Energy trading efficiency in ERCOT's day-ahead and real-time electricity markets

Article *in* The Journal of Energy Markets · January 2022

DOI: 10.21314/JEM.2022.017

Chen-Hao Tsai
Midcontinent Independent System Operator

Jay Zarnikau
University of Texas at Austin

Energy trading efficiency in ERCOT's day-ahead and real-time electricity markets

K.H. Cao[a], H.S. Qi[b], C.H. Tsai[c], C.K. Woo[d], J. Zarnikau[e,*]

[a] Department of Economics, Hong Kong Baptist University, Kowloon Tong, Hong Kong

[b] Shenzhen Audencia Fintech Institute, Shenzhen University, Guangdong, China

[c] Midcontinent Independent System Operator (MISO), Eagan, MN 55121, USA

[d] Department of Asian and Policy Studies, Education University of Hong Kong, Tai Po, Hong Kong

[e] Department of Economics, The University of Texas at Austin, TX 78712, USA

[*] Corresponding author

Email addresses: kanghuacao@hkbu.edu.hk (K.H. Cao); steffan@szu.edu.cn (H.S. Qi); ctsai@misoenergy.org (C.H. Tsai); chiwoo@euduhk.hk (C.K. Woo); jayz@utexas.edu (J. Zarnikau)

Keywords: Wholesale electricity market, efficient market hypothesis, energy trading efficiency, price level regressions, price difference regressions, ERCOT

Abstract

The efficient market hypothesis (EMH) is a fundamental tenet of active and unfettered market trading. The EMH for inter-temporal trading of a commodity like natural gas implies (a) today's futures price is an unbiased predictor of a future delivery period's spot price; and (b) the difference between today's futures and spot prices reflects the commodity's cost of carrying. The EMH for inter-regional trading requires the commodity's regional price difference to equal the inter-regional transportation cost. Using regional hourly data for 01/01/2011 to 12/31/2020 from the Electric Reliability Council of Texas (ERCOT), we update the answers to the following questions: (1) is the EMH empirically valid in ERCOT's wholesale electricity markets? (2) if not, what is the extent of energy trading inefficiency? and (3) what can be done to reduce ERCOT's energy trading inefficiency? By estimating a parsimonious system of eight price levels and four price difference regressions, we reject the inter-day EMH for all regions and the inter-regional EMH for all regional market pairs. However, ERCOT's extent of trading inefficiency is mild when compared to the wholesale energy prices. Our empirics yield two policy implications. First, enhancing ERCOT's inter-day trading efficiency entails improving the day-ahead forecasts for solar and wind generation and refining ERCOT's indicative real-time market prices. Second, enhancing ERCOT's inter-regional trading efficiency requires transmission capacity expansion to reduce transmission congestion and line losses.

1. Introduction

The efficient market hypothesis (EMH) of no arbitrage profit is a fundamental tenet of active and unfettered market trading (Malkiel, 2003, 2005). The EMH for inter-temporal trading of a non-electric commodity like natural gas implies (a) today's futures price is an unbiased predictor of a future delivery period's spot price; and (b) the difference between today's futures and spot prices reflects the commodity's cost of carrying (Eydeland and Wolyniec, 2003). The EMH for inter-regional trading requires the commodity's regional price difference to equal the inter-regional transportation cost (Woo et al., 2006).

While EMH for inter-temporal trading is largely valid for storable commodities such as natural gas and oil, it is rejected by a wholesale electricity market's statistically significant (*p*-value ≤ 0.05) forward premium found in California (Woo et al., 2015, 2016), Texas (Zarnikau et al., 2015, 2019), the Midcontinent (Woo et al., 2001; Cao et al., 2021), and the Pacific Northwest (Woo et al., 2011a).

The wholesale electricity markets in the US are, for the most part, integrated (Woo et al., 1997; Douglas and Popova, 2011). However, statistically significant regional price differences are found in Texas (Woo et al., 2011b) and the US Midcontinent (Cao et al., 2021), questioning the empirical validity of the EMH for inter-regional trading.

Texas's regional price differences before 2011 were mainly attributable to transmission constraints that limited electricity export from the West region with large-scale wind energy development but relatively low regional load to the non-West regions with dissimilar features (Woo et al., 2011b). That said, the competitive renewable energy zones (CREZ) project completed in 2014 had greatly mitigated these constraints (Du and Rubin, 2018).

Motivated by the EMH discussion in connection to Texas, this paper uses a large and recent sample of hourly data from Electric Reliability Council of Texas (ERCOT) to update the answers to the following questions: (1) is the EMH empirically valid in ERCOT's wholesale electricity markets? (2) if not, what is the extent of energy trading inefficiency? and (3) what can be done to enhance ERCOT's energy trading efficiency? These real-world relevant questions are policy important because energy trading inefficiency diminishes wholesale market competition's benefit of displacing high-cost supplies with low-cost supplies across space and time (Stoft, 2002).

Our analysis is shaped by Texas's wholesale electricity market design. Using the theory of nodal pricing (Stoft, 2002), ERCOT administers the day-ahead market (DAM) and real-time market (RTM) for six interdependent wholesale electricity products (Zarnikau et al., 2019).[1] To answer question (1) noted above, we empirically test the EMH for inter-day energy trading between the DAM and RTM in the largest four of ERCOT's eight Load Zones indexed by j = 1 to 4 shown in Figure 1: (1) West, (2) North, (3) South, and (4) Houston.

The EMH for inter-regional trading reflects buying (selling) an amount of energy in one regional market in hour h on day d and selling (buying) the same amount in another regional market in hour h on day d. The inter-regional EMH is empirically valid if inter-regional price differences are on average equal to inter-regional transmission costs (Woo et al., 1997).

The paper's econometric approach comprises: (1) four regressions for regional day-ahead energy price levels; (2) four regressions for day-ahead system AS price levels; and (3) four regressions for regional differences between DAM and RTM energy prices. Joint estimation of

[1] The DAM facilitates day-ahead trading of energy and ERCOT's day-ahead procurement of four ancillary services (AS): (1) responsive reserve (RRS), (2) regulation up (REGUP), (3) regulation down (REGDN), and (4) non-spinning reserve (NSPIN). The RTM settles imbalances between energy transactions scheduled on day d-1 and those realized on day d, accounting for a small share of ERCOT's total energy trading volume.

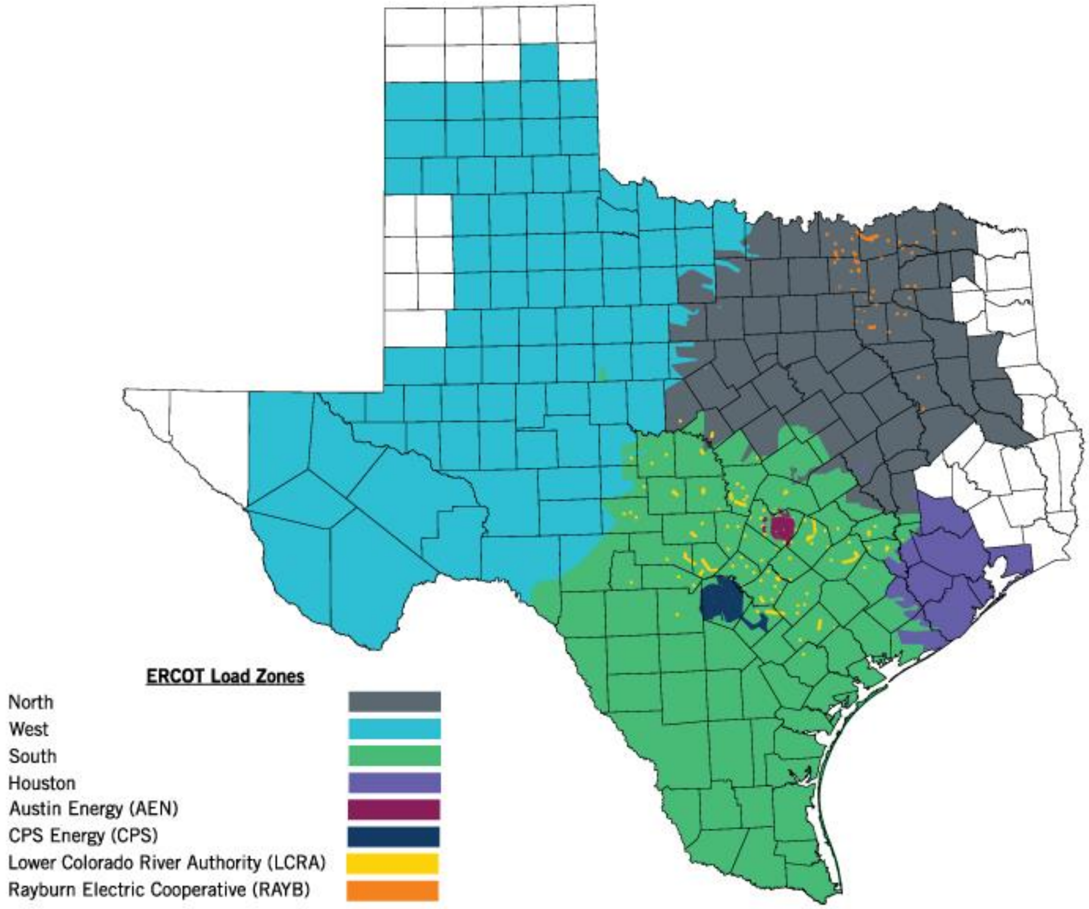

Figure 1. ERCOT's four wholesale market regions: West, North, South, and Houston, excluding the load zones of Rayburn, Austin Energy, LCRA and CPS that do not have retail competition.

(1) to (3) uses a large sample of ERCOT's regional hourly data for the 120-month period of 01/01/2011 to 12/31/2020.[2] The period's starting date reflects ERCOT's implementation of nodal pricing on 12/01/2010 to replace zonal pricing, and the ending date indicates the most recent data available at the time of writing.

Our paper's main contribution is the following newly developed empirics. First, the inter-day EMH is rejected for all regions based on the *p*-value ≤ 0.05 criterion used throughout this

[2] As the data sources are detailed in Zarnikau et al. (2019), they omitted for brevity. The complete dataset is available from the corresponding author upon request.

paper. However, the extent of inefficiency is mild because the regional forward premia are $1.22/MWh to $1.61/MWh, which are relatively small compared to the average regional DAM energy prices of $31.06/MWh to $34.99/MWh.[3]

Second, the inter-regional EMH is rejected for all market pairs, each formed by two different regions. Indicating modest inefficiency in inter-regional trading, the hourly inter-regional price differences average -2.12/MWh to $3.93/MWh for the DAM and -$2.23/MWh to $4.32/MWh for the RTM.[4]

Third, changes in the fundamental drivers that move ERCOT's regional DAM energy prices affect regional forward premia. The statistically significant drivers are the day-ahead natural gas price forecast, day-ahead system AS planned MW, day-ahead system load forecast, day-ahead system solar generation forecast, and day-ahead system wind generation forecast.[5]

Fourth, ERCOT's RTM energy prices for the summer peaking month of August increase in response to regulatory revision by the Public Utility Commission of Texas (PUCT) of the state's scarcity pricing scheme.

Fifth, ERCOT's DAM and RTM energy prices diverge because of the fundamental drivers' forecast errors measured by the differences between values realized on day *d* and those forecasted on day *d*-1.

Sixth, ERCOT's inter-regional DAM energy price differences depend on the DAM AS price levels, fundamental drivers' forecasts, and PUCT's revision of the state's scarcity pricing scheme.

[3] These estimates exceed the Midcontinent's zonal forward premia of $0.32/MWh to $0.83/MWh (Cao et al., 2021).
[4] These estimates are about 50% of those for the Midcontinent's zonal markets (Cao et al., 2021).
[5] In contrast, changes in ERCOT's energy price cap do not have statistically significant effects on regional forward premia and inter-regional price differences. Further, ERCOT's DAM energy prices did not change by a statistically significant amount after Texas's inter-regional transmission expansion completed in January 2014.

Finally, ERCOT's inter-regional RTM energy price differences increase with regional DAM energy prices and depend on system AS prices.

The rest of this paper proceeds as follows. Section 2 justifies our research focus on ERCOT, develops the 12-regression system, formulates the testable inter-day EMH and inter-regional EMH, and proposes an estimation strategy. Section 3 provides an initial exploration of energy trading efficiency across time and regions and presents our regression analysis's empirics. Section 4 contains conclusions and policy implications.

2. Materials and methods

2.1 Why ERCOT?

ERCOT is an important and interesting case study of energy trading efficiency because prior to the blackouts triggered by Winter Storm Uri in February 2021 (UT Austin, 2022), Texas was seen as a successful example of implementing market competition in the generation and retail segments of North America's electricity industry (Zarnikau et al., 2019).

ERCOT is big, accounting for over 9% of the nation's total electricity generation capacity. It serves ~90% of the state's total consumption, reaching a system peak demand of 74,328 MW on 08/13/2020.[6]

As shown in Figure 2, ERCOT has a diverse mix of generation capacities and energy outputs. Its marginal generation fuel is typically natural gas, implying that a $1/MMBtu increase in natural gas price tends to raise a region's DAM energy price by an amount close to the

[6] http://www.ercot.org/content/wcm/lists/197392/2020_Summer_Review_FINAL.pdf

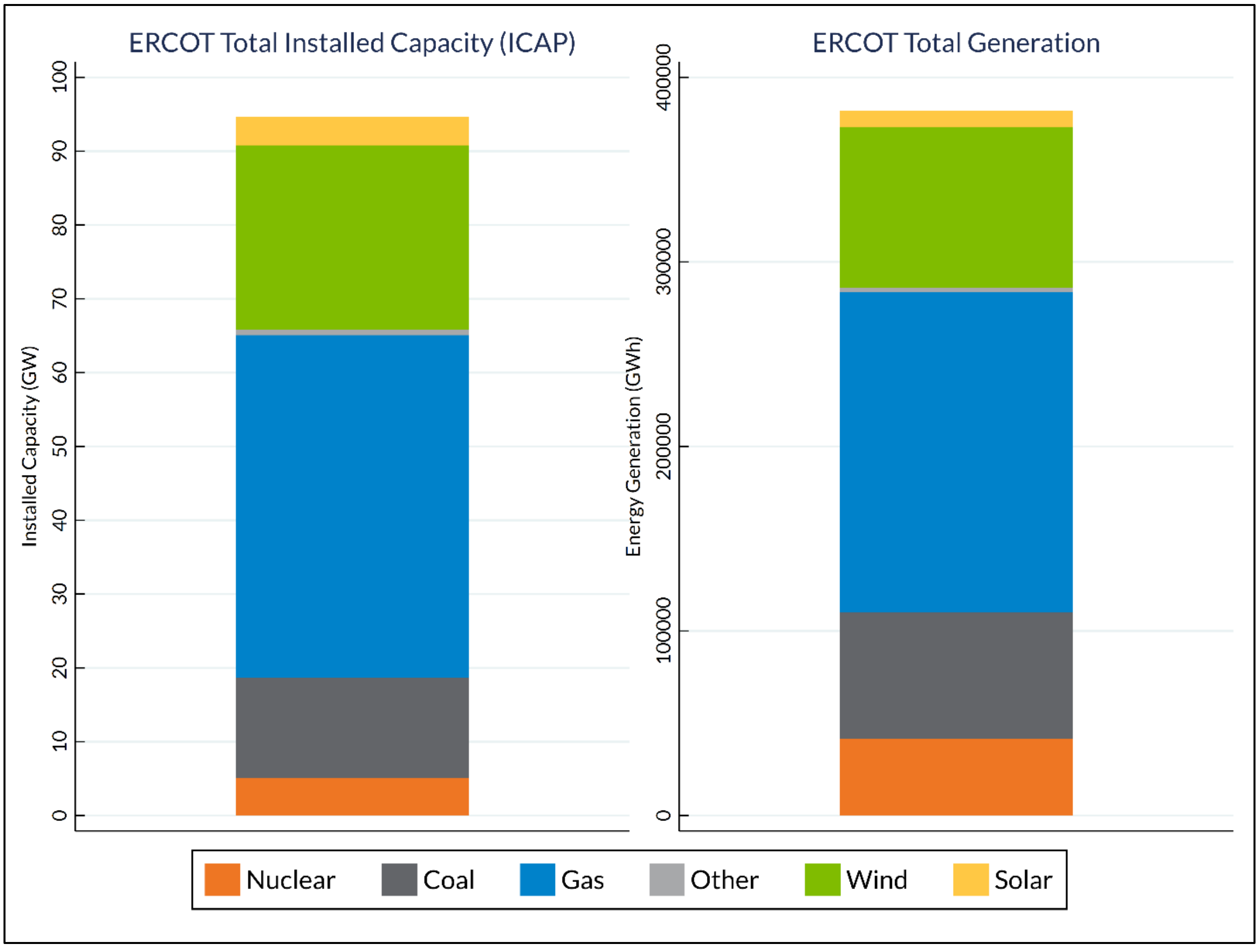

Figure 2. ERCOT's capacity and energy mix by fuel type in 2020. Note that capacity values do not necessarily reflect the capacity expected to be available at peak, particularly for wind, solar, and other resources.

engineering-based heat rates of ~7 MMBtu per MWh for a combined cycle gas turbine (CCGT) and ~9 MMBtu per MWh for a combustion turbine (CT).

Responding to the declining generation reserve margin, PUCT revised the state's scarcity pricing scheme based on the concept of an operating reserve demand curve (ORDC) in January 2019 (Zarnikau et al., 2020). The shift in the ORDC curve was implemented in two steps on 03/01/2019 and 03/01/2020 to increase the ORDC adder for RTM energy prices, thus raising the revenue of generation units that supply real-time energy when ERCOT's operating reserve falls below the 8,000-MW level.

ERCOT's cap on energy prices was \$3,000/MWh from 01/01/2011 to 07/31/2012. To encourage new plant construction, it was increased to \$4,500/MWh for 08/01/2012 to 05/31/2013, \$5,000/MWh for 06/01/2013 to 05/31/2014, \$7,000/MWh for 06/01/2014 to 05/31/2015, and \$9,000/MWh for the remaining months of our sample period.

Texas is the leading state in the US in wind generation development. In 2020, ERCOT had a total installed wind capacity of 25.1 GW and will have an expected addition of 36.7 GW by 2023 if all wind projects with interconnection agreements are timely completed. While solar generation's installed capacity was only 3.9 GW in 2020, ERCOT expects 22 GW of new solar capacity by 2023 if all solar projects with interconnection agreements are timely completed.

Motivated by ERCOT's salient features noted above, our regression analysis delineates the empirical effects of state's electricity policies on ERCOT's regional forward premia and inter-regional price spreads. The policies considered herein are renewable energy development, inter-regional transmission expansion, ERCOT's energy price cap, and PUCT's ORDC revision.

2.2 Regression system

Guided by Zarnikau et al. (2019) and Cao et al. (2021), this section specifies the regional DAM energy price regressions, the system AS price level regressions, and the regional DAM-RTM energy price difference regressions. Transparently portraying what moves ERCOT's regional forward premia and inter-regional price spreads, these regressions are linear rather than log-linear because of occasionally negative DAM and RTM energy prices and frequently negative DAM-RTM energy price differences.

2.3.1 Price level regressions

We begin by defining the endogenous variables of our price level regressions: (a) P_{jt} = region j' hourly DAM energy price (\$/MWh) in time interval t = 1 for hour ending 01:00 on

01/01/2011 and T = 87,684 for hour ending 24:00 on 12/31/2020; (b) A_{1t} = hourly systemwide DAM AS price ($/MW) for RRS; (c) A_{2t} = hourly systemwide DAM AS price for REGUP; (d) A_{3t} = hourly systemwide DAM AS price ($/MW) for REGDN; (e) A_{4t} = hourly systemwide DAM AS price ($/MW) for NSPIN; and (f) R_{jt} = region j's hourly RTM energy price ($/MWh) = MWh-weighted average of region j's 15-minute RTM prices within interval t, thereby matching the hourly frequency of DAM prices.

Associated with ERCOT's regions with retail competition are four regional DAM energy price level regressions. We assume that region j's DAM price level regression with random error ε_{jt} is:

$$P_{jt} = \theta_{jt} + \theta_{jCREZ}\, CREZ_t + \theta_{jCAP}\, CAP_t + \theta_{jG}\, G_t + \theta_{jD}\, D_t + \theta_{jN}\, N_t + \theta_{jS}\, S_t + \theta_{jW}\, W_t + \theta_{jY}\, Y_t + \varepsilon_{jt}. \quad (1)$$

In equation (1), θ_{jt} is region j's time-varying intercept, postulated as a linear function of intercept θ_j and binary indicators for the hour of the day, weekend, and month of the year. This function's coefficients are region-specific, implying that θ_{jt} varies across regions, accounting for the residual price effects uncaptured by the remaining regressors listed below.

The remaining regressors of equation (1) are as follows:

- Variable $CREZ_t$ is a binary indicator = 1 if t is after 2013, 0 otherwise. Its coefficient is $\theta_{jCREZ} > 0$ for $j = 1$, measuring CREZ completion's expected price increase effect in the West region due to the region's rising export of wind energy to the other regions. However, $\theta_{jCREZ} < 0$ for $j > 1$ because of the rising import of wind energy from the West region.
- Variable CAP_t is ERCOT's cap for energy prices, whose expected price effect is $\theta_{jCAP} > 0$, reflecting that a higher cap permits larger price spikes.

- Variable G_t is the day-ahead forecast of Henry Hub natural gas price (\$/MMBtu),[7] whose coefficient is $\theta_{jG} > 0$ that measures the market-based marginal heat rate (Woo et al., 2016). We expect θ_{jG}'s size to be 7 to 9 MMBtu/MWh, closely matching the engineering-based heat rates of CCGT and CT. As a result, the regional estimates for $\{\theta_{jG}\}$ help determine if equation (1) is an empirically reasonable representation of the data generation process (DGP) of regional DAM energy prices.
- Variable N_t is the day-ahead nuclear generation (MWh) forecast based on the amount cleared in the DAM. Its expected price reduction effect is $\theta_{jN} < 0$ because rising nuclear generation displaces marginal generation likely fuelled by natural gas.
- Variable D_t is ERCOT's day-ahead forecast of system load (MWh), whose marginal price effect is $\theta_{jD} > 0$ because rising load causes dispatch of generation units with higher per MWh fuel costs.[8]
- Variable S_t is ERCOT's day-ahead forecast of system solar generation (MWh), whose merit order effect is measured by $\theta_{jS} < 0$.
- Variable W_t is ERCOT's day-ahead forecast of system wind generation (MWh), whose merit order effect is measured by $\theta_{jW} < 0$.
- Variable Y_t is ERCOT's day-ahead planned AS MW. Its coefficient is $\theta_{jY} > 0$, reflecting that ERCOT's rising AS need tends to reduce supply bidding into region j's DAM energy market.

---

[7] We use the Henry Hub price because while highly correlated ($r > 0.95$) with Texas's intra-state natural gas prices, it is exogenously determined by natural gas market conditions in the US. As ERCOT does not provide day-ahead forecasts for G_t, we use PROC FORECAST in SAS to automatically produce the necessary data.

[8] Our initial regression investigation uses regional load forecasts as regressors. Half of the load-related coefficient estimates are statistically insignificant or have unexpectedly negative signs, leading to our decision to use the system load forecast to account for the demand-driven price effect.

Associated with ERCOT's AS products are four systemwide DAM AS price level regressions. Recognizing energy trading's dominance in the DAM, we assume the RRS price regression with intercept α_1 and error μ_{1t} is:

$$A_{1t} \quad = \quad \alpha_1 + \beta_1 P_t + \psi_1 Y_{1t} + \lambda_1 Z_{1t} + \mu_{1t}. \qquad (2)$$

In equation (2), α_1 is not time-varying because P_t is the load-weighted average of regional DAM energy prices $\{P_{jt}\}$, already embodying the effects of the hour of the day, weekend, and month of the year. We decide not to use $\{P_{jt}\}$ as separate regressors for three reasons. First, P_t and A_{1t} are dimensionally matched systemwide prices. Second, high correlations ($r > 0.90$) among $\{P_{jt}\}$ cause severe multicollinearity. Finally, equation (2) has been found empirically reasonable for characterizing A_{1t}'s data generating process (DGP) (Zarnikau et al., 2019).

We expect $\beta_1 > 0$ because when a supplier sees rising P_t, it tends to reduce its supply bidding into the DAM for RRS. We expect $\psi_1 > 0$ because an increase in Y_{1t} = RRS MW target has a positive demand-driven effect on A_{1t}. Variable Z_{1t} is the total RRS offered by eligible resources. Its coefficient is $\lambda_1 < 0$, reflecting the negative supply-driven effect on A_{1t}. We analogously specify the remaining three systemwide DAM AS price regressions.

There are four regional RTM energy price level regressions which we do not estimate but are necessary for deriving the DAM-RTM energy price difference regressions in Section 2.3.2 below. Reflecting energy trading's dominance in the DAM, we assume region j's RTM energy price level regression with intercept ϕ_j and random error η_{jt} is:

$$R_{jt} \quad = \quad \phi_j + \phi_{j8ORDC1}\, ORDC_t\, M_{8t}\, TOD_t + \phi_{j8ORDC2}\, ORDC_t\, M_{8t}\, (1 - TOD_t) + \phi_{jP}\, P_{jt} + \Sigma_m\, \phi_{jm}\, A_{mt} + E_{jt} + \eta_{jt}. \qquad (3)$$

The term $ORDC_t\, M_{8t}\, TOD_t$ in equation (3) aims to capture the RTM price effect of PUCT's ORDC revision, where $ORDC_t = 1$ if t is in the period of 03/01/2019 to 12/31/2020, 0 otherwise;

M_{8t} = 1 if t is in August, 0 otherwise; and TOD_t = 1 if t is in the 12:00 – 18:00 period, 0 otherwise.[9] This term's construction reflects that the ORDC revision's price effect is expected to occur when ERCOT has low operating reserves caused by hot summer weather (Potomac Economics, 2021). The coefficient for $ORDC_t\, M_{8t}\, TOD_t$ is $\theta_{j8ORDC1} > 0$, measuring the ORDC revision's expected price increase in the 12:00 – 18:00 period of the summer peaking month of August. Similarly, $\theta_{j8ORDC2} > 0$ is the ORDC revision's expected price increase for the hours outside the 12:00 – 18:00 period in August.

Region j's day-ahead energy price P_{jt}'s coefficient is $\phi_{jP} > 0$, measuring the expected marginal effect of P_{jt} on region j's real-time energy price R_{jt}. Further, $\phi_{jm} > 0$ is the expected marginal real-time price effect of AS price A_{mt}. Finally, $E_{jt} = \Sigma_q\, \varphi_{qj}\, E_{qjt}$ is the aggregate price impact of forecast errors $\{E_{qjt}\}$ related to the fundamental drivers of the DAM energy prices. While the estimates for $\{\varphi_{qj}\}$ are likely statistically significant, their signs are not *a prior* known.

2.3.2 DAM-RTM energy price difference regressions for testing inter-day EMH

The set of four price difference regressions is related to inter-day energy trading. Based on equation (3), region j's DAM-RTM price difference regression is:

$$\begin{aligned} P_{jt} - R_{jt} \quad = \quad & -\phi_j + (1 - \phi_{jP})\, P_{jt} - \phi_{j8ORDC1}\, ORDC_t\ \ M_{8t}\, TOD_t\, - \\ & \phi_{j8ORDC2}\, ORDC_t\ \ M_{8t}\, (1 - TOD_t) - \Sigma_m\, \phi_{jm}\, A_{mt} - E_{jt} - \eta_{jt}. \qquad (4) \end{aligned}$$

In equation (4), $(1 - \phi_{jP})$ is the expected effect of a \$1/MWh increase on the DAM-RTM price difference. If the inter-day EMH is empirically valid, region j's forward premium π_j = expected DAM-RTM price difference = $E(P_{jt} - R_{jt}) = 0$. Based on Table 1 and ERCOT's ongoing improvements in forecasting solar and wind generation, we assume the expected value of E_{jt} =

[9] Our exploratory regression analysis finds that the ORDC-related coefficient estimates for other months have p-values > 0.05, consistent with our expectation that the ORDC revision's price effects mainly occur in the state's peak demand month of August.

$E(E_{jt}) = 0$. Hence, the testable EMH based on $\pi_j = 0$ is **H1**: $\phi_j = 0$, $(1 - \phi_{jP}) = 0$, $\phi_{j8ORDC1} = 0$, $\phi_{j8ORDC2} = 0$, and $\phi_{jm} = 0$ for all m.

If **H1** is rejected, we use equation (4) to explain variations in region *j*'s DAM-RTM price difference. Specifically, region *j*'s DAM-RTM price difference variations can be traced to changes in the factors that affect the region *j*'s DAM prices for energy and AS. For example, if $(1 - \phi_{jP}) > 0$, an increase in system load or natural gas price that raises P_{jt} based on equation (1) tends to magnify region *j*'s DAM-RTM price difference based on equation (4). As $\phi_{j8ORDC1} > 0$ and $\phi_{j8ORDC2} > 0$, the PUCT's ORDC revision tends to reduce region *j*'s DAM-RTM price difference. Finally, if $\phi_{jm} \neq 0$, changes in A_{mt} based on equation (2) further affect region *j*'s DAM-RTM price difference.

2.3.3 The inter-regional EMH for DAM energy trading

To develop the inter-regional EMH for DAM energy trading, we recall equation (1) to find the inter-regional DAM energy price difference for $j < k$:

$$
\begin{aligned}
P_{jt} - P_{kt} \quad = \quad & \theta_{jkt} + \theta_{jkCREZ}\, CREZ_t + \theta_{jkCAP}\, CAP_t + \theta_{jkG}\, G_t + \theta_{jkD}\, D_t + \theta_{jkN}\, N_t + \theta_{jkS}\, S_t + \\
& \theta_{jkW}\, W_t + \theta_{jkY}\, Y_t + (\varepsilon_{jt} - \varepsilon_{kt}). \qquad (5)
\end{aligned}
$$

Estimation of equation (5) is unnecessary because its slope coefficients are linked to those in equation (1). For example, $\theta_{jkt} = (\theta_{jt} - \theta_{kt})$ is the difference between the time-varying intercepts for regions *j* and *k*. Similarly, $\theta_{jkCREZ} = (\theta_{jCREZ} - \theta_{kCREZ})$, $\theta_{jkCAP} = (\theta_{jCAP} - \theta_{kCAP})$, …, $\theta_{jkY} = (\theta_{jY} - \theta_{kY})$.

Empirical validity of the inter-regional EMH for DAM energy trading requires: (a) θ_{jkt} = day-ahead marginal cost of inter-regional transmission; ***and*** (b) all slope coefficients in equation (5) equal to zero. While not knowing (a), we can use (b) as the testable hypothesis **H2** ≡ EMH

Table 1. Fundamental driver forecast's mean error (ME) = average of actual values – average of forecast values; percentage of ME = ME ÷ average of actual values; sample period = 01/01/2011 – 12/31/2020

Day-ahead forecast	Average of realized values	Average of forecast values	Mean error (ME)	Percentage of ME
G_t = Henry Hub natural gas price ($/MMBtu)	3.07	3.07	0.00	0.00%
D_t = System load (MWh)	40266.28	40243.04	23.24	0.06%
N_t = Nuclear generation (MWh)	4557.98	4558.06	-0.08	0.00%
S_t = System solar generation (MWh)	233.70	239.49	-5.79	-2.48%
W_t = System wind generation (MWh)	5893.26	6116.73	-223.48	-3.79%

Table 2. Regional DAM price correlations in above-diagonal cells for the sample period of 01/01/2011 – 12/31/2020; price correlations = 1 for diagonal cells denoted by ◆; averages of regional DAM price differences in below-diagonal cells; average price difference = 0 for ◆; statistically significant (p-value $\leqslant$ 0.05) average price differences in **bold**

Region j	Region k			
	(1) West	(2) North	(3) South	(4) Houston
(1) West	◆	0.9818	0.9705	0.9792
(2) North	**3.9286**	◆	0.9882	0.9977
(3) South	**1.8118**	**-2.1168**	◆	0.9884
(4) Houston	**2.8447**	**-1.0839**	**1.0329**	◆

Table 3. Regional RTM price correlations in above-diagonal cells for the sample period of 01/01/2011 – 12/31/2020; price correlations = 1 for diagonal cells denoted by ◆; averages of regional RTM price differences in below-diagonal cells; average price difference = 0 for ◆; statistically significant (p-value $\leqslant$ 0.05) average price differences in **bold**

Region j	Region k			
	(1) West	(2) North	(3) South	(4) Houston
(1) West	◆	0.9511	0.8988	0.9185
(2) North	4.3172	◆	0.9402	0.9616
(3) South	2.0916	-2.2255	◆	0.9386
(4) Houston	3.1478	-1.1693	1.0562	◆

for inter-regional day-ahead energy trading based on the linear restrictions of $(\theta_{jCREZ} - \theta_{kCREZ}) = 0$, $(\theta_{jCAP} - \theta_{kCAP}) = 0$, …, $(\theta_{jY} - \theta_{kY}) = 0$.

2.3.4 The inter-regional EMH for real-time energy trading

To develop the inter-regional EMH for real-time energy trading, we use equation (4) and $E_{jt} = E_{kt}$ because they are systemwide numbers to find the RTM energy price difference between regions j and k:

$$R_{jt} - R_{kt} = \phi_{jk} + \phi_{jk8ORDC1}\, ORDC_t\ M_{8t}\, TOD_t + \phi_{jk8ORDC2}\, ORDC_t\ M_{8t}\, (1 - TOD_t) + \phi_{jP}\, P_{jt} - \phi_{kP}\, P_{kt} + \Sigma_m\, \phi_{jkm}\, A_{mt} + (\eta_{jt} - \eta_{kt}), \quad (6)$$

where $\phi_{jk} = (\phi_j - \phi_k)$, $\phi_{jk8ORDC1} = \phi_{j8ORDC1} - \phi_{k8ORDC1}$, $\phi_{jk8ORDC2} = \phi_{j8ORDC2} - \phi_{k8ORDC2}$, and $\phi_{jkm} = (\phi_{jm} - \phi_{km})$.

Empirical validity of the inter-regional EMH for real-time trading requires: (a) ϕ_{jk} = real-time marginal cost of inter-regional transmission; ***and*** (b) the non-intercept coefficients equal to zero. While not knowing (a), we use (b) as the testable hypothesis **H3** ≡ inter-regional EMH for RTM energy trading based on the linear restrictions of $(\phi_{j8ORDC1} - \phi_{k8ORDC1}) = 0$, $(\phi_{j8ORDC2} - \phi_{k8ORDC2}) = 0$, $\phi_{jP} = 0$, $\phi_{kP} = 0$, and $(\phi_{jm} - \phi_{km}) = 0$ for all $m = 1, \ldots, 4$.

2.4 Estimation strategy

As our system of 12 regressions have random errors that are likely contemporaneously and serially correlated, we use full information maximum likelihood (FIML) of PROC MODEL in SAS to estimate the system under the assumption these errors follow an AR(a) process for $a = 1$, …, 6. The final choice of $a = 4$ is empirically determined by the size and statistical significance of the AR parameter estimates.

3. Empirics

3.1 Initial exploration

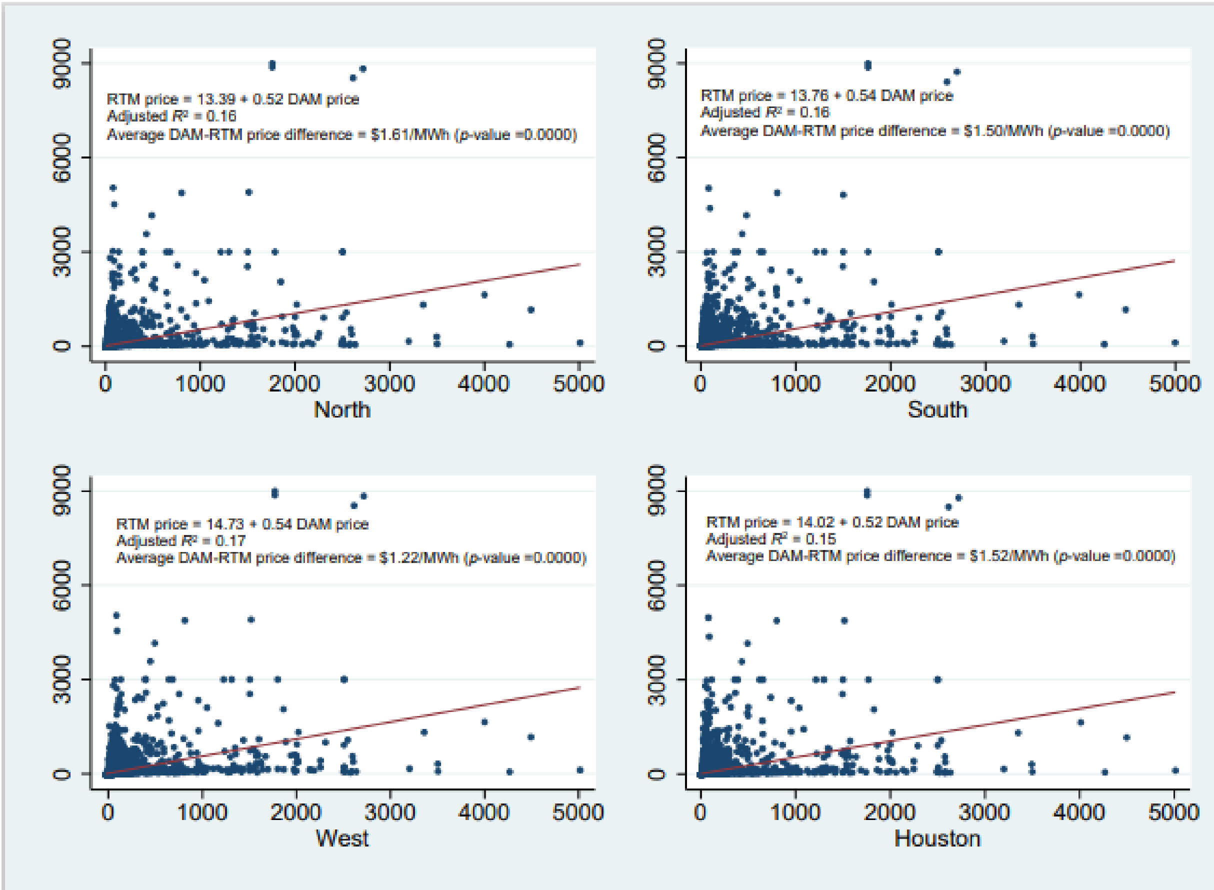

Figure 3. Scatter plots of regional RTM price (vertical axis in $ per MWh) vs. regional DAM price (horizontal axis in $ per MWh); sample period = 01/01/2001 - 12/31/2020; *F*-statistic's *p*-value < 0.0001 for testing H_0: intercept = 0 and slope = 1 in connection to each region's OLS regression line

To initially explore ERCOT's energy price differences, Figure 3 contains scatter plots of regional DAM energy price (horizontal axis) vs. regional RTM energy price (vertical axis). This figure questions the EMH's empirical validity for inter-day energy trading for two reasons. First, it rejects the EMH for inter-day trading when stated as H_0: intercept = 0 and slope = 1 in connection to each region's OLS regression line (Zarnikau et al., 2015). Second, each region's average DAM-RTM difference is positive and statistically significant.

Table 2 shows high DAM price correlations ($r > 0.97$) between two regional markets. Further, all six regional market pairs have statistically significant average price differences, doubting the EMH's empirical validity for inter-regional DAM energy trading. Based on the regional RTM price data, Table 3 corroborates the story told by Table 2.

While indicative, the preceding figures and tables do not untangle the determinants of ECORT's regional forward premia and inter-regional price differences, a task better achieved by the regression results presented below.

3.2 Regression results

This section presents our regression results in an order that matches Section 2.3's development of the 12-regression system. It begins with Table 4 that reports the descriptive statistics of the regressors of the four regional DAM price level regressions. It also reports price correlations that are, for the most part, consistent with our expectations.

3.2.1 Regional DAM energy price level regressions

Panel A of Table 5 reports the results for the DAM energy price level regressions. The mean DAM energy price levels are \$31/MWh to \$35/MWh, less than the ~\$38/MWh estimated volatility (i.e., RMSE) of the regression errors. The adjusted R^2 values are around 0.75, reflecting that these regressions are empirically plausible DGP of the noisy hourly DAM energy price data. While 12 of the 36 coefficient estimates have unexpected signs, they are all statistically insignificant.

The coefficient estimates in Panel A yield the following inferences:

- The estimates for $CREZ_t$ indicate that the regional DAM price levels are not significantly different between the pre- and post-CREZ periods, contrary to the expectation that the CREZ's completion should raise the DAM energy prices in the West region and reduce those in the non-West regions. We attribute this odd finding to (a) our use of $CREZ_t$, a binary indicator to crudely capture the price effects of transmission capacity expansion; and (b) our

Table 4. Descriptive statistics and price correlations of the metric regressors of the regional DAM price level regressions; sample period = 01/01/2011 – 12/31/2020; counter-intuitive price correlations in *italic*

Regressor	Definitions	Descriptive statistics				Correlation with regional DAM price levels			
		Mean	Standard deviation	Minimum	Maximum	(1) West	(2) North	(3) South	(4) Houston
CAP_t	ERCOT's price cap ($/MWh)	7076.81	2383.33	3000.00	9000.00	*-0.0481*	*-0.0517*	*-0.0392*	*-0.0438*
G_t	Day-ahead forecast of Henry Hub natural gas price ($/MMBtu)	3.07	0.83	0.64	8.28	0.0687	0.0853	0.0807	0.0825
D_t	Day-ahead forecast of system load (MWh)	40243.04	9678.43	20841.70	76137.93	0.2686	0.2395	0.2583	0.2485
N_t	Day-ahead forecast of system nuclear generation (MWh)	4558.06	96.80	4380.00	4729.00	-0.0199	-0.0368	-0.0244	-0.0322
S_t	Day-ahead forecast of system solar generation (MWh)	239.49	607.62	0.00	4322.20	*0.0482*	*0.0615*	*0.0849*	*0.0692*
W_t	Day-ahead forecast of system wind generation (MWh)	6116.73	4147.85	143.20	28612.20	-0.1182	-0.1005	-0.0956	-0.0979
Y_t	Day-ahead system planned AS MW	5001.27	387.80	3815.00	6550.00	-0.0419	-0.0467	-0.0579	-0.0543

sample period that includes months from 2018 to 2020 when Texas experienced diminishing planning reserve margin.

- Increases in ERCOT's price cap do not have a statistically significant effect on the regional DAM energy prices because the cap was seldom reached during our sample period.
- A \$1/MMBtu increase in the natural gas price tends to raise the regional DAM energy prices by \$7.1/MWh to \$8.3/MWh, implying that the market-based marginal heat rates for natural-gas-fired generation closely match the engineering-based heat rates of CT and CCGT. Mirroring the reality that natural gas is Texas's dominant marginal fuel, this finding lends support to the empirical plausibility of equation (1) in characterizing the DGP of the noisy DAM energy price data.
- A 1-MWh increase in system load tends to raise the regional DAM price levels by ~\$0.004/MWh, affirming the rising load's price increase effects.
- A 1-MWh increase in nuclear generation is found to have a statistically insignificant effect on DAM energy prices.
- The four coefficient estimates for solar generation are -\$0.0086/MWh to -\$0.0027/MWh, three of which are statistically significant. Hence, the regional merit order effects of solar generation appear to prevail in Texas.
- The four statistically significant coefficient estimates for wind generation are -\$0.0021/MWh to -\$0.0013/MWh, reinforcing the well-documented regional merit order effects of Texas's wind generation.
- A 1-MW increase in day-ahead total planned AS MW tends to raise the regional DAM prices by a statistically significant amount of ~\$0.05/MWh. Hence, reducing ERCOT's AS

Table 5. FIML results for the 12-regression system based on the empirically determined AR(4) process; sample period = 01/01/2011 – 12/31/2020; sample size = 87,679 hourly observations per region; statistically significant coefficient estimates (p-value < 0.05) in **bold**; coefficient estimates with wrong signs in *italic.*

Panel A. Regional DAM energy price level regressions based on equation (1)

Variable	(1) West	(2) North	(3) South	(4) Houston
Sample mean of P_{jt}	34.9863	31.0577	33.1745	32.1416
Root mean square error (RMSE)	38.0571	37.7963	37.9430	37.7596
Adjusted R^2	0.7567	0.7448	0.7481	0.7440
Intercept	**-610.07**	-214.28	-198.31	-157.51
$CREZ_t$ = 1 if t is after 2013, 0 otherwise.	*-1.9176*	*1.8338*	*1.4936*	*1.3680*
CAP_t = ERCOT's price cap ($/MWh)	*-0.0048*	*-0.0029*	*-0.0025*	*-0.0022*
G_t = Henry Hub natural gas price ($/MMBtu)	**7.0817**	**8.1839**	**8.2611**	**8.2058**
D_t = System load (MWh)	**0.0040**	**0.0036**	**0.0038**	**0.0036**
N_t = Nuclear generation (MWh)	*0.1077*	*0.0187*	*0.0128*	*0.0046*
S_t = System solar generation (MWh)	**-0.0086**	**-0.0036**	-0.0027	**-0.0036**
W_t = System wind generation (MWh)	**-0.0021**	**-0.0013**	**-0.0013**	**-0.0013**
Y_t = day-ahead total AS MW	**0.0058**	**0.0053**	**0.0053**	**0.0052**

Notes: (1) For brevity, this panel excludes the coefficient estimates for binary indicators of the hour of the day, weekend, and month of the year, ~16.5% of which are statistically significant.
(2) The AR(4) process is determined by the size and statistical significance of the AR parameter estimates for the entire regression system.

Panel B. System DAM AS price level regressions based on equation (2)

Variable	(1) RRS	(2) REGUP	(3) REGDN	(4) NSPIN
Sample mean of A_{mt}, where m = 1 for RRS, 2 for REGUP, 3 for REGDN, and 4 for NSPIN	14.7619	12.5726	6.4356	6.4641
Root mean square error (RMSE)	19.2864	22.1671	8.7919	31.7691
Adjusted R^2	0.9491	0.9159	0.5350	0.7209
Intercept	**-13.8403**	**-15.6100**	**-1.6545**	**-13.2443**
P_t = load weighted average of regional DAM energy prices ($/MWh)	**1.0686**	**0.9716**	**0.0784**	**0.6004**
Y_{mt} = day-ahead planned AS MW, where m = 1 for RRS, 2 for REGUP, 3 for REGDN, and 4 for NSPIN	**0.0033**	**0.0186**	**0.0327**	**0.0062**
Z_{mt} = total AS offer (MW), where m = 1 for RRS, 2 for REGUP, 3 for REGDN, and 4 for NSPIN	**-0.0031**	**-0.0055**	**-0.0040**	**-0.0023**

Panel C. Regional DAM-RTM energy price difference regressions based on equation (4)

Variable	(1) West	(2) North	(3) South	(4) Houston
Sample mean of ($P_{jt} – R_{jt}$)	1.2168	1.6055	1.4967	1.5200
Root mean square error (RMSE)	68.2158	65.1536	69.7378	69.2724
Adjusted R^2	0.5316	0.5351	0.5089	0.5089
Intercept	**3.5811**	**4.9081**	**4.8268**	**4.9677**
$ORDC_t \times M_{8t} \times TOD_t$	**67.1487**	**67.0998**	**71.6069**	**68.7739**
$ORDC_t \times M_{8t} \times (1-TOD_t)$	**17.7980**	**16.4929**	**15.4062**	**16.2335**
P_t = load weighted average of regional DAM energy prices ($/MWh)	*-0.0001*	**0.0683**	**0.0847**	**0.0535**
A_{1t} = hourly systemwide DAM AS price ($/MW) for RRS	**-0.6101**	**-0.5478**	**-0.4150**	**-0.5713**
A_{2t} = hourly systemwide DAM AS price ($/MW) for REGUP	**0.0629**	**0.0624**	**0.0430**	**0.0694**
A_{3t} = hourly systemwide DAM AS price ($/MW) for REGDN	0.1690	0.1401	0.1668	0.1158
A_{4t} = hourly systemwide DAM AS price ($/MW) for NSPIN	**0.1092**	**0.1131**	**-0.0548**	**0.1202**
E_{1jt} = Realized G_t - Projected G_t ($/MMBtu)	**9.1130**	**9.3598**	**11.6370**	**8.8034**
E_{2jt} = Realized D_t – Projected D_t (MWh)	**0.0033**	**0.0032**	**0.0036**	**0.0035**
E_{3jt} = Realized N_t – projected N_t (MWh)	-0.0001	-0.0001	-0.0001	-0.0003
E_{4jt} = Realized S_t – projected S_t (MWh)	**-0.0044**	-0.0031	-0.0024	-0.0029
E_{5jt} = Realized W_t – projected W_t (MWh)	**-0.0046**	**-0.0031**	**-0.0033**	**-0.0030**

Note: $ORDC_t$ = 1 if t is in the period of 03/01/2019 to 12/31/2020, 0 otherwise; M_{t8} = 1 if t is in August, 0 otherwise; TOD_t = 1 if t is in the six-hour window period of 12:00 - 18:00, 0 otherwise.

need by curtailing system load via demand response programs and improving the integration of renewable generation can materially decrease the regional DAM prices.

3.2.2 System DAM AS price level regressions

Panel B of Table 5 reports the results for the DAM AS price level regressions. The mean DAM AS prices of \$6.44/MW to \$14.76/MW are less than the estimated volatilities of the regression errors of \$8.79/MW to \$31.8/MW. The adjusted R^2 values range from 0.54 to 0.95, reflecting these regressions' mixed performance in characterizing the DGP of the volatile DAM AS prices. However, all coefficient estimates in Panel B have expected signs and are statistically significant.

The coefficient estimates in Panel B yield the following inferences:

- A \$1/MWh increase in the average DAM price level tends to raise the DAM AS price levels by \$0.08/MW for REGDN to \$1.07/MW for RRS. Hence, a DAM energy price increase triggered by a growing load or rising natural gas price tends to increase ERCOT's system AS prices.
- A 1-MW increase in ERCOT's day-ahead total AS MW tends to raise the DAM AS price levels by \$0.0033/MW for RRS to \$0.0327/MW for REGDN.
- A 1-MW increase in day-ahead AS offers tends to reduce the DAM AS price levels by \$0.0023/MW for NSPIN to \$0.0055/MW for REGUP.

3.2.3 Regional DAM-RTM energy price difference regressions

Panel C of Table 5 reports the results for the DAM-RTM energy price difference regressions. The mean price differences are relatively small at \$1.22/MWh to \$1.61/MWh, far below the estimated volatilities of the regression errors that range from \$65.2/MWh to \$69.7/MWh. The adjusted R^2 values are relatively low at 0.51 to 0.54, reflecting the high volatility of the DAM-RTM energy price difference data. Based on the statistically significant estimates for the average DAM energy price and system AS prices, we reject the EMH for inter-day energy trading given by **H1**: $\phi_j = 0$, $(1 - \phi_{jP}) = 0$, $\phi_{j8ORDC1} = 0$, $\phi_{j8ORDC2} = 0$, and $\phi_{jm} = 0$ for all m.

The coefficient estimates in Panel C yield the following inferences:

- The coefficient estimates for $ORDC_t \times M8t \times TOD_t$ are \$67.1/MWh to \$71.6/MWh and those for $ORDC_t \times M8t \times (1 - TOD_t)$ are \$15.4/MWh to \$17.8/MWh. These estimates by TOD have similar sizes because the ORDC adder uniformly applies to all regional RTM energy prices. They reveal the large reductions in ERCOT's regional forward premia in August due to the regional real-time energy price increases caused by the PUCT's ORDC revision.
- Except for the West region's insignificant estimate, a \$1/MWh increase in the average DAM price level tends to raise the DAM-RTM energy price differences by \$0.054/MWh to \$0.085/MWh. Hence, a DAM energy price increase due to load growth or natural gas price escalation tends to magnify ERCOT's regional forward premia. However, rising renewable generation that reduces the average DAM energy price is likely to shrink ERCOT's regional forward premia.
- The coefficient estimates for the DAM AS prices paint a picture of mixed effects on forward premia. Rising DAM AS prices for RRS tends to reduce forward premia. However, the same cannot be said for rising DAM AS prices for REGUP, REGDN and NSPIN.
- The coefficient estimates for the forecast errors are, for the most part, statistically significant. This finding implies that reducing these errors tends to make inter-day energy trading less risky (Cao et al., 2021), thus encouraging inter-day trading that likely shrinks forward premia (Zarnikau et al., 2015).

3.2.4 Testing the EMH for inter-regional DAM trading

Table 6 reports the slope coefficient estimates for the inter-regional DAM energy price difference given by equation (5). As most of the estimates are statistically significant, we reject **H2** ≡ EMH for inter-regional day-ahead energy trading that implies the linear restrictions of $(\theta_{jCREZ} - \theta_{kCREZ}) = 0, \ldots, (\theta_{jY} - \theta_{kY}) = 0$. This finding makes sense because the coefficient estimates in Table 6 reveal that while the regressors in the DAM price level regressions are systemwide variables, their price effects vary regionally.

3.2.5 Testing the EMH for inter-regional RTM trading

Table 7 reports the slope coefficient estimates for the inter-regional RTM energy price difference given by equation (6). As half of the estimates are statistically significant, we reject **H3** ≡ EMH for inter-regional real-time energy trading that implies the linear restrictions of $(\phi_j - \phi_k) = 0$, $(\phi_{j8ORDC1} - \phi_{k8ORDC1}) = 0$, $(\phi_{j8ORDC2} - \phi_{k8ORDC2}) = 0$, $\phi_{jP} = 0$, $\phi_{kP} = 0$, $(\phi_{jm} - \phi_{km}) = 0$ for all $m = 1, \ldots, 4$. This finding makes sense because the coefficient estimates in Table 7 measure the regionally differentiated effects of the regressors for the RTM price level regressions given by equation (3).

3.3. Final checks

We perform four final checks of Section 3.2's empirics. The first check entails unit-root tests to verify that the regression residuals are stationary, thereby mitigating concerns of spurious regressions (Davidson and Mackinnon, 1993).

The second check is related to the choice of an AR order. After assuming different AR($a \neq 4$) process for $a = 1, \ldots, 6$, we use FIML to re-estimate the 12-regression system, finding empirics closely resemble those in Section 3.2.

Table 6. Slope coefficient estimates for the inter-regional DAM energy price difference given by equation (5); statistically significant coefficient estimates (p-value < 0.05) in **bold**

Variable	Market pairs					
	West-South	West-North	West-Houston	North-South	North-Houston	South-Houston
$CREZ_t$ = 1 if t is after 2013, 0 otherwise.	**-3.4112**	**-3.7513**	**-3.2855**	0.3402	0.4658	0.1257
CAP_t = ERCOT's price cap ($/MWh)	**-0.0023**	**-0.0019**	**-0.0027**	-0.0004	**-0.0007**	-0.0003
G_t = Henry Hub natural gas price ($/MMBtu)	**-1.1794**	**-1.1022**	**-1.1241**	-0.0772	-0.0219	0.0553
D_t = System load (MWh)	**0.0002**	**0.0004**	**0.0003**	**-0.0002**	**0.0000**	**0.0002**
N_t = Nuclear generation (MWh)	**0.0949**	**0.0890**	**0.1031**	0.0059	**0.0140**	0.0082
S_t = System solar generation (MWh)	**-0.0059**	**-0.0050**	**-0.0051**	**-0.0009**	0.0000	**0.0008**
W_t = System wind generation (MWh)	**-0.0008**	**-0.0007**	**-0.0008**	-0.0001	**-0.0001**	0.0000
Y_t = day-ahead total planned AS MW	**0.0005**	**0.0005**	**0.0005**	-0.0001	0.0000	0.0001

The third check is related to the choice of an estimation period. To determine if a shorter estimation period matters, we use data for the 01/01/2016 to 12/31/2020 period to re-estimate the 12-regression system. This re-estimation does not qualitatively change the inferences based on the full sample.

The last final check entails alternative estimation methods of iterated seemingly unrelated regressions (ITSUR), iterated generalized method of moments (ITGMM) and iterated three-stage-least squares (IT3SLS). While the ITSUR results resemble the FIML results, the ITGMM and IT3SLS regression systems fail to converge after 10,000 iterations.

Table 7. Slope coefficient estimates for the inter-regional RTM energy price difference given by equation (6); statistically significant coefficient estimates (p-value < 0.05) in **bold**

Variable	Market pairs formed by regions j and k for $j < k$					
	West-South	West-North	West-Houston	North-South	North-Houston	South-Houston
$ORDC_t \times M_{8t} \times TOD_t$	-4.4582	0.0490	-1.6252	-4.5072	-1.6742	2.8330
$ORDC_t \times M_{8t} \times (1-TOD_t)$	2.3918	1.3050	1.5645	1.0868	0.2595	-0.8273
P_{jt} = region j's hourly DAM energy price ($/MWh)	**1.0001**	**1.0001**	**1.0001**	**0.9317**	**0.9317**	**0.9153**
P_{kt} = region k's hourly DAM energy price ($/MWh)	**0.9153**	**0.9317**	**0.9465**	**0.9153**	**0.9465**	**0.9465**
A_{1t} = hourly systemwide DAM AS price ($/MW) for RRS	**-0.1951**	**-0.0623**	-0.0388	**-0.1328**	0.0235	**0.1563**
A_{2t} = hourly systemwide DAM AS price ($/MW) for REGUP	0.0198	0.0005	-0.0066	**0.0194**	-0.0070	**-0.0264**
A_{3t} = hourly systemwide DAM AS price ($/MW) for REGDN	0.0022	0.0288	0.0531	-0.0267	0.0243	0.0509
A_{4t} = hourly systemwide DAM AS price ($/MW) for NSPIN	**0.1640**	-0.0039	-0.0110	**0.1679**	-0.0071	**-0.1750**

4. Conclusions and policy implications

In this paper, we use a large and recent sample of hourly data for the 120-month period of 01/01/2011 – 12/31/2020 to investigate the extent of inter-day and inter-regional energy trading efficiency in ERCOT's regionally differentiated DAM and RTM. Part 1 of this investigation is an initial exploration that reports mild inefficiency in ERCOT's inter-day and inter-regional energy trading. Part 2 entails the estimation of a parsimoniously specified system of eight price levels and four price difference regressions, finding that the inter-regional EMH is rejected for all regional market pairs and the inter-day EMH is rejected for all regions.

Our paper's empirics have two policy implications. First, enhancing ERCOT's inter-regional trading efficiency requires transmission capacity expansion to reduce transmission congestion and line losses (Stoft, 2002; Cao et al., 2021). Second, enhancing ERCOT's inter-day trading efficiency could occur through (a) improving the day-ahead forecasts for solar and wind generation (UL Services Group, 2021) and zonal loads;[10] and (b) refining ERCOT's Look-Ahead SCED that provides nodal price forecasts to aid market participants' trading decisions.[11]

We would be remiss had we ignored our paper's caveats. First, our paper narrowly focuses on trading efficiency in the DAM and RTM wholesale electricity markets. A complete assessment of the success of ERCOT as a competitive restructured market would involve an analysis of many metrics, including the reliability of service, the degree of competition and market power in generation and retail sectors, price levels, consumer satisfaction, and the degree of choices offered to consumers (Cao et al., 2021). Second, our paper does not consider that ERCOT is presently undergoing reforms to address the weaknesses exposed by Winter Storm Uri in February 2021. These reforms include the introduction of new ancillary services and more-conservative operating strategies. As these reforms are yet to complete, their impacts on trading efficiency and other measures of market success are currently unknown.

[10] While ERCOT's short-term load forecasts have improved over the years, a further increase in accuracy could be achieved through a better recognition of the response by the demand side of the market to anticipated transmission charges and anticipated spikes in wholesale generation prices. Further, private consulting firms (e.g., Arcus Power) have developed alternative short-term price and load forecasting in hopes of providing market participants with more-accurate alternatives to the information posted by ERCOT.

[11] http://www.ercot.com/content/cdr/html/rtd_ind_lmp_lz_hb.html

References

Cao, K.H., Qi, H.S., Tsai, C.H., Woo, C.K., Zarnikau, J., 2021. Energy trading efficiency in the US Midcontinent electricity markets. Applied Energy 302, 117505.

Davidson R, Mackinnon JG., 1993 Estimation and inference in econometrics. Oxford University Press.

Distributed Energy Financial Group. The Annual Baseline Assessment of Choice in Canada and the United States (ABACCUS). 2015. Available at: http://defgllc.com/publication/abaccus-2015-annual-baseline-assessment-of-choice-in-canada-and-the-united-states/ (accessed on June 22, 2021).

Du, X., Rubin, R., 2018. Transitioning and integration of the ERCOT market with the competitive renewable energy zones project. The Energy Journal 39(4), 235-57.

Eydeland, A., Wolyniec, K., 2003. Energy and power risk management: new developments in modeling, pricing, and hedging. John Wiley & Sons.

Potomac Economics. 2020 state of the market report for the ERCOT electricity markets. 2021. Available at https://www.puc.texas.gov/industry/electric/reports/ERCOT_annual_reports/2020annualreport.pdf (accessed on 15 July 2021)

Stoft, S., 2002. Power system economics: designing markets for electricity. Wiley-IEEE Press.

Woo, C.K,, Lloyd-Zannetti, D., Horowitz, I., 1997. Electricity market integration in the Pacific Northwest. The Energy Journal 18(3), 75-101.

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

Zarnikau, J., Woo, C.K., Gillett, C., Ho, T., Zhu, S., Leung, E., 2015. Day-ahead forward premiums in the Texas electricity market. Journal of Energy Markets 8(2),1-20.

Zarnikau, J., Woo, C.K., Zhu, S., Tsai, C.H., 2019. Market price behavior of wholesale electricity products: Texas. Energy Policy 125, 418-428.

Zarnikau, J., Zhu, S., Woo, C.K., Tsai, C.H., 2020. Texas's operating reserve demand curve's generation investment incentive. Energy Policy 137, 111143.