Day-ahead forward premiums in the Texas electricity market

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Abstract

We investigate market-price convergence in the competitive Texas electricity market in the presence of large-scale wind generation using a large data sample of over 30,000 hourly observations for the period of December 1, 2010 to May 31, 2014. Hourly premiums vary by time-of-day and month. Simple univariate analysis suggests patterns related to the day-of-the-week, although multivariate regression analysis reveals that this pattern is weak. The levels of the premiums are small and the forward premiums for a given hour exhibit serial correlation across days. An increase in wind generation tends to increase the premiums. This effect is significant for six of the 24 hours for non-West zones and half of the hours for the wind-rich West zone. The size of the effect of rising wind generation on the West zone's premium is larger than the effects on premiums in other zones. However, an increase in wind generation tends to reduce the forward premium's volatility in nearly all hours.

Taken together, these findings suggest that ERCOT's day-ahead market (DAM) and real-time market (RTM) exhibit modest trading inefficiency. But making a sizable arbitrage profit on a consistent basis is difficult because of the unpredictable nature of wind generation. To be sure, accurate wind generation may arguably improve arbitrage profitability, especially for the West zone that houses most of Texas' wind farms. However, if the wind forecast accuracy also improves price convergence, the arbitrage profit diminishes as well.

1. Introduction

Electricity market reform and deregulation in the U.S. have led to day-ahead and real-time wholesale market trading in the transmission grids of Pennsylvania–New Jersey–Maryland (PJM), New York, New England, California, and Texas (Sioshansi, 2013). A day-ahead hourly forward premium is the day-ahead market (DAM) price for a given hour minus the real-time market (RTM) price for the same hour.[1] A growing literature examines the relationship between spot market prices and forward or futures prices in these restructured electricity markets, in light of electricity's important role in modern economies and the unique attributes of this commodity. The high costs and technical challenges inherent in storing electricity make real-time electricity market prices exceptionally volatile and sensitive to various random factors that affect real time load-resource balances, including unanticipated power plant outages, unpredictable weather events, unanticipated fluctuations in demand, and intermittent wind and solar generation.

Forward or futures markets enable market participants to manage market price risks, while introducing opportunities for trading and risk allocation to electricity resellers (for example, local distribution companies and retail service providers), power generators, and financial market participants. The degree of convergence between forward and spot markets has been used to measure the trading efficiency of a restructured market (Borenstein et al. 2008; Eydeland and Wolyniec, 2003). And the introduction of forward or futures markets may impact the overall success of efforts to restructure electricity markets by reducing volatility in a spot market (Kalantzis and Milonas, 2013).

[1] While market structures vary, we shall use the term "real-time market" to refer to markets that set prices minutes ahead of pricing or settlement intervals. In the U.S., prices in the forward or futures markets are generally set on a day-ahead basis.

While Keynes (1930) speculated that a futures contract's forward premium (= futures price – spot price) should generally be negative, many studies report positive forward premiums. Such studies include analyses of electricity futures traded on the New York Mercantile Exchange for delivery at the California-Oregon Border by Shawky et al. (2003), day-ahead forward premiums in the New York market by Hadsell and Shawky (2007), day-ahead forward premiums in the California market by Borenstein et al. (2008), day-ahead forward premiums in the PJM market by Hadsell (2011), and month-ahead premiums in the Iberian power market by Herráiz and Monroy (2009). Persistent, positive (negative), and sufficiently-large forward premiums imply that arbitrage profit can be made by selling (buying) electricity in the day-ahead market and buying (selling) the same power in the real-time market.

While premiums in electricity markets tend to be positive, numerous studies report that they have significant seasonal or hourly patterns. While positive premiums are reported by Botterud et al. (2010) for the Nordic market, Lucia and Torró (2011) found that premiums vary seasonally and are negligible in the summer. Furió and Meneu (2010) find periods of positive and negative premiums in Spain's month-ahead futures market and attribute the periodic pattern to unexpected variations in demand and hydroelectric power generation. Bunn and Chen (2013) report large positive premiums in the U.K. futures market in the winter peak period, smaller positive premiums in the winter off-peak period, and small negative premiums in the summer peak and off-peak periods. Longstaff and Wang (2004) observe positive premiums during peak evening hours but negative premiums during early afternoon hours in the PJM market. Haugom and Ullrich (2012) find that PJM's premiums have been greatly reduced or eliminated in more-recent years. Viehmann (2011) reports positive premiums in the German market during evening peak hours in winter months and negative premiums during non-peak hours of low demand.

Woo et al. (under review) found that the positive day-ahead forward premiums in California's electricity markets depend on wind generation and vary by hour and month-of-year.

Virtual bidding (VB) that allows a trader to buy (sell) in the day-ahead market with the liquidation obligation to sell (buy) in the real-time market may improve convergence between the DAM and RTM market prices. Improvement is said to occur when the introduction of VB shrinks the forward premium's size and volatility. Examining the New York market, Hadsell and Shawky (2007) conclude that VB has decreased premiums during off-peak hours, but has increased premiums during peak hours. Hadsell (2007) finds VB has reduced the price volatility in New York's real-time and day-ahead markets, and Jha and Wolak (2013) and Woo et al. (under review) report a similar finding for the California electricity market.

This paper analyzes day-ahead hourly premiums in the Electric Reliability Council of Texas (ERCOT) market. Our interest in the ERCOT markets is motivated by three reasons. First, the ERCOT Interconnection is large, accounting for about 8% of the total electricity generation in the U.S.[2] Second, we are unaware of any prior published analyses of ERCOT markets' forward premiums,[3] even though, this is regarded as a very successful restructured market and the performance of futures markets, may provide an overall indication of the efficiency of a market. Third, Texas has the largest installed capacity of wind generation in the U.S. and rising wind generation has been found to dampen the ERCOT market prices (Woo, et al., 2011), although very little is known about how forward premiums move with the highly-

[2] Generation in ERCOT was 324,859.7 GWH in 2012, as reported to NERC: http://www.nerc.com/pa/RAPA/ESD/Pages/default.aspx. Total U.S. generation was 4,047,765 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.

[3] We note, however, that the excellent annual reports published by Potomac Economics, the market monitor for ERCOT, contribute simple graphical analyses of the performance of ERCOT's day-ahead and real-time markets.

unpredictable wind generation. As renewable energy generation in the world's electricity markets increases, its impact on the formation of electricity prices in competitive wholesale markets becomes increasingly important.

Our empirical examination has two parts. The first part is a descriptive analysis of hourly price data for the 36-month period from December 1, 2010 to May 31, 2014. The second component is an estimation of five location-specific sets of 24 hourly regressions based on prior studies of the fundamental drivers of wholesale electricity market prices (Woo, et al., 2011, 2013).

The key findings are as follows:

- As in many other electricity markets, electricity premiums are generally positive and vary by hour and month of the year.
- ERCOT's hourly DAM and RTM prices for various zones are noisy and weakly correlated. These prices can be negative and at times hit the price caps. This suggests modest trading inefficiency that deserves further investigation.
- Based on the descriptive statistics, ERCOT's zonal hourly day-ahead forward premiums are positive, on average, and highly correlated. The size of the average premiums is small – between \$1.5 and \$2.5 per MWh.
- Based on our regression results, the forward premiums for a given hour exhibit serial correlation across days. Rising wind generation tends to reduce the volatility of the forward premium.
- Based on our regression results, an increase in wind generation raises the forward premiums. This effect is significant for 25% of the 24 hours for non-West zones and half of the hours for the West zone. The sizes of the effects in the West zone are larger than in other zones.

- Based on our regression results, there are month-of-year effects.
- The day-of-week effects suggested by simple univariate graphical analysis tend to be insignificant in our multivariable regression models.

Taken together, these findings suggest that the ERCOT's DAM and RTM markets show modest trading inefficiency. But making sizable arbitrage profit consistently is difficult because of the unpredictable nature of wind generation. To be sure, accurate wind generation may arguably improve arbitrage profitability, especially for the West zone that houses most of Texas' wind farms. However, if the wind forecast accuracy also improves price convergence, the arbitrage profit diminishes as well.

The following section reviews ERCOT's electricity market features, offering a contextual background of our forward premium analysis. Section 3 describes our hourly data sample, explores temporal patterns in the forward premiums, and identifies a relationship between wind generation and the size of the premiums. In Section 4 we conduct a simple test for market efficiency. Section 5 provides regression results, conducted to better isolate the factors contributing to the observed patterns in the premiums. Section 6 concludes.

2. ERCOT market description

The ERCOT market is often cited as North America's most successful attempt to introduce competition in both generation and retail segments of the power industry (Distributed Energy Financial Group, 2011; Alliance for Retail Choice, 2007; and Center for Advancement of Energy Markets, 2003). This market covers about 75% of the area of America's leading state in electricity generation and consumption, and serves about 85% of Texas' total electricity load. Although there is no synchronous interconnection to North America's Eastern or Western grids, the Texas grid can exchange about 860 MW with other reliability councils in the U.S. and Mexico through direct current links.

In the wholesale sector, there is competition among a large number of generators, although one generation company, Luminant, holds a market share of roughly 20%. There presently is no "capacity market" to maintain a target reserve margin. Consequently, market forces are heavily relied upon to preserve reliability and resource adequacy and offer caps have been raised to relatively-high levels in hopes of providing sufficient compensation to the generation sector.

The competitive wholesale market has evolved over time, with an important structural change occurring on December 1, 2010, upon the introduction of a nodal market structure. Under the new structure, ERCOT assumed a central role in dispatching all resources using a security-constrained economic dispatch (SCED) model. Nodal prices are used to determine the compensation provided to generators, while a demand-weighted average of the nodal prices within various zones is calculated to bill load-serving entities (LSEs) for wholesale energy purchases (Zarnikau, et al., 2014).

The creation of a formal day-ahead market (DAM) with VB accompanied the nodal market's introduction. The DAM is a voluntary, financially-binding forward energy market, which matches willing buyers and sellers, subject to various constraints. In the DAM, offers to sell energy can take the form of either a three-part supply offer[4] or an energy-only offer. Offers and bids are location-specific. Hourly market-clearing DAM prices used to settle DAM's transactions result from the least-cost dispatch that co-optimizes with ancillary services and

[4] An offer may include the following three components: Startup Offer, a Minimum-Energy Offer, and an Energy Offer Curve.

certain congestion revenue rights. Deviations from a scheduled DAM transaction are settled at the 5-minute RTM prices. By providing market participants with a means to make financially-binding forward purchases and sales of power for delivery in real-time, the DAM enables market participants to hedge energy and congestion costs on a day-ahead basis, mitigate the risk of price volatility in real-time, and coordinate generation commitments.

In ERCOT, settlement point prices are calculated at three levels: resource nodes, load zones, and hubs (ERCOT, undated). A load zone is a set of adjacent electrical buses with similar prices, reflecting the expectation of minor intra-zonal transmission constraints. Given the role of load zones within ERCOT's settlement system, average locational marginal prices (LMPz) have significant importance to the market.

The zones used in the calculation of LMPz values generally correspond with those defined under the zonal market structure in place prior to December 1, 2010, although the former South zone was split up to permit Austin Energy, the Lower Colorado River Authority (LCRA), and CPS Energy (San Antonio) to have their own zones. The present zones are indicated in Figure 1.

The offer caps on wholesale market prices were raised to $3,000 per MWh at the start of the nodal market and DAM, and were further increased to $4,500 per MWh effective August 2012 to encourage the construction of new generating capacity. In August 2012, the Public Utility Commission of Texas (PUCT) approved a plan to gradually raise the offer caps to $9,000 per MWh, with an initial increase to $5,000 per MWh on June 1, 2013 and a further increased to $7,000 per MWh on June 1, 2014, just beyond the time frame examined here.

In the months following the introduction of the nodal market and the DAM, prices often spiked. A cold front in early February 2011 led to unusual winter price spikes. The summer of 2011 was one of the hottest on record in Texas, leading to higher-than-expected demand and numerous price spikes. In contrast, prices in 2013 reached the offer cap only once. This market's increasing reliance upon generation from wind farms has placed downward pressure on energy prices in recent years (Woo, et al., 2011).

3. Descriptive statistics

While the current ERCOT market is divided into eight zones, our analysis will focus on five zones: North, Houston, West, LCRA, and South. The North and Houston zones account for about 37% and 27%, respectively, of the energy sales in this market, while the South and West zones contribute 12% and 9%. The North, Houston, South, and West zones provide the stage for nearly all of the state's retail competition, and most of the competitive generation resides within those zones. The Lower Colorado River Authority (LCRA) zone is included in this analysis because it includes numerous rural electric cooperatives and municipal utilities. Our analysis does not include the CPS (San Antonio), AEN (Austin), and RAYBN (Rayburn) zones, chiefly because each of them is dominated by a single vertically-integrated utility system.

Our analysis for these five zones focuses on the time period beginning with the initiation of the nodal market and the DAM on December 1, 2010 through May 31, 2014. The zonal DAM price is the hourly price set in the DAM for each zone. The zonal RTM price is a load-weighted average of the RTM market prices in each zone.[5]

[5] While real-time prices are set at least every 5 minutes, 15-minute prices are used in ERCOT's market settlement processes. Thus, the 5-minute prices are first converted into 15-minute prices using a load-weighted average.

3.1 RTM price vs. DAM price

Figures 2 through 6 provide scatterplots of the hourly RTM price versus the hourly DAM price for each of the five zones selected for analysis. These figures suggest that the DAM and RTM prices are highly volatile and weakly correlated. At times they reach or exceed the price caps of $3000 per MWh, $4500 per MWh, and $5,000 per MWh in effect during our period of analysis. Prices in excess of the caps may occur when certain inter-zonal transmission constraints are binding during periods that coincide with the acceptance of high-price energy offers.[6]

3.2 Hourly day-ahead forward premiums

The hourly day-ahead forward premium is the hourly DAM price minus the hourly RTM price. Table 1 presents the premiums' summary statistics by zone. As in most other electricity markets, the forward premium is positive. The premium is considerably higher in the West zone and its adjacent LCRA zone. The West zone hosted the majority of the state's wind generation during this period. Moreover, premiums have the greatest volatility in the West zone, as evidenced by the higher standard deviation shown in Table 1. Since prices converge in the absence of transmission constraints, the premiums are mostly highly correlated with $r > 0.9$ (p-value < 0.0001).

3.3 Hour-of-day patterns in price premiums

Figures 7 through 18 show that the hourly premiums generally tend to have the same patterns among zones, as the high correlation among zones would suggest. However, in some

[6] For a more technical explanation, see Dan Jones, Potomac Economics, MCPE and Offer Cap/Floor Consistency, etc., presentation to ERCOT TAC/WMS, June 13, 2008, available at: www.ercot.com/content/meetings/wms/keydocs/2008/0613/Jones_TAC_(20080613).ppt.

fall and spring months, the West zone, in particular, displays a pattern in forward premiums that differ from the other zones. In these months, the ERCOT market has its greatest dependence upon wind generation. To wit, Figure 16 reports the divergence in patterns among zones for October.

Figures 19-21 portray the overall average of the hourly zonal premiums for three zones: North, Houston and West because the LRCA and South zones have the very similar premium patterns. Each figure demonstrates the premiums vary by hour with differing means and volatilities implied by the 5- and 95-percentiles. The range of premiums tends to be the greatest in the late afternoon in each zone, with the West zone exhibiting the greatest range, by far. The premiums significantly differ from zero in each zone at the hours ending at 8 a.m., 9 a.m., or both. In all three zones, the premiums are significantly different from zero during the last hour of each day. In contrast to the West zone, the North and Houston zones exhibit small ranges of premiums, yet significant values, during the hours ending 18 (6 p.m.) and 19 (7 p.m.).

3.4 Day-of-week patterns in price premiums.

Figures 22 - 24 suggest a day-of-week pattern in the premiums in North, Houston and West, with statistically significant means during Thursday, Friday, Saturday, and Sunday. However, the regression analysis presented later suggests that the day-of-week effects on premiums are generally insignificant after controlling for the influence of month-of-year and wind generation.

3.5 Month-of-year patterns in price premiums

Figures 25-27 show how ERCOT forward premiums in North, Houston and West, varied by month over the period of this study. These figures show the forward premiums' means and volatilities vary by month. The effects of the offer caps on the monthly means, however, are not discernible. As noted earlier, unusually hot weather during the summer of 2011 and a severe freeze during February 2011 resulted in numerous price spikes during those months. These figures suggest that these weather events affected the price premiums, as well. There have been far fewer price spikes in subsequent years, during which the price caps have been higher.

3.6. Wind generation and forward premiums

Large-scale wind generation provides power on an"as-available" basis, is intermittent, and is largely outside the control of the ERCOT Independent System Operator.[7] We explore wind generation as a potential determinant of forward premiums because rising wind energy output tends to reduce the RTM price (Woo et al., 2011, 2014), to the point that the RTM price can become negative,[8] thus greatly magnifying the forward premium. Wind generation data were obtained from the ERCOT website.[9] Wind generation data for the entire ERCOT market were used, since zone-specific data are not readily available.

Figures 28 through 30 suggest ERCOT forward premiums in the North, Houston and West zones depend on wind generation. Specifically, rising wind generation tends to increase the premiums' mean and reduce the premiums' volatility. The range of premiums in the West zone is far greater than in the North or Houston zones.

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[7] While an independent system operator can curtail wind generation, it cannot increase wind generation like dispatchable generation (e.g., natural-gas turbines).

[8] An example is the minimum-load condition when the system load cannot fully absorb the non-dispatchable generation output from wind farms. As a result, negative prices are used to induce dispatchable- generation (e.g., natural-gas turbines) owners to curtail their output so as to maintain the real-time load-resource balance.

[9] www.ercot.com.

4. Testing the market efficiency hypothesis

The efficient market hypothesis (EMH) suggests that, absent transaction cost, the RTM price moves in tandem with the DAM price with no arbitrage opportunity between the two prices (Siegel and Siegel, 1990). To test this hypothesis, we apply the simple bivariate regression model:

$$Y_{ht} = \alpha + \beta X_{ht} + \varepsilon_{ht} \tag{1}$$

where Y_{ht} = RTM price, X_{ht} = DAM price, and ε_{ht} = AR(n) error. The price data used to estimate equation (1) are stationary based on the Phillips-Perron (Phillips and Perron, 1988) unit root test results that firmly reject the hypothesis of non-stationarity for all zones (p-values < 0.01), thus assuaging any concerns about spurious price regression (Granger and Newbold, 1974). The testable hypothesis is H_0: $\alpha = 0$ and $\beta = 1$, whose rejection implies that the price data do not support the EMH under the assumption of zero transaction costs. Table 2 reports the regression results using the maximum likelihood method in the SAS/ETS PROC AUTOREG command. It yields the following observations:

- The R^2 values are around 0.2, indicating a modest data fit by the regressions.
- All regressions have statistically significant intercepts (p-value < 0.01). The slope estimates are also statistically significant, lying between 0.49 and 0.56.
- The AR parameter estimates suggest AR(5) errors.
- The F-statistics reject H_0: $\alpha = 0$ and $\beta = 1$ (p-value < 0.01) for all locations.

These observations suggest trading inefficiency and arbitrage opportunities.

5. Regression Analysis

5.1 Model

Figures 22 through 30 suggest that day-of-week, month-of-year, and wind generation may drive ERCOT's forward premiums. However, they do not delineate each driver's individual effect. Hence, we estimate 24 hourly regressions, each with the following specification:[10]

$$Z_{ht} = \gamma_h + \Sigma_d\, \delta_{hd}\, D_{dt} + \Sigma_m\, \mu_{hm}\, M_{mt} + \theta_h\, W_{ht} + \eta_{ht} \qquad (2)$$

In equation (2), the dependent variable is Z_{ht} = forward premium for hour h and day t for a particular market price series, representing the North, Houston, West, LCRA, and South zones.[11] The systematic portion is represented by the first four terms on the right hand side of equation (2).

The first independent variable on the right-hand-side of equation (1) is the hour-specific intercept γ_h. Based on the variables introduced below, γ_h measures the average premium for hour h in December on a Sunday, after controlling for the effects of month-of-year, day-of-week, and wind generation.

We use indicator $D_{mt} = 1$ to indicate if day t is $d = 1$ (Sunday), …, 6 (Friday); 0 otherwise. The day-of-week effect for hour h is measured by the coefficient δ_{hd}.

We use binary indicator $M_{mt} = 1$ to indicate if day t is in month $m = 1$ (January), …, 11 (November); 0 otherwise. The month-of-year effect for hour h is measured by the coefficient μ_{hm}.

[10] We tested a single equation approach that uses hourly dummies to capture the hour-of-day effects. The approach's assumption of constant month-of-year and wind generation effects are rejected by the data.

[11] We applied the Phillips-Perron unit-root test (Phillips and Perron, 1988) to decisively reject (p-value < 0.01) the hypothesis that the forward premium data series are non-stationary. The other metric variable in equation (2) is wind generation W_{ht}, which is also found to be stationary.

The last independent variable is W_{ht}, which is ERCOT's hourly wind generation (MW) in hour h on day t. Its hour-specific effect on the forward premium is given by the coefficient θ_h.

The hour-specific random error in equation (2) is η_{ht} for hour h on day t. We consider three stochastic specifications: (a) η_{ht} is AR(1), with an heteroskedastic variance that is an exponential function of wind generation (SAS, 2008, p.351); (b) η_{ht} is an AR(1) error; and (c) η_{ht} follows a GARCH (1, 1) process (Bollerslev, 1986). Obtained via PROC AUTOREG in SAS/ETS (2008), we adopt (a) because (b) is rejected by the data and (c) leads to a non-stationary GARCH (1, 1) process with undefined variance.

5.2 Results

Tables 3 through 12 report the regression results. Estimates presented in bold font are statistically significant at the 1% level. Using the 5% significance level results in an almost identical presentation of significant estimates.

Based on Tables 3 through 7, residuals are serially correlated for the same hour across days and statistically significant heteroskedasticity is evident in all zones. The hetero wind coefficient is consistently negative in all hours and in all zones, suggesting an increase in wind generation tends to reduce the volatility of the forward premium. This finding contrasts with the results from a similar modeling effort in California (Woo et al., under review), where the picture was not so clear.

The estimates of γ_h in Table 8 suggests that the hourly average premiums are mostly insignificant on a Saturday in December, after controlling for the effects of wind generation, month-of-year, and day-of-week. Yet, exceptions hold in some zones in hours ending 1 a.m., 2 a.m., 3 a.m., and 3 p.m.

The estimates of θ_h in Table 1 show the wind generation effect by hour, after controlling for the effects of day-of-week and month-of-year. An increase in wind generation tends to increase the forward premium. The effect is statistically significant in the hours ending 2 a.m., 3 a.m., and 7 p.m. (hour 19) in all zones. It is significant in the last hour of the day in four of the five zones. The size of the effect tends to be the highest in the wind-rich West zone, with significant estimates in half of the hours.

In contrast to the univariate analysis presented in Figures 22 through 24, Table 10 suggests that day-of-week effects are weak, after controlling for the effects of wind generation, monthly patterns, and autocorrelation.

Month-of-year effects are more-pronounced, as suggested in Tables 11 and 12. These effects are particularly significant in the hours ending 2 a.m., 3 a.m., and late afternoon hours.

6. Conclusion

In the competitive ERCOT electricity market, day-ahead hourly premiums vary by time-of-day and month. The levels of the premiums are small (between $1.5 and $2.5 per MWh), and the forward premiums for a given hour exhibit serial correlation across days. Day-ahead prices are poor predictors of real-time prices, thus suggesting a modest level of trading inefficiency and opportunities for arbitrage. An increase in wind generation tends to increase the premiums. This effect is significant for six of the 24 hours for non-West zones and half of the hours for the wind-rich West zone.

Making a sizable arbitrage profit on a consistent basis is difficult because of the unpredictable nature of wind generation. Wind generation tends to increase the premiums, although an increase in wind generation also tends to reduce the forward premium's volatility in nearly all hours. As Texas increases its reliance upon this renewable resource in the coming years and as other regions of the world increase their reliance upon renewable resources, an understanding of the relationship between intermittent resources and market prices will increase in importance.

Accurate forecasts of wind generation may arguably improve arbitrage profitability, especially for the West zone that houses most of Texas' wind farms. However, if the wind forecast accuracy also improves price convergence, the arbitrage profit diminishes as well. In recent years, improving the accuracy of wind generation forecasts has indeed been a priority for ERCOT. On February 26, 2008, a mismatch between load and generation led to a sudden drop in system frequency and outages resulted. ERCOT's day-ahead forecast anticipated 1,000 MW of wind that ultimately was not available. Following this event, ERCOT began deliberately under-forecasting wind power output.[12] Nearly two years later, on January 28, 2010, a strong cold front moved southward from the Texas Panhandle into the Sweetwater, Texas region. The approaching front stalled and then moved backward. ERCOT's wind forecast model was incapable of predicting wind generation levels under this unusual weather event and two different and conflicting 600 MW dispatch instructions to fossil fuel generators were issued -- one to ramp generation up and the other to ramp generation down. Following these events, the critical importance of accurate wind generation forecasts became apparent and ERCOT implemented a more-advanced wind forecasting system.

[12] NPRR210 Wind Forecasting Change to P50. Comments of Morgan Stanley. Presentation to Technical Advisory Committee of ERCOT. April 8, 2010.

These findings suggest that the ERCOT's day-ahead market (DAM) and real-time market (RTM) show modest trading inefficiency. Yet, such inefficiencies might be expected in the first three and a half years of a new market structure, particularly when a new nodal wholesale real-time pricing system is accompanied by a new formal day-ahead market. As noted earlier, forward premiums appear to have declined and efficiencies have been improved in other electricity markets in the U.S. as markets have matured. It will be interesting to see whether the ERCOT market demonstrates similar improvement in the coming years.

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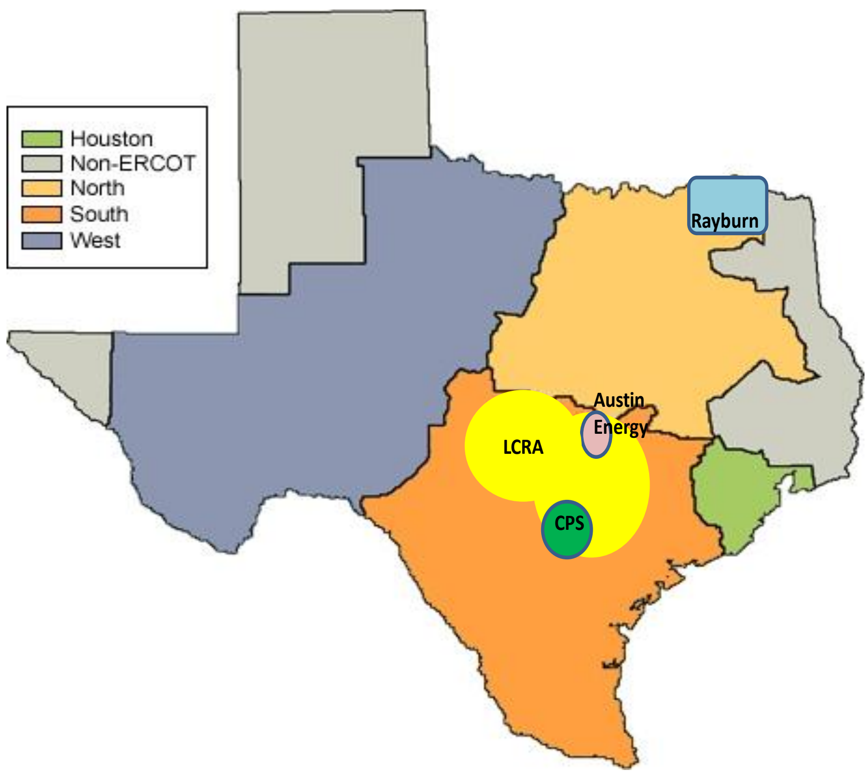

Figure 1. ERCOT Map with Zones Delineated. Approximate locations of the Austin Energy (AEN), LCRA, Rayburn, and CPS zones are indicated.

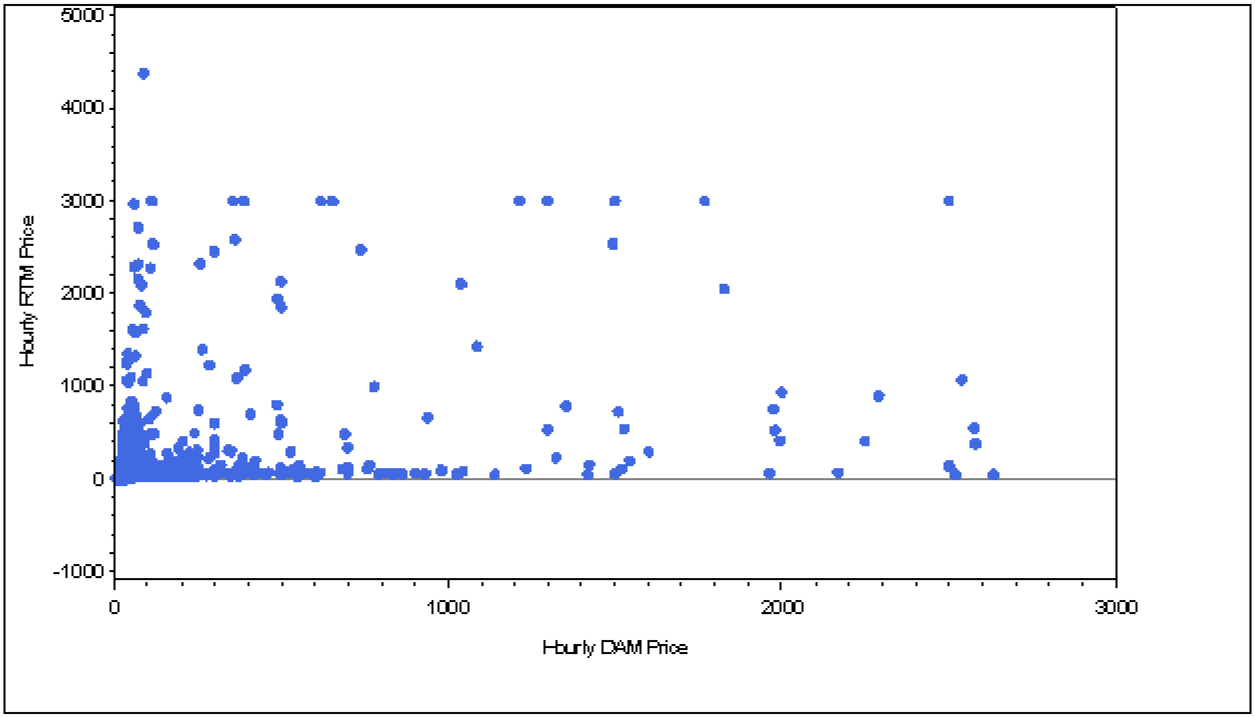

Figure 2. North zone's scatter plot of hourly RTM price vs. hourly DAM price for the period of 12/01/2010 – 05/31/2014 (r = 0.420).

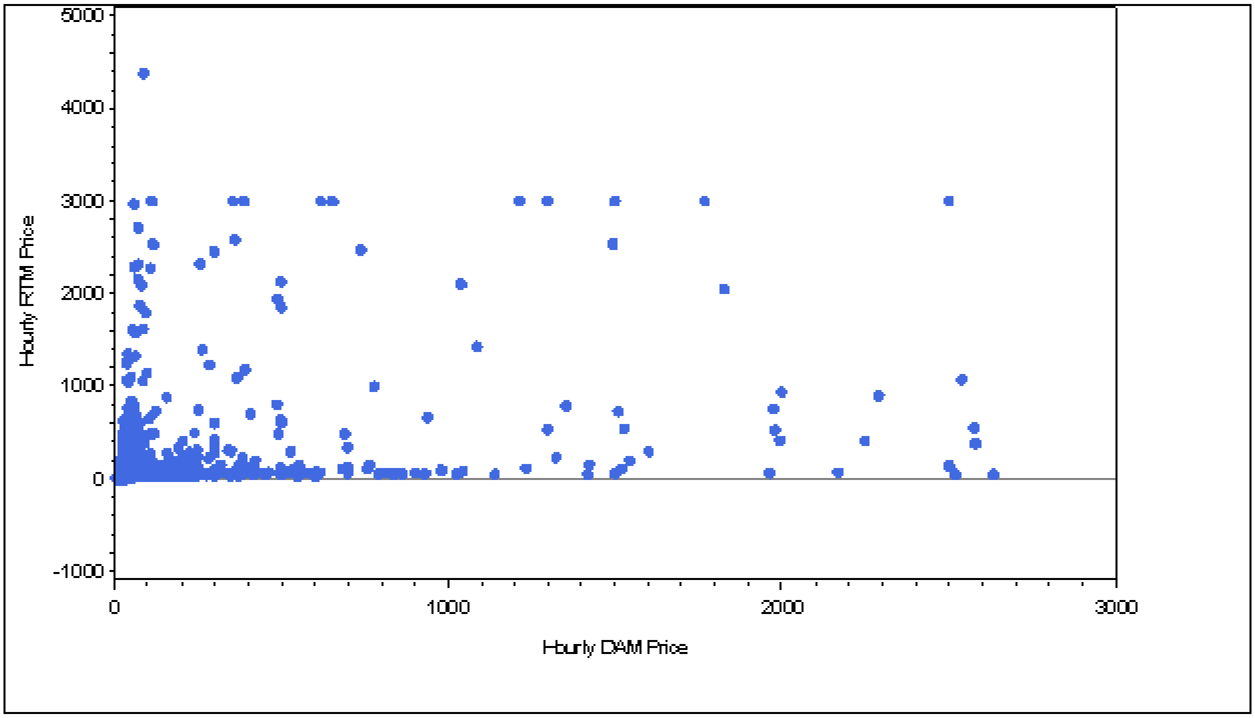

Figure 3 Houston zone's scatter plot of hourly RTM price vs. hourly DAM price for the period of 12/01/2010 – 05/31/2014 (r = 0.407).

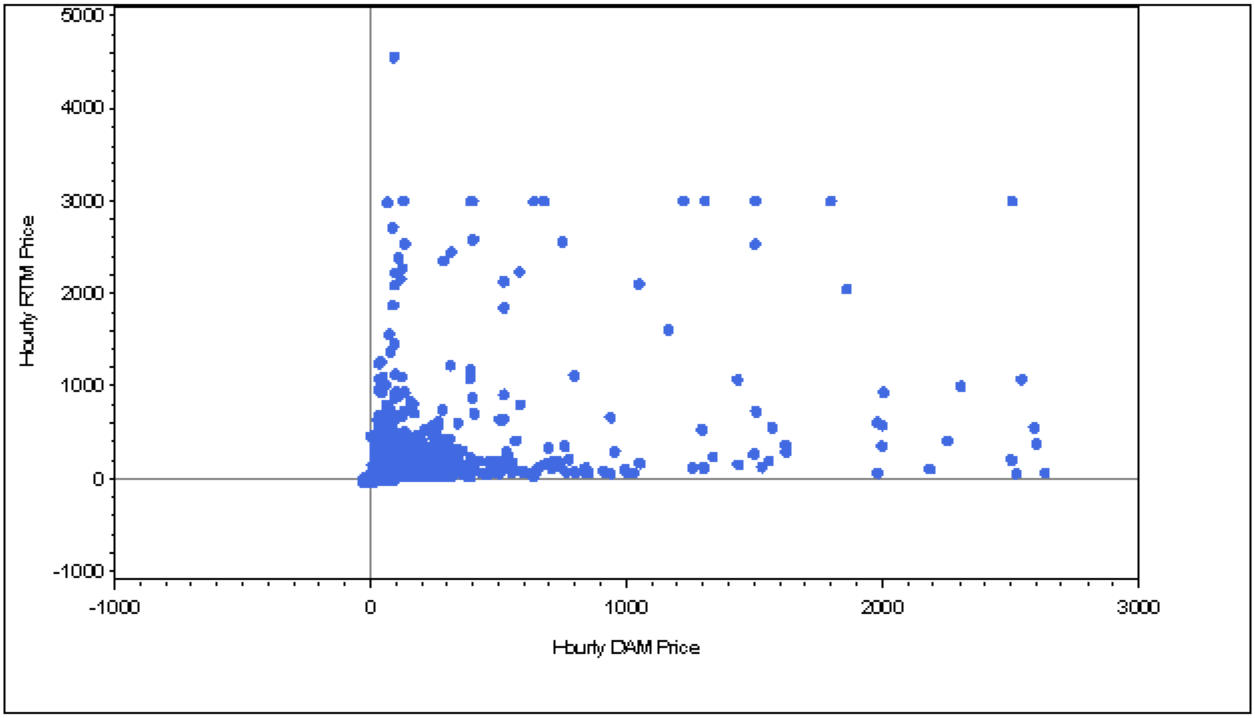

Figure 4. West zone's scatter plot of hourly RTM price vs. hourly DAM price for the period of 12/01/2010 – 05/31/2014 (r = 0.437).

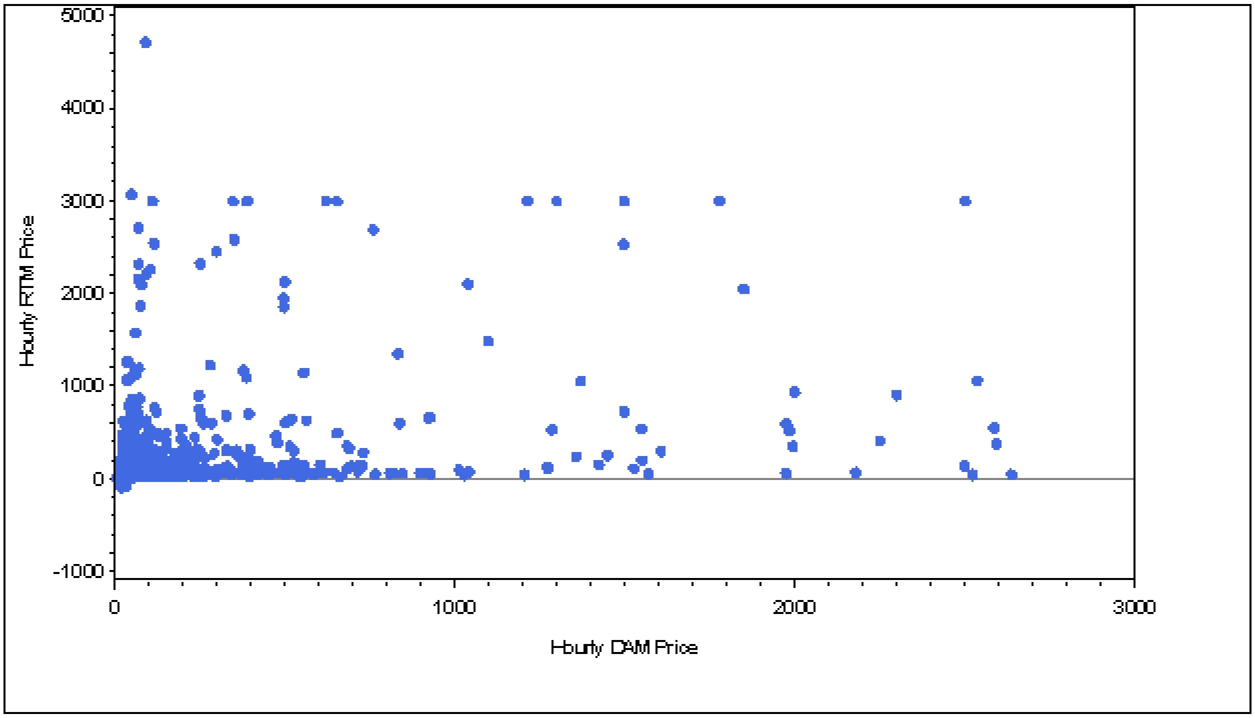

Figure 5. LCRA zone's scatter plot of hourly RTM price vs. hourly DAM price for the period of 12/01/2010 – 05/31/2014 (r = 0.418).

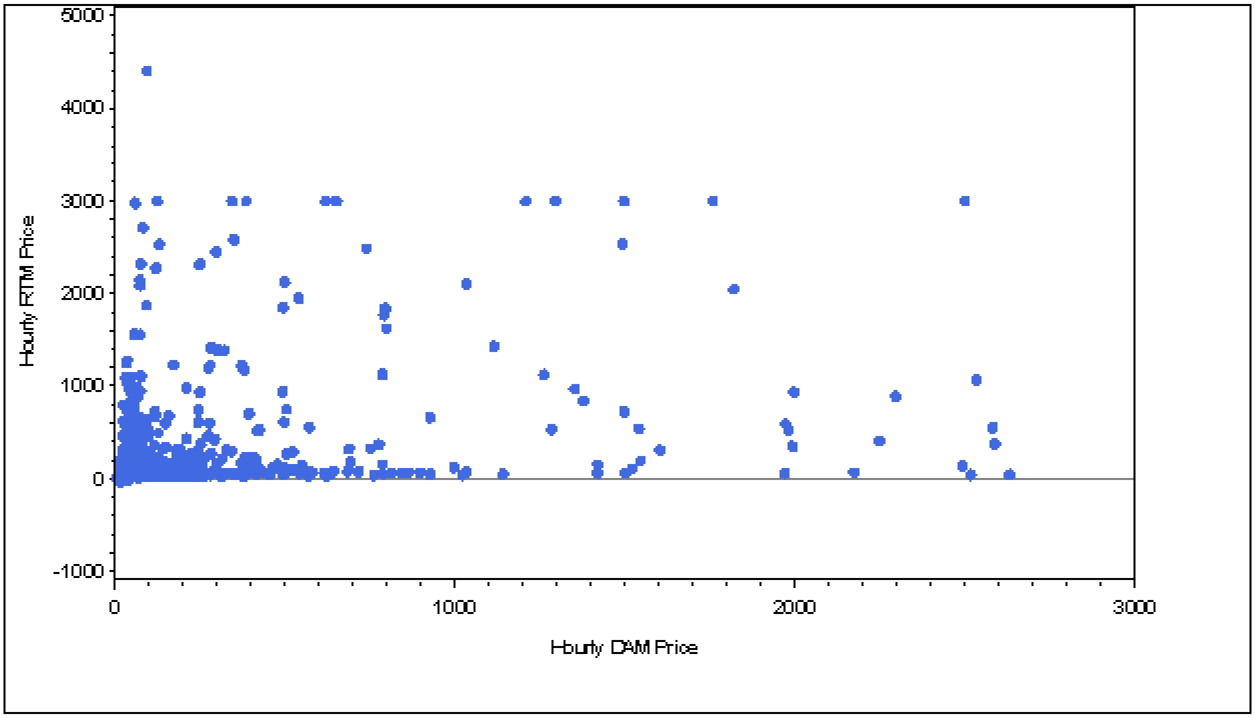

Figure 6. South zone's scatter plot of hourly RTM price vs. hourly DAM price for the period of 12/01/2010 – 05/31/2014 (r = 0.418).

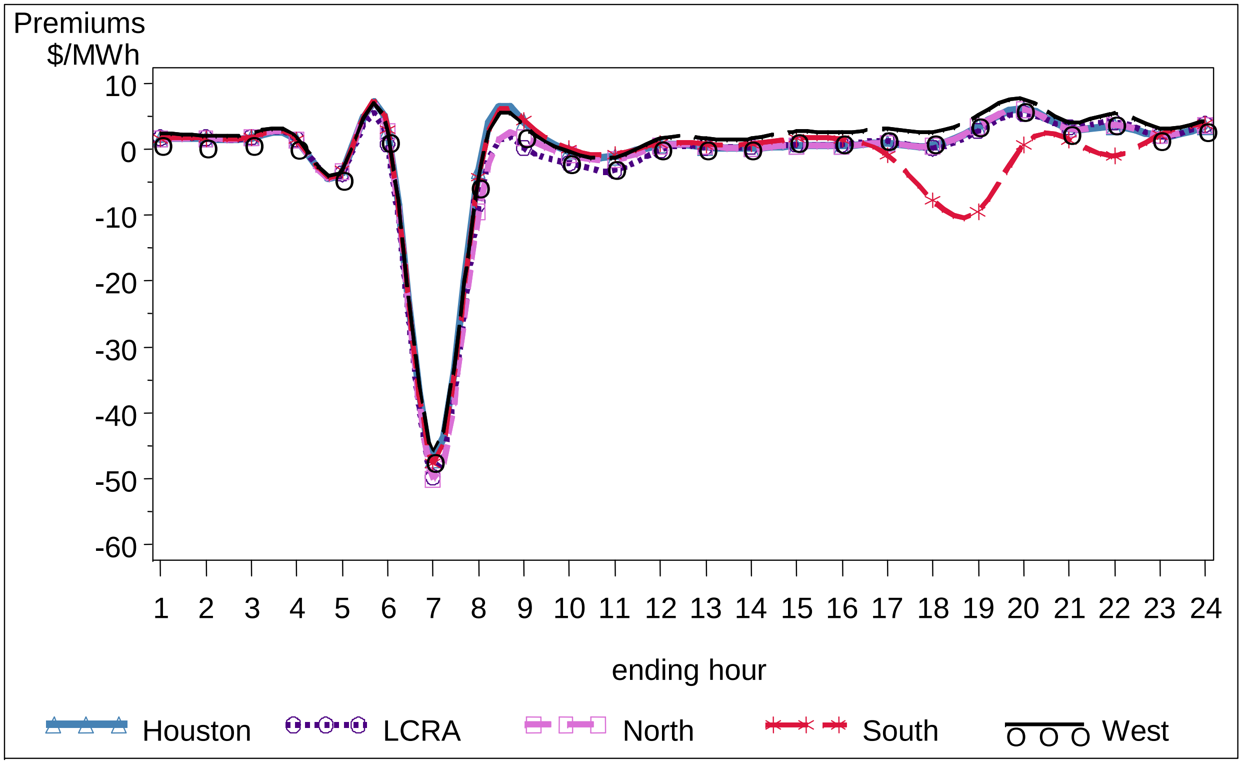

Figure 7. Comparison of average zonal premiums: January

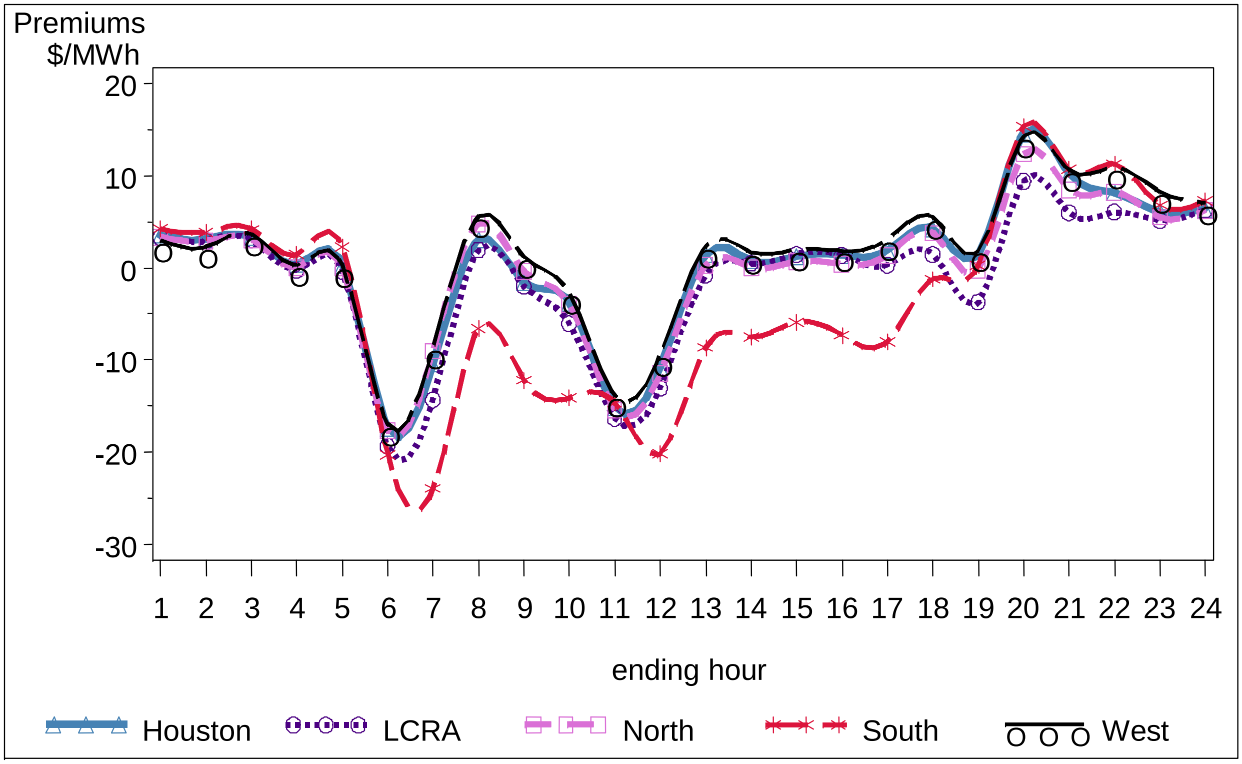

Figure 8. Comparison of average zonal premiums: February

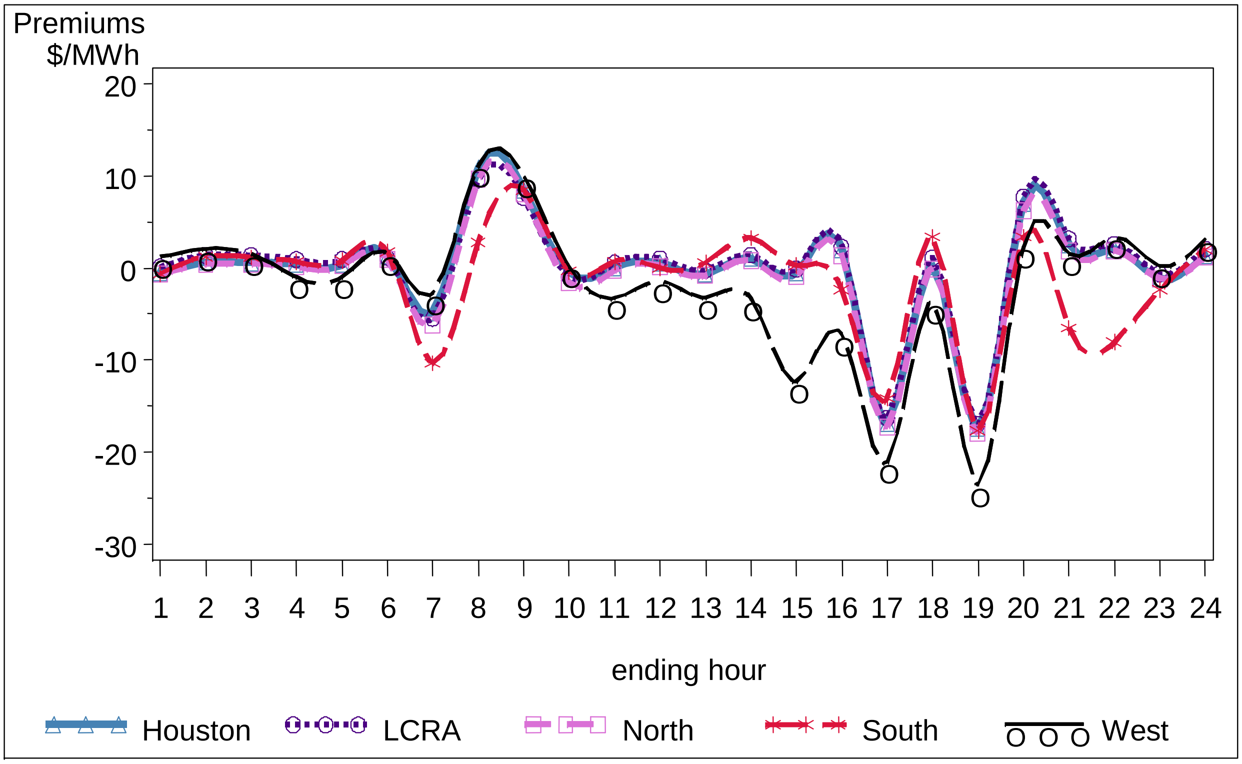

Figure 9. Comparison of average zonal premiums: March

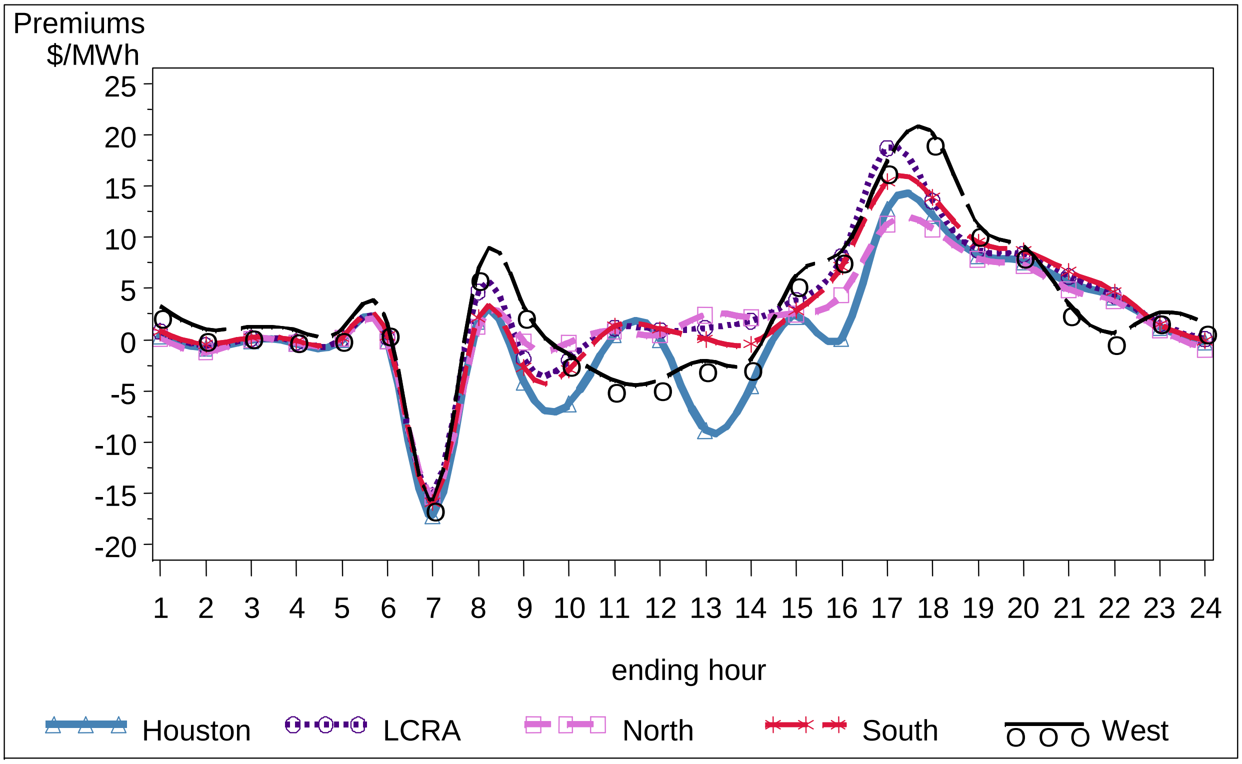

Figure 10. Comparison of average zonal premiums: April

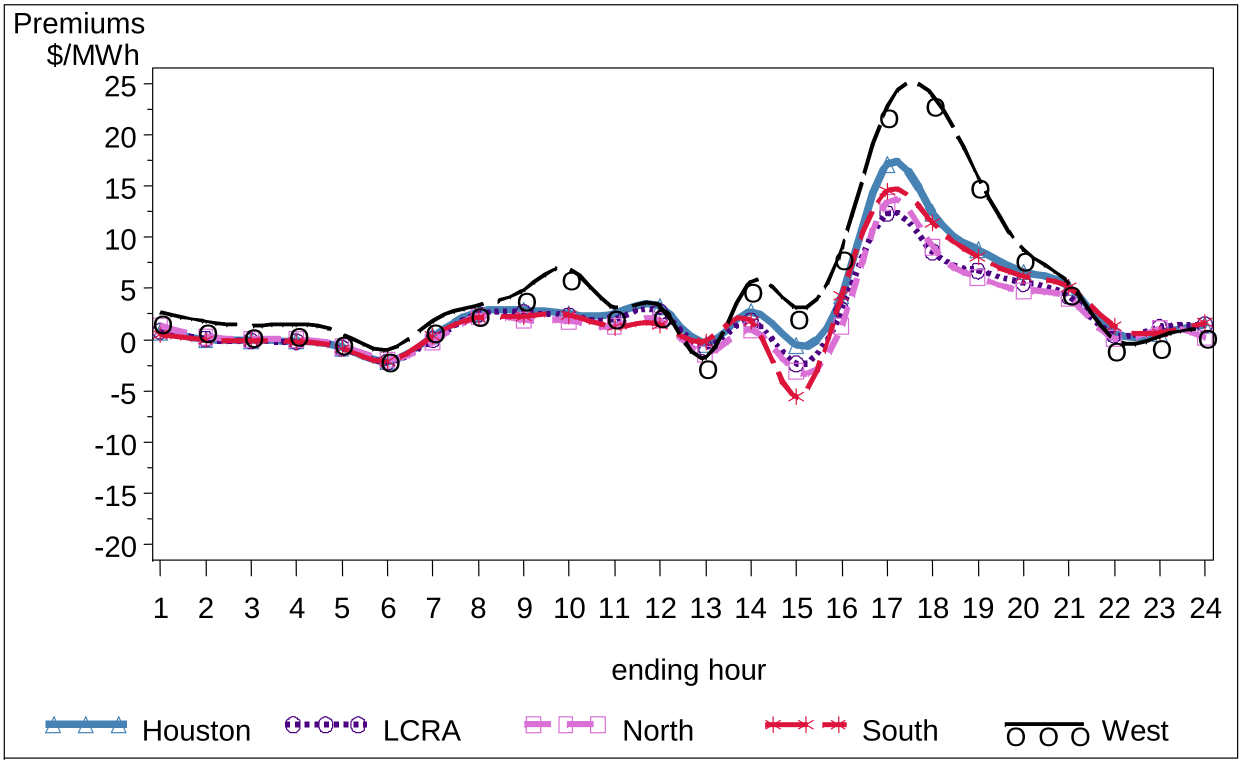

Figure 11. Comparison of average zonal premiums: May

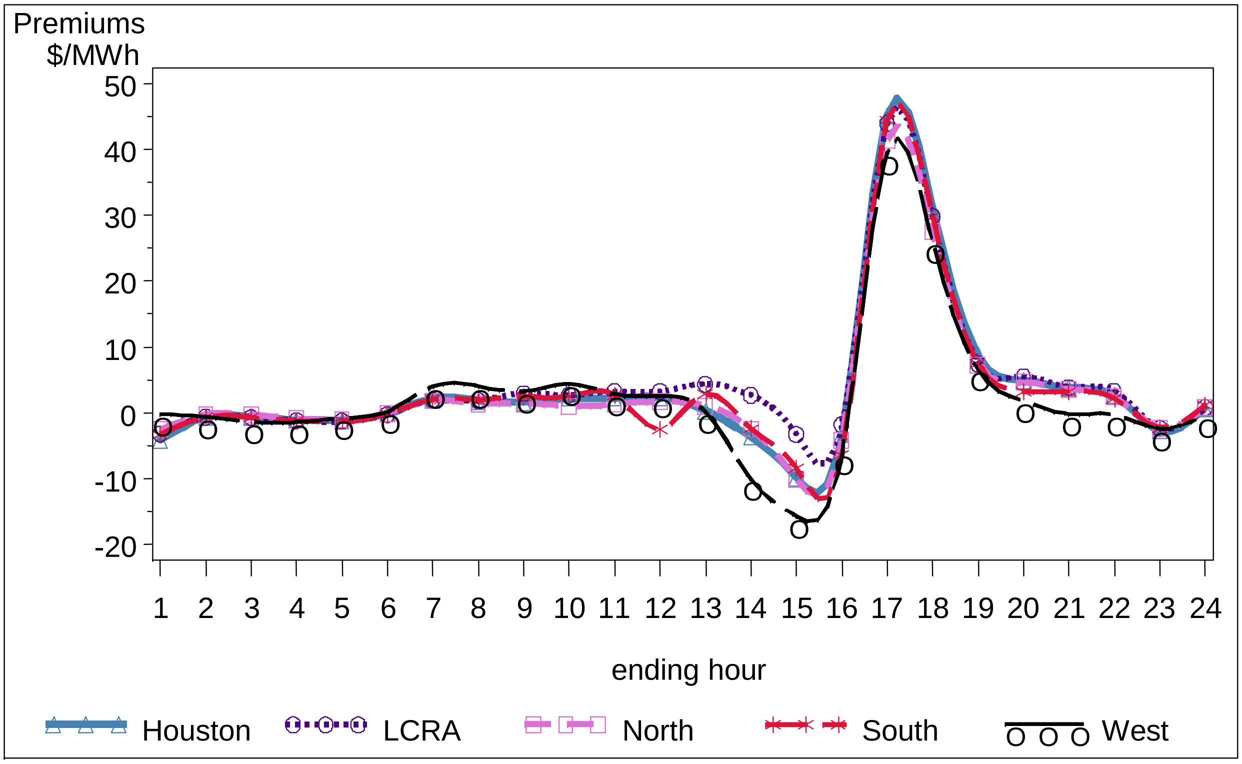

Figure 12. Comparison of average zonal premiums: June

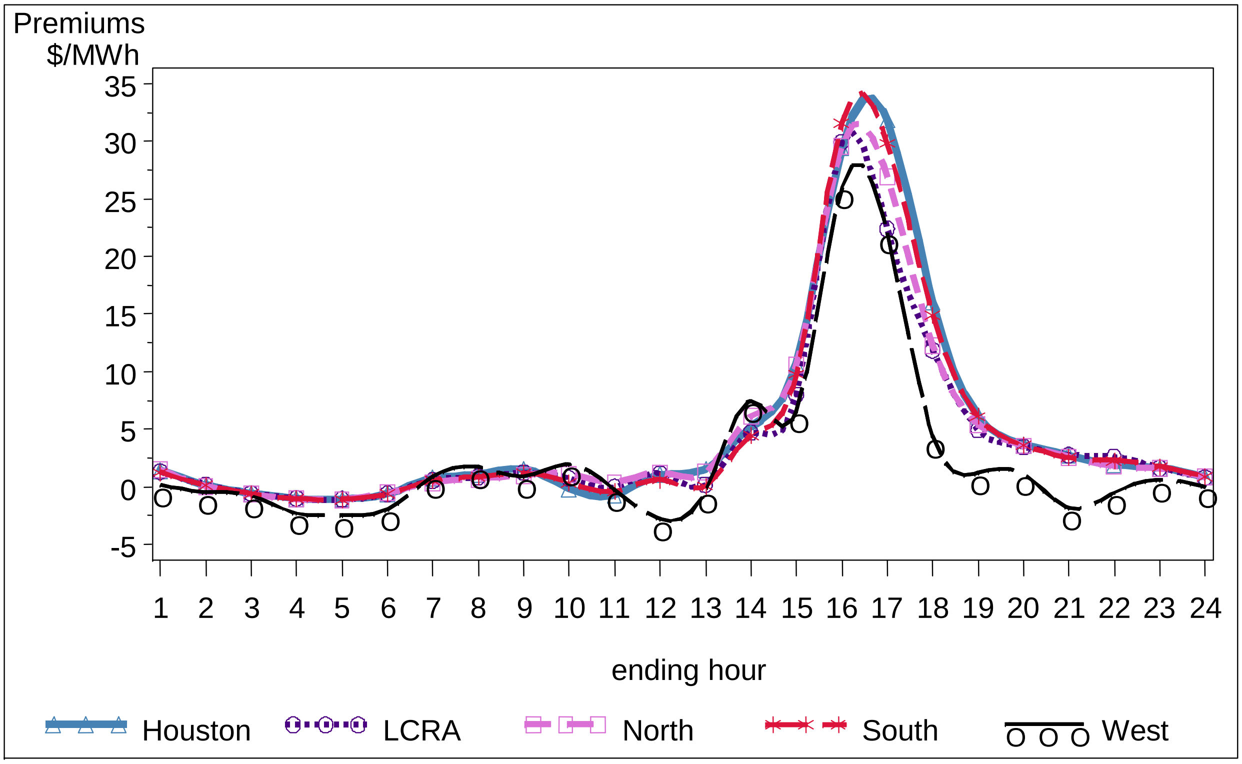

Figure 13. Comparison of average zonal premiums: July

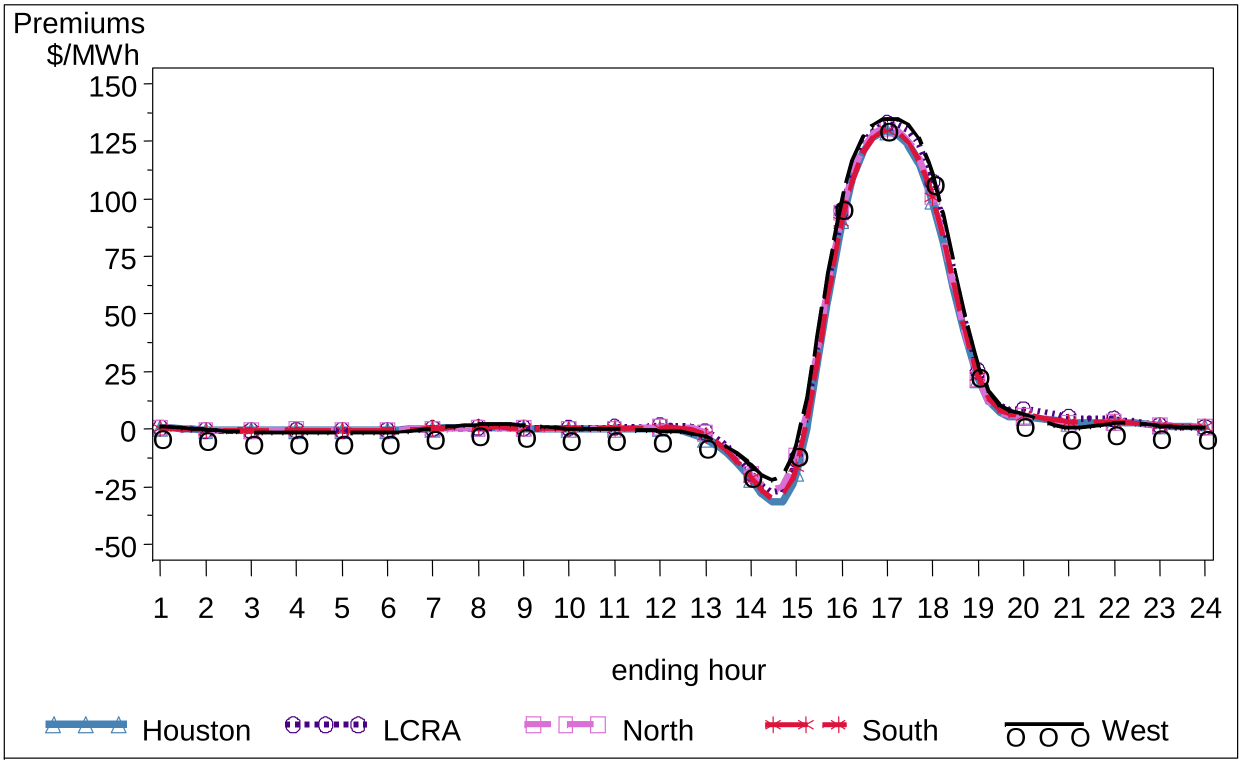

Figure 14. Comparison of average zonal premiums: August

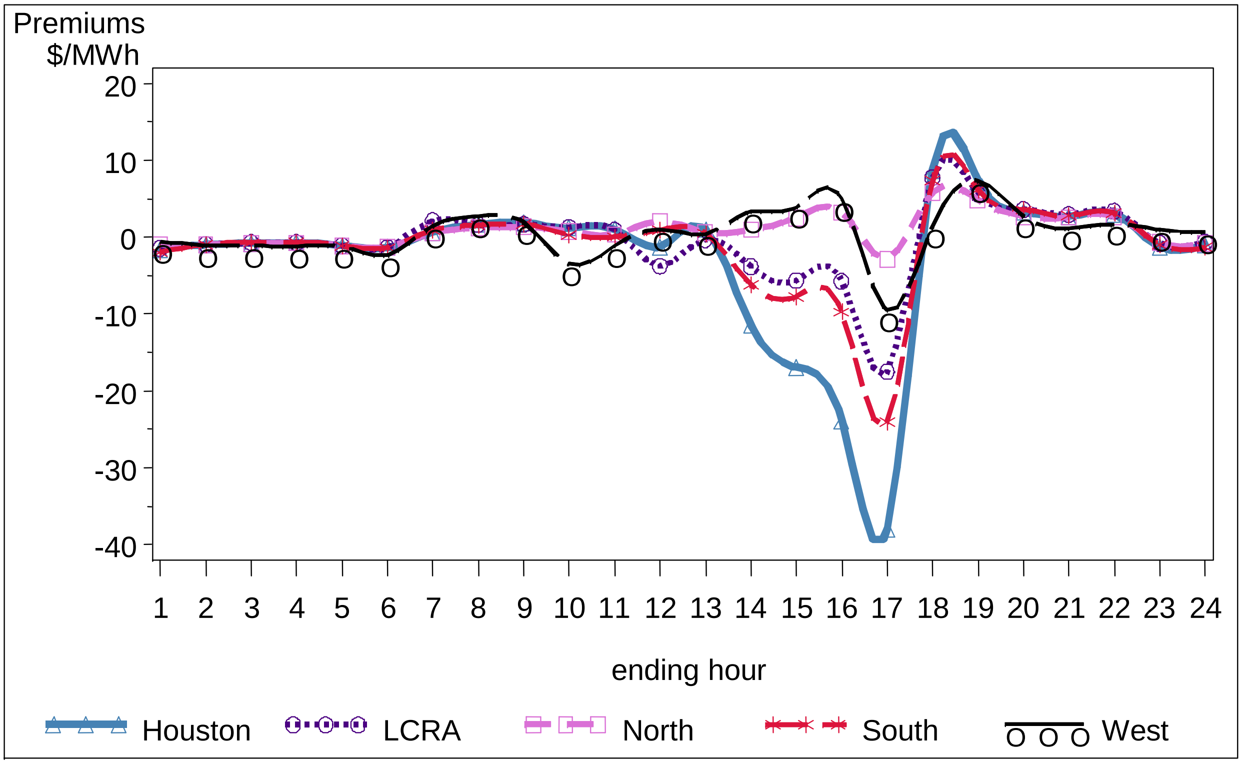

Figure 15. Comparison of average zonal premiums: September

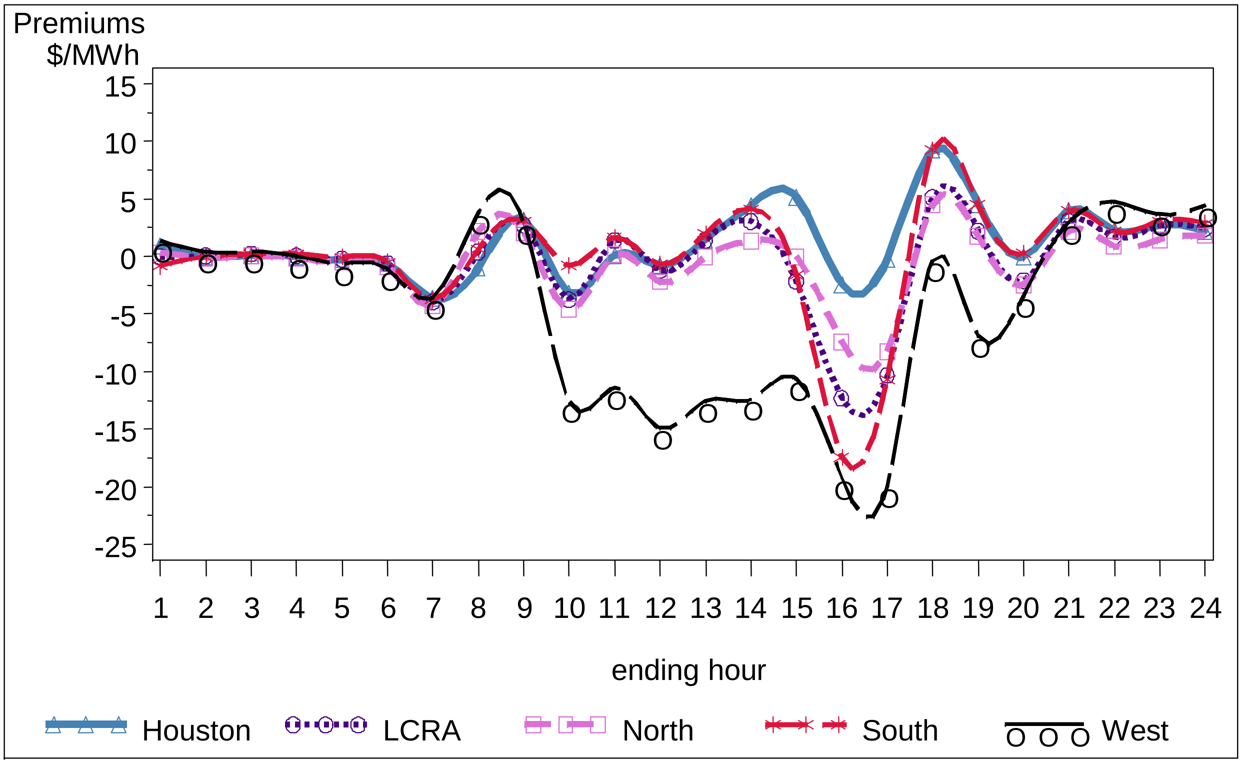

Figure 16. Comparison of average zonal premiums: October

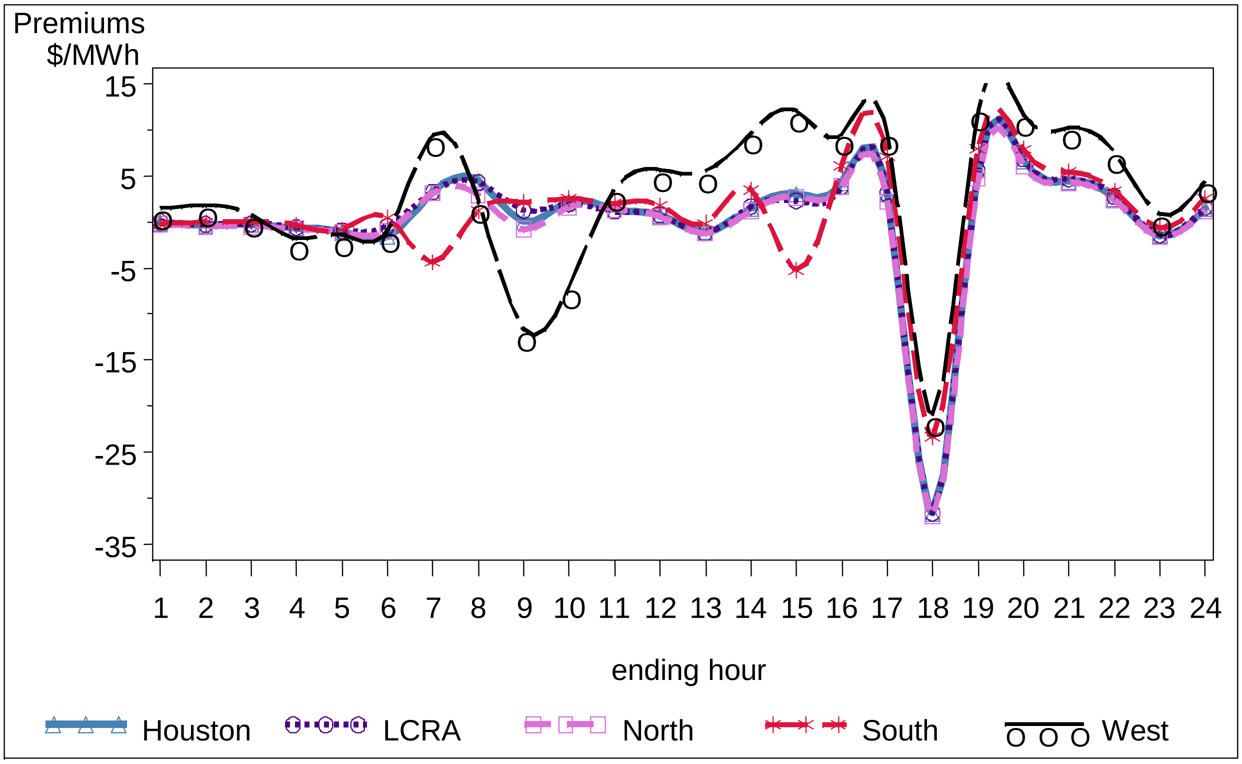

Figure 17. Comparison of average zonal premiums: November

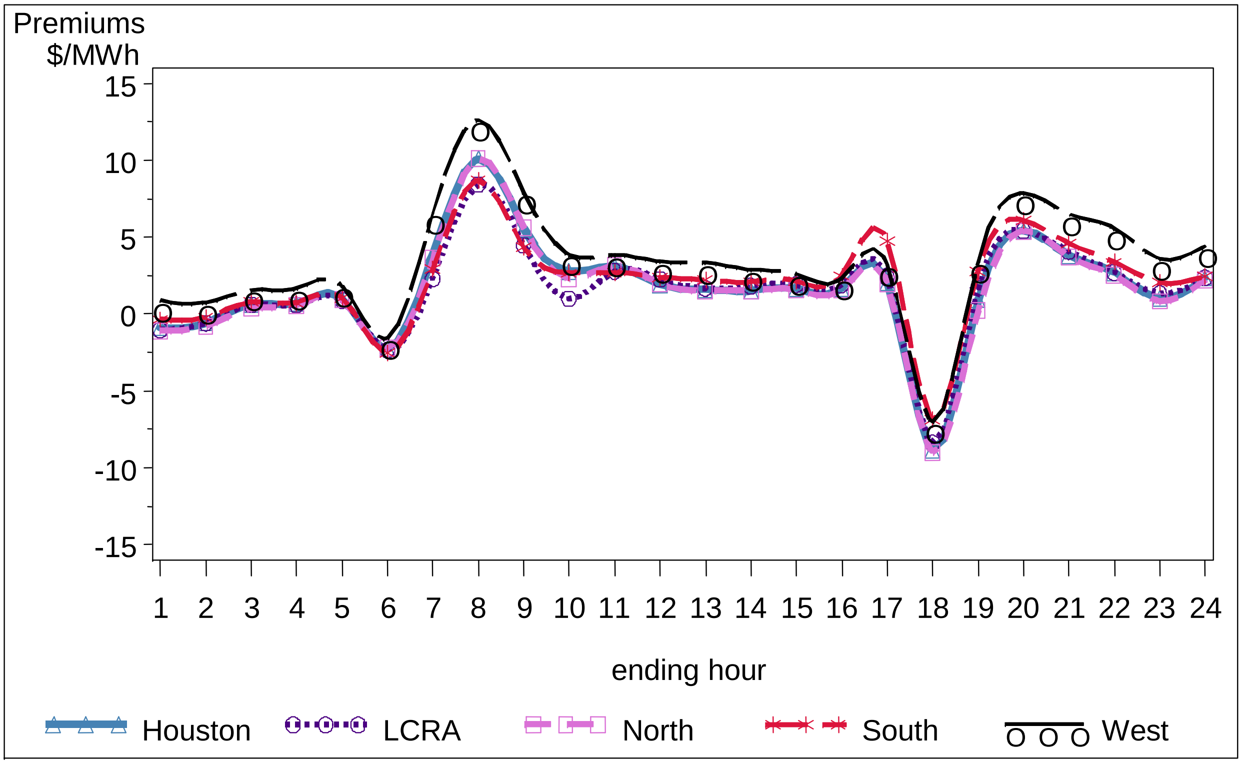

Figure 18. Comparison of average zonal premiums: December

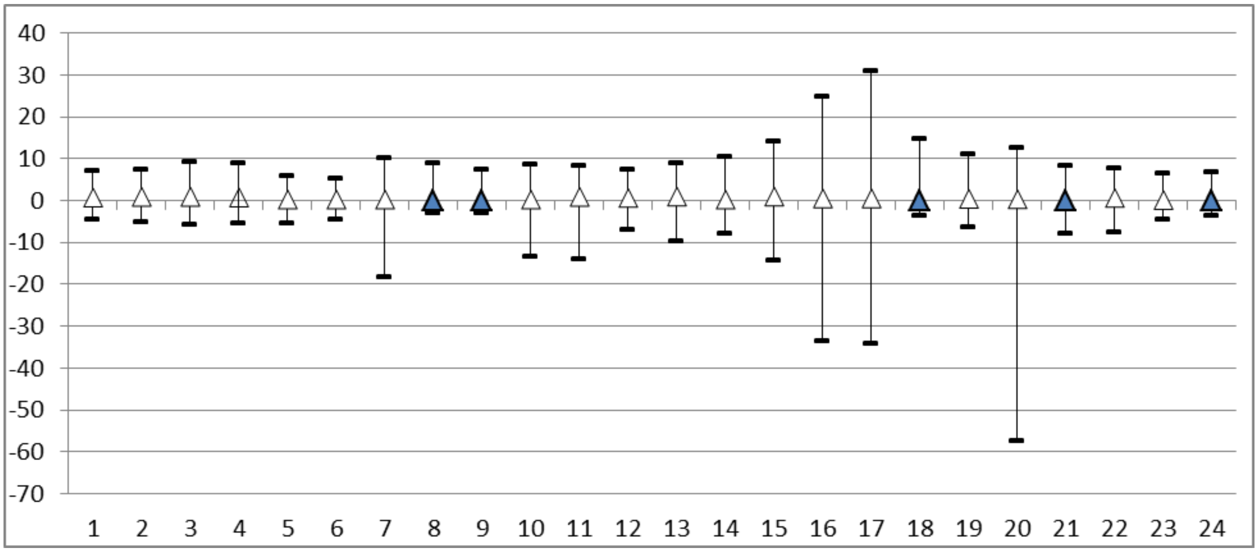

Figure 19. North zone's forward premiums' mean, 5th and 95th percentiles ($/MWh) by hour for the period of 12/01/2010 – 05/31/2014. For each hour, the bars "—" indicate the 5- and 95 percentiles, the unfilled triangles "∆" the means that are not statistically different from zero (p-value > 0.05), the solid triangles "▲" the means that are statistically different from zero (p-value ≤ 0.05).

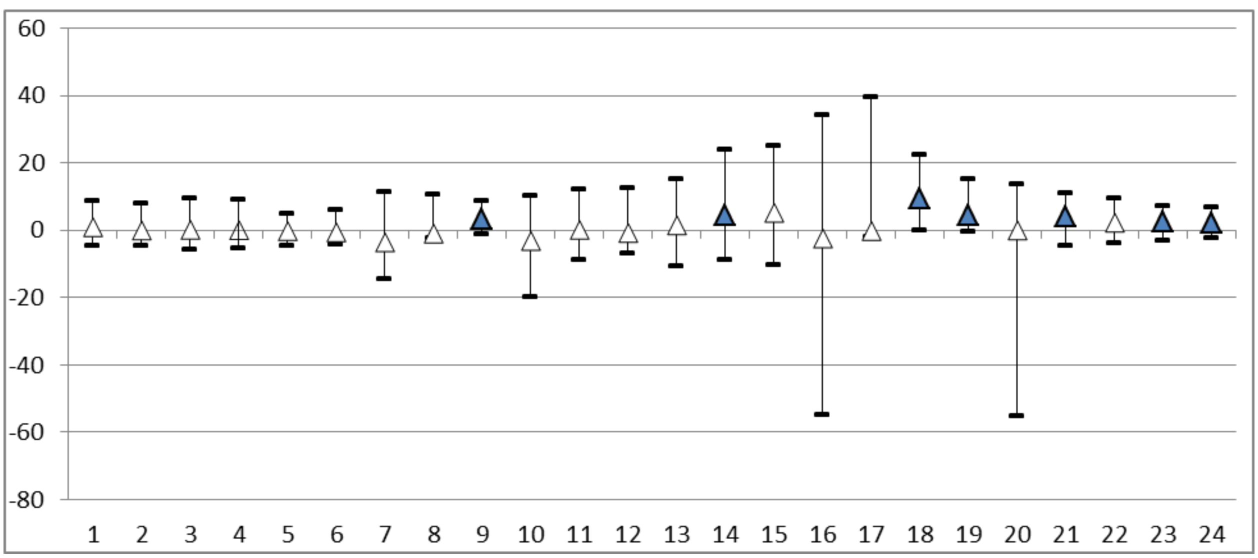

Figure 20. Houston zone's forward premiums' mean, 5th and 95th percentiles ($/MWh) by hour for the period of 12/01/2010 – 05/31/2014. For each hour, the bars "—" indicate the 5- and 95 percentiles, the unfilled triangles "∆" the means that are not statistically different from zero (p-value > 0.05), the solid triangles "▲" the means that are statistically different from zero (p-value ≤ 0.05).

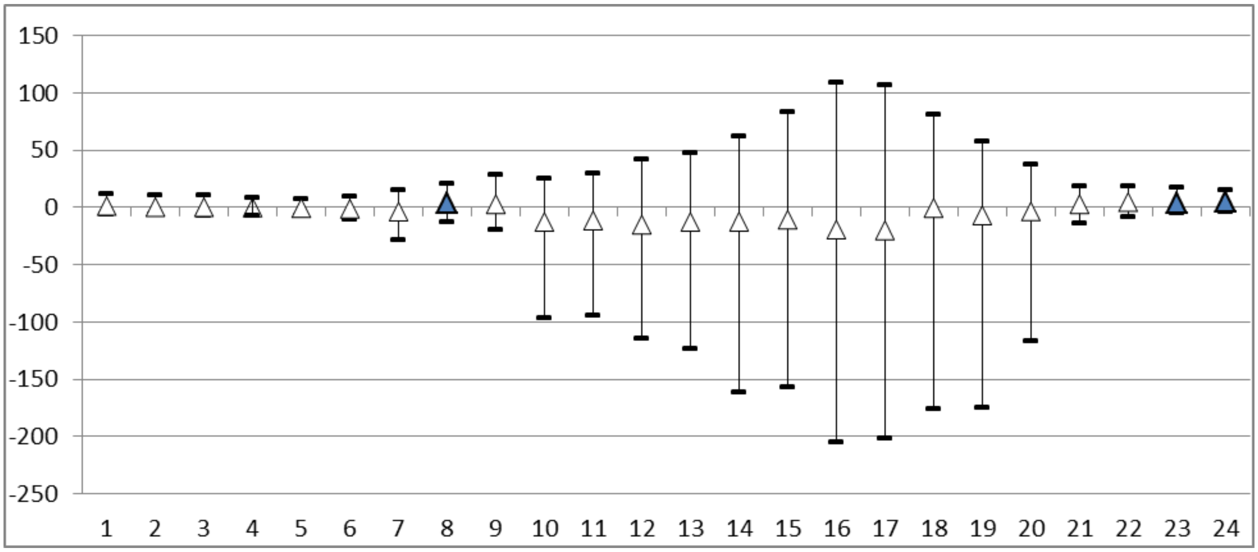

Figure 21. West zone's forward premiums' mean, 5th and 95th percentiles ($/MWh) by hour for the period of 12/01/2010 – 05/31/2014. For each hour, the bars "—" indicate the 5- and 95 percentiles, the unfilled triangles "△" the means that are not statistically different from zero (p-value > 0.05), the solid triangles "▲" the means that are statistically different from zero (p-value ≤ 0.05).

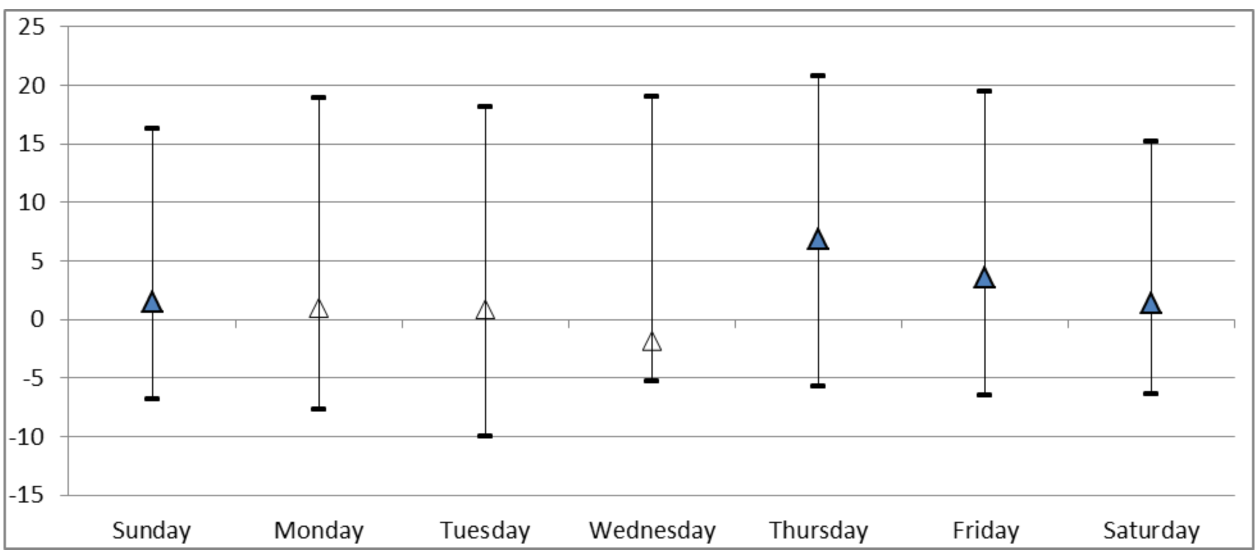

Figure 22. North zone's forward premiums' mean, 5th and 95th percentiles ($/MWh) by day-of-week for the period of 12/01/2010 – 05/31/2014. For each day of week, the bars "—" indicate the percentiles, the unfilled triangles "△" the means that are not statistically different from zero (p-value > 0.05), the solid triangles "▲" the means that are statistically different from zero (p-value ≤ 0.05).

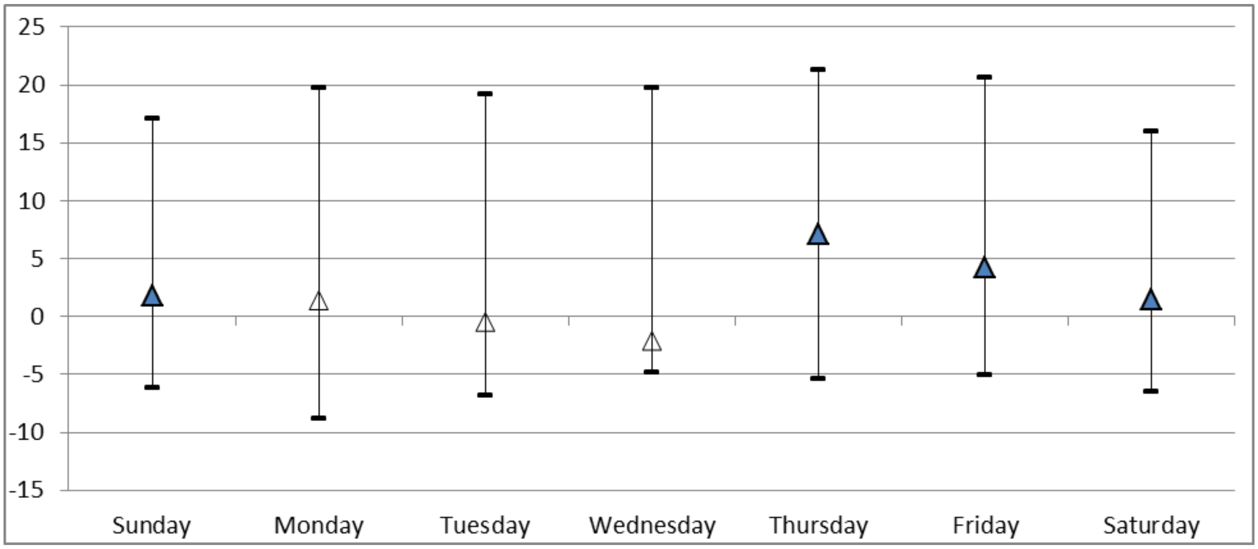

Figure 23. Houston zone's forward premiums' mean, 5^{th} and 95^{th} percentiles ($/MWh) by day-of-week for the period of 12/01/2010 – 05/31/2014. For each day of week, the bars "—" indicate the percentiles, the unfilled triangles "△" the means that are not statistically different from zero (p-value > 0.05), the solid triangles "▲" the means that are statistically different from zero (p-value ≤ 0.05).

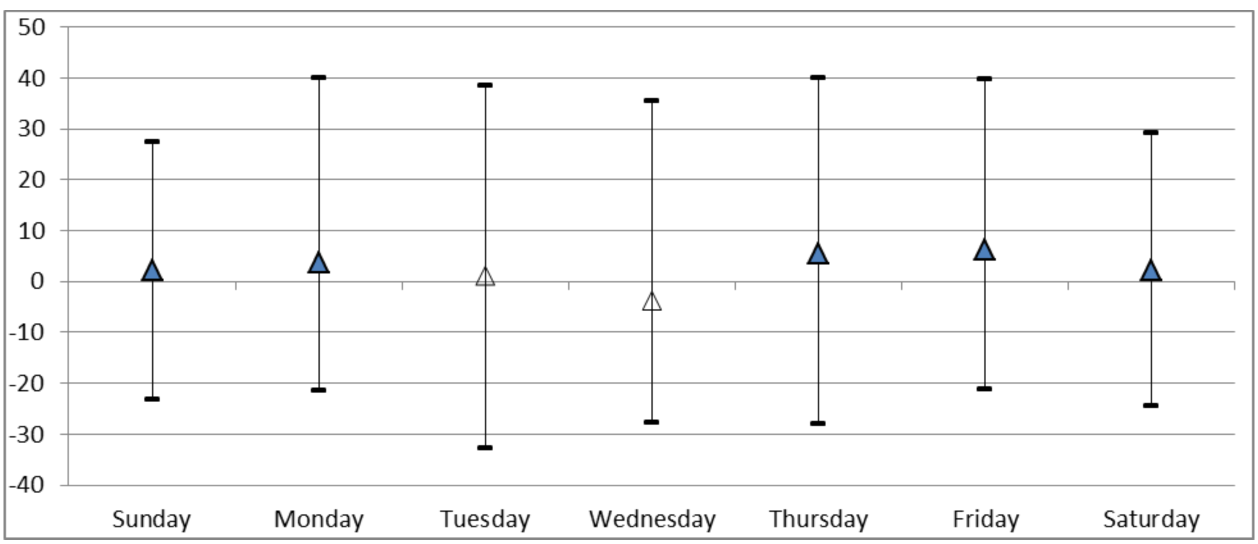

Figure 24. West zone's forward premiums' mean, 5^{th} and 95^{th} percentiles ($/MWh) by day-of-week for the period of 12/01/2010 – 05/31/2014. For each day of week, the bars "—" indicate the percentiles, the unfilled triangles "△" the means that are not statistically different from zero (p-value > 0.05), the solid triangles "▲" the means that are statistically different from zero (p-value ≤ 0.05).

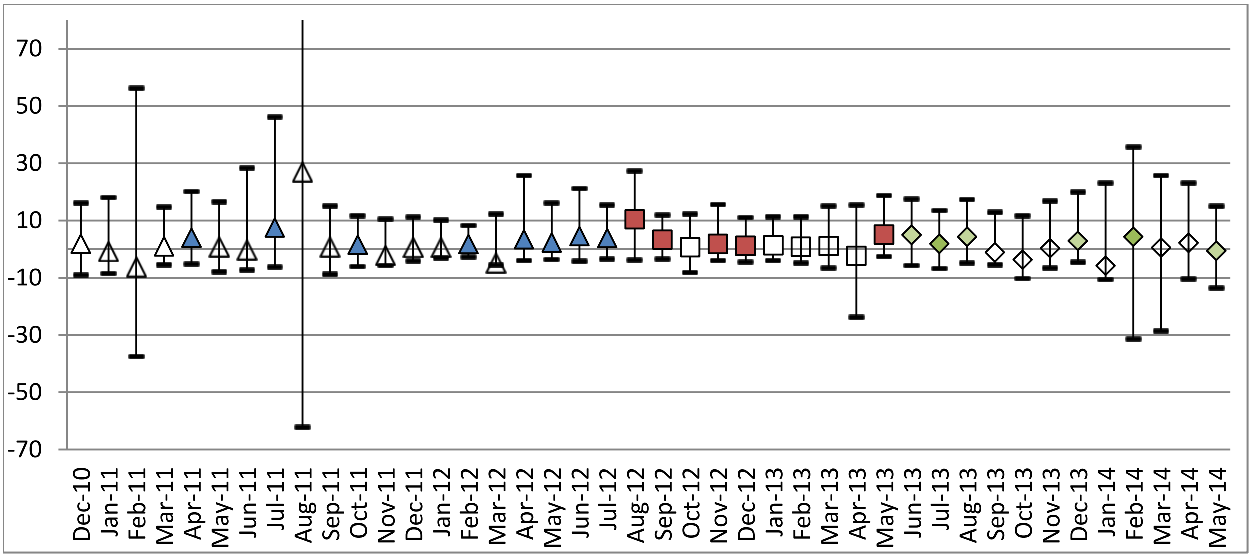

Figure 25. North zone's forward premiums' monthly mean, 5th and 95th percentiles ($/MWh) for the period of 12/01/2010 – 05/31/2014. For each month, the bars "—" indicate the percentiles. The triangles show the means for the $3000/MWh price cap period, the squares show the means for the $4500/MWh price cap period, and the diamonds show the means for the $5000/MWh price cap period. The solid triangles, squares and diamonds indicate means that are statistically different from zero (p-value ≤ 0.05)

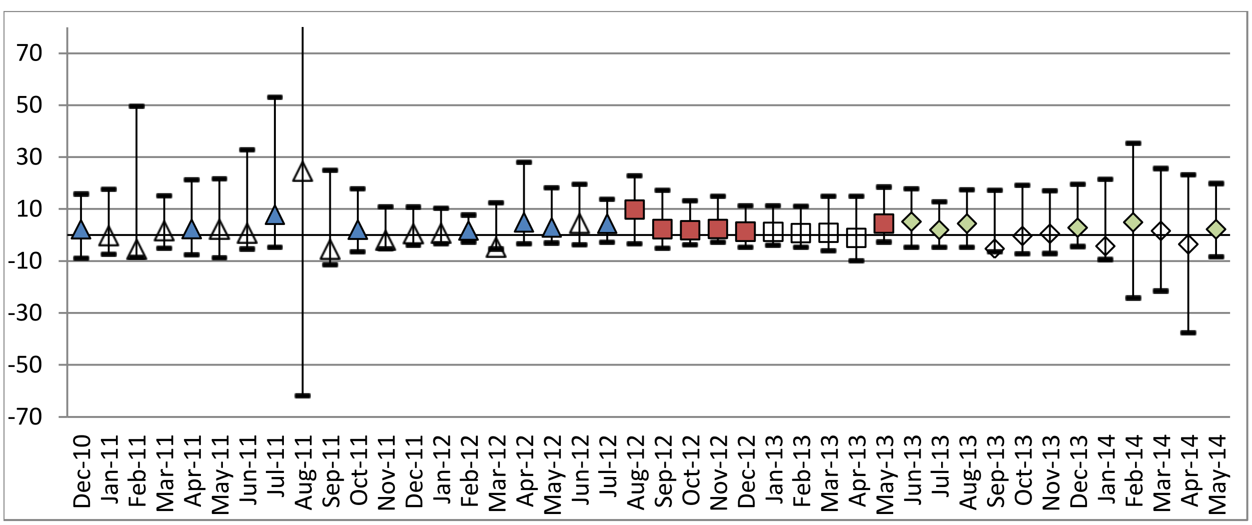

Figure 26. Houston zone's forward premiums' monthly mean, 5th and 95th percentiles ($/MWh) for the period of 12/01/2010 – 05/31/2014. For each month, the bars "—" indicate the percentiles. The triangles show the means for the $3000/MWh price cap period, the squares show the means for the $4500/MWh price cap period, and the diamonds show the means for the $5000/MWh price cap period. The solid triangles, squares and diamonds indicate means that are statistically different from zero (p-value ≤ 0.05).

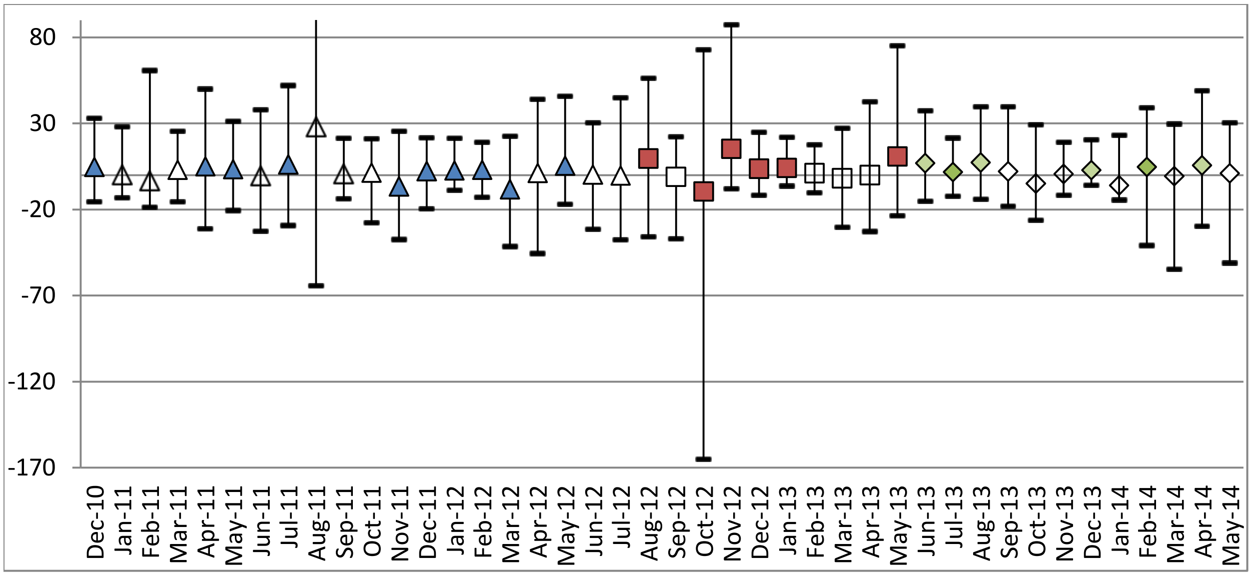

Figure 27: West zone's forward premiums' monthly mean, 5th and 95th percentiles (\$/MWh) for the period of 12/01/2010 – 05/31/2014. For each month, the bars "—" indicate the percentiles. The triangles show the means for the \$3000/MWh price cap period, the squares show the means for the \$4500/MWh price cap period, and the diamonds show the means for the \$5000/MWh price cap period. The solid triangles, squares and diamonds indicate means that are statistically different from zero (p-value ≤ 0.05).

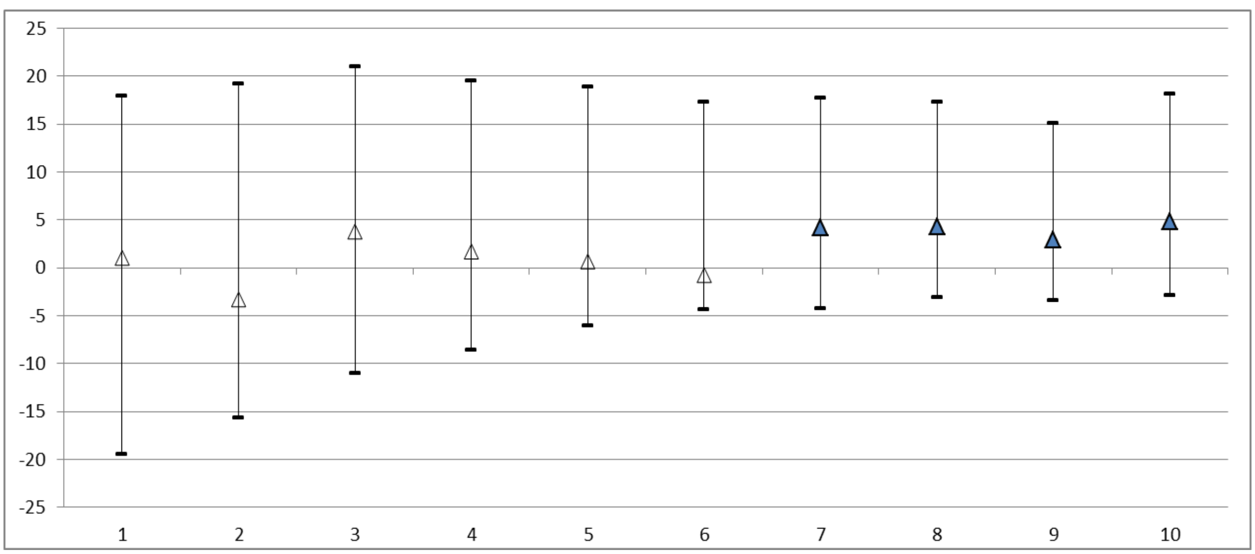

Figure 28. North zone's forward premiums' mean, 5th and 95th percentiles (\$/MWh) by wind generation interval for the period of 12/01/2010 – 05/31/2014. The interval definitions are: 1 = "0-10 percentile of wind generation data", …, 10 = "91-100 percentile of wind generation data". The bars "—" indicate the premiums' percentiles, the unfilled triangles "△" the means that are not statistically different from zero (p-value > 0.05), the solid triangles "▲" the means that are statistically different from zero (p-value ≤ 0.05).

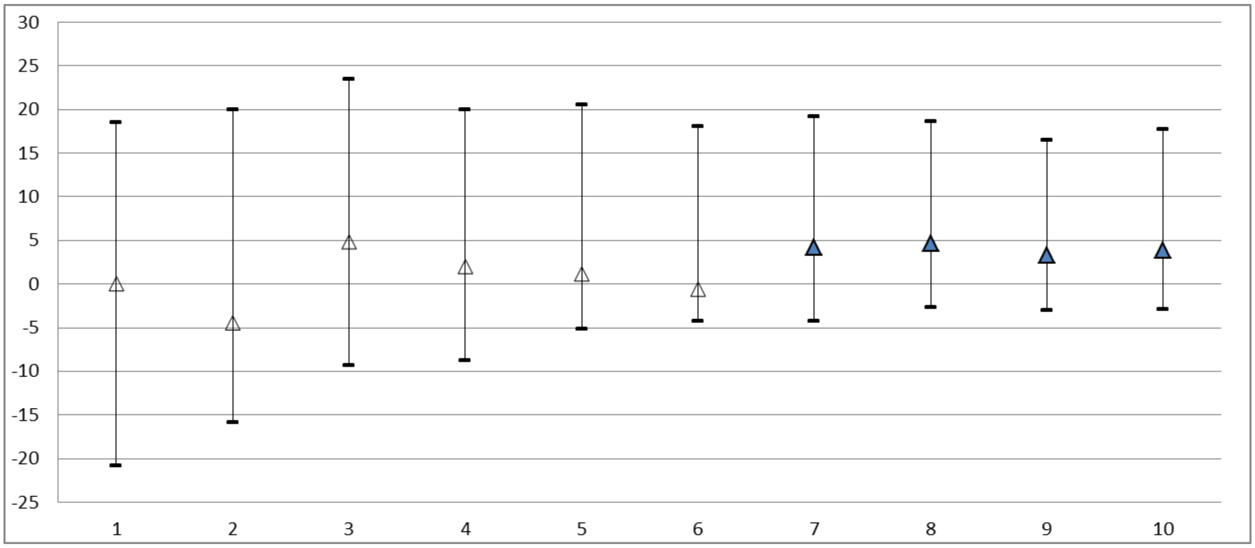

Figure 29. Houston zone's forward premiums' mean, 5th and 95th percentiles ($/MWh) by wind generation interval for the period of 12/01/2010 – 05/31/2014. The interval definitions are: 1 = "0-10 percentile of wind generation data", …, 10 = "91-100 percentile of wind generation data". The bars "━" indicate the premiums' percentiles, the unfilled triangles "△" the means that are not statistically different from zero (*p*-value > 0.05), the solid triangles "▲" the means that are statistically different from zero (*p*-value ≤ 0.05).

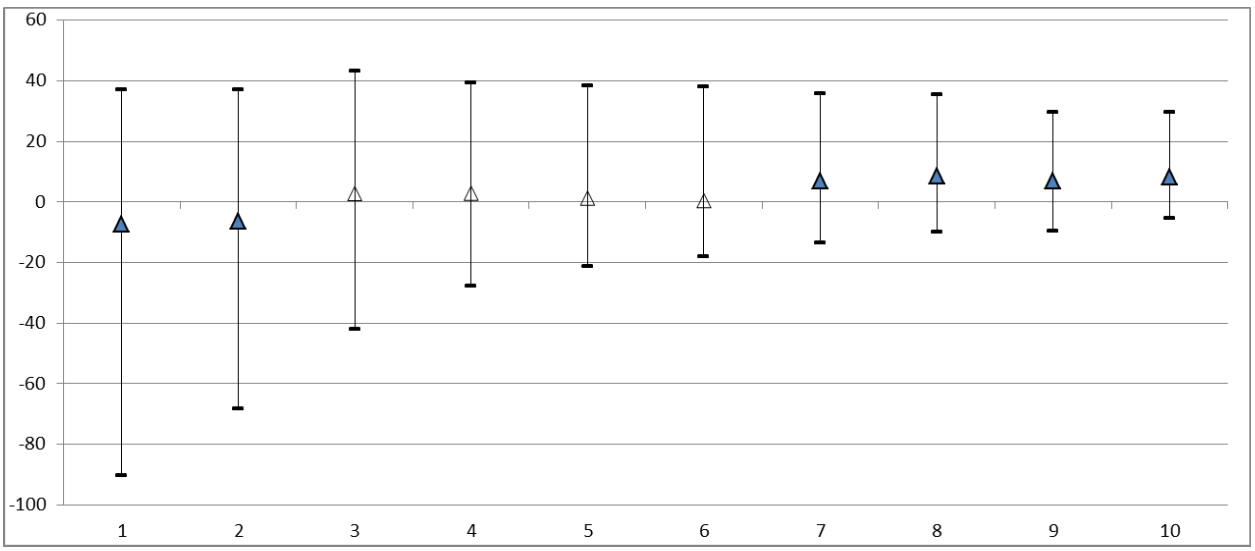

Figure 30. West zone's forward premiums' mean, 5th and 95th percentiles ($/MWh) by wind generation interval for the period of 12/01/2010 – 05/31/2014. The interval definitions are: 1 = "0-10 percentile of wind generation data", …, 10 = "91-100 percentile of wind generation data". The bars "━" indicate the premiums' percentiles, the unfilled triangles "△" the means that are not statistically different from zero (*p*-value > 0.05), the solid triangles "▲" the means that are statistically different from zero (*p*-value ≤ 0.05).

Table 2. Summary statistics of forward price premiums in the period of 12/01/2010 – 05/31/2014.

Zone	*N*	Mean	Std Dev	Sum	Minimum	Maximum
North	30,668	1.93	92	59155	-4439	2584
Houston	30,668	1.92	94	58763	-4296	2585
West	30,668	2.47	97	75666	-4465	2572
LCRA	30,668	2.03	94	62196	-4628	2593
South	30,668	1.54	95	47293	-4310	2589

Correlation coefficients					
Zone	North	Houston	West	LCRA	South
North	1	0.96	0.95	0.98	0.92
Houston	0.96	1	0.92	0.97	0.92
West	0.95	0.92	1	0.93	0.87
LCRA	0.98	0.97	0.93	1	0.93
South	0.92	0.92	0.87	0.93	1

Table 3. Maximum likelihood estimation of Equation (1): $Y_{ht} = \alpha + \beta X_{ht} + \varepsilon_{ht}$ where Y_{ht} = RTM price, X_{ht} = DAM price, and ε_{ht} = AR(5) error. Each regression's sample has 30,668 hourly observations for the period of 12/01/2010 – 05/31/2014

Variable	North	Houston	West	LCRA	South
Sample Mean RTM	34.15	34.51	37.96	34.84	35.46
Sample Mean DAM	36.08	36.43	40.43	36.87	37.00
RMSE	83.77	86.12	89.80	85.86	87.64
Adjusted R^2	0.2086	0.1959	0.2173	0.2067	0.2382
Intercept: α	16.26 (<.0001)	16.35 (<.0001)	16.09 (<.0001)	15.93 (<.0001)	14.77 (<.0001)
Slope: β	0.4957 (<.0001)	0.4985 (<.0001)	0.5408 (<.0001)	0.5127 (<.0001)	0.5590 (<.0001)
AR(1) parameter	0.1693 (<.0001)	0.1587 (<.0001)	0.1558 (<.0001)	0.1677 (<.0001)	0.2373 (<.0001)
AR(2) parameter	0.0383 (<.0001)	0.0468 (<.0001)	0.0274 (<.0001)	0.0351 (<.0001)	-0.0154 0.0098
AR(3) parameter	0.0424 (<.0001)	0.0403 (<.0001)	0.0456 (<.0001)	0.0375 (<.0001)	0.0453 (<.0001)
AR(4) parameter	-0.0302 (<.0001)	-0.0253 (<.0001)	-0.0280 (<.0001)	-0.0228 (<.0001)	-0.0307 (<.0001)
AR(5) parameter	-0.0650 (<.0001)	-0.0672 (<.0001)	-0.0608 (<.0001)	-0.0695 (<.0001)	-0.0637 (<.0001)
F-statistic for testing H_0: $\alpha = 0$ and $\beta = 1$,	3562 (<.0001)	3436 (<.0001)	4151 (<.0001)	3701 (<.0001)	3776 (<.0001)

Table 4. North zone's regression results based on Equation (2) that postulates (a) the hourly premium varies by day-of-week, month-of-year year and wind generation; and (b) the random error is AR(1) and has heteroskedastic variance that is an exponential function of wind generation. The regression's sample has 30,668 hourly observations for the period of 12/01/2010 – 05/31/2014. The **bold** estimates are significant at the 1% level.

Hour	Adjusted R^2	AR(1) parameter	Hetero Intercept	Hetero Wind
1	0.0405	-0.0282	**15.67**	**-0.00010**
2	0.0549	-0.0647	**11.48**	**-0.00018**
3	0.0778	**-0.1706**	**7.95**	**-0.00008**
4	0.0147	**-0.3570**	**8.00**	**0.00017**
5		**-0.1911**	**83.75**	**-0.00061**
6	0.0091	**-0.1553**	**85.54**	-0.00001
7	0.0194	**-0.1197**	**172.57**	**-0.00009**
8		**-0.1627**	**542.48**	**-0.00090**
9	0.0078	**-0.2742**	**71.45**	-0.00001
10	0.0072	**-0.1960**	**59.55**	0.00003
11	0.0104	**-0.1879**	**19.13**	**0.00066**
12	0.0146	-0.0685	**82.54**	**-0.00039**
13	0.0141	-0.0161	**40.05**	**-0.00054**
14	0.0012	-0.0643	**134.26**	**-0.00102**
15		**0.1954**	**328.87**	**-0.00135**
16	0.0127	**0.4412**	**261.37**	**-0.00070**
17	0.0276	**0.3739**	**308.76**	**-0.00065**
18	0.0379	**0.2937**	**199.31**	**-0.00066**
19	0.0184	**0.0877**	**126.16**	**-0.00077**
20	0.0618	**0.0731**	**34.48**	**-0.00039**
21	0.0341	0.0671	**32.22**	**-0.00029**
22	0.0191	0.0506	**35.90**	**-0.00036**
23	0.0288	0.0677	**28.89**	**-0.00025**
24	0.0373	0.0578	**20.49**	**-0.00024**

Table 5. Houston zone's regression results based on Equation (2) that postulates (a) the hourly premium varies by day-of-week, month-of-year year and wind generation; and (b) the random error is AR(1) and has heteroskedastic variance that is an exponential function of wind generation. The regression's sample has 30,668 hourly observations for the period of 12/01/2010 – 05/31/2014. The **bold** estimates are significant at the 1% level.

Hour	Adjusted R^2	AR(1) parameter	Hetero Intercept	Hetero Wind
1	0.0462	-0.0043	**16.44**	**-0.00012**
2	0.0589	0.0131	**10.85**	**-0.00021**
3	0.0840	-0.0308	**7.07**	**-0.00007**
4	0.0172	**-0.3745**	**7.73**	**0.00014**
5	0.0001	**-0.1980**	**82.41**	**-0.00063**
6	0.0082	**-0.1741**	**87.47**	-0.00002
7	0.0178	**-0.1182**	**753.16**	**-0.00083**
8	0.0085	**-0.1721**	**356.67**	**-0.00069**
9	0.0091	**-0.2612**	**70.08**	0.00000
10	0.0075	**-0.2292**	**24.72**	**0.00040**
11	0.0104	**-0.1990**	**21.57**	**0.00060**
12	0.0138	**-0.1044**	**59.60**	**-0.00016**
13	0.0020	-0.0208	**17.50**	**0.00041**
14	0.0158	-0.0444	**97.55**	**-0.00032**
15		**0.1746**	**329.87**	**-0.00119**
16	0.0147	**0.4015**	**278.09**	**-0.00065**
17	0.0273	**0.3462**	**345.44**	**-0.00070**
18	0.0381	**0.2992**	**193.12**	**-0.00064**
19	0.0189	**0.0803**	**125.03**	**-0.00079**
20	0.0872	0.0487	**30.75**	**-0.00039**
21	0.0398	0.0503	**32.33**	**-0.00032**
22	0.0221	0.0392	**35.76**	**-0.00036**
23	0.0302	**0.0945**	**28.15**	**-0.00027**
24	0.0479	0.0645	**22.53**	**-0.00043**

Table 6. West zone's regression results based on Equation (2) that postulates (a) the hourly premium varies by day-of-week, month-of-year year and wind generation; and (b) the random error is AR(1) and has heteroskedastic variance that is an exponential function of wind generation. The regression's sample has 30,668 hourly observations for the period of 12/01/2010 – 05/31/2014. The **bold** estimates are significant at the 1% level.

Hour	Adjusted R^2	AR(1) parameter	Hetero Intercept	Hetero Wind
1	0.0779	**0.0921**	**21.85**	**-0.00032**
2	0.0623	**0.0795**	**15.53**	**-0.00021**
3	0.0691	0.0611	**14.70**	**-0.00018**
4	0.0318	**-0.1899**	**29.74**	**-0.00027**
5	0.0103	**-0.1399**	**70.82**	**-0.00054**
6	0.0096	**-0.1816**	**85.13**	-0.00001
7	0.0180	**-0.1012**	**174.52**	**-0.00010**
8	0.0088	**-0.1645**	**441.10**	**-0.00078**
9	0.0122	**-0.2376**	**140.60**	**-0.00029**
10	0.0159	**-0.1781**	**69.42**	-0.00001
11	0.0185	**-0.1737**	**86.22**	0.00001
12	0.0300	-0.0479	**103.80**	**-0.00041**
13	0.0183	0.0189	**80.46**	**-0.00052**
14	0.0110	-0.0203	**135.13**	**-0.00065**
15	0.0101	**0.1914**	**268.29**	**-0.00081**
16	0.0200	**0.4204**	**261.17**	**-0.00058**
17	0.0333	**0.3563**	**302.94**	**-0.00055**
18	0.0447	**0.2854**	**196.37**	**-0.00055**
19	0.0350	**0.0873**	**130.17**	**-0.00061**
20	0.0639	0.0625	**49.97**	**-0.00040**
21	0.0308	0.0397	**54.19**	**-0.00044**
22	0.0305	**0.0746**	**49.69**	**-0.00047**
23	0.0522	**0.1219**	**31.80**	**-0.00039**
24	0.0781	**0.1336**	**22.96**	**-0.00028**

Table 7. LCRA zone's regression results based on Equation (2) that postulates (a) the hourly premium varies by day-of-week, month-of-year year and wind generation; and (b) the random error is AR(1) and has heteroskedastic variance that is an exponential function of wind generation. The regression's sample has 30,668 hourly observations for the period of 12/01/2010 – 05/31/2014. The **bold** estimates are significant at the 1% level.

Hour	Adjusted R^2	AR(1) parameter	Hetero Intercept	Hetero Wind
1	0.0462	-0.0080	**15.79**	**-0.00012**
2	0.0623	-0.0175	**10.95**	**-0.00020**
3	0.0926	**-0.0954**	**6.55**	**-0.00004**
4	0.0153	**-0.3277**	**6.67**	**0.00024**
5	0.0005	**-0.2071**	**85.33**	**-0.00061**
6	0.0095	**-0.1659**	**87.46**	-0.00001
7	0.0165	**-0.0849**	**790.05**	**-0.00087**
8	0.0065	**-0.1010**	**379.59**	**-0.00077**
9	0.0070	**-0.2379**	**96.61**	**-0.00014**
10	0.0072	**-0.2043**	**61.33**	0.00002
11	0.0115	**-0.1988**	**20.35**	**0.00063**
12	0.0159	**-0.0916**	**89.71**	**-0.00040**
13	0.0183	-0.0135	**30.14**	**-0.00016**
14	0.0117	-0.0505	**103.54**	**-0.00058**
15		**0.1965**	**276.52**	**-0.00105**
16	0.0142	**0.4411**	**264.61**	**-0.00069**
17	0.0281	**0.3675**	**319.44**	**-0.00066**
18	0.0413	**0.2984**	**195.70**	**-0.00062**
19	0.0175	**0.0907**	**129.21**	**-0.00074**
20	0.0505	**0.0947**	**38.45**	**-0.00044**
21	0.0336	0.0521	**30.91**	**-0.00020**
22	0.0252	0.0342	**35.16**	**-0.00028**
23	0.0328	0.0440	**27.84**	**-0.00025**
24	0.0529	0.0615	**22.71**	**-0.00043**

Table 8. South zone's regression results based on Equation (2) that postulates (a) the hourly premium varies by day-of-week, month-of-year year and wind generation; and (b) the random error is AR(1) and has heteroskedastic variance that is an exponential function of wind generation. The regression's sample has 30,668 hourly observations for the period of 12/01/2010 – 05/31/2014. The **bold** estimates are significant at the 1% level.

Hour	Adjusted R^2	AR(1) parameter	Hetero Intercept	Hetero Wind
1	0.0406	0.0027	**15.17**	**-0.00007**
2	0.0719	**0.0739**	**9.50**	**-0.00017**
3	0.0850	**0.0928**	**7.93**	**-0.00012**
4	0.0189	**-0.3274**	**11.59**	0.00002
5	0.0008	**-0.1657**	**82.95**	**-0.00064**
6	0.0108	**-0.1774**	**85.65**	-0.00001
7	0.0183	0.0214	**529.85**	**-0.00077**
8	0.0073	**0.1971**	**200.49**	**-0.00074**
9	0.0009	**0.2113**	**209.86**	**-0.00099**
10	0.0090	**0.2763**	**93.78**	**-0.00044**
11	0.0100	**-0.1416**	**75.98**	0.00003
12	0.0125	**0.3684**	**68.68**	**-0.00046**
13	0.0132	-0.0070	**50.77**	**-0.00022**
14	0.0168	-0.0537	**122.07**	**-0.00059**
15	0.0043	**0.1739**	**300.91**	**-0.00090**
16	0.0130	**0.4194**	**269.99**	**-0.00063**
17	0.0259	**0.3541**	**338.92**	**-0.00071**
18	0.0362	**0.2889**	**202.08**	**-0.00060**
19	0.0141	**0.1951**	**121.74**	**-0.00072**
20	0.0366	**0.1803**	**52.52**	**-0.00047**
21	0.0257	**0.0890**	**45.93**	**-0.00015**
22	0.0166	0.0277	**37.74**	0.00002
23	0.0350	**0.0728**	**27.75**	**-0.00021**
24	0.0567	**0.1153**	**21.34**	**-0.00041**

Table 9. Estimates of γ_h, the hourly premium in December on a Sunday, after controlling for the effects of month-of-year, day-of-week, and wind generation. They are based on Equation (2) with the AR(1) and heteroskedastic error specification for the period of 12/01/2010 – 05/31/2014. The **bold** estimates are significant at the 1% level.

Hour	North	Houston	South	LCRA	West
1	-5.1429	-5.5172	-5.0613	-5.8598	**-4.9089**
2	**-4.2804**	**-4.0905**	**-3.7935**	**-4.1404**	-4.0085
3	**-2.6724**	**-2.4963**	-2.6078	**-2.4464**	-3.3347
4	-1.6894	-1.4938	-1.6057	-1.6623	-1.4102
5	-1.2157	-1.0259	-1.1335	-0.9552	-1.2937
6	-2.7637	-2.6948	-3.8170	-2.7112	-4.9401
7	-2.2571	-8.1247	-9.1708	-10.6660	-4.3978
8	3.9558	6.4032	1.7231	3.5288	5.3828
9	6.0062	6.8011	1.7411	4.6829	4.4759
10	2.7368	5.0130	1.4447	1.9331	1.2812
11	2.1958	2.4105	0.9333	2.0617	-3.4144
12	-1.2930	-0.9524	0.3224	-0.6975	-3.9851
13	-1.4032	-2.1469	-1.3915	-2.6291	-1.1488
14	-3.1871	1.4889	2.5709	1.1089	-0.4740
15	**10.5360**	9.3599	4.4573	7.7699	2.3561
16	-4.7216	-1.9284	-7.9028	-3.7289	-9.3777
17	-9.8486	-6.9090	-9.0750	-8.5523	-13.8210
18	-26.0860	-25.5990	-23.7020	-24.7560	-28.0360
19	-6.9855	-5.0873	-3.2989	-0.1785	-6.2107
20	2.9402	4.1649	2.1319	6.0575	1.3401
21	0.1678	-0.3350	1.7329	1.9396	-1.2210
22	-2.0054	-1.7458	2.2376	-0.5137	-2.6296
23	-6.8994	-6.2320	-5.2810	-6.2565	-4.2551
24	-0.4835	-0.3366	-0.6981	-0.5544	-2.1710

Table 10. Estimates of θ_h, the wind generation effect by hour, after controlling for the effects of day-of-week and month-of-year. They are based on Equation (2) with the AR(1) and heteroskedastic error specification for the period of 12/01/2010 – 05/31/2014. The **bold** estimates are significant at the 1% level.

Hour	North	Houston	South	LCRA	West
1	0.0008	**0.0009**	0.0008	**0.0009**	**0.0013**
2	**0.0005**	**0.0005**	**0.0005**	**0.0005**	**0.0009**
3	**0.0005**	**0.0006**	**0.0006**	**0.0006**	**0.0011**
4	0.0004	0.0004	0.0004	0.0004	0.0008
5	0.0004	0.0004	0.0004	0.0004	0.0009
6	0.0007	0.0001	0.0010	0.0008	0.0015
7	0.0045	**0.0055**	**0.0064**	**0.0059**	0.0054
8	0.0015	0.0009	0.0022	0.0013	0.0016
9	-0.0004	-0.0004	0.0009	0.0001	0.0009
10	0.0004	-0.0001	0.0013	0.0004	0.0020
11	0.0007	0.0007	0.0009	0.0007	0.0031
12	0.0014	0.0013	0.0013	0.0015	**0.0031**
13	**0.0009**	0.0019	0.0014	0.0012	**0.0018**
14	**0.0007**	0.0008	0.0011	0.0010	**0.0017**
15	**-0.0008**	-0.0003	0.0011	-0.0002	0.0017
16	0.0015	0.0013	0.0024	0.0014	0.0030
17	0.0030	0.0027	0.0032	0.0028	0.0048
18	0.0022	0.0020	0.0022	0.0022	0.0033
19	**0.0023**	**0.0020**	**0.0023**	**0.0017**	**0.0034**
20	0.0005	0.0002	0.0010	0.0002	**0.0016**
21	0.0006	0.0007	0.0007	0.0005	**0.0017**
22	0.0006	0.0006	0.0000	0.0004	**0.0014**
23	0.0008	0.0008	0.0008	**0.0008**	**0.0014**
24	0.0006	**0.0006**	**0.0007**	**0.0007**	**0.0014**

Table 11. *p*-values for testing H_0: No day-of-week effects, after controlling for the effects of month-of-year and wind generation. They are based on Equation (2) with the AR(1) and heteroskedastic error specification for the period of 12/01/2010 – 05/31/2014. The **bold** estimates are significant at the 1% level.

Hour	North	Houston	South	LCRA	West
1	0.6946	0.7306	0.7478	0.6619	0.0485
2	0.1025	0.0309	0.0377	0.0469	0.0517
3	0.0600	0.1244	0.1164	0.1287	0.1149
4	0.9745	0.9796	0.9676	0.9841	0.6934
5	0.8473	0.9580	0.8734	0.9960	0.8646
6	0.9997	0.9995	0.9997	0.9997	0.9994
7	0.8774	**<.0001**	0.0635	**<.0001**	0.8557
8	0.8366	0.1728	0.0365	0.0325	0.0138
9	0.9993	0.9993	0.9782	0.9990	0.9840
10	0.9993	0.9734	0.9289	0.9978	0.9482
11	0.5758	0.7410	0.9997	0.6408	0.9764
12	0.9936	0.9997	0.9766	0.9971	0.1485
13	0.4655	0.5289	0.9999	0.9767	0.0832
14	**<.0001**	0.9877	0.1080	0.8134	0.1465
15	**<.0001**	0.2585	0.0435	0.3952	**0.0004**
16	0.3367	0.0272	0.0304	0.0590	0.0496
17	0.1458	0.0134	0.0823	0.0128	0.0160
18	0.1108	0.1937	0.4972	0.1505	0.0130
19	0.1644	0.8585	0.7986	0.4404	**0.0004**
20	0.8182	0.9292	0.2733	0.9580	0.1428
21	0.5666	0.9154	0.7641	0.9786	0.2032
22	0.9679	0.9463	0.9992	0.9749	0.0322
23	0.3368	0.4220	0.4545	0.4002	**0.0076**
24	0.8892	0.1969	0.0608	0.1319	0.0589

Table 12. p-values for testing H_0: No month-of-year effects, after controlling for the effects of day-of-week and wind generation. They are based on Equation (2) with the AR(1) and heteroskedastic error specification for the period of 12/01/2010 – 05/31/2014. The **bold** estimates are significant at the 1% level.

Hour	North	Houston	South	LCRA	West
1	0.8519	0.5829	0.5820	0.8075	0.1556
2	**<.0001**	**0.0007**	**0.0002**	**0.0009**	0.3299
3	**<.0001**	**<.0001**	**<.0001**	**<.0001**	0.1138
4	1.0000	0.9999	0.9992	1.0000	0.9214
5	0.9259	0.6656	0.3636	0.8271	0.8928
6	1.0000	1.0000	0.9998	1.0000	0.9999
7	0.4830	**<.0001**	0.0627	**<.0001**	0.7313
8	0.4536	0.9927	0.9937	0.7732	0.8134
9	1.0000	0.9999	0.4405	1.0000	0.9938
10	1.0000	0.9999	0.9994	1.0000	0.9980
11	0.3065	0.6264	1.0000	0.2087	0.9999
12	0.9794	0.9999	0.7651	0.9001	0.6581
13	0.2428	0.8351	0.9997	0.9992	0.1260
14	**<.0001**	0.9954	0.8113	0.8584	0.3198
15	**<.0001**	**<.0001**	0.9390	**0.0062**	0.4328
16	**<.0001**	**<.0001**	**<.0001**	**<.0001**	**<.0001**
17	**<.0001**	**<.0001**	**<.0001**	**<.0001**	**<.0001**
18	**<.0001**	**<.0001**	**<.0001**	**<.0001**	**<.0001**
19	**0.0008**	**0.0043**	0.4273	**0.0008**	0.0283
20	0.2131	0.1235	0.0602	0.0711	**0.0005**
21	0.7682	0.9667	0.7299	0.9933	**0.0007**
22	0.9997	0.9994	0.9983	0.9999	0.0905
23	0.9256	0.9026	0.7668	0.9574	**0.0005**
24	0.1406	**0.0003**	**0.0003**	**0.0007**	0.0148

Table 13. p-values for testing H_0: No day-of-week and month-of-year effects, after controlling for the effect of wind generation. They are based on Equation (2) with the AR(1) and heteroskedastic error specification for the period of 12/01/2010 – 05/31/2014. The **bold** estimates are significant at the 1% level.

Hour	North	Houston	South	LCRA	West
1	0.6341	0.3285	0.3432	0.4863	0.0355
2	**<.0001**	**<.0001**	**<.0001**	**<.0001**	0.0391
3	**<.0001**	**<.0001**	**<.0001**	**<.0001**	0.0383
4	1.0000	0.9999	0.9971	1.0000	0.7559
5	0.8979	0.6566	0.3337	0.9560	0.9037
6	1.0000	1.0000	1.0000	1.0000	1.0000
7	0.6508	**<.0001**	**0.0003**	**<.0001**	0.8555
8	0.1356	0.3438	**0.0065**	0.2804	0.1846
9	1.0000	1.0000	0.3888	1.0000	0.9902
10	1.0000	1.0000	0.9926	1.0000	0.9619
11	0.0685	0.4034	1.0000	0.0326	0.9999
12	0.9986	1.0000	0.9033	0.9824	0.3479
13	0.1602	0.6194	0.9999	0.9957	**0.0018**
14	**<.0001**	0.9998	0.3370	0.7623	0.0241
15	**<.0001**	**<.0001**	0.0301	**0.0006**	**<.0001**
16	**<.0001**	**<.0001**	**<.0001**	**<.0001**	**<.0001**
17	**<.0001**	**<.0001**	**<.0001**	**<.0001**	**<.0001**
18	**<.0001**	**<.0001**	**<.0001**	**<.0001**	**<.0001**
19	**<.0001**	**0.0004**	0.3451	**<.0001**	**<.0001**
20	0.1569	0.3074	0.0211	0.1224	**<.0001**
21	0.0109	0.8560	0.3013	0.9857	**0.0002**
22	0.9959	0.9964	0.7683	0.9724	**0.0047**
23	0.6446	0.7603	0.5422	0.7945	**<.0001**
24	0.0976	**<.0001**	**<.0001**	**0.0002**	0.0139