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Income Elasticity of Gasoline Demand: A Meta-Analysis

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Abstract:

In this paper we quantitatively synthesize empirical estimates of the income elasticity of gasoline demand reported in previous studies. The studies cover many countries and report a mean elasticity of 0.28 for the short run and 0.66 for the long run. We show, however, that these mean estimates are biased upwards because of publication bias—the tendency to suppress negative and insignificant estimates of the elasticity. Using mixed-effects multilevel meta-regression we filter out publication bias from the literature. Our results suggest that the income elasticity of gasoline demand is smaller than commonly thought: the corrected estimate is 0.1 for the short run and 0.46 for the long run.

Keywords: Gasoline, income elasticity, publication bias, meta-analysis

JEL: C83, Q41

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1 Introduction

The income elasticity of gasoline demand is a key parameter in energy and environmental economics. It helps us understand, among other things, how emissions of greenhouse gases stemming from the consumption of gasoline may evolve in the future as developing countries get richer. Because of its policy relevance, the elasticity has been estimated by hundreds of researchers in recent decades. Yet the results of these studies vary significantly. In this paper we synthesize the estimated income elasticities of gasoline demand and try to provide a benchmark value of the elasticity based on the available empirical literature. To this end we employ meta-analysis, the set of methods designed for quantitative literature surveys.

Meta-analysis was developed in medical science to summarize the results of clinical trials (Pearson, 1904). Clinical trials are costly and often can only use a handful of observations; aggregation of the results of clinical trials on the same topic increases the number of degrees of freedom and improves the robustness and precision of the resulting estimate. In the last few decades the methods of meta-analysis have spread from medical research to other fields; for example, the first meta-analysis in economics was Stanley & Jarrell (1989). The excellent survey by Nelson & Kennedy (2009) summarizes 140 meta-analyses conducted in environmental and natural resource economics since the early 1990s. Meta-analysis, we believe, is not a substitute for good narrative literature surveys, but it complements them with a formal treatment of various biases potentially present in the literature.

At least since Rosenthal (1979), researchers conducting literature surveys have been concerned with the so-called file-drawer problem, or publication bias. When some results are strongly predicted by the theory, researchers may treat the opposite findings with suspicion. Such results are often difficult to publish, and researchers may choose to hide them in their file drawers. The process can be unintentional and still result in publication bias; for example, if researchers use the "correct" sign of the estimated coefficient as a model selection test. The bias is particularly serious in medical research, and the best medical journals now require registration of clinical trials before publication so that the profession knows whether results end in file drawers (Krakovsky, 2004; Stanley, 2005). A well-known case of publication bias concerns the antidepressant drug Paxil, which was originally found to be effective by most published studies. When, however, unpublished results are included, the drug does not seem to outperform a sugar pill, and may actually make people more likely to commit suicide (Turner *et al.*, 2008).

The American Economic Association is also considering establishing a registry for controlled experiments because of potential publication bias (Siegfried, 2012, p. 648). But for non-experimental fields, such as the literature estimating the income elasticity of gasoline demand, meta-analysis tools remain the only way to correct for the bias. We suspect that negative estimates of the elasticity are reported less often than they should, which would bias the mean estimate in the literature upwards. The reason is that negative estimates of the income elasticity are counter-intuitive: it does not make much sense for gasoline demand to decrease in general with higher income. We suspect that researchers unintentionally discard negative estimates (which imply that gasoline is an inferior good), even though they should report them from time to time because of the sampling error, especially if the true elasticity is small. As discussed by Stanley & Doucouliagos (2012), such discarding of unintuitive results may paradoxically improve individual studies—it would not be correct to build conclusions on negative estimates of the elasticity. But the literature as a whole gets biased upwards as the negative results become underrepresented.

To our knowledge, there has been one meta-analysis on the income elasticity of gasoline demand. Espey (1998) examines the heterogeneity in the estimates and reports mean elasticities of 0.47 for the short run and 0.88 for the long run, but she does not take publication bias into account. Two meta-analyses have been conducted on the price elasticity of gasoline demand: Brons *et al.* (2008) and Havranek *et al.* (2012). Similarly to Espey (1998), Brons *et al.* (2008) focus on the heterogeneity stemming from the different methods used by the authors estimating the elasticity, and do not control for publication bias. Havranek *et al.* (2012) show there is substantial publication bias in the price elasticity of gasoline demand: the mean estimate of the price elasticity seems to be exaggerated twofold.

We use a large data set of gasoline demand elasticities collected and described by Dahl (2012). Because modern meta-analysis methods require information concerning the precision of the estimates of elasticities, we only use estimates for which standard errors or t-statistics are reported. The average reported elasticity for the short run is 0.28; for the long run it is 0.66. We find strong publication bias in the literature, especially for the estimates corresponding to the short run. To correct for publication bias we use mixed-effects multilevel meta-regression methods. The mixed-effects approach allows for between-study differences in the underlying elasticity, which is important because the studies in the data set estimate the elasticity for different countries. The method also assigns each study approximately the same weight, which is desirable because otherwise studies reporting many estimates would dominate the meta-analysis. Our results suggest that the corrected income elasticity of gasoline demand is, on average, only 0.1 for the short run and 0.46 for the long run. For the short run, for example, this is five times less than the number reported by Espey (1998); the difference is in part due to newer data and in part due to the correction for publication bias.

The remainder of the paper is structured as follows. In Section 2 we outline the models used for the estimation of the income elasticity of gasoline demand. In Section 3 we describe the meta-analysis models that we use in this paper. Section 4 presents the results of our meta-analysis. Section 5 concludes the paper. The data and Stata code used for the estimation are available in an online appendix at `meta-analysis.cz/gasoline`.

2 Estimating the Elasticity

In this section we review the econometric methods used for the estimation of gasoline demand elasticities. Energy demand exhibits some unique features that do not allow us to treat it in the same way as demand for other consumer products. The main point is that people do not demand energy directly; they demand transportation where gasoline serves as an input, so researchers often work with demand for gasoline in the same way as with derived demand. While gasoline is a non-durable good, this dependence on durable goods makes the estimation more difficult. For example, as people demand certain amounts of travel, their gasoline consumption depends on the efficiency and price of vehicles. Over the last 40 years, several estimation approaches have been suggested, but no consensus has been reached in the literature, as different researchers prefer different methodologies. All the econometric models described in this section are assumed to have homoskedastic disturbances with zero mean unless stated otherwise.

2.1 Basic Models

The models discussed over the years have one thing in common—gasoline demand is modeled as a function of the price of gasoline and real income per capita. If a study does not contain one of these factors, it is generally disregarded by researchers performing meta-analyses and literature reviews (Dahl & Sterner, 1991). Other regressors may include the automobile stock, average car efficiency, and prices of other inputs. The response variable, gasoline demand, is not usually taken as an aggregate value. Some researchers use gasoline demand per driver or, if such data are unavailable, they proxy the number of drivers by the adult population. Others use gasoline demand per vehicle. The main difference between the two types of models presented is the way they handle the dynamics—the question of how the adjustment of gasoline demand is laid out in time.

The so-called static models do not estimate short-run adjustment, but only model the overall response in the long run. Dahl (2012) suggests that results from static models should be treated as estimates for the "intermediate run" because they yield lower estimates compared with dynamic models. From here on, in all equations in this paper G will represent gasoline demanded, Y per capita income, P real prices, and Z_k other relevant explanatory variables. The benchmark static model then reads

$$\log G_t = \alpha + \beta_1 \log P_t + \beta_2 \log Y_t + \sum_{k=1}^{K} \beta_{k+2} Z_{kt} + u_t, \tag{1}$$

where betas denote the corresponding elasticities.

2.2 Dynamic Models

A different model, described by Kennedy (1974) and Houthakker *et al.* (1974), assumes different consumer adaptation in the short and long run. The function of demand is assumed to have the following log-linear form:

$$G^* = f_2(P, Y) = \alpha Y^\beta P^\gamma. \tag{2}$$

Given that the desired level may not match the actual demand for gasoline, there is adjustment over time toward the ideal demand level:

$$\frac{G_t}{G_{t-1}} = \left(\frac{G_t^*}{G_{t-1}} \right)^{1-\lambda} \tag{3}$$

After substituting (2) into (3), taking the logarithm of both sides of the equation, and adding a disturbance term, we arrive at

$$\log G_t = \log \alpha + (1-\lambda)\beta \log Y_t + (1-\lambda)\gamma \log P_t + \lambda \log G_{t-1} + u_t. \quad (4)$$

The regression coefficients corresponding to $\log Y_t$ and $\log P_t$ in Equation 4 are the short-run estimates of the income and price elasticities, respectively. Dividing them by $1-\lambda$, thus obtaining β and γ, we get the long-run estimates. Such an elegant combination of short- and long-run elasticities within one equation has made this model very popular. The simplified model assumes an identical lag structure for the explanatory variables, so lags of the regressors are sometimes included. A thorough overview, along with separation of these models into various groups, can be found in Dahl & Sterner (1991).

2.3 Cointegration and Error Correction Models

As econometric research progressed, new caveats surfaced for both dynamic and static models. Granger & Newbold (1974) point out that when two unit root processes are regressed on one another, their estimated relationship and R^2 may be incorrect, yielding so-called spurious regression. Nevertheless, when the two variables are found to be cointegrated, in the sense coined by Engle & Granger (1987), the problem no longer arises, as cointegration translates into a long-term relationship between the variables, despite their unit roots.

2.3.1 Unit Roots and Cointegration

Unit root testing was devised to check whether a variable is highly dependent on its first lag, its previous value. The test consists of finding out whether a process follows AR(1), where the lagged dependent variable has a parameter equal to unity. After rearrangement, the test boils down to finding out whether ϕ in (5) is significant; the model shown below is the augmented version of the Dickey-Fuller test (the original test without the summation is proposed in Dickey & Fuller (1979)):

$$\Delta x_t = \alpha + \beta t + \phi x_{t-1} + \sum_{i=1}^{n} \gamma_i \Delta x_{t-i} + \varepsilon_t. \quad (5)$$

Given non-standard distributions, alternative critical values were suggested for different sample sizes and number of lags in the augmented test, and for whether the drift and trend terms were included or not. In addition to the Dickey-Fuller test, several other testing methods are summarized in Engsted & Bentzen (1997).

Tests of unit roots in gasoline consumption, prices, and real income have been performed in various papers and the null hypothesis of a unit root could not usually be rejected using standard significance levels. See, for example, Alves & Bueno (2003), Akinboade *et al.* (2008) or Bentzen & Engsted (2001) for details. If a unit root is not rejected, a check for cointegration can be carried out; researchers are looking for a stationary linear combination of these unit root processes. The resulting coefficients then depict the long-run relationships. In our case, researchers can estimate the following model:

$$\log G_t = \alpha + \beta_1 \log Y_t + \beta_2 \log P_t + u_t. \tag{6}$$

If we rewrite this equation, leaving u_t on one side and all other variables on the other, we can see that if the linear combination of our three variables is stationary, the disturbances need to be stationary as well. Similarly to unit root testing, the null hypothesis of a unit root needs to be rejected in order for the disturbances to be stationary. As the disturbances are naturally unavailable, residuals are tested. Also, because there are more variables in question, different critical values are used—see Engle & Yoo (1987). This whole derivation in fact validates the long-run estimation using a static model, but only under strict assumptions of stationarity of the disturbances and non-stationarity of the other variables.

2.3.2 Error Correction Model

Cointegration alone does not describe the short-run adjustment, so Engle & Granger (1987) devise the error correction model (ECM) to this end. The rationale behind the ECM is that whenever the consumer is not in equilibrium, that is, when the residual resulting from (6) is non-zero, he will try to get back to the equilibrium in the following period. This adjustment toward equilibrium will allow us to estimate the short-run elasticities. The ECM is modeled as follows:

$$\Delta \log G_t = \alpha + \sum_{i=0}^{m} \beta_{1i} \Delta \log Y_{t-i} + \sum_{i=0}^{n} \beta_{2i} \Delta \log P_{t-i} + \sum_{i=1}^{s} \beta_{3i} \Delta \log G_{t-i} + \gamma \hat{u}_{t-1} + \varepsilon_t, \qquad (7)$$

where m, n, and s are selected so that ε_t is white noise, and $\hat{u}_{t-1}$ are the residuals from the cointegration equation, (6) in our case. Thanks to the fact that all G_t, Y_t, and P_t are I(1), their first differences are stationary, I(0), and the lagged residuals from (6) are stationary as well. So, the whole model involves only stationary variables, and its disturbances are white noise. In this setting the first-differenced lags of the response variables in question depict the short-run elasticity.

2.3.3 Revival of Dynamic Models

While it might seem that both the static and dynamic models have become dominated by the cointegration and ECM frameworks, it is not entirely so. The introduction of unit roots and cointegration certainly clarified the long-term adjustment behavior of consumers, but these methods have other disadvantages. In the work of Pesaran & Shin (1995) a crucial thought is explored: Given our understanding of I(1) processes and cointegration, how does the dynamic model perform? They go on to prove the consistency of both the short- and long-run estimates when using dynamic models, given that the underlying variables are I(1) and cointegrated. Also, the resulting t- and F-statistics are valid, so hypothesis testing can be carried out. Although cointegration and ECM provide a seemingly easy and straightforward approach, it is not without flaws, and recent research by Pesaran & Shin suggests that dynamic models do not have to be abandoned just yet.

2.3.4 Bounds Approach to Cointegration

Even though the two-step cointegration approach has become the leading method for gasoline demand estimation, some of the recent papers use a different technique that alleviates some of the limitations described in the previous subsection. The model proposed by Pesaran *et al.* (2001) does not require the underlying variables to be non-stationary and does not suffer from severe small-sample bias, but still remains consistent.

Allowing for both stationary and non-stationary variables in our models not only eases one assumption, but also widens the possibilities for our variables. The model once again combines both short- and long-run elasticities:

$$\Delta \log G_t = \alpha + \sum_{i=0}^{m} \beta_{1i} \Delta \log Y_{t-i} + \sum_{i=0}^{n} \beta_{2i} \Delta \log P_{t-i} + \sum_{i=1}^{s} \beta_{3i} \Delta \log G_{t-i} + \tag{8}$$
$$+ \gamma_1 \log P_{t-1} + \gamma_2 \log Y_{t-1} + \gamma_3 \log G_{t-1} + u_t.$$

The cointegration relationship test is carried out using an F-test with the null $\gamma_1 = \gamma_2 = \gamma_3 = 0$, stating there is no long-run relationship. Since the F-statistic was found to be non-standard, Pesaran *et al.* suggest upper and lower bounds for the test, rejecting the null if the upper bound is exceeded, and failing to reject if the statistic does not exceed the lower bound. The test is inconclusive if the F-statistic lies between these two values. The long-run elasticities in this model are computed as the ratios $-\frac{\gamma_1}{\gamma_3}$ and $-\frac{\gamma_2}{\gamma_3}$ for price and income, respectively. Given this indirect inference, their standard errors need to be computed additionally, for example using the delta method. In gasoline demand estimation this model is used by Akinboade *et al.* (2008) and Sa'ad (2009).

2.4 Data Selection and Pooling

A large majority of studies use annual data, but that of course means only several dozen observations are available at best. Given the asymptotic properties, small-sample performance, inability to use many explanatory variables, and other issues with modern econometric tools when short time series are available, researchers try to gather more data. There are two means of extending a data set and thus generally improving the resulting estimation: pooling and using micro-level data.

2.4.1 Pooling

The topic of pooling and comparing homogeneous and heterogeneous models is extensively covered in Baltagi & Griffin (1997). They use two factors to judge the quality of estimators. The first is the plausibility of the results given previous research and rationale, and the other factor is forecast quality. Leaving the last ten years as an out-of-sample control group, they order the estimators by their root mean squared error. They end up favoring the homogeneous estimators, partly thanks to the fact that their sample consists of 18 OECD economies that do not exhibit large cross-country differences.

One caveat of international pooling may be incompatibility of the data. Wheaton (1982) points out two specific problems. The first problem is a difference in standards, as he finds some countries to be reporting fuel efficiency differently than the rest, forcing him to create separate models. A second problem may arise with the difference in currencies. Wheaton points to Kravis *et al.* (1978), who constructed a cross-national GDP deflator for these inter-country comparison purposes.

2.4.2 Micro-Level Data

Using micro-level data allows researchers to investigate various subgroups within individual countries, separating them by income levels, regions, occupation, marital status, and other characteristics. These studies aim to estimate the heterogeneity that other researchers neglect, as they consider countries to be homogeneous. The downside of this method is the availability and extent of the data. Micro-level information is expensive to obtain and is usually gathered using surveys conducted far less frequently than annually, which is the frequency used in most of the studies utilizing aggregate data. See Greening (1995), Archibald & Gillingham (1981), or Nicol (2003) for more details on individual studies and Graham & Glaister (2002) (section "Micro-level Data: Individual and Household Demand Studies" and the summary in Table 6) for an overview.

2.5 Other Issues

2.5.1 Symmetry of Demand Elasticities

The problem of potential asymmetry of price elasticities has surfaced not only in gasoline consumption research, but in many other areas as well. The argument is that people are generally more sensitive to a price increase than to a price decrease, while estimation is usually performed assuming symmetry. A summary of research results on this topic in the area of gasoline demand can be found in Dahl (2012). The general practice is to augment the demand model so that it differentiates between new price maxima, price cuts, and sub-maximum price recoveries. One of the studies using US data reports a significantly larger adjustment when a new maximum is reached, specifically 30% higher elasticity than the symmetric estimate. Responses to price cuts are merely half of the estimates assuming symmetry. There are only a handful of studies including this decomposition, often reporting mixed results, so further research into this topic is necessary to obtain more reliable results.

2.5.2 Cointegration and Panel Data

Using the traditional static and dynamic models, researchers have not only explored single country data sets, but also dealt with heterogeneous groups of samples, employing techniques such as fixed/random effects and the like. This approach gets more difficult in unit root testing and cointegration. The augmented framework has been used in several studies, but still the great majority involves only one country at a time. See Baltagi & Kao (2000) for a comprehensive overview of econometric tools for panel data treatment in cointegration.

2.5.3 Influence of Study Design

Some of the discrepancy between the estimates in different studies on the same topic is attributed to the choice of econometric methods. This aspect is usually covered in overviews and meta-analyses (Espey, 1998; Fidrmuc & Korhonen, 2006; Havranek & Irsova, 2011). Another approach to corroborate this can be found in Baltagi & Griffin (1997). Using the same data set, they employ various methods in order to find out how influential their selection can be. They find great discrepancy in long-run price estimates, ranging from -0.24 to -1.42, and short-term income elasticity, estimated between -0.65 and -0.92. Apart from the influence of data selection, most notably the frequency of observations, such substantial volatility is of concern as well.

2.5.4 Cross-Country Differences

Gasoline demand in low-income economies generally differs from that in the rest of the world. On the one hand, the car stock in these countries is usually much lower; on the other hand, economic growth in developing countries is often faster. Studies covering these countries frequently yield high income elasticities, and Storchmann (2005) suggests this finding is due to a high marginal rate of consumption regarding automobiles. A consensus has not been reached, as some studies indicate smaller income elasticities in the developing world. Another differentiating factor is data availability in developing countries; even if researchers use the most advanced econometric techniques, missing information may severely hamper their estimation. For example, car stock information was shown to be a crucial moderator variable, as its omission can lead to severe overestimation of the income effect.

3 Meta-Analysis Methodology

Meta-analysis has long been used in science; the term was first coined by Glass (1976). The method later spread into economics following the publication of Stanley & Jarrell (1989). In this section we only describe the tools used in our analysis; for a complete overview of contemporary methods in meta-analysis see Nelson & Kennedy (2009) and Stanley *et al.* (2008). The idea behind meta-analysis is to explore factors that influence research results. After gathering as many studies on the same topic as possible, various pieces of information about each one are collected. These include the sample size, standard errors, econometric methods used for estimation, data used, specification, year of publication, and other characteristics. This approach aims to be more objective about modeling patterns in the literature than narrative survey methods. Nevertheless, it is still subjective in the way that the underlying data are collected and the models are constructed by the researcher, and their adjustment may affect the outcome.

Given that the variance of estimates is too large to be explained by the sampling error only, it is important to examine the sources of heterogeneity in the results. As Christensen (2003) points out, there are two types of heterogeneity: factual and methodological. Factual heterogeneity concerns actual population differences, for example based on countries where the research was conducted. In our case of gasoline demand elasticities we examine if there is a difference between developed and developing markets and expect gasoline demand in the latter countries to be more sensitive. Methodological heterogeneity stems from the different procedures used, be they econometric methods, data frequency, or other aspects of study design.

Apart from the obvious characteristics that influence the results, there is one other factor that can bias the outcome—researchers themselves. If a result is not in line with the theory or previous results, the researcher may choose to discard the finding, thus giving rise to publication bias. A related practice is to keep modifying the specification or data until the results are consistent with the standard outcomes. Insignificant estimates can result in a specification search as well. All of these practices need to be measured and accounted for, as they can bias our inference based on the sample of collected observations.

3.1 Graphical Approach

Before testing for publication bias using econometric methods, a simple visualization of the estimates may benefit the analysis. While this approach is less objective and less informative in the sense of finding the underlying population value of the elasticity, it helps us to get an overall picture concerning the literature. The so-called funnel plot, extensively covered in Stanley & Doucouliagos (2010), visually describes individual observations of the magnitude of the income elasticity on the horizontal axis along with their measure of precision, most commonly the inverted standard error, on the vertical axis. The idea behind this graph is that the most precise estimates—those with the shortest confidence intervals—will be at the top of what should be an inverted funnel.

The problem is that in practice the plot often does not resemble a funnel, because a part of it is missing, not reported in the literature. One of the reasons for this frequent finding may be that estimates that are inconsistent with the theory are underreported; this may be true especially if the underlying value of the parameter is close to zero. Such funnel asymmetry suggests publication bias. The assumed symmetry of the funnel plot in the absence of publication bias results from the assumptions that researchers make when they estimate the income elasticity of gasoline. They report t-statistics for their point estimates, which implies that the estimates and their standard errors should be independent and the elasticities should be approximately normally distributed around the average value.

3.2 Econometric Models

The intention to explain the variation in the reported elasticities using the characteristics of individual studies leads us to the following equation suggested by Stanley & Jarrell (1989). The estimate of elasticity is the dependent variable, explained by various factors Z_k, the underlying value of the elasticity, β, and disturbances e_j:

$$b_j = \beta + \sum_{k=1}^{K} \alpha_k Z_{jk} + e_j \qquad j = 1, 2, \ldots, L. \tag{9}$$

The variables Z_{jk} may include information about model specification, publication outlet, number of observations, and so on. As we will see later, this simple model has been extended and adjusted for various innovations in meta-analysis that have occurred since the early 1990s.

As we investigate publication bias using econometric methods, we are essentially testing the asymmetry of our funnel plot. Building upon the potential asymmetry, we can model publication bias in the following way:

$$b_j = \beta + \alpha_0 se_j + \sum_{k=1}^{K} \alpha_k Z_{jk} + e_j, \tag{10}$$

where the estimate depends not only upon the characteristics from (9), but also on its standard error se_j. In this specification, α_0 measures the degree of publication bias (Stanley, 2005).

Given the nature of the data, the disturbance e_j is unlikely to be homoskedastic. While this does not affect our point estimates from the regression, the reported standard errors for the parameters will be inflated. As a remedy, Stanley (2008) suggests to use weighted least squares instead, using the standard errors as weights. The response variable becomes the t-statistic, and we obtain the following specification:

$$t_j = \beta/se_j + \alpha_0 + \sum_{k=1}^{K} \alpha_k \frac{Z_{jk}}{se_j} + \varepsilon_j. \tag{11}$$

In this model the publication bias is treated as constant throughout the sample, but the constant can be decomposed using additional moderator variables:

$$t_j = \beta/se_j + \alpha_0 + \sum_{l=1}^{L} \delta_l Z_{jl} + \sum_{k=1}^{K} \alpha_k \frac{Z_{jk}}{se_j} + \varepsilon_j. \tag{12}$$

This constitutes a rich model allowing for examining heterogeneity in both the elasticity and the publication bias. For more precise estimation of the effect beyond publication bias, Stanley & Doucouliagos (2007) suggest that since the effect of standard errors may be quadratic, we can model the asymmetry in the following way (once again after weighting by inverted standard errors):

$$t_j = \beta/se_j + \gamma_0 se_j + \varepsilon_j. \tag{13}$$

Estimates from the same study often share the same qualities in terms of estimation methods, data, and priors of the researcher. This can result in correlation of these estimates, a problem described in Stanley & Jarrell (1989). The problem becomes even more pronounced as the number of estimates per study increases. In meta-analysis surveys, the median of this value is reported to be three (Nelson & Kennedy, 2009); in our case it is eight for both the short- and long-run estimates. As a remedy for potential within-study correlation, Nelson & Kennedy (2009) suggest the mixed-effects multilevel model, which has been used by many studies (for instance, Doucouliagos & Stanley, 2009; Daníšková & Fidrmuc, 2012). This setting allows us to add a random effect for each study, obtaining a composite error together with the estimate-level disturbance. If within-study correlation is large, the estimation gives less weight to elasticities coming from studies that report many results, so that all studies have approximately the same weight (Havranek & Irsova, 2011). Extending (12) and (13), respectively, we obtain

$$t_{ij} = \beta/se_{ij} + \alpha_0 + \sum_{l=1}^{L} \delta_l Z_{ijl} + \sum_{k=1}^{K} \alpha_k \frac{Z_{ijk}}{se_{ij}} + u_i + \varepsilon_{ij}, \tag{14}$$

$$t_{ij} = \beta/se_{ij} + \gamma_0 se_{ij} + u_i + \varepsilon_{ij}. \tag{15}$$

In the final specifications the quadratic effect of publication bias is denoted by the estimate of γ_0, and β reflects the underlying population value. Two sets of moderator variables α_k and δ_l denote the effect on the estimate itself and on publication bias, respectively. Our disturbance is split between a study-level error u_i and an estimate-level disturbance ε_{ij}. With $u_i|se_{ij} \sim N(0, \theta)$, $\varepsilon_{ij}|se_{ij} \sim N(0, \phi)$, and these errors being uncorrelated, the variance of the composite error is a simple sum, $\text{var}\,(u_i + \varepsilon_{ij}) = \theta + \phi$. The closer the study-level variance θ is to zero, the weaker is the case for using the mixed-effects framework instead of ordinary least squares (OLS).

4 Application of Meta-Analysis

With so much research interest in energy demand, various surveys and analyses of the literature on this topic emerged early on; non-econometric surveys include Dahl & Sterner (1991), Dahl (2012), and Graham & Glaister (2002). These papers stress the importance of model specification and stratify the studies by their choice of explanatory variables or lag structures. Having compared the studies within these clusters, Dahl & Sterner (1991) conclude *"[...] 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."* Apart from arithmetic means, medians, and visualization of the results, these surveys do not use any formal statistical frameworks to estimate the underlying value of gasoline demand elasticities.

To address this issue and provide an even more systematic synthesis, several meta-analyses on the topic have been performed, namely, Espey (1998), Brons *et al.* (2008), and Havranek *et al.* (2012). These analyses differ in various factors, including the choice of data, econometric toolset, and treatment of publication bias. Only Espey (1998) deals with income elasticity, reporting an average of 0.47 for the short run and 0.88 for the long run, with medians lying close to these values, namely, 0.39 and 0.81. The basic features of the three meta-analyses are summarized in Table 1. None of the previous surveys or analyses on income elasticity corrected the literature for publication bias; such treatment can only be found in Havranek *et al.* (2012), who researched price elasticity. That study was the first one to discuss the problem of publication bias in gasoline demand research.

Table 1: Overview of previous meta-analyses

	Espey	Brons *et al.*	Havranek *et al.*
No. of studies	101	43	41
Time span	1966–1997	1974–1999	1974–2011
No. of estimates	LR price 277, LR income 245, SR price 363, SR income 345	SR price 191, LR price 79	SR price 110, LR price 92
Approach	OLS	Seemingly unrelated regressions	mixed-effects, clustered OLS

LR and SR stand for long run and short run, respectively

4.1 Data Set

The three meta-analyses mentioned above collected mostly peer-reviewed journal articles, together using 150 unique studies. This paper employs a data set previously used in Dahl (2012). This contains several thousand observations, compiled from 240 papers, books, working papers, and mimeographs. Together it constitutes arguably the widest sample used in gasoline demand research, certainly the largest used for a meta-analysis in this field. This data set greatly exceeds the mean and median of the 125 meta-analyses surveyed by Nelson & Kennedy (2009) in terms of the number of observations (the mean is 191 and the median is 92). Furthermore, several aspects of this data set help us in our analysis:

- Pooling of published and unpublished studies will allow us to examine if such stratification has an impact either on the estimates themselves or on the degree of publication bias.
- The size of the data set will allow for more precise estimation; the number of degrees of freedom will not limit our selection of explanatory variables.
- Recorded t-statistics will allow us to control for publication bias.

The data set was further edited, as we removed entries without valid t-statistics, transformed model specifications into dummy variables, pooled countries into groups of OECD and non-OECD countries, and added information about journal publication. This augmented version is included in the online appendix at `meta-analysis.cz/gasoline`; the original version can be found at the website of Carol Dahl (Dahl, 2010).

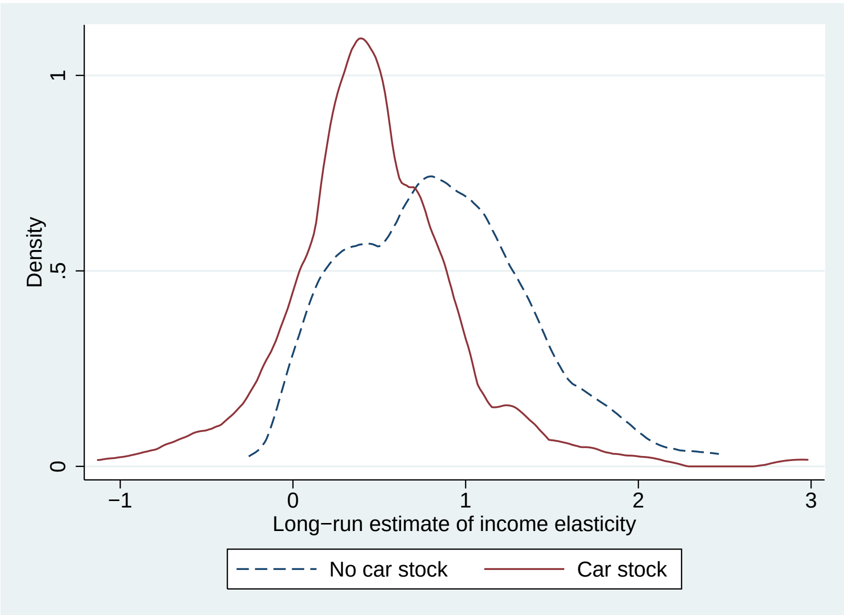

Figure 1: Densities of long-run estimates with and without car stock information

Even though data should generally not be further stratified in meta-analysis, as the use of moderator variables in meta-regression analysis is preferred by most researchers, we believe the case of including car stock information in the estimation of the income elasticity of gasoline demand is an exception. As discussed earlier, survey authors consider the use of a car stock indicator to have a major influence on the long-run estimates of income elasticity. A quick look at Figure 1 suggests that this might be true in our data set as well.

As will be shown later, the long-run elasticities without car stock information are usually almost twice as large as the rest, based on both weighted and unweighted averages. This finding strengthens our belief that the two subsamples represent two distinct phenomena and should be modeled separately. As car stock adjustment forms a major part of the effect based on income change, the estimates with this information present report the long-run income elasticity beyond car stock adjustment. The other estimates reflect the total adjustment to income variation. From now on, these two subsamples will be treated separately. Even though some surveys and analyses point to this discrepancy (Dahl & Sterner, 1991; Dahl, 2012; Espey, 1998), primary studies rarely acknowledge the problem.

4.2 Graphical Methods

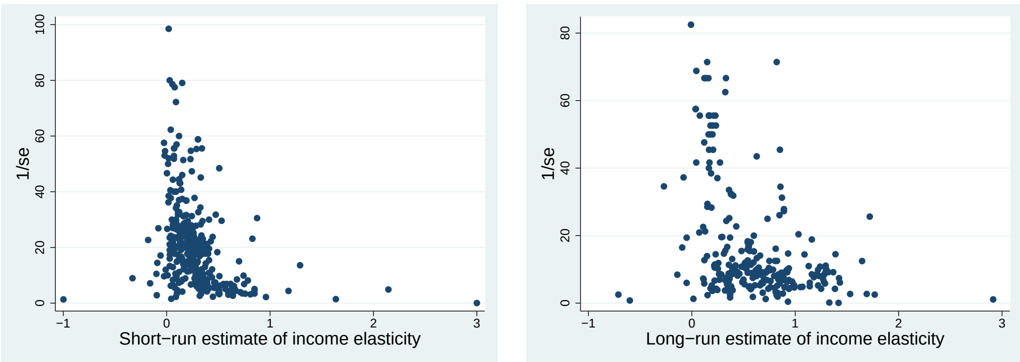

Figure 2: Funnel plots, only published estimates depicted

Prior to the econometric analysis itself, we inspect the data set using several graphical methods. Publication bias is expected to occur in the literature on gasoline demand elasticities, and there are multiple indicators of the bias based on data visualization. First, as we see from Figure 2, the funnel plots for this literature are heavily skewed. The left-hand part of the graph is almost completely missing in the funnel for short-run estimates, suggesting publication bias toward positive results, which are more consistent with the theory. The second funnel with long-run estimates shows two spikes (the values with the highest precision denoting the underlying value of the elasticity beyond publication bias), one for models with car stock information, and the other for models disregarding car stock information. This finding represents another reason for separating these two subsamples.

This asymmetry of the reported results causes simple estimators such as the arithmetic mean and the median to yield biased estimates; in our case these estimates will be biased upwards, as negative estimates of the short-run effect and insignificant positive estimates of the long-run effect are reported less often than they should be. The funnel asymmetry strengthens our case for using econometric methods that deal with publication selectivity. Second, the densities of the t-statistics of our estimates, depicted in Figure 3, exhibit a sharp increase around the value of 2. That roughly corresponds to a 5% significance level in a two-tail t-test for positive estimates—if researchers are striving for statistical significance they need t-statistics around two, and the evidence shown in Figure 3 is thus consistent with the presence of publication selection in the literature.

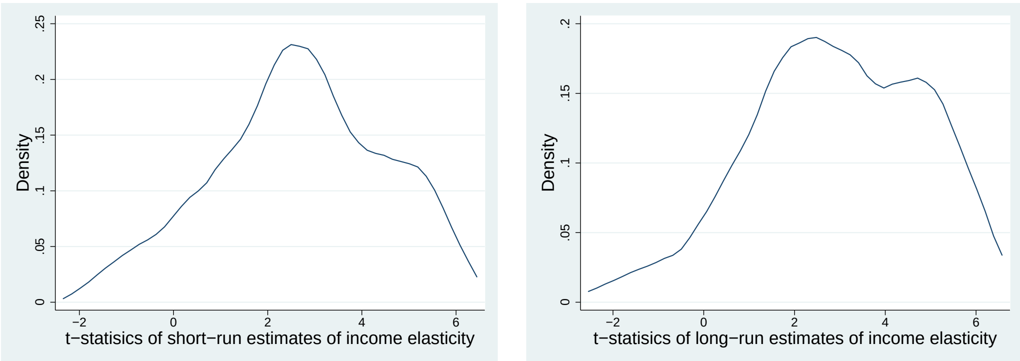

Figure 3: Kernel densities of t-statistics

Third, as Stanley *et al.* (2010) suggest, a quick way to test for potential publication bias is to take estimates with the highest inverted standard errors, i.e., those at the top of the funnel (usually 10% of the whole sample), and compute their mean. These points should represent the most precise estimates from the whole sample, thus their average should be close to the population value. Computing a weighted average for these subsamples, we arrive at 0.138, 0.329, and 0.636, respectively, for short-run, long-run with car stock, and long-run without car stock information. These values are lower than the means and medians reported in the summary statistics in Table 2. All these tests suggest the samples are skewed and reporting means or medians is not sufficient when looking for the underlying value of the elasticity.

Table 2: Summary statistics

	Obs.	Mean	Median	Std. Dev.	Min.	Max.
Short run	831	0.284	0.250	0.326	-1.17	3
Long run, car stock	346	0.465	0.395	0.509	-1.13	2.98
Long run, no car stock	346	0.861	0.838	0.519	-.256	2.466

4.3 Meta-Regression Results

First, we use the simplified funnel asymmetry test (15) and then the extended model (14) with moderator variables from our data set. The funnel asymmetry test only requires t-statistics, the estimates themselves, and stratification by studies, as the mixed-effects multilevel framework is used. Concerning the extended model, even though there are dozens of potential explanatory variables, we focus only on the following few that we consider especially important:

OECD membership As noted earlier, energy demand in less developed countries may be affected by a higher marginal rate of consumption, thus it is expected that the long-run income elasticity will be higher in these countries.

Publication Publishing a paper in a peer-reviewed journal signals that the study had to undergo a peer-review process, suggesting a certain expected standard of work.

Time dimension Studies employing annual data may yield different results than cross-section time series or pure cross sections, which usually have significantly more observations.

Car stock As noted earlier, the inclusion of car stock information greatly affects the resulting estimate, so for the long-run elasticity regression a dummy will be included to account for this information about the original model specification.

All the results presented below come from regressions using the mixed-effects framework presented in the previous section. The value of within-study correlation is large, and likelihood-ratio tests suggest that we cannot ignore it and simply use OLS. The basic funnel asymmetry test based on mixed-effects estimation yields the results depicted in Table 3. The extent of publication bias represented by the constant term is significant at the 10% level for all models. Thus, our impression based on the previously reported funnel plots is corroborated by formal econometric methods: negative and insignificant estimates of the income elasticity of gasoline demand tend to be reported less often than they should.

Table 3: Test of publication bias

	Short-run		Long-run			
	Whole sample		Car stock		No car stock	
1/se	0.0837***	(10.06)	0.209***	(7.71)	0.592***	(15.50)
Constant	2.997***	(7.97)	1.573**	(1.97)	3.032*	(1.77)
Observations	831		346		346	

Response variable: t-statistic of the estimate of elasticity
t-statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

To judge the extent of publication bias, Doucouliagos & Stanley (2013) run Monte Carlo simulations and construct thresholds for the value of the constant in the funnel asymmetry test to distinguish the degrees of publication bias. By their terminology our short-run and long-run without car stock samples exhibit "severe" publication bias, while the long-run with car stock sample contains a "substantial" amount of bias. To estimate the true underlying effect beyond publication bias, we employ Heckman meta-regression with a quadratic relationship between the estimates of the elasticities and their standard errors; the results are summarized in Table 4. As expected, all estimates of the underlying value of the elasticity (the coefficient for $1/se$) are larger than zero at the 1% level of significance.

Table 4: Test of the underlying elasticity beyond publication bias

	Short-run		Long-run			
	Whole sample		Car stock		No car stock	
1/se	0.0999***	(12.47)	0.234***	(9.76)	0.644***	(17.38)
se	-0.140	(-1.24)	-0.0501	(-0.11)	0.965***	(2.73)
Observations	831		346		346	

Response variable: t-statistic of the estimate of elasticity
t-statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 5 offers a comparison of our preferred regression results with respect to several widely used metrics. The weighted mean in the table is a result of mixed-effects regression without publication bias treatment. Looking at the discrepancy between the values, we can see that classical tools that do not take publication bias into account overstate the elasticity. This affects the inference based on these metrics. For example, Dahl (2012) estimates the decomposition of long-run income elasticity based on the discrepancy in the two subsamples based on car stock information. While we found the car stock sample to be about one third of the other estimate, Dahl found it to be one half, based on a sample average.

Table 5: Comparison of regression results with sample means

	Short-run	Long-run		
	Whole sample	Whole sample	Car stock	No car stock
Preferred estimate	0.0999	0.457	0.234	0.644
Sample mean	0.284	0.663	0.465	0.861
Weighted mean	0.349	0.614	0.424	0.857

Comparing our meta-regression results with the only available meta-analysis on the income elasticity of gasoline demand (Espey, 1998), we find her results—0.47 and 0.88 for short- and long-run elasticity, respectively—to be much closer to the sample averages than the final estimates from our analysis after correction for publication bias. While the long-run estimate is comparable with our sample mean, the short-run estimate is not only higher than our average, it is five times larger than our estimate beyond publication bias. This overestimation may be partly due to the lack of publication bias treatment, but also to the fact that Espey included estimates with unknown time structure in both the short- and long-run samples; she also truncated her data set by removing any negative estimates as inconsistent with the theory, thus pushing the mean upwards.

Results from an augmented regression corresponding to the long-run effect are reported in Table 6. Four variables are weighted by the standard errors so that we can observe their influence on the elasticity estimate itself; the reason for this weighting is described in the previous section introducing the meta-analysis methodology. One variable (publication status) is included unweighted so that we can estimate its effect on publication bias. To control for the separation by car stock, only a dummy variable is added, attaining one if car stock information is included, and zero otherwise. Other variables include OECD membership (=0 if the country is a member) and time frame (=1 if estimating a pure time series, =0 in the case of a cross section or a cross-section time series).

The result corroborates the notion that the gap between the samples based on car stock information is substantial. Also, our hypothesis about gasoline demand in less developed countries seems to be reasonable, as the results indicate higher estimates of the elasticity in non-OECD countries. Models based on time series tend to yield slightly larger estimates compared to

Table 6: Determinants of heterogeneity in the reported long-run elasticities

	Parameter estimates	
1/se	0.498***	(11.79)
unpublished	-0.0457	(-0.02)
unpublished (weighted)	0.206***	(4.19)
non-OECD (weighted)	0.149***	(2.64)
auto (weighted)	-0.460***	(-11.30)
time series (weighted)	0.150***	(3.32)
constant	1.103	(0.84)

Response variable: t-statistic of the estimate of elasticity
t-statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

cross-sectional models. Because of their limited number of degrees of freedom, time-series models usually yield less significant estimates (the average t-statistic for time-series models is half that of the rest). Given the selectivity and funnel asymmetry, the large average elasticity found on average in time-series studies is to be expected, as researchers need large estimates to offset the standard errors and obtain statistical significance. The insignificance of the unweighted variable `unpublished` shows that publication bias is common to both published and unpublished studies. Nevertheless, the weighted variant of the variable indicates that published studies tend to be more conservative, yielding lower estimates of the elasticity.

5 Concluding Remarks

In this paper we present a meta-analysis of the income elasticity of gasoline demand. We use the large data set of elasticities collected by Dahl (2012) and employ multilevel mixed-effects meta-regression methods to filter out publication bias from the literature. Our results suggest that publication bias is strong, especially for the estimates of short-run elasticities, and the corrected mean elasticity seems to be smaller than commonly thought. When publication bias is filtered out from the literature, the average reported short-run elasticity seems to be only 0.1, which is five times less than what Espey (1998) found in her meta-analysis. The long-run estimate corrected for publication bias is 0.46, which is about half the estimate of Espey (1998), which does not take into account publication bias (0.88).

The test for publication bias that we employ relies on the assumptions that researchers make when estimating the elasticity. Since they report t-statistics or symmetrical standard errors for their estimates, the estimates and their standard errors should not be correlated. In our sample these two statistics are strongly correlated, which suggests publication bias. This correlation has two possible sources. First, researchers may require statistically significant results, which means that they need large estimates of elasticity to offset standard errors. Second, researchers may discard negative estimates of the elasticity because such results are not intuitive; negative estimates would suggest that the demand for gasoline decreases when people get richer.

A limitation of our paper is that we do not examine thoroughly the heterogeneity in the estimated elasticities. Differences in estimation methods and their influence on the results have been the focus of several literature surveys; for example, Dahl (2012). Also the data set that we use includes elasticity estimates for many countries, among which the underlying elasticities may vary. We address this issue by employing mixed-effects multilevel methods, which allow for unobserved between-study differences in the elasticity. More discussion of cross-country differences can be found in Espey (1998). Even though we focus on publication bias and not on heterogeneity, we still examine several important features that may influence the long-run estimates of the elasticity. We find that specifications that include information concerning the car stock tend to find a much lower elasticity (on average, 0.23 after correction for publication bias) compared to specifications that ignore car stock information (0.64). Moreover, we find that the long-run income elasticity of gasoline demand is approximately 0.15 lower in OECD countries compared to the rest of the world.

In sum, our results suggest that the demand for gasoline in the short run is almost insensitive to changes in income and is relatively insensitive to income in the long run. We consider 0.64— the long-run estimate for models not including car stock information— to be a reasonable upper bound for the elasticity. Compared to previous estimates presented in the literature, these findings indicate a lower trajectory of future gasoline consumption and corresponding carbon emissions in emerging countries.

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