

# Using Meta-Analysis to Estimate World Oil Demand Elasticity

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## Abstract

Crude oil demand elasticities are important behavioral parameters for assessing the effectiveness of many energy policy proposals and the economic impact of crude oil market shocks. Most of the literature on crude oil demand computes elasticities for one specific petroleum product in a country or group of countries. There are fewer published values for world crude oil demand elasticity because it requires more complex estimation methods. Since world crude oil demand and price are simultaneously determined, the reduced-form single equation approach used in much of the petroleum product demand literature leads to endogeneity bias when applied to global demand. This study uses meta-analysis techniques to compute world crude oil demand elasticity. Metaregressions are first conducted to identify sources of variation in elasticity estimates for transportation and non-transportation sectors collected from 75 studies published from 2000 to 2015 using a consistent set of explanatory variables identified in the literature. The estimated coefficients from the metaregressions are then summarized into elasticity baseline values for several combinations of explanatory variable values. Finally, a global crude oil demand elasticity is computed as the consumption-weighted average of the two sectoral elasticities. Resulting mean values for the short-run crude oil demand elasticities with respect to price range from -0.07 to -0.14 depending on the attributes selected for the price variable. As expected from theory and empirical studies, crude oil demand is more price-responsive in the long run than in the short run. Long-run mean values range from -0.26 to -0.83.

## 1. Introduction

Crude oil demand elasticities are important behavioral parameters for assessing the effectiveness of many energy policy proposals and the economic impact of crude oil market shocks. Estimation of these parameters became a focus of attention during the crude oil crises of the 1970s, as the governments of industrialized countries looked for ways to improve energy efficiency and advance energy security, and it has remained an active research topic ever since. Elasticities must be periodically re-estimated to incorporate the effects of changes in technology, policy, and market factors.

With improvements in the availability and quality of energy consumption data (particularly for non-OECD countries) and the development of new econometric methods that enable better analysis of time series and panel data, demand elasticity estimation approaches have changed substantially over time. Estimation methodology also varies across petroleum products. Basso and Oum (2007) review the evolution of preferred model specifications for estimation of petroleum product demand in the light-duty transportation sector. Static demand equations and partial adjustment models were the most common choices for estimation of petroleum product demand in the transportation sector in the 1970s and 1980s. In the 1990s, econometricians introduced error correction and co-integration techniques for the analysis of time-series data and their application in transportation fuel demand elasticity estimation has steadily gained popularity (see Banerjee et al. (1993) for a detailed exposition of these techniques).<sup>1</sup> Even though the model specifications used to analyze vehicle fuel demand are sometimes applied to studies of other sectors, non-transportation petroleum product demand is often explored with distinct methodologies. For instance, interfuel substitution models are frequently used to estimate petroleum product own-price and cross-price elasticities in the industrial sector and at the household level.

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<sup>1</sup>Because researchers are typically interested in measuring demand responsiveness over a specific time period, time-series data have generally been considered more appropriate than cross-sectional data for estimating elasticities. However, crude oil demand analysis based on cross-sectional data has remained a parallel track. These studies produce long-run elasticities that summarize responses to all price and income conditions experienced by the survey respondents until the data collection period.

Most of the literature on crude oil demand computes elasticities for one particular region and/or petroleum product. There are fewer published values for world crude oil demand elasticity because estimating it is more difficult. For world crude oil demand, crude oil price is not exogenous and the reduced-form single equation approach used in much of the petroleum product demand literature leads to endogeneity bias. Instead, most estimations of world crude oil demand elasticities are based on systems of equations. Within this group, recent structural vector autoregression (SVAR) models whose results challenge the prevailing view that short-run world crude oil demand elasticity is very low have garnered much attention. For instance, Kilian and Murphy (2014) find world crude oil demand elasticities in the range of -0.26 to -0.44 in the first month after a supply shock using 1973-2009 data. Baumeister and Peersman (2013) obtain an average elasticity of -0.26 for that same period, but they allow for time-varying parameters which reveal a substantial steepening of the crude oil supply and demand curves after the mid-1980s. IMF (2011) employ a different approach to correct for endogeneity bias in their exploration of world crude oil demand elasticity and find a much lower elasticity (in absolute value). Taking advantage of cross-sectional variation in a 45-country data panel, they estimate fixed-effect models of OECD and non-OECD crude oil demand and average the resulting elasticities, using consumption weights, into short-run world elasticities of -0.04 using 1965-2009 data and -0.02 for the more recent 1990-2009 subperiod.<sup>2</sup> Together, the three studies referenced in this paragraph result in a very wide range of world crude oil demand elasticities. Section 4.2 attempts to explain some of the reasons for these diverging findings.

We contribute to the existing literature by constructing a “bottom-up” world crude oil demand elasticity, based on hundreds of estimates from dozens of studies focused on different portions of global crude oil demand. Several studies explore differences in crude oil demand responsiveness across uses and/or countries (Dargay and Gately, 2010; Dargay et al., 2007; Dees et al., 2007; IMF, 2011). These studies have agreed in their finding that crude oil demand elasticities in OECD countries have been higher than in other regions. As for sectors, Dargay et al. (2007) and Dargay and Gately (2010) argue that the OECD has already largely abandoned crude oil consumption in those uses where fuel switching was easier (e.g., electricity generation, space heating). Both of these studies conclude that world crude oil demand elasticity should be expected to decrease as the fraction of total oil demand originating in more inelastic regions and sectors increases. However, technology, policy, and/or behavioral changes could result in different future crude oil demand elasticity trends. For instance, elasticity in the transportation sector might increase as alternative fuels continue to be adopted and the non-OECD region might become more price responsive if price subsidies on petroleum products are phased out and economic growth sets the region in a trajectory that converges toward that of OECD countries.

Although other researchers have used metaregressions in surveys of the demand elasticities of gasoline (Espey, 1998; Brons et al., 2008; Havranek et al., 2012; Havranek and Kokes, 2015), petroleum products for industrial use (Stern, 2009), or multiple energy products (Labandeira et al., 2017), our study is the first that applies this methodology to gain insight on the value of world crude oil demand elasticity computed as a weighted average of the price responsiveness of two sectors (transportation and non-transportation). In specifying the metaregression model and selecting an econometric estimation approach, we aim to mitigate potential biases associated to the use of meta-data (Borenstein et al., 2009; Nelson and Kennedy, 2009): variance heterogeneity, publication bias, and within-study correlation of residuals. We weigh elasticity estimates by the inverse of their precision to avoid excessive influence of large, imprecise estimates. We test for publication bias—the idea that our metadata is not a random sample of the entire population of elasticity estimates due to higher likelihood of a study being published when estimate size or magnitude is consistent with economic theory and statistically significant. If publication bias is present, we add the variance of estimates as one of the explanatory variables in the metaregression to control for the relationship between the magnitude of an elasticity estimate and its variance. Finally, we use two alternative approaches to account for the lack of independence of residuals corresponding to elasticity estimates obtained from the same study: cluster-robust standard errors or addition of study-level random intercepts. Our choice of explanatory variables is driven by the objective of identifying sources of variation that are important to produce adequate elasticity values for specific empirical applications. For instance, a model exploring multi-year period responses to a policy (e.g., international carbon tax) and a model that depicts short-run responses to a crude oil supply shock require different elasticity inputs. We also pay attention to the relationship between elasticities and cross-sectional differences in price and income levels and assess the specific length of run (number of years) of long-run elasticity estimates.

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<sup>2</sup>The authors of the IMF study contend that any remaining endogeneity bias using their approach should be small because country-specific demand shocks will have little or no effect on the world crude oil price and common demand shocks are accounted for through inclusion of GDP as one of the explanatory variables.

## 2. Meta-Analysis Database Description

We performed queries in Google Scholar and Econlit as well as snowball searches to identify peer-reviewed journal articles and working papers published between 2000 and 2015 containing primary estimates of crude oil or petroleum product demand elasticities. We discarded studies that did not provide standard errors or other related information (t-statistic, p-value or confidence intervals) to infer the precision of the elasticity estimates. We excluded estimates with an absolute value outside of (-5,5) interval as well as observations that cannot be assigned to OECD/nonOECD regions or transportation/non-transportation sectors. Finally, we dropped observations for which the value of any of the explanatory variables to be included in the metaregression analysis are not available. The resulting dataset to be used in the metaregression analysis consists of 1983 observations from the 75 papers listed in Appendix A. Figure 1 shows the initial and final year of the data period considered in each of the papers in our database.

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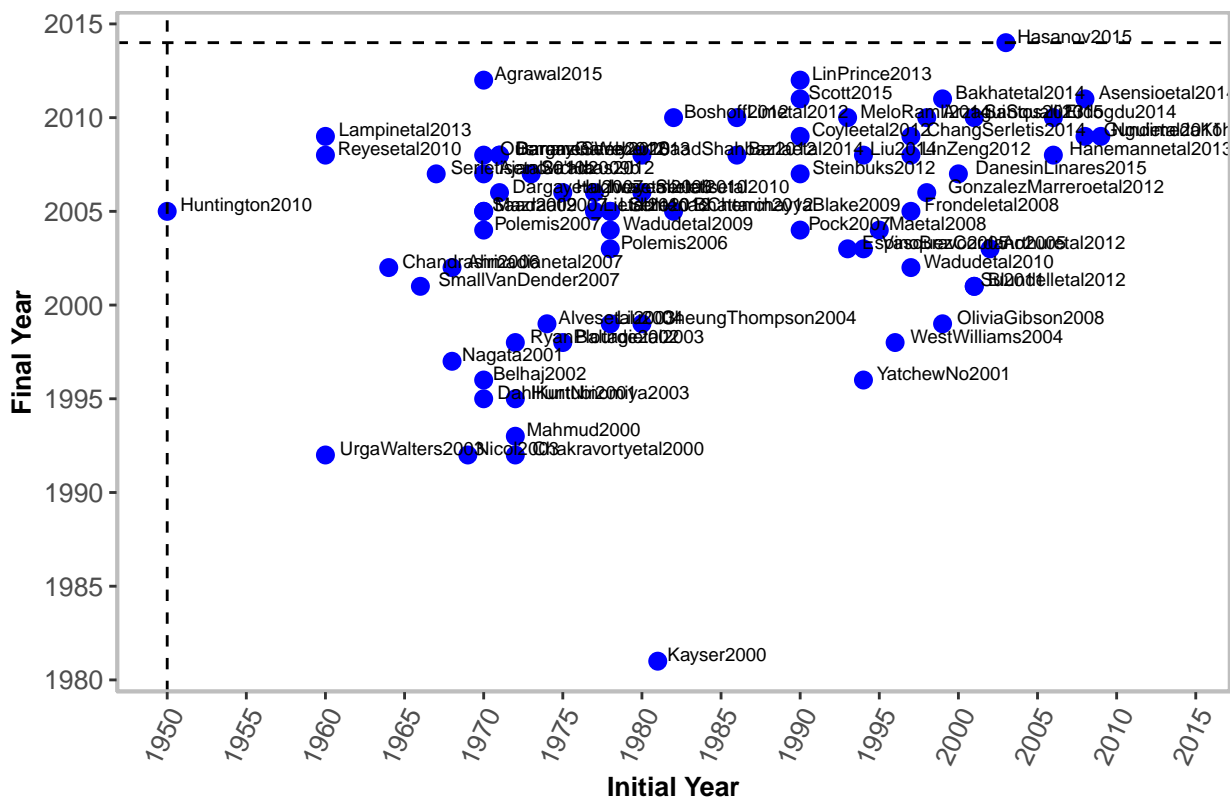


Figure 1. Periods of analysis in studies included in elasticity meta-analysis database

Even though 40 of the 75 papers in the database were published after 2009, only 12 contain data for 2010 or later. The average lag between publication year and end of analysis period is approximately 5 years. Studies based on time series data tend to analyze longer periods and result in an average elasticities that might be less representative of recent conditions than those from studies using more recent data panels.<sup>3</sup> The average years in this database are 1989, 1994, and 2004 for subsets of studies using time series, panel, and cross-sectional data respectively.

Beyond the usual segmentations by type (price or income) and length of run (short or long run), we also segment the database by sector (transportation or non-transportation) because the data sources and estimation methods used for generating these two elasticities tend to be different.<sup>4</sup> Segmentation by sector also enables a more tailored

<sup>3</sup>The average length of data period covered by papers in our database using time series and panel data is 28 and 17 years respectively.

<sup>4</sup>Gasoline or diesel demand elasticities were assigned to the transportation sector unless the study mentioned explicitly that its consumption data corresponded to a different sector. Elasticities in the non-transportation category include elasticities for petroleum demand in the industrial sector, residential sector (for uses other than transportation) or petroleum products used in those sectors (industrial use of diesel and gas oil, fuel oil, kerosene, liquefied petroleum gas, residual fuel oil, other petroleum products). Even though aviation is a transportation activity, jet fuel demand elasticities were assigned to the non-transportation category.

selection of moderator variables for the metaregression. We considered further segmenting the data by region (OECD versus non-OECD) but some of the resulting 16 groupings contained few observations making the validity of a metaregression analysis approach questionable. Instead, to control for regional differences, we include regional dummies and cross-sections of price and income levels as moderator variables in the metaregressions.

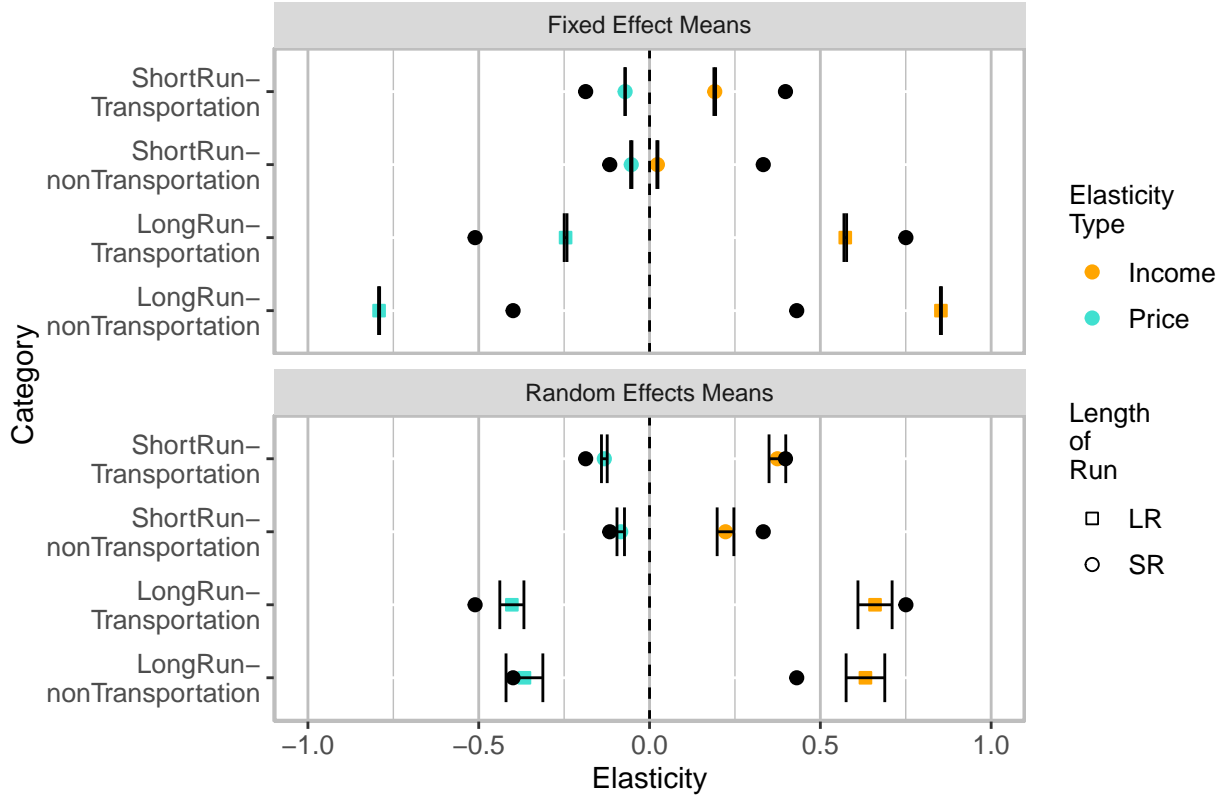
Accounting for response period is important when comparing elasticity estimates across studies. All else equal, demand responsiveness is expected to increase with the period over which the response is measured. We consider short-run elasticities as those that convey a first-period response: one year, one quarter, or one month depending on the data frequency used in each study. In addition, whenever possible, we assign long-run estimates a specific response length (in years). Dynamic demand specifications typically include a variable (lagged demand for partial adjustment models or error correction term in error correction models) whose estimated coefficient can be used to estimate the length of run implied by the long-run elasticities.<sup>5</sup> To our knowledge, this is the first meta-analysis that extracts this more detailed information on length of run from long-run elasticities. We classified most of the elasticities from cross sectional studies as long-run and assigned them a length of run in years equal to the average adjustment period for long-run elasticities in the same grouping (i.e., type-sector combination).<sup>6</sup>

As an initial exploratory step, Figure 2 displays unweighted means (alongside the fixed effect and random effects means typically computed in meta-analyses) for the 8 elasticity groupings being analyzed: 2 types (price and income) times 2 lengths of run (short and long) times two sectors (transportation and non-transportation). Fixed effect means are appropriate when all elasticities in a given group originate from the same population and the only reason why they differ is sampling error. In that case, estimates with lowest standard errors should be weighted more heavily and vice versa. On the other hand, random effects means assume that variability in a given set of elasticities is partly due to inherent differences in the true effect sizes (e.g., the true population mean is different across countries, over time and/or based on other attributes). The weights applied to random effects mean include an extra component to account for between-estimate variation (Borenstein et al., 2009). As in most social sciences applications of meta-analysis, the random effects model seems most appropriate to describe our dataset.

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<sup>5</sup>Balcombe et al. (2004) show that the number of periods to achieve 90% of the long-run elasticity estimated using an autoregressive distributed lag (ARDL) specification can be calculated as  $\ln(1 - 0.9)/\ln(\theta)$ .  $\theta$  is the estimated coefficient on lagged demand if the model specification is a partial adjustment model; for error correction models the formula is  $\ln(1 - 0.9)/\ln(\theta) + 1$

<sup>6</sup>The only cross-sectional elasticities classified as short-run come from 3 studies that used data from household surveys where the same household is interviewed multiple times at intervals equal or less than one year (e.g., Frondel et al., (2008)). Alternatively, data from these studies could have been categorized as a (very unbalanced) panel.



Note:

The black dots represent the unweighted means against which fixed effect and random effects means are compared. The error bars represent the 95% confidence interval around the fixed effect and random effects means.

**Figure 2. Forest plot of demand elasticities with respect to price and income**

All weighted and unweighted means are less than one in absolute value (i.e., inelastic). For both types of elasticity and both lengths of run, the unweighted average elasticities are greater for the transportation sector than for other sectors. The same result is true for the random effects means but not for the long-run fixed effect means. For all elasticity groupings except long-run non-transportation, the random effects mean is an intermediate value between the unweighted and fixed effect means. This result is consistent with a data set where the smaller effect sizes (elasticities in this case) are the most precisely measured. For long-run, nontransportation elasticities, fixed effect means are the largest. This result indicates that the relationship between effect size and precision of the estimate is weaker for that elasticity grouping.

### 3. Metaregression analysis: methods and explanatory variables

Our model specification and estimation method choices address the econometric issues that are typically present in energy and resource economics meta-analyses applications (e.g., Bel and Gradus (2016); Havranek and Kokes (2015); Ma et al. (2015); Daniel et al. (2009)). The starting point for metaregression specification is a linear relationship between a set of elasticity estimates  $\beta_i$ , an intercept  $\alpha_0$ , the set of explanatory variables  $X$  associated to the elasticity estimates, and a residual for each elasticity estimate  $e_i$ .

$$\beta_i = \alpha_0 + \sum_{k=1}^K \alpha_k * X_{i,k} + e_i$$

#### a) Variance heterogeneity (heteroskedasticity)

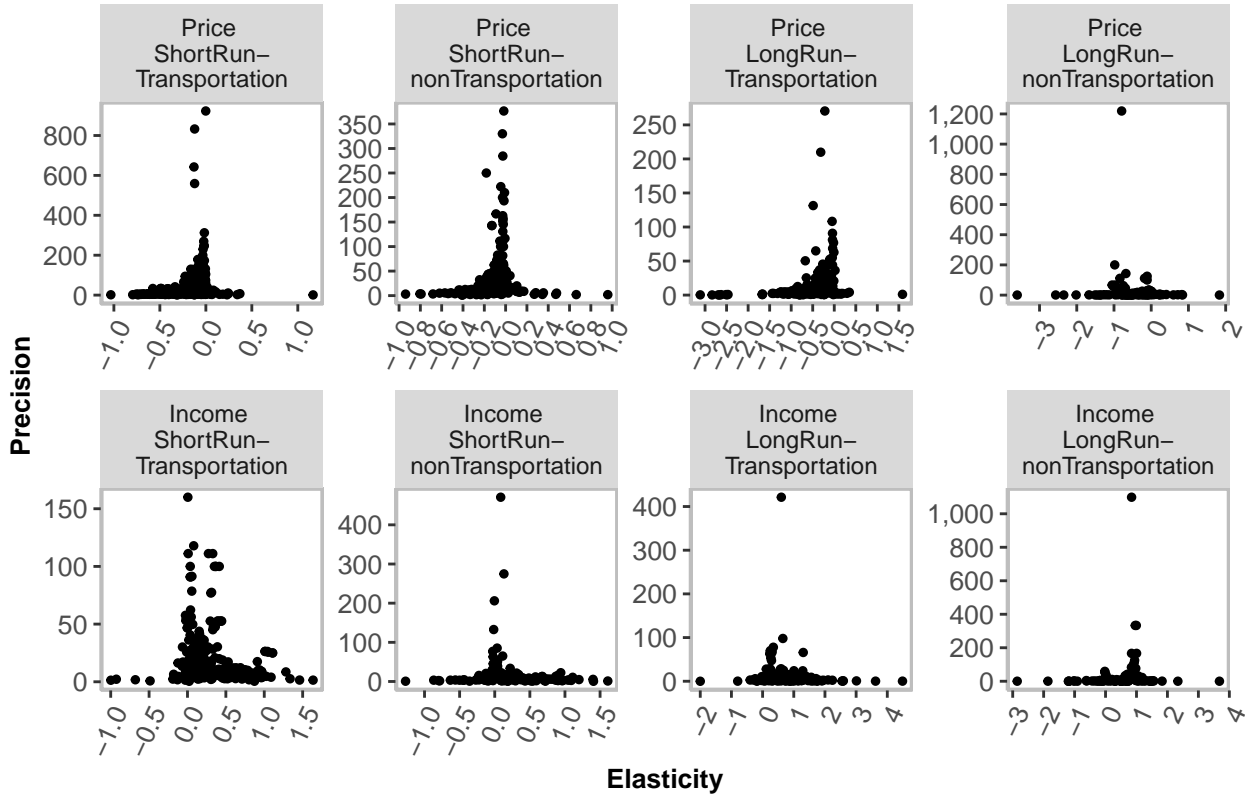
When variances of the elasticity estimates  $\beta_i$  are known, Borenstein et al.(2009) and Nelson and Kennedy(2009) recommend giving more weight to the more precise ones. We follow that approach to address the issue of variance

heterogeneity and estimate the model using weighted least squares with the inverse of standard error of each estimate ( $1/se_i$ ) as weights.

$$\frac{\beta_i}{se_i} = \frac{\alpha_0}{se_i} + \sum_{k=1}^K \alpha_i * \frac{X_{i,k}}{se_i} + \epsilon_i$$

#### b) Publication bias

Publication bias arises when the sample of published estimates is not a random sample of the full population of estimates. The bias results from researchers being more likely to submit, and journals being more likely to publish, studies finding larger effect sizes and/or estimates conforming to the theoretically expected sign. The panels in Figure 3 are funnel plots showing the relationship between the inverse of the standard error (i.e., precision) on the y-axis and the effect size on the x-axis for each of the 8 elasticity groupings. The more asymmetric a funnel plot is around the most precise estimate, the stronger publication bias there is (Havranek et al., 2012). Funnel asymmetry tests confirmed statistically significant asymmetry at the 10% confidence level in 7 of the 8 metaregressions. Long-run income elasticities in non-transportation sector is the only grouping for which funnel asymmetry can be rejected at the 10% confidence level.



**Figure 3. Funnel plots by elasticity grouping**

To correct for publication bias, we implement the *precision-effect estimate with standard error* (PEESE) method outlined in Stanley and Doucouliagos (2007) in which the variance of the effect sizes is included as one of the moderator variables in a weighted least squares estimation. PEESE is a modified version of the Heckman regression used to address sample selection bias. PEESE uses the heteroscedastic nature of standard errors in a meta-analysis database to capture the relationship between the precision of elasticity estimates and their probability of being published.

$$\frac{\beta_i}{se_i} = \frac{\alpha_0}{se_i} + \eta_0 * se_i + \sum_{k=1}^K \alpha_i * \frac{X_{i,k}}{se_i} + \epsilon_i$$

#### c) Within-study correlation of residuals

Most primary studies produce more than one elasticity estimate. In our database, we find that multiple effect sizes

from the same paper typically result from authors reporting results from multiple estimation methods or segmenting their datasets by household characteristics, geographical units, or time periods. Each additional estimate from the same study provides less additional information than an estimate from a different study and should be weighted accordingly in the metaregression.<sup>7</sup> Nelson and Kennedy (2009) advise researchers to control for the clustering of standard errors that results from having multiple effect sizes from the same study. Depending on the sample size and number of papers, it sometimes is advisable to just pick the mean estimate from each paper or select a preferred estimate. Here, such approach would result in very small sample sizes for some of the metaregressions.

We apply two alternative approaches to control for within-study correlation of residuals. The first approach adds a correction to the standard errors of parameter estimates to control for the correlation among residuals from each study.<sup>8</sup> In what follows, we refer to that specification as weighted-least squares (WLS) with cluster-robust standard errors. Without correction, WLS would tend to underestimate the variance of the estimated model coefficients (Cameron and Miller, 2015). The second variant is a linear mixed effects (LME) specification which acknowledges the presence of study-level clusters in the database more explicitly. In the LME specification, model variables and their standard errors have an extra index  $j$  that indicates the study (i.e., cluster) to which it belongs and the residual has a study-level component  $\nu_j$  and an observation-level component  $u_{ij}$  where  $i$  represents a study and  $j$  an elasticity estimate.

$$\frac{\beta_{ij}}{se_{ij}} = \frac{\alpha_0}{se_{ij}} + \eta_0 * se_{ij} + \sum_{k=1}^K \alpha_k * \frac{X_{ij,k}}{se_{ij}} + \nu_j + u_{ij}$$

For each of the 8 metaregressions, we report results from both approaches and perform likelihood ratio tests to select the one providing the best fit. The likelihood ratio tests find that the linear mixed effects estimation is generally preferred except in the 3 metaregressions with less than 20 clusters.

### 3.1 Explanatory variables

We use a general-to-specific approach to select explanatory variables for the metaregressions. The most general specification includes the subset of the explanatory variables listed below that are applicable to each elasticity grouping. In order to alleviate multicollinearity concerns, when the variance inflation factors (VIFs) of the estimated metaregressions are above 5 for any of the variables, we drop one explanatory variable at a time until all the VIFs are below 5.<sup>9</sup>

- *YrAvg.cent* (all metaregressions): average year of the period of analysis in the study that produced the elasticity estimate.
- *SPEEDYRS.cent* (long-run elasticity metaregressions): length of adjustment period (in years).
- *Quarterly* (short-run elasticity metaregressions): indicator variable that takes the value 1 for elasticity estimates obtained from quarterly data.
- *Monthly* (short-run elasticity metaregressions): indicator variable that takes the value 1 for elasticity estimates obtained from monthly data.
- *CS* (long-run metaregressions): indicator variable that takes the value 1 for elasticity estimates from cross-sectional studies.

<sup>7</sup>We argue that overweighting will be less severe if the metaregression includes moderator variables to capture the various data segments and estimation methods in each paper. We computed the number of “unique” observations in each grouping as those for which at least one of the moderator variables (other than VARIANCE) differs from all the other observations in the grouping. Standard error clustering should be strongest for the subgroups with the lowest fraction of unique observations out of their total number of observations: short-run nontransportation price (23%) and short-run transportation income (38%) elasticities.

<sup>8</sup>The cluster-robust standard errors were computed using the `cluster.vcov` function from the *multiwaycov* package in R. They incorporate degree of freedom corrections to mitigate over-rejection of the null hypothesis in coefficient tests when small number of clusters prevents application of asymptotic theory assumptions. The number of clusters in our database ranges between 13 for short-run income elasticities in non-transportation sectors and 58 for transportation short-run price elasticities.

<sup>9</sup>The VIF for estimated coefficient  $\beta_k$  is calculated as  $VIF_k = 1/(1 - R_k^2)$  where  $R_k^2$  is the proportion of variability in the independent variable  $X_k$  explained by a regression of  $X_k$  on the rest of independent variables in the model. VIF thresholds used in the literature as indicative of serious multicollinearity range from 5 to 10 (Menard, 1995; Hair et al., 1995).

- *CSTS* (all metaregressions): indicator variable that takes the value 1 for elasticity estimates from panel data analyses.
- *Pmax* (price elasticity metaregressions) : indicator variable that takes the value 1 if the elasticity is with respect to a new historical price maximum in the country or region being studied rather than an average elasticity over the full period of analysis.
- *Ymax* (income elasticity metaregressions) : indicator variable that takes the value 1 if the elasticity is with respect to a new historical income maximum rather than an average elasticity over the full period of analysis.<sup>10</sup>
- *StaticP* (price elasticity metaregressions) : indicator variable that takes the value 1 for elasticities estimated using static demand equations (in long-run metaregressions, all cointegration equations are codified with  $StaticP = 1$ ).
- *StaticY* (income elasticity metaregressions) : indicator variable that takes the value 1 for elasticities estimated using static demand equations (in long-run metaregressions, all cointegration equations are codified with  $StaticY = 1$ ).
- *StaticP.CS* (short-run price elasticity metaregressions) : interaction dummy that takes the value 1 for elasticities from cross-sectional studies estimated using static demand specifications.
- *StaticY.CS* (short-run income elasticity metaregressions) : interaction dummy that takes the value 1 for elasticities from cross-sectional studies estimated using static demand specifications.
- *PRICE.1998.cent* (transportation sector price elasticity metaregressions): average 1998 price for crude oil (Brent) or the relevant petroleum product in the country/region to which the elasticity refers.<sup>11</sup>
- *rgdpe\_cap.1998.cent* (income elasticity metaregressions): 1998 GDP per capita in real terms for the country or group of countries to which the elasticity estimate refers.<sup>12</sup>
- *EndUserP* (price, non-transportation sector metaregressions): indicator variable that takes the value 1 if the elasticity estimate is measured with respect to a petroleum product price and 0 if it is an elasticity with respect to the crude oil price.
- *DslTransp* (transportation sector metaregressions): indicator variable that takes the value 1 if the elasticity estimate corresponds to diesel consumption.
- *VehStk* (transportation sector metaregressions): indicator variable that takes the value 1 if the elasticity estimate comes from a study that includes a measure of vehicle stock as one of the explanatory variables for fuel demand.<sup>13</sup>
- *FuelSwitch* (non-transportation sector metaregressions): indicator variable that takes the value 1 if the elasticity estimate refers to a product or sector with abundant fuel switching options (residential or electricity generation sectors following the categorization in Dargay and Gately(2010)).
- *VARIANCE* (included in all metaregressions that require a correction for publication bias): the variance of the elasticity estimate.
- *CALC\_STERROR* (all metaregressions): indicator variable that takes the value 1 if the study did not report the standard error or t-statistic of the elasticity estimate but was calculated instead as a function of the

<sup>10</sup>Dargay (2007) and Dargay and Gately (2010) are the only two studies in the dataset that estimate multiple income elasticities for periods of income increases, income decreases, and new income maxima to detect asymmetries and nonlinearities in crude oil demand responsiveness to changes in income. They only apply this decomposition to explain crude oil demand decisions of oil exporting countries.

<sup>11</sup>The cross section of 1998 price data comes from the GIZ survey (<https://www.giz.de/expertise/html/4317.html>). Although the survey also includes prices for non-transportation related oil consumption, the number of countries with missing observations was large and would have severely cut the sample size for those metaregressions. The year 1998 was chosen because it is close to the average year in our dataset (1992) and covered the most countries out of all the available versions of the GIZ survey conducted in the mid to late 1990s.

<sup>12</sup>The data source for the 1998 GDP per capita is the Penn World Table, version 9.0 ([www.ggdnet.net/pwt](http://www.ggdnet.net/pwt))

<sup>13</sup>Havranek and Kokes(2015) found that studies of gasoline demand omitting this variable result in significantly larger income elasticity values.



standard error of other estimated coefficients using the Gaussian error propagation formula.<sup>14</sup> In his meta-analysis of the price elasticity of beer, Nelson (2014) finds that calculated standard errors tend to be larger than those directly reported in the papers.<sup>15</sup> To correct for possible bias, Nelson (2014) introduces a dummy variable in the metaregression that takes the value 1 for calculated standard errors. We use the same approach.

The .cent suffix for continuous variables *PRICE.1998.cent*, *YrAvg.cent*, *SPEEDYRS.cent*, and *rgdpe\_cap.1998.cent* indicates that they are centered around the average value within their grouping. For *PRICE.1998.cent*, centering is around the Brent crude oil price. With centered variables, the metaregression intercept has a straightforward interpretation as the elasticity evaluated at the average values of the continuous variables and zero values for the indicator variables.

## 4. Results from metaregression analysis

For each of the 8 elasticity groupings considered in this analysis, we estimate metaregressions using both the WLS and LME approaches described in Section 3 and conduct likelihood ratio tests to select which of the two model specifications provides the best fit. The null hypothesis tested by the likelihood ratio test is that the more parsimonious model (WLS) is the “true” model.<sup>16</sup> Table 1 shows the results from the tests.

**Table 1. Likelihood Ratio Tests Comparing Fit of Linear Mixed Effects and Weighted Least Squares Metaregression Specifications**

Grouping	Log Likelihood LME	Log Likelihood WLS	Statistic	Degrees of Freedom	p value	Number of Clusters
Price-SR-Transport	351.73	302.25	98.97	1	0.00	58
Price-SR-NonTransport	202.14	202.14	0.00	1	1.00	18
Price-LR-Transport	-26.73	-48.81	44.16	1	0.00	48
Price-LR-NonTransport	-27.51	-30.16	5.31	1	0.02	20
Income-SR-Transport	64.17	52.93	22.48	1	0.00	50
Income-SR-NonTransport	-38.47	-38.98	1.02	1	0.31	13
Income-LR-Transport	-114.24	-125.76	23.04	1	0.00	48
Income-LR-NonTransport	-62.39	-62.39	0.00	1	1.00	17

Based on the likelihood ratio test results, we conclude that the LME estimation is preferred for all the price elasticity metaregressions—except short-run, non-transportation—as well as for the transportation income elasticity metaregressions. For the remaining 3 metaregressions (short-run, nontransportation price, short-run nontransportation income, and long-run nontransportation income), the addition of a random intercept for each within-study cluster

<sup>14</sup>Given random variables  $x$  and  $y$  measured with standard errors  $\delta(x)$  and  $\delta(y)$  and assuming that  $x$  and  $y$  are uncorrelated, the Gaussian error propagation formula for the standard error of  $q = f(x, y)$  is  $\delta(q) = \sqrt{(\frac{\partial q}{\partial x} * \delta(x))^2 + (\frac{\partial q}{\partial y} * \delta(y))^2}$

<sup>15</sup>We conducted two tests to evaluate whether calculated standard errors appear to be biased. First, as recommended in Nelson (2014), we regressed standard errors on the elasticities and a dummy that takes the value 1 for calculated standard errors. The estimated coefficients were positive in most cases but only statistically significant for the short-run, transportation income elasticity and the long-run, nontransportation price elasticity. Second, we calculated standard errors for a subset of long-run elasticities for which directly reported standard errors were also available. The ratio of reported to calculated standard errors in that subset was 0.946 for price elasticities and 0.877 for income elasticities. These results suggest that calculated standard errors tend to be larger although not by a large amount.

<sup>16</sup>The likelihood ratio test statistic follows a chi-squared distribution with degrees of freedom equal to the difference in degrees of freedom between the two models compared.

of elasticity estimates does not lead to a statistically significant improvement in model fit and the simpler WLS specification is preferred. The number of clusters (i.e., number of studies) in each metaregression are also included in Table 1. The discussion of estimated metaregression coefficients in Table 2 through Table 9 focuses on the preferred specification in each case, but the results of the alternative specification are also shown in the tables for reference.

Table 2: Results from Short-Run Price Elasticity Metaregressions (Transportation)

	WLS cluster-robust.se	LME
YrAvg.cent	0.0029* (0.0016)	0.0044*** (0.0012)
Quarterly	-0.0644 (0.0568)	-0.0475 (0.0422)
Monthly	-0.0327 (0.0289)	-0.0569 (0.0527)
CSTS	-0.0352 (0.0230)	-0.0005 (0.0199)
Pmax	-0.0203 (0.0349)	-0.0382* (0.0203)
OECD	0.0378 (0.0241)	0.0163 (0.0184)
StaticP	-0.0983*** (0.0358)	-0.0577*** (0.0169)
StaticP.CS	-0.2420*** (0.0502)	-0.2770*** (0.0712)
PRICE.1998.cent	-0.0847** (0.0337)	-0.0696*** (0.0257)
DslTransp	-0.0161 (0.0116)	-0.0090 (0.0108)
VehStk	-0.0248 (0.0295)	-0.0771** (0.0350)
VARIANCE	-0.1702 (0.1613)	-0.0309 (0.1010)
CALC_STERROR	-0.0188 (0.0272)	-0.0308 (0.0371)
Constant	-0.0374** (0.0159)	-0.0805*** (0.0225)
Observations	432	432
R2	0.4038	
Adjusted R2	0.3853	
Log Likelihood		351.7318
Akaike Inf. Crit.		-671.4636

Bayesian Inf. Crit.	-606.3688
Residual Std. Error	0.5425 (df = 418)
F Statistic	21.7805*** (df = 13; 418)

Notes:                   \*\*\*Significant at the 1 percent level.  
                          \*\*Significant at the 5 percent level.  
                          \*Significant at the 10 percent level.

Table 1 indicated that LME is the preferred model for explaining short-run transportation price elasticities. The estimated intercept (-0.0805) in Table 2 can be interpreted as the baseline elasticity. The baseline is the value of the elasticity when all indicator variables are zero and all continuous variables are equal to their sample means.

Table 2 shows that the estimated coefficient on the *YrAvg.cent* variable is 0.0044. This can be interpreted as a decreasing trend (i.e., smaller absolute over time) on the short-run price responsiveness of the transportation sector. The baseline elasticity corresponds to 1993—the average year of the datasets in the studies that produced the elasticity estimates being explained by this metaregression. All else equal, the baseline elasticity for 1994 would be -0.0849.

In agreement with results from previous meta-analyses of gasoline demand, static model specifications yield larger (in absolute value) short-run price elasticities of transportation demand (Espey, 1998; Brons et al., 2008). The combination of static specification and cross-sectional data leads to even larger elasticities. Relative to the baseline elasticity of -0.0805, elasticities from models using cross-sectional data and a static specification are, on average, more than 4 times larger (-0.3575).

The estimated coefficient on *VehStk* is -0.0771 almost doubling price responsiveness relative to the baseline. The sign of this coefficient is contrary to the argument that elasticities from models accounting for changes in vehicle stock should be smaller (in absolute value) because they do not conflate demand responses to price with demand changes due to the evolution of average fleet attributes. However, since changes in stock are almost negligible within the length of period (one-year or less) considered in short-run elasticities, the argument for smaller elasticities resulting from models including that variable seems more relevant for the long-run elasticity metaregressions.

Short-run transportation fuel demand responsiveness to price is positively correlated with price level both when we compare price levels across countries at one point in time (*PRICE.1998.cent*) and when we compare responsiveness to a new price maximum versus average price responsiveness (*Pmax*). All else equal, estimated price responsiveness increases by 6.96 percentage points with each additional dollar in the 1998 price level (in \$ per liter) in the country or region of study relative to the price of Brent.<sup>17</sup> In addition, estimated price responsiveness is 3.82 percentage points larger when the observed price level is a new price maximum for the country or region being studied.

Based on the estimated coefficients for the *Quarterly*, *Monthly*, *CSTS*, and *DslTransp* variables, estimated elasticities from studies using quarterly, monthly, panel, or diesel data are larger (in absolute value) than the baseline of annual, time series, non-diesel demand data. However, these four effects are not statistically significant. Also statistically insignificant is the estimated coefficient on *OECD* which indicates that, all else equal, short-term price responsiveness is smaller in studies using data for OECD countries than non-OECD countries. Finally, neither *VARIANCE* nor *CALC\_STERROR* display a statistically significant coefficient meaning that 1) publication bias does not remain a concern after controlling for the effect of all other explanatory variables and 2) elasticity estimates for which the standard error was not displayed in the study and had to be calculated based on other parameters are not introducing bias into the metaregression.

Table 3: Results from short-run price elasticity metaregressions (non-transportation)

	BETA	BETA
	WLS cluster-robust.se	LME
YrAvg.cent	-0.0006 (0.0018)	-0.0006 (0.0014)

<sup>17</sup>The values of the *PRICE.1998.cent* variable range from -\$0.07/liter for Iran and Iraq to \$1.11/liter for Italy. Differences among the prices of most countries or regions are in the order of cents or tenths of dollars.

Monthly	0.1557** (0.0784)	0.1557 (0.2078)
CSTS	0.0582*** (0.0105)	0.0582*** (0.0186)
OECD	-0.0192 (0.0121)	-0.0192 (0.0128)
Pmax	-0.0249*** (0.0036)	-0.0249** (0.0119)
StaticP	0.0266 (0.0180)	0.0266 (0.0176)
EndUserP	-0.0449*** (0.0126)	-0.0449*** (0.0145)
FuelSwitch	0.0243 (0.0161)	0.0243 (0.0238)
VARIANCE	-0.4473 (0.4854)	-0.4473 (0.2942)
Constant	-0.0672*** (0.0142)	-0.0672*** (0.0195)
Observations	244	244
R2	0.2470	
Adjusted R2	0.2181	
Log Likelihood		202.1440
Akaike Inf. Crit.		-380.2879
Bayesian Inf. Crit.		-338.3219
Residual Std. Error	0.4615 (df = 234)	
F Statistic	8.5291*** (df = 9; 234)	

Notes:               \*\*\*Significant at the 1 percent level.  
                         \*\*Significant at the 5 percent level.  
                         \*Significant at the 10 percent level.

As indicated by Table 1, the LME estimation approach does not improve the fit of the short-run nontransportation price elasticity metaregression. Thus, the WLS model with cluster-robust standard errors is the preferred specification to be discussed next.

Table 3 displays 4 statistically significant effects as well as a statistically significant baseline short-run non-transportation price elasticity of -0.0672. All else equal, elasticities from the subset of studies using panel data are 5.82 percentage points smaller in absolute value than the time-series baseline. The effect of *Monthly*, studies based on monthly rather than annual data, is even larger (0.1557) such that keeping all other attributes from the baseline elasticity constant, it would result in a positive price elasticity.<sup>18</sup> The estimated coefficient for *EndUserP* (-0.0449) indicates that, all else equal, the demand response to an increase in the end user price of a petroleum product is 6.72 percentage points larger than the response to the same percentage increase in the price of crude oil. In addition, all else equal, elasticity with respect to a new price maximum is -2.49 percentage points larger (in absolute value) than the average elasticity across all price levels in the period of analysis.

<sup>18</sup>Vásquez-Cordano(2005) is the only study in the dataset that uses monthly data to estimate price elasticities outside of the transportation sector. The two elasticity estimates from that study going into this metaregression are for kerosene (0.269) and liquefied petroleum gas (-0.333) in Peru.

The rest of estimated coefficients shown in Table 3 are not statistically significant. Lack of statistical significance and very small magnitude of the estimated coefficient on *YrAvg.cent* mean that there is no visible trend in short-run non-transportation elasticities over time in these metadata. All else equal, estimated elasticities are 1.92 percentage points larger (i.e., more negative) for the subset of OECD elasticities than for the rest of the world. Contrary to the negative estimated coefficient for the *StaticP* variable for the transportation sector discussed in Table 2, using static model specifications to explain non-transportation crude oil demand leads to elasticities that are 2.66 percentage points smaller (less negative) than those from dynamic models. According to the estimated coefficient on *FuelSwitch*, the elasticities for petroleum products whose uses present more opportunities for fuel switching (residential, electricity generation) were not significantly different than those in other non-transportation activities during the period covered by the studies in this metaregression. Finally, the lack of statistical significance on the *VARIANCE* variable suggests that publication bias is not of key concern in this metaregression.

Table 4: Results from long-run price elasticity metaregressions (transportation)

	BETA WLS cluster-robust.se	BETA LME
YrAvg.cent	-0.0065* (0.0036)	-0.0017 (0.0034)
SPEEDYRS.cent	-0.0114*** (0.0030)	-0.0122*** (0.0022)
CS	-0.3747*** (0.0999)	-0.2796* (0.1555)
CSTS	-0.0106 (0.0550)	-0.0068 (0.0571)
Pmax	-0.5240*** (0.1428)	-0.4681*** (0.1429)
OECD	0.2440*** (0.0802)	0.1490** (0.0647)
StaticP	-0.0411 (0.0624)	0.0309 (0.0929)
PRICE.1998.cent	-0.6414*** (0.1727)	-0.5360*** (0.1246)
DslTransp	-0.0005 (0.0351)	0.0224 (0.0376)
VehStk	0.1258 (0.0884)	0.0313 (0.0899)
VARIANCE	-0.0227* (0.0119)	-0.0198* (0.0104)
CALC_STERROR	-0.0826 (0.0815)	-0.0471 (0.0952)
Constant	-0.1735** (0.0882)	-0.2638*** (0.1014)

Observations	258	258
R2	0.4097	
Adjusted R2	0.3807	
Log Likelihood		-26.7326
Akaike Inf. Crit.		83.4651
Bayesian Inf. Crit.		136.7595
Residual Std. Error	0.7447 (df = 245)	
F Statistic	14.1676*** (df = 12; 245)	

Notes:               \*\*\*Significant at the 1 percent level.  
                      \*\*Significant at the 5 percent level.  
                      \*Significant at the 10 percent level.

Table 1 showed that the LME estimation method is preferred for transportation sector long-run price elasticities. According to the estimated intercept in Table 4, the baseline value for this elasticity grouping is -0.2638. The estimated coefficient on *SPEEDYRS.cent* indicates that, for every extra year of adjustment, the estimated elasticity increases in absolute value by 1.22 percentage points. To place that number into context, the baseline elasticity of -0.2638 is for the sample mean adjustment period length (9.3 years); all else equal, the estimated elasticity would become -0.276 if the adjustment period were 10.3 years instead. Based on the estimated coefficient on *CS*, elasticities from studies using cross sectional data are, on average, 27.96 percentage points larger (more negative) than those based on time series data.

The estimated *Pmax* coefficient implies that responsiveness to a new price maximum is 46.81 percentage points larger than the average price responsiveness and the estimated coefficient on *PRICE.1998.cent* means that for each dollar per liter the 1998 price of transportation fuel increases relative to the price of Brent, demand responsiveness increases by 53.6 percentage points. OECD countries tend to have higher transportation fuel prices than the rest of the world, mostly due to higher taxes. However, for OECD countries, the effect of high price level on elasticity embodied in the *PRICE.1998.cent* variable is partly offset by the estimated coefficient on *OECD* which is of the opposite sign (0.149). The estimated coefficient on *VARIANCE* (-0.0198) is indicative of publication bias as it means that elasticity estimates with larger variances tend to also be larger in absolute value. However, the effect is small. Without controlling for this effect, the estimated baseline would be -0.2836 instead of -0.2638.

The remaining estimated coefficients are not statistically significant. Those on *YrAvg.cent* (-0.0017) and *CSTS* (-0.0068) are also small in magnitude suggesting no clear trend in long-run price responsiveness in the transportation sector and no significant differences in elasticity estimates from studies using panel (*CSTS*) versus time series data. Estimated coefficients on *StaticP*, *DslTransp*, and *VehStk* all imply decreases in price responsiveness in the 2–3 percentage point range associated with the use of static models, diesel (versus other transportation fuel) data, and the inclusion of vehicle stock as an explanatory variable. The lack of statistical significance of the *CALC\_STERROR* variable indicates that elasticity estimates for which the standard error was not displayed in the study and had to be calculated based on other parameters are not introducing bias into the metaregression.

Table 5: Results from long-run price elasticity metaregressions (non-transportation)

	BETA WLS cluster-robust.se	BETA LME
YrAvg.cent	-0.0076 (0.0064)	-0.0021 (0.0043)
SPEEDYRS.cent	-0.0152*** (0.0014)	-0.0144*** (0.0017)
CSTS	0.1427* (0.0852)	0.1289* (0.0772)
OECD	-0.0544	-0.0365

	(0.0797)	(0.0551)
Pmax	-0.1895*** (0.0334)	-0.1828*** (0.0623)
EndUserP	-0.1357*** (0.0521)	-0.1344** (0.0612)
VARIANCE	-0.1144 (0.1363)	-0.1364 (0.0910)
CALC_STERROR	-0.0059 (0.0850)	0.0431 (0.0828)
Constant	-0.3054*** (0.0953)	-0.3399*** (0.0789)
Observations	136	136
R2	0.8094	
Adjusted R2	0.7974	
Log Likelihood		-27.5082
Akaike Inf. Crit.		77.0164
Bayesian Inf. Crit.		109.0556
Residual Std. Error	0.7836 (df = 127)	
F Statistic	67.4316*** (df = 8; 127)	

Notes:               \*\*\*Significant at the 1 percent level.  
                      \*\*Significant at the 5 percent level.  
                      \*Significant at the 10 percent level.

Based on the likelihood ratio test p-value discussed in Table 1, LME is the preferred specification for this elasticity grouping. Table 5 displays the baseline elasticity (-0.3399) and estimated effects of the explanatory variables. Similar to the transportation sector findings in Table 4, each additional year of response period (*SPEEDYRS.cent*) leads to an increase of elasticity (in absolute value) of 1 percentage point. Long-run price elasticities outside of the transportation sector are, on average, 13 percentage points smaller in studies that use panel data rather than time series. Responsiveness to a new price maximum (*Pmax*) is 18 percentage points larger than the average price responsiveness. The estimated coefficient for *EndUserP* indicates that for a same percentage increase in the price of crude oil versus the end user price of a petroleum product, the demand response is 13 percentage points larger in the latter case.

The estimated coefficients on *YrAvg.cent* (-0.0021) and *OECD* (-0.0365) imply slight increase in price responsiveness over time and greater responsiveness in the OECD region versus the rest of the world, but neither of these two effects are statistically significant. Finally, the coefficients on *VARIANCE* and *CALC\_STERROR* are not statistically significant either which means that publication bias does not appear of grave concern within the set of studies considered in this metaregression and no sizable bias results from using error propagation methods to compute the standard errors of elasticity estimates in cases when those numbers are not directly published in the study.

Table 6: Results from short-run income elasticity metaregressions (transportation)

	BETA WLS cluster-robust.se	BETA LME
YrAvg.cent	0.0046* (0.0027)	0.0033 (0.0025)
Monthly	-0.1141*	-0.0886

	(0.0664)	(0.0917)
CSTS	-0.0920** (0.0456)	-0.1426*** (0.0422)
Ymax	0.0918** (0.0423)	0.0327 (0.0992)
StaticY	0.5637*** (0.0680)	0.5337*** (0.0392)
StaticY.CS	-0.4340*** (0.0949)	-0.4424*** (0.1312)
rgdpe_cap.1998.cent	-0.0008 (0.0016)	-0.0012 (0.0011)
DslTransp	-0.0072 (0.0446)	0.0599** (0.0283)
VehStk	-0.0249 (0.0323)	-0.0363 (0.0545)
VARIANCE	0.1349 (0.1166)	0.0995 (0.1251)
Constant	0.2096*** (0.0398)	0.2625*** (0.0331)
Observations	355	355
R2	0.5988	
Adjusted R2	0.5871	
Log Likelihood		64.1740
Akaike Inf. Crit.		-102.3480
Bayesian Inf. Crit.		-52.0105
Residual Std. Error	0.7224 (df = 344)	
F Statistic	51.3444*** (df = 10; 344)	

Notes:               \*\*\*Significant at the 1 percent level.  
                      \*\*Significant at the 5 percent level.  
                      \*Significant at the 10 percent level.

As discussed in Table 1, the likelihood ratio test indicates that inclusion of a study-level random effect is appropriate for the metaregression of short-run income elasticities in the transportation sector. Thus, the discussion of results from Table 6 focuses on the LME specification. According to the estimated intercept, the baseline income elasticity for the transportation sector demand is 0.2625. One of the attributes of that baseline elasticity value is that it corresponds to income elasticities of gasoline demand or overall transportation fuel demand. For studies of diesel demand, the estimated coefficient on *DslTransp* indicates that income elasticities are 5.99 percentage points larger. Studies based on panel data (*CSTS*) yield income elasticities 14.26 percentage points lower than those from studies using time series data. More than 80% of elasticities from panel data studies in this metaregression are for OECD countries. Thus, the *CSTS* variable might be partly reflecting lower income elasticities for that set of countries. Static model specifications (*StaticY*) result in 53.37 percentage points greater estimated income elasticities. For gasoline demand, Espey (1998) found a similarly large effect for this variable. However, for the subset of elasticities obtained from static models using cross sectional data, the effect of *StaticY* is largely offset by the opposite effect of the interaction dummy *StaticY.CS*.

The GDP per capita cross-sectional variable (*rgdpe\_cap.1998.cent*) suggests this elasticity is largely flat across



income levels. For every additional thousand dollars of GDP per capita relative to the sample mean, income elasticity becomes 0.12 percentage points lower.<sup>19</sup> Within a given country or region, responsiveness to a new maximum income level (*Ymax*) is 3.27 percentage points larger than the average responsiveness. However, neither of the two estimated coefficients related to income levels (*Ymax* and *rgdpe\_cap.1998.cent*) are statistically significant at the 10% level in the preferred LME specification. As found in previous meta-analyses of gasoline demand (e.g., Espey, 1998; Havranek and Kokes, 2015), including vehicle stock in the demand model (*VehStk*) results in smaller estimates of income elasticity. However, the magnitude of this coefficient is small (-0.0363) and it is not statistically significant. Finally, the lack of statistical significance on the *VARIANCE* variable suggests that, after controlling for the rest of explanatory variables, publication bias is not significantly affecting the estimated baseline for this elasticity.

Table 7: Results from short-run income elasticity metaregressions (non-transportation)

	BETA WLS cluster-robust.se	BETA LME
YrAvg.cent	-0.0090 (0.0117)	-0.0157* (0.0088)
Monthly	0.5742*** (0.1508)	0.6088 (0.3928)
CSTS	0.0952 (0.0661)	0.1083 (0.0685)
Ymax	0.0012 (0.0285)	0.0203 (0.0500)
StaticY	0.6443*** (0.0856)	0.6532*** (0.0691)
rgdpe_cap.1998.cent	-0.0002 (0.0009)	0.0000 (0.0013)
FuelSwitch	-0.0784 (0.0520)	-0.0266 (0.0934)
VARIANCE	0.1596 (0.2015)	0.1941 (0.2138)
Constant	0.0134 (0.0604)	-0.0013 (0.0537)
Observations	127	127
R2	0.4564	
Adjusted R2	0.4195	
Log Likelihood		-38.4708
Akaike Inf. Crit.		98.9416
Bayesian Inf. Crit.		130.2277
Residual Std. Error	0.8991 (df = 118)	
F Statistic	12.3833*** (df = 8; 118)	

Notes: \*\*\*Significant at the 1 percent level.

<sup>19</sup>The sample mean of 1998 real GDP per capita is \$27,173 and the range spans from \$408 for Nigeria to \$76,100 for the United Arab Emirates.

\*\*Significant at the 5 percent level.  
 \*Significant at the 10 percent level.

The results of likelihood ratio tests in Table 1 showed that the WLS model specification with standard errors clustered at the study level is preferred to the LME specification for analyzing the variability in short-run income elasticities outside of the transportation sector. The strongest effect revealed by the WLS metaregression in Table 7 is that of static versus dynamic model specifications. The estimated coefficient on *StaticY* indicates that using a static model results in 64.43 percentage points larger income elasticities for this portion of crude oil demand. This large effect is consistent with the interpretation of elasticities from static models as medium run rather than short-run (Espey, 1998). The only other statistically significant effect in the WLS specification in Table 7 is the one from the use of monthly data (*Monthly*) which results in an increase in income elasticity of 57.42 percentage points. However, this result should not be viewed as general or extrapolated outside of this specific metadata sample because it is based on only two elasticity estimates from a single study.<sup>20</sup>

The rest of estimated effects—increasing trend over time, larger elasticities from studies using panel data, larger responsiveness to a new GDP per capita maximum than other income levels, smaller income elasticities for higher income countries, smaller elasticities from studies of crude oil demand in the residential and electricity generation sectors, and direct relationship between elasticity estimates and their variance—are not statistically significant.

Table 8: Results from long-run income elasticity metaregressions (transportation)

	BETA WLS cluster-robust.se	BETA LME
YrAvg.cent	-0.0090 (0.0063)	-0.0076 (0.0050)
SPEEDYRS.cent	-0.0139*** (0.0031)	-0.0067** (0.0028)
CSTS	0.0825 (0.0709)	-0.0430 (0.0883)
Ymax	0.4976*** (0.1213)	0.4008 (0.2760)
rgdpe_cap.1998.cent	-0.0034* (0.0020)	-0.0023 (0.0016)
DslTransp	0.4783*** (0.0985)	0.5084*** (0.0685)
VehStk	-0.1034** (0.0505)	-0.1026 (0.0949)
VARIANCE	0.0002*** (0.0001)	0.0001 (0.0002)
CALC_STERROR	-0.3364*** (0.0989)	-0.1851** (0.0846)
Constant	0.6277*** (0.0410)	0.6918*** (0.0569)

<sup>20</sup>As for the counterpart price elasticities, Vásquez-Cordano(2005) is the only study in the dataset that uses monthly data to estimate income elasticities outside the transportation sector. The two elasticity estimates from that study going into this metaregression are for kerosene (0.702) and liquefied petroleum gas (0.101) in Peru.

Observations	227	227
R2	0.4658	
Adjusted R2	0.4436	
Log Likelihood		-114.2373
Akaike Inf. Crit.		252.4745
Bayesian Inf. Crit.		293.5739
Residual Std. Error	0.9172 (df = 217)	
F Statistic	21.0230*** (df = 9; 217)	

Notes:               \*\*\*Significant at the 1 percent level.  
                      \*\*Significant at the 5 percent level.  
                      \*Significant at the 10 percent level.

For long-run income elasticities in the transportation sector, the likelihood ratio test in Table 1 indicates that the LME specification is preferred. Results from that preferred specification in Table 8 indicate that the long-run responsiveness of transportation fuel demand to income is almost double for diesel versus other petroleum-based transportation fuels. The baseline elasticity value indicated by the intercept (0.6918) corresponds to studies using gasoline or aggregate transportation fuel demand data. All else equal, diesel demand studies find elasticities of 1.2002. None of the studies on long-run income elasticity of diesel demand are for the United States. Most elasticity estimates in this category are for European countries or low-income countries. Higher elasticities for diesel in Europe can be partly explained by the policy shift toward diesel consumption in that region in the 1990s and 2000s. As for high income elasticities for diesel in low-income countries, this result is consistent with the negative coefficient on 1998 income level (*rgdpe\_cap.1998.cent*). Contrary to the idea of larger demand responses over longer adjustment periods, within the set of studies included in this metaregression, long-run income elasticity in the transportation sector slightly decreases, by -1 percentage points, for each additional year of adjustment. The large negative effect of calculated standard errors (*CALC\_STERROR*) on effect size is indicative of bias in the calculated standard errors relative to those directly reported in the studies.

The rest of estimated effects—decreasing trend over time, smaller elasticities from studies using panel data, larger responsiveness to a new GDP per capita maximum than other income levels, smaller income elasticities for higher income countries, smaller elasticities from studies including vehicle stock as one of their explanatory variables, and direct relationship between elasticity estimates and their variance—are not statistically significant.

Table 9: Results from long-run income elasticity metaregressions (non-transportation)

	BETA WLS cluster-robust.se	BETA LME
YrAvg.cent	0.0137*** (0.0030)	0.0137*** (0.0035)
SPEEDYRS.cent	-0.0007 (0.0052)	-0.0007 (0.0052)
CSTS	0.1638 (0.1064)	0.1638 (0.1059)
Ymax	0.3799** (0.1570)	0.3799 (0.2594)
rgdpe_cap.1998.cent	-0.0022* (0.0012)	-0.0022 (0.0019)
CALC_STERROR	-0.4293*** (0.0988)	-0.4293*** (0.1016)

Constant	0.6716*** (0.0549)	0.6716*** (0.0584)
Observations	97	97
R2	0.6354	
Adjusted R2	0.6111	
Log Likelihood		-62.3946
Akaike Inf. Crit.		142.7892
Bayesian Inf. Crit.		165.9616
Residual Std. Error	0.9821 (df = 90)	
F Statistic	26.1400*** (df = 6; 90)	

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Notes:               \*\*\*Significant at the 1 percent level.  
                       \*\*Significant at the 5 percent level.  
                       \*Significant at the 10 percent level.

For long-run, income elasticities outside the transportation sector, the likelihood ratio test displayed in Table 1 indicates that the WLS specification is preferred. Table 9 shows that the baseline elasticity value implied by the intercept (0.6716) is similar to the one for the transportation sector (0.6918) as is the magnitude of the *CALC\_STERROR* coefficient—indicative of bias from the calculated standard errors that were not reported in the studies.<sup>21</sup> The estimated coefficient on *YrAvg.cent* is indicative of an increasing trend—1.37 percentage points increase per year—in income elasticity for the demand of petroleum products outside of the transportation sector. Income elasticities in response to a new GDP per capita maximum (*Ymax*) are 37.99 percentage points larger than for other income levels. The estimated coefficient on *rgdpe\_cap.1998.cent* means that long-run income elasticity outside of the transportation sector decreases by 0.22 percentage points for each additional thousand dollars 1998 GDP per capita. The other two estimated effects—decreasing elasticity as length of adjustment period increases and larger elasticities from studies using panel data—are not statistically significant.

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<sup>21</sup> *VARIANCE* was not included as an explanatory variable in this metaregression because the funnel asymmetry test did not find a statistically significant relationship between effect size and precision of the estimate.

## 4.1. World oil elasticity demand estimation

To translate the metaregression results into an estimate of world crude oil demand elasticity, a further processing step is required. Table 10 displays multiple summary metrics for each of the 8 metaregressions. Fitted means result from computing the sumproduct of the estimated coefficients and the sample mean values of the explanatory variables. The fitted means are generally smaller but not much different from the raw mean elasticities for each grouping. The remaining columns in Table 10 display alternative estimated baselines and their standard errors. Each baseline is constructed as the sumproduct of the estimated coefficients and a value of either 0,1, or the sample mean for each of the explanatory variables.<sup>22</sup> The 3 alternative baselines differ on the values at which price level-related explanatory variables are evaluated. The first baseline bsl should be interpreted as the demand elasticity with respect to the average crude oil price (*PRICE.1998* and *EndUserP* evaluated at zero in the transportation and non-transportation metaregressions respectively and *Pmax* and *Ymax* also evaluated at zero). The second baseline bsl.max is the demand elasticity with respect to a new crude oil price maximum or income maximum; it differs from the first in that *Pmax* and *Ymax* are assigned a value of 1 for the multiplication by their estimated coefficients. Finally, the third baseline bsl.prodppmax evaluates *Pmax*, *Ymax* at one, *PRICE.1998.cent* at the mean, and *EndUserP* at 1 and it conveys the demand responsiveness with respect to a new observed maximum in the petroleum product prices paid by final customers. The standard errors of the three alternative baselines are calculated using the Gaussian error propagation formula.

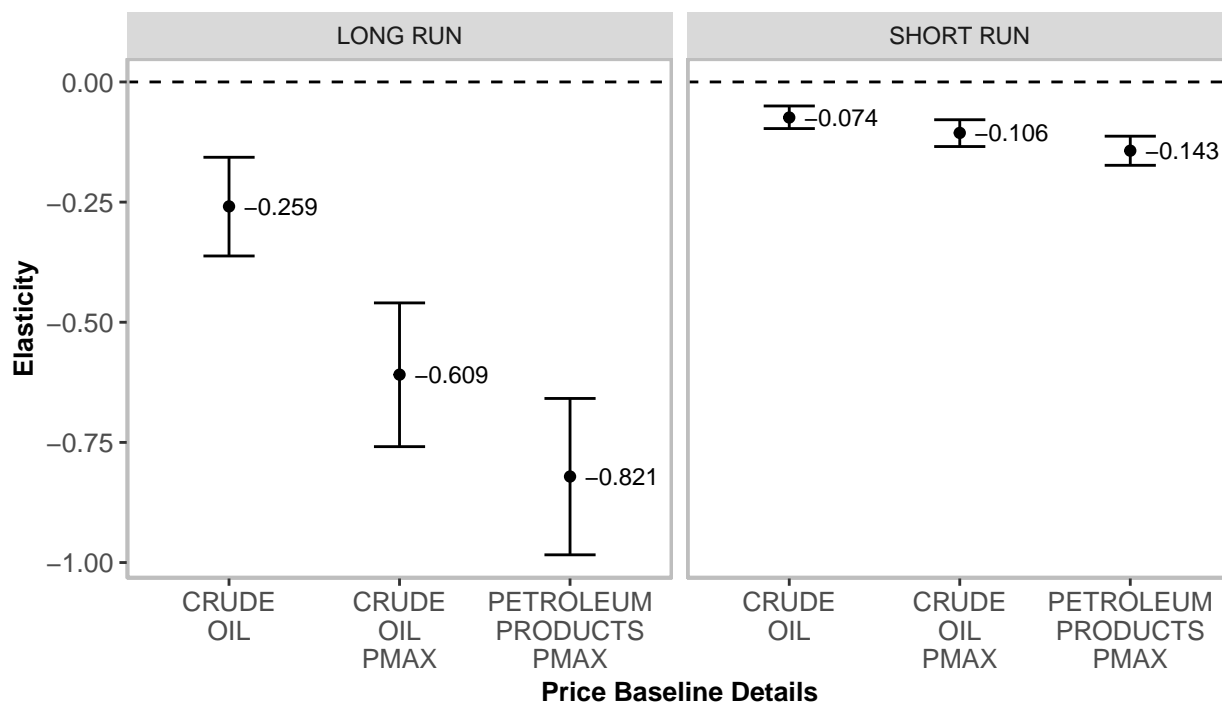
**Table 10. Estimated Elasticities (fitted means and baselines)**

Grouping	fittedmean	bsl	st.err	bsl.max	st.err.max	bsl.prodppmax	st.err.prodppmax
Price-SR-Transport	-0.168	-0.080	0.029	-0.119	0.035	-0.149	0.037
Price-SR-NonTransport	-0.105	-0.059	0.017	-0.084	0.017	-0.129	0.021
Price-LR-Transport	-0.452	-0.183	0.113	-0.651	0.182	-0.924	0.193
Price-LR-NonTransport	-0.451	-0.321	0.091	-0.504	0.110	-0.639	0.126
Income-SR-Transport	0.338	0.195	0.040	0.228	0.107	0.228	0.107
Income-SR-NonTransport	0.225	0.054	0.068	0.055	0.074	0.055	0.074
Income-LR-Transport	0.660	0.770	0.070	1.171	0.285	1.171	0.285
Income-LR-NonTransport	0.486	0.733	0.069	1.113	0.171	1.113	0.171

We construct world price and income elasticities as weighted averages of the baseline elasticities of the transportation and non-transportation sectors. The weights are based on crude oil consumption projections for the year 2017 from EIA's International Energy Outlook 2013 (56% transportation and 44% non-transportation). As additional step, we adjust the resulting short and long-run world crude oil demand price elasticities to include changes in income as an indirect mechanism by which demand responds to price shocks according to the formula  $\epsilon_{D,P}^* = \epsilon_{D,P} + \epsilon_{D,Y} * \epsilon_{GDP,P}$  where  $\epsilon_{A,B}$  is the elasticity of *A* with respect to *B*, *D* is demand, *P* is price, *Y* is income, and *GDP* is gross domestic product.<sup>23</sup> Using a value of -0.02 for the elasticity of GDP with respect to oil price  $\epsilon_{GDP,P}$  (DOE, 2016), this second-order effect does not increase the price elasticity value significantly. The mean and 68% confidence interval for the resulting world oil crude demand price elasticities, based on results from 20,000 random draws from normal distributions truncated at mean +/- one standard deviation for each of the 8 type-sector baselines, are shown in Figure 4. All the elasticities in Figure 4 are evaluated at the average length of run of the elasticity data points included in the metaregression analysis. The average length of run is 0.9 and 11.3 years for the short-run and long-run elasticities respectively.

<sup>22</sup> *YrAvg.cent*, *rgdpe\_cap.1998.cent*, *DslTransp*, *FuelSwitch*, *SPEEDYRS.cent*, *CS*, *CSTS*, *OECD*, *Monthly*, and *Quarterly* are evaluated at their mean values. *StaticP*, *StaticY*, *StaticP.CS*, *StaticY.CS* are evaluated at 0 for short-run elasticities and at their mean for long-run elasticities. *VehStk* is evaluated at the mean for short-run elasticities and at zero for long-run elasticities. The rest of the explanatory variables are evaluated at zero.

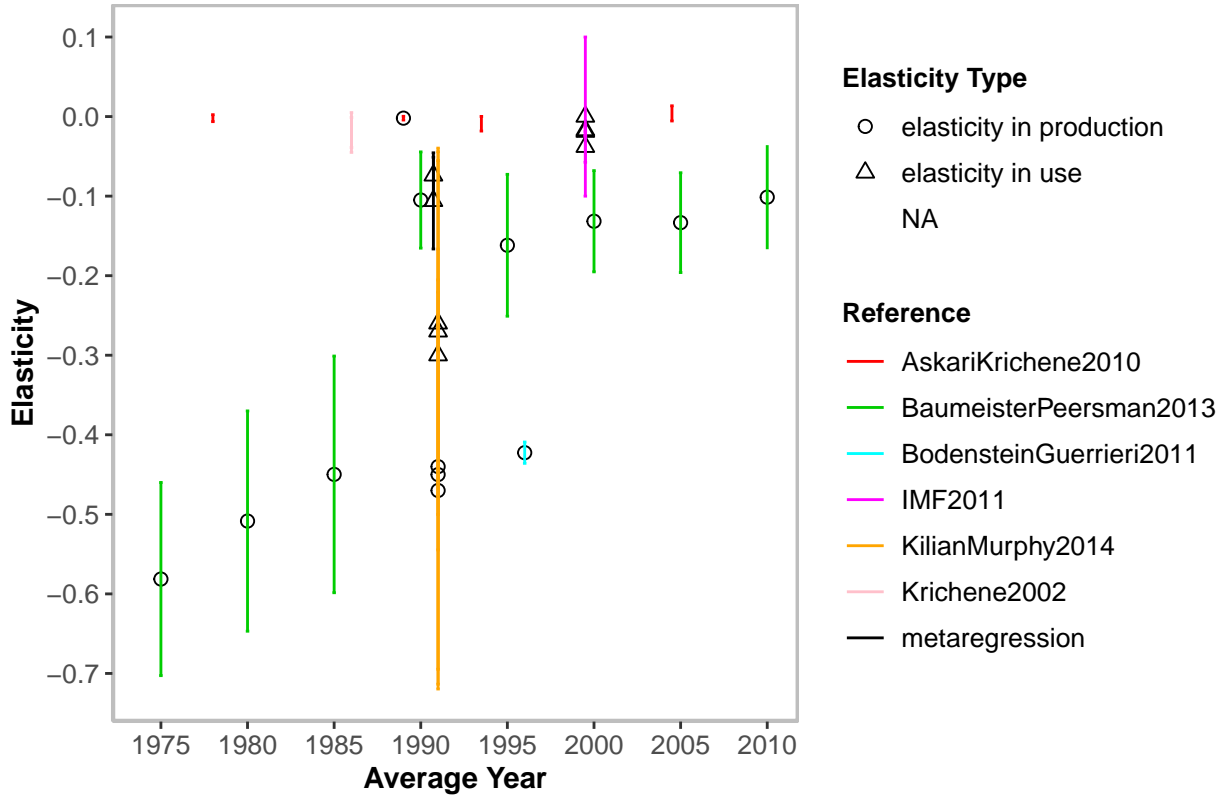
<sup>23</sup> Combining the direct and indirect effect (via income) of an oil price increase on demand is common when crude oil demand elasticity is used to assess the costs of oil supply shocks (e.g., Brown and Huntington, 2013) because those events have a well-documented macroeconomic impact. For different applications of the elasticity parameter, this adjustment might not be appropriate.



**Figure 4. Estimated short-run and long-run world crude oil demand elasticities with respect to price (including income effect)**

## 4.2. Comparison to other world elasticity estimates

Figure 5 places the world oil demand elasticities (with respect to crude oil price or a new crude oil price maximum) from the metaregression in the context of other world oil demand elasticity estimates in the literature and highlights attributes that can help understanding and, to some extent, reconciling the large differences in value.



**Figure 5. Short-run price elasticities of world crude oil demand (metaregression vs. other published results)**

First, except for IMF (2011), all other primary studies in Figure 5 estimate systems of equations: simultaneous equations (Krichene, 2002; Askari and Krichene, 2010), structural VARs (Baumeister and Peersman, 2013; Kilian and Murphy, 2014) or a dynamic stochastic general equilibrium model (Bodenstein and Guerrieri, 2011). In all those systems, the quantity variable refers to crude oil production data and changes in consumption are assumed to be equal to changes in crude oil output. The resulting demand elasticities with respect to price can be referred to as “elasticities-in-production”—terminology introduced in Kilian and Murphy (2014)—and they tend to overstate demand responsiveness because they do not take into account the smoothing role of inventories. Kilian and Murphy (2014) address this shortcoming by also computing a substantially smaller “elasticity-in-use” (−0.26 for the “elasticity-in-use” versus −0.44 for the “elasticity-in-production”).<sup>24</sup> In contrast, the majority of studies included in the metaregressions discussed in the previous section (as well as IMF(2011)) estimate reduced form equations with crude oil consumption data as the dependent variable.

Second, studies that consider the possibility of time-varying elasticities find crude oil demand elasticity to be declining over time (e.g., Baumeister and Peersman, 2013; Askari and Krichene, 2010). The crude oil market has experienced structural changes since the 1970s that have reduced crude oil demand responsiveness: the advent of liquid spot and future markets where participants can hedge their physical positions (Baumeister & Peersman, 2013); the reduced ability of the OECD non-transportation sector to substitute or reduce crude oil consumption after having taken advantage of “low hanging fruit” adjustments in the wake of the crude oil crises of the 1970s (Dargay and Gately, 2010); a given reduction in miles traveled provides progressively smaller fuel savings as vehicle fuel efficiency improves (Hughes et al., 2008). Thus, papers that compute a single elasticity over the long time period including the 1970s and early 1980s will likely obtain a larger elasticity than those starting later or allowing elasticity to vary over time.

Third, crude oil demand elasticities recovered from SVAR impulse response functions represent responses to shocks and those shocks are normalized to always result in a crude oil price increase. In contrast, elasticities estimated using

<sup>24</sup>Krichene (2002) and Askari and Krichene (2010) are exceptions to the otherwise larger “elasticities-in-production” summarized in Figure 5. However, their authors acknowledge the limitations of their two-stage least squares approach which takes GDP, natural gas prices, and exchange rates as exogenous. These estimates might be downward-biased due to endogeneity bias.

reduced form equations typically correspond to the average responsiveness over shocked and unshocked periods and various types of shocks implying crude oil price increases and decreases. The strong effect of the Pmax variable in the metaregressions is consistent with a larger responsiveness during that specific type of price increase. Relatedly, IMF (2011) finds world crude oil elasticity for the subset of observations in which price level was above the average price level (-0.038) to be double the average elasticity for the full price history (-0.019).

Not all authors using SVARs agree on the magnitude of crude oil demand elasticities. Imposing bounds on the value of crude oil demand elasticity has become a common part of the strategy for identification of structural parameters in SVAR crude oil market models. As shown in Caldara et al. (2016), the two observed patterns of 1) larger volatility in crude oil prices than crude oil output and 2) near-zero covariance between reduced form residuals for global crude oil output and crude oil price are consistent with a wide range of choices for supply and demand elasticity bounds. With many feasible combinations, the choice of bounds must rely on external information which involves either a literature review or primary estimation. In some cases, the selected pair of bounds involves a very small supply elasticity (0.025) and larger demand elasticity (-0.8) (Killian and Murphy (2014); Baumeister and Peersman (2013)) and in other cases the bounds or, in Bayesian SVARs, priors are similar in absolute value for supply and demand (e.g., 0.10 and -0.10 respectively in Baumeister and Hamilton (2015) and Caldara et al. (2016)).<sup>25</sup> Results from our metaregression generally agree with a short-run world crude oil demand elasticity of approximately -0.1.

## 5. Conclusions

The aggregate response of global crude oil demand to a price or income change is the combination of responses from multiple regions and sectors. Building on that idea, we construct a world crude oil demand elasticity based on a meta-analysis of elasticities for individual regions and sectors/petroleum products obtained from 75 studies published from 2000 to 2015. We then compare the metaregression results to other estimates of the world crude oil demand elasticity in the literature.

Global short-run elasticities with respect to crude oil price obtained from the metaregression are low (-0.08 and -0.059 for transportation and non-transportation sectors respectively). Estimated long-run elasticities reflecting decade-long adjustments are -0.183 for the transportation sector and -0.321 for other end uses. All estimated elasticities increase (in absolute value) when they convey response to a new price or income maximum and when they reflect response to end-use product prices rather than crude oil prices. The consumption-weighted average of elasticities from both sectors ranges, depending on details about the price baseline, from -0.074 to -0.143 in the short-run. The long-run range is wider (-0.259, -0.821).

Results indicate a slightly decreasing trend in short-run transportation elasticity over time. The estimated coefficient on the trend variable for the other price-elasticities is consistent with them increasing over time but it is not statistically significant. For income elasticities, statistically significant trends only appear for the non-transportation sector and suggest that short-run income elasticity has been decreasing but long-run elasticity has been increasing. We find that countries with higher end-use price levels (inclusive of taxes) are more price elastic. The estimated relationship between income elasticities and a cross-section of income levels is weaker but consistent with higher-income countries being less income-elastic.

No single study can produce an elasticity value well-suited for every empirical application. However, applied economists can benefit from systematic literature reviews and meta-analyses to select elasticity values useful to their specific research question. Attentiveness to key aspects of empirical application (e.g., duration of adjustment period being investigated, normal market conditions vs. disrupted market conditions) are important in selecting a value of crude oil demand elasticity. We illustrate these considerations by computing multiple elasticity baseline values.

Even though there is an extensive body of literature on petroleum product demand elasticity estimation, it continues to be unbalanced toward study of transportation demand in high-income countries. In addition, changes in demand elasticity due to technological and policy changes are often observed in the literature with a considerable lag since most studies compute average elasticities over decades-long analysis periods. This is particularly the case for studies using time series data since they need to cover a longer time period than studies using data with a cross-sectional dimension to ensure sufficient degrees of freedom in the estimation. Thus, there continues to be room for new

<sup>25</sup>The -0.8 bound on crude oil demand impulse elasticity is based on a single paper that estimates long-run price elasticity of gasoline for the United States using results from a household survey conducted in 1979 and 1988 (Hausman and Newey, 1995).



estimates to balance out the body of estimates from different regions and sectors and to capture evolution of elasticities over time.

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