Market price behavior of wholesale electricity products: Texas

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Abstract

Applying a regression-based approach to a newly developed sample of over 60,000 hourly observations for 01/01/2011 to 12/30/2017, we answer the question: what moves the day-ahead market (DAM) prices for energy and ancillary services (AS) and the real-time market (RTM) price for energy in the Electric Reliability Council of Texas (ERCOT)? Our answer comprises findings that capture the interdependence of ERCOT's energy and AS products. Specifically, the DAM energy price increases with the day-ahead forecasts of natural gas price, system load and AS requirements but declines with nuclear and wind generation's forecasts. The AS prices increase with the DAM energy price and the AS procurement forecasts but decline with the AS offer forecasts. The RTM energy price increases with the DAM energy and AS prices and diverges from the DAM energy price. Our answer's policy implications are: (a) reducing the DAM energy and AS prices may occur via wind generation development and demand-side-management *sans* increasing ERCOT's AS needs; (b) mitigating the AS prices is possible by reducing ERCOT's AS procurements and increasing market participants' AS offers; and (c) moderating the RTM energy price's volatility and divergence from the DAM energy price can come from improving ERCOT's forecast accuracy.

1. Introduction

Unlike other forms of energy (e.g., natural gas and gasoline), electricity cannot be economically stored on a large scale to date and must be supplied in real time to reliably meet demand. Real-time supply-demand balance is a difficult challenge for an electric grid's system operator (SO) because of factors hard to control or mitigate (Wood and Wollenberg, 2012). Examples of such factors include random fluctuations in hourly system loads, inaccurate forecasts of hourly system loads and annual peak demand, unexpected changes in generation by intermittent renewable resources, unforeseeable forced outages of major electrical facilities, and long lead times for generation and transmission construction.

Overcoming the above challenge, a SO uses least-cost resource planning to achieve: (a) a planning reserve margin for generation capacity under the commonly adopted criterion of 1-day-in-10 years loss-of-load-expectation; and (b) a robust grid that can withstand the loss of component (e.g. a transmission line or a generation facility) under the (N-1) contingency criterion (Hobbs, 1995). It also uses real-time least-cost dispatch to achieve the grid's safe and reliable operation, subject to the availability of generation and transmission facilities that aim to maintain a preset operation reserve margin (Stoft, 2002; Wood and Wollenberg, 2012). For a large system in the U.S., the planning reserve margin is about 15% of its annual peak MW forecast and the operating reserve margin is about 6.0% of its daily peak MW forecast.[1]

Exacerbating the aforementioned challenge is the introduction of wholesale market competition in the formerly regulated electricity sector of many countries (Sioshansi, 2013), with electricity transactions undertaken by generators, load-serving entities (e.g., local distribution companies) and wholesale traders. Procurement of various ancillary services (AS) by a SO is necessary to resolve a network's inevitable demand-supply imbalance that can wildly fluctuate in real time (Ellison et al., 2012).[2] A good case in point is that a bilateral transaction's MWh scheduled for delivery in hour h (= 1, …, 24) on day t-1 may sharply differ from the MWh actually delivered in the same hour on day t, causing an imbalance that the SO must resolve using the AS services typically procured on day t-1 and real-time energy on day t.

Evolution of competitive wholesale electricity markets has triggered growing interest in: (a) establishing performance standards for AS resources, (b) designing competitive markets for AS procurement, and (c) determining the optimal AS requirements (Oren, 2002). Increasing dependence on randomly intermittent renewable resources like solar and wind may increase a network's AS needs, sparking

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[1] https://www.nerc.com/pa/RAPA/ra/Reliability%20Assessments%20DL/2017%20Summer%20Assessment.pdf; http://www.caiso.com/Documents/2018SummerLoadsandResourcesAssessment.pdf

[2] The Federal Energy Regulatory Commission (FERC) defines AS as services "necessary to support the transmission of electric power from seller to purchaser given the obligations of control areas and transmitting utilities within those control areas to maintain reliable operations of the interconnected transmission system." See FERC Orders 888, 889, and 2000.

investigations on how such needs may be met in the future (GE Energy, 2008; ERCOT, 2013; Exeter Associates and GE Energy, 2012; National Renewable Energy Laboratory, 2011a, 2011b). Underscoring the important relevance of such investigations is the continuing trend of large-scale renewable energy development, a critical component of the worldwide effort to mitigate global warming caused by CO_2 emissions that mostly come from fossil fuel consumption (Williams et al., 2014).

Contributing to the literature on AS market design and price behavior, this paper answers the question: what moves the day-ahead market (DAM) prices for energy and AS and the real-time market (RTM) price for energy in the Electricity Reliability Council of Texas (ERCOT)? To do so, it uses a regression-based approach to empirically characterize the data generating process (DGP) of the prices for ERCOT's energy and AS products.

ERCOT's DAM determines on day t-1 the prices for day-ahead energy and four AS products: responsive (i.e., spinning) reserve service (RRS), non-spinning reserve service (NSRS), regulation up (REGUP) and regulation down (REGDN). ERCOT's RTM determines the 5-minute locational marginal prices received by generators actually dispatched on day t. These products are interdependent because (a) a resource unit (e.g., a combustion turbine) can offer to supply multiple products; (b) the amounts that the unit can deliver, however, is limited by the unit's capacity; and (c) the amounts actually delivered are determined by ERCOT's day-ahead and real-time least-cost dispatch decisions.

Exploiting the interdependence of ERCOT's electricity products, this characterization is meaningful for the following reasons. First, there has been little attention devoted to the market price behavior of AS, notwithstanding a review of historical prices in U.S. markets by Argonne National Laboratory (2016). Second, the U.S. market-based AS costs that move with the AS prices exceed US$500M per year (Argonne National Laboratory, 2016), ultimately borne by consumers due to load-serving entities' cost pass-through. Third, little is known on how AS prices may vary with a network's renewable generation, unlike the well-documented merit-order effect of renewable generation on DAM and RTM energy prices that reduces the investment incentive for natural-gas-fired generation (e.g., Woo et al., 2011a, 2013, 2014, 2015, 2016a, 2017a, 2017b, 2018; Zarnikau, et al., 2016; and the extensive references thereof).[3] Finally, there is presently no empirical evidence on the price behavior of ERCOT's electricity products, albeit such evidence's important policy implications for a sustainable and affordable electricity future in Texas.

[3] To be fair, large-scale wind generation development benefits electricity consumers when its incremental cost is more than offset by its reduction in a load serving entity's wholesale energy procurement cost.

Our DGP characterization is a system of six price regressions for analyzing a newly developed large sample of over 60,000 hourly observations for the seven-year period of 01/01/2011 to 12/30/2017. Our key findings are as follows:

- The DAM energy price declines with the nuclear and wind generation's forecasts but increases with the forecasts of AS requirements, natural gas price and system load.
- The AS prices increase with the DAM energy price. They also increase with ERCOT's AS demand measured by the procurement forecasts but decrease with ERCOT's AS supply measured by the offer forecasts.
- A $1/MWh increase in the DAM energy price increases the RRS and REGUP prices by about the same amount, reflecting AS suppliers' arbitrage behavior and ERCOT's co-optimization of resources that have offered to supply DAM energy, RRS and REGUP.
- A $1/MWh increase in the DAM energy price raises the NSRS price by a lesser amount, as NSRS providers are not on-line and thus incur lower costs.
- An increase in the share of RRS provided by load resources reduces the RRS price because ERCOT's interruptible loads often offer demand reductions at zero price, so as to indicate their willingness to accept the last-dispatched marginal generator's supply bid price.

- The RTM energy price increases with the DAM energy price, moves with the AS prices and diverges from the DAM energy price.

We make four contributions to the literature of electricity market price behavior. First, to the best of our knowledge, it is the only regression analysis of a large sample of hourly market price data for day-ahead energy, AS and real-time energy. Second, its analysis is comprehensive, encompassing ERCOT's six electricity products, a research feat unseen in prior studies of market price behavior in Texas. Third, its parsimonious regression specification is general, equally applicable to other jurisdictions with data availability similar to ERCOT's (e.g., California, New York, New England and PJM in the U.S.; and Germany, Spain, and U.K. in Europe). Finally, its conclusion presents policy recommendations to (a) reduce ERCOT's energy and AS prices; (b) shrink ERCOT's RTM-DAM price divergence to improve energy trading efficiency; and (c) reduce the RTM energy price's large volatility.

The paper proceeds as follows. Section 2 first provides an overview of ERCOT's market evolution, energy and AS products, and price determination process. It then proposes our regression specification, which is followed by a description of our data sample. Section 3 presents the regression results, which are then discussed in Section 4. Section 5 concludes by recapping the paper's key findings and discussing these findings' policy implications caveats.

2. Materials and methods

2.1 Why ERCOT?

ERCOT is an important case study of electricity price behavior since it serves 85% of the electrical needs of the largest electricity-consuming state in the U.S. (with a peak demand of over 73 GW recorded on 07/19/2018)[4] and accounts for over 9% of the nation's total electricity generation.[5] It is seen as a successful example of implementing market competition in the generation and retail segments of the power industry in North America (Distributed Energy Financial Group, 2015). Finally, ERCOT is of particular interest to academics, industry practitioners and policy analysts because Texas leads the U.S. in wind generation development, with an installed capacity 20.1 GW in 2017 and an expected addition of 8.6 GW by 2020.[6] Thus, the projected total wind generation capacity in 2020 can be as much as 40% of the state's annual peak demand driven by the system load surge during a summer heat storm. Historic data, however, indicate that hourly system loads and wind generation levels are negatively correlated in Texas, as similarly observed in other parts of the

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[4] https://www.forbes.com/sites/joshuarhodes/2018/07/19/texas-electric-grid-sets-new-system-wide-all-time-peak-demand-record-twice/#5e5765771521

[5] Generation in ERCOT was 375,890 GWh in 2017, as reported to NERC: http://www.nerc.com/pa/RAPA/ESD/Pages/default.aspx. Total U.S. generation at utility-scale facilities was 4,014,804 GWh in that year, according to the U.S. Department of Energy's Energy Information Administration: http://www.eia.gov/electricity/monthly/epm_table_grapher.cfm?t=epmt_1_1.

[6] ERCOT Monthly Operational Overview, Feb. 15, 2018, available at: http://www.ercot.com/content/wcm/key_documents_lists/27311/ERCOT_Monthly_Operational_Overview__201801.pdf

U.S. (e.g., California and the Pacific Northwest). This compounds ERCOT's reliability problem due to the increased volatility of ERCOT's system net load (= system load – wind generation).

Texas' wind generation development is attributable to federal tax credits; the state's enormous resource potential, renewable portfolio standard and tradable renewable energy credits; and ERCOT's favourable market rules (Zarnikau, 2011). With the Competitive Renewable Energy Zone (CREZ) completed in January 2014, the state now has 3,600 miles of 345kv transmission line to accommodate 18.5 GW of renewable capacity, further unlocking the vast wind potential in West Texas.

The state's large-scale wind generation development has prompted concerns of rising AS needs that may in turn trigger higher AS prices and costs. Further, it tends to magnify ERCOT's RTM energy price volatility (Woo et al., 2011a), cause transmission congestion (Woo et al., 2011b), and reduce investment incentive in natural-gas-fired generation (Woo et al., 2012). To be sure, Texas now sees little transmission congestion after the CREZ's completion and has added 7 GW of natural gas fired generation capacity during 2011-2017. Nevertheless, how wind generation has affected ERCOT's AS and energy prices can inform other regions with large-scale renewable energy development (e.g., California and the Pacific Northwest in the U.S. and European countries like Denmark, Spain and Germany).

2.2 The ERCOT markets

ERCOT has undergone gradual restructuring since the mid-1990s (Zarnikau, 2005; Adib and Zarnikau, 2006). Legislation enacted in 1995 required the Public Utility Commission of Texas to establish market rules to foster wholesale competition and create an independent system operator (ISO) to ensure non-discriminatory transmission access. Sweeping reforms in 1999 through Senate Bill 7 allowed customers of the investor-owned utilities to choose among competitive retail electric providers. Senate Bill 7 also enhanced the ISO's centralized control over Texas' wholesale market, leading to the creation of a DAM for AS and a RTM for balancing energy.

Based on the theory of locational marginal pricing (Stoft, 2002), ERCOT implemented a nodal market design on 12/01/2010, replacing the zonal market structure plagued by intra-zonal transmission congestion (Zarnikau et al, 2014a). The DAM was expanded to include day-ahead energy, like those in PJM, New York, New England and California. Hourly market-clearing DAM energy prices come from ERCOT's least-cost co-optimization of energy generation, AS procurement and congestion revenue rights.

Supply offers begin at 6 a.m. and end at 10 a.m. on day *t*-1 for ERCOT's day-ahead price determination between 10 a.m. and 1:30 p.m. Prices for day *t* are set around 6 p.m. after ERCOT completing the unit commitments necessary for grid reliability.[7] As actual wind generation and total system demand on day *t* are unknown on day *t*-1, the DAM prices for energy and AS depend on ERCOT's day-ahead forecasts of wind generation, hourly loads and AS requirements.

Unlike the ISOs in PJM, New York and New England, ERCOT does not have a capacity market that helps pay for a generator's fixed cost for O&M and returns on and of investment. To encourage investment in generation capacity, the offer cap on wholesale energy prices, which was $3,000 per MWh at the start of the nodal market and gradually increased to $9,000 per MWh by 06/01/2015.

ERCOT uses a dispatch algorithm to determine locational marginal prices (LMPs) or nodal settlement point prices at generation resource nodes. In this analysis, we use the prices faced by load-serving entities – the load-weighted average of all the LMP prices in a Load Zone, converted to 15-minute values.[8] Accounting for the operation limits (e.g., ramp rates and capacity limits) of generation units already online, each nodal price is the supply bid price of the last dispatched (marginal) generation unit affecting the cost of serving a node.[9] Absent transmission constraints,

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[7] See ERCOT training module, Module 2: Day-Ahead Operations, available at: http://www.ercot.com/content/wcm/training_courses/58/GEN101_M2_Jan2010.pdf

[8] For use in in our regression analysis, we further convert these 15-minute values to hourly values, to match the frequency of the DAM price data.

[9] Competition among generators implies that the RTM price tracks the marginal unit's per MWh cost for fuel and variable O&M and expected value of capacity. This makes sense based on the economic theory of a competitive market: the market equilibrium price is a competitive firm's marginal cost plus the markup required to balance the market's total demand and supply. Absent non-competitive behavior of market price manipulation, this markup is the premium that rations the market's limited supply

nodal prices tend to converge, reflecting the least-cost condition of equal marginal costs across all nodes. As natural-gas-fired generation units that dominate the state's generation fleet can supply DAM and RTM energy, price arbitrage by generators under the efficient market hypothesis (EMH) implies that the hourly DAM and RTM energy prices tend to move in tandem (Woo et al., 2016a).

2.3 ERCOT's AS products

ERCOT's four AS products are system-wide operating reserves, similar to those used by the ISOs of California, New York, New England and PJM. Contrary to the expectations of many, ERCOT's total AS requirement has declined very slightly in recent years, despite the state's rising wind generation (Potomac Economics, 2018).[10]

REGUP and REGDN capacities balance small fluctuations in supply and demand in real time to maintain system frequency close to 60Hz. Armed with automatic generation control, resources providing regulation services must be able to respond every four seconds and comply with ERCOT's instructions within five minutes.

Similar to the spinning reserves used in other electricity markets, RRS aim to maintain real-time demand-supply. Resources providing RRS must comply with

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capacity. It vanishes when the market has excess capacity.

[10] As noted by Potomac Economics, total AS requirements were 5,300 MW in 2015, 4,900 MW in 2016, and 4,800 MW in 2018.

ERCOT's instructions within 10 minutes. For North American networks outside Texas, RRS are mainly provided by online generation resources operating below full capacity. In contrast, nearly half of ERCOT's RRS requirements come from load resources equipped with under-frequency relays that instantaneously curtail load when frequency drops to 59.7 Hz. Since 05/31/2018, the total MW provided by load resources is capped at 60% of ERCOT's RRS requirement.

NSRS ensures sufficient capacity to cover large forecast errors or replace RRS already deployed. A resource providing NSRS must be able to start up and increase its output to ERCOT's target level within 30 minutes.

ERCOT assigns a load-serving entity's (LSE's) hourly AS obligations for day *t* based on the LSE's share of ERCOT's total load for the same hour on day *t*-1. The LSE can self-arrange to meet its AS obligation, with the residual obligation procured on behalf of the LSE by ERCOT. The total self-arranged AS amounts have been about 5% to 30% of ERCOT's total AS requirements in our sample period.

ERCOT co-optimizes generation and load resources offering day-ahead energy and AS. A selected resource in the DAM may provide AS or energy, depending upon where it has the most value. This least-cost outcome recognizes: (a) relatively few resources have the fast responsiveness necessary to supply REGDN and REGUP; and (b) there is an often over-abundance of load resources that like to offer RRS at a zero offer price, counting on generators to set the market clearing price. Hence, ERCOT's day-ahead energy and some AS are substitutes to a limited degree, implying product interdependence that rationalizes our regression specification below.

2.4 Price regressions

Our regression model recognizes: (a) the DAM energy and AS are interdependent products; and (b) DAM energy prices are mainly driven by such fundamental drivers as natural gas price, system load, nuclear generation, and wind generation (Woo, et al., 2011a; Zarnikau et al., 2014a, 2015).

It also recognizes that the DAM energy price moves the RTM energy price (Woo et al., 2016a). If empirically valid, the EMH implies the following bivariate regression: RTM energy price = a + b DAM energy price + error, where a = intercept estimate not statistically different from zero and b = slope estimate not statistically different from one. To test the EMH's validity in ERCOT, Fig. 1 is a scatter plot of DAM energy price vs. RTM energy price. While rejecting the EMH at the 1% level, it convincingly portrays the positive and statistically significant (p-value < 0.01) relationship between the RTM and DAM energy prices.

Let P_{jht} be the price for product j (= 1 for day-ahead energy, 2 for RRS, 3 for NSRS, 4 for REGUP, 5 for REGDN and 6 for real-time energy) in hour h (= 1, …, 24) on day t (= 01/01/2011, …, 12/30/2017). Generalizing the specification in Woo et al.

(2016a) to account for ERCOT's AS products, our postulated day-ahead energy price regression with random error ε_{1ht} is:[11]

$$P_{1ht} = \theta_{ht} + \theta_G\, G_t + \theta_N\, N_{ht} + \theta_D\, D_{ht} + \theta_W\, W_{ht} + \sum_{j=2}^{5} \theta_j\, Y_{jht} + \varepsilon_{1ht}\,. \qquad (1)$$

Proper chronological matching demands that the regressors in Eq. (1) have values that are known on a day-head basis (Woo et al., 2016a, 2017a, 2017b).

In Eq. (1), coefficient θ_{ht} is a time-varying intercept that captures the fixed effects of hour-of-day and month-of-year. Coefficient $\theta_G > 0$ is the market-based heat rate that measures the DAM energy price increase due to a $1/MMBtu increase in the natural gas price's day-ahead forecast G_t (Woo et al., 2014, 2016a, 2017a, 2017b). Coefficient $\theta_N < 0$ is the marginal price effect of the baseload nuclear generation's day-ahead forecast N_{ht}. Coefficients $\theta_D > 0$ aims to capture the marginal price effect of the system load's day-ahead forecast D_{ht}. Coefficient $\theta_W < 0$ measures the price-reduction (or merit-order) effect of wind generation's day-ahead forecast W_{ht}.

ERCOT only publishes data for D_{ht} and W_{ht}. Estimating Eq. (1), however, requires data for G_t and N_{ht}. Hence, we use an autoregressive method to produce the necessary forecast data.[12] To assess the resulting forecasts' reasonableness, we verify:

[11] We do not use the double-log specification because of the presence of zero and negative prices, whose natural log are missing values that cause data gaps in our regression analysis. The values of all quantity variables representing generation and load were converted from MWh values to GWH values, so that the coefficients associated with some of the variables could be better illuminated and all of these variables could be represented in the same units.

[12] As a quick and automatic way to generate forecasts for many time series, the stepwise autoregressive (STEPAR) method in PROC FORECAST of SAS (2004) combines a "time trend regression with an autoregressive model and uses a stepwise method to select the lags to use for the autoregressive process" (SAS, 2004, p.835). In short, the day-ahead forecasts are automatically

(a) the forecast data for the daily natural gas price and hourly nuclear generation are highly correlated ($r > 0.9$) with the actual data; and (b) the actual and forecast data move in tandem on an almost one-to-one basis.

Eq. (1) uses $\{Y_{jht}\}$ to capture the effects of ERCOT's day-ahead forecast of AS requirements on the DAM energy price, thus recognizing the energy-AS interdependence ignored by prior price regression analyses for Texas (Woo et al., 2011a; Zarnikau et al., 2014a, 2016).[13] We reason that $\{\theta_j\}$ are likely positive because rising AS requirements tend to encourage AS providers to increase their AS offers and reduce their DAM energy offers, thus possibly raising the DAM energy price. Whether our reasoning has empirically support is to be determined by the regression results reported in Section 3 below.

Let Q_{jht} = day-ahead forecast of ERCOT's procured MW of AS product j (= 2, 3, 4, 5) in hour h on day t, S_{ht} = day-ahead forecast of the portion of RRS of Q_{2ht} provided by load resources that typically have very low bid prices, and Z_{jth} = day-ahead forecast of the total MW of AS offer j in hour h on day t. As ERCOT does not publish the data for Q_{jht}, S_{ht} and Z_{jth}, we calculate such data, as similarly done for the natural gas price and nuclear generation. Since Q_{jht}, S_{ht} and Z_{jth} come from autoregressive modeling based on the data prior to day t, they are unrelated to the

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produced by PROC FORECAST *sans* additional modeling efforts by the authors.

[13] Based on the cited in this paper's references, the same can be said about the numerous studies for California, Pacific Northwest and PJM in the U.S., Germany, Spain and Australia.

DAM and RTM prices for day *t*. Hence, we can use Q_{jht}, S_{ht} and Z_{jth} as exogenous regressors in the AS price regressions below *sans* concerns of estimation bias due to the presence of endogenous regressors.

When developing our AS regressions, we consider the energy-AS interdependence and the large volume of DAM energy typically traded in a wholesale market. Hence, our postulated AS price regressions with random errors ε_{jht} are:

$$P_{2ht} = \alpha + \alpha_1 P_{1ht} + \alpha_2 Q_{2ht} + \alpha_S S_{ht} + \lambda_2 Z_{2\mathrm{h}t} + \varepsilon_{2ht}; \tag{2}$$

$$P_{3ht} = \beta + \beta_1 P_{1ht} + \beta_3 Q_{3ht} + \lambda_3 Z_{3\mathrm{h}t} + \varepsilon_{3ht}; \tag{3}$$

$$P_{4ht} = \gamma + \gamma_1 P_{1ht} + \gamma_4 Q_{4ht} + \lambda_4 Z_{4\mathrm{h}t} + \varepsilon_{4ht}; \tag{4}$$

$$P_{5ht} = \phi + \phi_1 P_{1ht} + \phi_5 Q_{5ht} + \lambda_5 Z_{5\mathrm{h}t} + \varepsilon_{5ht}. \tag{5}$$

Coefficient α in Eq.(2) is the intercept. Coefficient $\alpha_1 > 0$ measures the DAM energy price's effect on the RRS price. Hence, the change in a fundamental driver's forecast that alters the DAM energy price also impacts the RRS price. To wit, $\theta_G \alpha_1$ is the RRS price effect of a $1/MMBtu increase in the natural gas price forecast. Coefficient α_2 captures the demand-side price effect of Q_{2ht}. Finally, Eq. (2) uses coefficient $\lambda_2 < 0$ to measure the supply-side price effect of Z_{2ht}. As the interpretation of the remaining AS price regression is entirely analogous, it is omitted for brevity.

Extending the specification in Woo et al. (2016a) to include ERCOT's AS prices, the RTM price regression with intercept ψ and random error ε_{6ht} is:

$$P_{6ht} = \psi + \psi_1 P_{1ht} + \ldots + \psi_5 P_{5ht} + E_{th} + \varepsilon_{6ht}. \quad (6)$$

Eq. (6) states that the RTM energy price moves with the DAM energy and AS prices. The EMH, if empirically valid, suggests $\psi_1 \approx 1.0$. We do not *a priori* know the sign or size of ψ_j that measures the marginal effect of AS price j (= 2, …, 5), an issue to be empirically settled by the regression results in Section 3. Finally, E_{th} is the aggregate RTM price impact of forecast errors, postulated to be a linear function of the individual forecast errors for the natural gas price, system load, nuclear generation, wind generation, AS requirements, and AS procurements. We do not *a priori* know the size or sign of each forecast error's coefficient, although we expect these errors to materially contribute to the RTM price's divergence from the DAM energy price.

Thanks to product interdependence, the random errors in Eqs. (1) to (6) are contemporaneously correlated. As the hourly price data are likely serially correlated, we assume that the random errors follow an AR(n) process, whose order n is to be determined empirically. Further, the endogenous DAM energy price appears as a regressor in Eqs. (2) to (4) and along with the endogenous AS prices in Eq. (6). Thus, Eqs. (1) to (6) form a system of simultaneous regressions, which can be readily estimated using the iterated three-stage-least square (IT3SLS) technique in PROC MODEL of SAS (2004).

In summary, our newly postulated DGP for the price behavior of ERCOT's six electricity products is remarkably simple, comprising the parsimonious regressions given by Eq. (1) – (6).[14] Whether it is empirically reasonable is best judged by the regressions' fit with the voluminous noisy data and the coefficient estimates' plausibility and precision.

2.5 Data description

Obtained from the ERCOT website or through public data requests to ERCOT, our sample contains hourly data for 01/01/2011 – 12/30/2017. Our sample period closely matches the initiation of nodal pricing on 12/01/2010. Its beginning date is 01/01/2011 because coherent price data reflecting the new markets and zones were unavailable for December 2010. Its ending date is 12/30/2017, reflecting the data supplied to us by ERCOT at the time of our writing.

The data for constructing the variables used in our price regressions are described below:

- Generation (GWh) by fuel type for baseload nuclear power plants and wind farms for the ERCOT system.
- Hourly quantities (GW/hour) required by ERCOT, offered to the DAM, and procured through the DAM of each ancillary service.[15]

[14] Our initial exploration tests alternative models that use dummy variables to represent relevant changes in market rules and modifications to the formulas used by ERCOT to calculate AS requirements. These dummy variables' statistical insignificance leads us to conclude that the effects of these changes are already reflected in $\{Q_{jht}\}$.

[15] Some of our calculations may omit the small amounts that ERCOT procures through "supplemental auctions" for AS. ERCOT has implemented SASMs (supplemental auctions) 391 times since the start

- Hourly day-ahead price ($/MW) of each ancillary service, as well as the hourly day-ahead and real-time prices of energy ($/MWh).
- Share of the RRS requirement provided by interruptible load resources.
- Day-ahead forecast of system hourly load and wind generation announced by ERCOT prior to the start of the DAM.

Finally, the Henry Hub natural gas price data come from the US DOE Energy Information Agency. Highly correlated (r > 0.9) with the instate prices, the Henry Hub price serves as an instrument in our price regressions to circumvent the estimation bias potentially caused by the instate natural gas prices possibly being endogenous variables. Daily values were repeated for each hour of a day, and prices for days in which no trading took place (i.e., weekdays and holidays) were based on prices for the prior trading day.

Table 1 reports the descriptive statistics and price correlations of the variables used in our price regressions. All data series are found to be stationary at the 1% significance level based on the Phillip-Perron unit-root test (Phillips and Perron, 1988), obviating concerns of spurious regressions due to non-stationary data that follow a random walk (Granger and Newbold, 1974).

The data series in Table 1 are volatile, with large standard deviations and wide

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of the nodal market. See ERCOT (2018). ERCOT reports quantities in MW. The values in MW were converted to values in GW, so that the coefficient estimates could be better illuminated.

ranges defined by the series' minimum and maximum values. The price correlations in this table paint a picture that is largely consistent with our postulated DGP. Specifically, the DAM energy price is highly correlated ($r > 0.70$) with the RRS, NSRS and REGUP prices, though less so with the REGDN price ($r = 0.24$) or the RTM energy price ($r = 0.42$). The positive correlation coefficients ($r > 0.74$) for the market prices of RRS, NSRS, and REGUP suggest that these three market prices tend to move in tandem. However, the positive correlations of the REGDN price with the other three AS prices are weak ($r < 0.29$).

As expected, the DAM and RTM energy prices are positively correlated with the natural gas price and system load forecasts but negatively correlated with nuclear and wind generation's forecasts. The DAM energy price's correlations with the AS requirements, however, are very weak ($|r| < 0.1$), so are the AS prices' correlations with the AS procurement and offer forecasts. Finally, the RTM price's correlations with all AS-related quantity variables are close to zero ($|r| \leq 0.062$).

While indicative, the price correlations in Table 1 do not untangle the price effects of a determining factor. For example, they do not estimate wind generation forecast's merit-order effect on the DAM energy price and show how this estimated effect may in turn move the AS prices and RTM energy price. Hence, we estimate the price regressions given by Eqs. (1) – (6) to yield the generally reasonable empirics reported in the section below.

3. Results

Table 2 presents our IT3SLS regression results. The six price regressions have adjusted R^2 that range from 0.36 for REGDN to 0.93 for RRS, indicating a reasonable fit with the voluminous and noisy price data. The estimated price regressions are empirically plausible because nearly all of coefficient estimates unrelated to the forecast errors have expected signs and are highly significant (p-values < 0.01). Though positive as expected, the three insignificant estimates are those for the day-ahead requirement forecasts of RRS, NSRS and REGDN in the DAM energy price regression.

Focusing on the DAM energy price regression, we find that a $1/MMBtu increase in the natural gas price forecast tends to increase the DAM energy price by about $9.85/MWh. Hence, 9.85 MMBtu/MWh is the estimated market-based marginal heat rate, remarkably close to a new combustion turbine’s engineering heat rate of 9 MMBtu/MWh noted in Woo et al. (2017b, 2018). This makes sense as Texas has a thermal system whose marginal fuel is often natural gas for most hours of the year.

The remaining coefficient estimates indicate that a 1-GWh increase in the system load forecast tends to raise the DAM energy price by $2.64/MWh, while the same 1-GWh increase in the wind generation forecast tends to reduce the DAM price by $1.64/MWh. The nuclear generation forecast's estimated price reduction effect is $1.08/MWh. Finally, the estimated price effects of a 1-GW increase in the AS requirement forecasts are $19.6/MWh for the REGUP requirement forecast and it is between $1.5/MWh and $3.9/MWh for the other AS requirement forecasts.

Turing our attention to the AS price regressions, we find that a $1/MWh increase in the DAM energy price tends to raise the RRS and REGUP prices by about the same amount, though less for the NSRS and REGDN prices. The RRS price tends to decline by $1.26/MWh for a 0.1 increase in the forecast share of RRS supplied by load resources. The estimated demand-side effects of a 1-GW increase in ERCOT's AS procurement forecasts are price increases of $3.6/MW for RRS, $5.4/MW for NSRS, $16.7/MW for REGUP, and $31.4/MW for REGDN. These estimated price effects make sense, reflecting the relative availability of the resources that can supply these AS products. The estimated supply-side effects of a 1-GW increase in AS offer forecasts are AS price reductions of $2.14/MW for RRS, $0.88/MW for NSRS, $4.4/MW for REGUP, and $2.18/MW for REGDN.

The coefficient estimates of the RTM energy price regression indicate that a $1/MWh increase in the DAM energy price tends to increase the RTM price by $0.55/MWh. The estimated impacts of a $1/MW increase in the AS prices are small, less than \$0.13/MWh, thus indicating the AS prices' small impacts on the RTM energy price. Finally, the RTM price variations are found to move with the forecast errors. For example, a 1-GWh increase in the wind generation forecast error (= actual GWh – forecast GWh) tends to reduce the RTM price by a statistically significant (p-value < 0.01) amount of \$2.30/MWh.

4. Discussion

The empirics reported in Section 3 have important implications on generation investments and electricity bills. Specifically, the wind generation forecast's coefficient estimate in the DAM price regression affirms the order-merit effect that in turn reduces the RTM price, thus weakening the investment incentive for natural-gas-fired generation but helps cut electricity bills (Liu et al., 2016; Woo et al., 2012, 2016b). If rising wind generation also increases ERCOT's AS requirements, the order-merit effect diminishes. However, ERCOT's AS requirements have been stable in the last decade, despite the state's wind generation expansion. As a result, AS requirements do not seem to have offset the average DAM energy price reduction due to the large-scale wind generation development in Texas.

The AS regressions' coefficient estimates suggest that rising wind generation tends to reduce AS prices because of its merit-order effect on the DAM energy price, which in turn causes the AS prices to decline. If rising wind generation also increases

ERCOT’s AS procurements, it shrinks these AS price declines. However, ERCOT’s procurement quantities have also been stable in the last decade. As a result, AS procurements do not seem to have offset average AS price reductions due to the large-scale wind generation development in Texas.

Finally, the RTM regression results suggest what happens in the DAM does not stay in the DAM as the DAM energy price tends to systematically move the RTM energy price. Thus, policy measures that reduce the DAM energy price (e.g., wind generation development and demand-side management) can also reduce the RTM energy price. Further, ERCOT’s forecast errors impact the RTM energy price, contributing to the RTM price’s divergence from the DAM energy price. Hence, improving ERCOT’s forecast accuracy to reduce the AS requirements can also reduce the RTM price’s volatility and divergence from the DAM energy price.

5. Conclusions and policy implications

We conclude by first recapping our key findings. Applying a regression-based approach to a newly developed sample of over 60,000 hourly observations for 01/01/2011 to 12/ 30/2017, we document that ERCOT’s DAM energy price increases with the day-ahead forecasts of natural gas price, system load, and AS requirements but decreases with the forecasts of nuclear and wind generation. The AS prices increase with the DAM energy price and the AS procurement forecasts but decline with the AS offer forecasts. The RTM energy price increases with the DAM energy and AS prices and diverges from the DAM energy price.

We now state the above findings' policy implications. First, reducing the DAM energy and AS prices may occur via wind generation development *sans* substantial increase in ERCOT's AS needs. Second, mitigating the AS prices is possible through reducing ERCOT's AS procurements and increasing market participants' AS offers. Third, reducing the RTM energy price level can occur through wind generation development and demand-side management that reduce the DAM energy price. Fourth, the state's energy trading efficiency may be improved by reducing ERCOT's forecast errors to diminish the RTM-DAM energy price divergence. Finally, reducing the RTM price's volatility can also come from enhancing ERCOT's forecast accuracy. While specific to Texas, these policy implications are generally applicable to other wholesale markets in the U.S. and elsewhere.

We would be remiss had we failed to mention the following caveats of our price regression analysis. First, our analysis necessarily uses historic data that cannot reflect the potentially large future changes in ERCOT (e.g., adoption of new market rules and large-scale development of solar generation). To analyze the price impacts of such changes, market price simulation using engineering models is more appropriate than a regression analysis like the one reported herein (Woo, et al., 2015).

Second, our regression analysis, unlike those of Woo et al. (2012, 2015) and Liu et al. (2016), does not fully examine renewable generation's adverse effect on the investment incentive for natural-gas-fired generation, an increasingly thorny problem for ERCOT that has a projected summer reserve margin below the 13.75% target in the next few years.[16] Finally, our regression analysis assume that the price effects of the fundamental drivers and AS needs do not to vary by time-of-day or location, even though recent studies have suggested otherwise (e.g., Woo at al., 2017b, 2018).

In closing, adequately addressing the above caveats is well beyond this paper's intent and scope. Hence, our regression-based approach and empirics thus obtained should only be seen as a reasonable first step in understanding the price behavior of energy and AS products. A fruitful agenda of future research may include (a) enhancing the approach to analyze the energy and AS prices by time-of-day and location; and (b) collecting additional data in the coming years to capture the market price effects of the significant future changes in the electricity sector of Texas.

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16 https://www.nerc.com/pa/RAPA/ra/Reliability%20Assessments%20DL/2017%20Summer%20Assessment.pdf

of Liberal Arts and Social Sciences of the Education University of Hong Kong. Without implications, all errors are ours.

References

Adib, P., Zarnikau, J., 2006. Texas: The most robust competitive market in North America in Electricity Market Reform: An International Perspective, Ed. Fereidoon P. Sioshansi and Wolfgang Pfaffenberger. Elsevier, New York.

Argonne National Laboratory, 2016. Survey of U.S. Ancillary Services Markets. ANL/ESD-16/1. Available at: https://www.anl.gov/energy-systems/publication/survey-us-ancillary-services-markets (accessed on July 20, 2018).

ERCOT, 2013. Future Ancillary Services in ERCOT, concept paper. Available at: http://www.ercot.com/calendar/2013/10/24/32733-FAST (accessed on July 20, 2018).

Exeter Associates and GE Energy, 2012. Review of industry practice and experience in the integration of wind and solar generation, task report, November. Available at: https://www.pjm.com/~/media/committees-groups/subcommittees/irs/postings/pri s-task3b-best-practices-from-other-markets-final-report.ashx (accessed on July 20, 2018).

Distributed Energy Financial Group, 2015. The Annual Baseline Assessment of Choice in Canada and the United States (ABACCUS). Available at: http://defgllc.com/publication/abaccus-2015-annual-baseline-assessment-of-choice-in-canada-and-the-united-states/ (accessed on July 20, 2018).

Ellison, J.F., Tesfatsion, L.S., Loose, V.W., Byrne, R.H., 2012. Project Report: A survey of Operating Reserve Markets in U.S. ISO/RTO-managed Electric Energy Regions. Sandia National Laboratories, Albuquerque, New Mexico. Available at: https://www.sandia.gov/ess-ssl/publications/SAND2012_1000.pdf (accessed on July 29, 2018).

ERCOT, 2018. Study of the Operational Improvements and Other Benefits Associated with the Implementation of Real-Time Co-Optimization of Energy and Ancillary Services, June 29. Available at: http://www.ercot.com/content/wcm/lists/144930/Study_of_the_Benefits_of_Real-Time_Co-optimization_FINAL.pdf (accessed on July 20, 2018).

Hobbs, B.F., 1995. Optimization methods for utility resource planning. European Journal of Operational Research 83(1) 1-20.

GE Energy, 2008. Analysis of Wind Generation Impact on ERCOT Ancillary Services Requirements, prepared for ERCOT, March 28. Available at: http://www.uwig.org/attcha-ercot_a-s_study_exec_sum.pdf (accessed on July 20, 2018).

Granger, C.W.J., Newbold, P., 1974. Spurious regressions in econometrics. Journal of Econometrics 2, 111–120.

Liu, Y., Woo, C.K., Zarnikau, J., 2016. Ex post payoffs of a tolling agreement for natural-gas-fired generation in Texas. Journal of Energy Markets 9(1), 21-45.

National Renewable Energy Laboratory, 2011a. Operating reserves and variable generation. Technical Report: NREL/TP-5500-51978. Available at: https://www.nrel.gov/docs/fy11osti/51978.pdf (accessed on July 20, 2018).

National Renewable Energy Laboratory, 2011b. Effective ancillary services market designs on high wind power penetration systems. Conference Paper: NREL/CP-5500-53514. Available at: https://www.nrel.gov/docs/fy12osti/53514.pdf (accessed on July 20, 2018).

Oren, S.S., 2001. Design of ancillary service markets. Proceedings of the Hawaii International Conference on System Sciences, 0(c), 56. https://doi.org/10.1109/HICSS.2001.926283.

Phillips, P.C.B., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75, 335–346.

Potomac Economics, 2018. 2017 State of the Market Report for the ERCOT Electricity Market. Available at: https://www.potomaceconomics.com/wp-content/uploads/2018/05/2017-State-of-the-Market-Report.pdf (accessed on July 20, 2018).

Sioshansi, F.P., 2013. Evolution of Global Electricity Markets: New Paradigms, New Challenges, New Approaches. Elsevier, San Diego.

Stoft, S., 2002. Power System Economics: Designing Markets for Electricity. Wiley-IEEE Press, New York.

Williams, J.H., Haley, B., Karhl, J., Jones, A.D., Torn, M.S., McJeon, H., 2014. Pathways to deep decarbonization in the United States. Energy and Environmental Economics, Inc., San Francisco. Available at: https://www.ethree.com/publication/?fwp_authors=fritz-kahrl (accessed on July 29, 2018).

Woo, C.K., Horowitz, I., Moore, J., Pacheco A., 2011a. The impact of wind generation on the electricity spot-market price level and variance: the Texas experience. Energy Policy 39, 3939-3944.

Woo, C.K., Zarnikau, J., Moore, J., Horowitz, I., 2011b. Wind generation and zonal-market price divergence: evidence from Texas. Energy Policy 39(7), 3928-3938.

Woo, C.K., Horowitz, I., Horii, B., Orans, R., Zarnikau, J., 2012. Blowing in the wind: vanishing payoffs of a tolling agreement for natural-gas-fired generation of electricity in Texas. The Energy Journal 33(1), 207-229.

Woo, C.K., Zarnikau, J., Kadish, J., Horowitz, I., Wang, J., Olson, A., 2013. The impact of wind generation on wholesale electricity prices in the hydro-rich Pacific Northwest. IEEE Transactions on Power Systems 28(4), 4245-4253.

Woo, C.K., Ho, T., Zarnikau, J., Olson, A., Jones, R., Chait, M., Horowitz, I., Wang, J., 2014. Electricity-market price and nuclear power plant shutdown: evidence from California. Energy Policy 73, 234-244.

Woo, C.K., Moore, J. Schneiderman, B., Olson, A., Jones, R., Ho,T., Toyama, N., Wang, J., Zarnikau, J. 2015. Merit-order effects of day-ahead wind generation forecast in the hydro-rich Pacific Northwest. Electricity Journal 28(9), 52-62.

Woo, C.K., Moore, J., Schneiderman, B., Ho, T., Olson, A., Alagappan, L., Chawla, K., Toyama, N., Zarnikau, J., 2016a. Merit-order effects of renewable energy and price divergence in California's day-ahead and real-time electricity markets. Energy Policy 92, 299-312.

Woo, C.K., Horowitz, I., Zarnikau, J., Moore, J., Schneiderman, B., Ho, T., Leung, E., 2016b. What moves the ex post variable profit of natural-gas-fired generation in California? The Energy Journal 37(3), 29-57.

Woo, C.K., Olson, A., Chen, Y., Moore, J., Schlag, N., Ong, A., Ho, T., 2017a. Does California's CO_2 price affect wholesale electricity prices in the western U.S.A.? Energy Policy 110, 9-19.

Woo, C.K., Chen, Y., Olson, A., Moore, J., Schlag, N., Ong, A., Ho, T., 2017b. Electricity price behavior and carbon trading: new evidence from California. Applied Energy 204, 531-543.

Woo, C.K., Chen, Y., Zarnikau, J., Olson, A., Moore, J., Ho. T., 2018. Carbon trading's impact on California's real-time electricity market prices. Energy 159, 579-587.

Wood, A.J., Wollenberg, B.F., 2012. Power Generation, Operation, and Control. Wilely, New York.

Zarnikau, J., 2005. A review of efforts to restructure Texas' electricity market. Energy Policy 33, 15-25.

Zarnikau, J., Woo, C.K., Baldick, R. (2014a). Did the introduction of a nodal market structure impact wholesale electricity prices in the Texas (ERCOT) market? Journal of Regulatory Economics 45, 194-208.

Zarnikau, J., Woo, C.K., Gillett, C., Ho, T., Zhu, S., Leung, E. (2014b). Day-ahead forward premiums in the Texas electricity market, Journal of Energy Markets 8(2), 1-20.

Zarnikau, J., Woo, C.K., Zhu, S.S., 2016. Zonal merit-order effects of wind generation development on day-ahead and real-time electricity market prices in Texas. Journal of Energy Markets 9(4), 17-47.

Table 1. Descriptive statistics and price correlations; sample period: 01/01/2011 to 12/30/2017; sample size = 60,801 hourly observations; all data series are found to be stationary at the 1% level based on the Phillip-Perron unit-root test.

Variable: Definition	Descriptive statistics				Price correlation coefficients					
	Mean	Standard deviation	Minimum	Maximum	P_{1ht}	P_{2ht}	P_{3ht}:	P_{4ht}	P_{5ht}	P_{6ht}
P_{1ht}: DAM energy price ($/MWh) in hour h on day t	31.817	55.090	1.188	2636	1.0	0.952	0.707	0.893	0.235	0.4160
P_{2ht}: RRS price ($/MW) in hour h on day t	12.690	56.060	0.450	3000	0.953	1.0	0.790	0.931	0.284	0.3845
P_{3ht}: NSRS price ($/MW) in hour h on day t	5.288	32.230	0.010	3000	0.707	0.790	1.0	0.741	0.190	0.3035
P_{4ht}: REGUP price ($/MW) in hour h on day t	11.206	58.898	0.010	4999	0.893	0.931	0.741	1.0	0.278	0.3601
P_{5ht}: REGDN price ($/MW) in hour h on day t	6.398	8.980	0	593	0.235	0.283	0.190	0.278	1.0	0.0690
P_{6ht}: RTM price ($/MWh) in hour h on day t	30.367	70.063	-23.185	4574	0.416	0.385	0.304	0.360	0.069	1.0
G_t: Day-ahead Henry Hub natural gas price forecast ($/MMBtu) on day t	3.275	0.819	0.636	8.276	0.15667	0.063	0.046	0.064	0.161	0.113
N_{ht}: Day-ahead nuclear generation forecast (GWh) in hour h on day t	4.491	0.759	0.183	6.600	0.03015	0.021	0.022	0.019	-0.069	0.021
D_{ht}: Day-ahead system load forecast	38.839	9.312	20.842	70.676	0.27207	0.174	0.183	0.152	-0.193	0.173

(GWh) in hour *h* on day *t*										
W_{ht}: Day-ahead wind generation forecast (GWh) in hour *h* on day *t*	4.736	2.882	0.143	28.612	-0.140	-0.053	-0.074	-0.058	0.169	-0.106
Q_{2ht}: Day-ahead forecast of RRS procurement (GW) in hour *h* on day *t*	2.229	0.244	1.584	2.827	-0.060	-0.031	-0.046	-0.043	-0.007	-0.044
S_{ht}: Day-ahead forecast of the share of RRS requirement met by load resources in hour *h* on day *t*	0.482	0.033	0.268	0.511	-0.010	-0.013	-0.009	-0.012	0.007	0.011
Q_{3ht}: Day-ahead forecast of NSRS procurement (GW) in hour *h* on day *t*	1.495	0.313	0.429	2.732	0.017	0.026	0.071	0.025	-0.064	0.014
Q_{4ht}: Day-ahead forecast of REGUP procurement (GW) in hour *h* on day *t*	0.428	0.138	0.166	1.133	0.075	0.035	0.029	0.072	0.111	0.059
Q_{5ht}: Day-ahead forecast of REGDN procurement (GW) in hour *h* on day *t*	0.393	0.112	0.153	0.820	0.017	-0.010	-0.006	0.010	0.256	0.015
Y_{2ht}: Day-ahead forecast of RRS requirement (GW) in hour *h* on day *t*	2.671	0.209	2.148	3.131	-0.090	-0.065	-0.080	-0.066	0.007	-0.062
Y_{3ht}: Day-ahead forecast of NSRS requirement (GW) in hour *h* on day *t*	1.630	0.323	0.506	2.858	0.053	0.051	0.091	0.052	-0.022	0.033
Y_{4ht}: Day-ahead forecast of REGUP requirement (GW) in hour *h* on day *t*	0.440	0.145	0.177	1.135	0.075	0.035	0.030	0.073	0.111	0.058
Y_{5ht}: Day-ahead forecast of REGDN requirement (GW) in hour *h* on day *t*	0.396	0.118	0.157	0.855	0.034	0.003	0.004	0.022	0.256	0.026

Z_{2ht}: Day-ahead forecast of RRS offer (GW) in hour *h* on day *t*	4.919	0.813	3.104	7.693	0.006	-0.044	-0.023	-0.027	-0.049	0.018
Z_{3ht}: Day-ahead forecast of NSRS offer (GW) in hour *h* on day *t*	4.208	0.976	2.560	9.236	0.033	0.019	0.027	0.027	0.025	0.033
Z_{4ht}: Day-ahead forecast of REGUP offer (GW) in hour *h* on day *t*	2.088	0.494	1.090	3.634	-0.003	-0.043	-0.027	-0.029	-0.086	0.007
Z_{5ht}: Day-ahead forecast of REGDN offer (GW) in hour *h* on day *t*	1.722	0.598	0.769	3.491	0.015	-0.015	0.003	0.001	-0.033	0.018

Table 2. IT3SLS results for the six price regressions with AR(n = 3) errors; sample period: 01/01/2011 to 12/30/2017; sample size = 60,801 hourly observations; coefficient estimates in **bold** are significant at the 1% level; coefficient estimates with the wrong sign are in *italic*; the estimates in [ ] for Eq. (6) measure the effects of forecast errors on the RTM energy price

Variable: Definition	Eq. (1): P_{1ht} = DAM energy price ($/MWh) in hour *h* on day *t*	Eq. (2): P_{2ht} = RRS price ($/MW) in hour *h* on day *t*	Eq. (3): P_{3ht} = NSRS price ($/MW) in hour *h* on day *t*	Eq. (4): P_{4ht} = REGUP price ($/MW) in hour *h* on day *t*	Eq. (5): P_{5ht} = REGDN price ($/MW) in hour *h* on day *t*	Eq. (6): P_{6ht} = RTM energy price ($/MWh) in hour *h* on day *t*
Adjusted R^2	0.745	0.929	0.622	0.807	0.360	0.453
Root mean square error (*RMSE*)	27.94	14.97	19.89	25.96	7.04	51.95
P_{1ht} = DAM energy price ($/MWh) in hour *h* on day *t*		**0.982**	**0.436**	**0.955**	**0.038**	**0.551**
P_{2ht} = RRS price ($/MW) in hour *h* on day *t*						**-0.125**
P_{3ht} = NSRS price ($/MW) in hour *h* on day *t*						**0.042**
P_{4ht} = REGUP price ($/MW) in hour *h* on day *t*						**0.016**
P_{5ht} = REGDN price ($/MW) in hour *h* on day *t*						**-0.087**
G_t: Day-ahead Henry Hub natural gas price forecast ($/MMBtu) on day *t*	**9.851**					**[16.22]**
N_{ht}: Day-ahead nuclear generation forecast (GWh) in hour *h* on day *t*	**-1.085**					[-2.521]
D_{ht}: Day-ahead system load forecast (GWh) in hour *h* on day *t*	**2.644**					**[3.364]**
W_{ht}: Day-ahead wind generation forecast (GWh) in hour *h* on day *t*	**-1.645**					**[-2.309]**
Q_{2ht}: Day-ahead forecast of RRS procurement (GW)		**3.590**				[10.676]

in hour *h* on day *t*						
S_{ht}: Day-ahead forecast of the share of RRS requirement met by load resources in hour *h* on day *t*		**-12.557**				**[-72.783]**
Q_{3ht}: Day-ahead forecast of NSRS procurement (GW) in hour *h* on day *t*			**5.406**			[-16.083]
Q_{4ht}: Day-ahead forecast of REGUP procurement (GW) in hour *h* on day *t*				**16.686**		[-14.800]
Q_{5ht}: Day-ahead forecast of REGDN procurement (GW) in hour *h* on day *t*					**31.354**	[-6.297]
Y_{2ht}: Day-ahead forecast of RRS requirement (GW) in hour *h* on day *t*	3.908					[71.758]
Y_{3ht}: Day-ahead forecast of NSRS requirement (GW) in hour *h* on day *t*	1.501					[13.115]
Y_{4ht}: Day-ahead forecast of REGUP requirement (GW) in hour *h* on day *t*	**19.592**					[-114.614]
Y_{5ht}: Day-ahead forecast of REGDN requirement (GW) in hour *h* on day *t*	2.517					**[674.952]**
Z_{2ht}: Day-ahead forecast of RRS offer (GW) in hour *h* on day *t*		**-2.140**				[0.094]
Z_{3ht}: Day-ahead forecast of NSRS offer (GW) in hour *h* on day *t*			**-0.882**			[0.512]
Z_{4ht}: Day-ahead forecast of REGUP offer (GW) in				**-4.353**		**[-16.161]**

hour *h* on day *t*						
Z_{5ht}: Day-ahead forecast of REGDN offer (GW) in hour *h* on day *t*					**-2.178**	[9.176]

Note: For brevity, this table omits the highly significant (*p*-value < 0.01) intercept estimates. The AR order *n* = 3 is determined by their highly significant (*p*-value < 0.01) parameter estimates. Increasing *n* does not materially change the regression results because the resulting additional AR parameter estimates are close to zero with dwindling statistical significance. Finally, the regression-specific sums of the AR parameter estimates are positive and well below 1.0, suggesting that the regression residuals do not follow a random walk that can cause spurious regression results.

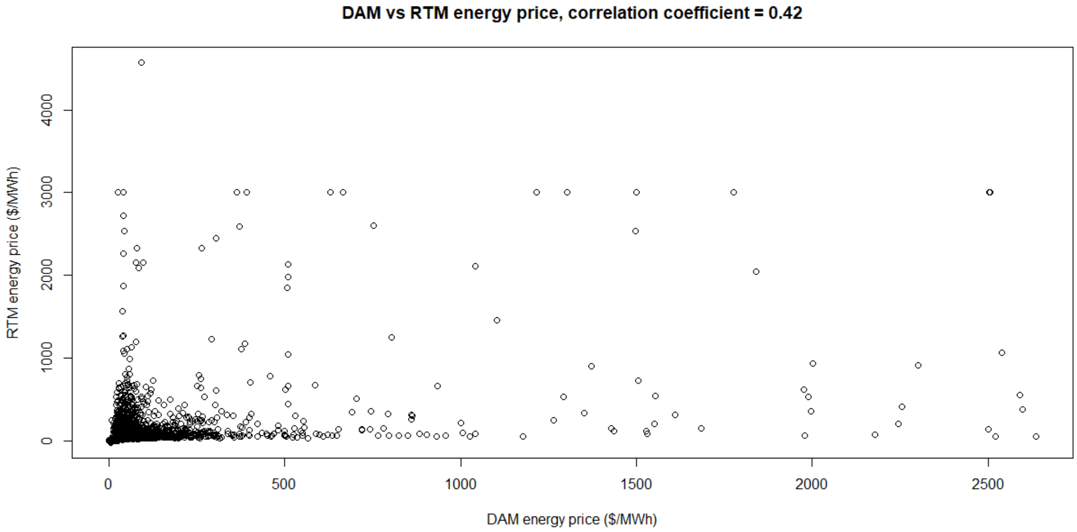

Fig. 1. Scatter plot of hourly DAM energy price vs. hourly RTM energy price. If empirically valid, the efficient market hypothesis (EMH) implies that the OLS regression, RTM energy price in hour *h* on day *t* = $\alpha + \beta$ DAM price in hour *h* on day *t* + error, should have an intercept estimate α close to zero and a slope coefficient β close to one. For the sample period: 01/01/2011 to 12/30/2017, we find a = 13.52 (p-value < 0.01) and b = 0.53 (p-value < 0.01). As b is positive and highly significant, the DAM energy price systematically moves the RTM energy price. However, the p-value of the F-statistic for testing the null hypothesis of $\alpha = 0$ and $\beta = 1$ is less than 0.01, causing us to decisively reject the EMH's empirical validity.