

Estimating Carbon Leakage and the Efficiency of Border Adjustments in General Equilibrium - Does Sectoral Aggregation Matter?

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Abstract

Estimates of the carbon leakage resulting from sub-global climate policies tend to be lower when using economy-wide general equilibrium models than what technology-specific bottom-up models suggest. In order to test whether this difference is due to excessive sectoral aggregation, I exploit disaggregated data and estimate unobserved values to create a dataset with rich industrial sector detail. The bias caused by sectoral aggregation is estimated by calibrating a general equilibrium model to this dataset and comparing results with those generated from more aggregated datasets.

A stylized unilateral carbon pricing policy is simulated. Results show that aggregated calibrations overestimate industrial output loss and underestimate the increase in CO_2 embodied in imports. The efficiency of border carbon adjustments at reducing leakage is also underestimated. However, I find that general equilibrium estimates of carbon prices and economy-wide leakage rates are mostly unaffected by the degree of industrial aggregation.

Keywords: general equilibrium, unilateral carbon policy, sectoral detail, aggregation bias, carbon leakage, border carbon adjustments

1 Introduction

As some countries put a price on CO_2 emissions, it is feared that production of carbon-intensive goods will be shifted to countries which have not introduced mitigation measures, inducing CO_2 emission leakage. A range of solutions including emission-right rebating schemes or border carbon adjustments (BCAs) - which can include carbon-intensity based tariffs, export rebates, or both- is discussed at the policy-making and academic levels.

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A number of studies estimate the extent of carbon leakage, the magnitude of necessary border adjustments and their leakage-reducing potential. Many rely on multi-sectoral, multi-regional general equilibrium models which allow both qualitative and quantitative assessments of economy-wide changes induced by climate policy. These models tend to predict modest leakage rates in the 10 to 30% range. However, currently available studies are characterized by a high degree of sectoral aggregation, which might be hiding significant leakage rates in highly carbon-intensive sectors. Indeed, another strand of literature relying on sector-specific partial equilibrium models generally predicts substantially higher leakage rates.

The approach taken in this paper is to increase sectoral detail within a computable general equilibrium model of the world economy. The objectives are to investigate how available data can be used to provide a more precise sectoral distribution of impacts, reassess leakage rates and the effectiveness of BCAs and quantify the "aggregation bias" which may be caused by relying on overly aggregated calibrations.

Increasing sectoral detail is relevant from a policy perspective as BCAs are discussed at a fairly fine degree of aggregation. In the United States (US), the Environmental Protection Agency [US-EPA 2009]¹ has identified 44 sectors² as presumptively eligible for allowance rebates, being particularly energy and trade intensive. In the European Union, about 105 sectors³ have been singled out as presumptively eligible. None of the general equilibrium studies in the literature use models which are capable of generating such a level of detail. Indeed, a majority of existing models are based on different aggregations of the same global trade and production dataset, Purdue University's Global Trade Analysis Project (GTAP), which has a coarse description of industrial sectors (it includes 16 sectors which can be defined as representing industry and manufacturing).

In this paper, I create a series of GTAP datasets based on different levels of industrial aggregation of GTAP. In addition, I develop GTAP-MECS, a micro-consistent dataset covering the whole world economy which uses GTAP as a starting point and expands the industrial sector coverage. Industrial sectors are often both energy intensive and heavily traded: they comprise 69% of total US imports in value and 80% of embodied CO_2 imports. They are thus central to the estimation of carbon leakage rates and the effectiveness of BCAs. GTAP-MECS includes sectors such as cement or aluminium which are the focus of partial equilibrium studies and are missing from GTAP. It exploits detailed industrial energy use (including fuel mix) data made available in the US by the Energy Information Administration's Manufacturing Energy Consumption Survey (MECS), as well as input-output data from the Bureau of Economic Analysis (BEA) and disaggregated international trade data. This information is integrated within the GTAP dataset and increases the number of industrial sectors from 16 to 51. Because energy intensity and input/output data outside of the US is not observed, the calibration relies on identifying assumptions for their estimation. The uncertainty due to these assumptions generates variability in results which will be accounted for.

The GTAP and GTAP-MECS datasets are used to calibrate a standard static constant-returns model of international trade based on the Armington differentiated goods assumption. In this class of general equilibrium models, increasing the degree of sectoral detail influences results in different ways: heterogeneity in CO_2 intensities can change substitution possibilities in final and intermediate demand; a more detailed description of technologies and fuel mixes can affect energy input substitution possibilities and overall

¹In a recommendation report prepared for the US's (now-defunct) H.R. 2454 Bill.

²At the North American Industrial Classification System (NAICS) 6-digit level.

³At the NACE-4 classification system.

abatement costs; finally, disaggregation can affect the model's trade response if it changes the sector-level correlation of trade and CO_2 intensities. The scope for import substitution depends on the sign of this correlation and is thus an empirical matter.

A simple counterfactual policy in which CO_2 emissions are reduced in a sub-set of countries is implemented. Results generated with the disaggregated GTAP-MECS calibration are compared with those generated by the calibration of the same model to different aggregations of the industrial sectors available in GTAP. I find that, as expected, the range and standard deviations of sectoral impacts increases with disaggregation. The increase in detail can also lead in qualitatively different predictions for some sectors, and changes the relative ranking of impacts across industries. I then estimate aggregation bias at the GTAP-sector detail level: the difference between impacts estimated with a GTAP calibration and the re-aggregated impacts from the disaggregated calibration. The magnitude of the bias is estimated to be large, with considerable differences between sectors both in sign and magnitude. This indicates that the GTAP-MECS dataset includes within-sector heterogeneity which is not captured by GTAP and can affect results substantially.

Importantly, sectoral-level biases tend to average out, and the amount of aggregation bias which remains at the overall industrial level is moderate. Relative to estimates generated using GTAP, the decrease in industrial output is predicted to be about 40% smaller. The increase in industrial imports is about 50% larger, and the increase in the CO_2 emissions embodied in these imports is about 60% larger. Trade related variables are most affected by aggregation. Because of the uncertainty due to unobserved parameters, the sign of aggregation bias for carbon prices and overall leakage rates cannot be identified. Despite this uncertainty, results show that the magnitude of the bias is small, and economy-wide leakage rates remain mostly unaffected by the level of industrial aggregation. The high sector-specific leakage rates indicated by bottom-up partial equilibrium studies do not translate into high economy-wide leakage rates when estimated in general equilibrium. Industrial detail does matter, however, in the estimation of the efficiency of carbon-intensity based import tariffs (BCAs), which are perceived to reduce about one third more leakage using the disaggregated calibration.

2 Literature

A large literature focusing on the magnitude of carbon leakage and the efficiency of BCAs dates back to Felder and Rutherford [1993]. Studies have adopted legal, statistical and model-based approaches. Within these, many rely on "top-down" computable general equilibrium analysis [Paltsev et al. 2005, Babiker and Rutherford 2005, Babiker 2005, McKibbin and Wilcoxon 2008, Elliott et al. 2010]. Leakage estimates from this literature are sensitive to underlying modeling assumptions, most notably industrial organization and trade structures. For example, Babiker [2005] finds leakage rates of up to 130% using an increasing returns to scale framework and a pure Heckscher-Ohlin trade model. Under the more standard assumptions of constant returns to scale and an Armington trade structure, leakage rates remain modest, with estimates generally ranging from 10% to 30%. Additionally, it is estimated that a large part of leakage will be caused not through direct production displacement, but by decreased pressure on global fossil fuel prices.

McKibbin and Wilcoxon [2008] and Fisher et al. [2010] point out that these small leakage rates might at least partially be explained by the high degree of sectoral aggregation which characterizes the aforementioned studies. Indeed, a vast majority of general equilibrium studies are based on various aggregations of the GTAP dataset. For example, the US Environmental Protection Agency, in US-EPA [2009], a report on the effects of climate

policy on international competitiveness and emissions leakage, relies on the FFEAT model which is based on only a handful of aggregated GTAP sectors. Many popular models include even less sectors (MIT’s EPPA [Paltsev et al. 2005] model includes 10 sectors, two of them only describing industry).

Another set of studies rely on partial equilibrium models and focus on specific energy-intensive sectors. These tend to estimate larger leakage rates. For example, Lanz et al. [2010] find rates of around 27% in the copper sector, Demailly and Quirion [2006] and Ponssard and Walker [2008] find rates of about 50% and 70% for cement, and Mathiesen and Mstad [2004] find leakage rates of between 26% and 53% in the steel industry.

A small strand of the general equilibrium literature has worked on increasing the level of detail in the modeling of other fields (see for example Grant et al. [2006] and Narayanan et al. [2009] for applications to agriculture and trade policy), but none have focused on the manufacturing and industrial sectors relevant to climate and energy policy analysis.

3 Modeling framework

As this paper’s focus is on the estimation of the value of sectoral disaggregation in calibrated general equilibrium models, I use a standard model based on common assumptions made in the literature. The static, multi-regional model of the global economy is similar in structure to the GTAP-EG model described in Rutherford and Paltsev [2000]. An algebraic description of the equilibrium zero-profit, market clearing and budget balance conditions can be found in Appendix A.

Production functions, consumer preferences and import demands are based on combinations of nested constant elasticity of substitution (CES) functions, which generate cost functions (or equivalently, expenditure functions) which can be expressed in calibrated share form as $c(p_i) = \bar{c} \left[\sum_i \theta_i \left(\frac{p_i}{\bar{p}_i} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$, where $\bar{c}$ and $\bar{p}_i$ are benchmark costs and prices, θ_i is the benchmark cost share of input i and σ is the elasticity of substitution between inputs.

Consumption Representative consumers in each region maximize welfare subject to a budget constraint which includes returns on the production factors they own. Their expenditure function is a nested CES composite whose structure is represented in Figure 1. Energy goods compete in a top nest with the M bundle of non-energy goods (including the disaggregated industrial sectors), which are grouped in a Cobb-Douglas sub-nest.

Production Production is modeled by constant return to scale technologies as represented by Figure 2. Energy goods are traded-off in a top-level nest with a leontief aggregate of domestic and imported intermediate inputs and primary factors. Substitution between labor and capital is governed by the sector specific elasticity of substitution σ_{KLi} . The share of each intermediate input (including the disaggregated industrial sectors) in the M bundle remains constant at benchmark values. Energy sources can be substituted for one another in the production of industrial goods and services, but not in the production of secondary sources of energy (refined oil and electricity). Fossil fuels (crude oil CRU, coal COL and natural gas GAS) are produced subject to decreasing returns to scale technology through the introduction of a sector specific resource input. The elasticity of substitution between sector specific resources and other inputs to fossil fuel production are calibrated to match desired supply elasticities⁴ (1 for COL, 0.25 for GAS, 0.5 for CRU). Finally, the

⁴See Babiker [2005].

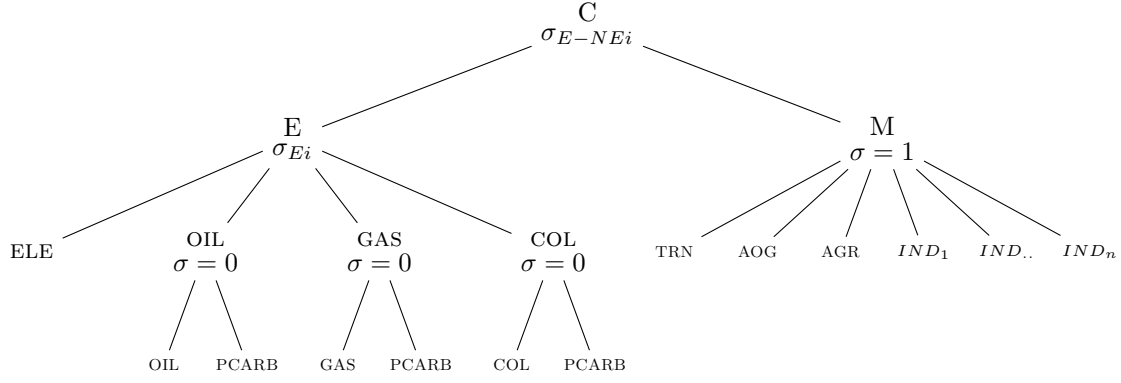


Figure 1: Consumption nesting structure

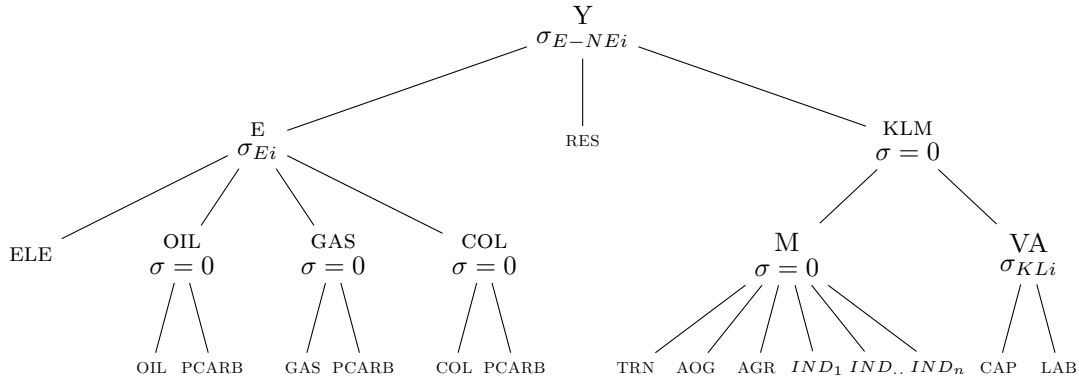


Figure 2: Production nesting structure

consumption of fossil fuels entails emissions of CO_2 , which are subject to a carbon price P_{carb} .

Trade All goods, except for CRU which is homogeneous across regions, are traded internationally following the Armington assumption of regionally differentiated products. Bilateral trade flows are determined by a constant-elasticity aggregate across goods provided by different regions. This is modeled by an Armington aggregator, in which domestic and intermediates are substituted with constant elasticity σ_{Di} .

Market closure and resolution Each commodity and factor market is perfectly competitive with fully endogenous prices. Factor markets satisfy full employment, with labor and capital mobile across industries within regions, but internationally fixed. Each region's net current account is fixed. The numerical model is formulated and solved as a mixed complementarity problem (MCP)⁵ format introduced by Mathiesen [1985].

⁵Using the MPSGE Mathematical Programming System for General Equilibrium analysis developed in Rutherford [1999a].

4 GTAP-MECS: A global dataset with rich industrial sector detail

I now describe the data sources which have been merged to build GTAP-MECS. Ideally, a model used to estimate leakage rates would be calibrated to a dataset which integrates trade, input/output, energy and CO_2 intensity data, as well as relevant substitution elasticities, for all regions and all disaggregated sectors. This would require the collection and adaptation of input/output tables from many countries, an extremely data- and time-consuming exercise which is out of the scope of this study. Instead, the calibration strategy has been to combine globally available international trade data with industrial production data from the US⁶ and extrapolate domestic production and demand outside of the US.

The data sources are summarized in Table 1. After being harmonized, a least-squares balancing procedure is used to achieve internal micro-consistency. Specific issues encountered in the matching and balancing procedures are described in appendix C. Note that this calibration procedure could easily be used to integrate input-output coefficients from other countries if desired.

4.1 Benchmark values

Non-industrial data Production and trade data for all non-industrial sectors and regions are extracted from GTAP [Narayanan and Walmsley 2008], a comprehensive international trade dataset which has been designed for usage with calibrated simulation models. The version used in this paper, GTAP7, contains production data for 57 commodities and 113 regions, as well as bilateral trade flows for each of these commodities. It is based on 2004 values. This dataset is the most widely used in the literature, and is the point of comparison for the more disaggregated GTAP-MECS dataset.

Energy intensity and fuel mix Reliable data describing energy inputs in industrial production is not generally available for large numbers of sectors. Following US-EPA [2009], data from the EIA’s 2006 Manufacturing Energy Consumption Survey (MECS) are used to describe the energy use (by energy type) of a range of manufacturing sectors.

Although the MECS dataset contains data for 79 sectors at the 3, 4 and 6-digit levels of the North American Industrial Classification System (NAICS), various issues in matching and merging (described in appendix C) limited the number of sectors included in GTAP-MECS to 51⁷. These account for 85% (measured by output) of what is reported in the MECS survey. Most of what is missing corresponds to oil refining, a sector for which GTAP data is retained.

MECS distinguishes 8 different energy sources which are matched to the 4 energy sectors in GTAP (indicated in parenthesis): electricity (ELE), residual fuel oil (OIL), distillate fuel oil (OIL), natural gas (GAS), LPG and NGL (GAS), Coal (COL), Coke and breeze (COL), and others (dropped)⁸. This data is used to compute energy intensity coefficients (fuel input per unit of output, in value terms), by energy source. It should be noted that there are significant differences in the industrial fuel mixes implied by MECS relative to GTAP, as can be seen in the first two columns of Table 2. Industrial usage of coal, although low in both datasets, is underestimated in GTAP, and the relative shares of refined oil and natural gas vary greatly. The ratios of CO_2 emissions to the value of energy

⁶Which has been chosen because of the availability of extensive industrial energy use data.

⁷They correspond to 16 industrial GTAP sectors through a many-to-many mapping. The production share of each GTAP-MECS sectors falling within a GTAP sector can be found in Table 15.

⁸See details in appendix C.

input, which reflect both physical emission coefficients and energy prices, also vary from dataset to dataset. Table 2 also underlines the differences in energy mixes across world regions (again, most differences are in the relative shares of gas and oil). MECS does not distinguish imported versus domestic energy inputs and the breakdown between the two is determined by the balancing procedure using shares from GTAP.

International trade Disaggregated trade data is extracted from the MAcMAP [CEPII 2006] database of bilateral trade flows at the 6-digit Harmonized system (HS6) level compiled by the Centre d’Etudes Prospectives et d’Informations Internationales (see Horridge and Laborde [2009]). This dataset contains more than 5000 goods which are aggregated to GTAP-MECS.

Input/output Social accounting data for the GTAP-MECS sectors are extracted from US Bureau of Economic Analysis (BEA) tables and are based on 2006⁹.

Table 1: Data sources in GTAP-MECS

	Parameter	Regions	Industrial sectors	Other sectors
	International trade data	all	UNCTAD / CEPII HS6 data	GTAP7
	SAMs	USA	BEA	GTAP7
		other	assumptions	GTAP7
Energy / CO_2 intensity and fuel mix		USA	MECS	GTAP7
		other	assumptions	GTAP7
	Armington Elasticities	all	assumptions	GTAP7
	Energy input substitution elasticities	all	MECS	GTAP7

4.2 Extrapolation of missing data outside of the US

Some assumptions have to be made to extrapolate US input/output and energy mix data to all regions. These are formulated in general terms in this section but are described in greater detail in appendix B.

Intermediate and final demand for industrial sectors Demand (final and intermediate) for the GTAP-MECS sectors outside of the US is estimated by combining the observed import and export totals for each sector, the observed demand for the GTAP sectors in which each sector is mapped, and each sector’s share of intermediate and final demand observed in the US input-output table. At the sub-GTAP level, each country’s technology matrix is constructed to be as similar as possible to the US’s, whilst fitting within the country’s economic structure¹⁰. The calibration procedure minimizes the deviations of each GTAP-MECS sector’s share of demand to their US equivalent, under the constraint that total domestic demand matches the benchmark value of the GTAP sectors to which they map. Imported intermediate demand is constrained to match the observed import totals in all regions. Thus, the (constructed) output levels for GTAP-MECS sectors reflect relative output levels from GTAP and the observed sector-specific export levels.

⁹This data is rescaled to 2004 values in the calibration procedure.

¹⁰As such, this procedure expands on the approach used in Grant et al. [2006], in which only relative export shares were used to estimate domestic output, resulting in an arbitrary input-output matrix.

Industrial sector input demand Each GTAP-MECS sector’s share of demand for factor and intermediate inputs is targeted to its equivalent value in the US input-output table, under the constraint that total industrial demand for domestic and imported intermediates and factors matches GTAP totals, per region. This assumes that the industrial techniques are similar between regions. Any source of comparative advantage which would result from different techniques at the sub-GTAP level is thus assumed away.

Energy inputs and CO_2 emissions The estimation of unobserved energy inputs and CO_2 emissions are crucial in the determination of leakage rates. For that reason, they are assigned under two distinct assumptions. The sensitivity of results to these assumptions will be tested in section 6.6. Under assumption EI-A1, energy inputs for the GTAP-MECS sectors are assigned by keeping the relative ranking of energy intensities from the US (MECS) combined with region-specific industrial fuel mixes and energy prices from GTAP. As these vary quite a bit across regions (see Table 2), the relative ranking of sectors will vary. Under EI-A2, energy inputs are assigned by taking in account the region-specific energy intensities of the 16 GTAP parent sectors, and the relative ranking of energy intensities from the US (MECS) is only kept at the sub-GTAP level. This second assumption makes the most use of available data and closely reflects sector- and region-specific differences in energy and CO_2 intensities.

In both cases, CO_2 emission totals are made to match GTAP totals, allowing direct comparison with GTAP-based calibrations. Mathematical formulations for assumptions EI-A1 and EI-A2 can be found in appendix B. Figure 3 illustrates the implications of the assumptions on the constructed distributions of CO_2 intensities in Europe and China relative to the observed distribution in the US (from MECS). As can be seen, both assumption take in account region-specific differences in average CO_2 intensities. Incorporating more information, EI-A2 generates more cross-regional variability in the relative rankings of sectors than EI-A1.

Table 2: Industrial energy mix per region

		USA MECS	USA GTAP	CHN	IND	RUS	EUR	RA1	EEX	MIC	LIC
energy (\$bn)	<i>oil</i>	2.8	38.9	39.6	10.0	6.7	45.9	29.7	16.4	67.2	1.3
	<i>gas</i>	58.4	24.7	0.0	1.2	3.8	15.7	5.1	7.3	14.4	0.8
	<i>coal</i>	5.4	0.6	9.1	0.8	0.1	1.1	1.1	0.2	4.4	0.2
	<i>ele.</i>	42.2	65.4	61.1	20.0	19.6	123.8	77.4	12.1	94.4	3.8
CO_2 (Mt)	<i>oil</i>	23.0	93.3	266.6	39.4	48.3	153.1	116.5	87.7	230.8	7.6
	<i>gas</i>	376.4	304.9	0.1		72.8	219.7	66.8	177.9	228.6	7.2
	<i>coal</i>	130.9	33.7	675.9	83.7	5.9	51.4	54.5	25.3	252.2	6.1
CO_2 / energy	<i>oil</i>	8.1	2.4	6.7	4.0	7.2	3.3	3.9	5.4	3.4	6.0
	<i>gas</i>	6.4	12.4	14.2	12.6	18.9	14.0	13.0	24.4	15.9	9.4
	<i>coal</i>	24.3	61.5	74.6	109.6	78.7	47.4	49.7	113.3	57.0	27.2

4.3 Elasticities

Expanding the number of sectors also requires a correspondingly larger set of response parameters. In the model described in section 3, industrial sectors enter a number of substitution nests. In the two M demand nests (final and intermediate), disaggregation implies the definition of more homogeneous goods which are closer substitutes to each other than aggregated goods would be. No econometric estimate of these substitution possibilities are available and nesting structures are left unchanged (Leontief for production, Cobb-Douglas for consumption). A glance at the type of industrial sectors in GTAP-MECS suggests that the degree of aggregation is still too high for them to be close substitutes in production, and the Leontief assumption remains plausible. Although the goods are

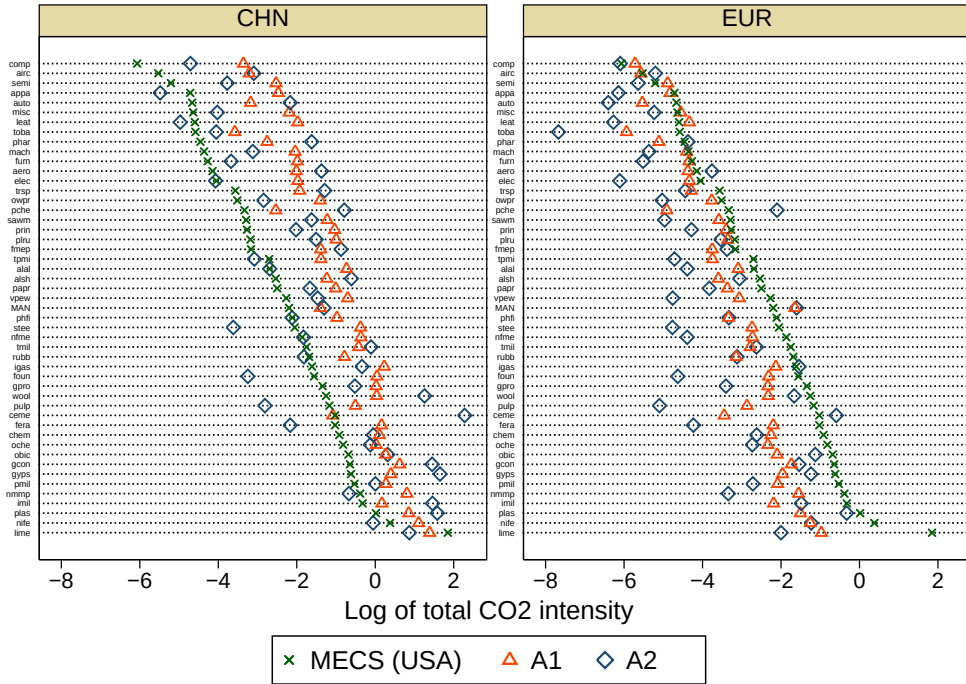


Figure 3: Assumptions made about energy intensities outside of US - comparing the between-sector distribution of (log) CO_2 intensities under EI-A1 and EI-A2 to the MECS distribution of intensities in the US. The left-hand side displays values for China, the right-hand side displays values for Europe.

substitutable in final demand, it is important to note that most of them are demanded primarily as intermediates.

I now discuss in more detail two crucial sets of substitution elasticities: Energy input substitution elasticities and Armington elasticities. All the elasticities used in the model are summarized in Table 3.

Table 3: Overview of elasticities in model

Elasticity		Consumption	gtap-mecs	Sectors		
				Others	ELE	COL, GAS, OIL
Energy - non-energy	σ_{E-NEi}	0.5	0.5	0.5	0.5	calibrated
Capital - Labor	σ_{KLi}	-	GTAP	GTAP	GTAP	GTAP
Between energy inputs	σ_{Ei}	0.25	MECS	1	0	0
Armington	σ_{Di}	GTAP	GTAPx1.31	GTAP	GTAP	GTAP

Note: "GTAP" estimates are available directly from the GTAP dataset

4.3.1 Energy input substitution elasticities

The industrial sectors' capacity to switch between energy sources is an important determinant of the overall cost of CO_2 emission abatement. Lacking precise sector-level elasticity estimates, many modeling exercises use a Cobb-Douglas functional form which relies entirely on benchmark value shares. Instead, I use fuel switching data made available by the MECS survey. Industrial establishments were asked about the quantity of each energy input they would be able to switch away from. This data is used to split the E nest of Figure 2 into the switchable and the non-switchable share of each energy inputs. Establishments were also asked about the level of price difference between an energy source and its alternative which would cause them to switch away from this energy source. The data includes a maximum of 5 price-quantity points for each sector-fuel combination from which OLS regressions are used to estimate own-price elasticities of demand η_{ei} (see Figure 10 in appendix C.4). The sector-specific elasticity of substitution between energy sources σ_{Ei} is then calibrated by weighing each own-price elasticity estimate by the corresponding input's initial cost share ω_{ei} such that $\sigma_{Ei} = \sum_e \omega_{ei} \frac{\eta_{ei}}{\omega_{ei}-1}$.

This data is useful in its ability to provide energy input substitution elasticities at a level of sectoral aggregation which matches that of GTAP-MECS. It includes switchable shares of energy data for 72% of all sector-fuel combinations (corresponding to 95% of total value), but only 34% of the necessary estimates of own-price elasticity elasticity (35% in value). Thus, there are 9 sectors for which σ_{Ei} cannot be built, but these correspond to only 6.2% of energy use. The distributions of switchable shares, η_{ei} , and σ_{Ei} can be found in Figures 11, 12 and 13 in Appendix C.4.

4.3.2 Armington trade elasticities

Armington trade elasticities are crucial parameters in the determination of leakage rates. The Armington assumption says that goods from different countries are heterogeneous. Elasticities should increase with the degree of disaggregation, as the goods under consideration are increasingly well defined, and thus substitutable for each other. This is confirmed empirically by Hummels [2001] and Balistreri and McDaniel [2002] among others.

While several studies estimate these elasticities at a level of disaggregation suitable for the purpose of this exercise (Gallaway et al. [2003] for example), they rely on cross-sectional data, a method which has been shown by Balistreri and McDaniel [2002] to generate estimates which are biased towards one. Due to the lack of robust estimates, Armington elasticities for the GTAP-MECS sectors are based on the elasticity of their GTAP

parent sector which is available in GTAP ¹¹. The increased degree of disaggregation is corrected for by multiplying these elasticities by a factor of 1.31, the ratio of the mean elasticity estimated by Hummels [2001] at the 4-digit aggregation level (8.26) to the mean estimate at the 2-digit level (6.26). The sensitivity of results to this assumption will be tested.

4.4 Data description

A complete list of the GTAP-MECS sectors can be found in Table 4 (Table 13 of the Appendix provides more detail). They are classified according to the North American Industrial Classification System (NAICS) at the 3-, 4- and 6-digit levels. Their size varies considerably, from lime to computer and electronic products. Sectors responsible for the largest amounts of CO_2 emissions are chemicals OBIC, paper mills PMIL, plastic materials and resins PLAS, and iron and steel mills IMIL. Sectors also vary widely in their CO_2 intensities, from 8.6 kg/USD for lime to 0.33 kg/USD for aerospace products and parts.

Table 4: List of industrial sectors in GTAP-MECS and GTAP

Industrial sectors in GTAP-MECS					
Code	NAICS	Sector Name	Code	NAICS	Sector Name
tmil	313	Textile Mills	rubb	325212	Synthetic Rubber
tpmi	314	Textile Product Mills	nife	325311	Nitrogenous Fertilizers
appa	315	Apparel	phfi	325312	Phosphatic Fertilizers
leat	316	Leather and Allied Products	gcon	327213	Glass Containers
prin	323	Printing and Related Support	ceme	327310	Cements
plru	326	Plastics and Rubber Products	lime	327410	Lime
nmmp	327	Nonmetallic Mineral Products	gyps	327420	Gypsum
fmep	332	Fabricated Metal Products	wool	327993	Mineral Wool
mach	333	Machinery	imil	331111	Iron and Steel Mills
comp	334	Computer and Electronic Products	fera	331112	Electrometallurgical Ferroalloy Prod.
elec	335	Electri. Equip., Appliances, and Compon.	alsh	331315	Aluminum Sheet, Plate and Foils
furn	337	Furniture and Related Products	semi	334413	Semiconductors and Related Devices
misc	339	Miscellaneous	airc	336411	Aircraft
toba	3122	Tobacco	pmil	322121-22-30	paper mills
vpew	3212	Veneer, Plywood, and Engineered Woods	papr	322X	Paper
owpr	3219	Other Wood Products	obic	325181-2-8	Other Basic Inorganic Chemicals
phar	3254	Pharmaceuticals and Medicines	oche	325192-3-9	Other basic organic chemical manuf.
stee	3312	Steel Products from Purchased Steel	chem	325X	Chemicals
nfme	3314	Nonferrous Metals, except Aluminum	gpro	327211-2-5	Glass Products from Purchased Glass
sawm	321113	Sawmills	alal	3313X	Alumina and Aluminum
pulp	322110	Pulp Mills	foun	3315X	Foundries
pche	325110	Petrochemicals	auto	336111-2	Automobiles and light trucks
igas	325120	Industrial Gases	aero	3364X	Aerospace Product and Parts
plas	325211	Plastics Materials and Resins	trsp	336X	Transportation Equipment
			MAN	Residual	Manufacturing residual
Industrial sectors in GTAP					
lea		Leather products	otn		Transport equipment nec
wap		Wearing apparel	lum		Wood products
omf		Manufactures nec	fmp		Metal products
nfm		Metals nec	ppp		Paper products Publishing
b.t		Beverages and tobacco products	mvh		Motor vehicles and parts
nmm		Mineral products nec	eeq		Electronic equipment
tex		Textiles	crp		Chemical rubber plastics
i.s		Ferrous metals	ome		Machinery and equipment nec

The dataset is also unique in its inclusion of bilateral trade flows between 113 regions and countries. Combined with CO_2 intensity from MECS and BEA, it allows the estimation of sectors responsible for the largest shares of global embodied CO_2 in trade (evaluated at US intensities)¹². Table 5 displays the embodied CO_2 in global trade for the 20 largest contributing sectors, as well as the largest exporters and importers. PLAS is responsible for 81Mt of embodied CO_2 trade, Germany being the largest exporter and China the largest importer.

¹¹Calculated as the weighted average of the Armington elasticity in case a sub-sector is mapped to several parents.

¹²Because of lack of CO_2 intensity data outside of the US, the dataset is not suitable for complete Multi-Regional Input/output (MRIO) embodied carbon computation.

Table 5: 20 largest contributors to embodied CO_2 in trade

Sector name	Code	All flows	Embodied CO_2 emissions in trade (Mt CO_2)						
			Largest exporter	Largest importer	Largest bilateral flow				
Plastics Materials and Resins	plas	81.44	DEU	10.83	CHN	13.20	TWN	CHN	3.66
Iron and Steel Mills	imil	41.11	JPN	3.80	USA	3.93	JPN	CHN	0.83
Other basic organic chemical manufacturing	oche	32.26	USA	3.81	USA	4.01	IRL	USA	0.92
Textile Mills	tmil	24.33	CHN	3.83	CHN	2.31	USA	MEX	0.58
Other Basic Inorganic Chemicals	obic	16.23	USA	2.69	USA	2.25	USA	JPN	0.53
Nonmetallic Mineral Products	nmmp	12.48	ITA	1.80	USA	2.27	ITA	USA	0.40
Chemicals	chem	12.33	DEU	1.66	USA	0.94	USA	CAN	0.37
Nitrogenous Fertilizers	nife	11.81	RUS	1.49	USA	2.24	CAN	USA	0.65
paper mills	pmil	10.71	DEU	1.30	USA	1.50	CAN	USA	0.97
Computer and Electronic Products	comp	10.65	USA	1.85	USA	1.86	MEX	USA	0.29
Plastics and Rubber Products	plru	8.23	DEU	1.12	USA	1.10	CAN	USA	0.32
Glass Containers	gcon	6.72	FRA	1.02	USA	1.03	MEX	USA	0.35
Glass Products from Purchased Glass	gpro	5.52	CHN	0.65	USA	0.75	CHN	USA	0.21
Transportation Equipment	trsp	5.10	DEU	0.65	USA	0.92	USA	CAN	0.32
Machinery	mach	4.52	DEU	0.75	USA	0.63	USA	CAN	0.16
Nonferrous Metals, except Aluminum	nfme	4.36	CHE	0.36	USA	0.51	CAN	USA	0.14
Pharmaceuticals and Medicines	phar	4.01	DEU	0.54	USA	0.57	IRL	BEL	0.17
Fabricated Metal Products	fmep	3.78	DEU	0.56	USA	0.59	CHN	USA	0.13
Electrometallurgical Ferroalloy Products	fera	3.54	CHN	0.54	JPN	0.39	CHN	JPN	0.13
Leather and Allied Products	leat	3.07	CHN	0.71	USA	0.66	CHN	USA	0.32

Notes : 2004 values. Embodied CO_2 emissions based on US CO_2 intensities from MECS and BEA

Figure 4 displays the relative importance of the GTAP-MECS sectors (shown for illustration as the share of the US economy). They are neither very important in size - their output only corresponds to about 13% of the economy - nor are they on average more energy intensive than the rest of the economy - they are responsible for 14% of total energy consumption. They are heavily traded, though, corresponding to 69% of imports, and almost all CO_2 embodied in imports to the US¹³, at 80% (which corresponds to almost all non-oil imports). The GTAP-MECS sectors can therefore be considered a critical part of any study focusing on carbon leakage.

Heterogeneity between industrial sectors can impact modeling results. Figure 5 displays (again for the US) heterogeneity in three dimensions which are important determinants of a sector's relative competitiveness under climate policy: energy intensity (amount of energy inputs per unit of output, in value terms), trade intensity (import and exports over imports and production), and output. The Figure allows direct comparison of the 16 industrial GTAP sectors with the 51 sectors included in the GTAP-MECS dataset. As can be seen, there is a wide range of variability in these three dimensions across sectors and across the datasets. GTAP-MECS contains 13 energy and trade intensive sectors (defined as having more than 5% energy intensity and 20% trade intensity) whereas as GTAP only contains 4 such sectors and misses some energy intensive sectors such as lime, and some particularly trade-exposed sectors such as non-ferrous metals.

5 Simulations

5.1 Scenarios

The general equilibrium model presented in section 3 is used to simulate a carbon pricing policy in a subset of countries and provide an estimate of resulting leakage rates as well as the effectiveness of BCAs. The implemented scenarios are voluntarily stylized in order to focus on the importance of sectoral aggregation, which is done by calibrating the same model to different datasets with varying degrees of sectoral detail. The 113 regions available in GTAP-MECS are aggregated to 9 regions. The regions, factors, and non-energy sectors included in the model are reported in Table 6.

¹³Based on total emission intensity coefficients.

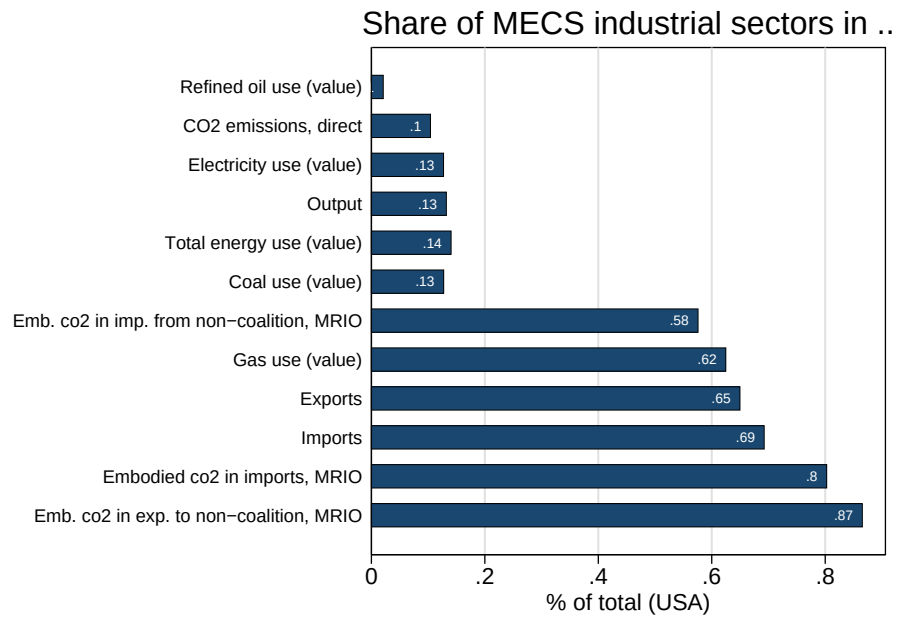


Figure 4: Relative importance of GTAP-MECS industrial sectors in the US economy

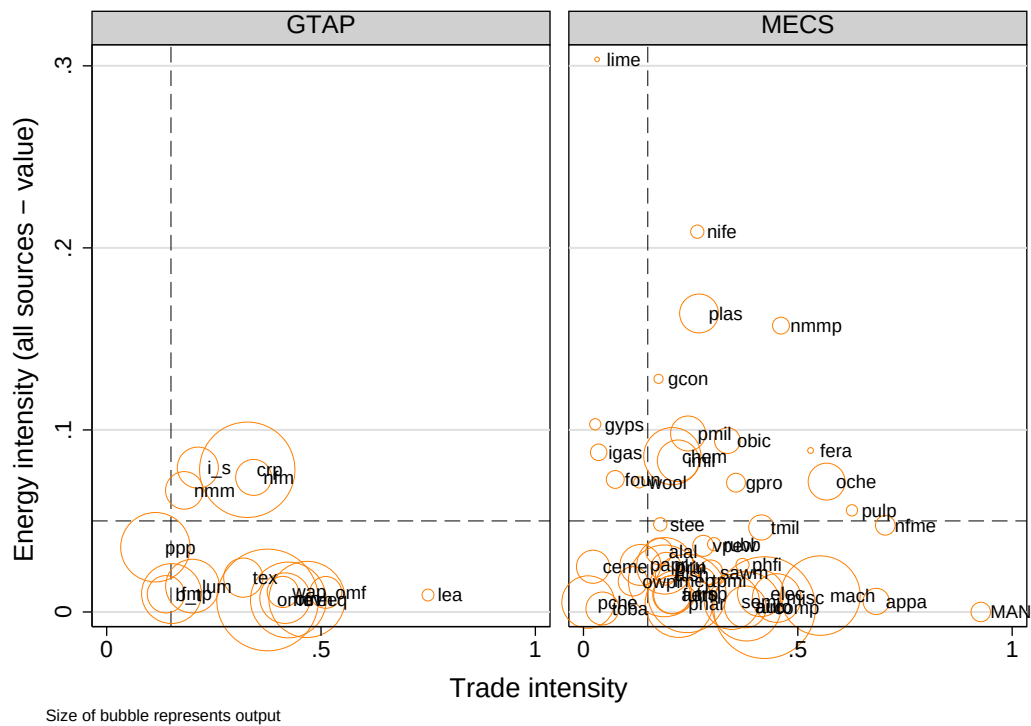


Figure 5: Comparing GTAP and GTAP-MECS sectors (2004 US values)

The REF scenario consists of a 20% reduction in CO_2 emissions in Annex 1 regions (USA, EUR, RA1) which is implemented by requiring each sector to purchase permits in proportion to the amount of CO_2 required for its production. The carbon price is then endogenously calculated to insure the required reduction. It can be thought of as the price of tradable permits as in a Cap-and-Trade policy (tradable across countries), or as an equivalent carbon tax (equal across carbon constrained regions). If only a subset $cc \in r$ of carbon-constrained regions imposes emission limits, a portion of their reductions can be offset by increases in the non carbon-constrained regions $ncc \in r$. This is measured by the carbon leakage statistic $\ell_{ncc} = 100 \times \frac{CE_{ncc} - \overline{CE}_{ncc}}{[\sum_{cc} (CE_{cc} - CE_{cc})]}$ in which CE_r corresponds to total CO_2 emissions in region r in the REF scenario and $\overline{CE}_r$ is the benchmark value. This shift in emissions can be caused by two mechanisms. First, the policy will reduce fossil fuel use in the cc regions, which will have a downward pressure on their price, consequently increasing demand in the ncc regions (the fossil fuel price channel). Second, the production of CO_2 intensive goods will be shifted to ncc countries, as relative prices shift in their favor, and imports from these regions will increase (trade induced leakage). Most studies find the fossil fuel channel to be quantitatively larger. In order to distinguish the two channels, the REF_FFP scenario implements the emission reduction with fixed fossil fuel prices, allowing the identification of trade-related leakage. I also approximate production relocation by computing the percentage change in the embodied CO_2 in imports.

Table 6: Sectors and regions in the model

Energy goods		Regions (*= carbon constrained)	
<i>COL</i>	Coal	<i>EUR*</i>	Europe (EU27 + EFTA)
<i>GAS</i>	Natural gas	<i>USA*</i>	United States
<i>CRU</i>	Crude oil	<i>RUS</i>	Russia
<i>OIL</i>	Refined oil	<i>RA1*</i>	Rest of Annex 1
<i>ELE</i>	Electricity	<i>CHN</i>	China
		<i>IND</i>	India
Non-energy sectors		<i>EEX</i>	Energy exporting countries (excluding Mexico)
<i>TRN</i>	Transport	<i>MIC</i>	Other middle-income countries
<i>AOG</i>	All other goods	<i>LIC</i>	Other low-income countries
<i>AGR</i>	Agriculture		
<i>Industrial</i>	set of manufacturing sectors (see table 4)		
Production factors			
<i>CAP</i>	Capital		
<i>LAB</i>	Labor		
<i>RES</i>	Resources		

In the TARIFF scenario, trade flows from unconstrained regions to constrained regions are subject to import tariffs which are computed such that imported goods face the same price for their embodied emissions than domestically produced goods: $\tau_{ncc,cc} = P_{cc}^{carb} \times P_{ncc}^{-1} \times content_{ncc}$ where $content_{i,ncc}$, the carbon intensity of imports, is calculated using the total emissions caused by the production of that good, including the indirect emissions embedded in both domestic and imported intermediates. These emissions are calculated using a Leontief inversion of the complete multi-regional input-output table. In all scenarios, results are compared to a baseline which corresponds to the observed 2004 equilibrium.

5.2 Aggregation levels

The model is calibrated to 4 levels of industrial detail. The first three use industrial sector data from the GTAP dataset. GTAP₁ aggregates all industrial sectors together in one industrial aggregate, as is done in many calibrated simulation exercises in the literature (for example in the MIT EPPA model [Paltsev et al. 2005]). GTAP₅ singles out the 4 most energy-intensive sectors (Non-metallic minerals NMM, Chemicals rubbers and plastics CRP, Iron and Steel ILS, Non-Ferrous metals NFM). GTAP₁₆ contains all 16 industrial sectors in GTAP and thus achieves the highest level of industrial detail achievable with that dataset. Finally, the model is calibrated to the 51 industrial sectors in GTAP-MECS. Unless noted otherwise, GTAP-MECS are displayed using the preferred set of assumptions EI-A2 and full calibration of energy input and Armington elasticities.

6 Results

6.1 Sector-level results

Figure 6 reports the distribution of sector-level results across aggregation levels. The top part of the figure shows results for three GTAP calibrations. They can be compared to the results from the GTAP-MECS calibration which are displayed in the bottom part. The Figure displays the distribution of total CO_2 intensities, the percentage changes in output in REF and embodied CO_2 emissions in imports in REF and TARIFF, as well as the distribution of tariffs. Results are as expected and are in general qualitatively similar across all levels of aggregation: the more CO_2 intensive the sector, the larger the decrease in output and the larger the increase in embodied CO_2 in imports. More CO_2 intensive sectors face larger import tariffs and the CO_2 embodied in their imports decreases the most in TARIFF.

In the GTAP-MECS calibration, sectors which are the most affected in terms of total output loss are Iron and steel mills IMIL (-14.0 \$bn) and Plastic materials and resins PLAS (-10.6). These are also the sectors responsible for the largest increases in embodied CO_2 in imports: IMIL, with an increase of 4.0 Mt CO_2 , is followed by PLAS (0.88), Nitrogenous fertilizers NIFE (0.68), Other basic organic chemicals OCHE (0.25), and Other basic inorganic chemicals OBIC (0.09). Lime (LIME) and Cement (CEME) also see large increases in embodied CO_2 in imports (1.76% and 1.55%).

A common criticism of aggregated models is that they are unable to identify large impacts on particularly CO_2 intensive sectors. The Figure can be used to compare the range of impacts across datasets, and reveals that GTAP-MECS results do indeed exhibit more variability than GTAP results. The range of percentage changes in output increases from (-4.45, 0.10) to (-5.19, 0.50), relative to GTAP₁₆. 10 low-intensity sectors see their output actually increase, compared to 4 in GTAP₁₆. For embodied CO_2 in imports, the increase in range is even more substantial: (-0.35, 1.70) to (-1.33, 7.98). The standard deviation of results doubles. Note that some sectors have predicted outcomes which are quantitatively different than what would be predicted by GTAP. For example, contrary to its GTAP parent sector Non-metallic minerals NMM, Glass products GPRO sees a decrease in imports. Similarly, the range of the distribution of advalorm tariffs increases from (0.08, 0.14) to (0.03, 0.51) relative to GTAP₁₆, and the standard deviation of the distribution in tariffs increases from 0.37 to 0.80. Interestingly, we see that the 5-sector aggregation of GTAP is capable of generating a between-sector variability which is quite comparable to the 16-sector aggregation.

Figure 6 also reveals that the correlation of sectoral impacts to sectoral CO_2 intensities

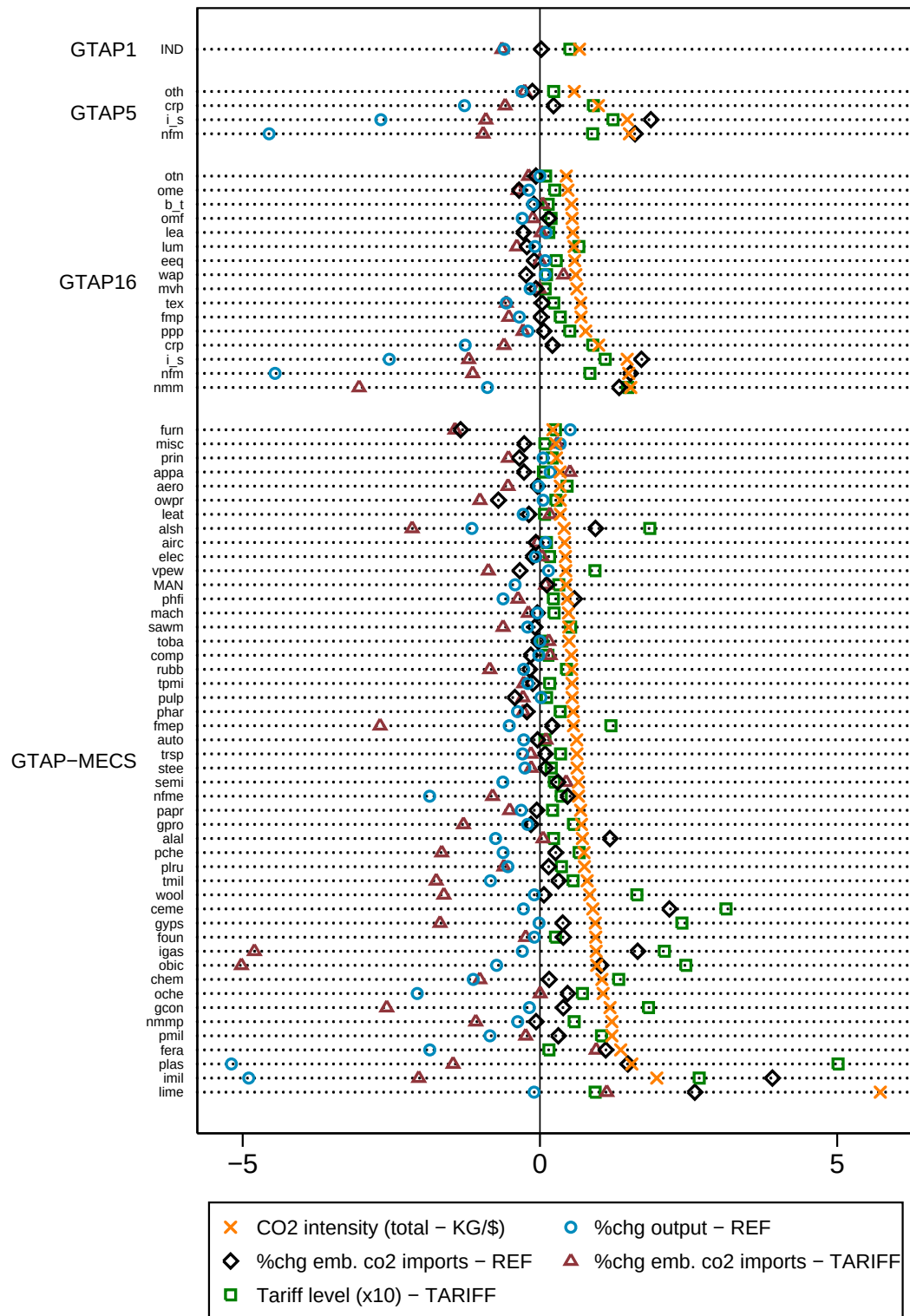


Figure 6: Comparison of the distribution of sectoral results across aggregation levels. From top to bottom: GTAP₁, GTAP₅, GTAP₁₆ and GTAP-MECS.

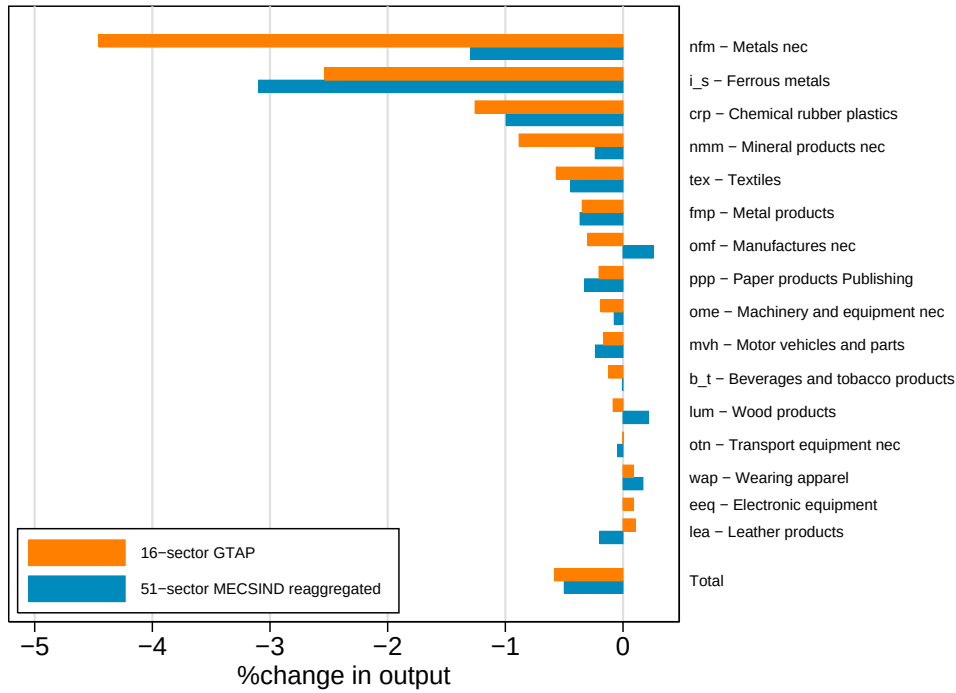


Figure 7: Sector-level aggregation bias - output

is somewhat weaker in GTAP-MECS. Some sectors with high CO_2 intensities (such as Lime LIME, Non-metallic mineral products NNMP and Glass containers GCON, for example) do not experience any substantive declines in output, whereas particularly trade intensive sectors see larger declines in output than their CO_2 intensities would suggest (Non-ferrous metals NFME, for example). The percent change in embodied CO_2 in imports in the REF scenario, a determinant of the increase in overall carbon leakage, is also somewhat less correlated with CO_2 intensities in GTAP-MECS. Cement CEME is more affected than its CO_2 intensity would suggest, while NNMP is not. These differences illustrate the value of detailed disaggregated data, which affects different parts of the model: trade patterns, import substitution possibilities, fuel substitution possibilities and changes in intermediate and final demand. Each of these elements, as well as their interaction, have an impact on sectoral results.

6.2 Aggregation bias at the gtap-sector level

Sector-level results such as those presented in Figure 6 can be interesting in their own right to any party with a stake in a particular sector's competitiveness, or to policy-makers interested in identifying particularly vulnerable sectors. From the modeler's point of view, though, the interest comes from estimating aggregation bias: does an overly aggregated model fail to correctly predict variables of interest, or is it on the contrary capable of replicating the results from a more disaggregated model?

I define aggregation bias as the difference between results estimated using an aggregated calibration to re-aggregated results from a disaggregated calibration. In this section, I reaggregate¹⁴ GTAP-MECS results to the 16-sector GTAP aggregation level in order to identify GTAP sector-level aggregation bias - the bias that occurs within a particular GTAP

¹⁴Using sector sizes as weights.

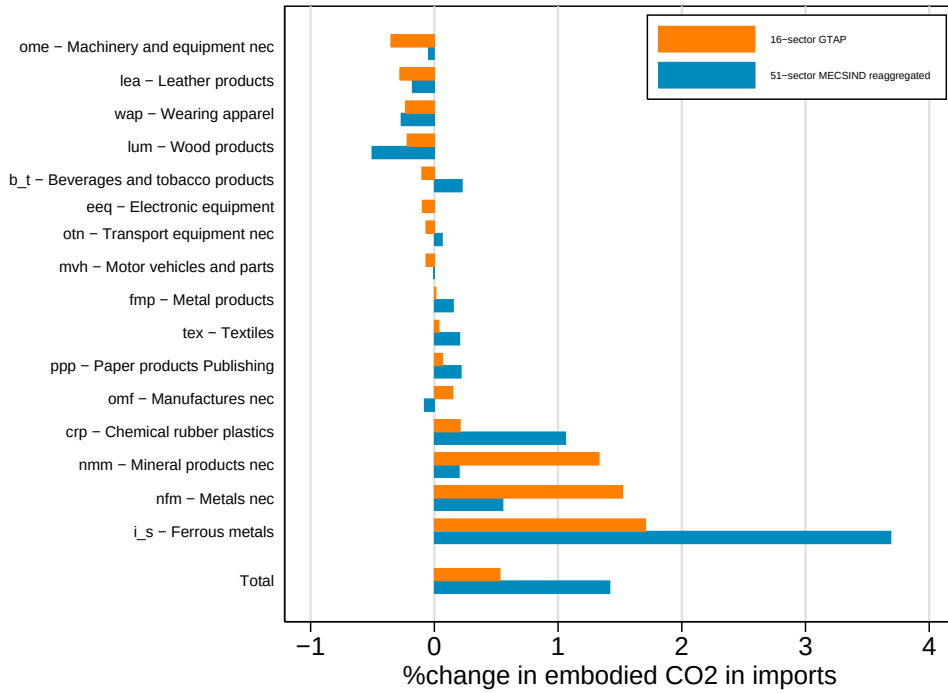


Figure 8: Sector-level aggregation bias - Embodied CO_2 in imports

sector because within-sector heterogeneity is neglected. Then, in section 6.3, I reaggregate all results to identify overall industrial aggregation bias.

Figures 7 and 8 display, for each of the 16 industrial sectors in GTAP, the sectoral impacts on output and embodied CO_2 in imports as predicted by GTAP and re-aggregated from GTAP-MECS. In all cases the calibration of Armington and fuel input substitution elasticities leads GTAP-MECS to predict larger sector-level responses. There is substantial bias in both variables in almost all sectors. When evaluated using the GTAP₁₆ calibration, output change is overestimated in most CO_2 intensive sectors. Non-ferrous metal NFM's output is overestimated by around 250% and non-metallic minerals NMM's by 275%. Iron and steel LS is the only CO_2 intensive sector for which output change is underestimated (by 18%). The biases are even larger for embodied CO_2 in imports, a variable which is greatly underestimated using GTAP₁₆ for LS and chemicals CRP (by -53% and -80%, respectively), and overestimated for NMM and NFM (560% and 174%). The last row of Figures 7 and 8 displays overall industrial bias: Although the sector-level biases average out, overall industrial results vary across aggregation levels. The following section focuses on this bias.

6.3 Overall industrial bias

Table 7 displays total percentage changes for all industrial sectors for various variables of interest across aggregation levels, in the case of the REF scenario. It allows the identification of variables most affected by aggregation bias and to determine its direction and magnitude. In order to reflect the uncertainty implied by unobserved parameters in the calibration, GTAP-MECS results include, on top of preferred estimates, the minimum and maximum estimates generated through the combination of energy intensity and elasticity assumptions. Sectoral output is affected by a clear but relatively small upwards bias: In-

creasing the number of sectors both within GTAP and to the GTAP-MECS detail level leads the model to predict smaller output loss. Estimates range from a -0.70% decrease using GTAP₅ to [-0.40%,-0.50%] using GTAP-MECS. This difference is partially due to increased substitution possibilities in the demand for these sectors.

Increasing the number of sectors can also modify substitution possibilities in the demand for energy inputs. Although no clear trend can be found for the decrease in energy demand, the decrease in industrial CO_2 emissions is lower in GTAP-MECS. Thus, the industrial fuel mix implied by the MECS survey implies less energy substitution possibilities than the technology matrix described by GTAP would predict.

The estimate of the increase in imports is more substantially affected, with a clear downward bias implied by aggregation. GTAP₁ predicts only a 0.02% increase and both GTAP₅ and GTAP₁₆ predict a 0.06% increase, which is only about half what is predicted by GTAP-MECS [0.07%,0.11%]. This bias is even clearer for the increase in embodied CO_2 in imports: the predicted percentage change grows from 3.3% to 9.1% when disaggregating GTAP from 1 to 16 sectors and to [7.1%,14.2%] with GTAP-MECS (note however that GTAP₅ generates an acceptable approximation, at 8.3%). The amount of embodied CO_2 in imports is a function of the CO_2 intensity of imported goods, which depends on specific assumptions made in the calibration of GTAP-MECS. In order to abstract from these assumptions, the last line of Table 7 re-calculates these estimates if evaluated holding CO_2 intensities fixed at US intensities (from the MECS survey). In this case the consequence of disaggregation is even larger. Disaggregating GTAP generates an increase from 0.023% to 0.53%, and the increase using GTAP-MECS is yet higher, at [0.68%,1.42%]. This variable is affected by the between-sector interaction of CO_2 and trade intensities.

To summarize, I found an upwards aggregation bias in predicted change in output, a downward bias in the predicted industrial CO_2 abatement, and a downward bias in the predicted increase in CO_2 embodied in imports.

Table 7: Total industrial sector bias (% changes REF)

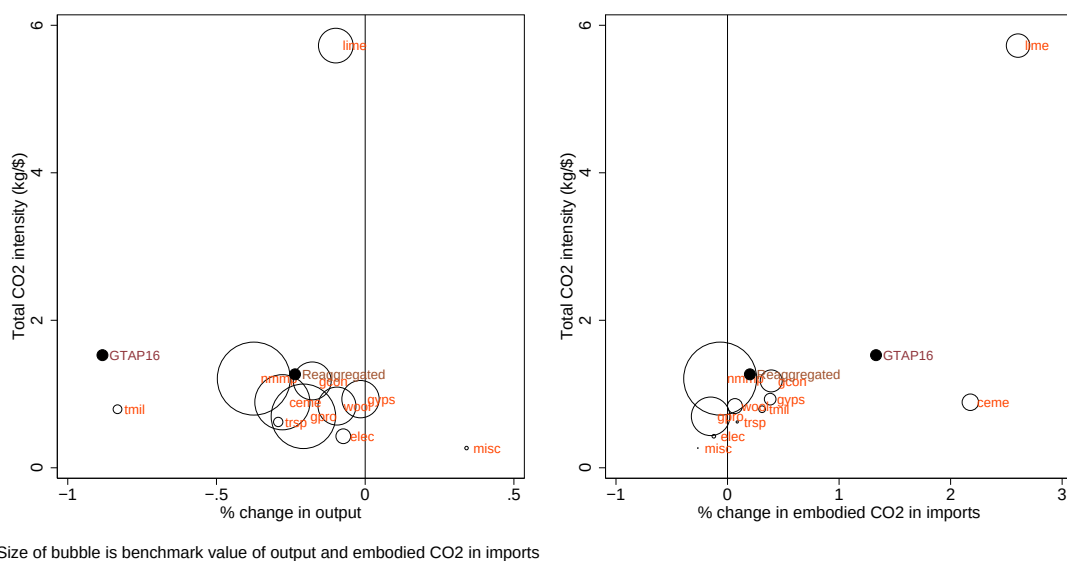
Dataset	GTAP1	GTAP5	GTAP16	min	GTAP-MECS preferred	max
Output	-0.60	-0.70	-0.58	-0.50	-0.50	-0.40
Energy demand	-6.77	-7.00	-7.15	-8.02	-8.02	-5.09
CO2 emissions	-22.25	-21.41	-24.45	-17.92	-17.37	-17.14
Imports	0.02	0.06	0.06	0.07	0.11	0.11
Embodied CO2 in imports	3.30	8.28	9.11	7.15	14.27	14.27
Embodied CO2 in imp (at MECS int.)	0.02	0.41	0.53	0.68	1.42	1.42

Notes: REF scenario corresponding to a 20% reduction in A1 countries; GTAP-MECS preferred results using full calibration of elasticities and assumption EI-A2; min and max correspond to the range of results stemming from the uncertainty implied by assumptions

6.4 An example: Non-metallic minerals (NMM)

Aggregation bias is illustrated by focusing on a single GTAP sector, Non-metallic minerals NMM. It is the most CO_2 intensive and one of the most affected by carbon pricing policy. 7 GTAP-MECS sectors are mapped primarily to NMM: Glass products GPRO, Mineral wool WOOL, Cement CEME, Gypsum GYPS, Glass containers GCON, Non-metallic mineral products NMMP and Lime LIME; 4 sectors are partially mapped to NMM: Transportation equipment TRSP, Textile mills TMIL, Electrical equipment ELEC, and Miscellaneous MISC. NMM thus bundles sub-sectors of very different nature: the large and trade and CO_2 intensive NMMP, the large but not very traded CEME, the CO_2 intensive LIME sector, the small, relatively clean and very trade intensive GPRO, etc..

Figure 9 displays the distribution of impacts on these sub-sectors. The left panel plots percentage change in output against CO_2 intensity, with bubble sizes corresponding to



disaggregation cannot be identified, disaggregate estimates are not substantially different from GTAP estimates.

In REF_FFP, fossil fuel prices are held fixed in order to estimate the importance of trade and international relocation. In this case, leakage rates increase with disaggregation: from 4% to 5% in GTAP to 7% with GTAP-MECS under preferred assumptions. As this trade-related leakage increases with disaggregation, import tariffs are also perceived to be more efficient. The amount of leakage reduction increases from 14% to 24% within GTAP, and to 34% with GTAP-MECS. Import tariffs in general are only effective at reducing trade-induced leakage. Indeed, we see that when fossil fuel prices are held fixed, leakage is almost completely eliminated by the tariffs. However, sufficient sectoral detail is required in order for the model to predict tariffs to reduce all leakage: efficiency of tariffs at reducing leakage is only 69% and 79% in GTAP₁ and GTAP₅. The GTAP₁₆ aggregation level is capable of approximating GTAP-MECS in this respect. Total tariff revenue is also higher in GTAP-MECS under preferred assumptions.

Table 8: Leakage rates and effectiveness of import tariffs across aggregation levels

Dataset	GTAP1	GTAP5	GTAP16	GTAP-MECS		
				min	preferred	max
Fossil Fuel Price channel on						
Carbon price (REF)	45	45	46	41	55	55
Leakage (REF)	15	16	17	13	16	16
Leakage (TARIFF)	13	13	13	8	11	11
Efficiency of Tariff (%leakage reduced)	14	18	24	33	33	35
Tariff revenue (bn USD)	57	56	58	49	65	65
Fossil Fuel Price channel off						
Leakage (REF_FFP)	4	5	5	4	7	7
Leakage (TARIFF_FFP)	1	1	0	0	1	1
Efficiency of Tariff (%leakage reduced)	69	79	102	84	84	110
Notes : corresponding to a 20% reduction in A1 countries - Carbon price in USD/kg						

6.6 Sensitivity analysis

GTAP-MECS results depend on the assumptions made about energy intensities outside of the US and about energy input substitution and Armington elasticities. This section investigates the sensitivity of GTAP-MECS results to different combinations of assumptions. Table 9 reveals that using EI-A1 instead of EI-A2 leads to smaller reductions in energy demand and lower carbon prices. This difference is data driven as EI-A2 generates more region-specific heterogeneity in energy intensities. More importantly, leakage rates are considerably lower under EI-A1 than under EI-A2 (13% instead of 16%), suggesting that leakage rates estimates are not robust to these assumptions. The range of uncertainty created implies that the GTAP-MECS dataset, although useful in understanding the bias caused by aggregation, is not suitable for estimating leakage rates precisely, lacking observed country-specific energy intensity data. For Armington elasticities, I compare the disaggregation-adjusted elasticities (A-DIS) to the GTAP elasticities (A-GTAP). As expected, the higher disaggregation-adjusted elasticities generate a larger trade response. The percentage change in imports is slightly lower when keeping the original GTAP elasticities (0.09% against 0.11%). Embodied CO_2 in imports is also slightly lower. The impact on total leakage is modest (15.8% instead of 16%).

For energy input substitution elasticities, I compare the calibration of MECS elasticities (ES-MECS) to the Cobb-Douglas between energy-source nesting used in the GTAP

calibrations (ES-CD). The Table reveals that the MECS elasticity calibration predicts smaller scope for substitution between energy sources. Thus, output changes are larger, abatement is more expensive and carbon prices are higher, and there is more substitution to imports leading to higher leakage rates. The calibration to MECS elasticities impacts results in a substantial manner. The Cobb-Douglas assumption used in many modeling exercises may be leading to an underestimation of industrial abatement costs. Finally, the Table shows that the estimated efficiency of BCAs at reducing leakage is robust to assumptions.

In conclusion, sensitivity analysis has shown that the direction of aggregation bias in industrial energy demand, the carbon price, the total leakage rate, and tariff revenue is not robust to assumptions embedded in the GTAP-MECS calibration.

Table 9: GTAP-MECS model results - sensitivity to assumptions

Energy intensity Assumption Armington elasticities Energy subst. Elasticities	EI-A2 A-DIS ES-MECS	EI-A2 A-DIS ES-GTAP	EI-A2 A-GTAP ES-MECS	EI-A2 A-GTAP ES-GTAP	EI-A1 A-DIS ES-MECS	EI-A1 A-DIS ES-GTAP	EI-A1 A-GTAP ES-MECS	EI-A1 A-GTAP ES-GTAP
Output (%chg REF)	-0.50	-0.43	-0.49	-0.42	-0.41	-0.44	-0.40	-0.43
Energy D (%chg REF)	-8.02	-6.95	-7.86	-6.85	-5.14	-5.92	-5.09	-5.87
Imports (%chg REF)	0.11	0.09	0.09	0.07	0.10	0.09	0.08	0.07
Emb. CO ₂ imp. (%chg REF)	1.42	1.11	1.04	0.82	0.94	1.04	0.68	0.76
(at MECS int) (%chg REF)	14.27	11.83	13.84	11.52	7.34	8.10	7.15	7.89
Carbon price REF	55.49	42.54	55.16	42.43	40.81	41.69	40.66	41.64
Total Leakage REF	16.00	15.51	15.79	15.30	13.04	14.18	12.92	14.04
Efficiency of Tariffs	33.20	34.27	33.32	34.39	34.65	34.31	34.42	34.07

7 Concluding remarks

Table 10: Direction and magnitude of bias caused by excessive aggregation - Magnitude computed as the ratio of GTAP results relative to disaggregated GTAP-MECS results

		Direction of aggregation bias	Magnitude of bias	
			GTAP ₁	GTAP ₁₆
Industrial sectors (%chg REF)				
	Output	upwards	21% to 51%	16% to 45%
	Energy Demand	assumption dependant	-15% to 33%	-11% to 40%
	CO ₂ emissions	downwards	-68% to -80%	-22% to -63%
	Imports	downwards	-68% to -80%	-23% to -52%
	Embodied CO ₂ in imports	downwards	-54% to -77%	28% to -36%
	Embodied CO ₂ in imports (at MECS intensities)	downwards	-97% to -98%	-22% to -63%
Economy-wide variables				
	Carbon Price (REF)	assumption dependant	11% to -18%	13% to -17%
	Total Leakage (REF)	assumption dependant	20% to -3%	30% to 5%
	Total Leakage (REF_FFP)	downwards	-15% to -49%	18% to -29%
	Total Leakage (TARIFF)	upwards	56% to 24%	51% to 20%
	Efficiency of BCA (%leakage reduced)	downwards	-57% to -58%	-29% to -32%
	Tariff Revenue	assumption dependant	17% to -12%	17% to -11%

Note: range of bias corresponds to different energy intensity and elasticity assumptions used in GTAP-MECS

The paper began with the observation that top-down general equilibrium models used to assess the efficiency of sub-global climate policies and leakage rates often work at low degrees of sectoral aggregation. Bottom-up partial equilibrium modeling exercises which focus on particularly affected sectors find leakage rates which far exceed leakage rates predicted by economy-wide models. Relying on the availability of yet-unused detailed industrial sector data, I have increased the degree of disaggregation in a general equilibrium

model. The exercise has allowed the estimation of the sign and magnitude of aggregation bias which studies working with the more aggregated GTAP dataset may suffer from.

Table 10 summarizes the direction and magnitude of the biases which are caused by using a single-sector industrial aggregation of GTAP (GTAP₁) or all sectors available in GTAP (GTAP₁₆) instead of the more detailed GTAP-MECS dataset. Instead of point estimates, the Table displays a range which reflects the uncertainty caused by assumptions made about energy intensities outside of the US and substitution elasticities. A calibration to GTAP biases industrial output change upwards, but the magnitude of the bias is modest. Depending on assumptions, a GTAP-based calibration can get within 16% to 45% of the value predicted by GTAP-MECS. The impact of disaggregation on energy input substitution possibilities and thus abatement costs is assumption dependent. In particular, I find that using energy input substitution elasticities considerably increases industrial abatement costs relative to the usual Cobb-Douglas assumption, a fact which should motivate further research into the estimation of these elasticities.

In general, industrial trade response to carbon pricing is underestimated in the more aggregated models: the increase in industrial imports as well as the CO_2 embodied in these imports is biased downwards. The amount of trade-related leakage (estimated by fixing fossil fuel prices) is thus underestimated, although the magnitude of this bias is not large. Total leakage, which is also affected by the reduction in fossil fuel prices caused by sub-global carbon pricing policy, remains largely unaffected by the level of industrial aggregation. The impact of industrial aggregation on leakage rates is much smaller than what may be caused by other modeling assumptions, such as trade structure or industrial organization, and in any case rates remain smaller than those suggested by partial equilibrium studies.

In conclusion, GTAP-based calibrations can provide a good approximation of most variables of interest. In many cases, this can even be attained with the inclusion of only a small number of energy intensive sectors (CRP, NMM, NFM and I.S). However, disaggregation beyond the GTAP level does increase the estimates of trade-related leakage and I find that finer sectoral detail is important in determining the efficiency of border carbon adjustments: In the disaggregated model import tariffs are perceived as being about one third more efficient.

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A Appendix: Algebraic model description

This section presents an algebraic description of the general equilibrium model. Following Mathiesen [1985], an equilibrium is defined by two types of equations: zero profit and market clearance. The model incorporate taxes, import tariffs and transport margins. As they are not central to this exercise, they are neglected in this exposition. Sectors are indexed by i or j , regions by r or s and factors by f . In each of the following cases, the θ 's correspond to base year value shares (sectoral indices are dropped to simplify notation).

Armington trade structure A zero-profit condition equalizes the import price to a CES cost index of imports from different regions, with elasticity of substitution σ_M :

$$pm_{ir} = cm_{ir} = \left(\sum_s \theta_s (py_{is})^{1-\sigma_M} \right)^{1/(1-\sigma_M)}$$

The domestic and imported varieties of each good enter a CES nest with elasticity of substitution

$$c_{ijr}^i = \left(\theta_d (py_{jr})^{1-\sigma_D} + (1 - \theta_d) (pm_{jr})^{1-\sigma_D} \right)^{1/(1-\sigma_D)}$$

Sectoral production Primary factors (capital and labor) are mobile across sectors and enter the VA value added CES nest, which defines the following unit cost function:

$$c_{jr}^f = \left(\sum_f \theta_f (pf_{fjr})^{1-\sigma_{KL}} \right)^{1/(1-\sigma_{KL})}$$

Energy goods e (ELE, OIL, GAS, COL) enter the E CES nest with an elasticity of substitution σ_E . The utilisation of fossil fuels (OIL, GAS, COL) requires the purchase of CO2 permits of price $pcarb$ according to their CO2 intensity ϵ .

$$c_{ejr}^e = \left(\sum_e \theta_e (py_{er} + \epsilon pcarb)^{1-\sigma_E} \right)^{1/(1-\sigma_E)}$$

Finally, sectoral unit costs are defined in a CES nest composed of energy goods and a Leontief composite of the costs of intermediate and primary factor inputs, with an elasticity of substitution σ_{E-NE} . See Figure 2.

$$c_{jr}^y = \left(\theta_e \left(c_{ejr}^e + \left(\sum_i \theta_i c_{ijr}^i + \theta_f c_{jr}^f \right) \right)^{1-\sigma_{E-NE}} \right)^{1/(1-\sigma_{E-NE})}$$

All sectors except primary fossil fuels (COL, CRU, GAS) are produced according to constant-return to scale, and zero-profit implies:

$$cy_{jr} = py_{jr}$$

Private and public demand Private and public demand combines domestic and imported varieties, as well as and energy sources (with a different σ_E) similarly. The consumer price index is defined as a CES nest combining energy goods and a Cobb-Douglas sub-nest of non-energy goods with an elasticity of substitution σ_{E-NE} . See Figure 1.

$$pc_r = \left(\left(\theta_e (c_{ejr}^e + \theta_i \prod_i (p_{ir}^c)^{\theta_i})^{1-\sigma_{E-NE}} \right)^{1/(1-\sigma_{E-NE})} \right)$$

The cost of public services is defined by Leontief cost coefficients:

$$\sum_i \theta_i p_{ir}^g = pg_r$$

Demand functions Compensated demand functions are defined for intermediate (ID), private (CD) and public (GD) domestic demand; intermediate (II), private (CI) and public (GI) imported demand; and primary factor demand (FD). CES compensated demand functions are formulated relative to benchmark demand values. For example, the demand for factor f in sector i is:

$$FD_{fir} = Y_{ir} \overline{FD}_{fir} \left(\frac{pf_{fr}}{c_{ir}^f} \right)^{\sigma_{KL}}$$

Market Clearance Conditions Supply of sector i to the domestic market equals intermediate (ID), private (CD) and public (GD) domestic demand:

$$D_{ir} = ID_{ir} + CD_{ir} + GD_{ir}.$$

Import supply of good i satisfies intermediate (II), private (CI) and public (GI) demand for imported goods:

$$M_{ir} = II_{ir} + CI_{ir} + GI_{ir}$$

The demand for each factor equals endowments E_{fr} :

$$\sum_i FD_{fir} = E_{fr}$$

Trade between all regions in each sector is balanced:

$$\sum_s \sum_r Y_{isr} = \sum_s \sum_r Y_{irs}$$

Budget balance The representative household's budget balance is:

$$\sum_i (CD_{ir} + CI_{ir}) = \sum_f E_{fr} + VB_r + T_r$$

.. in which VB_r represents the (exogenous) regional budget balance and T_r represents total tax and tariff revenue.

Solving Numerically, the equilibrium is formulated as a mixed complementarity problem (MCP) [Mathiesen 1985]. The problem is formulated in the GAMS algebraic language and uses the MPSGE mathematical programming system [Rutherford 1999b]. The model is solved using the PATH solver.

B Appendix: GTAP-MECS calibration and balancing

This appendix describes in detail the calibration and balancing procedures (presented in section 4) required to integrate the GTAP-MECS sectors within the GTAP dataset. Ready-made "disaggregation" tools (for example, Monash University's SPLITCOM utility) are not suitable because of the many-to-many mapping of GTAP to MECS sectors and the targeting to US input coefficients, so a specific calibration strategy has been developed.

The ind index denotes the 51 GTAP-MECS sectors, $gtapind$ denotes the 16 GTAP industrial sectors, g denotes all sectors plus private and government demand.

The only observed data for the ind sectors are international trade flows, except for the US where the full social accounting matrix is observed. Endogenous variables are denoted by $\star$, parameter values from different datasets corresponding to the same variables are identified by their exponent.

B.1 Demand calibration

This calibration procedure is run for each region independently, and the r subscript can be dropped. All calculations are done including sector specific tax rates, but these are ignored in the following description. $DI_{gtapind,ind,g}$ and $II_{gtapind,ind,g}$ are g 's domestic and imported demand for the ind industrial sectors within each $gtapind$ sector (see mapping in Table 15). Target coefficients are built by multiplying the shares of the ind sectors within industrial totals in the US input-output table (from the BEA) by GTAP totals:

$$X_{ind,g}^{TARGET} = \frac{X_{ind,g}^{BEA}}{\sum_{ind} X_{ind,g}^{BEA}} \sum_{gtapind} X_{gtapind,g}^{GTAP}, X \in (DD, DI)$$

In each region, the objective to be minimized is:

$$\Omega = \sum_X \left[\sum_{map(ind,gtapind,g)} (X_{gtapind,ind,g}^{\star} - X_{gtapind,ind,g}^{TARGET})^2 \right], X \in (DD, DI)$$

The calibration is subject to the following constraints. First, the supply of all ind sectors to their respective GTAP parent must sum to the total domestic demand for that sector:

$$\sum_{map(ind,gtapind)} DD_{gtapind,ind}^{\star} = DD_{gtapind}^{GTAP}, \forall gtapind$$

The imported intermediates for each ind sector must equal the observed level of international imports from the MAcMap dataset:

$$\sum_g II_{gtapind,ind,g}^{\star} = I_{gtapind,ind}^{MacMap}, \forall map(gtapind, ind)$$

The domestic intermediates for each ind sector must equal the endogenous level of total domestic demand:

$$\sum_g DI_{gtapind,ind,g}^{\star} = DD_{gtapind,ind}^{\star}, \forall map(gtapind, ind)$$

For each final demand sector g , intermediate demand of all ind sectors which map to a $gtapind$ sector must sum to total intermediate demand of that $gtapind$ sector by the g final demand sector:

$$\sum_{map(ind,gtapind)} [DI_{gtapind,ind,g}^{\star} + II_{gtapind,ind,g}^{\star}] = DI_{gtapind,g}^{GTAP} + II_{gtapind,g}^{GTAP}, \forall gtapind, g$$

For the US, ind sector supply is imposed to match the share of the sector within all $gtapind$ sectors, using the share of that sector's output from the BEA data (O_{ind}^{BEA}):

$$\sum_{gtapind} DD_{gtapind,ind}^{\star} + X_{ind}^{MACMAP} = \frac{O_{ind}^{BEA}}{\sum_{ind} O_{ind}^{BEA}} \sum_{gtapind} O_{gtapind}^{GTAP}, \forall ind$$

This calibration procedure takes in account region-specific supply from the parent $gtapind$ sectors, which combined with observed export values for the ind sectors, generates best possible estimates of sectoral output outside of the US.

B.2 Input demand calibration

In a second step, I calibrate industrial sector input demands $DI_{i,ind,r}$, $DI_{i,ind,r}$ and the factor demand $F_{f,ind,r}$. In order to satisfy market clearing conditions for all sectors, input demand for the non-industrial other sectors are allowed to adjust as well. The target values for intermediate supply of i to each ind are calculated from BEA and GTAP data as:

$$X_{i,ind}^{TARGET} = \frac{X_{i,ind}^{BEA}}{\sum_{ind} X_{ind,g}^{BEA}} \sum_{gtapind} X_{i,gtapind}^{GTAP}, X \in (DD, DI, F)$$

The objective function is:

$$\begin{aligned} \Omega = & \sum_X \left[\sum_{i,ind} (X_{i,ind}^* - X_{i,ind}^{TARGET})^2 \right], X \in (DD, DI, F) \\ & + \sum_X \left[\sum_{i,j} (X_{i,j}^* - X_{i,j}^{GTAP})^2 \right] \\ & + 10e5 \sum_{e,ind} \left[(DI_{e,ind} + II_{e,ind}) - enetar_{e,ind} \right]^2 \end{aligned}$$

.. in which energy inputs are targeted with a large penalty. Ω is minimized under the following constraints. The domestic and imported market clearing conditions for each input i imply that their demands must sum to GTAP totals:

$$\begin{aligned} \sum_j DI_{i,j}^* &= \sum_j DI_{i,j}^{GTAP}, \forall i \\ \sum_j II_{i,j}^* &= \sum_j II_{i,j}^{GTAP}, \forall i \end{aligned}$$

The zero-profit conditions for each sector j are:

$$\sum_i (DI_{i,j}^* + II_{i,j}^*) + \sum_f F_{f,j}^* = \sum_i (DI_{i,j}^{GTAP} + II_{i,j}^{GTAP}) + \sum_f F_{f,j}^{GTAP}, \forall j$$

B.3 Energy intensity targeting

Energy inputs are assigned by targeting energy intensity of output. For the US, energy inputs to the industrial sectors are assigned using energy intensities, by energy source, from MECS:

$$enetar_{e,ind,US} = O_{ind,US} INT_{e,i}^{US}$$

where $INT_{e,i}^{US} = \frac{EI_{e,i}^{MECS}}{O_{i,US}^{BEA}}$ is the energy intensity in the US, computed using the energy consumption $EI_{e,i}^{MECS}$ from MECS and BEA sectoral output $O_{i,US}^{BEA}$. For the other regions, energy intensity is unknown and $enetar_{e,ind,US}$ is determined according to assumptions EI-A1 or EI-A2.

In EI-A1, domestic and imported energy inputs are assigned such that relative energy intensities are the same as in the US, but total energy use is rescaled to match region-specific total energy demand values, $DD_{e,r}^{GTAP}$ (domestic) and $ID_{e,r}^{GTAP}$ (imported), for all industries and per energy source, where:

$$\begin{aligned} DD_{e,r}^{GTAP} &= \sum_{gtapind} DI_{e,gtapind}^{GTAP} \\ ID_{e,r}^{GTAP} &= \sum_{gtapind} II_{e,gtapind}^{GTAP} \end{aligned}$$

A region-specific fuel mix adjustment factor, is computed as:

$$ADJ1_{e,r} = \frac{DI_{e,r}^{GTAP} + II_{e,r}^{GTAP}}{\sum_{ind,e} INT_{e,ind}^{US} O_{ind,r}}$$

It is displayed in Table 11, which reveals substantial variations between regions. The last row shows the ratio of total energy use implied by GTAP relative to that implied by MECS. There are some deviations between the MECS fuel mix and GTAP fuel mix even in the US. GTAP implies much higher usage of OIL and ELE, much smaller of GAS and COAL. These adjustment factors are used to compute energy demand targets for the minimization procedure:

$$enetar_{e,ind,r}^{A1} = \left[\sum_e INT_{e,ind}^{US} \right] O_{ind,r} * ADJ1_{e,r}$$

Table 11: Fuel mix adjustment factor ADJ1, by region

	CHN	IND	USA	RUS	EUR	RA1	EEX	MIC	LIC
Oil	0.646	0.97	0.39	0.905	0.22	0.344	1.612	0.717	0.511
Natural gas	0		0.172	0.119	0.014	0.009	0.441	0.075	0.158
Coal	0.145	0.071	0.006	0.01	0.005	0.012	0.021	0.046	0.093
Electricity	0.981	1.872	0.653	2.6	0.573	0.861	1.141	0.983	1.562
All energy	1.772	2.913	1.221	3.634	0.812	1.226	3.215	1.821	2.324

Assumption EI-A2 exploits more information from GTAP parent sectors (based on the mapping of *ind* to *gtapind* found in Table 15 and the production share of each *ind* within its parents). First, the relative energy usage of each *ind* within each *gtapind* is calculated as:

$$ADJ2_{gtapind,ind,r} = \frac{\sum_e INT_{e,ind}^{US} O_{ind,r}}{\sum_{e,x} INT_{e,ind}^{US} O_{ind,r} \frac{O_{gtapind,ind,r}}{O_{ind}}}$$

They are used to calculate per-sector targets, summing over all of sector *ind*'s *gtapind* parents:

$$enetar_{e,ind,r}^{A2} = \sum_{gtapind} \left[\left(DI_{e,gtapind,r}^{GTAP} + II_{e,gtapind,r}^{GTAP} \right) ADJ2_{gtapind,ind,r} \right]$$

Energy use totals will be the same as in original data. CO_2 emissions are assigned by using average regional fuel-specific CO_2 intensities from GTAP (summing up imported and domestic totals). Totals are rescaled (rescaling is not large) to match GTAP CO_2 emission totals per region.

C Appendix: Data description

C.1 MECS data

Uses NAICS (North American Industrial Classification Standard) classification. All 6-digit NAICS sectors present in MECS are kept and, when possible, 3 and 4-digit sectors residuals are build as residuals, net of the included sub-sectors. Both energy quantities (in trillion BTUs) and energy expenditures are available. Some corrections are made in some sectors

in which MECS data is withheld to avoid disclosing data for individual establishments or withheld because Relative Standard Error is greater than 50 percent. These have been reconstructed using available totals. The only corrections of large magnitude are for sectors 325110 and 32519. It was necessary to make a few adjustment to reconcile value and quantity data. Both tables have missing values; but not necessarily for the same sectors. The assumption which was made was to rely on quantity data, adjusting value data using average prices per energy source. Value data which has no equivalent in the quantity data has been dropped. Table 12 summarizes data by fuel. "other" is mainly an input to petroleum refineries, as these are not included in the final data, it is dropped.

Table 12: MECS data summary, by energy source

	total	elect.	resid. oil	dist. oil	gas	lpg + npg	coal	coke	other
Matched to GTAP sector		ele	oil	oil	gas	gas	col	col	dropped
Qty (t BTU)	21584	2970	310	142	6126	2379	1509	284	8462
Value (\$bn)	141.161	51.995	2.227	1.891	47.675	24.322	4.712	1.912	6.526
Avg price	0.006	0.017	0.006	0.014	0.008	0.013	0.003	0.007	0.001

C.2 Production and input/output data from the BEA

Production shares and input shares are extracted from BEA input output tables. The matching was many-to-many and some of the NAICS sectors in MECS needed to be aggregated in order to match BEA sectors. Two sectors are in BEA but have no output data. Shares are always calculated as the share relative to the sum of all industrial sectors.

C.3 HS6-level international trade data from MAcMap

Bilateral trade and tariff data for more than 5000 HS6 codes (using the 1996 version of the codes) are available from the CEPII dataset. Data is extracted from Mark Horridge's TASTE utility, which already maps the data to the correct GTAP sectors. It is then mapped to the NAICS sectors in MECS using mapping an HS1996 to NAICS mapping. The MECS sectors correspond to a very large percentage of the total available codes (around 80%). One sector from MECS, "aluf", does not seem to have trade data, but was kept. Transport margins are assumed to be proportional to those of each HS6 sector's parent GTAP sector. Tariffs for the subsectors represent the true values taken from MAcMap and are simply aggregated. Export subsidies are assumed proportional to the combination of each HS6 sector's parent GTAP sector.

C.3.1 Final data set

All oil refining sectors from MECS are dropped. Because of mapping issues with BEA and HS6 data, some other sectors were aggregated. Finally, 51 sectors representing 61 of the sectors available in MECS remain in the final dataset. One "MAN" residual sector is constructed and represents the remaining NAICS sub-codes included in the 16 GTAP sectors which could not be mapped to trade and energy intensity data.

C.4 Energy input substitution elasticity calibration

Figures 10, 11, 12 and 13 relate to the calibration of energy input substitution elasticities as described in section 4.3.1.

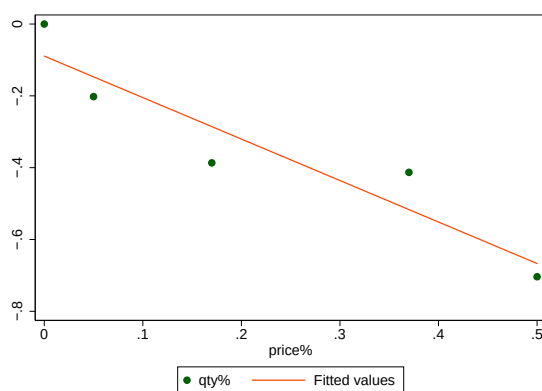


Figure 10: Own-price elasticity estimation OLS regressions. Example: Gas demand in foundries

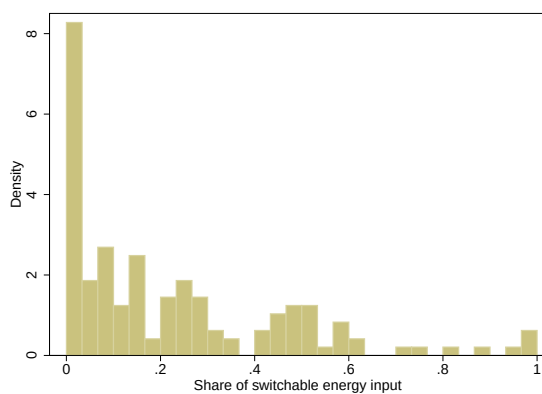


Figure 11: Distribution of shares of switchable energy, by sector-fuel pair.

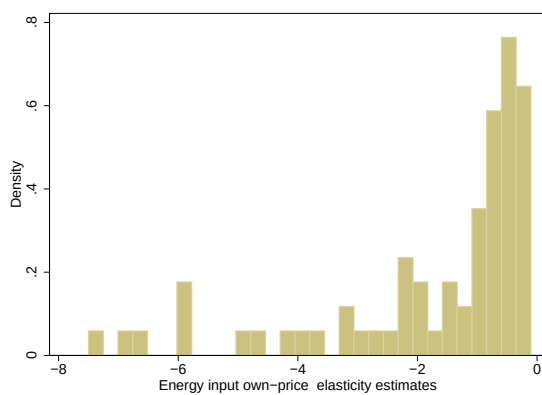


Figure 12: Distribution of own-price elasticity estimates, by sector-fuel pair.

Table 13: *ind* Industrial sectors in GTAP-MECS - X is residual sector

NAICS code	Code	Name	Output	Direct CO_2 emit.	MRIO CO_2 int.	Trade int.	Embodied CO_2 in Imports	% imports from OECD
			(\$bn)	(Mt CO_2)	(Kg/\$)	(I+E)/(Y+I)	(@US int. - Mt CO_2)	(%)
327410	lime	Lime	1.17	8.99	8.64	0.03	0.20	0.20
331112	fera	Electrometallurgical Ferroalloy Products	1.84	0.87	1.36	0.53	2.50	0.87
327213	gcon	Glass Containers	4.64	2.44	1.32	0.18	0.98	0.54
327993	wool	Mineral Wool	6.87	1.96	1.22	0.13	0.52	0.28
327420	gy ps	Gypsum	6.99	3.90	1.91	0.03	0.19	0.38
322110	pulp	Pulp Mills	7.14	13.27	2.47	0.63	6.99	0.19
325312	phfi	Phosphatic Fertilizers	9.59	1.16	2.18	0.37	2.80	0.17
325212	rubbb	Synthetic Rubber	9.60	2.19	0.95	0.30	1.08	0.39
325311	nife	Nitrogenous Fertilizers	9.76	14.31	2.74	0.27	7.80	0.64
3312	stee	Steel Products from Purchased Steel	9.86	2.24	0.99	0.18	1.66	0.63
316	leat	Leather and Allied Products	11.32	0.11	0.89	1.00	30.30	0.78
325120	igas	Industrial Gases	15.09	3.22	1.12	0.04	0.23	0.23
327	nmmp	Nonmetallic Mineral Products	15.91	11.87	1.60	0.46	15.07	0.54
3315X	foun	Foundries	17.62	4.74	1.03	0.07	0.79	0.62
327211-2-5	gpro	Glass Products from Purchased Glass	19.64	6.65	1.05	0.36	5.39	0.55
Residual	MAN	Manufacturing RESIDUAL	20.99	0.00	1.00	0.93	21.33	0.29
3314	nfme	Nonferrous Metals, except Aluminum	21.51	3.34	1.12	0.70	20.71	0.55
331315	alsh	Aluminum Sheet, Plate and Foils	22.70	1.94	0.97	0.19	2.04	0.21
3212	vpew	Veneer, Plywood, and Engineered Woods	24.56	8.32	1.03	0.28	7.98	0.28
321113	sawm	Sawmills	33.37	7.70	0.92	0.30	9.67	0.17
313	tmil	Textile Mills	34.97	6.88	1.18	0.41	10.60	0.63
325181-2-8	obic	Other Basic Inorganic Chemicals	36.86	20.82	1.48	0.34	9.89	0.36
315	appa	Apparel	37.99	0.34	0.69	0.68	44.34	0.91
314	tpmi	Textile Product Mills	38.04	2.55	0.97	0.28	10.79	0.84
3313X	alal	Alumina and Aluminum	39.05	4.43	1.18	0.18	7.97	0.37
3219	owpr	Other Wood Products	47.70	1.42	0.59	0.12	2.78	0.52
323	prin	Printing and Related Support	51.30	1.95	0.46	0.19	2.29	0.41
3122	toba	Tobacco	60.26	0.62	0.66	0.04	0.42	0.78
327310	ceme	Cements	60.98	27.17	1.12	0.02	1.45	0.61
322121-22-30	pmil	paper mills	67.77	110.80	2.87	0.24	35.59	0.10
325192-3-9	oche	Other basic organic chemical manufacturing	75.57	34.41	1.49	0.57	46.14	0.28
3364X	aero	Aerospace Product and Parts	79.64	1.50	0.33	0.21	1.49	0.21
337	furn	Furniture and Related Products	81.56	1.69	0.40	0.21	7.43	0.61
325211	plas	Plastics Materials and Resins	83.87	88.21	2.01	0.27	16.04	0.20
322X	papr	Paper	92.62	15.16	1.80	0.13	11.51	0.43
331111	imil	Iron and Steel Mills	96.23	72.39	1.87	0.22	35.35	0.57
336411	airc	Aircraft	96.96	0.38	0.41	0.38	5.61	0.24
335	elec	Electrical Equip., Appliances, and Components	120.28	3.54	0.53	0.41	22.91	0.65
339	misc	Miscellaneous	131.50	1.27	0.38	0.45	22.48	0.71
325110	pche	Petrochemicals	153.25	5.47	1.08	0.01	0.81	0.23
334413	semi	Semiconductors and Related Devices	168.44	1.06	0.46	0.35	12.26	0.69
326	plru	Plastics and Rubber Products	176.79	7.35	0.92	0.19	19.04	0.44
325X	chem	Chemicals	181.27	112.75	1.40	0.21	21.74	0.34
3254	phar	Pharmaceuticals and Medicines	252.96	3.35	0.50	0.22	17.03	0.14
336111-2	auto	Automobiles and light trucks	265.11	2.77	0.66	0.38	81.58	0.18
332	fmep	Fabricated Metal Products	286.15	12.10	0.58	0.19	21.22	0.53
336X	trsp	Transportation Equipment	339.85	9.96	0.59	0.24	35.45	0.43
333	mach	Machinery	350.21	4.61	0.46	0.55	62.06	0.31
334	comp	Computer and Electronic Products	573.75	1.33	0.35	0.42	76.57	0.73

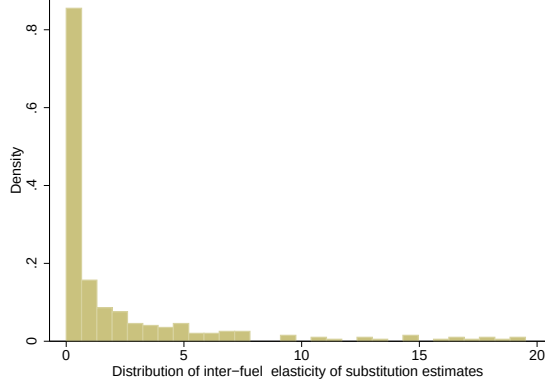


Figure 13: Distribution of inter-fuel elasticity of substitution estimates, by sector-fuel pair.

Table 14: *gtapind* GTAP industrial sectors

Code	Name	Output	Direct CO_2 emit.	MRIO CO_2 int.	Trade int.	Embodied CO_2 in Imports
		(\$bn)	(Mt CO_2)	(Kg/\$)	(I+E) / (Y+I)	(@US int. - Mt CO_2)
lea	Leather products	11.39	0.54	0.55	0.75	12.97
wap	Wearing apparel	77.89	2.93	0.60	0.41	28.75
omf	Manufactures nec	80.94	1.23	0.54	0.51	27.27
nfm	Metals nec	103.76	19.90	1.51	0.34	44.45
b_t	Beverages and tobacco products	111.85	5.59	0.53	0.14	6.65
nmm	Mineral products nec	113.24	78.51	1.53	0.18	25.16
tex	Textiles	123.45	7.57	0.68	0.32	24.35
i_s	Ferrous metals	135.36	52.71	1.47	0.21	34.49
otn	Transport equipment nec	204.76	4.58	0.44	0.42	16.16
lum	Wood products	230.86	12.24	0.57	0.20	26.88
fmp	Metal products	287.28	10.25	0.69	0.15	21.01
ppp	Paper products Publishing	386.97	56.12	0.78	0.11	18.85
mvh	Motor vehicles and parts	460.64	10.14	0.62	0.42	123.39
eeq	Electronic equipment	465.64	0.14	0.58	0.47	116.52
crp	Chemical rubber plastics	729.46	154.79	0.99	0.33	137.95
ome	Machinery and equipment nec	829.60	14.73	0.47	0.38	96.51

Table 15: Share of each GTAP-MECS sector with its GTAP parents

	b.t	tex	wap	lea	lum	ppp	crp	nmm	i.s	nfm	fmp	mvh	otn	ele	ome	omf
aero													1.000			
airc													1.000			
alal										0.923	0.016				0.062	
alex										1.000						
alsh										1.000						
appa		0.286	0.657	0.036		0.005	0.017									
auto												1.000				
ceme								1.000								
chem		0.083					0.913									0.004
comp							0.012						0.008	0.594	0.386	
elec							0.002	0.015					0.007	0.003	0.970	0.003
fera									1.000							
fmep							0.003		0.039	0.033	0.502	0.005	0.002		0.415	0.001
foun									0.196		0.253		0.365		0.186	
furn					0.971						0.027				0.002	
gcon								1.000								
gpro								0.904							0.086	0.010
gyps								1.000								
igas							1.000									
imil							0.000		1.000							
leat			0.003	0.199	0.147		0.406				0.245					
lime								1.000								
mach							0.002				0.009	0.222	0.126	0.013	0.629	
misc		0.007	0.000		0.001	0.010	0.088	0.001			0.009		0.004		0.406	0.474
nfme							0.049			0.888	0.007				0.041	0.015
nife							1.000									
nmmp							0.043	0.873	0.011						0.038	0.035
obic							1.000									
oche	0.002						0.998									
owpr					0.449						0.240	0.302				0.009
papr						0.621	0.372									0.007
pche							1.000									
phar							1.000									
phfi							1.000									
plas							1.000									
plru				0.001		0.000	0.987						0.001		0.011	0.000
pmil						1.000										
prin						0.983					0.001					0.015
pulp						1.000										
rubbb							1.000									
sawm					1.000											
semi							0.026							0.974		
ssaa										1.000						
stee											0.209					
tmil		0.984					0.001	0.015	0.791							
toba	1.000															
tpmi		0.847		0.063			0.084									0.006
trsp					0.007			0.004				0.716	0.125		0.149	
vpew					1.000											
wool								1.000								