Cap-and-Trade Climate Policies with Price-Regulated Firms: How Costly Are Free Allowances? *

Bruno Lanz[†] Sebastian Rausch[‡]

This version: June 2012

Preliminary draft, comments welcome, please do not cite without authors' permission

Abstract

We examine the impacts of alternative cap-and-trade allowance allocation designs in a model of the US economy where price-regulated electric utilities generate 30 percent of total CO_2 emissions. Our empirical model embeds a generator-level description of electricity production—comprising all 16,891 electricity generators in the contiguous US—in a multi-region multi-sector general equilibrium framework that features regulated monopolies and imperfectly competitive wholesale electricity markets. The model recognizes the considerable heterogeneity among households incorporating all 15,588 households from the Consumer and Expenditure Survey as individual agents in the model. Depending on the stringency of the policy, we find that distributing emission permits freely to regulated utilities increases the welfare cost of the policy by 40-80 percent relative to an auction if electricity rates do not reflect the opportunity costs of permits. Despite an implicit subsidy to electricity prices, efficiency costs are disproportionately borne by households in the lowest income deciles.

Keywords: Climate policy, Cap-and-trade, Emissions trading, Allowance allocation, Electricity Generation, Cost-of-service regulation.
JEL classification: C61, C68, D58, Q43, Q54

*Without implication, we would like to thank Elodie Blanc, Christoph Böhringer, Massimo Filippini, John M. Reilly, Charles G. Rossmann, and Thomas F. Rutherford for helpful comments and discussions. We also thank participants at the 2012 Conference on Sustainable Resource Use and Economic Dynamics, and the 2012 Cowles/Yale Summer Conference on Macroeconomics and Climate for helpful discussion and comments.

[†]Corresponding author. Swiss Federal Institute of Technology Zürich, Centre for Energy Policy and Economics and Chair for Integrative Risk Management and Economics, Zürichbergstrasse 18, 8092 Zürich, Switzerland (email: blanz@ethz.ch).

[‡]Massachusetts Institute of Technology, Joint Program on the Science and Policy of Global Change, 77 Massachusetts Avenue, Cambridge, MA 02139-4307 (email: rausch@mit.edu)

1 Introduction

Over the past three decades, market-based "cap-and-trade" (CAT) regulation has become a centerpiece of environmental policy in the United States and in Europe. While both emissions taxes and CAT regulations minimize compliance costs through equalization of marginal abatement costs across sources, CAT regulation is flexible with respect to the initial allocation of property rights over the cap (Stavins, 2008). Allowances can be auctioned to generate revenues to the state, thus providing a close counterpart to an emission tax. Since allowances are valuable assets, a free distribution to emissions sources could be used to compensate regulatory compliance costs by generating windfall profits (Goulder et al., 2010). In a frictionless world with no pre-existing distortions, the initial allocation of allowances does not affect the efficiency of the policy (Coase, 1960; Montgomery, 1972). However, the allocation of allowances determines the distributional outcome of the policy, making it a politically contentious issue.

In the United States, the electricity sector features a large number of regional monopolies that generate near 60 percent of total electric power and emit around 30 percent of economy-wide carbon dioxide (CO_2). To protect electricity consumers, public utility commissions (PUC) regulate electricity rates on an cost-of-service basis (Joskow, 2006), so that output prices will reflect the carbon price only if the CAT policy affects operation costs. Freely allocating allowances to regulated electricity producers would implicitly subsidize electricity rates for a subset of consumers, reducing incentives for electricity conservation and shifting abatement efforts to other sectors of the economy. By preventing electricity rates to reflect the opportunity cost of permits, PUCs would protect electricity consumers from large price increases.[1] If the value of free allowances received by regulated firms is instead passed on to consumers as lump-sum transfers, or if allowances are auctioned, electricity rates would fully reflect the carbon price signal, restoring the efficiency property of the policy.[2] Hence in the presence of price-regulated firms, the efficiency of CAT regulation may not be independent from the initial allowance allocation.

This paper empirically investigates the efficiency and distributional impacts of CAT regulation in the United States in the presence of cost-of-service regulation in the electricity sector. We focus on two design elements of CAT regulation: (i) the method of allowance allocation; and (ii) the baseline used to allocate allowances. To examine ex-ante how the value of allowances is transmitted in the economy, we employ a general equilibrium representation of the U.S. economy that captures key interactions between electricity generation technologies, price-regulated firms, structural changes across sectors and regions, pre-existing taxes and government budget constraint, as well as household heterogeneity.

Our modeling framework makes two methodological contributions. First, we embed a detailed representation of electricity generation in an economy-wide model representing aggregate economic activities, where the portfolio of generation technologies is based on all 16,891 generators active in 2006 (Energy Information Agency (EIA), 2007b). We identify 319 operators subject to cost-of-service regulation with significant generation capacity (EIA, 2007d), and model production decisions at the operator level. Generators owned by non-regulated operators compete on regional wholesale electricity markets that approximate the geographical coverage

1 Similarly, free permits allocated during the first phase of the European Emission Trading Scheme led to state intervention directed at mitigating electricity price increases (Radov and Klevnas, 2007; Sijm et al., 2008; Shuttleworth and Antstey, 2012).

2 There are some legitimate behavioral questions about how consumers will respond to a lump-sum transfer. Even if the PUC passes on the value of allowances independently from the amount of electricity consumed, associating such payment with electricity bills could still induce some distortions in consumption behavior. A CAT program where allowances are auctioned would avoid this issue altogether, but brings up the wider question of revenue recycling (see, for example, Goulder et al., 1999).

of the regional transmission organizations (RTOs). On each wholesale market, large operators are modeled as strategic Cournot players interacting with a competitive fringe.[3] Second, we incorporate data on all 15,588 households from the Consumer Expenditure Survey (CEX), a representative sample of the U.S. population (Bureau of Labor Statistics (BLS), 2006), with individual households' decisions stemming from a constrained utility maximization problem. Integrating real households as individual agents enables us to assess both sources and uses side effects of income in a general equilibrium setting and quantify household-level welfare impacts using well defined welfare indexes.[4]

This paper complements a number of existing studies. Paul et al. (2010) employ a partial equilibrium dynamic model for the US electricity sector to study alternative allowance allocation schemes. The model is based on 21 aggregate regions among which 12 regions are subject to cost-of-service regulation. Their framework suggests that freely allocating allowances in an electricity-only CAT would increase the price of allowances by 12 percent compared to an auction. Using the same partial equilibrium model, Burtraw et al. (2001) suggest that welfare costs from freely allocating allowances would be two times higher than under auctioning. Our framework improves upon these results with general equilibrium economy-wide welfare costs projections, and overcomes limitations inherent in a Marshallian demand formulation typically employed in partial equilibrium electricity models. Metcalf et al. (2010) examine distributional effects of carbon policies by focusing on how energy expenditure shares differ across income groups. In contrast, we consider not only the uses side effects of income but also the ways that the government's disposition of carbon revenue influences the distribution of policy impacts and affects the source side of income.

Our analysis is also germane to strands of both industrial organization and environmental economics literature that study interactions between PUC regulation and market-based environmental regulation. Theoretical work by Bohi and Burtraw (1992), Coggins and Smith (1993) and Fullerton et al. (1997) show that cost-of-service regulation can induce inefficient investment behavior. The impact of price regulation on compliance decisions is confirmed by empirical studies. In the context of the Clean Air Act, Arimura (2002) finds that PUCs in high-sulfur coal mining regions favored the use of high-sulfur coal, and that uncertain PUCs rulings mitigated incentives for allowance trading. In the NO_x Budget Program, Fowlie (2010) shows that regulated operators were more likely to invest in capital-intensive abatement technologies due to guaranteed rates of return. While a distinctive feature of CO_2 emissions is the absence of end-of-pipe abatement technologies, our results further support the view that the discretionary power of PUCs is a key factor in the efficiency of CAT regulations.

The paper proceeds as follows. Section 2 offers a simple graphical illustration of the central issue of this paper. Section 3 provides some background about electricity markets' structure and carbon intensity of electricity production in the United States. Section 4 describes our modeling framework. Section 5 lays out the policy scenarios and reports simulation results. Section 6 concludes.

[3] Although this is not the primary focus of this paper, the degree of competition on output markets is an important determinant of the outcome of market-based environmental policy (Malueg, 1990; Sartzetakis, 1997; Mansur, 2007a; Fowlie, 2009).

[4] See, for example, Atkinson and Stiglitz (1980) for a discussion of tax incidence impacts in the public finance literature differentiating uses and sources side of income effects.

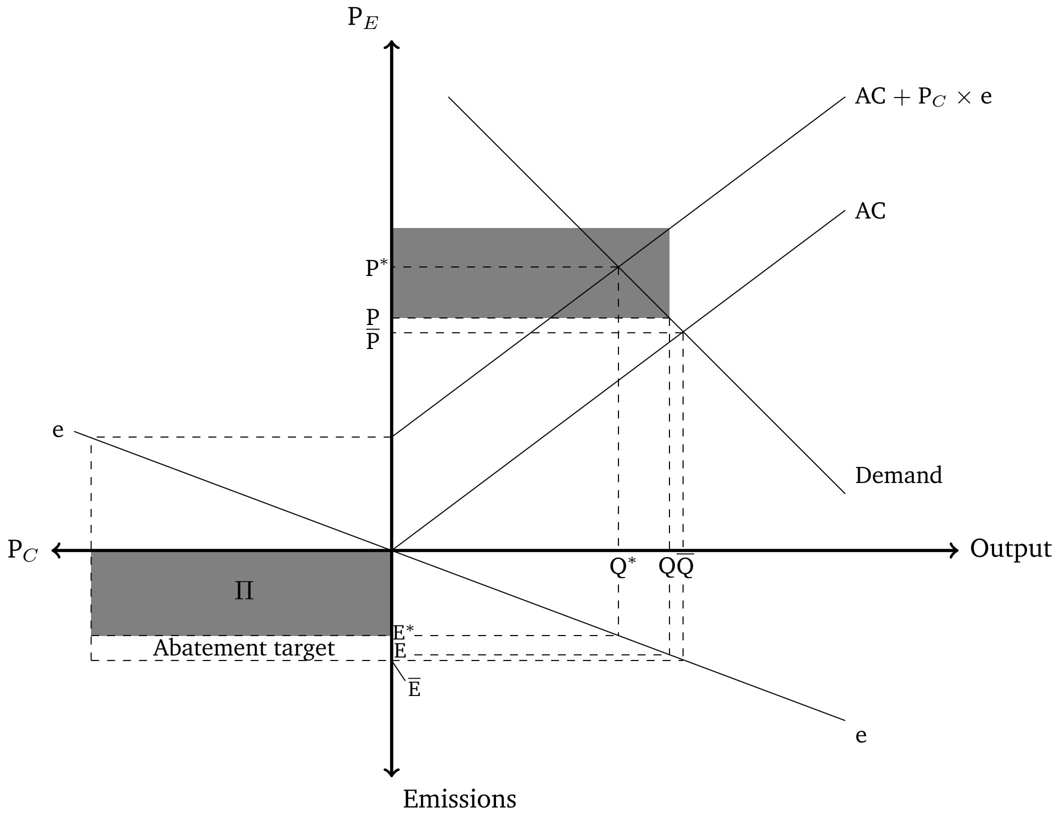


Figure 1: Market equilibrium, allowance allocation, and price regulation.

2 Allowances Allocation and Output Price Regulation: A Graphical Illustration

If output markets are subject to price regulation, allowance allocation design can impact the outcome of a CAT environmental policy. Figure 2 helps to convey the intuition about different policy designs.

Consider a monopolist with prices regulated to reflect average production costs in a partial equilibrium setting. In the initial equilibrium without environmental regulation, the output price and level are $\overline{P}$ and $\overline{Q}$, respectively. These are determined by the intersection of the market demand with the average cost schedule (AC) of the regulated monopolist. In order to focus on demand-side effects, assume a fixed rate of emissions per unit of output, denoted by e, yielding total benchmark emissions $\overline{E}$.

A CAT policy that sets a cap on total emissions and require sources to surrender allowances to cover their emissions gives rise to an emission price P_C. If allowances are auctioned, expenditures on allowances increase production costs, shifting the supply curve upwards ($AC + P_C \times e$). The new equilibrium (P^*, Q^*) associated with emissions E^* fully reflects emissions price P_C.

If allowances are freely allocated, the value represented by the shaded area Π in the bottom-left quadrant has to be passed forward to consumers. If Π is transferred to consumers as a lump-sum transfer, relative prices are not affected and equilibrium (P^*, Q^*, E^*) prevails. If Π is instead passed to the consumers through output prices, or if the intent of the legislation to have rates reflect the full CO_2 costs is frustrated by PUC rate setting, consumers misperceive the true value of output. The equilibrium is then characterized by a price $P \leq P^*$, and consumer behavior is distorted resulting in an output level $Q \geq Q^*$ and associated emissions $E \geq E^*$.

In turn, under a CAT regulation that covers all sectors of the economy, higher emissions from regulated firms mean that higher abatement is required in other sectors in order to meet the cap, which will increase compliance costs.

The relevance of this problem for policy design is an empirical question. In the context of U.S. climate policy, the extent to which the efficiency of CAT regulation is affected by alternative allowance allocation methods depends on the share of emissions stemming from regulated firms, on the response of electricity consumers, as well as abatement opportunities at regulated electricity producers and in other economic activities. Additionally, the differences among regions in terms of their electricity markets' structure and carbon intensity are important drivers of the regional incidence of welfare costs.

3 Electricity Markets and CO_2 Emissions in the U.S.

Historically, the US electricity sector developed through state-regulated regional monopolies, in which generation, transmission and distribution were vertically integrated. The most widely used form of regulation has been 'rate of return' regulation, where rates are set by public utility commissions (PUCs) to allow utilities to recover prudently incurred operating costs, so that consumers pay a price comparable to the average accounting cost of service. In the 1970s, a movement of deregulation took place across numerous regulated industries (Winston, 1993), and the Public Utilities Regulatory Policies Act in 1978 provided initial legal support for a separation of generation from transmission. In addition, limited economies of scale in modern generation technologies, and technological advances in high-voltage transmission technologies increased opportunities for mutually beneficial trades to take place in a highly balkanized system (Joskow and Schmalensee, 1983).

Through the regulatory and technological evolution, the traditional regional monopolies were progressively complemented by investor-owned independent power producers that had no network ownership and directly supplied large industrial activities. This situation created a demand from other industrial consumers to be able to purchase current from different electricity supplier, particularly in areas with high electricity prices (Joskow, 2005). Through the Energy Policy Act of 1992, the Federal Energy Regulatory Commission (FERC) was granted a right to order electric utilities to have electric current to transit on their network, implicitly inviting market transactions to take place on the network for a fee. In 1999, the FERC called for the creation of RTOs in order to provide independent supervision of transmission grids.

As of 2006, the base year of our model and data set, the continental electric power market can be divided into 10 regions, most of which have transferred the administration of transmission networks to an independent system operator (ISO) to supervise wholesale market transactions.[5] Figure 3 approximates the 10 power market regions by state-level borders (see Appendix A for the actual coverage of electricity regions and their acronyms). Table 1 reports electricity generation by power market region for 2006 and regional shares of electricity generated by independent electricity producers and traditional vertically integrated electric utilities (EIA, 2007d).[6]

Despite a trend towards competitive wholesale markets, around 60 percent of electric power is generated by traditional vertically integrated utilities. At the regional level, electric power in SEAST, SPP and MOUNT is almost entirely generated by regulated operators. The number

[5] This process is still ongoing and the coverage of ISOs and RTOs are expanding, although the pace of market liberalization slowed down after the electricity crisis in California in 2000-2001.

[6] Note that while state-border aggregation is an approximation of true geographical coverage of transmission regions, each regulated and non-regulated operator is mapped to its correct wholesale market or region.

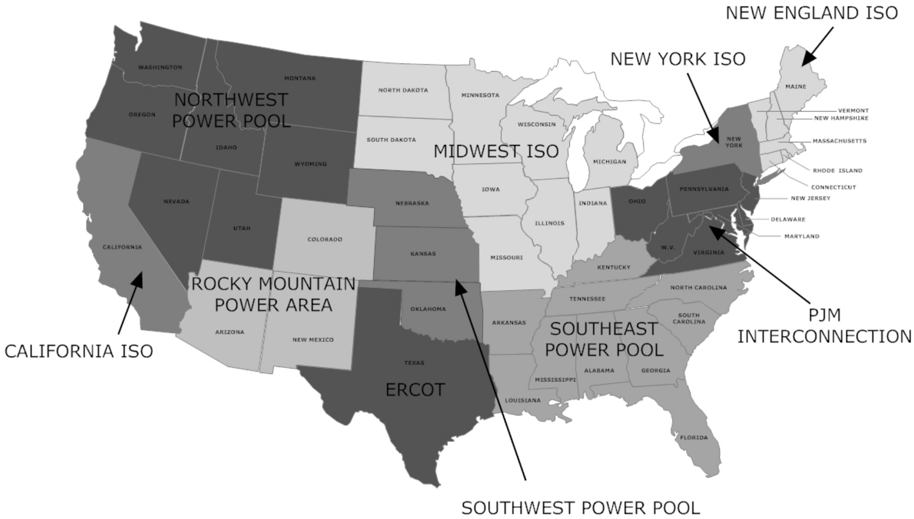


Figure 2: State-level aggregation of national electric power market regions.

of regulated operators shows large variations in the structure of regulated electricity production, with SPP and MISO featuring a large number of operators with small generation capacity. Regions such as NY and CA feature a small number of regulated operators with large, mainly hydroelectric capacity. In the state of Texas, where most electricity producers have joined the ERCOT market, some 20 regulated monopolies are active within state borders.

Non-regulated operators include independent power producers as well as co-generators that sell surplus power generated for the purpose of their primary industrial activity.[7] While there are several limitation of conventional market concentration indexes to measure imperfect competition on non-storable goods markets (Borenstein et al., 1999), there exists strong empirical evidence that US wholesale electricity markets are best described as oligopolies (for example, Wolak, 2003; Mansur, 2007b; Puller, 2007; Sweeting, 2007; Bushnell et al., 2008). With Herfindahl-Hirschman Indexes (HHI) of over 1,000, wholesale production in regions with a low share of non-regulated production (MISO, MOUNT, NWWP, and SPP) exhibit the highest concentration Conversely, in regions with a high share of generation from non-regulated operators, the HHI provides evidence of lower concentration on wholesale markets.

Carbon intensity of electricity generation from regulated operators is on average (for the whole US) 27 percent higher than for non-regulated operators, but large variations exist at the regional level. Electricity produced from regulated operators in NENGL and ERCOT emits almost twice as much CO_2 per MWh as compared to non-regulated operators. This is because non-regulated operators in these regions own a large share of low-carbon gas-fired plants. For three out of ten regions (i.e. CA, NWPP, and NY) the carbon intensity of non-regulated operators is higher relative to regulated operators, as the latter mainly hold hydro capacity.

Differences in carbon intensity across operators together with the substantial heterogeneity in the market structure of the US electricity sector imply that the allowance allocation design of CAT regulation is a key determinant for the efficiency and distributional consequences of the

[7] Note that regulated operators supply their customers directly but also operate on their regional wholesale market, either to purchase or sell power. The key feature of regulated operators is that they have a monopoly for selling power to their consumers with rates subject to approval by regulatory commission.

Table 1: Regional electricity generation, market structure and CO_2 intensity in 2006.

Region	Generation	Regulated generation			Non-regulated generation			
	(TWh)	%	N^a	tCO_2/MWh	%	N^b	HHI^c	tCO_2/MWh
SEAST	1,126.6	87.0	87	0.61	13.0	287	310	0.60
SPP	142.4	86.2	133	0.78	13.8	30	1,570	0.42
MOUNT	214.1	85.7	38	0.73	14.3	57	1,160	0.38
NWPP	317.4	79.5	64	0.38	20.5	154	1,130	0.63
MISO	724.4	67.7	305	0.85	32.3	315	1,680	0.47
CA	231.3	49.8	39	0.19	50.2	317	220	0.42
PJM	665.0	35.5	51	0.79	64.5	259	580	0.58
NY	142.9	29.6	14	0.30	70.4	148	550	0.37
ERCOT	348.9	13.2	20	0.84	86.8	157	820	0.52
NENGL	132.8	4.8	28	0.79	95.2	214	510	0.40
US-wide	4045.7	61.2	731	0.65	38.8	1938	–	0.51

Notes: [a] Number of traditional vertically integrated electric utilities. [b] Number of independent electric power producers. [c] Herfindahl-Hirschman index. *Sources*: Authors' own calculations. Data on generation and operator's regulatory status is from EIA Form 906-920 (2007d). CO_2 emissions are based on fuel consumption for each operator (EIA Form 906-920, 2007d) and fuel-specific CO_2 emissions factors (EIA, 2009a).

policy.

4 Benchmark Data, Modeling Framework and Computational Strategy

We employ a numerical model of the US economy to examine further the issues of free allowance distribution in the presence of price-regulated markets in a more realistic setting. The additional realism includes a detailed representation of regional electricity markets' structure—including regulated markets that are subject to cost-of-service regulation as well as imperfectly competitive regional wholesale markets—and a generator-level formulation of electricity production embedded in a multi-region general equilibrium (GE) representation of the US economy. We further incorporate a large number of heterogeneous household as individual agents in the model. The GE framework allows us to characterize abatement options in non-electric sectors, assess income and factor price changes, and assess distributional impacts through theoretically sound welfare cost indices.

4.1 Electricity Generation

4.1.1 Data

Electricity generation is based on a comprehensive data set of 16,891 generators active in 2006. Information on capacity, generation technology and multiple energy sources used is taken from EIA Form 860 (2007b). Appendix A provides a list of generation technologies and fuels.[8] Each generator is matched to monthly output and fuel consumption data at the plant level reported in

[8] We obtain the dependable capacity by scaling installed capacity figures from EIA Form 860 (2007b) with technology-specific availability data reported in the Generating Availability Report by the North American Electric Reliability Council.

Table 2: Distribution of market sizes for regulated operators with annual generation > 10 GWh.

Region	Number of operators	Market size: summary statistics (GWh/year) Mean	Median	Min	Max	IQR[a]
SEAST	58	16,897	3,334	19	155,170	16,700
MOUNT	17	10,796	3,502	17	55,129	13,765
PJM	27	8,748	650	13	67,686	9,655
NWPP	39	6,472	696	13	55,049	6,580
MISO	80	6,130	354	16	50,864	6,238
SPP	26	4,719	602	19	24,615	5,681
NY	10	4,233	448	25	27,308	2,388
CA	34	3,384	649	23	33,191	1,708
ERCOT	17	2,702	529	10	15,277	3,402
NENGL	11	575	176	11	4,583	235

Notes: [a] Interquartile range. *Sources*: Authors' own calculations based on EIA Form 906-920, (2007d).

EIA Form 906-920 (2007d).[9] EIA Form 906-920 also provides information about the operator of each plant, including its regulatory status and region of operation. Our final data thus contains information about the generation technology portfolio of each operator and its regulatory status, i.e. whether it is a traditional vertically integrated electric utility or an independent operator, and on observed output and fuel consumption at the plant level.

The cost function of generator g is composed of a constant marginal cost c^g (in $/MWh) comprising fuel costs and variable O&M costs. First, fuel costs are based on a plant-specific heat rate (MBTU/MWh) that is calculated using fuel consumption and electricity output reported in EIA Form 906-920 (2007d) and state-level fuel prices for 2006 ($/MBTU, from EIA, 2009d). We assume that if a given plant includes multiple generators of the same technology, these share the same efficiency. Carbon emissions rates (tCO_2/MWh) are calculated on the heat rate and the CO_2 content of the fuel (tCO_2/MBTU) from EIA (2008). Second, as O&M costs ($/MWh) are not observed at the plant level, we use technology-specific data from EIA (2009b) that includes labor, capital, material and waste disposition costs per unit of output.

Given the portfolio of generators, production decisions are modeled at the operator level. We distinguish two types of operators: (1) regulated regional monopolists, and (2) non-regulated operators selling power on one of ten regional wholesale markets. We now discuss these in turn.

4.1.2 Representation of Regulated Electricity Markets

We consider $f = 1, \ldots, 319$ regulated operators with annual output greater than 10 GWh according to EIA Form 906-920 (2007d), which corresponds approximately to operators with customer demand of 1,000 households or more.[10] Table 2 provides information on the number of regulated operators and the distribution of market size in each region. The market size of regulated operators varies drastically both across and within regions. In all regions, the distribution is highly skewed to the right, i.e. there are relatively few operators with a large market size.

Each regulated operator is modeled as a regional monopoly, with monthly benchmark de-

[9] A plant can include multiple generators. Information on output and fuel consumption at the generator level is not available.

[10] Generation from the 412 regulated operators that are not included in the model represents less than 0.1 percent of electricity generated in each region.

mand given by observed monthly output as reported in EIA Form 906-920 (2007d).[11] To capture limited substitution possibilities of electricity generated at different times in the year, as neither the supply of electricity nor the demand for electricity services can easily be shifted across time, yearly demand is divided into nine time slices. First, we aggregate data on monthly demand into three seasons (summer, winter and fall/spring). Second, observed fluctuations of the physical demand for electricity is captured by dividing each season into three load blocks (peak, intermediate, and base load) with region and season-specific load distribution data (EIA, 2009b).

Each regulated operator is assumed to minimize generation costs to meet the electricity demand. Thus a generator g owned by a regulated operator is only active in load segment t if its marginal generation cost c^g is lower than the cost of the marginal generator C_t^f used to cover the demand. For generators listed with multiple fuel options in the data, the fuel choice is endogenous.

Formally, in equilibrium the "zero profit" condition for each generator and load segment exhibits complementarity slackness with the output level Y_t^g:

$$c^g + \nu^g \tau + \mu_t^g \geq C_t^f \quad \perp \quad Y_t^g \geq 0 \tag{1}$$

where the $\perp$ operator indicates a complementary relationship, ν^g is the carbon intensity, which integrates the efficiency of the generator and fuel-specific carbon content, and τ denotes the price of carbon. μ_t^g represents the shadow value of installed capacity, and it is the complementarity variable of the capacity constraint of each generator:

$$Y_t^g \leq \kappa_t^g \quad \perp \quad \mu_t^g \geq 0\,, \tag{2}$$

where κ_t^g is the dependable capacity of generator g in load segment t. The equilibrium marginal generation cost C_t^f is determined by a market clearing condition for each load segment:

$$\sum_{g \in G_f} Y_t^g \geq d_t^f \quad \perp \quad C_t^f \geq 0\,, \tag{3}$$

where G_f and d_t^f denotes the set of generators owned by regulated operators f and the electricity demand at the regulated operator in time t, respectively.

Given the benchmark demand at each operator $\overline{d}_t^f$, we simulate benchmark output of each generator $\overline{Y}_t^g$ by solving expressions (1) to (3) as a MCP. In the benchmark the carbon price is zero and the price of electricity at regulated operator f is the yearly average generation cost. Specifically, since a majority of consumers face a nearly constant price for electricity, we assume that the price signal transmitted to consumers is updated once a year to reflect yearly average generation costs:

$$\overline{P}^f = \frac{\sum_{g \in G_f} \sum_t \overline{Y}_t^g c^g}{\overline{D}^f}\,, \tag{4}$$

where $\overline{D}^f = \sum_t \overline{d}_t^f$ is the total yearly demand for generation at operators f in the benchmark. Note that the capacity rents μ_t^g are not included in the price.

Under a carbon policy, generation costs increase proportionally with the emissions coefficient

[11] Our model focuses on generation rather than retail decisions, and we are concerned with the pricing rule of operators. This formulation does not rule out that regulated operators might be active on wholesale markets. For example, a regional monopolist could purchase power on the wholesale market to supply their customers. In this case, the customer will pay the wholesale price. If the regulated operator sells power on the wholesale market, customers on the wholesale market will pay the average cost of production.

ν_t^g. Changes in relative generation costs induce a reordering of the generators at each regulated operator, and the price transmitted to the consumer is given by:

$$P^f = \frac{\sum_{g \in G_f} \sum_t Y_t^g c^g + \nu_t^g \tau}{D^f} - s^f + \sum_t \varphi_t^f \,. \tag{5}$$

The key component of equation (5) is a firm-specific endogenous subsidy rate s^f, which equals the value of free allowances received by operator f, denoted V_f, divided by total yearly output:

$$s^f = \frac{V_f}{D^f} \,. \tag{6}$$

Subsidizing the price of output for operators with a sufficiently low carbon intensity can result in an overall price decrease, i.e. $P^f < \overline{P}^f$.[12]

The demand response at operator f is given by a linear function calibrated at the price $\overline{P}^f$ and demand $\overline{D}^f$:

$$D^f = \overline{D}^f \left(1 + \epsilon \left(\frac{P^f}{\overline{P}^f} - 1\right)\right) \,, \tag{7}$$

where $\epsilon < 0$ is the *local* price elasticity of demand. At the benchmark price $P^f = \overline{P}^f$, aggregate benchmark demand for firm f is thus given by $\overline{D}^f$. Assuming that the shape of the load profile is unchanged, demand at time t is given by $d_t^f = D^f \, \overline{d}_t^f / \overline{D}^f$.

Note that the linear function only serves as a local approximation of (non-linear) GE demand. As further discussed below, the electricity production model is integrated in the GE setting by sequentially updating $\overline{P}^f$ and $\overline{D}^f$ based on GE estimates.

4.1.3 Representation of Wholesale Electricity Markets

Data on monthly generation by non-regulated operators is aggregated at the regional level and represents the demand for wholesale power generation in each region. As for the regulated operators, monthly wholesale demand is aggregated into three seasons and shared across peak, intermediate, and base load segments. In each regional wholesale market $r = 1, \ldots, 10$, all generators of non-regulated operators compete to meet the demand. Electricity output by each generator is determined by the following zero profit condition:

$$-\pi_t^g \geq 0 \quad \perp \quad Y_t^g \geq 0 \,. \tag{8}$$

Market structure on regional wholesale markets is based on Bushnell et al. (2008) and Fowlie (2009). We model large operators as oligopolists, and assume that operators holding more than 3 percent of wholesale generation capacity behave as Cournot players and accordingly price output above marginal cost. Table 3 reports the number of Cournot players in each region. Smaller operators act as a competitive fringe and are assumed to be price takers. Let p_t^r denote the wholesale price in load block t and $D_t^r(p_t^r)^{-1}$ the inverse demand function. The Cournot-Nash equilibrium unit profit function for strategic players (denoted by the set G_r^{cournot}) and

[12] If demand exceeds total available capacity, then the price includes capacity rents φ_t^f:

$$d_t^f \leq \sum_{g \in G_f} \kappa_t^g \quad \perp \quad \varphi_t^f \geq 0 \,.$$

In reality, these rents are likely to be transferred to investors. Due to computational reasons we include these rents in the price.

Table 3: Characteristics of regional wholesale markets.

Region	Cournot operators[a]	Fringe operators	Price (\$/MWh) Observed	Price (\$/MWh) Simulated	CO_2 intensity (tCO_2/MWh) Observed	CO_2 intensity (tCO_2/MWh) Simulated
NWPP	11	143	50.2	48.6	0.63	0.62
SEAST	9	278	58.1	53.5	0.60	0.61
PJM	20	239	55.1	52.2	0.58	0.58
ERCOT	6	151	52.9	57.5	0.52	0.50
MISO	10	305	44.0	47.7	0.47	0.50
SPP	6	24	55.4	63.6	0.42	0.43
CA	12	305	48.9	48.7	0.42	0.34
NENGL	15	199	60.8	61.5	0.40	0.36
MOUNT	11	46	57.4	44.9	0.38	0.35
NY	17	131	70.2	71.2	0.37	0.36

Notes: [a] Number of regulated operators in regional wholesale markets holding more than 3 percent of generation capacity. *Sources*: Observed price is a load-weighted average reported by FERC for 2006; Observed CO_2 emissions are based on fuel consumption at for each operator (EIA Form 906-920, 2007d) and fuel-specific CO_2 emission factors (EIA, 2009a).

non-strategic players (denoted by the set G_r^{fringe}) are then given by, respectively:

$$\pi_t^g = \begin{cases} p_t^r + \frac{\partial D^r(p_t^r)^{-1}}{\partial Y_t^g} - c^g - \mu_t^g - \nu_t^g \tau & \text{if } g \in G_r^{\text{cournot}} \\ p_t^r - c^g - \mu_t^g - \nu_t^g \tau & \text{if } g \in G_r^{\text{fringe}} \,. \end{cases} \tag{9}$$

Note that in addition to the Cournot rents, independent operators who own generators with marginal cost below the market price earn capacity rents μ_t^g measuring the value of the installed capacity per unit of output (see equation 2).

In each time period, the wholesale price reflects (a function of) the generation costs of the marginal producer used to cover the demand. In equilibrium, p_t^r is orthogonal to the market clearing condition:

$$\sum_{g \in G_r} Y_t^g \geq d_t^r \quad \perp \quad p_t^r \geq 0 \,, \tag{10}$$

where G_r is the full set of generators in wholesale market r. As for regulated operators the wholesale price transmitted to consumers is constant over the year, and is given by an output-weighted average of the wholesale price in each load segment:

$$P^r = \frac{1}{\sum_t d_t^r} \sum_t p_t^r d_t^r \,. \tag{11}$$

The demand for non-regulated operators is *locally* approximated by a calibrated linear demand function:

$$D^r = \overline{D}^r \left(1 + \epsilon \left(\frac{P^r}{\overline{P}^r} - 1\right)\right) \,, \tag{12}$$

with $d_t^r = D^r \, \overline{d}_t^r / \overline{D}^r$.

4.2 Economy-wide Aggregate Economic Activities

4.2.1 Data

We use a comprehensive state-level energy-economy dataset that features a consistent representation of energy markets in physical units as well as detailed accounts of regional production and trade for 2006. Each state is described by a social accounting matrix (SAM) from the *2006 IMPLAN* (Minnesota IMPLAN Group, 2008) dataset which specifies benchmark economic accounts and identifies 509 commodities as well as existing taxes, revenues and transfers. This dataset only include aggregate energy accounts for each state, and given our focus we expand energy-related accounts with data on state-level nergy balances and prices from the 2006 State Energy Data System (EIA, 2009c).[13] Energy commodities identified in our study include *Coal* (COL), *Natural gas* (GAS), *Crude oil* (CRU), *Refined oil* (OIL), and *Electricity* (ELE), which allows us to distinguish energy goods and specify substitutability between fuels in energy demand.

Our commodity aggregation identifies a further nine non-energy composites. We distinguish *Energy-intensive products* (EIS) and a composite of *Other manufacturing products* (MAN), *Agriculture* (AGR), *Transportation* (TRN), and *Services* (SRV). Primary factors in the dataset are labor, capital, land, and fossil-fuel resources. We aggregate state-level data into 10 US regions that are identified in Figure 3 and approximately match wholesale transmission regions by state-level border.[14]

Table 4 reports benchmark CO_2 emissions, sectoral shares of total emissions, and total emission intensity by region. CO_2 emissions from electricity generation that is subject to cost-of-service regulation represent about 30 percent of total economy-wide emissions, but large regional variations exists. The second largest contributor to sectoral emissions is transportation comprising here the industrial and private transportation sector. Finally, there exist significant variation among regions with regard to emissions intensity of industrial output. By this metric, ERCOT is by far the most CO_2 intensive region, which can be attributed to large-scale activities in energy intensive industries and oil refining.

4.2.2 Model Structure

Our analysis draws on a multi-commodity, multi-region comparative-static numerical general equilibrium model of the US economy (Rausch et al., 2010). Electricity generation is exogenous and household decision-making is discussed in more details below. In the following we outline key structural assumption of the model while equilibrium conditions are reported in Appendix B.

Production technologies and firm behavior. For each industry ($i = 1, \dots, I$) in each region, gross output Y_i is produced using inputs of labor (L_i), capital (K_i), natural resources including coal, natural gas, crude oil, and land (R_{zi}, $z = \{1, \dots, Z\}$), and produced intermediate inputs (x_{ji}, $j = 1, \dots, I$). All industries are characterized by constant returns to scale (except for fossil fuels and agriculture, which are produced subject to decreasing returns to scale) and are traded in perfectly competitive markets (except for electricity, as described previously). Labor is assumed to be fully mobile across industries in a given region but is immobile across US regions,

[13] The aggregation and reconciliation of IMPLAN state-level economic accounts needed to generate a micro-consistent benchmark dataset which can be used for model calibration is accomplished using least-square optimization techniques to minimize required adjustments.

[14] Given our operator-level representation of regulated and non-regulated electricity markets, operators can be matched to their appropriate region and hence discrepancies between state-level borders and wholesale markets geography do not affect our analysis.

Table 4: Sectoral CO_2 emissions and regional emission intensity.

Region	Total emissions	Sectoral share of emissions (%)							Emission intensity
		Electricity sector		Non-electricity sectors					
	($MtCO_2$)	Wholesale	Regulated	AGR	EIS	SRV	TRN	OTH	(tCO_2/$)
ERCOT	639.9	27.8	6.5	1.0	26.5	2.6	32.2	3.4	0.71
SPP	204.1	5.3	45.1	3.2	8.9	3.1	30.1	4.3	0.65
SEAST	1335.3	5.9	43.0	0.8	10.6	1.3	36.4	2.0	0.52
MISO	1056.5	11.2	38.7	1.7	10.1	4.0	29.7	4.5	0.51
MOUNT	251.6	1.2	48.9	0.7	4.5	2.3	39.9	2.5	0.47
PJM	908.7	27.0	20.5	0.2	11.2	3.7	35.5	1.8	0.44
NWPP	313.0	13.8	30.0	1.9	5.5	2.2	44.8	1.8	0.43
NENGL	143.0	31.8	3.7	0.5	4.1	3.9	55.1	0.9	0.24
CA	359.0	9.6	5.6	0.7	6.9	3.9	67.7	5.7	0.23
NY	163.9	21.8	13.6	0.4	5.3	14.1	43.3	1.6	0.22
US-wide	5374.9	14.8	29.2	1.0	11.3	3.2	37.6	2.9	0.44

Sources: CO_2 emissions from the electricity sector are based on simulated fuel consumption in the benchmark and fuel-specific CO_2 emission factors (EIA, 2009a). Emissions calculations for non-electricity sectors are based on EIA's State Energy Data System (SEDS) (EIA, 2009c). The calculation of emissions intensity is based on SEDS data and economic value flows for industrial output from IMPLAN data (Minnesota IMPLAN Group, 2008).

while capital is mobile across regions and industries. Given input prices gross of taxes, firms maximize profits subject to the technology constraints by selling their products at a price equal to marginal costs.

We employ constant-elasticity-of-substitution (CES) functions to characterize the production technologies and distinguish three types of production activities in the model: primary energy sectors (indexed by $pe = \{coal, gas, oil\}$), agriculture (indexed by agr), and non-resource based industries (indexed by nr):[15]

$$Y_i = \begin{cases} f_i[KLE_i(g_i, E_i), M_i(x_{1i}, \ldots, x_{Ii})] & \text{if } i \in \{nr\} \\ f_i[KLM_i(g_i, M_i), R_{zi}] & \text{if } i \in \{pe\} \\ f_i[REM_i(R_i, EM_i), g_i(K_i, L_i)] & \text{if } i \in \{agr\}\,. \end{cases} \tag{13}$$

The supply response following a changes in relative prices is driven by substitution among inputs, and we use the nesting structure reported in Table 5. For example, the function f_i for $i \in \{nr\}$ is given by:

$$f(KLE, M) = \gamma_f[\alpha_f KLE^{\rho_f} + (1-\alpha_f)M^{\rho_f}]^{1/\rho_f} \tag{14}$$

where γ_f, α_f, and ρ_f are parameters. The parameter ρ_f is related to σ_f, the elasticity of substitution between KLE_i and M_i: $\rho_f = (\sigma_f - 1)/\sigma_f$. Elasticity parameters are reported in Appendix A.

Intra- and international trade. For a given region $r, s = 1, \ldots, R$ the elements x_{jr} in the E and M functions are Armington (1969) composites of locally, domestically, and foreign produced

[15] For simplicity, we suppress the region index.

Table 5: Nested production structure

Function	Description
$Y = f(KLE, M)$	Output: non-resource using sectors
$Y = f(KLM, R)$	Output: for primary energy sectors
$Y = f(REM, g)$	Output: agricultural sector
$KLE = KLE(g, E)$	Capital/labor-energy composite
$KLM = KLE(g, M)$	Capital/labor-materials composite
$REM = REM(R, EM)$	Resource-Energy/materials composite
$EM = EM(E, M)$	Energy-materials composite
$M = M(x_1, \ldots, x_I)$	Materials composite
$g = g(K, L)$	Capital-labor composite
$E = E(x_{ELE}, h)$	Energy composite
$h = h(x_{COL}, x_{GAS}, x_{OIL})$	Coal-gas-oil composite
$x_i = x_i(xD_i, xDT_i, xFT_i)$	Domestic-imported inputs composite
$I = I(x_1, \ldots, x_I)$	Materials composite

Notes: All functions are CES in form. The electricity sector is represented by the bottom-up electricity generation model (see Section 4.1).

varieties of Y goods:

$$
\begin{aligned}
x_{jr} \quad = \quad & \gamma_{xj} \left(\alpha_{xjr} xD_{jr}{}^{\rho_{xjr}} + (1-\alpha_{xjr})\gamma_{Tjr}\right. \\
& \left. \left[\beta_{xjr} xDT_{jr}{}^{\rho_{Tjr}} + (1-\beta_{xjr}) xFT_{jr}{}^{\rho_{Tjr}}\right]^{\rho_{xjr}/\rho_{Tjr}}\right)^{1/\rho_{xjr}}
\end{aligned}
\qquad (15)
$$

where xD_{jr}, xDT_{jr}, and xFT_{jr} denote local, domestic, and foreign inputs of type j in region r. The parameter ρ_{xjr} is related to σ_{xjr}, the elasticity of substitution between domestic and imported inputs: $\rho_{xjr} = (\sigma_{xjr} - 1)/\sigma_{xjr}$. Similarly, $\rho_{Tjr} = (\sigma_{Tjr} - 1)/\sigma_{Tjr}$ is related to the elasticity of substitution between domestically and foreign made inputs.

Depending on the type of commodity, we distinguish three different representations of intra-national regional trade:

$$
xDT_{jr} = \begin{cases} \gamma_{xDTjr}\left[\sum_s \phi_{xDTjr}\, xDT_{js}{}^{\rho_{xDTjr}}\right]^{1/\rho_{xDTjr}} & \text{if } j \in \{ne\} \\ xDT_j & \text{if } j \in \{e\} \\ xDT_{jp} & \text{if } j \in \{ele\} \text{ and } r \in p\,. \end{cases} \qquad (16)
$$

First, imports of non-energy good *ne* by region r are a CES aggregate of varieties of the same good produced in regions $s = 1, \ldots, R$, $s \neq r$. Second, domestically traded non-electricity energy goods *e* are assumed to be homogeneous products, i.e. there is a national pool that demands domestic exports and supplies domestic imports. This assumption reflects the high degree of integration of intra-US markets for natural gas, crude and refined oil, and coal. Third, we differentiate three regional electricity pools that are designed to provide an approximation of the three asynchronous interconnects in the US: the Eastern Interconnection, Western Electricity Coordinating Council (WECC), and the Electric Reliability Council of Texas (ERCOT).[16] We assume that traded electricity *ele* is a homogeneous good within each regional pool p and that there is no electricity trade between regional pools.

[16] In terms of the regional aggregation described in Figure 3, the Eastern Interconnection thus comprises SPP, MISO, SEAST, PJM, NY, and NENGL, and the WECC comprises CA, NWPP, and MOUNT.

The U.S. economy as a whole is modeled as a large open economy, i.e. we assume that world export demand and world imports supply functions for each traded good are elastic implying that the US can affect world market prices. Foreign closure of the model is determined through a national balance-of-payments (BOP) constraint. Hence, the total value of US exports equals the total value of US imports accounting for an initial BOP deficit given by 2006 statistics.

Investment and government demand. An aggregate investment good (I) is produced combining Armington goods x_{ir} in a Leontief fashion:

$$I_r = \min(I_{1r}, \ldots, I_{ir}, \ldots, I_{Ir})\,. \tag{17}$$

For later reference, let $p_r^I = \sum_i \alpha_{Iir} p_{ir}$ denote the price index (unit cost function) of I where α_{Iir} is a parameter and p_{ir}^x represents the price of the Armington good x_{ir}. Investment demands derives from household utility maximization (see Section 4.3).

We incorporate various tax rates to capture interactions between environmental regulation and the tax code. In each region, a single government entity approximates government activities at all levels—federal, state, and local. Aggregate government consumption is represented by a Leontief composite that combines Armington goods x_{ir}:

$$GP_r = \min(G_{1r}, \ldots, G_{ir}, \ldots, G_{Ir})\,. \tag{18}$$

The activities of the government sector in each region are purchasing goods and services, income transfers, and raising revenues through taxes. The model includes ad-valorem output taxes, corporate capital income taxes, and payroll taxes (employers' and employees' contribution). Thus government income is given by: $GOV_r = TAX_r - \sum_r T_r - B_r$, where TAX, T_r, and B are tax revenue, transfer payments to households and the initial balance of payments. Aggregate demand by the government is given by: $GP_r = GOV_r/p_r^G$ where p_r^G is the price of aggregate government consumption.

4.2.3 Electricity Transmission, Distribution and Market Integration

Integrating the multiple electricity markets into the top-down GE framework requires determining how electricity prices from $m = 1, \ldots, 329$ markets, comprising regulated markets ($f = 1, \ldots, 319$) and wholesale markets ($r = 1, \ldots, 10$), are transmitted to each regional market for electricity as represented in the GE model. In addition to the issue of price aggregation, the question arises to what extent regulated and regional wholesale markets within each region are integrated.[17] Significant differences in regional electricity prices in the US suggest that trade opportunities among operators and markets are limited reflecting both the existing regulatory structure and transmission constraints.

To represent barriers to market integration and allow for the aggregation of prices from multiple markets, we assume monopolistic competition among regulated and non-regulated operators. In our static setting with a fixed number of firms, monopolistic competition is equivalent to assuming that supplies from different operators are imperfect substitutes. Alternatively, treating electricity as a homogeneous good would require a structural model that explicitly represents the physical electricity network. Given our operator-level representation of the electric power sector, incorporating such detail would be hampered by data availability and dimensionality constraints.

[17] Note that inter-regional transfers of electricity are modeled according to an Armington trade formulation (see Section 4.2).

Our reduced-form approach posits that price differentiation (and aggregation) can be represented by the following CES aggregator:

$$P^r_{\text{ele}} = \left[\theta^r \left(\frac{P^r}{\overline{P}^r} \right)^{(1-\sigma)} + \sum_{f \in r} \theta^f \left(\frac{P^f}{\overline{P}^f} \right)^{(1-\sigma)} \right]^{\frac{1}{1-\sigma}}, \tag{19}$$

where θ^r and θ^f denote the observed benchmark market share for the wholesale market in region r and the regulated operator f, respectively. σ captures the degree of market integration.[18] Our base case assumption is "low integration" ($\sigma = 1$), and our analysis explores the implications of independents markets ($\sigma = 0.1$) and a "high integration" case ($\sigma = 10$).

Reconciling both models also requires to account for transmission and distribution costs ($\overline{TD}^r$) which are not included in the electricity model but are contained in regional retail electricity prices in the GE model (P^r_{retail}). We impute these as $\overline{TD}^r = \overline{P}^r_{\text{retail}} - \overline{P}^r_{\text{ele}}$, where $\overline{P}^r_{\text{retail}}$ is the observed benchmark retail price employed in the GE model and $\overline{P}^r_{\text{ele}}$ is an output-weighted average of benchmark prices determined in the electricity generation model: $\overline{P}^r = (\overline{D}^r + \sum_{f \in r} \overline{D}^f)^{-1}(\overline{D}^r \overline{P}^r + \sum_{f \in r} \overline{D}^f \overline{P}^f)$. We assume that $\overline{TD}^r$ is fixed at its benchmark level, i.e. transmission and distribution costs are assumed to be independent of the size of the electricity sector. Finally, the retail price of electricity in region r is given by: $P^r_{\text{retail}} = P^r_{\text{ele}} \overline{P}^r_{\text{ele}} + \overline{TD}^r$.

4.3 Household Behavior

4.3.1 Data

To capture household heterogeneity, we use the *2006 Consumer Expenditure Survey* (CEX), a widely used source of data on consumption expenditures, income sources, and demographic household characteristics (see, e.g., Attanasio, 1998, Fernandez-Villaverde and Krueger, 2006, and Metcalf et al., 2010) that is collected for the BLS. The CEX is designed to constitute a representative sample of the U.S. population. In the following, we describe the necessary steps in order to consistently integrate this data into our general equilibrium framework.

First, to obtain expenditure data that are consistent with the definition of consumption goods in our macroeconomic data, we have to map CEX expenditure categories to *North American Industry Classification System* (NAICS) accounts. This is accomplished by first aggregating CEX data into roughly 70 *Personal Consumption Expenditure* (PCE) categories, and then using a bridge matrix from the Bureau of Economic Analysis (2007) to map expenditures from PCE to NAICS categories.

Second, households with income above a certain level are "top-coded", i.e. their income is replaced with the national average. There are different thresholds for different types of income (e.g., \$150k for wage and salary income). At the household level, we see a substantial amount of top-coding for the top 4 percent of the income distribution when pre-tax income reaches \$250k. Note that top-coding can make income go both up and down because the replacement value may be higher than the real value. While we keep those households in the sample, this means that we cannot break out the top 4 percent income class.

Third, a well-known issue with household survey data in general and with the CEX data in particular is that capital income seems to be too low when compared to capital income based on National Account data (e.g., Deaton, 2003, and Rutherford and Tarr, 2008). A second prob-

[18] This structure assumes that trade opportunities among regulated operators and between each regulated operator and the wholesale market are similar. We have experimented with more complex substitution patterns but have found them to yield similar results as what is implied by Eq. (19).

lem with using CEX reported capital income is that it may misrepresent capital holdings across income groups (Metcalf et al., 2010). There are two possible reasons. First, the CEX focuses primarily on spending and the income data quality may not be as high quality as the spending data. Second, if holdings of growth stocks are disproportionately held by higher income groups then the CEX capital income measure will be biased towards more capital holdings in lower income groups. Following Metcalf et al. (2010) we correct for this bias by incorporating data on capital income shares by income decile from the *2007 Survey of Consumer Finances* (SCF).[19] More specifically, we replace CEX reported capital income for each household by imputed capital income based on capital income shares by income decile from SCF and total household income from CEX. To accommodate changes in capital income while keeping CEX reported total income fixed at the household level, we adjust labor income.

Fourth, imputing personal income tax rates based on reported tax payments and income in the CEX sample results in tax rates that are significantly lower than observed personal income tax rates. To address this issue we use data on 2006 average and marginal personal income tax rates by income decile from the *National Bureau of Economic Research*'s tax simulator Feenberg and Coutts (1993) for each household.

A final issue with the use of the CEX data is that for the purpose of including households in the general equilibrium model, we need to ensure that income balance is satisfied in the benchmark equilibrium. This condition requires that pre-tax household income is equal to the sum of consumption expenditures, tax payments, and savings. As savings are not reported directly in the CEX data, we impute savings as pre-tax household income minus the sum of consumption expenditures and tax payments, and use this approach to close the income balance. For about 35 percent of households in the sample, consumption expenditures exceed total household income, i.e. there is not sufficient current income to finance observed consumption. As there does not seem to be a perceivable pattern in the CEX data that would help to identify the type of income that falls short of observed expenditures, we assume for these households that consumption in excess of observable household income is financed by a stream of capital income. This approach ensures that benchmark household consumption is consistent with reported data.

Table 6 shows expenditure shares for electricity and natural gas, and income shares for capital and labor by annual income decile.[20] The share of income from capital is slightly declining up to the eighth decile at which point it begins to rise. The share of income from labor rises with income up to the 8th decile after which it starts to decline slightly. The capital-labor ratio generally decreases with income but sharply increases for the two top deciles.

[19] One advantage of using the SCF is that it disproportionately samples wealthy families. Each survey consists of a core representative sample combined with a high income supplement, which is drawn from the Internal Revenue Service's Statistics of Income data file. Further, the survey questionnaire consists of detailed questions on different components of family wealth holdings. For these reasons, the SCF is widely acknowledged to be the best at capturing both the wealth at the top of the distribution and the complete wealth portfolio of households in the middle. Since the wealth distribution is highly skewed towards the top, most other surveys (like the CEX) that have poor data on high income families tend to underreport measures of income and wealth.

[20] Government transfer income is the residual of the sum of capital and labor income shares. As we hold the price of transfer income constant, and express welfare changes relative to the LUMPSUM scenario, the share of transfer income does not play a role in determining the welfare impacts. This approach is justified in part based on the logic put forward by Browning and Johnson (1979) that government transfer policy is implicitly if not explicitly indexed. Based on a calculation of the actual indexing of U.S. government cash transfers, Fullerton et al. (2011) find that about 95 percent of transfer payments in the US are indexed. While it is certainly possible that government will adjust transfers as part of a larger adjustment to carbon pricing, it should be clear that such an adjustment mixes climate policy with a fiscal policy decision.

Table 6: Selected expenditure and income shares (%) and median household income (2006$) by annual income decile[a].

Income decile	Electricity	Natural Gas	Capital	Labor	Transfers	Capital-labor ratio	Median income
1	4.7	1.8	27.4	23.5	49.1	1.17	13,090
2	3.7	1.3	26.1	43.1	30.8	0.61	22,366
3	3.2	1.1	23.4	55.7	21.0	0.42	31,398
4	2.8	1.0	19.2	67.5	13.3	0.28	40,026
5	2.4	0.9	18.3	71.0	10.7	0.26	49,169
6	2.5	0.8	16.8	75.6	7.6	0.22	59,941
7	2.2	0.8	15.5	79.1	5.4	0.20	72,433
8	1.9	0.7	14.7	80.9	4.4	0.18	87,987
9	1.8	0.7	19.7	77.7	2.6	0.25	114,628
10	1.5	0.6	28.7	69.7	1.6	0.41	187,365
All	2.6	1.0	20.9	64.7	14.4	0.32	55,140

Notes: [a]Population-weighted within-income group averages based on benchmark data.

4.3.2 Utility Maximization Problem

Consumption, labor supply, and savings result from the decisions of $h = 1, \ldots, 15,588$ households, each maximizing his utility subject to an income constraint. Each household is incorporated in the general equilibrium framework as a separate agent, i.e. we do not aggregate preferences of individual households. Preferences for each household are calibrated based on observed consumption from the CEX data. Besides preference heterogeneity, households also differ with respect to their income shares.

Utility for each household is represented by a nested CES function that combines material consumption, savings, and leisure thus making consumption-investment and labor supply decisions endogenous. The nested utility structure is summarized in Table 7. The structure of material consumption is specified to reflect econometric estimates of substitution possibilities among energy and non-energy goods (Paltsev et al., 2005). At the top-level, a composite of Armington goods (x_{ih}) and savings (q_h) is combined with leisure (l_h):

$$U_h = \gamma_{ch} \left(\alpha_{ch} CI(x_{ih}, q_h)^{1/\rho_{ch}} + (1 - \alpha_{ch}) l_h^{1/\rho_{ch}} \right)^{1/\rho_{ch}} \tag{20}$$

where *CI* is a CES composite of x_{ih} and q_h, and where α_{ch} and ρ_{ch} are parameters. The parameter ρ_{ch} is related to σ_{ch}, the elasticity of substitution between *CI* and l: $\rho_{ch} = (\sigma_{ch} - 1)/\sigma_{ch}$. We assume that $\alpha_{ch} \geq 0$ and $0 \leq \sigma^{ch} \leq \infty$. We assume that utility from government spending is additively separable with utility derived from private consumption. Given the the short-term horizon of our analysis, we assume a constant savings rate and set $\sigma_{CS} = 0$. Following the approach described in Ballard (2000), we calibrate σ_{ch} to match an uncompensated (compensated) labor supply elasticity of 0.1 (0.3).

Household income is given by:

$$M_h = p^k \omega_h^k + p_r^l \omega_h^l + \sum_z p_r^z \omega_h^z + T_h \tag{21}$$

where p^k, p_r^l, and p_r^z are prices for capital, labor, and resources, ω's denote the initial endowment of capital, labor (including leisure time), and resources, and T_h is benchmark transfer income.

Table 7: Nested Utility Structure

Function	Description
$U = U(CI, l)$	Household utility
$CI = CI(C, q)$	Consumption-investment composite
$C = C(E, NE)$	Composite material consumption
$E = E(x_1, \ldots, x_I)\ , i \in \{e\}$	Energy consumption
$NE = NE(x_1, \ldots, x_I)\ , i \in \{ne\}$	Non-energy consumption

Notes: All functions are CES in form.

4.4 Computational Strategy

4.4.1 Calibration

Our integrated model replicates the benchmark across all data sources, i.e. the 2006 base year description of the US economy is calibrated to a set of regional and state-level SAM accounts that are consistent with observed (and simulated) generator-level electricity production and household consumption and income patterns as represented in the 2006 CEX data. Calibration of electricity demand for regulated and wholesale markets ensures that the model perfectly matches observed electricity output. However, benchmark utilization of technologies, fuel use, and hence benchmark carbon emissions are simulated based on relative costs of each generator.

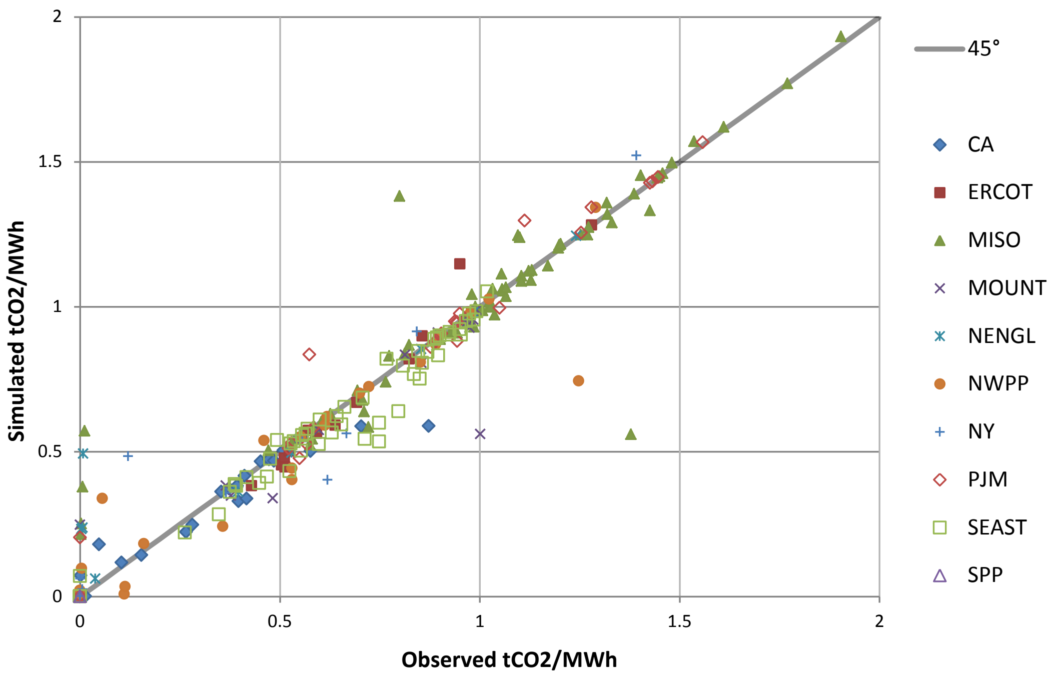
First, we compare observed output per fuel and technology reported in EIA Form 906-920 (2007d) with values simulated from our model. We find a R^2 of 90.2 and 84.1 percent for regulated operators and wholesale producers, respectively.[21] Second, we compare simulated regional wholesale prices with observed wholesale prices reported by FERC. Table 3 shows that simulated and observed yearly load-weighted average wholesale prices are very close. For regulated operators, comparable price data is not available.[22] Finally, we compare simulated and observed outcomes in terms of emissions intensity. The model accurately predicts carbon intensity for wholesale producers (Table 3) and for regulated operators (Figure 3).

Given the benchmark solution to the electricity sector model, our calibration procedure involves three major steps. First, we benchmark the GE model to the baseline solution of the electricity sub-model by using least-square optimization methods to re-estimate the SAM data given electricity sector outputs and inputs. Second, we achieve consistency of consumption choices by the single artificial agent and the aggregate of individual household choices by calibrating preference parameters of the artificial agent based on observed prices and consumption of real households. This procedure is described in Rutherford and Tarr (2008) and further detailed in Appendix D. Third, as is customary in applied GE analysis, we use prices and quantities of the integrated economic-energy data set for the base year to calibrate the value share and level parameters in the model. Exogenous elasticities determine the free parameters of the functional forms that capture production technologies and consumer preferences. Reference values for elasticity parameters are shown in Table 14.

[21] Formally, we compute: $R^2 = 1 - \frac{\sum_{\text{tech,fuel}}(y_{\text{tech,fuel}} - \hat{y}_{\text{tech,fuel}})^2}{\sum_{\text{tech,fuel}}(y_{\text{tech,fuel}} - \bar{y})^2}$ where $y_{\text{tech,fuel}}$ is observed output for each technology-fuel combination, $\hat{y}_{\text{tech,fuel}}$ is the model prediction, and $\bar{y}$ is the average observed outcome.

[22] EIA form 826 (2007a) and EIA form 861 (2007c) provide revenue data for regulated operators in our dataset, but no information is available that would allow us to separate out generation costs from transmission and distribution costs at the operator level.

Figure 3: Simulated and observed emission intensity for regulated operators.



4.4.2 Decomposition Algorithm

All components of the integrated modeling framework are solved as a mixed complementarity problem (MCP) (Mathiesen, 1985; Rutherford, 1995) where economic equilibrium is characterized by two classes of conditions: zero profit and market clearance. The former condition determines a vector of activity levels and the latter determines a vector of prices. We formulate the problem in GAMS and use the PATH solver (Dirkse and Ferris, 1995) to solve for non-negative prices and quantities.

Given the highly non-linear nature and large dimensionality of the numerical problem at hand, an integrated solution approach is not feasible. We make use of recent advances in decomposition methods to numerically compute the general equilibrium of the the integrated model encompassing a generator-level description of electricity generation and a large number of heterogenous households.

First, integration of the electric sector component in the GE setting is is based on a block decomposition algorithm by Böhringer and Rutherford (2009) that involves an iterative procedure allowing to separately compute the electricity model from the GE model. For this purpose, the supply of electricity in the GE model is treated as exogenous and is parametrized based on the solution of electricity sub-model. A linear demand function for electricity is used in the bottom-up model to locally approximate the demand response from the GE model. Convergence between the two models is achieved by successively re-calibrating the linear demand function based on the Marshallian price elasticity of demand and a candidate GE solution for electricity price and demand.

In addition to the link for electricity supply and demand, both models are also fully reconciled in terms of prices and demands for fuels, capital, labor, and other commodities and services used to produce electricity. These additional linkages are implemented by using candidate GE prices to parametrize the electricity sector model, and by updating exogenous demands for these commodities in the GE model based on the previous solution of the electricity sector model. Appendix C describes the implementation of the algorithm.

Integration of the GE and electricity sector model also require capturing profits earned by non-regulated electricity operators. There are two types of profits. First, generators with marginal costs below the equilibrium price for electricity earn sub-marginal profits that reflect the shadow value of installed capacity. Second, profits for Cournot players are due to markups on marginal generation costs. Total profits are implicitly included in the GE model by valuing parameterized electricity sector supplies and inputs at equilibrium market prices.

Second, as simultaneous solution methods are infeasible for the number of household we consider, we use a decomposition algorithm by Rutherford and Tarr (2008) to integrate all households endogenously within our general equilibrium model.The key idea of the algorithm is to solve a market economy with many households through the computation of equilibria for a sequence of representative agent (RA) economies. The algorithm decomposes the numerical problem into two sub-problems and employs an iterative procedure between them to find the equilibrium of the underlying model. The first sub-problem computes candidate equilibrium prices from a version of the GE model where the household demand side in each region is replaced by a single RA. The second sub-problem solves a partial equilibrium (PE) relaxation of the underlying model by evaluating demand functions for each of the 15,588 households given candidate GE prices from the RA problem. The iterative procedure between both sub-problems involves the re-calibration of preferences of the RA in each region based on PE quantity choices by "real" households. This ensures that the GE prices derived from the RA model, which include a mutually consistent GE response of firms and the demand by the RA, are consistent with PE demand by individual households. Appendix D describes the implementation of the decomposition algorithm in the current context.

5 Results

5.1 Allowance Allocation Design

In general equilibrium, allowance allocation designs translate into a statement about how the carbon revenue is distributed among households. Formally, let T_0 denote economy-wide CO_2 emissions in the benchmark, τ the equilibrium allowance price, ξ the emissions reduction target imposed by the CAT regulation (expressed as a fraction of benchmark emissions), and ϑ is the fraction of allowances retained by the government to achieve budget neutrality.[23] We can write the carbon revenue received by consumer h as:

$$A_h = \tau \xi T_0 (a_h + b_h + c_h) \cdot (1 - \vartheta)\,, \tag{22}$$

where a_h, b_h, c_h denote household's share of carbon revenue from allocating allowances to non-electricity sectors, to non-regulated electricity producers, and regulated electricity producers, respectively. Further define λ_m, the share of allowances allocated to electricity market $m = f \cup r$, as a linear combination of the share of benchmark electricity emissions, $\overline{E}_m$, and benchmark electricity output, $\overline{O}$:

$$\lambda_m = \alpha_E \frac{\overline{E}_m}{\sum_{m'} \overline{E}'_m} + (1 - \alpha_E) \frac{\overline{O}_m}{\sum_{m'} \overline{O}'_m}\,, \tag{23}$$

[23] In each scenario, we determine the amount of allowances required to compensate for changes in non-CO_2 tax revenue. This corresponds to a non-distortionary lump-sum tax and ensures that the budget of the government remains constant across all counterfactual equilibria.

where $\alpha_E \in [0, 1]$.

We now formulate our counterfactual policy scenarios in terms of parameters a_h, b_h, and c_h. Regarding allowances distributed to regulated electricity firms, we consider the following three scenarios:

- LUMPSUM: $\alpha_E = 1$, $c_h = \upsilon_h w \sum_f \lambda_f I_{r,h}$
- SUB_E: $\alpha_E = 1$, $c_h = 0$
- SUB_O: $\alpha_E = 0$, $c_h = 0$,

where υ_h denotes the population weight of household h in total population and $I_{f,h}$ is an indicator variable which is equal to one if household h is a consumer in market f, zero otherwise.

The LUMPSUM scenario represents a CAT policy where free allowances are allocated based on benchmark emissions and where the PUCs require regulated operators pass on the allowance value to households as a lump-sum transfer on a per-capita basis.[24] Alternatively, LUMPSUM can be viewed as a CAT policy where allowances are auctioned and revenue is distributed as per-capita lump sum transfers. While other lump-sum transfer schemes that are independent of electricity consumption are conceivable per capita transfers are often seen as politically most acceptable. Further, it seem plausible to rule out that PUCs would base the distribution of transfers explicitly on other household characteristics.

The SUB_E and SUB_O cases represent policies where free allowances are allocated based on benchmark emissions or output, respectively, and where each regulated electricity operators use the value of allowances received to subsidize its electricity rate. The two SUB scenarios reflect a situation where CAT regulation is aimed at sheltering some electricity consumers from adverse price impacts or where the intent of the legislation to have electricity prices reflect the full CO_2 costs is frustrated by PUC rate setting. The value of allowances allocated to regulated producer f in the SUB cases is given by $V_f = \tau \lambda_f w$ and determines the firm-specific endogenous subsidy rate s_f according to Eq. (6).

To identify the incidence of free allowances allocation to regulated electricity producers, in all scenarios non-electricity sectors and non-regulated electricity producers receive free allowances based on benchmark emissions. This reflects a case where windfall gains accrue to capital owners:

$$a_h = \kappa_h (1 - w) \tag{24}$$
$$b_h = \kappa_h w \sum_r \lambda_r \, , \tag{25}$$

where $w = \sum_m \overline{E}_m / T_0$ is the share of emissions from electricity sector in country-wide emissions and κ_h is the share of capital income of household h in aggregate capital income. While this is an imperfect approximation to capital ownership, keeping the policy treatment assigned to other sectors constant allows us to focus our attention to the incidence of SUB_E and SUB_O scenarios *relative* to the LUMPSUM scenario.

5.2 Aggregate Impacts

Figure 4 and Table 8 summarize the impacts of allowance allocation schemes on national welfare (net of welfare impacts from environmental changes). Aggregate welfare costs are the weighted

[24] We do not include the case $\alpha_E = 0$ and $c_h = \upsilon_h w \sum_f \lambda_f I_{r,h}$ as results are similar to those obtained for LUMPSUM.

Table 8: Compliance costs, carbon prices, and sectoral CO_2 abatement under alternative designs of cap-and-trade policy.

	LUMPSUM			SUB_E			SUB_O		
Reduction target (%)	10	20	30	10	20	30	10	20	30
Compliance cost[a]									
Total ($billion)	34.4	83.0	155.3	60.4	129.9	213.0	57.4	124.7	206.5
Per avoided ton of CO_2 ($)	58.8	70.9	88.4	103.8	111.4	121.6	98.4	106.8	117.8
Carbon price ($ per ton)	14.1	31.2	51.3	18.9	40.5	63.2	17.3	37.4	60.0
Electricity price (%)	19.1	43.9	73.2	13.7	33.9	59.9	15.3	36.8	62.9
Sectoral abatement									
Economy-wide (million tons)	585	1,170	1,756	585	1,170	1,756	585	1,170	1,756
Sectoral contribution (%)									
Regulated electricity (%)	38.1	38.9	38.8	19.3	23.7	28.8	25.3	27.9	31.4
Wholesale electricity (%)	11.0	14.0	16.5	17.8	20.5	20.8	15.8	19.1	19.7
Non-electricity sectors (%)	50.9	47.1	44.7	63.0	55.8	50.4	58.9	53.0	48.9

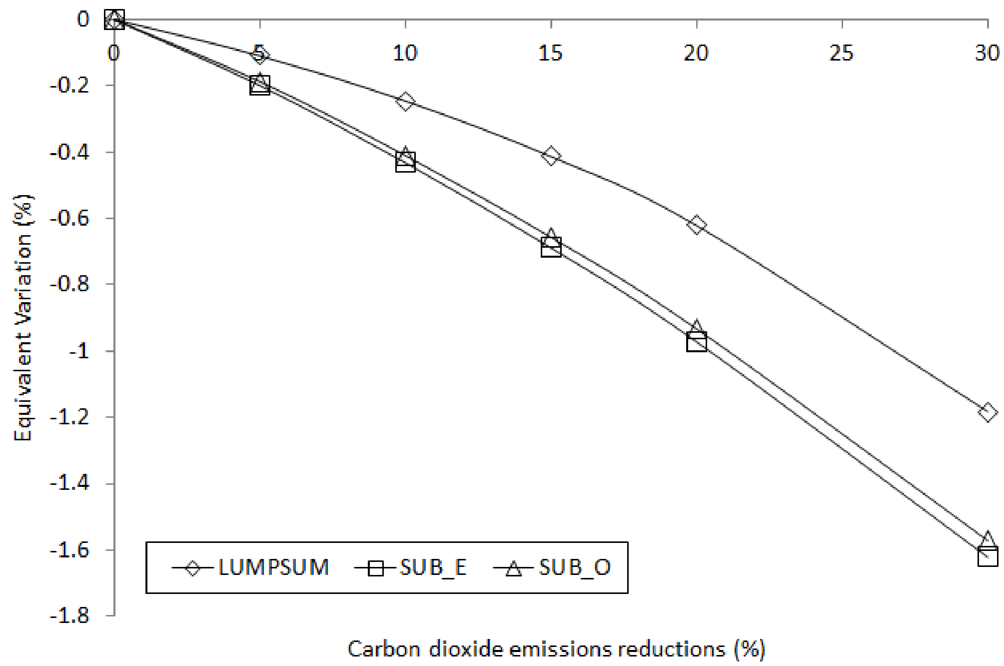
Notes: [a]Negative of the weighted sum of equivalent variations of each household. [b]Emissions reductions relative to benchmark.

average of each household's equivalent variation (EV) as a percentage of full income, where a household's weight is proportional to its share of the total population. If the value of freely allocated allowances is passed on to consumers through a subsidy of electricity rates, the welfare costs of the policy are between 1.4 and 1.8 times higher than if the value is transferred to consumers in a lump-sum fashion. For a 20 percent reduction target, this is equivalent to an additional burden of around 50 billion US$.

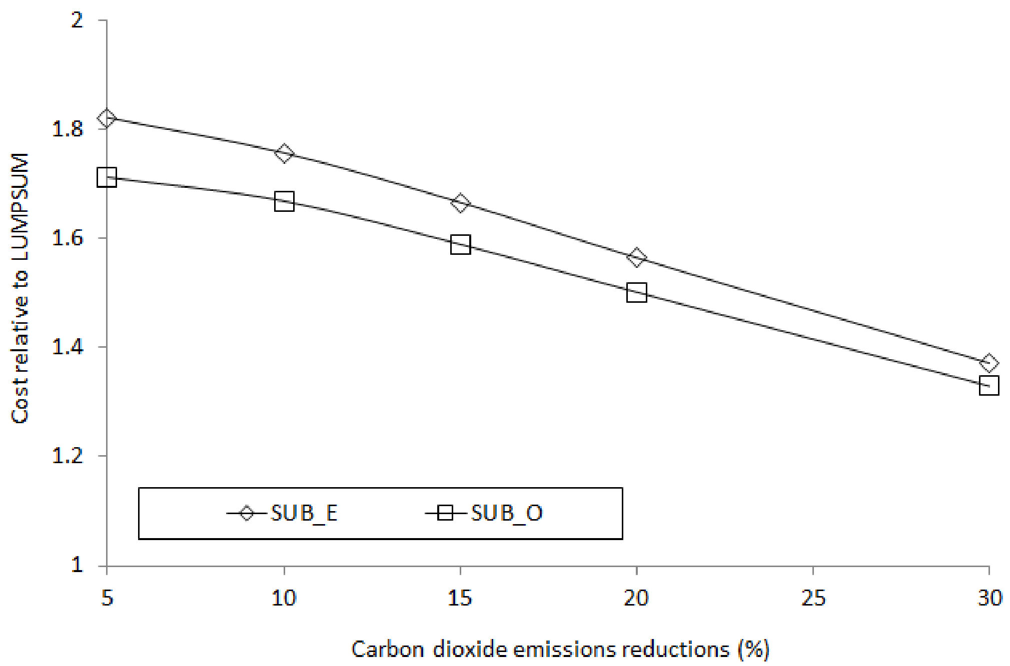
If regulated electricity producers are allowed to pass the value of free permits through electricity rates, a fraction of consumers do not see the carbon price signal. This leads to sub-optimal (i.e. too high) electricity consumption and CO_2 emissions from regulated electricity operators. A key driver of efficiency costs is the size of electricity price changes. While we find that the difference in average electricity price increase is modest, heterogeneity in generation technology portfolio at the operator level gives rises to large heterogeneity for market level price impacts. We summarize the distribution of operator-level electricity price changes (net of transmission and distribution costs) in Figure 5.

In the LUMPSUM scenario, the average price increase across the US is around 40 percent for regulated operators, and 20 percent for non-regulated operators. This reflects the higher carbon intensity of regulated producers, but also the lower substitution possibilities among technologies (mainly from coal to natural gas), as regulated operators typically hold a much smaller set of generators compared to the set of generators active on wholesale markets. The model suggests a substantial dispersion of price impacts across markets, ranging from about zero for producers with low carbon intensity to almost 250 percent for operators holding a portfolio of coal-fired plants and with relatively low electricity prices in the benchmark. The dispersion of price impacts across regions varies depending on the underlying dispersion in carbon intensity among operators in our data.

Subsidizing electricity prices drastically reduces both the mean and the dispersion of price changes. Under an emissions-based subsidy, the maximum price increase falls to about 50 percent. Under an output-based subsidy, the subsidy rate is identical among regulated operators, so that the price increase at operators with carbon-intensive technologies falls in between price



(a) Weighted average of equivalent variations of household and CO_2 abatement



(b) Excess welfare costs relative to LUMPSUM

Figure 4: Efficiency costs and environmental impact.

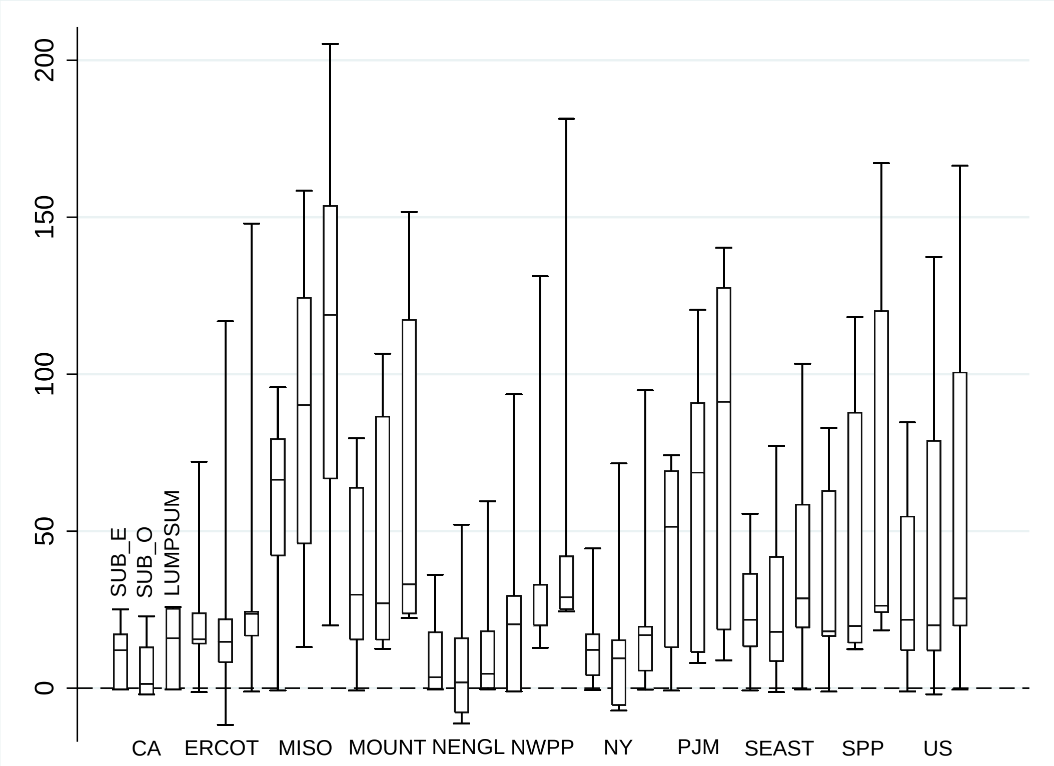


Figure 5: Distribution of electricity price changes by region ($\xi = 0.8$). For each region, the box-whisker plots from left to right refer to the LUMPSUM, SUB_O, and SUB_E cases, respectively. The whiskers show outlier values at the 5^{th} and 95^{th} percentile, respectively.

changes under LUMPSUM and the SUB_E cases. In regulated markets with large output and low carbon technologies, operators can be overcompensated by the subsidy therefore inducing a negative change in electricity prices.

Allocating allowances based on benchmark output induces smaller distortions of the carbon price, increasing incentives to abate at operators with high carbon intensity and reducing aggregate welfare costs. While the distribution of price impacts under emissions- and output-based allocation is different, aggregate price impacts is very similar for both allocation rules, so that differences in aggregate welfare costs are small. Moreover, as the stringency of the policy increases, inefficiencies relative to LUMPSUM represent a smaller share of total compliance costs, and differences between allocation rules become smaller.

The second key driver of efficiency costs is differences in abatement costs across sectors. Our data sugggest that electricity generation at regulated operators is—on average—relatively carbon intensive and that abatement is relatively cheap. Under the SUB_E and SUB_O scenarios, regulated operators are required to surrender permits to cover their emissions, and cost minimizing behavior implies that they respond to the opportunity cost of permits by reducing emissions. But without a distorted carbon price signal the reduction in electricity consumption is smaller. For a 20 percent cap on economy-wide emissions, regulated electricity producers contribute to about 39 percent of emissions reductions under LUMPSUM, while this number drops to 23 and 28 percent under SUB_E and SUB_O, respectively. The increase in the demand for emission permits raises the equilibrium carbon price consistent with incentivizing sub-optimally large levels of abatement in the wholesale electricity and non-electricity sectors. The contribution of non-regulated electricity producers increases from 14 percent under LUMPSUM to about

Table 9: Efficiency cost, subsidy rate, and CO_2 emissions by region ($\xi = 0.8$).

	Δ Welfare rel. to LUMPSUM (%)[a]		Subsidy rate (cents/kWh)[b]		Δ CO_2 emissions rel. to LUMPSUM (%)[a]	
	SUB_E	SUB_O	SUB_E	SUB_O	SUB_E	SUB_O
MOUNT	-0.99	-0.90	1.2	1.0	3.2	2.2
SPP	-0.90	-0.82	1.3	0.9	4.8	2.7
SEAST	-0.65	-0.63	1.0	0.9	1.0	1.7
MISO	-0.41	-0.37	1.2	0.8	3.7	1.9
NWPP	-0.31	-0.28	0.5	0.8	-0.2	-1.0
PJM	-0.23	-0.21	0.6	0.4	-1.4	-1.4
ERCOT	-0.13	-0.11	0.2	0.1	-4.5	-3.5
NY	-0.11	-0.09	0.3	0.3	-2.9	-1.8
CA	-0.09	-0.07	0.2	0.5	-2.8	-1.2
NENGL	-0.07	-0.05	0.1	0.1	-2.5	-1.8

Notes: [a]Difference in percentage points of percentage mean welfare changes under LUMPSUM relative to SUB_E/SUB_O. [b]Output-weighted average across regulated electricity producers in each region.

20 percent under both subsidy cases. Similarly, non-electricity sectors contribute about 47 percent of total abatement under LUMPSUM while their share increases to 56 and 53 percent under SUB_E and SUB_O, respectively.

5.3 Distributional Impacts

Regional Welfare Impacts and Subsidy Rates. Table 9 summarizes regional welfare changes relative to LUMPSUM allowance allocation design and the regional subsidy rate to consumers of regulated electricity (in cents/kWh) for a 20 percent target. The pattern of regional welfare losses correlates closely with the magnitude of subsidy rates. This indicates that the value of allowances allocated to regulated firms in a given region, expressed per unit of electricity output, is a strong driver of regional costs. On average, regions with the highest share of electricity produced under cost-of-service regulation—SEAST, SPP, MOUNT—suffer relatively large adverse welfare impacts from subsidizing electricity prices, while regions with a low degree of regulation—NENGL, ERCOT, NY, PJM—experience the smallest losses.

Another driver for the distribution of regional welfare impacts is the benchmark carbon intensity of regulated electricity generation. For example, although a relatively high share of electricity in CA is produced under regulation, it only experiences the second smallest welfare impact as it uses the least amount of CO_2 per kWh of electricity generated among all regions. This can be explained by the hydroelectric capacity in that state that is still under regulation. Conversely, despite the fact that the SEAST is characterized by the largest share of electricity produced under regulation, it only ranks third in terms of welfare losses as its carbon intensity is below the national average.

An allocation rule based on output is not directly tied to CO_2 emissions, generally creating smaller subsidy rates and partly preserving the carbon price signal. However, while the emissions- and output-based allocation schemes generate noticeable differences in the size of regional subsidy rates, both schemes result in very similar outcomes in terms of the regional distribution of welfare impacts—as for the national level results, the SUB_E scenarios leads to slightly larger costs compared to the SUB_O.

Regional and Sectoral CO_2 Abatement. The last two columns of Table 9 show changes in total CO_2 emissions by region relative to LUMPSUM. When electricity prices are subsidized, heavily regulated regions with a high carbon intensity—MOUNT, SPP, SEAST, MISO—emit be-

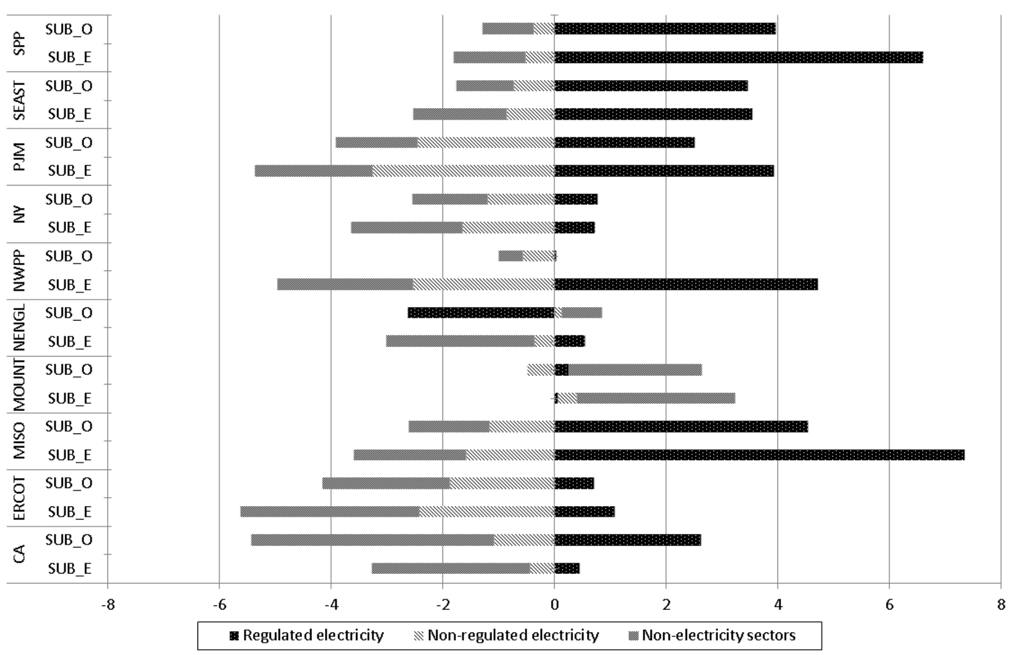


Figure 6: Sectoral decomposition of percentage change in CO_2 emissions by region (absolute difference with LUMPSUM, $\xi = 0.8$). For a given region, sum of changes across sectors corresponds to percentage change in total CO_2 emissions reported in Table 9.

tween 1 and 5 percent more. Consistent with the country-level cap, other regions—CA, NENGL, NY, NWPP and PJM—abate more by up to 3 percent. An output-based subsidy generally leads to a smaller redistribution of abatement efforts among regions relative to LUMPSUM. In only two regions emissions are higher under the SUB_O as compared to SUB_E: SEAST, which hosts a relatively small number of regulated operators with very large output and low emissions, and NWPP, where a few regulated operators hold very large hydro resources.

We further decompose the change in total CO_2 emissions by region in Figure 6, reporting emissions changes relative to LUMPSUM associated with production decisions in three aggregated sectors: regulated electricity generation, electricity sold on wholesale markets, and non-electricity sectors comprising the rest of the economy. In most regions, a subsidy forces more reductions in wholesale electricity and non-electricity sectors. The only exceptions are: (i) SUB_O in NWPP, where regulated operators mainly hold hydro resources, so that increased demand for subsidized output does not raise emissions; (ii) SUB_O in NENGL, where most regulated operators lose market shares to the wholesale producers; and (iii) both subsidy schemes in MOUNT, where trade effects compensate demand reductions. For most regions, however, more than a half of the redirected abatement comes from non-electricity sectors. This underlines the importance of using an economy-wide framework that includes a representation of abatement opportunities in non-electricity sectors of the economy.

Mean Household Impacts across Income. Table 10 displays the mean welfare impacts by income group expressed as the difference in percentage points of welfare changes under SUB_E and SUB_O relative to LUMPSUM. In the bottom 80 percent of the income distribution, both emissions- and output-based allocation schemes are slightly regressive with burdens ranging from -0.5 percent in the bottom decile to -0.25 percent in the eighth decile. For the top two deciles, the policies are slightly progressive with impacts of -.40 percent for the SUB_E case. Welfare impacts expressed in dollars per household are more negative for higher-income house-

Table 10: Mean welfare impacts across income groups (SUB_E relative to LUMPSUM, $\xi = 0.8$).

Income decile	SUB_E		SUB_O	
	%[a]	$ per household[b]	%[a]	$ per household[b]
1	-0.50	-76	-0.50	-77
2	-0.34	-91	-0.34	-90
3	-0.32	-111	-0.31	-108
4	-0.32	-136	-0.29	-127
5	-0.29	-151	-0.26	-139
6	-0.29	-182	-0.26	-163
7	-0.30	-220	-0.26	-194
8	-0.29	-253	-0.25	-220
9	-0.34	-362	-0.29	-308
10	-0.46	-676	-0.38	-564
All	-0.34	-227	-0.31	-200

Notes: [a]Difference in percentage points of population-weighted within-income group percentage welfare changes under SUB_E relative to LUMPSUM. [b]Population-weighted within-income group average of equivalent variation expressed in 2006$ relative to LUMPSUM (absolute difference).

holds with burdens ranging from $76 for the bottom decile to $676 for the top decile.[25] The SUB_O scenario shows slightly smaller welfare losses compared to SUB_E but a similar pattern across income groups.

The humped shaped profile of mean impacts across income deciles for the SUB_E and SUB_O cases (relative to LUMPSUM) is not an immediately intuitive result as one would expect that subsidizing electricity prices disproportionately benefits lower-income households who spend a larger fraction of their budget on electricity (see first column in Table 6). There are two factors that explain this result. First, removing the per-capita lump-sum transfers has an regressive effect for lower-income households, i.e. the value of lowered electricity rates in the subsidy cases does not fully compensate for the loss of transfer income that is received in the LUMPSUM case. Second, in a general equilibrium setting the effect of carbon pricing on welfare will also strongly depend on changes in factor prices, and the relative importance of uses versus source side effects of income. Households which rely heavily on factors whose prices fall relative to other factor prices will be adversely impacted. In our model, the policy increases the relative price of capital to labor ($\frac{r}{w}$) as perfectly mobile capital is a better substitute for carbon than labor which is mobile across sectors within a given region but not across regions. Subsidizing electricity in regulated markets then leads to smaller increases in $\frac{r}{w}$ relative to LUMPSUM, i.e. the following pattern is observed: $\frac{r}{w}_{\text{SUB\_E}} < \frac{r}{w}_{\text{SUB\_O}} < \frac{r}{w}_{\text{LUMPSUM}}$. This suggests that lower-income households and those in the top two income deciles—who rely more heavily on capital income (relative to labor income) are more adversely impacted on the sources side of income compared to middle income households. Efficiency costs from freely allocating allowances in the presence of a price-regulated electricity sector are therefore disproportionately borne by capital

[25] One caveat of our analysis is the use of annual income. It is recognized in the literature (see, for example, Davies et al., 1984; Poterba, 1989, 1991; Bull et al., 1994; and Lyon and Schwab, 1995) that consumption taxes—including energy taxes—look considerably less regressive when lifetime income measure are used than when annual income measures are used. The lifetime income approach, however, relies on strong assumptions about household consumption decisions. In particular it assumes that households base current consumption decisions knowing their full stream of earnings over their lifetime. Based on the Consumer Expenditure Survey and using proxies for lifetime income Rausch et al. (2011) find that the use of annual income does not strongly bias results towards regressivity.

owners, and benefits to consumers in the form of lowered energy prices are dominated by the sources side effects of income.

Heterogeneity in Household Impacts. Focusing on mean household impacts at the national level masks important variation in impacts across and within regions and income groups. Figures 7 and 8 show box-whisker plots for individual household impacts by region and income quintile for the LUMPSUM case relative to the "no-policy" benchmark and for SUB_E relative to LUMPSUM, respectively. We show graphs for SEAST, NWPP, and PJM because the patterns of household impacts in those regions is representative of other regions with a high, intermediate, and low degree of regulation in the electricity sector. The key insights are as follows.

First, it is important to note that focusing on averages across income groups obscures important variation within income groups that may swamp the variation in average effects across income groups. The variation within income groups is driven by differences among households with respect to expenditure shares on energy and income patterns.

Second, looking at impacts under LUMPSUM relative to a "no-policy" benchmark (Figure 7) shows an U-shaped profile of mean impacts across income quintiles. This is largely a result of how the allowance revenue is allocated. Distributing the value of free allowances allocated to regulated electricity producers on a per-capita lump-sum basis is progressive disproportionately benefiting lower-income households. As the remainder of the carbon revenue is distributed in proportion to capital income, lower-income households and higher-income households are relatively better off. We observe a similar pattern of impacts for the SUB_E case relative to a "no-policy" benchmark (not shown).

Third, a significant fraction of households gain from the carbon policy as the allowance allocation overcompensates adverse impacts felt through higher energy prices and reduced factor income. It is mostly households in the first and fifth quintile that gain as they benefit from the allocation scheme. In addition to income, households that gain also show (i) above-average shares of transfer income that insulates them from adverse effects on the sources side of income and (ii) below-average embodied carbon in consumption.

Fourth, the mean impacts by income quintile of SUB_E relative to LUMPSUM (Figure 8) follow an inverted U-shaped profile for highly regulated regions (here represented by SEAST) and a more neutral or slightly U-shaped profile for regions with low regulation in the electricity sector (here represented by NWPP and PJM). Larger impacts for higher-income households in highly regulated regions compared to regions with low regulation can be explained by larger reductions in the price of capital (relative to labor) under SUB_E relative to LUMPSUM in these regions.

5.4 Sensitivity Analysis

Here we consider the sensitivity of results to parameters affecting the integration of electricity markets both within and across ISO regions. Market integration can affect the size and regional distribution of efficiency costs associated subsidized electricity prices. First, many regulated operators trade power with independent operators, and substituting wholesale power for carbon intensive generation provides a different channel of reducing CO_2 emissions. Thus inter-operator trades can potentially induce different abatement decisions among regulated and wholesale producers of electricity. Integration between regulated and non-regulated operators is represented by the parameter σ (see Eq. (19)). A second important aspect of market integration relates to inter-regional trades across ISOs, represented by σ_{xELE} (see Eq. (16)).

In the first panel in Table 11, we summarize efficiency and distributional impacts of SUB_E and SUB_O for our central assumption regarding market integration parameters. Panel two shows results for a low market integration case. Reducing trade opportunities among regulated and non-regulated operators slightly increases carbon prices as flexibility to exploit relatively

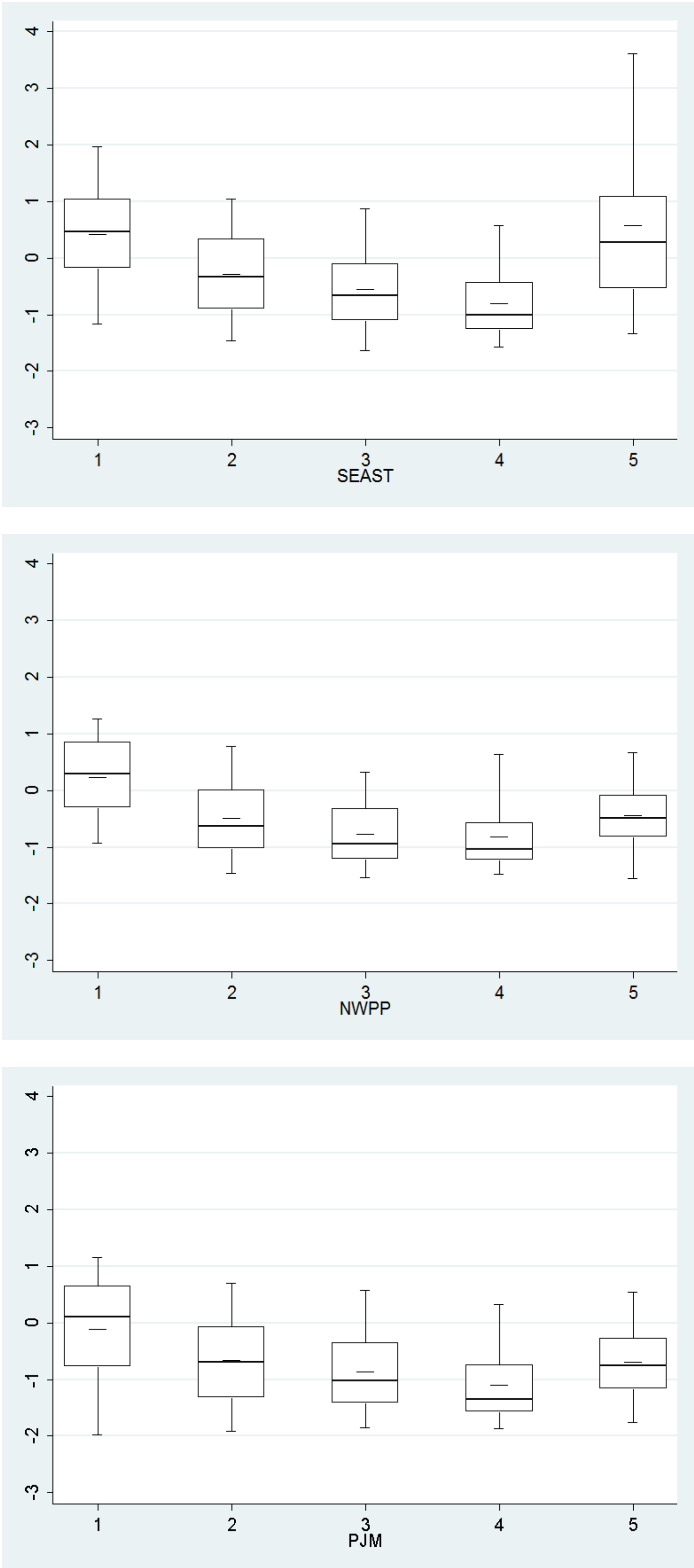


Figure 7: Regional within-income quintile distribution of percentage change of equivalent variation under LUMPSUM (relative to no policy case, $\xi = 0.8$). The whiskers show outlier values at the 5^{th} and 95^{th} percentile, respectively.

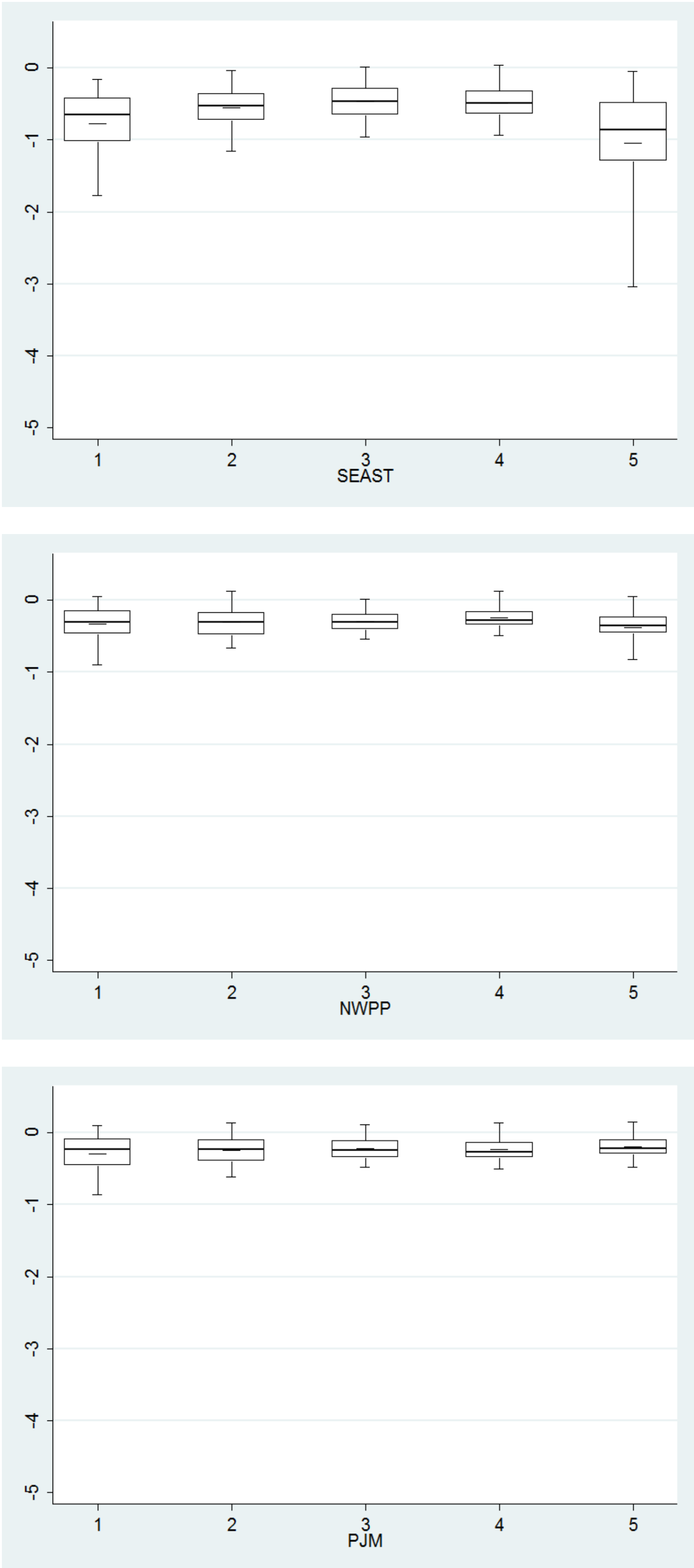


Figure 8: Regional within-income quintile distribution of percentage point difference in welfare impacts under SUB_E relative to LUMPSUM ($\xi = 0.8$). The whiskers show outlier values at the 5^{th} and 95^{th} percentile, respectively.

Table 11: Impacts of different cap-and-trade designs under alternative parameter assumptions.

	EV (%)	Carbon price (2006$/t$CO_2$)	Abatement reg. ele. (%)	Standard deviation of EV	Standard deviation of Mean EV by region	Standard deviation of Electricity price change	Standard deviation of Mean electricity price change by region
Central case ($\sigma = 1$, $\sigma_{xELE} = 0.5$)							
SUM_E	-0.58	29.1	12.2	0.79	0.13	0.21	0.09
SUM_O	-0.59	26.8	15.1	0.79	0.15	0.34	0.12
Low market integration ($\sigma = 0$)							
SUM_E	-0.59	29.8	11.3	0.74	0.15	0.26	0.09
SUM_O	-0.61	28.4	12.3	0.77	0.17	0.65	0.12
High market integration ($\sigma = 10$)							
SUM_E	-0.55	28.6	12.0	0.73	0.12	0.21	0.09
SUM_O	-0.58	26.0	15.1	0.77	0.14	0.33	0.12
High market integration ($\sigma = 10$) and high electricity trade elasticity ($\sigma_{xELE} = 5$)							
SUM_E	-0.52	27.8	13.2	0.69	0.11	0.19	0.08
SUM_O	-0.55	25.4	16.4	0.73	0.13	0.30	0.10

Notes: Results shown for $\xi = 0.8$.

cheap abatement are scarcer. Abatement at regulated operators declines, and compliance costs increase. An increase fragmentation of the electricity sector also increases somewhat the dispersion of mean regional welfare impacts.

Results for higher market integration in the third panel suggests that our results are very robust with respect to varying σ. The impact work in the other direction compared to the low market integration case, but follows the same intuition.

The bottom panel explores the case of high integration within and across regions, and is designed to provide an upper bound of the model response. As for the other cases before, our conclusions are unaffected. Carbon prices are lower compared to the central case translating into a smaller allowance value and lower subsidy rates. As regulated electricity producers are, on average, more carbon intensive, increased trade opportunities induce higher abatement as compared to the central case. Moreover, abatement is cheaper, which implies slightly smaller efficiency costs. Increased market integration also reduces the dispersion of regional welfare and electricity price impacts, reflecting realized trade opportunities.

6 Conclusions

This paper has examined the impacts of alternative allowance allocation designs of CAT policy in the presence of price-regulated electricity markets. The model links a detailed representation of electricity generation technologies and markets as well as data capturing household heterogeneity with a general equilibrium representation of the US economy. This framework enables us to account for the technology response at the operator-level, market structure, and economy-wide effects, and permits assessment of the distributional and efficiency impacts of environmental regulation using theoretically sound welfare cost metrics.

We find that compliance costs of the policy substantially increase if the value of free allowances is not reflected in electricity rates of electricity producers under cost-of-service regulation. Depending on the stringency of the emissions reduction target, our analysis suggests that compliance costs of a federal CAT regulation are between 40 and 80 percent higher if the value of free allowances allocated to regulated electricity producers is passed on to consumers through electricity rates.

The choice between auctioning or free allocation of allowances in a cap-and-trade system also influences crucially the regional distribution of welfare costs. Regions with a large degree of electricity market regulation and high carbon intensity of electricity production suffer the most adverse impacts. In contrast, regions with largely deregulated electricity sectors and substantial electricity imports benefit from lower electricity rates as the policy creates relatively small distortions within their regional economies while lowering the out-of-state price of electricity. An emissions-based schemes brings about a slightly higher welfare loss as compared to an output-based scheme, but the choice of how allowances are allocated only has a small impact on overall economic costs.

We find that alternative policy designs have widely differing implications for local electricity prices. For a 20 percent economy-wide cap in terms of CO_2 emissions, electricity price increases can be as high as 250 percent if allowance are auctioned. The large variation can be explained by the heterogeneity of the technology portfolio at the operator level. If freely allocated allowances are used to subsidize electricity rates at regulated operators, the variance of electricity price impacts is reduced drastically.

Contrary to what one might expect, subsidizing electricity prices does not disproportionately benefit lower-income households (who spend a large fraction of their income on electricity). Instead, the efficiency costs due to the failure to pass through the carbon price signal to consumers are borne largely by households with low and high incomes. This result can be traced back to the incidence of sources side effects of income due that overcompensate potentially progressive uses side effects of income. Differences in mean welfare impacts across income groups are larger for regions with a large degree of regulation in the electricity sector as sources side effects of income are more pronounced in these regions. Mean welfare impacts across income groups are neutral to slightly progressive in regions in which electricity markets are subject to relatively little regulation. Finally, exploiting household heterogeneity in terms income sources and preferences over different commodities, including energy,—based on the Consumer Expenditure Survey data set—we find substantial variation in within-income group household impacts. This suggests that focusing on averages across income groups obscures important variation within income groups that may swamp the variation in average effects across income groups.

We conclude this paper by highlighting that our static modeling framework cannot address the question of investment in low-carbon generation technologies. Given that regulated operators can expect a predetermined rate of return on investments, incentives for investments differ as compared to non-regulated operators. However, the issue analyzed in this paper is likely to be even more important in a dynamic setting, as the perception of the carbon price by consumers will incentivize investments in energy saving technologies, and the welfare costs of subsidizing electricity rates is thus likely to increase as time passes.

References

Arimura, T. (2002) "An empirical study of the SO_2 allowance market: Effects of puc regulations," *Journal of Environmental Economics and Management*, 44, pp. 271 – 289.

Armington, P. (1969) "A theory of demand for products distinguished by place of production," *International Monetary Fund Staff Papers*, 16, pp. 159–76.

Atkinson, A. and J. Stiglitz (1980) *Lectures on Public Economics*: McGraw-Hill, New York.

Attanasio, O. (1998) "Cohort analysis of saving behavior by u.s. households," *Journal of Human Resources*, 33, pp. 575–609.

Ballard, C. (2000) “How many hours are in a simulated day? the effect of time endowment on the results of tax-policy simulation models..” Working Paper, Michigan State University.

Bohi, D. and D. Burtraw (1992) “Utility investment behavior and emission trading market,” *Resources and Energy*, 14, pp. 129 – 153.

Böhringer, C. and T. F. Rutherford (2009) “Integrated assessment of energy policies: Decomposing top-down and bottom-up,” *Journal of Economic Dynamics and Control*, 33, pp. 1648–1661.

Borenstein, S., J. Bushnell, and C. Knittel (1999) “Market power in electricity markets: Beyond concentration measures,” *The Energy Journal*, 20 (4), pp. 65–88.

Browning and W. Johnson (1979) “The Distribution of the Tax Burden,” American Enterprise Institute, Washington DC.

Bull, N., K. A. Hassett, and G. E. Metcalf (1994) “Who pays broad-based energy taxes? computing lifetime and regional incidence,” *Energy Journal*, pp. 145–164.

Bureau of Economic Analysis (2007) “Annual i-o pce bridge matrix.”

Bureau of Labor Statistics (2006) “2006 consumer expenditure interview survey public use microdata documentation.” United States Department of Labor.

Burtraw, D., K. Palmer, R. Bharvirkar, and A. Paul (2001) “The effect of allowance allocation on the cost of carbon emission trading.” Resources For the Future Discussion Paper.

Bushnell, J. B., E. T. Mansur, and C. Saravia (2008) “Vertical arrangements, market structure and competition: An analysis of restructured us electricity markets,” *American Economic Review*, 98(1), pp. 237–266.

Coase, R. (1960) “The problem of social cost,” *Journal of Law and Economics*, 3, pp. 1 – 44.

Coggins, J. and V. Smith (1993) “Some welfare effects of emission allowance trading in a twice-regulated industry,” *Journal of Environmental Economics and Management*, 25, pp. 275 – 297.

Davies, J. B., F. St. Hilaire, and J. Whalley (1984) “Some calculations of lifetime tax incidence,” *American Economic Review*, 633-649.

Deaton, A. (2003) “Measuring poverty in a growing world (or measuring growth in a poor world).” NBER Working Paper w9822.

Dirkse, S. P. and M. C. Ferris (1995) “The PATH solver: a non-monontone stabilization scheme for mixed complementarity problems,” *Optimization Methods and Software*, 5, pp. 123–156.

Energy Information Administration (2007a) “Form EIA-826 data monthly electric utility sales and revenue data.” Washington, DC.

——— (2007b) “Form EIA-860 annual electric generator data.” Washington, DC.

——— (2007c) “Form EIA-861 annual electric utility data.” Washington, DC.

——— (2007d) “Form EIA-906-920 power plant operations data.” Washington, DC.

——— (2008) “Carbon dioxide uncontrolled emission factors, electric power annual data for 2000 – 2007.” Washington, DC.

——— (2009a) “Electric power annual 2007.” Office of coal, nuclear, electric and alternate fuels, US Department of Energy, Washington DC.

——— (2009b) “The electricity market module of the national energy modeling system.” Washington, DC.

——— (2009c) “State energy data system.” Washington, DC.

——— (2009d) “State energy price and expenditure report.” Washington, DC.

Feenberg, D. and E. Coutts (1993) “An introduction to the taxsim model,” *Journal of Policy Analysis and Management*, 12, 1. Data on personal marginal income tax rates are taken from the “Internet Taxsim (v9)” of the TAXSIM model.

Fernandez-Villaverde, J. and D. Krueger (2006) “Consumption over the life cycle: Facts from the consumer expenditure survey,” *Review of Economics and Statistics*, 89, 3, pp. 552–565.

Fowlie, M. L. (2009) “Incomplete environmental regulation, imperfect competition, and emissions leakage,” *American Economic Journal: Economic Policy*, 1 (2), pp. 72–112.

——— (2010) “Emissions trading, electricity restructuring, and investment in pollution abatement,” *American Economic Review*, 100, pp. 837 – 869.

Fullerton, D., S. P. McDermott, and J. P. Caulkins (1997) “Sulfur dioxide compliance of a regulated utility,” *Journal of Environmental Economics and Management*, 34, pp. 34–53.

Fullerton, D., G. Heutel, and G. E. Metcalf (2011) “Does the indexing of government transfers make carbon pricing progressive?” *American Journal of Agricultural Economics*, forthcoming.

Goulder, L. H., I. W. H. Parry, R. Williams III, and D. Burtraw (1999) “The cost-effectiveness of alternative instruments for environmental protection in a second-best setting,” *Journal of Public Economics*, 72 (3), pp. 329 – 360.

Goulder, L. H., M. A. Hafstead, and M. Dworsky (2010) “Impacts of alternative emissions allowance allocation methods under a federal cap-and-trade program,” *Journal of Environmental Economics and Management*, 60(3), pp. 161–181.

Joskow, P. L. (2005) “Transmission policy in the united states,” *Utilities Policy*, 13 (2), pp. 95–115.

——— (2006) “Markets for power in the united states: An interim assessment,” *The Energy Journal*, 27(1), pp. 1–36.

Joskow, P. L. and R. Schmalensee (1983) *Markets for Power: An analysis of Electric Utilities Deregulation*: MIT Press, Cambridge USA.

Lanz, B. and S. Rausch (2011) “General equilibrium, electricity generation technologies and the cost of carbon abatement.” MIT Joint Program on the Science and Policy of Global Change Report 194.

Lyon, A. B. and R. M. Schwab (1995) “Consumption taxes in a life-cycle framework: are sin taxes regressive,” *Review of Economics and Statistics*, pp. 389–406.

Malueg, D. A. (1990) “Welfare consequences of emission credit trading programs,” *Journal of Environmental Economics and Management*, 18 (1), pp. 66 – 77.

Mansur, E. T. (2007a) "Do oligopolists pollute less? evidence from a restructured electricity market," *Journal of Industrial Economics*, 55 (4), pp. 661 – 689.

——— (2007b) "Upstream competition and vertical integration in electricity markets," *Journal of Law and Economics*, 50(1), pp. 126–156.

Mathiesen, L. (1985) "Computation of economic equilibria by a sequence of linear complementarity problems," *Mathematical Programming Study*, 23, pp. 144–162.

Metcalf, G. E., A. Mathur, and K. A. Hassett (2010) "Distributional impacts in a comprehensive climate policy package." NBER Working Paper w16101.

Minnesota IMPLAN Group (2008) "State-level u.s. data for 2006." Stillwater, MN: Minnesota IMPLAN Group.

Montgomery, D. W. (1972) "Markets in licenses and efficient pollution control programs," *Journal of Economic Theory*, 5.

Paltsev, S., J. M. Reilly, H. Jacoby, R. Eckhaus, J. McFarland, M. Sarofim, M. Asadoorian, and M. Babiker (2005) "The mit emissions prediction and policy analysis (eppa) model: Version 4." MIT Joint Program on the Science and Policy of Global Change, Report 125, Cambridge, MA.

Paul, A., D. Burtraw, and K. Palmer (2010) "Compensation for electricity consumers under a us co2 emissions cap," in V. Ghosal ed. *Reforming Rules and Regulations: Laws, Institutions and Implementation*: Cambridge, MA: MIT Press.

Poterba, J. (1989) "Lifetime incidence and the distributional burden of excise taxes," *American Economic Review*, 32-330.

——— (1991) "Is the gasoline tax regressive," *American Economic Review*, 145Ű164.

Puller, S. L. (2007) "Pricing and firm conduct in california's deregulated electricity market," *Review of Economics and statistics*, 89, pp. 75–87.

Radov, D. and P. Klevnas (2007) "Co_2 cost pass through: German competition regulators' shaky economics," *Energy Regulation Insights*, 31, pp. 1 – 7.

Rausch, S., G. E. Metcalf, J. M. Reilly, and S. Paltsev (2010) "Distributional implications of alternative U.S. greenhouse gas control measures," *The B.E. Journal of Economic Analysis & Policy*, 10, 2. Symposium.

Rausch, S., G. E. Metcalf, and J. M. Reilly (2011) "Distributional impacts of carbon pricing: A general equilibrium approach with micro-data for households," *Energy Economics*, S20-S33.

Rausch, S. and T. F. Rutherford (2010) "Computation of equilibria in OLG models with many heterogeneous households," *Computational Economics*, 36, 2, pp. 71–189.

Rutherford, T. F. (1995) "Extension of GAMS for complementarity problems arising in applied economics," *Journal of Economic Dynamics and Control*, 19, 8, pp. 1299–1324.

Rutherford, T. F. and D. Tarr (2008) "Poverty effects of russia's wto accession: modeling "real" households with endogenous productivity effects," *Journal of International Economics*, 75, 1, pp. 131–150.

Sartzetakis, E. S. (1997) "Tradeable emission permits regulations in the presence of imperfectly competitive product markets: Welfare implications," *Environmental and Resource Economics*, 9 (1), pp. 1 – 19.

Shuttleworth, G. and G. Antstey (2012) "Irish Supreme Court restores common sense to the single electricity market," *Energy Regulation Insights*, 40, pp. 1 – 6.

Sijm, J., S. Hers, W. Lise, and B. Wetzelaer (2008) "The impact of the eu ets on electricity prices." Final reprot to DG Environment of the European Comission.

Stavins, R. N. (2008) "A meaningful u.s. cap-and-trade system to address climate change," *Harvard Environmental Law Review*, 32, pp. 293–371.

Sweeting, A. (2007) "Market power in the england and wales wholesale electricity market 1995–2000," *The Economic Journal*, 117, pp. 654–685.

Winston, C. (1993) "Economic deregulation: Days of reckoning for microeconomists," *Journal of Economic Literature*, 31, pp. 1263–1289.

Wolak, F. A. (2003) "Measuring unilateral market power in wholesale electricity markets: The california market, 1998–2000," *American Economic Review*, 93, pp. 425–430.

Appendix A: Supplemental Figures and Tables

Table 12: Definition of electricity pools

Regions	States
Western Electricity Coordinating Council	
California ISO (CA)	Most of California
Northwest Power Pool (NWPP)	All of Idaho, Oregon, Utah, Washington; most of Montana, Nevada, Wyoming; parts of California
Mountain Power Area (MOUNT)	All of Arizona, Colorado; parts of Nevada, New Mexico, South Dakota, Wyoming
Eastern Interconnection	
Southwest Power Pool (SPP)	All of Kansas, Oklahoma; most of Nebraska; parts of Arkansas, Louisiana, Missouri, Mississippi, New Mexico, Texas
Midwest ISO (MISO)	All of Iowa, Michigan, Minnesota, Nebraska, North Dakota, Wisconsin; most of Illinois, Indiana, Missouri, South Dakota; parts of Kentucky, Montana, Ohio.
Southeast Power Pool (SEAST)	All of Alabama, Florida, Georgia, Mississippi, North Carolina, South Carolina, Tennessee; most of Arkansas, Louisiana; parts of Kentucky, Missouri, Texas.
PJM Interconnection (PJM)	All of Delaware, District of Columbia, Maryland, New Jersey, Virginia, West Virginia; most of Ohio, Pennsylvania; parts of Illinois, Indiana, Kentucky, Michigan, North Carolina, Tennessee.
New York ISO (NY)	All of New York
New England ISO (NENGL)	All of Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island and Vermont
Electric Reliability Council of Texas	
Texas (ERCOT)	Most of Texas

Source: http://www.ferc.gov.

Table 13: List of Generation Technologies and Fuels in the Electricity Generation Model

Technologies	
	Combined cycle, combustion turbine, hydraulic turbine, internal combustion engine, photovoltaic, steam turbine, wind turbine
Fuels	
Coal:	
	Anthracite and bituminous coal, lignite coal, coal-based synfuel, sub-bituminous coal, waste and other coal
Natural gas:	
	Blast furnace gas, natural gas, other gas, gaseous propane
Oil:	
	Distillate fuel oil, jet fuel, kerosene, residual fuel oil
Other:	
	Agricultural crop, other biomass (gas, liquids, solids), black liquor, geothermal, landfill gas, municipal solid waste, nuclear fission, petroleum coke, other wastes, solar, wood and wood waste, wind, hydroelectric

Table 14: Parameter Values

Panel A: Elasticities of substitution in production

	Parameters for substitution margin										
	σ_f	$g-E$	$g-M$	$R-EM$	$E-M$	M components	$K-L$	$x_{ELE}-h$	E components	σ_{xjr}	σ_{Tjr}
Producing industry:											
1. Coal mining	0.6	-	0	-	-	0	1.0	-	-	5	5
2. Gas extraction	0.6	-	0	-	-	0	1.0	-	-	5	5
3. Oil extraction	0.6	-	0	-	-	0	1.0	-	-	5	5
4. Agriculture	0.7	-	-	0.6	0.3	0	1.0	0.5	1.0	5	5
5. Petroleum refining	0	0.5	-	-	-	0	1.0	0.5	1.0	5	5
6. Energy intensive industries	0	0.5	-	-	-	0	1.0	0.5	1.0	5	5
7. Other Manufacturing	0	0.5	-	-	-	0	1.0	0.5	1.0	5	5
8. Transportation services	0	0.5	-	-	-	0	1.0	0.5	1.0	5	5
9. Services	0	0.5	-	-	-	0	1.0	0.5	1.0	5	5

Panel B: Utility function parameters

	Parameters for substitution margin				
	σ_c	$C-I$	$E-NE$	E components	NE components
Value	[a]	0	0.25	0.4	0.65

Note: All functions are CES in form. [a]: Calibrated to match an uncompensated (compensated) labor supply elasticity of 0.1 (0.3).

Appendix B: Equilibrium conditions for GE model

This section lays out the equilibrium conditions for the economy-wide model. Our complementarity-based formulation of the economy-wide model distinguishes three classes of conditions that characterize the competitive equilibrium: zero-profit conditions, market clearance conditions, and income balance.[26] The zero-profit conditions determine a vector of activity levels (z) and the market clearance conditions determine a vector of prices (p).

Zero profit. Let $\Pi_{ir}^{X}(p)$ denote the unit profit function of industry i in region r which is calculated as the difference between unit revenue (R_{ir}) and unit costs (C_{ir}) where:

$$C_{ir}(p) = \mathit{min}\{p_r^l L_i + p^k K_i + p_r^z R_{zi} + \sum_j p_{jr} x_{ji} \mid F_{ir}(L_{ir}, K_{ir}, R_{zir}; x_{1ir}, \ldots, x_{10ir}) = 1\} \quad (26)$$

$$R_{ir}(p) = \mathit{max}\{\sum_j p_{ir} X_{ir} \mid X_{ir} = 1\}\,. \quad (27)$$

Zero profits implies that no production activity makes positive profits, i.e.:

$$-\,\Pi_{ir}^{X}(p) = C_{ir} - R_{ir} \geq 0 \qquad \perp \qquad X_{ir}\,. \quad (28)$$

Similar conditions hold for Armington aggregation ($\Pi_i^x r$).

Market clearance. The second class of equilibrium conditions is that at equilibrium prices and activity levels, the supply of any commodity must balance or exceed demand. For regional output markets we can express this condition as:

$$Y_{ir} \geq \sum_j x_{jr} \frac{\partial \Pi_{jr}^{x}(p)}{\partial p_{ir}^{Y}} \qquad \perp \qquad p_{ir}^{Y} \quad (29)$$

where p_{ir}^{Y} is the price of Y_{ir}. The market for Armington good i is in balance if:

$$x_{ir} \geq \sum_j Y_{jr} \frac{\partial \Pi_{jr}^{Y}(p)}{\partial p_{ir}^{x}} + \frac{\partial p_r^I}{\partial p_{ir}^{x}} I_r + \frac{\partial p_{GP}^{x}}{\partial p_{ir}^{x}} GP + d_{ir}(p, M_r) \qquad \perp \qquad p_{ir}^{x} \quad (30)$$

where by Shephard's Lemma the first three summands on the right-hand side represent the demand of good i by the constant returns to scale production, investment, and government sectors, respectively. Final demands $d_{ir}(p, M_r)$ are derived from the budget-constrained maximization:

$$d_{ir}(p, M_r) = \mathit{argmax}\{U(x_{1r}, \ldots, x_{10r}, q, w, l) \mid \sum_i p_{ir}^{x} x_{ir} + p_r^q q + p_r^w w + p_r^l l = M_r\} \quad (31)$$

where $U(\cdot)$ is a CES utility index and exhibits local non-satiation. Market clearance conditions for labor, capital, and natural resources are given by:

$$\sum_j Y_j \frac{\partial \Pi_{jr}^{Y}(p)}{\partial p_r^f} + d_{fr}(p, M_r) \geq \sum \omega_r^f \qquad \perp \qquad p_r^f \quad (32)$$

where $f = \{k, l; 1, \ldots, Z\}$ denotes the set for primary production factors (labor, capital, and natural resources). Market clearance conditions requiring balanced intra-national trade for non-

[26] The third condition simplifies implementation and may be substituted out of the model without altering the basic logic (as in Mathiesen, 1985).

energy goods that are traded on a bilateral basis are omitted here for simplicity.

Foreign closure of the model is warranted through a national balance-of-payments constraint which determines the price of foreign exchange:

$$\sum_i EX_i + B = \sum_i IM_i \frac{\partial pdfm_i}{\partial pfx} \qquad \perp \qquad pfx \tag{33}$$

where the level of foreign exports (EX) and imports (IM), is determined by conditions (**??**) and (**??**).

Income balance. The income balance conditions are given by (21).

Appendix C: Algebraic description of the solution algorithm to integrate the bottom-up electricity model within the GE model

This section provides an algebraic description of the integrated model.[27] Let $n = 1, \ldots, N$ denote an iteration index and consider first the economy-wide component. The least-cost input requirements obtained from solving the electricity generation model in iteration $(n-1)$ are used to parameterize the general equilibrium model in (n). This is accomplished by defining the market clearing condition for electricity (29) as:

$$\sum_{g,t} Y_t^{g^{(n-1)}} \geq \sum_j x_{jr}^{(n)} \frac{\partial \Pi_{jr}^{x^{(n)}}(p)}{\partial p_{ir}^{Y^{(n)}}} \qquad \perp \qquad p_{ir}^{Y^{(n)}} \qquad i = ele \tag{34}$$

where the left-hand side represents electricity supply as defined in (41). Demand for input i comprising fuels and other materials by the electricity sector is accommodated through:

$$Y_{ir}^{(n)} \geq \sum_j x_{jr}^{(n)} \frac{\partial \Pi_{jr}^{x^{(n)}}(p)}{\partial p_{ir}^{Y^{(n)}}} + \sum_{g,t} \phi_i^c \, c^g \, Y_t^{g^{(n-1)}} \qquad \perp \qquad p_{ir}^{Y^{(n)}} \tag{35}$$

where ϕ_i^f and ϕ_i^c represent the benchmark value share of good i in variable generation costs. Factor market conditions (32) for capital and labor are modified according to:

$$\sum_j Y_j^{(n)} \frac{\partial \Pi_{jr}^{(n)}(p)}{\partial p_r^{f^{(n)}}} + d_{fr}^{(n)}(p, M_r) + \sum_{g,t} \phi_f^c \, c^g \, Y_t^{g^{(n-1)}} \geq \sum \omega_r^f \qquad \perp \qquad p_r^f \tag{36}$$

In addition, we modify the income balance (21) to account for technology-specific rents and profits (Π_r^{ELE}):

$$M_r^{(n)} = p^{k^{(n)}} \omega_r^k + p_r^{l^{(n)}} \omega_r^l + \sum_z p_r^{z^{(n)}} \omega_r^z + T_r^{(n)} + \Pi_r^{ELE^{(n)}} \, . \tag{37}$$

Electricity-sector output and inputs are valued implicitly at market prices, and hence we do not need to include capacity rents and profits explicitly in the economy-wide model:

$$\Pi_r^{ELE^{(n)}} = \sum_{g \in r} \sum_t Y_t^{g^{(n-1)}} \left(p_{ele,r}^{Y^{(n)}} \, P^{r^{(n-1)}} - P_r^{\mathrm{c}^{(n)}} c^g \right) \tag{38}$$

where the price indexes for variable generation costs are updated according to:

$$P_r^{\mathrm{f}^{(n)}} = \sum_f \phi_f^f \, p_r^{f^{(n)}}$$

$$P_r^{c^{(n)}} = \sum_i \phi_i^c \, p_{ir}^{Y^{(n)}} + \sum_f \phi_f^c \, p_r^{f^{(n)}} \, ,$$

respectively.

[27] Before applying the algorithm, we reconcile the benchmark datasets of the two models. Initial agreement in the benchmark is achieved if electricity sector outputs and inputs over all regions and generators are consistent with the aggregate representation of the electricity sector in the SAM data that underlies the GE framework. This step is necessary to ensure that in the absence of a policy shock iterating between both sub-models always returns the no-policy benchmark equilibrium. The calibration procedure is described in Lanz and Rausch (2011).

In the electricity generation model, the demand schedules are parameterized to locally approximate the response of the top-down model. In each iteration step, the linear function is re-calibrated to price and quantities derived from the top-down solution. Hence the demand function for a regulated operator f in iteration n (compare with (7)) is updated according to:

$$D^{f^{(n)}} = \overline{D}^{f^{(n)}} \zeta^{f^{(n)}} \left(1 + \epsilon \left(\frac{P^{f^{(n)}}}{\overline{P}^{f^{(n)}} \xi^{f^{(n)}}} - 1 \right) \right) \tag{39}$$

where

$$\zeta^{f^{(n)}} = \sum_j x_{jr}^{(n)} \frac{\partial \Pi_{jr}^{x^{(n)}}(p)}{\partial p_{ir}^{Y^{(n)}}} \overline{D}^{f^{(0)}} \quad , f \in r$$

$$\xi^{f^{(n)}} = p_{ele,r}^{Y^{(n)}} \overline{P}^{f^{(0)}} \quad , f \in r$$

are scale factors that are based on the n^{th} solution of the economy-wide model, and reference demand ($D^{f^{(0)}}$) and price ($\overline{P}^{f^{(0)}}$). A similar updating rule applies to wholesale electricity demand in (12).

Finally, using the updated variable cost indexes, the revised unit profit functions for Cournot players and for price takers in iteration (n) are given by:

$$\pi_t^{g^{(n)}} = \begin{cases} p_t^{r^{(n)}} + \dfrac{\partial D^{r^{(n)}}(p_t^r)}{\partial Y_t^{g^{(n)}}}^{-1} - P_r^{c^{(n)}} c^g - \mu_t^{g(n)} & \text{if } g \in r \text{ is a Cournot player} \\ p_t^{r^{(n)}} - P_r^{c^{(n)}} c^g - \mu_t^{g^{(n)}} & \text{if } g \in r \text{ is a price taker} . \end{cases} \tag{40}$$

Non-negative profits and average cost pricing conditions for regulated operators in iteration (n) are given by:

$$P^{c^{(n)}} c^g \geq \overline{C}_t^{f^{(n)}} \quad \perp \quad Y_t^{g^{(n)}} \geq 0 , \tag{41}$$

$$P^{f^{(n)}} = \frac{\sum_{g \in G_f} \sum_t P^{c^{(n)}} Y_t^{g^{(n)}} c^g}{D^{f^{(n)}}} . \tag{42}$$

Appendix D: Algebraic description of the solution algorithm to integrate the heterogeneous households into the GE model

To illustrate the key idea of the algorithm, we develop the following notation for nested utility functions. Let the quantity choices be denoted by q_i, for $i = 1, \ldots, I$, corresponding to commodities with prices p_i, respectively. The utility tree consists of $N+1$ levels, $n = 0, 1, \ldots, N$; on each level we distinguish several utility components. At the highest level (indicated by $n = N$) of the utility tree there is only one component, which corresponds to overall utility; this component is a function of utility components at the next-lower level $n = N-1$. These utility components at $N-1$ are in turn each a function of disjoint groups of utility components at the next lower level $N-2$, and so on. Finally, the utility components at level $n = 1$ are functions of the the elementary utility components.

We specify the utility function for household h by specifying the utility components (for simplicity we suppress the region index). We assume that all the utility components are linear homogeneous CES-type functions of the associated components at the next lower level:

$$q^h_{n,i} = \left[\sum_{j \in i} \theta^h_{n-1,j} \left(\frac{q^h_{n-1,j}}{\bar{q}^h_{n-1,j}} \right)^{\rho^h_{n,i}} \right]^{\frac{1}{\rho^h_{n,i}}} \quad , \quad \rho^h_{n,i} = \frac{\sigma^h_{n,i} - 1}{\sigma^h_{n,i}} \, , \tag{43}$$

where $j \in i$ is used to indicate the set of components $q^h_{n-1,j}$ associated with $q^h_{n,i}$, and where $\sigma^h_{n,i}$ denotes the elasticity of substitution between commodities $j \in i$. Note that we write the nested utility function in calibrated share form (Rutherford, 1995); θ and $\bar{q}$ denote the value share and consumption in the benchmark equilibrium, respectively.

The decomposition algorithm is implemented by replacing in each region the household side with an artificial representative agent (RA) whose utility function exhibits the identical structure as household utility in Eq. (43):

$$Q_{n,i} = \left[\sum_{j \in i} \Theta_{n-1,j} \left(\frac{Q_{n-1,j}}{\bar{Q}_{n-1,j}} \right)^{\tilde{\rho}_{n,i}} \right]^{\frac{1}{\tilde{\rho}_{n,i}}} \quad , \quad \tilde{\rho}_{n,i} = \frac{\tilde{\sigma}_{n,i} - 1}{\tilde{\sigma}_{n,i}} \tag{44}$$

where $\Theta_{n,j}$ and $Q_{n,j}$ denote the respective counterparts for the RA to individual households as defined in Eq. (43). A key insight from Rausch and Rutherford (2010) is that the choice of $\tilde{\sigma}_{n,i}$ is entirely innocuous as this parameter bears no economic significance for the behavior of "real" households in the underlying economic model (it can, however, affect the convergence speed of the iterative solution procedure).

Given benchmark data on observable household demand $\bar{q}^h_i$ and prices $\bar{p}_i$, we initialize the RA general equilibrium model such that commodity demands are consistent with the aggregate of benchmark household demands. This is achieved by calibrating consumption ($\bar{Q}$) and value share (Θ) parameters as:

$$\bar{Q}_{n,j} = \sum_{h=1}^{H} \bar{q}^h_{n,j} \, , \tag{45}$$

$$\Theta_{n,j} = \frac{\bar{p}_{n,j} \bar{Q}_{n,j}}{\sum_{j' \in i} \bar{p}_{n,j'} \bar{Q}_{n,j'}} \, . \tag{46}$$

Solving for a carbon policy shock involves first solving the RA model to obtain a candidate vector of general equilibrium prices $\mathbf{p}^k$. k denotes an iteration index. The second step solves a partial equilibrium relaxation of the underlying economy by evaluating household demand functions

$q_{n,i}^{h,k}(\mathbf{p}^k, y^k)$, where household income y^k is updated sequentially at prices in iteration k. The key step in each iteration involves "re-calibrating" preferences of the RA based on partial equilibrium households' quantity choices:

$$\bar{Q}_{n,i}^{k+1} = \sum_{h=1}^{H} q_{n,i}^{h,k}(\mathbf{p}^k, y^k)\,, \tag{47}$$

$$\Theta_{n,j}^{k+1} = \frac{\bar{p}_{n,j}^k \sum_{h=1}^{H} q_{n,j}^{h,k}(\mathbf{p}^k, y^k)}{\sum_{j' \in i} \bar{p}_{n,j'}^k \sum_{h=1}^{H} q_{n,j'}^{h,k}(\mathbf{p}^k, y^k)}\,. \tag{48}$$

Note that this iterative procedure never alters preferences of the "real" households; it simply "re-benchmarks" successively the utility function of the artificial representative household to be consistent with the aggregated choices of individual households in each iteration.