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Abstract

As is the case with capital-energy substitution, interfuel substitutability has been of longstanding interest to the energy economics and policy community. However, no quantitative meta-analysis has yet been carried out of this literature. This paper fills this gap by analyzing a broad sample of studies of interfuel substitution in the industrial sector, manufacturing industry or subindustries, or macro-economy of a variety of developed and developing economies. Publication bias is controlled for by including the primary study sample size and the influence factor of the journal in the meta-regression. Results for the shadow elasticity of substitution between coal, oil, gas, and electricity for forty-five primary studies show that there are easy substitution possibilities between all the fuel pairs with the exception of gas and electricity. Model and data specification issues very significantly affect the estimates derived by each individual study. While publication bias does not seem to be present there is a relationship between sample size and the value of the elasticities with larger sample studies finding greater values of the elasticities.

Key Words: Meta-analysis, energy, substitution, elasticity, interfuel
JEL Codes: D24, Q40

1. Introduction

As is the case with capital-energy substitution (Koetse *et al*., 2008), interfuel substitutability has been of longstanding interest to the energy economics and policy community and is of critical importance in evaluating sustainability options and in estimating the economic cost of environmental policies such as a carbon tax. Apostolakis (1990) and Bacon (1992) surveyed some of the early studies of interfuel substitution elasticities for the OECD countries. Bacon found that studies that used panel data tended to find more substitutability between fuels as measured by the cross-price elasticities. He suggested that this was because this data represented long-run elasticities as opposed to short-run elasticities in time series data. Apostolakis (1990) came to a similar conclusion regarding substitution between aggregate energy and capital.[1] Apostolakis (1990) did not, however, come to as clear-cut conclusions regarding interfuel substitution. He found that coal and oil and coal and electricity were good substitutes with less substitutability between coal and gas and electricity and gas and a mixed picture for the remaining two combinations.

Given what we now know about cointegration in time series, whether time series estimates represent short-run elasticities or not depends on the type of time series model estimated and whether the time series cointegrate or not. Time series estimates in levels could represent long-run equilibrium elasticities if the variables cointegrate. Various other hypotheses might explain this difference in estimates. It could be that forcing parameters to be equal across individuals in panel data regressions results in greater estimated substitutability. Alternatively, substitution along an isoquant may only be really distinguishable from changes in the isoquants – in other words technical change – when the sample includes both time and cross-sectional dimensions. It is also possible that the larger sample size of most panel studies results in less-biased estimates of the elasticities. These and other hypotheses will be investigated in this paper.

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[1] Koetse *et al*.'s (2008) meta-analysis finds a mean value of the Morishima elasticity of substitution between capital and energy for a change in the price of energy of 0.216 for their time-series base case with significantly greater values for panel data of 0.592 and for cross-section data of 0.848.

Since Bacon's and Apostolakis' surveys, numerous additional primary studies have been carried out for both developed and developing economies. However, no quantitative meta-analysis of this literature has yet been carried out. This paper fills this gap by analyzing a broad sample of studies of interfuel substitution in either the industrial sector, manufacturing industry as a whole or manufacturing sub-industries, or the macro-economy of a variety of developed and developing economies. An initial glance at this literature shows a wide range of numerical values for substitution elasticities. Some studies show low substitutability between fuels (the shadow elasticity of substitution (McFadden, 1963) is between 0 and 1) and others show a high level of substitutability. Signs of cross-price elasticities also vary across studies and across countries within multi-country studies. Some simple hypotheses can be formulated to explain these patterns but they tend to be contradicted by outliers. For example, I hypothesized that studies that incorporate post 1973 or 1979 data show less substitutability than the classic Pindyck (1979) paper. But Jones (1996), using a linear logit model, found a high degree of substitutability (many of his Morishima elasticities are greater than Pindyck's) for most fuels apart from electricity. On the other hand, Considine (1989) also used a linear logit model but estimated very low elasticities. The value of a meta-analysis over a traditional literature review is that it can objectively untangle these patterns in the metadata.

Meta-analysis seeks to estimate the true value of a parameter or summary statistic given in many different primary research studies – known as an "effect size" in the jargon of the meta-analysis literature – and how it varies over the relevant population as well as accounting for the errors introduced by inaccurate measurement, differences in methodology, publication selection biases etc. In the simplest case, if we believed that the underlying parameter was a constant across the population – called a fixed effect size (FES) in the meta-analysis jargon - and had no information on the sources of variations in the various primary estimates nor the precision of the primary estimates themselves, we could compute the unweighted mean of all the effect sizes in all the primary studies (each primary study often has many individual observations) (Nelson and Kennedy, 2008). When the precision of primary estimates is known, the sum weighted by the inverse of the variances (i.e. the precisions) - called the FES weighted mean - can be computed.

It is more reasonable in most cases to maintain that the effect size in different studies is actually different and not purely the result of sampling error. This is called a random effect size – (RES). It is reasonable to assume that some of this second source of variance is explainable:

$$\varepsilon_i = \alpha_i + e_i, \qquad e_i \sim N(0, v_i^2) \tag{1}$$

$$\alpha_i = \alpha + x_i'\beta + u_i, \qquad u_i \sim N(0, w^2) \tag{2}$$

where ε_i is the effect size, $\alpha + x_i'\beta$ is a regression model on the explanatory variables x_i, u_i is the unexplainable variability across studies, and e_i the disturbance due to sampling error (Boys and Florax, 2007). If $w = 0$, the model can be estimated by GLS using the variances of the estimates from the primary studies as estimates of v_i^2. In the general case, more sophisticated estimators are required (see Nelson and Kennedy, 2008). Additional issues concerning meta-analysis are discussed in the methods section of this paper.

2. Methods

a. Choice of Dependent Variables

Stern (2008b) reviews the theoretical literature on the elasticity of substitution. With two inputs and constant returns to scale the elasticity of substitution is unambiguously defined. But the situation is much more complex for more general cases. Elasticities of substitution can be classified in three dimensions:

- **Gross and net elasticities**: Under non-constant returns to scale, some of the elasticities of substitution measured holding output constant (net substitution) and letting it vary optimally (gross substitution) differ. For non-homothetic technologies all the elasticities differ for net and gross substitution.
- **Primal and dual elasticities**: Also known as the distinction between elasticities of complementarity and elasticities of substitution. The familiar Allen-Uzawa elasticity is a dual elasticity in that is derived from the cost function. The Antonelli elasticities by contrast are derived from the input distance function, a primal representation of the technology.

- **Scalar, asymmetric ratio, and symmetric ratio elasticities**: The Allen-Uzawa elasticities measure the effect on the quantity of the factor demanded for a change in the price of another factor. These elasticities are symmetric. The Morishima elasticities measure the effect on the factor ratio of the change in a ratio of prices. But the elasticity takes a different value depending on which price in the ratio changes, such that these elasticities are not symmetric. By placing the restriction that cost is held constant on the Morishima elasticity we obtain the shadow elasticity of substitution. Ratio and scalar elasticities measure different concepts of substitution. The ratio elasticities measure the difficulty of substitution between inputs with values between zero and unity indicating poor substitutability and values greater than one indicating good substitutability. By contrast, the scalar elasticities can be positive or negative – for p-substitutes and p-complements respectively in the case of the Allen-Uzawa elasticities (or q-complements and q-substitutes respectively in the case of the Antonelli elasticities).

Most interfuel substitution studies look only at equations for fuel cost shares with the quantity of energy implicitly held constant and do not consider changes in output. A few studies such as Pindyck (1979) estimate an energy submodel and a capital-labor-energy-materials model ("super-model"). This allows computation of the "partial elasticities" which hold the quantity of energy constant and "total elasticities" which allow it to vary. Both of these are net elasticities – the level of output is held constant. Even so, few if any studies estimate the parameters necessary to compute the returns to scale in the super-model. Given this, it is not possible to compute the gross elasticities of substitution and I do not consider them further.

Most primary studies simply report the own and cross-price elasticities from which the Morishima elasticities can be derived as differences between cross-price and own-price elasticities and the shadow elasticities as share weighted averages of the Morishima elasticities (Chambers, 1988).[2] For the translog function:

[2] Some papers also report Allen-Uzawa elasticities or Morishima elasticities. But regardless of how the data is presented I compute the shadow elasticities from the information given. Most, but not all studies, also present the parameters of the cost function and/or the average cost shares, which can be of use in computing shadow elasticities and even cross-price elasticities that are not reported in the primary study - some studies only report one of each pair of cross-price elasticities.

$$\eta_{ii} = \frac{\partial \ln X_i(y,\mathbf{p})}{\partial \ln p_i} = \frac{\beta_{ii} + S_i^2 - S_i}{S_i} \;,\; \eta_{ij} = \frac{\partial \ln X_i(y,\mathbf{p})}{\partial \ln p_j} = \frac{\beta_{ij} + S_i S_j}{S_i} \tag{3}$$

where X_i is the quantity of input i, p_i its price, and S_i its cost share. β_{ij} is the relevant second order parameter from the translog cost function. y is output and $\mathbf{p}$ is the vector of factor prices. The Morishima elasticity for a change in price i can be derived as:

$$\mu_{ij} = \left. \frac{\partial \ln(X_j(y,\mathbf{p})/X_i(y,\mathbf{p}))}{\partial \ln(p_i/p_j)} \right|_{p_j} = \eta_{ij} - \eta_{ii} \tag{4}$$

and the shadow elasticity is:

$$\sigma_{ij} = \left. \frac{\partial \ln(X_j(y,\mathbf{p})/X_i(y,\mathbf{p}))}{\partial \ln(p_i/p_j)} \right|_{C} = \frac{S_i}{S_i + S_j}\mu_{ij} + \frac{S_i}{S_i + S_j}\mu_{ji} \tag{5}$$

The shadow elasticities should be non-negative [3]. As averages of the Morishima elasticities, the shadow elasticities are good summary statistics of the overall degree of substitutability between inputs. For any given number of inputs they are fewer in number than the cross-price, Morishima elasticities, or Allen-Uzawa elasticities. In the case of four fuels there are just six shadow elasticities. Therefore, in this paper I carry out a meta-analysis of the shadow elasticities.[4]

Equation (3) can be used to find the cost shares required to compute (5) when these are not given in the primary study if the study uses the translog function. The quadratic equation given by the own price elasticity and cost function parameter presented in the paper is solved for the cost

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3 Morishima elasticities are usually positive but are not necessarily so – one of pair for a factor combination can be positive and the other negative.

4 Koetse *et al*. (2008) carry out separate meta-analyses for the cross-price and Morishima elasticities but they only look at the capital-energy elasticity for a change in the price of energy. Hence they have just two meta-regressions vs. six in this paper. Boys and Florax estimate a single meta-regression for the Allen-Uzawa elasticity of substitution between capital and labor.

share. Alternatively, if a study presents both Allen-Uzawa elasticities and cross-price elasticities their ratio gives the unstated cost share.

b. Choice of Explanatory Variables

i Overview

Explanatory variables play two roles in a meta-analysis:

- Measuring differences between "effect sizes" that are real and that we want to measure.
- Accounting for outliers and explainable variability in the estimates around the true values of the parameter or statistic of interest.

Examples of the first category is measuring the difference between the elasticity of substitution in North America and Europe or between partial and total elasticities or between the industrial sector and the economy as a whole. An example of the second category is that the elasticity of substitution may differ depending on whether the primary studies modeled technical change or ignored it. If we argue that a best practice study includes some sort of time trends in the cost function we will want to use the fitted elasticities for the case where technological change was modeled while regarding the difference in effect size in the studies which ignored technological change as noise that we wish to account for.

I referred to the two existing meta-analyses of elasticities of substitution (Boys and Florax, 2007; Koetse *et al*., 2008) and reviewed the literature on interfuel substitution to develop a list of appropriate variables to include as explanatory variables in the meta-analysis. Many of my explanatory variables are the same as those of Koetse *et al*. (2008) or Boys and Florax (2007). There are a number of variables regarding model specification, which I collected but dropped from the final analysis because they only differentiated one or two studies from the remainder. An example is the use of stochastic technological change trends vs. deterministic trends. Only Harvey and Marshall (1991) and Morana (2003) used the stochastic specification. Similarly, only Jones (1996) omitted fixed effects from a panel regression with more than three or four time observations. In yet another example, very few studies used quarterly data. Some variables were collected but did not have significant effects in the meta-regressions and did not have strong theoretical reasons for inclusion. An example is a dummy variable I created for studies that did not include all four of the standard fuels.

ii Methodology Variables

From the introduction, we can see that some variables of clear interest are whether the primary study was estimated with time series, cross-section or panel data, whether a translog, linear logit, or other functional form was used, and whether technological change was modeled. However, data type is strongly correlated with sample size, which is a required variable in the regression, as explained below.[5] Therefore, I test the effects of the data type in an auxiliary regression.

To deal with functional form, I use dummies for translog, linear logit, and other functional forms. As there is no *a priori* reason to believe that one function is more appropriate than another it is desirable, therefore, that the base case is for a weighted mean of the different functional forms. I demean the functional form dummies and then subtract the translog dummy from each of the other two dummies, which are then in their transformed form used in the meta-regression. This ensures that the sum of the effects of these dummies in the sample is zero.

By contrast, I argue that models that omit technical change are misspecified and, therefore, it is desirable that the base case be for a model with technical change. I introduce a dummy equal to one if technical change variables are omitted in the energy submodel.

iii Data and Definition Variables

The variables mentioned in the previous section are questions of specification on the part of the researchers that do not reflect variations in the true values of the elasticities. As mentioned above, the region covered may be of interest. For the former, I introduce dummy variables for countries. A country is assigned its own individual dummy if it has at least two studies available for each elasticity for which that country has an estimate. Individual dummies are, therefore, assigned to Australia, China, India, Japan, Korea, France, Germany, Italy, Netherlands, UK, Canada, and USA. The remaining countries were assigned dummies for "other Europe" and

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[5] The time series samples are the smallest and the cross-section samples the largest.

"other Asia".[6] Again these dummies were demeaned and the dummy for the Netherlands was subtracted from the remaining dummies. The transformed dummies were used in the meta-regression.

Three dummies are used to account for data from different time periods – data from the 1940s through the 1960s, data from the 1970s and 80s, and data from the 1990s and beyond. Again demeaning is applied and the early dummy subtracted from the other two. Time dummies of this sort are preferable to continuous time variables for sample period as they have a lower correlation with the other explanatory variables.

I also introduce dummies for studies of the macroeconomy, manufacturing, and subsectors of manufacturing (industrial sector = 0). I also note whether an elasticity is a partial elasticity estimated from a submodel that holds energy constant or a total elasticity that allows energy use to vary (see Pindyck, 1979). The default is the partial elasticity. For dynamic models I note whether an elasticity is a short-run or a long-run elasticity. The default is an estimate from a static model.

It is possible that the elasticity varies with the level of economic development. Klump and de la Grandville (2000) argued that the income per capita will be higher in economies with more substitutability between capital and labor but there is no *a priori* theory in the case of interfuel substitution. I use the log of average GDP per capita in 2000 PPP Dollars for the sample period of the primary study (Heston *et al.*, 2006) relative to the sample size weighted arithmetic mean income ($15,489) to reflect the effect of the level of economic development. The base case is for a country with this average income.

iv Publication Quality and Publication Bias

I collected several variables related to publication quality or publication bias –citations received by the paper as of January 2009 in the *Web of Knowledge*, the 2007 citation impact factor of the journal (both 2 year and 5 year factors from *ISI*), the citation impact factor of the journal in the

[6] I also tested dummies for more aggregated regions but the hypothesis that the intercept term was constant across studies could be rejected for those models for all elasticities.

year of publication, the 2006 influence score of the journal from eigenfactor.org, the inverse of the square root of the sample size in the primary study, and the number of articles in the ISI database citing the authors other work apart from the paper in question. I discuss these factors in more detail in the following:

Sample Size: Stanley (2001) suggests including the sample size as an explanatory variable. In the case of that study the dependent variable was a test statistic and, therefore, this is a test of whether there is a true underlying effect. The t-statistic should increase with sample size if there is a true non-zero effect in the data. In our case, the true elasticity might just as well be zero. But the estimate is also likely to be closer to the true value in larger samples (Stanley, 2005). On the other hand, this effect should not be monotonic – studies of small sample size should be equally likely to report values above or below the true parameter in the absence of publication bias – as exemplified by the "funnel graph".[7] Publication bias can take various forms. Journals and researchers might only publish results that appear to be theoretically satisfactory – for example rejecting studies with positive own price elasticities. Or they may only accept studies with statistically significant effects. If both statistically significant and theoretically correct results are favored, a correlation between sample size and effect size will result because studies with small samples have to struggle to find larger effects (in the theoretically correct direction) in order to get statistically significant results (Stanley, 2005). One side of the true bell shaped distribution of effect sizes in studies has been censored to leave a monotonic relation between sample size and the remaining effect sizes. If the theoretical value is positive, this correlation will be negative and vice versa. If statistically significant results are favored regardless of sign then there will be no correlation with sample size but the distribution of effect sizes will be kurtotic.

In the presence of unidirectional publication bias the average effect size in the literature will be a biased estimate of the underlying parameter. Begg and Berlin (1988) argue that publication bias will be proportional to the inverse of the square root of sample size. Including this variable in a metaregression means that the intercept in the regression will estimate the value of the elasticity for a study with an infinite sample size, thus correcting for publication bias. This regression is

[7] The funnel graph plots sample size or precision on the y-axis and the effect size on the x axis.

then Stanley's (2005) "funnel asymmetry test" (FAT) estimator using the inverse of the square root of the sample size in place of the precision of the primary estimate.

I would expect that in the substitution literature researchers are not very concerned with significance because the cost function parameters themselves are not of much interest. However, positive own price elasticities are likely to be censored. If cross price elasticities are not affected, this would cause estimates of Morishima elasticities and consequently of shadow elasticities of substitution to be somewhat more positive than is actually the case.

Impact Factor: Murtaugh (2002) and Baker and Jackson (2006) argue that there might be a relationship between the impact factor of the journal a paper was published in and the paper's effect sizes. Baker and Jackson (2006) posit a model where authors order journals according to impact factor and first submit their paper to the journal with the highest impact factor that they think they can publish their paper in. If it is rejected they go to the next journal on their list. If there is a bias, the higher ranked journals are more likely to accept papers with larger or more significant effects and papers with smaller or less significant effects will get published by lesser journals. Thus a positive correlation between impact factor and effect size is expected if both theoretically consistent and statistically significant results are preferred by top journals. This would not be a problem if all papers were published in a journal of some sort. But some papers will be shelved after not getting accepted and some studies will not be written up or submitted because their authors believe they have no chance to be published.

This effect of journal quality on effect size would then be an indicator of publication bias that we would want to remove from our meta-estimate of the effect size. In this case our base case should instead be an unpublished paper. Of course, papers with better methodology are also likely to be published in better journals and it might be expected that these papers would have effect sizes nearer the true value of the parameter. But poorly conducted studies – especially when we control for sample size - would be expected to produce both small and large effect sizes. So in the absence of publication bias no correlation between effect size and journal quality should be expected *a priori*.

Taking out the effect of journal quality in the regression is equivalent to assuming that the true value of the parameter is likely to be represented by the average paper published in a zero impact journal. We are implicitly assuming that this is the mean effect. If the mean and median effect are equal we would be assuming that only half of the potential papers get published in journals with impact factors. This is an arbitrary assumption but better than ignoring the publication bias, I think.

Journal quality is, however, an endogenous variable if more statistically significant or theoretically compatible results result in publication in "higher quality" journals. We need to find an instrument that is not correlated with the effect size but is correlated with journal quality. One potential variable is the quality of the author. Again, assuming that studies by weak authors are equally likely to have small or large effect sizes (controlling for sample size and other factors), author quality should not have an effect on the effect size. But better authors may have better methodology, which helps them get published in better journals or the journals might simply be more likely to accept papers by authors that they think are "good". I collected the lifetime number of citing articles in the ISI database of the authors of each paper and subtracted the citations they received for the paper in question. I summed up the citation counts for multiple authors. The model is estimated by instrumental variables using the INST option in RATS. I found that the journal influence score from eigenfactor.com was far more strongly correlated with author citation count than the various ISI impact factors and, therefore, I adopted this as my indicator of journal quality.

Citations: The citations an article has received are certainly endogenous. We might include this variable if we think that results with more citations are higher quality, but again it is likely that if there is an effect here (controlling for sample size) it is due to bias with researchers citing papers that confirm theoretical expectations (Leimu and Koricheva, 2005). Again, why would lower quality studies all have the same bias in effect size? But the number of citations received can have no effect on whether a paper is published or not and so cannot be used to correct for publication bias. Neither can it explain the results researchers find. Therefore, I have not included it in the meta-model.

All the variables used are listed in Table 1.

c. Choice of Studies

I developed a database of articles by first searching the *Web of Science* and *RePEc* for all relevant published articles on interfuel substitution. I then checked the articles in these articles' reference lists and also all the articles that cited them in the *ISI Citation Index* and *Google Scholar*.

Only studies that looked at interfuel substitution in the industrial sector as a whole, the economy as a whole, manufacturing, or sub-industries within manufacturing for single countries, provinces or states within countries, or groups of countries were considered. Studies for industries such as agriculture, construction, or electricity generation were not included. Neither were studies of consumer demand or transport fuel demand. A study must include estimates of the cross-price elasticities or elasticities of substitution between at least two of: coal, oil, natural gas, and electricity. Where possible we used estimates for aggregate energy use rather than for fuel use only. Some studies break down the standard fuel categories into subtypes such as heavy and light oil (Taheri and Stevenson, 2002) or domestic and foreign coal (Perkins, 1994). In these cases I created additional observations. For example, for the Taheri and Stevenson results one observation treats heavy oil as representing the oil category and the other treats light oil as representing the oil category. The cross-price elasticity between the two types of oil is dropped.

I dropped Hall (1986) because only significant elasticities were reported. Harper and Field (1983) was dropped because only charts and no actual figures are reported. The selected studies are listed in Table 2. The table notes where some data were interpolated or extracted from other statistics. Because each primary study has a different number of estimates of the elasticity the data are an unbalanced panel.

d. Other Econometric Issues

This is the first meta-analysis of the elasticity of substitution to attempt to analyze the elasticities for multiple factor pairs. Koetse *et al.* (2008) investigate the capital-energy elasticity and Boys and Florax (2007) the capital-labor elasticity. The elasticities of substitution for the different fuel combinations are interrelated as they are all functions of jointly estimated regression parameters (which are subject to summation and symmetry conditions for the homothetic translog cost function) and the cost shares which sum to unity. Though there are no simple linear relationships between the elasticities, the residuals of meta-regression equations explaining each of them should be correlated. However, as the explanatory variables are the same in each equation seemingly unrelated regression estimates are identical to equation by equation estimates. And, though the standard errors of the coefficients are different in the two cases, as is well known there is no efficiency gain to joint estimation (Greene, 1993).

Nelson and Kennedy (2008) review the use of meta-analysis in environmental and natural resource economics and make a number of recommendations for best practice. Best practice is to weight the regression variables by the inverse of the standard errors of the estimates in the primary studies. This practice is followed by Koetse *et al*. (2008) and Boys and Florax (2007). As I transform the elasticities provided in the primary studies and do not have standard errors for the cost shares in almost all cases, I instead used the square root of sample size as my weights, which is the second best approach according to Nelson and Kennedy. The weights are implemented using the SPREAD option in RATS. I also estimate a robust covariance matrix for the coefficients using the ROBUSTERRORS option in RATS. Additionally, I test for residual heteroskedasticity using the Breusch-Pagan test.

Koetse *et al*. (2008) and Boys and Florax (2007) use mixed effects regression. According to Nelson and Kennedy there should not be much practical difference between such more sophisticated procedures and the standard random effects estimator. A problem arises in using the standard algorithm for random effects as it estimates the variances of the individual and random effects using a fixed effects regression. But in a meta-analysis dataset of this type many variables take exactly the same value for all observations of a given individual study. Therefore, there is a perfect correlation between the fixed individual effects and these variables and a fixed effects regression cannot be estimated. Instead, following Greene (1993, 475), we could estimate a weighted least squares regression as described above and carrying out an analysis of variance of its residuals using the PSTATS command in RATS. The analysis of variance produces estimates of the required individual and random effects variances. In the RATS package the procedure PREGRESS must be used for estimating the random effects model in unbalanced panels. This procedure does not allow the use of instrumental variables nor estimation of robust coefficient covariance matrices. I, therefore, used the WIV, robust covariance matrix procedure described in the previous paragraph and tested the residuals for equality of means across studies. As will be seen, in five out of six cases the null hypothesis of equal means could not be rejected. I also estimated simple random effects models using PREGRESS. The coefficients were not substantially different to OLS estimates of my model.

3. Results

a. Exploratory Meta-Analysis

There are 353 observations from 45 primary studies. Table 1 presents some summary statistics for the variables. The means and standard deviations are unweighted. The results weighted by sample size would look very different due to two papers (Bousquet and Ladoux, 2007; Fisher-Vanden *et al*., 2004) with much larger sample sizes than the other papers. Some key points that emerge include:

- The minimum value for all the elasticities is a theoretically inconsistent negative value and there is a wide range of estimates in the studies.
- The average sample size is 379 with samples as large as 25490 (Bousquet and Ladoux, 2007) and as small as 20 (Agostini *et al*., 1992).
- The average journal that the papers were published in is fairly high quality but of course there is a wide variance with several articles in influential journals and most articles in journals with influence scores below 0.7. The top journal is *Review of Economics and Statistics* (Pindyck, 1979). *The Energy Journal* is nearest the mean with an influence score of 0.96.
- The authors of the average paper have been fairly highly cited for their other work. Though on average papers have 1.95 authors, 400 citing articles in the ISI database is still a respectable score. However, the median author has only 39 citing articles. A few star authors such as Robert Pindyck (4010 citing articles), Andrew Harvey (2838), and Cheng Hsiao (2647) significantly affect the mean.
- 96% of observations were estimated with data from the 1970s and 1980s (these dataset can also include data from the other two periods). 66% of datasets include data from before 1970, but only 30% include data from after 1990.

- 35% of the observations are from Canada. The U.S. is next most represented country (18%) and then other Europe (14%), which mostly consists of observations for Greece.
- 15% of the observations are for total elasticities.
- 15% of the observations are for explicitly long-run elasticities and 6% for explicitly short-run elasticities.
- 64% of the observations are for the translog function. Only 8% use the linear logit functional form and the remainder use other functions such as the Fourier, Cobb Douglas etc.
- Only 57% of the observations model technical change.

Weighted means of the cost shares are (with standard errors in parentheses):

Coal	0.151 (0.086)
Oil	0.183 (0.018)
Gas	0.102 (0.020)
Electricity	0.568 (0.048)

Table 3 presents estimates of the mean elasticity computed using different methods. Because not all studies use the four standard fuels none of the elasticities has been estimated using the full 353 observations. The oil-electricity elasticity can, however, be estimated from the vast majority of the papers with 344 observations. Coal-gas is based on the smallest sample, especially considering that neither the Bousquet and Ladoux (2007) (no coal) nor the Fisher-Vanden et al. (2004) (no gas) studies provide estimates for the coal-gas combination.

The simple unweighted means show moderate substitutability for coal and oil and coal and gas, and oil, which have elasticities just above unity, though not significantly for coal-gas. The remaining elasticities are all below unity though the oil-gas elasticity is not significantly so. All the combinations with electricity show an elasticity of substitution of close to 0.8. The sample size weighted means alter this picture to some degree and provide a first illustration of the effect of sample size on the value of the elasticities. All but one of the elasticities increases with the oil-gas elasticity increasing the most and all but one of the elasticities are now greater than unity though not all are significantly so. This shows that, in general, studies with larger sample sizes tend to find higher values of the elasticities, which is the reverse of the sample size – effect size relationship in the presence of publication bias proposed by Stanley (2005).

Figures 1 to 6 present funnel graphs for the six elasticities. On the whole they only show limited funnel-like form. Figure 1 shows a broad scatter with the point from the largest sample (Fisher-Vanden *et al*., 2004) near the centre of the distribution, but the estimates from the next largest sample (Ma *et al*., 2008) are much smaller. The left side of the distribution shows more funnel-like form (if any). Figure 2 also shows more of a funnel profile on the left-hand side. Figure 3 is more funnel-like than the first two graphs, but in the core of the data there appears to be a tendency towards large sample sizes having larger effect sizes, but the data point from the largest sample (Fisher-Vanden *et al*., 2004) is only 0.33. Figure 4 shows a pronounced positive correlation between sample and effect size once some extreme outliers from small sample studies are ignored. Figure 5 is quite funnel-like though the estimates from the large sample studies (Bousquet and Ladoux, 2007; Fisher-Vanden *et al*., 2004) cover quite a range of values. Figure 6 is somewhat similar to Figure 4.

To further investigate this relationship, I estimated weighted least squares regressions of the elasticities on the inverse of the square root of sample size – Stanley's (2005) "Funnel Asymmetry Test" or FAT. The results are reported in Table 4 and the intercepts are also included in Table 3. Looking first at the intercepts, the trend seen in moving from OLS to WLS continues with coal-electricity elasticity declining and the other elasticities increasing. Elasticities involving gas seem large and those involving electricity relatively small. Four of the equations show significant negative coefficients for $\text{SAMPLE}^{-0.5}$ indicating that larger samples have greater elasticities. The coal-oil equation has no sample size effect and the coal-electricity equation has a positive effect in line with the publication bias hypothesis.

To investigate these results further I decompose sample size into the time series dimension (T), the cross-section dimension (N), and the number of independent equations (E). The results of regressions using these three variables are reported in Table 5 with the intercepts included in Table 3. The intercepts change in varying directions. The two equations where the time series dimension has a positive sign have negative intercepts. Only the coal-gas and coal-electricity equations have negative signs for all three variables. This is surprising, as the sign of $SAMPLE^{-0.5}$ was positive in the FAT regression for coal-electricity. But only the time dimension is statistically significant. For coal-gas all three dimensions have significant and negative signs. In all but these two equations, $E^{-0.5}$ has a positive coefficient. This might be due to the models that report total elasticities requiring more equations [8] and that models with more fuels also have more equations.

These results are not as clear-cut as one might like but it is clear that the effect of sample size on the estimated elasticity is not primarily due either to the cross-sectional or time-series dimension. This casts doubt on the ideas mentioned in the introduction that either cross-sectional regressions have larger elasticities because they represent long-run elasticities or because substitution and technical change cannot be distinguished in a pure time series. Datasets with larger time dimensions also show some tendency towards larger elasticities. It seems more likely that there is a small-sample bias in estimating elasticities of substitution than that there is publication bias of the type proposed by Stanley (2005)

b. Metaregression Analysis

The mean elasticities for each type of elasticity are reported in Table 3. With the exception of the oil-gas and gas-electricity elasticities, the mean elasticities from the base-model are larger than the FES means. Compared to the simple FAT model three are smaller and three are larger. Their standard errors are much larger than either those for FES or FAT.

In four out of six cases, the dynamic long-run elasticity is larger than the dynamic short-run elasticity. But only in half the equations is it greater than the static elasticity. There is no clear pattern to the total elasticity,which should theoretically be smaller than the partial elasticity (the base case). As only 15% of the sample are observations for total elasticities capital stocks are not a variable entering the majority of these models. Therefore, we would not expect there to be a large difference in the short and long run elasticities. Only 15% of estimates are for a long-run elasticity and none of the large sample studies compute anything but static elasticities. It is

[8] Adding the variable TOTAL to these NTE regressions only changed the sign of $E^{-0.5}$ in one equation.

possible that the there is a clearer difference for the Morishima and/or cross-price elasticities but that these effects are averaged out in the computation of the shadow elasticity (see equation 5).

There is a clearer picture for the elasticities for different levels of aggregation. With the exception of only one equation in each case, the macro-level elasticity is smaller than the industry level elasticity (base case), the manufacturing elasticity is larger and the sub-industry level elasticity is larger still. This relationship is similar to that which I proposed for the capital-energy elasticity (Stern, 1997). In that case I argued that substituting capital for energy at the micro-level required additional energy use elsewhere in the economy to produce that capital, so that the net macro-level reduction in energy use was less than the micro-level reduction. It is possible that reduction in the use of a fuel at the micro level results in increased usage of that fuel elsewhere in the economy. This is obvious in the case of substituting electricity for fossil fuels, though most of the papers with macro-level estimates that include electricity exclude the fossil fuels used in the power generation sector.

Table 6 presents the full set of metaregression coefficient estimates and t-statistics.

Publication quality In this more complete model, $\text{SAMPLE}^{-0.5}$ has a uniformly negative effect though two of the coefficients are insignificantly less than zero. The influence score has mixed effects, some positive, some negative and some close to zero. There do not seem to be strong signs here of the type of publication bias proposed by Murtaugh (2002).

Data Variables GDP per capita has mixed but mostly negative effects on the elasticities so that more developed economies have less substitutability, *ceteris paribus*. This is opposite to the prediction of Klump and de la Granville for capital and labor. The country effects have no apparent pattern except that the Netherlands has uniformly smaller than average elasticities and Korea uniformly larger than average. Similarly, no time period has uniformly greater or lesser substitutability.

Specification Variables The linear logit elasticities are mostly much greater than average and greater than the translog or other function estimates. Not including technical change trends in the energy model has mixed results, though the largest coefficients in absolute value are negative.

Table 5 presents some diagnostic statistics for the metaregressions. Goodness of fit is measured by Buse's (1973) R-Squared. All the equations have reasonable fits and several very close fits. For all equations, the Breusch-Pagan test rejects homoskedasticity at the 5% level. A test of equality of residual variances across studies also rejects homoskedasticity in four of the equations. This remaining heteroskedasticity is dealt with by the use of robust coefficient covariance estimates. By contrast, the test of equality intercepts across studies only rejects the null hypothesis in one case. As mentioned above, random effects estimates were fairly close to OLS estimates of the full model and so given the results in Table 7, I do not believe there is a need to estimate a more complex model.

4. Conclusions and Suggestions for Further Research

This first meta-analysis of interfuel substitution elasticities is able to answer several questions while leaving others open for future research. With the exception of the gas-electricity elasticity it seems that the true values of interfuel elasticities of substitution are greater than unity at the level of the industrial sector as a whole with coal and gas being the most substitutable pair. This would be good news for the prospects for sustainability involving replacing the direct use of some fossil fuels with renewable or nuclear generated electricity. However, the elasticities tend to be smaller at higher levels of economic aggregation with the most substitutability at the subindustry level and the least at the macro-economic level. At the macro level all but one of the elasticities (coal-gas) are not significantly greater than unity and two or three are not significantly different to zero. But the number of observations for the macro-economy is small and the standard errors large on these elasticities. There is some indication that there is less substitutability in high-income countries than in low-income countries. There is a strong tendency for elasticities estimated with the linear logit model to be significantly greater than those estimated using other methods. But this does not tell us whether this functional form is more appropriate or not.

The other major result is the relationship we found between sample size and effect size. In the full model larger samples are associated with greater substitutability. This does not seem to be strongly related to either the time series or cross-section dimension of the sample alone. This suggests a simple bias towards low estimates in small samples. On the other hand, there is no sign of publication bias in the shadow elasticities of substitution.

The next step in this research would be to repeat this meta-analysis for cross-price (and own-price) and Morishima elasticities. Potential follow-on research could attempt to identify whether a genuine bias exists in small sample estimates. While I found an apparent small sample bias in estimation of the elasticity of substitution between fuels, Koetse *et al*. (2008) did not test for the effects of sample size and publication bias. Therefore, it would be worthwhile to carry out the tests developed in this paper on their dataset to see if similar results are found. An alternative approach is to carry out a Monte Carlo simulation along the lines of Stern (1994). We would use the elasticities estimated in a meta-analysis of cross-price elasticities to generate a large dataset of quantities of inputs corresponding to randomly generated prices and random disturbances. Samples of varying size could then be extracted from the data set and used to estimate the cross-price elasticities. Finally, we only have two studies of interfuel substitution for large data sets of more than one thousand observations, one for China and one for France, neither of which include all four standard fuels. There is, therefore, no large sample study for the gas-coal elasticity nor for any other regions. Either existing firm level data sets could be exploited or created.

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Table 1. Variables

Name of Variable	Description	Maximum	Minimum	Mean	Standard Deviation
Elasticities					
SESCO	Shadow elasticity of substitution between coal and oil	4.0729	-0.8860	1.1244	0.8690
SESCG	Shadow elasticity of substitution between coal and gas	5.9242	-4.7896	1.1078	1.4415
SESCE	Shadow elasticity of substitution between coal and electricity	7.2980	-4.2206	0.7896	1.2075
SESOG	Shadow elasticity of substitution between oil and gas	6.2534	-22.0155	0.9194	1.7797
SESOE	Shadow elasticity of substitution between oil and electricity	8.9219	-3.2646	0.7920	0.9125
SESGE	Shadow elasticity of substitution between gas and electricity	48.539	-10.4867	0.8375	3.1407
Publication Quality Variables					
SAMPLE	Primary study sample size	25490	20	379.38	2273.58
INFLUENCE	eigenfactor.com influence score in 2006	3.4527	0	1.2554	1.2688
AUTHOR	Lifetime citations received by authors minus citations to this article	4010	0	786.76	1205.36
Data Variables					
EARLY	Dummy for inclusion of pre-1970 data	1	0	0.6629	0.4734
MIDDLE	Dummy for inclusion of data from 1970s and 1980s	1	0	0.9603	0.1954
LATE	Dummy for inclusion of post-1989 data.	1	0	0.3031	0.4603
AUSTRALIA	Dummy for Australia	1	0	0.0397	0.1954
CANADA	Dummy for Canada	1	0	0.3513	0.4781
CHINA	Dummy for China	1	0	0.0198	0.1396
FRANCE	Dummy for France	1	0	0.0368	0.1886

Name of Variable	Description	Maximum	Minimum	Mean	Standard Deviation
GERMANY	Dummy for Germany	1	0	0.0312	0.1740
INDIA	Dummy for India	1	0	0.0255	0.1579
ITALY	Dummy for Italy	1	0	0.0368	0.1886
JAPAN	Dummy for Japan	1	0	0.0567	0.2315
KOREA	Dummy for Korea	1	0	0.0595	0.2369
NETHERLANDS	Dummy for Netherlands	1	0	0.0368	0.1886
UK	Dummy for UK	1	0	0.0425	0.2020
USA	Dummy for USA	1	0	0.1785	0.3835
OTHEREUR	Dummy for other Europe	1	0	0.1445	0.3521
OTHERASI	Dummy for other Asia	1	0	0.0227	0.1490
GDP	GDP per Capita in 2000 PPP Dollars	33429	821.48	14219.9	5244.6
TOTAL	Dummy for Total Elasticity	1	0	0.1501	0.3577
DYNAMICSR	Dummy for short-run elasticity in a dynamic model	1	0	0.0623	0.2421
DYNAMICLR	Dummy for long-run elasticity in a dynamic model	1	0	0.1501	0.3577
MANUF	Dummy for manufacturing	1	0	0.1870	0.3904
MACRO	Dummy for macroeconomy	1	0	0.0680	0.2521
SUBIND	Dummy for sub-industry in the manufacturing sector	1	0	0.4844	0.5005
Model Specification Variables					
LINLOG	Dummy for linear logit	1	0	0.0765	0.2662
TRANSLOG	Dummy for translog	1	0	0.6346	0.4822
OTHERFUNC	Dummy for other functional form	1	0	0.2889	0.4539
NOTECH-ENERGY	Dummy for no technological change in the energy submodel	1	0	0.4306	0.4959

Table 2. Studies Included in the Meta-Analysis

Paper	Country/Sector	Used?	Fuels	Cost Shares	Sample Size
Agostini *et al.* (1992)	OECD Europe: 4 Sectors	Only use industry estimates	3 fuels – oil, gas, coal	Shares based on average of European countries in Jones (1996)	20
Andrikopoulos et al. (1989)	Ontario: 7 industries	Use all estimates	Four standard fuels	AES / CPE ratio	63
Borges and Pereira (1992)	Portugal: Manufacturing	Use all estimates	3 fuels - electricity, oil, coal	AES / CPE ratio	20-80
Bousquet and Ladoux (2006).	France: Industry	Use estimates averaged over fuel patterns	3 fuels - Oil, gas, and electricity	Quadratic formula	25490
Buranakunaporn, and Oczkowski (2007)	Thailand: Manufacturing	Use all short-run estimates	5 fuels – three types of petroleum + coal and electricity	Quadratic formula	147
Cho *et al*. (2004)	Korea: Macro	Use all estimates	3 fuels – does not include natural gas	Quadratic formula	136-272
Christopoulos (2000)	Greece: Manufacturing	Use all estimates	3 fuels – electricity and two types of oil	Quadratic formula	42-84
Considine (1989)	U.S.A.: Industry	Only use estimates for total industrial sector	Four standard fuels	Use translog intercepts as cost shares	45
Duncan and Binswanger (1976)	Australia: 5 industries	Drop elasticities for “other fuels”	5 fuels – includes “other”	Given in paper	72
Eltony (2008)	Kuwait: Manufacturing	Use all estimates	3 fuels	Used quantity shares from the paper – given very low price of electricity in Kuwait this is reasonable	50-75

Paper	Country/Sector	Used?	Fuels	Cost Shares	Sample Size
Fisher-Vanden *et al*. (2004)	China:	Use all estimates	Three fuels – not including natural gas	Provided by author	23238
Floros and Vlachou (2005)	Greece: 18 industries	Use all estimates	3 fuels – electricity and 2 types of oil	Quadratic formula	34
Fuss (1977)	Canada: Manufacturing	Used all estimates	6 fuels – breaks oil and nat gas each into into 2 enduser products	Quadratic formula	200-400
Hall (1983)	G7 Economies: Industry	Included all estimates	Four standard fuels	Use shares from Jones, 1996	399
Halvorsen R. (1977)	U.S.: Manufacturing	Used all estimates	Four standard fuels	Derived from relation between total and partial elasticities for aggregate industry and using quadratic formula for subindustries	462
Hang and Tu (2007)	China: Macro	Included all estimates	Three fuels – not including natural gas	Used shares from Ma et al. (2008)	60
Harvey and Marshall (1991)	UK: Industry	Used “other industry” estimates	Four standard fuels	Use shares from Jones, 1996	180
Iqbal (1986)	Pakistan: Manufacturing	Included all interfuel estimates	Four standard fuels	AES / CPE ratio	66
Jones (1995)	U.S.A.: Industry	Used aggregate energy use only	Four standard fuels	Use shares from Jones (1996)	96
Jones (1996)	G7 Economies: Industry	Included all estimates	Four standard fuels	Given in paper	651

Paper	Country/Sector	Used?	Fuels	Cost Shares	Sample Size
Kim and Labys (1988)	Korea: 12 subsectors/sectors	Used estimates for total manufacturing, 4 manufacturing subsectors, and total economy	Coal, oil, and Electricity	Quadratic formula	42
Lakshmanan *et al*. (1984)	U.S.A. States: Manufacturing	Used all estimates	3 fuels – no coal	Use shares from Halvorsen (1977) as US average and used quadratic formula to get state shares	400-1000
Ma *et al*. (2008)	China: Macro	Used all estimates	4 fuels – but uses diesel instead of natural gas	Given in paper	930-1550
Magnus and Woodland (1987)	Netherlands: Manufacturing	Used all estimates	Four standard fuels	Given in paper for total manufacturing, used AES/CPE ratio for subindustries	54-324
Mahmud (2006)	Pakistan: Manufacturing	Used all estimates	3 fuels – electricity, gas, and oil	Quadratic formula	44
Morana (2000)	Italy: Macro	Included all estimates	Four standard fuels	AES / CPE ratio	192
Perkins (1994)	Japan: Macro	Included all estimates	5 fuels including 2 types of coal	Quadratic formula	96-432
Mountain and Hsiao (1989)	Ontario and Quebec: 15 industries	Included all estimates	3 fuels – no coal	Used shares from Mountain et al with some interpolation	36
Mountain et al. (1989)	Ontario: 11 industries	Included all estimates	3 fuels – no coal	Given in the paper and interpolated for missing years	46

Paper	Country/Sector	Used?	Fuels	Cost Shares	Sample Size
Murty (1986)	India: Manufacturing	Included all estimates	3 fuels – no gas	AES / CPE ratio	50-90
Pindyck (1979)	Ten OECD Economies: Industry	Included all estimates	Four standard fuels	Quadratic formula	84-376
Renou-Maissant (1999)	G7 Economies: Industry	Used all estimates	3 fuels – does not include coal	Quadratic formula with missing values from Jones (1996)	72-102
Serletis and Shahmoradi (2008)	U.S.A.: Macro	Used all estimates	3 fuels – does not include electricity	AES / CPE ratio	70
Shin (1981)	Korea: Macro	Used all estimates	3 fuels – does not include gas	Given in paper	28
Taheri (1994)	U.S.A.: 11 Industries Panel	Used all estimates	5 fuels – two types of oil	Quadratic formula	308
Taheri. and Stevenson (2002)	U.S.A. 10 Industries Panel	Used all estimates	5 fuels – two types of oil	Quadratic formula	440
Truong (1985)	NSW: Industry	Dropped "other fuels" elasticities	5 fuels – 4 standard and "other"	Used conditional marginal shares in the paper	52-91
Turnovsky et al. (1982)	Australia: Manufacturing	Included all estimates	Four standard fuels	Quadratic formula	87-174
Urga (1999)	U.S.A.: Industry	Included all estimates	Four standard fuels	AES / CPE ratio	128
Urga and Walters (2003)	U.S.A.: Industry	Included all estimates	Four standard fuels	AES / CPE ratio	54-96
Uri (1979)	India: Industry	Use mining and manufacturing and total estimates	3 fuels – electricity, oil, coal	Use translog intercepts as cost shares	120
Uri (1979)	UK: Macro	Included all estimates	Four standard fuels	Given in paper	51
Uri (1982)	U.K.: Industry	Included all estimates	Four standard fuels	Given in paper	96

Paper	Country/Sector	Used?	Fuels	Cost Shares	Sample Size
Vlachou and Samouilidis (1986)	Greece: Industry	Use Industry Total Only	3 fuels – electricity solid and liquid	Given in paper	42
Westoby (1984)	UK: Industry (also domestic sector)	Use industry estimates	5 fuels – also includes coke	Quadratic formula	88

Table 3. Mean Elasticities

Elasticity	σ_{CO}	σ_{CG}	σ_{CE}	σ_{OG}	σ_{OE}	σ_{GE}
Number of Observations	176	125	173	257	344	257
Unweighted Mean	1.124 (0.065)	1.108 (0.128)	0.790 (0.092)	0.919 (0.111)	0.792 (0.049)	0.837 (0.196)
FES Weighted Mean	1.236 (0.096)	1.422 (0.136)	0.649 (0.121)	2.021 (0.205)	1.043 (0.132)	1.095 (0.169)
FAT	1.237 (0.157)	2.046 (0.274)	0.504 (0.150)	2.557 (0.145)	1.156 (0.188)	1.296 (0.187)
NTE	1.426 (0.674)	4.396 (0.961)	1.264 (0.427)	1.531 (0.384)	-0.062 (0.351)	-0.396 (0.309)
Base Model Mean	1.401 (0.299)	1.903 (0.447)	1.276 (0.380)	1.579 (0.357)	1.342 (0.288)	0.481 (0.422)
Dynamic SR Elasticity	1.565 (0.286)	1.610 (0.393)	2.069 (0.383)	0.827 (0.422)	1.807 (0.668)	0.459 (0.382)
Dynamic LR Elasticity	1.978 (0.209)	1.617 (0.483)	1.448 (0.312)	1.288 (0.616)	1.500 (0.321)	1.052 (0.469)
Total Elasticity	1.281 (0.293)	1.788 (0.426)	1.326 (0.400)	1.588 (0.393)	1.565 (0.273)	0.677 (0.406)
Macro Elasticity	1.162 (0.442)	2.841 (0.627)	0.796 (0.584)	0.546 (0.761)	1.059 (0.352)	0.289 (0.730)
Manufacturing Elasticity	1.973 (0.313)	1.629 (0.377)	1.414 (0.358)	3.204 (0.296)	1.591 (0.155)	1.283 (0.205)
Sub-industry Elasticity	2.161 (0.441)	2.651 (0.948)	1.478 (0.525)	1.606 (1.507)	1.775 (0.326)	3.481 (2.377)

C = Coal, O = Oil, G = Natural Gas, E = Electricity
Standard errors (computed using ROBUSTERRORS in RATS) in parentheses

Table 4. FAT Regression Results

Elasticity	σ_{CO}	σ_{CG}	σ_{CE}	σ_{OG}	σ_{OE}	σ_{GE}
Constant	1.237 (0.157)	2.046 (0.274)	0.504 (0.150)	2.557 (0.145)	1.156 (0.188)	1.296 (0.187)
$SAMPLE^{-0.5}$	-0.028 (1.958)	-10.743 (3.214)	3.723 (2.240)	-16.06 (1.963)	-3.526 (2.057)	-5.997 (2.925)
Buse R-Squared	0.5846	0.5118	0.3402	0.6156	0.0689	0.1493

C = Coal, O = Oil, G = Natural Gas, E = Electricity
Standard errors (computed using ROBUSTERRORS in RATS) in parentheses

Table 5. NTE Regression Results

Elasticity	σ_{CO}	σ_{CG}	σ_{CE}	σ_{OG}	σ_{OE}	σ_{GE}
Constant	1.426 (0.674)	4.396 (3.214)	1.264 (0.427)	1.531 (0.385)	-0.062 (0.351)	-0.396 (0.309)
$E^{-0.5}$	0.568 (0.707)	-3.492 (1.392)	-0.323 (0.767)	1.922 (0.639)	1.480 (0.333)	0.763 (0.607)
$T^{-0.5}$	-1.025 (0.881)	-0.640 (0.322)	-1.040 (0.458)	-0.376 (0.438)	0.370 (0.361)	1.352 (0.398)
$N^{-0.5}$	-0.352 (0.380)	-1.938 (0.428)	-0.156 (0.245)	-2.014 (0.343)	-0.122 (0.318)	0.457 (0.522)
Buse R-Squared	0.6005	0.5640	0.3591	0.6323	0.2376	0.2059

C = Coal, O = Oil, G = Natural Gas, E = Electricity
Standard errors (computed using ROBUSTERRORS in RATS) in parentheses

Table 6. Meta-Regression Results

Dependent Variable	σ_{CO}	σ_{CG}	σ_{CE}	σ_{OG}	σ_{OE}	σ_{GE}
Constant	1.4010	1.9029	1.2761	1.5797	1.3420	0.4811
	(4.6871)	(4.2602)	(3.3559)	(4.4276)	(4.6574)	(1.1386)
$SAMPLE^{-0.5}$	-11.3975	-14.7997	-11.4880	-4.4162	-5.1919	-10.8991
	(-4.5935)	-(3.1216)	(-3.7606)	(-0.6809)	(-2.6815)	(-0.8846)
INFLUENCE	0.0882	0.5456	-0.2007	-0.1814	-0.0104	0.0714
	(1.3377)	(4.6897)	(-1.6794)	(-1.5521)	(-0.1867)	(0.3653)
TOTAL	-0.1195	-0.1145	0.0503	0.0080	0.2234	0.1964
	(-1.3087)	(-0.6690)	(0.3606)	(0.0668)	(2.7116)	(1.5672)
DYNAMICSR	0.1643	-0.2931	0.7926	-0.7522	0.4646	-0.0214
	(0.6847)	(-1.1357)	(2.5864)	(-2.0668)	(0.9786)	(-0.0410)
DYNAMICLR	0.5766	-0.7354	0.1714	-0.2922	0.1589	0.5708
	(2.6753)	(-2.9086)	(0.5554)	(-0.6677)	(0.9331)	(0.7410)
MACRO	-0.2385	0.9384	-0.4803	-1.0337	-0.2830	-0.1917
	(-1.0080)	(2.6211)	(-1.3956)	(-1.7300)	(-1.5327)	(-0.2155)
MANUF	0.5716	-0.2734	0.1379	1.6245	0.2489	0.8016
	(2.7398)	(-1.7458)	(0.6748)	(5.7816)	(1.2304)	(2.8540)
SUBIND	0.7603	0.7486	0.2017	0.0268	0.4333	3.0001
	(2.6266)	(1.1785)	(0.5830)	(0.0189)	(2.0575)	(1.1018)
TRANSLOG	-0.4886	-0.4204	0.1701	-0.8043	-0.2357	0.4615
LINLOG	0.7019	0.2759	0.8654	0.6467	0.5672	-0.0572
	(5.0817)	(1.0139)	(3.4723)	(3.4271)	(4.4533)	(-0.2883)
OTHERFUNC	-0.2133	0.1445	-1.0355	0.1576	-0.3315	-0.4043
	(-1.4963)	(0.4375)	(-4.6302)	(0.4347)	(-2.6811)	(-0.6590)
NOTECHENERGY	0.2514	0.1873	-0.0970	0.1549	-0.5615	-0.5173
	(1.8556)	(1.0976)	(-0.4391)	(0.9111)	(-3.0917)	(-3.4474)

Dependent Variable	σ_{CO}	σ_{CG}	σ_{CE}	σ_{OG}	σ_{OE}	σ_{GE}
LGDP	-0.2793	1.9146	-0.5588	-0.3937	0.1134	-0.3459
	(-1.5575)	(1.7614)	(-2.5552)	(-1.5378)	(0.9189)	(-1.2792)
AUSTRALIA	0.8338	-0.5293	-0.5691	-1.9062	-0.6058	3.3390
	(3.3077)	(-0.9086)	(-1.3709)	(-1.2218)	(-2.8649)	(1.0961)
CHINA	0.2058	-3.5208	1.6118	4.3071	-0.1944	-3.1177
	(0.5469)	(-1.1367)	(2.9874)	(0.9565)	(-0.6848)	(-0.7288)
INDIA	0.0380		-0.0736		2.1501	
	(0.0969)		(-0.1740)		(5.8109)	
JAPAN	-0.2639	0.3701	-0.3731	-0.1507	-0.2017	0.0628
	(-2.0773)	(1.3436)	(-1.9152)	(-0.9249)	(-1.5841)	(0.3366)
KOREA	0.5897		1.1145		0.2608	
	(2.7446)		(3.7326)		(1.3547)	
OTHERASI	-0.4946	3.3340	-1.2976	-2.1891	-1.1603	-0.3593
	(-0.9600)	(1.8622)	(-3.0363)	(-2.3773)	(-2.4091)	(-0.2811)
FRANCE	0.0325	0.1070	-0.0180	0.6594	0.2138	-0.1042
	(0.1886)	(0.6163)	(-0.1222)	(2.3818)	(1.8004)	(-0.2600)
GERMANY	-0.1142	0.6458	0.0220	-0.3541	-0.1801	-0.4822
	(-0.7331)	(1.2649)	(0.1367)	(-2.1553)	(-1.5665)	(-1.5766)
ITALY	-0.2798	0.0600	-0.1300	-0.1509	-0.1679	-0.1577
	(-3.1842)	(0.2995)	(-0.9890)	(-0.8054)	(-1.2585)	(-0.9232)
NETHERLANDS	-0.9122	-0.0138	-0.4781	-0.8705	-0.3414	-0.0836
UK	-0.0260	-0.0039	-0.1770	0.1179	-0.0136	0.3162
	(-0.1895)	(-0.0200)	(-1.0632)	(0.7204)	(-0.1280)	(1.5755)
OTHEREUR	-0.2378	0.8357	0.0696	0.7175	-0.1266	
	(-2.5243)	(0.6655)	(0.5685)	(0.3041)	(-1.1195)	

Dependent Variable	σ_{CO}	σ_{CG}	σ_{CE}	σ_{OG}	σ_{OE}	σ_{GE}
CANADA	0.0823	-0.2859	-0.1411	0.0119	0.2536	-0.3391
	(0.5419)	(-1.6700)	(-0.8496)	(0.0544)	(2.0640)	(-1.3816)
USA	0.5463	-0.9989	0.4397	-0.1924	0.1134	0.9258
	(3.7773)	(-3.2074)	(1.9865)	(-0.4900)	(1.0144)	(1.5367)
EARLY	-0.0371	1.0960	-0.0792	-0.1462	-0.4257	0.2621
MIDDLE	0.6216	-0.0017	1.3858	-0.4240	0.3859	-0.8597
	(3.0057)	(-0.0044)	(4.1753)	(-0.8378)	(1.3850)	(-0.9785)
LATE	-0.5845	-1.0943	-1.3066	0.5702	0.0398	0.5976
	(-3.6358)	(-3.1265)	(-4.5835)	(2.9229)	(0.2806)	(2.8202)

t-statistics are in parentheses below the coefficient values.

Table 7. Metaregression Diagnostics

	σ_{CO}	σ_{CG}	σ_{CE}	σ_{OG}	σ_{OE}	σ_{GE}
Buse R Squared	0.8932	0.8575	0.6050	0.7584	0.5574	0.3272
Breusch-Pagan Test for Remaining Heteroskedasticity	44.526	57.901	57.976	43.200	43.553	45.259
	(0.018)	(0.000)	(0.000)	(0.025)	(0.023)	(0.015)
Chi-Squared Test for equal variances across studies	47.508	41.329	76.696	66.612	100.979	72.310
	(0.332)	(0.587)	(0.002)	(0.015)	(0.000)	(0.005)
F-Test for equal means across studies	1.364	0.520	0.933	1.083	2.901	0.601
	(0.092)	(0.990)	(0.594)	(0.347)	(0.000)	(0.977)

p-values in parentheses

Figure 1: Coal-Oil Funnel Chart

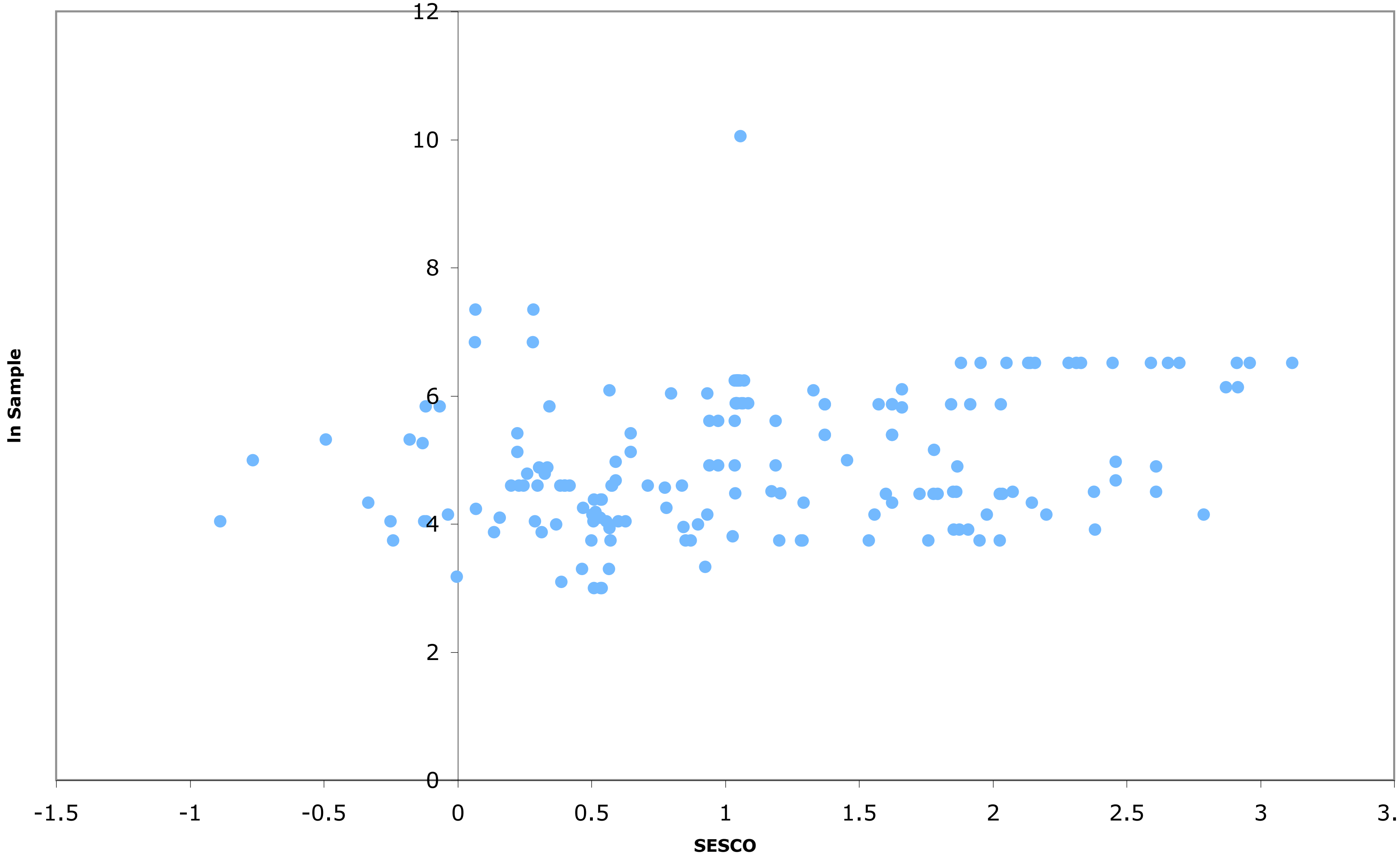

Figure 2: Coal-Gas Funnel Chart

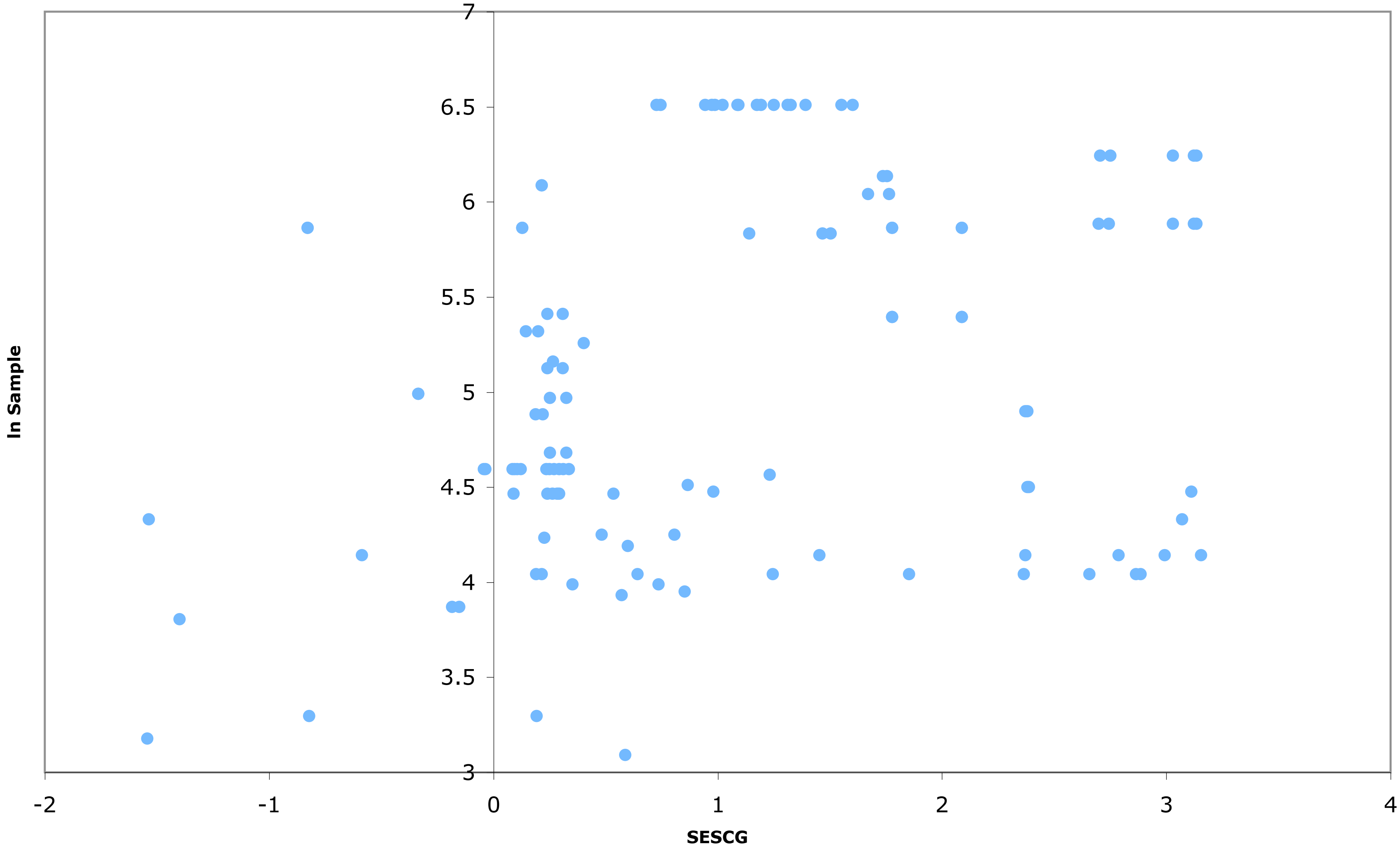

Figure 3: Coal-Elec Funnel Chart

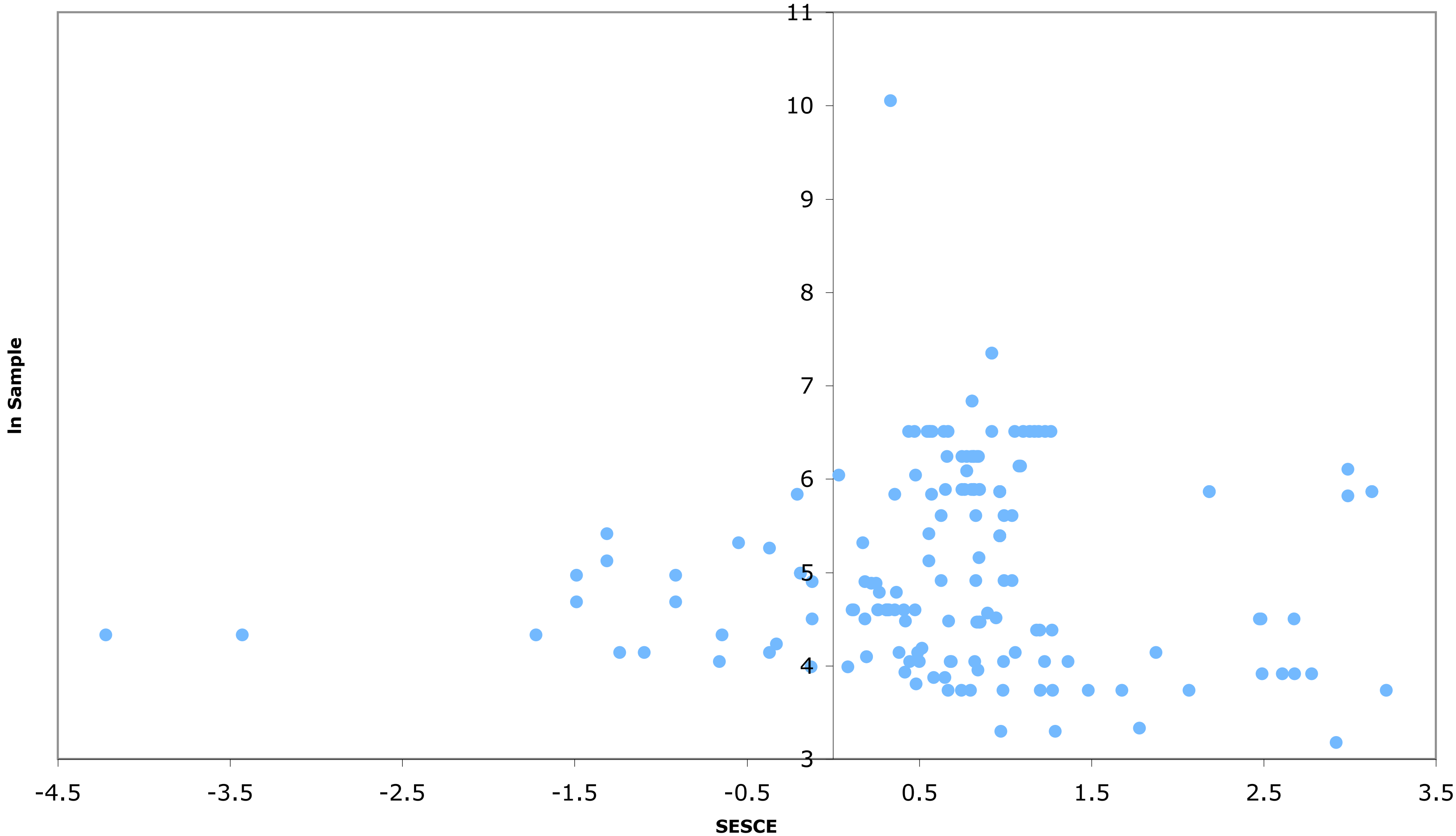

Figure 4: Oil-Gas Funnel Chart

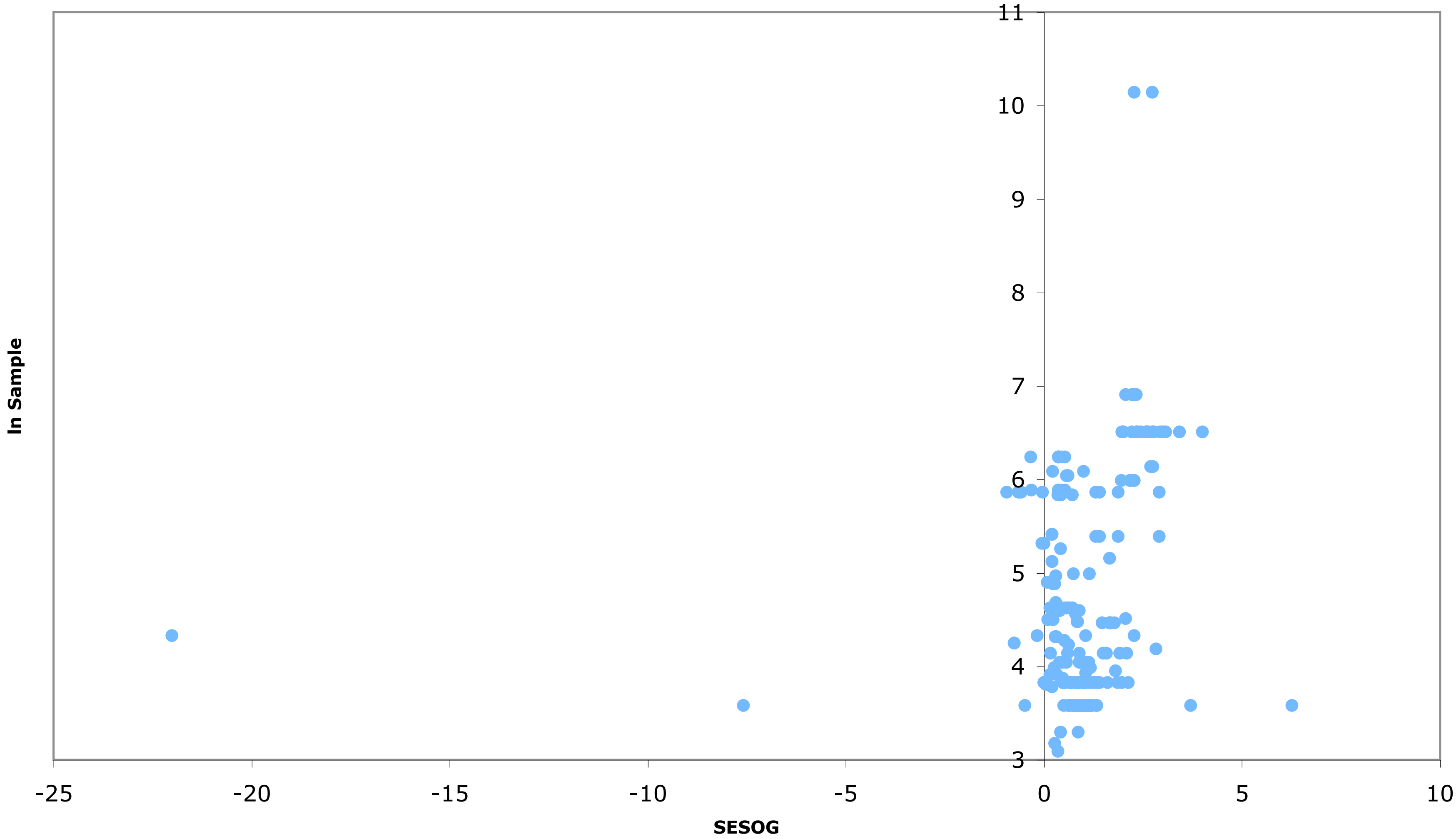

Figure 5: Oil-Elec Funnel Chart

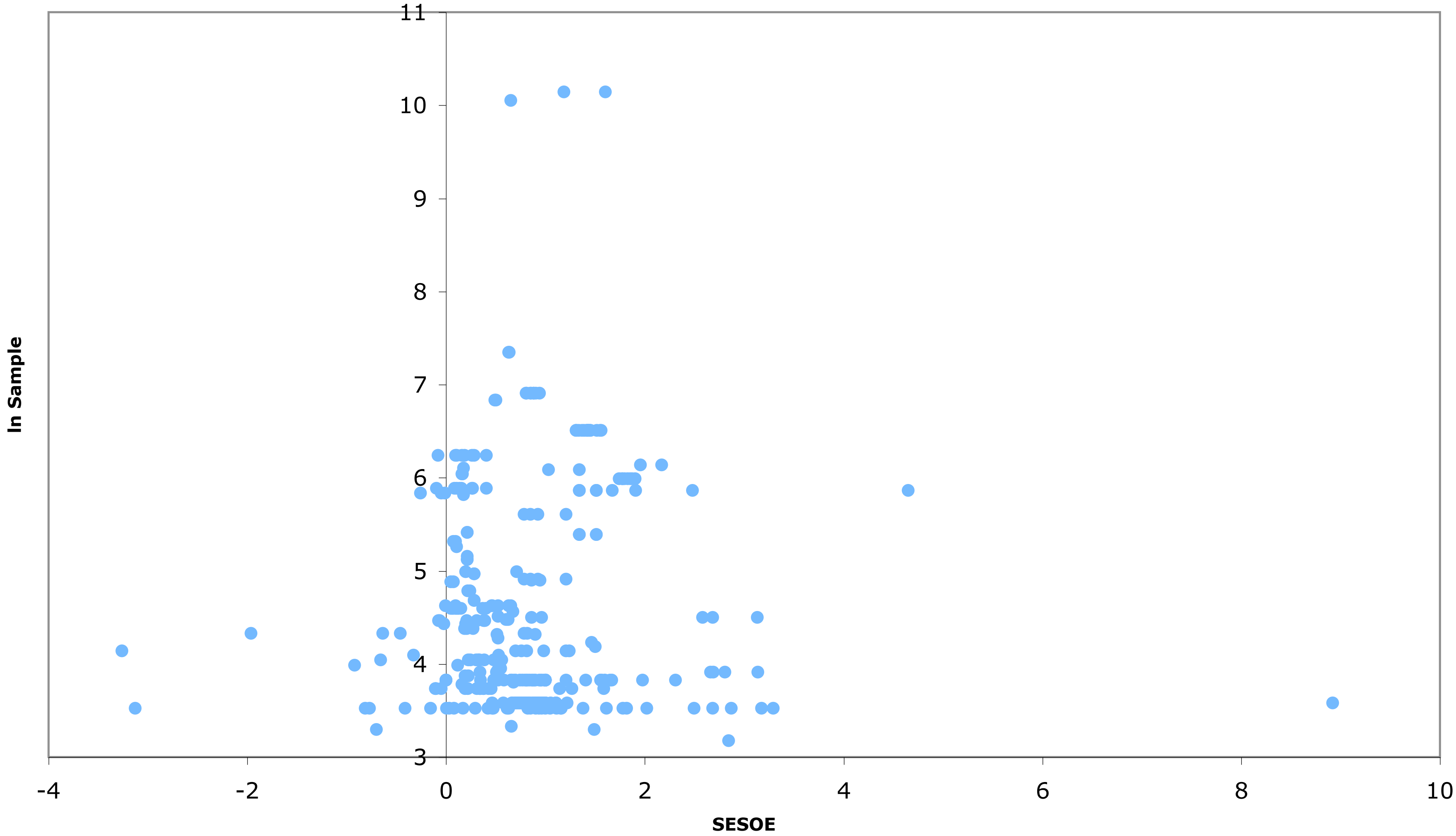

Figure 6: Gas-Elec Funnel Chart