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What Moves the *Ex Post* Variable Profit of Natural-Gas-Fired Generation in California?

Chi-Keung Woo,^a Ira Horowitz,^b Jay Zarnikau,^c Jack Moore,^d Brendan Schneiderman,^d Tony Ho,^e
and Eric Leung^e

ABSTRACT

We use a large California database of over 32,000 hourly observations in the 45-month period of April 2010 through December 2013 to document the *ex post* variable profit effects of multiple fundamental drivers on natural-gas-fired electricity generation. These drivers are the natural-gas price, system loads, nuclear capacities available, hydro conditions, and renewable generation. We find that profits are reduced by increases in generation from nuclear plants and wind farms, and are increased by increases in the natural-gas price and loads. Solar generation has a statistically insignificant effect, although this will likely change as solar energy increases its generation share in California's electricity market. Our findings support California's adopted resource adequacy program under which the state's load-serving entities may sign long-term bilateral contracts with generation developers to provide sufficient revenues to enable construction of new natural-gas-fired generation plants.

Keywords: Revenue adequacy, Profit effect, Natural-gas-fired generation, Resource adequacy

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1. INTRODUCTION

This paper is motivated by Professor Paul Joskow's insightful observation that: "Revenue adequacy has emerged as a problem in many organized wholesale electricity markets and has been of growing concern in liberalized electricity markets in the U.S. and Europe. The revenue adequacy or 'missing money' problem arises when the expected net revenues from sales of energy and ancillary services at market prices provide inadequate incentives for merchant investors in new generating capacity or equivalent demand-side resources to invest in sufficient new capacity to match administrative reliability criteria at the system and individual load serving entity levels" (Joskow, 2013, p. i).

^a Corresponding author. Department of Economics, Hong Kong Baptist University, Hong Kong. E-mail: chiwoo@hkbu.edu.hk. Phone: +852 3411 2177; fax: +852 3411 5580.

^b Warrington College of Business Administration, University of Florida, Gainesville, FL 32611, USA.

^c Frontier Associates LLC, 1515 S. Capital of Texas Highway, Suite 110, Austin, Texas 78746, USA; LBJ School of Public Affairs and Department of Statistics, University of Texas, Austin, TX 78713, USA.

^d Energy and Environmental Economics, Inc., 101 Montgomery Street, Suite 1600, San Francisco, CA 94104, USA.

^e Department of Economics, Hong Kong Baptist University, Hong Kong.

Joskow's observation applies to California and mirrors the concern of Peter Griffes, a senior manager of Pacific Gas and Electric Company (PG&E):¹ "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).

The "missing money" problem stems from two transformative events that took place in the electricity industry around the turn of the century. The first event comprises the electricity market reforms that have resulted in competitive wholesale markets in parts of Europe, North America, South America, Australia, and New Zealand (Sioshansi and Pfaffenberger, 2006; Woo et al., 2006a; Sioshansi, 2013). Wholesale electricity spot-market prices are inherently volatile due to: (a) daily fuel-cost variations, especially for the natural gas that is now widely used by combustion turbines (CT) and combined-cycle gas turbines (CCGT); (b) hourly weather-sensitive demands with intra-day and inter-day fluctuations, which must be met in real time by generation and transmission facilities 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; Tishler et al., 2008; Newcomer et al., 2008).²

These volatile spot-market prices, even with occasional spikes during hours of severe shortage, may not suffice to justify the generation investment necessary for reliable grid operation (Neuhoff and De Vries, 2004; Wangensteen et al., 2005; Roques et al., 2005; Newbery, 2010; Milstein and Tishler, 2012; Brattle Group, 2012; CAISO, 2014c). To remedy the "missing money" problem, capacity markets were introduced in the late 1990s in the U.S. deregulated markets of California, New York, PJM, and New England (Spees et al., 2013). A notable exception is Texas (Brattle Group, 2012), which continues to use an energy-only market design with a high price cap (e.g., US\$7,000/MWh in 2014) to provide generation investment incentives.

The second event contributing to the "missing money" problem is the development of wind and solar generation in many parts of the world due to resource abundance (e.g., 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., renewable portfolio standards (RPS)), cap-and-trade programs for carbon emissions certificates, and renewable-energy credits).³

1. PG&E is a large local distribution company (LDC) that serves Northern California. It had an annual peak demand of 20,916 MW in 2013. Southern California Edison (SCE) is the state's other large LDC and serves Southern California. Its annual peak demand in 2013 was 22,498 MW.

2. The price volatility with occasional spikes has led to extensive research on electricity price behavior (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; Janczura and Weron, 2010; Marckhoff and Wimschulte, 2009; 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., 2006b; Huisman et al., 2009; Camona and Ludkovski, 2008; Ryabchenko and Uryasev, 2011; Thompson, 2013).

3. 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).

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Wind generation 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), Denmark (Munksgaard and Morthorst, 2008; Jacobsen and Zvingilaite, 2010), Australia (Cutler et al., 2011), Texas (Woo et al., 2011b), PJM (Gil and Lin, 2013), the Pacific Northwest (Woo et al., 2013), and California (Woo et al., 2014a). While benefiting electricity consumers (e.g., Gil and Lin, 2013; Woo et al., 2011a, 2013, 2014a), the merit-order effect weakens the investment incentive for the CT and CCGT, as documented by the simulation study of Traber and Kemfert (2011), the regression analysis of Woo et al. (2012), and the descriptive assessment of Stegals et al. (2011).⁴

The goal of this paper is to answer the question: what moves the *ex post* variable profit of natural-gas-fired generation in California, the ninth largest economy in the world?⁵ Based on a regression analysis of a large sample of over 32,000 hourly observations over the 45-month period of April 2010 through December 2013, our answer disentangles the state's "missing money" problem, thereby highlighting the challenges in developing energy policies for a clean, reliable, and affordable electricity future (CEC, 2014). In particular, wind and solar generation development tends to reduce energy market prices in California. But it may also reduce investment incentives for the CT and CCGT, whose flexibility is essential for the California Independent System Operator (CAISO) to maintain the state's load-resource balance in real time (Griffes, 2014; CAISO, 2014a). Similarly, while expanding demand response (DR) programs can clip the state's peak demand,⁶ it may also cut the market price spikes that afford the most profitable opportunities for a CT or a CCGT plant.

Our regression-based analysis comprehensively examines the *ex post*, or realized, profit effects of a set of fundamental drivers on natural-gas-fired generation in California. These drivers include the natural-gas price, system loads, nuclear capacities available, hydro conditions,⁷ and renewable-generation resources of small hydro, solar, and wind.⁸ We are unaware of any study that has undertaken a similar examination to jointly assess the profit effects of all these drivers within a single empirical analysis.

Based on the background information in Section 2, we choose California for our analysis of the *ex post* variable profit, which is defined here as the non-negative per MWH payoff, $V = \max(\text{hourly price} - \text{per MWH variable generation cost}, 0)$, from an assumed 1-MW ownership of natural-gas-fired generation.⁹ For conciseness, we use the term "profit" to mean "*ex post* variable profit" throughout the rest of the paper.

4. Unlike the rich literature on electricity price behavior and dynamics and risk management (*supra* note 2), the literature on the empirical effect of renewable resources, including wind, on the conventional generation investment incentives is sparse.

5. http://www.lao.ca.gov/reports/2013/calfacts/calfacts_010213.aspx

6. For discussions of the DR programs and their benefits, see e.g., Figueiredo et al. (2005), Brattle Group (2007), FERC (2008), Su and Kirschen (2009), Woo and Greening (2010), and Woo et al. (2008, 2014b).

7. Following a referee's suggestion, we explicitly include hydro conditions in the profit analysis that is reported below.

8. We focus on these resources because (a) their random as-available output presents integration challenges to the CAISO's reliable grid operation, and (b) their output fluctuations move the state's market prices via the merit-order effect. Further, our exploratory analysis indicated that biogas, biomass, and geothermal resources have small positive but statistically insignificant ($p\text{-value} > 0.05$) price effects. As these positive price effects are unexpected and counter-intuitive, we exclude biogas, biomass, and geothermal generation from our analysis.

9. The 1-MW size assumption is reasonable because a CT's size is 50MW to 200 MW and a CCGT's size is 500 MW to 800 MW (CEC, 2010, p. 49, Table 11), which is dwarfed by the state's vast fleet of natural-gas-fired generation plants, totaling almost 50,000 MW as reported in http://energyalmanac.ca.gov/electricity/electric_generation_capacity.html. Adding

Consistent with what one would expect, we find that an increase in load within an electric region tends to increase profits from a gas turbine. Profits are reduced by increases in generation from baseload nuclear plants and wind farms. Our data analysis, however, reveals that changes in solar generation have a statistically insignificant effect on the profitability of natural-gas plants, although one may anticipate that this will change as solar energy increases its generation share in California's electricity market. Though raising a natural-gas power-plant's operating cost, an increase in natural-gas prices nonetheless enhances the plant's profits.

This paper makes the following contributions. First, the analysis is new and comprehensive, and extends the extant studies, which in the main focus on the profit effect on market prices of a single resource such as wind generation (Steggals et al., 2011; Traber and Kemfert, 2011; Woo et al., 2012) or nuclear generation (Traber and Kemfert, 2012).

Second, the paper reports the diminishing investment incentives for natural-gas-fired generation under California's adopted energy policy that promotes DR and renewable energy.¹⁰ It corroborates the positive price and profit effects of nuclear-generation-plant shutdowns in Germany, which were estimated by Traber and Kemfert (2012).

Third, its finding of diminishing investment incentives supports the state's adopted resource-adequacy program: "[e]ach LSE [load serving entity] is required to file with the [California Public Utilities] Commission demonstrating that they have procured sufficient capacity resources including reserves needed to serve its aggregate system load on a monthly basis. Each LSE's system requirement is 100 percent of its total forecast load plus a 15 percent reserve, for a total of 115 percent."¹¹

Finally, the paper enriches the extant literature by presenting an approach that can be used to analyze the profits from natural-gas-fired generation in other deregulated electricity markets that have data similar to those of California (e.g., Alberta and Ontario in Canada; Texas, PJM, New York and New England in the U.S; Germany and Spain in Europe; and Australia and New Zealand in the Asia Pacific region). For example, the same approach can be used to analyze how the retirement of baseload coal-power plants, aimed at reducing emissions of coal-fired generation (Venkatesh et al., 2012), affects the profit of natural-gas-fired generation.

The paper proceeds as follows: Section 2 provides the background for our analysis; Section 3 presents our methodology; Section 4 describes our data and documents their construction; Section 5 presents our results; and Section 6 provides general conclusions.

a CT or CCGT to the state's fleet is unlikely to alter the state's market prices or the unit's ability to sell its output at these prices. Hence, a generation unit's total profit per year is its per MW profit per year times its MW size.

10. "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." (CEC, 2014, p. 1).

11. <http://www.cpuc.ca.gov/PUC/energy/Procurement/RA/>

12. California's 2013 population was 38.3 million and its GDP was \$2,207 billion, both of which rank first in the U.S. (<http://www.bea.gov/regional/bearfacts/action.cfm>).

13. Except for the 15-minute stream-flow data from the U.S. Geological Survey (USGS) (<http://waterdata.usgs.gov/nwis/rt>) and the daily nuclear capacity availability data from the U.S. Nuclear Regulatory Commission (<http://www.nrc.gov>), all our data are from the CAISO (www.caiso.com).

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2. BACKGROUND

In addition to the state's size¹² and data availability,¹³ we choose California for our study because it has features that enable an estimation of the profit effects of a set of fundamental drivers. First, the CAISO uses a nodal market design with real-time markets (RTM) and day-ahead markets (DAM) that are intended to improve system operation and prevent a repeat of the 2000–2001 energy crisis.¹⁴ Based on locational marginal pricing (Bohn et al., 1984; Hogan, 1992), these RTM and DAM prices¹⁵ allow us to compute the per MWH profit of a natural-gas-fired generation plant in each of the state's two major electric regions of NP15 in Northern California and SP15 in Southern California.¹⁶

Second, California's generation mix is dominated by natural-gas-fired generation plants,¹⁷ implying that the state's marginal generation unit is likely fueled by natural gas, except for the non-peak hours during which the market prices can become negative.¹⁸ This allows us to analyze the dependence of the *realized* profit on the natural-gas price.¹⁹ The effect on profit of the natural-gas price is unclear *a priori*. While a decrease in the price of natural gas reduces the operating costs of a natural-gas-fired generation plant, it also reduces the wholesale market price of electricity and therefore the plant's operating revenues.

Third, the state's planned central generation stations are CT and CCGT (CEC, 2014, p.138). Those stations help replace the capacity of the San Onofre nuclear power plant, which was lost due to its January 31, 2012 shutdown and subsequent retirement caused by the premature wear on over 3,000 tubes in 15,000 places (CEC, 2014, Chapter 6). The San Onofre shutdown was estimated to have increased the state's wholesale market prices by \$6 to \$9/MWH (Woo 2014a). This suggests a positive profit effect that may also occur elsewhere because of the planned nuclear-generation shutdowns and construction moratorium in the aftermath of the March 11, 2011 Fukushima nuclear disaster (Baetz, 2011; Faris, 2011; Traber and Kemfert, 2012; Joskow and Parson, 2012; Wald, 2013).

Fourth, the state's hourly loads are weather-sensitive, with afternoon demand spikes that typically occur on hot summer weekdays (Miller et al., 2008). A load reduction due to the state's

14. For details of the crisis, see e.g., Woo (2001), Joskow and Khan (2002), Jurewitz (2002), Borenstein (2002), and Wolak (2003).

15. For a description of the CAISO's price-determination process, see <http://www.aiso.com/market/Pages/Market-Processes.aspx>; and <http://www.aiso.com/market/Pages/ProductsServices/Default.aspx>

16. A map of the CAISO's electric regions is available at: <http://oasis.aiso.com/mrioasis/logon.do;jsessionid=62154A776235A9D611AE51B0BDB82B2C>

17. Natural-gas-fired generation comprised 61% of the state's 2013 in-state installed capacity of 78,133 MW (http://energyalmanac.ca.gov/electricity/electric_generation_capacity.html). Of the 46,532 operational power plants in California that use natural gas as their primary fuel (CEC's database of California power plants, http://energyalmanac.ca.gov/power-plants/Power_plants.xls, accessed on March 6, 2015), there are approximately 20,392 MW from CCGT plants (including cogeneration combined cycle), representing approximately 43% of total gas-fired capacity, and 11,470 MW from CTs, approximately 25% of the total gas-fired fleet in California. The remaining gas fired fleet includes steam plants and internal combustion engines. Because of their lower heat rates, the CCGTs are more likely to be at the margin than the CTs.

18. During the low-demand hours of 02:00 and 05:00, California's market prices can become negative due to the minimum-load condition when the system load cannot fully absorb the non-dispatchable generation output from nuclear plants and wind farms. As a result, negative prices are used to induce dispatchable generation (e.g., CCGT) owners to curtail their outputs so as to maintain the state's real-time load-resource balance (CAISO, 2014a; Griffes, 2014).

19. Thanks to the shale-gas boom in the U.S., natural-gas prices began a steep decline in 2008 that bottomed out in 2012. Prices have subsequently risen due to the increased use of natural gas, which is relatively clean and inexpensive by comparison with the oil and coal used in fossil-fuel electricity generation (Venkatesh et al., 2012).

activation of its DR programs tends to reduce market prices during severe capacity shortages. The profit effect of the DR-load reduction, however, is not well documented.

Fifth, California has central hydro stations that mainly reside in the north,²⁰ the outputs of which decline as a result of a prolonged drought, such as the current on-going drought that is not expected to end anytime soon.²¹ While improved hydro conditions tend to reduce market prices (e.g., Woo et al., 2007, 2013), little is known about their profit effect.

Finally, California's legislated RPS requires renewable generation to meet a preset share of the state's electricity consumption by a targeted year.²² Having adopted a 33% RPS by 2020, the state is now investigating the challenges in achieving a 40% or 50% RPS by 2030.²³ The state's rich data on renewable generation help determine the profit effect of the state's renewable energy development.

3. METHODOLOGY

3.1 Profit Formula

We first define the hourly ex post variable profit, whose formula is necessary for our data construction and profit-effect estimation. For expositional ease, where there is minimal risk of confusing the reader, we suppress subscripts whose eventual inclusion in the formal regression model delineates our observations with respect to region (j), hour-of-the-day (h), day-of-the-week (d), month-of-the-year (m), and day-in-the-sample (t). Based on CEC (2010), the daily per MWH variable cost of a natural-gas-fired generation plant is:

$$C = H(G + T) + OM, \quad (1)$$

where H = heat rate (MMBTU/MWH) = rate of converting natural gas into electricity, G = daily natural-gas price (\$/MMBTU), T = transportation cost for natural gas (\$/MMBTU), and OM = variable O&M cost of generation (\$/MWH).²⁴

20. The stations constituted 15.7% of the state's 2013 in-state installed capacity of 78,133 MW (http://energyalmanac.ca.gov/electricity/electric_generation_capacity.html).

21. "With California facing one of the most severe droughts on record, Governor Brown declared a drought State of Emergency in January [2015] and directed state officials to take all necessary actions to prepare for water shortages. The state has continued to lead the way to make sure California is able to cope with an unprecedented drought." (<http://ca.gov/drought/>).

22. Renewable generation made up 18.8% of the state's 2013 in-state installed generation capacity of 78,133 MW, comprising biomass generation of 1,128 MW, geothermal generation of 2,703 MW, small-hydro generation of 1,609 MW, solar generation of 3,072 MW, and wind generation of 6,205 (http://energyalmanac.ca.gov/electricity/electric_generation_capacity.html).

23. See Energy & Environmental Economics (2014), a report jointly sponsored by California's five largest electric utilities to analyze the operational impact of a 40% or 50% RPS by 2030, as well as the analysis by the CAISO using a 40% RPS level for a 2024 planning case (http://www.caiso.com/Documents/Presentation_2014LTPPSystemFlexibilityStudy_SHcall.pdf).

24. While CEC (2010, p. 14, Table 14) reports the per kW-year fixed O&M costs, we do not include them in our per-MWH variable profit calculation. For a new CT (or CCGT) to be financially viable, its total variable profit per year (= average per-MWH variable profit * annual MWH output) needs to cover the per kW-year fixed O&M costs, depreciation, and return on investment.

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Suppose the hourly market price is P (\$/MWH). The plant's hourly profit from 1-MW of generation ownership is:

$$V = \max(P - C, 0), \quad (2)$$

which is also the hourly payoff of an hourly call option with a daily-varying strike price equal to C .²⁵ As will be shown below, up to 90% of the state's hourly V values are zero. While a Tobit-type model (Maddala, 1983) can reveal how V varies with its drivers (Woo et al., 2012), the profit effects of the drivers are not easily inferred.²⁶

There is an alternative calculation of V whose implications for the profit effects of the drivers from a standard linear-regression analysis are more transparent. Specifically, we define the hourly per MWH procurement cost of a local distribution company (LDC) owning natural-gas-fired generation to be:

$$Y = \min(P, C). \quad (3)$$

The latter measures what the LDC pays for 1 MWH of electricity, since the LDC can buy from the market if $P < C$, and self-generate otherwise (Woo et al., 2006b).

We can now compute the hourly per MWH profit as:

$$V = P - Y. \quad (4)$$

We verify the validity of equation (4) by considering the following two cases:

- Case 1: $P > C$ and $V = \max(P - C, 0) = P - C$. As $Y = \min(P, C) = C$, we find $P - Y = P - C = V$.
- Case 2: $P \leq C$ and $V = \max(P - C, 0) = 0$. As $Y = \min(P, C) = P$, we find $P - Y = 0 = V$.

Unlike the V data series with many zeros, the P and Y data series have few zeros and can be analyzed using standard regression techniques (e.g., Woo et al., 2006b).

Based on equation (4), the profit effect of a driver X (which can be the natural-gas price, system load, nuclear capacity available, renewable generation, or hydro condition) is the arithmetic difference of two marginal effects:

$$\partial V / \partial X = \partial P / \partial X - \partial Y / \partial X. \quad (5)$$

Equation (5) enables us to readily infer $\partial V / \partial X$ after our estimation of the market price and per MWH procurement cost regressions. While the regression-based approach is not new (Woo et al., 2006b), our innovation lies in the use of the regressions' coefficient estimates to identify and quantify the *profit effects* of a set of fundamental drivers on natural-gas-fired generation.

25. The same payoff concept underlies the valuation of a tolling agreement, which is a useful instrument for risk management and project financing (Stern, 1998; Deng et al., 2001; Eydeland and Wolyniec, 2003; Deng and Oren, 2006; Deng and Xia, 2006; Ryabchenko and Uryasev, 2011; Thompson, 2013).

26. Computing the profit effect of a single driver (e.g., wind generation) based on a Tobit-type model entails a multi-step simulation process (e.g., Woo et al., 2012, pp. 216–217). When there are multiple drivers to consider, the computation of their profit effects becomes tedious and time-consuming, unlike the relatively simple approach proposed below.

3.2 Linear Regression Model

Our profit-effect estimates are derived from the parameter estimates for a system of seemingly unrelated regressions (SUR). Based on Woo et al. (2006b, 2014a), we empirically identify six linear regressions for California's two electric regions:

$$P_{jht} = \alpha_{jhdmt} + \alpha_{jG} G_{jt} + \alpha_{j1} X_{1ht} + \dots + \alpha_{j11} X_{11ht} + \varepsilon_{jht}; \quad (6.a)$$

$$Y_{jht} = \beta_{jhdmt} + \beta_{jG} G_{jt} + \beta_{j1} X_{1ht} + \dots + \beta_{j11} X_{11ht} + \mu_{jht}; \quad (6.b)$$

$$Z_{jht} = \theta_{jhdmt} + \theta_{jG} G_{jt} + \theta_{j1} X_{1ht} + \dots + \theta_{j11} X_{11ht} + \eta_{jht}. \quad (6.c)$$

The left-hand-side (LHS) variables are the hourly RTM price (P_{jht}), the per MWH procurement costs based on the 1-MW ownership of a CCGT (Y_{jht}), and the per MWH procurement costs based on the 1-MW ownership of a CT (Z_{jht}), for region $j = 1, 2$, during hour $h = 1, \dots, 24$, on sample day $t = 04/20/2010, \dots, 12/31/2013$. Section 4 below details the construction of these LHS variables.

The time-dependent intercepts are α_{jhdmt} , β_{jhdmt} , and θ_{jhdmt} , which represent linear functions of binary indicators to control for the effects of hour-of-the-day, day-of-the-week, and month-of-year. Specifically, let: I_{ht} denote the indicator that is equal to unity during hour h , and is zero otherwise; I_{dt} denote the indicator that is equal to unity when day t falls on $d = 1$ (Monday), $\dots, 7$ (Sunday), and is zero otherwise; and I_{mt} denote the indicator that is equal to unity when day t occurs during $m = 1$ (January), $\dots, 12$ (December), and is zero otherwise. Then, $\alpha_{jhdmt} = \alpha_j + \sum_t \delta_h I_{ht} + \sum_d \delta_d I_{dt} + \sum_m \delta_m I_{mt}$, where the respective sums are over $h = 1, \dots, 23$, $d = 1, \dots, 6$, and $m = 1, \dots, 11$. Hence, the δ 's are the coefficients to be estimated in the regression process and α_j is the regression's constant intercept. The other time-dependent intercepts are similarly determined.²⁷

The right-hand-side (RHS) variables are the profit drivers, including the daily natural-gas price G_{jt} which is region-specific and the metric variables (X_{1ht}, \dots, X_{11ht}) that measure hourly system loads, daily nuclear capacities available, hourly hydro conditions measured by three Northern Californian rivers' stream flows, and hourly renewable generation outputs. Section 4 below describes these RHS variables in greater detail.

The slope coefficients of the RHS variables measure the drivers' marginal effects on the hourly RTM price and the per MWH procurement costs. We hypothesize that: (a) the coefficients for the daily natural-gas price and hourly loads are positive, since an increase in each of these drivers should tend to raise both the hourly RTM price and the per MWH procurement costs; and (b) the coefficients for the daily nuclear capacities available, hourly stream flows, and hourly renewable generation are negative, since an increase in each of these drivers should tend to reduce the hourly RTM price and the per MWH procurement costs.

The random-error terms are ε_{jht} , μ_{jht} and η_{jht} , which may well be contemporaneously and serially correlated. To allow for this contingency, we employ the iterated seemingly unrelated regression (ITSUR) method in PROC MODEL of SAS (2004) to jointly estimate the six regressions for the two electric regions, yielding the results reported in Section 5.

The underlying arguments in support of our chosen specification are as follows:

27. Our initial data exploration decisively rejects (p -value < 0.0001) the assumption of constant intercepts, a finding also reported in Woo et al. (2011b, 2014a).

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- Linear functional form. Equation (4) states that the hourly profit is the arithmetic difference between the hourly market price and the procurement cost, which lends support to our preference for the linear form over, say, a logarithmic functional form. Still further, using a *double-log* form would have excluded about 4% of the sample, because of the negative market prices.
- Transparent and readily interpreted coefficient estimates. The chosen specification helps achieve our primary goal of estimating the effect upon profits of a given driver. Consider, for example, the estimates for the natural-gas-price coefficients of $(\alpha_{jG}, \beta_{jG}, \theta_{jG})$, denoted here by a_{jG} , b_{jG} and q_{jG} . Equation (5) implies that the profit effect of the natural-gas price is the arithmetic difference of the coefficient estimates: $(a_{jG} - b_{jG})$ for a CCGT and $(a_{jG} - q_{jG})$ for a CT. Based on Mood et al. (1974, p. 179), we can readily find each profit-effect estimate's variance (e.g., $\text{var}(a_{jG} - b_{jG}) = \text{var}(a_{jG}) - 2\text{cov}(a_{jG}, b_{jG}) + \text{var}(b_{jG})$), which enables us to subject that effect to a *t*-test of the null hypothesis that there is a zero profit effect.
- Large number of slope coefficients. The hourly price data are noisy, making precise detection of profit effects difficult. Even with the parsimonious specification given by equations (6.a)–(6.c), we already have $6 * 12 = 72$ slope coefficients to estimate and interpret for the fundamental drivers, to say nothing of the $6 * (23 + 6 + 11) = 240$ coefficients attached to the six time-dependent intercepts. Adding more RHS variables would not seem to improve the insights gleaned from our profit-effect estimation. In particular, before settling on our final specification, we did indeed include in our estimations various interaction terms that allowed the slope coefficients to vary by trading period.²⁸ The majority of the expanded regressions' coefficient estimates are statistically insignificant (p -value > 0.05), an indication of over-specification that produces imprecise estimates. To account for possible nonlinearities, we also re-estimated the system of equations including both squared and interaction terms formed by the drivers to account for possible nonlinearities. Once again the result was that a majority of the coefficient estimates were statistically insignificant (p -value > 0.05).
- Serial correlation. Our data decisively reject (p -value < 0.0001) the null hypothesis of no serial correlation. As a result, we initially assumed that our random-error terms followed an AR(5) process, which led us to ultimately conclude that an AR(4) process is the empirically appropriate specification that yields the statistically significant (p -value < 0.05) parameter estimates shown in Section 5 below.
- Empirical plausibility of the results. As discussed below, our regression results are empirically plausible. That is, most of the slope-coefficient estimates have the hypothesized sign and are of plausible size.

4. DATA

4.1 Data Construction

This subsection details the construction of our data sample. To construct the per MWH variable cost C as defined in equation (1), we make the following assumptions:

28. To form these interaction terms, we first define a binary indicator D_{ht} for the standard period definition used in bilateral trading: (a) the on-peak period of 06:00–22:00, Monday–Saturday; and (b) the off-peak period of the remaining hours (Woo et al., 2013). This indicator equals unity if hour h on day t is in the on-peak period, and is zero otherwise. Each interaction term is the product of D_{ht} and a profit driver. Including these interaction terms doubles the number of slope coefficients to be estimated.

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- Heat rate (MMBTU/MWH). The heat rate is $H = 7$ for a CCGT and $H = 9$ for a CT (CEC, 2010, p.49, Table 11).²⁹
- Daily natural-gas price (\$/MMBTU). The natural-gas price is $G_{1t} =$ CAISO's daily PGE2 gas index for Northern California and $G_{2t} =$ CAISO's daily SCE1 gas index for Southern California (CAISO, 2013).³⁰
- Natural-gas transportation cost (\$/MMBTU). The transportation cost is $T = \$0.5$ (CAISO, 2014b).³¹
- Variable O&M cost (\$/MWH). This variable cost is $OM = 5$ (CEC, 2010, p. 54, Table 14).³²

We make several additional assumptions for our data construction:

- Sample period. Our sample period is the 45-month period of 04/20/2010 to 12/31/2013, which results in 32,448 hourly observations. The starting date reflects when the CAISO first reported hourly renewable generation. The ending date reflects the end of the calendar year of 2013.
- Hourly market prices (\$/MWH). These prices are RTM and DAM hourly prices that are available from the CAISO.³³ These prices, along with the variable costs per MWH, allow us to use equation (3) to compute the procurement costs per MWH for electric region $j = 1$ for NP15 and $j = 2$ for SP15. The resultant per MWH procurement costs for region j are: $Y_{jht} = \min[P_{jht}, 7 * (G_{jt} + T) + OM]$ for the CCGT and $Z_{jht} = \min[P_{jht}, 9 * (G_{jt} + T) + OM]$ for the CT.
- Hourly system loads (MW). These are the hourly loads published by the CAISO for the state's two large LDCs: PG&E in Northern California and Southern California Edison (SCE) in Southern California.
- Daily nuclear capacities available (MW). A nuclear plant's daily capacity available is its installed capacity multiplied by the plant's daily availability factor. PG&E's Diablo Canyon plant's installed capacity is 2,160 MW and that of SCE's San Onofre plant was 2,150 MW.³⁴ The Palo Verde plant in Arizona has an installed capacity of 3,739 MW and is partially owned by SCE (15.8%), the Southern California Public Power Authority (10.2%), and the Los Angeles Department of Water and Power (5.7%).³⁵ The daily availability factors for the three plants come from the U.S. Nuclear Regulatory Commission.³⁶

29. We verified that minor variations in H do not materially alter our statistical results.

30. These natural-gas prices are used by the CAISO (CAISO, 2013, 2014b). Hence, they can better represent California's marginal fuel costs that drive the CAISO's DAM and RTM prices than the state's wholesale natural-gas prices at hubs like PG&E Citygate and SoCal Citygate. A map of the major Western natural-gas hubs is available from the U.S. Federal Energy Regulatory Commission at <https://www.ferc.gov/market-oversight/mkt-gas/western.asp>

31. We verified that minor variations in T do not materially alter our statistical results.

32. CEC (2010, pp. 54–56, Tables 14–16) reports three variable cost ranges: (1) average case: \$2.69 to \$4.17/MWH; (2) high case: \$3.42 to \$9.05/MWH; and (3) low case: \$0.79–\$2.19/MWH. Hence, we assume a \$5/MWH variable cost which is approximately the mid-point for the combined range of \$0.79–\$9.05/MWH.

33. We use the 12 5-minute intra-hour RTM prices to compute the average RTM price for each hour. We choose not to use the 5-minute RTM price data in our analysis for the following reasons. First, equation (2) assumes an hourly dispatch, rather than a 5-minute dispatch. Second, except for the daily natural-gas price and nuclear capacity data, all the metric variables are measured through hourly data. Finally, 0.99 is the correlation between (a) the hourly payoffs based on the hourly RTM prices, and (b) the hourly averages of the 5-minute payoffs based on the 5-minute RTM prices. This almost perfect correlation holds for both NP15 and SP15, thus obviating any concern that our use of hourly RTM price data may yield results notably different from those based on the 5-minute RTM price data.

34. <http://www.energy.ca.gov/nuclear/california.html>.

35. <http://www.srpnet.com/about/stations/paloverde.aspx>

36. <http://www.nrc.gov/reading-rm/doc-collections/event-status/reactor-status/index.html>

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- Hourly hydro conditions (000ft³/second). The hydro conditions are proxied by the U.S. Geological Survey's hourly average of the 15-minute stream flows for the three major rivers in Northern California: the Klamath near the California-Oregon border, and the American and Sacramento in the Central Valley.³⁷ Figure 1 portrays the daily averages of the 15-minute stream flows of these rivers, which reflect the worsening drought in California. The Klamath's flows are moderately correlated ($r < 0.65$) with those of the American and Sacramento rivers. The flows of the American and Sacramento, however, are highly correlated ($r = 0.81$).
- Hourly renewable generation (MW). The three generation sources are small hydro, solar, and wind generation, the data for which are published by the CAISO.³⁸

4.2 DAM or RTM Prices?

We now consider which of the two price series—the DAM or the RTM—would be more appropriate to use for our profit analysis.³⁹ At first blush, the DAM prices seem preferable, since over 95% of the MWH traded in the CAISO's markets are settled at the DAM prices.⁴⁰ Nonetheless, we decided to use the RTM prices, thereby circumventing the difficulty noted by Woo et al. (2013) of obtaining day-ahead forecast data to properly match with the DAM price data.⁴¹

Our decision is also supported by the following observations. First, Figures 2 and 3 show that on average a \$1/MWH movement in the DAM prices is matched by a \$1/MWH movement in the RTM prices.

Second, the owner of a CT (or CCGT) can always choose to transact in the RTM or DAM, even though the RTM has a smaller trading volume than the DAM. The hourly DAM-based profits are likely to be less than the hourly RTM-based profits because (a) these profits are the payoff of a call option, and (b) the hourly DAM prices are less volatile than the hourly RTM prices. Using the cost and price data described in the last subsection, Table 1 confirms that for the entire sample

37. We do not to use the CAISO's hydro generation to measure the state's hourly hydro conditions because the hourly hydro generation may be endogenous due to its response to the system loads and market prices. The stream-flow data for the three rivers come from:

- http://waterdata.usgs.gov/ca/nwis/uv/?site_no=11530500&PARAMeter_cd=00065,00060 for the Klamath River;
- http://waterdata.usgs.gov/ca/nwis/uv/?site_no=11446500&PARAMeter_cd=00065,00060 for the American River; and
- http://waterdata.usgs.gov/ca/nwis/uv/?site_no=11447650&PARAMeter_cd=00065,00060 for the Sacramento River.

A complete list of California's stream-flow data at 492 sites is available at: <http://waterdata.usgs.gov/ca/nwis/current/?type=flow>

38. We do not include biogas, biomass, and geothermal for reasons given in *supra* note 8.

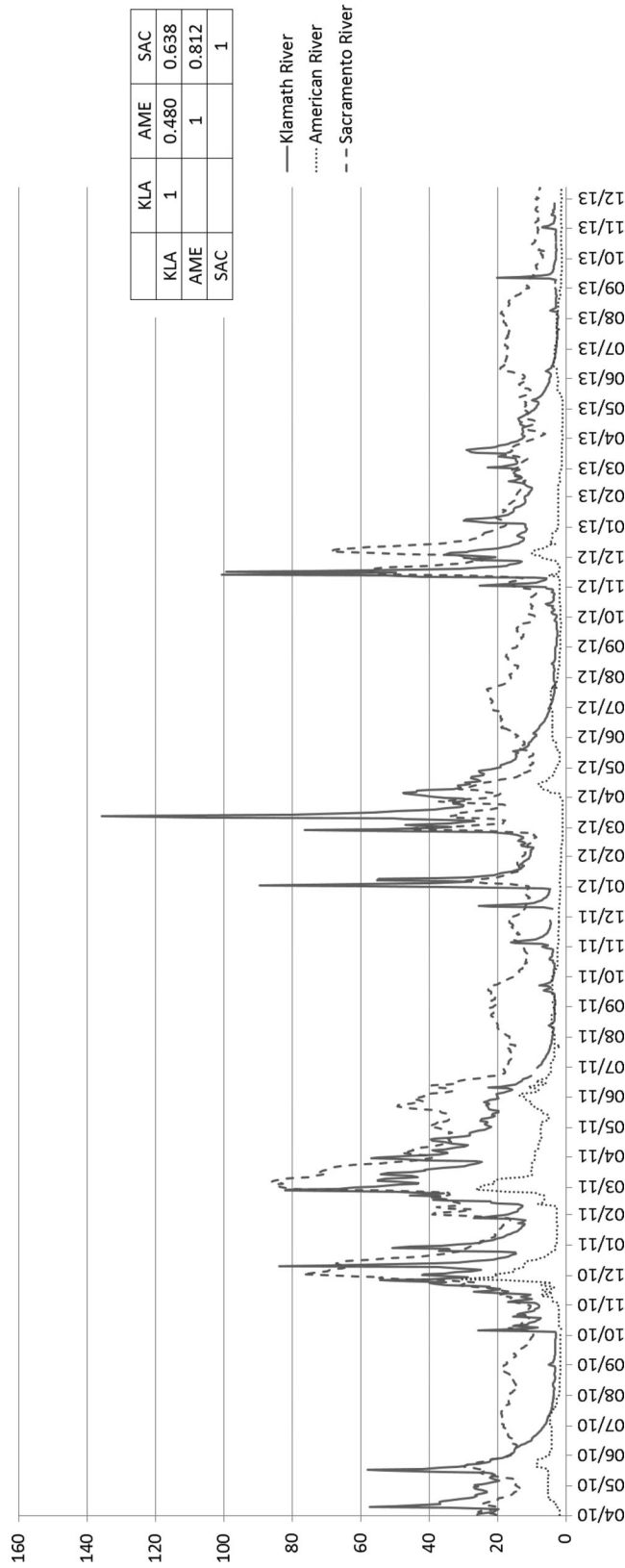
39. We thank a referee for suggesting the analysis in this subsection.

40. See CAISO (2014c, pp.66–68).

41. Assuredly, one can use the ARIMA method (e.g., PROC FORECAST in SAS (2004)) to make reasonable day-ahead forecasts for such drivers as the natural-gas price, nuclear capacities available, and stream flows. The quality and reliability of such forecasts, however, may invite questions as to the empirical validity of our analysis of *ex post* profits (e.g., “Are the forecasts constructed by the authors reflective of those used by market participants?” “Are the authors’ forecasts sensitive to the choice of forecasting technique?”). While the CAISO publishes day-ahead load forecasts (<http://oasis.caiso.com/mrioasis/logon.do?sessionid=8BE96B340BDE4D2C4772E65DB499B2CC>), it only publishes day-ahead forecasts for solar and wind generation since December 2012, through its OASIS site (<http://oasis.caiso.com/mrioasis/logon.do?sessionid=03863D12C2A297D0BB3CBB82798A69A7>). As a result, we do not have day-ahead forecast data for the highly unpredictable solar and wind generation for the entire sample period.

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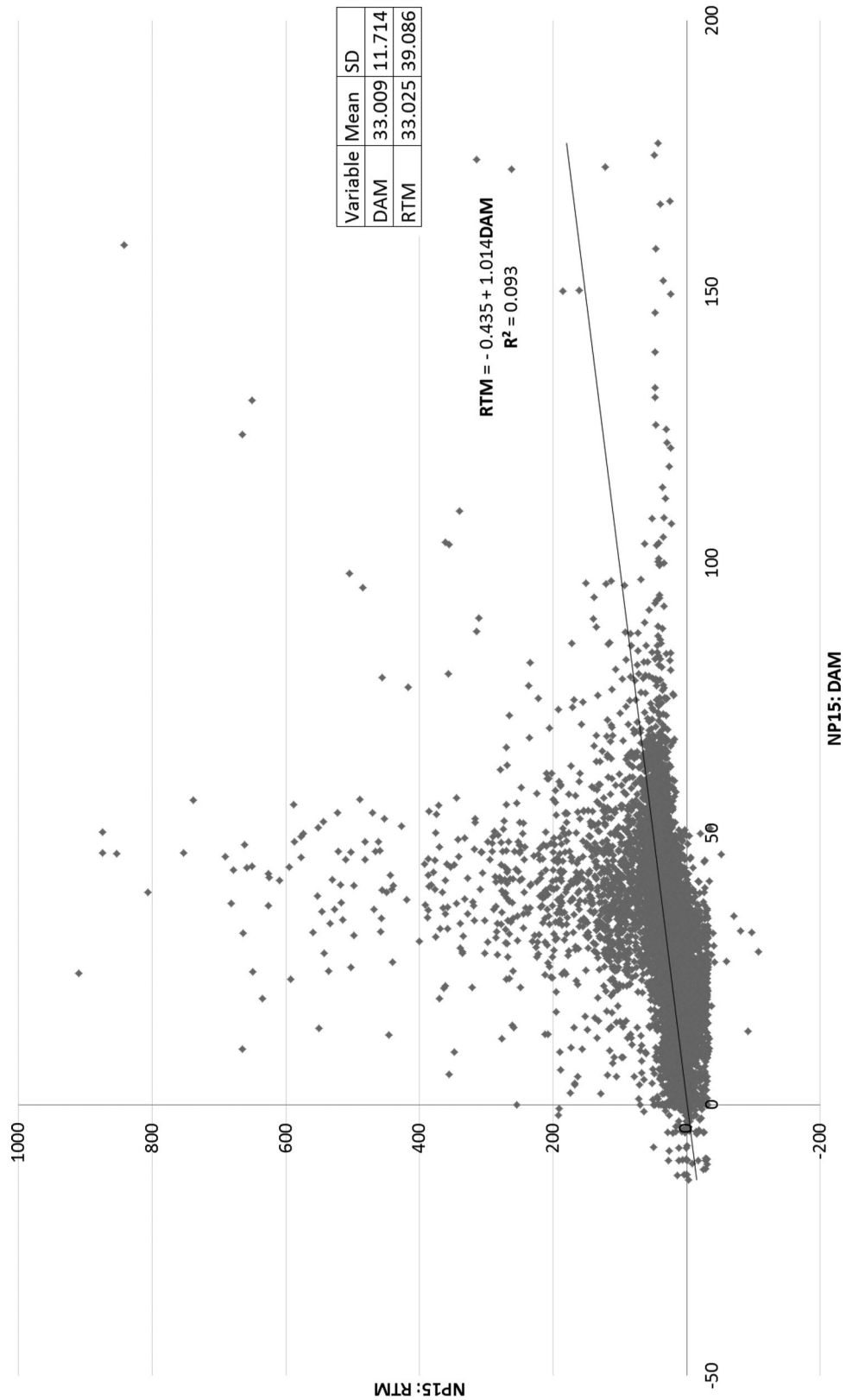
**Figure 1: Daily Stream Flows (000ft³ per second) for the Klamath River (KLA), American River (AME), and Sacramento River (SAC);
 Sample Period: 04/20/2010–01/31/2013**

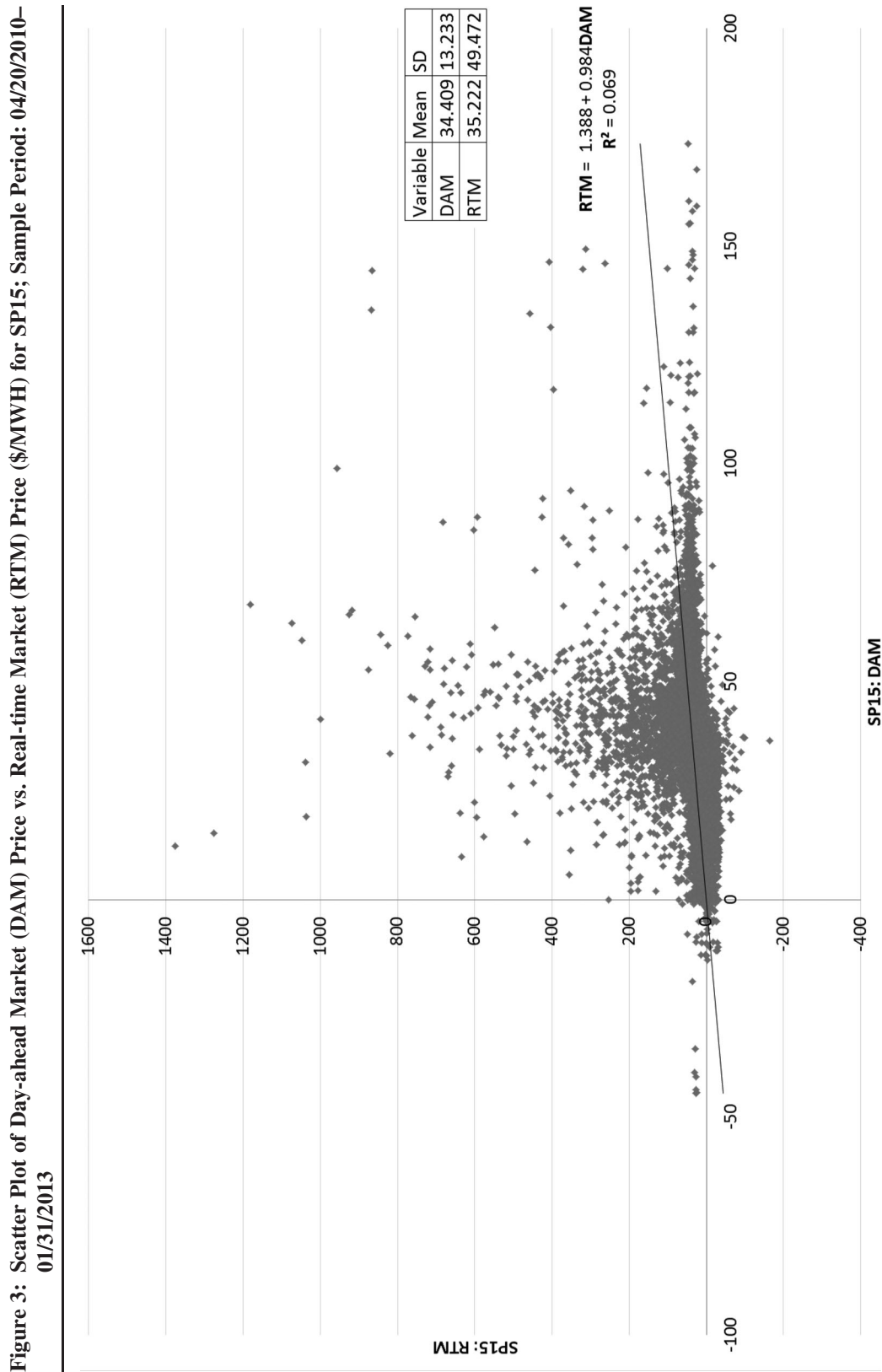


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Figure 2: Scatter Plot of Day-ahead Market (DAM) Price vs. Real-time Market (RTM) Price (\$/MWH) for NP15; Sample Period: 04/20/2010–01/31/2013





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Table 1: Descriptive Statistics for DAM- and RTM-based Profits (\$/MWH) for the Period of 04/20/2010 through 12/31/2013 under the Heat Rate Assumptions of $H = 7$ MMBTU/MWH for a CCGT and $H = 9$ MMBTU/MWH for a CT

Statistic	NP15				SP15			
	$H = 7$		$H = 9$		$H = 7$		$H = 9$	
	MMBTU/MWH		MMBTU/MWH		MMBTU/MWH		MMBTU/MWH	
	DAM	RTM	DAM	RTM	DAM	RTM	DAM	RTM
Mean	1.99	5.78	0.52	4.70	2.84	7.79	0.97	6.65
S.D.	5.77	35.57	4.10	34.35	7.24	46.05	5.08	44.72
Minimum	0	0	0	0	0	0	0	0
Maximum	142.41	882.52	134.69	876.08	134.03	1,347.61	125.16	1,340.63

period, the average DAM-based profits are \$0.52/MWH to \$2.84/MWH. These profits are substantially less than the average RTM-based profits of \$4.70/MWH to \$7.79/MWH.

4.3 Descriptive Statistics

Panel A of Table 2 reports the descriptive statistics for the RTM price and per MWH procurement-cost data used in our regression analysis. To address possible concerns about a spurious price regression due to non-stationary data (Granger and Newbold, 1974), we apply the Phillips-Perron unit-root test (Phillips and Perron, 1988) and determine that all data series in Panel A are stationary.

The hourly price data have means of \$33/MWH for NP15 and \$35/MWH for SP15. The data are volatile, as reflected in their respective standard deviations of \$39/MWH and \$49/MWH, minimum values of $-\$107/\text{MWH}$ and $-\$164/\text{MWH}$,⁴² and maximum values of \$910/MWH and \$1,377/MWH. Relative to the price data, the per MWH procurement-cost data have lower means, and much smaller standard deviations and maximum values, principally because generation ownership caps the per MWH procurement costs well below the market price spikes.

Panel B shows the comparable statistics for the profit drivers. The natural-gas-price data series are non-stationary and have means of \$4.17/MMBTU for NP15 and \$4.32/MMBTU for SP15. The remaining series, however, are stationary.

The PG&E and SCE hourly load data are volatile and have large standard deviations and maximum values. The statistics for the available nuclear capacities suggest that, during the sample period, each nuclear plant had high capacity availability, unless it was shut down, as in the case of the San Onofre plant. There are three hourly non-dispatchable renewable-generation series: small hydro, solar, and wind. Their statistics suggest that the three series are highly volatile. The average wind generation is about 3.0 times the size of the average small-hydro generation, and 3.6 times the size of the average solar generation.

Rows 2 to 7 of Table 3 report that the hourly prices are positively correlated ($r = 0.63$). The hourly prices and per MWH procurement costs are also positively correlated and at times strongly so ($r \geq 0.50$). Finally, the per MWH procurement costs are highly correlated ($r > 0.88$).

The last 12 rows of Table 3 report the coefficients of correlation of the hourly prices and per MWH procurement costs with their respective drivers. Even though these coefficients are quite

42. The share of negative prices is 4.28% for NP15 and 4.20% for SP15.

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Table 2: Descriptive Statistics, where $h = \text{hour index} = 1, \dots, 24$, $t = \text{day index} = 04/20/2010, \dots, 12/31/2013$ under the Heat Rate Assumptions of $H = 7$ MMBTU/MWH for a CCGT and $H = 9$ MMBTU/MWH for a CT

Panel A: Real-time Market Prices and per MWH Procurement Costs

Variable definition	Stationary at the 5% significance level?	Mean	S.D.	Minimum	Maximum
P_{1hr} : NP15 hourly real-time market price (\$/MWH)	Yes	33.02	39.09	-107.15	910.06
Y_{1hr} : NP15 hourly procurement cost at $H = 7$ MMBTU/ MWH = $\text{Min}[P_{1hr}, 7 * (G_{1t} + T) + OM]$	Yes	27.26	11.86	-107.15	55.96
Z_{1hr} : NP15 hourly procurement cost at $H = 9$ MMBTU/ MWH = $\text{Min}[P_{1hr}, 9 * (G_{1t} + T) + OM]$	Yes	28.34	13.17	-107.15	70.52
P_{2hr} : SP15 hourly real-time market price (\$/MWH)	Yes	35.22	49.47	-164.12	1,377.04
Y_{2hr} : SP15 hourly procurement cost at $H = 7$ MMBTU/ MWH = $\text{Min}[P_{1hr}, 7 * (G_{2t} + T) + OM]$	Yes	27.45	12.44	-164.12	66.53
Z_{2hr} : SP15 hourly procurement cost at $H = 9$ MMBTU/ MWH = $\text{Min}[P_{1hr}, 9 * (G_{2t} + T) + OM]$	Yes	28.59	13.82	-164.12	84.11

Note: Cost-data assumptions: (a) G_{1t} = CAISO's daily PGE2 price index (\$/MMBTU); (b) G_{2t} = CAISO's daily SCE1 natural-gas price index (\$/MMBTU); (c) T = natural-gas transportation cost = \$0.5/MMBTU; and (d) OM = natural-gas generation variable O&M cost = \$5/MWH.

Panel B: Profit Drivers

Variable definition	Stationary at the 5% significance level?	Mean	Standard deviation	Minimum	Maximum
G_{1t} : Daily PGE2 natural-gas price index (\$/MMBTU) for NP15	No	4.17	0.60	2.57	6.78
G_{2t} : Daily SCE1 natural-gas price index (\$/MMBTU) for SP15	No	4.32	0.62	2.73	8.29
X_{1hr} : Hourly PG&E load (MW)	Yes	12,193.05	1,921.94	8,569	21,180
X_{2hr} : Hourly SCE load (MW)	Yes	12,122.99	2,406.29	7,947	23,276
X_{3t} : Daily nuclear capacity available: Diablo Canyon (MW)	Yes	2,041.65	426.12	0	2,160
X_{4t} : Daily nuclear capacity available: San Onofre (MW)	Yes	2,023.41	509.83	0	2,150
X_{5t} : Daily nuclear capacity available: Palo Verde (MW)	Yes	3,393.73	564.76	1,249	3,739
X_{6hr} : Hourly stream flow (000ft ³ /sec): Klamath River	Yes	14.47	15.15	2.30	152.0
X_{7hr} : Hourly stream flow (000ft ³ /sec): American River	Yes	3.60	3.48	0.83	31.18
X_{8hr} : Hourly stream flow (000ft ³ /sec): Sacramento River	Yes	20.47	13.95	0	87.0
X_{9hr} : Hourly small hydro generation (MW)	Yes	350.99	105.69	56.0	646.0
X_{10hr} : Hourly solar generation (MW)	Yes	286.49	521.59	0	2,893
X_{11hr} : Hourly wind generation (MW)	Yes	1,049.77	853.95	-21.0	4,215

Note: The San Onofre plant's descriptive statistics are based on the observations before the plant's shutdown on January 31, 2012, as the plant's capacity available is zero after the shutdown. Negative wind generation occurs due to on-site plant use.

low ($|r| < 0.38$), they are broadly consistent with what one would expect: (a) the prices and per MWH procurement costs are positively correlated with the loads and natural-gas prices; and (b) they are negatively correlated with the nuclear capacities available, hydro conditions, and renewable generation. The notable exception is solar generation, which has small but positive correlation coefficients ($r < 0.17$).

Table 4 reports the share of sample observations with zero hourly profits, as well as the mean hourly profits over the 45-month sample period. The share of hours with zero profit is large,

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Table 3: Correlation Coefficients; the San Onofre Plant's Correlation Based on the Data before the Plant's Shutdown on January 31, 2012 under the Heat Rate Assumptions of $H = 7$ MMBTU/MWH for a CCGT and $H = 9$ MMBTU/MWH for a CT

Variable definition	P_{1hr}	Y_{1hr}	Z_{1hr}	P_{2hr}	Y_{2hr}	Z_{2hr}
P_{1hr} : NP15 hourly price (\$/MWH)	1	0.437	0.508	0.627	0.391	0.446
Y_{1hr} : NP15 hourly procurement cost (\$/MWH) at $H = 7$	0.437	1	0.981	0.322	0.896	0.873
Z_{1hr} : NP15 hourly procurement cost (\$/MWH) at $H = 9$	0.508	0.981	1	0.372	0.882	0.888
P_{2hr} : SP15 hourly price (\$/MWH)	0.627	0.322	0.372	1	0.394	0.469
Y_{2hr} : SP15 hourly procurement cost (\$/MWH) at $H = 7$	0.391	0.896	0.882	0.394	1	0.981
Z_{2hr} : NP15 hourly procurement cost (\$/MWH) at $H = 9$	0.446	0.873	0.888	0.469	0.981	1
G_{1r} : Daily PGE2 natural-gas price index (\$/MMBTU)	0.081	0.234	0.235	0.055	0.223	0.219
G_{2r} : Daily SCE1 natural-gas price index (\$/MMBTU)	0.073	0.220	0.223	0.053	0.221	0.217
X_{1hr} : Hourly PG&E load (MW)	0.218	0.325	0.351	0.189	0.346	0.366
X_{2hr} : Hourly SCE load (MW)	0.197	0.321	0.342	0.211	0.354	0.376
X_{3r} : Daily nuclear capacity available: Diablo Canyon (MW)	0.008	0.070	0.066	-0.003	0.057	0.049
X_{4r} : Daily nuclear capacity available: San Onofre (MW)	-0.078	-0.151	-0.141	-0.057	-0.128	-0.122
X_{5r} : Daily nuclear capacity available: Palo Verde (MW)	-0.026	-0.056	-0.058	-0.006	-0.033	-0.033
X_{6hr} : Hourly stream flow (000ft ³ /sec): Klamath River	-0.047	-0.214	-0.199	-0.037	-0.202	-0.185
X_{7hr} : Hourly stream flow (000ft ³ /sec): American River	-0.026	-0.159	-0.146	-0.023	-0.138	-0.125
X_{8hr} : Hourly stream flow (000ft ³ /sec): Sacramento River	-0.036	-0.173	-0.159	-0.023	-0.152	-0.137
X_{9hr} : Hourly small hydro generation (MW)	-0.013	-0.192	-0.171	0.009	-0.135	-0.113
X_{10hr} : Hourly solar generation (MW)	0.059	0.167	0.168	0.056	0.163	0.164
X_{11hr} : Hourly wind generation (MW)	-0.089	-0.184	-0.180	-0.089	-0.174	-0.174

up to 94% for a CT,⁴³ showing that natural-gas-fired generation is unprofitable for a majority of the year.⁴⁴ These data also highlight the necessity of using a Tobit-type model to directly analyze the *ex post* profit data in a regression analysis (Maddala, 1983), unless one circumvents the problem, as we do here. For the entire sample period, the NP15 mean profit is \$5.8/MWH for a CCGT and \$4.7/MWH for a CT, about \$2/MWH less than the corresponding SP15 mean profits.

5. RESULTS

5.1 Regression Results

Table 5 presents our hourly regression results that do not include the coefficient estimates related to the time-dependent intercepts. The following observations speak to the empirical plausibility of these results.

43. Woo et al. (2012) document similarly large shares for the ERCOT market.

44. There is a noticeable drop in the share of zero-profit hours for the CCGT's heat rate of $H = 7$ MMBTU/MWH between 2012 and 2013, which may be attributable to the state's worsening drought.

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Table 4: Sample Shares with Zero Profit and Mean Profits (\$/MWH) for the Period of 04/20/2010 through 12/31/2013 under the Heat Rate Assumptions of $H = 7$ MMBTU/MWH for a CCGT and $H = 9$ MMBTU/MWH for a CT

Panel A: NP15

Year	Heat rate $H = 7$ MMBTU/MWH			Heat rate $H = 9$ MMBTU/MWH		
	Sample share with zero hourly profit	Mean of positive hourly profits	Mean of all hourly profits	Sample share with zero hourly profit	Mean of positive hourly profits	Mean of all hourly profits
2010	80.13%	38.849	7.720	92.99%	94.134	6.600
2011	87.90%	44.685	5.407	94.35%	81.394	4.598
2012	87.35%	44.799	5.668	94.31%	88.403	5.030
2013	69.84%	16.187	4.883	91.08%	35.054	3.128
All years	81.41%	31.068	5.775	93.20%	69.098	4.699

Panel B: SP15

Year	Heat rate $H = 7$ MMBTU/MWH			Heat rate $H = 9$ MMBTU/MWH		
	Sample share with zero hourly profit	Mean of positive hourly profits	Mean of all hourly profits	Sample share with zero hourly profit	Mean of positive hourly profits	Mean of all hourly profits
2010	80.54%	49.752	9.684	91.75%	102.664	8.473
2011	88.42%	54.150	6.268	94.01%	90.496	5.419
2012	86.71%	63.653	8.460	92.34%	100.222	7.679
2013	70.39%	24.710	7.316	90.88%	61.101	5.570
All years	81.61%	42.358	7.791	92.29%	86.217	6.650

First, the adjusted R^2 is 0.20 for the NP15 price regression and 0.16 for that of SP15. These relatively modest values reflect the noisy and volatile hourly price data. By contrast, the hourly per MWH procurement-cost regressions have adjusted R^2 values above 0.56, chiefly because the per MWH procurement costs are far less volatile than the market prices.

Second, relying on the criterion of a p -value < 0.05 , which is used throughout the rest of the paper, the positive AR parameter estimates are statistically significant. Their regression-specific sum is less than 0.6, thus suggesting a stationary AR(4) error process. Hence, the regression residuals do not follow a random walk and the regression results in Table 5 are not subject to spurious interpretation (Davidson and MacKinnon, 1993, Chapter 19).

Third, most of the slope-coefficient estimates for the drivers are statistically significant and have the hypothesized sign. Specifically, 59 (82%) of the 72 slope-coefficient estimates are statistically significant. There are two insignificant load-related estimates: (1) Northern California's hourly PG&E load in the Southern California SP15 price regression; and (2) Southern California's hourly SCE load in the Northern California NP15 price regression. The statistical insignificance of these estimates is understandable, because of the locational difference between loads and prices and the occasional transmission congestion on the Path 15 interface between Northern and Southern California. Out of the 18 estimates associated with the stream flows of the three rivers, 12 are insignificant. In response to a referee's comment, however, we retain the stream flows as RHS variables to explicitly account for the impact of hydro conditions.

Fourth, all of the estimated slope coefficients have the "right" sign, except for the three that are associated with the stream flow of the Klamath River and that of the American River. The Klamath River's stream flow has two statistically significant coefficient estimates in the price regressions. These two estimates are judged to have the "wrong" sign, because one would expect improved hydro conditions to induce lower market prices.

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Table 5: Hourly Regression Results with p -values in () for the Period of 04/20/2011 through 12/31/2013 under the Heat Rate Assumptions of $H = 7$ MMBTU/MWH for a CCGT and $H = 9$ MMBTU/MWH for a CT

Variable definition	NP15			SP15		
	Hourly price (\$/MWH)	Hourly procurement cost (\$/MWH) at $H = 7$	Hourly procurement cost (\$/MWH) at $H = 9$	Hourly price (\$/MWH)	Hourly procurement cost (\$/MWH) at $H = 7$	Hourly procurement cost (\$/MWH) at $H = 9$
Adjusted R^2	0.1999	0.5923	0.5938	0.1565	0.5631	0.5613
Root mean squared error	34.8644	7.5498	8.3669	45.0853	8.2071	9.1495
AR(1) parameter	0.2840 ($<.0001$)	0.4063 ($<.0001$)	0.3956 ($<.0001$)	0.2277 ($<.0001$)	0.3892 ($<.0001$)	0.3753 ($<.0001$)
AR(2) parameter	0.0880 ($<.0001$)	0.0628 ($<.0001$)	0.0712 ($<.0001$)	0.1085 ($<.0001$)	0.0615 ($<.0001$)	0.0724 ($<.0001$)
AR(3) parameter	0.0205 ($<.0001$)	0.0549 ($<.0001$)	0.0546 ($<.0001$)	0.0089 (0.0489)	0.0481 ($<.0001$)	0.0484 ($<.0001$)
AR(4) parameter	0.0138 (0.0016)	0.0203 ($<.0001$)	0.0229 ($<.0001$)	0.0296 ($<.0001$)	0.0212 ($<.0001$)	0.0240 ($<.0001$)
G_i : Daily electric region-specific natural-gas price (\$/MMBTU)	8.6469 ($<.0001$)	7.5861 ($<.0001$)	8.3414 ($<.0001$)	9.6302 ($<.0001$)	7.8269 ($<.0001$)	8.5377 ($<.0001$)
X_{1hr} : Hourly PG&E load (MW)	0.0087 ($<.0001$)	0.0025 ($<.0001$)	0.0032 ($<.0001$)	0.0011 (0.0840)	0.0017 ($<.0001$)	0.0020 ($<.0001$)
X_{2hr} : Hourly SCE load (MW)	0.0001 (0.8947)	0.0005 ($<.0001$)	0.0006 ($<.0001$)	0.0071 ($<.0001$)	0.0012 ($<.0001$)	0.0017 ($<.0001$)
X_{3i} : Daily nuclear capacity available: Diablo Canyon (MW)	-0.0020 (0.0266)	-0.0010 ($<.0001$)	-0.0011 ($<.0001$)	-0.0033 (0.0027)	-0.0016 ($<.0001$)	-0.0019 ($<.0001$)
X_{4i} : Daily nuclear capacity available: San Onofre (MW)	-0.0031 ($<.0001$)	-0.0024 ($<.0001$)	-0.0027 ($<.0001$)	-0.0048 ($<.0001$)	-0.0028 ($<.0001$)	-0.0032 ($<.0001$)
X_{5i} : Daily nuclear capacity available: Palo Verde (MW)	-0.0034 (0.0002)	-0.0006 (0.0140)	-0.0012 ($<.0001$)	-0.0023 (0.0427)	-0.0005 (0.0387)	-0.0009 (0.0019)
X_{6hr} : Hourly stream flow (000ft ³ /sec): Klamath River	0.0934 (0.0086)	-0.0056 (0.5706)	0.0001 (0.9909)	0.0987 (0.0246)	-0.0074 (0.4768)	-0.0016 (0.8899)
X_{7hr} : Hourly stream flow (000ft ³ /sec): American River	0.0581 (0.7330)	-0.0832 (0.0766)	-0.0986 (0.0578)	-0.1109 (0.5961)	-0.0443 (0.3632)	-0.0629 (0.2462)
X_{8hr} : Hourly stream flow (000ft ³ /sec): Sacramento River	-0.0686 (0.1392)	-0.0582 ($<.0001$)	-0.0551 ($<.0001$)	-0.0360 (0.5280)	-0.0594 ($<.0001$)	-0.0565 ($<.0001$)
X_{9hr} : Hourly small hydro generation (MW)	-0.0196 (0.0006)	-0.0232 ($<.0001$)	-0.0251 ($<.0001$)	-0.0244 (0.0006)	-0.0238 ($<.0001$)	-0.0253 ($<.0001$)
X_{10hr} : Hourly solar generation (MW)	-0.0020 (0.0214)	-0.0018 ($<.0001$)	-0.0020 ($<.0001$)	-0.0040 (0.0001)	-0.0021 ($<.0001$)	-0.0023 ($<.0001$)
X_{11hr} : Hourly wind generation (MW)	-0.0060 ($<.0001$)	-0.0032 ($<.0001$)	-0.0037 ($<.0001$)	-0.0084 ($<.0001$)	-0.0037 ($<.0001$)	-0.0043 ($<.0001$)

Note: For brevity, this table does not report the coefficient estimates for the intercept and the binary indicators that indicate statistically-significant (p -value ≤ 0.05) time-dependence of the hourly real-time market prices and procurement costs.

Finally, the sizes of the estimated slope coefficients pass the test of plausibility. In particular, the coefficient estimates for the natural-gas price in both price regressions indicate that the market-based marginal heat rate over the sample period is 8.65 MMBTU/MWH in Northern California and 9.63 per MMBTU/MWH in Southern California.⁴⁵ These market-based marginal heat rates are in line with our heat-rate assumptions of 7 MMBTU/MWH for the CCGT and 9 MMBTU/MWH for the CT.

The coefficient estimates for the other drivers in the price regressions, namely, hourly loads, daily nuclear capacities available, and hourly renewable generation, are very similar to those reported in Woo et al. (2014a) for the 33-month sample period of April 2010 through December 2012. The interpretation of these coefficient estimates as marginal effects is straightforward, and we omit it for the sake of conciseness.

Turning our attention to the coefficient estimates for the per MWH procurement-cost regressions, we find that (a) they generally have the same sign as those in the price regressions, and (b) they are generally smaller in size than those in the price regressions. These results again would be in line with our prior conjectures in light of the capping effect of generation ownership on the per MWH procurement costs.

5.2 Profit Effects

Based on equation (5), Table 6 reports the estimated profit effects of each of the 12 fundamental drivers. Each estimate measures the marginal change in profit due to a marginal increase in the associated driver. These profit-effect estimates lead to the following inferences.

First, the estimated profit effect of the natural-gas price suggests that a \$1/MMBTU increase tends to increase profit by as much as \$1.80/MWH for SP15 at the assumed heat rate of $H = 7$ MMBTU/MWH for a CCGT. Only that one estimate, however, is statistically significant, although under a more lax standard of statistical significance, say a p -value ≤ 0.10 , the estimate of \$1.06/MWH at $H = 7$ MMBTU/MWH for NP15 would also pass muster. All four estimates, however, have the hypothesized sign.

Second, a 1-MW increase in the PG&E (SCE) load has a small, positive and statistically significant effect on the NP15 (SP15) profit, but has no impact on the SP15 (NP15) profit.

Third, increasing nuclear generation tends to reduce profits, but its estimated effects are only significant for the San Onofre and Palo Verde plants in the SP15 and NP 15 regions, respectively.

Fourth, the profit effects of the river flows are mixed. The flow at the Klamath River has a positive and statistically significant profit effect, in both regions, which in the main is due to the unanticipated result shown in Table 5 of the river's stream flow having a positive effect on price.

Fifth, small-hydro and solar generation in Northern California have statistically insignificant profit-effect estimates. This is in accordance with the estimates in Table 5 that show that small-hydro and solar generation have comparable impacts on both price and procurement costs in the

45. The market-based heat-rate interpretation is based on a competitive electricity market in which the market price tracks the per MWH variable cost of the marginal generation unit. Suppose there is no capacity shortage so that the market price of P (\$/MWH) is equal to the unit's per MWH cost C in equation (1). The marginal effect of the natural-gas price G (\$/MMBTU) on P is $\partial P/\partial G = (\partial P/\partial C)(\partial C/\partial G)$. While $\partial P/\partial C = 1$, we need to find $\partial C/\partial G$. Let TVC denote the unit's total variable cost for producing Q MWH. Invoking Shephard's Lemma (Varian, 1992, p. 74), $\partial TVC/\partial G$ is the plant's total natural-gas consumption. As $\partial(TVC/Q)/\partial G = \partial C/\partial G$ is the per MWH fuel requirement, we find $\partial P/\partial G = \partial C/\partial G$ is the marginal market-based heat rate (MMBTU/MWH).

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Table 6: Profit-Effect Estimates with p -values in () under the Heat Rate Assumptions of $H = 7$ MMBTU/MWH for a CCGT and $H = 9$ MMBTU/MWH for a CT

Variable definition	NP15		SP15	
	$H = 7$	$H = 9$	$H = 7$	$H = 9$
G_t : Daily electric-region-specific natural-gas price (\$/MMBTU)	1.0608 (0.0999)	0.3055 (0.6244)	1.8033 (0.0214)	1.0924 (0.1516)
X_{1hr} : Hourly PG&E load (MW)	0.0062 ($<.0001$)	0.0055 ($<.0001$)	-0.0006 (0.3522)	-0.0008 (0.1728)
X_{2hr} : Hourly SCE load (MW)	-0.0005 (0.2323)	-0.0005 (0.1581)	0.0059 ($<.0001$)	0.0054 ($<.0001$)
X_{3r} : Daily nuclear capacity available: Diablo Canyon (MW)	-0.0010 (0.2266)	-0.0009 (0.2743)	-0.0017 (0.1128)	-0.0014 (0.1640)
X_{4r} : Daily nuclear capacity available: San Onofre (MW)	-0.0007 (0.0828)	-0.0004 (0.3020)	-0.0020 ($<.0001$)	-0.0016 (0.0015)
X_{5r} : Daily nuclear capacity available: Palo Verde (MW)	-0.0028 (0.0011)	-0.0022 (0.0074)	-0.0017 (0.1074)	-0.0014 (0.1931)
X_{6hr} : Hourly stream flow (000ft ³ /sec): Klamath River	0.0990 (0.0033)	0.0933 (0.0042)	0.1060 (0.0117)	0.1003 (0.014)
X_{7hr} : Hourly stream flow (000ft ³ /sec): American River	0.1413 (0.3820)	0.1567 (0.3158)	-0.0666 (0.7399)	-0.0480 (0.8055)
X_{8hr} : Hourly stream flow (000ft ³ /sec): Sacramento River	-0.0104 (0.8141)	-0.0134 (0.7524)	0.0234 (0.6682)	0.0206 (0.6983)
X_{9hr} : Hourly small hydro generation (MW)	0.0036 (0.5129)	0.0055 (0.2969)	-0.0006 (0.9286)	0.0009 (0.8977)
X_{10hr} : Hourly solar generation (MW)	-0.0002 (0.8525)	0.0000 (0.9898)	-0.0019 (0.0527)	-0.0017 (0.0777)
X_{11hr} : Hourly wind generation (MW)	-0.0028 ($<.0001$)	-0.0023 ($<.0001$)	-0.0047 ($<.0001$)	-0.0041 ($<.0001$)

north. In Southern California, however, where solar generation plays a greater role, the negative profit of solar generation is more pronounced and close to being statistically significant (p -value = 0.053) at the assumed heat rate of $H = 7$ MMBTU/MWH for a CCGT. The magnitude of this effect, however, is less than half that of wind.

Finally, wind generation has negative and statistically significant profit effects, which is consistent with the main finding in the extant literature on the merit-order effect of wind generation, and its ensuing impact on generation investment incentives.

5.3 Profit Changes

As an illustrative application of our profit-effect estimates, we estimate the profit changes resulting from each of a series of hypothetical events. These profit-change estimates aid our understanding of how each event may impact the incentives to invest in natural-gas-fired generation. One should bear in mind, however, that rather than being predictive, the estimated changes are only indicative of what might occur in the future, because the hypothetical events will not necessarily materialize in that future, and our parameter estimates may not be sufficiently robust over more extended sample periods to shore up our confidence in any predictions about that future.⁴⁶

46. For example, California is expanding its solar-energy development under the state's solar-energy initiative (<http://www.gosolarcalifornia.ca.gov/csi/index.php>). This may introduce a structural change that our regressions cannot capture. Nonetheless, an outright rejection of the results of our regression analysis by reason of a possible structural change is unproductive, because the same reason can rule out *any* regression analysis of *ex post* prices and profits that are necessarily recorded from actual market data.

Table 7: Estimated Profit Changes (\$/MWH) by Hypothetical Event under the Heat Rate Assumptions of $H = 7$ MMBTU/MWH for a CCGT and $H = 9$ MMBTU/MWH for a CT; Each number in () = Estimated Profit Change \div Mean Profit in the “No change” Row; Statistically-Significant (p -value < 0.05) Estimated Profit Changes in Bold

Event description	NP15		SP15	
	$H = 7$	$H = 9$	$H = 7$	$H = 9$
No change to reflect the sample period's <i>ex post</i> conditions	5.775	4.699	7.791	6.650
+ \$1/MMBTU increase in the natural-gas price	1.0608 (0.1840)	0.3055 (0.0651)	1.8033 (0.2318)	1.0924 (0.1645)
– 1,000 MW due to PG&E's DR-load reduction for 60 hours per year (= 10 days per year for 6 hours of 12:00–18:00)	–0.0427 (–0.0074)	–0.0375 (–0.008)	0.0040 (0.0005)	0.0057 (0.0009)
– 1,000 MW due to SCE's DR-load reduction for 60 hours per year (= 10 days per year for 6 hours of 12:00–18:00)	0.0031 (0.0005)	0.0036 (0.0008)	–0.0405 (–0.0052)	–0.0372 (–0.0056)
– 1,075 MW due to the loss of 1/2 of the 2,150-MW Diablo Canyon plant's capacity	1.1073 (0.192)	0.9675 (0.2062)	1.8168 (0.2335)	1.548 (0.2331)
– 1,246 MW due to the loss of 1/3 of the 3,739-MW Palo Verde plant's capacity	3.5022 (0.6074)	2.7793 (0.5924)	2.1437 (0.2756)	1.6826 (0.2534)
+ 175.5 MW due to a 50% increase in the average small hydro generation of 351 MW	0.6248 (0.1084)	0.9635 (0.2054)	–0.1071 (–0.0138)	0.1492 (0.0225)
+ 146 MW due to a 50% increase in the average small solar generation of 286 MW	–0.0215 (–0.0037)	0.0014 (0.0003)	–0.2774 (–0.0357)	–0.2460 (–0.037)
+ 525 MW due to a 50% increase in the average wind generation of 1,050 MW	–1.4910 (–0.2586)	–1.2285 (–0.2619)	–2.4465 (–0.3145)	–2.1368 (–0.3218)

Notes: (1) The profit numbers in the “no change” row are the sample mean profits in Table 2. An estimated profit change is the estimated profit effect multiplied by the change in the driver due to the event. (2) We do not compute the estimated profit change for the San Onofre plant because the average profit numbers in Table 2 have already captured the effect of the plant's shutdown. More importantly, a counter-factual computation for the San Onofre plant is meaningless, as the plant's shutdown is permanent. (3) We assume that the 50% increase [$= (50\%/33\%) - 1 \approx 0.5$] in renewable generation is caused by California's raising the 33%-RPS to a 50%-RPS.

Table 7 describes these hypothetical events and reports the estimated profit changes under the *ceteris paribus* assumption:

Suppose there is a \$1/MMBTU increase in the natural-gas price. That increase reflects the increasing demand for natural gas due to the U.S. economic recovery and rising natural-gas exports.⁴⁷ The estimated profit increases can be as high as 23% of the sample's mean profits, as shown by the statistically-significant SP15 estimate for a CCGT with $H = 7$ MMBTU/MWH. The profit effects, however, are relatively small and statistically insignificant for a CT with $H = 9$ MMBTU/MWH, chiefly because the natural-gas price increase has similar impacts on the market price and the CT's fuel cost.

- Suppose there is a 1,000-MW DR-load reduction that occurs 60 hours per year, reflecting our assumption of 10 DR days per year during California's peak hours of 12:00–18:00 (Moore et al., 2010). The 1,000-MW DR-load reduction is based on the state's DR target of 5% and PG&E's and SCE's system annual peaks in 2013. We find the change in estimated profit as

47. The EIA identified export scenarios resulting in U.S. natural-gas prices for producers at 4% to 11% more than the AEO 2014 reference case over the 2015–40 period (<http://www.eia.gov/analysis/requests/fe/pdf/Ing.pdf>). That study indicates that larger gas demand from higher economic growth assumptions could also lead to projected increases in gas prices by more than \$1/MMBTU in the 2020–2025 period.

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the hourly load's average profit effect * 1,000 MW * (60 hours / 8760 hours). Though statistically significant, the estimated profit reductions are less than 1% of the sample's mean profits, implying that when the number of DR hours is small, the estimated profit reductions are also likely to be small.⁴⁸

- Suppose the Diablo Canyon nuclear plant loses one of its two reactors. While statistically insignificant, the estimated profit increases are about 20% of the sample's mean profits.
- Suppose the Palo Verde nuclear plant loses one of its three reactors. The estimated profit increases are large and statistically significant for NP15, and mount up to 60% of the sample's mean profits. This may be attributable to the increased exports from the NP15 to SP15 region after loss of the unit.
- Suppose there is a 50% (175.5 MW) increase in the average small-hydro generation due to California's raising its RPS from 33% to 50% of electricity usage. The estimated profit changes are mixed and statistically insignificant.
- Suppose there is a 50% increase (146 MW) in the average solar generation due to the state raising its RPS from 33% to 50% of electricity usage. The profit- reduction estimates are statistically insignificant and equal to only 0% to 4% of the sample's mean profits.
- Suppose there is a 50% increase (525 MW) in the average wind generation due to California's raising its RPS from 33% to 50% of electricity usage. The estimated profit reductions are statistically significant and equal to 26% to 32% of the mean profits. These estimated reductions imply that wind generation's negative profit-elasticity estimates are -0.53^{49} to -0.64^{50} , which are larger in size than the negative estimates of -0.20 to -0.33 for Texas (Woo et al., 2012)⁵¹ and -0.12 to -0.33 for Germany (Trabert and Kamfert, 2011).⁵²

In summary, these estimated profit changes show that the natural-gas price, DR-based load reduction, nuclear capacity available, and wind generation can have statistically significant impacts on the ex post profits of natural-gas-fired generation. Except for the DR-load reduction, the estimated impacts can be quite large, which corroborates the commonly held view regarding the "missing money" problem.

6. CONCLUSION

The profit-change estimates in Table 7 suggest that an increase in generation investment incentives in California might occur given an increase in natural-gas prices and the loss of a nuclear reactor, whose occurrence is uncertain. In contrast, we know with certainty that California has a

48. To be sure, the estimate reported here reflects the average profit effect of a load change, based on our regression analysis. That profit effect can be smaller than the profit effect during the peak hours. Our possible understatement of the profit impact, however, is mitigated by the load increase that likely occurs in the shoulder-peak hours immediately before and after a DR-event. For example, critical-peak pricing tends to shift end-use loads in the critical-peak hours to the shoulder-peak hours (e.g., Faruqui and Segici, 2010). Thus, when the DR-load reduction during the peak hours is compensated for by the load increase in the shoulder-peak hours, the profit effect estimable from our regression analysis is empirically plausible.

49. This is based on a 26% reduction in profit \div 50% increase in wind generation.

50. This is based on a 32% reduction in profit \div 50% increase in wind generation.

51. This is based on the estimated profit reduction of 8% to 13% caused by a 40% increase in wind generation.

52. This is based on the estimated profit reduction of 12% to 33% caused by a doubling in wind generation.

legislated 33% RPS by 2020 target that is now being implemented. Based on Table 7, this known development of renewable energy is projected to reduce the state's generation investment incentives.

The expected growth of renewable energy in California highlights the need for resource-adequacy requirements to address the state's diminished incentives to invest in natural-gas-fired generating capacity, absent increases in natural-gas prices or additional nuclear power plant closures. Under the state's adopted resource-adequacy program "[e]ach LSE's system requirement is 100 percent of its total forecast load plus a 15 percent reserve, for a total of 115 percent."⁵³ In compliance with its system requirement, an LDC such as PG&E prepares a long-term procurement plan for the approval of the California Public Utilities Commission, announces its capacity needs based on the approved procurement plan, and issues requests for proposals (RFP) to buy conventional and renewable generation, as well as DR resources.⁵⁴

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 and the subsequently signed contract of a chosen developer should contain sufficient revenues to enable the new plant's construction.

We would be remiss if we failed to acknowledge the potential pitfalls in our analysis. First, our mixed and unanticipated results related to the hydro conditions in California suggest that improved modeling of the state's hydro conditions is an area that merits future attention. An extensive exploration of how to better represent the state's hydro conditions is complex and well beyond the scope and intent of the current paper.

Second, our estimated profit changes assume that the estimated regressions are sufficiently stable as to allow us to make these computations. California's electricity industry is undergoing such on-going changes as the retirement of old thermal plants and rapid expansion of solar generation. These changes may render this assumption inappropriate. With additional data to be collected in the next two to three years, however, one can re-estimate and update the estimated system of regressions, an effort that will take pride of place on our future research agenda.⁵⁵

Third, our analysis assumes 1-MW generation ownership, which presumes that a natural-gas-fired generation plant can sell as much output as it desires at the prevailing market prices. But renewable energy procurement by LDCs to comply with the state's RPS may limit the owner's sales volume. We have not investigated this volume effect, an important aspect of the revenue adequacy problem noted by Griffes (2014).

Finally, our regression-based approach is an *ex post* profit analysis, thanks to its unavoidable use of historical recorded data. To the extent that the future does not resemble the past, our approach would be inappropriate for making long-term inferences about the incentives for invest-

53. <http://www.cpuc.ca.gov/PUC/energy/Procurement/RA/>

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

55. It would be particularly useful to examine whether the profit impact of solar generation remains stable over the next two to three years. Our regression results presently show that: (a) incremental solar generation has less than half the downward profit effect for SP-15 Southern California gas generators as incremental wind generation; and (b) incremental solar generation does not have a statistically significant profit effect in Northern California. In light of the "duck curve" in CAISO (2014a), which portrays the state's net afternoon hourly loads resulting from the projected vast solar expansion, it would be useful to know whether this relative impact of solar versus wind will continue to hold as solar grows to become a larger share of total renewable generation than wind, or whether the impact of solar generation on profits will greatly change with its growth.

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ment in natural-gas-fired generation, which would justify the development and use of a market-simulation model along the lines of Morales and Conejo (2011) and Traber and Kemfert (2011, 2012).

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