Online Appendix: "Border Carbon Adjustments When Carbon Intensity Varies Across Producers: Evidence from California"

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This appendix provides details on the computational model of the Western Electricity Coordinating Council (WECC) used in the main article. Section A briefly describes the geographic structure of the data and assignments used in the model. Sections B and C describe our data sources and highlight assumptions and methods used to construct the dataset. Finally, Section D details the model itself.

A Geographic structure

The WECC electricity data was aggregated into four sub-regions - California, Northwest, Southwest, and Rockies. These four sub-regions are reflective of the aggregation used by many of our data sources, such as the EIA and EPA eGrid. The regions were assembled through the assignment of balancing authorities, as illustrated in Figure A.1 and described in Table A.1.

Figure A.1: Illustration of balancing authority regional designations

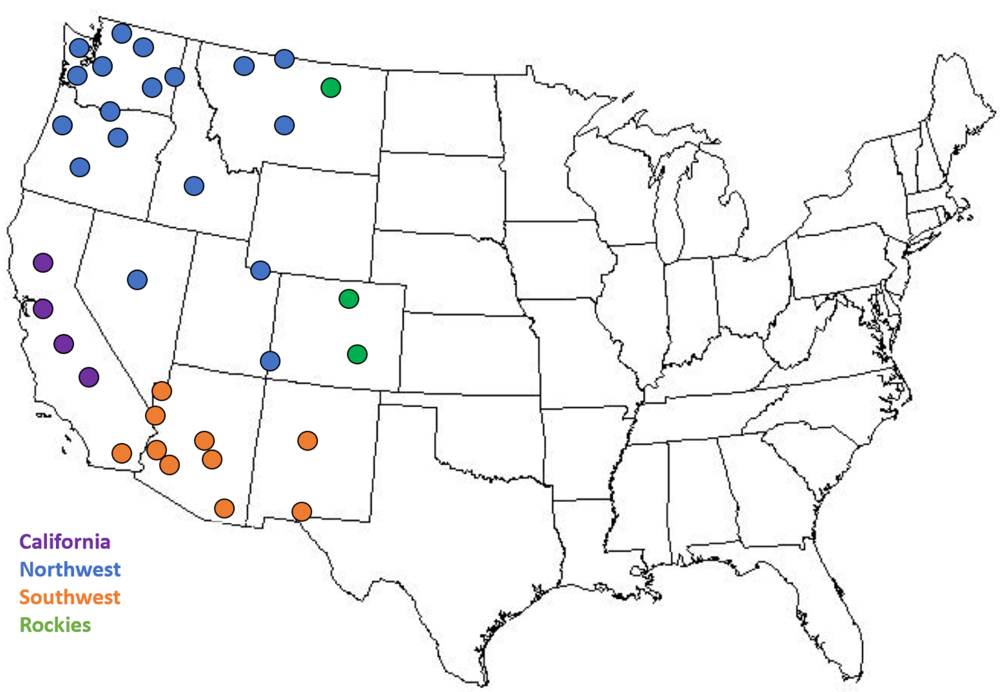

Table A.1: Balancing authorities mapped to their four sub-regions

California	**Northwest**	**Southwest**	**Rockies**
BANC	AVRN	AZPS	PSCO
CISO	AVA	DEAA	WACM
LDWP	BPAT	EPE	WAUW
TIDC	TPWR	GRMA	
	GRID	GRIF	
	IPCO	IID	
	GWA	HGMA	
	WWA	PNM	
	NEVP	SRP	
	NWMT	TEPC	
	PACE	WALC	
	PACW		
	PGE		
	CHPD		
	GCPD		
	DOPD		
	PSEI		
	SCL		

B Plant-Level Variables

Our marginal cost and capacity metrics were calibrated at the plant-level using the EPA's Emissions & Generation Resource Integrated Database (eGrid),[1] then aggregated by sub-region. According to the EPA, the eGrid database is "a comprehensive source of data on the environmental characteristics of almost all electric power generated in the United States." Although our hourly market data was from the year 2019, we used the 2018 eGrid database, as the estimates are released biannually. Given the extended lifetimes of power plants, we are confident that the 2018 data is also reflective of 2019.

There were certain assumptions that went into using the eGrid variables, which we will describe in the following three subsections.

B.1 eGrid Capacity Variables

Our model used the eGrid generator-level data to calibrate nameplate capacities (MW), capacity factors, and annual net generation (MWh). Our simulation model dispatches generators to meet demand in ascending order of operating cost subject to coarsely defined transmission system constraints. Our model does not explicitly capture local transmission system constraints in detail. The result is that, for a subset of natural gas generators in California located close to large demand hubs such as Los Angeles and San Francisco, our basic simulations predict that these generators would hardly operate due to relatively high marginal costs, when in reality they are frequently running. To accommodate this issue, we imposed minimum net generation limits for this small set of generators.

More precisely, we invoke the following assumption: If a generator is within a certain distance

[1] `https://www.epa.gov/egrid/download-data`

of Los Angeles or San Francisco (within 100 miles), has a sufficiently large marginal cost (above 38 USD/MWh), and has a sufficiently large capacity factor (above 40%), we flag the natural gas plant as one that frequently runs out-of-merit. We manually set the generator's annual net generation to align with observed capacity factor. These efforts assured that the model would not underestimate natural gas electricity generation in constrained areas of California where essential plants are run more intensively than they would be absent system constraints.

B.2 Marginal Cost Estimates from eGrid Heat Rate Variables

We use the eGrid plant-level heat rate variable (BTU/kWh) to calculate the marginal cost of combustion-based electricity generation. Based on the primary fuel type reported by each generator, we calculate the marginal cost of electricity according to the equations outlined in Table B.1.

Table B.1: Calculating marginal cost from heat rates, by fuel

Fuel Type	**Marginal Cost Calculation Assumption**
GAS in California	MC (USD/MWh) = HR (BTU/kWh)*1000*3.87(USD/BTU)+ 3(USD/MWh)
GAS in all other regions	MC (USD/MWh) = HR (BTU/kWh)*1000*3.2(USD/BTU)+ 3(USD/MWh)
COAL	MC (USD/MWh) = HR (BTU/kWh)*1000*2(USD/BTU)+ 5(USD/MWh)
OIL	MC (USD/MWh) = HR (BTU/kWh)*1000*14(USD/BTU)+ 3(USD/MWh)

The red terms in Table B.1 are the costs of fuel per unit of heat for each type of fuel. For natural gas, we obtained the fuel costs from the EIA Natural Gas Summary Tables.[2] In the year 2019, in California, the cost of natural gas was estimated to be 3.87 US dollars per thousand cubic feet, which is an equivalent unit to US dollars per BTU. The cost of natural gas for the other three sub-regions is based on the Nevada estimate of 3.2 US dollars per BTU.

The red terms for coal and oil are derived from the EIA Short Term Energy Outlook Data Browser.[3] In the year 2019, the Power Generation Fuel Costs for coal in the US electricity sector were 2.01 US dollars per BTU. The Power Generation Fuel Costs for oil were split into two categories - residential and distillate. We chose the average heating cost between those two metrics.

The blue terms in Table B.1 represent the operational and maintenance costs of the various fuels in US dollars per MWh. The EPA's National Electric Energy Data System (NEEDS)[4] documentation outlines the components that go into these operational costs, and provides a range of values for each fuel. Keeping with the recommendations in the EPA documentation, we chose to use operational and maintenance costs that came out to be approximately 10% of MC for natural gas and oil, and 20% of MC for coal. The operational and maintenance costs for coal are higher relative to the other fuels due to the necessary addition of emission abatement technologies.

B.3 Emission Costs Estimates from eGrid CO2 Emission Rates

To calibrate the emissions intensity of a generating unit, we use the emission rates reported in the eGrid database on a plant-level basis in pounds of CO2 per MWh of electricity generated. We calculate the marginal cost of CO2 emissions by converting the emission rate to tons of CO2 per MWh, and then multiplying by an assumed cost of carbon. The social cost of carbon is a metric that is highly debated, but for this analysis, we assigned the cost of carbon to be 40 US dollars per ton of CO2 emitted.

[2] https://www.eia.gov/dnav/ng/ng_sum_lsum_a_EPG0_PEU_DMcf_a.htm

[3] https://www.eia.gov/outlooks/steo/data/browser/

[4] https://www.epa.gov/sites/production/files/2018-05/documents/epa_platform_v6_documentation_-_chapter_4.pdf

C Market Variables

The electricity market variables used in our model were assembled on an hourly basis for the calendar year of 2019. In the following two sections, we describe the two online sources used to construct these hourly electricity generation, demand, transmission, and price data.

C.1 EIA Electric System Operating Data

The EIA's U.S. Electric System Operating Data[5] has hourly data spanning our year of interest for electricity generation by source, electricity demand, and transfers of electricity. The data is aggregated both at the regional level and for all WECC balancing authorities.

In the EIA database, the WECC is split into three sub-regions, unlike the four that our model uses. Therefore, directly downloading and using the sub-regional data was not compatible with our method. Instead, we identified the handful of differing balancing authority assignments and reassigned the select electricity generation, demand, and transfers data to their proper sub-region.

C.2 California ISO OASIS

We used the California ISO Open Access Same-time Information System (OASIS)[6] site to assemble hourly electricity prices. We downloaded hourly Day Ahead Market, Locational Marginal Electricity Prices on a nodal level. We then used the ATLAS Reference dropdown in OASIS to map those nodes to Transmission Access Charge (TAC) Zones, which could then be assigned to different sub-regions according to Table C.1.

Table C.1: TAC Zone Mapping to Regions

TAC AREA ID	**REGION**
TAC_NORTH	California
TAC_ECNTR	California
TAC_SOUTH	California
TAC_AZPS	Southwest
TAC_PAC	Northwest
TAC_NEVP	Northwest
TAC_PGE	Northwest
TAC_PSEI	Northwest

By taking the median value of the aggregated pricing nodes, we assigned a singular hourly price to each sub-region in Table C.1. It is worth noting that the Rockies sub-region is not represented in Table C.1. Therefore, we assigned the Northwest sub-region electricity price to the Rockies sub-region, as well.

D Model

The simulation model uses information about generating units and electricity market variables to solve for the optimal electricity price, demand, transfers, and unit generation in the WECC. In this modeling context, the optimal solution is one which maximizes surplus subject to a suite of

[5] `https://www.eia.gov/opendata/qb.php?category=2123635`
[6] `http://oasis.caiso.com/mrioasis/logon.do`

specified constraints, which we detail later in this section. We simulate market outcomes under four different methods of taxing emissions outside of California's borders, as described in the main body of the paper.

The simulation model is run using the Julia programming language coupled with JuMP, an algebraic modeling language, and an Ipopt interface. Ipopt is an open source software package designed for large, nonlinear optimization problems. It utilizes an interior point line algorithm method to find local solutions that optimize our objective function while meeting all defined constraints.[7]

D.1 Cases

The four cases explored in the main body of the paper are differentiated in the simulation model based on the definition of the taxed emissions rate. Table D.1 provides a formulaic approach to understanding the different cases.

Table D.1: Taxed Emissions Rates by Case

Case	Taxed Emissions Rate (er_tax) Definition
Complete Regulation	$\text{er\_tax}_{u,r} = \text{er}_{u,r}$
Incomplete Regulation	$\text{er\_tax}_{u,r} = \text{er}_{u,r} * \text{istax}_{u,r}$
Uniform BCA	$\text{er\_tax}_{u,r} = \text{er}_{u,r} * \text{istax}_{u,r} + \text{default} * (1 - \text{istax}_{u,r})$
Differentiated BCA	$\text{er\_tax}_{u,r} = \text{er}_{u,r} * \text{istax}_{u,r} + MIN(\text{default}, \text{er}_{u,r}) * (1 - \text{istax}_{u,r})$

In Table D.1, "er" defines each generating unit's GHG emissions rate, "default" is equal to the default emissions rate (0.428 tonnes CO2/MWh), and "istax" is a dummy variable equal to one if the generating unit is operating within California's tax jurisdiction.

In the Complete Regulation case, the taxed emissions rate is simply each generating unit's emissions rate for all units in the WECC. In the Incomplete Regulation case, the taxed emissions rate is the generating unit's emissions rate if the unit is within California's tax jurisdiction, and 0 otherwise. In the Uniform BCA case, the taxed emissions rate is the generating unit's emissions rate if the unit is within California's tax jurisdiction, and the default rate otherwise. Finally, in the Differentiated BCA, the taxed emissions rate is the unit's emissions rate if the generating unit is within California's tax jurisdiction, and the minimum of the default rate and the unit's emissions rate otherwise.

Within the simulation model, the "er_tax" variable is multiplied by the carbon tax and the quantity of electricity produced at each unit to determine that unit's total emissions cost.

D.2 Variables

The variables utilized in the simulation model can be categorized using two conceptual frameworks. First, they can be labeled as either input variables (i.e. integrated into the model) or output variables (i.e. solved for within the model). Second, the variables can be organized in terms of their iterable categories. For example, there are some variables that vary by generating unit and by sub-region, while other variables vary over time. Table D.2 attempts to illustrate these categorizations, while offering a brief description for each variable.

[7] Ipopt Documentation: `coin-or.github.io`

D.3 Objective Function

The simulation model is set up maximize total consumer and producer surplus in the wholesale electricity market subject to a series of constraints. More precisely, we search for the allocation of electricity generation that maximizes the joint surplus of all the sub-regions contained in WECC, accounting for the fact that GHG externalities might only be partially internalized depending on the policy design. The production incentives faced by the firms in the market vary across the policy design scenarios we consider.

Using the variables described in Table D.2, the objective function at each time period takes the form of:

$$\max \ \text{surplus}_t - \text{totalcost}_t - \text{totalecost}_t \tag{1}$$

The maximized market surplus is the area beneath the demand curve minus the fuel costs from generation and the emissions-related compliance costs imposed by the assumed carbon pricing regime.

D.4 Constraints

In what follows, we describe the constraints we impose on this constrained optimizaiton problem.

D.4.1 Demand Constraints

Using the variable and parameter definitions in Table D.2, we assume a linear demand curve of the form:

$$\text{demand}_{rt} = \text{a}_{rt} - b_{rt} * price_{rt} \tag{2}$$

Demand in each sub-region must be equal to all electricity generated in that sub-region (including all generation from the must-run units, and the optimal generation from the fossil fuel units) combined with the net transfers into and out of the sub-region.

D.4.2 Generation Constraints

The solar, wind, nuclear, and hydroelectric generating units are encompassed in the "qmr" variable in Table D.2. These units are constrained to run when available (in the case of non dispatchable solar and wind). In other words, we fix generation from these units at observed levels across simulations.

The fossil fuel generation units are constrained to produce within a specific range. Units must produce no less than 0 MWh of electricity and no more than 95 percent of their nameplate capacity. Some units, described in greater detail in Section B.1 of this appendix, are constrained to generate no less than their nameplate capacity multiplied by their capacity factor, and no more than 95 percent of their nameplate capacity.

D.4.3 Transmission Constraints

The transmission constraints implemented in this simulation model are based on those used by (Bushnell 2017).[8] The constraints accomplish two main objectives. First, they interact the electricity transfers with factors designed to simulate the distribution of electricity flowing through the transmission lines. Essentially, these factors map the proportion of electricity that follows

[8] Bushnell, James B., Stephen P.Holland,Jonathan E. Hughes,and Christopher R. Knittel.2017."Strategic policy choice in state-level reg-ulation: The EPA's clean power plan."American Economic Journal: EconomicPolicy.

the different possible flow-paths through the grid. Second, the constraints limit the capacity of the electricity passing through each transmission line. Based off the variables in Table D.2, the transmission constraints take the following form:

$$-lines_l \leq \sum_{r \notin CA} fct_l * yflow_{rt} \leq \text{lines}_l \tag{3}$$

D.4.4 California Accounting Constraints

Several variables, specifically the ones with the "_ca" tag in Table D.2, allow the model to keep track of which units of electricity are being imported to California, and therefore, which units of electricity are included in California's border carbon adjustment. The California accounting constraints assign electricity generated ("q") to be California electricity ("q_ca") if the generating unit is in California, or taxed as if it is in California. Using the variables in Table D.2, that constraint holds if either "istax" or "isca" are equal to 1. The inclusion of these constraints allows firms to reshuffle their emissions depending on whether or not it is favorable to send electricity to California in the current BCA case.

Table D.2: Variable Descriptions

Variable Name	**In-put**	**Out-put**	**Description**	**Unit** (u)	**Time** (t)	**Region** (r)	**Trans-mission Lines** (l)
a	x		Electricity demanded when price is zero		x	x	
b	x		Slope of electricity demand curve		x	x	
qmr	x		Quantity of electricity from wind, solar, nuclear, and hydroelectric energy sources, which "must run" in the model		x	x	
mc	x		Marginal cost of electricity production	x		x	
er	x		Emissions rate	x		x	
mw	x		Capacity	x		x	
cf	x		Capacity factor	x		x	
congestion	x		Dummy variable flagging natural gas units near large cities to mandate a minimum required generation	x		x	
isca	x		Dummy variable indicating the generating unit is in California	x		x	
istax	x		Dummy variable indicating the generating unit is in California's tax jurisdiction	x		x	
lines	x		Maximum capacity that can flow through transmission lines				x
fct	x		Distribution of electricity flow originating in a region along the transmission lines			x	x
price		x	Electricity price		x	x	
demand		x	Electricity demand		x	x	
yflow		x	Net electricity transmissions originating in a region		x	x	
q		x	Electricity generated from fossil fuels	x	x	x	
q_ca		x	Quantity of electricity from fossil fuels that was generated in or sent to California	x	x	x	
qmr_ca		x	Quantity of electricity from solar, wind, nuclear, or hydroelectric energy sources that was generated in or sent to California		x	x	
surplus		x	The area underneath the demand curve to the left of the final quantity demanded		x		
totalcost		x	Cost from fuel		x		
totalecost		x	Cost from taxed emissions, i.e., the taxed emissions rate defined by Table D.1, multiplied by the cost of carbon and unit generation		x		
totale		x	Fossil fuel emissions		x	x	
totale_ca		x	Fossil fuel emissions from generating units in California		x		
totale_ca _claimed		x	Fossil fuel emissions from generating units in California's tax jurisdiction		x		
totale_ca _instate		x	total_ca_claimed + fossil fuel emissions from imported electricity		x		