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Carbon trading's impact on California's real-time electricity market prices

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ABSTRACT

What is the extent of a real-time electricity market's pass-through of the marginal cost of CO_2 emissions due to a cap-and-trade (C&T) program? This is an important policy question, as an incomplete pass-through would suggest the program's limited effectiveness in achieving efficient pricing of electricity. To answer the question, we perform a regression analysis of California's electricity market data for a 65-month period of 01/01/2011–05/31/2016. Based on this newly constructed large sample, we find that the California Independent System Operator's real-time market prices contain a CO_2 premium that closely tracks the marginal cost of CO_2 emissions of California's natural-gas-fired generation units, which are often at margin that determines the power prices. While the CO_2 premium provides much needed incentives for renewable energy development, it does little to improve the incentive for natural-gas-fired generation investment in California. Hence, procurement of dispatchable generation capacity via long-term contracts continues to be useful for the state to meet the mandatory criteria for resource adequacy and system reliability.

1. Introduction

Restructuring the electricity sectors in Europe, North America, South America, Australia, New Zealand, and Asia has fostered wholesale trading of electricity [1]. Wholesale electricity prices are inherently volatile with sharp spikes and dives,[1] prompting extensive research in price behavior [2,3], risk management [4,5], product differentiation [6], system operation [7], and integrated resource planning [8].

Along with competitive electricity trading, there have been efforts to decarbonize, or reduce CO_2 emissions of electricity generation. Despite the Trump administration's withdrawal of the U.S. commitment made in the 2015 Paris Climate Change Summit and unwillingness to implement the Clean Power Plan, California and other states have reaffirmed their efforts to combat global warming.[2] In particular, California will continue to pursue its legislated program for cap-and-trade (C&T) of CO_2 allowances.[3] Carbon trading is a market-based mechanism for effective and efficient decarbonization [9]. The extent of the CO_2 cost pass-through in electricity prices is an important policy question because it aids efficient pricing of electricity and encourages investment in clean energy and energy efficiency [10].

Extant regression analyses of market data have not reached a

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[1] Wholesale electricity prices are inherently volatile due to: (a) daily fuel-cost variations, especially for the natural gas that is widely used by combustion turbines and combined-cycle gas turbines; (b) hourly weather-sensitive demands and wind and solar resources with intra-day and inter-day fluctuations, which must be balanced in real time by dispatchable generation and transmission already in place; (c) planned and forced outages of electrical facilities; (d) hydro conditions for systems with significant hydro resources; (e) carbon-price fluctuations affecting thermal generation that uses fossil fuels; (f) transmission constraints that cause transmission congestion and generation re-dispatch; and (g) lumpy capacity additions that can only occur with long lead times.

[2] https://insideclimatenews.org/news/21092017/states-paris-trump-climate-change-alliance-leadership-jerry-brown-cuomo-inslee-nrdc-2050.

[3] https://www.arb.ca.gov/cc/pillars/pillars.htm.

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consensus on the CO_2 cost pass-through in electricity market prices. Notable examples include: (a) an almost 100% pass-through in the Spanish electricity prices [11]; (b) a pass-through of 84%–104% in the German electricity prices [12]; (c) a statistically insignificant pass-through for the second phase of the European Union Emission Trading System (EU ETS) [13]; (d) rising CO_2 prices of EU ETS permits having a stronger impact on wholesale electricity prices than falling CO_2 prices [14]; (e) an approximately 0.32% increase in the European electricity prices due to a 1% increase in the CO_2 price [15]; and (f) a 100% pass-through of California's CO_2 price in the day-ahead market (DAM) prices of the Pacific Northwest [16] and California [17].

This paper is a regression analysis of real-time market (RTM) data available from the California Independent System Operator (CAISO) for the period of 01/01/2011 to 05/31/2016. Based on this newly constructed large sample, the analysis aims to answer three interrelated questions of substantive policy relevance:

(1) Do the CAISO's RTM prices contain a CO_2 premium that measures the RTM price increase in response to carbon trading? If the RTM prices' estimated CO_2 premium tracks marginal cost (*MC*) of CO_2 emissions from electricity generation, California's C&T program is deemed effective in internalizing the formerly unpriced CO_2 emissions.
(2) How big is the CO_2 premium for natural-gas-fired generation? An engineering estimate of *MC* is the product of the CO_2 price, the CO_2 emissions per MMBtu of natural gas usage, and the marginal generation unit's heat rate (*HR*). When the marginal unit in a given hour is an aging combustion turbine (CT) with a relatively high *HR*, an owner of infra-marginal units, such as a relatively new CT or a combined cycle combustion turbine (CCGT) with a lower emission rate, can profit from that hour's relatively high CO_2 premium.[4]
(3) Does the CO_2 premium vary by time-of-day (TOD) period? This question is related to an electricity grid's marginal *HR*. For example, an aging CT (ACT) may be the marginal unit during the peak hours when the system experiences very high system loads, though not in the remaining non-peak hours when a relatively new CT or CCGT is the marginal unit. If the CO_2 premium's time pattern is found to match the marginal *HR*'s, it lends further support to the effectiveness of carbon trading in internalizing the formerly unpriced CO_2 emissions.

We summarize our findings to answer the aforementioned three questions. First, the CAISO's RTM prices are found to contain a non-trivial and time-varying CO_2 premium that closely tracks the daily CO_2 permit price. It corroborates the prior findings for Spain [11] and Germany [12], as well as the Pacific Northwest [16] and California [17]. Along with results in Refs. [11,12,16,17], this finding affirms the efficiency of wholesale electricity markets in those countries or regions to fully pass through the marginal cost of CO_2 emissions of generation plants, notwithstanding that these markets have different demand profiles and resource mixes (e.g., European countries vs. regions in the U.S.A.), trading platforms (e.g., bilateral trading in the Pacific Northwest vs. centralized markets in California and Texas), and trading time frames (e.g., California's DAM vs. RTM). Hence, it affirms the use of a C&T program to achieve an economy's deep decarbonization goal.

Second, the CAISO's RTM prices move with their fundamental drivers. Specifically, they tend to decline with renewable generation and available nuclear capacity but increase with the natural gas price and market demands. While intuitively appealing, this finding corroborates the documented price-dependence on fundamental drivers for California [18], the Pacific Northwest [19], Texas [20], and other regions (e.g., the 13 states served by the PJM grid and the European countries referenced in Ref. [18]).

Our paper makes two main contributions, especially to the current policy debates of using C&T in pursuit of sustainability in the power sector while minimizing interference with wholesale electricity market operations. First, it reports a comprehensive set of estimates of the CO_2 cost pass-through in California's RTM prices. To the best of our knowledge, these estimates are new, chiefly because they are based on a database that has not been considered in the extant literature. Together with the recently developed DAM estimates in Ref. [17], they confirm the California C&T program's effectiveness in pricing CO_2 emissions in the CAISO's electricity markets so that producers can effectively internalize emission costs in their bids. Second, it documents the fundamental drivers' estimated RTM price effects by TOD period. In particular, they show that the estimated merit-order effects of renewable energy such as wind and solar are time-dependent, sharply contrasting the time-invariant estimates previously reported for California [18], the Pacific Northwest [19], Texas [20], and other regions like PJM, Germany, Denmark and Spain noted in Ref. [18].

The rest of this paper proceeds as follows. Section 2 describes the CAISO markets, explains the RTM prices' pass-through of natural-gas-fired generation's marginal cost of CO_2 emissions, specifies our RTM price regressions, and describes our data sample. Section 3 reports our regression results. Section 4 concludes.

2. Materials and methods

2.1. The CAISO electricity markets

With a gross domestic product of US$2.45 trillion in 2015, California is the sixth largest economy of the world.[5] Its vast electric system has an in-state generation capacity of roughly 80,000 MW in 2015,[6] diversely fueled by natural gas (~59%), large hydro (~16%), renewables (~22%), and nuclear (~3%).[7] The CAISO operates the DAM and RTM for energy, as well as co-optimizing procurement of ancillary services (AS) for regulation and contingency reserves.[8] The DAM accounts for 90+% of the CAISO's energy transactions, while the remainder is transacted through the RTM. Though accounting for less than 10%, the RTM's trading volume is substantial because the state's total generation in 2015 was 196,819 GWh,[9] the fourth largest in the U.S.A.[10]

The CAISO's DAM and RTM are distinctly different. To see this point, consider that the DAM opens for bidding seven days before and closes at 1:00 p.m. the day prior to the trade date. The CAISO

[4] To see this point, consider the case of a 100% pass-through of *MC*. When an aging CT is the marginal unit, the CO_2 premium is based on this CT's heat rate HR_{ACT}. A CCGT owner benefits from carbon trading because $HR_{CCGT} < HR_{ACT}$, resulting in a per MWh benefit equal to the product of the CO_2 price, the per-MMBtu CO_2 emissions, and the heat rate difference of $(HR_{ACT} - HR_{CCGT}) > 0$.

[5] http://fortune.com/2016/06/17/california-france-6th-largest-economy/.

[6] http://energyalmanac.ca.gov/electricity/electric_generation_capacity.html.

[7] The ~22% renewable capacity is the sum of biomass (1.6%), geothermal (3.4%), small hydro (2.1%), solar PV (5.9%), solar thermal (1.6%), and wind (7.5%).

[8] To maintain the state's grid stability and reliability, the CAISO uses four types of AS products: regulation up, regulation down, spinning reserve and non-spinning reserve. As these products' primary goal is to provide frequency stability and standby and quick-start capacity, an analysis of the AS market prices is well beyond the scope of this paper.

[9] http://www.energy.ca.gov/almanac/electricity_data/electric_generation_capacity.html.

[10] https://www.eia.gov/electricity/state/california/.

determines the **hourly** DAM prices as follows. First, it daily runs a market power mitigation test to exclude generation supply bids with price quotes exceeding its preset benchmarks. Second, it determines the day-ahead forecast of the state's hourly locational loads. Finally, it uses a full network model to analyze the active transmission and generation resources to find the least-cost resource mix to serve the forecast loads. The model's results are the hourly day-ahead schedules for generation resources and loads, as well as the DAM prices for settling the day-ahead transactions.

Now consider the RTM, a spot market that opens after the DAM and closes 75 min before the start of the trading hour. Further detailed in Section 2.2 below, the CAISO's real-time economic dispatch automatically runs every 5 min to obtain imbalance energy and energy from ancillary services. As real-time energy imbalances are the result of unanticipated deviations from the day-ahead schedules of loads and resources, their resolution leads to **5-min** RTM prices that tend to fluctuate significantly more than the DAM prices.[11]

Both the hourly DAM and 5-min RTM prices are highly volatile, have sharp spikes and dips, occasionally have negative values,[12] move with their fundamental drivers, and can regionally diverge due to intra-state transmission congestion [18]. Further, the hourly DAM prices have been found to move with the CO_2 price resulting from the state's C&T program established under Assembly Bill 32 (AB32), the Global Warming Solutions Act of 2006 [17]. However, little is known about the effects of C&T on the RTM. A higher than 100% pass-through of the carbon price indicate that producers tend to over-estimate their emissions costs, or deliberately markup their bids to take advantage of the RTM. A lower than 100% pass-through, however, suggests that producers tend to under-estimate their emissions costs, causing an unnecessary financial risk exposure. Hence, deviations from a 100% pass-through distort the price signal of carbon trading, thereby affecting incentives of long-run investment in the power market.

Fig. 1 shows the state's two major wholesale electricity trading hubs: (1) North of Path 15 (NP15) in northern California, whose major local distribution company (LDC) is Pacific Gas and Electric (PG and E); and (2) South of Path 15 (SP15) in southern California, whose largest LDC is Southern California Edison (SCE).[13] Along with the Mid-Columbia hub in the Pacific Northwest and the Palo Verde hub in the Desert Southwest, the NP15 and SP15 hubs are major delivery points in the Western Interconnection, a vast electricity grid encompassing the western portion of North America. Our primary research goal is to determine the impact of carbon trading on the NP15 and SP15 RTM prices.

[11] In November 2014, the CAISO launched the western energy imbalance market (EIM), a real-time bulk power trading market in the Western U.S.A. (https://www.westerneim.com/Pages/About/default.aspx). This EIM is evolving, with planned entries by electric utilities likely to cover 65% Western Interconnection load by 2020, spanning 7 states and one Canadian province. The EIM essentially extends the CAISO RTM to balancing authority areas (BAAs) beyond CAISO's boundaries, creating pricing nodes for a much broader range of locations. Our paper does not consider the EIM prices nodes outside of CAISO for the following reasons. Including the EIM prices in our regression analysis would greatly reduce our 65-month sample period by 36 months. Also, all currently participating EIM zones (excluding CAISO) are located outside of the state of California, and therefore their generation is not subject to the California C&T regulations.

[12] Negative prices occur when the grid's demands cannot fully absorb the output from non-dispatchable generation units like nuclear, wind, and solar. The CAISO uses negative prices to induce generators to curtail their output for maintaining California's real-time load-resource balance.

[13] "Path 15 connects the transmission grids between northern and southern California and plays an important role in maintaining regional electric system reliability and market efficiency" (http://www.datcllc.com/projects/path-15/).

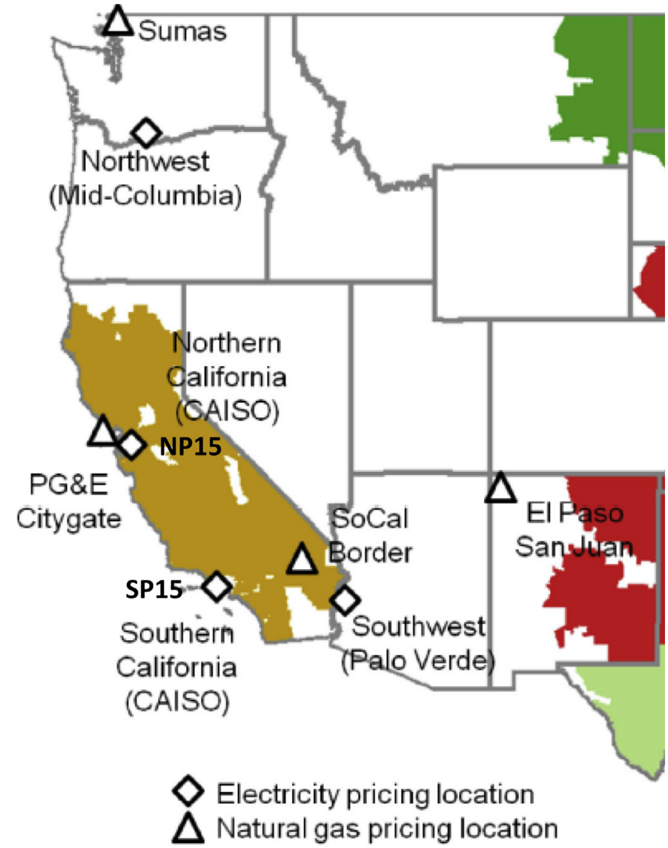

Fig. 1. Major pricing locations in the Western Interconnection (Source: https://www.eia.gov/electricity/monthly/update/wholesale_markets.cfm#tabs_wh_price-3).

2.2. *Competitive bidding and the RTM price's CO_2 cost pass-through*

To establish the theoretical underpinning of our empirical results, consider a natural-gas-fired generation unit's competitive supply bid into the CAISO's RTM. In addition to the unit's hours of availability, dispatchability, delivery rate, and points of injection and withdrawal, the bid specifies the 5-min MW quantity at a price that the unit's operator is willing to accept.

After receiving the supply bids from all generation participants in the RTM, the CAISO performs a security-constrained, least-cost dispatch of the online units under its control, so as to maintain real-time load-resource balance and determine the 5-mintue market-clearing price at each electrical node. Absent transmission congestion, these nodal RTM prices tends to converge, reflecting the least-cost condition of equal line-loss-adjusted marginal costs across electrical nodes. As the volume of 5-min price data are huge and the intra-hour prices tend to be similar, our empirical analysis uses hourly price data, with a given hour's RTM price ($/MWh) being the equally-weighted average of the 12 intra-hour RTM prices in that hour.

All dispatched generation units receive market-clearing prices not less than their bid prices. In the absence of market power, each generator has the incentive to truthfully submit a bid price equal to the sum of its short-run marginal costs for fuel, variable O&M, and CO_2 emissions [21]. Under C&T, a natural-gas-fired generation unit's marginal cost for CO_2 emissions is given by[14]

[14] The U.S. EIA reports that the CO_2 content of burning natural gas is 117 pounds/MMBtu = 53 kg/MMBtu (https://www.eia.gov/tools/faqs/faq.cfm?id=73&t=11).

$$MC = CO_2\text{price}(\$/\text{metric ton}) \times CO_2\text{emissions from burning natural gas}(= 0.053\text{metric ton/MMBtu})^{14} \times \text{Generator's } HR(\text{MMBtu/MWh}). \quad (1)$$

If the RTM price's CO_2 premium when a natural gas-fired unit is at margin equals MC defined in (1), the RTM's CO_2 cost pass-through is said to be 100%. When this premium is above (below) MC, we infer that the pass-through is more (less) than 100%. For a competitive electricity market with price-insensitive demands, the extent of CO_2 cost pass-through is expected to be close to 100% [3].

2.3. Real-time price regressions

Regression analysis is used to quantify the impact of the CO_2 price on the RTM electricity price. The left-hand-side (LHS) variable of each TOD-specific price regression is P_{jkt}, the average price (\$/MWh) of RTM j (= 1 for NP15 and 2 for SP15) in TOD period k (= 1 for 00:00–06:00, 2 for 06:00–10:00, 3 for 10:00–14:00, 4 for 14:00–18:00, 5 for 18:00–22:00, 6 for 22:00–24:00) on day t (= 01/01/2011–05/31/2016).[15] Guided by a clustering analysis of hourly RTM price data, these TOD periods are defined to match the time-of-use pricing periods used by PG&E and SCE, as well as those used in bilateral trading in the Western Interconnection. Omitted here for brevity, the details for deriving these TOD periods are available in Ref. [17].

Using the NP15 and SP15 average RTM price data for six TOD periods, we estimate a total of 12 price regressions. Each price regression's specification is as follows:

$$P_{jkt} = \alpha_{jkt} + \beta_{jk}C_t + \gamma_{jk}G_t + \theta_{1jk}X_{1kt} + \ldots + \theta_{10k}X_{10t} + \varepsilon_{jkt}. \quad (2)$$

As equation (2) is a linear regression, each coefficient measures the marginal price effect of a right-hand-side (RHS) variable. Admittedly simple and therefore easy to understand, it is chosen herein due to its empirical usefulness in our prior studies of electricity market price behavior in the Pacific Northwest, California and Texas [16–20]. As reported below, it yields sharp findings *sans* a complicated formulation, an important consideration in the public debate on an economy's decarbonization policy.[16] It is unrestrictive, readily allowing the use of different RHS variables to explain the TOD price movements observed in other jurisdictions. We decide not to use the log-linear or double-log specification that causes undefined values for the regressand because of the presence of negative and zero RTM prices in our sample.

In equation (2), α_{jkt} is assumed to be a linear function of a constant, six binary indicators for the RTM price's day of week (= Monday, …, Saturday), and 11 binary indicators for the RTM price's month of year (= January, …, November). Inclusion of those fixed-effect specifications serves to capture the residual price variations not explained by the other RHS variables, which are the fundamental drivers of electricity market prices identified by the price regression analyses reported in Refs. [16–20].

The variable C_t is the daily CO_2 price, whose expected marginal effect on P_{jkt} is $\beta_{jk} > 0$, reflecting how the C&T program tends to raise a natural gas generator's bid price. Based on Eq. [1], β_{jk} for a competitive RTM with price-insensitive demands should approximately equal the product of (a) 0.053 metric ton of CO2 emissions from burning one MMBtu of natural gas (see equation (1)); and (b) RTM j's marginal HR in period k. Hence, we can use the β_{jk} estimates to gauge the extent of CO_2 cost pass-through.

The variable G_t is the daily natural gas price (\$/MMBtu) at the Henry Hub, the spot market for the U.S. natural gas futures.[17] Highly correlated ($r > 0.9$) with the California natural gas price at the PG&E Citygate or SoCal Border hub in Fig. 1, it is used here to circumvent the potential bias caused by the bidirectional causal relationship between California's wholesale electricity and natural gas prices [22].

The marginal effect of G_t on P_{jkt} is γ_{jk}, the market-based marginal heat rate for RTM j in TOD period k [18]. For most daytime hours, the γ_{jk} estimate is likely between 7 MMBtu/MWh and 11MMBtu/MWh, the range of the marginal engineering-based heat rates of natural-gas-fired generation in California.[18] For the nighttime hours or midday hours with high solar output, however, the γ_{jk} estimate can be less than 7 MMBtu/MWh because these hours' marginal unit may sometimes be hydro, nuclear, or renewable generation.

The next two variables are X_{1kt} and X_{2kt}, PG&E's and SCE's average hourly demands (MWh) in TOD period k of day t, respectively. Expected to be positive, their corresponding marginal price effects are θ_{1jk} and θ_{2jk}.

The variables X_{3kt} and X_{4kt} are California's average wind and solar generation (MWh) in TOD period j on day t. Their expected marginal price effects are $\theta_{3jk} < 0$ and $\theta_{4jk} < 0$, mirroring renewable energy's merit-order effect of reducing RTM prices [18].

During the sample period, California's nuclear energy came from: (1) the Diablo Canyon plant in Northern California, (2) the San Onofre plant in Southern California, which was shut down since 01/31/2012, and (3) the Palo-Verde plant in Arizona. We include X_{5t}, X_{6t} and X_{7t}, these plants' capacities (MW) available on day t, as the RHS variables in the RTM price regressions. Because nuclear generation is baseload that displaces the state's natural-gas-fired generation, we expect the marginal price effects of X_{5t}, X_{6t} and X_{7t} measured by θ_{5jk}, θ_{6jk} and θ_{7jk} to be all negative.

Our sample period contains the prolonged drought that hampered the state's hydro generation in Northern California.[19] To account for the hydro conditions' marginal price effects, we use X_{8kt} and X_{9kt} to denote the daily average discharge (1000 ft^3/sec) in period k on day t of Sacramento River and Klamath River, the two watersheds with main hydro facilities. We also use X_{10t} to denote the state's daily hydro index (1 = driest, …, 7 = wettest) as our last RHS variable in order to capture the impacts by other hydro facilities with a smaller size. The marginal price effects of X_{8kt}, X_{9kt} and X_{10t} are θ_{8jk}, θ_{9jk} and θ_{10jk} are all expected to be negative.

The random error of the RTM price regression is ε_{jkt}, assumed to be contemporaneously correlated. Hence, we use the method of iterative seemingly unrelated regressions (ITSUR) in PROC MODEL of SAS/ETS [23] to jointly estimate the system of 12 RTM price regressions. To gauge the coefficient estimates' precision and statistical significance, we use robust standard errors that are autocorrelation- and heteroscedasticity-consistent [24], thereby circumventing the empirical challenge of suitably identifying the random error's stochastic specification.

15 While P_{jkt} is a daily TOD-specific value, it is an equally-weighted average based on the 5-min RTM prices. The averaging is done for the following reasons. First, the 5-min prices exhibit little intra-hour variations. Second, estimating 24 hourly RTM price regressions would generate voluminous regression results and would not materially aid our understanding of the RTM's CO_2 cost pass-through.

16 While engineering simulation can demonstrate the price effect of carbon trading, its results are hard to verify by stakeholders who lack deep knowledge and experience in power engineering and economics.

17 https://www.cmegroup.com/confluence/display/EPICSANDBOX/Natural+Gas.

18 The engineering-based heat rate data come from the California Energy Commission available at http://www.energy.ca.gov/2009publications/CEC-200-2009-017/CEC-200-2009-017-SF.PDF.

19 https://ca.water.usgs.gov/data/drought/.

2.4. Data description

Table 1 presents the descriptive statistics of the RTM prices and their fundamental drivers, showing that the data series are volatile. Table 2 reports the price correlation coefficients, indicating that a TOD period's RTM price on day t at a given hub (e.g., NP15) is positively correlated with the other TOD period's on the same day at the same hub (i.e., NP15). Further, the NP15 and SP15 RTM prices on day t for a given TOD period are modestly correlated, reflecting moderate real-time transmission congestion between the NP15 and

Table 1
Descriptive statics for the real-time market prices and their fundamental drivers for the sample period of 01/01/2011–05/31/2016.

Variable	Time of day period	Mean	Standard deviation	Minimum	Maximum
NP15 real-time price ($/MWh)	00:00–06:00	25.38	13.48	−57.75	123.42
	06:00–10:00	32.06	23.47	−56.78	315.45
	10:00–14:00	33.90	24.95	−36.09	422.26
	14:00–18:00	39.57	40.70	−38.45	771.83
	18:00–22:00	42.62	27.02	−8.87	256.94
	22:00–24:00	32.27	18.21	−24.58	311.35
SP15 real-time price ($/MWh)	00:00–06:00	26.28	19.11	−82.50	364.26
	06:00–10:00	31.31	27.52	−105.48	357.40
	10:00–14:00	33.23	29.36	−141.36	390.88
	14:00–18:00	41.71	44.31	−181.55	554.28
	18:00–22:00	44.55	29.02	−21.65	434.39
	22:00–24:00	33.20	21.36	−69.08	316.99
California's CO_2 price ($/metric ton)	00:00–24:00	8.07	6.22	0.00	16.45
Henry Hub natural gas price ($/MMBtu)	00:00–24:00	3.38	0.91	1.49	8.15
PG&E's daily average load (MWh)	00:00–06:00	10203.04	805.30	8475.67	13401.67
	06:00–10:00	11798.02	966.61	9216.25	15432.25
	10:00–14:00	12595.53	1500.68	9660.25	19162.50
	14:00–18:00	13189.69	2129.89	9593.75	20725.25
	18:00–22:00	13595.79	1628.37	10469.25	19635.75
	22:00–24:00	11679.78	1216.69	9602.00	16520.50
SCE's average load (MWh)	00:00–06:00	9823.28	894.41	7909.50	13370.33
	06:00–10:00	11316.49	1250.83	8094.50	15647.00
	10:00–14:00	12803.63	2167.54	8420.25	20806.50
	14:00–18:00	13556.75	2838.48	9223.25	22898.50
	18:00–22:00	13516.14	1966.66	10214.00	21447.50
	22:00–24:00	11516.27	1420.30	9196.00	16743.50
California's average wind energy (MWh)	00:00–06:00	1398.78	996.35	0.00	4259.17
	06:00–10:00	1032.68	833.52	0.00	4181.75
	10:00–14:00	921.09	854.35	0.00	4020.50
	14:00–18:00	1245.09	1003.16	0.00	4473.00
	18:00–22:00	1527.88	1086.17	0.00	4548.25
	22:00–24:00	1561.92	1102.38	0.00	4393.00
California's average solar energy (MWh)	00:00–06:00	0.00	0.00	0.00	0.00
	06:00–10:00	1016.47	928.95	0.00	4123.75
	10:00–14:00	2364.18	1925.12	0.00	7266.25
	14:00–18:00	1556.53	1493.18	0.00	6187.75
	18:00–22:00	108.29	148.02	0.00	755.75
	22:00–24:00	0.00	0.00	0.00	0.00
Diablo Canyon's available capacity (MW)	00:00–24:00	1956.80	416.28	0.00	2160.00
San Onofre's available capacity (MW)	00:00–24:00	383.20	791.27	0.00	2150.00
Palo Verde's available capacity (MW)	00:00–24:00	3674.51	587.40	1335.00	4005.00
Sacramento River's average discharge (000ft^3/sec)	00:00–06:00	16.91	13.96	2.04	85.91
	06:00–10:00	16.92	13.89	1.02	86.08
	10:00–14:00	17.93	13.61	0.67	85.99
	14:00–18:00	17.28	13.87	1.06	85.98
	18:00–22:00	16.90	13.98	0.98	86.72
	22:00–24:00	17.33	13.91	0.21	85.46
Klamath River's average discharge (000ft^3/sec)	00:00–06:00	14.15	17.18	2.01	170.88
	06:00–10:00	14.14	17.21	2.00	196.06
	10:00–14:00	14.17	17.20	2.01	185.13
	14:00–18:00	14.18	17.16	2.01	170.25
	18:00–22:00	14.17	17.13	2.01	165.88
	22:00–24:00	14.16	17.15	2.02	157.25
California's hydro index (1 = driest, …, 7 = wettest)	00:00–24:00	3.60	0.72	1.00	5.65

Notes: (1) The RTM prices can be negative during low-load hours (e.g., 00:00–06:00) when the grid's demands cannot fully absorb the output from non-dispatchable generation units like nuclear and wind. The CAISO uses these negative prices to induce dispatchable generators to curtail their output for maintaining California's real-time load-resource balance. These negative RTM prices discourage us from using a double-log regression specification because their natural log values are undefined. Finally, solar energy for the 00:00–06:00 and 22:00–24:00 periods is zero.

(2) Our data sources are as follows. The CAISO provides the data for the RTM price, CO_2 price, system loads, and solar and wind output (http://oasis.caiso.com/mrioasis/logon.do;jsessionid=5D9A2B355EF0330B4D1D9631157487E5). The natural gas price data come from SNL (www.snl.com). The nuclear capacity data are from the U.S. Nuclear Regulatory Commission (http://www.nrc.gov/reading-rm/doc-collections/event-status/reactor-status/index.html). Finally, the U.S. Geological Survey (USGS) supplies the California hydro index (http://waterwatch.usgs.gov/index.php?r=ca&id=pa01d&sid=w__table2) and river discharge data http://waterdata.usgs.gov/ca/nwis/rt). The Klamath River's station is USGS 11530500 and the Sacramento River's station USGS 11447650.

(3) The California CO_2 price is zero prior to the C&T program's 01/01/2013 commencement. Further, the California CO_2 price data since the C&T program's first trading date of 01/01/2013 have been stable, with an average of about $13/metric ton and a standard deviation of about $2/metric ton. The San Onofre available capacity is zero after the plant's 01/31/2012 shutdown.

Table 2
Real-time price correlations for the sample period of 01/01/2011–05/31/2016.

Time of day period	NP15 price						SP15 price					
	00:00 –06:00	06:00 –10:00	10:00 –14:00	14:00 –18:00	18:00 –22:00	22:00 –24:00	00:00 –06:00	06:00 –10:00	10:00 –14:00	14:00 –18:00	18:00 –22:00	22:00 –24:00
Panel A: NP15 price												
00:00–06:00	1.0000	0.3547	0.2301	0.1621	0.2476	0.3123	0.6549	0.2570	0.1353	0.1367	0.2478	0.2618
06:00–10:00	0.3547	1.0000	0.3847	0.1557	0.1797	0.1885	0.2145	0.7448	0.2025	0.0801	0.1932	0.1870
10:00–14:00	0.2301	0.3847	1.0000	0.3155	0.1876	0.1748	0.1492	0.2385	0.5610	0.2337	0.1507	0.1818
14:00–18:00	0.1621	0.1557	0.3155	1.0000	0.3127	0.1598	0.1005	0.1255	0.2039	0.6320	0.1798	0.1053
18:00–22:00	0.2476	0.1797	0.1876	0.3127	1.0000	0.3599	0.1746	0.1872	0.1098	0.2140	0.7541	0.2838
22:00–24:00	0.3123	0.1885	0.1748	0.1598	0.3599	1.0000	0.2598	0.2402	0.0893	0.1215	0.3391	0.7536
Panel B: SP15 price												
00:00–06:00	0.6549	0.2145	0.1492	0.1005	0.1746	0.2598	1.0000	0.3273	0.1747	0.1262	0.1879	0.2638
06:00–10:00	0.2570	0.7448	0.2385	0.1255	0.1872	0.2402	0.3273	1.0000	0.3048	0.1356	0.1951	0.2144
10:00–14:00	0.1353	0.2025	0.5610	0.2039	0.1098	0.0893	0.1747	0.3048	1.0000	0.3875	0.1194	0.1191
14:00–18:00	0.1367	0.0801	0.2337	0.6320	0.2140	0.1215	0.1262	0.1356	0.3875	1.0000	0.2534	0.1071
18:00–22:00	0.2478	0.1932	0.1507	0.1798	0.7541	0.3391	0.1879	0.1951	0.1194	0.2534	1.0000	0.3213
22:00–24:00	0.2618	0.1870	0.1818	0.1053	0.2838	0.7536	0.2638	0.2144	0.1191	0.1071	0.3213	1.0000

SP15 electricity zones.

Table 3 reports the correlations between a TOD period's RTM price and its fundamental drivers. Though not used as the basis for our key findings reported in Section 3 below, these correlations presage whether our regression-based approach is likely fruitful for quantifying California's RTM price behavior. While largely consistent with the fundamental drivers' expected price effects, they do not delineate the marginal effects of the daily CO_2 price on the RTM prices or those of the remaining drivers, an empirical issue to be settled by the regression results reported in the next section.

3. Results

3.1. Empirical evidence

Table 4 reports the ITSUR results for the 12 RTM price regressions, whose relatively low adjusted R^2 values of 0.14–0.40 echo our parsimonious regression setup to explain the highly volatile RTM price data. We use the Phillips-Perron test [25] to reject the null hypothesis of the regressions' residuals following a random walk, thus obviating concerns of spurious regressions [26]. Finally, while 26 of the 140 coefficient estimates for the fundamental drivers have the wrong sign, only two of those are statistically significant at the 5% level. Thus, Table 4 portrays an empirically plausible data generating process underlying the volatile RTM prices.

Using the estimates of the CO_2 price's coefficient β_{jk} and their standard errors, we construct the 95% confidence intervals reported in Table 5. Based on these intervals, eight of the 12 regressions have β_{jk} estimates ***not*** statistically different from a CCGT's *MC*-benchmark of \$0.371/MWh (= \$1/metric ton increase in the CO_2 price $\times$ 0.053 metric ton/MMBtu $\times$ CCGT's *HR* of 7 MMBtu per

Table 3
Real-time price's correlation with their fundamental drivers for the sample period of 01/01/2011–05/31/2016.

Fundamental driver	Time of day period					
	00:00–06:00	06:00–10:00	10:00–14:00	14:00–18:00	18:00–22:00	22:00–24:00
Panel A: NP15 price						
California's CO_2 price (\$/metric ton)	0.3764	0.1255	0.0792	0.0385	0.1283	0.1396
Henry Hub price (\$/MMBtu)	0.3197	0.2452	0.2254	0.1549	0.2536	0.3494
PG&E's average load (MWh)	0.0020	0.1093	0.1478	0.3214	0.1574	0.0088
SCE's average load (MWh)	0.0627	0.1002	0.1300	0.2764	0.1400	0.0040
California's average wind energy (MWh)	−0.1350	−0.1482	−0.1097	−0.1381	−0.0748	−0.1331
California's average solar energy (MWh)	0.0000	−0.0889	−0.0997	−0.0160	0.0093	0.0000
Diablo Canyon's available capacity (MW)	0.0070	*0.0164*	−0.0003	−0.0200	−0.0277	−0.0111
San Onofre's available capacity (MW)	−0.2751	−0.1181	−0.0404	−0.0600	−0.0856	−0.0356
Palo Verde's available capacity (MW)	−0.0151	−0.0607	−0.0275	0.0418	0.0185	−0.0287
Sacramento River's average discharge (000ft^3/sec)	−0.3077	−0.0746	−0.1029	−0.1307	−0.1065	−0.1021
Klamath River's average discharge (000ft^3/sec)	−0.2720	−0.0457	−0.1295	−0.1676	−0.1295	−0.1075
California's hydro index (1 = driest, …, 7 = wettest)	−0.3725	−0.1393	−0.0866	−0.0867	−0.1409	−0.1555
Panel B: SP15 price						
California's CO_2 price (\$/metric ton)	0.2491	0.0773	−0.0426	0.0043	0.1658	0.1022
Henry Hub price (\$/MMBtu)	0.2074	0.2120	0.2146	0.1565	0.2511	0.2911
PG&E's average load (MWh)	*−0.0294*	0.1169	0.2175	0.3025	0.0506	−0.0057
SCE's average load (MWh)	0.0429	0.1150	0.2620	0.3632	0.0890	0.0101
California's average wind energy (MWh)	−0.1351	−0.2073	−0.2269	−0.1723	−0.0877	−0.1615
California's average solar energy (MWh)	0.0000	−0.1383	−0.2165	−0.0644	−0.0110	0.0000
Diablo Canyon's available capacity (MW)	−0.0417	−0.0368	−0.0397	−0.0278	−0.0409	−0.0052
San Onofre's available capacity (MW)	−0.2234	−0.0937	*0.0194*	−0.0413	−0.0962	−0.0498
Palo Verde's available capacity (MW)	−0.0410	−0.0192	*0.0205*	*0.0581*	*0.0010*	−0.0357
Sacramento River's average discharge (000ft^3/sec)	−0.1982	−0.0312	−0.0297	−0.1125	−0.1061	−0.0510
Klamath River's average discharge (000ft^3/sec)	−0.1534	−0.0090	−0.1219	−0.1718	−0.1039	−0.0897
California's hydro index (1 = driest, …, 7 = wettest)	−0.2385	−0.0776	0.0257	−0.0252	−0.1413	−0.0988

Note: Solar energy for the 00:00–06:00 and 22:00–24:00 periods is zero. Correlation coefficients in *italic* are at odds with our expectations.

Table 4
ITSUR results for the CAISO's daily real-time market price ($/MWh) regressions for the sample period of 01/01/2011–05/31/2016 by time-of-day period; autocorrelation-heteroscedasticity-consistent standard errors in ( ); "*" = "significant at the 5% level".

Variable	NP15						SP15					
	00:00 –06:00	06:00 –10:00	10:00 –14:00	14:00 –18:00	18:00 –22:00	22:00 –24:00	00:00 –06:00	06:00 –10:00	10:00 –14:00	14:00 –18:00	18:00 –22:00	22:00 –24:00
Adjusted R^2	0.3952	0.2187	0.1241	0.1846	0.1500	0.1981	0.2032	0.1906	0.1970	0.2162	0.1409	0.1557
California's CO_2 price ($/metric ton)	0.5443*	0.4116*	1.0719*	0.5613*	0.3737*	0.3032*	0.4606*	0.5401*	1.1052*	0.7777*	0.7228*	0.2760*
	(0.0495)	(0.1460)	(0.1901)	(0.2325)	(0.1330)	(0.0748)	(0.1219)	(0.1809)	(0.2214)	(0.2654)	(0.1330)	(0.1203)
Henry Hub price ($/MMBtu)	5.6811*	7.5397*	4.3312*	6.0246*	9.0108*	7.7186*	5.8213*	7.2641*	3.7377*	6.0356*	9.7248*	7.9175*
	(0.3649)	(0.8217)	(0.8627)	(1.1309)	(0.7178)	(0.5407)	(0.4597)	(0.9629)	(0.8491)	(1.0628)	(0.8311)	(0.5675)
PG&E's average load (MWh)	0.0024*	0.0076*	0.0041*	0.0097*	0.0052*	0.0039*	*−0.0014*	0.0061*	*−0.0014*	*−0.0010*	*−0.0005*	0.0021*
	(0.0008)	(0.0014)	(0.0009)	(0.0020)	(0.0013)	(0.0009)	(0.0013)	(0.0019)	(0.0011)	(0.0019)	(0.0009)	(0.0011)
SCE's average load (MWh)	0.0006	0.0001	0.0008	0.0004	0.0004	*−0.0005*	0.0034*	0.0018	0.0056*	0.0095*	0.0035*	0.0014*
	(0.0006)	(0.0009)	(0.0006)	(0.0010)	(0.0009)	(0.0006)	(0.0009)	(0.0013)	(0.0009)	(0.0016)	(0.0008)	(0.0007)
California's average wind energy (MWh)	−0.0042*	−0.0038*	−0.0050*	−0.0085*	−0.0050*	−0.0042*	−0.0058*	−0.0075*	−0.0086*	−0.0095*	−0.0066*	−0.0054*
	(0.0003)	(0.0006)	(0.0007)	(0.0010)	(0.0007)	(0.0005)	(0.0005)	(0.0008)	(0.0008)	(0.0010)	(0.0008)	(0.0005)
California's average solar energy (MWh)		−0.0032*	−0.0036*	−0.0033*	*0.0107*			−0.0046*	−0.0052*	−0.0042*	*0.0173**	
		(0.0008)	(0.0005)	(0.0007)	(0.0058)			(0.0010)	(0.0005)	(0.0009)	(0.0060)	
Diablo Canyon's available capacity (MW)	−0.0002	*0.0008*	−0.0001	−0.0034	−0.0023	−0.0004	−0.0017	−0.0028	−0.0029	−0.0038	−0.0015	*0.0002*
	(0.0007)	(0.0011)	(0.0014)	(0.0028)	(0.0015)	(0.0012)	(0.0013)	(0.0018)	(0.0017)	(0.0029)	(0.0015)	(0.0012)
San Onofre's available capacity (MW)	−0.0031*	−0.0052*	−0.0017	−0.0040*	−0.0037*	−0.0006	−0.0055*	−0.0066*	−0.0036*	−0.0059*	−0.0043*	−0.0033*
	(0.0005)	(0.0010)	(0.0012)	(0.0016)	(0.0013)	(0.0008)	(0.0007)	(0.0009)	(0.0013)	(0.0018)	(0.0012)	(0.0011)
Palo Verde's available capacity (MW)	−0.0017*	−0.0039*	−0.0024	−0.0011	−0.0019	−0.0001	−0.0027*	−0.0038*	−0.0023	*0.0004*	−0.0010	−0.0005
	(0.0006)	(0.0013)	(0.0019)	(0.0015)	(0.0011)	(0.0008)	(0.0008)	(0.0015)	(0.0017)	(0.0018)	(0.0013)	(0.0010)
Sacramento River's average discharge (000ft^3/sec)	−0.0957*	*0.0098*	−0.1464	−0.1979*	−0.0224	−0.0446	−0.1100*	−0.0249	−0.0673	−0.2494*	−0.1439*	*0.0153*
	(0.0288)	(0.0675)	(0.0800)	(0.0881)	(0.0580)	(0.0481)	(0.0345)	(0.0740)	(0.1018)	(0.0828)	(0.0674)	(0.0642)
Klamath River's average discharge (000ft^3/sec)	−0.0155	*0.0474*	*0.0211*	*0.0901**	*0.0457*	*0.0695*	*0.0030*	*0.1031*	*0.0628*	*0.0595*	*0.0339*	*0.0028*
	(0.0324)	(0.0557)	(0.0501)	(0.0435)	(0.0415)	(0.0369)	(0.0589)	(0.0696)	(0.0621)	(0.0466)	(0.0482)	(0.0365)
California's hydro index (1 = driest, …, 7 = wettest)	−2.0867*	−2.6379*	−0.9027	−2.9180	−1.8822	−3.2678*	−0.3952	−0.9924	*0.6746*	*3.2474*	*1.2834*	−1.2139
	(0.7496)	(1.3300)	(2.1876)	(1.8771)	(1.1170)	(0.7647)	(0.9922)	(1.3665)	(2.1366)	(2.1192)	(1.1689)	(0.9197)

Note: For brevity, this table does not report the estimates for the intercepts and effects of day-of-week and month-of-year, which are mostly significant at the 5% level. 26 of the 140 coefficient estimates for the fundamental drivers in *italic* have the wrong sign. Of these 26 coefficient estimates, only two are statistically significant.

Table 5
95% confidence intervals (CI) of the coefficient estimates in Table 4 for the CO_2 price.

Variable	NP15						SP15					
	00:00 –06:00	06:00 –10:00	10:00 –14:00	14:00 –18:00	18:00 –22:00	22:00 –24:00	00:00 –06:00	06:00 –10:00	10:00 –14:00	14:00 –18:00	18:00 –22:00	22:00 –24:00
Estimate	0.544	0.412	1.072	0.561	0.374	0.303	0.461	0.540	1.105	0.778	0.723	0.276
Lower bound = Estimate − 1.965 × standard error	0.447	0.125	0.698	0.104	0.112	0.156	0.221	0.185	0.670	0.256	0.461	0.040
Upper bound = Estimate + 1.965 × standard error	0.642	0.699	1.445	1.018	0.635	0.450	0.700	0.896	1.540	1.299	0.984	0.512

MWH). Further, nine regressions have β_{jk} estimates ***not*** statistically different from a CT's *MC*-benchmark of $0.477/MWh at $HR = 9$ MMBtu/MWh and an ACT's *MC*-benchmark of $0.583/MWh at $HR = 11$ MMBtu/MWh. Taken together, the β_{jk} estimates suggest that the RTM prices contain a CO_2 premium that approximately equals the marginal cost of CO_2 emissions attributable to the California's C&T program.

We construct the 95% confidence intervals of the market-based marginal heat rate estimates, which are given by the Henry Hub price's coefficient estimates. Table 6 shows that eight of these 12 intervals contain natural-gas-fired generation's engineering-based heat rates of 7 MMBtu/MWh to 11 MMBtu/MWh. Thus, Table 6 indicates that natural gas is California's marginal fuel for most hours of the day.

Table 6
95% confidence intervals (CI) of the coefficient estimates in Table 4 for the Henry Hub's natural gas price.

Variable	NP15						SP15					
	00:00 –06:00	06:00 –10:00	10:00 –14:00	14:00 –18:00	18:00 –22:00	22:00 –24:00	00:00 –06:00	06:00 –10:00	10:00 –14:00	14:00 –18:00	18:00 –22:00	22:00 –24:00
Estimate	5.681	7.540	4.331	6.025	9.011	7.719	5.821	7.264	3.738	6.036	9.725	7.917
Lower bound = Estimate − 1.965 × standard error	4.964	5.925	2.636	3.802	7.600	6.656	4.918	5.372	2.069	3.947	8.092	6.802
Upper bound = Estimate + 1.965 × standard error	6.398	9.154	6.026	8.247	10.421	8.781	6.725	9.156	5.406	8.124	11.358	9.033

Table 7
P-values of the Wald statistic for testing the 100% pass-through of the marginal cost of CO_2 at natural-gas-fired generation's engineering heat rate of a CCGT, a CT, or an aging CT.

Null hypothesis: 100% pass through of the marginal cost of CO_2 emissions at natural-gas-fired generation's engineering heat rate	NP15						SP15					
	00:00 −06:00	06:00 −10:00	10:00 −14:00	14:00 −18:00	18:00 −22:00	22:00 −24:00	00:00 −06:00	06:00 −10:00	10:00 −14:00	14:00 −18:00	18:00 −22:00	22:00 −24:00
H1: $\beta_{jk} = \$0.371$/MWh and $\gamma_{jk} = 7$ MMBtu/MWh	*<.0001*	0.5096	*0.0006*	0.5071	*0.0193*	0.2841	*0.0133*	0.4980	*0.0002*	0.2633	*<.0001*	0.2433
H2: $\beta_{jk} = \$0.477$/MWh and $\gamma_{jk} = 9$ MMBtu/MWh	*<.0001*	*0.0191*	*<.0001*	*0.0304*	0.7389	*0.0034*	*<.0001*	0.1796	*<.0001*	*0.0181*	0.1105	*0.0173*
H3: $\beta_{jk} = \$0.583$/MWh and $\gamma_{jk} = 11$ MMBtu/MWh	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*0.0045*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	0.1958	*<.0001*

Note: A *p*-value in *italic* indicates that the null hypothesis in question is rejected at the 5% level. If **H1** to **H3** are ***all*** rejected for a TOD period's RTM price regression, we infer that the 100% pass-through of the marginal CO_2 cost of natural-gas-fired generation is inconsistent with California's marginal generation fuel being natural gas for that TOD period.

As a final check that was not done in Ref. [17], we consider whether the estimates for the marginal CO_2 cost's pass-through in Table 5 are consistent with those for the market-based heat rates in Table 6. Hence, we use the Wald test to statistically test the following null hypotheses for each of the twelve RTM price regressions:

- H1: $\beta_{jk} = \$0.371$/MWh and $\gamma_{jk} = 7$ MMBtu/MWh, implying that the pass-through is 100% and the marginal generation unit's market-based heat rate equals a CCGT's engineering heat rate.
- H2: $\beta_{jk} = \$0.477$/MWh and $\gamma_{jk} = 9$ MMBtu/MWh, implying that the pass-through is 100% and the marginal generation unit's market-based heat rate equals a CT's engineering heat rate.
- H3: $\beta_{jk} = \$0.583$/MWh and $\gamma_{jk} = 11$ MMBtu/MWh, implying that the pass-through is 100% and the marginal generation unit's market-based heat rate equals an aging CT's engineering heat rate.

If H1 to H3 are ***all*** rejected for a TOD-specific RTM price regression, we infer that the 100% pass-through of the marginal CO_2 cost of natural-gas-fired generation is inconsistent with the view that California's marginal generation fuel is natural gas for that TOD period, an important assumption upon which we base our analyses.

Table 7 reports the *p*-values of the Wald statistic, showing that **H1** − **H3** are rejected for only four of the twelve cases. These test results reinforce our inferences based on Tables 5 and 6: (1) the RTM prices generally contain a carbon premium equal to natural-gas fired generation's marginal cost of CO_2 emissions; and (2) California's marginal generation fuel is mostly natural gas.

The remaining coefficient estimates in Table 4 suggest the following findings. First, an increase in the system loads likely raises the RTM prices, and its estimated price effects vary by TOD period and location. Second, an increase in the renewable energy tends to lower the RTM prices by amounts that change in commensurate with TOD period and location. Third, an increase in nuclear capacities available tends to reduce the RTM prices, with estimated price effects that also vary by TOD period and location. Finally, the coefficient estimates for the hydro conditions suggest that a prolonged drought tends to raise market prices.

4. Conclusion

This paper presents a comprehensive regression analysis of the daily market data for a 65-month period of 01/01/2011–05/31/2016, documenting that the CAISO's NP15 and SP15 RTM prices by TOD period contain natural-gas-fired generation's marginal costs of CO_2 emissions. Further, these prices are found to decline with renewable generation and nuclear capacities available but increase with the natural gas price and RTM demands.

These estimated price effects are good and bad news. The good news is that the California C&T program is deemed effective in internalizing the in-state CO_2 emissions. The bad news is that it is unlikely to improve natural-gas-fired generation's investment incentive because California's marginal fuel is mainly natural gas rather than coal, whose higher CO_2 emissions cost could have further increased the state's market price. At the engineering-based *HR* of ~11 MMBtu/MWh, a CT investor is unlikely to see an increase in the unit's per-MWh profit, chiefly because the CO_2-related price increase is offset by the CO_2-related cost increase. While a CCGT investor may benefit from carbon trading due to the small increase in the unit's per MWh profit,[20] this profit increase cannot overcome the problem of insufficient investment incentive, which will likely worsen over time due to California's large-scale renewable energy deployment [27].[21] Hence, the policy implication of our findings' is that California should continue its use of long-term contacts to procure dispatchable generation capacity to meet the Western Interconnection's criteria for system reliability and the state's resource adequacy targets.

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References

[1] Sioshansi FP. Evolution of global electricity markets: new paradigms, new challenges, new approaches. San Diego, California: Elsevier; 2013.
[2] Weron R. Modeling and forecasting electricity loads and prices. New York, New York: John Wiley; 2006.
[3] Gal N, Milstein I, Tishler A, Woo CK. Fuel cost uncertainty, capacity investment and price in a competitive electricity market. Energy Econ 2017;61:233–40.
[4] Eydeland A, Wolyniec K. Energy and power risk management: new development in modeling, pricing and hedging. Hoboken, New Jersey: John Wiley & Sons; 2003.
[5] Deng SJ, Oren SS. Electricity derivatives and risk management. Energy 2006;31:940–53.
[6] Woo CK, Sreedharan P, Hargreaves J, Kahrl F, Wang J, Horowitz I. A review of electricity product differentiation. Appl Energy 2014;114:262–72.

[20] The profit increase is the product of the heat rate difference, the average CO_2 price, and the CO_2 emissions from burning natural gas. It is equal to \$0.212/MWh (= 2 MMBtu/MWh × \$13/metric ton × 0.053 metric ton/MMBtu).

[21] The estimated price increases due to California's load growth and nuclear plant retirement can only partially offset the merit-order effects of renewable energy on market prices [18]. This is because the state's projected scale of renewable energy development far exceeds the combined size of load growth and retired nuclear capacity.

[7] Thompson M. Optimal economic dispatch and risk management of thermal power plants in deregulated markets. Oper Res 2013;61:791–809.
[8] Sreedharan P, Miller D, Price S, Woo CK. Avoided cost estimation and cost-effectiveness of permanent load shifting in California. Appl Energy 2012;96:115–21.
[9] Palmer KL, Paul A. A primer on comprehensive policy options for states to comply with the Clean Power Plan. 2015. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2622697. [Accessed 6 September 2016].
[10] Paul A, Palmer KL, Woerman M. Incentives, margins, and cost effectiveness in comprehensive climate policy for the power sector. Climate Change Economics 2015;6(4). http://www.worldscientific.com/doi/abs/10.1142/S2010007815500165. [Accessed 6 September 2016].
[11] Fabra N, Reguant R. Pass-through of emissions costs in electricity markets. Am Econ Rev 2014;104(9):2872–99.
[12] Hintermann B. Pass-through of CO_2 emission costs to hourly electricity prices in Germany. J Associa Environ Resource Econo 2016;3(4):857–91.
[13] Lo Prete CL, Norman CS. Rockets and feathers in power futures markets? Evidence from the second phase of the EU ETS. Energy Econ 2013;36:312–21.
[14] Zachmann G, Von Hirschhausen C. First evidence of asymmetric cost pass-through of EU emissions allowances: examining wholesale electricity prices in Germany. Econ Lett 2008;99(3):465–9.
[15] Fezzi C, Bunn DW. Structural interactions of European carbon trading and energy prices. Journal of Energy Markets 2009;2(4):53–69.
[16] Woo CK, Olson A, Chen Y, Moore J, Schlag N, Ong A, Ho T. Does California's CO_2 price affect wholesale electricity prices in the Western U.S.A. Energy Pol 2017;110:9–19.
[17] Woo CK, Chen Y, Olson A, Moore J, Schlag N, Ong A, Ho T. Electricity price behavior and carbon trading: new evidence from California. Appl Energy 2017;204:531–43.
[18] Woo CK, Moore J, Schneiderman B, Ho T, Olson A, Alagappan L, Chawla K, Toyama N, Zarnikau J. Merit-order effects of renewable energy and price divergence in California's day-ahead and real-time electricity markets. Energy Pol 2016;92:299–312.
[19] Woo CK, Zarnikau J, Kadish J, Horowitz I, Wang J, Olson A. The impact of wind generation on wholesale electricity prices in the hydro-rich Pacific Northwest. IEEE Trans Power Syst 2013;28(4):4245–53.
[20] Woo CK, Horowitz I, Moore J, Pacheco A. The impact of wind generation on the electricity spot-market price level and variance: the Texas experience. Energy Pol 2011;39:3939–44.
[21] Laffont JJ, Tirole JA. Theory of incentives in procurement and regulation. Cambridge, Massachusetts: MIT Press; 1993.
[22] Woo CK, Olson A, Horowitz I, Luk S. Bi-directional causality in California's electricity and natural-gas markets. Energy Pol 2006;34:2060–70.
[23] SAS/ETS 9.1 User's guide. Cary, North Carolina: SAS Institute; 2004.
[24] Wooldridge JM. Econometric analysis of cross section and panel data. Cambridge, Massachusetts: MIT Press; 2010. 2010.
[25] Phillips PCB, Perron P. Testing for a unit root in time series regression. Biometrika 1988;75:335–46.
[26] Davidson R, Mackinnon JG. Estimation and inference in econometrics. New York: Oxford University Press; 1993.
[27] Woo CK, Horowitz I, Zarnikau J, Moore J, Schneiderman B, Ho T, Leung E. What moves the ex post variable profit of natural-gas-fired generation in California? Energy J 2016;37(3):29–57.