could not estimate long-run income elasticities without imposing a priori restrictions on the lag structure.

[13] The registry and sales data exclude only heavy duty passenger and cargo trucks (camiones), and motorcycles. The latter represents 2.5% of the stock registered in 1988. Only heavy-duty vehicles use diesel in Mexico.

[14] As of 1988, nova amounted to 99.5% of the gasoline consumption for cars.

ing these characteristics should be included, to avoid the omitted variable problem. A state-specific constant is introduced to summarize the effect of such differences between states, to the extent that the characteristics do not change over time. To the extent that demand is influenced by state characteristics that change over time (in a way that is not fully reflected in changes in income or highways, for example), our model is unable to capture this.

The second econometric problem is due to the dynamic nature of the model [15]. If there is a lagged endogenous variable among the explanatory variables, then the variance components estimator under the random effects model and the least squares dummy variable estimator under the fixed effects model are biased, and for fixed time series are also inconsistent.

The third issue is the errors we have in the income variable. Even if we assume that the disaggregate income figures are correct for the years that are published, intermediate years are only estimates of the actual figures, and therefore have errors in them. Due to the interpolation methodology, the errors are uncorrelated across time and across states, but nevertheless, any error is sufficient to cause the OLS estimators to be inconsistent.

We can solve the first problem by using the differenced data, i.e., by redefining the variables to be changes across years, or by using the least squares dummy variable estimation (LSDV) or covariance estimation (CV) methods. As pointed out by Hsiao, 1986, if we difference the data, the individual effects, whether they are fixed or random, will cancel out because these effects do not change over time [16]. If this were the only problem, after differencing, OLS estimation method would have given unbiased and consistent estimates. However, having a lagged dependent variable as an explanatory variable or having measurement errors, render OLS, LSDV and CV estimation methods invalid.

The second and the third problems can be solved through the method of IV estimators. If we select instruments that are highly correlated with the explanatory variables, but not correlated with the errors, we can obtain consistent estimates of the coefficients, even for panel data with short time series.

The instruments we have chosen are lagged values of the gasoline consumption and lagged values of income. Since we do not have measurement error problem for the prices, we use the current prices. The data is differenced for estimation; therefore, the second lag of gas consumption will be correlated with the lagged differenced gas consumption that shows up as an explanatory variable, but it will not be correlated with the error term. Similarly, the second lag of income will be correlated with the differenced income variable, but because the measurement

[15] For a good exposition, see Hsiao (1986).

[16] Hsiao (1986, pages 75 and 89).

Table 1
Elasticities for gasoline consumption per car

| | Short run | Implied long run (5 yr) |
|---|---|---|
| Gasoline price elasticity | −1.04 | −1.39 |
| Car price elasticity | −0.04 | −0.05 |
| Income elasticity | 0.63 | 0.84 |

errors are uncorrelated, this instrument will also be uncorrelated with the error term.

## 4. Results

The model developed in section two links changes in prices and income to total gasoline consumption through their effect on gasoline utilization per car and the stock of cars. The stock of cars is in turn a function of new car sales and depreciation. For each of these components, we estimate the dynamic effects of prices and income by utilizing the equations defined in Section 2.1 and techniques that are discussed in Section 3. The coefficient estimates of the regressions are given in Appendix A; in this section, we report the relevant elasticities and calculations (Table 1).

For gasoline consumption per car, we observe a rapid, but not instantaneous adjustment to changes in prices and income. The resulting elasticities for gasoline consumption per car are in Table 1 [17]. Most of the impact is within the first year and the rest is spread to no more than five years. The income elasticities are below unity, and the gasoline price elasticity is minus one for the first year, and is equal to minus 1.39 for the long-run. Lagged income variables are not significant, and we take this as an indicator that consumers do not consider their income beyond their current income (consistent with the view that the consumption per car decision is a model of utilization, a short-term decision). Car prices, as one might expect, do not have more than a slight effect on gasoline consumption per car. An interesting result is that gasoline consumption per car is positively correlated with miles of highway per car (see Appendix A). Thus, new highway construction increases car utilization more than it improves fuel efficiency via better roads and less congestion.

Our short-term elasticities are quite different from those estimated by Berndt and Botero (1985). They do not include car prices in their model, but report elasticities of −0.23 and 0.23 with respect to gasoline price and income. Their reported long-run elasticities are less distinct from ours, at −0.96 and 0.94. In their study, they use only one lag of the dependent variable. It is estimated with a

[17] Short-run elasticities are the regression coefficients; long-run elasticities are obtained by solving the difference equations implied.

Table 2
Elasticities for investment in new cars

| | Short run | Long run (3 yr) |
|---|---|---|
| Gasoline price elasticity | 0.77 | 0.77 |
| Car price elasticity | −0.58 | −0.58 |
| Income elasticity | 4.71 | 2.50 |

high coefficient, which implies that the total effect of a change in income (on utilization) spreads over more than 15 years. We test for optimal lags, conclude with two, resulting in more rapid adjustment and larger elasticities [18].

The model for investment in new cars displays large income elasticities (Table 2), confirming our expectations that developing countries tend to have a higher income elasticity for car purchases than developed countries [19]. The lag structure and its interpretation is as follows. Buyers adjust investment to new levels, using income changes over the last three years as basis for optimal investment. They tend to overestimate the persistence of a change in income, and correct it in the following two years [20]. After all the adjustments, from the third year onwards, investment has stabilized at a new level that reflects a long-term income elasticity of investment of 2.50.

The elasticity of new car purchases with respect to own price is −0.58. The elasticity with respect to gasoline prices is positive. This result cannot be ruled out a priori if we allow for the possibility that part of the attraction with new cars is

[18] With only one lag, our estimated elasticities would be smaller, with no statistically significant difference between the long and the short run. Berndt and Botero, 1985 do not report testing for alternative lag structures.

[19] One would believe income elasticities for vehicles to be highest when a high density of households enter into vehicle owning income ranges. In the US, however, modelers overestimated a downturn in vehicle demand partly because (a) the tendency towards multivehicle households was underestimated and (b) the average household size declined through the 1970s and 1980s. Pindyck (1979) conjectures, and finds, higher aggregate income elasticities for commercial energy in developing than in industrialized countries. He believes 'recruitment' is the driving force (modernization recruits more households to the classes holding equipment: vehicles, appliances, electricity connections, etc.). For gasoline, he does not test this conjecture by including vehicle registration in his LDC models. For electricity demand in Mexico, Berndt and Samaniego (1984) finds the income elasticity of new connections to partly explain the high income elasticities in aggregate demand.

[20] The structure of the lags means that investment does not reflect partial adjustment to an optimal stock, often proposed for 'sluggish' purchases of integer-type durable items (investment should, then, initially underestimate the permanency of an income change). Pindyck (1979) rejects evidence of stock adjustment in his aggregate data (p. 230), since the lagged stock coefficient is small enough to reflect depreciation only. Berndt and Botero, 1985 find some evidence that can be interpreted as partial adjustment, but with a lagged stock coefficient so small (2.4%) that it may reflect the depreciation of last year's stock only. Our data yields a lagged stock coefficient of 2%, but subsequent lags are inconsistent with partial adjustment.

Table 3
Elasticities for stock of cars

| | Short run | 5 yr | 10 yr | Very long run |
|---|---|---|---|---|
| Gasoline price elasticity | 0.03 | 0.14 | 0.26 | 0.77 |
| Car price elasticity | −0.02 | −0.11 | −0.19 | −0.58 |
| Income elasticity | 0.19 | 0.58 | 0.93 | 2.50 |

that they are more fuel-efficient, so that there is some substitutability between new cars and gasoline [21].

When we estimate a depreciation model, neither income nor prices have a significant effect on depreciation. A model of depreciation as a constant share of the stock is thus not rejected, and we use an estimated constant depreciation rate of 3% (estimation results are given in Appendix A).

The model for investment in new cars, with a constant depreciation ratio, leads to a model of the stock of vehicles (Table 3). We calculate the short-run stock elasticities by multiplying the investment elasticities by the ratio of investment to stock. The short-run income elasticity of car stock is calculated to be 0.19, which is the average investment to stock ratio, 0.04, times the income elasticity of investment, 4.71. Similarly, the short-run elasticities of the stock with respect to own and gasoline prices are −0.02 and 0.03, respectively.

For long-term developments in the stock, the model has the following property. If an exogenous variable such as income (or a price) changes from one to a new permanent level, investment changes to settle on a new permanent level within three years. The stock will continue to change, converging to a new level as the depreciation level (always 3% of last year's stock) approaches the new investment level. As convergence is slow (95% within 70 years), the more relevant parameters will be intermediate figures, and we report five-year and ten-year elasticities [22]. In the very long run, the car stock changes 2.5% for a one percent change in income (equivalent to the income elasticity of investment), whereas in five and ten years stocks change 0.58% and 0.93% respectively. We calculate these elasticities by accumulating the difference between investment and depreciation for the indicated intervals. The results for prices and income are given in Table 3.

We can use the results presented above to calculate elasticities for total gasoline consumption. So far, only the gasoline consumption elasticities per car have been

[21] Kahn (1986) finds support for an 'asset pricing model' on US data for used cars (evidence that the price premium for fuel efficient cars is increasing in fuel prices). The model of Manski (1983) yields a similar result if fuel efficiency is negatively correlated with the probability of repair requirements.

[22] Relevance could be seen as given by the immediacy of the policy objective, for instance reflected in a discount rate. Long-term elasticities reflecting this would converge faster (Discounting at 5%, 95% is reached in 35 years) and at lower values, corresponding roughly to the 10-year (undiscounted) elasticities reported here.

Table 4
Elasticities for the total gasoline consumption

| | Short run | 5 yr | 10 yr | Very long run |
|---|---|---|---|---|
| Gasoline price elasticity | −1.01 | −1.25 | −1.13 | −0.62 |
| Car price elasticity | −0.06 | −0.16 | −0.24 | −0.63 |
| Income elasticity | 0.82 | 1.42 | 1.77 | 3.34 |

presented. Total gasoline consumption varies not only due to changes in consumption per car, but also due to changes in the car stock. Eq. (1) shows how the elasticities for total consumption are obtained by simple addition of the corresponding elasticities for consumption per car and for the stock (Table 4).

From a policy management perspective, such as the management of pollution or congestion associated with car use, Table 4 provides the most relevant inputs. Total gasoline consumption is a luxury good apart from in the very short time perspective: a five-year income elasticity of 1.42 results as the sum of an income elasticity of gasoline consumption per car, 0.84, and of car stocks, 0.58. Elasticities with respect to car prices and income display the familiar feature that longer term elasticities are larger in absolute value than shorter term elasticities. For the own price elasticity of gasoline, this pattern is broken, due to the positive cross price elasticity between gasoline prices and the car stock (Table 3). An example may illustrate the effect. Higher gasoline prices, apart from suppressing consumption per car, also have a stimulating effect on stocks. The reason is that they lead to higher investments in new cars, and the depreciation rate is unaffected. The effect on total gasoline consumption becomes more important over the years, as increased investments increasingly have an effect on the stock.

Again from a policy perspective, the 5-year and 10-year elasticities should probably be seen as the most important ones. Three arguments for this view are as follows: Discounting certainly makes a very long time perspective irrelevant. Also, the deviation of the 'very long-run' elasticities rests heavily on the constancy of the depreciation rate. One may suspect that depreciation rates will be endogenous in the long run, even though our tests did not reject the hypothesis of constancy. The effect of endogenous depreciation, suggested by models such as that of Manski, would be a model with elasticities for the very long run less extreme than those reported, perhaps more like those reported for 5–10 years in Tables 3 and 4. Finally, referring to practically implementable strategies in pollution control and congestion, such as emission standards, mandatory inspection and maintenance programs, vehicle stock conversion and replacement programs, toll road and infrastructure investments — all of these require an intermediate time perspective (haste makes them very costly, while if one is not interested in the short- to medium-term effects, one should wait). Thus, if one wants to combine demand management with other strategies, the elasticities for 5–10 years would be appropriate.

For tests of sensitivity, we identified three states that had incomes substantially higher than the rest. We used dummy variables to differentiate these states and let the dummy variables interact with the income and price variables. The results were that none of the coefficients of the dummy variables were significantly different from zero. We thus conclude that there is no significant difference in elasticities between the rich states and the rest. We present these results without regression outputs not to crowd the exposition.

Finally, we should reiterate that the estimated model is in per capita terms. Thus, quantities will be scaled up by population growth with elasticities of one as long as GNP per capita is held constant, while the model parameters show how total consumption per person changes with changes in income per person.

## 5. Summary and conclusions

Assuming that demand for cars and their use is determined, predominantly, by income, road availability, prices of vehicles, fuels and other goods and services, we have used data from 31 states and the federal district over 7 years to estimate a demand model. The model incorporates adjustments in vehicle stock as well as in consumption per car. Moreover, it is estimated as a per capita model, and thus assumes that the vehicle stock and total gasoline consumption will grow in parallel with the economy if the economy grows but maintains per capita income constant.

The model estimates short-term elasticities of total gasoline consumption (similar to short-term elasticities for gasoline consumption per car) of $-1$ and 0.82 with respect to own price and income, respectively. For the longer term, developments in car stocks are important. Investments in new cars are found to adjust rather quickly from one level to another as a result of a permanent shift in income or prices. Stock levels, in contrast, converge only in the very long term — implying that elasticities for the 'very long term' are quite different from those for the intermediate to long term (say, five to ten years). We argue that one should focus on five- to ten-year elasticities: First, it reflects a suitable time perspective for policy purposes — this is evident if one discounts future quantity changes. Secondly, the 'very long-term effects' rest on our result that the depreciation rate is not influenced by prices and income. We suspect that in reality it would be — although the hypothesis of a constant depreciation rate is not rejected in our seven-year data panel. Within a time horizon of five to ten years, the own-price and income elasticities for total gasoline consumption vary with 15 to 20 percent, and come out quite large: the five-year elasticities are $-1.25$ and 1.42, respectively.

A long-run income elasticity of 1.4 and above is in the upper range of a review and estimates given by Sterner (1990). However, Pindyck, and Berndt and Botero also find higher long-run income elasticities, the latter in a study for Mexico. Our estimates of five- to 10-year price elasticities for total gasoline demand are higher than those found for the long run by Pindyck, and close to those reported by Sterner. Our five- to 10-year elasticity is also somewhat larger than that of Berndt and Botero, and our short-term price elasticity is larger.

When medium to long-term price elasticities are large, as in our case, pricing matters a great deal for resource allocation. In the case of polluting goods and services, it shows that demand management will be important in delivering emission reductions in a low-cost control program. Another way of stating this fact is that the social costs of adopting pricing policies that do not reflect social costs (costs of production and pollution, for instance) will be high, because the consequent behavioral adjustments will be large. When income elastic stocks of durable goods plays a role, as in the gasoline market, appropriate pricing becomes particularly important.

In a recent study, Eskeland (1994) explored the value of including a gasoline tax in the tool-kit of a pollution control agency. The tax would be adjusted so that the marginal costs of emission reductions would be equalized for mandated abatement (cleaner cars) and the gas tax (demand reduction). Such a matching of instruments, commanded by cost-effectiveness, is necessary to mimic the incentives that would have been given by an emission tax. The gasoline demand elasticity feeds into the analysis of a pollution control program in the following way: if a control cost curve describes options for pollution control via technical controls, then this curve is shifted downwards when a matching gasoline tax is included in the program. The area between the two curves is the welfare cost of not including a gasoline tax in the control strategy, and this area is greater, the greater the elasticity. Using our estimated price elasticity of $-1.25$, in an otherwise well designed program for Mexico City, failure to use the gasoline tax would make the program 44.9% more expensive, since more expensive technical controls would have to be applied.

Eskeland (1994), in contrast, assumed a price elasticity of $-0.8$, from Berndt and Botero (1985). With this lower assumed elasticity, failure to use the gasoline tax would make the control program only 24% more expensive (with lower elasticities, the program as a whole would be costlier under either regime, of course). The comparison between 44.9% and 24% thus illustrates how demand management instruments are more useful — more costly to ignore — the more manageable is demand.

The tax rate would be 26% ad valorem, producing 19.5% of the emission reductions. None of the individual abatement initiatives in the program produced emission reductions of that magnitude.

The fact that demand is responsive may also be used as input in discussion of other demand management instruments, such as parking fees, subway fares, tolls, cordon pricing, etc. As pointed out elsewhere, the slope of the demand curve can be viewed as an expression of the costs to consumers of sacrificing a marginally attractive trip. In that context, one need be careful with certain aggregation issues. The most important one is, perhaps, the fact that the slope of estimated the demand curve is an aggregate demand curve, and that there are income distribution effects associated with demand management instruments. Thus, the curve reflects how trips would be sacrificed according to willingness to pay at different price levels, with a self-selection of trips between households, as well as for each household. The incidence among households requires analysis of data at the household level. Also, if revenue generating instruments such as gasoline taxes are used, incidence analysis would require assumptions about how the revenues are to be used.

Our motivation was to find out whether demand for these goods and services is at all responsive to pricing, and the results yield little support for 'elasticity pessimism': demand is responsive, and pricing matters.

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## Appendix A

The estimation results are presented in this appendix. For all results, the following apply:

The standard errors are robust to heteroscedasticity.

The Wald tests are used for the significance of the overall regression.

The Sargan test is used, with the null hypothesis that there is no specification error, including the choice of the instruments. The test statistic is distributed $c^2$ under the null hypothesis. A Sargan Test Statistic that is too high with respect to the degrees of freedom indicates misspecification.

Robust test for serial correlation tests for serial correlation in the error terms. In differenced data, we expect first order serial correlation, but not second order serial correlation. This test statistics is distributed standard normal under the null hypothesis of no serial correlation. A statistic that is greater than 2 in absolute value indicates serial correlation.

We use a Generalized Method of Moments procedure to estimate the model (see Hansen (1982), MacKinnon and Davis (1993) and Arellano and Bond (1991)). Regressions are run with Dynamic Panel Data programs written in GAUSS by Arellano and Bond. Differences are used in the utilization and investment equations and levels are used in the stock equations. Results given here are from the per capita model.

Lag length of the dependent variable is chosen to eliminate any second order serial correlation in the error terms.

Utilization equation (gasoline consumption per car)

Dependent variable: $\ln C_{it}$

| Exogenous variable | Coefficient estimate | Standard error | $p$-value |
|---|---|---|---|
| $\ln C_{it-1}$ | 0.192 | 0.035 | 0.000 |
| $\ln C_{it-2}$ | 0.059 | 0.028 | 0.038 |
| $\ln \mathrm{GASPR}_t$ | −1.039 | 0.164 | 0.000 |
| $\ln \mathrm{CARPR}_t$ | −0.039 | 0.008 | 0.000 |
| $\ln Y_{it}$ | 0.625 | 0.098 | 0.000 |
| $\ln \mathrm{HW}_{it}$ | 0.775 | 0.067 | 0.000 |

Wald test of joint significance: 5563.591 (df = 6)

Sargan test: 26.503 (df = 22)

Robust test for first order serial correlation: −1.845

Robust test for second order serial correlation: 0.154

The heteroscedasticity consistent standard errors and $p$-values indicate that all the coefficients are significantly different from zero at 95% confidence level. Wald test rejects the hypothesis that all the coefficients are jointly equal to zero. Sargan test accepts the set of instruments used in the estimation, and the robust test for second-order serial correlation indicate that there is no detectable correlation in the error term.

Lagged income variables did not have significant coefficients.

Investment equation: (new car purchases)

Dependent Variable: $\ln I_{it}$

| Exogenous variable | Coefficient estimate | Standard error | $p$-value |
|---|---|---|---|
| $\ln \mathrm{GASPR}_t$ | 0.771 | 0.131 | 0.007 |
| $\ln \mathrm{CARPR}_t$ | −0.584 | 0.033 | 0.000 |
| $\ln Y_{it}$ | 4.714 | 0.374 | 0.000 |
| $\ln Y_{it-1}$ | −1.127 | 0.147 | 0.000 |
| $\ln Y_{it-2}$ | −1.091 | 0.144 | 0.000 |
| $\ln \mathrm{STOCK}_{it-1}$ | 0.111 | 0.041 | 0.000 |

Wald test of joint significance: 1975.947 (df = 6)

Sargan test: 20.534 (df = 18)

Robust test for first order serial correlation: −2.688

Robust test for second order serial correlation: −0.188

The heteroscedasticity consistent standard errors and $p$-values indicate that all the coefficients are significantly different from zero at 95% confidence level. Wald test rejects the hypothesis that all the coefficients are jointly equal to zero. Similar to the utilization equation, Sargan test accepts the set of instruments used in the estimation, and the robust test for second order serial correlation indicate that there is no detectable correlation in the error term.

For this model, although dynamics were allowed in this regression, there are no lagged dependent variables because the robust statistics indicated that there were no dynamics detectable in the error terms, and lagged dependent variable coefficients were insignificant. Similarly, the coefficient of the highway variable was insignificant; therefore, we eliminated it in the final estimation. We included income up to two lags because additional lagged income made the current income insignificant.

Depreciation equation: (with constant depreciation)

Dependent variable: $(S_{it} - I_{it})$

| Exogenous variable | Coefficient estimate | Standard error | $p$-value |
|---|---|---|---|
| Constant | 4936.129 | 582.505 | 0.001 |
| $S_{it-1}$ | 0.970 | 0.008 | 0.000 |

Wald test of joint significance: 12.762 (df = 1)
Robust test for first order serial correlation: $-0.176$
Robust test for second order serial correlation: $-0.969$

The heteroscedasticity consistent standard errors and $p$-values indicate that all the coefficients are significantly different from zero at 95% confidence level. Wald test rejects the hypothesis that all the coefficients are jointly equal to zero. Robust test for second-order serial correlation indicate that there is no detectable correlation in the error term.

The coefficient of lagged stock variable indicates that the depreciation rate is equal to 3% (= 1 − 0.97).

Depreciation equation: (with variable depreciation)

Dependent variable: $(S_{it-1} - (S_{it} - I_{it}))/S_{it-1}$

| Exogenous variable | Coefficient estimate | Standard error | $p$-value |
|---|---|---|---|
| $\ln GASPR_t$ | $-0.380$ | 0.564 | 0.501 |
| $\ln CARPR_t$ | $-0.027$ | 0.036 | 0.450 |
| $\ln Y_{it}$ | 3.641 | 2.016 | 0.071 |

Wald test of joint significance: 3.455 (df = 4)
Robust test for first order serial correlation: $-3.024$
Robust test for second order serial correlation: $-0.429$

The heteroscedasticity consistent standard errors and $p$-values indicate that none of the coefficients are significantly different from zero at 95% confidence level. Wald test does not reject the hypothesis that all the coefficients are jointly equal to zero. The robust test for second-order serial correlation indicate that there is no detectable correlation in the error term.

This regression is derived from Eq. (9) in Section 2.1:

$$S_{it} = (1 - \delta_{it}) S_{it-1} + I_{it}$$

where

$$\delta_{it} = \delta_0 + \delta_1 \ln GASPR_t + \delta_2 \ln CARPR_t + \delta_3 \ln Y_{it}.$$

When we solve for depreciation, we get

$$(S_{it-1} - (S_{it} - I_{it}))/S_{it-1} = \delta_{it} = \delta_0 + \delta_1 \ln GASPR_t + \delta_2 \ln CARPR_t + \delta_3 \ln Y_{it}.$$

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