Elasticity of Substitution Between Electricity and Non-Electric Energy in the Context of Carbon Neutrality in China

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Elasticity of substitution between electricity and non-electric energy in the context of carbon neutrality in China

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Abstract

Electricity penetration is an important part of China's pursuit of carbon neutrality. Understanding the costs of replacing fossil fuel with electricity helps to understand the costs of reaching carbon neutrality in China. This study uses econometrics techniques to estimate the constant elasticity of substitution (CES) parameter between electricity and non-electric energy for China. Results show that the value is around 1.8 – higher than the ones that have been used in the literature. We show that our estimated results are non-linearly stable. We compare our econometrically estimated parameter with two representative values that have been used in the literature. We apply these three parameter values in scenarios in which China reaches carbon neutrality in 2060. Simulation results suggest that the two representative values lead to overestimations of GDP costs and carbon price levels, and underestimations of electricity generation and energy consumption.

Key words: CGE, CES, econometrics estimation, carbon neutrality, China, electricity
JEL: C68, E17, Q43, Q47, Q48, Q54

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1. Introduction

China aims to reach carbon neutrality before 2060. At the centre of the challenge is to reduce fossil fuel combustion, the single largest source of greenhouse gas emissions in China. To reduce fossil fuel use, total energy consumption shall be controlled, and the share of cleaner energy shall increase in total energy consumption. Energy production and consumption patterns are both expected to change. Concerted efforts are required to drive such changes. Energy-using efficiency shall be improved. Renewable power generation costs shall fall. Energy-using preference shall be geared towards cleaner energy. The power system should run with a larger share of wind power and solar power. Negative emissions technologies, such as carbon capture and storage (CCS), shall be widely applied.

Replacing direct fossil fuel use with electricity (*i.e.*, electrification, hereafter) is at the heart of these efforts. Electricity is a safer, cleaner, and more efficient source of energy than the direct burning of fossil fuel. With higher electrification, renewable energy can become a major part of the energy system, and total energy consumption would not have to fall to very low levels to make carbon neutrality possible.

Electrification, however, would involve profound changes. More furnaces need to be fired by electricity instead of coal or gas. More cars need to run on electricity instead of petroleum. More electrical machineries are to be purchased, and more complicated power transmission and distribution networks to be built. For energy users to make such behavioural changes, essentially, they need to perceive the cost of electricity as less than that of its dirtier counterparts. Hence a price, explicitly or implicitly, on carbon emissions is needed to support all these changes. Such transitions would take time too. Labours and assets shall move across sectors. New production lines, new infrastructure, new regulations, and new social norms shall be formed. It is of great importance to plan and prepare for such transitions in advance.

Quantitative analyses are required to support economic planning and policy making. There is a lack of systematic analyses regarding how the economic system will develop and accommodate an energy system transformation. What is the total amount of energy needed by 2060 to satisfy demand? How much fossil fuel can still be used and how much carbon dioxide emissions shall be removed by CCS technologies? How much can energy efficiency improvement or preferences changes contribute to emission reduction? What is the level of the carbon price that is required to contain emissions-intensive activities? Will carbon neutrality efforts reduce consumption, GDP, or employment, and if so, by how much? What will be the final effects after many rounds of shocks over the years? To answer these questions, one needs to have a modelling framework that can find equilibrium conditions for the whole economy and at the same time also be able to incorporate structural changes in the energy system.

Computable general equilibrium (CGE) modelling is a suitable tool for such analyses. CGE models are based on input-output modelling. Like input-output (IO) modelling, CGE modelling has the supply-demand links between commodity supplier and industry users, between commodity sellers and final demanders, and between factor suppliers and industry users. It also helps to find equilibrium conditions when all markets clear (supply equals demand) simultaneously. CGE modelling advances from IO modelling by allowing various types of production functions. Production technologies can differ from the Leontief form and adjust according to relative price changes in input prices. These price-induced behavioural changes are critical when considering the required level of carbon prices. CGE modelling can also represent different types of energy sources and emissions by incorporating physical quantity accounts for energy use and emissions. Moreover, CGE modelling, especially dynamic CGE modelling, is forward looking. By setting up different scenarios, CGE modelling helps to compare economic performance and energy structure in different development paths. Indeed, CGE modelling has been widely used in energy, environment, and climate policy analyses (Babatunde et al., 2017, Freire-González, 2018, Wei et al., 2015).

The accuracy of CGE modelling, however, is often called into questions. The focus often lies in the accuracy of the elasticity of substitution parameters used in the CGE models. This study focuses on the estimation of the constant elasticity of substitution parameter between electricity and non-electric energy (σ_{Enr}) in industries' production functions. The value of this parameter is important as it represents the price-sensitiveness of producers when choosing between electricity and non-electric energy inputs. Hence it governs the extent to which an agent switch to low carbon energy (in this case, electricity) when fossil fuel become relatively more expensive as emissions are constrained. After using econometrics to estimate the value of this parameter, we apply it in a scenario that leads to carbon neutrality in China. We then test whether our estimated σ_{Enr} does lead to significant different simulation results compared with two representative values that have been widely used in previous studies do.

Section 2 discusses the three literature gaps that the current paper attempts to fill. In Section 3, we estimate the elasticity of substitution between electricity and a non-electric energy bundle for China. In Section 4, we apply the σ_{Enr} estimated in the previous section in a CGE model to analyse the implications of reaching carbon neutrality in China. Section 5 draws concluding remarks.

2. Literature review

The accuracy of CGE modelling has been an issue that generates great interests. Yet only a few attempts have been made to discuss the validity of CGE models as a forecasting tool. One such study, Dixon and Rimmer (2013), examined carefully the accuracy of a CGE model, namely USGE, and concluded that CGE could provide more accurate sector level results than past trends extrapolation could for the US economy. Another such study, Beckman et al. (2011), stresses that using econometrically estimated elasticity of substitution parameters could provide much more accurate simulation results, especially results for energy uses and prices.

Some CGE exercises have conducted sensitivity analyses to check their own simulation results. Contrary to the validation articles, many such studies show that their results are robust when key elasticity parameters vary. Such studies tend to suffer from some limitations though. For example, Duarte et al. (2018) find that their main results are robust given variations in key elasticity parameters from their initial values. It is unclear, however, how much they have changed from their initial parameter levels. Some studies do state how much they have altered their initial parameter values. For example, Le Treut et al. (2021) tested the elasticity of substitution between energy and capital from the initial value of 0.15[4] with a range of [0, 0.3]. Similarly, Zhou et al. (2018b) vary their key elasticity parameters (between capital and energy, and between fossil fuel and non-fossil fuel electricity) by plus and minus 10%. Although both studies pass their own sensitivity tests, it is worth noting that their tested range are small. We will see in later part of this section that CGE exercises have adopted much broader parameter ranges than the ones adopted in these studies.

Moreover, some self-checking sensitivity analyses find that their results are sensitive to changes in key elasticity parameters. For example, Dai et al. (2011) found that a 10% change in the value of energy-capital elasticity has a significantly impact on simulation results. Not all results are necessarily sensitive to all parameter changes, and small changes in selected sectors are unlikely to lead to big changes in macroeconomic variables either. It really matters when changes in some key parameters lead to significant changes in main results. For example, Zhou et al. (2018a) found that inter-fuel substitutability does not change macroeconomic results significantly but it does affect the magnitude of rebound effects significantly. Similarly, Vrontisi et al. (2020) found that aggregate trade activities are not sensitive to changes in Armington elasticities but sector results are.

Some studies are designed to systematically analyse the sensitivity of CGE modelling results to a set elasticity parameters. Energy-related elasticities have received much more attention than other parameters have done in recent years. Such studies generally found significant influence of energy-related elasticities to mitigation costs. For example, Antimiani et al. (2015) applied three different sets of energy-related elasticities of substitution parameters in two policy cases, using the GTAP model. They show that mitigation costs can vary not only when elasticity parameters vary, but also vary by different degrees under different policies and across different regions and sectors. They thus recommend using econometrically estimated elasticities that differentiate regions and sectors at the most detailed levels. In another example, although the sensitivity analysis performed by Lu and Stern (2016) found that global mitigation efforts would only reduce GDP by a few percentage points, their results show significant variations across regions. In particular, China's real GDP could fall by 3.04% to 6.28% in 2030, should elasticity of substitution parameters vary by plus or minus 50% from their initial values in the G-Cubed model (McKibbin and Wilcoxen, 1999). These are very significant differences, especially considering that their carbon price levels are mostly assumed to be below US$50 per tonne of CO_2 in 2005 US dollars. Carbon price levels can be many times higher in 2060 should China reach carbon neutrality, implying much larger GDP cost ranges.

Not only that elasticity parameter can greatly affect simulation results, sometimes they can be more deterministic than other simulation assumptions. A recent study by Feng et al. (2021) shows that a 0.2 percentage points (plus and minus) variation in the elasticity of substitution parameters among different electricity generation types lead to larger real GDP variations than 20% changes in other quantifiable assumptions and non-quantifiable assumptions do under a same total emissions path to carbon neutrality. The other quantifiable assumptions include energy efficiency, energy preference changes, the contribution of direct air carbon capture and

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[4] It is indeed -0.15. We use absolute values for elasticity parameters throughout this article.

storage to total mitigation, and the unit abatement cost of using carbon capture and storage facilities. The other non-quantifiable assumptions include different carbon pricing revenues recycling mechanisms, whether China adopts a boarder adjustment mechanism and whether the rest of the world exerts comparable mitigation efforts as China does. None of the other assumptions turn out to affect real GDP and other key economic results as much as the 0.2 percentage points variation in power generation elasticity does.

Hence, there has been long-standing and increasingly stronger arguments for CGE modellers to employ econometrically estimated elasticity parameters in their analyses. Despite this, the CGE literature still struggle to produce such analyses. This is not because the inter-fuel substitution literature is deficient, but rather that there seems to exist a lack of connection between the two literatures.

Inter-fuel substitution has been a hot topic in the econometrics and energy economics literature. Many investigated inter-fuel substitution of a given economy (Cho et al., 2004, Morana, 2000, Perkins, 1994, Serletisa and Shahmoradib, 2008, Uri, 1979). A larger number of studies have investigated interfuel substitution of some broad sectors within a given economy (Borges and Pereira, 2014, Oczkowski, 2007, Duncan and Binswanger, 1976, Fuss, 1977, Halvorsen, 1977, Harvey and Marshall, 1991, Iqbal, 1986, Magnus and Woodland, 1987, Uri, 1982, Bousquet and Ladoux, 2006). Many studies have analysed inter-fuel substitution in China, both at the macro level (Hang and Tu, 2007, Ma et al., 2008, Ma et al., 2009, Li and Lin, 2016) and at the sector level (Fisher-Vanden et al., 2004, Lin and Tian, 2017, Lin and Liu, 2017, Lin and Du, 2017). Some did comparisons of different economies (Steinbuks and Narayanan, 2015, Serletis et al., 2010, Serletis et al., 2011). Despite the large number of studies, survey results show little consensus about inter-fuel elasticities (Bhattacharyya, 1996, Apostolakis, 1990). A meta-analysis conducted by Stern (2012) suggests that more primary studies shall be taken.

Table 1: Inter-fuel elasticities of substitution, electricity related, for China from the literature

	$\sigma_{CO\text{-}EL}$	$\sigma_{EL\text{-}CO}$	$\sigma_{OI\text{-}EL}$	$\sigma_{EL\text{-}OI}$	$\sigma_{EL\text{-}GA}$	$\sigma_{GA\text{-}EL}$	$\sigma_{DI\text{-}EL}$	$\sigma_{EL\text{-}DI}$
Fisher-Vanden et al. (2004)	0.29		0.97					
Hang and Tu (2007)	0.598	0.403	0.110	0.120				
Ma et al. (2008)	0.164	0.596			0.015	0.072	0.029	0.123
Ma et al. (2009)	1.49					0.60		0.68
Serletis et al. (2011)	0.19		0.11					
Smyth et al. (2011)	1.01		1.09					
Li and Lin (2016)	0.070	0.059	0.038	0.027				
Ma and Stern (2016) – DE	0.06		0.97			1.42		0.51
Ma and Stern (2016) – FE	0.00		0.02			0.05		0.00

Note: DE denotes difference estimator, FE denotes fixed estimator. DE and FE represent the upper- and lower-bounds of the interfuel substitution elasticities estimated by Ma and Stern (2016).

Many inter-fuel substitution studies consider electricity as a single type of energy (e.g., Borges and Pereira, 2014, Bousquet and Ladoux, 2006, Oczkowski, 2007). Among the studies that focus on China, Hang and Tu (2007), Ma et al. (2008), Ma et al. (2009), Li and Lin (2016), and others, all treat electricity as a single type of energy. Table 1 summarises the inter-fuel substitution of electricity for China in the literature. Five types of fuel are most often identified, namely coal, oil, gasoline, diesel, and electricity. Elasticities are estimated for pairs of individual fuels, as cross-price elasticities. For each pair of fuels, there could be two elasticities. For example, between coal and electricity, there could be a cross-price elasticity of coal use with respect to electricity price (σ_{CO-EL}), and also a cross-price elasticity of electricity use with respect to coal price (σ_{EL-CO}). Some studies, though, do not estimate both ways of a pair. For example, Fisher-Vanden et al. (2004) estimated σ_{CO-EL} but not σ_{EL-CO}.

CGE models that identify electricity as a fuel type should, in theory, use the results from the inter-fuel substitution literature. This, unfortunately, has not been a normality. Among the CGE studies we have surveyed, few has conducted econometrics estimations themselves. Early studies tend to assume a given elasticity apply for all countries. and later studies tend to take these earlier assumptions as given. The main reason for the lack of using econometrically estimated elasticity of substitution parameters in CGE studies, we suspect, is that the results of the inter-fuel substitution literature are not directly compatible with the structure of the CGE models.

First, the inter-fuel substitution literature generally adopt translog cost functions for energy production (e.g., Ma and Stern, 2016, Li and Lin, 2016), but most CGE models rely on constant elasticity of substitution (CES) functions (e.g., Burniaux and Truong, 2002). We know that translog functions would lead to pairs of cross-price elasticities between two types of fuel, as listed in Table 1, but a CES function would only have one elasticity of substitution parameter. It is thus unclear as to how to use results of the inter-fuel substitution literature directly in CGE models.

Second, the inter-fuel substitution literature estimate elasticities for each pair of individual fuel types, but CGE models often combine several types of fuel into a single bundle. In another word, the inter-fuel substitution literature has been using different nesting structures to the CGE literature. In such cases, an energy nest normally has two types of energy, namely electricity and non-electric energy. However, the inter-fuel substitution literature has not estimated the elasticity of substitution between electricity and a non-electric energy bundle. Therefore, it has been difficult for a CGE model to rely on results from the inter-fuel substitution literature.

The CGE literature has rarely used self-estimated, CES parameters between electricity and non-electricity energy either. In the absence of suitable reference from the literature, one might expect CGE modellers to use econometrics methods to estimate these elasticities for their own model. This will help to ensure the consistency between the modelling structure of their econometrics models and their CGE model. Table 2 summarises the CGE models of China that treat electricity as an individual fuel. These elasticity values are mostly taken from much earlier econometrics analyses which rely on very old data from other countries. The range of the parameter values is between 0.16 and 10.7. This is a very large range. If we treat 10.7 as an outlier as it is much higher than any other values used, and only appears in one study, then the range is narrowed to [0.16, 2]. This is still a big range, none of the sensitivity analyses we reviewed have tested a range for this parameter as big as this. Nevertheless, two representative values can be summarized. A relatively lower value is 0.5. This is the one adopted by the EPPA model (Jacoby et al., 2006), the C-GEM model (Zhang et al., 2013, Zhang et al., 2016) and many other studies. A relatively higher value is 1, as adopted by the CETM model (Rutherford et al., 1997) and the widely used GTAP-E model (Burniaux and Truong, 2002).

Table 2: CES parameter values between electricity and non-electricity used in CGE models

Models (studies)	CES parameter	Country
GREEN (Burniaux et al., 1991)	CES ($0.25< \sigma <2$)	All
CETM (Rutherford et al., 1997)	$\sigma = 1$	All
BMR (Babiker et al., 1997)	$\sigma = 10.7$	All
GTAP-E (Burniaux and Truong, 2002)	$\sigma = 1$	All
EPPA (Jacoby et al., 2006)	$\sigma = 0.5$	All
C-GEM (Zhang et al., 2013)	$\sigma = 0.5$	China
CHINAGEM (Cui et al., 2020)	$\sigma = 0.16$	China

Only a few studies have attempted to use purposely estimated CES parameters in CGE models of China. Feng and Zhang (2018) was the first attempt to use econometrically estimated CES parameters to find a suitable fuel-factor nesting structure for China. Their work only focuses on the top nesting level. Their model did not distinguish between electricity and non-electricity energy sources. And they only tested the economic implications of different parameter values using hypothetic shocks whilst only using a static CGE model. They did not test real policy implications in a long-run, dynamic CGE model. Wang et al. (2021) advances by econometrically estimating a CES parameter and apply that in a real policy application, by using a global, dynamic CGE model. However, they estimated the value of CES parameter for fossil-fuel and non-fossil fuel power generation for the Northeast Asia as a whole. Theirs hence are not directly applicable in our quest to learn the implications of carbon neutrality in China.

Three gaps of the literature can thus be summarized. First, studies have estimated the elasticity of substitution between electricity and other individual energy sources. Few, though, have estimated the elasticity of substitution between electricity and all non-electric energy as a single bundle. Second, studies have used CGE models to estimate the costs of climate mitigation or environmental protection. Few, however, have used econometrically estimated elasticity of substitution parameters that are compatible with the CGE models they used. Third, no study has evaluated the economic and energy implications of carbon neutrality in China using as detailed econometrically estimated elasticity parameters as ours do.

This study attempts to bridge these gaps. We do so by specifically focusing on finding the elasticity of substitution between electricity and a non-electric energy bundle, for China – something that has not been done in the literature. Moreover, we would use a CES production function that is consistent with CGE models to estimate the elasticity. These would ensure that the econometric analysis and the CGE model share the same underlying structure, thus allowing direct application of econometrics results in CGE models. In addition, we further contribute to the literature by testing the energy and economic implication of using different values of electricity-non electricity CES parameters to the context of China reaching carbon neutrality in 2060.

Section 3 illustrates our methods in detail and shows the estimation results. In Section 4, we carry out CGE simulations to compare the implications of using our econometrically estimate results with parameters that has been widely adopted in the literature. Section 5 draws concluding remarks.

3. Econometrics model, data, function form and results

We start from the conventional translog function. Similar to Li and Lin (2016), Ma and Stern (2016) and many others, we begin with a translog function in the form of Eq (1).

$$\ln E_t = \beta_0 + \beta_1 \ln Elec_t + \beta_2 \ln NonE_t + 0.5\beta_{11}\left(\ln Elec_t\right)^2$$

$$+0.5\beta_{22}\left(\ln NonE_t\right)^2 + \beta_{12}\left(\ln Elec_t\right)\left(\ln NonE_t\right) \quad (1)$$

where *ln* denotes the natural logarithm, E_t is total energy used in equilibrium, $Elec_t$ is the electricity consumption, $NonE_t$ is defined as the sum of other energy consumption, including coal, total petroleum products and gas.

Panel data have been used. We gather energy use data from China Energy Statistical Yearbook, covering 31 provinces and 21 years, between 1995 and 2015. All energy use units have been converted into standard coal equivalent units, using the conversion factors supplied by the China Energy Statistical Yearbook.

Given energy use data, and Eq.1, first, we perform a standard pooled OLS estimation. Table 3 shows the estimation results. All parameters are significant at the 1% level, and the R-squared value even reach to the point 0.96. The results thus suggest that the translog function fits well.

Table 3: translog estimation results.

β_0	β_1	β_2	β_{11}	β_{22}	β_{12}	Adj. R^2
0.65***	0.362***	0.635***	0.105***	0.105***	-0.105***	0.96
(0.0066)	(0.0027)	(0.0028)	(0.016)	(0.016)	(0.016)	

Note: Standard errors are given in parentheses. (***) Significantly different from 0 at the 1% level. (**) Significantly different from 0 at the 5% level. (*) Significantly different from 0 at the 10% level.

Several conditions need to be met to decide if Eq.1 is compatible with a CGE model. First, we test if the translog function can degenerate into a CES function. We set the following hypotheses with respect to Eq.1, to test if this is the case. If the null hypothesis (H0) stands, then Eq.1 can be seen as a linearized CES function, and its original form can also be a linearized CES function. Then, we could accept that the production function between electricity and an electricity bundle is a CES function.

$$H0: \beta_{11} = \beta_{22} = -\beta_{12}$$

H1: at least one of them is false

We apply the Wald test. Results show that the restrictions on the translog function (H0) cannot be rejected at any reasonable significance level (p-value is 0.73). Therefore, we accept that the translog production function in Eq.1 is a linear expansion of a CES function. Second, we check if the energy production function would degenerate into a Cobb-Douglas form. As shows in Table 1, the OLS estimation results show that all coefficients β11, β22 and β12 are different from zero at the 1% level, so the underlying technology of the energy production function would not degenerate to the Cobb-Douglas form.

Third, it is generally accepted that in a standard CGE application, a linearized CES production function would exhibit constant return to scale (CRS). Eq.1 can then be written as Eq.2,

$$\ln E_t = c + m\delta \ln Elec_t + m(1-\delta)\ln NonE_t - 0.5m\rho(\ln Elec_t - \ln NonE_t)^2 \quad \text{Eq.2}$$

Where δ, m, and ρ are the share parameter, the scale parameter, and the elasticity of substitution, respectively, such that,

$$\delta = \frac{1}{\beta_1 + \beta_2} \quad \text{Eq.3}$$

$$m = \beta_1 + \beta_2 \quad \text{Eq.4}$$

$$\sigma = \frac{1}{1+\rho} = \frac{1}{1 + \frac{\beta_{12}(\beta_1 + \beta_2)}{\beta_1 \beta_2}} \quad \text{Eq.5}$$

We use the F-test (H0: m = 1, H1: m≠1) to check if a CRS condition (m=1) is met. It shows that the null hypothesis of CRS cannot be rejected at any reasonable level of significance. We therefore accept that our linearly estimated CES functions have the CRS property.

Putting results of Table 3 into equations 3, 4 and 5, we obtain the key results for our CES function. Please see Table 4. All results are economically meaningful (share parameters lie in between 0 and 1) and statistically significant (at 1% significance level). The estimated CES parameter between electricity and the non-electricity bundle is σ =1.836. Again, the function is not a CD function as σ value is clearly different from 1.

Table 4: CES estimation results.

δ	m	σ
0.364***	0.998***	1.836***
(0.0027)	(0.0006)	(0.02)

We double check the accuracy of our estimation by plotting the fitted values against the actual dependent variable (Total energy consumption). Figure 1 shows that the estimated values fit reasonably well with the actual values.

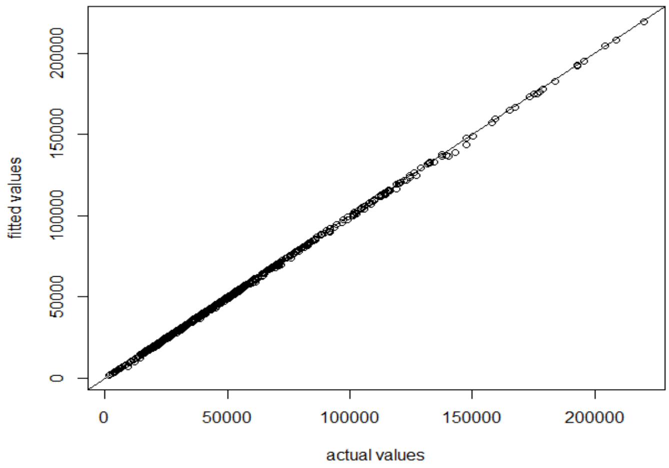

Figure 1: Fitted values against actual energy use

The last step is to check if our estimation is robust under the non-linear CES system (the original form). A linearized CES estimation may biased if we direct estimate its log-linear form (Sun, Henderson and Kumbhakar, 2011). The problem may cause by the truncation of Taylor series or the value of parameter we choose to linearize the function is far away from the true one (Thursby and Lovell 1978). We use non-linear least square method to check our results by minimizing the sum square of residuals.

$$\min \mathrm{RSS} = \sum_{t=1}^{T}\left(Y_t - \widehat{Y}_t\right)^2 \qquad \text{Eq.6}$$

where Y_t = CES ($Elec_t$, $NonE_t$) Eq.7

A non-linear objective function like Eq. 6 that estimates a CES function by least-squares often falls into local minima, especially when the values of the substitution parameters (ρ) have a wide range. Sometimes this might generate results that do not have economic meanings. To avoid this problem, we perform a grid search. The optimization problem in Eq. 6 has two inputs, so we solve it by a one-dimensional grid search for ρ, where the pre-selected values for ρ are between −0.67 and 2 (i.e. the substitution rate between electricity consumption and non-electricity is (0.33, 3)) with an increment of 0.1. The remaining parameters (the share parameters and the return to scale parameter) are solved by a non-linear least square (NLS) optimization[5] problem. The estimated parameters are then used to construct the fitted values ($\widehat{Y}$), which are substituted into Eq.6. We look for ρ values that would give the least sum of residual squares (RSS) values.

Table 5: results of grid search

δ	m	σ
0.346***	1.002***	1.854***
(0.0058)	(0.0056)	(0.068)

The new NLS estimation results[6] are presented in Table 5. As the differences between the NLS method and the corresponding value calculated by OLS (see Table 4) are tiny, we can conclude that our estimation results are stable.

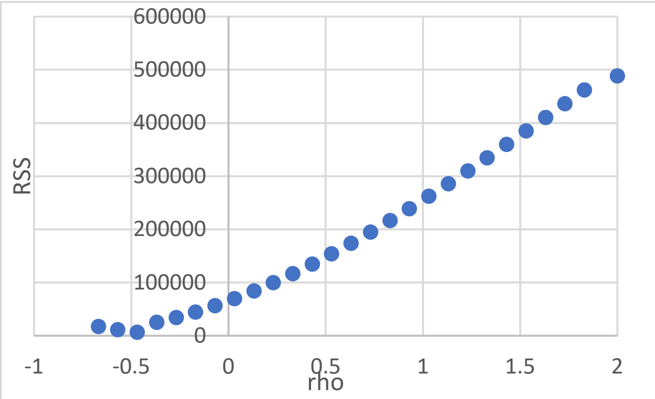

Figure 2: Sum of squared residuals depending on ρ.

The relationship between the substitution parameter and the corresponding sums of the squared residuals are shown in Figure 2. The RSS value is the lowest when ρ is around the point -0.46 – that is, when the elasticity of substitution between electricity and non-electricity in China is 1.854. We thus have shown that this elasticity of substitution is robust under both linear and non-linear optimization.

4. CGE analysis

4.1 CGE Model

We apply our estimated elasticity by using the CHINAGEM-E model. CHINAGEM-E is an

[5] We use the Newton-Raphson method to solve this optimisation problem.

[6] The algorithm converges after 4 iterations.

advanced version of the standard CHINAGEM model (Mai et al., 2010), a recursive dynamic CGE model of China. CHINAGEM-E advances from CHINAGEM by having 1) a more detailed energy sectors specification, 2) a new multi-level fuel-factor nesting structure, 3) accounts for energy and carbon dioxide emissions in physical quantities, 4) carbon pricing and carbon pricing revenues recycling mechanisms and 5) CCS mechanisms. We summarise the main advances here. Please consult Feng et al. (2021) for more details.

We split the 149 sectors[7] in the original Chinese Input-output table of 2017 into 157 commodities and 158 industries. We show mappings from the original sectors to the new commodities and sectors in Table 6. Two original sectors (Crude oil and gas and Electricity) are disaggregated. There is one more industry than commodity in the new CHIANGEM-E database because two industries, Onshore wind power and Offshore wind power, produce the same commodity Wind power.

Table 6: mappings from original sectors in Chinese IO table to new commodities and industries in CHIANGEM-E

Original sectors	New commodities	New industries
Crude oil and gas	Crude oil	Crude oil
	Gas	Gas
Electricity	Hydroelectricity	Hydroelectricity
	Coal-fired power generation	Coal-fired power generation
	Gas-fired power generation	Gas-fired power generation
	Nuclear power	Nuclear power
	Wind power	Onshore wind power
		Offshore wind power
	Solar power	Solar power
	Bioelectricity	Bioelectricity
	Power transmission & distribution	Power transmission & distribution

We design a new multi-level fuel-factor nesting structure of production in CHAINGEM-E. Figure 3 shows a schematic structure. Table 7 shows the corresponding CES parameter values.

The broad nesting system is akin to recent exercises in the literature, in which the top level is usually a CES nest of production factors and an energy composite. In our case, we have a capital-energy composite (please see (Feng and Zhang, 2018) for the reasoning of this top level nesting form). The corresponding CES values (SKEL = 0.78, SGKE = 0.72) are econometrically-estimated by Feng and Zhang (2018).

The energy nest is a CES composite between electricity and non-electricity. The CES parameter for this level (SENR in Figure 3) is the one that we estimated in Section 3. The whole fuel-factor

[7] We use the term 'sectors' to denote both commodities and industries. The original IO table of China is symmetrical. A commodity is only produced by one industry and an industry only produces one commodity.

nesting structure cannot stop at this level, though, as carbon neutrality simulations require carbon pricing and other signals to motivate producers to use more cleaner fuels to replace dirtier fuels. The non-electricity nest, and the corresponding elasticity of substitution parameters (SNEL = 0.5 and SNCC = 1), are similar to those used in GTAP-E (Burniaux and Truong, 2002). The electricity nest is firstly a Leontief combination of Electricity transmission and distribution (ElecDist) and an electricity generation bundle (ElecGen). The nesting structure so far is broadly consistent with the advanced models in the literature.

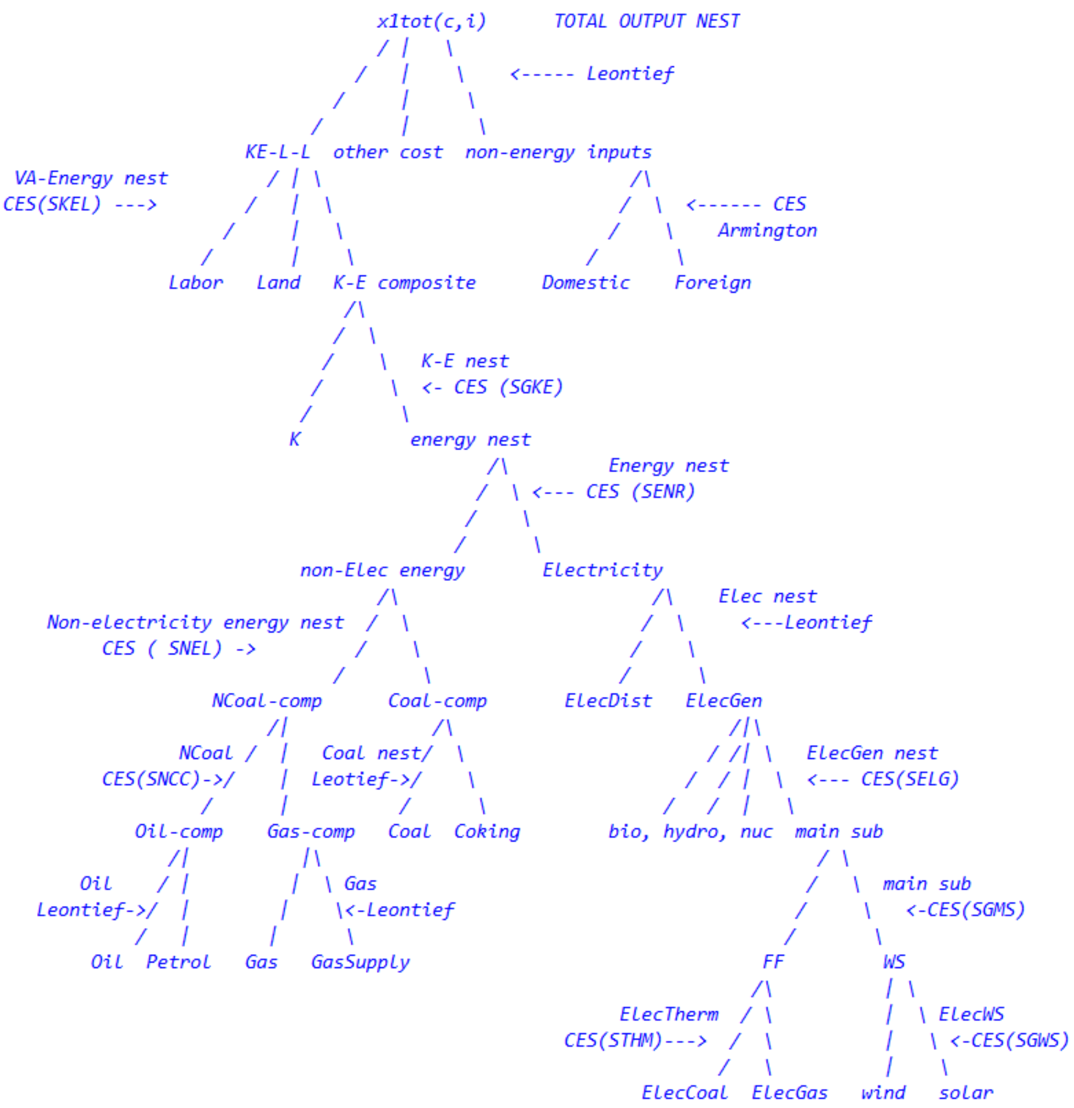

Figure 3: multi-level fuel-factor nesting production structure in CHIANGEM-E

Table 7: CES parameter values for the multi-level fuel-factor nesting production structure in CHINAGEM-E

	STHM	SGWS	SGMS	SELG	SNCC	SNEL	SGKE	SKEL

CES value	2	0.5	1.5	0.5	1	0.5	0.72	0.78

The ElecGen bundle, however, adopts a new nesting structure. The first level in the electricity generation is a CES nest with four paralleled inputs, namely bioelectricity, hydroelectricity, nuclear electricity, and a 'main substitution bundle (main sub)'. This level is designed so that the CES parameter can be set at a relatively low value (SELG = 0.5). This is to reflect the believe that substitution among these four types of power products is not so sensitive to price changes but is rather heavily influenced by geological, seasonal, technological, political, or other reasons.

The 'main sub' bundle is a CES composite of a fossil fuel power generation bundle and a wind and solar power generation bundle. This level is design to accommodate the most important substitution in the power generation system in the pursuit of carbon neutrality. We set the CES parameter at a relatively high value (SGMS = 1.5) to reflect the believe that strong mitigation efforts, including policy guidelines, will make substitution between thermal power and wind and solar power more price sensitive.

There are two nests at the bottom of the production nesting tree. The thermal power nest (ElecTherm) is a CES composite of coal-fired power and gas-fired power, with a CES parameter value set at 2 (STHM = 2). This is the highest value adopted in the nesting structure, this is to reflect the relative easiness to switch between two coal and gas in power generation. The wind-solar power nest (ElecWS) is a CES composite of solar power and wind power, with a CES parameter value set at 0.5 (SGWS = 0.5). This relatively low level of elasticity reflects the believe that the substation between these two sources is not often guided by price signals. Mitigation requires the development of both wind and solar power. Competition between these two types of clean power sources may not be strong.

It is worth noting that all the four elasticity of substitution parameter values in the electricity generation nest are set by the authors. We do not find comparable values in neither the econometrics literature nor the CGE literature because the nesting structure is new. That said, as discussed before, Feng et al (2021) showed small changes in these parameters can lead to big changes in simulation results. Hence further econometrics analyses regarding these parameter values, although beyond the scope of the current study, are desirable.

4.2 simulation scenarios

We set three simulation scenarios. We adapted our simulation scenarios from Feng *et. al.* (2021). Feng et.al. (2021) developed a base-case scenario (BCS) and a main carbon neutrality scenario (CNS) using the same CHINAGM-E model as we do in this study. They implemented four sets of assumptions in their main carbon neutrality scenario, namely: 1) energy efficiency assumptions, 2) energy-use preference assumptions, 3) carbon capture and storage related assumptions, and 4) a CO_2 emissions path to zero net carbon emissions in 2060. Also in their carbon neutrality scenario, carbon prices are endogenized to allow CO2 emissions to be on course to carbon neutrality. GDP costs are therefore strongly influenced by the levels of carbon prices – higher carbon prices increase costs to economic activities and lead to lower GDP. Their simulations run from 2017 to 2060. A full account of model database, model structure and simulation assumptions can be found in Feng et. al. (2021). The current study replicates the base-case scenario of Feng et. al. (2021). We further replicate the main carbon neutrality scenario of Feng et. al. (2021), except for one parameter, the CES parameter between electricity and non-electric energy.

Table 8: simulation scenarios

Scenario	S1	S2	S3
CES parameter (σ_{Enr})	0.500	1.000	1.854
References:	EPPA model (Jacoby et al., 2006)	GTAP-E model (Burniaux and Truong, 2002)	This study

We choose three values for σ_E in the three simulation scenarios. The three parameter values are shown in Table 8. In first two scenarios we choose two representative values from the literature. In scenario 1, we set σ_E = 0.5. This is the value used in the EPPA model, which has been widely adopted and has long-standing applications in China (e.g., Zhang et al. (2013) and (Zhang et al., 2016)) which is a widely cited study using a widely used model,. In scenario 2, we set σ_E = 1, which is the value used in the widely-used GTAP-E model. In Scenario 3, we set σ_E = 1.854, this is the value we estimated in Section 3, specifically for China using econometrics techniques. It can be expected that it is the hardest to replace non-electric energy with electricity in Scenario 1 (S1), as the elasticity of substitution between the two energy sources is the lowest. It is difficult to predict, however, how much easier than it would be in Scenario 3. Therefore, we need to experiment with a CGE model.

4. 2 Simulation results

We show real GDP costs in Figure 4. Simulation results suggest that when the values of the CES parameter between electricity and non-electricity are 0.5, 1 and 1.85, for China to reach carbon neutrality in 2060, the costs to real GDP, cumulated over the 40 years between 2021 and 2060, are 1.98%, 1.63% and 1.36%, respectively. These are significant differences considering all other assumptions are kept same. It also shows the extent to which existing CES values in the literature would overestimate the real GDP costs for China to reach carbon neutrality.

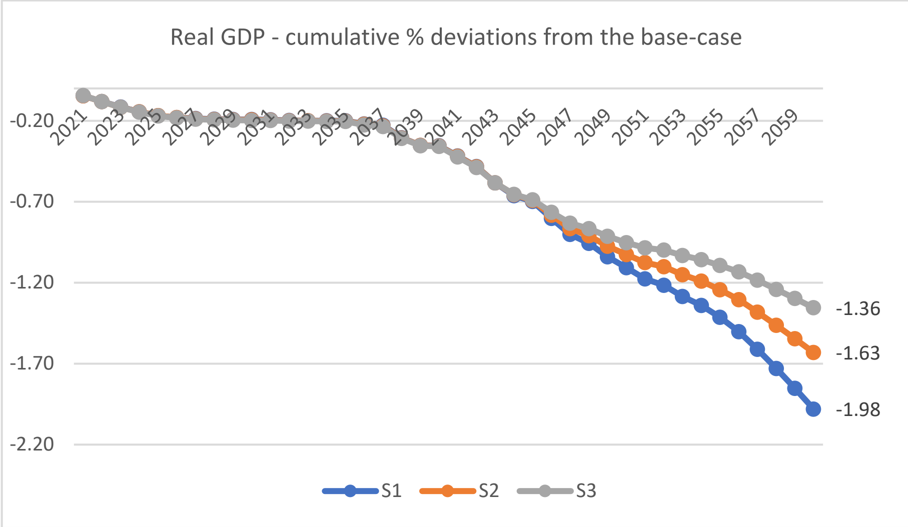

Figure 4: Comparison of real GDP results

Real GDP costs are affected by the levels of carbon prices. We show the levels of carbon prices for the three scenarios in Figure 5. The levels of carbon prices are so much higher in S1 (3466 yuan/tCO_2[8]) and S2 (2348 yuan/tCO_2) that that is in S3 (1614 yuan/tCo2). In fact, the level of carbon price in S1 is more than two times higher than that is in S3. Even in S2, a level of more than 2000 yuan/tCo2 in 2060 might attract very strong sectoral and political resistance. Our new estimates hence mean that the level of carbon price could be significantly lower than it would otherwise be inferred by the existing CES parameters between electricity and non-electricity.

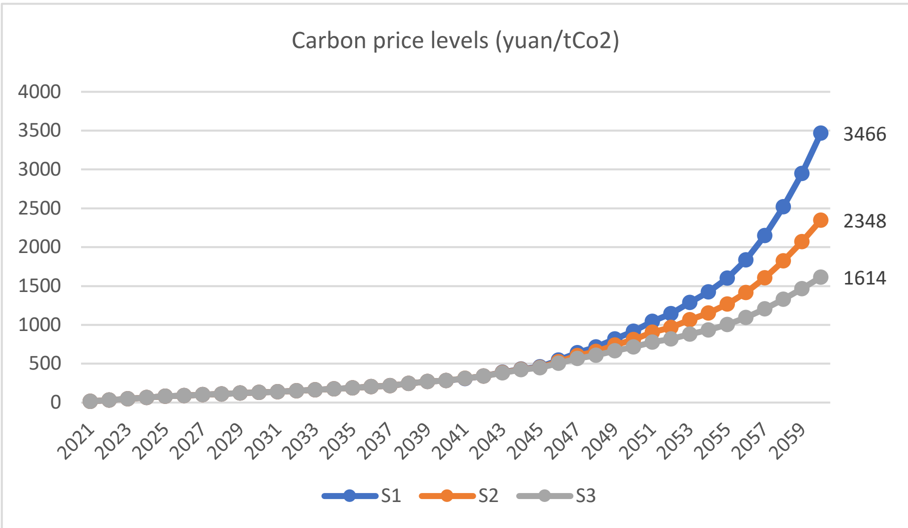

Figure 5: Comparison of carbon price results

We show employment results in Figure 6. By 2060, the cumulative deviations in employment

[8] yuan/tCO_2 is short for Chinese yuan per tonne of carbon dioxide emissions

from the BCS are -0.1%, -0.3% and -0.6% in S3, S2 and S1, respectively. Our results show that unemployment caused by carbon neutrality by 2060 can be about 6 times higher if estimated using $\sigma_E = 0.5$ than estimate using $\sigma_E = 1.854$. Our newly estimated results thus give a much better perspective in terms of employment than previous CES values might have suggested.

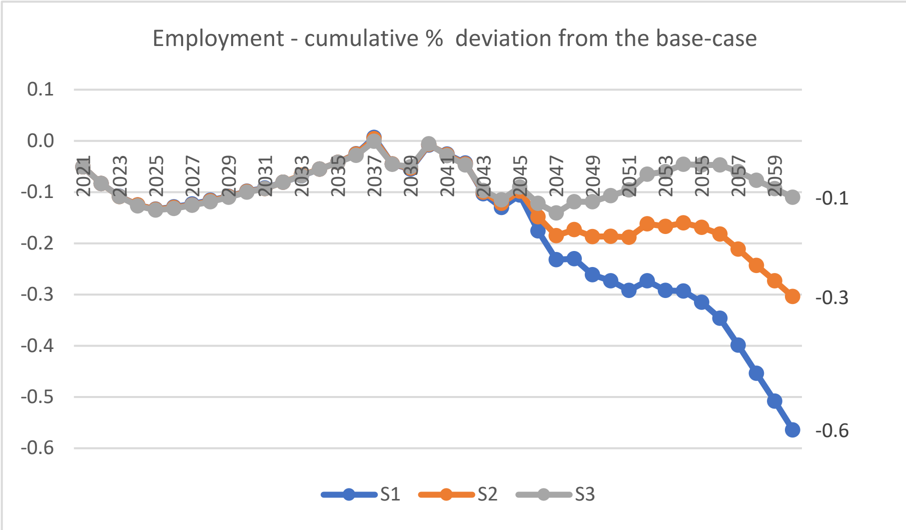

Figure 6: Comparison of employment results

We show primary energy consumption results in Figure 7. Primary energy consumption in the three scenarios all go up from the 2021 level, reach a plateau in the 2030s and begin to fall in the early 2040s. From mid-2040s, however, total primary energy consumption levels begin to depart. In S1, it continues to fall and the fall accelerates from mid-2050s. In S3, however, total primary energy increases slightly and falls back to roughly the same level as it is in the mid-2040s. By 2060, total primary energy in S1, S2 and S3 are 5326 mtce[9], 5484 mtce, and 5579 mtce, respectively. We can thus observe that when the value of the CES parameter between elasticity and non-elasticity increases from 0.5 to 1.85, total primary energy consumption can increase from 5326 mtce to 5579 mtce (by 252 mtce or by 4.6%), in 2060, while achieving carbon neutrality in 2060. Our newly estimated parameter, therefore, means that China does not have to cut energy consumption as much as previous parameters could have inferred.

[9] mtce stands for million tonnes of coal equivalent

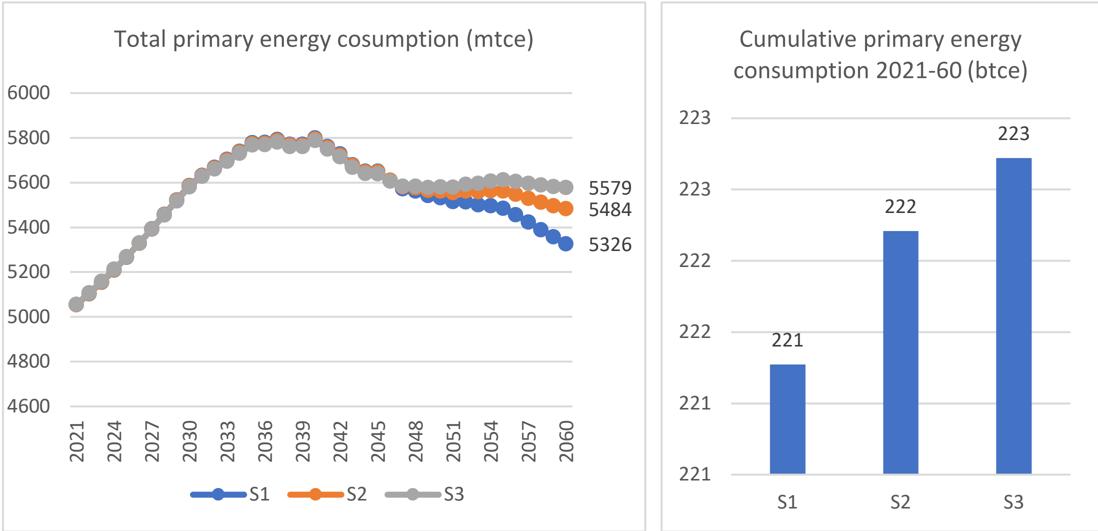

Figure 7: Comparison of primary energy consumption results

Although total primary energy consumption levels are significantly different in 2060 between the three scenarios, their cumulative differences over the policy years are small. Over the 40 years between 2021 and 2060, cumulative primary energy consumption levels are 221 btce[10], 222 btce and 223 btce, in S1, S2, and S3, respectively (Figure 7). Cumulative primary energy consumption in S3 is only 0.7% higher than it is in S1. This is because total primary energy consumption levels only begin to depart among the three scenarios from the mid-2040s. Differences in the last 15 years or so are not significant enough to make a large percentage difference in cumulative primary energy consumption between the three scenarios over the 40 years. That said, the absolute cumulative difference between S1 and S3 is 1.4 btce, which is quite significant.

We show share of non-fossil fuel energy (NFF/E) in total primary energy consumption in Figure 8. The results are very close between the three scenarios. China aims to increase NFF/E to around 25% in 2030. Our simulations show that all three scenarios lead to NFF/E to be 25% in 2030. By 2060, NFF/E increase to 73% in all three scenarios. Between 2021 and 2060, the cumulative non-fossil fuel share in total primary energy consumption is 42.3%, 42.4% and 42/5%, in S1, S2 and S3, respectively. Hence, the value of the CES parameter between electricity and non-electricity hardly affect the share of non-fossil fuel in total primary energy consumption over the simulation years.

[10] btce stands for billion tonnes of coal equivalent

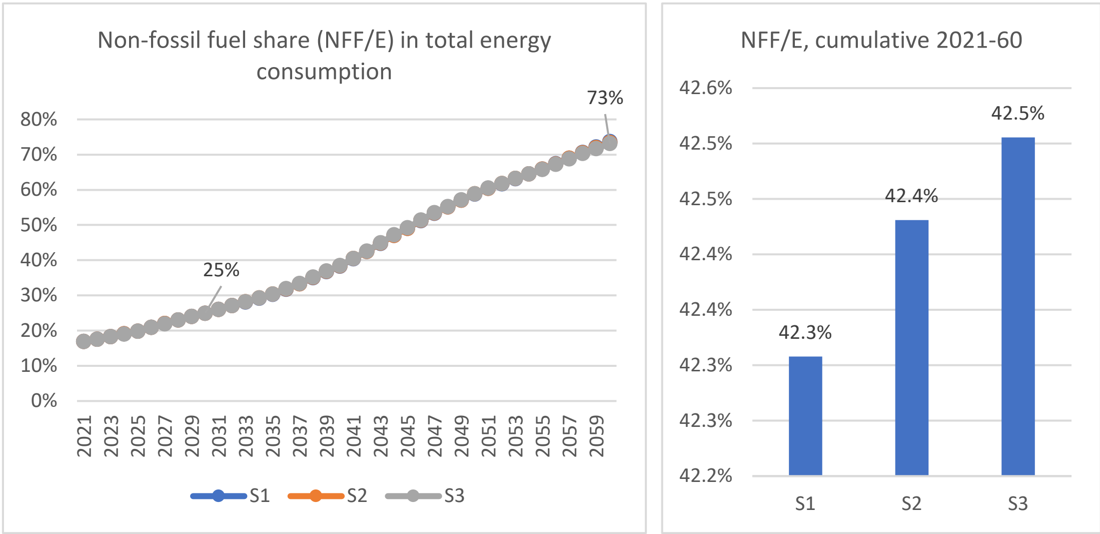

Figure 8: Comparison of non-fossil fuel in primary energy share results

We show total electricity generation results in Figure 9. Total electricity generation continue to increase in all three scenarios. The higher the value of the CES parameter between electricity and non-electricity, the more electricity output there could be. Our simulation results show that, by 2060, total electricity generation are 14.8 petawatt hour (PWh), 15.5 PWh, and 15.9 PWh, in S1, S2, and S3, respectively. Hence, electricity output in S3 is 7.4% higher than it is in S1, in 2060. Cumulative power output, between 2021 and 2060, are 477 PWh, 482 PWh, and 485 PWh, in S1, S2, and S3, respectively. Cumulative power output in S3 is 8.2 PWh, or 1.7% higher than it is in S1.

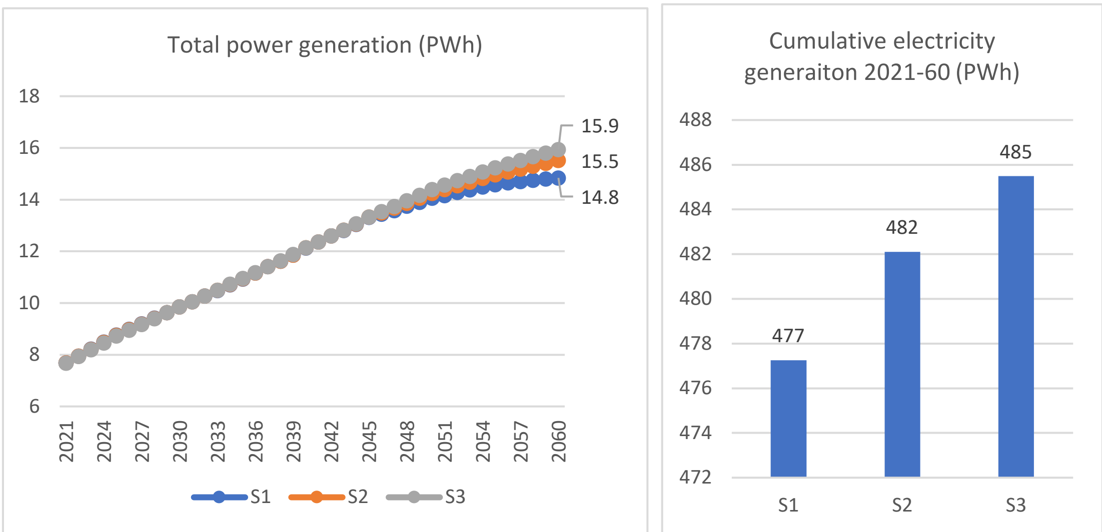

Figure 9: Comparison of total power generation results

We show carbon dioxide emissions results in Figure 10. Carbon dioxide emissions paths are almost identical for the three scenarios. Between 2021 and 2060, the cumulative emissions are also so very close, they are 240.8 btCo2, 240.6 btCo2, and 240.3 btCo2, in S1, S2, and S3, respectively. Our simulation results thus suggest that while all achieving carbon neutrality with similar levels of total carbon dioxide emissions, our newly estimated parameter could lead to much lower carbon prices and significantly smaller reduction in real GDP.

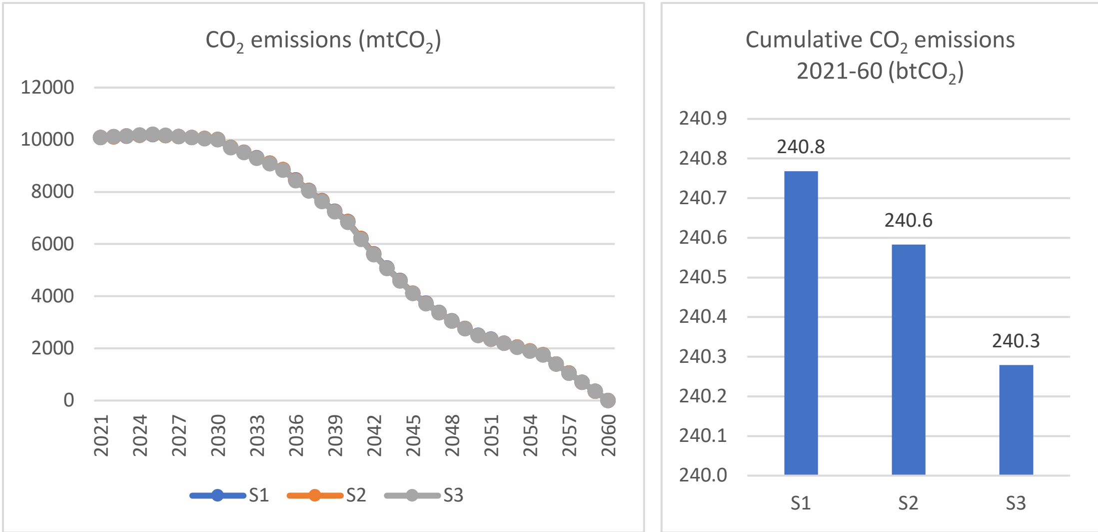

Figure 10: Comparison of carbon dioxide emissions results

Source: authors simulation using CHINAGEM-E

5. Concluding remarks

There has been a gap in the environmental and energy economics literature for using econometrically estimated parameters in CGE modelling. The problem has been that the econometrics literature has not produced parameters that are consistent with conventional CGE model structures. This study is a step forward to close this gap. In addition, we further show the implication of adopting our newly estimated parameter in the context of carbon neutrality in China.

A critical CES parameter in CGE modelling is the elasticity of substitution between electricity and non-electric energy (σ_E). This study uses econometrics techniques to estimate the elasticity of substitution between electricity and a non-electric energy bundle for China. Panel data (by energy type, year, and province) have been used.

We use a log-linear energy production function to estimate σ_E. Our estimations show that σ_E for China is 1.854. We then perform a few tests to check if our estimation can be readily applied in a CGE model. First, we confirmed that the function is indeed a CES function. Second, we showed that it is of constant return to scale. Third, we confirmed that it is not a Cobb-Douglas function. The first three tests confirm that the underlying structure of our econometrics estimation is consistent with the conventional structure of a CGE model. Fourth, we further demonstrated that our result is also stable in a non-linear system. Hence, we produced a stable, and model-consistent, CES parameter (σ_E=1.854) between electricity and non-electric energy that can be readily applied in a CGE model of China.

We then examine the implication of applying our newly estimated CES parameter. That requires using a CGE model. We used the CHINAGEM-E model, a recursive dynamic CGE model, with the 2017 input-output tables as the core database. We chose two values that have been previously used in CGE models and used them in Scenario 1 (σ_E=0.5) and Scenario 2 (σ_E=1.0). In Scenario 3, we set σ_E=1.854 – our newly estimated value. We put these three different CES parameters into the main carbon neutrality scenario of Feng *et. al.* (2021) to set up three simulation scenarios.

We examine the implications of the differences in these parameters by forcing China's economy to achieve net zero emissions by 2060. Simulation results show that real GDP in 2060 are 1.98%, 1.63%, and 1.36% lower than the base-case level in S1, S2, and S3, respectively. Hence, applying our new, econometrically estimated parameter could lead to lower-than-expected GDP losses. In addition, results also show that cumulative CO2 emissions remain at the same level across the three scenarios. Hence, our results suggest that by using our new CES parameter, China could reduce losses in real GDP while emitting the same level of carbon dioxide emissions as previous values might have suggested.

Our results, however, do not show significant differences across the three scenarios in terms of fossil fuel share in total energy consumption. Future studies may further explore the elasticity possibilities between different electricity sources, especially between renewable and non-renewable electric energy.

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