

Interfuel Substitution in Electricity Generation Sector: A Meta-analysis

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1. Introduction

The environmental issues caused by fossil fuels are no doubt raising concerns in recent decades in the world, especially the developing countries. Sometimes the local governments in developing countries are willing to sacrifice the environment to gain more economic profits. Moreover, the lack of environmental laws in these countries make it possible for some companies to pollute the air with no cost.

The interfuel substitution stands for the elasticity of substitution among the fuel inputs in the industry sector. For instance, the elasticity of substitution between the coal and natural gas. If the interfuel elasticity of substitution is high (greater than 1) between a fossil fuel (e.g., coal) and a kind of clean energy (e.g., solar energy), which means the fuels can be substitutes, then the cost would be relatively low for policy makers or the factory owners to switch from fossil fuels to clean energy.

The interfuel substitution is also an issue in some developed countries. For example, in the US, the electric power sector accounted for 91% of all coal consumption and 29% of all natural gas consumption in 2008 (Gao, Nelson, and Zhang, 2013). Also, given the fact that the electricity generation industry was restructuring and regulation is moving from state to regional and national levels, Gao, Nelson, and Zhang (2013) thought it was essential to estimate the fuel and factor use accurately before any policies were to be made.

The governments and researchers around the world have sought to set policies which could restrain carbon emissions or steer economies toward or away from certain fuels (Serletis, Timilsina, and Vasetsky, 2010). For example, in Canada, Jadidzadeh and Serletis (2016) made some progress and found strong substitutability between light fuel oil and natural gas in residential, commercial, and industrial sectors. How the regional emission trading scheme affects

the fuel choice and consumption in electricity generation has been an interest of research (Linden, Makela, and Uusivuori, 2013). The flexibility that fuel switching could take place within existing power plants (Pettersson, Söderholm, and Lundmark, 2012) also makes the power sector a major target for policy makers.

Following the paper on interfuel substitution by Stern (2012), I would like to continue under the same topic and explore further. Stern (2012) is stated to be the first meta-analysis in the literature discussing the interfuel substitutability. It covered the industrial sector, the manufacturing industry or sub-industries and the macro-economy in both developed and developing countries. However, the electricity generation industry was not included. In this paper, I am going to look into interfuel substitution in electricity generation industry based on the same method – meta-analysis. For this paper, I also limit the fuels used to three standard fuels: coal, gas, and oil like Stern did.¹ I constructed my own database for the meta-regression and analysis. Through the research process, I went through lots of literature discussing the interfuel substitution in various sectors (electricity generation, industrial, residential, etc.) and came to get a basic idea of the trends of the substitutability of fuel in recent decades in both developed and developing countries. Based on the database I constructed and the estimation results, I can observe a possible barrier in the process of fuel transition (from fossil fuels to clean energy). The coal is still the dominant fuel in the power sector. In terms of simple mean elasticities, the substitutability between coal and gas is moderate, while the coal-oil and oil-gas substitutability are more significant. However, for static time-series mean elasticities, the coal-gas demonstrates stronger substitutability than coal-oil and oil-gas. The panel (with fixed effects) estimate of elasticity for coal-oil is the biggest, for coal-gas is the smallest.

¹ Stern (2012) also included the electricity as one of the fuels, however, it does not apply to the case in this paper.

The remaining sections of this paper is divided into six sections. The second section is the literature review and the third section is the model explanation and data description. In the fourth section, I focus on the empirical results gained from the meta-regression. The last section is the discussion and conclusion.

2. Literature Review

Most of the previous studies on electricity generation focused on the elasticity of substitution among three standard fossil fuels: Coal, (natural) gas, and oil. The scale of the studies varied which may include a country, an economic region (e.g., Wesseh and Lin, 2016), and a separate electric power market/region in a country (e.g., Gao, Nelson, and Zhang, 2013).

According to Wesseh and Lin (2016), the nonrenewable energy promised greater benefits for the economic transition of Economic Community of West African States (ECOWAS), with estimated substitution elasticities ranging from 0.02 to 0.94. They also stated that a scaled and efficient electricity generation from fossil energy in the short run, with a gradual switch towards renewable power in the long-run, would be a sustainable policy solution for ECOWAS, whose power generation accounted for the vast majority of secondary energy.² The variables they used included real GDP, total renewable/nonrenewable electric power consumption, labor, and capital (active population and the state of technological progress). Wesseh and Lin (2016) employed a log linear translog production function as the estimation model. The substitution elasticities were

² A secondary energy source is one that is made using a primary resource. In this case, electricity is a secondary resource, and can be generated by coal, oil, natural gas, etc.

estimated to be positive and between 0.02 and 0.94 for all countries. The reason why their paper is not included in my database is because this paper focused on the general concepts of renewable and nonrenewable energy, for example, the capital-labor tradeoff, but did not go into details of different fuels.

Ko and Dahl (2001) looked into the interfuel substitution in US electricity generation. They used translog cost model in their analysis. The data they used was from the FERC Form 423, which collected monthly survey data on the cost and quality of fossil fuels delivered to electric generating plants in 1993 (nameplate capacity of 50 or more megawatts).³ Ko and Dahl (2001) stated that coal's own price elasticity tended to be inelastic whereas gas and oil had their own price elasticities in the elastic range. They also found that gas and coal were better substitutes with a less fettered gas market. Oil and gas also showed more responsiveness to coal prices than vice versa from the empirical results. Little evidence of substitution between oil and gas was seen but both were substitutes for coal in a utility that used three fuels. While in a two-fuel context each fuel was a substitute with the best substitutes being coal and oil, the worst substitutes being gas and oil.

Gao, Nelson, and Zhang (2013) estimated the interfuel substitution under static and dynamic scenarios in the electricity generation sector in eastern US. Their two-stage estimation revealed that the elasticity of substitution varied widely depending on the region, coal technology, capital and R&D activities. From their results, all the regions' own price elasticities for three fuels (coal, oil and gas) were negative except New York and Texas. Among these three fuels, oil had the largest magnitude of own price elasticities while coal had the smallest. However, the

³ The Form No. 423 is a compilation of data for cost and quality of fuels delivered to electric power plants to be used for determination of electric Rates from the Federal Energy Regulatory Commission (FERC).

complementarity was found between coal and oil (except New York and Texas), while substitutability was found both between oil and gas and between coal and gas (again except New York and Texas). The positive signs for New York and Texas were contrary to theory but were thought to be plausible because the coal consumption and coal cost shares were very low in these regions. They also pointed out the possible undesirable effects that can be caused by policies which were applied to regions with widely differing elasticities of substitution.

Similar to Gao, Nelson, and Zhang (2013), Elbakidze and Zaynutdinova (2016) estimated the substitution in the power generation sector at the state-level based on the EIA (Energy Information Administration) database from 2001 to 2014. They found that 2009 was the date of potential structural shift in most of the data series, which can be associated with the 2008 recession. Natural gas, coal, and oil were found to be substitutes of each other. However, the elasticity of substitution showed more limited substitutability between gas and coal and between gas and oil compared to Gao et al. (2013). Elbakidze and Zaynutdinova (2016) thought they highlighted the heterogeneity in the patterns of price elasticities and elasticities of substitution at the state level.

Söderholm (2001) focused on the interfuel substitution in west European power generation, as well as the impact of system load factors on fossil fuel choice. According to Söderholm (2001), the size of the capital stock was a vital determinant of the fuel cost shares. Again, a translog cost share model was used. This paper pooled time series data across six west European countries: Belgium, Ireland, Italy, Netherlands, Spain, and the United Kingdom. Söderholm (2001) concluded that the interfuel substitution in existing power plants was substantial, especially between oil and gas. Since he estimated the short-run interfuel substitution, the result was consistent with the notion that short-run fuel substitution took place in dual- or multi-fired

plants. His empirical results also indicated that system load factor was a notable determinant of fossil fuel choices in west Europe.

Shahiduzzaman and Alam (2013) investigated the possibilities of interfuel substitution in Australia. They examined the substitution for the aggregate economy, the manufacturing sector, as well as the electricity generation sector through the translog cost share model. Generally, weak-form substitutability was found between different energy types, while higher possibilities were indicated for substitution at lower levels of aggregation. For the electricity generation sector, which appeared to be the centre of the CO₂ emission problems, the significant but weak substitutability was found to be between coal and oil. Moreover, the substitution possibilities were even weaker between gas and coal (only when the price of coal changed). Shahiduzzaman and Alam (2013) concluded that a large increase in relative prices would be needed to stimulate the market for low-emission technologies.

Moxnes (1990) used a dynamic model to investigate the substitution in OECD-European power generation. One of the most important findings was that there was a bias toward choosing coal in 1970s in west Europe. Choosing a different model, Pettersson, Söderholm, and Lundmark (2012) analyzed the price-induced switching behavior between fossil fuels in the western European electricity generation sector. The analysis was conducted within a Generalized Leontief cost function using pooled data across eight countries from 1978 to 2004. Notable short-run interfuel substitution between oil and gas was found based on the empirical results, especially in countries where fossil fuels were used extensively for both base and peak load purposes. The fuel substitution was predicted to take place in dual- and multi-fired plants through switching load between different single-fuel fired plants and the conversion of power plants. They also stated that different public policies aiming to improve electricity market

liberalization had profound positive impacts on fossil fuel choices: short-term fuel switching made it possible for power generators to explore price differentials in fuel prices and then fuel suppliers may faced a ceiling on their fuel prices charged, as a consequence, the intention to exploit any market power became more limited.

Serletis, Timilsina, and Vasetsky (2010) estimated interfuel substitution elasticities in the selected developing and developed economies at the sector level. The result from their paper showed that the interfuel substitution elasticities were consistently below unity, which meant the limited ability to substitute between major energy commodities (coal, oil, gas, and electricity). What is more, industrial and residential sectors tended to exhibit higher potential for substitution between energy inputs on average compared to the electricity generation sector (except US). Also the developed economies had higher potential for interfuel substitution than emerging economies. They concluded that the structure of the economy, not the level of economic development, decided the interfuel substitution. Serletis, Timilsina, and Vasetsky (2010) also insisted that bigger changes in relative prices were expected when switching toward a lower carbon economy.

Xingang and Pingkuo (2013) looked into the interfuel substitution issue in China from another perspective. They investigated the use of biomass energy as a substitute energy source in industrial sectors in China. Based on the data from 1987 to 2009, they employed translog cost functions to conduct empirical analysis to get the substitution elasticities. Xingang and Pingkuo (2013) concluded that biomass was an effective substitute for traditional fossil fuels given the existence of positive cross-price elasticities between biomass and traditional fossil fuel. They also found that the trend of net substitution was enhancing with the reduction of biomass prices. Price-induced conservation was stated to promote the substitution between biomass and

traditional fossil fuel energy.

Bopp and Costello (1990) estimated the fossil fuel cost shares in the electricity generation sector in the US using two models: one national and one regional. Then they compared the different results from those two different translog cost models to get a better understanding of the underlying economics of fuel choice problem. Bopp and Costello (1990) found that the regional model provided more plausible elasticity estimates based on the 1977-1987 data. In addition, the base load fuel was found to be the most inelastic fuel in each region. Compared to the national model, the regional model performed as well as the national model in predicting coal cost shares and quantities but outperformed in the prediction of oil and gas shares and quantities.

According to the report produced by EIA (U.S. Energy Information Administration) in 2012, the patterns of dispatching power generation had changed noticeably over the past few years. It concluded that the volatile fossil fuel costs was the main contributor to the alteration of energy sources. EIA (2012) also updated earlier work on fuel substitution for the period 2005-2010. One of their findings was that the generators' use of petroleum was much more responsive to relative fuel price changes compared to coal and gas in the US. For instance, it stated that a 10-percent increase in the price ratio of gas to oil would lead to 19-percent increase in the relative use of oil compared with gas.

Tauchmann (2006) estimated interfuel substitution in the German electricity generation sector based on panel data from 1968 to 1998. He also looked into the investment decisions that determined the long-run fuel mix. He concluded that the fuel mix of electric utilities was price inelastic in Germany.

3. Methodology & Data

3.1 Model

Meta-regression is similar to simple regression, in which an outcome variable is predicted according to the values of one or more explanatory variables. Basically, the same approach as multiple regression analysis is used in conducting meta-regression except that the covariates are at the level of the study rather than the level of the subject. Moreover, meta-regression can be viewed as an extension to subgroup analyses that allows the effect of continuous, as well as categorical, characteristics to be investigated. It also in principle allows the effects of multiple factors to be investigated simultaneously.

In meta-regression, the outcome variable is the effect estimate, while the explanatory variables are characteristics of studies that might influence the size of intervention effect. Two approaches are primarily used in meta-regression: fixed-effects approach and random-effects approach. The “random effects” stands for the random study effect that is included to take into account the between-study variation. Detailed methods used in this paper will be discussed below.

3.2 Dependent Variables

According to Stern (2012), there are two types of elasticities of substitution:

1. Gross/Net elasticities: computed through holding output constant (net) or letting output vary

optimally (gross substitution);

2. Ratio elasticities (three sub-types: scalar/asymmetric/symmetric):

(1) scalar elasticities of substitution: measures the effect on the quantity of the factor demanded of a change in the price of another factor scaled by the cost share of that factor;

(2) asymmetric ratio elasticities: measures the effect on the factor input ratio of a change in a ratio of prices (the effect depends on which price in the ratio changes);

(3) symmetric ratio elasticities: imposing additional restrictions to made the asymmetric ratio elasticities symmetric.

Ratio elasticities measure the difficulty of substitution between inputs and consider the involvement of cost shares in the production function, and are always positive.

Since the shadow elasticities were stated to be good summary statistics of the overall degree of substitutability between inputs (Stern, 2012), this paper will also use the shadow elasticities in the model estimation.

For the relationship between those elasticities:

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

where X_i is the demand function for input i , p_i its price and S_i its predicted cost share. β_{ij} is the relevant second order parameter from the translog function, y is the output and \mathbf{p} is the vector of factor prices.

If the means of y and \mathbf{p} are unity (data are normalized), then we could get:

$$\eta_{ii}(\mathbf{1}, \mathbf{e}) = \frac{\beta_{ii} + \beta_i^2 - \beta_i}{\beta_i}, \quad \eta_{ij}(\mathbf{1}, \mathbf{e}) = \frac{\beta_{ij} + \beta_i \beta_j}{\beta_i}$$

where \mathbf{e} is a vector of ones and β_i is the relevant first-order parameter of the translog cost function. Then the Morishima elasticity of substitution (an asymmetric elasticity) for a change in

price i can be derived as:

$$\mu_{ij} = \frac{\partial \ln\left(\frac{x_j(y,p)}{x_i(y,p)}\right)}{\partial \ln\left(\frac{p_i}{p_j}\right)} \Big|_{p_j} = \eta_{ji} - \eta_{ii}$$

and the shadow elasticity of substitution is (Chambers, 1998):

$$\sigma_{ij} = \frac{\partial \ln\left(\frac{x_j(y,p)}{x_i(y,p)}\right)}{\partial \ln\left(\frac{p_i}{p_j}\right)} \Big|_c = \frac{s_i}{s_i+s_j} \mu_{ij} + \frac{s_j}{s_i+s_j} \mu_{ji}$$

where the cost c is held constant.

As the shadow elasticities can be viewed as good summary statistics of the substitution (as averages of Morishima elasticities), I would convert the various elasticities found in the literatures into shadow elasticities through the equations above and conduct a meta-analysis of the shadow elasticities. In the calculation process, since many literatures reported positive own-price elasticities (it is customary in economics to report price elasticities as positive, i.e., the absolute values), I inserted the negative sign in front of them before converting them into Morishima elasticities.

3.3 Explanatory Variables

For the explanatory variables, I included indicator dummy variables for which kind of data the study was based on: panel data and time series data.⁴ In the meta-regression, I treated static

⁴ One study in my database used a cross-section study, however, due to the limited number, the effect of cross-section versus other kinds of estimates may not be accurately estimated (Stern, 2012). I finally dropped it in the estimation in order to improve the robustness of the model.

time series estimates as the default and set dummy variables for studies using panel data.⁵ 24% of the studies in the database employed time-series data, while 76% of the studies included used panel data. I did not divided studies using panel data into two categories: panel data with FE (fixed effects in panel regression) and OLS panel data (like what Stern (2012) did), since almost all of the studies in my database used fixed effects panel regression model. It also indicates that the panel regression model with fixed effects is the main model used in interfuel substitution analysis inside the power industry. There is one thing in common with Stern (2012) – no studies use RE (panel data with random effects). I also set a dummy variable for explicitly long run elasticities in a dynamic model with a mean value of 0.364.

For the functional form, I treated the translog function as the default functional form and it dominated the studies in my database (91%) and set one dummy variable for the linear logit.

For different countries, I also control for them using dummy variables. The US was set as the default and individual dummies were assigned to other regions/countries including: West Europe, Northern Europe, selected developing countries (Turkey and Mexico), UK, selected Asian developed countries (Australia and Japan).

3.4 Publication bias & Choice of studies

For the publication bias, two types of them are mentioned in Stern (2012). One of them is the selection of results for statistical significance (researchers in substitution literatures may be not very concerned about the significance of the results). Another is the censoring of theoretically inconsistent values of the effects in equation, which means that positive own

⁵ For dummy variables, there is theoretically no big difference in choosing which variable as the default in the estimation. In this case, I also estimated the scenario when I set panel estimates as the default, the significance of the results does not change much.

elasticities are likely to be censored and it may lead the estimates of Morishima elasticities and shadow elasticities to be more positive than they should be (Stern, 2012). So, I will also introduce the inverse of the square root of sample size as a control for the publication bias.⁶

For the choice of studies, I developed my own database by searching relevant literature covering the time from 1980 to 2016 on interfuel substitution. The databases I searched include but not limited to: ScienceDirect, Routledge, Elsevier, ProQuest. I put my search focus in electricity generation sector. Only studies include estimates of cross-price elasticities or elasticities of substitution between coal, oil, and (natural) gas are selected.

4. Results

4.1 Exploratory meta-analysis

There are 33 observations from 12 primary studies in the original database. However, I removed one observation in the estimation due to relevance (that observation looked into the wood fuel). So, I finally used 32 observations from 11 primary studies in the meta-analysis. Weighted means of the cost shares are presented below (weights are the primary study sample size, standard errors in parentheses):

Weighted means of the cost shares

⁶ According to Begg and Berlin (1998), the publication bias would be proportional to the inverse of the square root of sample size. The inverse of the square root would also make the intercept in the regression estimate the value of the elasticity for a study with an infinite sample size.

Coal	0.554 (0.037)
Oil	0.150 (0.020)
Gas	0.318 (0.055)

One thing to notice here is that we only include three fuel types in the meta-analysis instead of four types as in Stern's (2012) since I only focus on the electricity generation sector. From the table above we can see that coal is the dominant fuel in the electricity generation sector of countries covered in the database with a percentage around 55%, while oil has the smallest share (15%).

Table 1 presents the summary statistics for the variables in the full sample. Shadow elasticity of substitution between oil and gas has the largest mean and maximum values among these three shadow elasticity variables. It indicates a potential stronger substitution relationship between oil and gas than oil-coal and gas-coal in the electricity generation industry. We can also conclude that the minimum values for all the shadow elasticities are positive, which are theoretically consistent. The minimum values in Stern's (2012) results, however, were negative.⁷ There were a range of studies covered in Stern (2012), which made it possible that negative estimates of elasticities appeared in some of the studies. Moreover, the median values of those shadow elasticities were much closer to positive values compared to negative values, which indicated that most of the estimates were positive in Stern's (2012) database. Returning to my paper, the average sample size is 84 with samples as large as 186 and as small as 6. Unlike Stern (2012), the data in electricity generation sector are dominated by panel estimates (76%). The data also demonstrates the uniqueness of the power generation industry. The time-series data is 24%

⁷ Minimum shadow elasticities ranged from -22.016 (oil-gas) to -0.886 (coal-oil) in Stern (2012).

in the database.

Regarding the regions covered, 58% of the observations are from the US. The next most represented country/region is West Europe (excluding UK) with 18%. In dynamic models, 36% of the observations are explicitly for long-run elasticities.

In the first part of Table 2, the mean elasticities are computed using different methods. The simple unweighted and weighted means of elasticities are presented in the first two rows. For the simple unweighted means, the substitutability between coal and oil and oil and gas are significant above unity with values of 1.429 and 2.273, while coal and gas has a moderate substitutability of 1.063. We can conclude that the elasticities involving coal are smaller. For the sample size weighted means, all of the three elasticities decrease. This indicates that studies with larger sample sizes tend to gain lower values of the elasticities.⁸ The substitutability between coal and gas decreases to 0.835 after weighting by the sample size. All estimates for mean elasticities are significant at 1% level. The effect-size relationship found here is contrary to Stern's (2012) finding that studies with larger sample sizes tend to find higher values of elasticities.

4.2 Meta-regression Analysis

The second part of the Table 2 reports the mean elasticities derived from the meta-regression model, data types and level of aggregation. The static time-series estimate is the intercept of the meta-regression model. Apart from the time-series elasticity, each of these elasticities is a linear combination of the estimated regression coefficients. For dynamic long run

⁸ This relationship is consistent with Stanley's (2005) sample size – effect size relationship given the existence of publication bias

elasticity, the right hand side is the time-series estimates and long run estimates. For FE estimates, the explanatory variables in the equation become time-series estimates and panel estimates with fixed effects. All the reported estimates in Table 2 are for the US.

The static time-series mean elasticities for coal-oil and coal-gas are significantly above unity with values of 2.278 (significant at 10% level) and 2.678 (significant at 1% level). The oil-gas elasticity of substitution is the lowest but still above unity with a value of 1.246 in time-series estimates. Each of the dynamic elasticities (long run) includes the time-series effect in addition to the effect of the long run dynamic dummy. All three long run dynamic elasticities are smaller than the static time-series estimates, and all are not statistically significant. This is probably due to the limited number of studies employing long run elasticity estimates in dynamic models. The panel (with fixed effects) estimates for both coal-oil and coal-gas elasticities are smaller than time-series estimates (coal-oil: 1.849, statistically significant at 5% level; coal-gas: 1.413, significant at 5% level), while the oil-gas elasticity sees a small increase.

Table 3 presents the full set of meta-regression coefficient estimates and t-statistics. The publication bias variable, $SAMPLE^{-0.5}$ has an insignificant effect. Although all three coefficients are positive, but none of them are statistically significant at reasonable levels. The effect of model form (linear logit or translog) is significant in this study since the linear logit elasticities are smaller than translog elasticities.

For the countries (regions) selected, West Europe (excluding UK), Northern Europe, selected developing countries (Mexico and Turkey), selected Asian developed countries (Australia and Japan), and UK all have less substitutability than the US. The largest average

difference in elasticity between countries in West Europe and the US is 0.9758 in coal-gas.⁹ The average differences in elasticity are smaller between Asian developed countries and the US (0.3956 in coal-oil, 0.0467 in coal-gas, and 1.4224 in oil-gas), as well as between Northern Europe and the US. However, limited number of observations for each region prevent this study from giving estimation with real precision.

Table 4 presents the diagnostic statistics for the meta-regressions. Goodness of fit is measured by the Buse's (1973) R-squared. More than half of the variance is explained by each regression (except for the coal-oil case, whose statistic is 0.4368). The results from all other three tests (heteroscedasticity, equal variances, and F-test) are significant at 5% level.

5. Conclusions

This paper presents the first meta-analysis of interfuel substitution elasticities in the electricity generation sector. The results indicate the potential costs of fuel switching are expected to be low in some developed countries (e.g., US), but may still be high in other less developed or developing countries in electricity generation sector. But we have to notice that the regional results are mostly statistically insignificant due to the small number of studies for each region. We are able to observe significant substitutability both between coal and oil and oil and gas, and a moderate level of substitutability between coal and (natural) gas. In terms of simple mean elasticities (both unweighted and sample weighted), the substitutability between coal and gas is moderate, while the coal-oil and oil-gas substitutability are more significant. For both static time-series and dynamic long run mean elasticities, the coal-gas demonstrates the strongest

⁹ The average differences in elasticity between countries in West Europe and the US are 0.4675 in coal-oil and 0.8629 in oil-gas.

substitutability while the oil-gas is the weakest.¹⁰ The panel (with fixed effects) estimate of elasticity for coal-oil is the biggest, and for coal-gas is the smallest. The results are probably good news for pollution control policies, but given the dominant level of coal fuel, there is still a lot of work to do.

For the countries/regions selected, West Europe (excluding UK), Northern Europe, selected developing countries (Mexico and Turkey), selected Asian developed countries (Australia and Japan), and the UK all have less substitutability than the US.

Further study could explore more on the firm level data sets and the relationship between firm level and nation level data. More observations in each region/country would be desired if more studies in electricity generation sector are available. What's more, combining this study with Stern (2012) to produce an interfuel estimation covering more industries could also be a choice.

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¹⁰ All three long run dynamic elasticities are not statistically significant.

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Appendix

Table 1: Summary Statistics

Variables	Description	Maximum	Minimum	Mean	Standard Deviation
SESCO	Shadow elasticity of substitution between coal and oil	5.551	0.009	1.429	1.414
SESCG	Shadow elasticity of substitution between coal and gas	3.954	0.041	1.063	1.057
SESOG	Shadow elasticity of substitution between oil and gas	10.896	0.026	2.273	2.834
SAMPLE	Primary study sample size	186	6	84.000	43.345
LINLOG	Dummy for linear	1	0	0.091	0.292

logit					
WESTEURO	Dummy for West Europe (excluding UK)	1	0	0.182	0.392
NOREURO	Dummy for Northern Europe	1	0	0.061	0.242
DEVEING	Dummy for selected developing countries (Mexico, Turkey)	1	0	0.061	0.242
UK	Dummy for UK	1	0	0.061	0.242
ASIADEVED	Dummy for selected developed countries in Asia	1	0	0.061	0.242
PANEL	Dummy for panel data	1	0	0.758	0.435
DYNAMICLR	Dummy for long run elasticity in a dynamic model	1	0	0.364	0.489

Table 2: Mean Elasticities

Elasticity	σ_{CO}	σ_{CG}	σ_{OG}
Number of observations	32	32	32
Unweighted Mean	1.429 (0.419)	1.063 (0.336)	2.273 (0.797)
Sample size weighted mean	1.169 (0.339)	0.835 (0.294)	1.813 (0.615)
Meta-regression analysis			
Static time-series	2.278 (1.371)	2.678 (1.008)	1.246 (1.970)
Dynamic LR elasticity	0.926	1.354	-0.137

	(1.346)	(0.946)	(2.056)
FE	1.849 (0.907)	1.413 (0.638)	1.713 (1.462)

C=coal, O=oil, G=natural gas; standard errors in parentheses

Table 3: Meta-Regression Results

Elasticity	σ_{CO}	σ_{CG}	σ_{OG}
Constant	2.2783 (1.6618)	2.6777 (2.6552)	1.2463 (0.6327)
SAMPLE ^{-0.5}	1.6747 (0.2098)	0.8667 (0.1347)	13.7923 (0.9358)
DYNAMICLR	-1.3520 (-2.4164)	-1.3239 (-5.1860)	-1.3837 (-3.5506)
LINLOG	-0.7656 (-1.6919)	-0.1035 (-0.3248)	-0.5640 (-1.4788)
WESTEURO	-0.4675 (-0.9359)	-0.9758 (-3.6100)	-0.8629 (-1.8091)

NOREURO	-0.4018 (-0.6939)	-0.8441 (-3.0432)	-0.6097 (-1.7367)
DEVEING	-0.4617 (-0.8139)	-0.0809 (-0.4590)	-1.0725 (-2.8685)
UK	-0.4980 (-1.1031)	-0.4155 (-1.0605)	-1.3527 (-3.4373)
ASIADEVED	-0.3956 (-0.5932)	-0.0467 (-0.2519)	-1.4224 (-3.7482)
PANEL	-0.4291 (-0.7059)	-1.2643 (-2.8055)	0.4670 (0.8471)

t-statistics are in parentheses below the coefficient values.

Table 4: Meta-Regression Diagnostics

Elasticity	σ_{CO}	σ_{CG}	σ_{OG}
Sample size	32	32	32
Buse's R-squared	0.4368	0.5903	0.7064
Breusch-Pagan test for remaining heteroscedasticity	35.519 (0.049)	43.730 (0.027)	33.631 (0.056)
Chi-squared test for equal variances across studies	49.509 (0.355)	65.647 (0.017)	65.472 (0.017)
F-test for equal means	1.012	3.507	1.547

across studies	(0.466)	(0.006)	(0.188)
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p-values in parentheses.