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An analysis of gasoline demand elasticities at the national and local levels in Mexico

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ABSTRACT

The majority of evidence on gasoline demand elasticities is derived from models based on national data. Since the largest growth in population is now taking place in cities in the developing world it is important that we understand whether this national evidence is applicable to demand conditions at the local level. The aim of this paper is to estimate and compare gasoline per vehicle demand elasticities at the national and local levels in Mexico. National elasticities with respect to price, income, vehicle stock and metro fares are estimated using both a time series cointegration model and a panel GMM model for Mexican states. Estimates for Mexico City are derived by modifying national estimates according to mode shares as suggested by Graham and Glaister (2006), and by estimating a panel Within Groups model with data aggregated by borough. Although all models agree on the sign of the elasticities the magnitudes differ greatly. Elasticities change over time and differ between the national and local levels, with smaller price responses in Mexico City. In general, price elasticities are smaller than those reported in the gasoline demand surveys, a pattern previously found in developing countries. The fact that income and vehicle stock elasticities increase over time may suggest that vehicles are being used more intensively in recent years and that Mexico City residents are purchasing larger vehicles. Elasticities with respect to metro fares are negligible, which suggests little substitution between modes. Finally, the fact that fuel efficiency elasticities are smaller than vehicle stock elasticities suggests that vehicle stock size, rather than its composition, has a larger impact on gasoline consumption in Mexico City.

1. Introduction

Although there is an extensive literature on the effect that prices, incomes, and other factors have on the demand for gasoline, most studies use national data that produce elasticity estimates at the country level. There is, however, no *a priori* evidence to presume that gasoline demand elasticities estimated with national data reflect conditions at the local level.[1] Half the world's population now lives in urban areas, and the largest growth in population is taking place in cities in the developing world (UNFPA, 2007). Therefore, for rapidly growing cities to adopt sustainable policies to respond appropriately to urban and global environmental challenges from excessive use of the private car, it is of paramount interest to concentrate on the estimation of gasoline demand elasticities at the local level.

Data from the International Energy Agency show that Mexico is the 5th largest gasoline consumer among OECD countries, with total gasoline consumption comparable to that of Germany and the UK. Per capita gasoline consumption in Mexico City is equivalent to that of developed countries such as New Zealand and Switzerland, taking 6th place among OECD countries. Therefore, due to increasing concerns of the contribution of road transport to climate change, and the rapid rate at which cities in the developing world are growing, the aim of this study is to estimate and compare gasoline demand elasticities at the national and local level in Mexico.

In order to obtain reliable demand estimates for a specific transport sector, one cannot rely on average estimates for similar sectors or countries; a detailed study of that market must be performed, which is the aim of this paper. The study places special attention on the methodological issues and theoretical foundations of the latest econometric techniques developed in the recent literature.

Elasticities with respect to price, income, vehicle stock, and metro fares are estimated for Mexico at the national level with a time series cointegration model for the period 1980–2006 and a panel GMM model with data from 30 Mexican states over the

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[1] For instance, Wadud et al. (2010) found that rural households in the US are less responsive to gasoline price changes than urban households, perhaps showing the lack of alternative modes in rural areas.

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period 1993–2004. Even though monthly data on gasoline consumption for Mexico City are available since 1993, data on income at the Mexico City level are only collected annually and proxies for monthly income are either only available at the national level or for a very short time series. Therefore, due to lack of availability of a time series or panel data set for Mexico City, gasoline per vehicle demand elasticities for Mexico City are derived from national elasticities and mode shares at the national and local level, as suggested by Graham and Glaister (2006). We also estimate local elasticities with a panel Within Groups model with data aggregated at the Mexico City borough level where gasoline consumption per vehicle is derived from car kilometres and fuel efficiency per vehicle for the period 2001–2004.

The remainder of this paper is structured as follows: Section 2 presents a brief literature review of elasticities of demand for gasoline and presents the results from previous studies for Mexico. Sections 3 and 4 describe the gasoline market in Mexico and the data available for this study. Section 5 presents the econometric techniques used for the treatment of time series and panel data. Section 6 presents the results. The last section concludes.

2. Previous research

A wide range of studies has been conducted to explain how road transport gasoline demand is related to income, price, and other variables, such as vehicle stock and vehicle characteristics. Although there is a great variation in results of these studies, gasoline demand surveys show that generalisations can be made when the studies are classified by type of data used; either aggregate data collected at a region or country level (cross-section, time series, and cross-section time series), or disaggregate data that look at individuals' socio-economic features and travel behaviour. Elasticity estimates also differ depending on the time stratification of the data (monthly, quarterly, annually), model structure (static or dynamic), demand specification (functional form and variables included), and econometric approach.

Several gasoline demand surveys have been conducted, for studies before the early 1990s see, for instance, Dahl and Sterner (1991) and Goodwin (1992). For more recent surveys see Graham and Glaister (2002) and Goodwin et al. (2004). The findings from these studies are briefly summarised below.

Dahl and Sterner (1991) argue that the shorter the time period, the greater the emphasis on the short run character of the elasticity. However, monthly and quarterly data may produce biased long run parameters if seasonality is not captured correctly in the model. Traditionally, seasonal dummies are used to remove seasonal fluctuations in monthly and quarterly data; however, Abeysinghe (1994) shows that when seasonality is not deterministic (the underlying seasonal pattern is not regular throughout the series), the use of seasonal dummies leads to spurious regressions. In such instances, Hylleberg et al. (1990) suggest testing for seasonal cointegration.

The specification of the demand model also affects elasticity estimates. Static models usually give coefficients that fall between the short and long run estimates of dynamic models that capture the fact that adaptation takes time, due to costs of adjustment and imperfect information. Long run demand elasticity estimates tend to be more elastic than short run values, essentially capturing vehicle purchase decisions and changes in residence location.

Static models typically define gasoline per capita as a function of the real price of gasoline and real income per capita. Vehicle stock and stock characteristics, such as fuel efficiency, can also enter the model, as well as several other variables, for instance, public transport fares and measures of public transport infrastructure, as long as they are uncorrelated with price and income. In such cases income elasticity estimates are lower.

For dynamic models that include lags of the dependent and/or independent variables Dahl and Sterner (1991) argue that variables tend to have identical gradually diminishing effects through time, which is a strong model restriction. Alternatively, they suggest a gasoline consumption per vehicle demand specification where price and income elasticities do not include the changes in the number of automobiles, only the changes in utilisation. Gasoline consumption per vehicle models tend to give lower elasticities.

Different econometric models also affect the magnitude of the elasticities. Section 5 describes the most recent econometric techniques for the treatment of time series and panel data. In summary, there is no correct specification to be used for every demand model. It will depend on the correlation between explanatory variables, the information available, and the relevant features of each market. In some cases it will be sufficient to estimate fuel elasticities only with income and price as explanatory variables due to the fact that they tend to capture the confounding effect of other variables. Cameron and Trivedi (2005) argue that confounding takes place when the variables omitted from a regression are correlated with the observable explanatory variables.

The gasoline demand surveys of Graham and Glaister (2002) and Goodwin et al. (2004) find consensus on the range of elasticities found in the literature. Graham and Glaister (2002) argue that, in general, short run price elasticities lie between -0.2 and -0.3, whilst long run price elasticities tend to be between -0.6 and -0.8. Income elasticities in the short run are in the range 0.35–0.55, whilst long run income elasticities are typically greater than one, between 1.1 and 1.3.

With regards to gasoline demand in Mexico, Table 1 presents the elasticity estimates found in previous studies and shows the type of data used for estimation as well as its periodicity, the time period analysed, and the geographical scope of the data. In general, price elasticities are lower than those found in gasoline demand surveys, which are mostly based on developed countries. For income, most studies report higher elasticities than the range suggested in the surveys, especially for long run adjustments.

Although in most cases these studies were conducted with great academic rigour, the fact that some of the studies were published over 10 years ago poses two concerns. First, the data used for estimation are outdated. Elasticities may change over time for instance as a result of economic, political, or technological changes. Recent data must be used in order to obtain reliable elasticity estimates that reflect current market conditions. Second, new econometric techniques have been developed that treat the data more appropriately.

Three issues emerge with regards to the methodologies used: the treatment of seasonality with the use of monthly or quarterly data, the treatment of non-stationarity, and correlation between the lagged dependent variable and the error term with the use of dynamic panel models. As described above, without special treatment for seasonality the classical approach produces spurious results. Similarly, with the presence of stationary variables (means and variances differ across time) traditional econometric techniques generate spurious estimates. Likewise, correlation between the lagged dependent variable and the residuals in dynamic panel models violates one of the classical assumptions and produces biased and inconsistent coefficients. However, these methods were not widely available at the time most of the studies presented in Table 1 were conducted.

Berndt and Botero (1985) use time series and panel data to analyse the demand for energy in the Mexican transport sectors, focusing on rail, air transport, and motor vehicle modes. For road

Table 1
Summary of previous results of price and income elasticities of the demand for gasoline in Mexico.

Study		Data type	Data freq.	Region	Period	Price elasticity			Income elasticity		
						Short run	Medium run	Long run	Short run	Medium run	Long run
Berndt and Botero (1985)	Model 1	Time Series	A	N	1960–1979	−0.17		−0.33	0.70		1.35
	Model 2					−0.16		−0.49	0.16		4.78
	Model 3					−0.24		−1.21	0.35		2.76
	Model 1	Panel	A	S	1973–1978	−0.17		−1.04	0.15		0.90
	Model 2					−0.07		−0.65	0.05		0.41
	Model 3					−0.24		−0.96	0.31		1.25
Eskeland and Feyzioglu (1997a)	Before ban	Time Series	Q	MCMA	1984–1992		−0.17			0.06	
	Under ban						−0.05			0.24	
Eskeland and Feyzioglu (1997b)		Panel	A	S	1982–1988	−1.01		−1.13	0.82		1.77
Galindo and Salinas (1997)		Time Series	M	MCMA	1987–1995	0.00		−0.05	0.56		1.31
Haro and Ibarrola (2000)		Panel	M	R	1995–999		−0.24 to −0.42			0.40–0.58	
				S			−0.31			0.40	
Galindo (2005)		Time Series	A	N	1965–001		−0.09			0.84	

A=Annual, Q=Quarterly, M=Monthly, N=National level, R=Regional level, S=State level, and MCMA=Mexico City Metropolitan Area.

traffic they use 3 different models: (1) average energy consumption per vehicle, (2) vehicle replacement and investment factors, and (3) a combination of the two models. There is a large variation in results depending on the model specification. Their annual time series data consists of 20 observations only and gives no special treatment to stationarity, whilst the lag of the dependent variable is correlated with the residuals in their dynamic panel data model.

Eskeland and Feyzioglu (1997a) estimate gasoline demand elasticities in Mexico City before and after the introduction of the 'one day without a car' programme. Their model simulates the effects of income and price changes on gasoline demand if the programme had not been introduced. However, the model used for estimation only includes price and income as explanatory variables and uses a static specification excluding the effect of population changes. The study uses quarterly data but gives no special treatment to seasonality and although the proxy for income is found to be non-stationary the authors still use OLS, which produces spurious results.

Eskeland and Feyzioglu (1997b) improve on the previous studies by applying more advanced econometric techniques to a dynamic panel model of the demand for gasoline and vehicle stock in Mexico. Their *difference* GMM specification gives short and long run price elasticities of gasoline above unity in absolute terms, which reflects the fact that gasoline prices changed considerably during the period analysed (1982–1988).

An interesting result is that of Galindo and Salinas (1997). They use a cointegration approach and an Error Correction Model to estimate the demand for gasoline in the Mexico City Metropolitan Area (MCMA) for the period 1987–1995. They find that short and long run price elasticities of the demand for gasoline are negligible. The study uses monthly data but seasonality fluctuations are ignored, and the proxy used for income for the MCMA is a production index at the national level.

Haro and Ibarrola (2000) estimate two separate models for Mexican regions and states across the border with the US to determine the effect that cheaper US gasoline prices have on gasoline consumption in Mexico. Their estimates are more elastic for regions within close proximity to the US than for those further away, showing the importance of the existence of a substitute good. Again, the study uses quarterly data but gives no special treatment to seasonality, and the model specification is static, which ignores the fact that economic agents take time to react to changes in incomes and prices.

Finally, Galindo (2005) models the demand for energy in Mexico with a rather different approach. He defines the demand for transport energy consumption as a function of transport output, and the relative price of energy. Although the elasticities are not estimated exclusively for road transport, the results are in line with those found in previous vehicle gasoline demand studies.

In summary, econometric estimates of elasticities of motor vehicle gasoline demand in Mexico suggest that gasoline is affected in a significant manner by changes in price and income. In general, price elasticities are smaller than the values reported in the literature, whilst income elasticities are higher. This is supported by studies such as Wohlgemuth (1997) that estimate gasoline elasticities with a panel of countries and find lower price elasticities and higher income elasticities in developing countries.

As more advanced econometric techniques were not available at the time most of the Mexico gasoline demand studies were conducted, we improve on previous work by exploring the non-stationary nature of the data more adequately and use cointegration techniques to avoid the problem of spurious estimation. We also give special treatment to dynamic panel models where the lag of gasoline is correlated with the equation's residuals, and use

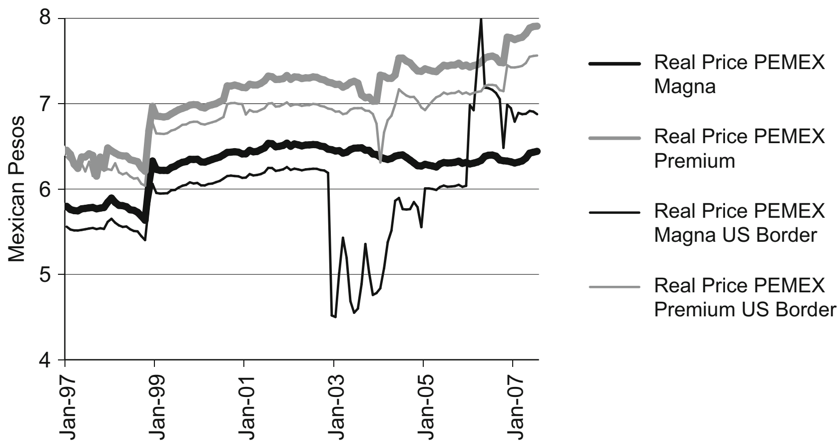

Fig. 1. Real gasoline prices by type of gasoline and location. Source: PEMEX Investor Relations Office.

up to date data to represent more recent conditions in the gasoline market in Mexico.

3. Background on Mexico and the petroleum industry

The 2005 population census estimates Mexico's population at over 103 million inhabitants. Mexico City is the political capital and along with some municipalities of the State of Mexico comprises the Mexico City Metropolitan Area (MCMA) with over 18.5 million inhabitants. The particular geographic and demographic characteristics of the MCMA (low urban population density, concentration of economic activities in certain areas, development of satellite cities and new towns, and enormous population) require long commute distances every day. There are nearly 22 million weekday trips in the MCMA of which 31.5% are made by private car or taxi (INEGI, 2007).

The national oil company (Petróleos Mexicanos, PEMEX) is in charge of refining, storing, transporting, distributing, and marketing gasoline for automobile consumption, as well as importing the necessary gasoline to meet demand. It delivers gasoline to consumers through a franchise system where PEMEX franchise service stations are privately owned. PEMEX supplies equipment, technology, and the company brand name and logo to franchise holders. There are over 6900 service stations in Mexico, all of them operated through this franchise system.

PEMEX supplies two types of unleaded gasoline for automobile consumption: PEMEX Magna with 87 octanes introduced in 1991, and the low sulphur gasoline PEMEX Premium with 92 octanes introduced in 1996. Mexico stopped production of leaded gasoline in 1997 and diesel is only consumed by a very limited number of passenger cars introduced to the market in 2005. PEMEX Premium accounted for 19.3% of gasoline sales in 2006, up from 11% in the year 2000.

Gasoline prices vary depending on the type of gasoline and the point of sale. PEMEX Premium's price is on average 11–23% higher than PEMEX Magna. Since 1990 service stations close to the border with the United States have lower prices in order to compete with the cheaper American substitutes.[2] Fig. 1 shows the trend of real prices for both types of gasoline for cities near the US border and the rest of the country from 1997 to 2007. For reference, PEMEX Magna was $7.13 Mexican pesos (MXN) per litre in May 31 2008, equivalent to US$0.69 per litre (US$1 was worth MXN$10.375 on June 6 2008).[3]

Fig. 1 does not show the price equilibrium resulting from the interaction of supply and demand in a free market economy. Article 31 section X of the Public Administration Law (Ley Orgánica de la Administración Pública Federal) states that the Ministry of Finance, with advice from the Ministry of the Economy and any other relevant public agency, determines the prices of goods supplied by a public enterprise. As a result, PEMEX Magna real price has been stable for the last 10 years in order to control inflation and minimise the negative impact that higher gasoline prices have on the lower income sectors of the economy. The changes in its nominal price are mainly to adjust for inflation, or due to technical improvements that increase efficiency and reduce emissions, rather than a reflection of international gasoline prices.

4. The data

The Ministry of Energy (Secretaría de Energía) provided two data sets for this study: an annual time series at a national level for the period 1980–2006, and an annual panel of 30 states for the period 1993–2006.[4] The data sets include total consumption and two types of nominal prices (for states near the border with the US and for the rest of the country). Data for income (GDP), vehicle stock, and population were obtained from the National Institute of Statistics, Geography and Informatics (Instituto Nacional de Estadística, Geografía e Informática, INEGI). Mexico City single metro fares, used as a proxy for national public transport fares[5], were provided by the Mexico City metro (Sistema de Transporte Colectivo Metro). Inflation was obtained from the Bank of Mexico.

Fig. 2 shows national gasoline consumption per vehicle, PEMEX Magna real price, real income per capita, vehicle stock per capita, and real Mexico City metro fares for the period

[2] However, in December 2007 gasoline prices in the US were higher than in Mexico for the first time since 1990.

[3] Exchange rate from the Bank of Mexico (www.banxico.org.mx).

[4] Mexico is divided into 31 states and a federal district (Mexico City). The data set provided by the Ministry of Energy includes data for the whole country, the two smallest states are added to neighboring states to form 30 cross-sectional units.

[5] Public transport fares are determined by local governments and therefore vary across the country. For instance, single metro tickets cost MXN$2 in Mexico City, whilst in Guadalajara and Monterrey, the second and third largest cities in Mexico, single metro tickets cost MXN$5 and MXN$4.5, respectively. However, data on public transport fares for different towns or cities are not available for a long time series, therefore we use Mexico City metro fares as a proxy for fares across the country.

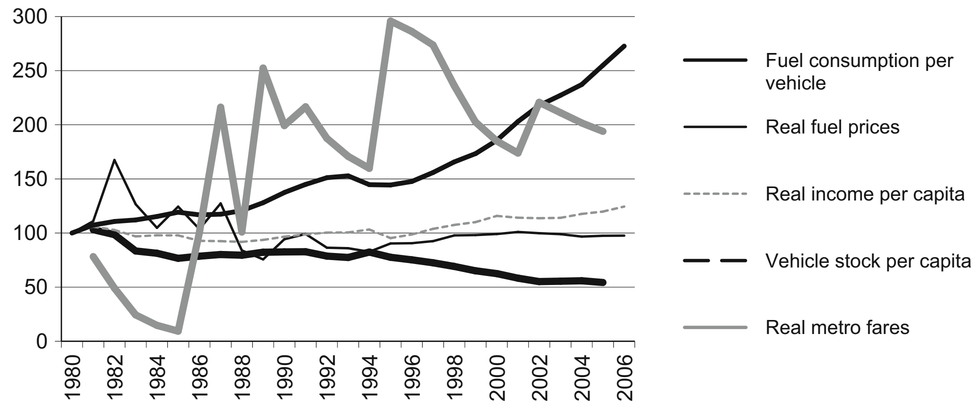

Fig. 2. Mexico gasoline consumption per vehicle, real price of PEMEX Magna, real income per capita, vehicle stock per capita, and real Mexico City metro fares for the period 1980–2006.

1980–2006. Figures are indexed to 100 in 1980. There seems to be a weak relationship between gasoline per vehicle and gasoline prices. For instance, there were significant real price changes from 1980 to 1992 but consumption per vehicle seems to be unaffected by these price changes. However, between 1994 and 1999 price changes have a negative association with consumption. The relationship between gasoline per vehicle and income is clearly positive between 1980 and 1990, however, higher incomes between 1994 and 2000 seem to be negatively associated with consumption. Vehicle stock appears to have a negative relationship with gasoline consumption per vehicle, as the stock of vehicles increases, vehicles are used less intensively. Finally, gasoline per vehicle appears unaffected by changes in the price of single Mexico City metro fares.

As mentioned in Section 2, a demand model for gasoline consumption typically includes amongst its exogenous variables some measure of prices and income, as well as other variables such as vehicle stock and public transport fares. An ideal aggregate time series model for Mexico City would therefore include either at least around 30 annual observations for each of these variables, or monthly data for a shorter period of time. Alternatively, a panel approach would include time series data for a number of cross-sectional units, for instance at the Mexico City borough level.

Data for Mexico City are available from 1993 on a monthly basis. Unfortunately, the only level of aggregation available is for the four PEMEX distribution centres in the Mexico City Metropolitan Area, which is of no use for our purposes, as data such as income and vehicle stock are not available at this level of aggregation. Therefore we are unable to use a panel approach with Mexico City cross-sections using these data.

Although monthly gasoline prices are available for the same period, we are unable to use a monthly time series approach since data on Mexico City income and vehicle stock are only available annually. Proxies for monthly income such as production indexes are only available at the national level and are not useful for this study, as for instance, the level of economic activity differs between the service-oriented urban areas and the manufacturing sector in northern Mexico. Besides, although monthly employment in Mexico City is available from 2005, monthly data on other variables that are expected to influence gasoline consumption, such as vehicle stock, are not available.

An annual time series approach with only 14 annual observations for the period (1993–2006) would produce unreliable estimates. Graham and Glaister (2006) develop a framework to derive local gasoline demand elasticities from national estimates. Their model assumes constant prices at the local and national levels and relates gasoline price elasticities to cross elasticities of other modes. They conclude that local elasticities can be derived from national estimates and mode shares at the national and local level. Therefore, due to lack of data availability to estimate gasoline demand elasticities for Mexico City, we first estimate elasticities at the national level and use the framework developed by Graham and Glaister (2006) to derive local elasticities. Then we estimate the elasticities with a different approach where gasoline consumption is derived from vehicle kilometres and fuel efficiency at the Mexico City borough level.

We derive gasoline consumption per vehicle from car kilometres and fuel efficiency per vehicle for the period 2001–2004, aggregated at the Mexico City borough level.[6] Car kilometres were taken from vehicle inspection centres' data provided by the Mexico City Ministry of the Environment (Secretaría del Medio Ambiente) for the period 1999–2004. Average fuel efficiency per type of vehicle, as published by the manufacturer, was taken from the Corporate Average Fuel Economy (CAFE) data.[7]

The use of CAFE data for the Mexican fleet provides the best approximation for the fuel consumption of the fleet. The vehicles sold in Mexico are quite similar to those in the US, although the vintage of vehicles may be older and the driving conditions may vary. The CAFE database accounts for vehicle age, although it may not reflect deteriorating maintenance over time. The driving cycle on which the CAFE estimates are made may also differ. Many of these issues are often cited as problems with using this data in the US and given the lack of alternative sources we feel this is the best estimate available.

Odometer readings are recorded at inspection centres twice a year in the MCMA when vehicles are subject to emissions and maintenance tests. The purpose of the tests is to determine whether the 'one day without a car' ban applies to the vehicle depending on its pollutant emissions. Kojima and Bacon (2001) provide a description and evolution of the vehicle usage restriction programme in the MCMA.

Since the data sets provided by the Ministry of the Environment also include vehicle serial number, make, model, and borough where each vehicle is registered, we were able to track

[6] Gasoline consumption per vehicle was calculated as the quotient of VKT and vehicle efficiency: Gasoline per vehicle (litres)=VKT (km)/Efficiency (km/litre). This measure is only an approximation of gasoline consumed. Engines consume more gasoline when cold and at certain speeds. Also, driving behaviour, like sudden acceleration, affects the level of gasoline consumed.

[7] Provided by John DeCicco of University of Michigan. The Mexican vehicle fleet is broadly similar to the US fleet. For Mexican vehicles not included in the CAFE data, a value of fuel efficiency from a similar vehicle was used.

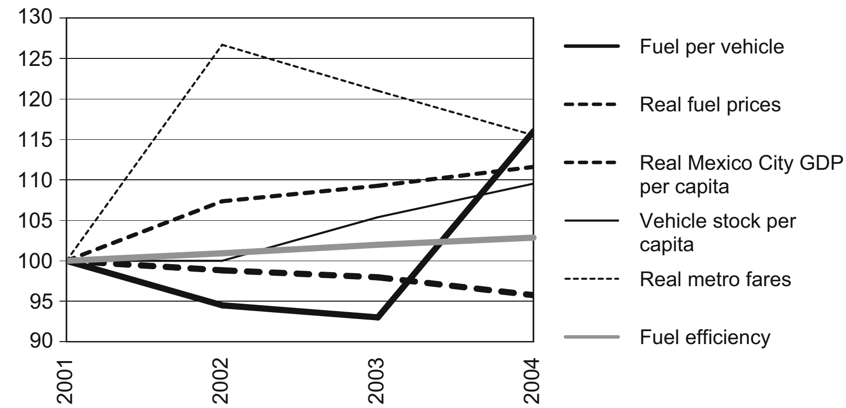

Fig. 3. Mexico City gasoline consumption per vehicle, real price of PEMEX Magna, real income per capita, vehicle stock per capita, real Mexico City metro fares, and fuel efficiency for the period 2001–2004.

vehicles across the bi-annual data sets to measure VKT as the difference between odometer readings from one period to the next.[8] As data on income and vehicle stock provided by INEGI are only available annually for the Mexico City boroughs but not for the municipalities of the State of Mexico that belong to the MCMA, we calculated VKT per year only for the 16 Mexico City boroughs.[9]

The make and model information were used to match a corresponding fuel efficiency value from the CAFE data to each vehicle in our data sets. Population per borough is only available every 10 years therefore we built a population variable based on population data for 2000 and births and deaths per borough per year but excluding possible migration between boroughs. Mexico City gasoline consumption per vehicle, real gasoline prices, real income per capita, vehicle stock per capita, real metro fares, and fuel efficiency are depicted in Fig. 2 for the period 2001–2004 and indexed to 100 in 2001 for comparison purposes.[10]

The relationship between gasoline per vehicle and gasoline prices is positive for the first three years of data, which would suggest gasoline is not an ordinary good. However, Fig. 3 shows values aggregated at the Mexico City level. The association between the variables varies in magnitude and direction between the 16 Mexico City boroughs. Gasoline per vehicle and real income also appear to have a counterintuitive relationship, as gasoline per vehicle decreases when incomes increase for the first three years of data. The relationship between vehicle stock per capita and gasoline per vehicle is unclear, vehicle stock increases cause gasoline per vehicle to decrease, but the relationship changes for the last year of data. A similar effect occurs with gasoline per vehicle and fuel efficiency. Finally, gasoline per vehicle and metro fares seem to have a negative relationship for the first and last years of data, which is also counterintuitive.

[8] Due to the fact that vehicles not older than two years and with emissions below a certain threshold are exempted from the inspection programme, VKT for the first two years of age of those vehicles is calculated as an average of subsequent years. Data on VKT for low emission vehicles with model year 2003 and 2004 that are exempted from the programme are not accounted for in our estimation.

[9] As serial number and odometer readings are recorded manually at inspection centres, the data were subject to numerous cleaning procedures, for instance if odometer readings from future periods are smaller than previous records, or if serial numbers are not complete.

[10] The data provided by the Ministry of the Environment suggest a drop in VKT of about 25% from 1999 to 2000, which raises concerns about the quality of the data for 1999, the first year of records. As the one million observations for 1999 is about half the number of observations of the rest of the data sets, the year 1999 is excluded from the analysis.

5. Estimation methods

This section presents the methods used in this analysis for the treatment of time series and panel data. For time series, in order to avoid spurious results when the data are non-stationary (means and variances are not constant over time), cointegration is the most widely used technique in the literature. For panel data with a relatively large number of cross-sections and small observations over time, as is the case with our data, the generalised method of moments technique (GMM) is used for dynamic demand specifications.

5.1. Time series cointegration

As a result of structural changes in the economy, caused for instance by political or technological changes, most economic data tend to have variable means and variances over time. Therefore, the classical econometric time series models that assume data to be stationary (constant means and variances across time) may produce spurious estimates. Such models usually produce relatively high measures of goodness of fit, such as R^2, as a result of the presence of a common trend in the regressors, rather than an adequate model specification. For stochastic data, that is, if the trend for some periods is different from the trend of other periods, the cointegration technique avoids the problem of spurious regression. The attractiveness of the method is that short and long run parameters can be estimated as well as the speed of adjustment towards the long run.

Cointegration follows three basic steps. First, unit root tests such as the Dickey–Fuller–GLS (DF-GLS) test by Elliot et al. (1996), and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test by Kwiatkowski et al. (1992) are applied to the variables included in the model to determine whether they are stationary or not.

To reject the null hypothesis of the DF-GLS test that the variable in levels contains a unit root (is non-stationary), the coefficient of the lagged value of the unit root test must be statistically significant and smaller than the unit root test critical values. If the null hypothesis is rejected for all variables, then the classical approach does not lead to spurious results. In contrast, if the null hypothesis of non-stationarity cannot be rejected, the variable at levels is non-stationary and may be transformed into stationarity by differencing.

Second, the long run elasticities are estimated through a cointegrating regression if the residuals are stationary. Finally, the short run elasticities and the rate of adjustment towards the long run are estimated through an Error Correction Model (ECM). The ECM of a gasoline demand model with income and price as explanatory variables follows the form:

$$\Delta \ln G_t = \alpha_0 + \sum_{i=0}^{n} \alpha_{1i} \Delta \ln P_{t-i} + \sum_{i=0}^{m} \alpha_{2i} \Delta \ln Y_{t-i} + \sum_{i+1}^{s} \alpha_{3i} \Delta \ln G_{t-i} + \alpha_4 e_{t-1} + Z_t \quad (1)$$

where G=gasoline consumption, P=price, and Y=income. The lag order n, m, and s are chosen so as to make Z_t white noise[11], and

$$e_{t-1} = \ln G_{t-1} - \beta_0 - \beta_1 \ln P_{t-1} - \beta_2 \ln Y_{t-1} \quad (2)$$

The coefficients α_{1i} and α_{2i} give the short run price and income elasticities, respectively, while α_4 represents the rate of adjustment towards the long run equilibrium (this coefficient must be negative and statistically significant to confirm cointegration). For a comprehensive summary of the cointegrating process see Hendry and Juselius (2000). For series with different orders of integration see Banerjee et al. (2001).

5.2. Panel data

The most appropriate econometric method for the treatment of dynamic panel models with large N and small T is the Generalised Method of Moments (GMM) technique. Biased and inconsistent parameters can result from OLS when unobserved individual effects are not accounted for explicitly, due to the fact that at least one of the regressors (the lagged dependent variable) is correlated with the disturbance term. Even with an adequate modelling of individual specific effects, for instance with the Within Group Estimator, the transformed lagged dependent variable and the transformed disturbance remain correlated. Consider the following dynamic model:

$$y_{i,t} = \gamma y_{i,t} + \beta x_{i,t} + \alpha_i + u_{i,t} \quad (3)$$

for cross-sectional units $i=1, \ldots, N$ and time $t=1, \ldots, T$, where $x_{i,t}$ is a vector of exogenous explanatory variables, γ and β are parameters to be estimated, α_i is a fixed or random unobservable individual effect, and $u_{i,t}$ is a random error. The treatment of the individual effects as fixed or random is not important here because first differencing, the starting point of the Arellano and Bond (1991) *difference* GMM estimator, removes the individual specific effects:

$$y_{i,t} - y_{i,t-1} = \gamma(y_{i,t-1} - y_{i,t-2}) + \beta(x_{i,t} - x_{i,t-1}) + u_{i,t} - u_{i,t-1} \quad (4)$$

However, $y_{i,t-1}$ and $u_{i,t-1}$ are by construction correlated in Eq. (4). In order to obtain consistent estimates, GMM estimation uses instrumental variables that are not correlated with the error term.

Assuming no serial correlation, Anderson and Hsiao (1981) show that $y_{it-2} - y_{it-3}$ and y_{it-2} are indeed correlated with $y_{it-1} - y_{it-2}$, however, they are not correlated with $u_{it} - u_{it-1}$, they are therefore valid instruments to estimate consistent parameters in Eq. (4). This gives GMM a great flexibility since a large number of instruments can be used for estimation, including endogenous and exogenous variables lagging two periods or more.

Blundell and Bond (1998) suggest that large downward finite sample biases can occur when instrumental variables are weak; this occurs as the autoregressive parameter in an AR(1) model approaches unity. Therefore, *difference* GMM performs poorly if lagged values of the variables in levels are weak instruments for subsequent first differences when the time series are persistent and T is small. More reasonable estimates can be achieved if lagged first differences are used as instruments for equations in levels, in addition to the lagged variables in levels as instruments for equations in first differences, which leads to the so-called *system* GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998).

Bond et al. (2001) note that finite sample biases can be detected by comparing the *difference* GMM estimate of the autoregressive parameter γ with that of OLS levels and the Within Group estimator. Hsiao (1986) shows that the parameter γ from OLS levels is biased upwards, whilst Nickell (1981) shows that the Within Groups estimator in short panels gives an estimate of γ that is biased downwards. Therefore, biases due to weak instruments may be important if the autoregressive parameter γ from *difference* GMM estimation does not lie between that of OLS levels and Within Groups, or if it is close to any of these estimates.

Arellano and Bond (1991) also develop a test to check whether the disturbance term is serially correlated. If it is, the GMM estimators will not be consistent due to the fact that some of the instruments will be invalid. They also develop the Sargan test of overidentifying restrictions, which determines whether the moment conditions selected are valid.

The drawback of the Sargan test is that apart from detecting serial correlation, it can reject the restrictions if the model is misspecified. Imbens et al. (1998) show that the Sargan test has poor size properties and propose alternative Tilting Parameter tests of overidentifying restrictions, however, Bowsher (2002) finds that the Tilting Parameter is only preferred to the Sargan test when few moment conditions are tested, which applies with panels with small T, or when few variables are treated as predetermined or strictly exogenous. The results from the Sargan test should therefore be interpreted with care. For *system* GMM the Sargan test can be used to determine the validity of the additional instruments, as well as the Difference Sargan test that compares the results from *difference* and *system* GMM.

6. Results

This section presents the results of a national time series cointegration approach and a national panel GMM model. Approximate elasticities are derived for Mexico City as suggested by Graham and Glaister (2006). This section also presents the results of a panel Within Groups model for Mexico City.

6.1. National time series cointegration

We first test for stationarity the logarithmic form of each series with the use of the DF-GLS and KPSS unit root tests. Table 2 shows the t-statistics of the unit root tests of the variables in levels and first differences. As the DF-GLS test takes non-stationarity as the null hypothesis and the KPSS test uses stationarity as the null, Maddala and Kim (2004) suggest that both tests can be used for confirmatory analysis.

The DF-GLS t-statistics of the variables in levels are not statistically significant for any of the variables, which means the null hypothesis that the variables in levels are non-stationary cannot be rejected. The KPSS t-statistics also confirms the non-stationarity of all variables at levels. The t-statistics of both unit root tests show that the variables were transformed into stationarity by differencing once, that is they are integrated to order 1, $I(1)$. The inclusion of a deterministic trend does not affect the results of any of the tests.

Once the order of integration has been established, the next step is to estimate a cointegrating regression to obtain the long run elasticities and test the residuals for unit roots. If the residuals are stationary, $I(0)$, there is cointegration. Maddala and Kim (2004) suggest that there are difficulties with obtaining the long

[11] Z_t is white noise if it is distributed $N[0,\sigma^2]$.

Table 2
DF-GLS and KPSS *t*-tests for stationarity. National level (1980–2006).

Variable	Trend	Levels		1st differences	
		DF-GLS	KPSS	DF-GLS	KPSS
ln *G/V*	*With trend*	−1.481	0.342[a]	−3.164[c]	0.085
	Without trend	0.807	0.966[a]	−2.751[a]	0.086
ln *P*	*With trend*	−2.744	0.173[b]	−5.025[a]	0.179
	Without trend	−1.141	0.359[c]	−3.568[a]	0.077
ln *Y*	*With trend*	−1.503	0.210[b]	−3.168[c]	0.052
	Without trend	−0.301	0.730[b]	−2.908[a]	0.299
ln *V*	*With trend*	−1.813	0.248[a]	−3.258[c]	0.089
	Without trend	0.440	1.060[a]	−2.306[c]	0.270
ln *F*	*With trend*	−0.705	0.149[b]	−3.401[c]	0.074
	Without trend	−0.390	0.565[b]	−3.394[a]	0.066

DF-GLS has a unit root null hypothesis whilst KPSS has stationarity as the null.
[a], [b], and [c] denote significance at the 1%, 5%, and 10% levels, respectively. G/V=gasoline consumption per vehicle, P=average of real prices of available gasoline types, Y=real GDP per capita, V=vehicle stock per capita, and F=real metro fares.

Table 3
Results of the time series cointegrating regressions. Dependent variable: gasoline consumption per vehicle (ln G/V). National level (1980–2006).

Variable	OLS	FMOLS
ln *P*	−0.062	−0.292[a]
ln *Y*	0.757[a]	0.533[a]
ln *V*	−0.899[a]	−0.399[a]
ln *F*	0.041[a]	−0.002[a]
Constant	−2.355	13.352
Adjusted R^2	0.912	0.872
Residual unit root test (DF-GLS)	−5.002[a]	−3.496[b]
Residual unit root test (KPSS)	0.095	0.107

[a] and [b] denote significance at the 1% and 5 % levels, respectively. FMOLS shows the results from the Phillips and Hansen Fully Modified OLS.

run parameters through a cointegrating regression based on a traditional OLS static model, as possible dynamics are not considered. We also employ the Phillips and Hansen (1990) fully modified OLS (FMOLS) estimator that applies semi-parametric adjustments to the OLS estimator to correct for possible endogeneity and serial correlation in the errors.[12] Table 3 shows the results.[13]

The results of the cointegrating regressions and the residuals unit root tests confirm cointegration since the residuals are stationary at levels, *I*(0). Therefore the coefficients of ln *P*, ln *Y*, ln *V*, and ln *F* are the long run price, income, vehicle, and cross elasticities, respectively. Although both techniques agree on the sign of the price, income, and vehicle stock elasticities, the magnitude of the coefficients significantly changes between estimators. However, as previously mentioned, estimating long run parameters through a static OLS model produces biased estimates since gradual adjustment to changes is not accounted for. The fact that the cross-elasticities approach zero for both models may show that either public transport is not considered as an option for vehicle users, or that Mexico City metro fares are not a good proxy for the cost of public transport across the country. The results of the ECM are presented in Table 4.

Table 4
Results of the Error Correction Model, dependent variable $\Delta\ln G/V$. National level (1980–2006).

Variable	OLS	FMOLS
$\Delta\ln P$	−0.056	−0.104
$\Delta\ln Y$	0.782[a]	0.426[a]
$\Delta\ln V$	−1.012[a]	−0.264[a]
$\Delta\ln F$	0.025[a]	0.013[a]
$\Delta\ln G/V_{t-1}$	0.477[a]	0.422[a]
res_{t-1}	−0.199[a]	−0.289[a]
Constant	−0.006	−0.006
Adjusted R^2	0.650	0.691

The model also includes one lag of price and income, and two lags of vehicle stock in order to make the error white noise. The results are omitted for brevity.

[a] Significant at the 1% level.

The short run elasticities are the coefficients of the unlagged differenced variables. The negative and significant coefficient of the lag of the residual from the cointegration regression confirms there is cointegration and represents the rate of adjustment from the short to the long run. The coefficients show that between 20% and 29% of the effect of changes in the explanatory variables occurs during the first year. The elasticities from the national time series data are summarised in Table 5.

Both models suggest smaller short run price elasticities than the ranges suggested in the gasoline demand surveys, a pattern found in developing countries.

As the dependent variable in our model is gasoline per vehicle, rather than gasoline per capita (dividing gasoline consumption by vehicle stock reduces multicollinearity and thus lowers the risk of biased estimates)[14], by definition the vehicle stock elasticity will be negative due to the fact that both sides of the demand equation were divided by vehicle stock. For simplicity consider the static model

$$G = P^{\beta_1}Y^{\beta_2}F^{\beta_3}S^{\beta_4} \approx G/S = P^{\beta_1}Y^{\beta_2}F^{\beta_3}S^{\delta} \tag{5}$$

where G=gasoline consumption, P=gasoline prices, Y=income, F=public transport fares, S=vehicle stock, and $\delta=\beta_4-1$ or $\beta_4=\delta+1$. Therefore, in order to make the vehicle stock elasticity comparable to elasticities of gasoline per capita models, we must add one unit to the vehicle stock parameter.

6.2. National panel GMM

Table 6 shows the results from applying OLS levels, Within Groups, *difference* and *system* GMM to the panel of 30 Mexican states for the period 1993–2004. For the GMM estimators, gasoline prices are treated as strictly exogenous since they are directly determined by government and do not follow any interaction between supply and demand for gasoline.[15]

For *difference* GMM several specifications were tested but the magnitude of the coefficients does not change significantly. Only one lag of the dependent variable is included to avoid any second order serial correlation in the error terms. In general we find that the inclusion of lags of independent variables, especially income, affects the results of the Sargan test, showing model specification

[12] An alternative approach is the Johansen procedure for series with large *T*.

[13] As income and vehicle stock tend to be strongly associated, the inclusion of both explanatory variables may produce problems of multicollinearity. However, the zero order correlation coefficient between income and vehicle stock is 0.655, which suggests multicollinearity is not an issue here. This is supported by the fact that the R^2 is high for both models and the coefficients are statistically significant.

[14] As mentioned in Section 2 of this paper, Dahl and Sterner (1991) suggest the use of gasoline consumption per vehicle as the dependent variable when lags of both dependent and independent variables are used in order to reduce the specificity of the model. In such cases price and income elasticities do not include the changes in the number of automobiles, only the changes in utilisation.

[15] The zero order correlation coefficient between income and vehicle stock for the panel data is 0.702. The fact that most coefficients are significant suggests that the correlation between these variables does not produce multicollinearity.

Table 5
Summary of elasticity estimates from time series cointegration models. National level (1980–2006).

Method	*P*		*Y*		*V*		*F*	
	Short run	Long run	Short run	Long run	Short run	Long run	Short run	Long run
OLS	−0.056	−0.062	0.782[a]	0.757[a]	−1.012[a]	−0.899[a]	0.025[a]	0.041[a]
FMOLS	−0.104	−0.292[a]	0.426[a]	0.533[a]	−0.264[a]	−0.399[a]	0.013[a]	−0.002[a]

[a] Significant at the 1% level.

Table 6
Results of the dynamic panel models. National level (1993–2004). National level (1993–2004).

Variable	OLS levels	Within groups	Diff GMM	Sys GMM
ln *P*	−0.094[a]	−0.193[a]	−0.152[c]	−0.087
ln *Y*	0.015	0.614[a]	0.469[a]	0.093
ln *V*	−0.941[a]	−0.735[a]	−0.376[a]	−0.099
ln *F*	−0.081[a]	−0.009	−0.052	0.029
ln G/V_{t-1}	0.946[a]	0.239[a]	0.605[a]	0.786[a]
D1995	0.004	−0.071	0.001	−0.017
AB AR(1)	–	–	0.013	0.003
AB AR(2)	–	–	0.140	0.154
Sargan	–	–	0.166	0.023
Dif Sargan	–	–	0.236	0.283
No. instruments	–	–	13	27
No. observations	330	330	300	330

[a] and [c] denote significance at the 1% and 10 % level, respectively.

error, even though the coefficients are significant. We therefore proceed with an ADL(1,0) partial adjustment model. Various combinations of time dummies were also included in the model but in general they had little influence in the parameter estimates. Although the time dummy for 1995 is statistically insignificant, which shows the economic crisis of 1995 did not systematically affect consumption of gasoline per vehicle, its inclusion in the model is not rejected by the Sargan test.

The choice of model was first based on the Arellano–Bond tests for AR(1) and AR(2) in first differences, the Sargan and Hansen tests of overidentifying restrictions, and the Difference-in-Hansen tests of exogeneity of instrument subsets. As various *difference* GMM specifications pass the error serial correlation tests and instrument validity tests, the selection of the final model presented in Table 6 was also based on the relevance of the instruments tested using an *F*-statistic, *t*-tests and the R^2 value of the first stage of the Two Stage Least Squares method. Stock et al. (2002) suggest that a rule of thumb to evaluate relevant instruments is that the first stage *F*-statistic must be greater than 10, the *t*-test of each exogenous variable must be greater than 3.5, and the R^2 must be greater than 30%. We find that several specifications also satisfy these conditions, we therefore select the instruments that produce the highest first stage R^2.

For *System* GMM the Sargan test always shows model specification error. In some specifications the signs of the elasticities are counterintuitive and in most cases the estimates for price and vehicle stock are statistically insignificant. The results show that the additional instruments available for *system* GMM are weak instruments. Therefore the preferred model is the *difference* GMM specification with a time dummy for 1995, collapsed number of instruments, and robust disturbance terms.

6.3. Derivation of local elasticities

Table 7 shows the short and long run price, income, vehicle stock, and cross elasticities of demand for gasoline in Mexico

Table 7
Summary of elasticity estimates from time series cointegration and panel GMM models. National level.

Variable	Time series (1980–2006)		Panel (1993–2004)	
	Short run	Long run	Short run	Long run
P	0	−0.292	−0.152	−0.385
Y	0.426	0.533	0.469	1.187
V	0.736	0.601	0.624	1.580
F	0.013	−0.002	0	0

obtained from a national time series cointegration model for the period 1980–2006 and a *difference* GMM model from 30 Mexican states for the period 1993–2004.

The elasticities shown for time series data are obtained with the FMOLS estimator, whilst the elasticities shown for panel data correspond to the *difference* GMM estimator. In order to make our gasoline per vehicle elasticities comparable to those from gasoline per capita specifications, a value of one was added to the vehicle stock coefficients, as mentioned above. Short run income and vehicle stock elasticities estimated with time series and panel data are somewhat similar, however, the absolute values of panel long run price elasticities are significantly higher than the time series estimates. Also, the panel long run income and vehicle stock elasticities are more than twice the magnitude of the coefficients obtained with time series data.

Eskeland and Feyzioglu (1997b) estimate long run price elasticities as high as −1.13 with national data from 1982 to 1988, a period with great fluctuation in gasoline prices, whilst Galindo and Salinas (1997) find values as small as −0.05 for the Mexico City Metropolitan Area for the period 1987–1995. Therefore, our time series long run price elasticity of −0.29 and our panel elasticity of −0.38 reflect the fact that elasticities change over time and across space.

Graham and Glaister (2006) develop a framework to derive local elasticities from national estimates. They show that local elasticities are the product of the national values and a measure of local and national mode share that follow the formula:

$$\eta^L = \eta^N \left(\frac{x_i^N / x^N}{x_i^L / x^L} \right) \tag{6}$$

where η^L and η^N are the local and national elasticities, respectively, x_i is the proportion of trips made by private automobile and taxis, and x is the total number of trips. The superscripts N and L represent national and local values, respectively.

Mode shares for Mexico City were obtained from the 1994 origin destination survey[16] with 16.7% of trips made by private vehicles and 2.5% by taxi. Data for traffic between Mexican cities

[16] The latest origin destination survey available was conducted in 2007. Unfortunately the publicly available data only contains mode share for the Mexico City Metropolitan Area, rather than for Mexico City proper. Disaggregate mode shares were not available for this study.

Table 8
Mexico City elasticities derived from national estimates and national and local mode share.

Variable	Time series (1980–2006)		Panel (1993–2004)	
	Short run	Long run	Short run	Long run
P	0	−0.200	−0.104	−0.263
Y	0.291	0.365	0.321	0.812
V	0.503	0.411	0.427	1.081
F	0.009	−0.001	0	0

obtained from the 2006 Ministry of Transport and Communications Statistics Yearbook (Anuario Estadístico 2006, Secretaría de Comunicaciones y Transportes) were used as a proxy for national mode shares, with road traffic representing 73% of the total number of trips, of which 18% are made by car and the rest by coach. Therefore, an approximation of elasticities for Mexico City can be estimated by multiplying the national estimates by a factor of 0.684. Table 8 shows the short and long run price, income, vehicle stock, and cross elasticities for Mexico City.

6.4. *Mexico City panel GMM model*

The approximate elasticities for Mexico City derived from national estimates and mode shares provide an insight into the effect that changes in income, prices, vehicle stock, and public transport fares have on the demand for gasoline in Mexico City. However, one could argue that apart from mode shares, other factors determine the difference in elasticities between the national and local level. For instance, due to the fact that Mexico City GDP per capita is higher than the average national income, it may be reasonable to argue that newer more fuel efficient vehicles are driven in Mexico City, and therefore price responses would be even less elastic. It could also be argued, however, that higher incomes result in the purchase of bigger less fuel efficient vehicles, such as sport cars or 4X4s, or vehicles equipped with air conditioning, which reduces fuel efficiency, and may increase the magnitude of the elasticities. Nonetheless, data on the composition of vehicle stock are not available at the national level. Also, the framework developed by Graham and Glaister (2006) assumes constant prices across geographical areas, which is a strong restriction, especially for Mexico where gasoline prices vary for regions closer to the US border.

For these reasons, we attempt to estimate elasticities for Mexico City with gasoline consumption per vehicle derived from car kilometres and fuel efficiency of the vehicle fleet, with data from Mexico City rather than for the country as a whole. As mentioned earlier, this specification also gives approximate elasticities, as fuel efficiency per vehicle depends on several factors such as driving behaviour, speeds, and the condition of the roads infrastructure.

Table 9 shows the results from applying static and dynamic OLS levels, static and dynamic Within Groups, and *difference* and *system* GMM to the panel of the 16 Mexico City boroughs over the period 2001–2004. Again, the panel GMM models treat gasoline prices as strictly exogenous. Numerous specifications were tested in order to eliminate second order serial correlation in the error terms and pass the Sargan test of error specification. The last four columns in Table 9 show the results of two *difference* and two *system* GMM specifications, for models that pass and fail the Sargan test. In general the Sargan test in the *difference* GMM models rejects the null hypothesis that there is no specification error when all variables are included in the model (price, income, vehicle stock, metro fares, and fuel efficiency). We estimate the first stage of the Two Stage Least Squares method to identify and eliminate the weaker instruments from the model, however, by doing this the coefficient of the lagged dependent variable is below that of the Within Groups estimator, which suggest the results are biased downwards. In addition, only the vehicle stock coefficient is statistically significant, even though the static Within Groups specification (that gives unbiased estimates if no lags of the dependent variable are included amongst the explanatory variables) also produces significant estimates for price and income. The coefficient of metro fares is always negative which appears to be counterintuitive, although it is statistically insignificant. We find that by eliminating metro fares from the model and by choosing the instrument matrix with the highest first stage R^2 the Sargan test is not rejected and the fuel efficiency coefficient is significant. However, by applying the estimated coefficients to the most recent year of data, the forecast error is over 50% for all Mexico City boroughs and in some cases over 100%. Also, the long run income elasticity is as high as 3.7, which causes serious concerns especially as this high adjustment would have occurred in only 4 years.

The *system* GMM models also appear to produce biased estimates as the coefficient of the autoregressive term is smaller than the corresponding Within Groups estimate, which suggests the instruments may be weak and the coefficients downward biased. As with *difference* GMM, the elimination of metro fares from the model and the selection of the instruments with highest first stage R^2 suggest the choice of instruments is valid, however, the income coefficient is statistically insignificant, which contradicts the results from the unbiased static Within Groups estimator.

Thus, it would seem that the GMM specifications produce biased and unreliable estimates as the instruments available are weak and the coefficient of the lagged dependent variable is too close to the corresponding dynamic Within Groups model. Table 9 also shows the results for OLS levels and Within Groups. The results from an *F*-test suggest the Within Groups results are preferred over OLS, and a Hausman test suggests fixed effects are preferred over random effects. Since by definition dynamic fixed effects results are biased, we tend to rely on the results of static Within Groups. This specification does not allow us to estimate short and long run elasticities, as no dynamics are incorporated into the model. Dahl and Sterner (1991) suggest that static models tend to produce medium term elasticities, which is consistent with the short period analysed in this study (2001–2004).

The last column in Table 10 shows the medium run price, income, vehicle stock, metro fares, and fuel efficiency elasticities of demand for gasoline in Mexico City obtained from a static Within Groups model with data aggregated at the Mexico City borough for the period 2001–2004. The vehicle stock elasticity corresponds to the estimated coefficient plus one in order to make it comparable to gasoline per capita models.

Although the magnitude of the elasticities depends on the data set employed, as well as the model specification and the econometric technique used for estimation, the summary of results in Table 10 shows that gasoline per vehicle demand in Mexico City is somewhat price elastic, with long run estimates between −0.2 and −0.26. These results are smaller than the average estimates reported in the gasoline demand surveys, which are consistent with previous findings in developing countries. Although all models agree on the sign of the elasticities, the magnitude differs greatly, which shows elasticities change over time and differ between the national and local levels, with smaller price responses in Mexico City.

As vehicle stock is included in our model, income elasticities represent changes in vehicle utilisation. The overall effect that income has on gasoline consumption through vehicle stock and

Table 9
Results of the Mexico City panel models (2001–2004).

Variable	Static OLS levels	Dynamic OLS levels	Static within groups	Dynamic within groups	Diff GMM (full model)	Diff GMM (restricted model)	Sys GMM (full model)	Sys GMM (restricted model)
ln *P*	−0.343	−0.386[a]	−0.218[a]	−0.189[a]	−0.174	−0.141[a]	−0.108[a]	−0.180[a]
ln *Y*	0.159[a]	0.041	0.495[a]	0.529[a]	−0.444	0.687[a]	0.536[a]	−0.118
ln *V*	−0.487	−0.008	−0.466[a]	−0.376[a]	−0.549[a]	−0.451[a]	−0.692[a]	−0.287[a]
ln *F*	−0.029	−0.105	−0.039	−0.084	−0.105	–	−0.091	–
ln *E*	−0.040	−0.029	0.032	−0.097	0.032	−0.082[a]	−0.099	0.024
ln G_{t-1}	–	0.907[a]	–	0.657[a]	0.629[a]	0.816[a]	0.651[a]	0.701[a]
AB AR(1)	–	–	–	–	0.009	0.005	0.017	0.467
AB AR(2)	–	–	–	–	0.359	0.667	0.279	0.743
Sargan	–	–	–	–	0.003	0.895	0.053	0.534
Dif Sargan	–	–	–	–	0.238	0.466	0.462	0.293
No. instruments	–	–	–	–	7	13	11	16
No. observations	64	48	64	48	32	32	48	48

The figures reported for the Sargan and Difference Sargan tests are the *p*-values of the null hypothesis that the instruments are uncorrelated with the residuals.
[a] Denotes significance at the 1% level.

Table 10
Summary of elasticity estimates for Mexico City from time series cointegration and panel GMM models.

Variable	Time series national		Panel national		Panel Mexico City
	Short run	Long run	Short run	Long run	Medium run
P	0	−0.200[a]	−0.104[a]	−0.263[a]	−0.218[a]
Y	0.291[a]	0.365[a]	0.321[a]	0.812[a]	0.495[a]
V	0.503[a]	0.411[a]	0.427[a]	1.081[a]	0.534[a]
F	0.009[a]	−0.001[a]	0	0	0
E	–	–	–	–	0

[a] Denotes significance at the 1% level.

vehicle utilisation has increased over time and is above unity in the long run. The estimates from both national and Mexico City data show that most of the income effect occurs through vehicle ownership. The fact that the demand models with more recent data give higher long run income and vehicle stock elasticities may suggest that vehicles are being used more intensively in recent years and that Mexico City residents are purchasing larger vehicles. Additional vehicles are used more intensively as long run vehicle stock elasticities are above unity.

All models show that changes in public transport fares have negligible effects on gasoline consumption, suggesting little substitution between modes. Also, the fuel economy elasticities show that more fuel efficient technologies have had a negligible effect on gasoline consumption. Finally, the fact that fuel efficiency elasticities are smaller than vehicle stock elasticities suggests that vehicle stock size, rather than its composition, has a higher impact on gasoline consumption in Mexico City.

7. Conclusions and policy issues

Short and long run price, income, vehicle stock, and cross elasticities of the demand for gasoline per vehicle were estimated for Mexico with a time series cointegration model for the period 1980–2006 and a panel GMM model with data from 30 states over the period 1993–2004. Approximate elasticities for Mexico City were derived from national estimates and mode shares at the national and local level as suggested by Graham and Glaister (2006). In addition, elasticities for Mexico City were estimated with a panel Within Groups model with data aggregated at the Mexico City borough level for the period 2001–2004, where average gasoline consumption per vehicle was derived from car kilometres and fuel efficiency.

Although all models agree on the sign of the elasticities, the magnitude differs greatly. Elasticities change over time and differ between the national and local levels, with smaller price responses in Mexico City. The long run price elasticity in Mexico City is in the range −0.2 to −0.26, while previous gasoline demand surveys mainly based on country data report average elasticities between −0.6 and −0.8. In addition, all models show that changes in public transport fares have negligible effects on gasoline consumption. These values may show the lack of available substitutes such as public transport, or simply that economic agents do not consider public transport as a viable substitute to the car. Estimates of fuel economy elasticities suggest that more fuel efficient technologies have had a negligible effect on gasoline consumption, and the fact that fuel efficiency elasticities are smaller than vehicle stock elasticities suggests that vehicle stock size, rather than its composition, has a higher impact on gasoline consumption in Mexico City. The absolute value of short and long run income elasticity estimates is greater than the absolute value of the price elasticity.

Various policy issues are implied by the results of this study. The income elasticity estimates imply that gasoline prices would need to increase faster than GDP growth if the policy objective is to keep gasoline consumption at present levels. Most governments are seeking to reduce carbon emissions, thus this result implies a need for some policy action to actually reduce gasoline consumption. Most developing countries are facing this dilemma of rapid growth in carbon emissions versus demands for increased motorization.

Other possible policies have been examined using some of the elasticity estimates from this work. Crôtte et al. (2010) applied these elasticities and other travel demand elasticities to estimate the impact of various pricing policies in Mexico City. This included congestion pricing and environmental taxes to manage demand. Congestion charges provided the largest decrease in traffic and also a large increase in revenue, which could potentially be recycled to support alternative modes or other policies to reduce carbon emissions.

While we note the caveats of the data used in this study it provides a first step to analysing these types of policies. The tradeoff between the desire to motorize and the need to reduce carbon emissions will become increasingly critical for developing countries and further more detailed data and analysis will be necessary. This study is a first step in analysing these issues.

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