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Merit-order effects of renewable energy and price divergence in California's day-ahead and real-time electricity markets

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HIGHLIGHTS

- Estimate the day-ahead and real-time merit-order effects of renewable energy in California.
- Document statistically significant merit-order effects of solar and wind energy.
- Document the difference between the day-ahead and real-time prices.
- Attribute the price differences to forecast errors for load, solar and wind energy.
- Discuss the evidence's implications for California's energy policy.

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ABSTRACT

We answer two policy questions: (1) what are the estimated merit-order effects of renewable energy in the California Independent System Operator's (CAISO's) day-ahead market (DAM) and real-time market (RTM)? and (2) what causes the hourly DAM and RTM prices to systematically diverge? The first question is timely and relevant because if the merit-order effect estimates are small, California's renewable energy development is of limited help in cutting electricity consumers' bills but also has a lesser adverse impact on the state's investment incentive for natural-gas-fired generation. The second question is related to the efficient market hypothesis under which the hourly RTM and DAM prices tend to converge. Using a sample of about 21,000 hourly observations of CAISO market prices and their fundamental drivers during 12/12/2012–04/30/2015, we document statistically significant estimates (p-value ≤ 0.01) for the DAM and RTM merit-order effects. This finding lends support to California's adopted procurement process to provide sufficient investment incentives for natural-gas-fired generation. We document that the RTM-DAM price divergence partly depends on the CASIO's day-ahead forecast errors for system loads and renewable energy. This finding suggests that improving the performance of the CAISO's day-ahead forecasts can enhance trading efficiency in California's DAM and RTM electricity markets.

1. Introduction

This paper is motivated by two transformative events that have already taken place in the electricity industry. The first event is the electricity market reforms that have led to competitive wholesale markets in Europe, North America, South America, Australia, and New Zealand (Sioshansi, 2013). In the U.S., wholesale electricity trading may occur in the centralized day-ahead market (DAM) and real-time market (RTM) operated by an independent system operator (ISO). An important case in fact is the California Independent System Operator (CAISO). Based on the concept of locational marginal pricing (LMP) (Bohn et al., 1984; Hogan, 1992; Stoft, 2002), the CAISO determines DAM and RTM prices daily via least-cost dispatch of generators' supply offers to reliably meet the locational demands.

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Wholesale electricity prices are inherently volatile due to: (a) daily fuel-cost variations, especially for natural gas, which is widely used by combustion turbines (CT) and combined-cycle gas turbines (CCGT) in North America; (b) hourly weather-sensitive demands with intra-day and inter-day fluctuations, which must be met in real time by 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 (Li and Flynn, 2006; Bunn and Fezzi, 2007; Woo et al., 1998, 2007, 2011c; Miller et al., 2008; Newcomer et al., 2008; Tishler et al., 2008).[1]

The volatile spot-market prices, even with occasional spikes during hours of severe shortage, may not suffice to justify the CT and CCGT investment necessary for reliable grid operation (Neuhoff and Vries, 2004; Wangensteen et al., 2005; Roques et al., 2005; Newbery, 2010; Milstein and Tishler, 2012; Brattle Group, 2012). This generation investment problem was recently noted by a senior manager of Pacific Gas & Electric (PG&E), the largest utility in Northern California: "Energy revenues based on competitive prices are often not compensatory to cover longer-term cost of building and operating a new plant. For example, in the California market in 2013, the Department of Market Monitoring estimated that energy market revenues for a new combined cycle plant would be $296.39/kW-yr. in comparison to the $256.78/kW-yr. in operating costs and $175.80/kW-yr in annualized fixed costs" (Griffes, 2014, p.27).

To remedy the "missing money" problem of inadequate investment incentive described by Joskow (2013), California adopted an administrative resource adequacy policy in 2004 which obligates the state's investor-owned utilities to bilaterally contract with generators to meet anticipated needs: "Each [load serving entity's] system requirement is 100 percent of its total forecast load plus a 15 percent reserve, for a total of 115 percent."[2] In compliance with its system requirement, a local distribution company (LDC) such as PG&E prepares a long-term procurement plan for the approval of the California Public Utilities Commission (CPUC), announces its capacity needs based on the approved procurement plan, and issues requests for proposals (RFP) from suppliers of conventional and renewable generation, as well as demand response resources.[3]

Under the LDC's RFP process, a developer of a new CCGT (or CT) may submit its proposal for a long-term contract, which presumably contains sufficient revenues to cover the annualized fixed and variable costs of the new plant. The winning proposal of a chosen developer should contain sufficient revenues to enable the new plant's construction, thus solving the "missing money" problem.

To address the "missing money" problems outside California, capacity markets were introduced in the late 1990 s in the U.S. deregulated markets of New York, PJM, and New England (Spees et al., 2013). The notable exception is the Electric Reliability Council of Texas (ERCOT), which continues to use an energy-only market design with a high offer cap ($9,000/MWh beginning June 1, 2015) to provide generation investment incentives.

The second event motivating this paper is the development of solar and wind energy in many parts of the world due to resource abundance (Hoogwijk et al., 2004; Lu et al., 2009; Marini et al., 2014) and government policies that include easy and low-cost transmission access, financial incentives (e.g., feed-in-tariffs, government loans and grants, and tax credits), and quota programs (e.g., renewables portfolio standards, or RPS, cap-and-trade programs for carbon emissions certificates, and renewable-energy credits).[4]

Wind energy displaces thermal generation with relatively high fuel costs and reduces wholesale market prices (European Wind Energy Association, 2010). This price-reduction effect, also known as the merit-order effect, has been demonstrated through model simulations (e.g., Morales and Conejo, 2011; Traber and Kemfert, 2011), as well as through regression analysis of market data for Spain (Gelabert et al., 2011; Gil et al., 2012), Germany (Sensfuß et al., 2008; Ketterer, 2014; Paraschiv, et al., 2014), Denmark (Munksgaard and Morthorst, 2008; Jacobsen and Zvingilaite, 2010), Australia (Cutler et al., 2011), Texas (Woo et al., 2011b; Zarnikau et al., 2014), PJM (Gil and Lin, 2013), the Pacific Northwest (Woo et al., 2013), and California (Woo et al., 2014, 2015a).

While potentially benefiting electricity consumers by reducing electricity prices and monthly bills (Gil and Lin, 2013; Woo et al., 2013, 2014),[5] the merit-order effect also weakens the investment incentive for the CT and CCGT, as documented by the simulation study of Traber and Kemfert (2011) for Germany, the regression analyses of Woo et al. (2012, 2015a) for Texas and California, and the descriptive assessment of Steggals et al. (2011) for Great Britain.

Applying a regression-based approach to a recent sample about 21,000 hourly observations of CAISO market prices and their fundamental drivers for 12/12/2012–04/30/2015, this paper answers two policy questions that are of interest to academics and policy makers. The first question is what are the estimated merit-order effects of renewable energy in the CAISO's DAM and RTM? This timely and relevant question reflects the CAISO's DAM trading, which accounts for over 90% of the total MWh transacted in 2014. If the DAM merit-order effect estimate is found to be small, California's renewable energy development is of limited help in mitigating the adverse bill impacts of such events as escalating natural gas prices, rapid load growths or nuclear plant shutdowns. To be fair, a small DAM merit-order effect may also imply a small "missing money" problem.

The second question is what causes the hourly DAM and RTM prices to systematically diverge? Under the efficient market hypothesis (Eydeland and Wolyniec, 2003), the CAISO's DAM and RTM prices tend to converge. If an expected DAM price is less than an expected RTM price, buying electricity in the DAM for resale in the RTM yields a per MWh arbitrage profit equal to the expected

[1] Price volatility with occasional spikes has led to extensive research on electricity price behavior and dynamics (e.g., Johnsen, 2001; Bessembinder and Lemmon, 2002, 2006; Longstaff and Wang, 2004; Knittel and Roberts, 2005; Park et al., 2006; Haldrup and Nielsen, 2006; Mount et al., 2006; Weron, 2006; Guthrie and Videbeck, 2007; Benth and Koekebakker, 2008; Karakatsani and Bunn, 2008; Redl et al., 2009; Marckhoff and Wimschulte, 2009; Janczura and Weron, 2010; Douglas and Popova, 2011). That volatility has also engendered extensive research on electricity derivatives and risk management (e.g., Deng et al., 2001; Lucia and Schwartz, 2002; Eydeland and Wolyniec, 2003; Burger et al., 2004; Kleindorfer and Li, 2005; Deng and Oren, 2006; Deng and Xia, 2006; Woo et al., 2004a, 2004b, 2006; Huisman et al., 2009; Camona and Ludkovski, 2008; Ryabchenko and Uryasev, 2011; Thompson, 2013).

[2] http://www.cpuc.ca.gov/PUC/energy/Procurement/RA/.

[3] CPUC, "2014 Final RA Guide", http://www.cpuc.ca.gov/NR/rdonlyres/0C2512A4-AE6C – 4BB7-BC0D – 75D2F40741BA/0/Final2014RAGuide.docx.

[4] These policies are detailed in Haas et al. (2008), Schmalensee (2009), Barroso et al. (2010), Pollitt (2010), Alagappan et al. (2011), Woo et al. (2011a), Zarnikau (2011), Yatchew and Baziliauskas (2011), and Green and Yatchew (2012).

[5] In California, renewable energy's per-MWh procurement cost includes the renewable energy cost and incremental transmission and grid integration costs. These procurement costs are typically higher than wholesale market prices and must be paid by the customers of a load serving entity such as an LDC. As renewable energy can also reduce wholesale market prices, the net bill effect to customers is the difference between (a) the incremental above-market procurement cost of renewable energy; and (b) the cost savings due to lower market prices for the MWh supplied by non-renewable generation. The LDC's customers enjoy net bill savings when (a) is less than (b).

price difference between the RTM and DAM. The ensuing inter-market electricity trading causes the DAM and RTM prices to converge.

The CAISO's DAM prices are found to contain forward premiums, even after the February 2011 adoption of virtual bidding that enables a trader to buy (sell) in the DAM with the liquidation obligation to sell (buy) in the RTM (Woo et al., 2015b). If the DAM–RTM price divergence is found to systematically depend on the CAISO's day-ahead forecast errors for renewable energy, improving the CAISO's forecast performance would enhance electricity trading efficiency under virtual bidding.

We make four main contributions:

- To the best of our knowledge, our paper is the first comprehensive analysis that uses a large sample of hourly data to jointly estimate solar and wind energy's merit-order effects by market type: DAM vs. RTM. It complements extant studies that focus on either the DAM effect or the RTM effect but not both within a single unified setting.
- Our regression model of DAM and RTM price behavior reflects the CAISO's price determination process. Both the DAM and RTM prices depend on the day-ahead forecasts for system loads and renewable energy. The RTM prices also depend on the CAISO's forecast errors (=actual MWh − forecast MWh), a market reality absent in the extant RTM price regression studies.
- We answer the first question by documenting statistically significant (p-value < 0.01) estimates for the DAM and RTM merit-order effects in California.
- We answer the second question by documenting that the DAM–RTM price divergence is partly attributable to the CAISO's day-ahead forecast errors for renewable energy.

The paper proceeds as follows. Section 2 explains our choice of California for our empirical investigation. It also describes our data sample, proposes our regression specification, and sets forth our testable hypotheses. Section 3 presents the regression results. Section 4 discusses these results. Section 5 contains our conclusions and policy implications.

2. Materials and methods

2.1. Why California?

We choose California for several reasons. The first and foremost reason is data availability. Our sample is recent and large, with about 21,000 hourly observations of CAISO prices and their fundamental drivers for the 30-month period of 12/12/2012–04/30/2015. The period's start date is when the CAISO first published its day-ahead forecasts of solar and wind energy. Its end date reflects the most recent data available at the time of our writing. As the state's 2160-MW San Onofre nuclear plant retired in 2011, the sample enables an initial look at the post-San Onofre merit-order effects in California.

The remaining reasons reflect the state's electricity features.[6] Our second reason is market size. California is the largest state economy in the U.S. and the eighth largest economy in the world,[7] thus accentuating our empirical findings' real-world relevance.

Third, California is a good candidate for studying renewable energy's merit-order effects because its marginal fuel is likely natural-gas, except for the low-demand hours during which the RTM prices can become negative.[8] The state's installed generation's nameplate capacity of 78,995 MW in 2014 included natural gas units (58.6%), large hydro (15.7%), nuclear (2.9%), other thermal generation (0.5%), and renewable resources (22.1%), which were comprised of biomass (1.6%), geothermal (3.4%), small hydro (2.1%), solar PV (5.9%), solar thermal (1.6%), and wind (7.5%).[9] Its in-state electricity generation in 2014 was fueled by natural gas (61.5%), large hydro (7.1%), nuclear (8.6%), and renewable (22.2%) that includes biomass (3.2%), geothermal (6.1%), small hydro (1.2%), solar (5.2%), wind (6.5%), and other (0.5%).[10] The state's total generation of 296,843 GWH in 2014 was the in-state generation of 198,973 GWH plus power imports of 37,261 GWH from the Pacific Northwest and 60,609 GWH from the Desert Southwest.[11]

Fourth, California has substantial renewable energy because of its ambitious renewables energy programs (e.g., an RPS of 33% by 2020 and net energy metering).[12] The state's solar energy has begun to create a "duck curve" of relatively low net loads during 12:00–15:00 and relatively high net loads during 06:00–09:00 and 18:00–21:00 (CAISO, 2014). Although the state is historically afternoon-peaking at around 16:00, the "duck curve" will likely sharpen in the next ten years with additional solar generation coming online in California due to the Senate Bill 350 enacted in September 2015, setting the state's RPS at 50% by 2030.

2.2. The CAISO's price determination process

To develop our DAM and RTM price regressions, we discuss the CAISO's price determination process.[13] Based on the theory of LMP, the CAISO determines its nodal DAM and RTM prices. The DAM opens seven days prior to the trade date and closes at 1:00 p.m. the day before the trade date. The CAISO uses a full network model to determine unit commitments and day-ahead hourly market-clearing prices while incorporating must-run needs and any bid mitigation. The model ensures that in-state generation plus imports are equal to the sum of projected loads, exports, and transmission losses. Thus, it yields the least-cost day-ahead dispatch for the conventional resources to meet the CAISO-controlled grid's day-ahead projected net loads (= forecast loads-forecast solar and wind energy). Its net load formulation implies that the marginal price effects of forecast loads and forecast solar and wind energy should sum to zero, a testable hypothesis presented in Section 2.7 below.

The RTM market opens after the DAM closes, and it remains open until 75 min before the start of the trading hour. The CAISO uses Real-Time Economic Dispatch that automatically runs every five minutes to dispatch imbalance energy and energy from ancillary services. As the real-time energy imbalances are the result of unanticipated deviations from the day-ahead schedules of loads and resources, the CAISO's forecast errors likely contribute to the RTM price fluctuations. Thus, a regression model of the CAISO's RTM price behavior should include forecast errors in its set of explanatory variables, as shown in Section 2.6 below.

[6] Additional details (e.g., the market reform history and the 2010–2011 crisis) of California's electricity industry are available in Woo (2001) and Woo et al. (2014, 2015a).

[7] http://www.lao.ca.gov/LAOEconTax/Article/Detail/1.

[8] During the low-demand hours of 02:00 and 05:00, the state's system loads at times cannot fully absorb the generation output from nuclear plants and wind farms. Hence, the CAISO uses negative prices to induce generation curtailment to maintain the state's real-time load-resource balance.

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

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

[11] http://energyalmanac.ca.gov/electricity/total_system_power.html

[12] http://www.cpuc.ca.gov/PUC/energy/Renewables/; http://www.cpuc.ca.gov/PUC/energy/Renewables/hot/feedintariffs.htm; http://www.cpuc.ca.gov/PUC/energy/DistGen/netmetering.htm

[13] http://www.caiso.com/market/Pages/MarketProcesses.aspx; http://www.caiso.com/market/Pages/ProductsServices/Default.aspx.

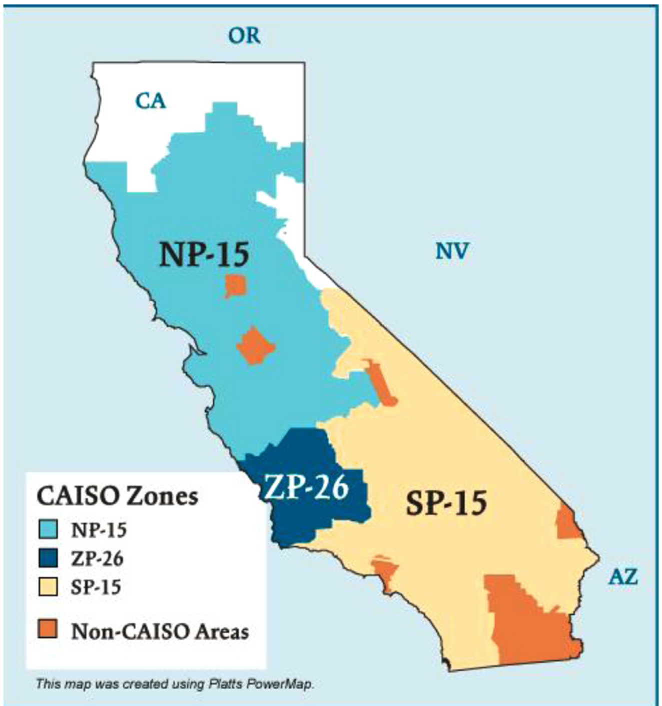

Fig. 1. The CAISO's major electric regions (Source: https://www.ferc.gov/market-oversight/mkt-electric/california/2008/05 – 2008-elec-ca-archive.pdf).

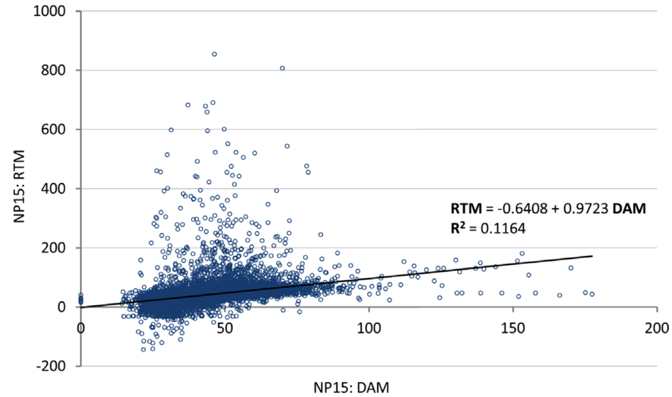

Fig. 2. Scatter plot of the NP15 region's day-ahead market (DAM) price vs. real-time market (RTM) price ($/MWh) for the sample period of 12/12/2012–04/30/2015; estimated OLS regression with standard errors in ( ): RTM$=-0.6408$ $(0.8011)+0.9723$ (0.0185) DAM; p-value<0.0001 for the F-statistic that tests HA: OLS regression's intercept$=0$ and slope$=1$.

2.3. Data description

2.3.1. Variables

Fig. 1 is a map of the CAISO's three major electric regions: NP15, SP15 and ZP26. The major LDC in the NP15 region is PG&E,[14] which had an annual peak demand of 19,526 MW in 2014. The largest LDC in the SP15 region is Southern California Edison (SCE), which serves Southern California and had an annual peak demand of 22,987 MW in 2014. We do not consider the ZP26 region because: (a) this region is much smaller than the NP15 and SP15 regions; and (b) the CAISO does not publish ZP26 forecasts for solar and wind energy for our entire sample period.

The left-hand-side (LHS) variables of our proposed price regression analysis are the hourly DAM and RTM prices for the NP15 and SP15 regions.[15] Each price is the per MWh revenue earned by a CCGT or CT when the unit's economic dispatch yields an operating profit of max(market price – per MWh cost, 0)>0 (Woo et al., 2012, 2015a).

Fig. 2 is a scatter plot portraying the relationship between (a) Y_{1ht}, the hourly NP15 DAM price ($/MWh) and (b) Y_{2ht}, the hourly NP15 RTM price ($/MWh) at hour $h=1, \ldots, 24$ on day $t=12/12/2012, \ldots, 04/30/2015$. It shows that the NP15 DAM and NP15 RTM prices are volatile with large spikes and they occasionally diverge. The DAM prices are at times equal to zero and RTM prices negative.

Fig. 2 reports that the estimated OLS regression line with standard error in ( ) is $Y_{2ht}=-0.6408$ $(0.8011)+0.9723$ Y_{1ht} (0.0185). Its low adjusted R^2 of 0.1163 suggests the DAM's low effectiveness in hedging against the RTM's price risk (Chen, et al., 2003).[16] Its slope estimate indicates that a $1/MWh movement in the NP15 DAM price is on average associated with a $0.97/MWh movement in the NP15 RTM price. Under the efficient market hypothesis, E(Y_{2ht})=E(Y_{1ht}) and the DAM price is an accurate predictor of the RTM price. When E(Y_{2ht})=E(Y_{1ht}), the OLS regression's intercept$=0$ and slope$=1$, which we shall refer to as the hypothesis of accuracy (**HA**). Based on the statistical significance criterion of p-value $\leq$ 0.01 used throughout this paper, the F-statistic (p-value<0.0001) for testing **HA** rejects that the NP15 DAM price is an accurate predictor of the NP15 RTM price.

Fig. 3 is a scatter plot portraying the relationship between (a) Z_{1ht}, the hourly SP15 DAM price ($/MWh) and (b) Z_{2ht}, the hourly SP15 RTM price ($/MWh). It resembles Fig. 2, thus telling a similar story about the two SP15 prices.

We now turn our attention to our price regressions' right-hand-side (RHS) variables, the fundamental drivers identified in our prior research (Woo, et al., 2007, 2011b, 2013, 2014, 2015a).[17] The first variable is fuel-cost related. Denoted by X_{1t}, the daily Henry Hub natural gas price ($/MMBTU) is published by the U.S. Department of Energy's Energy Information Agency.[18] Highly correlated with the NP15 fuel price index ($r=0.83$) and the SP15 fuel price index ($r=0.91$) published by the CAISO, X_{1t} serves as an instrument in our price regressions to circumvent the estimation bias potentially caused by the local natural gas prices possibly being endogenous variables. The expected price effect of X_{1t} is positive because rising natural gas prices tend to raise the state's

[14] http://www.ferc.gov/market-oversight/mkt-electric/california.asp.

[15] All CAISO data used in this paper come from: http://oasis.caiso.com/mrioasis/logon.do;jsessionid=5D9A2B355EF0330B4D1D9631157487E5.

[16] The low R^2 also explains the likely large profit volatility under virtual bidding. Consider the following OLS regression that suppresses the subscripts h and t without any loss of generality: $Y_2=a+(1-b)\ Y_1+e$, where a=intercept estimate, $(1-b)$=slope estimate, and e=regression error whose variance is s^2. Suppose Y_1 is known with certainty and $Y_1>Y_2$ forecast$=a+(1-b)\ Y_1$. The arbitrage profit forecast from selling 1 MWh in the DAM and buying 1 MWh in the RTM is $(Y_1-Y_2)=-a+b\ \ Y_1+e$, whose variance is $\mathrm{var}(Y_1-Y_2)=\mathrm{var}(a)-2\ \ \mathrm{cov}(a,\ b)+\mathrm{var}(b)\ Y_1^2+s^2$. As the low R^2 reflects a large s^2, it implies a large profit volatility of $[\mathrm{var}(Y_1-Y_2)]^{1/2}$. The profit risk further increases when Y_1 is stochastic (Feldstein, 1971). The reason for Y_1 being stochastic from a trader's perspective is that the trader must submit its DAM purchase order before the CAISO's DAM price determination.

[17] An insightful reviewer suggests power imports and temperature as two additional RHS variables in our regression analysis. We respectfully decline to do so for the following reasons. First, our proposed regression analysis uses fundamental drivers that are known to be exogenous. Hence, our set of RHS variables do not include the in-state large-hydro generation and the power imports from the Pacific Northwest and Desert Southwest because they are endogenously determined by the procurement decisions of load-serving entities (e.g., PG&E, SCE and SDG&E) to meet their resale obligations. Second, while we concur that temperature can be a fundamental driver for wholesale market prices (Woo et al., 2013), we already use the hourly system loads to model the hourly DAM and RTM price behavior. Hence, we exclude temperature from the set of RHS variables, as the price-insensitive system loads for a given hour (e.g., 15:00–16:00) on a given day (e.g., Wednesday in July) have captured that day's weather.

[18] http://www.eia.gov/dnav/ng/hist/rngwhhdd.htm

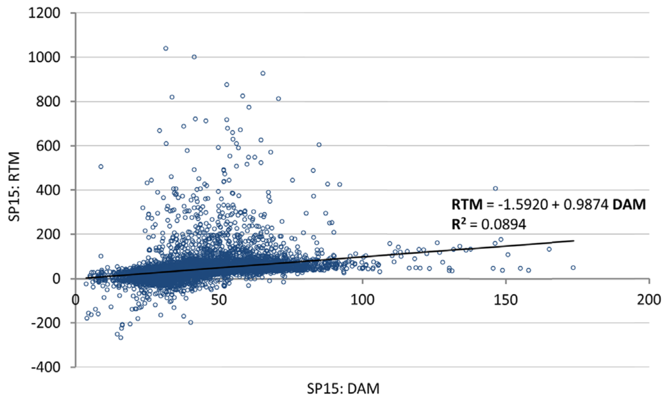

Fig. 3. Scatter plot of the SP15 region's day-ahead market (DAM) price vs. real-time market (RTM) price (\$/MWh) for the sample period of 12/12/2012–04/30/2015; estimated OLS regression with standard errors in ( ): RTM = −1.5920 (0.9720) + 0.9874 (0.0218) DAM; p-value < 0.0001 for the F-statistic that tests HA: OLS regression's intercept = 0 and slope = 1.

marginal fuel costs.

The next two variables are related to the state's daily nuclear MW available based on the plant availability data published by the Nuclear Regulatory Commission.[19] After the San Onofre plant's premature retirement in 2011, the state's daily nuclear MW available come from: (a) the 2150-MW Diablo Canyon plant in California solely owned by PG&E; and (b) the 3739-MW Palo Verde plant in Arizona partially owned by SCE (15.8%), the Southern California Public Power Authority (5.9%), and the Los Angeles Department of Water and Power (5.7%).[20] Denoted by X_{2t} and X_{3t}, these daily MW are expected to have negative price effects because nuclear generation displaces the state's natural-gas-fired generation.

California's prolonged drought has adversely affected the state's hydro generation that mainly resides in the NP15 region. Based on the data published by the U.S. Geological Survey (USGS), we use three variables to characterize the state's hydro conditions, whose improvement tends to lower the market prices. The first hydro variable is X_{4t}, the daily California hydro index which ranges from 1 = driest to 7 = wettest based on the USGS's comparison of the daily stream flows at the state's hydro stations to their historical values.[21] The remaining two hydro variables are X_{5ht} and X_{6ht}, the hourly discharges (000 ft^3/second) of the hydro stations at the Klamath River and Sacramento River in Northern California.[22]

The next set of RHS variables is demand-related. Hourly system demands on a given day are largely price-insensitive and mainly weather-driven. Rising hourly demands on a given day tend to increase the hourly market prices for that day. To measure the actual demands, we use X_{7ht} and X_{8ht}, the hourly actual system MWh of PG&E and SCE published by the CAISO.[23] To measure the forecast demands, we use F_{7ht} and F_{8ht}, the PG&E and SCE system MWh forecasts published by the CAISO.

The last set of RHS variables is related to renewable energy whose increase tends to reduce market prices via the merit-order effect. We focus on solar and wind energy for four reasons. The first reason is data availability. The CAISO does not publish day-ahead forecast for the other types of renewable energy: biomass, geothermal and small hydro. Second, solar and wind constitute 68.6% of the state's 2014 total installed renewable capacity of 17,581 MW and their capacities are expected to grow in the coming years. Third, small hydro is only about 9.2% of the state's 2014 total installed renewable capacity, and Woo et al. (2014) find its RTM merit-order effect insignificant. Finally, our preliminary exploration indicates that biomass and geothermal energy have positive, though insignificant, price effects. As these positive estimates are counter-intuitive, we exclude biomass and geothermal generation from our analysis.

Fig. 4 portrays the hourly shapes of actual solar energy by region based on the latest 12 months (May 2014–April 2015) of complete data in our sample for PG&E tariffs' summer season (May-October) and winter season (November–April).[24] This figure shows hourly solar energy tracks daily sunshine, thus explaining the "duck curve" attributable to the rapid growth of solar generation (CAISO, 2014). It also shows that solar energy complements wind energy which tends to dip during daytime hours.

Fig. 5 portrays the hourly shapes of actual wind energy by region. It shows higher wind energy during the daytime hours than nighttime hours. Excess wind energy beyond what can be absorbed by the California grid contributes to the CAISO's zero DAM prices and negative RTM prices.

We use X_{9ht} and X_{10ht} to denote the hourly actual solar and wind energy for the NP15 region and X_{11ht} and X_{12ht} for the SP15 region. The CAISO's forecasts of X_{9ht} to X_{12ht} are denoted by F_{9ht} to F_{12ht}.

2.4. Performance of the CAISO's forecasts

Fig. 6 is a scatter plot of forecast vs. actual loads for NP15. This figure shows the forecast and actual loads move closely in tandem. Nonetheless, the **HA** hypothesis is decisively rejected (p-value < 0.0001). Fig. 7 paints a similar picture for SP15.

Fig. 8 is a scatter plot of forecast vs. actual solar energy for NP15. It shows the forecast and actual solar energy often diverge, at times by a large amount. In contrast, Fig. 9 shows that the CAISO's SP15 solar energy forecast closely tracks the actual solar energy.

Fig. 10 is a scatter plot of forecast vs. actual wind energy for NP15. One MWh increase in forecast wind energy is on average associated with a 1.12 MWh increase in actual wind energy. Fig. 11 resembles Fig. 10 and therefore conveys a similar message.

Table 1 reports the CAISO's day-ahead forecast performance metrics. Except for the SP15 system load, the mean error (ME) values are all statistically significant (p-value < 0.0001). The CAISO's load and net load forecasts perform much better than solar and wind energy forecasts, as evidenced by a comparison of their mean absolute percentage error (MAPE) values. In summary, Table 1 highlights the difficulty in accurately forecasting solar and wind energy on a day-ahead basis.

2.5. Descriptive statistics and price correlations

Table 2 reports the descriptive statistics and price correlations of the variables used in our price regressions. It shows that all data series are stationary based on the Phillip-Perron unit-root test (Phillips and Perron, 1988) at the 1% significance level, thus eliminating possible concerns about a spurious price regression

[19] http://www.nrc.gov/reading-rm/doc-collections/event-status/reactor-status/index.html

[20] https://www.starsalliance.com/members/paloverde.php

[21] This index is a weighted average of the station-specific indices in California available at http://waterwatch.usgs.gov/index.php?r=ca&id=pa01d&sid=w__table2.

[22] The discharge data come from http://waterdata.usgs.gov/ca/nwis/rt. The Klamath River's station is USGS 11530500 and the Sacramento River's station USGS 11447650.

[23] The system demand of the San Diego Gas & Electric (SDG&E), the second largest LDC in SP−15, is highly correlated with that of SCE.

[24] The SCE tariffs' seasons are: summer (June–October) and winter (November–May).

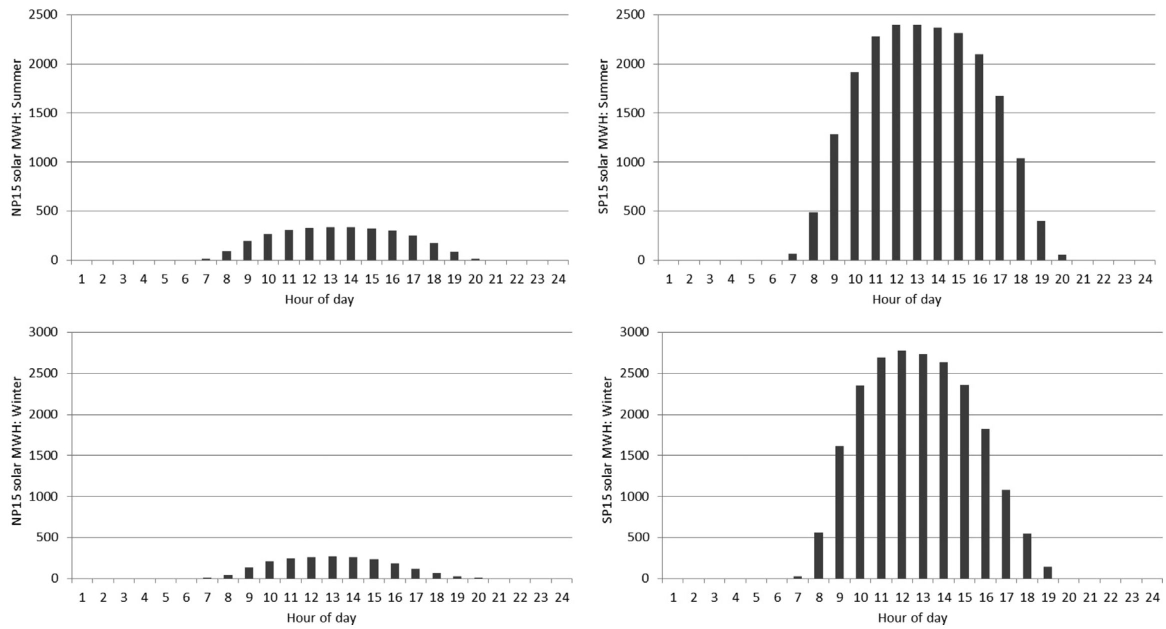

Fig. 4. Average hourly MWh of actual solar energy by region based on the most recent year of complete data for PG&E tariffs' summer season (May 2014–October, 2014) and winter season (November 2014–April 2015).

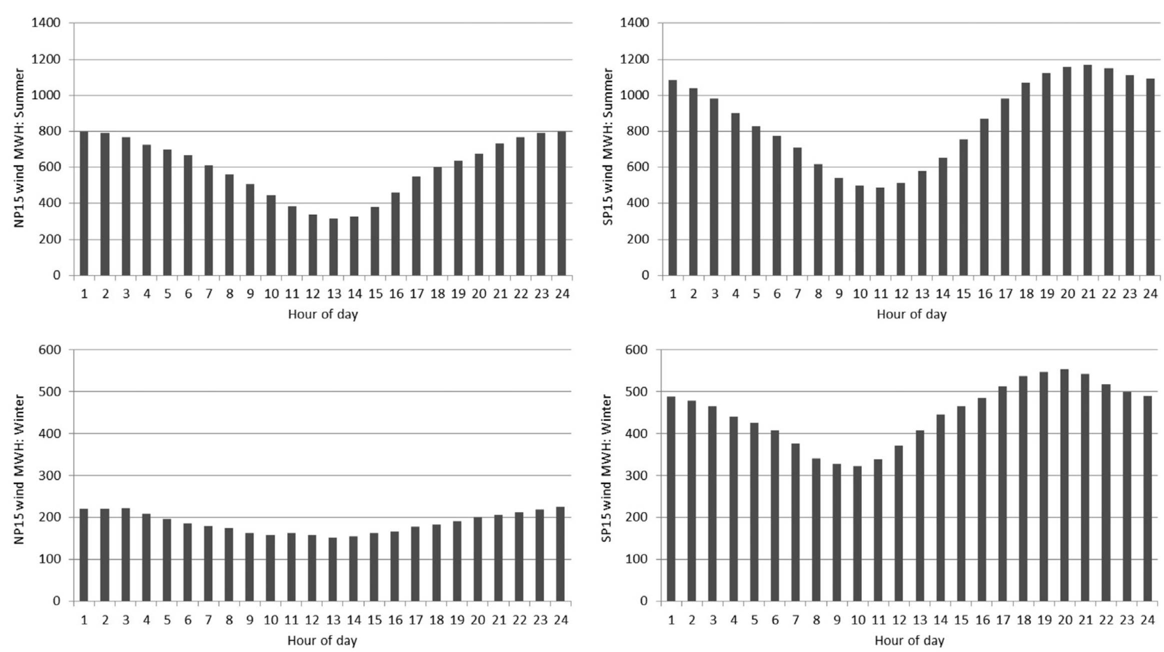

Fig. 5. Average hourly MWh of actual wind energy by region based on the most recent year of complete data for PG&E tariffs' summer season (May 2014–October, 2014) and winter season (November 2014–April 2015).

due to non-stationary data (Granger and Newbold, 1974). It also shows that the data series are volatile, with large standard deviations and ranges defined by the series' minimum and maximum values. In particular, the RTM prices are much more volatile than the DAM prices, with the RTM price standard deviations about thrice the DAM price standard deviations. The negative minimum values for actual solar and wind MWh reflect the on-site plant use of electricity by renewable generators.

The correlation coefficients in Table 2 motivate our formulation of a system of seemingly unrelated price regressions in the next subsection. Under LMP, the NP15 and SP15 prices should be almost perfectly correlated *sans* transmission constraints between the two regions. The NP15 DAM prices are indeed highly correlated ($r = 0.91$) with the SP15 DAM prices, reflecting the CAISO's day-ahead expectation of few inter-regional transmission constraints. The NP15 RTM and SP15 RTM prices, however, are only moderately correlated ($r = 0.64$), suggesting that such constraints occur more often in real time.

Looking at the fundamental drivers' price correlation coefficients, we find most of them small in size ($|r| < 0.1$), except for the natural gas price and system loads (e.g., $r > 0.48$ for the natural gas price in connection to the DAM prices). Nearly all correlation coefficients have the expected signs (e.g., positive coefficients for the natural gas price and system loads; negative coefficients for the hydro, nuclear, and renewable energy variables). While qualitatively informative, the correlation coefficients in Table 2 do not reveal the size or statistical significance of each driver's marginal price effects. Hence, we propose a regression-based approach to

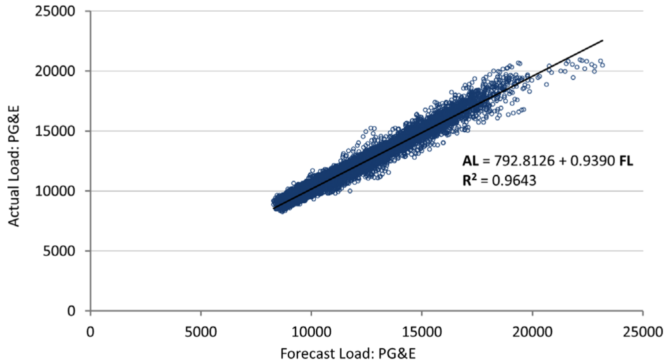

Fig. 6. Scatter plot of the CAISO's hourly day-ahead forecast load (FL) vs. actual load (AL) (MWh) for PG&E for the sample period of 12/12/2012–04/30/2015; estimated OLS regression with standard errors in ( ): AL=792.8 (15.1)+0.9390 (0.0013) FL; *p*-value < 0.0001 for the *F*-statistic that tests HA: OLS regression's intercept=0 and slope=1.

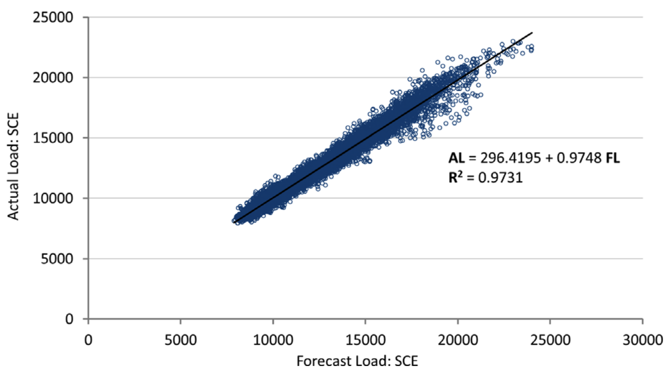

Fig. 7. Scatter plot of the CAISO's hourly day-ahead forecast load (FL) vs. actual load (AL) (MWh) for SCE for the sample period of 12/12/2012–04/30/2015; estimated OLS regression with standard errors in ( ): AL=296.4 (13.6)+0.9748 (0.0011) FL; *p*-value < 0.0001 for the *F*-statistic that tests HA: OLS regression's intercept=0 and slope=1.

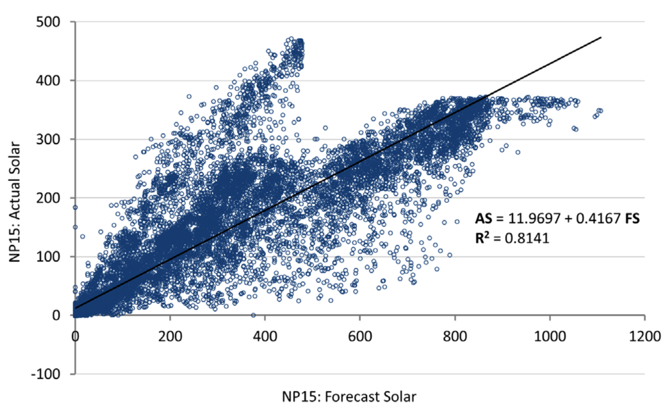

Fig. 8. Scatter plot of the CAISO's hourly day-ahead forecast solar (FS) vs. actual solar (AS) MWh in the NP15 region for the sample period of 12/12/2012–04/30/2015; estimated OLS regression with standard errors in ( ): AS=11.97 (0.42)+0.4167 (0.0014) FS; *p*-value < 0.0001 for the *F*-statistic that tests HA: OLS regression's intercept=0 and slope=1.

statistically delineate each driver's marginal price effects.

2.6. DAM and RTM price regressions

2.6.1. Model

Our model aims to capture the CAISO's price determination process. To this end, we assume the following system of price regressions given by Eqs. (1)–(4) below:

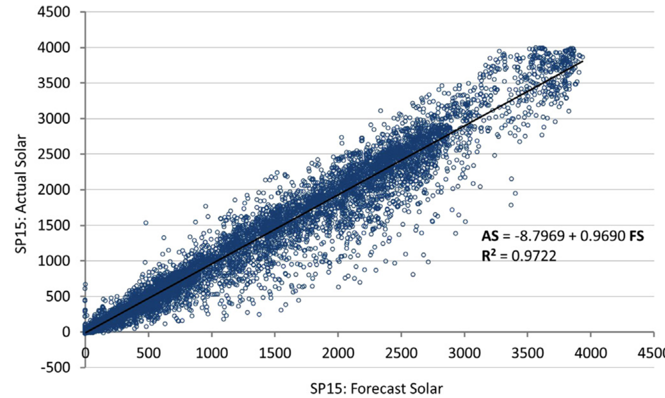

Fig. 9. Scatter plot of the CAISO's hourly day-ahead forecast solar (FS) vs. actual solar (AS) MWh in the SP15 region for the sample period of 12/12/2012–04/30/2015; estimated OLS regression with standard errors in ( ): AS=−8.80 (1.19)+0.9690 (0.0011) FS; *p*-value < 0.0001 for the *F*-statistic that tests HA: OLS regression's intercept=0 and slope=1.

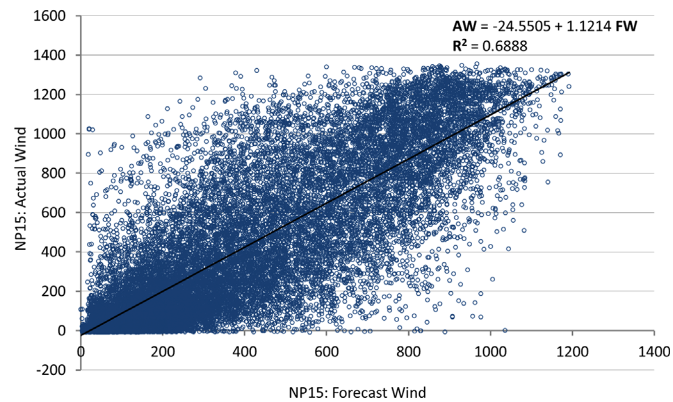

Fig. 10. Scatter plot of the CAISO's hourly day-ahead forecast wind (FW) vs. actual wind (AW) MWh in the NP15 region for the sample period of 12/12/2012–04/30/2015; estimated OLS regression with standard errors in ( ): AW=−24.55 (2.45)+1.1214 (0.0052) FW; *p*-value < 0.0001 for the *F*-statistic that tests HA: OLS regression's intercept=0 and slope=1.

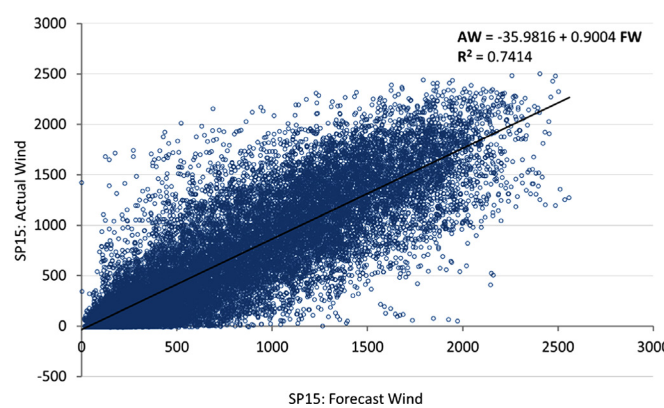

Fig. 11. Scatter plot of the CAISO's hourly day-ahead forecast wind (FW) vs. actual wind (AW) MWh in the SP15 region for the sample period of 12/12/2012–04/30/2015; estimated OLS regression with standard errors in ( ): AW=−35.98 (3.41)+0.9004 (0.0037) FW; *p*-value < 0.0001 for the *F*-statistic that tests HA: OLS regression's intercept=0 and slope=1.

NP15 DAM price: $Y_{1ht} = \alpha_{ht} + \alpha_1 X_{1t} + \ldots + \alpha_6 X_{6ht} + \alpha_7 F_{7ht} + \ldots + \alpha_{12} F_{12ht} + \varepsilon_{ht}$;

SP15 DAM price: $Z_{1ht} = \beta_{ht} + \beta_1 X_{1t} + \ldots + \beta_6 X_{6ht} + \beta_7 F_{7ht} + \ldots + \beta_{12} F_{12ht} + \mu_{ht}$; (2)

Table 1
The CAISO day-ahead forecast performance metrics for the sample period of 12/12/2012–04/30/2015; p-value in ( ).

Variable	NP15 region Mean error (ME)	Mean absolute error (MAE)	Mean absolute percentage error (MAPE)	SP15 region Mean error (ME)	Mean absolute error (MAE)	Mean absolute percentage error (MAPE)
System load	67.1 (< .0001)	287.9 (< .0001)	2.43 (< .0001)	−2.6 (0.3404)	271.6 (< .0001)	2.23 (< .0001)
Solar energy	−90.9 (< .0001)	94.4 (< .0001)	161.7 (< .0001)	−25.7 (< .0001)	64.7 (< .0001)	92.5 (0.0281)
Wind energy	21.5 (< .0001)	164.5 (< .0001)	1578 (0.0894)	−108.6 (< .0001)	243.0 (< .0001)	776.8 (< .0001)
System net load = System load − solar energy − wind energy	136.4 (< .0001)	371.4 (< .0001)	3.24 (< .0001)	131.6 (< .0001)	389.8 (< .0001)	3.70 (< .0001)

Note: The forecast performance metrics are: ME = average of (actual hourly MWh-forecast hourly MWh); MAE = average of |actual hourly MWh-forecast hourly MWh|; MAPE = average of 100 × |actual hourly MWh-forecast hourly MWh|/actual hourly MWh. All metrics are calculated using observations with positive MWh values to avoid anomalous results (e.g., actual solar and wind MWh have small negative values due to onsite plant use of electricity). When the actual MWh values are zero, the MAPE numbers are undefined and treated as missing values.

Table 2
Descriptive statistics and price correlations, where h = hour index = 1, …, 24 and t = day index = 12/12/2012–04/30/2015; the price correlation coefficients in **bold** have unexpected signs.

Variable	Definition	Stationary at α = 0.01?	Mean	Median	Maximum	Minimum	Standard deviation	Price correlation coefficents Y_{1ht}	Y_{2ht}	Z_{1ht}	Z_{2ht}
Y_{1ht}	Hourly NP15 DAM price ($/MWh)	Yes	41.76	40.26	177.43	0.00	11.19	1.000	0.341	0.914	0.277
Y_{2ht},	Hourly NP15 RTM price ($/MWh)	Yes	39.96	36.14	853.70	−144.59	31.90	0.341	1.000	0.313	0.642
Z_{1ht}	Hourly SP15 DAM price ($/MWh)	Yes	42.80	41.40	173.61	3.68	12.53	0.914	0.313	1.000	0.299
Z_{2ht},	Hourly SP15 RTM price ($/MWh)	Yes	40.67	36.25	1039.18	−267.58	41.41	0.277	0.642	0.299	1.000
X_{1t}	Daily natural gas price ($/MMBTU): Henry Hub	Yes	3.86	3.82	8.15	2.50	0.73	0.545	0.170	0.483	0.129
X_{2t}	Daily nuclear MW available: Diablo Canyon	Yes	2016.69	2240.00	2240.00	280.50	430.16	−0.193	−0.033	−0.203	−0.038
X_{3t}	Daily nuclear MW available: Palo Verde	Yes	3449.38	3747.00	3747.00	1249.00	552.88	-0.034	-0.026	**0.009**	**0.007**
X_{4t}	Daily California hydro index (1 = driest, …, 7 = wettest)	Yes	3.23	3.15	5.30	2.27	0.48	−0.185	−0.071	−0.095	−0.019
X_{5ht}	Hourly discharge (000 ft^3/second): Klamath River	Yes	10.31	7.62	172.00	2.00	12.26	−0.155	−0.074	−0.128	−0.053
X_{6ht}	Hourly discharge (000 ft^3/second): Sacramento River	Yes	12.69	11.88	71.45	-5.90	9.74	−0.154	−0.061	−0.089	−0.027
X_{7ht}	Hourly actual system MWh: PG&E	Yes	11962.22	11800.00	20916.00	8246.00	1920.21	0.551	0.210	0.567	0.177
F_{7ht}	Hourly forecast system MWh: PG&E	Yes	11895.17	11785.73	23169.96	8288.28	2008.04	0.569	0.202	0.584	0.175
X_{8ht}	Hourly actual system MWh: SCE	Yes	11866.58	11587.00	22987.00	7928.00	2338.63	0.533	0.198	0.572	0.197
F_{8ht}	Hourly forecast system MWh: SCE	Yes	11869.14	11615.26	24003.00	7890.91	2366.62	0.543	0.189	0.574	0.181
X_{9ht}	Hourly actual solar MWh: NP15	Yes	83.92	6.24	470.88	−1.55	115.37	**0.079**	**0.008**	**0.017**	−0.041
F_{9ht}	Hourly forecast solar MWh: NP15	Yes	174.84	3.57	1107.07	0	252.68	**0.156**	**0.050**	**0.091**	-0.007
X_{10ht}	Hourly actual wind MWh: NP15	Yes	392.23	250.13	1354.57	−9.99	392.34	−0.027	−0.094	−0.028	−0.059
F_{10ht}	Hourly forecast wind MWh: NP15	Yes	370.72	294.41	1192.20	0	289.43	−0.007	−0.025	−0.017	−0.020
X_{11ht}	Hourly actual solar MWh: SP15	Yes	523.95	10.78	3997.90	-22.62	866.74	−0.013	−0.023	−0.112	−0.079
F_{11ht}	Hourly forecast solar MWh: SP15	Yes	549.65	11.60	3935.10	0	881.20	−0.010	−0.006	−0.110	−0.067
X_{12ht}	Hourly actual wind MWh: SP15	Yes	622.53	440.52	2501.77	−17.61	597.50	**0.037**	−0.082	−0.020	−0.113
F_{12ht}	Hourly forecast wind MWh: SP15	Yes	731.02	586.50	2558.70	0	571.15	**0.038**	−0.026	−0.022	−0.054

Note: The actual solar and wind MWh data have small negative minimum values because of on-site plant use of electricity.

NP15 RTM Price: $Y_{2ht}=[\gamma_{ht}+\gamma_1 X_{1t}+\ldots+\gamma_6 X_{6ht}+\gamma_7 F_{7ht}+\ldots+\gamma_{12}F_{12ht}]+[\psi_7 E_{7ht}+\ldots+\psi_{12}\ E_{12ht}\ ]+\eta_{ht};$ (3)

SP15 RTM price: $Z_{2ht}=[\theta_{ht}+\theta_1 X_{1t}+\ldots+\theta_6\ \ X_{6ht}+\theta_7 F_{7ht}+\ldots+\theta_{12}F_{12ht}]+[\zeta_7 E_{7ht}+\ldots+\zeta_{12}\ E_{12ht}]\ +\upsilon_{ht}.$ (4)

For easy reference, the RHS variables of the above equations are fully described in Table 3 that presents our regression results.

The system's random errors are $(\varepsilon_{ht},\mu_{ht},\eta_{ht},\upsilon_{ht})$, each assumed to have zero mean and finite variance, be contemporaneously correlated, and follow a stationary AR(4) process.[25] This stochastic assumption implies that the system can be efficiently estimated using the iterated seemingly unrelated regression (ITSUR) technique in PROC MODEL of SAS (2004).

2.6.2. The DAM price regressions

Eq. (1) is the NP15 DAM price regression that explains the price variations using the time-varying intercept α_{ht} and fundamental drivers. The following reasons justify Eq. (1)'s specification. First, the linear specification is a first-order approximation of an unknown functional form. Second, it helps develop the linear restrictions for testing the hypotheses posited in the next subsection.

[25] The AR(4) process is identified by an exploratory analysis that considers the AR(5) alternative, finding the AR(5) parameter estimates to be statistically insignificant. The same analysis considers the errors are GARCH(1,1) with time-dependent variances (Bollerslev, 1986). The estimated GARCH processes for the RTM price regressions are non-stationary and therefore not adopted.

Table 3
ITSUR regression results for the DAM and RTM price regressions for the 30-month period of 12/12/2012–04/30/2015; p-value in ( ); estimates in **bold** have p-values < 0.01; estimates in *italic* have unexpected signs. Thus, a coefficient estimate in ***bold italic*** means that the estimate is expected to be positive (negative) but turns out to be significantly negative (positive).

Variable: definition	Dependent variable: definition and regression specification			
	Day-ahead market (DAM)		Real-time market (RTM)	
	Y_{1ht}: Hourly NP15 DAM price (\$/MWh) based on Eq. (1)	Z_{1ht}: Hourly SP15 DAM price (\$/MWh) based on Eq. (2)	Y_{2ht}: Hourly NP15 RTM price (\$/MWh) based on Eq. (3)	Z_{2ht}: Hourly SP15 RTM price (\$/MWh) based on Eq. (4)
Adjusted R^2	0.9455	0.9390	0.2168	0.1937
Root mean squared error	2.6247	3.1158	28.5245	37.5638
AR(1) parameter	**0.8724** (< .0001)	**0.8834** (< .0001)	**0.2241** (< .0001)	**0.2308** (< .0001)
AR(2) parameter	0.0177 (0.0265)	− **0.0556** (< .0001)	**0.0584** (< .0001)	**0.0712** (< .0001)
AR(3) parameter	− **0.0299** (0.0002)	0.0098 (0.2219)	**0.0504** (< .0001)	**0.0334** (< .0001)
AR(4) parameter	0.0138 (0.0207)	**0.0213** (0.0003)	**0.0280** (< .0001)	**0.0212** (0.0005)
X_{1t}: Daily natural gas price (\$/MMBTU): Henry Hub	**7.4447** (< .0001)	**7.5083** (< .0001)	**8.1570** (< .0001)	**8.6995** (< .0001)
X_{2t}: Daily nuclear MW available: Diablo Canyon	− **0.0021** (< .0001)	− **0.0025** (< .0001)	0.0010 (0.2652)	0.0021 (0.0884)
X_{3t}: Daily nuclear MW available: Palo Verde	− **0.0015** (< .0001)	− **0.0016** (< .0001)	− **0.0030** (0.0014)	− 0.0020 (0.0959)
X_{4t}: Daily California hydro index (1 = driest, …, 7 = wettest)	− **3.3415** (< .0001)	-0.9444 (0.0226)	− **3.5505** (0.0015)	-0.1409 (0.9238)
X_{5ht}: Hourly discharge (000 ft^3/second): Klamath River	0.0103 (0.4797)	− 0.0222 (0.1593)	− 0.0589 (0.0956)	− 0.0956 (0.0387)
X_{6ht}: Hourly discharge (000 ft^3/second): Sacramento River	0.0044 (0.6172)	0.0112 (0.2780)	0.0000 (1.0000)	− 0.0214 (0.7208)
F_{7ht}: Hourly forecast system MWh: PG&E	**0.0046** (< .0001)	**0.0038** (< .0001)	**0.0066** (< .0001)	0.0014 (0.0831)
F_{8ht}: Hourly forecast system MWh: SCE	**0.0018** (< .0001)	**0.0034** (< .0001)	-0.00003 (0.9530)	**0.0055** (< .0001)
F_{9ht}: Hourly forecast solar MWh: NP15	− **0.0053** (< .0001)	− **0.0032** (< .0001)	− **0.0220** (0.0032)	− **0.0367** (0.0002)
F_{10ht}: Hourly forecast wind MWh: NP15	− **0.0033** (< .0001)	− **0.0014** (0.0015)	− 0.0028 (0.1121)	− 0.0015 (0.5193)
F_{11ht}: Hourly forecast solar MWh: SP15	− **0.0019** (< .0001)	− **0.0040** (< .0001)	− 0.0010 (0.1970)	− **0.0034** (0.0008)
F_{12ht}: Hourly forecast wind MWh: SP15	− **0.0015** (< .0001)	− **0.0034** (< .0001)	**-0.0062** (< .0001)	− **0.0114** (< .0001)
E_{7ht}: Hourly forecast error for system MWh: PG&E			**0.0070** (< .0001)	0.0012 (0.3064)
E_{8ht}: Hourly forecast error for system MWh: SCE			**0.0057** (< .0001)	**0.0134** (< .0001)
E_{9ht}: Hourly forecast error for solar MWh: NP15			− **0.0274** (0.0009)	− **0.0412** (0.0002)
E_{10ht}: Hourly forecast error for wind MWh: NP15			− **0.0174** (< .0001)	− **0.0112** (< .0001)
E_{11ht}: Hourly forecast error for solar MWh: SP15			− **0.0226** (< .0001)	− **0.0223** (< .0001)
E_{12ht}: Hourly forecast error for wind MWh: SP15			− **0.0144** (< .0001)	− **0.0214** (< .0001)

Note: For brevity, this table does not report the coefficient estimates for the intercept and the binary indicators that indicate statistically-significant (p-value < 0.01) time-dependence of the hourly market prices.

Third, a nonlinear specification with second-order terms formed by the 12 continuous variables of X_{1t}, …, X_{6ht}, F_{7ht}, …, F_{12ht} increases the number of RHS variables by 78, rendering our development of testable hypotheses intractable. Third, while the marginal price effects of the fundamental drivers may be time-dependent as noted by a referee, allowing the 12 continuous variables' coefficients to vary by time of day period (e.g., daytime vs. nighttime) yields many insignificant coefficient estimates, similar to what has been found by Woo et al. (2014). Fourth, we cannot use a double-log specification because of the zero DAM prices that cause missing natural-log values and therefore data gaps in our regression analysis. Finally and most importantly, our ITUSR regression results in Table 3 show that Eq. (1) has an adjusted R^2 of 0.94, indicating an almost perfect fit that allays concerns on the need of including more RHS variables in Eq. (1).

Eq. (1) uses α_{ht} to account for the residual price variations not captured by the other RHS variables. We assume α_{ht} is observation-specific, given by a linear function of an intercept, 23 binary indicators for the hour of day, six binary indicators for the day of week, and 11 binary indicators for the month of year.

We assume the NP15 DAM price depends on the *actual* values of X_{1ht} to X_{6ht}, which are drivers unrelated to system hourly loads and solar and wind energy: (a) the daily natural gas price, (b) the daily nuclear MW available, and (c) the California hydro index and the two rivers' discharges. This assumption reflects that there are no publicly-available day-ahead forecasts of these drivers to use in our regression analysis, and developing such forecasts is well beyond the scope of this paper. Further, existing literature indicates that these variables with relatively small hour-to-hour and day-to-day changes can be accurately forecast via time-series modeling (e.g., ARIMA) in the day-ahead time frame (Weron, 2006).

We assume that the NP15 DAM price depends on the CAISO's forecasts of PG&E's system MWh, SCE's system MWh, and the solar and wind MWh in the NP15 and SP15 regions. This assumption chronologically matches the NP15 DAM prices with the day-ahead forecasts used in the CAISO's DAM price determination.

The drivers' coefficients are $\{\alpha_k\}$ for $k=1,.., 12$, each measuring a given driver's marginal price effect. The natural gas price's effect is $\alpha_1>0$, the nuclear effects are $\alpha_2<0$ and $\alpha_3<0$, the hydro effects are $\alpha_4<0$, $\alpha_5<0$ and $\alpha_6<0$, the system load effects are $\alpha_7>0$ and $\alpha_8>0$, the solar effects are $\alpha_9<0$ and $\alpha_{10}<0$, and the wind effects are $\alpha_{11}<0$ and $\alpha_{12}<0$.

Eq. (2) is the SP15 DAM price regression. Since it is analogous to Eq. (1), its discussion is omitted here for brevity.

2.6.3. The RTM price regressions

Eq. (3) is the NP15 RTM price regression that has two RHS terms in [ ]. The first term has the time-dependent intercept γ_{ht} and coefficients (γ_1, …, γ_{12}) for the variables (X_{1t}, …, X_{6ht}, F_{7ht}, …, F_{12ht}), similar to the RHS systematic component of the NP15 DAM price regression. The second term contains (ψ_7, …, ψ_{12}), the coefficients for the forecast errors ($E_{7ht}=X_{7ht}-F_{7ht}$, …, $E_{12ht}=X_{12ht}-F_{12ht}$).

Eq. (3) generalizes the RTM price regressions in Woo et al. (2014, 2015a). Specifically, if $\gamma_7=\psi_7$, …, $\gamma_{12}=\psi_{12}$, Eq. (3) becomes:

$$\text{NP15 RTM: } Y_{2ht}=\gamma_{ht}+\gamma_1X_{1t}+\ldots+\gamma_6X_{6ht}+\gamma_7X_{7ht}+\ldots+\gamma_{12}X_{12ht}+\eta_{ht}. \quad (5)$$

Eq. (5) shows that the NP15 RTM price moves with the actual loads, actual solar energy and actual wind energy.

We use Eq. (3) to identify the RTM merit-order effect of an expected increase in NP15 wind energy caused by an increase in the state's wind generation capacity.[26] An increase in wind speed is not used as the basis for the expected wind energy increase because it is a weather event unrelated to the state's renewable energy policy.

To identify wind energy's merit-order effect, we reason that the wind capacity increase causes the CAISO to raise its NP15 wind energy forecast. Based on Fig. 10, a 1-MWh increase in the NP15 forecast wind energy is assumed to associate with an expected 1-MWh increase in the NP15 actual wind energy. There are three cases to consider:

(1) Suppose the CAISO's forecast errors vanish under perfect foresight so that $E_{7ht}=\ldots=E_{12ht}=0$. As the second [ ] term in the RTM price regression becomes zero, γ_{10} measures NP15 wind energy's marginal RTM merit-order effect.
(2) Suppose the forecast errors are not equal to zero. Eq. (3) shows that (γ_{10} $-\psi_{10}$) is the marginal merit-order effect of NP15 forecast wind energy F_{10ht} and ψ_{10} is that of E(X_{10ht}). As a result, γ_{10} [$=(\gamma_{10}-\psi_{10})+\psi_{10}$] measures NP15 wind energy's marginal RTM merit-order effect.
(3) Suppose $\gamma_{10}=0$. Eq. (3) shows that -ψ_{10} is the marginal merit-order effect of F_{10ht} and ψ_{10} is that of E(X_{10ht}). Hence, NP15 wind energy's marginal RTM merit-order effect is zero.

These three cases show that γ_{10} measures NP15 wind energy's marginal merit-order effect in the NP15 RTM. Using similar reasoning, we establish that γ_9, γ_{11} and γ_{12} measure the marginal NP15 RTM merit-order effects of NP15 solar energy, SP15 solar energy and SP15 wind energy.[27]

Eq. (4) is the SP15 RTM price regression. Since it is analogous to Eq. (3), its discussion is omitted here for brevity.

2.7. Testable hypotheses

We develop testable hypotheses based on Eqs. (1)–(4). Amenable to the Wald test (Davidson and Mackinnon, 1993), each null hypothesis is stated as a set of linear restrictions on the regression coefficients.

2.7.1. Forecast load vs. forecast renewable energy in the DAM

Recall the net load formulation in the CAISO's DAM price determination process in Section 2.2. As suggested by an insightful referee, our first hypothesis is:

H1. : A 1-MWh increase in a region's load forecast has the same DAM price effect as a 1-MWh decrease in the same region's renewable energy forecast.

Corresponding to **H1** are the following individual linear restrictions: (**H1A**) NP15 solar energy: $(\alpha_7+\alpha_9)=0$; (**H1B**) NP15 wind energy: $(\alpha_7+\alpha_{10})=0$; (**H1C**) SP15 solar energy: $(\beta_8+\beta_{11})=0$; and (**H1D**) SP15 wind energy: $(\beta_8+\beta_{12})=0$. Not rejecting these restrictions lends empirical support to our DAM regression specification.

2.7.2. DAM merit-order effects vs. RTM merit-order effects

Our second hypothesis is:

H2. : A 1-MWh increase in a region's renewable energy has the same merit-order effects on the region's DAM and RTM prices.

Corresponding to **H2** are the following set of regional restrictions: (1) NP15 region: $\alpha_9=\gamma_9$ for NP15 solar energy, and $\alpha_{10}=\gamma_{10}$

[26] The discussion that follows equally applies to the case of solar energy.

[27] Fig. 8 does not portray that a 1-MWh increase in NP15 forecast solar energy is associated with an expected 1-MWh increase in NP15 actual solar energy. However, Fig. 8 will likely resemble Fig. 9 in future years as the CAISO improves its NP15 solar energy forecast.

for NP15 wind energy; and (2) SP15 region: $\beta_{11}=\theta_{11}$ for SP15 solar energy, and $\beta_{12}=\theta_{12}$ for SP15 wind energy. Rejecting **H2** indicates renewable energy development's differential impacts on the regional DAM and RTM prices.

2.7.3. DAM–RTM price divergence

To identify a possible cause for the DAM–RTM divergence, we test the following hypothesis:

H3. : The CAISO's forecast errors do not affect the RTM prices.

Corresponding to **H3** are the following linear restrictions: (1) $\psi_7=\ldots=\psi_{12}=0$ for the NP15 RTM; and (2) $\zeta_7=\ldots=\zeta_{12}=0$ for the SP15 RTM. Rejecting **H3** suggests that the price divergence is partly due to the CAISO's forecast errors. The other causes for the price divergence are the differences in the fundamental drivers' effects on the DAM and RTM prices, as exemplified by a rejection of **H2**.

3. Results

Table 3 reports the ITSUR results for Eqs. (1)–(4). For easy inference, this table highlights in **bold** the coefficient estimates that are statistically significant. It reports in *italic* the coefficient estimates with unexpected signs. Thus, a coefficient estimate in ***bold italic*** indicates that it is expected to be positive (negative) but turns out to be significantly negative (positive). Happily, Table 3 does not contain coefficient estimates in ***bold italic***, which would have raised concerns regarding the price regressions' empirical reasonableness.

3.1. DAM price regressions

Table 3 indicates that the adjusted R^2 values are about 0.94 for the NP15 and SP15 DAM price regressions, indicating these regressions' nice fit with the DAM price data. The AR parameter estimates indicate that our AR(4) assumption is empirically appropriate. Each DAM price regression's sum of the four AR parameter estimates is less than 1.0. Thus, the two AR(4) processes are stationary, obviating concerns of spurious regression (Davidson and Mackinnon, 1993). Finally, the coefficient estimates for most of the fundamental drivers are significant. All significant coefficient estimates in **bold** have the expected signs. While there are five coefficient estimates in *italic* with unexpected signs for the hourly discharge variables, they are insignificant.

We now turn our attention to the fundamental drivers' coefficient estimates. The natural gas price's coefficient estimates indicate that a natural-gas price increase of $1/MMBTU raises the DAM prices by about $7.5/MWh. As these estimates measure the market-based marginal heat rates (Woo et al., 2014, 2015), they approximately match a new CCGT's heat rate of about 7 MMBTU/MWh (California Energy Commission, 2010).

The coefficient estimates for the nuclear MW available indicate that a 1000-MW decrease in nuclear capacity (about the size of one nuclear generation unit) may cause the DAM prices to rise by $2.1/MWh–$2.5/MWh.

The coefficient estimates for the California hydro index are -0.34 (p-value $<.0001$) for the NP15 DAM price and -0.94 (p-value $=0.0226$) for the SP15 DAM price, suggesting that the state's severe drought has raised the CAISO's DAM prices.

The coefficient estimates for the forecast system loads indicate that a 1000-MWh increase in PG&E's load may raise the NP15 DAM price by $4.6/MWh and the SP15 DAM price by $3.8/MWh. The same size increase in the SCE's load may raise the NP15 DAM price by $1.8/MWh and the SP15 DAM price by $3.4/MWh.

A 1000-MWh increase of solar energy in the NP15 region is estimated to reduce the NP15 DAM price by $5.3/MWh and the SP15 DAM price $3.2/MWh. The same size solar energy increase in the SP15 region is estimated to reduce NP15 DAM price by $1.9/MWh and the SP15 DAM price $4.0/MWh.

A 1000-MWh increase of wind energy in the NP15 region is estimated to reduce the NP15 DAM price by $3.3/MWh and the SP15 DAM price $1.4/MWh. The same size wind energy increase in the SP15 region is estimated to reduce NP15 DAM price by $1.5/MWh and the SP15 DAM price $3.4/MWh.

3.2. RTM price regressions

Table 3 indicates that the adjusted R^2 values are about 0.20 for the NP15 and SP15 RTM price regressions, reflecting that the RTM prices are much more volatile than the DAM prices. The AR parameter estimates indicate that our AR(4) assumption is empirically appropriate. Finally, all significant coefficient estimates for the fundamental drivers have the expected signs.

The natural gas price's coefficient estimates indicate that a gas price increase of $1/MMBTU raises the RTM prices by $8.2/MWh–$8.7/MWh, implying market-based marginal heat rates that approximately match a new a new CT's heat rate of about 9 MMBTU/MWh (California Energy Commission, 2010).

The coefficient estimates for the Diablo Canyon nuclear plant's available capacity are insignificant. A 1000-MW decrease in the Palo Verde nuclear plant's available capacity, however, can cause the RTM prices to rise by $2.0/MWh–$3.0/MWh.

There is only one hydro-related significant coefficient estimate of -3.55 (p-value $<.0001$) for the California hydro index, which suggests that the state's severe drought has raised the CAISO's NP15 RTM prices.

The coefficient estimates for the forecast loads indicate that a 1000-MWh increase in PG&E's load may raise the NP15 RTM price by $6.6/MWh and the SP15 RTM price by $1.4/MWh. The same size increase in SCE's load has no effect on the NP15 RTM price but raises the SP15 RTM price by $5.5/MWh.

A 1000-MWh increase of solar energy in the NP15 region is estimated to reduce the NP15 RTM price by $2.2/MWh and the SP15 RTM price $3.7/MWh. The same size solar energy increase in the SP15 region is estimated to reduce NP15 RTM price by $1.0/MWh and the SP15 RTM price $3.4/MWh.

A 1000-MWh increase of wind energy in the NP15 region is estimated to reduce the NP15 RTM price by $2.8/MWh and the SP15 RTM price $1.5/MWh. The same size wind energy increase in the SP15 region is estimated to reduce NP15 RTM price by $6.2/MWh and the SP15 RTM price $11.4/MWh.

Finally, the coefficient estimates for the forecast errors suggest that rising load forecast errors tend to increase the RTM prices because they raise the real-time net loads. In contrast, rising solar and wind energy forecast errors tend to reduce the RTM prices because unanticipated increases in renewable energy reduce the real-time net loads.

3.3. Hypothesis testing

Table 4 reports the p-values of the Wald statistics for testing the hypotheses developed in Section 2.7.3, leading to the following findings. First, **H1A**, **H1C** and **H1D** are not rejected but **H1B** is rejected. Taken together, these Wald test results largely support that the marginal DAM price effect of a 1-MWh increase in the forecast load increase is offset by that of a 1-MWh increase in the renewable energy forecast.

Second, **H2** is rejected, implying that the marginal DAM merit-order effects of a region's renewable energy differ from the RTM merit-order effects. Based on Table 3, the DAM and RTM merit

Table 4
P-values of the Wald statistics for testing the null hypotheses developed in Section 2.7.3

Hypothesis	Restrictions	*p*-value
H1A: A 1-MWh increase in the NP15 load forecast has the same effect on the NP15 DAM price as a 1-MWh decrease in the NP15 solar energy forecast.	$\alpha_7+\alpha_9 = 0$	0.1475
H1B: A 1-MWh increase in the NP15 load forecast has the same effect on the NP15 DAM price as a 1-MWh decrease in the NP15 wind energy forecast.	$\alpha_7+\alpha_{10} = 0$	0.0008
H1C: A 1-MWh increase in the SP15 load forecast has the same effect on the SP15 DAM price as a 1-MWh decrease in the SP15 solar energy forecast.	$\beta_8+\beta_{11} = 0$	0.8294
H1D: A 1-MWh increase in the SP15 load forecast has the same effect on the SP15 DAM price as a 1-MWh decrease in the SP15 wind energy forecast.	$\beta_8+\beta_{12} = 0$	0.1245
H2: A 1-MWh increase in a region's renewable energy has the same merit-order effects on the region's DAM and RTM prices.	$\alpha_9=\gamma_9$, $\alpha_{10}=\gamma_{10}$, $\beta_{11}=\theta_{11}$, $\beta_{12}=\theta_{12}$	< 0.0001
H3: The CAISO's forecast errors do not affect the RTM prices.	$\psi_7 = \ldots = \psi_{12} = \zeta_7 = \ldots = \zeta_{12} = 0$	< 0.0001

order effects are mostly comparable, except for the \$8/MWh difference between the SP15 DAM and RTM merit-order effects of the SP15 wind energy.[28]

Finally, **H3** is rejected, implying that the RTM prices move with the CAISO's forecast errors. Hence, the DAM–RTM price divergence is partly attributable to these errors.

4. Discussion

The regression results in Table 3 suggest that rising natural gas prices can substantially increase the state's electricity prices. While today's natural gas prices are low due to the abundance of shale gas, these prices may rise if the U.S. experiences a slowdown in shale gas production, an increase in natural gas consumption in concert with economic growth, or an increase in the nation's future export of natural gas to other nations. In short, California may not count on low gas prices to guard its consumers against possible escalation in future electricity prices.

The state's electricity prices may also rise if the state loses more nuclear generation, an event not beyond the realm of possibility in light of the San Onofre plant's premature retirement. While the ensuing adverse price impact can be offset by such actions as load reduction and renewable energy development, the final bill impact on electricity consumers depends on the actions' implementation costs (Woo et al., 2014). To the extent that the EE and DSM programs are cost-effective from the ratepayer perspective, their program cost recovery via a CPUC-adopted public goods charge is not expected to raise Californian ratepayers' electricity bills (Baskette, et al., 2006). Raising the state's 33% RPS by 2020 to the 50% RPS by 2030, however, is projected to raise ratepayers' electricity bills by 9 – 23%.[29]

The system loads' estimated price effects suggest that energy efficiency (EE) and demand side management (DSM) policies can effectively mitigate the price increases due to the state's economic recovery following the severe recession triggered by the 2008–2009 financial crisis.

Solar and wind energy's merit-order effects are found to exist in California's electricity markets. As pointed out by a helpful reviewer, the reduction in prices due to the state's renewable energy development may only be transitional. If natural-gas-fired generation plants continue to see depressed profits, market exit by some plants may raise the market prices in the longer-term equilibrium. However, this market price reversal is unlikely in the next 10 years for two reasons. First, renewable generation buildout is projected to continue growing through 2030 under the state's recently adopted RPS of 50% by 2030. Second, natural-gas-fired generation plants are increasingly needed to maintain system flexibility to accommodate the state's renewable energy integration. These plants are compensated in part through the ancillary services market and in part through resource adequacy contracts in California.

Finally, the DAM–RTM price differences are attributable to the CAISO's renewable energy forecast errors. Hence, an improvement in the CAISO's forecast performance may improve the state's DAM–RTM price convergence and electricity trading efficiency.

5. Conclusions and policy implications

Our regression results lead us to conclude that natural gas price escalation, nuclear plant retirement and economic growth tend to increase the CAISO's electricity prices. The ensuing electricity price increases, however, can be mitigated by the state's EE and DSM programs, as well as renewable energy development.

These conclusions lend support to California's energy policy stated in its 2013 Integrated Energy Policy Report: "The state's 'Loading Order' is a guiding policy which places energy efficiency (using less energy to do the same job) and demand response (modifying energy usage when needed for optimal grid operation) as top priorities for meeting California's energy needs. Next, the loading order calls for renewable resources and distributed generation. To produce the energy needed by a growing population and recovering economy, maximizing the use of these 'preferred resources' becomes even more important as California works toward reducing greenhouse gas emissions to 80 percent below 1990 levels by 2050." (California Energy Commission, 2014, p.1).

Finally, California is currently on track to increase its renewable energy to the state's adopted RPS target of 33% by 2020. Its RPS of 50% by 2030 requires more wind and solar energy development in the next 10 – 15 years. We plan to extend our sample in the future to update the estimates of renewable energy's merit-order effects, thereby informing the state's electricity policy formulation in the years to come.

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[28] A 1000-MWh increase in SP15 wind energy has a merit-order effect of \$3.4/MWh on the SP15 DAM price and \$11.4/MWh on the SP15 RTM price. Hence, the merit-order effects' difference is \$8/MWh (=11.4–3.4).

[29] https://ethree.com/documents/E3_Final_RPS_Report_2014_01_06_with_appendices.pdf.

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