Analysing gasoline demand elasticities: a survey

Carol Dahl and Thomas Sterner

This paper is a survey of studies on gasoline demand. Although there are very many different studies in this field which sometimes appear to arrive at contradictory results, we find that with proper stratification of studies by model and data type much of the conflict turns to consensus. In this survey we classify studies by data type and by ten different categories of model and with the exception of estimates on seasonal data, which tend to be unstable, and of certain inappropriate model formulations, we find a fair degree of agreement concerning average short-run and even long-run income and price elasticities.

Keywords: Gasoline demands; Elasticities; Fuel price

Gasoline has become the most heavily taxed and most thoroughly studied of the petroleum products. The mobility afforded by the private automobile has revolutionized transport in the industrialized world – a revolution that the developing world and liberalizing centrally planned economies are likely to emulate. Hence, gasoline with fewer competitive substitutes than the heavier end of the barrel should remain a heavily sought after commodity. However, with increasing prosperity and travel, petroleum dependence and vulnerability to disruption, as well as emissions, will also increase. Hence, forecasting gasoline consumption is of interest not only to producers planning to increase capacity, but also to consumer countries concerned about balance of payments and increasing energy dependence, and to those concerned by the ecological effects of the transport system.

Responding to these needs we provide policy-makers and forecasters with the most comprehensive summary of gasoline and other transport fuel demand studies to date. We concentrate our analysis on price (ε_p) and income (ε_y) elasticities, since they contain the basic information necessary for forecasting and policy evaluation. The short-run elasticity (ε^{SR}) measures the adjustment during the first month, quarter, or year depending on the periodicity of the data, while the long-run elasticity (ε^{LR}) measures the total adjustment which could take many years.

The many studies on gasoline demand sometimes arrive at apparently conflicting results. This is quite natural since the studies surveyed are based on different models, types of data, countries, time periods, different functional forms and econometric techniques. However, by a careful comparison we find that if properly stratified, compared and interpreted, different models and data types do tend to produce a reasonable degree of consistency. Our main interest here is to summarize these findings and compare elasticities in different categories of models and on different data types. Given the voluminous nature of this work (which surveys over a hundred studies) we are unable to focus on individual studies, but rather concentrate on summary statistics for all the basic categories of model and data type.[1]

Model stratification

We break the studies into the 10 model types discussed more completely in Sterner and Dahl [8]. The simplest

Carol Dahl is with the Department of Economics, Louisiana State University, Baton Rouge, Louisiana 70803 6306, USA and Thomas Sterner is with the Department of Economics, University of Gothenburg, Viktoriag 30; 41125 Gothenburg, Sweden.

Financial support from the Swedish Transport Research Board is gratefully acknowledged.

Final manuscript received 21 December 1990.

[1] For more detail, see Dahl and Sterner [5], which includes a complete bibliography and a summary of the most important features for individual studies including elasticities, data type and region. An appendix with detailed summaries is also available and we would appreciate receiving new studies for addition to this appendix.

model is the static model where gasoline demand (G) is a function of the real price of gasoline (P) and real income (Y). Studies that do not include some form of income and price in their model are considered mis-specified and are not included.[2]

$$G=f_1(P,Y) \tag{1}$$

Given that gasoline consumption depends on the vehicle stock, adjustments are likely to take longer than the periodicity of most data used for estimation. Hence, use of this type of model may not capture the total adjustment when time series are used.

The second set of models essentially used to capture the fact that adaptation takes time are dynamic. If income or prices change in one year, but some consumers defer their reaction to a later year, then today's consumption is not only a function of today's income and price structure but of earlier incomes and prices as well. There have been various strategies for modelling this dynamic dependence.

An early, but widely used representation of dynamic behaviour, is the partial adjustment model. It gives the quantity of gasoline demanded (G) as a function of the real price of gasoline (P), real income (Y), and the quantity of gasoline demanded last period (G_{t-1}) or

$$G=f_2(P,Y,G_{t-1}) \tag{2}$$

This formulation, referred to as the lagged endogenous model, is easy to interpret and not overdemanding in terms of data requirements. In practice the lagged quantity, which represents the inertia of economic behaviour, tends to improve the statistical fit considerably.[3]

Since adjustment involves the stock of vehicles, another popular alternative is to include some measure of this stock (V) directly as in the simple vehicle model

$$G=f_3(P,Y,V) \tag{3}$$

In some cases the model may also include some measure of alternative transport. However, since they fail to capture the adaptation which takes place through the replacement of vehicles, we expect that estimated price and income coefficients will mainly pick up short-term effects. Long-run effects, which are embedded in the vehicle stock, would require a model with simultaneous equations for both gasoline and vehicle demand.

Some studies of auto demand indicate that it is the size and characteristics rather than the number of automobiles that are sensitive to the price of gasoline. Some gasoline studies therefore include variables such as vehicle efficiency, or proxies such as average size or weight of vehicles. If these models, which we call vehicle characteristic models, *VChar*, capture the long-run adjustment through the quantity and characteristics (*CHAR*) of the vehicle stock, then the elasticities on income (ε_y) and prices (ε_p) should represent short-run changes in utilization.[4]

$$G=f_4\,(P,Y,V,CHAR) \tag{4}$$

Moving back to dynamic formulations we note that although the implied lags from Equation (2) form a rather reasonable geometric series, there is the strong implication that price and income have identical lag structures. Relaxing this restriction leads to a distributed lags dynamic, which we call an other lag model.

$$G=f_5(\textstyle\sum P_{t-i},\sum y_{t-i}) \tag{5}$$

Although this formulation again allows us to distinguish short-from long-run elasticities, it can be difficult to estimate so many parameters on the often fairly limited number of observations available. A partial remedy is to restrict the structure of the lag to lie upon a polynomial of a certain degree. While this type of model, the polynomial distributed lag has some appeal, it has been used relatively infrequently because it still requires long series of data and collinearity between the lagged values often renders results inadequate.

Since collinearity is the result of an absence of information in the data, information can be added by further restrictions on the lag structure. The above geometric lag is one example, another is an 'inverted V', which implies that adjustment is low at first, due to a perception lag, then increasing, and finally decreasing. There are several ways to allow for such a lag structure, but the two we choose both include a lagged endogenous along with other lags, hence we call the model lagged endogenous other lag, LE-OL. In Equation (6) a lagged endogenous term is combined with one (or more) lags on the exogenous variables. Alternatively we could assume that the weights on the lagged P and Y in Equation (5) follow a Pascal lag to give the estimation model Equation (7):

$$G=f_6(\textstyle\sum_i P_{t-i},\sum_i Y_{t-i},G_{t-1}) \tag{6}$$

$$G=f_7(P,Y,G_{t-1},G_{t-2}) \tag{7}$$

[2]Because aggregation and money illusion influence model results the preferred specification for Equation (1) has prices and income deflated while income and gasoline consumption are in *per capita* terms. However, in actual practice the differences in estimated elasticities due to these factors appears to be minimal.

[3]This model can be deduced from assumptions of partial adjustment or from adaptive expectations. Although the interpretation of elasticities is the same, estimation is somewhat different, see Sterner and Dahl [8].

[4]Dahl [4] discusses studies that model demand adjustment by estimating a miles travelled equation and a miles per gallon in place of or along with a demand for gasoline.

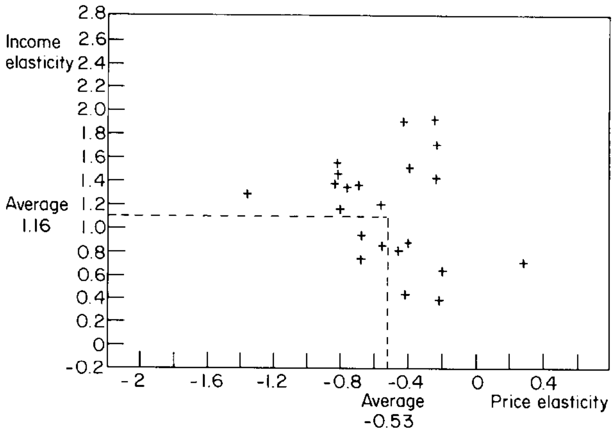

Figure 1. Static models.

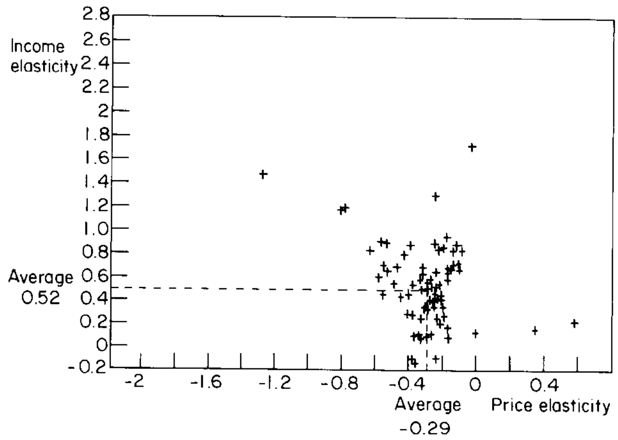

Figure 2. Static models.

Vehicle models have been made dynamic by including both vehicles and lagged values on price and income as in the vehicle other lag model, V-OL:

$$G=f_8\sum_i(P_{t-i},\sum_i Y_{t-i},V) \tag{8}$$

Alternatively using a Koyck transformation in this context gives a vehicle lagged endogenous model, V-LE:

$$G=f_9(P,Y,V,G_{t-1}) \tag{9}$$

Equation (9) has the disadvantage that all variables including vehicles have a geometrically declining lag structure. A preferable alternative is a model of gasoline consumption per automobile which we call the vehicle-use lagged endogenous, VU-LE:

$$G/V=f_9(P,Y,V,G/V_{t-1}) \tag{10}$$

A last approach considered is taken by Drollas [6]. It first disaggregates gasoline use into utilization (G/V) and autos (V). By modelling these demands separately and combining them he gets a function with lagged endogenous, vehicle price (*Pveh*), other transport prices (*Ptrans*) and lagged gasoline price and income.

$$G=f_{10}\,(Pgas,\ Ptrans,\ Y,\ Pveh,\ Pgas_{t-1},\ Y_{t-1},\ G_{t-1}) \tag{11}$$

This model is the most demanding in terms of data and it can be particularly difficult to obtain a unique price for 'alternative modes of transport'.

Data stratification

Just as model types influence the results, different data types might capture different adjustments. The traditional argument is that time series reflect short-run adjustments giving smaller elasticities; while on cross-sections, where exogenous variables tend to vary more and each region has adjusted to this variation, we may capture closer to long-run adjustment.

For time series data one must distinguish between monthly (m), quarterly (q) and yearly (y) data. For monthly and quarterly data problems of seasonal variation are inevitable. Presumably, the shorter the time period the greater the emphasis on the short-run character of the elasticity. Data types may first be divided into panel (P) or data for individual households, and aggregate data for a region or country. The latter may be time series (TS), cross-section (CS), or cross-section–time series (CSTS). Lagged endogenous models are further stratified by the length of the lag – one month (1m), twelve months (12m), one quarter (1q) or four quarters (4q).

Survey results

Static model

Figure 1 shows all the (22) elasticity estimates found based on the static model, Equation (1), with yearly data. Their mean elasticities are 1.16 for income and −0.53 for price, see Category 1 (C1), Table 1. Figure 2 shows monthly/quarterly elasticities for the same model, which have an average elasticity of roughly half the yearly values, see C2 in Table 1. These lower

Table 1. Summary of average elasticities by category.

<table>
<tr><th rowspan="2">Category</th><th rowspan="2">Model type</th><th rowspan="2">Data type</th><th rowspan="2">Data period</th><th colspan="2">Price elasticity</th><th colspan="2">Income elasticity</th><th rowspan="2">Vehicle elasticity</th><th rowspan="2">$Q(t-1)$</th><th rowspan="2">Number of estimates</th></tr>
<tr><th>SR</th><th>LR</th><th>SR</th><th>LR</th></tr>
<tr><td>C1</td><td>Equation (1) (Stat)</td><td>TS</td><td>t</td><td colspan="2">−0.53</td><td colspan="2">1.16</td><td></td><td></td><td>22</td></tr>
<tr><td>C2</td><td>Equation (1) (Stat)</td><td>TS</td><td>m,q</td><td colspan="2">−0.29</td><td colspan="2">0.52</td><td></td><td></td><td>81</td></tr>
<tr><td>C3</td><td>Equation (2) (LE)[a]</td><td>CSTS/TS</td><td>y</td><td>−0.24</td><td>−0.80</td><td>0.45</td><td>1.31</td><td></td><td>0.65</td><td>38</td></tr>
<tr><td>C4</td><td>Equation (2) (LE1q)[a]</td><td>CSTS/TS</td><td>q</td><td>−0.13</td><td>−0.28</td><td>0.44</td><td>1.02</td><td></td><td>0.56</td><td>17</td></tr>
<tr><td>C5</td><td>Equation (2) (LE4q)</td><td>TS</td><td>q</td><td>−0.14</td><td>−0.59</td><td>0.20</td><td>0.75</td><td></td><td>0.75</td><td>10</td></tr>
<tr><td>C6</td><td>Equation (2) (LE1m)</td><td>TS</td><td>m</td><td>−0.20</td><td>−0.23</td><td>0.58</td><td>0.85</td><td></td><td>0.33</td><td>4</td></tr>
<tr><td>C7</td><td>Equation (2) (LE12m)</td><td>TS</td><td>m</td><td>−0.19</td><td>−0.88</td><td>0.22</td><td>0.64</td><td></td><td>0.63</td><td>5</td></tr>
<tr><td>C8</td><td>Equation (3) (Veh)[a]</td><td>CSTS/TS</td><td>y</td><td colspan="2">−0.31</td><td colspan="2">0.52</td><td>0.52</td><td></td><td>50</td></tr>
<tr><td>C9</td><td>Equation (3) (Veh)</td><td>TS</td><td>m,q</td><td colspan="2">−0.42</td><td colspan="2">0.18</td><td>0.91</td><td></td><td>5</td></tr>
<tr><td>C10</td><td>Equation (4) (VChar)</td><td>CSTS/TS</td><td>y</td><td colspan="2">−0.16</td><td colspan="2">0.29</td><td>0.48</td><td></td><td>6</td></tr>
<tr><td>C11</td><td>Equation (4) (VChar)</td><td>CSTS/TS</td><td>m,q</td><td colspan="2">−0.32</td><td colspan="2">0.17</td><td>0.45</td><td></td><td>8</td></tr>
<tr><td>C12</td><td>Equation (4) (VChar)</td><td>Panel</td><td>q,y</td><td colspan="2">−0.52</td><td colspan="2">0.41</td><td></td><td></td><td>5</td></tr>
<tr><td>C13</td><td>Equation (4) and (1)</td><td>CS</td><td>y</td><td colspan="2">−1.01</td><td colspan="2">0.76</td><td>0.40</td><td></td><td>7</td></tr>
<tr><td>C14</td><td>Equation (9) (V–LE)</td><td>CSTS/TS</td><td>y</td><td>−0.12</td><td>−0.29</td><td>0.38</td><td>0.60</td><td>0.19/0.32</td><td>0.40</td><td>8</td></tr>
<tr><td>C15</td><td>Equation (10) (VU–LE)</td><td>CSTS</td><td>y</td><td>−0.17</td><td>−1.05</td><td>0.14</td><td>0.87</td><td></td><td>0.84</td><td>4</td></tr>
<tr><td>C16</td><td>Equation (8) (V–OL)</td><td>CSTS/TS</td><td>y</td><td>−0.08</td><td>−0.97</td><td colspan="2">0.57</td><td></td><td></td><td>4</td></tr>
<tr><td>C17</td><td>Equations (5), (6) and (7) (LE–OL)</td><td>TS</td><td>y</td><td>−0.22</td><td>−0.94</td><td>0.39</td><td>1.09</td><td></td><td></td><td>13</td></tr>
<tr><td>C18</td><td>Equation (11) (Drol)</td><td>TS</td><td>y</td><td>−0.41</td><td>−0.77</td><td>0.42</td><td>1.11</td><td></td><td></td><td>9</td></tr>
</table>

[a]Averages from individual CSTS and TS estimates in Dahl and Sterner [5]. Model types and categories refer to explanations in the text.

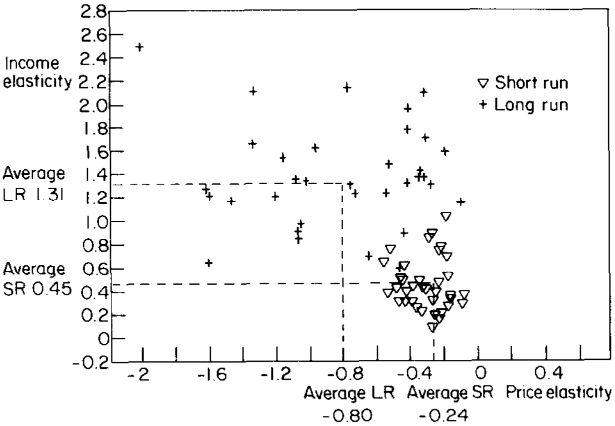

Figure 3. Short and long run.

elasticities support the contention that less adjustment is captured the shorter the periodicity of the data.[5]

Lagged endogenous model

This model, Equation (2), provides us with both short- and long-run elasticities. Although we might expect cross-section time series data to provide higher elasticities than time series, we found no significant difference and have therefore added these two groups of studies on yearly data, see C3 in Table 1. Figure 3 illustrates the individual short- and long-run elasticities in this category. Average long-run price elasticity is -0.80 and for income it is 1.31. The equivalent short-run elasticities are about a third of the long-run values.

Comparing these values to the static model we find the static price elasticity -0.53 seems to be an intermediate elasticity between the short- and long-run of the lagged endogenous model, but the static income elasticity at 1.16 appears to pick up much more of the long-run elasticity.[6] Such evidence could suggest that consumers have a clearer idea of their future income than of future gasoline prices and can adjust to income changes faster. An equally appealing argument is that income is more correlated over time than price and, hence, omitting variables for income causes less bias in the estimates than the omission of price variables. The implication for forecasting and policy analysis is that static models tend to underestimate long-run adjustments to price changes but not necessarily to income changes.

Categories 4–7 summarize studies using the lagged endogenous model with seasonal data. All use TS data except Category 4 in which we again find we could pool TS and CSTS.[7] These four categories show the difficulties that seasonal variation can make to interpreting results. Whether the lag on this seasonal data is one period (LE1q or LE1m) or one year (LE4q/LE12m), the short-run price elasticities vary only minimally between -0.13 and -0.20. However, estimates with a quarterly or monthly lag seem to pick up smaller long-run price elasticities, while those on annual lags appear to pick up smaller income effects. Such a pattern can be explained by the seasonal patterns with current gasoline consumption more highly correlated with consumption the same season last year than last season. These inconsistencies on seasonal data suggest that researchers should pay close attention to seasonal effects before using such estimates for overall long-run forecasting or policy analysis.

Vehicle and vehicle characteristic models

The vehicle model, Equation (3), captures short-run adjustment by inclusion of the vehicle stock. Again the bulk of the studies use annual data. Since we again found no significant difference between CSTS and TS we pool them into Category 8 (Table 1, C8) and show all the elasticities from individual studies in Figure 4.[8] The averages for gasoline price, income and vehicle elasticity are respectively -0.31, 0.52 and 0.52. If we compare vehicle model results with the simpler static model (C1), we find that they imply that roughly half of the annual

[5]The differences between the monthly/quarterly and yearly estimates were found to be significant at the 1% level with $F(2,96)=7.35$ and 26.38 for price and income respectively. These and all subsequent tests are one way analysis of variance which concludes in favour of different means if the variation across categories is significantly larger than the variation within categories. Under the null hypothesis of no difference, the statistic

$$\left\{\sum_{j=1}^{m} n_j(X_{j\cdot}-X_{\cdot\cdot})^2/(m-1)\right\} \Big/ \left\{\sum_{j=1}^{m}\sum_{i=1}^{n_j}(X_{ij}-X_{\cdot j})^2 \Big/ \left(\sum_{j=1}^{m} n_j - m\right)\right\}$$

is distributed as an $F(m-1,\ t-j)$, where t is the total number of observations in all categories, $X_{\cdot\cdot}$ is the total mean of all categories being tested, and $X_{j\cdot}$ is the mean elasticity in category j. j is an index for our 18 different categories in Table 1.

As in all empirical work, assumptions for these tests will not exactly hold. Since we are comparing estimates and not raw data we might expect some sampling biases for instance from authors picking only results considered 'publishable'. We have, however, found that the distribution of the estimates is, in general not too far from normal (see Dahl and Sterner [5]). Hence, we feel that such formal testing is a useful way to summarize results that would otherwise be too numerous for direct comparison.

[6] ε_p (C1) $=\varepsilon_p^{SR}$ (C3) rejected 5% level, $F(1,58)=22.00$.

ε_p (C1) $=\varepsilon_p^{LR}$ (C3) rejected 5% level, $F(1,58)=5.654$.

ε_y (C1) $=\varepsilon_y^{SR}$ (C3) rejected 5% level, $F(1,58)=74.43$.

ε_y (C1) $=\varepsilon_y^{LR}$ (C3) not rejected 5% level, $F(1,58)=1.616$.

[7]ε_p^{SR}, $F(1,15)=1.13$. ε_p^{LR}, $F(1,15)=0.16$. ε_y^{SR}, $F(1,15)=2.18$. ε_y^{LR}, $F(1,15)=0.02$.

[8]Tests for price, income, and vehicle elasticities for vehicle models (Equation (3)) CSTS v TS $=F(1,48)=0.22$, 0.33, and 1.32, respectively.

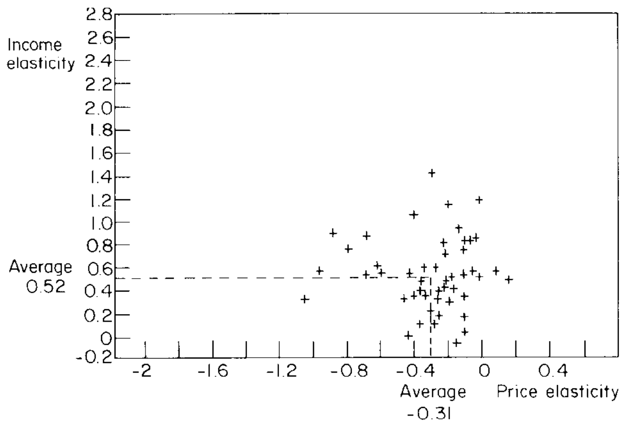

Figure 4. Vehicle models.

adjustment (−0.31/−0.53 for price and 0.52/1.16 for income) comes through utilization or changes in vehicle characteristics rather than changes in the number of vehicles. Everything else equal, adding 1% to the vehicle stock adds only 0.5% to gasoline consumption implying each additional vehicle is used less intensely.

The average price and income elasticities are also surprisingly close to the short-run estimates of price and income elasticities from the annual lagged endogenous model (C3), which supports the interpretation of both of these as short-run elasticities. Comparing the vehicle to the vehicle characteristics models, Equation (4), allows us to further distinguish between changing utilization and changing vehicle characteristics (Table 1, C8 and C10). They suggest that about one third (−0.16/0.53) of early adjustment to price comes from changes in utilization and a somewhat smaller proportion 0.29/1.16 of early adjustment to income comes from changes in utilization. In all the vehicle and vehicle characteristic models the average vehicle elasticities stay close to 0.5.

Again the monthly/quarterly data (C11) do not provide the sort of insights into adjustment that we would like. Price becomes unexpectedly more elastic while income becomes less so. Given that quarterly vehicle and characteristic data are no doubt extrapolated some of their seasonal variation might be picked up by the price elasticity. Again the results show that periodicities shorter than a year may be unreliable.

The few studies on panel or household data (C12) give more elastic responses to price and income than the other annual vehicle characteristic model (C10).[9] The next category (C13) lets us investigate further the effects of pure cross-sectional variation. Although we hypothesized that cross-sectional variation should provide long-run elasticities, the evidence on CSTS *v* TS so far has suggested no statistical difference between the two. Unfortunately there are only seven studies on strict CS aggregate data. Two are static with a lot of demographic variables, five are some sort of vehicle or vehicle characteristic model. They do, however, all clearly pick up a very elastic price response (−1.01).

There are two interpretations of the differences in these price elasticities that bear looking into. If the cross-section really does provide more price variation and hence measures more adjustment than that caught using for instance the lagged endogenous model on time series data, then the true long-run price elasticity may be greater than one in absolute value. The second interpretation is that cross-sections provide much more variation in non-income, price and vehicle variables. If these differences are attributed to price we may simply be overestimating elasticities.

Baltagi and Griffin [1] argue strongly that pooling has a number of very important advantages over individual time-series estimates. The most important of these is the gain in efficiency due to the far larger number of observations. According to this argument CSTS data are always preferable to pure TS or CS data; CSTS data may, however, be more sensitive to the choice of estimator. They test several generalized least squares estimators and find that results may vary for price elasticity from −0.6 to −0.9 depending on the estimation method used. These low results depend partly on the use of gasoline per vehicle as the dependent variable. The elasticity of the vehicle stock to gasoline prices is implicitly assumed to be zero.

Other dynamic models

The more complicated sets of dynamic models in Categories 14–18 include combinations of lags and/or vehicle variables, Equations (5)–(11). Unfortunately as models get more complicated they also tend to become less comparable within categories. Nevertheless they still provide insight into lag structure. In Category 14 we include estimates using the vehicle lagged endogenous model Equation (9) which does not seem to pick up long-run adjustment. This formulation can hardly be recommended.

A better alternative is for the dependent variable to be gasoline per auto as in our vehicle use lagged endogenous model Equation (10) with estimates shown in Category 15. Under this formulation our elasticities for price and income do not include the changes in the number of automobiles only the changes in utilization.[10] Long-run price estimates under this second

[9]The difference is significant at the 1% level for price, F(1,9) = 13.21

[10]To compute gasoline vehicle elasticities in Equation (10) the vehicle terms have to be moved to the right. Since the way vehicles were treated is not comparable across models these terms have not been included in C15 or C16.

interpretation are rather elastic at -1.05. If these elasticities do not contain total adjustment then they suggest that price may be more elastic than that implied by the simpler lagged endogenous model. Income elasticities compared to the lagged endogenous model in C3 suggest that a third of the long-run elasticity comes from changes in the number of vehicles and the rest from changes in utilization and the characteristics of the vehicle stock.

In (C16) we have included the four consistent studies found using the 'vehicle other lag' model (Equation (8)) with a lag on price but not on income or vehicles. Hence, they are dynamic in price but static in income and vehicles. Surprisingly their long- and short-run price elasticities are similar to the simpler dynamic models (C3) but their income elasticity is similar to the simpler non-dynamic vehicle models (C8).

In Category 17 we have combined other lag (Equation (5)) with lagged endogenous and other lag models (Equations (6) and (7)). Average price and income elasticities are somewhat similar to the more simple lagged endogenous. However, within this category are five studies that are inverted V lags while the others are not. Averages for the inverted V studies are -1.21 for the long-run price elasticity compared to averages for the other studies of -0.60. If we divide the studies in the vehicle other lag category (C16) between those with an inverted V and those with a declining lag we find this same dichotomy for the price elasticity with averages of -1.20 and -0.65 respectively.[11]

Category 18 contains results from Drollas [6] that are of particular interest, see description of model, Equation (11), above. His long-run price elasticities are quite similar to the lagged endogenous model but income elasticities are somewhat smaller. Constraining the lag structure to be an inverted V or a geometric lag did not seem (as with C16 and C17) to make such systematic difference.

Summary of findings

The first impression when reading a hundred gasoline demand studies is their wide range of results. Stratifying these studies by model and data type we have, however, found a number of modelling and data similarities and differences. These patterns, that should be of use to analysts of gasoline demand as well as other demand analysts, are summarized below.

The difference between annual and seasonal data is striking. Although in simple static models with only income and gasoline price, we found the expected differences between annual and monthly/quarterly data, for other more complex models the differences were less predictable. We expect that seasonal variations in behaviour and data deficiencies might contribute to this lack of consistency and we conclude that seasonal data is inappropriate particularly for long-run adjustment. With this in mind the rest of the conclusions will be restricted to estimates on annual data.

The simple static models on annual data seem to measure only an intermediate price elasticity but an income elasticity closer to the long run. Simple vehicle and vehicle characteristics models measure short-run income and price adjustments and suggest that between a quarter and a third of short-run adjustment comes from changes in utilization of the vehicle stock.

Some vehicle models tend to provide high long-run estimates but care should be exercised in choosing the structure of the model. If vehicles are entered in a static way but price dynamically, the model seems to measure long-run price but only short-run income response. If vehicles are entered in a way that implies a geometrically declining lag on the vehicle stock and other variables, long-run adjustment does not seem to be measured.

Although the lagged endogenous model appears to be quite robust, the issue of lag structure in unresolved. There is some evidence that an inverted V implies a more elastic price response than a geometric lag. Since both types of lags have economic appeal, more systematic testing of this issue is in order.

As for the type of data, there is some evidence (though not from very many studies) that strict cross-section measures a larger price response than time series. We feel inclined to agree with Baltagi and Griffin [1] who argue in favour of cross-sectional variation picking up long-run effects, and of using pooled data to increase the degrees of freedom of the estimates. As for average results, however, we find little statistical difference between cross-section time series and ordinary time series, but the latter do vary more.

The latest studies on gasoline demand show that there is continued interest in pooled data. Other areas of current research are careful scrutiny of lag structure, as well as model and error specification, with particular emphasis on such issues as the co-integration of dependent and independent variables. An example is Hughes [7] which finds very high long-run price elasticities (approaching -1.4) using error models on pooled OECD data.

Once stratified and interpreted we found a number of models that provide alternative estimates for representative short- and long-run elasticities and we summarize their averages by category in Table 2. Although there is wider divergence between long-run than short-run estimates, testing across these alternative estimates did not find any statistical difference across any of these categories. Hence, we took an average of the elasticities in all of

[11] If we pool C17 and C16 and stratify by lag type, we find the difference between the price elasticity for the geometric and the inverted V lag to be significant at the 5% level, $F_{1,11} = 8.95$.

Table 2. Comparison of results with earlier surveys.

	Price SR	LR	Income SR	LR	Number of studies	Date of most recent
Dahl and Sterner	−0.24 (C3)	−0.80 (C3)	0.45 (C3)	1.16 (C1)	97	1988
	−0.31 (C8)	−1.01 (C13)	0.52 (C8)	1.31 (C3)		
	−0.22 (C14–C18)	−0.92 (C15–C18)	0.44 (C16–C19)	1.10 (C17–C18)		
Average	−0.26	−0.86	0.48	1.21		
Dahl ([4], p 73)	−0.29	−1.02 (CS)	0.47	1.38	68	1984
		−0.60 (LE,OL)				
Bohi and Zimmerman ([3], p 140)	−0.26	−0.70	0.42	0.80	9	1982
Bohi ([2], p 117)	−0.22	−0.58	0.39	1.09	11	1979

these studies to come up with overall average elasticities.

Similar representative elasticities from three earlier surveys have been included as well. The values for Bohi [2] and Bohi and Zimmerman [3] are simple averages of the values they have interpreted as short and long run. Dahl [5] interprets the strict cross-section estimates as long run with a representative price elasticity of −1.02, which is also supported by indirect evidence on vehicle efficiency and mileage equations. Her lagged endogenous and other lag models provide a somewhat lower elasticity interpreted as intermediate run.

In comparing elasticities from earlier surveys we find representative elasticities for the short run do not vary greatly. A wide range of model types seem to capture the same short-run adjustment and although the numerous additional recent studies may suggest a somewhat more elastic response, they do not change our perception of short-run elasticity very greatly.

Long-run estimates of elasticity across surveys vary more widely. But as in the earlier works there is strong evidence that gasoline consumption is very responsive to prices and income and if anything the inclusion of the latest studies suggests that response may be getting larger. Strict cross-sections still tend to provide the most elastic price response as in Dahl [4] but averages for the lagged endogenous and more complicated lag models seem to have now converged somewhat towards the cross-section estimates.

These estimates have important policy implications. Since there is fairly strong evidence that the average long-run income elasticity is greater than one, if unchecked, we can expect gasoline demand to continue to grow. Since average long-run price elasticities are also quite high, gasoline taxes could be quite effective in curtailing this demand.

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