CAPTURING TECHNOLOGICAL CHANGE IN AN IO MODEL

WITH APPLICATION TO CALCULATIONS OF EMBODIED CARBON EMISSIONS

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Abstract: *I incorporate technological change into the Leontief production function and derive a procedure for updating input-output flow tables for exogenously given efficiency improvements that in general are heterogeneous across sectors. In an application, I compare forecasts of the sectoral impact of carbon taxes with and without taking into account the induced as well as business-as-usual technology changes. Future energy efficiency improvements are deduced from an engineering study by the DOE, "Clean Energy Futures Report", DOE (2001). I find that technological (energy efficiency) changes significantly impact the size of the estimates of tax burdens faced by individual industries as well as the ranking of different industries.*

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I. INTRODUCTION

There are various studies that estimate the impact of stabilizing the CO2 emissions at 1990 levels as would be required the Kyoto protocol. Estimates of the impact of environmental tax reforms (ETR) in European countries, geared towards the emission stabilization goal, range from positive +2.5% to negative –5% impact on GDP. Of the one hundred and four simulations reviewed in Hoerner and Bosquet (2001), almost three-quarters predict a modest effect in the range +0.5% to –0.5% relative to a reference scenario. Given the relatively modest aggregate impact, it is natural to focus on the distribution of the impact of an ETR on different industries.

In this paper, I estimate the distributional impacts of an ETR studied by the US DOE in its 'Clean Energy Futures Report' DOE (2001); referred to as CEF. I demonstrate the importance of the treatment of technological change even in cross-sectional comparisons. I use modified input-output tables that reflect the changes in energy efficiency due in part to the policy package modeled and calculate carbon embodied in each of the 498 commodities in the BEA classification. Assuming a full pass-through of the components of the ETR, the increase of the costs of production of these commodities is then proportional to the embodied carbon.

Input-output (IO) analysis can be used to trace the direct and indirect price and quantity impacts of specified changes in manufacturing inputs (including value-added inputs like labor compensation and profits) through the economy in a consistent national income accounting framework. However, it poses an extreme assumption on the production function, implying limited factor substitutability and, hence, it is not suitable for estimating microeconomic or macroeconomic behavioral responses to price changes. These must be estimated using other approaches. However, once those impacts have been estimated using other techniques, IO analysis provides the best available framework for following them through the economy, particularly if a high degree of sectoral disaggregation is required.[2].

IO analysis has been extended to represent interactions between the economy and the environment in the late 1960s and later by Leontief (1970, 1973, 1976), Leontief and Ford (1972), and many others. James et al. (1978) offers a good survey of the early work. Energy applications of IO analysis appeared in the 1970s and early '80s (for example, Forsund, 1985). Recently, a variety of topics have been studied with the aid of IO analysis, such as questions relating to greenhouse gas emissions, typically focusing primarily or exclusively on carbon dioxide. These include distributional analysis by industry (Goulder 1992); efforts to decompose economy-wide carbon intensity changes into within-industry and between-industry effects (Weir 1998; Rose and Chen 1991; Proops et al. 1993); distribution of tax burden by income class (Casler and Rafiqui 1993);

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[2] As a result, many large macroeconomic models contain imbedded IO models in order to capture a finer level of sectoral detail. See, e.g., the LIFT, MUDAN, or DUNA models by Inforum at the University of Maryland (Almon 1993; Almon and Mahmood 1997) or the DRI model (DRI 1992).

and computation of direct and indirect greenhouse gas requirements for a given vector of final demand (Lenzen 1998).

In IO analysis, it is a common convention to apply the law of one price—that is a unified market for a uniform good, only one price for that good can prevail. This assumption simplifies the analysis considerably. However, this approximation does not hold very well in the energy area. Fuel prices vary across industries by a factor of two to four, depending on the fuel.[3] There has been some previous work using hybrid IO approaches in mixed energy and dollar units (see, e.g., Bullard and Herendeen 1975; Dossani and Preziosi 1980) but recent efforts to use IO analysis to estimate the carbon content or carbon tax burden of final demand (or the carbon tax burden on that demand) (Goulder 1992; Bernow et al. 1997a, 1997b) have generally used the "one price" model. The application in this paper considers an econometric specification for the fuel price each sector pays.

The major disadvantage of the assumption of fixed input-output coefficients is that it does not allow for any responses of manufacturers to price changes of their inputs. Furthermore, it also makes accounting for technological change somewhat difficult.[4] In this paper I overcome these shortcomings by using additional information to modify the input output coefficients.

Inadequate attention to technological change is a weakness of many other models. In the top-down models the rate of technological change is most commonly modeled with time trends (possibly sectoral specific) in the econometric estimation of (industrial or consumer) demand equations. Therefore, there is an implicit assumption that the rate of technological change can be interpolated from past data. While this may be plausible in the aggregate, it is less likely to work for a more detailed analysis. Consider the estimation of a typical energy demand equation for an industry. Let's abstract from inputs other than energy by assuming some nesting with respect to the other inputs. The researcher has data on output of the industry, its consumption of major fuels and other factors of production and their price for this industry for the past several years or decades. S/he assumes some functional form for the industry's production function and proceeds to use the data to estimate it. What s/he has to distinguish in the estimation are reactions of the industry to relative price changes (substituting petroleum for coal when coal becomes relatively more expensive) from technological change (e.g. using diesel locomotives instead older steam engines that consume coal). By making specific assumptions on the functional form of the production function and deducing the demand equations using economic theory, the researcher concentrates on the energy substitution due to price fluctuations. S/he then assumes that the unexplained time trends left in the data are results of technological change and these time trends are then extrapolated to the future. For examples of such approach see, e.g. Labey (1999).

[3] See the discussion and estimation of the relationship between energy intensity and fuel prices in Hoerner and Mutl (2001).
[4] Although these difficulties arise in context of any production function specification, at least to some extent.

On the other hand, bottom-up models typically do not look at the input substitution due to price changes but usually implicitly assume that the relative prices are fixed at current levels. However, these models look at information about specific technologies that will become available and deduce the impact of these technologies on the composition of inputs. Hence, the future rate of technological change is deduced from specific engineering data. Supplementing such models with demand functions capturing price-induced substitution would result, in my opinion, in the optimal use of all available data.

II. THEORETICAL MODEL

In the practical application, I will use entries in current dollar use table together with prices implied by an empirical relationship with energy intensity (energy expenditures relative to value added and total value of output) to estimate the energy consumption in physical units which will then be translated to a direct carbon consumption by each sector. This vector of 'direct' carbon emissions will then be translated into a vector of 'total' embodied carbon emissions. Therefore, I need to update entries in the current dollar input-output table for a predicted/observed technological change. My approach will assume that the coefficient (requirement) matrix in real units of production has been modified in a known way.

2.1 Technological Change

Let me illustrate the situation on a simplified example: suppose that the only change that occurred was that the steel industry requires 10% less coal per unit of its product (e.g., 10% less Btu's per ton of steel). Let's trace the changes that this fact implies in the IO tables. Start with the base year (e.g., 1997) current dollar flow matrices – use, make, value added and final demand. I will continue working in the base year prices – this will enable me to use my (nonlinear) fuel price imputation formula. If the final demand stayed the same, the steel industry would need to buy 10% less of the product coal (reduce the corresponding cell in the use matrix by 10%). Therefore, there will be $\underline{x}$% less of the product coal needed in the economy (remember we express this in constant prices), where $\underline{x}$ is 10 times the share of steel industry purchases of the product coal in the total sales of the product coal. Hence I need to scale down the production of the product coal by $\underline{x}$% - that is, decrease each element of the corresponding column in the make matrix by $\underline{x}$%. As a result, output of every industry that produces coal decreases by a certain percentage. If there is only one industry making coal and coal is the only product it makes, its output would go down by exactly $\underline{x}$%. If there are more industries producing coal or if the coal industry produces products other than coal (i.e., there are off diagonal entries in the make matrix), then the output of several industries might be decreased by a percentage lower than $\underline{x}$. That requires a decrease in the purchases these industries make by a corresponding proportion, i.e., scale the columns of the use matrix, leading to changes to its columns. Therefore, I need to scale down the rows of the make matrix and so on. It is relatively easy to show that this process converges; note that the procedure is just an evaluation of an algebraic expansion of an inverse of a matrix by a sum of an infinite series.

In the adjustment process, I change the elements of the value-added row but I do not change the elements of the final demand (I assumed it to be fixed). By looking at the purchases of coal in the 'new' use matrix, obtained by the above procedure, and dividing them by the imputed coal prices, I obtain the coal (in Btu's) that each sector needs to buy in 2010 (or 2020) had the final demand been the same as in 1996.

The above adjustment process has a simple algebraic representation. Assuming a known change in technology is expressed by a change in the input output coefficient table, I can derive the new flow tables as follows. Denote **A** the IO coefficient matrix (abstracting from the difference between commodities and industries), and assume that the technology has changed so that the new technical coefficient matrix is

(1) $\mathbf{A^*} = \mathbf{A} + \mathbf{T}$

where the matrix **T** captures the improvement in technology. Denote the old and new vectors of output **X** and **X*** respectively and the vector of final demand **Y**. The relationship between final demand and new required outputs is

(2) $\mathbf{X^*} = \mathbf{A^*X^*} + \mathbf{Y}$

The new flow matrix is then given by multiplying columns of the new coefficient matrix **A*** by corresponding elements of the new output vector **X***. Hence the new flow matrix is:

(3) $\mathbf{F^*}_{i,j} = \mathbf{A^*}_{i,j}\,\mathbf{X^*}_j = \mathbf{A^*}_{i,j}\,\{[\mathbf{I} - \mathbf{A^*}]^{-1}\,\mathbf{Y}\}_j$

The iterations described above represent an approximation of the $[\mathbf{I} - \mathbf{A^*}]^{-1}$ matrix by expansion via a sum of an infinite geometric series.

2.2 Embodied Carbon and Price Change Calculations

Let's now turn to the carbon embodied in the 498 commodities as defined by the BEA classification system. I start with a vector of *direct emissions*, i.e., emissions that are actually emitted during the production process in a particular industry. My goal is then to obtain a vector of *total emissions* that are embodied in each commodity through both direct emission (emitted during the production process), as well as the emissions associated with inputs that are used in the production of each commodity.

Abstract for a while from the commodity and industry distinction and denote the total emissions embodied in commodity *i* by $\mathbf{T}_i$, the direct emissions by $\mathbf{D}_i$,[5] the input of commodity *j* into the production of commodity *i* by $\mathbf{f}_{j,i}$ (measured in current dollars), and the total current-dollar economy-wide output of commodity j by $\mathbf{Q}_j$. Assuming that the total carbon emissions embodied in a commodity are proportionally assigned to its uses as intermediate input and in final demand according to the dollar values of the intermediate inputs and final demand, we can write the total embodied emissions in a commodity *j* as:

$$(4) \qquad \mathbf{T}_i = \mathbf{T}_1 * (\mathbf{f}_{1,i} / \mathbf{Q}_1) + \mathbf{T}_2 * (\mathbf{f}_{2,i} / \mathbf{Q}_2) + ... + \mathbf{T}_{498} * (\mathbf{f}_{498,i} / \mathbf{Q}_{498}) + \mathbf{D}_i$$

where 498 is the number of commodities in the BEA classification. Equation (5) states the above assertion that the total emissions embodied in each commodity consist of the total emissions embodied in the inputs that were used in producing the commodity and the direct carbon emitted during the production process. The system of these equations for all the commodities can be written conveniently in matrix notation as:

$$(5) \qquad \mathbf{T} = \mathbf{B'}\, \mathbf{T} + \mathbf{D}$$

where matrix **B** has elements $\mathbf{b}_{i,j} = \mathbf{f}_{i,j} / \mathbf{Q}_j$; **T** and **D** are the vectors of total and direct emissions; and **Q** is the vector of commodity outputs. Notice that the matrix **B** is similar to the regular commodity-by-commodity coefficient input-output matrix **A** with elements $\mathbf{a}_{i,j} = \mathbf{f}_{i,j} / \mathbf{Q}_{i,}$ but **B** has the rows rather than the columns of the flow input-output matrix divided by total commodity outputs.

Solving the above equation gives us the formula I have used in determining the total emissions:

$$(6) \qquad \mathbf{T} = (\mathbf{I} - \mathbf{B'})^{-1}\ \mathbf{D}$$

where **I** is an identity matrix. How does this relate to the Leontief price model? We can multiply equation (1) by per unit carbon tax and divide by $\mathbf{Q}_i$ to translate the total emissions $\mathbf{T}_i$ into changes of the price of commodity *i* ($\Delta\mathbf{P}_i$)[6]. The direct emissions $\mathbf{D}_i$ are then translated into the share of the carbon tax in the value of commodity *i*, which is the change in the value added share due to the carbon tax ($\Delta\mathbf{K}_i$). Hence, equation (6) would become:

$$(7) \qquad \Delta\mathbf{P} = (\mathbf{I} - \mathbf{A'})\ \ \Delta\mathbf{K}$$

and this is exactly the Leontief price model, as in for example equation 9-93 in Miller and Blair (1985).

[5] The total and direct emissions are in MtC units; they are economy-wide emissions associated with the current production levels of each commodity. They are not emissions per unit of a commodity.

[6] Assuming the cost increases due to the carbon tax are fully passed through to the consumers, i.e., any cost increase is reflected on a one-to-one basis in the increased price of each commodity.

In the following I will restate the Leontief price model, paying more attention to the role of different parts of value added. Intuitively the Leontief price model can be described as follows. Let's assume that a part of value added changes due to, for example, the carbon tax. Let's further assume that the cost increases are fully passed through to the customers, i.e., any cost increase is reflected on a one-to-one basis in the increased price of each commodity. Then the final price increase for commodity *i* consists of the weighted average of the final price increases of the inputs used in production of that commodity plus the direct change in the proportion of the value added. The weights are the (dollar) share of each input in the total (dollar) value of commodity *i*.

That is:

$$(8) \qquad \Delta\mathbf{P}_i = \Delta\mathbf{P}_1 \; (\mathbf{f}_{1,i} / \mathbf{Q}_i) \; + \; \Delta\mathbf{P}_2 \; (\mathbf{f}_{2,i} / \mathbf{Q}_i) \; + \; ... \; + \; \Delta\mathbf{P}_{498} \; (\mathbf{f}_{498,i} / \mathbf{Q}_i) \; + \; \Delta\mathbf{K}_i$$

or, in matrix notation:

$$(9) \qquad \Delta\mathbf{P} = \mathbf{A}' \, \Delta\mathbf{P} + \Delta\mathbf{K}$$

yielding the Leontief price equation as in (7).

The same analysis that was done above for changes in the value added can be done to its levels; more precisely to the proportion of the value added instead of changes in that proportion. This than gives us equations for deriving the share of labor and capital payments, as well as the carbon tax or payroll tax reduction, in the dollar value of each commodity.

III. AN APPLICATION

I have used the procedure for updating the flow input-output tables to calibrate the BEA input-output tables for technological change implied by the CEF study. I have then used energy purchase entries in the use table to construct an estimate of energy consumption for each sector and its associated direct carbon emissions. The direct emissions were then used to construct a vector of total embodied carbon emissions.

The ETR modeled in this paper is based on the proposal described in the CEF study. The two major components were a $50 per metric ton of carbon tax and recycling of the revenue trough a labor tax cut. Therefore, I have redistributed the carbon tax revenue in proportion to the number of employees in each sector based on BLS data. The tax decreases were also assumed to be passed through and, therefore, I have used the same methodology for calculating the total impact as for the tax increases.

The CEF policy package included a variety of other policies summarized in table 3.1. Of these I have modeled the doubling of federal government appropriations for cost-shared research development, and demonstration (RD&D) in efficient and clean-energy technologies. Since these resources are spent in public/private RD&D partnerships, they are matched by private-sector funds, resulting in an assumed increase of $1.4 billion per year by approximately 2005 (half as federal appropriations and half as private-sector cost share) and continuing through 2020.

Table 3.1 Key Policies in the Advanced Scenario*

Buildings	**Industry**
–Efficiency standards for equipment –Voluntary labeling and deployment programs	–Voluntary programs –Voluntary agreements with individual industries and trade associations
Transportation	**Electric Generators**
–Voluntary fuel economy agreements with auto manufacturers –"Pay-at-the-pump" auto insurance	–Renewable energy portfolio standards and production tax credits –Electric industry restructuring
Cross-Sector Policies	
– Doubled federal R&D	–Domestic carbon cap and trade system

*The scenarios are defined by approximately 50 policies. The 10 in this table are the most important ones in the Advanced scenario. Each policy is specified in terms of magnitude and timing. For instance, "Efficiency standards for equipment" comprise 16 new equipment standards introduced in various years with specific levels of minimum efficiencies. These voluntary agreements, because they are met in the Advanced scenario, would have the same effect as a CAFE standard of the same level. For details see the CEF report.

To illustrate the magnitude of the $50 carbon tax, table 3.2 shows the direct tax burden for common fuels. Table 3.3, on the other hand, shows the entire effect of the policy package on fossil fuel producing industries.

Table 3.2 Prices and Tax Burden on Major Fuels, 1997 values

Fuel	Price	Tax burden	Tax as % of price
Petroleum ($ per gallon)			
- motor gasoline	1.21	0.13	10.98 %
- diesel fuel	1.07	0.15	14.28 %
- heating oil	0.42	0.18	41.86 %
- kerosine	0.83	0.15	17.72 %
Natural Gas ($ per 1000 cubic feet)	4.75	0.82	17.26 %
Electricity (cents per kWh)	6.88	0.92	13.36 %
Coal ($ per metric ton)			
- residential use	60.76	34.82	57.30 %
- commercial use	36.94	34.82	94.25 %
- industrial use	38.35	34.50	89.98 %
- electric utilities	28.77	32.16	111.77 %

Source: prices are national averages from State Price and Expenditure Data Report 1997 (EIA 2000), except kerosine which is weighted average of residential, commercial and industrial use with nominal expenditures as weights; tax burden was calculated based on carbon content coefficient reported in GHG (EIA, 1998) and the heat content reported in State Energy Data Report 1997 (EIA, 2000); electricity was based on generation from and carbon emissions by electric generators from the CEF study (DOE, 2001).

Table 3.2 Total Fossil Fuel Price Increases
Including the effects of ETR with labor tax rebate, additional investment costs and energy bill savings

Fuel	1997	2010 BAU	2010 Adv.	2020 BAU	2020 Adv.
Coal	131.40%	130.93%	132.35%	130.39%	129.48%
Petroleum	24.82%	24.78%	25.24%	24.52%	24.07%
Natural Gas	17.84%	17.78%	18.02%	17.69%	17.29%
Electricity	13.78%	13.72%	13.84%	13.65%	13.40%

3.1 Technology Change Data

The engineering model that I use to calibrate the input-output model is the 'Clean Energy Future Report', DOE (2001), recently conducted by five U.S. Department of Energy national laboratories. The CEF report quantifies the potential for energy saving technologies to address the issues such as global warming. The study examines effects of key policies in the major sectors of the economy and than uses National Energy Modeling System (NEMS) as an integrating analytical framework to analyze the interactions among the different sectors and policies.

The model, called CEF-NEMS, simulates the behavior of U.S. energy markets. It achieves a supply/demand balance in nine end-use demand regions by solving for the prices of each energy product that will balance the quantities producers are willing to supply with the quantities consumers wish to consume. The model reflects market economics, industry structure, and many energy policies and regulations that influence market behavior. The impacts of standards and fiscal policies are generally assessed within CEF-NEMS, while the impacts of policies such as voluntary agreements, enhanced R&D, and technical assistance have been largely evaluated outside CEF-NEMS and translated into inputs for CEF-NEMS. The integration step of CEF-NEMS allows the estimated effects of changes in energy use in each sector to be taken into account in the energy use patterns of the other sectors. For instance, if electric generators should shift significantly to natural gas while at the same time energy consumption in buildings and industry continued to grow, natural gas prices would rise and some switching to other fuels would result.

I have used the following estimated changes in energy requirements per unit of output to modify the input output flow tables. In the manufacturing sector I used energy consumption projections together with the growth rate of real output of the manufacturing sector that was used in deriving the CEF results. The energy intensity change in 2020 (reported in tables 3.3 and 3.4) was then calculated as:

$$(E_{2020}/Y_{2020}) / (E_{1997}/Y_{1997}) = (E_{2020}/E_{1997}) / (Y_{1997}/Y_{2020}) = (E_{2020}/E_{1997}) * (1+g_y)^{23}$$

where E is energy consumption of particular fuel in Btu’s, Y is the sector’s output in constant prices and g is the assumed growth rate of Y; subscripts refer to time.

The same data was available for the commercial sector and, hence I have used the same formula. However, in the transportation sector, I was able to use efficiency data directly. The CEF reports projected efficiency improvements for the fleet of autos, light and freight trucks as well as improvements in Btu’s per seat mile in the air transportation sector, and Btu’s per ton-mile in the rail transportation and Btu per ton-mile in the water transportation sector.

Table 3.3 Advanced scenario change in energy intensity
(Btu/$ in 2020)/(Btu/$ in 1997); constant prices

	Petroleum	Natural Gas	Coal	Electricity
Energy Intensive Manufacturing				
- Iron and Steel	0.11	0.41	0.57	0.46
- Paper	0.38	0.42	0.18	0.44
- Cement	0.49	0.97	0.44	0.52
- Other Energy-Intensive Manufacturing	0.60	0.73	0.32	0.46
Non-Energy-Intensive Manufacturing	0.78	0.71	0.54	0.66
Commercial Sector	0.38	0.69	0.63	0.62
Transportation				
- Road Transportation	0.70	1	n/a	2
- Air Transportation	0.78	n/a	n/a	2
- Rail Transportation	0.72	n/a	n/a	0.72
- Marine Transportation	1.20	n/a	n/a	1.56
- Pipelines	n/a	1.14	n/a	n/a
Electricity Generation	0.81	0.56	0.99	1

The changes in fuel intensities reflect both the changes in available technology, as well as substitution among energy sources towards less carbon intensive ones. The magnitude of adjustment implied by the CEF study varies substantially across the different sectors, ranging from more than 50 percent decreases in the energy intensive sectors, to much smaller cuts in the commercial sector.

Table 3.4 Advanced scenario change in energy intensity
(Btu/$ in 2010)/(Btu/$ in 1997); constant prices

	Petroleum	Natural Gas	Coal	Electricity
Energy Intensive Manufacturing				
- Iron and Steel	0.26	0.54	0.68	0.61
- Paper	0.52	0.42	0.24	0.61
- Cement	0.77	1.16	0.58	0.70
- Other Energy-Intensive Manufacturing	0.79	0.81	0.39	0.65
Non-Energy-Intensive Manufacturing	0.90	0.84	0.64	0.80
Commercial Sector	0.46	0.83	0.76	0.79
Transportation				
- Road Transportation	0.87	1	n/a	2
- Air Transportation	0.85	n/a	n/a	2
- Rail Transportation	0.82	n/a	n/a	0.72
- Marine Transportation	1.05	n/a	n/a	1.71
- Pipelines	n/a	1.04	n/a	n/a
Electricity Generation	0.63	0.61	0.99	1

3.2 Energy Data Sources

The primary sources for calculating direct carbon emissions in the base year for the 498 sectors were EIA carbon emissions for main sectors (EIA, 1997) and dollar purchases of energy by type (coal, petroleum, natural gas and electricity) from the 1996 input-output tables assembled by the BEA (Planting, 2000). I have used various supplemental sources such as Manufacturing Energy Consumption Survey, MECS (EIA, 1997) in the industrial sector, Transportation Energy Databook (ORNL, 1998) and Residential Transportation Energy Consumption Survey, RTECS (EIA, 1993) in the transportation sector, Electric Power Annual (EIA, 1998) for fuel consumption by utilities and non-utilities. The future carbon emissions were based on the projections in the CEF study.

I have adjusted the carbon emissions estimates for the proportion of non-fuel energy use in the industrial sector (based on data in the MECS). I have also calculated average carbon content of fossil fuel generated electricity and added an 'equalizing charge' on the nuclear and large head hydro electricity. This imputes same carbon content per kWh for nuclear and hydro electricity. As a result, my carbon emissions are not actual carbon emissions, but rather taxable equivalent carbon emissions. Multiplying my emissions vector by a carbon tax rate yields an estimate of the actual tax burden for each industry. I have used the employment projection from the BLS (BLS 1999) to determine the size of payroll tax reduction.

3.3 Price imputation

It is conventional in input-output analysis to use the law of one price to impute physical units of a manufacturing input from the dollar purchases. The constant price for each commodity is equal to the total purchases of that commodity in dollars divided by the total purchases in physical units (such as barrels or tons). Once this ratio has been calculated for each energy commodity in the IO classification, one can assume that the price each sector pays for the particular energy commodity is uniform across all the 498 classifications.

The assumption of the law of one price is firmly rejected by the data in the sector for which we have the best available data, manufacturing. A review of the prices paid for various fuel types by manufacturing industries reveals a large variation in energy prices. Using data from the 1994 Manufacturing Energy Consumption Survey (MECS) of the Energy Information Administration (EIA), I found that the price paid per physical unit of fuel varied between the least and most energy-intensive industries by a factor of two to four, depending on the fuel, with the most energy-intensive industries paying the lowest price.

In response, an imputation strategy was used to estimate the consumption of fuels and electricity by the IO classifications in the commercial and industrial sectors (transportation was treated separately). First, for each fuel, the price of that fuel was econometrically estimated for each industry. Second, the expenditure recorded in the IO table for a fuel is divided by the estimated price to yield the preliminary estimate of consumption of that fuel type by that industry. Finally, for each of the sectors (commercial, industrial, and transportation) I summed the consumption of each major fuel type and then forced the sum to equal sectoral control totals by applying a uniform percentage adjustment across the fuel-sector category. The control totals were the electricity or fuel totals for that sector from the EIA's greenhouse gas emissions report (EIA, 1998) and the projections from the CEF report (DOE, 2001).

Using data from the MECS, table A1, I tested a wide range of functional relationships between energy intensity and price using OLS regression. The following nonlinear functional relationship between the energy price to each sector and its ratio of energy expenditures to the value added generally yielded the best results:

$$p_i = \alpha + \beta \ln (E_i / VA_i)$$

where p_i is the price for a particular fuel type that sector i pays in dollars per physical unit and VA_i is the total value added of that sector. (Note that a full system of such equations would also require fuel-type subscripts on p_i, α, β, and E_i). Based on the estimates of the above relationship for each type of energy, the consumption of each fuel type by each sector can be calculated by:

$$F_i = E_i [\alpha + \beta \ln (E_i / VA_i)],$$

where E_i and VA_i are available for all 498 industries in the IO table. This imputation procedure was carried out for each fossil fuel type and for electricity.[7]

After estimating the consumption of each of the 498 industrial classifications for each fuel type using the imputation procedure outlined in section A.2 (except for the transportation section, which used a different procedure described below), the sectoral totals for each fuel type and for electricity were forced to sum to control totals for that fuel and sector. Forcing was accomplished by multiplying the fuel use for each industry classification in the sector by the ratio of the control total to the sectoral total. The control totals were the totals for that fuel/sector category from the GHG (EIA 1998), with the following adjustments.

Industrial—Emissions from fuel consumption by nonutility power producers (NPP) have been moved from the industrial sector into the electricity sector.[8] The NPP category includes companies producing only electricity, and also co-generators that produce both electricity and some other form of energy that is used in a production process. Therefore,

[7] Econometric results for the fuel equations are available from the author.
[8] Fuel consumption and electricity delivery data for NPP were taken from Electric Power Annual 1997, volume II, table 53 (EIA 1998).

the fuel consumption in the industrial sector was adjusted to exclude the part of fuel consumption attributable to production of electricity.[9] This is equivalent to assuming that co-generators produce electricity as a secondary product. In other words, I assume that if this electricity were not generated (and sold off-site), the utility sector would have to cover the demand for electricity, using a mix of fuels similar to its current average mix.
Commercial—No adjustments were made to the commercial sector emission totals. However, the sector was expanded to include IO transportation categories that provide only services connected with transportation and do not include actual transportation.[10]
Transportation—Residential transportation emissions were subtracted from the transportation sector emissions, based on data from the EIA's Residential Transportation Energy Consumption Survey (RTECS).[11] The transportation sector constitutes only seven IO industrial categories and the transportation emissions were divided among the transportation sector IO classifications[12] using fuel consumption estimates from the Oak Ridge National Laboratory (ORNL, 1998, table 2.9), rather than the imputation formula described in the imputation section (A.3).
Electricity—Emissions of nonutility power producers, which were subtracted from the manufacturing sector, were added to the electric utility sector[13] (for estimation method, see the discussion for the industrial sector above).[14] For electricity, like fossil fuels, tax increases are distributed across purchasing industrial categories based on purchases measured in physical units (kWh) rather than measured in dollars.

3.4 Final Demand Changes

The final demand underlying the estimates in the CEF study is different for different scenarios and times. Therefore, I need to obtain coefficient matrices out of the adjusted flow use and make matrices. Thus, I divide (element by element) the columns of the use matrix and the rows of the make matrix by the old vector of final demand. This produces coefficient matrices that record inter-industry purchases required per unit of their output.

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[9] From the Electric Power Annual, part I, the fuel efficiency of electric utilities for each of the four fuel categories (coal, petroleum, natural gas, and other gases) was calculated. Given these efficiencies, fuel use was calculated based on the reported electric generation for all NNPs, both co-generators and independent power producers. These fuel uses were converted to carbon using carbon coefficients from the SEDS utility sector (EIA 1997), and this figure was then subtracted from the emissions of the industrial sector and added to the electricity sector. For co-generators, this methodology is equivalent to treating the process energy produced as a byproduct of electric generation.
[10] In particular, these are BEA categories 650302, 650400, 650500, 650600, 650701, and 650702.
[11] Residential transportation usage is reported in the RTECS with a three-year periodicity. The most recent years available for my analysis are 1991 and 1994. Consequently, SEDS transportation fuel use data for 1991 and 1994 were used together with the RTECS to construct residential transportation share in the total transportation energy use. The analysis did not reveal any significant time variation and, thus, the SEDS 1995 transportation energy usage along with the 1994 residential share ratio allowed us to construct an estimate of 1995 residential transportation energy usage in the SEDS categories in Btu units. The GHG carbon content coefficients were used to calculate the resulting carbon dioxide emissions that were then subtracted from the transportation sector emissions reported in the GHG.
[12] The transportation sector was redefined to include IO categories 650100, 650200, 650301, 650400, 650500, 650600, and 680201.
[13] Electricity sector includes IO-code categories 680100, 780200, and 790200. However, in the commodity classification, only category 680100 has non-zero entries.
[14] The emissions associated with electricity production were calculated based on fuel consumption only; the onsite consumption of electricity was handled alongside other nonfuel requirements for electricity production (maintenance, equipment amortization, etc.) through total requirement matrix.

The linear technology assumption means that, when final demand changes, I can just multiply (element by element) the rows of the use and the columns of the make matrices and obtain the flow matrices that are required for the new vector of final demand.

From the CEF study, I know what is the amount of coal (in Btu's or tons of carbon) each sub-sector purchases *after* both technology and final demand changed in 2020. Hence I just take the coal vector for the old final demand and force its sub-sectoral totals to equal the CEF numbers. This means that I assume that the numbers in the CEF study reflect forecasts of the changes in the composition and level of the final demand as well as the changes in technology.

The procedure described above yields an estimate of fuel consumption (in Btu's) for each fuel and industry. These are easily translated, via the carbon coefficients, to a vector of direct carbon emissions by industry in 2010 and 2020.

IV. RESULTS AND CONCLUSION

Tables 4.1 shows the results of my analysis. If the distribution of tax burdens of the policy package was modeled on impact by an IO analysis without taking into account the phase in period and technological change, there would be a handful of energy intensive sectors facing steep cost of production increases of 2 and more percent. For more detailed tables of results and in depth discussion of policy implication, please see Hoerner and Mutl (2001).

Table 4.1 Distribution of Price Changes Weighted by Share in GDP

Price change	No technological change	Technological change in 2010	Technological change in 2010
+4% and more	3.29%	3.30%	3.20%
+3 to +4%	0.03%	1.05%	0.04%
+2 to +3%	2.18%	1.98%	0.08%
+1 to +2%	4.00%	6.63%	0.10%
0 to +1%	29.15%	43.70%	11.17%
-1 to 0%	51.05%	42.09%	76.38%
-2 to –1%	9.42%	0.73%	7.66%
-3 to –2%	0.37%	0.52%	1.04%
-3% and less	0.52%	0.00%	0.33%

The potentially most impacted industries would have the highest incentives to improve their energy efficiency. The CEF study demonstrates that there is a substantial room for improvements in the most energy intensive sectors. For example, aluminum casts would be 4.6% more costly to produce on impact without taking into account possible efficiency improvements. However, in 2020 after the industry had time to invest in efficiency improvement in reaction to changes in its input prices, the cost of production increase would be only 1.70%.

The other most energy intensive industries exhibit a similar pattern: price change in Cement industry drops from 11.1% to 5.2%, Lime from 7.6% to 5.0%, Metal Ores Mining from 7.2% to 3.9% Metal Cans from 5.6% to 2.3% or Steel from 5.6% to 2.6%. Exceptions to this trend are increases in water and pipeline transportation energy intensity, perhaps due to increased utilization of these modes of transportation, resulting in more difficult and more energy intensive routes being serviced.

Overall, the proportion of inversely impacted industries changes dramatically. Without technological change, an IO analysis would suggest that 38.7 percent of US industries (weighted by their contribution to GDP) would be hurt by the ETR. This proportion drops to mere 14.6 percent in 2020. These comparisons demonstrate the important role technological progress plays and it shows that it could be the single most important factor determining the outcome of modeling efforts in the energy area.

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