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Implications of Updating the Input-output Database of a Computable General Equilibrium Model on Emissions Mitigation Policy Analyses

Wei-Hong Hong[1,2], Hui-Chih Chai[2], Y.-H. Henry Chen[1,3], John M. Reilly[3] and Sergey Paltsev[3]

Abstract: Updating the input-output database is a crucial part in the maintenance and development of large-scale economy-wide equilibrium models used for various policy analyses. In general, a goal of model maintenance is to adopt the latest database for modeling exercises, but rarely if ever is there a careful evaluation of the implications of this update in terms of the effect on policy conclusions. In this study, we provide a critical evaluation of upgrading the input-output data of a global energy-economic computable general equilibrium model. Specifically, we will answer the following question: How could datasets with different reference years affect results of policy simulations that aim at reducing CO_2 emissions? We argue that the existence of temporary fuel price spikes can lead to short-run disequilibrium in fuel use and fuel cost shares that are reflected in an input-output table constructed for a year with these temporary price spikes. Based on our analytical framework, we demonstrate that for a given percentage of emissions cut, a database with temporarily higher fossil fuel cost shares will result in higher CO_2 mitigation costs. This will be an inaccurate assessment of policy costs, because if prices remained at those levels, fuel use and fuel use costs will fall even without a further carbon tax as the economy comes into equilibrium with these new price levels. Alternatively, if the price spike is temporary and perceived as such, cost shares should fall back to the pre-spike level. We then provide a numerical example for this finding comparing results for models using different base year input-output tables. We propose an adjustment to address the concerns of using input-output data that embed the combination of prices and consumption that may exhibit this disequilibrium condition.

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1. Introduction

Global economy-wide general equilibrium models with energy details are widely used in climate or energy policy analyses. A typical strategy in building these models is to parameterize them according to the input-output structure of the economy for a particular year and a set of elasticities representing the substitution possibilities between inputs. For instance, the Global Trade Analysis Project (GTAP) database provides the regional input-output data of the world economy, and it also includes estimates of various types of elasticities that are used in the GTAP model (Hertel *et al.*, 2014), one of the global computable general equilibrium (CGE) models that is often used for a diverse range of policy analyses. Another example is the World Input-Output Database (WIOD), which offers the regional input-output structure of the world economy without the elasticities (Timmer *et al.*, 2015). Researchers working on other CGE models often draw the input-output data from these databases, and get the elasticity estimates based on literature reviews or expert elicitation, since different CGE models may have distinct settings in the nesting structures for the production or consumption activities, and therefore the corresponding substitution elasticities needed may not be the same as those provided by GTAP. In general, a goal of model maintenance is to adopt the latest input-output database for modeling exercises, but rarely if ever is there a careful evaluation of the implications of this update in terms of the effect on policy conclusions. Chai *et al.* (2017) found that climate policy costs were significantly higher for an identical percentage reduction when they formulated a model based on the GTAP 2011 reference year data base than an identical model based on earlier year data bases (2004, 2007). In this paper, we seek to provide an explanation for this difference.

We present an analytical framework and numerical examples to justify explanations for the CO_2 reduction simulation results of a global energy-economic CGE model based on input-output data with various base years. We note that fuel prices are a likely culprit since they are subject to unanticipated temporary price shocks, and since fuel use is a primary target for reducing emissions. Our analysis confirms this hypothesis, showing that this crucial yet largely ignored factor could lead to significant differences in modeling results under a given CO_2 mitigation policy. Our analysis also points out that, when using a base year dataset with fossil fuel prices that are temporarily extreme due to short-term fluctuation, a newer data set may not necessarily give improved policy conclusions. We also propose a solution that could, under certain circumstances, overcome this limitation. The rest of the paper is organized as follows: Section 2 presents the analytical framework; Section 3 provides numerical examples; and Section 4 concludes the study and points out a potential path for future research.

2. Analytical Framework

To study the effect of higher fossil fuel prices on CO_2 prices when the emissions mitigation policy is in place, let us consider a simple closed small open economy with a representative consumer, an aggregated sector A, and two primary factors N (non-energy) and E (energy). Since our focus is on the technology on the supply side, we begin by assuming that the representative consumer has a perfectly inelastic demand for the output of sector A. Later we extend the analysis to the case with an elastic demand for that output. In the economy, we assume the factor prices P_N and P_E are determined internationally rather than domestically, and for every unit of E the sector uses, it produces one unit of emissions. This means that a constraint on energy use is equivalent to a constraint on emissions.

Let us assume that sector A is characterized by a two-input constant elasticity of substitution (CES) production technology as follows:

$$Y = F(E,N) = (\alpha E^{\rho} + (1-\alpha)\ N^{\rho}\ )^{1/\rho} \tag{1}$$

where Y is the output, F is the CES production function, and α is the cost share parameter for E (the larger the α, the higher the energy cost share). In addition, we assume that the commodity market of sector A is perfectly competitive so that each firm in sector A is a price taker for its output.

Since our focus is to answer the question, other things equal, what is the effect of calibrating the technology under different energy prices, let us consider two different sets of base year data. One is compiled at the time point T_0 under the energy price of P_E^l, and the other is done at T_1 following a sudden energy price hike so that the price becomes P_E^h ($P_E^h > P_E^l$). We assume that the substitution between E and N is possible only in the long-run, and $T_1 - T_0$ is considered a short-run that allows no input substitution. Further assume no economic growth so that the two datasets observed have the same levels of inputs (N_0,E_0).

Under these considerations, the technology that is calibrated at T_0 based on (N_0,E_0;P_N,P_E^l) will be F_l, and that which is calibrated at T_1 based on the after-shock data (N_0,E_0;P_N,P_E^h) will be F_h. Without the constraint on energy use (or emissions) level, let us denote the equilibrium output and price levels under the technology F_i by Y_0^i and P_0^i, respectively. The optimization problem of each firm in sector A is:

$$max\ P_0^i \cdot\ F_i - P_N \cdot N - P_E \cdot E \tag{2}$$

The first-order conditions of the problem are:

$$P_0^i \frac{\partial F_i}{\partial N} \mid_{F_i=Y^*} = P_N \quad (3)$$

$$P_0^i \frac{\partial F_i}{\partial E} \mid_{F_i=Y^*} = P_E \quad (4)$$

Condition (3) says the marginal revenue product of labor equals the marginal cost of hiring an additional unit of labor, which is P_N, and similarly, Condition (4) suggests that the marginal revenue product of energy equals the marginal cost of using an additional unit of energy (P_E). In both conditions, Y^* is the optimal output level for this problem. Now, suppose that to achieve the emissions reduction target, the energy use should be reduced from E_0 to E_1, i.e., the optimization problem is now subject to a binding constraint $E=E_1$. Let us denote the equilibrium output and price levels under the technology F_i by Y_1^i and P_1^i, respectively ($i=l$ or h). The constrained optimization problem becomes:

$$max \quad P^i \cdot F_i - P_N \cdot N - P_E \cdot E \quad s.t. \quad E_1 - E = 0 \quad (5)$$

The Lagrangian function of the problem can be formulated as:

$$L = P^i \cdot F_i - P_N \cdot N - P_E \cdot E + \lambda_i \ (E_1 - E) \quad (6)$$

The first-order conditions of the problem are:

$$P^i \frac{\partial F_i}{\partial N} \mid_{F_i=Y^*} = P_N \quad (7)$$

$$P^i \frac{\partial F_i}{\partial E} \mid_{F_i=Y^*} = P_E + \lambda_i \quad (8)$$

$$E = E_1 \quad (9)$$

Note that since the demand is perfectly inelastic, the optimal output remains at Y^* after the energy constraint is imposed. The interpretation of Condition (7) is similar to that of Condition (3), and Condition (8) means that under this constrained optimization problem, the marginal revenue product of energy equals the marginal cost of using an additional unit of energy (P_E) plus the shadow price of the energy-use constraint, which is Condition (9). In addition, if the technology is calibrated based on (N_0,E_0;P_N,P_E^l), the non-energy input should be increased from N_0 to N_1^l. On the other hand, if (N_0,E_0;P_N,P_E^h) is used to calibrate the technology, the non-energy input needs to increase from N_0 to N_1^h, with $N_1^h > N_1^l$ (**Figure 1**). In addition, according to Condition (8), under the constraint $E=E_1$, the shadow price for the constraint is λ_i for the technology F_i ($i=l$ or h). Note that for the technology F_i, the optimal input bundle (N_1^i,E_1) for the constrained optimization problem (Problem (5)) is also the solution to the unconstrained optimization problem facing the relative price of $-P_N/(P_E+\lambda_i)$ (see Condition (8)). Therefore, if we impose an energy tax of λ_i for each unit of energy use, the energy consumption level would decrease to E_1. To answer our research question, we will show that $\lambda_h > \lambda_l$ holds.

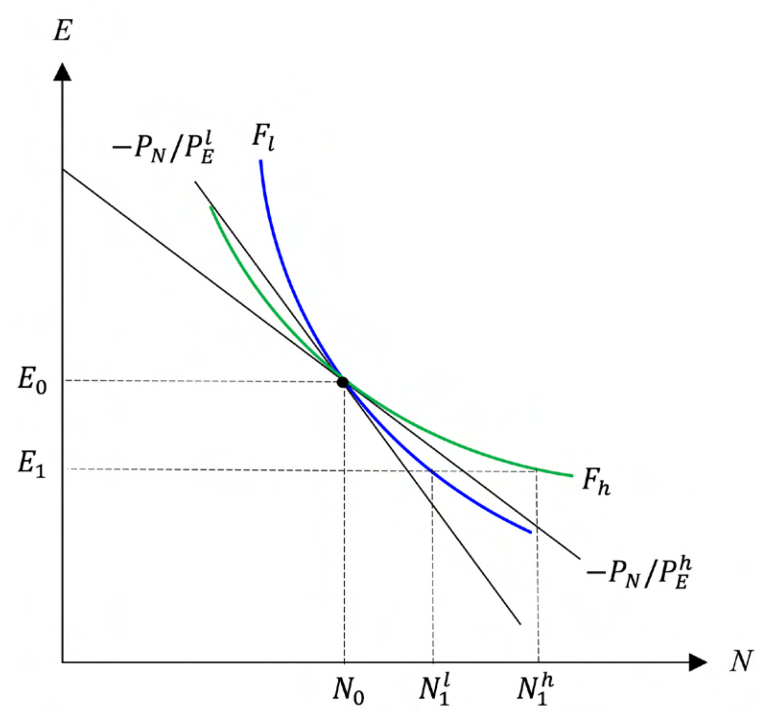

Figure 1. Two-input production technologies calibrated to different prices.

Proposition 3.1

For the economy considered in this section, if the technology is calibrated to the same input bundle (N_0, E_0) but with a higher energy price level P_E^h (and therefore it has a higher energy cost share parameter α_h), then the shadow price of cutting the energy use (and therefore the CO_2 level) will be higher.

Proof:

From Conditions (4) and (8), $\lambda_i = P_1^i \frac{\partial F_i}{\partial E} |_{F_i = Y^*}; E_1 - P_0^i \frac{\partial F_i}{\partial E} |_{F_i = Y^*}; E_0$. Also, $P_1^i > P_0^i$ since imposing the energy constraint raises the production cost and consequently the equilibrium price of Y. Therefore, $\lambda_i > P_0^i \left(\frac{\partial F_i}{\partial E} |_{F_i = Y^*}; E_1 \right) - \frac{\partial F_i}{\partial E} |_{F_i = Y^*}; E_0$. Since $\frac{\partial F_i}{\partial E} = \alpha_i \left(\frac{F_i}{E} \right)^{1-\rho}$, $\lambda_i > P_0^i \left[\alpha_i \left(\frac{Y^*}{E_1} \right)^{1-\rho} - \alpha_i \left(\frac{Y^*}{E_0} \right)^{1-\rho} \right] > 0$. Note that under F_h the marginal cost of producing Y is higher due to the higher energy cost, and in equilibrium the price equals the marginal cost, therefore we have $P_0^h > P_0^l$. As a result, $\lambda_h - \lambda_l > P_0^h \cdot (\alpha_h - \alpha_l) \cdot \left[\left(\frac{Y^*}{E_1} \right)^{1-\rho} - \left(\frac{Y^*}{E_0} \right)^{1-\rho} \right] > 0$ since $\alpha_h > \alpha_l$ and $E_1 < E_0$.

Based on the above analysis, we can derive the following relations:

$$Y_0 = Y_0^l = Y_0^h = Y_1^l = Y_1^h \tag{10}$$

$$P_1^l - P_0^l > 0 \tag{11}$$

$$P_1^h - P_0^h > 0 \tag{12}$$

$$P_0^h > P_0^l \tag{13}$$

$$P_1^h > P_1^l \tag{14}$$

Condition (10) is simply the result of the demand assumption, Conditions (11), (12), and (13) have been demonstrated in the proof for Proposition 3.1. Condition (14) holds because of Condition (13), $\alpha_h > \alpha_l$, and $\lambda_h | Y > \lambda_l | Y$ (Proposition 3.1). **Figure 2** provides an example for illustration purposes.

In the following proposition, we will demonstrate that under a binding energy use constraint, the shadow price of that constraint will increase when the output increases.

Proposition 3.2

For the economy considered in this section, for a given technology, the shadow price of the constraint on energy use is an increasing function of the output.

Proof:

Since F is homogeneous of degree one, the expansion path is a straight line. Suppose under the binding constraint $E = E_1$, the optimal bundle is (N_1, E_1) with a relative price of $-P_N / (P_E + \lambda_1 | Y_1)$, where λ_1 is the shadow price of the energy use constraint under the output level Y_1 (**Figure 3**). Along the expansion path, let us consider the output level Y_2 ($Y_2 > Y_1$) that is achieved by the input bundle of $(\tilde{N}_2, \tilde{E}_2)$ (see point B in Figure 3). Note that since $\tilde{N}_2 > E_1$, to achieve the output level Y_2 with $E = E_1$, the input bundle (N_2, E_1) must have $N_2 > \tilde{N}_2$ (see point C in Figure 3). Note that the tangent line of $F|Y_2$ at $(\tilde{N}_2, \tilde{E}_2)$ has the same slope of that of $F|Y_1$ at (N_1, E_1). Therefore, we have $\lambda_2 | Y_2 > \lambda_1 | Y_1$ since F is convex.

Under the same technology assumption, let us consider the case with an elastic demand. Without a constraint on

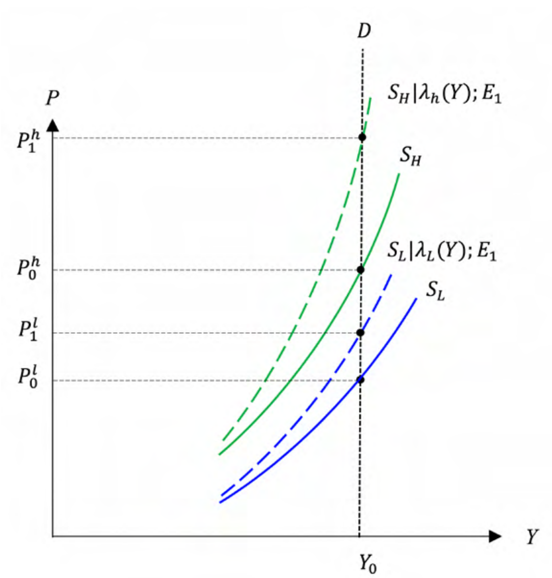

Figure 2. Equilibrium price and output when the demand is perfectly inelastic.

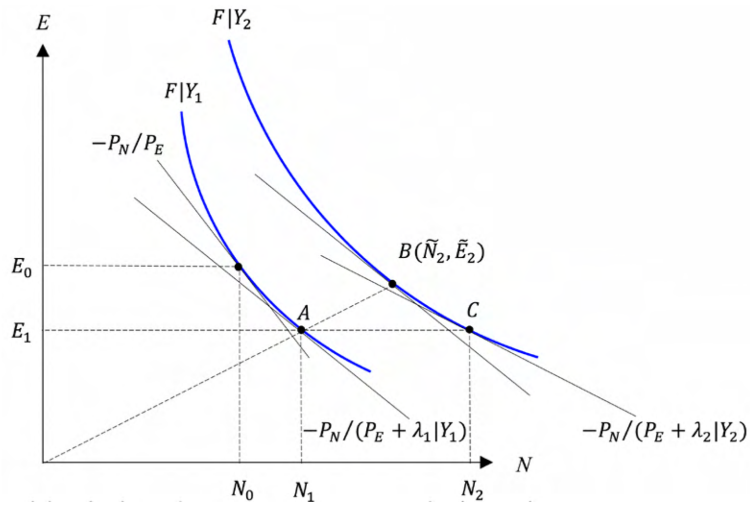

Figure 3. Input, output and the shadow price on energy use constraint ($E = E_1$).

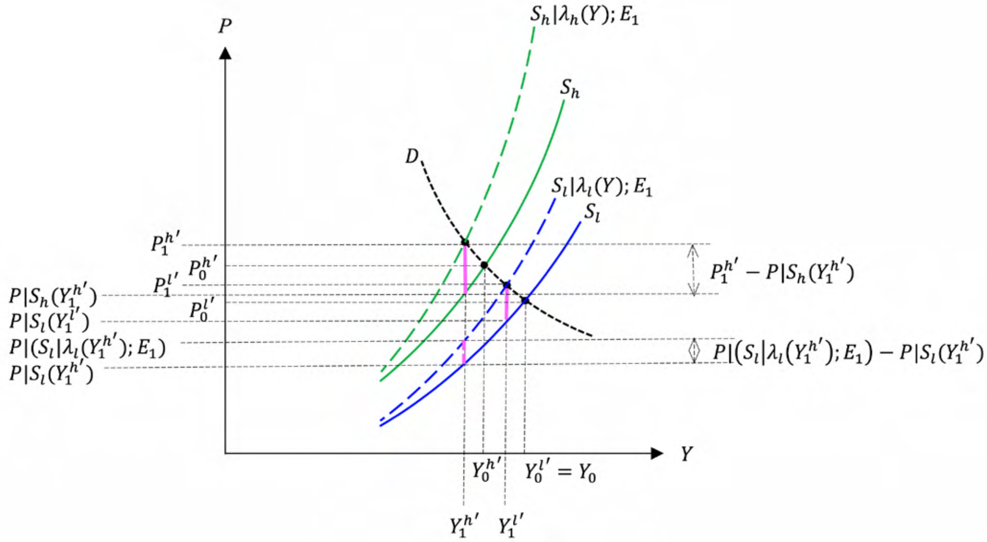

Figure 4. Equilibrium price and output with an elastic demand and the constraint $E = E_1$

energy use, the equilibrium output and price levels under the technology F_i are denoted by $Y_0^{i\prime}$ and $P_0^{i\prime}$, respectively. Similarly, when the energy use is capped at E_1, we denote the equilibrium output and price levels under the technology F_i by $Y_1^{i\prime}$ and $P_1^{i\prime}$, respectively. Based on these considerations, we have:

$$Y_0 = Y_0^{l\prime} > Y_0^{h\prime} \quad (15)$$

$$Y_0^{l\prime} > Y_1^{l\prime} \quad (16)$$

$$Y_0^{h\prime} > Y_1^{h\prime} \quad (17)$$

$$P_1^{h\prime} - P|S_h(Y_1^{h\prime}) > P|(S_l|\lambda_l(Y_1^{h\prime}); E_1) - P|S_l(Y_1^{h\prime}) \quad (18)$$

$$P_1^{l\prime} - P|S_l(Y_1^{l\prime}) > P|(S_l|\lambda_l(Y_1^{h\prime}); E_1) - P|S_l(Y_1^{h\prime}) \quad (19)$$

These properties are presented graphically in **Figure 4**. In particular, Conditions (15) through (17) hold because the demand is elastic, Condition (18) can be derived based on $\lambda_h|Y > \lambda_l|Y$ (Proposition 3.1) and $\alpha_h > \alpha_l$, and Condition (19) is justified by Proposition 3.2.

One thing that is uncertain is under the same energy use constraint, whether the corresponding shadow price with a technology calibrated based on a higher energy price (F_h) will still be higher than the one calibrated based on a lower energy price (F_l), i.e., whether $\lambda_h|Y_1^{h\prime} > \lambda_l|Y_1^{l\prime}$ holds. The uncertainty exists because the equilibrium output with F_l is higher than that with F_h (i.e., $Y_1^{l\prime} > Y_1^{h\prime}$). Note that Condition (20) below is the necessary condition for $\lambda_h|Y_1^{h\prime} > \lambda_l|Y_1^{l\prime}$:

$$P_1^{h\prime} - P|S_h(Y_1^{h\prime}) > P_1^{l\prime} - P|S_l(Y_1^{l\prime}) \quad (20)$$

Also, compared with $Y_1^{l\prime}$, $Y_1^{h\prime}$ will be reduced further under a higher price elasticity of demand. Consequently, if the demand elasticity is high enough, Condition (20) may not hold, and in that case $\lambda_h \mid Y_1^{h\prime} > \lambda_l \mid Y_1^{l\prime}$ will not hold. Nevertheless, if the price elasticity of demand is not too high such that the change in equilibrium output $Y_1^{l\prime} - Y_1^{h\prime}$ is small, then under the technology F_l, if we compare the shadow price for the energy use constraint associated with the output level of $Y_1^{l\prime}$ with that associated with the output level of $Y_1^{h\prime}$, the difference will be small, i.e., $\lambda_l \mid Y_1^{l\prime} - \lambda_l \mid Y_h^{l\prime}$ will be a small positive number. Since $\lambda_h \mid Y_h^{l\prime} > \lambda_l \mid Y_h^{l\prime}$ (Proposition 3.1), if $\lambda_l \mid Y_1^{l\prime} - \lambda_l \mid Y_h^{l\prime}$ is small enough, we will have $\lambda_h \mid Y_h^{l\prime} > \lambda_l \mid Y_l^{l\prime}$, i.e., when the price elasticity of demand is not too high so the demand response is relatively low, the shadow price for the energy use constraint $E = E_1$ will still be higher when the underlying technology is calibrated based on a higher energy cost price.

Finally, let us consider the case with a change in economic output (e.g., economic growth) such that the two input-output data compiled at different time point have different output levels. We will consider the case where the mitigation goal is to cut the emissions level (and therefore the energy use) proportionally and the demand is elastic.

Proposition 3.3

Let us consider the case where F_l calibrated based on the input-output data D_0 compiled at T_0 has an output level Y_0, and F_h calibrated accordingly to the input-output data D_1 compiled at T_1 has an output level Y_1, and $T_0 < T_1$; $Y_0 \neq Y_1$. If the goal is to cut the emissions (and therefore energy use) proportionally, using D_1 will always result in a higher shadow price on the energy use constraint than the case of using D_0, even under an elastic demand.

Proof:

For the technology F_i ($i = l$ or h), the unconstrained input bundles (N_0, E_0) and (N_1, E_1) produce output levels Y_0 and Y_1, respectively, and the constrained input bundles $(N_0{}', E_0{}')$ and $(N_1{}', E_1{}')$ produce output levels Y_0 and Y_1, respectively, with $r = E_0{}'/E_0 = E_1{}'/E_1 \in (0,1)$, as the energy reduction proportion is constant (**Figure 5**). Since F is homogeneous of degree one, the expansion path is a straight line, and the tangents to the isoquant along the expansion path are parallel to each other. Therefore, $\lambda_i \mid Y_1 = \lambda_i \mid Y_0$ $(Y_1 \neq Y_0)$. According to Proposition 3.1, $\lambda_h - \lambda_l > 0$ for a given level of output Y, so, we have $\lambda_h \mid Y_1 > \lambda_l \mid Y_1 = \lambda_l \mid Y_0$ and $\lambda_h \mid Y_0 > \lambda_l \mid Y_0 = \lambda_l \mid Y_1$, which means under the proportional reduction, $\lambda_h - \lambda_l > 0$ always holds regardless of the corresponding output levels.

Proposition 3.3 demonstrates that for the economy considered in this section, when the underlying input-output databases have different output levels and energy cost shares, if the goal is to cut the emissions level (and therefore the energy use) proportionally, using the input-output data with a higher energy cost share can always result in a higher shadow price on energy constraint, even when the demand is elastic. The findings of this section will provide explanations for results of numerical simulations presented in the following section.

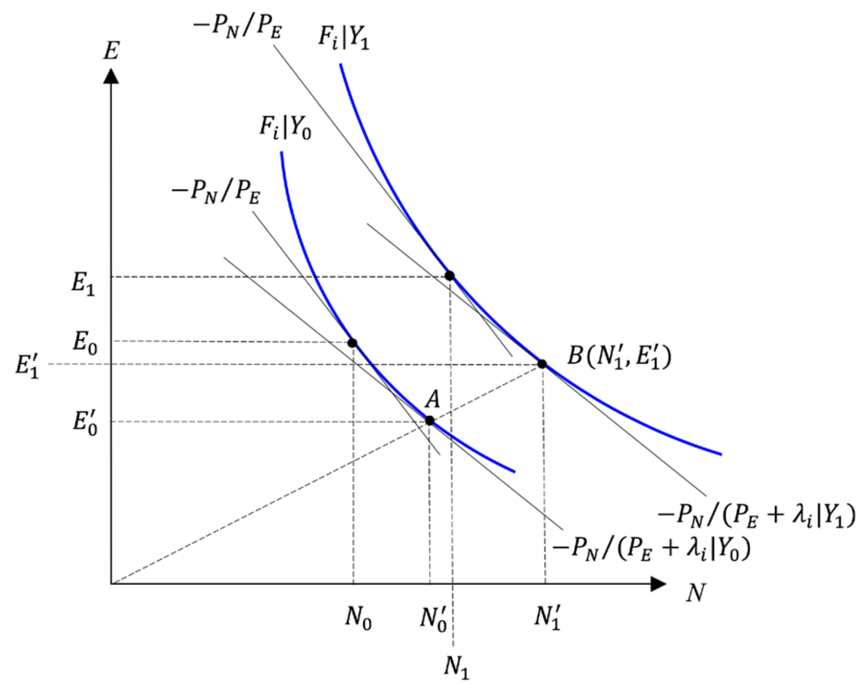

Figure 5. Input, output and the shadow price on energy use constraint ($r \in (0,1)$).

3. Numerical Examples

To provide numerical examples for our theoretical analysis, in this section, using different base year data, we simulate the CO_2 prices under a carbon mitigation scenario based on a global computable general equilibrium (CGE) model, which will be introduced shortly. With various base year data, besides differences in fossil fuel prices, other economic and physical variables that affect CO_2 prices may also vary due to shocks other than changes in fossil fuel prices. As a result, we will also reproduce data that control for those shocks beyond fossil fuel prices and demonstrate numerically the effect of changes in fossil fuel prices on CO_2 prices. In addition, we will provide a solution to address the issue of using a base year database with extreme fossil fuel prices due to short-term fluctuations.

3.1 Model

We use the static version of the Economic Projection and Policy Analysis model for Taiwan (EPPA-Taiwan) to demonstrate numerically the implications of using input-output data of various years on CO_2 prices when a global CO_2 reduction policy is in place. The model is a multi-region and multi-sector energy-economic CGE model of the world economy. For each region in the model, there is a representative household, a government, and a representative producer for each production sector. The household is the owner of primary factors, including labor, capital, and natural resources. It earns income by providing the primary factors to producers, and allocates income to consumption and savings. Producers convert intermediate inputs and primary factors into goods and services, and then sell them to other domestic or foreign producers, households, or governments. In each region, the government consumption and transfers are financed by taxes the government collects from producers and the representative household.

Similar to the theoretical framework presented in Section 2, EPPA-Taiwan uses CES functions to represent production technologies and preferences, which are both formulated in mixed complementary problems (MCP) (Mathiesen, 1985; Rutherford, 1995; Ferris and Peng, 1997). The model is written and solved using the modeling languages of General Algebraic Modeling System (GAMS) and Mathematical Programming System for General Equilibrium analysis (MPSGE), which is now a subsystem of GAMS (Rutherford, 1999). Interested readers may refer to Chai *et al.* (2017) for more details about the model.

The input-output data of EPPA-Taiwan are from the GTAP 9 database (Aguiar *et al.*, 2016), which provides three reference years: 2004, 2007, and 2011, and classifies the world economy into 140 regions, 57 sectors, and 5 primary factors. For EPPA-Taiwan currently we aggregate the data into 19 regions (**Table 1**), and combine them into 14 sectors and 4 primary factors (**Appendix A**).

3.2 Simulations

We present the response of EPPA-Taiwan to a global CO_2 abatement policy using the data for the two different base years (2007 and 2011) provided in GTAP 9. We note that Reilly *et al.* (2016) estimated that getting on a path consistent with the world remaining below 2 degrees C of warming would require about a 40% reduction from reference emissions in 2030, with further reductions in later years. Intended only as an example, we apply a similar 40% global emissions reduction as an illustrative policy. For each region, the target is achieved by imposing an economy-wide carbon tax.

When comparing the 2007 and 2011 datasets, in general the 2011 fossil fuel prices are much higher (except for the lower gas price in the U.S. for that year) (**Figure 6**). If we regard the fossil fuel price hikes in 2011 as temporary and—to

Table 1. Regions in EPPA-Taiwan.

Symbol	EPPA-Taiwan region
USA	United States
CAN	Canada
MEX	Mexico
JPN	Japan
ANZ	Australia, New Zealand & Oceania
EUR	The European Union+
ROE	Eastern Europe and Central Asia
RUS	Russia
ASI	East Asia
TWN	Taiwan
KOR	South Korea
IDZ	Indonesia
CHN	China
IND	India
BRA	Brazil
AFR	Africa
MES	Middle East
LAM	Latin America
REA	Rest of Asia

Note: The European Union (EU-28) plus Norway, Switzerland, Iceland, and Liechtenstein. See details in Chai *et al.* (2017).

avoid overestimating the CO_2 prices and simultaneously control for factors beyond fossil fuel prices—replace the 2011 fossil fuel prices in the input-output data with those of the 2007 levels, we can produce an adjusted database for 2011 with a shock only from changes in fossil fuel costs, which are set to the 2007 levels. With the adjustment, while equilibrium prices and quantities will not be the same as the pre-shock levels, the changes are only induced from the cost shock. We can then use the adjusted database as the input for EPPA-Taiwan, conduct a CO_2 mitigation policy, and compare CO_2 prices with those using the original 2011 and 2007 data. This is exactly how we present the following example for demonstration purposes. It is worth emphasizing that our goal is simply numerical. Whether the fossil fuel prices in 2007 can be considered as long-run equilibrium levels is a separate research topic.

To produce the adjusted database, we put the GTAP 9 data into EPPA-Taiwan, using 2011 data for all except fossil fuel prices, for which we use the lower 2007 levels (in this scenario, therefore, costs are also lower, since according to the model's setting economic profits are zero in equilibrium). Results from running this scenario, which constitute the adjusted 2011 data, are used as inputs of EPPA-Taiwan for running the CO_2 reduction simulation, which will be presented below. Compared with the original 2011 data, in the adjusted data, global average cost shares decrease in both industrial use and final consumption for refined oil by about 4.0% and 6.2%, for coal by 18.7% and 0.2%, and for gas by 1.6% and 12.1%, respectively.

We now compare the regional CO_2 prices for the original data and adjusted data under a 40% emissions reduction. The results demonstrate that, as expected, using the adjusted data leads to lower CO_2 prices (**Figure 7**). The regional CO_2 prices based on the 2007 data are also presented for comparison purposes. All prices are in 2007 US dollars.

We proceed by calculating the world average CO_2 prices weighted by regional emissions levels. We find that using the original 2011 data, the adjusted 2011 data, and the 2007 data, the world average CO_2 prices are \$135.9/t-CO_2, 115.1\$/t-CO_2, and \$119.3/t-CO_2, respectively, i.e., the sim-

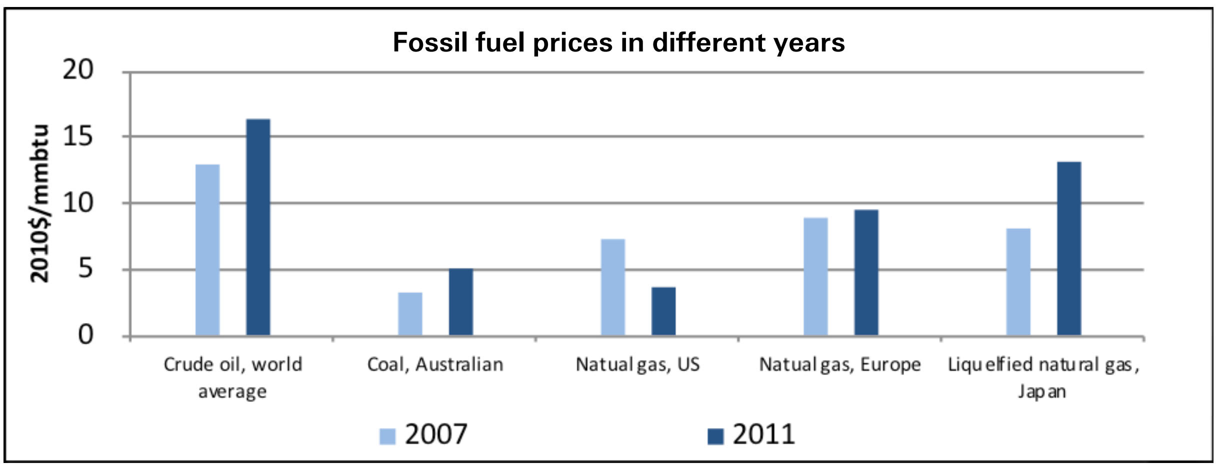

Figure 6. Fossil fuel prices in different years (source: The World Bank, 2017; EIA, 2017).

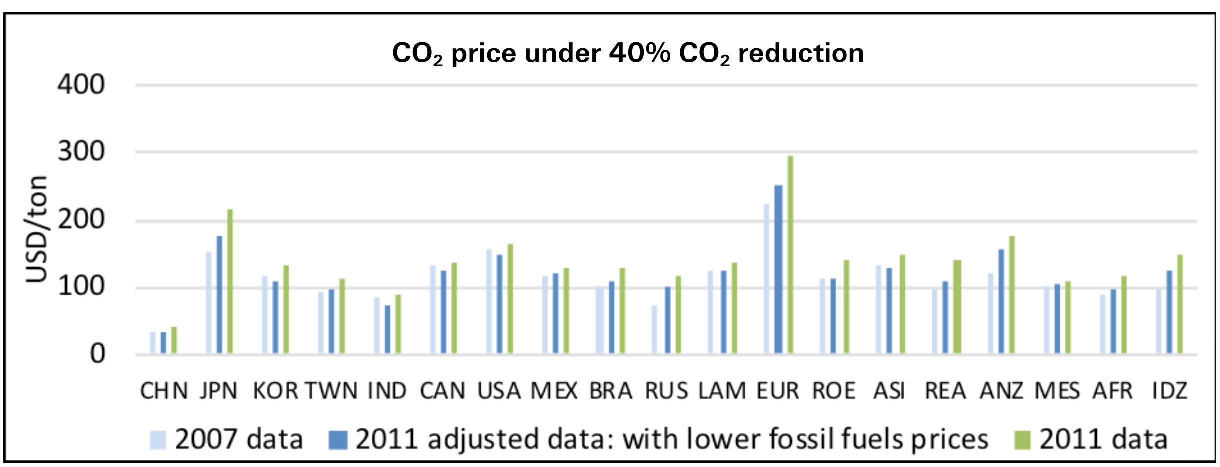

Figure 7. CO_2 prices using the original and adjusted databases.

ulated CO_2 price using the adjusted 2011 data is much closer to that using the 2007 data with only 3.5% deviation, as opposed to the simulated CO_2 price using the original 2011 data, which deviates from that using the 2007 data by 13.9% (**Figure 8**).

Therefore, if one believes that fossil fuel prices in 2007 are closer to the long-run equilibrium levels and those price hikes in 2011 are simply short-term phenomena, then using the original 2011 data to simulate a carbon constraint scenario would overestimate the world average CO_2 price by 18%, compared with the simulated CO_2 price using the 2011 data adjusted with 2007 fossil fuel prices.

Fossil fuels have been subject to periodic price spikes with relatively long periods in between of fairly stable, lower prices. The price spikes are generally unanticipated. Reducing fuel use in response to such prices is generally going to take some time since such adjustment depends on sunk capital, fuel contracts, and other considerations. Especially if fuel users see these prices spikes as temporary, they may have little reason to substitute away from the fuel. Even when the changes are considered as permanent, it takes time to retire old technologies and replace them with new ones or, more generally, to adjust the structure of the economy. Since the input-output data CGE models use can be regarded as a snapshot of the economy, we do not expect the data to be free from potential issues caused by short-term price fluctuations, as in the database there is no dimension to distinguish short-term phenomena from longer-term ones. Further, since intrinsically the input-output data assume the underlying economy is in equilibrium, they also cannot, for example, reflect the ongoing technological adjustments under higher fossil fuel prices that are considered as perpetual.

With all those potential issues, another important question to ask is: if the underlying fossil fuel prices embedded in the input-output data of CGE models could inadvertently change the estimates for emissions mitigation costs, as our finding demonstrates, which estimates are more plausible than others? While a comprehensive solution to fix these issues is beyond the scope of our research, one way to

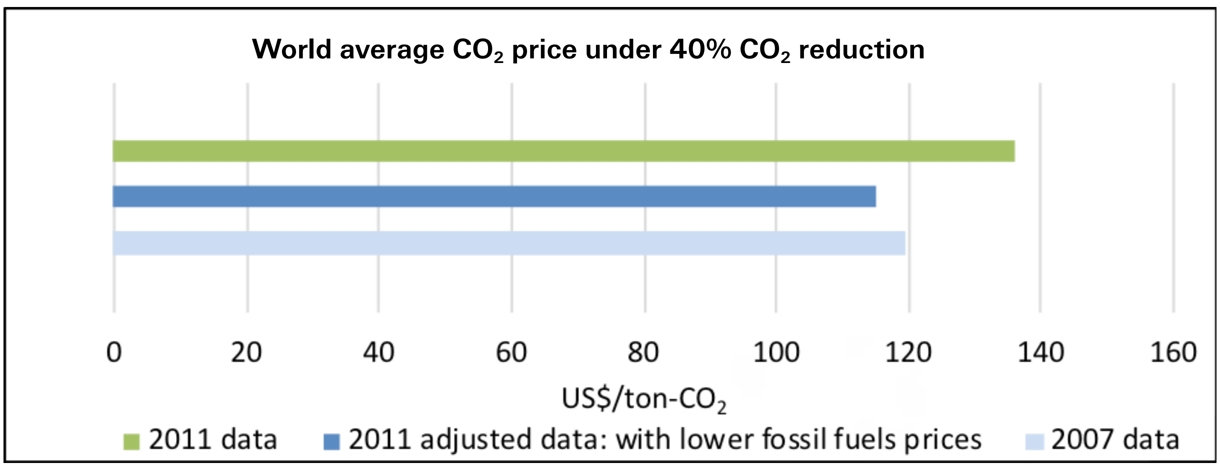

Figure 8. World CO_2 prices using the original and adjusted databases.

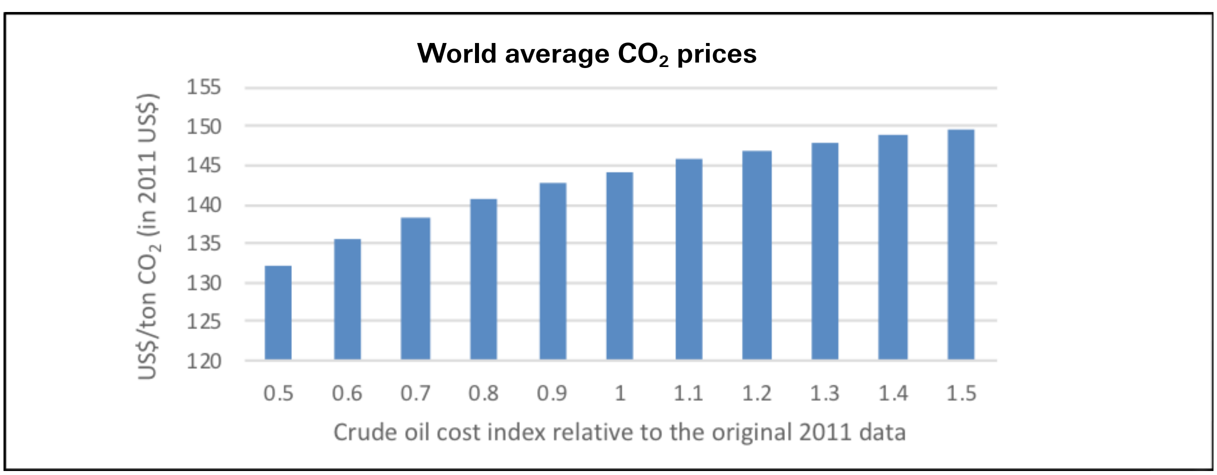

Figure 9. World CO_2 prices using databases with various crude oil cost assumptions.

address the concern is to check the underlying fossil fuel prices presented in the input-output data and adjust price levels that are considered extreme to more reasonable ones based on other studies.

Taking the 2011 data from GTAP 9 as an example, we adjust the crude oil price levels by changing the associated marginal costs in EPPA-Taiwan, while keeping other fossil fuel prices at their original levels. The simulation results from running the model with the cost shock produce the adjusted 2011 input-output data with revised crude oil costs/prices. Using the adjusted data to run a CO_2 reduction simulation, we conduct a sensitivity analysis on the world average CO_2 price under different crude oil price assumptions (**Figure 9**). For instance, using the 2011 input-output data when the crude oil prices were \$94.88/barrel (WTI - Cushing, Oklahoma) and \$111.26/barrel (Brent, Europe) (EIA, 2018), if one believes those price hikes were simply short-term phenomena and more reasonable price levels should be just 70% of the 2011 levels, under the same world-wide 40% emissions reduction scenario considered previously, compared with results based on the original 2011 data that lead to a CO_2 price of \$144/t-CO_2, the projected CO_2 price would decrease by 4.1% to around \$138/t-CO_2, as Figure 9 shows.

One caveat to the adjustment is: lowering the oil price may induce a higher level of the baseline (reference or no policy case) emissions, and similarly, increasing the oil price could reduce baseline emissions. Therefore, if the reduction targets are expressed in emissions levels rather than the percentage reduction relative to the baseline, then how CO_2 price might change would also depend on the model parameterization.

4. Conclusions

Large-scale economy-wide equilibrium models are widely used for assessing energy or climate policies. As different models often produce diversified outcomes for similar policies, researchers have been trying to understand reasons behind this observation, including cost assumptions for mitigation options, model structure, policy design, and timing (Clarke *et al.*, 2015; Chen *et al.*, 2016). In this study, we focus on analyzing how updating the input-output database of a CGE model could inadvertently change the model output, which has not been carefully examined but could also be an important source that accounts for variations in simulation results of distinct models.

To answer the research question, we provide an analytical framework that elucidates how using a database with a higher energy price raises the CO_2 mitigation cost when the substitution between inputs is relatively limited in the short-run, or when the price hike is considered as temporary. We also provide a numerical example for the analysis, and propose an adjustment that could, under the same percentage reduction in emissions, address the concerns of using the input-output data with prices for fossil fuels and their consumption levels deviating from a more sustainable state.

Our focus in this paper is on how changes in fossil fuel cost shares of input-output data affect the CO_2 mitigation costs. Over time, economic development as well as policy intervention may drastically change things beyond fossil fuel cost shares, and therefore result in, for instance, a shift from fossil generation to low-carbon alternatives, or a transition toward a less energy-intensive economy. In these cases, the underlying industrial structure would be very different from before. As a result, future research may explore the roles of these changes in determining emissions or pollution mitigation costs, as those changes could constitute another crucial dimension that contributes to variations in simulation results based on databases with different reference years.

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APPENDIX A. Sectors and primary factors in EPPA-Taiwan

Table A1. Sectors.

Symbol	Sector	Symbol	EPPA-Taiwan sector
CROP	Crops	**GAS**	Gas
LIVE	Livestock	**ELEC**	Electricity
FORS	Forestry	**EINT**	Energy-Intensive Industries
FOOD	Food Products	**OTHR**	Other Industries
COAL	Coal	**DWE**	Ownership of Dwellings
OIL	Crude Oil	**SERV**	Services
ROIL	Refined Oil	**TRAN**	Transport

Note: See details in Chai *et al.* (2017).

Table A2. Primary factors.

Symbol	Primary factors
CAP	Capital
LAB	Labor
LND	Land
FIX	Natural resources

Note: See details in Chai *et al.* (2017).

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