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A Meta-Analysis of the Price Elasticity of Gasoline Demand. A System of Equations Approach

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Abstract

Automobile gasoline demand can be expressed as a multiplicative function of fuel efficiency, mileage per car and car ownership. This implies a linear relationship between the price elasticity of total fuel demand and the price elasticities of fuel efficiency, mileage per car and car ownership. In this meta-analytical study we aim to investigate and explain the variation in empirical estimates of the price elasticity of gasoline demand. A methodological novelty is that we use the linear relationship between the elasticities to develop a meta-analytical estimation approach based on a system of equations. This approach enables us to combine observations of different elasticities and thus increase our sample size. Furthermore it allows for a more detailed interpretation of our meta-regression results. The empirical results of the study demonstrate that the system of equations approach leads to more precise results (i.e., lower standard errors) than a standard meta-analytical approach. We find that, with a mean price elasticity of -0.53, the demand for gasoline is not very price sensitive. The impact a change in the gasoline price on demand is mainly driven by a response in fuel efficiency and car ownership and to a lesser degree by changes in the mileage per car. Furthermore, we find that study characteristics relating to the geographic area studied, the year of the study, the type of data used, the time horizon and the functional specification of the demand equation have a significant impact on the estimated value of the price elasticity of gasoline demand.

Key words: Meta-analysis; Price elasticities; Gasoline demand; System of equations

JEL code: C30, C42, C51, L91, Q40, Q48

1. Introduction

In a world where energy-conservation is an issue of great concern, both from a political, environmental and economic point of view, the demand for gasoline has received a great deal of

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attention as a research topic. Understanding the determinants of gasoline demand has been of interest to economists for almost three decades. Especially since the 1973 energy crisis, there have been a growing number of study efforts that aim to model the demand for gasoline. Initially, studies mainly addressed concerns about the availability of depletable resources and national security concerns raised by the oil supply shocks of the 1970s. Lately, studies have increasingly addressed the various environmental consequences of gasoline consumption, particularly with respect to the emission of greenhouse gases (Kayser, 2000). Gasoline demand studies have always paid particular attention to the impact of the price level of gasoline. For environmental and political reasons, policy makers are highly interested in the impact of gasoline taxes and autonomous price changes on demand.

A wide range of fiscal instruments is applied to the use of road transport in the European Union, including registration tax, road and insurance tax, fuel taxes and infrastructure charges. Discussion of economic instruments focuses on methods of improving the tax system to better align usage costs with external effects rather than determining the optimal tax. Recent political activities suggest that European economies will face in the long run a change in the structure of transport cost towards variabilization strategies, which shift taxation away from fixed fees such as vehicle licensing to usage fees such as fuel taxes and road usage pricing (English et al., 2000). Recent European fuel pricing policy mainly focuses on harmonization of member states tax rates and on the promotion of the use of bio-fuels or other renewable fuels for transport (EC, 2003a,b); minimum rates of taxation are set for *inter alia* motor fuel although member states are allowed to apply total or partial exemptions or reductions in the level of taxation to, *inter alia* biofuels. Efforts to promote fuel efficiency in the European Union are mainly represented by regulations on pollution emissions and consumer information on fuel economy. In the US, mandatory corporate fuel efficiency (CAFE) standards have been in effect since 1975; car manufacturers who fail to meet the standards are confronted with financial penalties.[1] There has been considerable debate about the influence of the standards. Proponents see them as a proven[2] way to decrease the demand for gasoline while opponents argue that they are a costly and cumbersome way to reduce gasoline consumption and that fuel taxes are more effective.

[1] As of 1990, the CAFE standard for passenger car fuel economy is 11.7 kilometer per liter.
[2] See for example Goldberg (1998)

In order to assess the impact of pricing policies, information is required about the relationship between gasoline price and demand. A useful notion in this context is that gasoline demand can be seen as a function of fuel efficiency, car mileage and car ownership. A change in the gasoline price may lead to changes in each of these variables. The size of these individual effects determines the total impact of a price change on the demand for gasoline. Empirical study results indicate a high variation among estimates of the price elasticity of gasoline demand. This is hardly surprising, given the large amount of variation in estimation techniques, model specifications and other study characteristics. Hence, meta-analysis seems to be an appropriate and useful approach to study the price elasticity of gasoline demand. Meta-analysis is a quantitative research synthesis technique that applies statistical and econometric techniques in order to investigate, summarize or integrate a body of literature consisting of studies that investigate and report the size and sign of a specific effect of interest, also called *effect size*, which is typically an elasticity or nominal value. As such, meta-analysis can be used to estimate the true underlying value of the effect size and to investigate and explain the variation in the estimates of the effect size that is found in the literature. For an extensive overview of meta-analysis see Sutton (2000).

In this study we use meta-analytical techniques to (i) estimate the price elasticity of gasoline demand and decompose this into estimates of the price elasticities of fuel efficiency, mileage per car and car ownership with respect to gasoline price and (ii) determine the impact of study characteristics on the estimated elasticity values. To this purpose, we collect empirical estimates of price elasticities of gasoline demand as well as empirical estimates on price elasticities of fuel efficiency, mileage per car, car ownership, traffic volume and gasoline consumption per car, together with information about the empirical studies from which they are collected. We develop a novel estimation approach, based on a system of meta-analytical equations, in which we make use of our knowledge on the functional relationships between the elasticities. Unlike the standard techniques that are used in earlier meta-analytical studies on the price elasticity of gasoline demand (Espey, 1998; and Graham and Glaister, 2002; Hanly, 2002), our approach enables us to combine information of different types of elasticities in order to obtain more accurate estimates. Furthermore, it enables us to interpret and explain the results in a more precise and detailed fashion.

This study is structured as follows. In Section 2 we discuss the relationship between the demand for gasoline, fuel efficiency, car mileage and car ownership. We show that there is a linear relationship between the elasticities of these variables, and those of traffic volume and gasoline consumption per car, with respect to the gasoline price. In Section 3 we introduce a meta-analytical approach, based on a system of equations, which accommodates the combining of estimates of the various price elasticities that we discuss in Section 2. Furthermore, we discuss two meta-analytical models that are based on this approach. Section 4 presents the empirical results of the meta-analytical models discussed in Section 3. Section 5 concludes.

2. The relationship between gasoline price and demand

Figure 5.1 shows the real price of gasoline and the consumption of gasoline in the US - the largest consumer of gasoline - between 1949 and 2003. During this period, gasoline consumption has grown from 2,410 to 8,937 thousand barrels per day. Growth was particularly rapid in the period between 1949 and 1973. Between 1973 and 1992, the growth rate slowed down and even reached negative values in certain years. Since 1992, the growth rate has been strictly positive again, although in a less dramatic fashion than in the period before 1973.

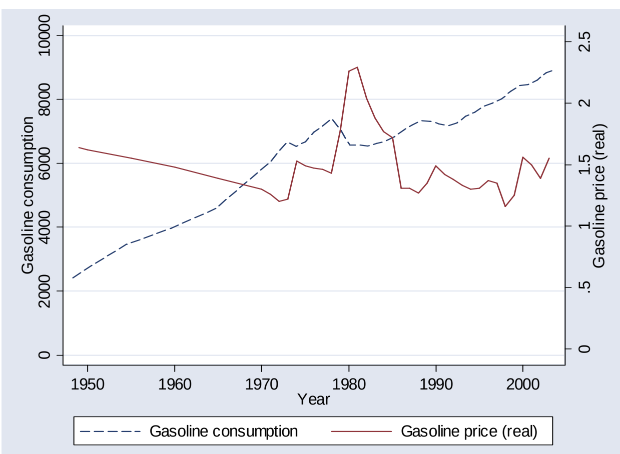

Figure 1: Real gasoline price and annual gasoline consumption between 1949 and 2003. Gasoline consumption is in thousands barrels per day. Gasoline price is in dollars per liter. Source: The Annual Energy Review (2003).

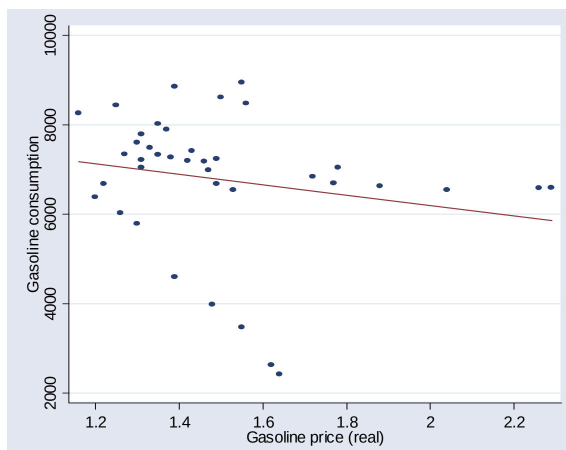

Figure 2: The relation between real gasoline price and annual gasoline demand in the period between 1949 and 2003. Source: based on historical data from the Annual Energy Review (2003).

With respect to gasoline price there has been considerable variation between 1949 and 2003, with a minimal value of $1.16 per liter in 1998 and a maximum value of $2.29 per liter in 1981. At first, during the period between 1949 and 1973, the gasoline price gradually decreased. As a consequence of three major political events, i.e. the energy crisis caused by the OPEC oil embargo (1973), the Iranian revolution (1979) and the Iraq-Iran war (1980-1988), the gasoline price was very high during the period between 1973 and 1985. Since 1985, the gasoline price has been relatively stable. The scatter plot in Figure 5.2 shows that the correlation between gasoline consumption and gasoline prices has been negative between 1949 and 2003, with a correlation coefficient value of -0.50.

Gasoline demand can be expressed as the mathematical product of three other variables; gasoline demand per kilometer, mileage per car and car ownership:

$$G = FE^{-1} \times \frac{KM}{C} \times C \qquad (1)$$

where G, FE, KM and C denote gasoline demand, fuel efficiency, mileage and car ownership, respectively. Fuel efficiency is defined as the number of kilometers per liter of gasoline, i.e., $FE = KM / G$. Changes in the gasoline price may lead to changes in each of the right-hand-side terms. The relative size of these changes depends on the behavioral response of the consumer when faced with a gasoline price change[3]. For example, faced with a price increase, a consumer may decide to travel less by car, either by switching to alternative transport modes or by traveling less in general. Furthermore, a car owner may respond by selling her car or by switching to a more fuel-efficient model. All of these responses ultimately affect the demand for gasoline. Thus, a change in gasoline price affects the total demand for gasoline via (i) fuel efficiency, (ii) mileage per car and (iii) car ownership. The consumer response to a change in price may depend on the response time. In the short run, people might respond mainly by changing their mileage per car, i.e. the number of kilometers they drive which each car they own. Switches to more fuel-efficient car models and changes in the number of cars owned are probably more common in the long-run.

The sensitivity of gasoline demand to changes in the gasoline price is measured by calculating or estimating the *price elasticity of gasoline demand*. This indicator measures the responsiveness of demand to a change in price, with all other factors held constant. It is defined as the magnitude of a proportionate change in demand divided by a proportionate change in

[3] While the impact of gasoline price on mileage per car and car ownership depends largely on consumer behavior, the impact of the gasoline price on *fuel efficiency* is, to a certain extent, determined by fuel efficiency target policy such as the 1975 Energy Policy and Conservation act (see for example Greene 1990).

price. If the changes are taken infinitely small, the term *point elasticity* is used. The point elasticity of gasoline demand with respect to gasoline price, denoted by ε_G, is expressed as[4]

$$\varepsilon_G = \frac{\partial G}{\partial P_G}\frac{P_G}{G} = \frac{\partial \ln G}{\partial \ln P_G} \tag{2}$$

where P_G denotes the gasoline price. By substituting (1) in (2), ε_G can be decomposed as follows:

$$\varepsilon_G = -\varepsilon_{FE} + \varepsilon_{KM/C} + \varepsilon_C \tag{3}$$

where ε_{FE}, $\varepsilon_{KM/C}$ and ε_C represent the point elasticities of fuel efficiency, mileage per car and car ownership with respect to the gasoline price, respectively. These elasticities indicate the response in fuel efficiency, mileage per car and car ownership to a change in the price of gasoline. Note that there is a linear relationship between the elasticities. By subtracting ε_C on both sides of (3), a linear relationship can be established between the point elasticity of gasoline consumption per car with respect to the gasoline price, denoted by $\varepsilon_{G/C}$, and the point elasticities of fuel efficiency and of mileage per car:

$$\varepsilon_{G/C} = -\varepsilon_{FE} + \varepsilon_{KM/C} \tag{4}$$

The price sensitivity of gasoline demand per car is thus decomposed into sensitivity measures for fuel efficiency and mileage per car. Finally, by adding ε_{FE} to (3) we establish a linear relationship between the point elasticity of traffic volume, i.e. the total number of car kilometers, with respect to gasoline price, denoted by ε_{KM}, and the point elasticities of mileage per car and car ownership:

[4] Price elasticities of demand are typically estimated by a double log demand equation: $\ln \boldsymbol{G} = \alpha \ln \boldsymbol{P_G} + \boldsymbol{X\beta} + \boldsymbol{\mu}$. The coefficient α is used as an estimate for ε_G. $\boldsymbol{X}$ and $\boldsymbol{\beta}$ represent the data matrix and coefficients used to account for other explanatory variables.

$$\varepsilon_{KM} = \varepsilon_{KM/C} + \varepsilon_{C} \tag{5}$$

The point elasticity of traffic volume is thus decomposed into price sensitivity measures for mileage per car and car ownership. In the next section, we develop a meta-analytical estimation model, based on a system of meta-regression equations. These meta-regression equations are based on the relationships between the point elasticities, ε_G, ε_{FE}, $\varepsilon_{KM/C}$, ε_C, $\varepsilon_{G/C}$ and ε_{KM} that we established in (3), (4) and (5).

3. A meta-analytical approach based on a system of equations

Due to large variation in empirical estimates, the use of meta-analysis seems to be an appropriate and useful approach to study the price elasticity of gasoline demand. Previous research efforts by Espey (1998), Hanly et al. (2002) and Graham and Glaister (2002) have used such an approach. These studies analyze the variation in the price elasticity estimates of gasoline by using a so called meta-regression model where the price elasticity of gasoline demand is regressed on a number of moderator variables. While some of these studies discuss the relationship between the price elasticities of gasoline demand, fuel efficiency, car ownership and mileage per car, the meta-analytical contributions focus exclusively on the price elasticities of gasoline demand.

In the literature, estimates can be found for each of the six point elasticities discussed in Section 2, together with information about the studies they come from. From a meta-analytical point of view, the question is pertinent whether these sets of elasticity estimates can be combined by making use of the linear relationship between the point elasticities. In the remainder of this section, we investigate this question in more detail. We base our theoretical analysis on the following meta-analytical equation[5]:

$$e_{\lambda,i} = \varepsilon_{\lambda,i} + \mu_{\lambda,i} \tag{6}$$

where $e_{\lambda,i}$, $\varepsilon_{\lambda,i}$ and $\mu_{\lambda,i}$ denote the *i*-th estimate of the price elasticity of a variable λ[6], the true underlying effect size of that estimate, and the associated disturbance term, respectively.

[5] Depending on the specification of $\theta_{\lambda,i}$ this general model accommodates both a fixed effects model and a fixed effects regression model.

[6] In the present context, examples of λ are $G, FE, KM/C, C, G/C, KM$.

3.1 A meta-analytical model based on a system of fixed effects equations

The fixed effects model for combining effect sizes is based on the assumption that there is no variation in the effect sizes beyond what is caused by sampling error; the effect sizes are assumed to be estimating a single true underlying effect size (Sutton et al. 2000), i.e., we have that $\varepsilon_{\lambda,i} = \alpha_{\lambda}$, where α_{λ} is a constant. Under the assumption that the fixed effects assumption holds with respect to each of the point elasticities discussed in Section 2, we obtain the following set of fixed effects models:

$$e_{\lambda,i} = \alpha_{\lambda} + \mu_{\lambda,i} \forall \lambda \in \{G, FE, KM/C, C, G/C, KM\} \tag{7}$$

Each of these equations can be estimated separately as a fixed effects model, using weighted least squares (WLS) to account for accuracy of the primary estimates, with observation weights equal to the inverse of the estimation variance.[7] Alternatively, by substituting (3), (4) and (5), which capture the linear relationship between the true underlying values of the elasticities, into the set of fixed effects models (7) we can establish the following *system* of fixed effects equations:

$$\begin{aligned}
e_{G,i} &= -\alpha_{FE} + \alpha_{KM/C} + \alpha_{C} + \mu_{G,i} \\
e_{FE,i} &= \alpha_{FE} + \mu_{FE,i} \\
e_{KM/C,i} &= \alpha_{KM/C} + \mu_{KM/C,i} \\
e_{C,i} &= \alpha_{C} + \mu_{C,i} \\
e_{G/C,i} &= -\alpha_{FE} + \alpha_{KM/C} + \mu_{G/C,i} \\
e_{KM,i} &= \alpha_{KM/C} + \alpha_{C} + \mu_{KM,i}
\end{aligned} \tag{8}$$

We estimate (8) as a SUR with Cross Equation Restrictions[8], using WLS to account for accuracy of the primary estimates. With the estimates for α_{FE}, $\alpha_{KM/C}$ and α_{C} we can compute unbiased estimates for α_{G}, $\alpha_{G/C}$ and α_{KM} by using the following equalities with respect to the

[7] Note that the fixed effects model is usually estimated by direct calculation of the weighted mean of the effect size estimates. Weighted least squares regression of the effect size on a constant is equivalent and yields the same estimation results. Moreover, the latter approach accommodates the estimation of the *system* of fixed effects approach discussed later on in this section.

[8] See Wooldridge (2002, Chapter 7.7.2).

coefficients[9]: $\alpha_G = -\alpha_{FE} + \alpha_{KM/C} + \alpha_C$, $\alpha_{G/C} = -\alpha_{FE} + \alpha_{KM/C}$ and $\alpha_{KM} = \alpha_{KM/C} + \alpha_C$. The coefficient estimates that we thus obtain are based on a larger sample of observations than the estimates we would obtain by separate estimation of the fixed effects models in (7). Furthermore, it enables us to decompose the overall estimate of the price elasticity of gasoline demand into estimates of the price elasticities of fuel efficiency, mileage per car and car ownership.

3.2 A meta-analytical model based on a system of fixed effects regression equations

The fixed effects regression model for combining effect sizes is based on the assumption that all variation in the effect sizes beyond sampling error is systematic; the true underlying effect size of each study depends on a number of moderator variables, i.e. study characteristics (Sutton et al. 2000), so we have that $\varepsilon_{\lambda,i} = \boldsymbol{x}'_{\lambda,i}\boldsymbol{\beta}_\lambda$, where the vector $\boldsymbol{x}'_{\lambda,i}$ denotes the values of the moderator variables with respect to the *i*-th estimate of the price elasticity of a variable λ and $\boldsymbol{\beta}_\lambda$ denotes the associated vector of coefficients.

Under the assumption that the fixed effects regression assumption holds with respect to each of the point elasticities discussed in Section 2, we obtain the following set of fixed effects regression models:

$$e_{\lambda,i} = \boldsymbol{x}'_{\lambda,i}\boldsymbol{\beta}_\lambda + \mu_{\lambda,i} \forall \lambda \in \{G, FE, KM/C, C, G/C, KM\} \tag{9}$$

Each of these equations can be estimated separately as a fixed effects regression model, using WLS to account for accuracy of the primary estimates, with observation weights equal to the inverse of the estimation variance. Alternatively, by substituting (3), (4) and (5), into the set of fixed effects regression equations (9) we obtain the following set of equations[10]:

[9] These equalities follow directly from (7) and (8).

[10] Note that for any estimate, $e_{G,i}$, we have that $\boldsymbol{x}'_{G,i} = \boldsymbol{x}'_{FE,i} = \boldsymbol{x}'_{KM/C,i} = \boldsymbol{x}'_{C,i}$. Analogously, for any estimate $e_{G/C,i}$ or $e_{KM,i}$, we have that $\boldsymbol{x}'_{G/C,i} = \boldsymbol{x}'_{FE,i} = \boldsymbol{x}'_{KM/C,i}$ and $\boldsymbol{x}'_{KM,i} = \boldsymbol{x}'_{KM/C,i} = \boldsymbol{x}'_{C,i}$, respectively. For these equalities to hold, it is required that the *sets* of moderator variables associated with estimates of ε_G, ε_{FE}, $\varepsilon_{KM/C}$, ε_C, $\varepsilon_{G/C}$ and ε_{KM} are identical. Note that the choice of these sets is under the control of the analyst.

$$
\begin{aligned}
e_{G,i} &= \boldsymbol{x}'_{\boldsymbol{G},i}(-\boldsymbol{\beta}_{\boldsymbol{FE}} + \boldsymbol{\beta}_{\boldsymbol{KM/C}} + \boldsymbol{\beta}_{\boldsymbol{C}}) + \mu_{G,i} \\
e_{FE,i} &= \boldsymbol{x}'_{\boldsymbol{FE},i}\boldsymbol{\beta}_{\boldsymbol{FE}} + \mu_{\boldsymbol{FE},i} \\
e_{KM/C,i} &= \boldsymbol{x}'_{\boldsymbol{KM/C},i}\boldsymbol{\beta}_{\boldsymbol{KM/C}} + \mu_{KM/C,i} \\
e_{C,i} &= \boldsymbol{x}'_{\boldsymbol{C},i}\boldsymbol{\beta}_{\boldsymbol{C}} + \mu_{C,i} \\
e_{G/C,i} &= \boldsymbol{x}'_{\boldsymbol{G/C},i}(-\boldsymbol{\beta}_{\boldsymbol{FE}} + \boldsymbol{\beta}_{\boldsymbol{KM}}) + \mu_{G/C,i} \\
e_{KM,i} &= \boldsymbol{x}'_{\boldsymbol{KM},i}(\boldsymbol{\beta}_{\boldsymbol{KM/C}} + \boldsymbol{\beta}_{\boldsymbol{C}}) + \mu_{KM,i}
\end{aligned}
\tag{10}
$$

We estimate (10) as a SUR with Cross Equation Restrictions, using WLS to account for accuracy of the primary estimates. With the estimates for $\boldsymbol{\beta}_{\boldsymbol{FE}}$, $\boldsymbol{\beta}_{\boldsymbol{KM/C}}$ and $\boldsymbol{\beta}_{\boldsymbol{C}}$, we can compute unbiased estimates for the coefficients, $\boldsymbol{\beta}_{\boldsymbol{G/C}}$ and $\boldsymbol{\beta}_{\boldsymbol{KM}}$ by using the following equalities with respect to the estimation coefficients[11]: $\boldsymbol{\beta}_{\boldsymbol{G}} = -\boldsymbol{\beta}_{\boldsymbol{FE}} + \boldsymbol{\beta}_{\boldsymbol{KM/C}} + \boldsymbol{\beta}_{\boldsymbol{C}}$, $\boldsymbol{\beta}_{\boldsymbol{G/C}} = -\boldsymbol{\beta}_{\boldsymbol{FE}} + \boldsymbol{\beta}_{\boldsymbol{KM/C}}$ and $\boldsymbol{\beta}_{\boldsymbol{KM}} = \boldsymbol{\beta}_{\boldsymbol{KM/C}}\boldsymbol{\beta}_{\boldsymbol{C}}$. The estimates that we thus obtain are based on a larger sample of observations than the estimates we would obtain by separate estimation of the fixed effects regression models in (9). Furthermore, it enables us to decompose the meta-regression estimates with respect to the price elasticity of gasoline demand into estimates with respect to the other price elasticities.

4. Estimation results

In this section, we discuss the results of our empirical analysis, which is based on the estimation of the meta-analytical models discussed in Section 3. We use a dataset that consists of 312 elasticity observations, from 43 primary studies (the list of primary studies is given in Table 1). The set of observations contains 158 price elasticities of total gasoline demand (ε_G), 15 price elasticities of fuel efficiency (ε_{FE}), 3 price elasticities of mileage per car ($\varepsilon_{KM/C}$), 15 price elasticities of car ownership (ε_C), 111 price elasticities of gasoline demand per car ($\varepsilon_{G/C}$) and 10 price elasticities of traffic volume (ε_{KM}).

Figure 5.3 shows the distribution of the estimates of price elasticity gasoline demand. The estimated values lie between -2.04 to 0.28, but the vast majority lies between -1.0 and 0.0. Furthermore, we see that the distribution is skewed in the sense that the value zero appears to be a cut-off point.

[11] These equalities follow directly from (9) and (10).

Table 1: List of primary studies used

Abdel-Khalek (1988)	Drollas (1984)	Mehta et al. (1978)
Archibald and Gillingham (1980)	Eltony (1993)	Mount and Williams (1981)
Archibald and Gillingham (1981a)	Eltony and Al-Mutairi (1995)	Ramanathan (1999)
Archibald and Gillingham (1981b)	Gallini (1983)	Ramsey et al. (1975)
Baltagi and Griffin (1983)	Gately (1990)	Reza and Spiro (1979)
Baltagi and Griffin (1997)	Gately (1992a)	Romilly et al. (1998)
Banaszak S et al.	Greene (1982)	Samimi (1995)
Bentzen (1994)	Greene (1990)	Sterner (1991)
Berndt and Botero (1985)	Greene and Chen (1983)	Tishler (1980)
Berzeg (1982)	Houthakker et al. (1974)	Tishler (1983)
Blair et al. (1984)	Kennedy (1974)	Uri and Hassanein (1985)
Dahl (1978)	Kraft and Rodekohr (1978)	Wheaton (1982)
Dahl (1979)	Kwast (1980)	Wirl (1991)
Dahl (1982)	Lin et al. (1985)	
Donnelly (1982)	McRae (1994)	

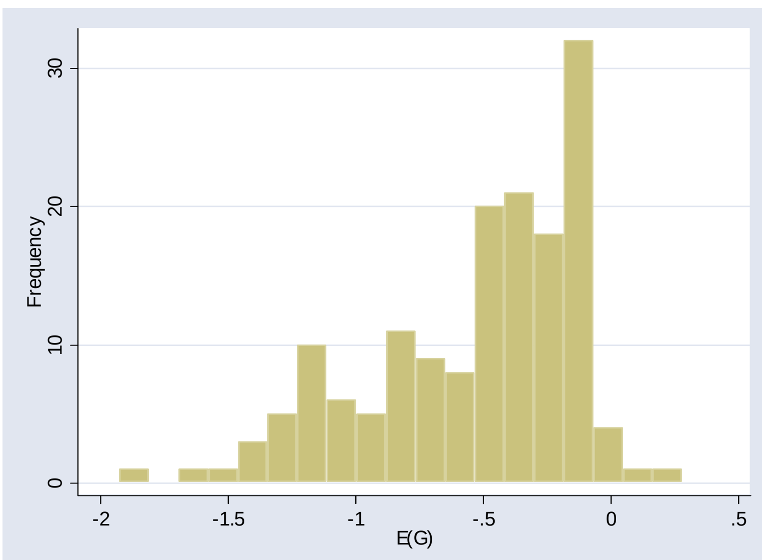

Figure 3: The distribution of the estimates of the price elasticity of gasoline demand

4.1 Estimation results of the model based on a system of fixed effects

In this section we estimate the mean price elasticities of fuel efficiency, mileage per car, car ownership, gasoline consumption per car and traffic volume for the standard fixed effects model and the system of fixed effects model. First, we carry out a series of standard fixed effects analyses based on the set of equations in (7). Next, we estimate the system of fixed effects model in (8). For both models we use the estimation procedure described in Section 3. The estimation results are shown in Table 2.

Table 2: Estimated means of the price elasticity of fuel efficiency, mileage per car, car ownership, gasoline consumption per car and traffic volume for the standard fixed effects model and the system of fixed effects model

Estimation model	ε_G	ε_{FE}	$\varepsilon_{KM/C}$	ε_C	$\varepsilon_{G/C}$	ε_{KM}
Standard fixed effects model	-0.54	0.12	-0.55	-0.32	-0.32	-0.04
	(0.03)	(0.10)	(0.22)	(0.10)	(0.04)	(0.12)
N	158	15	3	14	111	10
System of fixed effects model	-0.53	0.22	-0.10	-0.22	-0.32	-0.32
	(0.04)	(0.02)	(0.03)	(0.15)	(0.03)	(0.13)
N				312		

The standard model leads to rather unintuitive results., in the sense that the estimated means do not reflect the relationship between the true underlying effect sizes. Furthermore, the results differ substantially from the results found in Espey (1998), Hanly et al. (2002) and Graham and Glaister (2002), shown in Table 3. This might be related to the fact that the number of observations for some of the elasticities is too low to calculate reliable means. These issues are resolved by estimating the system of equations model. The lower standard errors of the latter approach indicate increased reliability of the estimated means. The results show that the estimated mean price elasticity of gasoline demand is -0.53. This value lies between the values found in Espey (1998), Hanly et al. (2002) and Graham and Glaister (2002), which are -0.44, -0.69 and -0.45, respectively (see Table 3). Apparently, automobilists are not very sensitive to changes in the price of gasoline. The estimated value for the price elasticity of gasoline demand (-0.53) can be decomposed into estimations for the price elasticities of fuel efficiency (0.22), mileage per car (-0.10) and car ownership (-0.22). These estimated values indicate that the response in demand resulting from a change in gasoline price is mostly driven by responses in fuel efficiency and car ownership and to a lesser degree by a response in mileage per car.

Hanly et al. (2002) find higher price sensitivity of the mileage per car and car ownership (see Table 3). However, their estimates are based on standard fixed effects equations, without making use of the functional relationship between elasticities. As a result, they are based on a relatively small sample size. Graham and Glaister (2002) find higher estimates for the price sensitivity of fuel efficiency. Graham and Glaister do make use of the functional relationship between the elasticities but take a different approach, in which they estimate the price elasticities of gasoline demand and traffic volume separately and use them to derive the elasticity of fuel efficiency ex-post. Again, this leads to a reduction in the sample size.

Table 3: Estimates of the price elasticity of gasoline demand, fuel efficiency, mileage per car and car ownership found in other meta-analytical studies[12]

Study	ε_G	ε_{FE}	$\varepsilon_{KM/C}$	ε_C	$\varepsilon_{G/C}$	ε_{KM}
Graham and Glaister (2002)	-0.698	0.373	-	-	-	-0.312
Hanly et al. (2002)	-0.450	-	-0.303	-0.148	-0.324	-0.257
Espey (1998)	-0.442	-	-	-	-	-

In general, the inelastic results that we find suggest that automobilists are not very sensitive to changes in gasoline prices. Hence, pricing policy based on gasoline taxes may not be a very effective instrument to decrease the demand for gasoline.

4.2 Estimation results of the model based on a system of fixed effects regressions

The result of a *Q*-test[13] on the observations of the price elasticity of gasoline demand indicates that the hypothesis of homogeneity should be rejected. Hence, in this section we investigate the variation in the effect sizes in a multivariate way, by focusing on the impact of study characteristics on the estimated values of the price elasticities. First, we carry out a standard fixed effects regression analysis on the price elasticity of gasoline demand based on equation (9). Next, we estimate the system of equations model in (10). The latter model enables us to interpret the effect of study characteristics on the elasticity of gasoline demand by deconstructing it in the effects on the elasticities of fuel efficiency, mileage per car and car ownership. For both models we use the weighted estimation procedure described in Section 3.

Table 4 shows the list of moderator variables we include in order to investigate the variation in the estimated effect sizes. Most of these are categorical variables. To account for regional differences in estimates we use a dummy variable for studies based on US, Canada or Australia (UCA) data and estimates that are based on data from other countries. We include two time-based moderator variables; a trend variable based on the average year of the data used, and a dummy variable for study results based on data from the period between 1974 and 1981, in order to account for a change in impact during the period following the oil crisis. Next, we include a set of dummy variables that account for the type of data that is used in the primary studies, i.e. cross-section data, time series data or pooled cross-section time series data.

[12] The reported mean values are calculated as the average of the mean short- and long-run estimates reported in these studies, weighting for the number of observations. This also holds for the values of the partial elasticities.
[13] The value of the Q-statistic is 1717.927 on 157 degrees of freedom. Based on this result, the hypothesis of homogeneity should be rejected.

Table 4: List of moderator variables

Name of variable	Categories
Geographical region	UCA; Other regions
Trend variable	(continuous variable)
Data period	1974 – 1981; other period
Database type	Cross-section; Time series; Pooled CS-TS
Time horizon	Short run estimate; Long-run estimate
Dynamic specification	Dynamic model; Static model
Functional form	Loglinear; Non-linear
Number of explanatory variables	(continuous variable)
Included variables	Lagged price; No lagged price

Furthermore, we use a dummy variable to distinguish between dynamic and static models. We consider an observation to be dynamic if the model includes a lagged dependent variable or a (series of) lagged gasoline price(s). In order to investigate the impact of the response time on the price sensitivity, we include a dummy variable to distinguish between short run and long-run estimates. Observations are categorized as long-run estimates if they are based on a dynamic specification and incorporate lagged price effects. In order to account for functional form, we use a dummy variable for nonlinear models. The demand equation in the primary study typically includes variables related to income, car ownership and prices of other commodities. If any of these variables are not included the impact on demand is (partly) picked up by the coefficient of the price variable, which leads to biased estimates of the price elasticity. In order to account for this, we use a moderator variable for the number of explanatory variables that are included in the demand equation.

Table 5 shows the result of the standard fixed effects regression analysis of the price elasticity of gasoline demand. The significant negative coefficient of the regional dummy indicates that price sensitivity is lower in the US, Canada and Australia. Espey (1998) and Hanly et al (2002) have found similar results. One possible explanation for this is that the combination of high income and low gasoline prices renders consumers less price sensitive. Another explanation might be that, due to the combination of sparse population and relatively underdeveloped public transport infrastructure, car dependence is higher in these countries. The coefficient of the trend variable indicates that there is no significant time trend in the price elasticity of gasoline demand. Furthermore, the 1974-1981 period dummy indicates that during the years after the oil embargo there was no significant change in price sensitivity. The negative coefficient of the dummy for cross-section studies may be explained by the observation of some authors that time series estimates without extensive lag structures typically yield short term elasticity estimates while the estimation results from a cross-sectional study are more likely to be indicative of the long-run effect (see Abrahams, 1983).

Table 5: Estimation results, based on the standard fixed effects regression model, of the impact of study characteristics on the price elasticity of gasoline demand

Variable	Coefficient	Std. error
(Constant)	9.879	9.975
UCA	0.130 *	0.064
Trend variable (x100)	-0.005	0.005
1974-1981	0.002	0.113
Cross-section	-0.439 **	0.099
Pooled	-0.031	0.067
Long-run estimate	-0.458 **	0.069
Dynamic	0.160 **	0.070
Non-linear	-0.229 *	0.120
Number of included variables	0.022 *	0.010
N	158	
R^2-adjusted	0.387	

* significant at the 5% level
** significant at the 1% level

Further results show that the price sensitivity is significantly higher in the long-run than in the short-run, which confirms the results by Espey (1998), Graham and Glaister (2002) and Hanly et al. (2002). This indicates that a longer response period gives consumers more options to adjust to the price change. The use of a dynamic model significantly decreases the price sensitivity. Similar results were found in Espey (1998) and Graham and Glaister (2002). Assuming negative correlation between price and lagged demand and positive correlation between demand and lagged demand, this result may be caused by omitted variable bias (see Greene, 2003, p.148). The use of a non-linear demand model does not have any significant impact on the price elasticity. This implies that price sensitivity behavior can be adequately modeled by means of a (log-)linear equation. Finally, the number of regressors included in the demand specification has a significant (negative) effect on the elasticity estimate, which indicates that a parsimonious demand equation may result in biased estimates.

The estimation results of the system of fixed effects regression equations are shown in Table 6. Column 1 shows the impact of the moderator variables on the price elasticity of total gasoline demand while Column 2-4 show the impact of the moderator variables on the price elasticities of fuel efficiency, mileage per car and car ownership, respectively. The estimated coefficients in Column 1 are very similar to those in Table 5, despite the fact that 153 additional observations were included, which might be taken as an indication of robustness. The same holds for the sign pattern, with only one (insignificant) coefficient changing signs. However, there are some changes in the significance pattern. For the system of equations model, the standard errors of all estimated coefficients are smaller. This is caused by the inclusion of additional observations, which has increased the sample size. The coefficients of the dummy variables for UCA studies, cross-section data, long-run estimates and dynamic specification, which are significant for the standard fixed effects regression model, remain so for the system of equations model. In addition to these, the time trend variable becomes significant, while the coefficient of the number of regressors used becomes insignificant.

Table 6: Estimation results, based on a system of fixed effects regression equations, of the impact of study characteristics on the price elasticities of gasoline demand, fuel efficiency, mileage per car and car ownership.

Dependent variable:	ε_G (1)	ε_{FE} (2)	$\varepsilon_{KM/C}$ (3)	ε_C (4)
Constant	-0.107			
	(0.067)			
UCA	0.148 **	0.039	-0.016	0.204 **
	(0.038)	(0.436)	(0.441)	(0.069)
Trend variable (x100)	-0.021 **	0.006	-0.013	-0.001
	(0.005)	(0.022)	(0.023)	(0.005)
1974-1981	0.114	0.123	0.419	-0.181
	(0.078)	(0.207)	(0.272)	(0.191)
Cross-section	-0.226 **	-0.057	-0.628	0.344 *
	(0.724)	(0.440)	(0.481)	(0.173)
Pooled	0.054	-0.155	-0.257	0.156 **
	(0.039)	(0.179)	(0.184)	(0.052)
Long-run estimate	-0.366 **	0.130	-0.327 *	0.091
	(0.047)	(0.109)	(0.130)	(0.083)
Dynamic	0.197 **	-0.295 **	-0.168	0.069
	(0.041)	(0.100)	(0.104)	(0.057)
Non-linear	-0.182	0.105	-0.024	-0.053
	(0.108)	(0.201)	(0.765)	(0.731)
Number of included variables	0.004	-0.001	0.027 *	-0.024 *
	(0.006)	(0.008)	(0.012)	(0.010)
N	311			
Degrees of freedom	251			
Mean squared residual	0.030			

* significant at the 5% level
** significant at the 1% level

The coefficients in Columns 2-4 enable us to decompose the estimated impact coefficients in Column 1 into the impact of moderator variables on the price elasticities of fuel efficiency, mileage per car and car ownership. For example, the result that price sensitivity with respect to gasoline demand is lower in UCA studies is caused mainly by significantly lower price sensitivity with respect to car ownership. With respect to the price sensitivity of fuel efficiency and mileage per car, no significant difference is found between UCA studies and other studies. In the case of an increase in the gasoline price, the interpretation is as follows. UCA consumers respond to the price increase by improving fuel efficiency and decreasing the use of existing cars to the same degree as their counterparts in other parts of the world. However, UCA consumers are less willing to decrease the number of cars they own. Therefore, the total impact of the price change on gasoline demand is lower than in the rest of the world.

The negative coefficient of the trend variable indicates that consumers' demand for gasoline have become more price sensitive between 1949 and 2003. This could be due to the increase in gasoline consumption in this period, which has in turn lead to an increase in the share of income that is spent on gasoline; consumers tend to be more price sensitive with respect to consumer goods that take up a larger share of income. None of the other time trend coefficients are significant. The coefficient of the 1974-1981 period dummy indicates that the use of data from the period following the oil embargo does not have a significant effect on any of the price elasticities.

Further results show that the significant negative impact of the use of cross-section data on the price elasticity of demand for gasoline is mainly caused by the negative impact on car use, although the latter result is not significant. As discussed before, the reason might be that time series estimates without extensive lag structures typically yield short term elasticity estimates while the estimation results from a cross-sectional study are more likely to be indicative of the long-run effect. Following this line of reasoning, the negative impact on mileage per car is consistent with the fact that the positive impact of the response time on the price sensitivity with respect to gasoline demand is mainly caused by the positive impact on the price sensitivity of the mileage per car. We find no significant or negative results with respect to fuel efficiency and car ownership. This is unexpected, because a longer response time would give a consumer more room for structural adjustments such as a change in the number of cars owned or a switch to a more (or less) fuel-efficient model. The negative impact of the use of a dynamic model on the price sensitivity of gasoline demand, is mainly caused by a positive impact on the price sensitivity of fuel efficiency. Assuming positive correlation between price and lagged fuel efficiency and positive correlation between fuel efficiency and lagged fuel efficiency, this result can be explained with the omitted variable formula (Greene, 2003, p.148). The use of a non-linear demand model does not have a significant effect on the price elasticity of gasoline demand nor on any of the price elasticities. Apparently, a loglinear model specification is sufficient to estimate the elasticity coefficients correctly.

6. Summary and Conclusion

In this study we use meta-analytical techniques to (i) estimate the price elasticity of gasoline demand and decompose this into estimates of the price elasticities of fuel efficiency, mileage per car and car ownership with respect to gasoline price and (ii) determine the impact of study characteristics on the estimated elasticity values. In Section 2, we discuss the causal relationship between the gasoline price and the consumer demand for gasoline. We establish a series of linear relationships between the price elasticities of demand, fuel efficiency, mileage per car, car ownership, traffic volume and gasoline consumption per car. In section 3 we use the linear relationship between the elasticities to develop a meta-analytical estimation approach based on a system of equations, which, as far as we know, is novel. This approach enables us to combine empirical estimates of different elasticities and thus increase our sample size and it allows for a more detailed interpretation of our meta-regression results.

In Section 4, we discuss the results of our empirical analysis, which is based on a dataset of 312 elasticity observations of price elasticities of gasoline demand, fuel efficiency, mileage per car, car ownership, gasoline demand and traffic volume. Based on the estimation of a system of fixed effects equations, we find a mean price elasticity of gasoline demand of -0.53, which indicates that consumers are not very price sensitive to price changes. This suggests that fuel taxes alone do not seem to be very effective in reducing the external costs of road transport and that addition (tax) instruments are necessary. In this context, one could think of fuel efficiency standards such as CAFÉ or innovative tax arrangements such as the "feebate" concept, introduced in certain countries, which is based on the stimulation of energy efficient technology through fuel efficiency tax-cuts and subsidization. Further results show that the demand response to a change in the fuel price is mainly caused by responses in fuel efficiency and car ownership. The relatively low price sensitivity of car mileage, compared to that of car ownership, casts some doubts on the expected benefits of variabilization.

In Section 4.2, we investigate the impact of study characteristics on the price elasticity of gasoline demand. The main results, based on the estimation of a system of fixed effects regression equations, are as follows. We find a lower price sensitivity with respect to total gasoline demand in the US, Canada and Australia, which is primarily due to lower price sensitivity with respect to car ownership. This result points to the high dependence of consumers on automobile transport and indicates that pricing policy could be more effective if gasoline taxation is applied in combination with other types of charges such as registration fees or fixed charges on vehicle purchase. Further results show that there is a negative time trend in the price elasticity of gasoline demand. In the design of long-run policy instruments, this increase in price sensitivity over the years should be taken into account. Cross-section studies are found to report higher absolute elasticity estimates than time-series studies. Furthermore, we find that a longer response time leads to higher price sensitivity of gasoline demand, which is something that needs to be acknowledged in the design of long-run policy instruments. The increase in price sensitivity in the long-run is mainly explained by an increase in the price sensitivity with respect to mileage per car. Finally, we find that the use of a dynamic specification decreases the price sensitivity.

The results demonstrate that the system of equations approach has several advantages over the standard meta-analysis approach as it allows us to combine our observations of different elasticities. In the case of the fixed effects model this leads to estimation results that are more precise (i.e., lower standard errors) and more intuitive in that they reflect the underlying linear relationship between the elasticities. The differences were the most dramatic for the elasticity for which we had the lowest number of observations, i.e. the elasticity of mileage per car. Also in the case of the fixed effects regression model, the systems of equations approach resulted in more precise results. Furthermore, it allowed for a detailed analysis, based on the decomposition of the effect of study characteristics on the price elasticity of demand into the effects on the price elasticities of fuel efficiency, mileage per car and car ownership, which would not have been possible with standard meta-analytical techniques.

Based on the findings of this study, we conclude that the systems of equations approach is a useful estimation technique for meta-analyses in which the effect size of interest is a linear function of a set of related effect sizes that are by itself of interest to the analyst. It appears to be a particularly useful approach if the effect size is an elasticity. First, the decomposition of an elasticity into a set of related elasticities is usually based on a linear relationship, which prevents the need for complex estimation techniques.[14] Second, the set of related effect sizes usually has a clear interpretation as they represent causal relationships. There are some restrictions to the

[14] This is because the *variable of effect* can usually be conveniently expressed as a multiplicative function of a set of related variables. This is for example the case in this study on gasoline demand (see Equation (1)).

application of the systems of equation approach. First, observations are required for each of the effect sizes. If observations are not available for one of the effect sizes, the estimation problem degenerates to a set of unrelated models. In this case, the results with respect to the observed effect sizes are estimated separately by standard meta-analytical techniques. The results with respect to the unobserved effect size can then be calculated ex-post, using the linear relationship between the effect sizes. If observations are not available for two or more effect sizes, the results with respect to the unobserved effect sizes cannot be estimated nor calculated ex-post. Second, while a limited number of available observations for any individual effect size does not cause any estimation problems, the number of observations for all effect sizes combined should exceed the number of moderator variables multiplied by the number of effect sizes. If these conditions are satisfied, meta-analytical modeling based on a system of equations is an interesting and useful estimation approach, which offers several advantages to standard meta-analytical techniques.

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