Analyzing Carbon Pricing Policies using a General Equilibrium Model with production parameters estimated using firm data

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December 2019

Abstract

Computable General Equilibrium (CGE) models are extensively used in simulating important public policies, such as carbon taxes or cap and trade policies. The simulation results from these models hinge on the production functions and the elasticities of substitution among inputs such as capital, labor and energy, or sub-tier substitution among different energy types. Many CGE models rely on parameters that are derived from other countries, other industries or from earlier periods given the difficulty in obtaining them; a common source of parameters is the GTAP database which is carefully compiled but only has a small set of elasticities. In the empirical studies of China, there are few studies of production functions with energy input using firm-level data. We use firm level data, and the Ackerberg-Caves-Frazer method to estimate CES production functions by industry and find significant heterogeneity in substitution elasticities across different industries. We then incorporate these empirically estimated elasticities into the CGE model to simulate carbon price policies to reach China's NDC targets in 2030. We compare simulated results using GTAP parameters and our empirically estimated coefficients. We find our empirical CGE model project lower base case GDP growth and higher total energy use, but with lower coal use and carbon emissions. In the carbon tax exercises, we found that empirical parameters would cause slightly larger GDP loss and greater energy use and carbon emission reductions, compared to GTAP parameters. Finally, we also conduct a sensitivity analysis applying empirical parameters in limited sectors to test the model sensitivity.

Key Words: CGE Model, production function, empirical parameters, GTAP parameters

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1 Introduction

From the energy shocks in the 1970s to the current concern about the environment, economists have devoted great efforts to study the industrial demand for energy in order to design policies to conserve energy use and reduce pollution. The debates about whether energy and other inputs are substitutes or complements have been on-going for decades, yet there is little consensus about the value of elasticities or the most suitable representation in simulation models. This is in part due to the lack of micro-level evidence on the elasticities of substitution between energy and other inputs. Much of the empirical work to date uses data at the industry or national level and fails to capture heterogeneity across firms. However, with the more recent availability of firm-level data and introduction of methods to deal with endogeneity issues, there has been a substantial effort at estimating firm-level production functions (Olley and Pakes 1996, Levinsohn and Petrin 2003, Ackerberg et al. 2015). This more recent literature, however, has focused on capital and labor inputs and not devoted much attention to energy inputs.

Estimating the substitution elasticity of energy is of great importance both in theory and in practice. The substitutability of energy is a crucial parameter in energy-economic models, especially computable general equilibrium (CGE) models, which are used to analyze policies. The simulated effects of policies or external shocks using CGE models hinge on the choices of functional forms (Lecca et al. 2011) and elasticities. Okagawa and Ban (2008) estimated elasticities using panel data from OECD and concluded that the commonly used parameters in CGE models for climate policy analysis tend to overestimate carbon prices by more than 40% compared to simulations using their estimated elasticities. Van der Werf (2008) investigated the choice of production structure and how it affects the elasticities and factor-specific technical change and, in turn, how these have big effects on the analyses of climate policies. Through estimating a nested CES production function using the World Input-Output Database, Koesler and Schymura (2015) find common practices of using Cobb-Douglas and Leontief production functions are not supported by their results.

The substitutability of energy for other inputs is essential for estimating the costs of energy and environmental policies since it reflects the potential of energy savings and costs of abating pollutant emissions. It plays a critical role in energy-economic models used to analyze public policies such as emission trading schemes, carbon taxes, environmental regulation, and energy-efficiency regulations. There have been great efforts at estimating the substitution elasticities, beginning with studies using industry-level data such as Berndt and Wood (1975), Griffin and Gregory (1976) among many others (see also the meta-analysis by Koetse et al. 2008 and the review of econometric methods for production in Jorgenson 1986).

A lot of information is lost in aggregating firm data to the industry level and much effort has since been put into developing data and methods for firm-level analysis (see review by Oberfield and Raval 2014). There are, however, fewer analyses using China data. Notable exceptions are Lu and Yu (2015), Berkowitz et al. (2017), Brandt et al. (2017), which employed firm-level data of China to estimate markup, substitution elasticity and productivity. Nevertheless, energy is hardly ever considered as a separate input in this strand of literature. In this paper we employ firm-level data in China to estimate production functions with energy, capital and other inputs and recover energy elasticities of substitution.

To illustrate the value of providing more empirical estimates of the elasticities, we compare them to those used by many simulation models – the GTAP database. We put our estimated elasticities into our multi-sector economic growth model of China to simulate the effect of a carbon price. We then compare the results to those derived from the original version of the model that uses GTAP elasticities. We find our empirical CGE model project lower GDP growth and higher energy projections, however with lower coal use and carbon emissions. In the counterfactual carbon tax exercises, we found compared to the GTAP parameter case simulations, our empirical case would cause slightly larger GDP loss and greater energy use and carbon emission reductions. Finally, we also conduct a sensitivity analysis on only switching a few sectors, especially energy sectors.

Our estimates of the parameters of Constant Elasticity of Substitution (CES) functions for each of 33 industries would be useful for other modelers looking for such information for countries similar to China's level of development.

2 Identification issues in estimating production functions

There are multiple econometric and measurement issues that should be taken into account in the estimation of production functions using firm data. The most common identification problem is simultaneity bias. Ackerberg et al. (2015) has an excellent discussion of this and we summarize it here. Consider a Cobb-Douglas production function for firm i at time t, where y_{it} is the log of output:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \omega_{it} + \epsilon_{it} \tag{1}$$

w_{it} is the total factor productivity (TFP), which is unobservable for the econometrician but known to the firm when it decides capital and labor inputs. ϵ_{it} represents the unanticipated productivity shock.

Capital input k_{it} is regarded as a predetermined input, and labor l_{it} is a flexible input that is determined after firms observe its TFP. Therefore, l_{it} is directly correlated with the unobserved w_{it}. This correlation induces the classical omitted variable bias to conventional estimation methods such as ordinary least squares. Moreover, this simultaneity bias could also exist for the predetermined input. Since k_{it} is determined by the firm's decisions in the past periods, and are correlated with the disturbance in the past, the simultaneity problem still applies if the disturbance w_{it} is serially correlated.

The control function method, first proposed by Olley and Pakes (1996), is now the dominant approach to deal with this endogenous problem. The idea is that one can invert optimal input decisions to get this unobserved TFP term. Olley and Pakes used investment as a monotonic and invertible function of w_{it}. Investment, however, is not always a good proxy variable because investment data can be lumpy in practice, i.e. firms are likely to make zero or tiny investments in most periods. Therefore, Levinsohn and Petrin (2003) suggest using the demand function for intermediate input m_{it} to invert out the unobserved productivity. Later on, Ackerberg et al. (2015) notice that it is impossible to identify b_L in the first stage of control function method and suggest to estimate b_L and b_K together in the second stage.

Specifically, Ackerberg et al. (2015) assume the demand function for intermediate input is given by:

$$m_{it} = f_t(k_{it}, l_{it}, w_{it}) \tag{2}$$

Under the assumption that the demand function is monotonically increasing in ω_{it}, productivity can be inverted as $\omega_{it} = f_t^{-1}(k_{it}, l_{it}, m_{it})$. Substituting this control function into the production function we have:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + f_t^{-1}(k_{it}, l_{it}, m_{it}) + \epsilon_{it} = \Phi_t(k_{it}, l_{it}, m_{it}) + \epsilon_{it} \tag{3}$$

where f_t^{-1} is treated nonparametrically and since the first two terms are not identified they are subsumed into $\Phi_t(\cdot)$, which is approximated by a high-order polynomial function.

In the first stage Ackerberg et al. (2015) obtain the estimated output $\hat{\Phi}_{it}$ and $\hat{\epsilon}_{it}$. A key assumption of this approach is that ω_{it} follows a first-order Markov process:

$$\omega_{it} = g(\omega_{it-1}) + \xi_{it} \tag{4}$$

For any value of β_K and β_L, combining (1) and (4), we can write $\epsilon_{it} + \xi_{it}$ as:

$$\zeta_{it}(\beta) = \epsilon_{it} + \xi_{it} = y_{it} - \beta_0 - \beta_K k_{it} - \beta_L l_{it} - g(\hat{\Phi}_{t-1} - \beta_0 - \beta_K k_{it-1} - \beta_L l_{it-1}) \tag{5}$$

Ackerberg et al. (2015) exploit the following moment conditions in the second stage to estimate β_K and β_L:

$$E(\zeta_{it}(\beta) z_{it}) = 0 \tag{6}$$

where z_{it} is the set of instruments that includes a constant, k_{it}, l_{it-1} and Φ_{it-1}.

Nevertheless, as noted by Gandhi et al. (2017), this method of proxying productivity using material inputs in the control function can only be applied to value-added production functions. When it comes to a gross-output production function, there is no exogenous variation in the proxy variables because intermediate input is an endogenous variable (determined by capital, labor and productivity) and does not admit any source of variation from outside the production function.

Besides this simultaneity problem, omitted price bias is another common problem. Most datasets have only data for values of firm output and inputs, there is no information on real quantities or input prices and thus industry-level price indices are usually used to deflate output and input expenditures. However, since input choices are correlated with firm-level price variation, this omitted price will result in omitted variable bias.

To illustrate this, let y_{it} denote the logarithm of actual output quantity, and r_{it} be the output index derived by deflating output value by the industry average price $\bar{p}_{it}$:

$$\tilde{r}_{it} = p_{it} + y_{it} - \bar{p}_{it} = \beta_L l_{it} + \beta_K k_{it} + (p_{it} - \bar{p}_{it}) + \omega_{it} + e_{it} \tag{7}$$

where p_{it} represents the logarithm of firm-level output price and $\bar{p}_{it}$ represents the logarithm of industry-level price deflators.

If input choices are allowed to be correlated with the unobserved differences between firm-level prices and industry-level prices, i.e. $E((l_{it}(p_{it} - \bar{p}_{it})) \neq 0$ or $E((k_{it}(p_{it} - \bar{p}_{it})) \neq 0$, omitted-variable bias will be introduced into the estimates of input coefficients.

More specifically, following the standard supply and demand framework, output prices and output quantities are negatively correlated while input and output quantities are positively correlated. Therefore, the estimated coefficients on inputs suffer a downward bias. Furthermore, suppose efficient producers pass through some cost savings to consumers by charging lower output prices, then the firm-level price is lower than industry-level price. This results in under-estimation of outputs, hence under-estimation of TFP.

Besides unobservable output prices, the omitted price bias could also appear due to input prices, especially for capital and materials, whose quantities are usually unavailable. Consider a gross output production function, where m_{it} denotes the true quantity of intermediate inputs, $\tilde{m}_{it}$ is the quantity derived from using industry average deflators and p_{it}^K and p_{it}^M are the input prices:

$$\begin{aligned} y_{it} &= \beta_L l_{it} + \beta_K \tilde{k}_{it} + \beta_m \tilde{m}_{it} + \omega_{it} + e_{it} \\ &= \beta_L l_{it} + \beta_K k_{it} + \beta_m m_{it} + \beta_K (p_{it}^K - \bar{p}_{it}^K) + \beta_M (p_{it}^M - \bar{p}_{it}^M) + \omega_{it} + e_{it} \end{aligned} \tag{8}$$

If a firm is able to obtain lower prices for a given input, then using industry-level deflators will under-estimate the firm's input use. Moreover, the correlation between input prices and input quantities could also bias the production function estimation as long as the industry-level input price indices fail to capture all variations of firm-level input prices. For the discussion below, we write the output function more generally as:

$$y_{it} = f(\tilde{x}_{it}; \beta) + B(p_{it}, \tilde{x}_{it}, \beta) + \omega_{it} + e_{it} \tag{9}$$

where $f(\tilde{x}_{it};\beta)$ is the output function with inputs $\tilde{x}_{it}$ derived from average deflators and $B(\cdot)$ captures the unobserved effects of firm-specific prices.

De Loecker et al. (2016) argue that the quality of output and inputs are related to output and input prices, and that the quality of output is related the firm's market share and export status. Therefore, the unobserved input price p_{it} is a function of market share ms_{it} and export status ex_{it}, i.e. $p_{it} = p\left(ms_{it}, ex_{it}\right)$[1]. Substituting this function into the unobserved price control function $B(\cdot)$ yields:

$$B(p_{it},\tilde{x}_{it},\beta) = B((ms_{it},ex_{it})\times\tilde{x}_{it}^{c};\beta,\delta) \tag{10}$$

where $\tilde{x}_{it}^{c} = \left\{1,\tilde{x}_{it}\right\}$ to ensure that both the input price term $p(\cdot)$ itself and its interactions with input expenditures $\tilde{x}_{it}$ enter the price control function $B(\cdot)$. δ represents the additional parameter vector to be estimated in the control function.

3 Energy production function estimation

3.1 Production model and estimation strategy

We consider a production function with six factors – capital, labor, electricity, coal, oil and non-energy intermediate inputs, denoted by K, L, ELC, CL, OIL and M. Gross output of firm *i* at time *t* is thus $Q_{it} = Q(K_{it}, K_{Lt}, ELC_{it}, CL_{it}, OIL_{it}, M_{it})$. We assume that this may be represented by a set of nested constant elasticity of substitution (CES) functions where the top tier gives output as a function of a value-added-energy aggregate and non-energy intermediates, $Q_{it} = Q(VE_{it}, M_{it})$. The CES functions for the value-added-energy (VE) bundle and subaggregates for value-added (VA) and energy (E) are written as:

$$VE_{it} = \Omega_{it}\left[\alpha_{VAi}VA_{it}^{\rho_{VE}} + (1-\alpha_{VAi})E_{it}^{\rho_{VE}}\right]^{\frac{1}{\rho_{VE}}} \tag{11}$$

$$VA_{it} = \left[\alpha_{Ki}K_{it}^{\rho_{VA}} + (1-\alpha_{Ki})L_{it}^{\rho_{VA}}\right]^{\frac{1}{\rho_{VA}}} \tag{12}$$

[1] De Loecker et al. (2016) further use output price, location and product dummies as additional controls. We omit them here for brevity.

$$E_{it} = \left[a_{ELC} ELC_{it}^{r_E} + a_{Coal} Coal_{it}^{r_E} + a_{Oil} Oil_{it}^{r_E} \right]^{\frac{1}{r_E}} \tag{13}$$

In eq. (11) Ω_{it} is the total factor productivity term. There are no TFP terms in the sub-aggregates (12) and (13); VA_{it} and E_{it} are variables constructed from the components, they not independently measured values. Q_{it} is the index of output and VE_{it} is derived by subtracting the non-energy input measure from Q_{it}. In the above form the elasticity of substitution between value-added and energy is $\sigma_{VE} = 1/(1-\rho_{VE})$.

Given the discussion in Section 2 of bias from unobserved productivity and omitted firm-level prices, we utilize the control function method in Ackerberg et al. (2015) to estimate the CES production function with non-energy intermediate input as our proxy variable . In this paper we do not estimate the top tier function for gross output but only the nests in eqs. (11)-(13). First, we rewrite the value-added-energy production function as:

$$\ln(VE_{it}) = f(K_{it}, L_{it}, ELC_{it}, CL_{it}, OIL_{it}; \beta) + \omega_{it} + \epsilon_{it} \tag{14}$$

where β represents all the parameters in (11)-(13), w_{it} is the TFP term and ϵ_{it} is an i.i.d. error term.

To proxy productivity w_{it}, we assume that the non-energy intermediate input M_{it} is determined by:

$$M_{it} = h_t(K_{it}, L_{it}, ELC_{it}, CL_{it}, OIL_{it}, w_{it}, ex_{it}, ms_{it}) \tag{15}$$

where ex_{it} is the ratio of firm-level export to total sales, ms_{it} is the market share of firm i in its 4-digit industry. This follows the setup in De Loecker and Warzynski (2012) described above in eq. (10), with energy inputs as additional control variables.

Given the assumption that intermediate input is monotonically increasing in productivity, w_{it} can be inverted as:

$$w_{it} = h_t^{-1}(K_{it}, L_{it}, M_{it}, ELC_{it}, CL_{it}, OIL_{it}, ex_{it}, ms_{it}) \tag{16}$$

Employment and energy inputs are recorded in physical quantities in our dataset, while outputs and capital inputs are only available in monetary values. We assume that effective labor input may be proxied by employment. We do not have firm-level prices and the nominal variables are deflated by provincial industry-level price indices. As discussed in Section 2 (eq. 7), the variations between firm-level prices and aggregated price indices can induce omitted variable bias and to control for the unobserved variations, we modify the production function as:

$$\ln(VE_{it}) = f(\tilde{K}_{it}, L_{it}, ELC_{it}, CL_{it}, OIL_{it};\beta) + B(p_{it}, \tilde{X}_{it};\beta) + \omega_{it} + \epsilon_{it} \tag{17}$$

where $B(\cdot)$ is a control function denoting the omitted firm-specific prices, $\tilde{X}_{it} = (\tilde{K}_{it}, L_{it}, ELC_{it}, CL_{it}, OIL_{it})$ is the vector of calculated quantities (compared to the true unobserved quantities X_{it}).

We follow the approach of De Loecker et al. (2016) by using market shares and export shares to proxy the unobserved prices as in eq. (10) above. The control function $B(p_{it}, \tilde{X}_{it})$ is thus written as:

$$B(p_{it}, \tilde{X}_{it};\beta) = B((ms_{it}, ex_{it}) \times \tilde{X}_{it}^{c};\beta,\gamma) \tag{18}$$

where $\tilde{X}_{it}^{c} = \left\{1, \tilde{X}_{it}\right\}$ and γ is an additional set of parameters to be estimated for the control function.

The production function (17) can thus be represented as:

$$\ln(VE_{it}) = f(\tilde{K}_{it}, L_{it}, ELC_{it}, CL_{it}, OIL_{it};\beta) + B((ms_{it}, ex_{it}) \times \tilde{X}_{it}^{c};\beta,\gamma) + \omega_{it} + \epsilon_{it} \tag{19}$$

We use a two-step procedure to estimate the function. In the first stage, we utilize a flexible polynomial function to approximate VE_{it}:

$$\ln(VE_{it}) = \Phi_{t}(\tilde{K}_{it}, L_{it}, M_{it}, ELC_{it}, CL_{it}, OIL_{it}, ex_{it}, ms_{it}) + \epsilon_{it} \tag{20}$$

where $\Phi_{t}(\cdot)$ is a second-order polynomial function.

Based on the estimates in the first stage, for any values of β and γ, we can compute productivity with the fitted values $\hat{\Phi}_{it}$ from (20):

$$\omega_{it} = \hat{\Phi}_{it} - f(\tilde{K}_{it}, L_{it}, ELC_{it}, CL_{it}, OIL_{it};\beta) - B((ms_{it}, ex_{it}) \times \tilde{X}_{it}^{c};\beta,\gamma) \tag{21}$$

In the second stage, in order to recover the coefficients in the production function, we assume the law of motion for productivity follows a first-order Markov process:

$$w_{it} = g(w_{it-1}) + x_{it}$$

where x_{it} is an idiosyncratic shock.

Therefore, given b and g we can non-parametrically regress w_{it} on w_{it-1} to obtain the idiosyncratic shock $x_{it}(b,g)$ as explained in eq. (6) above.

To obtain the estimates of the production function (b,g), we can finally apply the moment conditions:

$$E(x_{it}(b,g)Z_{it}) = 0 \tag{22}$$

where Z_{it} is a set of instruments including current capital, lagged labor, energy and non-energy intermediate inputs, and their higher order and interaction terms, as well as lagged market shares and export shares, and their interactions, with the appropriately lagged inputs.

3.2 Data

We use firm survey data from the China State Administration of Taxation (SAT), Ministry of Finance, to estimate the production functions and elasticities of substitution between inputs. This dataset includes 1,824,400 firms with 4,946,500 observations from 2007 to 2015. More specifically, there are 220,000 firms in 2007, increasing to 699,900 firms in 2015. The original sample distribution is summarized in Table 1.

Since neither intermediate input nor value-added is available in the SAT dataset, we construct firm-level intermediate input by aggregating the purchasing costs of inputs (excluding fixed assets), administrative expenses, operating expenses, selling expenses and financial expenses. Nominal value-added is then calculated by the difference between gross output and intermediate input. We use the province-level purchasing price index to deflate material inputs and provincial-level producer price indices for 2-digit sectors to deflate outputs. The province-level price indices are obtained from the China Price Statistical Yearbook[2].

[2] China Price Statistical Yearbook 2018, Tables 2-1-5 and 2-2-2 give the most recent changes in producer price and purchasing price indices.

We combine several datasets together to construct firm real capital stock. Our primary source is the SAT dataset, which gives us the (net) book value of firms' fixed capital stock. Because of the essential difference in service lives between equipment and structures, we employ the industry-level data of equipment and structure capital stock to decompose firms' fixed capital into the two parts. In order to obtain the initial capital stock, we use the 1993 industrial census provided by Brandt et al. (2012) to measure the capital stock growth rates. Investment deflators on equipment and structure from China Fixed Asset Statistical Yearbook are used to deflate the nominal investment. The data construction details can be found in the appendix.

We obtain province-level prices of electricity, coal (bituminous coal), gasoline (93# unleaded gasoline) from the WIND database[3], which collects energy prices in various regions and industries from the National Development and Reform Commission (NDRC) and related industry associations in China. We need energy prices because in the SAT dataset, energy inputs are measured in real quantities, i.e. tons or kW·h, but gross outputs and intermediate inputs are in monetary values. Energy prices are used to calculate energy expenditures which is then used to calculate non-energy intermediate inputs.

Our next step is to delete the observations with obvious errors, i.e. the missing observations with negative or zero gross outputs, labor and capital inputs. Furthermore, we delete implausible or extremely volatile observations as described in the appendix. Removing these implausible data yields a sample with 634,633 firms and 1,487,822 observations. Table 1 presents the summary statistics for the samples after deleting observations with obvious and likely errors.

Table 1: Summary statistics of 634,633 firm sample

Variable	Obs.	Mean	Median	SD	Min	Max
VE	1487822	55793	9222	159252	88	1184964
K	1487822	1967	206	6374	0	48804
L	1487822	192	69	366	5	2468
M	1487822	42292	7219	115637	34	846396
ELC	1487822	547	42	1915	1	14762

[3] Energy prices are collected from WIND database maintained by Wind Information Co. Ltd (https://www.wind.com.cn/), which, like China's Bloomberg, consolidates various data sources and offers comprehensive data access to China's financial and macroeconomic data.

CL	1487822	807	0	4505	0	38685
OIL	1487822	70	0	304	0	2491

4. CGE Model and Carbon Pricing Scenario Setting

To illustrate the impacts of parameter differences on economic model simulations, we applied a recursive Computable General Equilibrium (CGE) model to conduct simulations on carbon pricing in China, with two alternative sets of production function parameters. One set of the parameters are based on GTAP elasticities, and the other set of the parameters are based on our estimated elasticity parameters.

The detail CGE model that used in this paper is described in Nielsen and Ho (2013, Appendix A) and we summarize the key features of the current version here.

The model is a Solow-type dynamic recursive one where an exogenous savings rate determines investment that are projected to fall over time. The savings is allocated to investment and financing the (exogenous) government and current account deficits. Investment adds to next period's capital stock. Labor supply is set exogenously, that is, there is no leisure demand and no elastic supply response to wages. Enterprises pay VAT and taxes on capital income, and retain part of the profits for investment, resulting in a "dividend payout" rate that is smaller than 1.

The model is based on the social accounting matrix table of year 2014, updated from 2012 national input-output table of China. There are 33 industries identified and production is represented by Constant Elasticity of Substitution functions with constant returns to scale. Product markets are competitive are assumed to be competitive and prices equal marginal cost. Labor is mobile across sectors, which simplifies the reality of structural barriers.

Our CGE model presents the same structure with our empirical model framework (Eq. 11-13). At the top tier, output is a function of the primary factor-energy basket (VE) and the non-energy intermediate input basket (M), $QI_{jt} = f(VE_{jt}, M_{jt}, t)$. The VE basket is an aggregate of value added (VA) and the energy basket (E). Value added is a function of the 3 primary factors – capital (K), labor (L) and land (T). The energy aggregate is a CES function of coal, oil mining, gas mining, petroleum refining & coal products, electricity and gas commodities. The materials aggregate (M) is a Cobb-Douglas function of the 27 non-energy commodities.

We assume that capital that is inherited from the previous period is fixed in each sector, but new capital is mobile across sectors. The actual capital market in China is fragmented with large state-owned banks favoring certain sectors and certain state-owned enterprises. Just as in the product markets, recognizing these non-competitive features would be a complicated diversion from the simple objective of assessing demographic effects on consumption and overall growth.

For each commodity, domestic goods are combined with imports to form the total supply. Total demand for a commodity is the sum of intermediate demands, consumption, government, investment and exports. Consumption is given by a translog demand function that depends on future demographic composition; as the population age and incomes rise, the consumption basket shifts towards income-elastic goods and those consumed by older households. These changes in consumption demand affects the composition of supply and thus the demand for labor.

The model distinguishes industries from commodities as in the official Use and Make input-output tables. Each industry may make a few commodities and each commodity may be made by a few industries; e.g. the Refining industry produces Refining commodity and Chemical commodity, and the Chemical commodity comes from Refining, Chemical, Primary Metal and other industries.

There are taxes and subsidies on industry gross output (or sales tax) and we represent the net value by the ad-valorem tax rate. Public revenue comes from direct taxes on capital and labor, value-added taxes, indirect taxes on output, consumption taxes, tariffs on imports, externality taxes, and other non-tax fees. For carbon pricing, we adopt a gradually increased carbon pricing regime from 2020 to 2030, to reach China’s NDC target under the commitment for Paris Agreement. We assume the carbon pricing regime is implemented under the neutral tax reform framework, which means the increased revenue from carbon taxes were used to reduce the other pre-existing taxes proportionally, so that the government revenue is kept the same in the base case and the counterfactual policy case. The detail scenarios for our model analysis were listed in table 2. We compare the difference between carbon tax scenario with base case, and then examine the alternative when using common GTAP parameters or using our estimated production function parameters.

Table 2: Base Case and Carbon Pricing Scenarios

Scenarios	Features
Base Case	No Carbon Pricing, using GTAP parameters
Base Case _ E	No Carbon Pricing, using empirically estimated parameters
Carbon Tax	Carbon Pricing, using GTAP parameters, and same carbon tax regime as Carbon Tax_E, to meet NDC target, note in this scenario would not be necessarily equal to 62.5%, it is actually roughly 63% in our simulation
Carbon Tax _E (65%)	Carbon Pricing, using empirically estimated parameters, carbon tax policy reach NDC 62.5% carbon intensity target in 2030

5. Results

5.1 Elasticities of substitution

Table 2 presents the estimated elasticities for all three of the nested CES production functions in equations (11-13); $\sigma = 1/(1-\rho)$. All elasticities are positive, suggesting those inputs are substitutes. However, the elasticities vary significantly across sectors. Coal and oil mining sectors have the largest energy substitution elasticities (σ_E). Overall, the substitution elasticities among energy inputs (electricity, coal and oil) are larger than the substitution elasticity between capital and labor (σ_{VA}), while the substitution elasticities between value-added and energy (σ_{VE}) are the smallest among the three elasticities in most sectors. The simple average energy elasticity is 0.928 and 0.734 for capital-labor and 0.756 for value-added-energy. The median elasticities are 0.855, 0.684 and 0.685, respectively. This indicates that, although different types of energy are typically substitutable, it is the most difficult to replace energy inputs with capital and labor, i.e. reduction of energy use requires more capital and labor inputs than other substitution relation.

Table 2: Estimation results on the elasticities of substitution

Sector	s_{VE}		s_{VA}		s_{E}	
Agriculture	0.764	(0.098)	0.663	(0.066)	0.896	(0.068)
Coal Mining	0.693	(0.057)	0.716	(0.057)	2.263	(0.930)
Oil Mining	0.560	(0.069)	0.684	(0.392)	1.593	(0.846)
Nonenergy mining	0.612	(2.411)	0.881	(0.447)	0.543	(0.117)
Food mfg	0.782	(0.327)	0.620	(0.217)	0.713	(0.118)
Textiles	0.663	(0.072)	0.622	(0.067)	0.881	(0.111)
Apparel, leather	0.786	(0.076)	0.724	(0.124)	0.854	(0.071)
Sawmills and furniture	0.916	(2.390)	0.528	(0.128)	0.752	(0.128)
Paper, printing, recording media	0.482	(0.030)	1.273	(0.246)	0.814	(0.687)
Petroleum processing	0.503	(0.125)	0.836	(1.065)	0.518	(0.099)
Chemicals	1.172	(0.519)	0.852	(0.152)	1.251	(0.997)
Nonmetal mineral products	0.986	(0.115)	0.551	(0.171)	1.579	(0.411)
Primary metals	0.736	(0.132)	0.685	(0.264)	1.005	(0.323)
Metal products	0.670	(0.084)	0.681	(0.059)	1.001	(0.459)
Machinery	0.748	(0.071)	0.674	(5.084)	0.972	(0.078)
Transportation equipment	1.909	(2.718)	0.716	(0.107)	0.726	(0.116)
Electrical machinery	0.838	(0.164)	0.607	(0.085)	0.911	(0.089)
Comm. equip, computer, electronic	0.731	(0.128)	0.748	(0.147)	1.138	(1.032)
Water utilities	0.445	(0.124)	0.610	(0.323)	0.915	(0.813)
Other manufacturing, recycling	0.655	(0.101)	0.652	(0.463)	0.746	(0.091)
Electricity, steam	0.665	(0.080)	0.653	(0.083)	0.845	(0.104)
Gas utilities	0.663	(0.193)	0.604	(0.137)	0.828	(0.135)
Construction	0.705	(0.068)	0.677	(0.064)	0.864	(0.076)
Transportation svc	0.685	(0.116)	0.597	(0.394)	0.676	(0.131)
Telecommunications, Software and IT	1.336	(0.318)	0.556	(0.045)	0.855	(0.082)
Wholesale and Retail	0.677	(0.042)	0.725	(0.107)	0.965	(0.048)
Hotels and Restaurants	0.729	(0.781)	0.797	(0.291)	0.795	(0.138)
Finance	0.679	(0.120)	0.718	(0.126)	0.752	(0.085)
Real estate	0.406	(0.615)	1.312	(0.245)	0.960	(0.128)
Business services	0.579	(0.172)	0.713	(7.311)	0.722	(0.136)
Other services	0.675	(0.246)	1.083	(0.830)	0.423	(0.091)

Notes: Standard errors, obtained by bootstrapping 500 times for each sector, are reported in brackets.

Comparison to other elasticity estimates

There are only a few estimates of production function elasticities for China industries using firm-level data. Berkowitz et al. (2017), using value-added functions, find the elasticity of substitution between labor and capital is greater than 1 in most sectors and on average is 1.553. They also use the control function approach, but did not consider omitted price bias or the non-identification problem of gross output functions. In contrast, only 3 of our 31 sectors have capital-labor substitution elasticity greater than 1. The estimates of capital-labor substitution elasticity for other countries are typically smaller than 1, as summarized by Raval (2019), which compare 44 estimates from the literature and find the median estimate is only 0.54.

For substitution elasticities among energy inputs, only Fisher-Vanden et al. (2004) employ firm-level data to estimate the elasticities for China; this earlier work use simple regressions that do not address the endogeneity issues discussed in Section 2 and find the elasticities range from 0.29 to 1.31. Other studies use industrial and provincial data, such as Smyth et al. (2011), Ma and Stern (2016). Smyth et al. (2011) find the interfuel elasticities are close to 1, while the results of Ma and Stern (2016) are just around 0.5 in most cases. Zha and Zhou (2014) also estimate a nested CES production function using industry-level data, and find the average elasticity between value-added and energy is 0.94.

5.2 Base Case Simulation of CGE Model

The main variables of the base case path are given in Table 3. GDP grows at 6.5% during 2014-2020, then decelerates to 5.0% in 2020-30[4]. Energy consumption is calibrated to the projections in IEA (2016) and total energy use grows at 1.6% during 2017-30 with a substantial switch from coal to oil and gas. Coal consumption only grow at 0.90% annually. Oil will rise relatively faster than coal use, while natural gas grows more than twice speed of oil. Given IEA's conservative view of China's coal use forecast, total CO_2 emissions (including processed carbon emissions in the cement sector) only grow at 1.2% per year during 2017-30, fossil-fuel combusted carbon emissions grow at 1.4%. Our economic growth projection for 2030 is roughly doubling of the 2017 level, based on US$2005 PPP level.

[4] This is consistent with the deceleration observed during 2010-2016, and with the government target of 6.5% growth for the 13th Five Year Plan. These growth projections are also similar to those in World Bank-DRC (2013) and IEA (2014).

Table 3. Base case projection of output and energy use

	GTAP Case			Empirical Case		
Variable	2020	2030	2017-30 growth rate	2020	2030	2017-30 growth rate
Population (million)	1,403	1,416	0.16%	1,403	1,416	0.16%
Effective labor supply (bil. 2014 yuan)	27,433	25,527	-0.61%	27,433	25,527	-0.61%
GDP (billion 2014 yuan)	93,065	151,463	5.30%	92,853	141,242	4.72%
Consumption/GDP	0.46	0.53		0.47	0.57	
Energy use (million tons sce*)	4,697	5,456	1.62%	4,944	5,696	1.73%
Coal use (million tons)	4,240	4,721	0.90%	4,372	4,688	0.69%
Oil use (million tons)	665	799	2.23%	721	871	2.56%
Gas use (million cubic meters)	291,908	458,128	5.27%	310,306	470,799	5.21%
Electricity use (TWh)	6,898	7,869	1.57%	7,460	8,792	2.11%
CO_2 emissions (fossil fuel, million tons)	10,164	11,741	1.40%	11,871	12,932	1.04%
CO_2 emissions (total, million tons)	11,451	12,955	1.23%	12,364	12,973	0.92%
Carbon intensity (kg CO2/yuan)	0.123	0.086	-3.86%	0.128	0.092	-3.52%
GDP per capita (2014 yuan)	66,340	107,000		66,189	99,780	
GDP per capita; PPP US$2005	11,734	18,926		11,708	17,649	

Now we revise the basic CES parameters that cited from GTAP modeling database[5]. Table 3 also presents the basic economic indicators, energy use and carbon emission output results using the empirically estimated parameters given in table 2. Since the parameters used for base case and counterfactual carbon tax scenarios, so we present both scenarios to compare with the one using GTAP parameters.

We can see from table 3 that, the GDP grows slower in the empirical case. Total energy grows at similar pattern, however in the empirical case coal use grows slower, while oil use grows faster. The gas use is similar, but the electricity use is much higher in the empirical case. Given the coal use grows slower, the carbon emissions accordingly also grow slower than the

[5] Detail see GTAP7 Manual book, Chap.7 Behavior Parameters by Hertel et. al;

GTAP case. Carbon intensity, GDP per capita, or GDP per capita in PPP terms are slightly smaller in the empirical case.

5.3 Carbon Pricing Simulations

In the economic model, we assume competitive markets and carbon tax were imposed on fossil fuel uses according to their carbon contents. With the carbon tax at upstream of fossil fuels on coal, oil and gas, the output price of other commodities would also increase due to the input-output linkages. The complete set of equations is given in a technical report (Cao and Ho 2017); here we note the main aspects to clarify the implementation of the policy scenarios as summarized in Table 2.

Table 4. Comparing Carbon Tax Policy Impacts using GTAP parameters and Our Empirical Case

	GTAP case		**Empirical case**	
Variable	**Base case 2030**	**policy case -63.21%**	**Base case 2030**	**policy case -62.50%**
GDP (billion yuan 2014)	151,463	-0.150	141,242	-0.163
Consumption (bil yuan 2014)	75,687	-0.182	75,952	-0.203
Investment (bil yuan 2014)	56,907	-0.211	49,459	-0.188
Government consumption (bil yuan 2014)	13,313	0.000	10,397	0.000
Energy use (million tons of sce)	5,456	-8.11	5,696	-11.75
Coal use (million tons)	4,722	-11.97	4,688	-20.16
Oil use (million tons)	799	-2.51	871	-5.72
Gas use (billion cubic meters)	458,128	-7.58	470,799	-6.19
Electricity (billion kWh)	7,869	-3.34	8,792	-3.9
CO2 emissions (inc cement; mil tons)	12,826	-9.51	12,973	-13.3
carbon tax revenue as %total revenue		2.31%		2.4%

Table 4 provides the comparison between the carbon tax simulations in the GTAP parameter case and Empirical parameter case. We first set a carbon tax imposed at the upstream mine mouth of coal, oil and natural gas, then the price signals would send forward through inter-sectoral linkages using the updated SAM tables. We can see that, using empirical parameters not only affect the base case, the confound impacts lead to relatively larger impacts on GDP and consumption, but slightly lower impacts on investment. The impacts on energy use, coal use, oil use are bigger, while impacts on natural gas are smaller. The impact on electricity use is slightly higher. Given the impacts on coal and primary energy are larger, the impact on carbon reduction is also bigger. Tax revenue as a share of total revenue is slightly higher, with very similar magnitude.

5.4 Sensitivity Analysis

In addition, we conduct a sensitivity analysis by varying certain key sectors, while keeping the other sectors with the same GTAP parameters as baseline GTAP-CGE model to test for the sensitivity of sectoral elasticities. We consider the following scenarios: 1) only coal sector use empirical estimated parameters; 2) electricity sector only; 3) all energy sectors, including coal, oil, natural gas, refining sector, electricity and gas product sector; 4) all energy intensity and trade exposed (EITE) sectors, including all energy sectors, and paper, chemical, non-mineral product (mainly cement), primary metal, metal; 5) all sectors are using empirically estimated parameters.

Table 5 provides the results of this sensitivity analysis assuming we adopt different parameters while keeping the other sectors using GTAP parameters, to checking if any sector is more sensitive to the parameter changes. We found that we start from single sector coal and electricity sector, both of them would have similar impacts on GDP, but not the same impacts on consumption and investment. Changing coal sector parameters would bring larger impacts on consumption but smaller impacts on investment. The impacts on energy and carbon are relatively smaller for revising coal sector than revising electricity sector, except the impact on natural gas.

However, when we compound more sectors into the analysis, such as revising all energy sector parameters, some of the effects may confound, but some may offset with each other. Finally, we add more EITE sectors upon energy sectors, then we found that the overall impacts on coal use would be compounded, leading to a larger impacts of carbon reductions using empirical parameter model. The impacts on GDP, consumption and investment depend on the real case, and the net results may offset with different assumptions.

Figure 5. Sensitivity analysis with empirical parameters limited to certain sectors

	Sensitivity Analysis				
Variable	coal	electricity	energy	eite	all
2030 carbon intensity reduction	-63.30%	-63.60%	-63.70%	-63.70%	-62.50%
GDP (billion yuan 2014)	-0.157	-0.150	-0.082	-0.189	-0.163
Consumption (bil yuan 2014)	-0.186	-0.096	-0.044	-0.210	-0.203
Investment (bil yuan 2014)	-0.217	-0.293	-0.209	-0.235	-0.188
Government consumption (bil yuan 2014)	0.000	0.000	0.000	0.000	0.000
Energy use (million tons of sce)	-8.58	-9.43	-9.23	-11.40	-11.75
Coal use (million tons)	-12.90	-13.89	-14.63	-17.96	-20.16
Oil use (million tons)	-2.35	-2.62	-1.68	-2.41	-5.72
Gas use (billion cubic meters)	-7.57	-7.28	-5.54	-8.54	-6.19
Electricity (billion kWh)	-3.18	-4.56	-3.45	-5.15	-3.86
CO2 emissions (inc cement; mil tons)	-9.94	-11.21	-11.16	-12.81	-13.26
carbon taxes as %total revenue	2.31%	2.29%	2.28%	2.29%	2.44%

6. Conclusion

Estimating the substitution elasticity of energy is of great importance both in theory and in practice. The substitutability of energy is a crucial parameter in energy-economic models, especially computable general equilibrium (CGE) models, which are used to analyze policies. However, such parameters are often not estimated for single countries, so most CGE model developer would have to rely on GTAP or other parameters in the literature. In this field, gasoline elasticity or simple electricity elasticity are often found in the micro-empirical studies, while the tier structure of energy substitution are still lacking in the literature. Therefore, in this paper we use ACF method to estimate sectoral CES production functions and find significant heterogeneity in substitution elasticities across different industries. Then we incorporate these empirically estimated elasticities into the CGE model to simulate China's carbon pricing policies to reach NDC targets in 2030.

Our study would potentially provide useful by sectoral energy elasticities for CGE modelers to use, or as robustness or sensitivity analysis. In order to compare how our empirical CGE parameters differ from the general case using GTAP parameters, we use a carbon tax policy in China to reach the medium NDC target as an example to test for the model sensitivity. We find our empirical CGE model project lower GDP growth and higher energy projections, however with lower coal use and carbon emissions. In the counterfactual carbon tax exercises, we found compared to the GTAP parameter case simulations, our empirical case would cause slightly larger GDP loss and greater energy use and carbon emission reductions. Finally, we also conduct a sensitivity analysis on only switching a few sectors, especially energy sectors, found the impact on energy use and carbon emissions can be confounded, while other factors may offset and net effects are uncertain.

A Appendix

A.1 Constructing real capital

Let VK^{b}_{it} denotes the book value of capital of firm i at year t in the SAT dataset. Data from Wu (2015) is used to decompose VK^{b}_{it} into two parts: structure capital (VK^{bs}_{it}) and equipment capital (VK^{be}_{it}). Wu's industry classification is based on the Chinese Industry Production (CIP) code and we match it with the national economic industrial code from NBS. We also use this data to decompose the firm-level capital stock in 1993 VK^{b}_{i1993} provided by Brandt et al. (2012) into VK^{bs}_{i1993} and VK^{be}_{i1993}.

Let t_0 be the year when firm i first appears in the SAT dataset and t^* be the year when the firm was established. We first establish the industry average growth rate of capital between 1993 and t_0 using the 1993 data. The average firm capital stock in industry j and province p in 1993, for structure and equipment, is:

$$\overline{VK^{bs}_{jp1993}} = \frac{1}{nf_{jp}} \sum_{i \in j,p} VK^{bs}_{i1993}$$

where nf_{jp} is the number of firms of type jp in the 1993 dataset. We compute a similar average for firms in the NBS data:

$$\overline{VK^{bs}_{jpt}} = \frac{1}{nf_{jp}} \sum_{i \in j,p} VK^{bs}_{it}$$

Then the average growth rate of the firms in industry j and province p between 1993 and t_0 is:

$$g^{be}_{jpt} = (\overline{VK^{be}_{jpt_0}} / \overline{VK^{be}_{jp1993}})^{1/(t_0 - 1993)} - 1$$

If the firm was established after 1992, we assume that the initial equipment and structure stock at t^* is given by a constant growth rate equal to the industry/province rate calculated above. For the years between t^* and t_0, we use the same growth rates to calculate the nominal stock. For the firms established before 1993, we make further simplifying assumptions, i.e. its nominal capital stock in 1993 may be given by the industry average growth rate.

Next, we calculate industry-level equipment and structure stock growth rates g_{jt}^{s} and g_{jt}^{e} from 1981 to 1993 using national industry stock estimates in Wu (2015). Following Brandt et al. (2012), we assume the earliest possible establishment year is 1978, the beginning of the economic market reforms. We also assume the industry-level growth rate from 1978 to 1980 is the same as the growth rate in 1981. The book value in year t is thus estimated as

$$VK_{it}^{bs} = VK_{it^*}^{bs} \times (1+g_{jt_0}^{s})^{(t-t^*)}, t = t^*, ..., t_0$$

In the SAT dataset, some firms don't have continuous observations during the sample period. To fill in the gaps, we use the years next to the gap years to linearly interpolate the missing years.

After constructing the time series of book values of the equipment and structure stocks for each firm since establishment, we can calculate the real capital stock series. The nominal net investment (new investment less disposals) is simply given by $VK_{it}^{bs} - VK_{it-1}^{bs}$. We take the national investment goods price indices (PK_t^s, PK_t^e) from the China Statistical Yearbook to deflate these nominal investments. Depreciation rates for assets in China (d_s, d_e) are taken from Harry Wu.

The initial real equipment and structure stocks in year t^* are:

$$K_{it^*}^{e} = VK_{it^*}^{be} / PK_{t^*}^{e}, K_{it^*}^{s} = VK_{it^*}^{bs} / PK_{t^*}^{s}$$

Table 3 reports the summary statistics for nominal and real equipment and structure stock. The mean of real equipment stock is less than the mean of nominal equipment stock, but the mean of real structure stock is quite close to the mean of nominal equipment stock. This is because the price index for structure has been rising for most of the sample period, while the index for equipment has been relatively stable. This also highlights the importance of distinguishing the two categories of fixed capital.

Table 3: Summary statistics on nominal and real equipment and structure stock

Variable	Obs.	Mean	Median	SD	Min	Max
VK^{bs}	5061903	28663	203	661556	0	269253300
K^{s}	5061903	25682	323	574253	0	192639184
VK^{be}	5061903	9320	68	214061	0	98660536
K^{e}	5061903	10099	124	250069	0	116241488

As noted in Jorgenson et al. (2005), one should distinguish between capital stocks and annual service flows since the depreciation rates of different assets vary widely. We apply a simple form of the capital cost in Jorgenson et al. (2005), ignoring tax complications. The ex-ante annual rental costs of a unit of equipment and structure are given by:

$$PKD_t^e = (r_t - \rho_t^e + \delta_e)PK_{t-1}^e, PKD_t^s = (r_t - \rho_t^s + \delta_s)PK_{t-1}^s$$

where $\rho_t^a = PK_t^a / PK_{t-1}^a - 1$ is the rate of capital gains, r_t is discount rate that we proxy with the national one-year loan rate decided by the central bank. We have to use a national cost of capital since we do not have regional or industry investment deflators.

The total annual capital cost for firm i is the sum of the two categories of capital:

$$PKD_t^e K_{it}^e + PKD_t^s K_{it}^s = VKD_{it}$$

where VKD_{it} denotes the nominal value of capital input.

For the first period, we normalize real capital input as $KD_{i_0} = VKD_{i_0}$. For later periods, we define the real capital input of firm i as the Tornqvist index over the two asset types:

$$ln\frac{KD_{it}}{KD_{it-1}} = \bar{v}_{it}^s ln\frac{K_{it}^s}{K_{it-1}^s} + \bar{v}_{it}^e ln\frac{K_{it}^e}{K_{it-1}^e}$$

where the weights are:

$$\bar{v}_{it}^a = (v_{it}^a + v_{it-1}^a)/2, v_{it}^a = PKD_t^a K_t^a / VKD_{it}$$

The firm-level capital rental price is therefore given by $PKD_{it} = VKD_{it} / KD_{it}$.

A.2 Data cleaning procedures

Besides deleting the observations with obvious errors, i.e. the missing observations with non-positive gross outputs, labor and capital inputs, we employ the following algorithms to delete implausible or extremely volatile observations:

• Values of outputs, intermediate inputs, sales revenues that are unchanged in current consecutive years (23,891).

• Real output growth rate is greater than 1, but intermediate input growth rate is less than 0.5 in that year, and capital, labor growth rates are less than 0.5 during recent previous five years (11,995).

• Labor growth rate is greater than 5 in current year but fall by more than -0.5 in the next year, or it's less than -0.5 in current year but greater than 5 in the next year (13,061).

• Labor growth rate is greater than 1 but output growth rate is less than -0.5 (14,019).

• Wage (per worker) growth rate is greater than 1 and wage is greater than 10000, but output growth rate is less than -0.5 and labor growth rate is greater than -0.5 (31,100).

• Labor, capital, output, wage growth rate is less than -0.99 (32,288).

• Labor, capital, output, wage growth is greater than 30 (57,178).

• Output/capital and output/labor growth rates are greater than 1, value-added/capital, value-added/labor growth rates are less than -0.5, intermediate input/capital, intermediate input/labor growth rates are less than -0.5 (24,538).

• Outputs or intermediate inputs are rounded to very few significant digits for consecutive years, e.g. 160000. We exclude observations which are divisible by 100 for 3 or more years (32,439).

Removing these implausible data yields a sample with 634,461 firms and 1,487,822 observations. The distribution of the cleaned sample is presented in the second and third panels of Table 4, from which we can see that deleting these observations do not change the yearly distribution of the original data.

Table 4: Sample distributions before and after deleting observations with obvious and hidden errors

	Original sample		After deleting non-positive energy inputs		After deleting implausible obs.	
	Obs.	Percent	Obs.	Percent	Obs.	Percent
2007	313,051	5.59	116,108	3.82	68,685	4.62
2008	404,170	7.21	169,066	5.57	101,920	6.85
2009	624,076	11.14	335,068	11.03	171,807	11.55
2010	746,770	13.33	343,237	11.29	197,491	13.27
2011	691,865	12.35	368,131	12.12	197,883	13.30
2012	690,826	12.33	447,253	14.73	201,924	13.57
2013	714,606	12.75	477,634	15.73	199,799	13.43
2014	717,477	12.81	408,923	13.46	173,678	11.67
2015	699,918	12.49	371,575	12.23	174,635	11.74

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