The Impact of Sectoral Aggregation on Elasticities of Substitution Using Translog Cost Function

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The Impact of Sectoral Aggregation on Elasticities of Substitution Using Translog Cost Function

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Abstract

Economic models are widely used to simulate policy scenarios, in which elasticities are used as measures of substitutability between production inputs. These models need appropriate levels of sector aggregation to produce policy-relevant results and to capture the variations of input substitutability among different sectors, while still adhering to the monotonicity and concavity requirements of aggregate production function. The purposes of this study are (i) to assess the cost (production) functions that fulfill these requirements appropriately, (ii) to analyze the impact of sector aggregation on the elasticities, and (iii) to determine the optimum resolution level for modelling cost function. This study utilized two databases to construct an industry-level panel dataset for 1995–2016, EU-KLEMS to obtain the price indices of the capital and labor inputs, and time-series monetary EXIOBASE v3.6, in both current and constant prices, to obtain the monetary inputs and price indices of intermediate inputs. Dynamic translog in GMM estimation is selected to derive the elasticities of substitution on different levels of sector aggregation since it performs better in reducing concavity violations, compared to pooled and fixed-effect estimation method. Selecting a higher resolution level is preferred to produce better model fittings, but it occasionally results in more concavity violations. Modelling cost functions at a more aggregated level leads to a larger estimate of the elasticity of substitution. The optimized level of sector aggregation for modelling cost function obtained in this study is at 86 industry sectors, capturing the different elasticities of substitution in various mining and manufacturing sectors of basic materials and electricity production.

Keywords: cost function, translog form, KLEMS, sectoral aggregation, macroeconomic model, econometrics, GMM estimation

1. Introduction

Computable General Equilibrium (CGE) or macroeconomic input-output (IO-) models are widely applied to simulate the economy-wide effects of transformations in production recipes (Gerlagh & Kuik, 2014; Wiebe & Lutz, 2016) as well as policy interventions, such as carbon tax (Caron et al., 2018; Kirchner et al., 2019). In order to produce sensible results to inform policy makers, these models need to be parametrized using empirical data that represents the production structure appropriately. The use of inappropriate estimates or arbitrary values of those parameters has resulted in skepticism in the usefulness of these models, especially from an econometric perspective (McKitrick, 1998; Antimiani et al., 2015).

A production function mathematically represents the relationship in a production process between the output and inputs, describing the maximum output from a definite set of inputs (Shephard, 1970; Coelli et al., 2005). Theoretically, the possibility of substitutional relationships comes from the aggregation of several rigid production functions for each individual process within the modelled industrial sector (Felipe & Fisher, 2003; Temple, 2006). Aggregate production function is often used to model substitutability of inputs, which can be characterized with elasticity measures (Felipe & McCombie, 2013).

Economists have been debating the conditions where neoclassical micro production functions can be aggregated into a neoclassical aggregate production function, also known as Cambridge capital controversies (Felipe & Adams, 2005). The post-Keynesian proponents concluded that conditions for aggregation are so stringent that a substantial model of the actual economy is not to be expected (Robinson, 1954; Fisher, 1971; Fisher & Monz, 1992). Meanwhile, the neoclassical defenders argued that those models remain heuristically important for the basis for empirical work that are tractable and policy-relevant (Solow, 1957; Cohen & Harcourt, 2003).

Due to this aggregation presumption, the estimated economic impacts for distinctive sectors simulated at different levels of sector disaggregation might be different, where a low degree could produce distorted assessment results (Alexeeva-Talebi et al., 2012; Caron, 2012; Brockmeier & Bektasoglu, 2014). As a result of the diverse selection of IO-tables in different resolution levels of sector aggregation, the selected level needs to be justifiable to answer research questions or provide the economic policy analysis appropriately instead of an ad hoc selection, in order to refrain from inappropriate models that violated substitutability assumption or inaccurate values of elasticities (Shumway & Davis, 2001).

Studies in modelling production functions to estimate elasticities have been conducted on a diverse level of industrial sectors and regions. Numerous studies modelled production functions specifically for manufacturing sectors at different levels of sector aggregation to study substitutability of capital and energy using CES functions (Kemfert, 1998; Okagawa & Ban, 2008; van der Werf, 2008) or translog cost functions (Adkins et al., 2003; Koetse et al., 2008; Fiorito & van den Bergh, 2016), while others observed regional aggregation using cross-country data to estimate production functions (Duffy & Papageorgiou, 2000; Evans et al., 2002). These studies are conducted at either the level of primary sectors or the highest resolution level; 56 sectors for WIOD (Timmer et al., 2015) and 65 sectors for GTAP (Corong et al., 2017). While assessment on the aggregation presumption is provided in these studies, there has been no studies that observe the changes in these results when aggregation level changes.

Optimizing aggregation level is also relevant for IO-tables in assessing environmental impacts (Tukker et al., 2009, 2018; Su et al., 2010). The sensitivity of environmentally-extended IO (EEIO-) tables to aggregation requires a proper evaluation of the aggregation level, since after a certain level it is more computationally efficient to apply a bottom-up Life-Cycle Assessment (LCA) approach rather than to build a more specific EEIO table (Majeau-Bettez et al., 2011).

In macroeconomic models, studies on the optimum level of sector aggregation in CGE or IO models to measure macroeconomic effects or environmental impacts are relatively abundant (Alexeeva-Talebi et al., 2012; Caron, 2012; Brockmeier & Bektasoglu, 2014). However, these studies are built on elasticities values in a more aggregated level, e.g. GTAP elasticities data (Dimaranan et al., 2006). Additionally, the production functions modelled to obtain these elasticities values are not evaluated on whether these functions adhere to the neoclassical assumptions, e.g. monotonicity and concavity of the functions (Coelli et al., 2005). Therefore, there is a research gap to obtain a set of elasticities of substitution at the optimum resolution level which is modelled from production functions that fulfill the neoclassical assumptions.

The purposes of this study are (i) to model the production function that represents the production relationship appropriately, which fulfills the neoclassical economic assumptions, (ii) to analyze how different levels of sector aggregation influence the empirically computed elasticities of substitution of production factors, and (iii) to determine an optimum resolution level of sector aggregation for modelling production function to capture the variations in substitution elasticity of different sectors, based on the monotonicity and concavity criteria (for optimality). In addition to obtaining the optimum resolution level, the information on elasticity values is valuable for economic modelers to apply a set of empirically-derived elasticities.

2. Review on Aggregate Production Functions and Elasticities of Substitution

Problems in aggregation raise due to two issues; first, the selection of macro (aggregate) or micro (firm-level) production functions to predict aggregate variables of production output (Pesaran et al., 1989), and second the aggregation bias due to deviation of macro parameters from the average of the corresponding micro parameters (Lee et al., 1990). Focus on the first part to investigate the proper aggregation methodology is important to ultimately answer the question of substitutability, which can only be satisfactorily settled when the aggregate

production functions are modelled at the adequately detailed level, since further aggregation will bias any measured elasticities (Solow, 1987; Nguyen & Streitwieser, 2008).

Pioneering studies on aggregation issues assessed that while disaggregation has certain benefits (Solow, 1987; Haller & Hyland, 2014), an aggregate production function may explain the aggregate data better than all micro equations combined since the aggregate production function would model different configurations of production recipes (with different production relationship) more appropriately (Grunfeld & Griliches, 1960; Wiedmann et al., 2007; Stern, 2011a). Production recipes are defined as the empirical composition of the inputs from other sectors required to produce various commodities in the economy (Lan et al., 2012).

It is argued that aggregate production function only persists because there have not been any proposed alternative replacements by the proponents, despite the concept being criticized at the fundamental level (Temple, 2006). Nevertheless, its adherence with neoclassical economics have made it largely used in modelling the economic impacts of market-based environmental policy instruments (Baumol & Oates, 1971; Kirchgassner & Schneider, 2018). Neoclassical models is argued to better simulate the effects of taxes and subsidies on the market, compared to the alternative schools of thought, e.g. New-Keynesian (Chari et al., 2009).

Initially, aggregation level was assessed by comparing the goodness-of-fit (R-squared) in production function models (Pesaran et al., 1989). Another study compared production functions from the micro-level data with those resulting from macro-level (aggregated) data using panel data from manufacturing plants (Biørn & Skjerpen, 2004). Regions could also be added as a panel data dimension (Wooldridge, 2010), aggregating regional production functions as a meta-production function (Hayami, 1969; Lau & Yotopoulos, 1989; Battese et al., 2004).

Testing autocorrelation in modelling aggregate production function is also considered important, to validate whether the functional form applied are appropriate (Berndt &

Christensen, 1973). It is demonstrated that parameters estimated with aggregate data might contain distributional biases and not capture the individual heterogeneity across panel data (Stoker, 1986). Failure to deal with the problem of autocorrelated error terms in modelling production functions is recognized as harmful to parameter estimates (Sinai & Stokes, 1972).

Four restrictive conditions to aggregate production functions formally according to neoclassical assumptions are listed below (Coelli et al., 2005; Hritonenko & Yatsenko, 2014).

1. Essentiality of inputs: If at least one production input (X_i) is zero, then the production output (Y) is also zero, since production is not possible without any of the inputs.

2. Positive returns (monotonicity):

$$f_i = \frac{\partial y}{\partial x_i} > 0 \tag{1}$$

   The production output increases if any production input increases.

3. Diminishing returns (downward-concavity):

$$f_{ij} = \frac{\partial^2 y}{\partial x_i \partial x_j} < 0 \tag{2}$$

   It is presumed that if only one input X_i increases and the other inputs X_j remain constant, then the efficiency of using the input X_i decreases.

4. Constant returns to scale:

$$f(lx) = l.f(x), l > 0 \tag{3}$$

   The function f(X) is linearly homogeneous, where the output increases linearly with respect to a proportional increase of all inputs.

Production functions are modelled in various functional forms to impose the conditions aforementioned (Griffin et al., 1987; Thompson, 1988). Four major functional forms are

Leontief (Leontief, 1967), Cobb-Douglas (Cobb & Douglas, 1928), Constant Elasticity of Substitution (CES) (Arrow et al., 1961), and translog (Christensen et al., 1973).

CES is often applied to obtain elasticity values because it fits better with the neoclassical theory of economic growth (Arrow et al., 1961). It also is capable to model varying degrees of substitution among commodities and among inputs, ranging from no substitution (Leontief model) to perfect substitution (linearity) (Sancho, 2009). However, the specification of the technical progress applied in econometric studies on CES function is often restrictive, thus making CES function not suitable for long term time-series data (Klump & Preissler, 2000).

In addition, despite the flexibility in modelling price changes (e.g. CGE models), estimating CES function is more difficult due to its non-linear nature (Kmenta, 1967). Due to the difficulty to model production function in CES form, translog function is more widely used since its functional form is more flexible, especially in modelling technical progress (Heathfield & Wibe, 1987). Technical change has been regarded as important in many studies, e.g. observing the impacts of technical innovations on capital and labor productivity (Marquetti, 2003), labor market inequality (Acemoglu, 2002), and changes on income shares (Acemoglu, 2003).

Cost functions are often applied rather than production functions in estimating production parameters since it uses prices as independent (exogenous) variables rather than factor quantities, which, at the firm or industry level, are endogenous (Berndt & Wood, 1975). Cost functions also minimize errors in estimating elasticities of substitution since the matrix of estimates of the production function coefficients does not have to be inverted to derive estimates of elasticities of substitution when a cost function is used (Binswanger, 1974; Kim & Heo, 2013). Ultimately, high multicollinearity among the input variables in production function modelling often causes problems. Since there is usually little multicollinearity among factor prices, this problem does not arise in cost function modelling (Fiorito & van den Bergh, 2016).

Several studies often test different functional forms to determine the most fitting functional form to model their data (Jones, 1995; Urga & Walters, 2003; Brännlund & Lundgren, 2004; Cho et al., 2004), since an inappropriate selection of functional form might impact the estimates of elasticities substantially (Considine, 1989; Roy et al., 2006).

Elasticities of substitution are often obtained from these production (cost) functions to simulate the substitutability between production factors (Besanko & Braeutigam, 2010). Several studies in modelling CES function (Kemfert, 1998; Okagawa & Ban, 2008; van der Werf, 2008), or translog function (Adkins et al., 2003; Roy et al., 2006; Koetse et al., 2008; Costantini & Paglialunga, 2014; Fiorito & van den Bergh, 2016) have also included the estimation of substitution elasticities. Most frequently used measures are Own- and Cross-Price Elasticities (CPE), Allen (AES), and Morishima Elasticities of Substitution (MES). Both CPE and AES measure the impact on the change in input (quantity) due to change in price, while MES measures the impact on the change in the input ratio (Stern, 2011b). CPE is often preferred as the measure of substitution elasticities, since it is better in differentiating between substitution or complementary relationship (Sorrell, 2014), and is asymmetrical to which production factor changes in the relationship (Blackorby & Russell, 1989; Sorrell, 2014).

3. Data Sources and Methodology

Various databases have been developed to facilitate modelling of industry-level production functions across countries. The most commonly used one, EU-KLEMS includes measures of sectoral output and input, covering capital (K), labor (L), energy (E), material (M), and service (S) inputs, collected from 1970 to 2005 for EU-25, United States, and Japan in 34 industrial sectors (O'Mahony & Timmer, 2009), although measures for more recent years (2006-2015) are only available as aggregated intermediate inputs (van Ark & Jäger, 2017). Other studies extract the required information from a static IO-table with higher level of details such as

EXIOBASE v2 (Dombi, 2018), or from a time-series of IO-tables available at both current and constant prices such as WIOD (Pablo-Romero & Sánchez-Braza, 2015; Inklaar, 2016).

This study utilized two databases, EU-KLEMS, supply and use tables (SUTs) of monetary EXIOBASE v3.6, in both current and constant price. EU-KLEMS was used to obtain the price indices of the capital and labor inputs (value-added) required in aggregate industries (Stehrer et al., 2019), while monetary EXIOBASE is employed to obtain all the inputs (value-added and intermediate inputs) required. EXIOBASE 3 is selected as the primary database in this study as it covers time-series IO tables for 49 countries and regions during 1995 to 2016 for 163 sectors, providing a more detailed industrial classification than EU-KLEMS (Stadler et al., 2018). More studies have been utilizing time-series EXIOBASE 3 in both current and constant price, e.g. Structural Decomposition Analysis (SDA) of Swedish carbon footprint (Schmidt et al., 2018).

The large number of 163 sectors provides the possibility to observe the importance of aggregation level (de Koning et al., 2015) by aggregating those sectors into a set of broader sectors. Due to the constraint of the minimum number of observations, the highest resolution of sector aggregation in this study was set at 160 sectors. These sectors were aggregated into five different aggregation levels based on ISIC Rev. 3, illustrated in Figure 1.

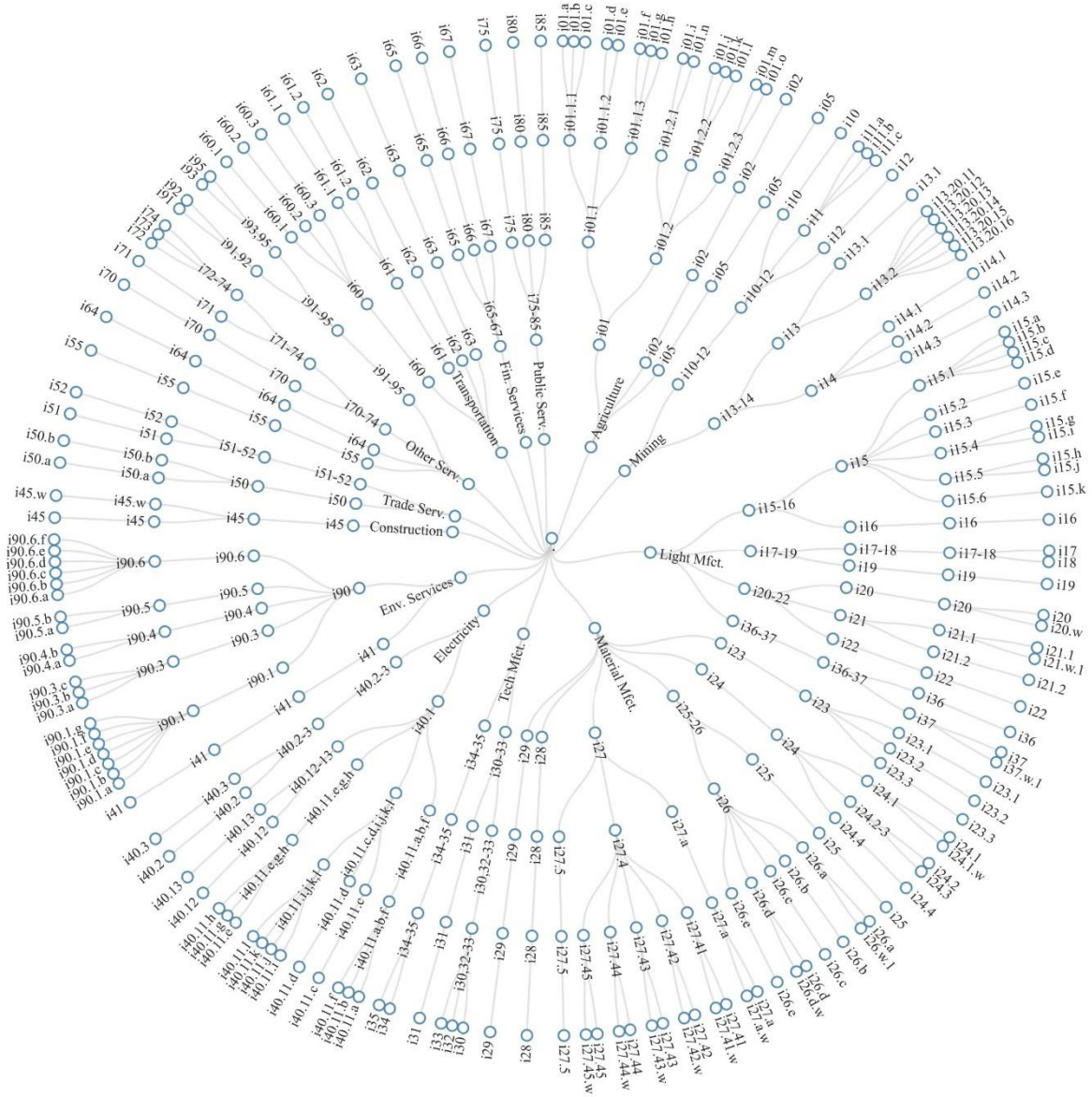

Figure 1 – The industrial sectors aggregated into five different aggregation levels, with 160, 96, 55, 35, and 13 sectors at each level, respectively.

3.1 Collecting Cost Function Parameters in Current and Constant Prices

Deflating supply and use tables (SUTs) at constant price is preferred since SUTs are able to facilitate the optimum balancing process for more consistent macroeconomic data (Nicolardi, 2013). SUTs in EXIOBASE are available in basic price, with matrices of trade margins and taxes provided to convert the values in use table from basic price to purchasers' price. Structure of SUTs and matrices of trade margins and taxes in EXIOBASE is illustrated in Figure 2.

a) Supply Table

Supply Table (EXIOBASE)	Ind. 1	Ind. 2	...	Ind. n
Product Supplied 1	$Sp_{1,1}$	$Sp_{1,2}$	...	$Sp_{1,n}$
Product Supplied 2	$Sp_{2,1}$	$Sp_{2,2}$	...	$Sp_{2,n}$
...	...	...	...	...
Product Supplied m	$Sp_{m,1}$	$Sp_{m,2}$	...	$Sp_{m,n}$
Industry Output	GO_1	GO_2	...	GO_n

b) Use Table

Use Table (EXIOBASE)	Ind. 1	Ind. 2	...	Ind. n	Final Demand
Product Consumed 1	$II_{1,1}$	$II_{1,2}$	...	$II_{1,n}$	FD_1
Product Consumed 2	$II_{2,1}$	$II_{2,2}$	...	$II_{2,n}$	FD_2
...	...	...	...	...	...
Product Consumed m	$II_{m,1}$	$II_{m,2}$	...	$II_{m,n}$	FD_m
Taxes Less Subsidies on Products	ToP_1	ToP_2		ToP_n	ToP_{FD}
Value Added	VA_1	VA_2	...	VA_n	
Industry Output	GO_1	GO_2	...	GO_n	

c) Matrix of Taxes on Products

Product Tax (EXIOBASE)	Ind. 1	Ind. 2	...	Ind. n	Final Demand
Product Consumed 1	$ToP_{1,1}$	$ToP_{1,2}$	...	$ToP_{1,n}$	$ToP_{1,FD}$
Product Consumed 2	$ToP_{2,1}$	$ToP_{2,2}$	...	$ToP_{2,n}$	$ToP_{2,FD}$
...	...	...	...	...	...
Product Consumed m	$ToP_{m,1}$	$ToP_{m,2}$	...	$ToP_{m,n}$	$ToP_{m,FD}$
Industry Output	ToP_1	ToP_2	...	ToP_n	ToP_{FD}

d) Matrix of Trade and Transport Margins

Margin (EXIOBASE)	Ind. 1	Ind. 2	...	Ind. n	Final Demand
Product Consumed 1	$TTM_{1,1}$	$TTM_{1,2}$	...	$TTM_{1,n}$	$TTM_{1,FD}$
Product Consumed 2	$TTM_{2,1}$	$TTM_{2,2}$	...	$TTM_{2,n}$	$TTM_{2,FD}$
...	...	...	...	...	...
Product Consumed m	$TTM_{m,1}$	$TTM_{m,2}$	...	$TTM_{m,n}$	$TTM_{m,FD}$
Industry Output	0	0	...	0	0

Figure 2 - Structure of SUTs and Matrices of Trade Margins and Taxes in EXIOBASE

Intermediate inputs in current price were converted from basic price into purchasers' price by adding the taxes and trade margins (Equation 4). Aggregate inputs (E, M, and S) were collected by summing all the intermediate inputs recorded in the use table based on the input classification (Equation 5). Capital and labor inputs in current price were collected from Consumption of Fixed Capital (CFC) and compensation of employees.

While many studies applied capital stock as a proxy for capital input, there are little effects between these inputs in the elasticity estimates (Doms, 1996). Gross outputs in current price were calculated by either summing all the intermediate inputs in purchasers' price and value added of each industry, or all products supplied by each industry (Equation 6).

$$II_{pp,i,j} = II_{bp,i,j} + ToP_{i,j} + TTM_{i,j} \tag{4}$$

$$(i = 1, 2, 3, \dots, \mathrm{m};\ j = 1, 2, 3, \dots, n)$$

$$I_j = \sum_{iI} II_{pp,i,j} \quad I \in \{E, M, S\} \tag{5}$$

$$GO_j = \sum_i II_{pp,i,j} + VA_j = \sum_i Sp_{i,j} \tag{6}$$

While EXIOBASE datasets in constant price are not readily available, Producer Price Indices (PPIs) are available to deflate national SUTs (Södersten et al., 2018). Using double deflation approach in deflating SUTs provides a closer balance than deflating the MRIO table directly (Lan et al., 2016). Double deflation approach measures the deflated value added is calculated as the difference between the deflated gross output and the deflated intermediate inputs. However, this approach might lead to negative value added values when changes in IO structure or relative price changes are too large (Dietzenbacher & Hoen, 1999). Following the former approach (Lan et al., 2016), we applied the double deflation approach without a strict balancing procedure (e.g. RAS method). While other deflating methods have been developed, e.g. heuristic approach (Dietzenbacher & Hoen, 1998), this method needs value added and gross output data in constant price, which data is unavailable at a higher resolution level.

Intermediate inputs in constant price were obtained by dividing the intermediate inputs in current price by the price indices (Equation 7). Although the price indices available are PPIs, this approach was chosen since numerous intermediate inputs that are present in more recent year were not present in the initial year, which made a more accurate calculation by considering changes in the tax or margin ratio more difficult. This difference might happen due to product recipe changes or balancing problem at a higher resolution level in the EXIOBASE SUTs.

$$II_{C,i,j} = \frac{II_{pp,i,j}}{PI_i} \tag{7}$$

Aggregate inputs (E, M, and S) in constant price were collected by summing all the previously calculated intermediate inputs in constant price based on the input classification (Equation 8). Gross outputs in constant price were calculated by summing all products supplied by each industry from supply table, divided by their corresponding price indices (Equation 9). Capital and labor inputs in constant price were calculated by dividing the inputs in current price by their corresponding price indices, collected from EU-KLEMS dataset (Equation 10). Since these

indices are only available at lower resolution level, the capital and labor price indices of the industries belonging to the same industrial classification will have identical values. The price indices for each production input are illustrated in Figure 3.

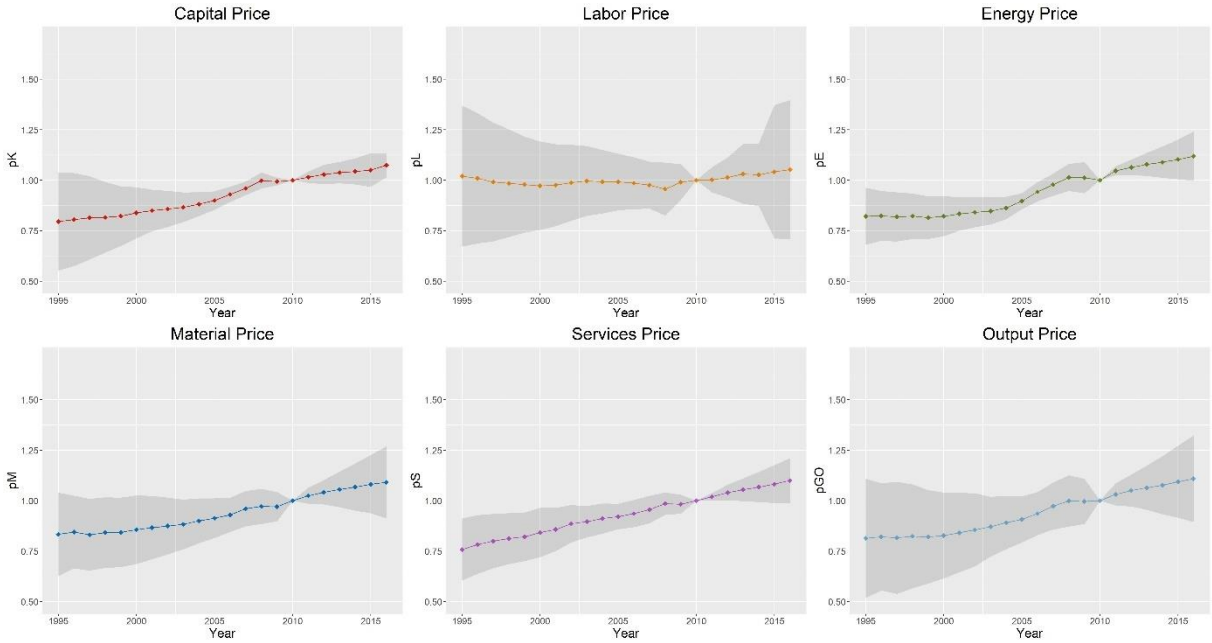

Figure 3 – Price indices of production inputs and output obtained from time-series EXIOBASE at the 4D level. The shaded area depicts the standard deviation of the indices.

$$I_{C,j} = \sum_{I} II_{C,i,j} \quad I \in \{E, M, S\} \tag{8}$$

$$GO_{C,j} = \sum_{i} \frac{Sp_{i,j}}{P_{I,i}} \tag{9}$$

$$K_{C,i,j} = \frac{K_{i,j}}{P_{K,j}} \quad L_{C,i,j} = \frac{L_{i,j}}{P_{L,j}} \tag{10}$$

3.2 Modelling Cost Functions and Estimating Elasticities of Substitution

Translog form is chosen due to its flexible functional form and easiness to model more than two inputs and technical change effectively, compared to CES (Stern, 1997), which general formulae are expressed in Equations 11-12 (Binswanger, 1974; Berndt, 1991). The variables used in these equations are enlisted in Table 1. Price indices are defined as the normalized average of price for a given aggregation of products in a specific region, for a specific interval

of time (year). This study applied simultaneous system of equations using Shephard's lemma, which has been particularly useful in imposing constant returns to scale.

$$S_{it} = \beta_i + \beta_{iy} \ln Y_t + \sum_j \beta_{ij} \ln p_{jt} + \beta_{it} t + u_{it} \tag{11}$$

$$\beta_{ij} = \beta_{ji}, \qquad \sum_i \beta_i = 1, \qquad \sum_i \beta_{ij} = \sum_j \beta_{ij} = \sum_i \beta_{iy} = \sum_i \beta_{it} = 0 \tag{12}$$

$$i, j \in \{\mathrm{K, L, E, M, S}\}$$

Table 1 – List of variables used in modelling translog cost function

Variable	Short	Definition
Gross Output	Y	Gross Output in current price (Million Euro)
Capital Price	P_K	Price index of consumption of fixed capital
Labor Price	P_L	Price index of compensation of employees
Energy Price	P_E	Price index of energy input
Material Price	P_M	Price index of material input
Services Price	P_S	Price index of services input
Total Cost	C	Total input cost in current price (Million Euro)
Capital Share	S_K	Share of capital input in total cost
Labor Share	S_L	Share of labor input in total cost
Energy Share	S_E	Share of energy input in total cost
Material Share	S_M	Share of material input in total cost
Services Share	S_S	Share of services input in total cost
Year	T	Year index, starting at 1995

The price variables are being normalized with the services price to reduce the number of equations being modelled into four and to relax the restrictions in Equation (12) (Antonioli & Filippini, 2002). While several studies applied the fixed-effect model (Roy et al., 2006), others applied the dynamic translog model to reduce the violations of concavity, where the estimated own-price elasticities are positive (Urga & Walters, 2003; Brännlund & Lundgren, 2004; Cho et al., 2004). In this study, three types of translog form are tested in the highest resolution level of aggregation to avoid functional form misspecification, i.e. functional form that violates the neoclassical assumptions or fails the autocorrelation test, prior to calculating the elasticities of

substitution. They are pooled translog (Equation 13), fixed-effect translog (Equation 14), and dynamic translog model (Equation 15-16).

$$S_{it} = \beta_i + \beta_{iy} \ln Y_t + \sum_j \beta_{ij} \ln \frac{p_{jt}}{p_{St}} + \beta_{it} T + u_{it} \tag{13}$$

$$S_{it} = \beta_{i,C} + \beta_{iy} \ln Y_t + \sum_j \beta_{ij} \ln \frac{p_{jt}}{p_{St}} + \beta_{it} T + u_{it} \tag{14}$$

$$S_{it} = \beta_i^* + \beta_{iy}^* \ln Y_t + \sum_j \beta_{ij}^* \ln \frac{p_{jt}}{p_{St}} + \beta_{it}^* T + \lambda S_{it-1} + u_{it} \tag{15}$$

$$\beta_i^* = \beta_i(1-\lambda), \quad \beta_{iy}^* = \beta_{iy}(1-\lambda), \quad \beta_{ij}^* = \beta_{ij}(1-\lambda), \quad \beta_{it}^* = \beta_{it}(1-\lambda) \tag{16}$$

$$i, j \in \{\mathrm{K}, \mathrm{L}, \mathrm{E}, \mathrm{M}\}$$

The pooled and fixed-effect translog models are modelled in Seemingly Unrelated Regression (SUR) (Urga & Walters, 2003), while the dynamic translog model is modelled in Generalized Method of Moments (GMM) (Pablo-Romero et al., 2019). Fixed-effect model includes the country intercept dummies in the model ($\beta_{i,C}$), to take into account the country effect on the cost share (Griffin & Gregory, 1976). Meanwhile, GMM is specifically applied in the dynamic translog model to avoid endogeneity, due to the introduction of share variables in period t-1 (S_{t-1}) in the equation systems. Since the share in period t (S_t) is dependent of S_{t-1}, St will also then be influenced by the output and the prices in the preceding period (Y_{t-1} and p_{t-1}). Therefore, these variables are used as the instrumental variables in the GMM, considering that the output and prices are endogenous (Pablo-Romero et al., 2019).

The descriptive statistics of these variables are available in Table 2. Compared to WIOD dataset (Koesler & Schymura, 2015), the gross output is lower in this study due to the higher resolution in EXIOBASE. The cost share of each production input for each industrial sector at the original resolution level of EXIOBASE is provided in Figure 4.

Table 2 – Descriptive statistics of translog cost function variables, collected from 160 industries and 23 countries

Variable	Short	Mean	Standard Deviation
Gross Output	Y	17,641	91,399
Capital Price	P_K	0.946	0.135
Labor Price	P_L	1.000	0.265
Energy Price	P_E	0.958	0.142
Material Price	P_M	0.956	0.157
Services Price	P_S	0.947	0.142
Total Cost	C	15,311	81,108
Capital Share	S_K	0.118	0.127
Labor Share	S_L	0.227	0.171
Energy Share	S_E	0.066	0.125
Material Share	S_M	0.238	0.208
Services Share	S_S	0.351	0.203
Number of Observations			58,946

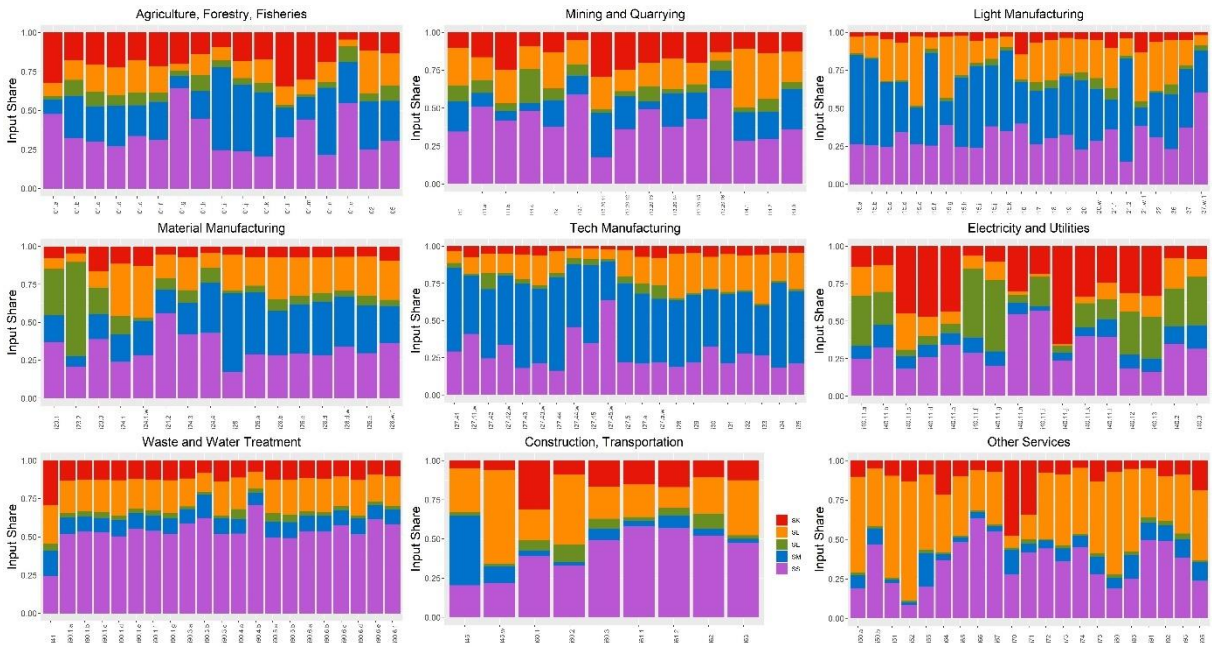

Figure 4 – Average cost share of each production input for each industrial sector at 4D aggregation level, for 23 countries

When modelling cost functions at a lower resolution level, the production inputs within the same aggregate sector are summed up, maintaining a relatively similar number of observations across resolution level. Own-price and cross-price elasticities are calculated as in Equations (17) and (18), respectively. The standard errors of elasticities are calculated using the Delta method (Vega-Cervera & Medina, 2000; Medina & Vega-Cervera, 2001).

$$\varepsilon_{ii} = \frac{\beta_{ii}}{S_i} + S_i - 1 \tag{17}$$

$$\varepsilon_{ij} = \frac{\beta_{ij}}{S_i} + S_i \tag{18}$$

3.3 Selecting the Appropriate Resolution Level

In selecting the appropriate resolution level, the dynamic translog model using the GMM estimation method is selected to model the cost functions. The empirical reasoning behind choosing the dynamic translog over the other translog forms is corroborated in Chapter 4.1, where we demonstrate that the dynamic translog results in better fitting (higher R^2 values) and reduces the number of concavity violations (Urga & Walters, 2003; Cho et al., 2004).

While higher resolution level is preferred to differentiate the production function parameters and elasticities of substitution more accurately (Koesler & Schymura, 2015), it is important to select an aggregation level that adheres to the conditions of aggregate production function (Equation 1-3) appropriately. The appropriate aggregation level is defined as the highest resolution level of the sector where the production recipes could fit to the modelled cost function for each aggregate sector (Grunfeld & Griliches, 1960; Stern, 2011a).

In order to observe the significance of the structural difference between the regression models, the Pearson's chi-square test is conducted to compare the regression model of the aggregate sector and that of its corresponding sectors at the highest resolution level (4D) (Greene, 2008). In the case where the cost functions for a set of corresponding sectors are not significantly different to the cost function of their aggregate sector according to the chi-square test, the aggregate sector is selected to minimize the number of sectors in the optimum level.

To investigate the problem of autocorrelation, Breusch-Godfrey (BG) test (Breusch, 1978; Godfrey, 1978) to identify the presence of autocorrelation in the error terms was employed and

to ensure that the selected functional form explains the variation in the independent variables adequately (Li & Lin, 2016; Wang et al., 2019; Alataş, 2020).

Additionally, the model in the selected aggregation level shall satisfy the assumption of monotonicity and concavity in all observations (Coelli et al., 2005; Greer, 2012). It means that the fitted share values should be greater than zero (Equation 19) and the fitted own-price elasticities should be lower than zero (Equation 20) for all observations.

$$\frac{\partial \ln C}{\partial p_i} = \beta_i^* + \beta_{iy}^* \ln Y_t + \sum_j \beta_{ij}^* \ln \frac{p_{jt}}{p_{St}} + \beta_{it}^* T + \lambda S_{it-1} > 0 \tag{19}$$

$$\frac{\partial^2 \ln C}{(\partial p_i)^2} = \frac{\beta_{ii}}{S_{i,t}} + S_{i,t} - 1 < 0 \tag{20}$$

The most optimum aggregation level selected is defined as the most detailed aggregation level, where all of the modelled cost functions pass the cut-off (threshold) criteria of the monotonicity and concavity. The cut-off score for monotonicity is set at 85%, while that for concavity is set lower at 70% (Kim & Hewings, 2018). The R^2 values for all functions also have to be higher than 0.75, and the p-values for their BG-tests are higher than 0.001.

4. Results and Discussion

Based on the estimated translog cost functions at five different levels of aggregation, own- and cross-price elasticities are derived to assess the optimum level of aggregation. These elasticities are also compared with those of a previous study (Kirchner et al., 2019). This study is selected as a reference because both studies collect their data from IO tables and employ translog functional form, in order to enable an equivalent comparison (Koesler & Schymura, 2015).

Due to the large number of equations modelled in this study, the results of the estimated cost functions are reported in Supplementary Information (SI), where the detailed information of regression models using three translog functional forms is available in SI1, while that of the

selected model at different aggregation levels is available in SI2. The detailed information covers the R-squared of each regression model, p-values of BG test to observe autocorrelation, number of observations adhering to monotonocity and concavity, and parameter estimates, standard errors, and p-values of regression coefficients of each model. Additionally, p-values of chi-square test to observe structural change of regression models at different aggregation levels are available in SI2. Finally, the estimated own- and cross-price elasticities and their uncertainty ranges for all aggregation levels are available in SI3.

4.1 Regression Estimates in Translog and Dynamic Translog Models

In principle, a well-behaved cost function must provide a relatively good fit and satisfy the condition of monotonicity and concavity (Coelli et al., 2005; Hritonenko & Yatsenko, 2014). It should also capture most of the variations in the observations, assessed by the autocorrelation (BG) test. Figure 5 describes the R-squared measures (column A-D) and p-values of BG test (column E-H) for four regression equations of the estimated sector-specific cost functions at the most detailed resolution level (4D) in three different translog forms. Additionally, the share of total observations obeying monotonicity and concavity is also provided (column I-J).

Based on the R-squared measures, the pooled translog model gives much poorer fits (average R-squared 0.18) compared to the other two specifications. Meanwhile, all three models mostly pass the autocorrelation (BG) test, where most p-values of the BG tests are larger than 0.01. In general, the three models give fits with small number of monotonicity violations. However, although the fixed-effect translog model results in fits (average R-squared 0.81) as good as the dynamic one (0.87), the former leads to more concavity violations (44.9% of observations) than the latter (1.5%). Based on the observation of these four indicators (goodness of fit, autocorrelation, monotonicity, and concavity), in general dynamic translog functional form

gives better models that adhere more closely to the neoclassical assumption. Hence, this form is selected to further model the cost functions at different aggregation level.

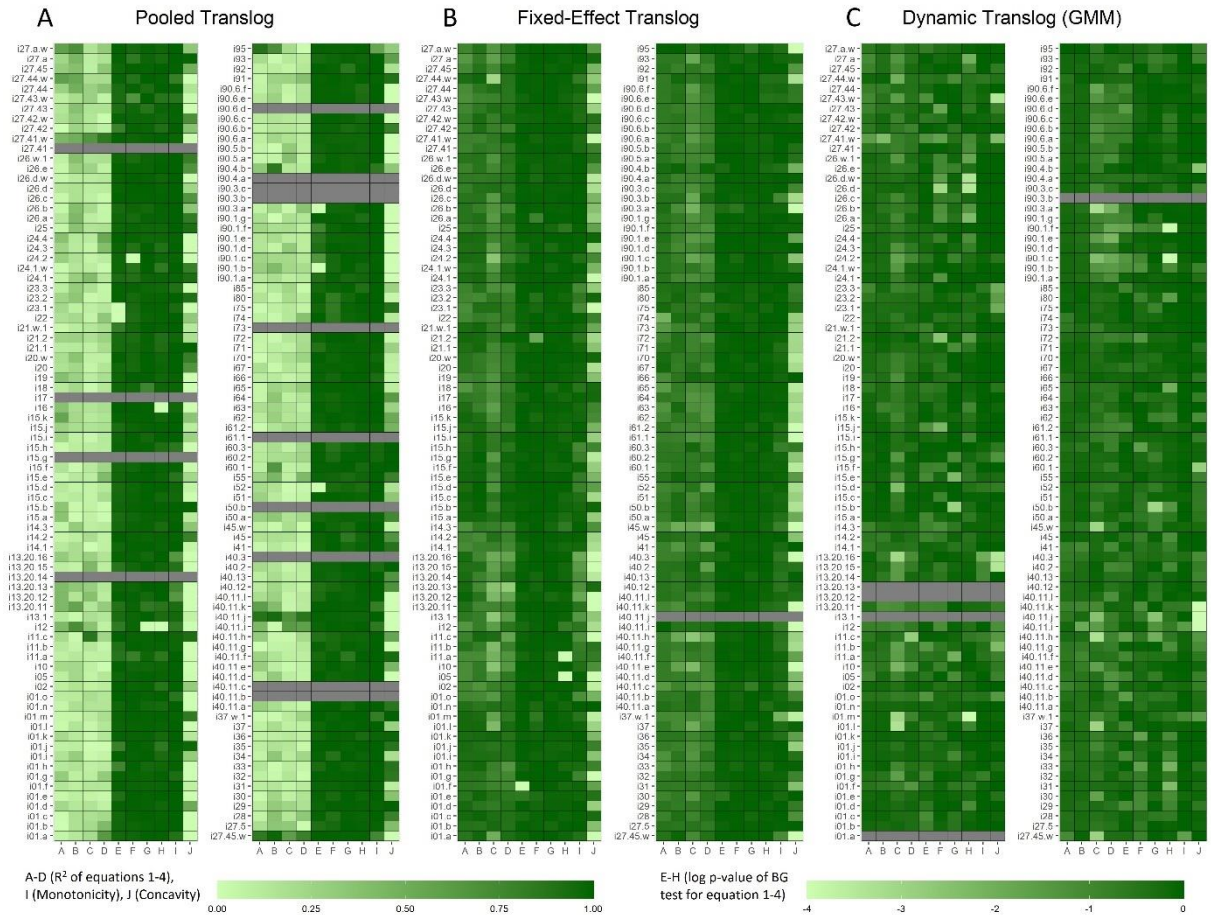

Figure 5 – Regression summary of R-squared, p-value of autocorrelation tests (Breusch-Godfrey tests), monotonicity, and concavity specifications for three translog functional forms. The x-axis represents the regression measures, while the y-axis represents the 163 industrial sectors of EXIOBASE. The autocorrelation tests are conducted for each regression equation.

Rather different than the other studies comparing static and dynamic translog models (Jones, 1995; Urga & Walters, 2003), this study demonstrate stark differences in concavity violations between the two models. The other studies suggest to apply the linear logit functional form instead, since there is no difference between the two translog functional forms. We suggest that these differences are likely due to the use of price variables in this study that have been normalized to the price of services, since in another study comparing translog and linear logit

functional form (Deininger et al., 2018), both translog form modelled using normalized variables and linear logit give fits with small number of concavity violations.

4.2 Estimated Regression Parameters at Different Aggregation Level

To illustrate how aggregation alters the regression results, copper production (i27.44) is selected as an example. The regression results of the estimated cost function of this exemplary sector at different aggregation levels are provided in Table 3.

Table 3 - The regression results of the estimated cost function at different aggregation levels: The case of copper production (i27.44) sector

4D level	S_K	S_L	S_E	S_M
β_i	-0.0090 (0.0050)	-0.0471 ** (0.0181)	0.0094 (0.0076)	0.0509 (0.0304)
ln K	-0.0072 (0.0060)	0.0068 * (0.0035)	-0.0025 (0.0065)	0.0024 (0.0033)
ln L	0.0068 * (0.0035)	-0.0044 (0.0082)	-0.0099 (0.0057)	0.0277 *** (0.0093)
ln E	-0.0025 (0.0065)	0.0099 (0.0057)	-0.0053 (0.0112)	0.0020 (0.0049)
ln M	0.0024 (0.0033)	0.0277 *** (0.0093)	0.0020 (0.0049)	-0.0439 * (0.0186)
ln Y	0.0004 (0.0002)	0.0018 * (0.0008)	-0.0005 (0.0004)	-0.0029 (0.0016)
T	-0.0001 (0.0001)	0.0003 (0.0003)	-0.0001 (0.0001)	0.0000 (0.0006)
ln $S_{i,\,t-1}$	1.0258 *** (0.0165)	1.0258 *** (0.0165)	1.0258 *** (0.0165)	1.0258 *** (0.0165)
R^2	0.81	0.82	0.90	0.90
BG test	0.576	0.933	0.879	0.392
N	314	N passing monotonicity test		305
		N passing concavity test		314

3D level	S_K	S_L	S_E	S_M
β_i	-0.0095 (0.0049)	-0.0464 * (0.0182)	0.0078 (0.0077)	0.0540 (0.0299)
ln K	-0.0067 (0.0061)	0.0071 * (0.0035)	-0.0026 (0.0066)	0.0033 (0.0033)
ln L	0.0071 * (0.0035)	-0.0041 (0.0085)	-0.0106 (0.0057)	0.0275 *** (0.0093)
ln E	-0.0026 (0.0066)	-0.0106 (0.0057)	-0.0045 (0.0111)	0.0018 (0.0049)
ln M	0.0033	0.0275	0.0018	-0.0434 *

	(0.0033)	(0.0093)	(0.0049)	(0.0184)
ln Y	0.0004 (0.0002)	0.0018 * (0.0008)	-0.0004 (0.0004)	-0.0031 * (0.0016)
T	0.0001 (0.0001)	0.0002 (0.0003)	-0.0001 (0.0001)	0.0000 (0.0005)
ln $S_{i,\,t-1}$	1.0293 *** (0.0165)	1.0293 *** (0.0165)	1.0293 *** (0.0165)	1.0293 *** (0.0165)
R^2	0.81	0.84	0.90	0.90
BG test	0.532	0.896	0.895	0.297
N	314	N passing monotonicity test		312
		N passing concavity test		314

400

2D level	S_K	S_L	S_E	S_M
β_i	-0.0038 (0.0054)	-0.0102 (0.0134)	0.0060 (0.0090)	0.0446 (0.0289)
ln K	0.0005 (0.0048)	0.0056 (0.0031)	-0.0028 (0.0053)	0.0005 (0.0031)
ln L	0.0056 (0.0031)	-0.0081 (0.0060)	-0.0013 (0.0056)	0.0178 ** (0.0066)
ln E	-0.0028 (0.0053)	-0.0013 (0.0056)	-0.0061 (0.0103)	-0.0044 (0.0051)
ln M	0.0005 (0.0031)	0.0178 ** (0.0066)	-0.0044 (0.0051)	-0.0250 (0.0157)
ln Y	0.0002 (0.0002)	0.0004 (0.0006)	-0.0002 (0.0004)	-0.0008 (0.0013)
T	0.0001 (0.0001)	-0.0003 (0.0002)	0.0000 (0.0001)	0.0003 (0.0004)
ln $S_{i,\,t-1}$	0.9634 *** (0.0102)	0.9634 *** (0.0102)	0.9634 *** (0.0102)	0.9634 *** (0.0102)
R^2	0.88	0.92	0.88	0.95
BG test	0.078	0.412	0.198	0.364
N	314	N passing monotonicity test		314
		N passing concavity test		314

401

1D level	S_K	S_L	S_E	S_M
β_i	-0.0009 (0.0064)	-0.0044 (0.0145)	-0.0031 (0.0105)	0.0519 (0.0285)
ln K	-0.0006 (0.0061)	0.0061 (0.0039)	0.0000 (0.0071)	0.0013 (0.0041)
ln L	0.0061 (0.0039)	-0.0115 (0.0068)	-0.0014 (0.0070)	0.0196 ** (0.0074)
ln E	0.0000 (0.0071)	-0.0014 (0.0070)	-0.0023 (0.0134)	-0.0045 (0.0065)
ln M	0.0013 (0.0041)	0.0196 ** (0.0074)	-0.0045 (0.0065)	-0.0256 (0.0164)
ln Y	0.0001 (0.0003)	0.0002 (0.0006)	0.0002 (0.0004)	-0.0009 (0.0012)
T	0.0000	-0.0004	0.0000	0.0004

	(0.0001)	(0.0002)	(0.0002)	(0.0004)
ln $S_{i, t-1}$	0.9533 *** (0.0114)	0.9533 *** (0.0114)	0.9533 *** (0.0114)	0.9533 *** (0.0114)
R^2	0.85	0.91	0.85	0.92
BG test	0.258	0.242	0.252	0.523
N	314	N passing monotonicity test		314
		N passing concavity test		314

0D level	S_K	S_L	S_E	S_M
β_i	-0.0057 (0.0063)	-0.0218 (0.0169)	0.0295 (0.0187)	0.0298 (0.0215)
ln K	0.0001 (0.0039)	-0.0027 (0.0033)	0.0016 (0.0056)	0.0023 (0.0034)
ln L	-0.0027 (0.0033)	-0.0219 * (0.0089)	0.0266 * (0.0110)	0.0252 *** (0.0080)
ln E	0.0016 (0.0056)	0.0266 * (0.0110)	-0.0435 * (0.0195)	-0.0203 * (0.0100)
ln M	0.0023 (0.0034)	0.0252 *** (0.0080)	-0.0203 * (0.0100)	-0.0192 (0.0124)
ln Y	0.0002 (0.0002)	0.0007 (0.0007)	-0.0009 (0.0007)	-0.0008 (0.0008)
T	0.0000 (0.0001)	-0.0003 (0.0002)	0.0002 (0.0002)	0.0004 * (0.0002)
ln $S_{i, t-1}$	0.9883 *** (0.0106)	0.9883 *** (0.0106)	0.9883 *** (0.0106)	0.9883 *** (0.0106)
R^2	0.89	0.94	0.93	0.94
BG test	0.007	0.037	0.980	0.018
N	308	N passing monotonicity test		308
		N passing concavity test		308

N represents the number of observations. ***, **, and * represent statistically significant at 0.5%, 1%, and 5% level of significance. See the SI for standard errors and other details.

Based on these regression results, it is observed that the aggregation level influences the regression coefficients, autocorrelation, monotonicity, and concavity depend on the sector modelled. Compared to other studies showing decreases in the model fitting due to sector aggregation (Solow, 1987; Haller & Hyland, 2014), the R^2 values of the regression models in this study are relatively similar across resolution levels. The R^2 values are not changing much because the sector aggregation in this study adds up several sectors into an aggregate sector, instead of pooling the data points to increase the number of observations.

Meanwhile, although the copper production sector (i27.44) passes the autocorrelation tests at every resolution level, the regressions modelled generally fail the autocorrelation tests at the more aggregated levels. This trend is mostly observed in heavy manufacturing sectors, since further aggregation obscures the variations within the production recipes and thus a higher sector resolution is preferred (Urga & Walters, 2003). Additionally, a higher resolution level is more capable to highlight the statistical significance of the variable relationships in these cost functions. In copper production (i27.44) sector, more variables have p-values less than 0.005 as the resolution level increases, implying that these variables are statistically significant.

However, a higher resolution level increases the share of observations violating the concavity test. In most mining and metal recycling sectors, the share decreases as the sector being aggregated. Using time series data with highly aggregated sectors might have reduced the probability of violating monotonicity and concavity (Kim & Hewings, 2018). Additionally, these violations is highly likely happen due to very small factor cost shares, which might occur in EXIOBASE due to the balancing procedure (Kim & Hewings, 2018; Stadler et al., 2018).

4.3 Assessing Elasticities at Different Level of Sector Aggregation

The own-price elasticities of each production input are plotted in Figure 6. Since dynamic translog model reduces the number of concavity violations, the own-price elasticities obtained in this study are almost all negatives. Positive own-price elasticities violates the concavity assumption, since own-price elasticities are the representation of the second partial derivatives of a proper cost function, which values must be negative in a downward-concave cost function (Considine, 1989). In addition to model misspecification, they might also imply that the price effect is weaker than the income or population effect in changing the input demand (Hang & Tu, 2007), or the price is strictly controlled by the government (Fan et al., 2007).

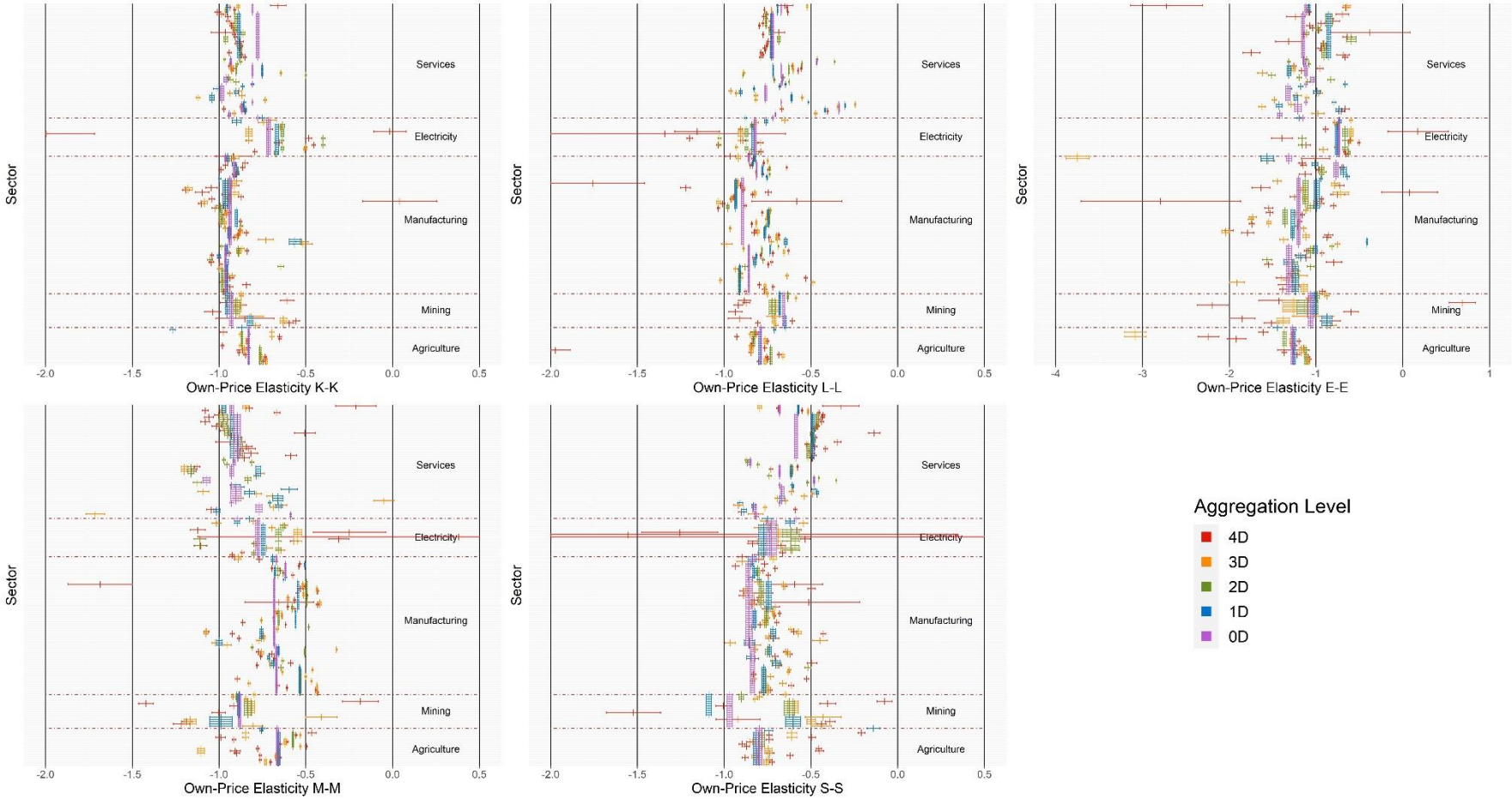

Figure 6 – Own-price elasticities of production inputs at different aggregation level. The x-axis represents the elasticities value on different aggregation level, while the y-axis represents the sectors. The bars represent the uncertainty range of the elasticities for each aggregation level. The numerical data are supplied in the SI.

Larger variations in own-price elasticities happens in the production inputs with larger share, or in sectors with higher variations in the cost shares. For example, own-price elasticity of energy (ε_E) in the manufacture of fuel products (i23) is smaller (-0.41) than the elasticity in other manufacturing sectors, since this sector has a larger share of energy input compared to others. Similarly, own-price elasticities of labor (ε_L) vary more widely in services sectors, and own-price elasticities of material (ε_M) are more diverse in manufacturing sectors. Own-price elasticity of material (ε_M) obtained in the manufacture of aggregate chemicals (i24) (-0.76) does not capture the differences between the lower ε_M of the manufacture of other chemicals (i24.4) (-0.66) and the higher elasticity of ε_M of the manufacture of fertilizers (i24.2,3) (-1.08).

The cross-price elasticities of selected pairs of production inputs are plotted in Figure 7. Similar to own-price elasticities, cross-price elasticities show more variations in a higher resolution level. At 3D aggregation level, cross-price elasticities between capital and material (ε_{KM}) of copper production (i27.44) and aluminum production (i27.42) are 0.74 and 0.46, respectively, while ε_{KM} of those sectors at a more aggregated level (1D) is 0.53. This differentiation is beneficial to distinguish between weak and strong substitution relationship (Blonigen, 2001).

Furthermore, this study supports another study concluding that more aggregate data are biased towards finding higher degrees of substitution since the production recipes at detailed level vary less (Haller & Hyland, 2014). This study shows that in several cases, modelling cost functions at a higher resolution level decreases the cross-price elasticities. As an example, the average ε_{KM} of manufacturing sectors at 3D level is 0.407±0.03, while that at 1D level is 0.452±0.03.

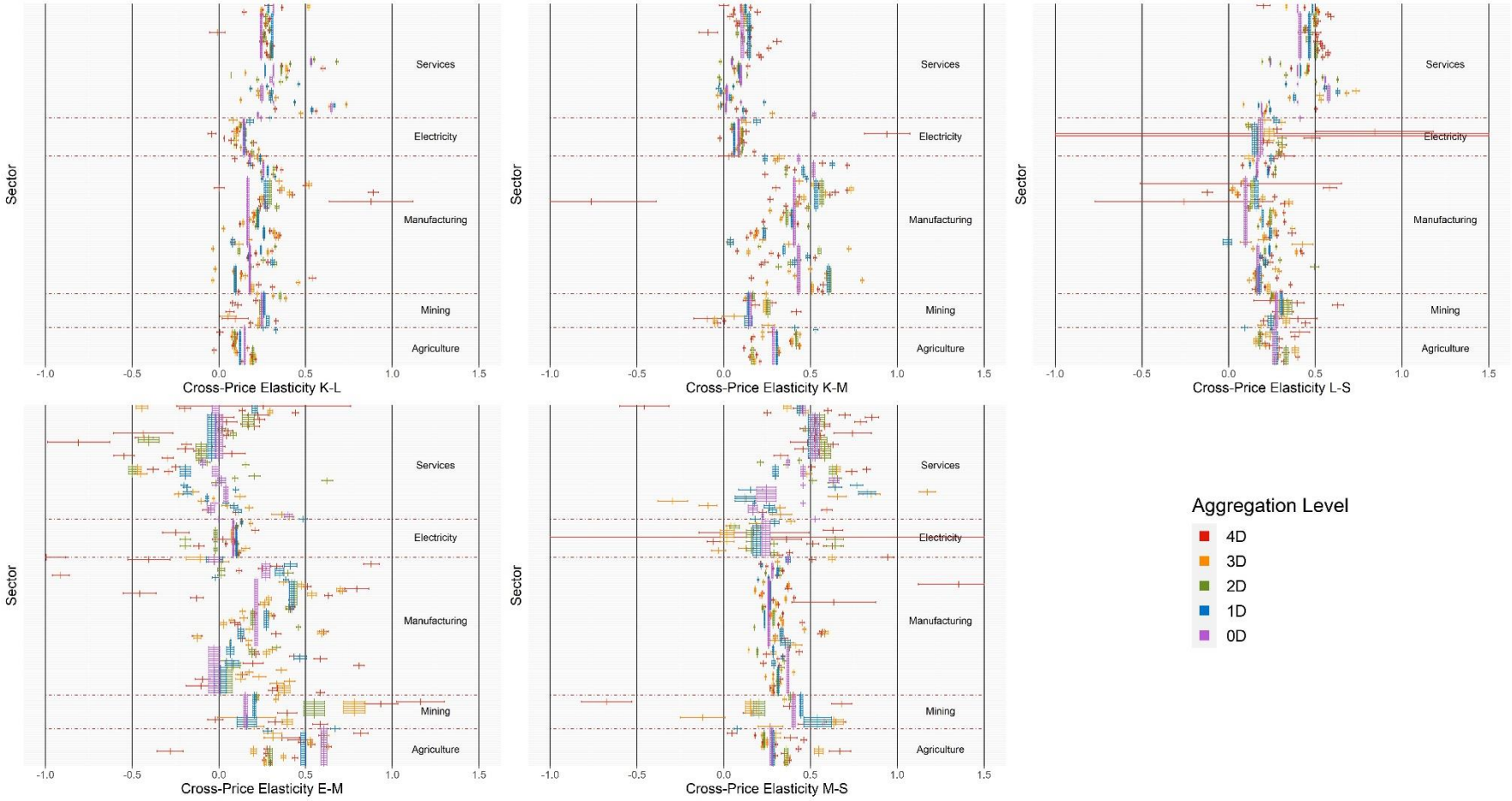

Figure 7 – Cross-price elasticities of selected pairs of inputs at different aggregation level

4.4 Assessing the Optimum Resolution Level of Sector Aggregation

We started our selection of the optimum aggregation level from the most detailed aggregation level (4D), and applied the aggregation when the modelled cost functions do not pass the criteria of the monotonicity and concavity (Kim & Hewings, 2018). Moreover, the sectors are further aggregated if the cost functions for a set of similar sectors are not significantly different to the cost function of their aggregate sector according to the chi-square test, e.g. the manufacture of non-metallic mineral products (i26). Detailed methodology is described in Section 3.3.

Based on the elasticities and the chi-squared tests, the optimum resolution level of sector aggregation is estimated at around 3D level (87 sectors). This study shows a higher optimum resolution level possible to model substitution, since most studies of CGE models are conducted at around 50 sectors; e.g. WIOD (Timmer et al., 2015) and GTAP (Corong et al., 2017).

Compared to the previous study (Kirchner et al., 2019), the elasticities obtained in this study are relatively similar for cross-price elasticities, but rather different for own-price elasticities of energy (ε_E). The comparison between elasticities of these studies is illustrated in Figure 8.

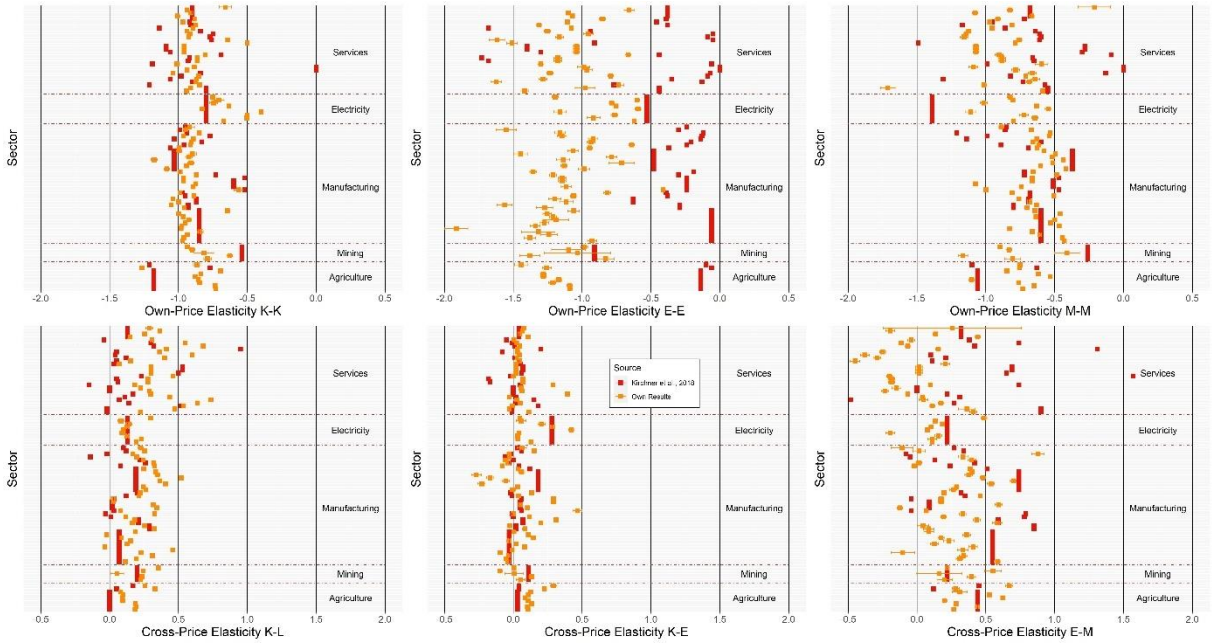

Figure 8 – Own- and cross-price elasticities at the optimum level of sector aggregation, compared to the results of Kirchner et al. (2019).

Differences between elasticities can be explained by the underlying differences in study characteristics, such as differences in model specification (Koetse et al., 2008). In the previous study, cost functions are modelled in a KLEMdMm model, differentiating between domestic and imported material. This specification difference might explain a larger difference in cross-price elasticities of energy-material (ε_{EM}), particularly at light manufacturing and services sectors. For example, the ε_{EM} of manufacture of textiles and wearing apparel (i17, 18) in this study is 0.08, while the ε_{EM} reference is 0.85 (Kirchner et al., 2019).

Difference in resolution levels might also explain the differences in elasticities obtained in this study, since the superiority of sector resolution in EXIOBASE (de Koning et al., 2015) might reduce the aggregate bias towards obtaining higher degrees of elasticities (Haller & Hyland, 2014). With the exception of energy sectors, such as energy fuels (i23) and electricity (i40), most sectors have lower own-price elasticities of energy (ε_E) at around -1.0. Low ε_E values imply that an energy price increase will have a higher impact on the decrease of energy demand.

Larger variation of own-price elasticities is more observable in material input (ε_M). For example, while ε_M in copper production (i27.44) in this study (-0.42) is similar to that from previous study (-0.37) (Kirchner et al., 2019), the higher resolution in this study is capable to observe the lower ε_E in manufacturing of aluminum (i27.42) (-0.60) and iron and steel products (i27.a) (-0.58). These differences are also observed at own-price elasticities of energy (ε_E), e.g. in extraction of petroleum and natural gas (i11). Its ε_E in this study (-1.38) is different than that in the previous study (-0.91) (Kirchner et al., 2019), but the ε_E of other mining sectors are relatively similar. Regions could also explain the differences in cost function models (Koetse et al., 2008), since the previous study (Kirchner et al., 2019) was modelled using a dataset of 27 EU countries, while this study also includes data from Japan and the United States.

The higher resolution also captures the different elasticities of substitution in different sectors. Cross-price elasticity of capital-energy (ε_{KE}) of transmission and distribution of electricity (i40.12, 13) is similar to that from previous study (0.28) (Kirchner et al., 2019). However, ε_{KE} of other renewable electricity production (e.g. biomass, geothermal) (i40.11.g, i, j, k, l) is higher, at 0.42, while those of nuclear (i40.11.c) and emerging renewable electricity production (e.g. photovoltaic, wind) (i40.11.e, h) are lower, at 0.03 and 0.04, respectively.

In the manufacturing of other basic materials, the changes in elasticities are less noticable. This fixed values might be explained by how EXIOBASE is being aggregated and built (Stadler et al., 2014). The production recipe of major basic metal products is being modelled from ecoinvent, assuming that each industry has its own specific way of production, irrespective of differences in production recipes at national level (Majeau-Bettez et al., 2016).

4.5 Elasticities at the Optimum Aggregation Level and Their Policy Implication

The elasticities of substitution are deemed crucial in environment-economic models used for climate and policy modelling (Antimiani et al., 2015). There have been studies demonstrating

the importance of elasticity parameters in modelling climate change policies, especially with regard to carbon leakage (Kuik & Hofkes, 2010; Burniaux & Martins, 2012; Antimiani et al., 2013) and rebound effect (Turner, 2009; Vivanco et al., 2014; Saunders, 2015). The elasticities of substitution in the optimum resolution level (87 sectors) are visualized in Figure 9.

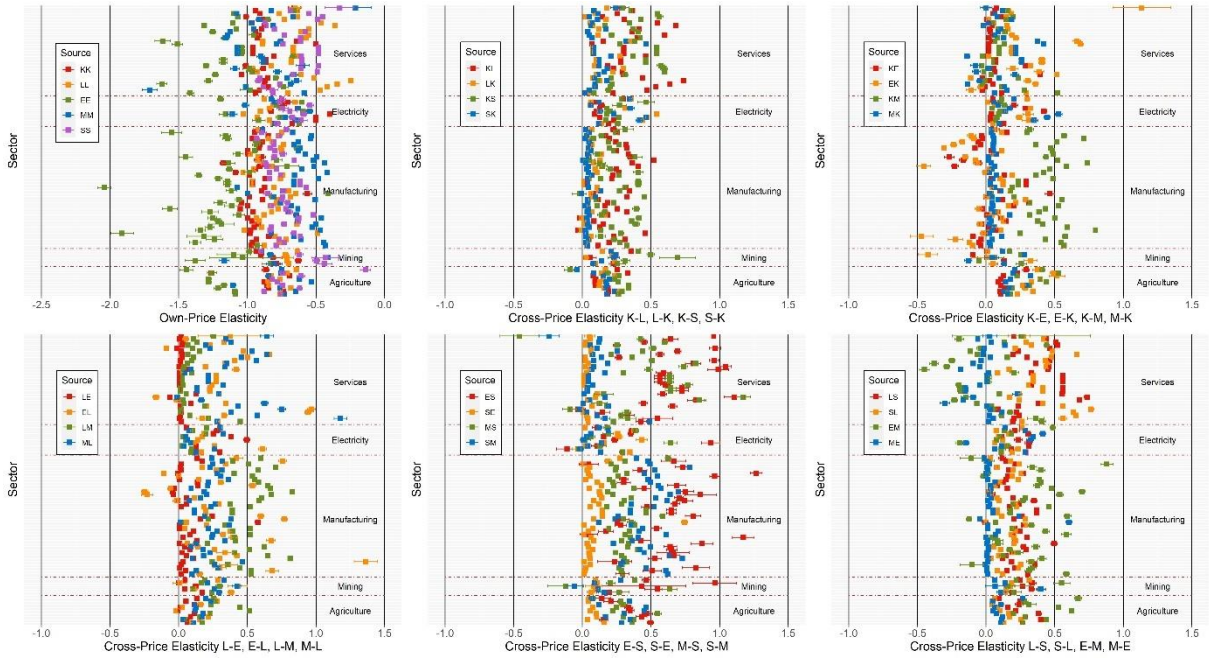

Figure 9 – Cross-Price Elasticities at the Optimum Level of Sector Aggregation. The optimum level is the most detailed resolution level, where 85% of the observations still adhere to monotonicity and 70% adhere to concavity.

Compared to the cross-price elasticities of other production inputs (Figure 8), the elasticities of substitution between energy and other inputs (material and services) have a higher level of uncertainty. This higher uncertainty is largely due to the smaller share of energy in cost shares and the larger variation of energy inputs. The uncertainty range could be reduced by modelling the cost functions at a more aggregated level, with a trade-off in capturing elasticities variation.

The distinction of elasticities is useful in simulating CGE model for climate policies. The elasticities of substitution between energy and capital (ε_{EK}) or services input (ε_{ES}) are useful

measures of the flexibility degree in energy consumption. The higher their values, the lower the output reduction will be required to achieve the required energy reduction target (Golub, 2013).

5. Conclusions and Future Research

The identification of an optimum level of sector aggregation to cost function supports the growing research in increasing the resolution level for CGE models (Antimiani et al., 2015), since variations of elasticities across different sectors, particularly for manufacturing of basic material sectors, could be captured more distinctively, while adhering to the neoclassical assumption. While this study does not provide methodological innovation in modelling cost functions, this study demonstrates a procedure to select an appropriate level of sector aggregation to model cost function, with a detailed reporting on uncertainty range.

The limitation of this study is the absence of strict imposition of monotonicity and concavity, which could be conducted using Bayesian approach (Griffiths et al., 2000; O'Donnell & Coelli, 2005; Kim, 2016; Kim & Hewings, 2018). They are not imposed in this study since it might distort the actual elasticities of substitution and force all inputs to be substitutes (Terrell, 1996).

Another limitation in this study is the use of aggregate inputs in modelling the industry-level production (cost) functions. The potential output produced by different firms consuming heterogeneous composition of capitals within the same industry cannot be measured properly due to capital aggregation (Felipe & Fisher, 2003), which is the case for capital input in most IO tables. In addition to capital, aggregation problem also exists over other production inputs such as energy (Berndt & Wood, 1975; Kaufmann, 1994; Thompson, 2006), material (Németh et al., 2011; Turner et al., 2012), and services (Banga & Goldar, 2007; O'Mahony & Timmer, 2009). From the microeconomic point of view, firm-level production functions are more capable to capture the distinguishing features of a given industry, such as the scales of operation (Aigner & Chu, 1968) and intangible capitals (e.g. organizational investments, product and

service innovation) (Brynjolfsson & Hitt, 2000). This aggregation limits the modelling of endogenous growth theory (Arrow, 1962; Romer, 2011), since physical capital is lumped together with human (Gibbons & Waldman, 2004) or natural capital (Costanza & Daly, 1992). In terms of aggregate energy inputs, the elasticities between different types of energy sources (inter-fuel substitution) are also deemed crucial (Antimiani et al., 2015).

This study also relies on the assumption that constant prices represent adequately physical measures of production inputs and output. It is argued that aggregate production function only exists due to accounting identity, and physical data has to be applied to model production function properly instead of monetary data (Felipe & McCombie, 2013). Furthermore, to properly model change towards substantially more efficient consumption of physical capital, an explicit module that tracks the cohorts of physical capital stocks has to be integrated into a macro-economic model (Pauliuk et al., 2014). While theoretical framework on physical production function has been developed (Heijungs, 1999; van den Bergh, 1999), there has been little empirical study on it (Thompson, 2016). Time-series production data in physical units (Merciai & Schmidt, 2017) makes modelling physical production function possible to answer whether substitutability is possibly modelled properly in physical units and if possible, to ultimately determine the appropriate resolution level to model aggregate production function.

Availability of Data and Materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request. The datasets generated and/or analyzed during the current study are available in the GitHub repository, https://github.com/ghardadi/CostFunction_TL_GMM

Competing Interests

The authors declare that they have no competing interests.

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Authors' Contributions

G.H. and S.P. conceived and designed the research. G.H. performed the computations, analyzed the results, and wrote the paper with inputs from S.P. Both authors read and approved the final manuscript.

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