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Price and Volatility Spillovers in the Electricity Reliability Council of Texas Day-Ahead Electricity Market

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ABSTRACT

This paper examines price and volatility spillovers in the day-ahead electricity market among the four Hubs in the electricity reliability council of texas (ERCOT) and the Southwest Power Pool (SPP). Tests of causality and impulse response functions based on a vector autoregressive model suggest cross-market spillovers from SPP to ERCOT hubs, and from North to other hubs. Examination of volatility dynamics using multivariate GARCH-BEKK suggests positively significant own ARCH and GARCH effects in North and South hubs. Examination of conditional correlations using constant conditional correlation and dynamic conditional correlation models suggest high conditional correlations between Houston and South, Houston and North, and South and North; Mid-range correlations between West and other ERCOT hubs; and low correlations between ERCOT hubs and SPP. The findings suggest that the ERCOT ISO will potentially benefit from integration with the SPP as well as improvements in transmission systems from the West to other hubs.

Keywords: Electricity Reliability Council of Texas, Day-ahead Electricity Market, Volatility Spillovers
JEL Classifications: C01, C51, L11

1. INTRODUCTION

Electric reliability council of texas (ERCOT) was formed in 1970 by Texas Interconnected System (TIS) to comply with requirements of the North American Reliability Council (NERC). Currently, NERC is organized into five interconnections including the Eastern, Western, Texas, Québec and Alaska Interconnections. The Texas interconnection operated by the ERCOT is the Independent System Operator (ISO) which covers most of Texas. Within the United States, ERCOT ISO and its participating utilities do not fall under the Federal Energy Regulatory Commission (FERC) authority since portion of the electric grid in the State of Texas that is under the administration of ERCOT is unconnected to electric grids in other states. ERCOT is one of eight ISO in North America, and one of nine regional electric reliability councils under NERC. ERCOT manages the flow of electric power to 23 million Texas customers, representing 85% of the state's electric load and 75% of the Texas land area and schedules power on an electric grid that connects 40,500 miles of transmission lines and more than 550 generation units.[1]

Although ERCOT has its own interconnections, it may not be isolated from other ISO's and Regional Transmission Organizations (RTO's) due to a number of factors: (1) it has the capacity to exchange about 860 MW with Southwest Power Pool (SPP) and Mexico through the direct current links, (2) the transcontinental natural gas pipelines have served as a reliable natural gas supply to electricity generating plants across North America. Texas is the number one producer of natural gas in the United States by producing 7,240,315 million cubic feet and consuming about 3,458,000 million Btu yearly, the remainder which it presumably exports to other States (Energy Information Administration).

ERCOT's transition from the Zonal market to the Nodal market design in December 2010 has brought about fundamental

1 See ERCOT website at http://www.ercot.com/about/profile/

improvements due to the establishment of a centralized day-ahead market, which allows participants to make financially binding forward purchases and sales of power for delivery in real-time. While the existence of day-ahead market helps in the creation of an efficient market, limitations of the interconnectors and congestions between zones raises the possibility that the day-ahead prices are relatively segmented. The ERCOT market has four Trading hubs: Houston, North, South and West.[2] We examine the dynamics of price movements and their volatility across the four markets as well as with the SPP market.

There are at least four motivations for undertaking this study. First, the ERCOT market is fairly unknown. Thus our study sheds some light on the performance of this market. Second, as Higgs (2009) points out, modeling the dynamics of electricity prices and their conditional variance will provide a framework to investigate the efficiency of pricing in the day-ahead market and the potential impact of interconnections across hubs. Third, a good understanding of the pricing and volatility relationships across ERCOT hubs as well as with markets outside of ERCOT will enable us to better assess the role of interconnections. Finally, the findings also provide good policy inputs for the construction of new interconnectors as well as for preparation of guidelines for the reform of existing market mechanisms.

There is a large body of literature on modeling electricity prices and their dynamics. Based on the methodology used, the literature on price and volatility spillovers can be divided into four categories. The first three categories use univariate models. The first group of studies is based on ARIMA models, which are concerned about modeling mean prices. They do not address price and/or volatility spillover across markets. Examples of this line of research include Contreras et al. (2003) and Conejo et al. (2005). The second group uses ARIMA-GARCH models to capture spillover in prices and volatility over time within each market. Examples of research which use this model include Solibakke (2002), Bowden and Payne (2007) and Hickey et al. (2012). The third category models spillovers in prices across markets using vector autoregressive models (VAR), Cointegration and vector error correction models but does not address spillovers in volatility. De Vany and Walls (1999), Wolak (1997) and Longstaff and Wang (2004) are some examples of this line of research. The final group uses VAR-MGARCH models to investigate cross market spillovers in both price and volatility. Bystrom (2003) applies the constant correlation bivariate GARCH model to the short-term hedging of the Nordic spot electricity prices with electricity futures; Worthington et al. (2005) and Higgs (2009) investigate the transmission of spot price and its volatility among the regional Australian electricity markets; Mohammadi and Loomis (2012) examine the dynamics of wholesale electricity price changes, their volatility, and their correlations across seven regional electricity markets in the United States; Le Pen and Sevi (2010) examine the possibility of spillovers in return and in volatility across the German, the Dutch and the British forward electricity markets.

The ERCOT market is fairly unknown, and only a limited number of studies have investigated the behavior of day-ahead prices in this market. Chen and Jiang (2006) discuss how system-wide load-capacity ratio and generation-forced outages impact day-ahead electricity spot prices. They incorporate these two key factors in the price modeling and forecasting the ERCOT market. Kim and Warren (2011) propose an hour-ahead prediction model for electricity prices that capture the heavy tailed behavior frequently observed in the hourly spot market in the ERCOT and PJM West hub grids. However, to our knowledge, no study has addressed mean and volatility spillovers in the four ERCOT Hubs, as well as their relations to neighboring ISOs, such as the SPP.

The purpose of this paper is to investigate the price spillovers as well as volatility inter-relationships across the four ERCOT Hubs. We examine spillovers in price using a vector autoregressive model along with multivariate tests of causality and impulse response functions. For spillovers in volatility, we employ three MGARCH models namely: The Engle and Kroner (1995) multivariate BEKK-GARCH model, the Bollerslev's (1990) constant conditional correlation (CCC) and Engle's (2002) dynamic conditional correlation (DCC) models. These models have a number of advantages over the alternatives. For example, they are flexible enough to represent the dynamics of the conditional variances and covariances, and are parsimonious enough to allow for relatively easy estimation and interpretation of their parameters (Mohammadi and Loomis, 2012). We will also investigate price and volatility spillovers between ERCOT hubs and an aggregate of prices from the Southwest Public Company nodes in the SPP market. In the absence of a significant inter-relationship among the hubs, the ability of ERCOT to foster an integrated and efficient electricity market is in doubt. Also, lack of significant inter-relationships between the ERCOT hubs and SPP, suggest the absence of interaction between the two markets.

The remainder of the paper is organized as follows: Section 2 looks at the trading of electricity among the hubs. Section 3 explains the daily price data and presents the summary statistics. Section 4 discusses the methodology employed. Section 5 reports the results; and section 6 provides the concluding remarks.

2. ELECTRICITY TRADING IN ERCOT

Prior to the establishment of the Nodal Market Design in December 1, 2010, the ERCOT region was divided into four congestion zones. Under the Zonal Market, congestion costs were directly assigned to zones and shared by their participants. However, not all congestions were zonal. In the Nodal Market Design, the entire ERCOT market is divided into 4,000 pricing "nodes," or points of electricity entry/exit, locations where electricity is uploaded by generators or downloaded by retailers of electricity. Congestion costs are directly assigned to the identified cost causers and resolved more economically and efficiently.[3]

ERCOT load demand and generation shares among the zones are rather similar. With respect to load demand as of 2011, the North

2 A hub is an aggregation of representative buses grouped by regions and creates a common point for commercial energy trading. I use zones and hubs interchangeably when referring to physical locations. However, I will use hub prices since their determinants may differ across hubs.

3 See Texas Office of Public Utility Counsel at http://www.opuc.texas.gov/ERCOT.html

Zone is the largest (with about 39% of the total ERCOT load); the South and Houston Zones are comparable (27% each), while the West Zone is the smallest (7%). The generation capacity among the ERCOT zones is similar to the distribution of demand with the exception of the large amount of wind capacity in the West Zone. The North Zone accounts for approximately 36% of capacity, the South Zone 28%, the Houston Zone 22%, and the West Zone 14%. The Houston Zone typically imports power, while the West Zone typically exports power.

Table 1 presents descriptive statistics for daily day-ahead market total energy traded in various ERCOT hubs from January 23, 2013 to April 5, 2013. North is the largest energy purchaser with daily average purchase of 5443.3 MW, while west is the smallest purchaser with 249.1 MW. North is also the largest energy seller with daily average sale of 2475.2 MW and Houston the smallest energy seller with daily average sale of 300.3 MW. All the hubs appear to be net importers with the exception of West, which has daily average exports of 92 MW.

3. DATA AND DESCRIPTIVE STATISTICS

The data used for this study consist of time-series of daily day-ahead Locational Marginal Pricing (LMP) in four Trading Hubs in ERCOT – Houston, North, South and West Hubs as well as in SPP. ERCOT's day-ahead market was establishment in December 2010. Therefore, the sample period covers December 01, 2010 to January 31, 2013. The data were originally obtained on an hourly basis with 24 trading intervals in each day and with 19032 observations.[4] The 24-h trading intervals were averaged to yield 793 daily observations in each zone. All data for ERCOT are obtained from the Electric Reliability Council of Texas (ERCOT) website. The prices for SPP also consist of 793 daily observations and were obtained from the SPP website.

Figure 1 provide plots of daily price data in ERCOT and SPP over the sample period. ERCOT prices follow similar patterns across the four hubs and are more stable relative to prices in SPP. They, however, are subject to a limited number of sharp price jumps. In particular, four price jumps are noticeable: The first price spike is on February 3rd, 2011, the second is between August 3th and August 6th, 2011, the third between August 8th and August 10th, 2011 and the final spike between August 23rd and August 29th, 2011. These periods were marked by an ice storm[5], heat waves[6], severe thunderstorms[7] and severe storms[8] respectively in parts of Texas.

Table 2 presents the summary of descriptive statistics for daily prices and their natural logarithms. Six things are noticeable from this Table 1. The average day-ahead electricity prices for the four

4 Using hourly data comes with a number of challenges. In particular, my hourly price data are highly serially correlated and it had a large data which made it very difficult to model. Using daily prices removes a lot of the serial correlation and produces a more parsimonious model.

5 See http://www.srh.noaa.gov/crp/?n=feb2011_icestorm

6 See http://www.reuters.com/article/2011/08/04/us-utilities-ercot-heatwave-idUSTRE7736OT20110804

7 See http://www.srh.noaa.gov/ama/?n=aug9reports

8 See http://www.srh.noaa.gov/crp/?n=aug252011severe

Figure 1: Plots of electricity prices in ERCOT hubs and in SPP

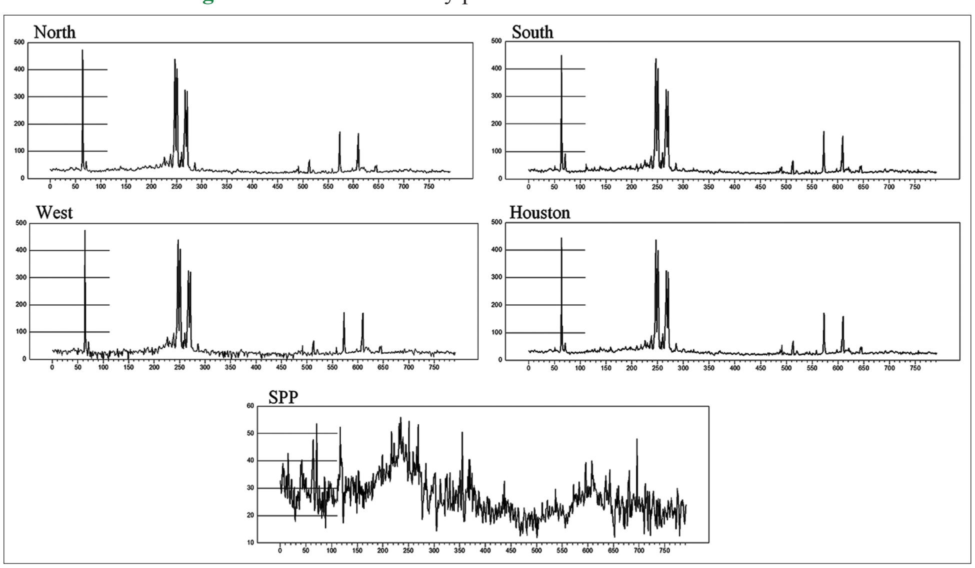


Table 1: Total energy traded in the day-ahead market

Statistics	Purchased				sold				Net import/export			
	H	N	S	W	H	N	S	W	H	N	S	W
Mean	1,232.6	5,443.3	1,970.0	249.1	300.3	2,475.2	389.4	341.2	−932.2	−2,968.1	−1,508.0	92.0
Std error	453.7	964.4	332.7	142.5	106.2	619.2	95.2	142.6	499.6	1,118.1	333.5	254.5
Max	487.4	3,815.2	1,238.8	17.1	146.5	1,417.8	185.1	136.1	−1,805.4	−6,953.0	−2,327.3	−542.1
Min	2,004.8	8,784.7	2,602.8	678.2	643.9	3.2	577.4	779.8	−38.2	−1,034.0	−741.2	707.6

Notes. Purchases and sales are in units of Mega Watts. H: Houston hub, N: North hub, S: South hub, W: West hub

Table 2: Summary statistics of daily day-ahead prices (\$/MW h) and natural logarithms of day ahead prices

Statistics	Day ahead electricity prices					Log of day ahead electricity prices				
	H	N	S	W	SPP	H	N	S	W	SPP
Mean	36.08	36.02	35.92	32.88	26.81	3.44	3.43	3.44	3.27	3.25
Median	28.47	28.36	28.62	25.85	25.55	3.35	3.34	3.35	3.25	3.24
Maximum	445.85	474.03	450.45	475.85	56.00	6.10	6.16	6.11	6.17	4.03
Minimum	17.71	17.72	17.69	0.17	11.79	2.87	2.87	2.87	−1.75	2.47
Std. Dev.	37.94	38.69	38.13	39.71	7.27	0.41	0.42	0.41	0.60	0.26
Skewness	7.45	7.48	7.45	7.20	0.88	3.17	3.15	3.24	−0.51	0.06
Kurtosis	66.28	67.42	66.34	63.89	4.10	16.98	16.69	17.42	17.60	3.04
CV	1.05	1.07	1.06	1.21	0.27	0.12	0.12	0.12	0.18	0.08
Jarque-Bera	139,625	144,527	139,886	129,384	141	7,787	7,509	8,258	7,082	0.56
Probability	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	−0.75
ADF	−7.02	−7.04	−8.08	−7.00	−3.53	−6.30	−6.28	−6.46	−6.26	−3.53
prob	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	−0.75
Observations	793	793	793	793	793	793	793	793	793	793

Prices are in units of Mega Watts Hours. H: Houston hub; N=North hub; S=South hub; W=West hub. P values in parentheses. Significant at 5% is designated by a *

hubs range from \$32.76/MWH (West) to \$36.08/MWH (Houston). The highest average prices are in Houston (\$36.08/MWH) and North (\$36.02/MWH). (2) The standard deviation of electricity prices ranges from \$88.92 (South) to \$90.63 (West). (3) The coefficient of variation, which measures the degree of price variation relative to the mean, is in the range of 1.05–1.21. On this basis, prices in Houston and South are less variable than those of West and North. (4) All prices are positively skewed, ranging from 19.15 (West) to 19.75 (South), indicating asymmetry in prices and a greater likelihood of large price increases than price falls. (4) The kurtosis is also large, ranging from 439.32 for West to 462.17 for South, which exceeds three, suggesting fat tails in the distribution. (5) The calculated Jarque–Bera statistics and corresponding p-values in Table 2 rejects the null hypothesis that the distribution of day-ahead electricity prices is normally distributed. (6) The respective Augmented Dickey-Fuller (ADF) statistics rejects the null hypothesis of non-stationarity at 0.01 significance level. The SPP price also follows the similar distributional characteristics but appears less volatile.

4. MODEL SPECIFICATION

Electricity prices while stationary, have a long memory. This is reflected in the autocorrelation of price series, which does not die out fast enough.[9] Any modeling of electricity prices should account for the existence of such a long memory. Thus, our modeling strategy consists of three steps. First, we test for fractional integration in each price series following the non-parametric procedure proposed by Robinson (1992), estimate the differencing parameter, and appropriately account for long-memory by fractional differencing each price series. Second, we model the behavior of mean prices using a vector autoregressive (VAR) model. This allows for investigation of own and cross-market spillovers in prices using tests of causality and impulse response functions. The VAR model also account for two aspects of daily electricity prices: (a) prices are subject to day-of-the-week effect as they differ between weekdays and other days of the week including holidays and weekends. We account for these differences using a day-of-the-week dummy variable; (b) daily prices are subject to a limited number of spikes, which are also accounted for using a dummy variable.[10] The resulting VAR model is,

$$P_t = A_0 + A_1 P_{t-1} + \ldots A_k P_{t-k} + BX_t + \ {}_t \qquad (1)$$
$${}_t \mid \ {}_t \sim D(0, H_t)$$

where P_t is the vector of fractionally-differenced log of electricity prices in ERCOT and SPP; $A_i (i=1,\ldots\ldots k)$ are parameter matrices, capturing own and cross-market effects; X_t is the vector of exogenous variables including day-of-the-week and price spike dummy variables; ε_t is a vector of serially uncorrelated innovations with zero mean and variance-covariance matrix H_t.

We examine the behavior of H_t, and the possibility of spillovers in volatility across markets, using three alternative multivariate generalized autoregressive conditional heteroskedastistic (MGARCH) models – the BEKK model of Engle and Kroner (1995), the constant conditional correlation model of Bollerslev (1990), and the dynamic conditional correlation model of Engle (2002). The BEKK (Engle and Kroner, 1995) model assumes the conditional variance-covariance matrix H_t depends on the squares and cross products of innovations ε_t as well as the lagged volatility and cross-market volatility, H_{t-1}, in all markets. We follow the BEKK model of the form:

$$H_t = C'C + A'\varepsilon_t \varepsilon_{t-1} A + B' H_{t-1} B \qquad (2)$$

The variance-covariance matrix of equations depends on the squares and cross products of one-period lagged innovations, ε_{t-1}, and one-period lagged volatility, H_{t-1}, for each market. c_{ij} are elements of an $m \times m$ symmetric matrix of constants C, the elements a_{ij} of the symmetric $m \times m$ matrix A measure the degree of innovation from market i to market j, and the elements b_{ij} of the symmetric $m \times m$ matrix B reflect persistence in conditional volatility between market i and market j.

9 In the original daily data, even after adding 12 lags there was evidence of serial correlation. We use fractional differencing to account for this persistence.
See http://www.estima.com/forum/viewtopic.php?f=7&t=1541&p=5715&hilit=fractional#p5715 for how fractional differencing is done.

10 We treat price changes that exceed 3 standard deviations or more as outliers.

Bollerslev (1990) proposes a constant conditional correlation (CCC) MGARCH model. This model assumes constant conditional correlations through time. The conditional covariance matrix H_t may be expressed as:

$$H_t = D_t R D_t \quad (3)$$

where D_t is an $m \times m$ diagonal matrix with elements $\sqrt{h_{it}}, i=1,2,\ldots,m$ denoting the conditional volatilities of electricity prices. That is, $h_{it} = Var\,(\varepsilon_{it} \mid \Omega_{t-1})$

h_{it}. Similarly, R is a symmetric $m \times m$ matrix representing conditional correlations between the *ith* and the *jth* prices. That is, $-1 \le \rho_{ij} \le 1$ and $\rho_{ij}=1$ for $i=j$ And

$$\rho_{ij} = \frac{h_{ijt}}{\sqrt{h_{iit} h_{jjt}}}, j = 1,\ldots\ldots, m; i = j+1,\ldots\ldots, m \quad H_t = D_t R_t D_t \quad (4)$$

Engle (2002) extends the CCC to dynamic conditional correlation (DCC) model by allowing a time-varying correlation. The model assumes that each conditional variance term follows a univariate GARCH process. Thus it has the flexibility of univariate GARCH processes coupled with parsimonious parametric models for the correlations. The conditional covariance matrix H_t may be expressed as:

$$H_t = D_t R_t D_t \quad (5)$$

where D_t is an $m \times m$ diagonal matrix with elements $\sqrt{h_{it}}, i=1,2,\ldots,m$ denoting the conditional volatilities of electricity prices. That is $h_{it} = Var\,(\varepsilon_{it} \mid \Omega_{t-1})$. Similarly, R_t is a symmetric $m \times m$ matrix representing the time varying conditional correlations between the *ith* and the *jth* prices. That is, $-1 \le \rho_{ij} \le 1$ and $\rho_{ij}=1$ for $i=j$

More specifically, the $(i,j)th$ conditional correlation is modeled as:

$$\rho_{ijt} = \frac{q_{ijt}}{\sqrt{q_{iit} q_{jjt}}},$$

where q_{ijt} are given by $q_{ijt} = \bar{\rho}_{ij}\left(1 - \varnothing_1 - \varnothing_2\right) + \varnothing_1 q_{ij,t-1} + \varnothing_2 \tilde{\varepsilon}_{it}\tilde{\varepsilon}_{jt}$ (6)

Here $\bar{\rho}_{ij}$ is the $(i,j)th$ unconditional correlation, $\varnothing_1, \varnothing_2$ are parameters such that $\varnothing_1, \varnothing_2 < 1$ and $\tilde{\varepsilon}_i, \tilde{\varepsilon}_j$ are the standardized innovations.

5. EMPIRICAL RESULTS

We begin with an examination of the spillover in (fractionally differenced) prices using a VAR model. Using a VAR (3) process specified by the Hannan-Quinn criterion, we carry out tests of causality among electricity prices, and examine the patterns of impulse responses to own as well as cross-market shocks.

Table 3 reports the F-statistics and the corresponding significance levels (in parentheses) associated with tests of causality in electricity prices associated with the five-variable VAR (3) model, which includes prices in the four ERCOT hubs and in SPP. Three patterns are evident: (1) Prices in most markets are persistent as reflected by the joint significance of the estimated coefficients on their own past prices. Thus, there is evidence of over-time price spillovers in these markets. Exceptions are prices in South and in Houston where the effects of own past prices are not jointly significant. (2) Prices in each of the ERCOT hubs are significantly affected by prices in at least one of the other hubs, reflecting the possibility of cross-market spillovers. This pattern of cross-market spillover is reflective of close proximity and existence of interconnections among the hubs. (3) SPP prices Granger-cause prices in each of the ERCOT hubs, but ERCOT prices do not Granger-cause SPP prices. These findings broadly suggest the existence of price spillovers over time and across ERCOT hubs.

Figure 2 plots the impulse response of prices to their own shocks as well as to shocks in each of other prices along with their 95% confidence bounds. Four patterns of responses are evident: First, the response of prices to their own shocks (figures along the diagonal) are positive in the first day but oscillates and dies out after that. Second, the response of ERCOT prices to shocks in SPP (Column 1) while positive, dies out after two days. Third, the response of SPP prices to shocks in ERCOT (Row 1) is not significantly different from zero. Finally, the response of each ERCOT price to cross-market innovations in other ERCOT prices varies: (a) Each ERCOT price responds to price shocks in the North (Column 2). Thus, events in the North hub have a significant effect on prices across all markets. (b) Prices do not respond to shocks in West (Column 3), South (Column 4) and Houston (Column 5). In summary, impulse response functions suggest rapid dissemination of price information across ERCOT hubs, which is consistent with an efficient operation of the market.

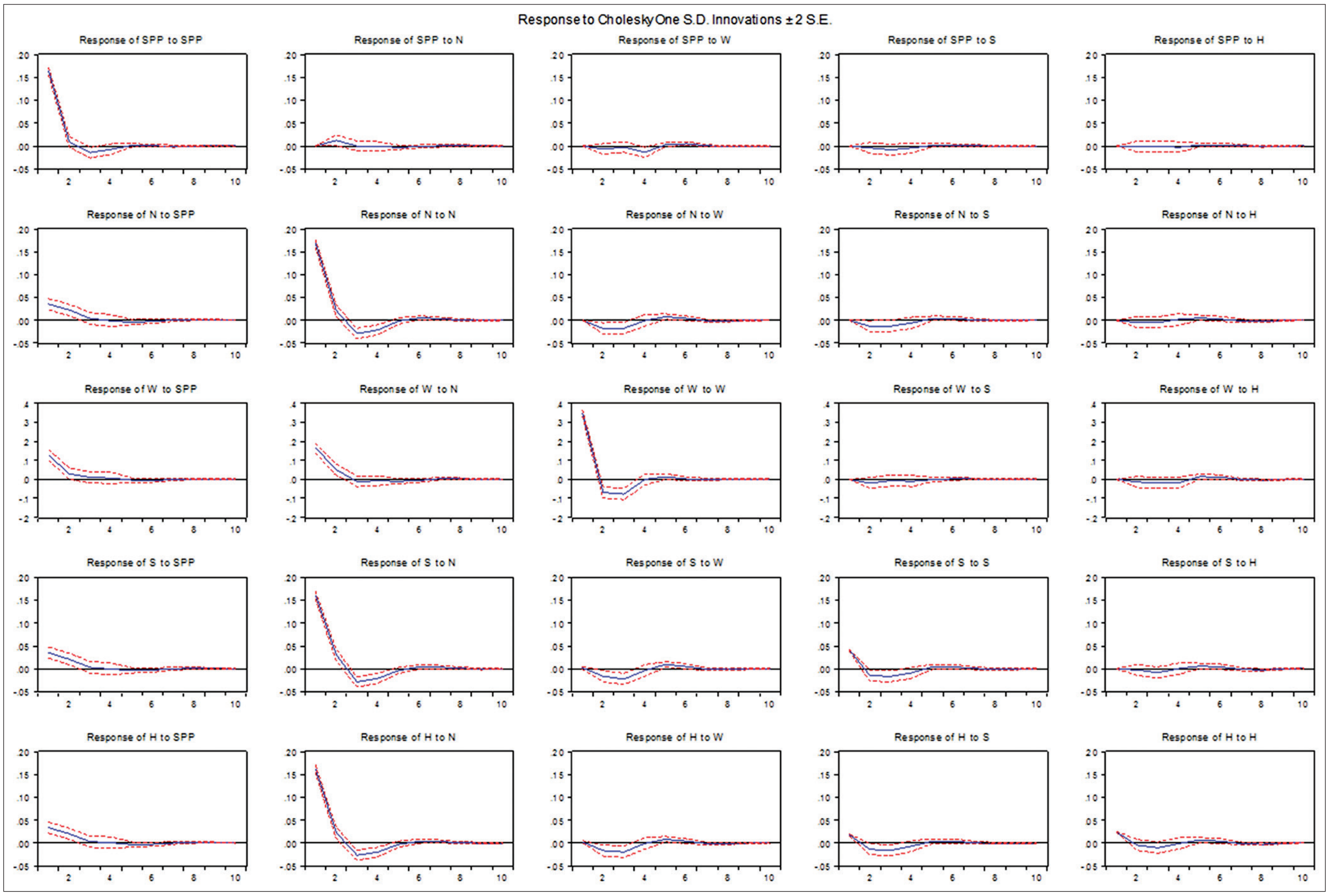
Next, we examine the patterns of conditional volatility in prices, the possibility of volatility spillover across markets, and the dynamics of conditional correlations in prices across the ERCOT hubs and the SPP. We begin with the estimation results for the BEKK-MGARCH

Table 3: F-tests of causality in prices

Hubs	Dependent variables				
	SPP	N	W	S	H
SPP	2.95 (0.03)*	5.39 (0.00)*	2.99 (0.030)*	4.20 (0.01)*	4.40 (0.00)*
N	1.12 (0.34)	3.44 (0.02)*	3.82 (0.01)*	5.04 (0.00)*	5.11 (0.00)*
W	2.28 (0.08)	4.22 (0.01)*	15.04 (0.00)*	5.20 (0.00)*	4.32 (0.01)*
S	0.40 (0.75)	1.17 (0.32)	0.37 (0.77)	1.84 (0.14)	1.09 (0.35)
H	0.09 (0.97)	0.35 (0.79)	1.99 (0.11)	0.60 (0.61)	1.18 (0.32)

Tests of causality are based on a VAR (3). The lag length was chosen using HQ criterion. P values in parentheses. Significant at 5% or better is designated by a *

Figure 2: Impulse response functions



model, which are reported in Table 4. Here, *A(i.,)* and *B(i.,)* are the corresponding ARCH and GARCH parameters associated with hub *i*. The *A(i.,)* ARCH parameters captures the responses of volatility in market *i* to squared standardized innovations in each of the five markets. For example, the estimated ARCH response for North (i=2) to its own innovations is A(2,2) = 1.02; to innovations in SPP is A(2,1) = -0.07; to innovations in West is A(2,3)=0.45; to innovations in South is A(2,4)=0.12; and to innovations in Houston is A(2,5)=0.09. Thus the ARCH response of North to all ERCOT shocks is positive and significant but is negative and insignificant to shocks from SPP. The largest ARCH response, however, is to its own innovations.

The ARCH effects demonstrate three unique patterns: (1) The ARCH response to own innovations are positive and statistically significant in all hubs but Houston, which is positive but statistically insignificant. (2) The ARCH response to cross-market innovations varies across ERCOT hubs: North and South respond positively and significantly to other ERCOT shocks; Houston responds negatively; and the response of West is statistically insignificant. And (3) the ARCH response of SPP to cross-market shocks is negative and statistically significant. In summary, with the exception of West, all markets demonstrate a significant degree of over-time and cross-market ARCH effects. Similarly, the *B(i.,)* GARCH parameters captures the responses of volatility in market *i* to past volatility in each of the five markets. For example, the estimated GARCH response for North (i=2) to its own volatility is B(2,2) = 0.71; to volatility in SPP is B(2,1) = -0.07; to volatility in West is B(2,3)=1.86; to volatility in South is B(2,4)=0.05; and to volatility in Houston is B(2,5)=-0.04. Thus, North responds positively and significantly to past volatility across all ERCOT hubs with the exception of the volatility in Houston. It's response to past volatility in SPP, however, is statistically insignificant.

The GARCH effects reveal three patterns: (1) The GARCH response to own past volatility is positive and significant in all but West, suggesting spillover in volatility over time. The latter is significantly negative and thus counterintuitive. (2) The GARCH response to cross-market volatility varies across hubs: South responds positively and significantly to all past volatilities in ERCOT and SPP but West; North responds positively to all but SPP and Houston; West and Houston respond negatively to all. And (3) the GARCH responses of SPP to past ERCOT volatilities are statistically insignificant. In summary, North and South demonstrate a noticeable degree of cross-market volatility spillovers which are positive and statistically significant. As for the other three prices, the negative findings are counterintuitive. There is also no evidence of significant volatility spillover from ERCOT to SPP, which reflects the segmentation of the two ISOs.

Next, we examine the estimated patterns of conditional correlations between electricity prices across ERCOT and SPP markets using the CCC model of Bollerslev (1990). The results are reported in Table 5. All estimated conditional correlations are positive and significantly different from zero at better than 1% significance level. However, three patterns of correlation emerge: (a) high correlations of 0.95 or

Table 4: Parameter estimates for multivariate GARCH BEKK model

Variable	SPP *(i=1)*	N *(i=2)*	*W (i=3)*	*S (i=4)*	H *(i=5)*
	Coeff	Coeff	Coeff	Coeff	Coeff
C (i, 1)	0.15 (0.00)*	0.03 (0.00)*	0.03 (0.00)*	0.02 (0.00)*	0.03 (0.00)*
i, 2)	0.03 (0.00)*	0.06 (0.00)*	0.06 (0.00)*	0.06 (0.00)*	0.06 (0.00)*
C (i, 3)	0.03 (0.00)*	0.06 (0.00)*	0.00 (0.69)	0.00 (0.24)	0.00 (0.01)*
C (i, 4)	0.02 (0.00)*	0.06 (0.00)*	0.00 (0.24)	0.00 (0.98)	0.00 (0.98)
C (i, 5)	0.03 (0.00)*	0.06 (0.00)*	0.00 (0.01)*	0.00 (0.98)	0.00 (1.00)
A (i, 1)	0.13 (0.00)*	-0.07 (0.79)	0.01 (0.53)	0.98 (0.00)*	-0.83 (0.01)*
A (i, 2)	-0.06 (0.01)*	1.02 (0.00)*	0.00 (0.90)	0.41 (0.01)*	-0.76 (0.00)*
A (i, 3)	-0.07 (0.01)*	0.45 (0.00)*	0.44 (0.00)*	0.76 (0.00)*	-0.98 (0.00)*
A (i, 4)	-0.06 (0.02)*	0.12 (0.00)*	-0.01 (0.38)	0.98 (0.00)*	-0.48 (0.00)*
A (i, 5)	-0.07 (0.00)*	0.09 (0.00)*	0.00 (0.63)	0.38 (0.01)*	0.17 (0.26)
B (i, 1)	0.20 (0.14)	-0.07 (0.62)	-0.13 (0.00)*	0.58 (0.01)*	-0.45 (0.03)*
B (i, 2)	-0.12 (0.18)	0.71 (0.00)*	-0.05 (0.00)*	0.13 (0.02)*	-0.13 (0.01)*
B (i, 3)	-0.10 (0.32)	1.86 (0.00)*	-1.00 (0.00)*	0.14 (0.55)	-0.36 (0.15)*
B (i, 4)	-0.02 (0.84)	0.05 (0.04)*	-0.07 (0.00)*	0.73 (0.00)*	-0.01 (0.87)*
B (i, 5)	-0.12 (0.21)	-0.04 (0.00)*	-0.06 (0.00)*	0.12 (0.02)*	0.65 (0.00)*

Notes. P values in parentheses. Significant at 5% is designated by a *. *C (i,.)* are constants; *A (i,.)* are coefficients of ARCH effect; *B (i,.)* are coefficients of GARCH effect

Table 5: Conditional correlations (Volatility spillover): CCC-MGARCH

Hubs	SPP	N	W	S	H
SPP		0.29 (0.00)*	0.38 (0.00)*	0.29 (0.00)*	0.29 (0.00)*
N			0.62 (0.00)*	0.95 (0.00)*	0.97 (0.00)*
W				0.61 (0.00)*	0.63 (0.00)*
S					0.97 (0.00)*

Notes. P values in parentheses. Significant at 5% or better is designated by a *

more occur between Houston and South, Houston and North, and South and North; Mid-range correlations occur between West and Houston (0.63), West and North (0.62) and West and South (0.61); and low correlations occur between ERCOT markets and SPP (North and SPP (0.28)); West and SPP (0.38)); South and SPP (0.29)); and Houston and SPP (0.29)). The high conditional correlations across ERCOT hubs reflect the presence of interconnectivity and close proximity between these hubs. The low conditional correlations between ERCOT and SPP reflect the absence of direct interconnectors between the two ISOs. Midrange correlations may reflect the relative distance and potential bottlenecks in the transmission system between the West and other ERCOT hubs.

Table 6 reports the parameter estimates for the DCC model. Four patterns are evident: (1) the estimated ARCH effects (α) are all positive and significant but differ significantly between SPP and ERCOT hubs. They range from 0.66 to 0.70 across ERCOT hubs but only 0.14 for SPP. (2) The estimated GARCH effects (β) are also positive and significant and range from the high of 0.80 for SPP to low of 0.53 for North and Houston. Thus, conditional volatility for SPP has a small ARCH effect but relatively large GARCH effect. As for ERCOT hubs, the estimated values of ARCH and GARCH parameters are fairly similar. (3) The estimated persistent parameter (α+β) varies across SPP and ERCOT hubs. It is less than one for SPP, suggesting a mean-reverting conditional volatility process. It is greater than one across all ERCOT hubs, implying that volatility shocks in these markets are permanent in nature. Finally, the estimated $\emptyset_1$ and $\emptyset_2$ parameters associated with the dynamic conditional correlations are both positive and statistically significant, suggesting that the assumption of constant conditional correlation does not hold.

Figure 3 plots the resulting time-varying conditional correlations associated with the DCC model. The dynamic correlations exhibit three patterns: (1) High and stable conditional correlations exist between the triangle consisting of North and South, North and Houston, and South and Houston. There is, however, sharp drops in correlations around the 100th, 150th and 750th observations. Further inspection reveals that these observations are marked by natural events which occurred in all or part of Texas. The 100th and 150th periods, which correspond to May 8th 2011 and April 28th 2011respectively, witnessed tornadoes in parts of Texas.[11,12] The 750th period falls on December 19th 2012 on which day Texas witnessed a severe dust storm.[13] These events may explain the sharp drops in correlations of prices across ERCOT hubs. (2) There is moderate correlation between West and the other ERCOT hubs but North. However, correlations are more variable. They drop to about -0.4 around the 100th and 150th periods, rise back up and remain around the average of 0.63 for the remainder of the period. (3) The correlations between SPP and ERCOT hubs are mostly positive but highly variable. The average correlation is around 0.28, and there is no specific pattern of correlation between the markets. In summary, the strong significant positive conditional correlations between the ERCOT hubs together with the mean-reverting plots of the dynamic conditional correlations over the sample period indicate that ERCOT has fostered an integrated and stable day-ahead electricity market within its region. Also, its low correlation with SPP also affirms the fact that ERCOT is not well interconnected with markets outside its

11 See http://www.srh.noaa.gov/shv/events/select.php?date=03082011_1
12 See http://en.wikipedia.org/wiki/April_25%E2%80%9328,_2011_tornado_outbreak
13 See http://www.srh.weather.gov/lub/?n=events-2012-20121219-dust

Figure 3: Time-varying conditional correlations between markets. (a) High conditional correlations, (b) Medium conditional correlation (c)

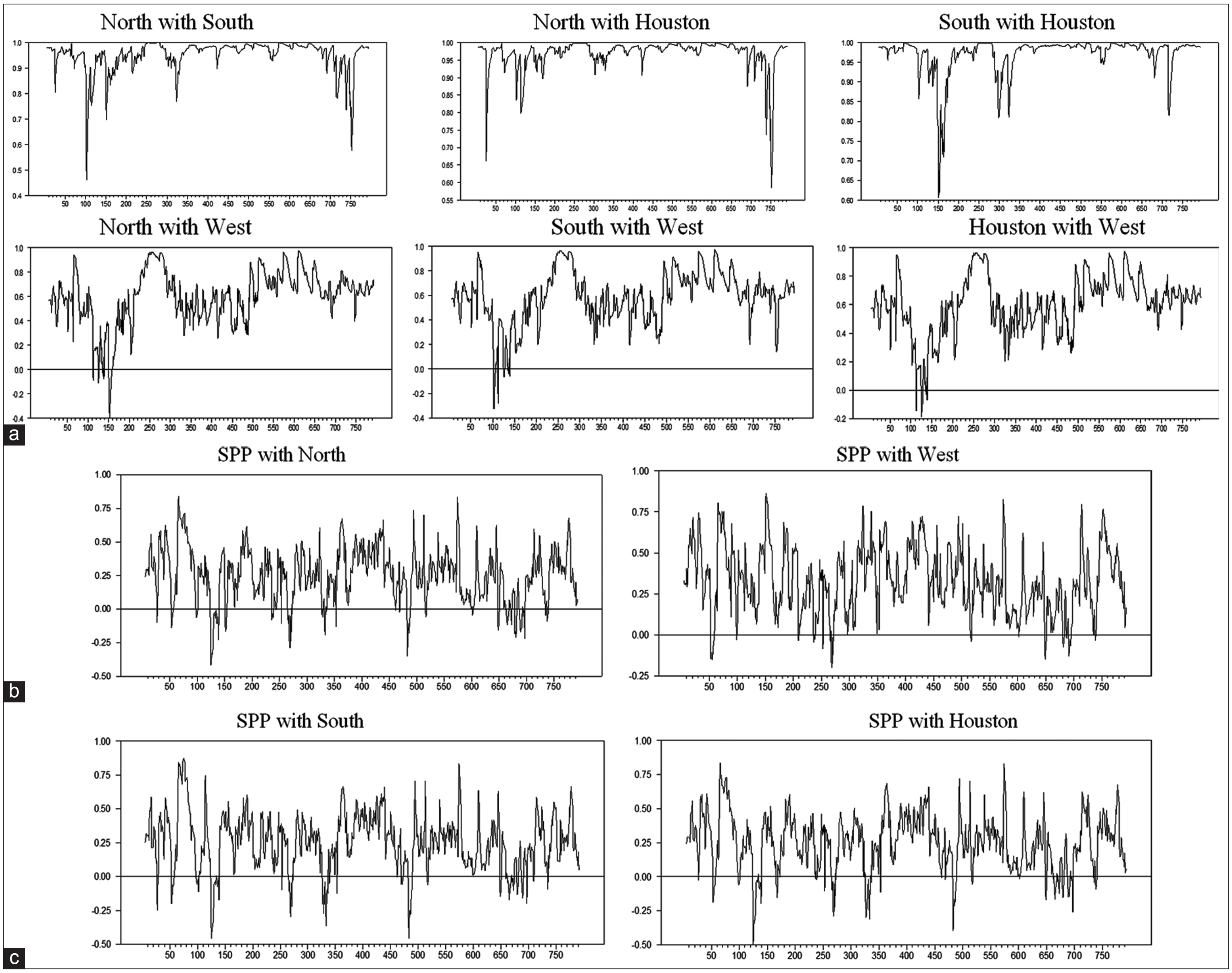


Table 6: Conditional correlations (Volatility spillover): DCC-MGARCH

Variable	SPP	N	W	S	H
C	0.00 (0.04)*	0.00 (0.00)*	0.00 (0.01)*	0.00 (0.00)*	0.00 (0.00)*
α	0.14 (0.00)*	0.67 (0.00)*	0.70 (0.00)*	0.66 (0.00)*	0.67 (0.00)*
β	0.80 (0.00)*	0.53 (0.00)*	0.64 (0.00)*	0.54 (0.00)*	0.53 (0.00)*
α+β	0.94	1.2	1.34	1.2	1.2
$\emptyset_1$	0.15 (0.00)*				
$\emptyset_2$	0.83 (0.00)*				

Notes. P values in parentheses. Significant at 5% or better is designated by a *

region. This finding is consistent with (Mohammadi and Loomis, 2012) where they found low correlations of ERCOT with NY, NE and PJMP markets.

6. CONCLUSIONS

This paper examined the price and volatility inter-relationships in the day ahead electricity market among the four ERCOT pricing hubs of Houston, North, South and West. It also examined the price and volatility inter-relationships between the ERCOT hubs and SPP. The data consisted of daily LMP prices for the period December 1st 2010 to January 31st 2013.

The results of VAR analyses revealed significant over-time spillovers in all the EROT hubs and SPP and cross-market spillovers in North and SPP. These are reflected in tests of causality and impulse response functions. However, impulses are relatively short and disappear after one to two days. ERCOT prices responds to shocks in SPP, but SPP prices do not respond to any of the shocks in ERCOT prices.

We examined the dynamics of volatility relations using three alternative multivariate GARCH models - the BEKK, CCC and DCC models. The BEKK suggests own ARCH and GARCH effects are positive and statistically significant in North and South.

The conditional correlation volatility spillovers of the CCC model are positive and significant for all pairs of markets, indicating the presence of positive volatility effects between pairs of markets. The highest conditional correlations are evident between the ERCOT markets. However, correlation is low between ERCOT hubs and SPP due to lack of established interconnections. The DCC model also suggests time-varying conditional correlations in the ERCOT hubs. All ARCH and GARCH coefficients are positive and significant. The conditional volatility for SPP has a small ARCH effect but relatively large GARCH effect while ERCOT hubs have ARCH and GARCH parameters which are fairly similar.

The findings of this study may have implications on the way market participants, retailers and generators anticipate electricity price volatility and thus incorporate that in their bids in the day-ahead market. Furthermore, the evaluation of the price, volatility and cross-market interactions provides evidence in support of significant electricity price volatility and this may provide policy makers with greater understanding of the day-ahead electricity dynamics, the efficient distribution of energy within and outside ERCOT and policy inputs for the construction of new interconnectors as well as for preparation of guidelines for the reform of existing markets.

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