California's cap-and-trade program and emission leakage in the Western Interconnection: comparing econometric and partial equilibrium model estimates

Chiara Lo Prete Ashish Tyagi Qingyu Xu*

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Abstract

We compare the effects of California's AB 32 cap-and-trade program on leakage in the electricity sector using two methods: a simulation-based partial equilibrium model that accounts for details of policy implementation and is parameterized using market data; and an econometric model applying a quasi-experimental design with matching and a robust inference method that does not require parallel trends to hold exactly. Based on the estimated shifts in electricity generation, we infer CO_2 emission leakage predictions in 2013 and 2016. The comparison allows us to identify critical assumptions driving the simulation results, and to benchmark the empirical results in a complex policy setting where threats to identification undermine attempts at statistical inference. Over the study period, we find significant leakage potential *ex ante* and empirical evidence that is consistent with some resource shuffling *ex post*. Limiting the ability of electricity importers to claim the default emission factor may reduce leakage risks.

*Lo Prete: John and Willie Leone Family Department of Energy and Mineral Engineering, The Pennsylvania State University, University Park, PA (email: chiaraloprete@psu.edu); Tyagi: Frankfurt School of Finance & Management, Frankfurt am Main (a.tyagi@fs.de); Xu: Andlinger Center For Energy And Environment at Princeton University (qingyux@princeton.edu). Cody Hohl provided excellent research assistance. We thank the editor and three anonymous referees for insightful comments and suggestions, which have greatly improved the quality of our paper. We are grateful for feedback from seminar participants at Penn State, Harvard University, Lehigh University, Sandia National Laboratories and Sant'Anna School of Advanced Studies, as well as conference participants at the 2016 USAEE/IAEE North American Conference, 2016 Annual Meetings of the Southern Economic Association, 2017 USAEE/IAEE North American Conference, 2017 International Workshop in Empirical Methods on Energy Economics, 2017 Rutgers Annual Eastern Conference, 2018 Atlantic Workshop on Energy and Environmental Economics, 2018 Mannheim Energy Conference, 2019 Annual Conference of the European Association of Environmental and Resource Economists, and 2019 USAEE/IAEE North American Conference. All errors are our own. Lo Prete gratefully acknowledges the support of The Pennsylvania State University, the Alfred P. Sloan Foundation (grant 2018-11301) and the National Science Foundation (grant 1832290). Tyagi thanks the Robert Bosch Foundation for financial support. Xu gratefully acknowledges funding from The Johns Hopkins University and the Department of Energy (SETO EE0008215). The authors have no affiliation or involvement in an organization or entity with a financial or non-financial interest in the subject matter or materials discussed in this manuscript.

1 Introduction

California has been at the forefront of U.S. environmental policies for years. The Global Warming Solutions Act of 2006 (also known as Assembly Bill 32 or AB 32) set the state's target to reduce greenhouse gas (GHG) emissions to 1990 levels by 2020. In September 2016, California passed Senate Bill 32 (SB 32), which limited emissions to 40% below 1990 levels by 2030. Further, Executive Order S-3-05 set a GHG emission reduction target of 80% below 1990 levels by 2050. In order to achieve these ambitious goals, the state relies on a suite of policies, including a multi-sector cap-and-trade program that covers about 85% of the state's emissions from large industrial facilities, electricity generators and importers, and transportation fuel suppliers.

A central issue in the implementation of cap-and-trade programs is represented by the choice of the point of regulation. For example, the Regional Greenhouse Gas Initiative (RGGI), an emission trading system for CO_2 emissions from electricity generation in U.S. Northeastern and mid-Atlantic states, adopted a source-based approach where the point of regulation is at the generator level. Given its reliance on imports to satisfy electricity consumption,[1] California opted instead for a first deliverer approach, whereby entities that own electricity at the first point of delivery in the state represent the point of regulation: in-state generators must monitor and report their emissions following a source-based paradigm, while electricity importers are responsible for emissions associated with in-state sales.

The introduction of a border adjustment mechanism for the electricity sector was intended to mitigate concerns of leakage, defined as the shift in production and associated emissions from the region where climate regulations apply to surrounding unregulated jurisdictions (Stavins et al., 2010). However, simulation-based studies quantifying the impacts of the prospective cap-and-trade scheme concluded that resource shuffling may enable substantial leakage (Bushnell, Peterman and Wolfram, 2008; Fowlie, 2009; Chen et al., 2011; Bushnell et al., 2014). Contract shuffling represents a prime example. Under contract shuffling, electricity contracts are rearranged so that production from low emission sources serving out-of-state consumption (or load) is directed to California, while production from higher emission sources is assigned to serve out-of-state load (Burtraw et al., 2018). This would result in apparent emission reductions due to changes in the composition of imports to California, although emissions in exporting regions are unchanged or even increase. In recent years, the decrease in GHG emissions from the electric power sector in California has been attributed primarily to measured reductions in emissions from imports (California Air Resources Board, 2020b). This underscores the importance of assessing whether leakage has occurred and considering potential policy modifications to

[1] In 2016, California imported about a third of its total electricity consumption from out of state (California Energy Commission, 2017).

mitigate its impacts.

In this paper, we seek to identify CO_2 emission leakage in the electricity sector from California's AB 32 cap-and-trade program in the first four years of policy implementation. We estimate shifts in electricity generation at baseload power plants in the Western Interconnection[2] based on two models: a simulation-based partial equilibrium model of the electricity sector that includes salient features of the observed cap-and-trade program and is parameterized using market data in 2013-2016; and an econometric model applying a quasi-experimental design with matching and a robust inference method that does not require the parallel trends assumption to hold exactly. Based on the estimated shifts in electricity generation, we infer CO_2 emission leakage predictions in 2013 and 2016. We then compare the *ex ante* expected impacts of the policy to the *ex post* realized impacts. This allows us to identify critical assumptions driving the simulation results, and to benchmark the empirical results in a complex setting where threats to identification (i.e., the suite of changes that affected California's electricity market over the period of our study, and challenges associated with the construction of credible counterfactual outcomes) undermine attempts at statistical inference. Earlier studies compared *ex ante* estimates of the effect of regional environmental policies with *ex post* empirical results (Carlson et al., 2000; Ellerman et al., 2000; Carbone et al., 2020). To our knowledge, ours is the first attempt to benchmark emission leakage predictions based on estimates from a quasi-experimental econometric model against the results of a partial equilibrium model designed to study the effects of a cap-and-trade program.

The remainder of the paper is organized as follows. Section 2 reviews the literature on emission leakage. Section 3 provides an overview of California's cap-and-trade program and complementary emission reduction measures under AB 32. Section 4 presents the econometric model specification, data and results. Section 5 describes the simulation model and results. Section 6 compares the econometric and simulation results, and Section 7 provides concluding remarks.

2 Literature review

The potential for emission leakage in the electricity sector under regional climate policies has been analyzed using numerical models. A first strand of the literature includes simulation-based partial equilibrium models of the electricity sector. For example, Fowlie (2009), Chen et al. (2011), Bushnell and Chen (2012) and Bushnell et al. (2014) explore leakage in the context of California's prospective cap-and-trade program for

[2] California is part of the Western Interconnection, a synchronous electric grid that encompasses all or parts of 14 Western states in the U.S., the Canadian provinces of Alberta and British Columbia, and Northern Baja California in Mexico. Since reliability within the area is overseen by the Western Electric Coordinating Council, this synchronous grid is commonly referred to as WECC. Figure 1 presents the U.S. part of WECC.

GHG emissions (i.e., before regulations were finalized). Fowlie (2009) presents an analytical model to develop intuition about how industry features affect emission leakage and social welfare in an incompletely regulated and imperfectly competitive industry. Based on the theoretical framework, she develops a numerical model to simulate CO_2 emissions and other equilibrium outcomes in California's electricity sector under three carbon policy scenarios and alternative assumptions about firm conduct. Results suggest that a cap-and-trade program that only applies to in-state electricity producers would achieve about a third of emission reductions obtained under complete regulation at a higher cost per ton. Chen et al. (2011) formulate a market equilibrium model to compare source-based, load-based and first deliverer approaches for cap-and-trade regulation in California, and examine economic and emission implications on the electricity market. Under the first deliverer approach that was ultimately pursued in California, total emissions in the Western Interconnection decrease much less than regulated emissions, implying a leakage rate of 85%. Simulation results also indicate that significant reshuffling takes place under this scenario: while the emissions of electricity imports to California decrease due to changes in their composition, the emissions in the rest of the Western Interconnection actually increase under regulation. In a similar vein, Bushnell and Chen (2012) and Bushnell et al. (2014) simulate the impacts of CO_2 caps that only apply to California or cover all states in the Western U.S. under alternate assumptions, and conclude that a first deliverer approach in California is vulnerable to leakage due to laundering and reshuffling of import resources. Finally, Xu and Hobbs (2021) examine the potential cost and emission impacts of alternate border carbon adjustment (BCA) schemes under California's AB 32 cap-and-trade system using the Johns Hopkins Stochastic Multistage Integrated Network Expansion (JHSMINE) model. They find that dynamically setting a facility-neutral deemed rate based on marginal units outside of California would provide efficiency gains, relative to facility-based schemes like the one that is currently implemented.

The impacts of regional climate policies have also been studied with computable general equilibrium models (Carbone and Rivers, 2017). While the partial equilibrium models discussed above focus on short-run operations, general equilibrium models are useful to illustrate the impacts of carbon pricing policies on other sectors of the economy, and may consider the effects on long-run capital decisions (Shawhan et al., 2014). In the context of California's cap-and-trade program, Caron et al. (2015) find that the policy would result in only a small amount of emission leakage (9%), when imported electricity is included in the cap and provisions to prevent reshuffling are enforced. Without such measures, the authors estimate that 45% of emission reductions would be offset by leakage, in line with the range of predictions obtained by general equilibrium models for RGGI (Shawhan et al., 2014; Sue Wing and Kolodziej, 2009).

Empirical analyses of leakage are less common in the literature. For example, Aichele and Felbermayr (2013a), Aichele and Felbermayr (2013b) and Aichele and Felbermayr (2015) examine leakage in the context of the Kyoto Protocol. With respect to RGGI, Kindle et al. (2011) analyze the relation between CO_2 permit prices and transmission power flows on seven high-voltage interties between New York and Pennsylvania between 2008 and 2010. Higher net flows from Pennsylvania to New York associated with a higher RGGI allowance price would indicate leakage. The authors do not find a significant impact of RGGI permit prices on PA-NY transmission flows, but prices may have been too low to affect leakage in the early years of the program. Fell and Maniloff (2018) use a differences-in-differences model to estimate how RGGI affected the operations of power plants in the regulated region and nearby states, and examine changes in electricity transmission flows into the RGGI region after policy implementation. They find that the cap-and-trade program led to a reduction in coal-fired generation in the regulated region and an increase in cleaner NGCC generation in the unregulated region, resulting in lower total emissions across regions. The implied leakage rate of approximately 50% is within the range of *ex post* leakage predictions from subsequent empirical analyses (Zhou and Huang, 2021). Chan and Morrow (2019) also investigate leakage from RGGI, but their analysis focuses on SO_2 emissions and associated damages, instead of CO_2 emissions.

Finally, a growing body of research in economics assesses the potential for leakage risk across sectors (Fowlie and Reguant, 2018), and explores how environmental regulation affects trade flows and the location choice of firms in the long run (Levinson and Taylor, 2008; Kahn and Mansur, 2013; Aldy and Pizer, 2015; Fowlie et al., 2016; Panhans et al., 2017; Saussay and Sato, 2018).

Our paper is most closely related to Xu and Hobbs (2021) and Fell and Maniloff (2018), but differs from these earlier contributions to the literature in several important ways. The version of JHSMINE in this paper contributes to the literature because it enables more direct comparisons with the econometric results than those allowed by previous simulation models, which may make assumptions that do not align with the details of actual policy implementation or use different data for parameterization. In particular, we revise the model formulation in Xu and Hobbs (2021) to accommodate the observed cap-and-trade regime, and parameterize the model using actual market data in 2013-2016. Relative to Fell and Maniloff (2018), we strengthen the identification strategy using coarsened exact matching, adopt robust methods to conduct statistical inference under potential violations of parallel trends, and benchmark leakage predictions based on the empirical estimates against simulation-based results. However, we are unable to estimate a model of inter-regional electricity transmission due to the lack of historical data on hourly power flows between balancing authorities in WECC over the period of our analysis.

3 Policy background

California adopted legislation limiting GHGs by passing AB 32, which established a statewide target of reducing GHG emissions to their 1990 levels (431 million metric tons of CO_2e (California Air Resources Board, 2014)) by 2020. To achieve the expected emission reductions to meet the 2020 limit (79 million metric tons of CO_2e), the California Air Resources Board (CARB) outlined a mix of recommended actions combining direct regulations, market-based approaches and incentives in the initial Scoping Plan (California Air Resources Board, 2008) and First Update (California Air Resources Board, 2014). A key element of CARB's emission reduction strategy was the development of a cap-and-trade program to provide a firm cap on the sectors responsible for the majority of California's GHG emissions (i.e., transportation, electricity and industrial sectors). Within the capped sectors, emission reductions would be accomplished through price incentives created by allowance prices, as well as direct regulations. CARB also recommended reduction measures for the uncapped sectors (e.g., agriculture, recycling and waste). The rationale for this combination of approaches was that complementary measures are needed to overcome market barriers that would persist, if the cap-and-trade system were the only policy employed to implement AB 32 (California Air Resources Board, 2008). The next sections provide an overview of the cap-and-trade-program and complementary measures aimed at reducing emissions from the energy sector.

3.1 Cap-and-trade program overview

California's cap-and-trade program regulates GHG emissions from large industrial facilities, electricity generators and importers, and transportation fuel suppliers. Covered entities emit at least 25,000 metric tons of CO_2e per year and are responsible for about 85% of the state's 2015 GHG emissions (California Air Resources Board, 2010, 2013). The first phase of compliance for the program began on January 1, 2013. The 2013 emission cap was set at approximately 98% of forecast 2012 emissions, with an annual decline of 2% in 2014 and 3% from 2015 through 2020. Based on CARB projections, the program was expected to drive about 23% of emission reductions needed to reach 1990 levels (California Air Resources Board, 2013). In July 2017, the scheme was extended through 2030 with bipartisan support.

CARB issues annual emission allowances equal to the cap, and each allowance represents a permit to emit one ton of carbon dioxide equivalent. Entities must monitor and annually report their emissions, and return an amount of allowances equivalent to their GHG emissions each year. Capped sources that keep emissions below the allowance amount can sell excess permits on the market, while sources that cannot cover total emissions may take measures to reduce pollution and/or buy allowances on the market.[3] Emission allowances are distributed to covered entities through a mix of free allocation and quarterly auctions, with a declining share of free permits over time (California Air Resources Board, 2022a): in 2016, the last year in our period of study, 50% of allowances were given away for free, and 46% were auctioned (Legislative Analyst's Office, 2017).[4] California adopts an output-based benchmarking allocation approach for most industrial sectors, whereby the allocation of allowances is set at 90% of average emissions, based on benchmarks that reward efficient facilities, and updated annually according the production at each facility. Allowances are allocated to electric distribution utilities (EDUs) based on historical emissions, current generation mix, sales, and efforts at reducing emissions since the passage of AB 32 (Alcorn, 2013). Investor-owned utilities (IOUs) must consign their allowances to auction, while publicly owned utilities (POUs) may put their allowances up for auction or use them to meet compliance obligations. The revenue from these auctions must be used to provide rebates or bill relief to utility customers (Legislative Analyst's Office, 2017). CARB allows banking and borrowing of allowances, and the risk of unexpected price changes and excess volatility is mitigated through a price collar; secondary market allowance prices have generally hovered at or near the auction price floor from market launch to 2016 (Cullenward and Coghlan, 2016).

Under California's approach to regulate the electricity sector, the first entity that delivers load to the California grid has a compliance obligation. When electricity generation occurs within the state, generators must submit compliance instruments (allowances and offset credits) for the associated emissions. When electricity generation occurs out of state, the compliance obligation falls instead on the electricity importers, who must submit compliance instruments to cover the emissions generated for each MWh of imported electricity. Since energy entering the grid flows over the path of least resistance (rather than directly from an injection point to a withdrawal point), the CO_2 intensity of electricity imported in California from the rest of the Western Interconnection cannot generally be determined unambiguously.[5] To address the issue, CARB classifies imports as specified or unspecified source power.

Specified sources include generation resources owned by or under long-term contract to California's load serving entities, as well as generation resources owned by non-California entities that are approved and registered by CARB (California Air Resources Board, 2022c). First deliverers may claim facility-specific emission factors for power imports from out-of-state generation resources that are owned or under long-term

[3] Covered entities may also use carbon offsets (e.g., GHG emission reductions from projects outside the scope of the cap-and-trade regulation) to cover up to 8% of their emissions.

[4] The remaining 4% were made available at predetermined prices to reduce price volatility.

[5] The e-Tag functionality has been used to track proof of energy delivery within the Western Interconnection, but is complex to implement (WECC Staff, 2019).

contract. Further, CARB has developed the designation of Asset-Controlling Suppliers for out-of-state electric power entities that operate interconnected generating facilities. Once approved and registered by CARB, Asset-Controlling Suppliers are assigned a system emission factor for wholesale electricity procured from their systems and imported into California. For example, specified source power from Bonneville Power Administration (BPA) and Powerex (a subsidiary of BC Hydro) must be reported using CARB-approved emission factors reflecting the hydro-dominant resource portfolio of these systems (California Air Resources Board, 2022b). Specified sources mainly consist of coal, natural gas and nuclear power from the Southwest, and of hydro and wind power from the Northwest (California Energy Commission, 2017).[6]

In contrast, unspecified source power corresponds to wholesale market purchases from power plants that do not have a contract with a California utility and have not gone through the CARB process to become specified. Between 2013 and 2016, unspecified power represented about 26% of total imports, on average (California Air Resources Board, 2020a). Since in this case the generation source is unknown, unspecified sources are assigned a default emission factor of 0.428 metric ton CO_2/MWh, which was set by CARB based on the generation technology expected to be at the margin in WECC (Bushnell et al., 2014). Much of the Northwest spot market purchases are served by surplus hydro and gas-fired plants, while Southwest spot market purchases generally come from coal and natural gas combined cycles (California Energy Commission, 2017). The presence of a default emission factor creates an incentive for electricity importers to not report the emission content of out-of-state higher-emitting generation resources, in order to attain the lower default emission factor ("laundering"). This has been identified as one of the primary types of resource shuffling (Alcorn, 2013), defined by CARB as "any plan, scheme, or artifice undertaken by a First Deliverer of Electricity to substitute electricity deliveries from sources with relatively lower emissions for electricity deliveries from sources with relatively higher emissions to reduce its emissions compliance obligation" (Cal. Code Regs., Title 17, Article 5, § 95802(a)). As discussed in Section 1, resource shuffling would lead to apparent emission reductions due to changes in the composition of imports to California, although emissions in the exporting regions are unchanged or even increase. As a result, it creates potentially severe leakage risks for the electricity sector in California. In response to these concerns, CARB released a guidance document listing a number of "safe harbor" exceptions to the regulatory ban on resource shuffling (i.e., transactions deemed not to be resource shuffling) (Cal. Code Regs., Title 17, Article 5, § 95852(b)(2)). This approach has been controversial because it is difficult to identify all potential violations *ex ante* (Bushnell et al., 2014). Further, allowance

[6] According to the Commission's definition, the Northwest region includes Alberta, British Columbia, Idaho, Montana, Oregon, South Dakota, Washington and Wyoming. The Southwest region includes Arizona, Baja California, Colorado, Mexico, Nevada, New Mexico, Texas and Utah (California Energy Commission, 2017).

prices hovering near the auction floor have been interpreted as evidence that contract shuffling is taking place, enabling regulated entities to avoid a significant part of their carbon liability and reducing demand for allowances (Borenstein et al., 2014; Cullenward and Coghlan, 2016).

3.2 Overview of AB 32 complementary measures in the energy sector

In addition to creating a cap-and-trade program, the initial Scoping Plan and its Update set forth a comprehensive list of recommended actions for improving energy efficiency, expanding the use of renewable energy resources and cleaner transportation, and reducing waste (California Air Resources Board, 2008, 2014). This section highlights significant measures to help achieve the state's 2020 target and support GHG emission reductions in the energy sector. However, measures that are designed to directly address GHG reductions in other sectors, which are not discussed here, may also have impacts on the energy sector (e.g., electrification in the transportation sector increases electricity demand).

A key measure to support the high-level objectives for the energy sector is California's renewable portfolio standard (RPS). Originally enacted in 2002, the RPS set a goal of achieving a statewide renewable energy mix of 20% by 2010. In 2011, Senate Bill 2 created one of the most aggressive renewable energy goals in the United States, requiring California's electric utilities and retail sellers to serve 33% of customer needs with clean renewable energy by 2020, with intermediate requirements of 20% by 2013 and 25% by 2016. The RPS, combined with programs like the California Solar Initiative and federal tax credits, spurred significant growth in utility-scale projects and customer installations over the period of our study (Bushnell and Novan, 2018). CARB estimated that achieving a 33% renewable mix by 2020 would avoid about 11 million metric tons of CO_2e (California Air Resources Board, 2013), and counted the avoided emissions towards the reductions needed to achieve the 2020 target established by AB 32.

Energy efficiency recommendations set new targets for statewide annual energy demand reductions of 32,000 GWh and 800 million therms. Strategies include, among others, more stringent building and appliance efficiency standards, and utility energy efficiency programs in the residential and non-residential sectors. Based on CARB projections, energy efficiency measures would drive approximately 12 million metric tons of CO_2e of emission reductions by 2020 (California Air Resources Board, 2013). The Scoping Plan also requires increased use of combined heat and power units by setting a goal for 4,000 MW of new installed capacity by 2020, enough to displace about 30,000 GWh of demand from other power generation sources. Finally, the Plan establishes incentive programs to promote the installation of 200,000 solar water heaters and 3,000 MW of new rooftop solar capacity (Million Solar Roofs initiative) by 2017.

4 Econometric model

We econometrically estimate shifts in electricity generation in the Western Interconnection after the introduction of California's cap-and-trade program using a differences-in-differences framework with matching. Based on these estimates and their confidence intervals, we infer CO_2 emission leakage predictions in 2013 and 2016. This section describes our empirical strategy and results.

4.1 Treated and control designation

The primary leakage mechanism would consist in replacing power generation in the regulated region (California) with generation in the unregulated regions ("leakers" in the Western Interconnection). Since contract shuffling and policy-induced changes in the dispatch order reallocate production among California plants and *all* out-of-state plants in WECC, every plant in the Western Interconnection may be a potential leaker. WECC's footprint includes the Canadian provinces of Alberta and British Columbia, the northern portion of Baja California, Mexico, and all or portions of 14 Western U.S. states. Since data availability is limited for the two Canadian provinces and Northern Baja California, we exclude them from our analysis, and only consider leakers in the U.S. part of the Western Interconnection. Thus, the treated set consists of NGCC and coal-fired plants in the U.S. part of the Western Interconnection (California or leakers), while the control set consists of plants of the same technology type in five NERC regions in the Eastern and Texas Interconnections (FRCC, MRO-US, SERC, SPP and TRE) (Figure 1).[7]

Power plants fall under the operational control of a balancing authority (BA), which is responsible for dispatching generation units and maintaining consumption-interchange-generation balance within a region of the electric grid (National Electric Reliability Council, 2022); WECC balancing authorities in the U.S. are presented in Figure 2. Following the classification in WECC's production cost model (WECC Staff, 2015), leaker balancing authorities are divided into three regions of contiguous connected electrical components. The Northwest (NW) region includes AVA, BPAT, NEVP, PACE, PACW, PGE and PSEI, as well as Utah plants in the LDWP footprint and Nevada plants in the CAISO footprint. Loosely speaking, this region corresponds to the Pacific Northwest, Nevada and Utah. The Southwest (SW) include AZPS, HGMA, SRP, TEPC, WALC, and plants within the CAISO footprint but located in Arizona. Loosely speaking, this region corresponds to Arizona. The Rest of WECC (RoW) includes all other balancing authorities in WECC, i.e. EPE, IPCO, NWMT, PNM, PSCO, WAUW, and WACM. Table 1 presents summary statistics for NGCC

[7]We do not include power plants in RFC and NPCC as controls because these NERC regions largely overlap with the footprint of RGGI, the cap-and-trade program for CO_2 emissions from power generation in the Northeastern and mid-Atlantic United States.

treated and control plants, while Table 2 presents statistics for coal-fired treated and control plants. Since the period of our study was characterized by significant fuel mix changes in the California market, we also report summary statistics for nuclear, hydro and renewable generation in Table A1 of the Appendix.

4.2 Matching

The simplest estimates of the treatment effects of interest can be obtained using an unconditional differences-in-differences (DID) estimator that measures the effect of California's cap-and-trade program on average plant utilization. This approach has some drawbacks. First, constructing counterfactual outcomes using observations on plants from another interconnection poses a challenge, because these plants may have inherently different characteristics from the treated plants. Further, plants with similar average utilization over a period of time may be operated very differently.[8] Constructing counterfactual estimates based on control plants that have similar average utilization over blocks of hours to the treated units allows us to identify pairs that, before policy implementation, held a similar position in the dispatch order of their respective balancing authority. The treatment effect of interest could then be obtained estimating a DID model in which the impact of other changes and shocks affecting plant utilization is captured by the covariates.

In order to mitigate potential bias in the unconditional DID estimates, we improve balance between treated and control groups by matching on pre treatment hourly variables. The basic idea of matching is to find untreated units that are similar to the treated ones in terms of variables that influence the outcome of interest (i.e., so called "matching variables"), except for treatment status. When a matching estimator (like a nearest neighbor estimator or a propensity score-based estimator) is applied, counterfactual outcomes for treated plant j are then inferred using a weighted average of the outcomes of units that are comparable to j, but receive a different treatment. Control units whose observable characteristics are closer to those of plant j are weighed more heavily in the construction of the counterfactual estimate. While earlier empirical work in energy and environmental economics relied on parametric and semi-parametric matching methods,[9] we explore the use of coarsened exact matching (CEM) (Blackwell et al., 2009; Iacus et al., 2011, 2012) to improve balance between treated and control observations before applying a differences-in-differences

[8] To illustrate, consider two periods (1 and 2) and two plants (A in WECC and B in one of the control regions). Suppose that plant A does not produce electricity in period 1 and is operated at 80% of its capacity in period 2, while plant B is operated at 40% of its capacity in both periods. The two plants have the same average utilization, but serve a different role in their respective grid. As a result, A and B do not represent a suitable pair of treated-control observations.

[9] In the context of Southern California's RECLAIM program, Fowlie et al. (2012) use a semi-parametric DID matching estimator of the ATT that compares differences between post and pre treatment NO_x emissions across treated and control plants, and a regression-based adjustment to mitigate bias introduced by poor match quality (Heckman et al., 1997, 1998). As a robustness check, the authors implement a propensity score matching estimator, which relies on a parametric regression model to estimate the propensity score. One disadvantage of this approach is that a misspecified matching model may produce greater imbalance in variables that are omitted from the matching procedure.

estimator. The first step of the CEM procedure is to identify observable variables to match members of the treatment and control populations. Each matching variable is coarsened to a discrete number of bins using a binning strategy, and each combination of bins across matching variables represents a stratum (or archetype). Based on their values for the matching variables, units in the sample are assigned to one stratum, which is used to exactly match members of the two populations. Only units with the same stratum are matched.[10] To correct for the imbalance between the number of treated and control units in each stratum, matched control units receive a weight that normalizes the stratum to the distribution within the treatment group (Iacus et al., 2008). Unlike approximate matching methods (e.g., based on the propensity score), CEM bounds the maximum imbalance between treated and control groups by choosing the coarsening *ex ante*: as the bins for the matching variables become narrower, the bound on the maximum imbalance on the moments of the variables gets tighter. Further, unlike model dependent methods, CEM does not extrapolate counterfactual outcomes when there is limited overlap in the distributions of covariates across treatment and control groups, because matched data are restricted to areas of common empirical support. Recent applications of this matching method are presented in Simcoe and Toffel (2014), Guignet et al. (2018) and Ek and Miliute-Plepiene (2018).

The objective of our matching procedure is to achieve statistically indistinguishable means between treated and control plants across a set of exogenous covariates that are highly correlated with the outcomes of interest (i.e., daily, hourly or time-of-day measures of plant utilization). We use average capacity factors over four blocks of hours within the day, averaged over 2009-2010, as matching variables.[11] Our matching strategy proceeds as follows. First, we choose 2009 and 2010 as pre treatment period, since 2011 was a wet hydrological year in which NGCC plants ran at much lower capacity factors than usual (Nyberg, 2018), and 2012 was the year before compliance obligations began.[12] For each power plant, we average hourly capacity factors over four blocks of hours (morning, afternoon, evening, and night).[13] Next, for each combination of technology type (coal-fired and NGCC) and region (treated and controls), we create a histogram of capacity factors by

[10] To illustrate, consider two matching variables. The first variable is divided into 3 bins (A, B, and C), while the second variable is divided into 2 bins (D and E). The resulting strata are AD, BD, CD, AE, BE and CE. Control units in any stratum are matched to treated units in the same stratum.

[11] Capacity factors are a percentage measure of plant utilization over a period of time and represent the dependent variable of our DID model, as discussed in Section 4.3. Historic capacity factors over blocks of hours in 2009-2010 are expected to be a good predictor of capacity utilization in the following years: hence, we choose them as matching variables. We also experiment with matching on other observable factors that could be correlated with plant utilization, such as heat rate (a measure of efficiency) and age. Since including these factors as additional matching variables reduces the control sample size without substantially improving the quality of our matches, we do not take this approach.

[12] We also remove from the matching dataset outliers (i.e., plants for which generation from CEMS is greater than generating capacity from EIA) and plants that were operating for less than 3 years over the period of our study.

[13] Following NREL's classification (National Renewable Energy Laboratory, 2019), the morning block is from 6am to 1pm, the afternoon block is from 1pm to 5pm, the evening block is from 5pm to 10pm, and the night block is from 10pm to 6am.

block of hours (averaged over 2009-2010) with 10 bins of equal width. The empirical distributions of capacity factors by technology type, treated/control region and block of hours are presented in Figure 3.[14] We then define four matching bins corresponding to different levels of plant utilization in each block: matching bin 1 (low utilization) includes the first three histogram bins in the lower tail of the distribution; matching bin 2 (medium-low utilization) includes histogram bins 4 and 5; matching bin 3 (medium-high utilization) includes histogram bins 6 and 7; matching bin 4 (high utilization) includes the last three histogram bins in the upper tail of the distribution. In order to improve the quality of our matches, we create smaller matching bins in the middle of the distribution. Further, we coarsen each matching variable according to cut points given by the upper and lower limits of the matching bins for the treated plants. The final step is to perform exact matching on these bins and discard observations from bins that do not contain both treated and control observations.[15]

4.3 Differences-in-differences

After pruning observations that have no close matches on pre treatment variables in both treated and control groups, we econometrically estimate changes in power plant utilization in the Western Interconnection using the following DID model specification:

$$Y_{jt} = \alpha_C TREAT_{jt}^{C} + \sum_{L} \alpha_L TREAT_{jt}^{L} + \mathbf{X}_{jt}^{'}\underline{\beta} + \gamma_j + \gamma_y + \gamma_{dw} + \gamma_{sm} + \epsilon_{jt} \qquad (1)$$

where j indexes a plant-technology, t indicates a period, L denotes a leaker region, and y, dw and sm stand for year, day-of-week and state by month-of-year respectively. We focus on two baseload technology types that are most likely affected by the policies (natural gas combined cycle or NGCC plants and coal-fired plants), and run separate regressions by technology.[16] The dependent variable Y_{jt} is the capacity factor of plant-technology j in period t (day or hour), defined as the ratio of net generation over operating capacity multiplied by total number of hours in the period.[17]

[14] Figure A1 in the Appendix presents additional detail by WECC region.

[15] We experiment with an alternate two-step strategy that matches by annual average capacity factors on blocks of hours first, and then by seasonal average capacity factors on those blocks. We also test robustness to an alternate binning strategy with five matching bins, where matching bin 1 includes the first two histogram bins in the lower tail of the distribution; matching bin 2 includes histogram bins 3 and 4; and so on. Both strategies yield results that are similar to those in the baseline, and thus we do not present them in the paper.

[16] Natural gas steam turbines represent a small fraction of generating capacity in the WECC region. Other technology types like natural gas combustion turbines and oil turbines that are used as peaker plants during high load periods are unlikely to have responded to California's carbon policy, given the modest level of permit prices over the period of our study.

[17] Capacity factors provide a measure of capacity utilization that is independent of plant size. Based on the estimated shifts in capacity utilization, we infer CO_2 emission leakage effects. An alternate (and more direct) approach consists in estimating a model with net generation or emissions at the plant as dependent variable, and capacity as an additional covariate to control for plant size. During the period of our study, there is no significant variation in installed capacity, which is thus correlated with

The treatment of interest is the introduction of California's cap-and-trade program on January 1, 2013. Subject to the identification assumptions in Section 4.5.2, the estimated treatment effects α_C and α_L measure the average effect of the cap-and-trade program on capacity factors of matched facilities in California and the leaker regions, conditional on the covariates. $TREAT_{jt}^{C}$ is a treatment dummy equal to 1 if plant j is in California and t is January 2013 or later; $TREAT_{jt}^{L}$ is similarly defined for plants in leaker region L. The construction of a credible counterfactual against which to measure the effects of the cap-and-trade program is difficult because a suite of coincident changes affected California's electricity market over the study period. For example, the increase in solar generation brought about by the aggressive renewable portfolio standard significantly impacted California's wholesale electricity market outcomes (Bushnell and Novan, 2018). Other complementary measures in the Scoping Plan under AB 32 also affected utilization of baseload power plants in the Western Interconnection. We control for the impacts of these coincident changes through a broad set of determinants of capacity factors in $\mathbf{X}_{jt}^{'}$, as discussed below.

Hydro, nuclear and renewable generation affect capacity utilization at NGCC and coal-fired plants, and are available at the monthly level over the period of our study. Since BAs are responsible for dispatching generation units and maintaining consumption-interchange-generation balance within a region of the electric grid, we might conceivably control for non-fossil generation within the plant's BA. Instead, we consider in-state (not in-BA) non-fossil generation for two reasons. First, renewable portfolio standards are defined at the state level, and state policies may impact nuclear power use and capacity. Second, our dataset includes many small BAs (e.g., GRMA and HGMA), as well as large BAs spanning several states (e.g., MISO and SPP): when BAs are too small, hydro, nuclear and renewable generation is sparse, and does not allow for the use of cubic splines; when BAs are too large, in-BA nuclear and renewable generation conflate the effects of various policies at the state level. We model in-state hydro, nuclear and renewable generation using cubic splines, with coefficients that may vary by NERC interconnection and time of day.

We also control for non-fossil substitutes of a plant at two additional geographic scales. First, we calculate monthly shares for hydro-nuclear generation and renewable generation outside the plant's BA, but in the same region.[18] These shares take a non-zero value for all plants in the Eastern and Western Interconnections, and a value of zero for plants in the Texas Interconnection, which largely overlaps with the ERCOT BA. We

plant fixed effects, raising concerns of collinearity. For this reason, we estimate DID models with capacity factor (rather than net generation or emissions) as dependent variable.

[18] Since nuclear generation at the BA level is sparse, we merge nuclear and hydro generation into one series. With regard to regional classification, for treated units in the Western Interconnection, BAs fall into one of four regions (California and three leaker regions), as discussed in Section 4.1. For control units in the Eastern Interconnection, we follow the regional classification in U.S. Energy Information Administration (2022d).

model the shares using linear functions, with coefficients that do not vary across markets.[19]

Second, we focus on the indirect effects of non-fossil generation in the North and South regions on capacity utilization at NGCC plants in California, and calculate monthly shares of hydro-nuclear and renewable generation in each of the two regions. These shares take a non-zero value for all plants in California, and a value of zero for plants in the leaker or control regions. We model the shares using linear functions. Other indirect effects in WECC are not considered for two reasons: California imports a substantial share of its electricity consumption from out of state (but does not often export electricity), and the net interchange between other regions in WECC is not significant in the period of our analysis. In line with the strategy adopted for WECC, we do not consider cross-regional effects in the Eastern Interconnection. Lastly, cross-regional effects are not present in the Texas Interconnection, which largely overlaps with ERCOT. Table 3 describes our control strategy for hydro, nuclear and renewable generation in each model specification.

Electricity consumption in the plant's planning area is modeled with a logarithmic functional form implying low responsiveness of capacity factors when electricity consumption is high (Bushnell, Mansur and Saravia, 2008; Davis and Hausman, 2016). We control for power imports into CAISO and imports from Canada into MRO-US and WECC. Specifically, imports into CAISO have a positive value for plants in California, and are equal to zero otherwise. Imports from Alberta and British Columbia are assigned to plants in the NW and RoW regions of WECC, while imports from Manitoba and Saskatchewan are assigned to plants in MRO-US; imports from Canada take a value of zero for all other plants in the dataset. We also account for factors that may affect plant productivity, like temperature (measured by heating and cooling degree days in the plant's climate division) and precipitation (measured by the Standardized Precipitation Index in the plant's climate division). In order to assess plant competitiveness, we calculate monthly fuel cost ratios. For coal plants, the coal-to-gas cost ratio divides plant-specific variable cost of generation by state average variable cost of natural gas for power generation. Similarly, for natural gas plants the gas-to-coal ratio divides plant-specific variable cost of generation by state average variable cost of coal for power generation. We include the fuel cost ratios with both linear and quadratic terms to account for potential nonlinear responses to input prices (Cullen and Mansur, 2017). Further, we consider local economic activity and different recovery rates from the Great Recession through percent changes in state monthly seasonally-adjusted employment levels in energy intensive sectors (mining and logging, manufacturing, and construction). Finally, we include

[19]Cubic splines with invariant coefficients by region yield similar results. Creating splines varying by interconnection presents some challenges in the coal regression: specifically, splines cannot be created for shares of solar-wind-other renewable generation in the Eastern Interconnection because more than half of the observations have a share equal to 0. A hybrid approach based on a combination of cubic splines and a linear function for solar-wind-other renewable generation in the Eastern Interconnection yields estimates that are in line with the baseline, but parallel trends for this specification are not as robust.

individual, regional and time fixed effects in the regressions. Plant specific effects, γ_j, may be associated with time invariant differences in plant characteristics, like ownership (private utilities or political subdivision) and vintage. γ_y and γ_{dw} capture differential changes in average utilization that are common to all plants in a given year or day of the week. State by month-of-year fixed effects γ_{sm} account for seasonality (which is important when plants are part of a vast interconnection like WECC) and control for differential changes that are common to all plants within a state in a given month. Finally, the error term ϵ_{jt} is assumed independent of the covariates and treatment indicators.

4.4 Data

The econometric model uses a novel panel dataset built from publicly available sources including the U.S. Department of Energy's Energy Information Administration (EIA), the U.S. Environmental Protection Agency (EPA), the Federal Energy Regulatory Commission (FERC) and the California Independent System Operator (CAISO). The period of our study spans January 2009 through December 2016, including four years before and four years after the treatment date (January 1, 2013).

4.4.1 EIA data

U.S. electric generating facilities with more than one MW of capacity are required to complete an annual survey to report plant characteristics. Form EIA-860 collects information on the status of existing plants in the U.S., while EIA-923 gathers information on plant operations. Relying on these surveys, we assemble a dataset for power plants within the U.S. portion of six NERC regions (FRCC, MRO-US, SERC, SPP, TRE and WECC) from 2009 to 2016 (Figure 1). A plant consists of at least one, but typically several, generating units, which may be added to or retired from service over its lifetime. Although energy output, operating capacity and fuel input are available at the unit level, we aggregate units of the same technology to plants to provide an accurate representation of capacity factors and heat rates for combined cycle plants.[20] The advantage of EIA data is that its coverage is comprehensive, including not only large thermal plants, but also nuclear, hydro and renewable facilities. Plant-level characteristics reported at the annual level include primary fuel type, operating capacity, month and year when each unit was in service, NERC region and subregion,

[20]In combined cycle plants, gas is burned in a combustion turbine that generates electricity, and the waste heat from the turbine is captured and used to create steam that runs a second generator (the steam turbine) to produce additional electricity. The EIA reports energy output, operating capacity and fuel input for the combustion turbine part (denoted as CT) and the steam part (denoted as CA) separately but, in general, the CT of a NGCC plant cannot operate independently from its CA. Calculating capacity factors and heat rates for individual units that report separate output does not provide an accurate representation of plant utilization and efficiency, since the CT and CA parts of a NGCC plant cannot operate independently. Therefore, we aggregate energy output, operating capacity and fuel input for CT and CA units within the same combined cycle plant, and calculate plant-level capacity factors and heat rates. For consistency, we use plant-level data for the other technology types.

balancing authority and planning area. In addition, the EIA provides monthly plant operating statistics like energy output (measured by megawatt-hours or MWh of net electricity generation),[21] consumption and heat content by fuel type, and cost of fuel delivered to the plant. We rely on Form EIA-860 for primary fuel type and operating capacity (U.S. Energy Information Administration, 2022b), and Form EIA-923 for other plant characteristics (U.S. Energy Information Administration, 2022c). We exclude plants with operating capacity below 25 MW.[22]

Plant fuel costs are used to calculate monthly ratios to assess competitiveness (Section 4.3). Fuel costs are not publicly available for non-regulated plants and plants with nameplate capacity below 50 MW. In these instances, we use state average costs of fossil fuels for electricity generation provided by the U.S. Energy Information Administration (2022a). If state average costs are also not available, we impute the fuel costs assuming the same growth rate of Rocky Mountain Colorado Rail coal prices (with a heat rate of 11,700 Btu/lb and a sulfur content of 0.8 lb/MMBtu) and NW Opal WY natural gas prices from SNL Energy.

4.4.2 CEMS data

We assemble a database of hourly gross electricity generation, heat input and CO_2 emissions for NGCC and coal-fired plants from the EPA's Continuous Emissions Monitoring System (U.S. Environmental Protection Agency, 2022). CEMS represents the only publicly available information on high frequency operating data for thermal power plants in the U.S., and has been widely used in empirical studies (Joskow and Kahn, 2002; Mansur, 2007; Puller, 2007; Graff Zivin et al., 2014; Kotchen and Mansur, 2014; Davis and Hausman, 2016; Cullen and Mansur, 2017). We match units in CEMS to EIA generators using a 2015 crosswalk provided by the EPA (personal communication), and aggregate unit-level information from CEMS at the plant level by EIA site code and technology type. This step allows us to assign operating capacity to each power plant for which EPA data is available. We convert CEMS gross generation to net generation using technology-specific parasitic loss factors from the U.S. Environmental Protection Agency (2020). Finally, as noted above only thermal plants with capacity above 25 MW are required to report to CEMS; cogeneration, industrial and commercial facilities are also generally not in CEMS. These exceptions do not result in a substantial loss of coverage for our analysis: net generation of NGCC (coal-fired) plants from CEMS represents about 86% (97%) of EIA generation in WECC over the period of our study.

[21] Net generation excludes power consumption for plant operations.

[22] 25 MW corresponds to the minimum size of generators subject to requirements for monitoring and reporting emissions under the EPA's Continuous Emissions Monitoring System (U.S. Environmental Protection Agency, 2022). Plants with capacity below 25 MW generally use renewable energy sources and represent less than 5% of generating capacity in our sample.

4.4.3 Other data

We complement information on the operations and status of electric power plants with data from other sources. We collect hourly scheduled net power imports into the California ISO on twelve transmission interfaces connecting the state's electrical grid to the rest of WECC, which are identified based on the analysis of annual reports on the frequency of import congestion on each intertie (U.S. Department of Energy, 2014; California Independent System Operator, 2022a). Data are available from April 2009 to October 2015 from the Open Access Same-time Information System (California Independent System Operator, 2022c). In addition, hourly total power imports into the California grid are available from April 2010 to December 2016 from the California Independent System Operator (2022b). We merge these sources to create a time series of daily power imports into the California grid from April 1, 2009 to December 31, 2016. We also collect monthly net imports of power from Alberta, British Columbia, Manitoba and Saskatchewan by U.S. destination (National Energy Board of Canada, 2022), and aggregate them to the interconnection level (MRO-US and WECC). Hourly power flows between balancing authorities in WECC and the other interconnections are not publicly available over the period of our analysis.

Electricity consumption comes from the Federal Energy Regulatory Commission (FERC). FERC Form 714 provides hourly load information by planning area (Federal Energy Regulatory Commission, 2022). We aggregate load to the monthly and daily level, and assign it to power plants based on their planning area. Monthly population-weighted heating and cooling degree days, as well as measures of water scarcity by state climate division are from the National Oceanic and Atmospheric Administration (2022). The monthly seasonally-adjusted employment level in the mining and logging, construction and manufacturing sectors by state is from the Bureau of Labor Statistics (2022). Finally, we obtain daily carbon futures prices for year vintage allowances expiring in December of the same year, in $/ton, from the California Carbon Dashboard (Climate Policy Initiative, 2022).

4.5 Results

4.5.1 Shifts in electricity generation

Table 4 shows the estimates based on equation (1), using daily capacity factors from CEMS as dependent variable (i.e., t in equation (1) corresponds to one day). For specification (1), covariates include the natural log of electricity consumption in the plant's planning area; temperature and precipitation variables; cubic splines with three knots for each of the state-level hydro, nuclear and renewable generation variables; linear and quadratic terms for the fuel cost ratio; change in state employment levels in energy intensive sectors; power imports from Canada; and power imports into CAISO. Covariates are at the monthly level, except electric load by planning area and power imports into CAISO, which are available at the daily level. Robust standard errors are clustered at the plant level.

Leakage would result in lower natural gas generation in California and higher coal and/or natural gas generation in the rest of WECC. Therefore, in the presence of leakage we would expect a negative and statistically significant α_C, and positive and statistically significant α_D and α_I for the leaker regions. Provided that the DID identification assumptions hold, our empirical results suggest that daily capacity factors for matched NGCC plants in California decreased by 5.8% in response to the introduction of the cap-and-trade program, relative to similar control facilities. In contrast, capacity factors for matched coal-fired plants increased by 4.7% in the Pacific Northwest, Nevada and Utah, and by 4.4% in Central and Eastern WECC. Other estimates are not statistically significant.

Specifications (2)-(4) represent robustness checks. The dependent and independent variables are measured at the same frequency noted above. In (2), we let spline coefficients vary by NERC interconnection. Relative to (1), daily capacity factors for matched NGCC plants in California decrease less and at a lower level of statistical significance; in addition, we find evidence of increased NGCC generation in the Pacific Northwest, Nevada and Utah, albeit only at a 10% significance level. In (3), we evaluate robustness to more conservative clustering. Specifically, we consider clustering by balancing authority as a compromise between widening the scope of clustering to be more in line with the level of treatment (which is assigned at the interconnection level), and having a sufficient number of clusters for inference. Lastly, in (4) we present results based on an alternate matching set. As in (1), we use pre treatment average capacity factors over four hour blocks during the day as matching variables. However, we coarsen the matching variables based on an alternate set of cut points (0.3, 0.5 and 0.7 for NGCC plants, 0.6 and 0.8 for coal-fired plants), which are based on visual inspection of the empirical distribution of the 2009-2010 average capacity factors by hour.[23] Results from specifications (3) and (4) are consistent with those in (1).

In Table 5, we explore potential treatment heterogeneity between day and night using hourly measures of plant utilization based on the CEMS data (i.e., t in equation (1) corresponds to one hour). Electric load by planning area also has hourly frequency, while all other covariates are measured at the same frequency noted above. The treatment effects in equation (1) are interacted with a time-of-day indicator (equal to 1 between 7am and 7pm) to yield separate estimates for day and night. Specification (5) is similar to (1), but uses

[23]Coal-fired plants (particularly in the Southwest region of WECC) tend to be more heavily utilized than NGCC plants, motivating our choice of higher capacity factors as cut points for this technology type.

hourly (rather than daily) capacity factors as dependent variable. Results suggest a statistically significant reduction of NGCC capacity factors in California by 8.9% during daylight hours, relative to matched control facilities. In contrast, relative increases in capacity utilization at Western coal plants (outside California) occur throughout the day (i.e., during both daylight and evening hours), and are higher in the evening hours.[24] We also estimate separate effects for every hour of the day by interacting each treatment indicator with 24 hourly indicators. Results are presented in Figure 4, and suggest a statistically significant reduction in NGCC capacity factors in California between 8am and 8pm. Increases in capacity utilization at Western coal plants are statistically significant during all hours of the day in the NW. Further, relative increases in capacity utilization in the NW and RoW regions happen in the evening hours. Note that changes in utilization rates do not tend to occur around the same hour, but are concentrated during daylight hours for California and in the evening hours for the leakers. These patterns urge caution in lending a causal interpretation to the empirical estimates, which may be biased due to confounding factors.

Specifications (6)-(8) are robustness checks that control for nuclear and renewable generation more flexibly, as described in Table 3.[25] The dependent and independent variables are measured at the same frequency as in (5). The comparison of results from (5) and (6)-(8) yields two insights. First, the reduction of NGCC capacity factors in California during the day remains statistically significant but decreases in absolute value (i.e., the treatment effect gets closer to zero) in the more flexible specifications. Thus, (5) tends to overestimate the reduction in NGCC plant utilization from the cap-and-trade program during daylight hours, due to the symmetric structure imposed on the relationship between NGCC capacity factors and non-fossil generation. Second, statistically significant coal treatment effects in the leaker regions generally increase in magnitude, as we control for non-fossil generation more flexibly. Robustness checks also suggest a statistically significant increase in utilization of NGCC plants in the NW and coal-fired plants in the SW, albeit only at a 10% level. Thus, (5) tends to slightly underestimate the policy-induced increase in plant utilization outside California. Overall, the bias in the estimates from the coal regressions appears to be smaller than that associated with the estimates from the NGCC regressions.

As a last robustness check, Figure A3 in the Appendix shows the changes in plant utilization rates across hours of the day, relative to matched counterparts, based on specification (6). Here, bias from solar is

[24] To address concerns that imports may be "bad controls" in this setting because they are themselves outcomes of the cap-and-trade policy, we removed imports as a control variable to test robustness. Results are in line with those in Table 5, suggesting that controlling for CAISO imports is not biasing the results. This is consistent with imports not increasing significantly as a result of the cap-and-trade policy, though their composition may have changed, and in line with the findings of Davis and Hausman (2016).

[25] Specification (8) can only be run for NGCC because the number of observations in the coal database is not sufficient to create nuclear splines that vary by interconnection.

expected to be less of a concern, because we allow for more flexible estimation of in-state non-fossil generation and add controls for non-fossil generation in the neighbouring regions. However, the estimated patterns look similar to those in Figure 4.

4.5.2 Evaluating the identification assumptions

Several assumptions must hold for our empirical estimates to provide an unbiased measure of the effect of California's cap-and-trade program on baseload power plant operations in the Western Interconnection. We examine the plausibility of each assumption in turn.

Unconfoundedness. Our empirical strategy assumes that, conditional on observable plant characteristics, the distribution of the outcome is the same among treated and control plants. If this holds, biases in the unconditional differences-in-differences estimates are removed. As noted above, we match on capacity factors over four blocks of hours within the day, averaged over 2009-2010. Table 6 presents the t-statistics of tests of identical means of capacity factors (by hour and block of hours) in the treated and control groups, based on the matching procedure described in Section 4.2. Tables A2 and A3 in the Appendix show balance results for two additional plant characteristics: heat rate (a measure of efficiency) and age. The balancing tests confirm that matching achieves statistically indistinguishable means between treated plants in WECC and control plants. Before matching, there are significant differences between plant characteristics, particularly with respect to plant efficiency; after matching, the null of identical means in both groups is no longer rejected for any of the variables. This suggests that our matching procedure removes much of the potential bias.

Parallel trends. A second key assumption is that utilization of matched treated and control plants would follow parallel trajectories over time, in the absence of the treatment (Angrist and Pischke, 2009). Constructing counterfactual outcomes using observations on plants from another interconnection poses a challenge, because these plants do not "share the same economic environment" (Heckman et al., 1997) as the WECC plants; in particular, California's electricity market was transformed at a rapid pace over the period of our study. The parallel trends assumption cannot be directly tested, but we assess its plausibility in several ways. Figure A2 in the Appendix shows the capacity factor trajectories of matched treated and control plants by technology type between 2009 and 2016.[26] We conduct two tests to examine whether treated and control plants follow systematically different trends in the outcome variable before treatment. A common approach in the literature is to test the equivalence of time trends between treated and control groups prior to the intervention (Autor, 2003; Kearney and Levine, 2015; Fell and Maniloff, 2018; Jaeger et al., 2020). We use

[26]Note that these trajectories are unconditional, and the inclusion of covariates in the DID model serves to adjust for observable differences between treated and control groups in these plots.

the following regression:

$$Y_{jt} = \sum_{qd} \alpha_C^{qd} B^q D_j^C T_t^d + \sum_L \sum_{qd} \alpha_L^{qd} B^q D_j^L T_t^d + \mathbf{X}_{jt}^{'} \underline{\beta} + \gamma_j + \gamma_y + \gamma_{dw} + \gamma_t + \epsilon_{jt} \quad (2)$$

where B^q is a seasonal dummy equal to 1 if t lies in season q and 0 otherwise, $D_j^C = 1$ if plant j is in California, $D_j^L = 1$ if plant j is in one of the leaker regions in WECC, T_t^d is a time-of-day indicator to yield separate estimates for day and night (where index d is equal to 1 if t is between 7am and 7pm, and 0 otherwise), and α_C^{qd} and α_L^{qd} are the seasonal effects (or event study coefficients) estimated for specific times of the day.[27] Other variables are defined as in specification (5). Pre treatment seasonal effects that are statistically significantly different from zero would support the assumption of parallel trends between treated and control groups prior to the intervention. Figures 5 and 6 present the event study coefficients by treated region, technology type and time of day. While in most cases the pre treatment effects are not individually statistically different from zero, these coefficients are imprecisely estimated. Therefore, the test results do not provide conclusive evidence to rule out the possibility of statistically significant pre treatment effects.

Next, we conduct a parallel trends test that compares the treatment effects in the baseline to the treatment effects in a specification that includes group-specific trends (Kearney and Levine, 2016; Kahn-Lang and Lang, 2020). If adding a trend changes the interpretation of the coefficients of interest, trend differences between treated and control groups prior to the intervention cannot be ruled out. We introduce linear and quadratic trends for each of the treatment group in hourly specification (5). If a treatment effect is statistically significant, we examine how the introduction of a trend affects its sign and significance, and present the results in Table 7. Adding a trend does not change the sign and significance of the estimated treatment effects for coal-fired plants in NW. The change in utilization rates at RoW coal-fired plants in the evening hours also remains positive and statistically significant when group-specific trends are included. However, the estimated effects for NGCC in California and Coal in RoW during daylight hours are not robust to the inclusion of trends, raising concerns about the causal interpretation of our results. Based on the evidence from the two parallel trends tests, we cannot rule out that treated and control groups were trending differentially before 2013.

To address this challenge, we adopt the robust inference method proposed by Rambachan and Roth (2022a) to test sensitivity of statistically significant average treatment effects to violations of parallel trends.[28]

[27]We use seasonal dummies to account for cyclical factors that may affect plant utilization. In line with National Renewable Energy Laboratory (2011), seasons are defined as follows: Summer = June, July, and August; Fall = September and October; Winter = November, December, January, and February; Spring = March, April, and May.

[28]In a similar vein, Ang (2021) and Rose (2021) use this method to conduct robust inference on statistically significant

Their approach builds on the intuition that, even if pre trends are not parallel, the difference in trends observed before treatment is informative about post treatment differences that would have occurred absent treatment. The researcher chooses the extent to which the counterfactual difference in trends post treatment deviates from the extrapolation of the pre-existing difference in trends by specifying a parameter M, which may be informed by context-specific knowledge: the bigger M is, the larger the deviation from the pre-existing difference in trends. Given a value of M, we can construct a robust confidence interval for the treatment effect. Further, we can examine robustness of the estimated treatment effect under varying assumptions on potential violations of parallel trends. For example, we can examine what deviation from the pre-existing difference in trends is needed to render a treatment effect statistically insignificant. Tighter bounds on the confidence intervals may be obtained by imposing sign and monotonicity restrictions that draw on context-specific knowledge.

Using equation (2), we estimate seasonal treatment effects for all regions and baseload technology types in WECC. Next, we construct robust confidence intervals for the seasonal treatment effects that do not pass the test in Table 7 (i.e., CA NGCC Day and RoW Coal Day), using the R code HonestDiD (Rambachan and Roth, 2022b). To illustrate, Figure 7 presents sensitivity analyses for these event study coefficients in the first period after treatment (Jan and Feb 2013). We compare the OLS confidence intervals (in blue) to the 95% confidence intervals from Rambachan and Roth's method (in red), under varying restrictions and for different values of M. Each panel represents a specific set of restrictions on the sign of the bias of the post period event study coefficients (which are appropriate in cases with simultaneous policy changes) and monotonicity of the underlying difference in trends. For example, our treatment effects for California may overestimate the reduction in NGCC plant utilization from the cap-and-trade program, due to potential confounders that would have a coincident negative effect on capacity factors (e.g., complementary measures under AB 32). Therefore, in panel (b) we impose that the bias of California's event study coefficients after treatment is negative. On the other hand, the net effect of the confounders on NGCC capacity factors may also be positive (e.g., if the SONGS replacement strategy empirically identified by Davis and Hausman (2016) continued after the introduction of the cap-and-trade policy, and gas utilization in California to meet the lost generation from SONGS increased more than it decreased due to the effect of complementary measures under AB 32). Although this seems less likely, in light of the discussion in Section 4.5.1, we test the robustness of our results by considering positive bias in panel (c). Lastly, it is reasonable to assume that the downward sloping pre trend in California's NGCC utilization in Figure 5 would have continued in the absence of the cap-and-trade

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average treatment effects.

program, due to the effect of other policies promoting renewable investment and generation in 2013-2016. This motivates our restriction of a monotone decreasing trend for California. Following Rambachan and Roth (2022a)'s recommendation, we use fixed length confidence intervals (FLCIs) when no restrictions are imposed, and conditional FLCIs under sign and monotonicity restrictions.

Turning to the results presented in each panel, a value of M equal to zero corresponds to a linear extrapolation of the pre-existing trend to the post treatment period; higher values of M reflect group-specific deviations from the pre existing trends that are calibrated on empirical estimates, and are driven by the evolution of factors that affect NGCC plant utilization in California (solar generation) and coal-fired plant utilization in the leaker regions (natural gas prices and thus coal-to-gas ratios) beyond the climate legislation. We benchmark M following Rambachan and Roth (2022a). First, we run a regression of capacity factor on standardized nuclear and renewable covariates and other determinants in $\mathbf{X}_{jt}^{'}$ for each region and technology type. We find that a 1 standard deviation increase in solar generation corresponds to a 0.010 decrease in NGCC generation in California over the period of our study. Further, a 1 standard deviation increase in the coal-to-gas ratio corresponds to a 0.0763 (0.02361) decrease in NW (RoW) coal capacity factors. Next, we use these estimates to benchmark the value of M in each region. For California, a value of M equal to 0.0003 (0.001) {0.004} corresponds to changes in the differential slope of solar generation of about one fortieth (one tenth) {one third} of a standard deviation. For the RoW region, a value of M equal to 0.0006 (0.002) would correspond with allowing for changes in the differential slope of the coal-to-gas ratio of about one fortieth (one tenth) of a standard deviation. We also construct robust confidence intervals for an intermediate value of 0.0013.

The estimated treatment effect for California in January-February 2013 is negative, and the OLS confidence intervals rule out zero. When we assume a linear extrapolation of the pre-existing trend to the post treatment period (M=0), our conclusions are similar, but confidence intervals are tighter. As M grows larger, confidence intervals become less informative, as expected. However, the estimated confidence intervals exclude zero for all values of M, indicating that, given plausible non-linear deviations from the pre-existing differences in trends, we cannot rule out a statistically significant treatment effect of the policy in the first period after treatment. In the RoW, the OLS estimate is slightly negative but the confidence interval includes zero. When we allow for linear violations of parallel trends, we cannot rule out a statistically significant increase in coal-fired capacity factors in the first period after treatment.

Robust confidence intervals for all treatment effects under varying restrictions and for different values of M are presented in Figures A4-A5 in the Appendix. For $M = 0$, we find that 9 seasonal daily effects in

California (out of 17 post treatment effects) are statistically significant under no restrictions; 16 seasonal effects are statistically significant under monotonicity and negative bias; and 10 seasonal effects are statistically significant under monotonicity and positive bias. Further, 8 seasonal daily effects are statistically significant in RoW, and 7 of these are in the first part of the post treatment period (Jan-Feb 2013 till Summer 2014).

Stability of unit treatment values. The empirical framework assumes that plant-level capacity utilization depends on the treatment status of the corresponding plant, but is independent of the treatment status of other plants. This is the stable unit treatment value assumption. By designating control plants outside of WECC, we assume that the policy does not affect facilities in other NERC regions This is plausible, because the Western, Eastern and Texas Interconnections operate largely independently from each other and power transfers between them are limited. As a result, spillovers and market equilibrium effects on the designated control plants in the Eastern and Texas Interconnection are unlikely. Although not testable in principle, we believe that the SUTVA holds in our study.

Treatment exogeneity and overlap. Two additional assumptions that are required for identification are treatment exogeneity and overlap. In our setting, treatment is exogenous because participation in the cap-and-trade program does not depend on the outcomes. The overlap assumption requires the support of the distribution of covariates in the treated group to overlap the support of the distribution of these covariates in the control group. Coarsened exact matching automatically restricts the matched data to areas of common support, as discussed in Section 4.2: this helps avoid making inferences based on extrapolation, which are known to be highly model dependent. Thus, we believe that the overlap condition is satisfied in our study.

4.5.3 Leakage estimates

Based on seasonal effects estimated for specific times of the day and their confidence intervals, we infer CO_2 emission leakage predictions in 2013 and 2016. Our focus on these two years is intended to enable more direct comparisons with the simulation results. The leakage rates in Table 8 consider seasonal effects for regions and technology types that are statistically significant for at least one time of the day, based on specification (5) (i.e., CA NGCC, NW Coal and RoW Coal).[29] Further, these rates are based on robust confidence intervals that allow for linear violations of parallel trends (M=0) for CA NGCC Day and RoW Coal Day, and OLS confidence intervals for CA NGCC Night, NW Coal Day and Night, and RoW Coal Night. We assume negative bias and monotonicity restrictions for CA NGCC Day, and no restrictions for RoW Coal Day. To calculate the leakage rates implied by the econometric model, we proceed as follows.

[29]Leakage bounds based on seasonal impacts for all regions and baseload technology types (NGCC and Coal) are too wide to be informative, and thus we do not present them in the paper.

First, we identify seasons and times of day with contemporaneous changes in capacity factors in California and the leaker regions in the expected direction (negative for California, and positive for at least one of the leaker regions). Only these seasons/periods are included in the leakage calculation based on our empirical estimates. In contrast, if a season/time-of-day does not exhibit contemporaneous changes in capacity factors, or if the estimated changes are not in the expected direction (i.e., positive changes in California's capacity factors, or negative changes in California's capacity factors coupled with zero or negative changes in capacity factors for all leaker regions), we do not consider it in the leakage calculation. We use the lower (upper) bound of the 95% confidence interval for the estimated seasonal effects to calculate a lower (upper) bound for the generation, emissions and leakage rates associated with the econometric estimates.

Next, we find the estimated generation leakage by multiplying the seasonal treatment effects by the total generation capacity of matched plants by region, year and technology, and the number of hours in that season. Based on these generation leakage estimates, we calculate the change in local CO_2 emissions in California (E_1) and WECC-NonCA emissions (E_4), based on region-, year- and technology-specific heat rates and CO_2 emission rates. The resulting change in WECC emissions ($E_5 = E_1 + E_4$) is between -10.49 and 15.26 million metric tons in 2013, and between -15.60 and 11.35 million metric tons in 2016.

As noted above, emissions subject to the cap-and-trade regulation include not only in-state emissions, but also emissions associated with power imports into California. As a result, the change in regulated emissions includes the change in local emissions in California (E_1), as well as the change in emissions associated with power imports into California, relative to a counterfactual (E_2). Since the change in import emissions E_2 cannot be obtained from the econometric estimates, we proceed as follows. First, denote as I_1 the "Total Covered Emissions" for electricity importers reported by CARB in its annual GHG emission inventories (California Air Resources Board, 2022d). These emissions (36.20 million metric tons CO_2e in 2013 and 21.02 million metric tons CO_2e in 2016) form the basis to determine compliance obligations in the cap-and-trade program. Next, we construct the year-specific counterfactual import emissions I_2 assuming the same percentage change between counterfactual emissions and emissions under the carbon cap predicted by JHSMINE. The difference between I_1 and I_2 yields the estimated emission reduction E_2 on Table 8.[30]

Finally, we calculate the implied leakage rates. A common metric used in the literature (e.g., Bushnell et al. (2014); Caron et al. (2015); Fell and Maniloff (2018)) is the physical leakage rate, which reflects the share of local emission reductions that is offset by emission increases in the rest of the system. In our setting,

[30]To illustrate, in 2013 JHSMINE predicts import emissions of 51.25 million metric tons for the no cap scenario and 39.41 million metric tons for the carbon cap scenario. This implies that no cap emissions would be 30% higher than emissions under the cap. Hence, the counterfactual import emissions for the empirical analysis are 47.07 ($= 36.20 \times 1.30$) million metric tons CO_2e, and the estimated import emission reduction is 10.87 ($= 36.20 - 47.07$) million metric tons CO_2e in 2013.

this would be defined as $100\% \times (-E_4/E_1)$. Given California's first deliverer approach, we adopt an alternate leakage metric that considers the difference between the decrease in regulated emissions and the decrease in system-wide emissions in WECC. In line with Chen et al. (2011) and Xu and Hobbs (2021), we define leakage as $100\% - E_5/E_3 = (1 - E_5/E_3) \times 100\%$. A positive leakage rate indicates a mismatch between WECC emissions and California's regulated emissions. In particular, if the leakage rate is positive but below 100%, regulated emissions decrease, but total emissions in WECC fall by a lower amount; if the leakage rate exceeds 100%, regulated emissions fall, but WECC emissions actually increase. Given robust confidence intervals that allow for linear violations of parallel trends, the leakage rates implied by our econometric estimates are between 40.8% and 217.9% in 2013, and between 17.4% and 177.4% in 2016. The lower bounds of these intervals are within the range of earlier empirical estimates: for example, in the context of RGGI, Fell and Maniloff (2018) find an electricity-sector specific leakage of about 50%, while the leakage interval predicted by Zhou and Huang (2021) is 43%-85%. However, direct comparisons are difficult due to the use of different metrics that are less relevant in our setting: for instance, both studies cited above calculate a physical leakage rate.

5 Simulation model

We use a partial equilibrium model of the electricity sector (JHSMINE) to simulate shifts in electricity generation in the Western Interconnection in response to the introduction of California's cap-and-trade program. Based on these estimates, we infer CO_2 emission leakage predictions in 2013 and 2016. This section presents an overview of the model, describes the scenarios and sources of data used for JHSMINE, and discusses the simulation results. The model formulation is presented in Section A of the Appendix.

5.1 Overview

The Johns Hopkins Stochastic Multistage Integrated Network Expansion model is a long-term transmission-generation-storage expansion planning model of the electricity sector based on scenario-based stochastic programming. The model was applied to the Western Electricity Coordinating Council using a reduced network based on the WECC 2026 Common Case (WECC Staff, 2016) to provide insights into the transmission planning process (Hobbs et al., 2016; Xu and Hobbs, 2019) and efficiency of border carbon adjustment schemes in the Western U.S. (Xu and Hobbs, 2021). The reduced network consists of 361 buses, 712 transmission lines, and 1,504 existing aggregate generators of various technology types, including coal steam plants and combined cycles. Key modeling assumptions include perfectly inelastic demand, perfect competition, and perfect foresight of market participants.

The version of JHSMINE in this paper builds on the one in Xu and Hobbs (2021), but differs from it in several important ways. While Xu and Hobbs (2021) consider a capacity expansion planning model, we run a production cost model that simulates hourly commitment and dispatch decisions under alternate carbon pricing scenarios, taking generation capacity as given. Further, in order to generate plausible leakage predictions, we introduce features that enhance realism in the model formulation. First, we approximate power flows on the transmission network by a direct current (DC) load flow (Gabriel et al., 2013). The resulting DC OPF uses a linearized approximation of the alternating current (AC) power flow equations (Schweppe et al., 1988), and allows for a more accurate representation of power flows than the transshipment model in earlier formulations, which ignores Kirchhoff's Voltage Law. Second, we include relaxed (non-integer) unit commitment variables in the model. Third, with respect to power imports into California, the original model can only simulate a scenario in which all imports are considered specified power and assigned facility-specific emission factors (100% specified), or a scenario in which all imports are considered unspecified and assigned the default emission factor of 0.428 metric ton CO_2/MWh (0% specified). The observed regime in California is a hybrid of the two, where source specification was not possible for about 26% of electricity imports, on average between 2013 and 2016 (California Air Resources Board, 2020a). To make simulation results more directly comparable with the empirical estimates, we revise the formulation of JHSMINE by unbundling the non-electrical attributes of power generation (emissions and renewable energy credits, or RECs). Xu and Hobbs (2021) model these attributes with one variable, cpf, representing the emissions and RECs associated with a contract (in MW) sold by a generator to a load serving entity. In contrast, we allow for emissions and RECs to be traded through separate contracts. This change allows us to model a regime where (a) electricity producers can enter bilateral contracts where power is specified, or sell unspecified power to a pool, and (b) load serving entities can buy specified power through bilateral contracts, or unspecified power from the pool. To obtain the emissions of power imports to California, energy contracts between the California LSE and out-of-state generation companies are assigned an emission rate. When imports are considered specified power, the emission rate is plant-specific. When imports are considered unspecified power, the emission rate is set equal to the default emission factor of 0.428 metric ton CO_2/MWh.

5.2 Scenarios

We consider two scenarios: (a) a benchmark scenario with no regulation of GHG emissions (“No cap”); (b) a scenario where California generators and the California LSE are subject to a first deliverer cap-and-trade program (“Carbon cap”). The carbon price is assumed and set equal to average historical values over the period of our study, rather than determined endogenously in the model. In both scenarios, specified electricity imports to California are assigned facility-specific emission factors, while unspecified imports are assigned the default emission factor of 0.428 metric ton CO_2/MWh. Further, both scenarios include RPSs and assume the same share and composition of specified imports into California.

5.3 Data

To ensure comparability of the data used for the econometric model and the simulation model, we modify the JHSMINE dataset in Xu and Hobbs (2021) making use of the installed generation capacity, average fuel costs and load from the econometric model dataset. In addition, we parameterize the shares of California imports by fossil fuel generation type based on historical data from CARB, in order to ensure that the level and composition of power imports into California in JHSMINE are comparable to historical values.

As noted in Section 5.1, JHSMINE’s test system is a network reduction of the Western Interconnection that consists of 1,504 existing aggregate generators. There is no one-to-one correspondence between aggregate generators in JHSMINE and power plants in the empirical analysis. However, unit-level data is the basis for modeling the aggregate generators. Thus, we replace the existing generation capacity in JHSMINE (based on WECC’s 2026 Common Case database) with unit-level operating capacity from Form EIA-860 in 2013 and 2016 (U.S. Energy Information Administration, 2022b). Average fuel costs by state, technology type and month-year are from the econometric model database, while CO_2 emission rates by fuel type are from the U.S. Energy Information Administration (2022e).[31] Minimum up/down times for coal plants, NGCCs and combustion turbines are drawn from Herrero et al. (2018). JHSMINE assumes that all transmission reinforcements in the WECC 2026 Common Case have been brought online. We are unable to replicate the network topology in 2013-2016 because the reduction algorithm (Shi et al., 2012) does not provide a one-to-one correspondence between the aggregated branches and the original transmission lines. Consequently, removing the lines added between 2013 to 2026 would not be possible without recreating the transmission network database. However, the use of the 2026 network topology does not significantly affect our results,

[31] The CO_2 emission rates from the EIA are 117 lb/MMBtu for natural gas and 205.70 lb/MMBtu for bituminous coal. These values are closely aligned to the average emission rates from the econometric model dataset (118.05 lb/MMBtu for natural gas in California, 208.37 lb/MMBtu for coal in NW WECC, and 208.74 lb/MMBtu for coal in RoW WECC).

because reinforcements on high-voltage transmission lines only add 88.5 GW, expanding capacity to 4,040.9 GW.[32]

Electricity consumption in JHSMINE is from WECC's long term planning tool (LTPT) (Xu and Hobbs, 2021). To ensure comparability with the demand levels in our econometric analysis, we replace load from the LTPT with hourly consumption by planning area from FERC Form 714 (Federal Energy Regulatory Commission, 2022). Next, we identify forty-eight representative days per year to run the model in 2013 and 2016, and select at least six representative days for each season of the year (as defined in Section 4.5.2).

Table A4 in the Appendix summarizes the assumed state-level RPS requirements for 2013 and 2016, which are drawn from the DSIRE database (DSIRE, 2022).[33] Load serving entities in states with an RPS are subject to an alternative compliance penalty of 100 $/MWh if they fall short of renewable energy credits. The shares of specified imports over total power imports in California (SSI_y), as well as the shares of imports by fossil fuel generation type ($SSI_{f,y}$), are calculated based on historical data from the California Air Resources Board (2020a); these shares are presented in Table A5 in the Appendix. Finally, the carbon price is set equal to average historical values in California ($ 13.53/metric ton CO_2e in 2013, and $12.84/metric ton CO_2e in 2016).

5.4 Results

5.4.1 Shifts in electricity generation

Table 9 presents the predicted impact of California's cap-and-trade program on capacity factors in WECC. We run JHSMINE for forty-eight representative days in 2013 and 2016, under a no cap and a carbon cap scenario. As noted above, WECC Regions and seasons are defined as in the econometric model. The introduction of the carbon policy mainly affects utilization at NGCC and coal-fired plants in WECC, supporting our choice to focus on these technology types in the empirical analysis. Comparing counterfactual (no cap) scenarios across years, generation shifts are due to lower natural gas prices and higher RPS requirements in 2016. For example, lower natural gas prices in 2016 determine an increase in NGCC generation in all WECC regions, and solar capacity factors are higher in regions with a more stringent RPS requirement in 2016 (e.g., California, Arizona and New Mexico). Comparing counterfactual and policy scenarios for the same year, the introduction of the carbon policy yields minor generation shifts in 2013: capacity utilization decreases by about 0.7% at California NGCC plants, and the highest increase outside California is in the NW region (+1%).

[32]The list of line additions is available on the Release Notes for WECC 2026 Common Case, Version 1.5, p.23.

[33]When a state sets RPS targets for multiple types of utilities, we apply the target for investor-owned utilities to all utilities in that state. This is unlikely to significantly affect our results since the target mostly impacts long-term investment.

Note that natural gas prices are relatively high in 2013: as a result, coal-fired plants are heavily utilized, and power imports into California in the carbon cap scenario are sourced at NGCC plants elsewhere in WECC. Generation shifts are more evident in 2016, when coal and carbon prices are at comparable levels but natural gas prices are lower, relative to 2013. The counterfactual scenario in 2016 is thus characterized by lower generation at coal-fired plants, leaving more room for leakage from this technology type after the introduction of a carbon price. This yields a large policy-induced decrease in NGCC capacity factors in California (9.6%), a combined increase in capacity utilization by 3.8% at Western coal plants outside California (mainly in the NW region), and by 12.8% at Western NGCC plants outside California (mainly in the SW region).

JHSMINE is well suited to identifying average changes in hourly capacity utilization that are solely due to the effects of the cap-and-trade policy, ceteris paribus. Thus, we calculate average changes in capacity factors between the two simulated scenarios (carbon cap - no cap) at hours 0-23 for each WECC region and technology type (Figures 8 and 9). In 2013, California's NGCC capacity factors decrease between 8am and 7pm due to the cap-and-trade policy. Note that bias from solar is not a concern in these results, because solar generation is the same under both scenarios. Lower capacity factors in California are mainly offset by coincident changes in utilization rates at NGCC units in the NW and RoW leaker regions. Moreover, in the evening hours NGCC capacity factors at California's gas plants decrease slightly while coal capacity utilization in the NW and RoW increases, albeit by a smaller magnitude than predicted by the econometric model. In 2016, the average reduction of in-state capacity utilization predicted by JHSMINE is more substantial, particularly between 2pm and 7pm. This is offset by coincident positive changes in utilization rates at NGCC plants in the rest of WECC, mainly in the SW and RoW. Coal capacity factors also increase throughout the day in NW, and in the early morning hours in SW and RoW.

5.4.2 Leakage estimates

Table 10 presents the distribution of emissions among WECC regions, as well as the implied leakage rates (as defined in Section 4.5.3) in 2013 and 2016. We emphasize two important differences, relative to the results in Table 8. First, when calculating leakage based on empirical estimates, we use seasonal average impacts estimated for specific times of the day. As noted above, we consider seasons and times of day that exhibit contemporaneous changes in capacity factors in the expected direction, regardless of statistical significance. Further, we consider seasonal effects for regions and technology types that are statistically significant for at least one time of the day in specification (5) (i.e., CA NGCC, NW Coal and RoW Coal). In contrast, the results in Table 10 are based on daily averages for all technology types and WECC regions. Second, for a given technology type and region, the econometric model only accounts for changes in emissions associated with the subset of treated units for which good matches exist among available controls, while JHSMINE considers all aggregate generators.

We find that local emissions in California (E_1) decrease by only 1.10 million metric tons in 2013, but by 6.58 million metric tons in 2016. Given the estimated changes in import emissions relative to the no cap scenario (11.83 million metric tons CO_2e in 2013 and 13.88 million metric tons CO_2e in 2016), regulated emissions in California decrease in both 2013 and 2016 (by 12.94 and 20.46 million metric tons, respectively), but total emissions in WECC fall by much less (in 2013) or slightly increase (in 2016) due to higher unregulated emissions out-of-state. In particular, JHSMINE suggests that most policy-induced change in out-of-state generation and emissions takes place in the NW and SW regions of WECC. Plants in the RoW only adjust their output slightly in response to California's cap-and-trade program, leading to small emission increases. This contrasts with our empirical estimates, which suggest that coal-fired generation increased in the Northwest and RoW regions, while other treatment effects are not statistically significant. The leakage rates implied by JHSMINE are 94.3% in 2013 and 110% in 2016, in line with the predictions from earlier simulation-based partial equilibrium models that use the same leakage metric (Chen et al., 2011; Xu and Hobbs, 2021).

6 Comparison of results

JHSMINE is well suited to isolating the effects of California's cap-and-trade program on power plant operations in WECC, but yields *ex ante* predictions based on assumed firm behavior under perfectly inelastic demand, perfect competition, and perfect foresight of market participants. Although we parameterize the model using historical data, it is not surprising that its predictions may differ greatly from seasonal changes in plant utilization that are observed in the data. For example, a comparison of estimated and simulated coal-fired capacity factors in NW in Spring 2016 shows that JHSMINE does not predict a drop in coal utilization due to record low natural gas prices in the U.S. (U.S. Energy Information Administration, 2020), which is captured by a negative and statistically significant seasonal effect. In contrast, the econometric model measures the *ex post* realized effects of the policy, but the empirical estimates may be imprecise due to threats to identification in this policy setting and inaccurate representation of transmission network constraints.

In this section, we compare the *ex ante* expected impacts of the policy with its *ex post* realized impacts, starting with the effects on electricity generation shifts. With regard to the predicted source of leakage in WECC, JHSMINE suggests that the policy-induced reduction in capacity factors at California NGCC plants was offset by higher NGCC capacity utilization in the NW and SW regions of WECC, as well as coal capacity utilization in the NW; in contrast, the econometric model suggests increases in capacity utilization at coal plants in the NW and RoW. What factors may explain these differences? In the simulation model, the shares of specified imports into California by fossil fuel generation type are parameterized based on historical values, but the composition of unspecified imports is unknown. Thus, the findings of the econometric model may be consistent with higher levels of imports of out-of-state coal generation as unspecified power (relative to the *ex ante* predictions), and an incentive for electricity importers to not report the emission content of out-of-state higher-emitting generation resources in order to attain the lower default emission rate for GHG compliance obligations ("laundering").

With regard to heterogeneity between day and night, the changes in plant utilization rates across hours of the day based on the simulation model (Figures 8 and 9) are generally consistent with the expected substitution patterns at regulated and leaker units (i.e., decreases/increases in utilization rates that tend to occur at the same hour, given limited energy storage capacity over the study period). In contrast, the changes based on the econometric model (Figure 4) suggest that capacity factor reductions at California's gas plants mainly occur in the middle of the day, while coal capacity factor increases outside California are concentrated in the evening hours. Direct comparisons between these sets of results are difficult because the changes based on the econometric model are relative to matched controls, while the changes based on the simulation model are relative to the benchmark scenario with no regulation of GHG emissions. Further, the empirical model yields average effects throughout the post treatment period (2013-2016), while JHSMINE yields results for specific years (2013 and 2016). Bearing these caveats in mind, the changes based on the econometric model are likely to be confounded by the effects of coincident policies and market developments, such as increased solar generation brought about by California's renewable portfolio standard. However, the diurnal patterns observed in Figure 4 are not solely driven by NGCC being crowded out by solar generation, because the changes based on the simulation model (where bias from solar and other confounding factors is not a concern) also suggest a policy-induced reduction in utilization at California's gas plants during daylight hours.

Lastly, we compare the impacts of the policy on emissions and leakage. The results in Tables 8 and 10 differ for the reasons discussed in Section 5.4.2. To enable more direct comparisons, we calculate the leakage rates implied by JHSMINE when considering only emission changes associated with NGCC plants in California and coal-fired plants in the NW and RoW leaker regions. Table 11 presents the results, and shows robustness of confidence intervals from the econometric model to removing bias and monotonicity restrictions, under linear ($M = 0$) violations of parallel trends. The CO_2 emission leakage rates predicted by JHSMINE are 95.5% in 2013 and 83.3% in 2016. Note that the aforementioned adjustment does not significantly affect the 2013 rate, relative to Table 10, but yields lower leakage in 2016, because it does not consider higher emissions in the Southwest region of WECC. Turning to the confidence intervals implied by our empirical estimates, the lower bound estimates from the econometric model are in the 40.8%-42% range in 2013 and 17.4%-23.1% range in 2016. *Ex post* rates below *ex ante* rates are consistent with contracts not being shuffled as easily as predicted by the simulation model, which does not account for transaction costs that would discourage these rearrangements. This result is also in line with previous findings in the literature: for example, in the context of RGGI, Chen (2009) predicts relative leakage rates of 90%-100%, while empirical estimates from Zhou and Huang (2021) are in the 43%-85% range. On the other hand, the upper bound estimates from the econometric model are around 200%. This level is outside the range of predictions from simulation-based partial equilibrium models in the literature that use the same leakage metric, but is not entirely unrealistic: similar rates would be observed if the reduction in NGCC generation in California was offset by an increase in coal-fired generation outside California of the same magnitude, and there was no change in emissions associated with power imports.[34]

7 Concluding remarks

In this paper, we seek to identify CO_2 emission leakage in the electricity sector from California's AB 32 cap-and-trade program in the first four years of policy implementation. We estimate shifts in electricity generation at baseload power plants in the Western Interconnection based on two models: a simulation-based partial equilibrium model of the electricity sector (JHSMINE) that includes salient features of the observed cap-and-trade program and is parameterized using market data in 2013-2016; and an econometric model applying a quasi-experimental design with coarsened exact matching and a robust inference method that does not require the parallel trends assumption to hold exactly. Based on the estimated shifts in electricity generation, we infer CO_2 emission leakage predictions in 2013 and 2016. We then compare the *ex ante* expected impacts of the policy to the *ex post* realized impacts. This allows us to identify critical assumptions driving the simulation results, and to benchmark the empirical results in a complex setting where threats to identification (i.e., the suite of changes that affected California's electricity market over the period of our study, and challenges associated with the construction of credible counterfactual outcomes) undermine

[34]Coal combustion emits almost twice as much carbon dioxide per unit of energy as does the combustion of natural gas.

attempts at statistical inference.

Both models predict reduced utilization at California's gas plants, but insights differ with respect to the predicted source of leakage at Western plants outside California. JHSMINE suggests relative increases in the utilization of gas plants in the NW and SW regions of WECC and, to a more limited extent, of coal plants in the NW; in contrast, the econometric model finds that capacity utilization mostly increases at coal plants in the NW and RoW regions over this study period. As discussed in the paper, the effects of coincident policy changes and market developments likely confound our empirical estimates. However, the composition of unspecified imports is not parameterized based on historical data in the simulation model. Thus, the *ex post* findings may be consistent with higher levels of imports of out-of-state coal generation as unspecified power (relative to the *ex ante* predictions), and an incentive for electricity importers to not report the emission content of out-of-state higher-emitting generation resources in order to attain the lower default emission rate for GHG compliance obligations ("laundering"). Thus, limiting the ability of electricity importers to claim the default emission factor may reduce leakage risks.

With regard to policy impacts on emissions, JHSMINE finds a significant potential for leakage in WECC, with predicted rates of 95.5% in 2013 and 83.3% in 2016. Predictions based on the econometric model suggest some empirical evidence of leakage, with rates implied by the lower bound of robust confidence intervals of about 40% in 2013 and 20% in 2016. *Ex post* rates below *ex ante* rates are consistent with contracts not being shuffled as easily as predicted by the simulation model, which does not account for transaction costs that would discourage these rearrangements.

Our study shows that simulation models and econometric models can play complementary roles in the evaluation of carbon policy impacts. To support comparisons between simulation results and empirical estimates, future research in this area could enhance representation of network effects in empirical analyses and simulate power market outcomes under relaxed assumptions on the degree of market competition, demand elasticity and foresight of market participants.

References

Aichele, Rahel, and Gabriel Felbermayr. 2013a. The Effect of the Kyoto Protocol on Carbon Emissions. *Journal of Policy Analysis and Management* 32(4): 731-7-57.

------. 2013b. Estimating the Effects of Kyoto on Bilateral Trade Flows Using Matching Econometrics. *The World Economy*: 36(3): 303–330.

------. 2015. Kyoto and Carbon Leakage: an Empirical Analysis of the Carbon Content of Bilateral Trade. *Review of Economics and Statistics* 97 (1): 104–115.

Alcorn, Thomas. 2013. The Constitutionality of California's Cap-and-Trade Program and Recommendations for Design of Future State Programs. *Michigan Journal of Environmental and Administrative Law* 3 (1): 87–177.

Aldy, Joseph, and William Pizer. 2015. The Competitiveness Impacts of Climate Change Mitigation Policies. *Journal of the Association of Environmental Resource Economists* 2 (4): 565–595.

Ang, Desmond. 2021. The Effects of Police Violence on Inner-City Students. *The Quarterly Journal of Economics* 136 (1): 115–168.

Angrist, Joshua, and Jörn-Steffen Pischke. 2009. *Mostly Harmless Econometrics*. Princeton: Princeton University Press.

Autor, David. 2003. Outsourcing at Will: the Contribution of Unjust Dismissal Doctrine to the Growth of Employment Outsourcing. *Journal of Labor Economics* 21 (1): 1–42.

Blackwell, Matthew, Stefano Iacus, Gary King, and Giuseppe Porro. 2009. CEM: Coarsened Exact Matching in Stata. *The Stata Journal* 9 (4): 524–546.

Borenstein, Severin, James Bushnell, Frank Wolak, and Matthew Zaragoza-Watkins. 2014. *Report of the Market Simulation Group on Competitive Supply/Demand Balance in the California Allowance Market and the Potential for Market Manipulation.* http://www.arb.ca.gov/cc/capandtrade/simulationgroup/msg_final_v25.pdf.

Bureau of Labor Statistics. 2022. *Employment, Hours, and Earnings - State and Metro Area.* http://www.bls.gov/data/#employment.

Burtraw, Dallas, Ann Carlson, Danny Cullenward, Quentin Foster, and Meredith Fowlie. 2018. *2018 Annual Report of the Independent Emissions Market Advisory Committee.* http://calepa.ca.gov/wp-content/uploads/sites/6/2018/10/Final_2018_IEMAC_Annual_Report_10-22-2018.pdf.

Bushnell, James, and Yihsu Chen. 2012. Allocation and Leakage in Regional Cap-and-Trade Markets for CO_2. *Resource and Energy Economics* 34: 647–668.

Bushnell, James, Yihsu Chen, and Matthew Zaragoza-Watkins. 2014. Downstream Regulation of CO_2 Emissions in California's Electricity Sector. *Energy Policy* 64: 313–323.

Bushnell, James, and Kevin Novan. 2018. *Setting with the Sun: the Impacts of Renewable Energy on Wholesale Power Markets.* NBER Working Paper 24980, National Bureau of Economic Research, Cambridge, MA.

Bushnell, James, Carla Peterman, and Catherine Wolfram. 2008. Local Solutions to Global Problems: Climate Change Policies and Regulatory Jurisdiction. *Review of Environmental Economics and Policy* 2 (2): 175–193.

Bushnell, James, Erin Mansur, and Celeste Saravia. 2008. Vertical Arrangements, Market Structure and Competition: an Analysis of Restructured U.S. Electricity Markets. *American Economic Review* 98 (1): 237–266.

California Air Resources Board. 2008. *Climate Change Scoping Plan.* https://ww2.arb.ca.gov/sites/default/files/classic//cc/scopingplan/document/adopted_scoping_plan.pdf.

------. 2010. *California GHG Emissions - Forecast (2008-2020).* https://ww3.arb.ca.gov/cc/inventory/data/tables/2020_ghg_emissions_forecast_2010-10-28.pdf

------. 2013. *Semi-Annual Report to the Joint Legislative Budget Committee on Assembly Bill 32.* https://ww2.arb.ca.gov/sites/default/files/classic//research/apr/reports/california-global-warming-solutions-act-2006.pdf.

------. 2014. *First Update to the Climate Change Scoping Plan.* https://ww2.arb.ca.gov/sites/default/files/classic//cc/scopingplan/2013_update/first_update_climate_change_scoping_plan.pdf.

------. 2020a. *2000-2018 GHG Inventory (2020 Edition).* https://ww2.arb.ca.gov/ghg-inventory-archive.

------. 2020b. *California Greenhouse Gas Emissions for 2000 to 2018 - Trends of Emissions and Other Indicators.* https://ww3.arb.ca.gov/cc/inventory/pubs/reports/2000_2018/ghg_inventory_trends_00-18.pdf.

------. 2022a. *Electrical Distribution Utility and Natural Gas Supplier Allowance Allocation.* https://ww2.arb.ca.gov/our-work/programs/cap-and-trade-program/allowance-allocation/edu-ngs.

------. 2022b. *Mandatory GHG Reporting - Asset Controlling Supplier.* http://ww2.arb.ca.gov/mrr-acs.

------. 2022c. *Mandatory GHG Reporting - Electric Power Entities.* http://ww2.arb.ca.gov/mrr-epe.

California Energy Commission. 2017. *2016 Total System Electric Generation.* http://www.energy.ca.gov/data-reports/energy-almanac/california-electricity-data/2018-total-system-electric-generation/2016.

California Independent System Operator. 2022a. *Annual and Quarterly Reports*. http://www.caiso.com/market/Pages/MarketMonitoring/AnnualQuarterlyReports/Default.aspx.

------. 2022b. *Daily Renewables Watch*. http://www.caiso.com/market/Pages/ReportsBulletins/RenewablesReporting.aspx.

------. 2022c. *Open Access Same-time Information System (OASIS)*. http://oasis.caiso.com/mrioasis/logon.do.

Carbone, Jared, and Nicholas Rivers. 2017. The Impacts of Unilateral Climate Policy on Competitiveness: Evidence from Computable General Equilibrium Models. *Review of Environmental Economics and Policy* 11 (1): 24–42.

Carbone, Jared, Nicholas Rivers, Akio Yamazaki, and Hidemichi Yonezawa. 2020. Comparing Applied General Equilibrium and Econometric Estimates of the Effect of an Environmental Policy Shock. *Journal of the Association of Environmental and Resource Economists* 7 (4): 687–719.

Carlson, Curtis, Dallas Burtraw, Maureen Cropper, and Karen Palmer. 2000. Sulfur Dioxide Control by Electric Utilities: What Are the Gains from Trade?. *Journal of Political Economy* 108 (6): 1292–1326.

Caron, Justin, Sebastian Rausch, and Niven Winchester. 2015. Leakage from Sub-National Climate Policy: the Case of California's Cap-and-Trade Program. *The Energy Journal* 36 (2): 167–190.

Chan, Nathan, and John Morrow. 2019. Unintended Consequences of Cap-and-Trade? Evidence from the Regional Greenhouse Gas Initiative. *Energy Economics* 80: 411–422.

Chen, Yihsu. 2009. Does a regional greenhouse gas policy make sense? A case study of carbon leakage and emissions spillover. *Energy Economics* 31 (5): 667–675.

Chen, Yihsu, Andrew Liu, and Benjamin Hobbs. 2011. Economic and Emissions Implications of Load-Based, Source-Based, and First-Seller Emissions Trading Programs under California AB 32. *Operations Research* 59 (3): 696–712.

Climate Policy Initiative. 2022. *California Carbon Dashboard*. http://calcarbondash.org/.

Cullen, Joseph, and Erin Mansur. 2017. Inferring Carbon Abatement Costs in Electricity Markets: a Revealed Preference Approach using the Shale Revolution. *American Economic Journal: Economic Policy* 9 (3): 106–133.

Cullenward, Danny, and Andy Coghlan. 2016. Structural Oversupply and Credibility in California's Carbon Market. *The Electricity Journal* 29: 7–14.

Davis, Lucas, and Catherine Hausman. 2016. Market Impacts of a Nuclear Power Plant Closure. *American Economic Journal: Applied Economics* 8 (2): 92–122.

DSIRE. 2022. *Database of State Incentives for Renewables and Efficiency*. https://www.dsireusa.org/.

Ek, Claes, and Jurate Miliute-Plepiene. 2018. Behavioral Spillovers from Food-Waste Collection in Swedish Municipalities. *Journal of Environmental Economics and Management* 89: 168–186.

Ellerman, Denny, Paul Joskow, Richard Schmalensee, Elizabeth Bailey, and Juan-Pablo Montero. 2000. *Markets for Clean Air: The U.S. Acide Rain Program*. Cambridge University Press.

Federal Energy Regulatory Commission. 2022. *Form No. 714 - Annual Electric Balancing Authority Area and Planning Area Report*. https://www.ferc.gov/industries-data/electric/general-information/electric-industry-forms/form-no-714-annual-electric/data.

Fell, Harrison, and Peter Maniloff. 2018. Leakage in Regional Environmental Policy: the Case of the Regional Greenhouse Gas Initiative. *Journal of Environmental Economics and Management* 87: 1–23.

Fowlie, Meredith. 2009. Incomplete Environmental Regulation, Imperfect Competition, and Emissions Leakage. *American Economic Journal: Economic Policy* 1 (2): 72–112.

Fowlie, Meredith, Stephen Holland, and Erin Mansur. 2012. What Do Emissions Markets Deliver and To Whom? Evidence from Southern California's NO_x Trading Program. *American Economic Review* 102 (2): 965–993.

Fowlie, Meredith, and Mar Reguant. 2018. Challenges in the Measurement of Leakage Risk. *AEA Papers and Proceedings* 108: 124–129.

Fowlie, Meredith, Mar Reguant, and Stephen Ryan. 2016. Market-Based Environmental Regulation and Industry Dynamics. *Journal of Political Economy* 124 (1): 249–302.

Gabriel, Steven, Antonio Conejo, J. David Fuller, Benjamin Hobbs, and Carlos Ruiz. 2013. *Complementarity Modeling in Energy Markets*. Springer.

Graff Zivin, Joshua, Matthew Kotchen, and Erin Mansur. 2014. Spatial and Temporal Heterogeneity of Marginal Emissions: Implications for Electric Cars and Other Electricity-Shifting Policies. *Journal of Economic Behavior and Organization* 107 (Part A): 248–268.

Guignet, Dennis, Robin Jenkins, Matthew Ranson, and Patrick Walsh. 2018. Contamination and Incomplete Information: Bounding Implicit Prices using High-Profile Leaks. *Journal of Environmental Economics and Management* 88: 259–282.

Heckman, James, Hidehiko Ichimura, Jeffrey Smith, and Petra Todd. 1998. Characterizing Selection Bias Using Experimental Data. *Econometrica* 66 (5): 1017–1098.

Heckman, James, Hidehiko Ichimura, and Petra Todd. 1997. Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Program. *Review of Economic Studies* 64 (4):

605–654.

Herrero, Ignacio, Pablo Rodilla, and Carlos Batlle. 2018. Enhancing Intraday Price Signals in U.S. ISO Markets for a Better Integration of Variable Energy Resources. *The Energy Journal* 39 (3): 141–165.

Hobbs, Benjamin, Qingyu Xu, Jonathan Ho, Pearl Donohoo, Saamrat Kasina, Jasmine Ouyang, Sang Woo Park, Joseph Eto, and Vijay Satyal. 2016. Adaptive Transmission Planning: Implementing a New Paradigm for Managing Economic Risks in Grid Expansion. *IEEE Power & Energy Magazine* July-August: 30–40.

Iacus, Stefano, Gary King, and Giuseppe Porro. 2008. *Matching for Causal Inference Without Balance Checking*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1152391.

------. 2011. Multivariate Matching Methods that are Monotonic Imbalance Bounding. *Journal of the American Statistical Association* 106 (493): 345–361.

------. 2012. Causal Inference without Balance Checking: Coarsened Exact Matching. *Political Analysis* 20: 1–24.

Jaeger, David, Theodore Joyce and Robert Kaestner. 2020. A Cautionary Tale of Evaluating Identifying Assumptions: Did Reality TV Really Cause a Decline in Teenage Childbearing? *Journal of Business & Economics Statistics* 38 (2): 317–326.

Joskow, Paul, and Edward Kahn. 2002. A Quantitative Analysis of Pricing Behavior in California's Wholesale Electricity Market During Summer 2000. *The Energy Journal* 23 (4): 1–35.

Kahn, Matthew, and Erin Mansur. 2013. Do Local Energy Prices and Regulation Affect the Geographic Concentration of Employment? *Journal of Public Economics* 101: 105–114.

Kahn-Lang, Ariella, and Kevin Lang. 2020. The Promise and Pitfalls of Differences-in-Differences: Reflections on *16 and Pregnant* and Other Applications. *Journal of Business & Economics Statistics* 38 (3): 613–620.

Kearney, Melissa, and Phillip Levine. 2015. Media Influences on Social Outcomes: The Impact of MTV's *16 and Pregnant* on Teen Childbearing. *American Economic Review* 105: 3597–3632.

------. 2016. *Does Reality TV Induce Real Effects? A Response to Jaeger, Joyce and Kaestner*. IZA Discussion Paper 10318, Bonn, Germany.

Kindle, Andrew, Daniel Shawhan, and Michael Swider. 2011. *An Empirical Test for Inter-State Carbon-Dioxide Emissions Leakage Resulting from the Regional Greenhouse Gas Initiative*. Unpublished manuscript.

Kotchen, Matthew, and Erin Mansur. 2014. How Stringent Are the U.S. EPA's Proposed Carbon Pollution Standards for New Power Plants? *Review of Environmental Economics and Policy* 8 (2): 290–306.

Legislative Analyst's Office. 2017. *The 2017-18 Budget: Cap-and-Trade*. http://www.lao.ca.gov/reports/2017/3553/cap-and-trade-021317.pdf.

Levinson, Arik, and M. Scott Taylor. 2008. Unmasking the Pollution Haven Effect. *International Economic Review* 49 (1): 223–254.

Mansur, Erin. 2007. Do Oligopolists Pollute Less? Evidence from a Restructured Electricity Market. *Journal of Industrial Economics* 55 (4): 661–689.

National Electric Reliability Council. 2022. *Glossary of Terms Used in NERC Reliability Standards*. https://www.nerc.com/pa/Stand/Glossary%20of%20Terms/Glossary_of_Terms.pdf.

National Energy Board of Canada. 2022. *Commodity Statistics*. http://apps.neb-one.gc.ca/CommodityStatistics/Statistics.aspx?language=english.

National Renewable Energy Laboratory. 2011. *Regional Energy Deployment System (ReEDS)*. https://www.nrel.gov/docs/fy12osti/46534.pdf.

------. 2019. *Regional Energy Deployment System (ReEDS) Model Documentation: Version 2019*. https://www.nrel.gov/docs/fy20osti/74111.pdf.

National Oceanic and Atmospheric Administration. 2022. *National Centers for Environmental Information*. http://www.ncdc.noaa.gov/.

Nyberg, Michael. 2018. *Thermal Efficiency of Natural Gas-Fired Generation in California: 2017 Update*. https://www.energy.ca.gov/publications/2018/thermal-efficiency-natural-gas-fired-generation-california-2017-update.

Panhans, Matthew, Lucia Lavric, and Nick Hanley. 2017. The Effects of Electricity Costs on Firm Re-location Decisions: Insights for the Pollution Haven Hypothesis. *Environmental and Resource Economics* 68 (4): 893–914.

Puller, Steven. 2007. Pricing and Firm Conduct in California's Deregulated Electricity Market. *Review of Economics and Statistics* 89 (1): 75–87.

Rambachan, Ashesh and Jonathan Roth. 2022a. *A More Credible Approach to Parallel Trends*. https://jonathandroth.github.io/assets/files/HonestParallelTrends_Main.pdf.

------. 2022b. *HonestDiD R package*. https://github.com/asheshrambachan/HonestDiD.

Rose, Evan. 2021. Who Gets a Second Chance? Effectiveness and Equity in Supervision of Criminal Offenders. *The Quarterly Journal of Economics* 136 (2): 1199–1253.

Saussay, Aurélien and Misato Sato. 2018. *The Impacts of Energy Prices on Industrial Foreign Investment Location: Evidence from Global Firm Level Data*. Centre for Climate Change Economics and Policy

Working Paper 344, London School of Economics, London, U.K.

Schweppe, Fred, Michael Caramanis, Richard Tabors, and Roger Bohn. 1988. *Spot Pricing of Electricity.* Kluwer.

Shawhan, Daniel, John Taber, Di Shi, Ray Zimmerman, Jubo Yan, Charles Marquet, Yingying Qi, Biao Mao, Richard Schuler, William Schulze, and Daniel Tylavsky. 2014. Does a Detailed Model of the Electricity Grid Matter? Estimating the Impacts of the Regional Greenhouse Gas Initiative. *Resource and Energy Economics* 36 (1): 191–207.

Shi, Di, Daniel Shawhan, Nan Li, Daniel Tylavsky, John Taber, Ray Zimmerman, and William Schulze. 2012. Optimal Generation Investment Planning: Pt. 1: Network Equivalents. In *2012 North American Power Symposium (NAPS)*, 1–6.

Simcoe, Timothy, and Michael Toffel. 2014. Government Green Procurement Spillovers: Evidence from Municipal Building Policies in California. *Journal of Environmental Economics and Management* 68: 411–434.

Stavins, Robert, Jonathan Borck, and Todd Schatzki. 2010. *Options for Addressing Leakage in California's Climate Policy.* https://www.analysisgroup.com/Insights/publishing/options-for-addressing-leakage-in-california-s-climate-policy/.

Sue Wing, Ian and Marek Kolodziej. 2009. *The Regional Greenhouse Gas Initiative: Emission Leakage and the Effectiveness of Interstate Border Adjustments.* http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1448748.

U.S. Department of Energy. 2014. *Transmission Constraints and Congestion in the Western and Eastern Interconnections.* https://www.energy.gov/oe/downloads/transmission-constraints-and-congestion-western-and-eastern-interconnections-2009-2012.

U.S. Energy Information Administration. 2020. *As U.S. Coal-Fired Capacity and Utilization Decline, Operators Consider Seasonal Operation.* https://www.eia.gov/todayinenergy/detail.php?id=44976.

------. 2022a. *Average Cost of Fossil Fuels for Electricity Generation.* http://www.eia.gov/electricity/data.cfm.

------. 2022b. *Form EIA-860.* http://www.eia.gov/electricity/data/eia860/.

------. 2022c. *Form EIA-923.* http://www.eia.gov/electricity/data/eia923/.

------. 2022d. *Form EIA-930.* https://www.eia.gov/beta/electricity/gridmonitor/about.

------. 2022e. *How Much Carbon Dioxide Is Produced When Different Fuels Are Burned?.* https://www.eia.gov/tools/faqs/faq.php?id=73&t=11.

U.S. Environmental Protection Agency. 2020. *AVoided Emissions and geneRation Tool (AVERT)*. https://www.epa.gov/sites/production/files/2020-09/documents/avert_user_manual_09-12-20_508.pdf.

------. 2022. *Air Market Program Data*. http://ampd.epa.gov/ampd/.

WECC Staff. 2015. *Loads and Resources Methods and Assumptions*. http://www.wecc.biz/Reliability/2015LAR_MethodsAssumptions.pdf.

------. 2016. *WECC 2026 Common Case Version 1.5*. http://www.wecc.org/SystemAdequacyPlanning/Pages/Datasets.aspx.

------. 2019. *WREGIS System e-Tag User Training*. http://www.wecc.org/Administrative/WREGIS%20System%20e-Tag%20User%20Training%20-%20Updated%20022019.pdf.

Xu, Qingyu, and Benjamin Hobbs. 2019. Value of Model Enhancements: Quantifying the Benefit of Improved Transmission Planning Models. *IET Generation, Transmission & Distribution* 13 (13): 2836–2845.

------. 2021. Economic Efficiency of Alternative Border Carbon Adjustment Schemes: A Case Study of California Carbon Pricing and the Western North American Power Market. *Energy Policy* 156, article 112463.

Zhou, Yihsu, and Ling Huang. 2021. How Regional Policies Reduce Carbon Emissions in Electricity Markets: Fuel Switching or Emission Leakage. *Energy Economics* 97, article 105209.

Figures

Figure 1: NERC regions in the United States, 2016

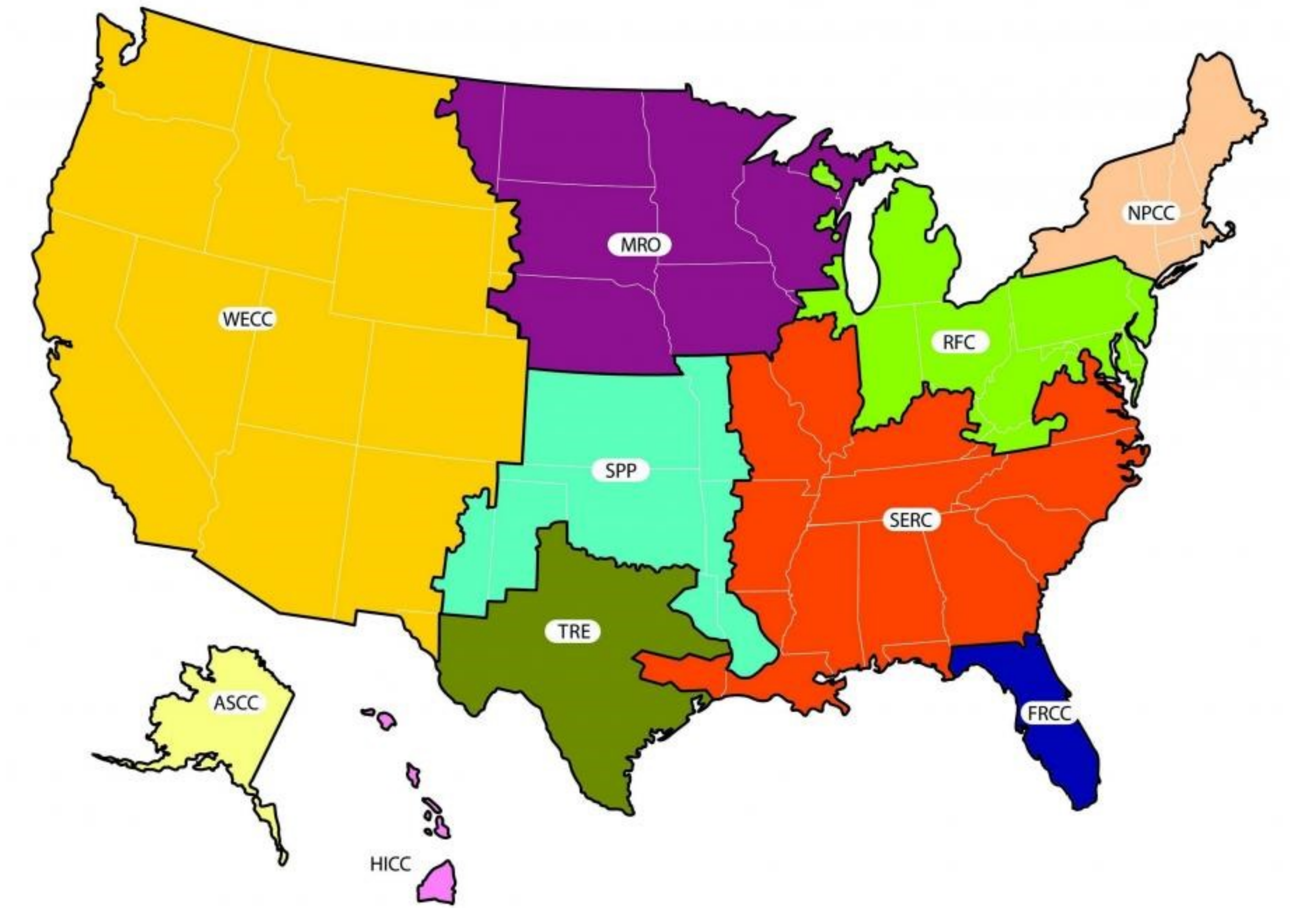
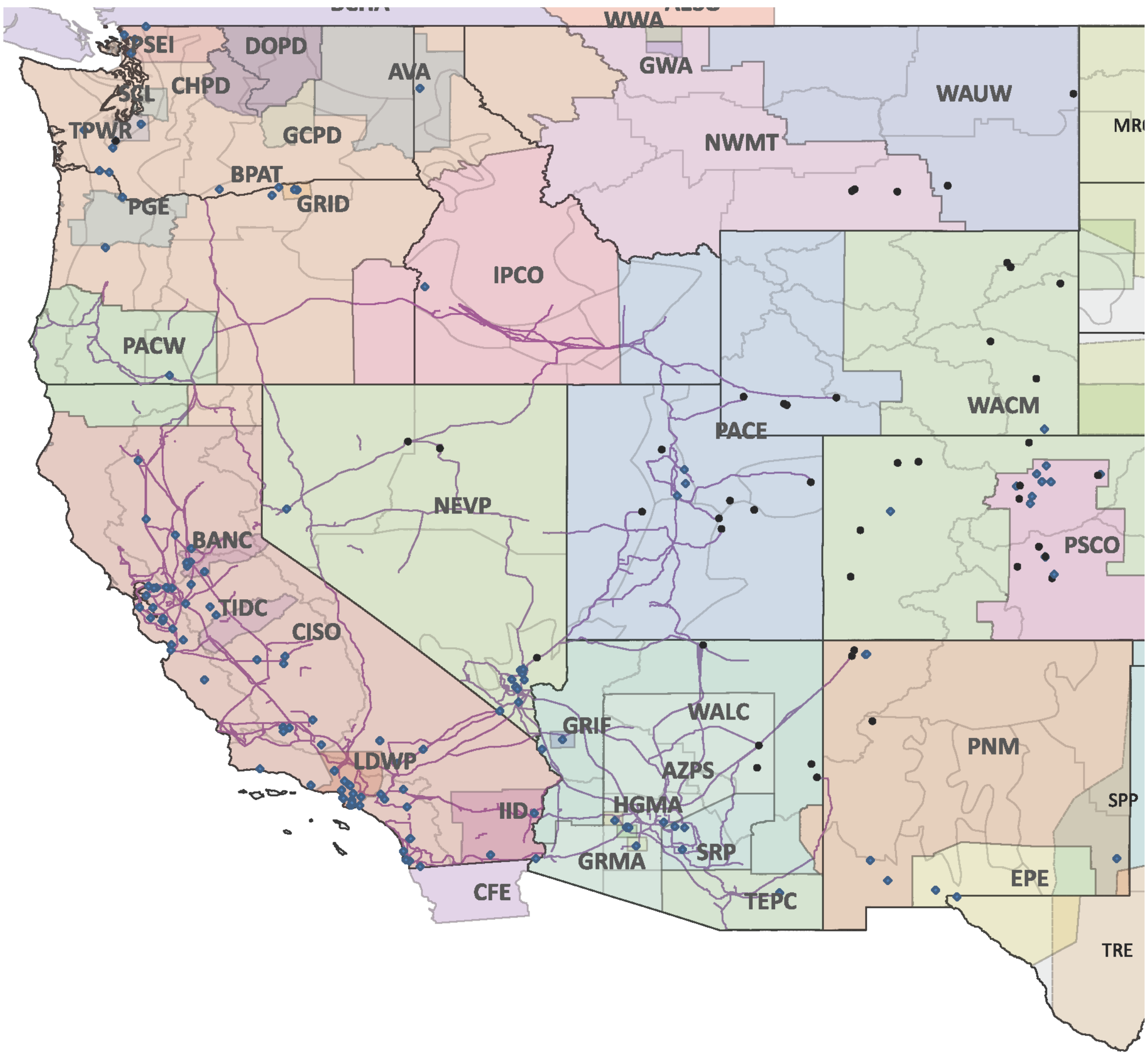


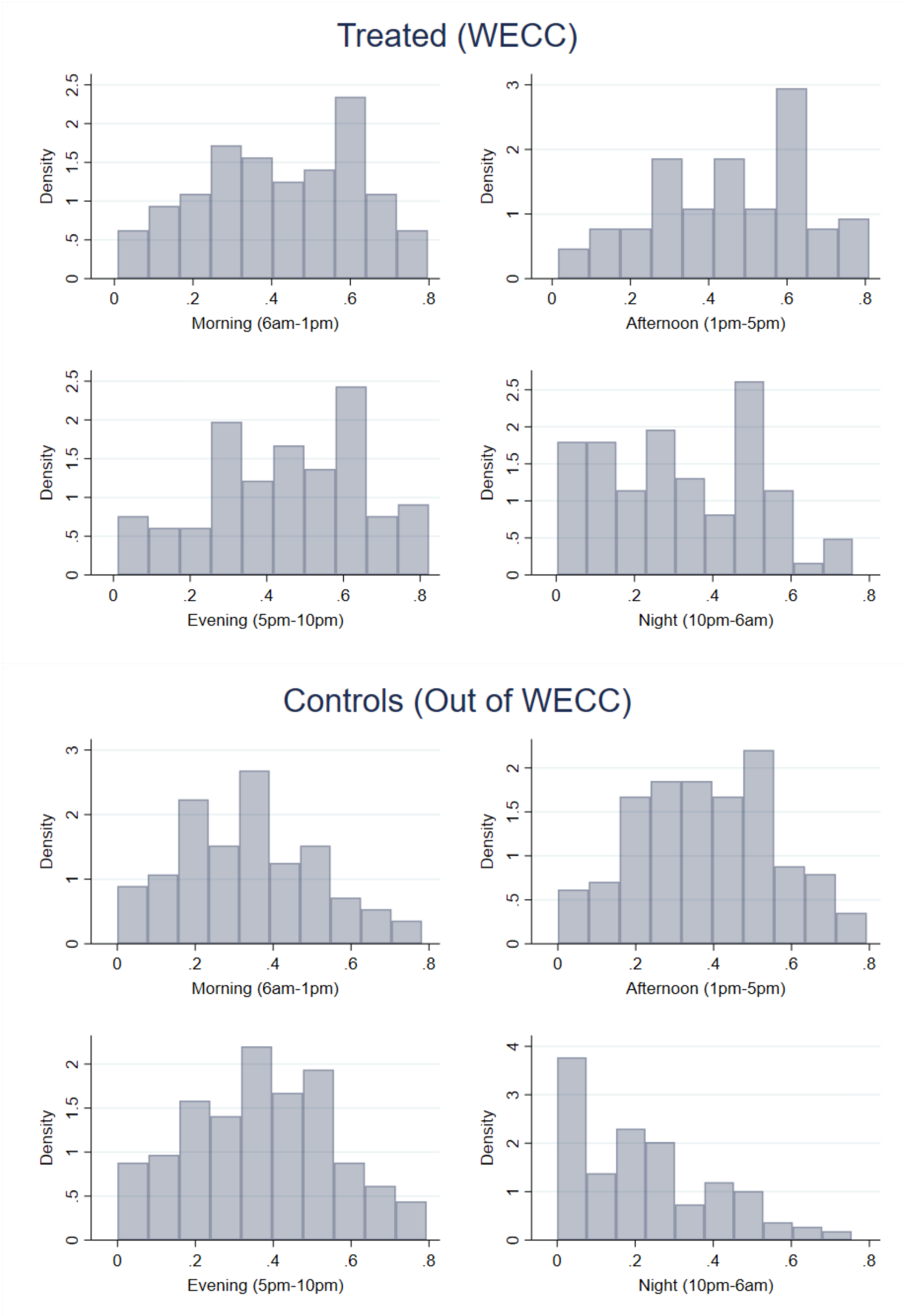
Figure 2: WECC balancing authorities in the United States, 2016



Note: Black dots represent coal-fired power plants, blue diamonds represent NGCC plants.

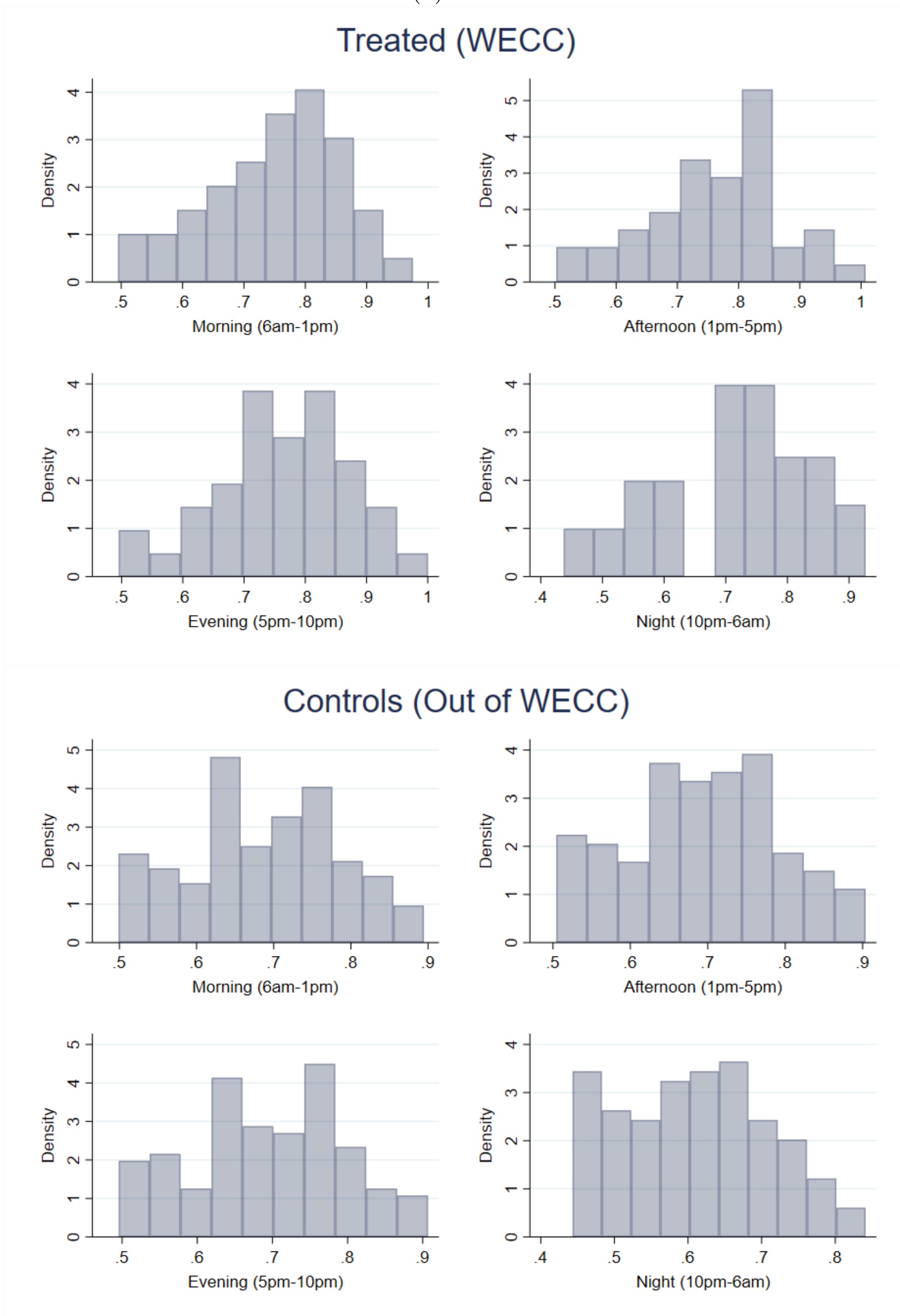
Figure 3: Empirical distribution of 2009-10 average capacity factors by technology, region and block of hour

(a) NGCC



Note: Histograms for the control plants are constrained to include capacity factors below 0.797, 0.810, 0.823, and 0.758 corresponding to the highest capacity factor of WECC plants (i.e., the upper limit of the last matching bin for the treated plants) in the morning, afternoon, evening and night period, respectively.

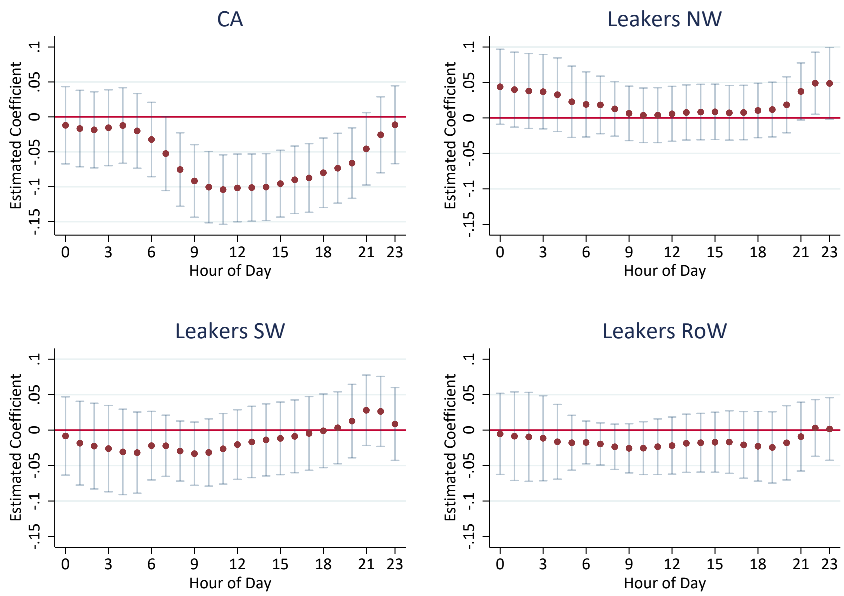
(b) Coal



Note: Histograms for the control plants are constrained to include capacity factors above 0.495, 0.502, 0.495, and 0.437 corresponding to the lowest capacity factor of WECC plants (i.e., the lower limit of the first matching bin for the treated plants) in the morning, afternoon, evening and night period, respectively.

Figure 4: Treatment heterogeneity by hour of day based on specification (5)

(a) NGCC



(b) Coal

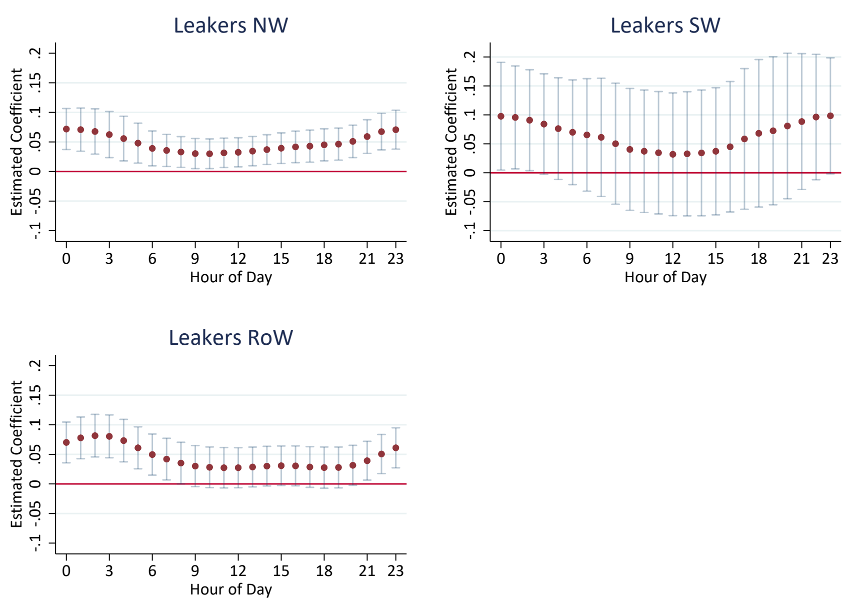
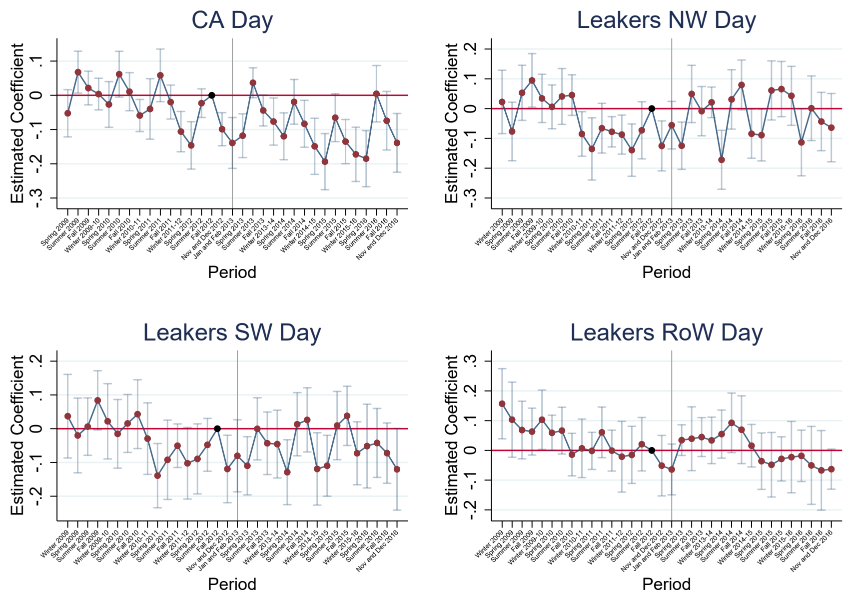
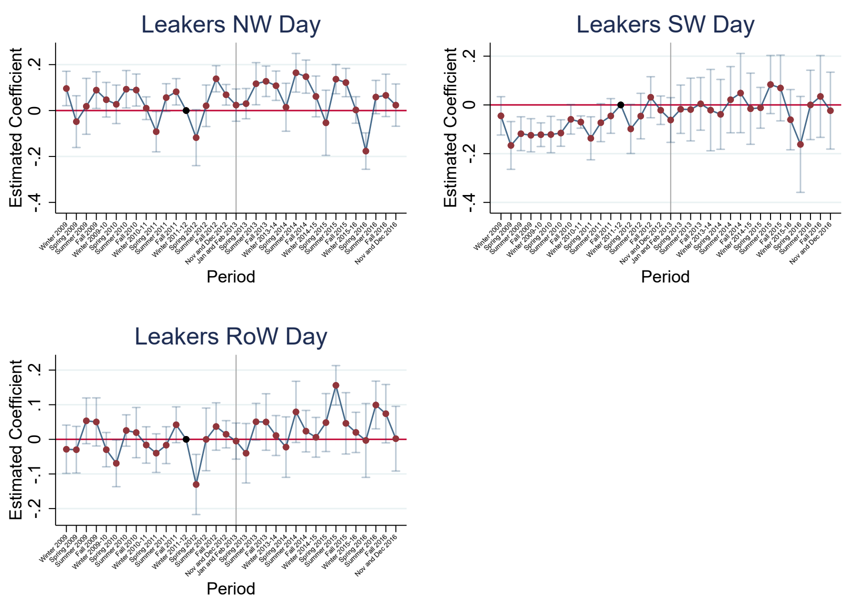


Figure 5: Parallel trend tests between treated and control regions - Day

(a) NGCC



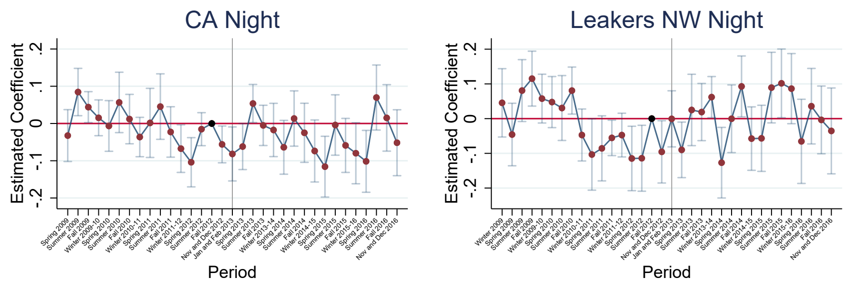
(b) Coal



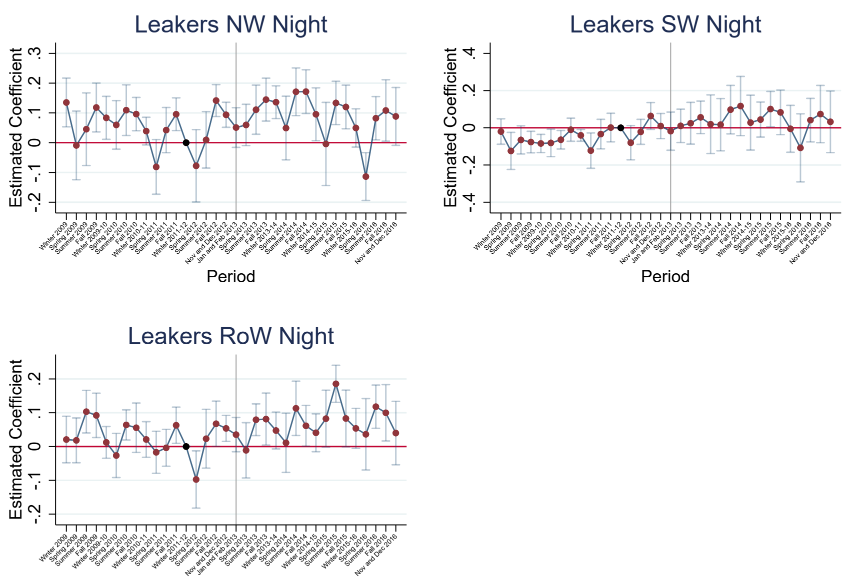
Note: The vertical line indicates the start date of the cap-and-trade program. In the CA Day plot, Winter 2009 is dropped due to lack of import data until April 1, 2009. The reference period (Fall 2012 for NGCC and Winter 2011-12 for Coal) is represented by a black dot at zero and no confidence interval, and corresponds to the reference period of choice for robust inference using Rambachan and Roth (2022a)'s approach.

Figure 6: Parallel trend tests between treated and control regions - Night

(a) NGCC



(b) Coal

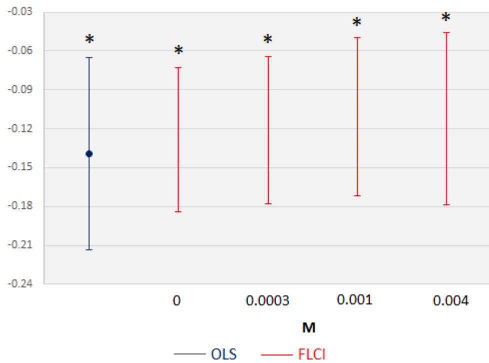


Note: The vertical line indicates the start date of the cap-and-trade program. In the CA Night plot, Winter 2009 is dropped due to lack of import data until April 1, 2009. The reference period (Fall 2012 for NGCC and Winter 2011-12 for Coal) is represented by a black dot at zero and no confidence interval, and corresponds to the reference period of choice for robust inference using Rambachan and Roth (2022a)'s approach.

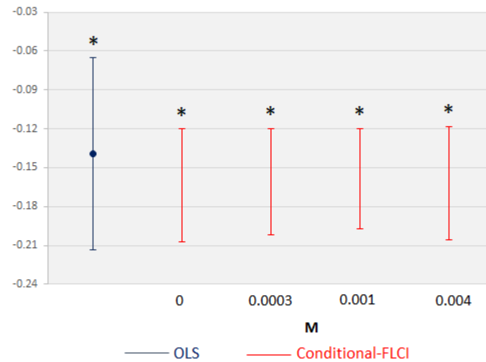
Figure 7: Sensitivity analysis for the event study coefficients in Jan-Feb 2013

California NGCC (Day)

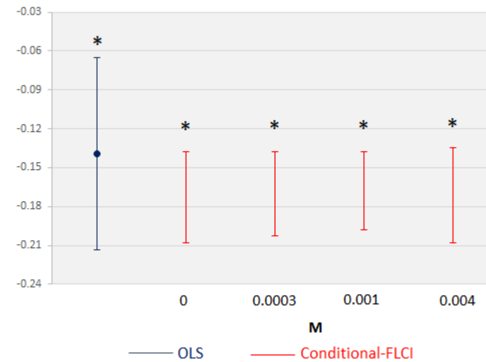
(a) No restrictions



(b) Monotonicity and negative bias

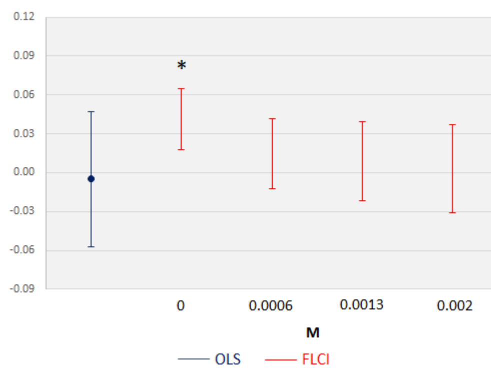


(c) Monotonicity and positive bias



RoW Coal (Day)

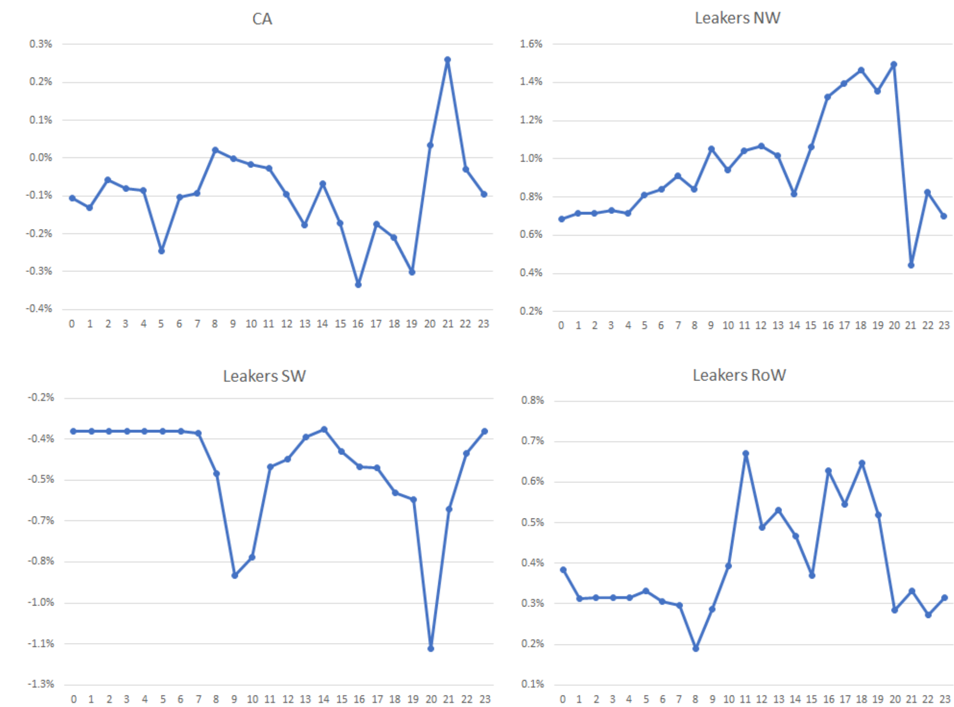
(a) No restrictions



Note: In each panel, "OLS" refers to the 95% confidence intervals for Jan-Feb 2013 treatmed effect estimated using OLS. "FLCI" ("Conditional FLCI") indicates the 95% fixed length confidence interval (conditional fixed length confidence interval) using the Rambachan and Roth (2022a) robust inference method. Stars indicate intervals that do not cross zero.

Figure 8: Change in average capacity factors by region, tech type and hour of day based on 2013 simulation results

(a) NGCC



(b) Coal

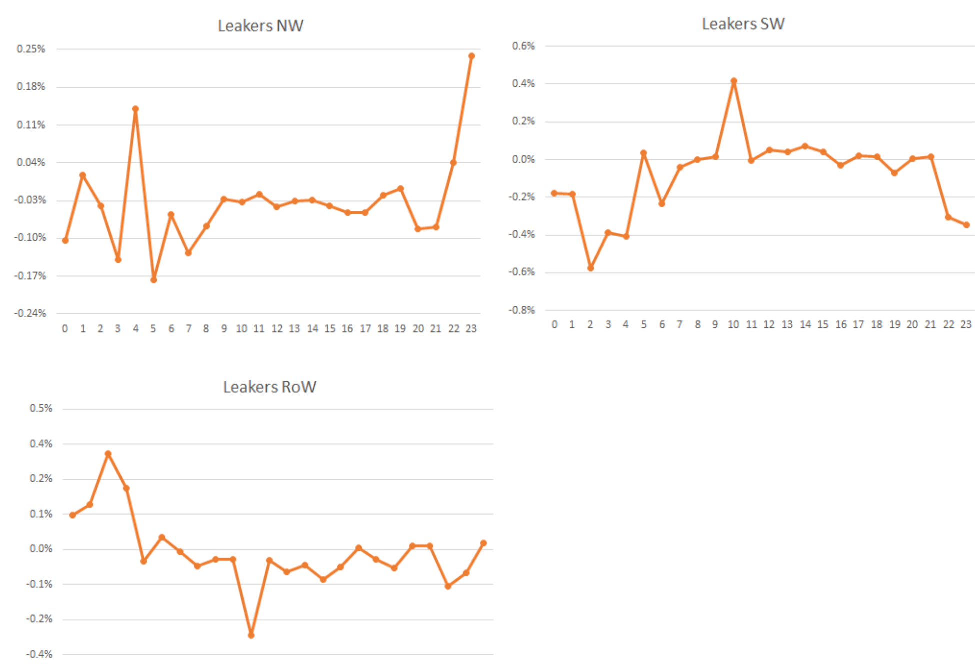
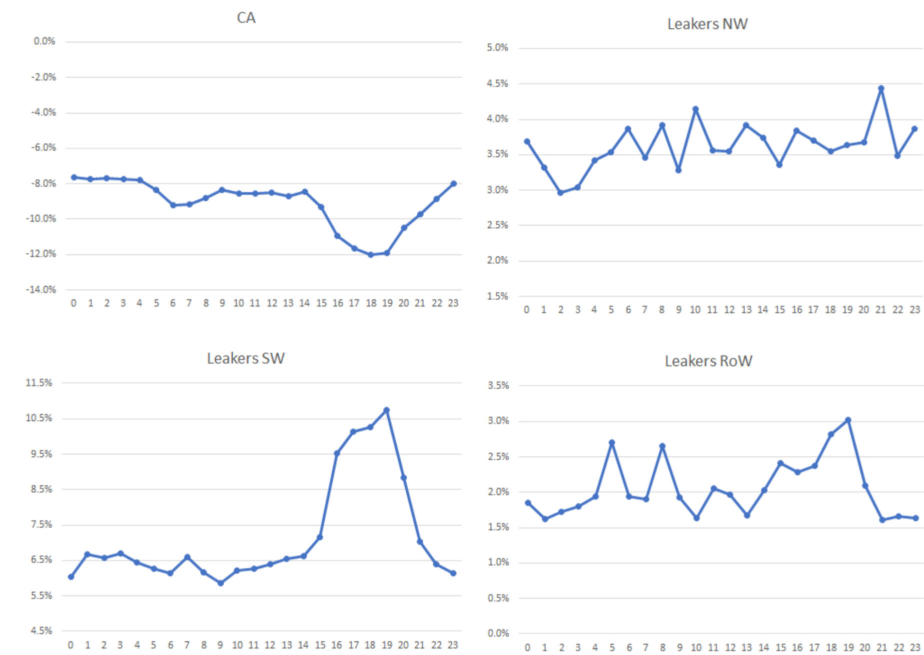
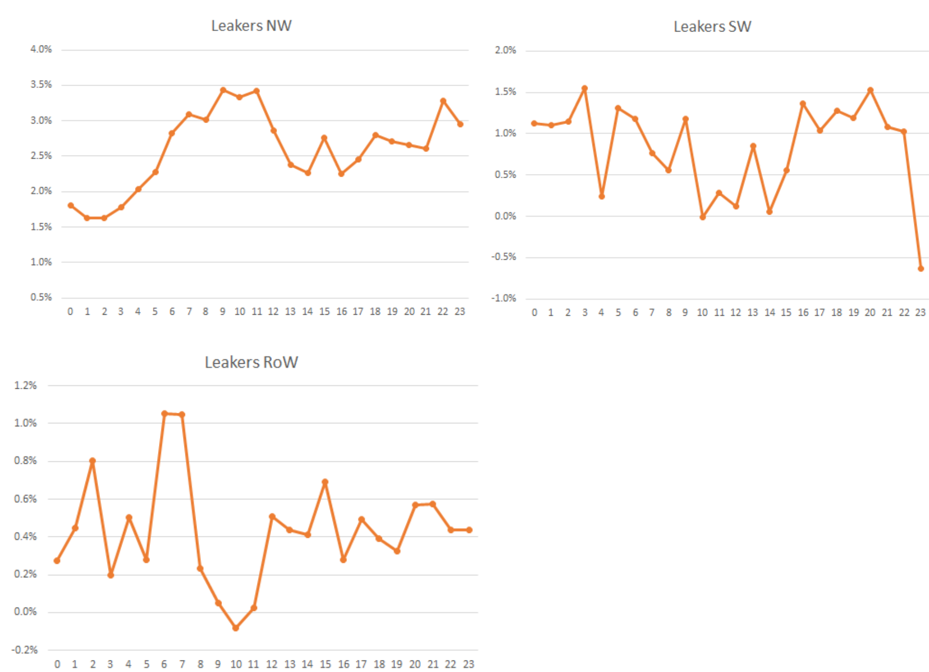


Figure 9: Change in average capacity factors by region, tech type and hour of day based on 2016 simulation results

(a) NGCC



(b) Coal



Tables

Table 1: Summary statistics for NGCC plants

Region	Pre ETS						Post ETS					
	Number of plants	Nameplate capacity (MW)	Capacity factor (%)	Heat rate (Btu/kWh)	CO_2 emission rate (lb/MMBtu)	Age (years)	Number of plants	Nameplate Capacity (MW)	Capacity factor (%)	Heat rate (Btu/kWh)	CO_2 emission rate (lb/MMBtu)	Age (years)
WECC												
CA	67	309	0.54	9,028	118.14	10.67	69	332	0.49	8,913	117.98	11.88
		(334)	(0.31)	(2,246)	(1.45)	(11.30)		(329)	(0.31)	(2,356)	(2.37)	(7.87)
NW	34	456	0.46	8,259	118.41	8.34	34	479	0.50	7,967	118.51	11.98
		(280)	(0.32)	(2,667)	(1.41)	(4.46)		(308)	(0.30)	(1,246)	(0.73)	(4.77)
RoW	15	361	0.23	9,924	118.23	11.30	15	371	0.28	9,373	118.38	11.76
		(260)	(0.20)	(4,178)	(1.06)	(8.33)		(253)	(0.25)	(3,732)	(0.81)	(5.99)
SW	13	875	0.36	8,176	118.44	7.65	13	905	0.34	8,138	118.50	11.69
		(673)	(0.26)	(1,276)	(0.75)	(1.77)		(665)	(0.25)	(1,777)	(0.78)	(1.78)
Controls												
FRCC	31	835	0.49	8,139	118.78	16.27	31	911	0.52	7,915	118.84	18.96
		(877)	(0.21)	(1,637)	(1.07)	(12.55)		(964)	(0.24)	(1,621)	(1.02)	(12.70)
MRO-US	17	381	0.13	9,054	118.55	12.70	17	361	0.21	9,186	118.54	16.11
		(217)	(0.15)	(3,426)	(1.15)	(13.98)		(216)	(0.20)	(3,717)	(1.03)	(14.58)
SERC	58	670	0.46	8,777	118.91	9.53	58	671	0.51	8,723	118.88	13.22
		(476)	(0.28)	(3,198)	(11.23)	(5.15)		(473)	(0.27)	(3,082)	(9.65)	(5.94)
SPP	21	598	0.38	8,256	118.54	19.15	21	597	0.37	8,306	118.56	23.14
		(388)	(0.26)	(1,424)	(0.71)	(16.96)		(385)	(0.26)	(1,596)	(0.68)	(16.95)
TRE	58	652	0.44	9,147	118.39	11.60	58	656	0.45	9,090	118.04	15.09
		(381)	(0.24)	(2,721)	(1.29)	(8.88)		(387)	(0.24)	(2,772)	(4.14)	(9.21)

Note: Summary statistics are based on monthly data from the U.S. Energy Information Administration. Pre ETS refers to January 2009-December 2012 and post ETS to January 2013-December 2016. Standard deviations are reported in parentheses.

Table 2: Summary statistics for coal-fired plants

Region	Pre ETS						Post ETS					
	Number of plants	Nameplate capacity (MW)	Capacity factor (%)	Heat rate (Btu/kWh)	CO_2 emission rate (lb/MMBtu)	Age (years)	Number of plants	Nameplate Capacity (MW)	Capacity factor (%)	Heat rate (Btu/kWh)	CO_2 emission rate (lb/MMBtu)	Age (years)
WECC												
NW	18	779	0.73	11,472	207.58	32.48	18	765	0.69	12,527	208.13	35.56
		(648)	(0.23)	(4,801)	(2.33)	(11.53)		(660)	(0.24)	(7,566)	(2.14)	(11.05)
RoW	25	537	0.74	12,484	208.57	29.53	25	558	0.72	11,878	208.55	29.84
		(659)	(0.21)	(4,911)	(3.01)	(15.44)		(669)	(0.22)	(3,404)	(4.28)	(15.74)
SW	7	1,289	0.72	12,229	206.22	31.09	6	1,376	0.70	10,497	206.45	34.75
		(837)	(0.17)	(4,652)	(3.29)	(8.92)		(688)	(0.17)	(418)	(2.45)	(8.91)
Controls												
FRCC	10	1,081	0.53	11,197	201.53	26.85	10	1,078	0.43	11,287	198.50	30.92
		(678)	(0.22)	(2,415)	(26.34)	(7.67)		(678)	(0.22)	(2,092)	(17.29)	(7.64)
MRO-US	49	459	0.54	13,814	209.84	38.18	56	491	0.52	13,591	210.55	40.55
		(515)	(0.23)	(6,538)	(3.17)	(11.06)		(512)	(0.23)	(6,409)	(3.98)	(11.43)
SERC	71	1,232	0.59	11,675	205.92	38.68	71	1,247	0.51	11,801	205.78	41.26
		(836)	(0.23)	(4,764)	(8.47)	(10.80)		(835)	(0.24)	(4,722)	(9.64)	(11.96)
SPP	35	689	0.63	11,730	208.44	33.70	35	706	0.55	11,680	208.87	34.47
		(546)	(0.24)	(2,980)	(5.73)	(9.86)		(529)	(0.26)	(3,395)	(7.78)	(13.06)
TRE	18	1,134	0.72	10,870	213.14	26.14	20	1,167	0.64	11,170	213.06	26.97
		(762)	(0.26)	(1,051)	(5.22)	(8.91)		(739)	(0.26)	(2,203)	(5.28)	(12.21)

Note: Summary statistics are based on monthly data from the U.S. Energy Information Administration. Pre ETS refers to January 2009-December 2012 and post ETS to January 2013-December 2016. Standard deviations are reported in parentheses.

Table 3: Control strategy for hydro, nuclear and renewable generation by model specification

Model specification	In-state hydro and nuclear generation	In-state renewable generation	Controls for hydro, nuclear and renewable generation at two additional geographic scales?	Capacity factor frequency
(1), (3), (4)	Each series is modeled with a cubic spline; spline coefficients do not vary across markets	Modeled with a cubic spline; spline coefficients do not vary across markets	No	Daily
(2)	Hydro and nuclear generation are combined into one series, which is modeled with a cubic spline; spline coefficients vary by interconnection	Modeled with a cubic spline; spline coefficients vary by interconnection	No	Daily
(5)	Each series is modeled with a cubic spline; spline coefficients do not vary across markets	Modeled with a cubic spline; spline coefficients do not vary across markets	No	Hourly
(6)	Hydro and nuclear generation are combined into one series, which is modeled with a cubic spline; spline coefficients vary by interconnection	Modeled with a cubic spline; spline coefficients vary by interconnection	Yes	Hourly
(7)	Hydro and nuclear generation are combined into one series, which is modeled with a cubic spline; spline coefficients vary by interconnection	Modeled with a cubic spline; spline coefficients vary by interconnection and time of day	No	Hourly
(8)	Each series is modeled with a cubic spline; hydro spline coefficients do not vary across markets, nuclear spline coefficients vary by interconnection	Modeled with a cubic spline; spline coefficients vary by interconnection and time of day	No	Hourly

Table 4: Econometric model results: Treatment effects based on daily capacity factors

	(1)		(2)		(3)		(4)	
	NGCC	Coal	NGCC	Coal	NGCC	Coal	NGCC	Coal
	Spline coeff. invariant across markets		*Spline coeff. vary by interconnection*		*Standard errors clustered by BA*		*Alternate matching set*	
CA	-0.058^{**}	-	-0.044^{*}	-	-0.058^{**}	-	-0.060^{**}	-
	(0.025)	-	(0.025)	-	(0.025)	-	(0.027)	-
NW	0.021	0.047^{***}	0.038^{*}	0.048^{***}	0.021	0.047^{***}	0.015	0.041^{***}
	(0.020)	(0.013)	(0.022)	(0.013)	(0.017)	(0.017)	(0.019)	(0.011)
RoW	-0.015	0.044^{***}	0.001	0.049^{***}	-0.015	0.044^{**}	-0.034	0.043^{***}
	(0.018)	(0.016)	(0.021)	(0.016)	(0.016)	(0.020)	(0.025)	(0.015)
SW	-0.011	0.059	0.005	0.074	-0.011	0.059	-0.014	0.065
	(0.023)	(0.047)	(0.026)	(0.046)	(0.029)	(0.054)	(0.023)	(0.055)
Before matching								
CA plants	40	-	40	-	40	-	40	-
Leaker plants	48	42	48	42	48	42	48	42
Control plants	153	170	153	170	153	170	153	170
After matching								
CA plants	33	-	33	-	33	-	34	-
Leaker plants	40	40	40	40	40	40	44	41
Control plants	128	94	128	94	128	94	140	150
Observations	567,484	379,028	567,484	379,028	567,484	379,028	616,666	533,642
Clusters	201	134	201	134	38	28	218	191

Note: The unit of observation is plant-day. All regressions include plant, year, day-of-week and state by month-year fixed effects. Standard errors are reported in parentheses, and clustered by plant in specifications (1), (2) and (4), and by balancing authority in (3). *, **, and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table 5: Econometric model results: Treatment effects based on hourly capacity factors

	(5)		(6)		(7)		(8)
	NGCC	Coal	NGCC	Coal	NGCC	Coal	NGCC
	Spline coeff. invariant across markets		*Spline coeff. vary by interconnection, controls for hydro, nuclear and renewable generation at two additional geographic scales (outside-BA but in-region, and outside-CA but in-WECC)*		*Spline coeff. vary by interconnection, renewable spline coeff. also vary by time of day*		*Hydro spline coeff. invariant across markets, nuclear spline coeff. vary by interconnection, renewable spline coeff. vary by interconnection and time of day*
Day							
CA	-0.089^{***}	-	-0.057^{**}	-	-0.063^{**}	-	-0.049^{**}
	(0.024)	-	(0.025)	-	(0.026)	-	(0.024)
NW	0.008	0.035^{***}	0.019	0.037^{**}	0.028	0.045^{***}	0.019
	(0.019)	(0.012)	(0.020)	(0.014)	(0.020)	(0.014)	(0.020)
RoW	-0.020	0.031^{*}	-0.014	0.038^{**}	0.001	0.043^{***}	-0.003
	(0.019)	(0.017)	(0.021)	(0.016)	(0.020)	(0.016)	(0.020)
SW	-0.018	0.050	-0.004	0.060	-0.001	0.075	-0.008
	(0.023)	(0.061)	(0.026)	(0.056)	(0.026)	(0.056)	(0.025)
Night							
CA	-0.028	-	0.002	-	-0.026	-	-0.012
	(0.026)	-	(0.026)	-	(0.026)	-	(0.023)
NW	0.033	0.058^{***}	0.043^{*}	0.060^{***}	0.047^{*}	0.048^{***}	0.038
	(0.022)	(0.015)	(0.026)	(0.015)	(0.024)	(0.014)	(0.024)
RoW	-0.011	0.059^{***}	-0.004	0.066^{***}	0.002	0.054^{***}	-0.002
	(0.020)	(0.017)	(0.024)	(0.016)	(0.023)	(0.016)	(0.023)
SW	-0.006	0.091	0.006	0.102^{*}	0.011	0.091^{*}	0.003
	(0.025)	(0.057)	(0.027)	(0.051)	(0.027)	(0.052)	(0.026)
Observations	13,619,137	9,096,375	13,619,137	9,096,375	13,619,137	9,096,375	13,619,137
Clusters	201	134	201	134	201	134	201

Note: The unit of observation is plant-hour for all specifications. All regressions include plant, time-of-day, day-of-week, year and state by month-year fixed effects. Standard errors are clustered by plant and reported in parentheses.

Table 6: Balancing tests on plant capacity factors

	NGCC		Coal	
	Before matching	After matching	Before matching	After matching
Hour 0	2.075**	0.192	6.364***	1.004
Hour 1	1.932*	0.064	6.670***	1.207
Hour 2	1.856*	−0.001	6.779***	1.263
Hour 3	1.835*	−0.041	6.707***	1.171
Hour 4	1.869*	−0.051	6.357***	0.892
Hour 5	1.772*	−0.160	5.832***	0.564
Hour 6	1.859*	−0.120	5.064***	0.126
Hour 7	2.001**	−0.043	4.636***	−0.028
Hour 8	1.917*	−0.185	4.381***	−0.057
Hour 9	1.621	−0.509	4.244***	−0.021
Hour 10	1.377	−0.662	4.215***	0.055
Hour 11	1.266	−0.692	4.217***	0.058
Hour 12	1.298	−0.601	4.249***	0.047
Hour 13	1.380	−0.529	4.350***	0.135
Hour 14	1.399	−0.502	4.468***	0.195
Hour 15	1.392	−0.502	4.542***	0.272
Hour 16	1.339	−0.542	4.528***	0.229
Hour 17	1.383	−0.503	4.380***	0.151
Hour 18	1.426	−0.488	4.218***	0.048
Hour 19	1.500	−0.405	4.172***	0.005
Hour 20	1.659*	−0.203	4.427***	0.133
Hour 21	2.100**	0.391	4.852***	0.290
Hour 22	2.320**	0.567	5.442***	0.590
Hour 23	2.283**	0.441	5.929***	0.771
Morning	1.646	−0.402	4.447***	0.026
Afternoon	1.378	−0.519	4.473***	0.208
Evening	1.627	−0.240	4.419***	0.128
Night	2.009**	0.129	6.308***	0.945

Note: The table reports t statistics of a two-sided test of mean comparisons between treated and control groups before and after matching. *, **, and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table 7: Parallel trends test: Treatment effects with and without trends

	No trend		Linear trend		Quadratic trend	
	NGCC	Coal	NGCC	Coal	NGCC	Coal
Day						
CA	-0.089^{***}	-	-0.018	-	-0.013	-
	(0.024)	-	(0.027)	-	(0.027)	-
NW	0.008	0.035^{***}	-	0.098^{***}	-	0.099^{***}
	(0.019)	(0.012)	-	(0.030)	-	(0.030)
RoW	-0.020	0.031^{*}	-	0.026	-	0.025
	(0.019)	(0.017)	-	(0.021)	-	(0.021)
SW	-0.018	0.050	-	-	-	-
	(0.023)	(0.061)	-	-	-	-
Night						
CA	-0.028	-	-	-	-	-
	(0.026)	-	-	-	-	-
NW	0.033	0.058^{***}	-	0.121^{***}	-	0.122^{***}
	(0.022)	(0.015)	-	(0.026)	-	(0.026)
RoW	-0.011	0.059^{***}	-	0.054^{***}	-	0.053^{***}
	(0.020)	(0.017)	-	(0.020)	-	(0.020)
SW	-0.006	0.091	-	-	-	-
	(0.025)	(0.057)	-	-	-	-

Note: If a treatment effect is statistically significant in the baseline regression ("No trend"), we augment the model with a group-specific linear (quadratic) trend for all treated regions. The table presents the estimated coefficients in the augmented models. Standard errors are clustered by plant and reported in parentheses.

Table 8: Econometric model results: Emissions and leakage based on the econometric estimates, 2013 and 2016

2013	Lower bound of the robust 95% CI	Upper bound of the robust 95% CI
Change in CA local emissions (E_1)	-6.84	-2.07
Change in CA import emissions (E_2)	-10.87	-10.87
Change in CA regulated emissions ($E_3 = E_1 + E_2$)	-17.71	-12.94
Change in WECC-NonCA emissions (E_4)	-3.65	17.33
- NW	1.26	12.82
- RoW	-4.91	4.51
Change in WECC emissions ($E_5 = E_1 + E_4$)	-10.49	15.26
Leakage $[(1 - E_5/E_3) \times 100\%]$	*40.8%*	*217.9%*

2016	Lower bound of the robust 95% CI	Upper bound of the robust 95% CI
Change in CA local emissions (E_1)	-7.09	-2.86
Change in CA import emissions (E_2)	-11.81	-11.81
Change in CA regulated emissions ($E_3 = E_1 + E_2$)	-18.90	-14.67
Change in WECC-NonCA emissions (E_4)	-8.51	14.21
- NW	-4.54	7.27
- RoW	-3.97	6.94
Change in WECC emissions ($E_5 = E_1 + E_4$)	-15.60	11.35
Leakage $[(1 - E_5/E_3) \times 100\%]$	*17.4%*	*177.4%*

Note: Emissions are in million metric tons of CO_2 per year. Results are based on robust confidence intervals for CA NGCC Day and RoW Coal Day that allow for linear violations of parallel trends (M=0), and OLS confidence intervals for CA NGCC Night, NW Coal Day and Night, and RoW Coal Night. We assume negative bias and monotonicity restrictions for CA NGCC Day, and no restrictions for RoW Coal Day. Only contemporaneous (i.e., same season and time of day) changes in capacity factors in the regulated and unregulated regions are included for the leakage calculation.

Table 9: Simulation model results: Effect of California's cap-and-trade program on capacity factors in WECC, 2013 and 2016

		2013			*2016*		
		No cap	Carbon cap	Δ	No cap	Carbon cap	Δ
CA	Hydro	24.9%	24.9%	-	30.1%	30.1%	-
	NGCC	50.2%	49.5%	-0.7%	43.3%	33.8%	-9.6%
	NGCT	6.1%	5.5%	-0.6%	4.4%	4.4%	-
	Nuclear	95.0%	95.0%	-	95.0%	95.0%	-
	Oil	5.3%	5.3%	-	5.3%	5.3%	-
	Solar	9.8%	9.8%	-	19.2%	19.2%	-
	Wind	19.9%	19.9%	-	19.7%	19.7%	-
NW	Coal	87.5%	87.5%	-	76.6%	79.2%	+2.6%
	Hydro	29.9%	29.9%	-	31.0%	31.0%	-
	NGCC	56.9%	57.9%	+1.0%	59.0%	62.5%	+3.5%
	NGCT	1.6%	2.0%	+0.4%	1.6%	2.8%	+1.2%
	Nuclear	95.0%	95.0%	-	95.0%	95.0%	-
	Oil	94.0%	94.0%	-	94.0%	94.0%	-
	Solar	21.4%	21.4%	-	20.5%	20.5%	-
	Wind	16.8%	16.8%	-	17.6%	17.6%	-
RoW	Coal	87.1%	87.1%	-	79.2%	79.6%	+0.4%
	Hydro	32.0%	32.0%	-	38.5%	38.5%	-
	NGCC	19.5%	19.9%	+0.4%	33.1%	35.2%	+2.1%
	NGCT	0.9%	1.0%	+0.1%	4.1%	4.7%	+0.6%
	Nuclear	-	-	-	-	-	-
	Oil	18.2%	18.2%	-	18.2%	18.2%	-
	Solar	16.7%	16.7%	-	15.0%	15.0%	-
	Wind	29.9%	29.9%	-	31.9%	31.9%	-
SW	Coal	83.3%	83.2%	-0.1%	59.4%	60.2%	+0.8%
	Hydro	32.1%	32.1%	-	37.0%	37.0%	-
	NGCC	19.5%	19.0%	-0.5%	34.1%	41.3%	+7.2%
	NGCT	1.0%	1.1%	+0.1%	1.0%	1.3%	+0.3%
	Nuclear	95.0%	95.0%	-	95.0%	95.0%	-
	Oil	-	-	-	-	-	-
	Solar	17.5%	17.5%	-	26.0%	26.0%	-
	Wind	9.3%	9.3%	-	9.9%	9.9%	-

Note: The oil-fired capacity in the NW region is only 13.80 MW, resulting in high capacity factors for this peak technology.

Table 10: Simulation model results: Effect of California's cap-and-trade program on emissions and leakage, 2013 and 2016

2013	No cap	Carbon cap	
Local emissions in CA	39.79	38.68	
Emissions of CA imports	51.25	39.41	
Regulated emissions in CA	91.03	78.10	
Emissions in WECC-NonCA	265.42	265.78	
- NW	113.28	113.78	
- RoW	90.99	91.06	
- SW	61.15	60.94	
Total emissions in WECC	305.21	304.47	
Change in CA local emissions (E_1)			-1.10
Change in CA import emissions (E_2)			-11.83
Change in CA regulated emissions ($E_3 = E_1 + E_2$)			-12.94
Change in WECC-NonCA emissions (E_4)			$+0.36$
Change in WECC emissions (E_5)			-0.74
Leakage $[(1 - E_5/E_3) \times 100\%]$			*94.3%*

2016	No cap	Carbon cap	
Local emissions in CA	35.85	29.27	
Emissions of CA imports	38.59	24.71	
Regulated emissions in CA	74.45	53.99	
Emissions in WECC-NonCA	232.81	241.44	
- NW	102.58	107.15	
- RoW	83.39	84.31	
- SW	46.84	49.98	
Total emissions in WECC	268.67	270.71	
Change in CA local emissions (E_1)			-6.58
Change in CA import emissions (E_2)			-13.88
Change in CA regulated emissions ($E_3 = E_1 + E_2$)			-20.46
Change in WECC-NonCA emissions (E_4)			$+8.62$
Change in WECC emissions (E_5)			$+2.04$
Leakage $[(1 - E_5/E_3) \times 100\%]$			*110.0%*

Note: Emissions are in million metric tons of CO_2 per year.

Table 11: Comparison of emissions and leakage results, 2013 and 2016

2013	Simulation model	Econometric model 95% CI, No restrictions		Econometric model 95% CI, With restrictions	
		LB	UB	LB	UB
Change in CA local emissions (E_1)	-0.51	-6.33	-0.35	-6.84	-2.07
Change in CA import emissions (E_2)	-11.83	-10.87	-10.87	-10.87	-10.87
Change in CA regulated emissions ($E_3 = E_1 + E_2$)	-12.35	-17.20	-11.22	-17.71	-12.94
Change in WECC-NonCA emissions (E_4)	-0.05	-3.65	17.33	-3.65	17.33
Change in WECC emissions ($E_5 = E_1 + E_4$)	-0.56	-9.98	16.98	-10.49	15.26
Leakage $[(1 - E_5/E_3) \times 100\%]$	*95.5%*	*42.0%*	*251.4%*	*40.8%*	*217.9%*

2016	Simulation model	Econometric model 95% CI, No restrictions		Econometric model 95% CI, With restrictions	
		LB	UB	LB	UB
Change in CA local emissions (E_1)	-6.35	-5.73	0.31	-7.09	-2.86
Change in CA import emissions (E_2)	-13.88	-11.81	-11.81	-11.81	-11.81
Change in CA regulated emissions ($E_3 = E_1 + E_2$)	-20.24	-17.54	-11.50	-18.90	-14.67
Change in WECC-NonCA emissions (E_4)	2.97	-7.75	11.36	-8.51	14.21
Change in WECC emissions ($E_5 = E_1 + E_4$)	-3.38	-13.48	11.67	-15.60	11.35
Leakage $[(1 - E_5/E_3) \times 100\%]$	*83.3%*	*23.1%*	*201.5%*	*17.4%*	*177.4%*

Note: Changes in emissions are in million metric tons of CO_2 per year. When calculating leakage from the empirical estimates, we use robust confidence intervals for CA NGCC Day and RoW Coal Day (allowing for linear violations of parallel trends, or $M = 0$), and OLS confidence intervals for CA NGCC Night, NW Coal Day and Night, and RoW Coal Night. LB indicates the lower bound of the 95% confidence interval, while UB refers to its upper bound. Only contemporaneous (i.e., same season and time of day) changes in capacity factors in the regulated and unregulated regions are included for the leakage calculation. In the model with restrictions, we assume negative bias and monotonicity restrictions for CA NGCC Day, and no restrictions for RoW Coal Day.