

Impacts of day-ahead versus real-time market prices on wholesale electricity demand in Texas

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Abstract

The somewhat recent nodal market structure in Texas impacts wholesale day-ahead market (DAM) and real-time market (RTM) prices. However, comparative insights on consumer responses to both these prices have not received attention. This paper attempts to fill this void by developing a system-wide demand response model to better understand price elasticities under DAM and RTM pricing. These insights may also assist grid operators develop improved short-term forecasts of electricity demand. Using a large dataset from the Electric Reliability Council of Texas and a hierarchical Bayesian population model, we offer new insights on how DAM and RTM pricing shapes demand for electricity, and the related consequences for maintaining a reliable electricity market.

Keywords: Electricity Demand; Energy Forecast; Price Effects; Bayesian Inference

JEL codes: Q41, Q47, Q02, L94, L97, L51

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1 Introduction

Research Motivation. Today’s competitive wholesale markets for electricity tend to operate two formal markets for energy: a day-ahead market (DAM) and a real-time market (RTM); see Stoft (2002). Both DAM and RTM markets are now operational in the Northeast U.S.; New York; California; the Midwest U.S.; the Scandinavian nations; Ontario; and Texas; see Sioshansi (2013). A similar market structure will soon be implemented in Mexico.

DAM lets market participants commit to buy or sell wholesale electricity one day before the operating day, to help avoid price volatility (Zarnikau et al. (2014b)). The RTM energy market lets market participants buy and sell wholesale electricity during the course of the operating day. Some notice period would normally be required to enable response to changing prices by both retail consumers exposed to wholesale prices and load-serving entities operating demand response programs. This would suggest that response to DAM prices may be more practical, and thus DAM prices might have a greater impact on demand. Yet, RTM prices tend to be much more volatile and tend to reach higher price levels. The higher levels of RTM price spikes could elicit greater attention from consumers and load-serving entities. In one sense, RTM prices are the result of what could be called “forecast error” from a DAM pricing model. The latter are spot prices set a day in advance, predicated on anticipated demand and exogenous conditions such as weather forecasts. If for some reason (like a poor weather forecast) there is a surge in demand, RTM prices would likely increase. This aspect of RTM pricing could affect how DAM prices are set in the future. On the other hand,

we would not expect DAM prices to have a similar impact on future RTM prices.

Very few studies have sought to quantify the aggregate response of energy consumers to changing prices in a restructured electricity market. Customer response to DAM prices has been quantified for the electricity market in the Netherlands (Lijesen (2007)) and upstate New York (Hopper et al. (2006)). The price elasticity of demand to changes in 30-minute prices in the England and Wales market has been studied by Patrick and Wolak (2001). In the England and Wales market, energy prices are largely known by 4 pm on the day prior to consumption, although some components of the price are not known with certainty. Thus, the England and Wales market may not be readily categorized as either a pure DAM or RTM market. Customer response to RTM prices has been quantified for South Australia (Fan and Hyndman (2011)), Ontario (Choi et al. (2011)), and Texas (Zarnikau and Hallett (2008), Zarnikau et al. (2014a)).

Grid operators benefit from knowing which set of prices may be more important to their short-term load forecasting efforts. Likewise, policymakers benefit from knowing how changes in the rules which govern day-ahead and real-time markets may affect energy demand. We are unaware of any prior attempt to compare consumer response to DAM versus RTM prices in regions where both types of markets are present.

The Electric Reliability Council of Texas (ERCOT) Market Place. In ERCOT's wholesale sector, there is competition among a large number of generators, although one generator, Vistra Energy, holds a market share of roughly 20%. Other leading suppliers of generation include NRG, CPS

Energy of San Antonio, and Calpine. In the areas opened to competition, Reliant Energy (an affiliate of NRG), TXU Energy (affiliated with Vistra Energy), and Direct Energy lead in market share, though many smaller players are present. ERCOT’s competitive wholesale market has evolved over time, with an important structural change occurring on December 1, 2010, with the introduction of a nodal market structure wherein 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 for wholesale energy purchases (Zarnikau et al. (2014b)). The creation of a formal DAM 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 or an energy-only offer. Offers and bids are location-specific. Hourly market-clearing DAM prices result from a least-cost dispatch that co-optimizes energy generation with ancillary services and certain congestion revenue rights. Deviations from a transaction scheduled via the DAM are settled at the RTM prices, which typically change every five minutes. 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.

On day $t - 1$, the DAM opens at 6 a.m., with a clearing process that

begins at 10 a.m. and ends around 6 p.m. As actual wind generation and total system demand on day t are unknown on day $t - 1$, the formation of DAM prices depends on ERCOT’s day-ahead forecasts of wind generation, and hourly loads, along with other information pertaining to generator operating plans and transmission system status. Based on the forecasted information posted by ERCOT, a qualified scheduling entity (QSE) representing a resource or a load-serving entity may submit offers to sell energy or bids to buy energy. At 10 a.m. on day $t - 1$, ERCOT starts the clearing process, using a multi-hour mixed integer programming algorithm to maximize bid-based revenues minus the offer-based costs over day t , subject to security and other constraints. By 1:30 p.m. on day $t - 1$, ERCOT notifies market participants of the cleared DAM transactions. Transmission security analysis and reliability unit commitment (RUC) is then performed to ensure sufficient generation and ancillary services are committed to reliably serve the location-specific load forecasts. The RUC process generally completes by 6:00 p.m. on day $t - 1$, allowing each QSE to adjust its trades, self-schedules, and resource commitments until ERCOT’s real-time operation begins on day t .

The hourly RTM energy price used in our analysis originates from ERCOT’s 5-minute real-time energy prices based on ERCOT’s real-time operation. ERCOT uses SCED to simultaneously manage energy, system power balance and network congestion, yielding 5-minute locational marginal prices (LMPs) for each electrical bus within the market. The SCED process seeks to maximize bid-based revenues minus offer-based costs, subject to power balance and network constraints. The zonal settlement price for a load-

serving entity’s real-time energy purchase is a load-weighted average of all 5-minute LMPs in a load zone, converted to 15-minute values. For our analysis, we further convert these 15-minute values to hourly values to match the frequency of the hourly DAM price data.

Research Issues & Questions. Researchers who analyze patterns in the demand for energy in electricity markets and seek to estimate the price elasticity of demand are often faced with a choice of which price series to use: DAM or RTM prices. While these prices are correlated, there are occasions in which a spike in prices in one market will not coincide with a spike in prices in the other market. Further, prices during a spike could reach different levels in the two markets. Is the response to DAM prices stronger than the response to RTM prices? Or, do RTM prices have a greater influence on the demand for electricity? If the demand side of markets responds to both, is one more important than the other? Additionally, interested parties are keen on forecasting day-ahead wholesale demand to better anticipate reactions to price volatilities. Thus, in addition to estimation insights needed to answer the above questions, there is also a need for improved short-term demand forecasts. Thus, responses to DAM and RTM prices are important in terms of their real-world relevance.

The analysis in this paper seeks to inform the above decisions.

Methodological Contribution & Findings. We explore this topic using hourly data for the years 2011-2016 from the ERCOT market. Divided into four major zones—North, Houston, South, West—ERCOT serves 85% of the electrical needs of the largest electricity-consuming state in the U.S.; it accounts for about 8% of the nation’s total electricity generation, and is

repeatedly 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, 2015).¹

Methodological Contribution. A hierarchical, Bayesian population model is used to jointly model both zonal and ERCOT-wide demand. This approach, which to the best of our knowledge has not been used in studying demand for electricity, obviates structural equation estimation by estimating interdependent demand-price probability distributions at each level of the hierarchical model.

Findings. In all four zones and ERCOT as a whole, load demanded is price inelastic to DAM and RTM pricing with DAM prices being slightly more elastic. However, during periods of very high prices (above \$2000 per MWh) demand is elastic in North, Houston and South, but somewhat inelastic in the West. DAM pricing spikes have a significantly larger impact on demand than RTM pricing spikes in the three zones—demand reductions between 9 and 14% are seen under DAM pricing, whereas under RTM pricing these reductions vary between 3 and 4%. Demand responses to volatilities in RTM and DAM pricing are roughly the same. The response to transmission prices, as expected, are not statistically different under the two pricing models. Likewise, weather impacts demand somewhat uniformly in all regions under both pricing models. In the four zones, the Markovian property of demand from one-day to the next is significant since current day’s load

¹Strictly speaking, there are eight ERCOT zones, wherein South encompasses three smaller sub-zones (Austin, LCRA, San Antonio) and North includes a tiny area (Rayburn). From a modeling perspective, there is no loss in generality by focusing on the four major zones that account for close to 85% of ERCOT’s load.

positively affects subsequent day’s demand. However, this effect is the same under both pricing structures for ERCOT as a whole.

Paper Organization. Section 2 describes the data and variables used in the study. The population hierarchical model that models all four regions within ERCOT is detailed in Section 3. Section 4 provides both the estimation and forecast results, followed by a discussion and directions for future research in Section 5.

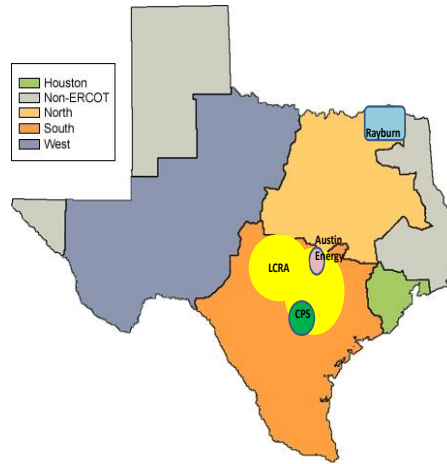
2 Data and variables

This section describes the data used in the analytic models, including geographical scope and sample period.

2.1 Geographical scope

The current ERCOT market with its four zones—North, Houston, South and West—is the focus of the paper; see Figure 1 for a map of ERCOT. The North and Houston zones account for about 37% and 27%, respectively, of ERCOT market energy sales, while the South and West zones contribute 12% and 9%. Further, these four zones account for nearly all of the state’s retail competition, and most of the competitive generation resides within these zones. Thus, this study uses a very rich and large database to better understand the differences between DAM and RTM prices on wholesale demand.

Figure 1: Zonal Map of Electric Reliability Council of Texas (ERCOT)



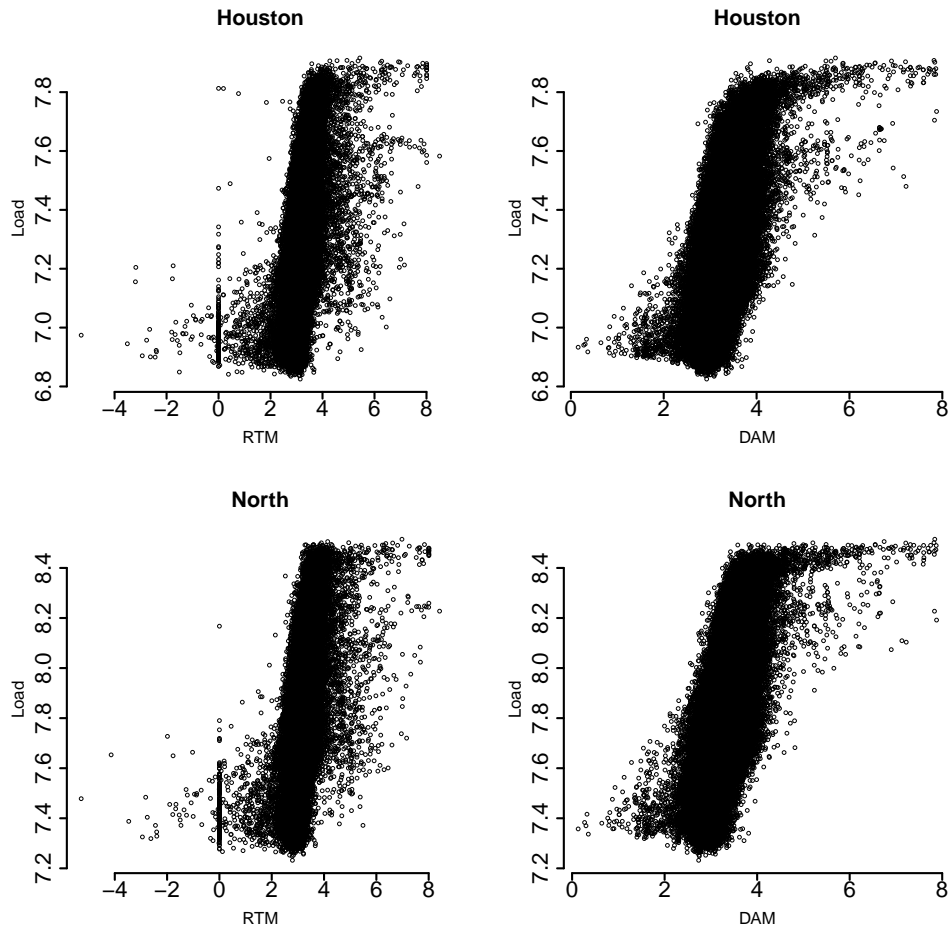
Notes: The four main regions in ERCOT are Houston, North, South and West. South encompasses three smaller sub-zones (Austin, LCRA, San Antonio) and North includes a tiny area (Rayburn).

2.2 Sample period and variables

The sample period closely matches the initiation of nodal pricing and the DAM on December 1, 2010. It begins on January 1, 2011, as price data reflecting the new markets and zones were unavailable for December 2010. It ends on June 29, 2016. In this time frame, the data were analyzed at the hourly load level; that is, for each hour in a 24-hour cycle, complete data on all the variables used in the analysis were employed, leading to a very large dataset for each of the four zones. In addition to the response variable—wholesale load demand data (measured in MWH)—in each zone, a brief discussion of each of the independent variables now follows. These variables were selected based on careful data exploration via summary plots/correlation tables, practical considerations of data size, modeling aims, and computational complexities. Additionally, price formation in the ERCOT market has been analyzed in a variety of antecedent studies using many of the same data sources and variables employed in this study; see, Woo et al. (2011); Woo et al. (2012); Zarnikau et al. (2016); Tsai and Eryilmaz (2018); Zarnikau et al. (2019). Price formation in other wholesale markets with similar variables has been examined by Park et al. (2006); Redl et al. (2009); Woo et al. (2014a); Woo et al. (2014b); and Woo et al. (2018).

DAM and RTM price effects. The zonal DAM price is the hourly settlement price in each zone’s day-ahead market. The hourly zonal RTM price is the load-weighted average of the RTM settlement prices within each zone. Both prices are volatile, have large spikes and occasionally diverge. The

Figure 2: DAM & RTM prices versus load: Houston and North zones



RTM prices are at times negative, accompanied by DAM prices of below \$50/MWH.² Consider Figure 2. The four panels show the log-log plots of demand versus DAM and RTM prices for Houston and North regions, along with their correlations.³ Price and demand are positively correlated, reflecting the slope of the supply curve for electricity generation. However, there are some key points to note. First, beyond a certain price point, the curve is concave, suggesting demand is increasing at a decreasing rate. Second, there are several anomalies in the data at various points where an inverse relationship might hold. Third, the data suggest that price response is not sensitive to the size of the operation. Energy consumers exposed to wholesale market prices start reducing their demand when prices reach \$300 per MWh, and as prices rise above that threshold there is additional demand reduction. All these suggest that price by itself is not sufficient to capture the dynamics of demand and price. Hence, we entertain the following three additional price variables in the model.

Lagged price. This makes economic sense for DAM prices, as they are known one-day in advance. Likewise, if RTM prices peak on a given day, then it could lead to a reduction in demand the following day. We test this in the analysis.

Price dummy for spike at \$2000. ERCOT analysts have noted that industrial customers tend to significantly scale back when prices exceed

²Texas electricity wholesale prices as a whole can be negative. If energy is generated from a renewable energy source, the generator will receive a federal tax credit. Wind generators offer electricity at a slightly negative price, as they receive a tax credit and earn a margin on the sale if they are selected.

³Plots for South and West are omitted, as they are virtually identical to the ones in Figure 2.

\$2000. Since we also include lagged demand as an independent variable in the model, it would be prudent not to over fit by using too many dummy variables. So, only one binary variable for extreme price spikes is used whose lower threshold is \$2000. Note, also, that this would affect transmission costs discussed below. Thus, we hope to capture the downward push on demand via this dummy variable.

Moving average of RTM price. Two-hour moving average of RTM prices is used in the DAM model for reasons explained in the Introduction. In the short-term, the rate of change due to this variable might be positive or negative, depending on the zonal and system-wide increase in demand. Some industrial customers may cut back production even when RTM prices reach, say \$300, whereas others might react only if prices spike to very high levels.

Cooling degree hours (CDH). Since demand for electricity is most affected by summer months in Texas, CDH captures the weather factor. It is defined as the number of degrees in Fahrenheit by which the hourly average indoor temperature is below or above 65 degrees. This variable is a forecast obtained from local weather services and is expected to be positively related to demand. DAM prices are set, based on such forecasts which would likely influence demand.

Dummy variable for time-of-day. This binary variable measures the impact of extra demand during the peak hours of 5 to 7 pm each day. Generally, this variable's marginal effect would be positive, but depending on the zonal temperatures (especially in the West and North) one can expect instances where a negative effect might result. Another reason an inverse

relationship between demand and the time-of-day indicator variable might hold stems from successful energy conservation programs during peak load hours in certain zones.

Lagged load. Concurrent days of high demand are encapsulated via a one-day lag; the marginal effect here is likely to be positive.

Transmission cost. This cost is typically a response of load serving entities and large industrial energy consumers, based on contributions to system peak demand in four summer months (aka 4 Coincident Peaks, abbreviated 4CP). ERCOT's staff analysis suggests demand could potentially fall by 1,000 MW during a 4CP period. In reality, since transmission cost is based on the four highest demand readings, it is not a DAM or RTM phenomenon; as such it cannot be calculated until the end of a summer. This makes it difficult to know what 15-minute intervals to use in the calculation until each month is complete. Typically, one would expect the slope coefficient to be negative, as transmission prices are charged to large industrial energy consumers and load serving entities during 4CPs. However, based on the preceding description, there is considerable uncertainty in these cost data and we can expect significant fluctuation in parameter estimates.⁴

⁴Demand response to transmission costs can approach 1 GW in this system with a peak demand of 71 GW, while response to energy market prices is estimated to be about half of that: see, *Analysis of load reductions associated with 4-CP transmission charges and price responsive load/retail DR*: Raish's presentation to the ERCOT Demand Side Working Group: available at: <http://www.ercot.com/calendar/2017/3/24/115556-DSWG>

3 Models

A primary research focus of this paper is to answer the following: are there meaningful differences in load consumption solely attributable to the inherent difference underlying RTM and DAM pricing structures? To better answer this question, a population dynamic model for demand across the four ERCOT zones is constructed. We see this as a new contribution to the energy demand literature for the following reasons.

Under each of the two pricing structures, the interconnected nature of the four ERCOT zones is accounted for by concurrently modeling the demand for these zones via a population, hierarchical model; see, for instance, Lindley and Smith (1972), Gelfand et al. (1990), and Koop et al. (2007). Recall the zonal map of ERCOT shown in Figure 1. The entire region’s demand is the population level of the Bayesian model’s hierarchy, and this demand arises from a common population distribution for ERCOT. Now, within this population, the demand for each region arises from its individual demand distribution; on the map, this would correspond to demand distributions for each zone whose boundaries are shown in the figure. This zone-by-zone demand variability is encapsulated via a second layer in our hierarchical representation. Finally, within each zone, demand is modeled as a function of regressors discussed in the data section. The rates of change and intercepts in these zonal level models vary around the ERCOT-level population parameters. This dynamic *learning* aspect is critical, for there is no *a priori* reason to assume that these zonal rates and intercepts would be the same. Importantly, the hierarchy also lets one model the zone-by-zone

volatility in demand by assigning different probability representations for the variances in the demand distributions.

As an example of the above process, under DAM the rate at which changes in price impacts demand in Houston could be quite different than the impact in the West. Likewise, the fluctuation (volatility) in demand in Houston could be different from the variability in the West. One would also expect to see some interdependency in these demands due to the interconnected nature of ERCOT’s nodal market. Thus, the proposed hierarchical model “borrows strength” from each zone to better understand the cumulative effect on demand due to DAM price changes, and vice-versa, for ERCOT as a whole.

The above modeling process is then applied to RTM pricing which would elicit a different ERCOT-wide demand response to RTM price changes. Thus, the population, hierarchical model structure enables us to understand the differences in demand responses under DAM and RTM through a very rich, interdependent modeling process.

Here is one of the key research questions posed earlier: is demand response to DAM prices stronger than the response to RTM prices? An answer to this is obtained by examining the ERCOT-level posterior distributions of the demand rates under DAM and RTM. Additionally, one can go down a layer in the hierarchy to the zone level to pinpoint differences in the demand rates under the two pricing structures.

Remark 1. The mathematical development below highlights the crucial interplay between demand and price. At the zonal level, demand is an *explicit* function of price. At the population level, once all the zonal prices are

known, the ERCOT level price distribution is updated by *demands from all the zones*. In the subsequent Bayesian update, each of the four price distributions are *implicit* functions of ERCOT-level demand. This conditional learning process is one of the strengths of our proposed model. As discussed in the final section, there is little or no empirical evidence to suggest a simultaneous relationship between demand and price in this application. Nonetheless, the population, Bayesian model accounts for such relationships between demand and price via *interconnected* probability distributions on all model parameters, bypassing the difficult issues inherent in estimating a systems model.⁵ Demand responses at the ERCOT level implicitly influence price at the zonal level from the top level of the hierarchy to the bottom levels; the latter, in turn, updates the ERCOT-level price parameters via the probability structures shown in the conditional distributions below. Thus, structural estimation is replaced via interrelated demand-price probability distributions at each level of the layered model.

3.1 Population hierarchical model for demand

Let Y_{rt} , $r = 1, \dots, R$ and $t = 1, \dots, T$ denote the demand for region r at time t on the natural log scale. Suppose there are P_r regressors in each region r . For each region, collect these independent variables in a $T \times P_r$ matrix X_r , where X_{rt} is a row vector of $1 \times (P_r - 1)$. Let β_r be the $P_r \times 1$ vector of parameters, where the first element would be the intercept. Let

⁵See Lindley and Smith (1972) and Chapter 5 of Gelman et al. (2013) for additional insights on such types of models.

$Y = (Y_1, \dots, Y_R)'$ where

$$Y_r = \begin{bmatrix} Y_{r1} \\ \vdots \\ Y_{rT} \end{bmatrix}, \quad X_r = \begin{bmatrix} 1 & X_{r1} \\ \vdots & \vdots \\ 1 & X_{rT} \end{bmatrix}. \quad (1)$$

Denoting the error term in each of the regressions by σ_r^2 , collate these errors in $\sigma^2 = (\sigma_1^2, \dots, \sigma_R^2)$. We assume that the error term in each of the R demand regression equations follows a $\text{Normal}(0, \sigma_r^2)$ distribution. Based on the above,

$$Y_{rt} | \beta_r, \sigma_r^2, X_{rt} \sim \text{Normal}(X_{rt}\beta_r, \sigma_r^2). \quad (2)$$

The population dynamics across the $R = 4$ ERCOT zones is then modeled by assuming that the intercepts and slopes in each of the r regressions arise from a common population model:

$$\beta_r \sim \text{Normal}(\mu, \Sigma),$$

where μ is a $P_r \times 1$ vector and Σ is a $P_r \times P_r$ covariance matrix. These population level parameters correspond to the entire ERCOT region. In other words, each region's demand model contributes to ERCOT's network, via interdependent demand models.

We complete the Bayesian framework by specifying the following prior distributions for the parameters. These choices are recommended by Gelfand et al. (1990) and Gelman et al. (2013). These prior distributions are useful since they lead to a conditionally conjugate hierarchical model in the result-

ing Gibbs sampler. Additionally, the prior settings for the hyper-parameters lend themselves to encapsulate both vague or strong prior beliefs. We have:

$$\sigma_r^2 | a_r, b_r \sim \text{InverseGamma}(a_r, b_r) \quad (3)$$

$$\mu | m, C \sim \text{Normal}(m, C) \quad (4)$$

$$\Sigma | \rho, S \sim \text{Wishart}([\rho S]^{-1}, \rho) \quad (5)$$

where $a_r > 0, b_r > 0, \rho > 0$ are given constants, and C, S are positive definite $P_r \times P_r$ matrices.

The posterior joint distribution for all the model parameters, by Bayes Theorem, is now given by:

$$\begin{aligned} p(\Psi | Y) &\propto \left[\prod_{r=1}^R p(Y_{rt} | X_{rt}, \beta_i, \sigma_r^2) p(\beta_r | \mu, \Sigma^{-1}) p(\sigma_r^2 | a_r, b_r) \right] \\ &\times p(\mu | m, C) p(\Sigma^{-1} | \rho, S), \end{aligned} \quad (6)$$

with $\Psi = (\{\beta_r\}, \mu, \Sigma^{-1}, \{\sigma_r^2\})$. Letting ψ denote an element in Ψ , the notation $\Psi_{-\psi}$ represents all parameters in Ψ except ψ .

The following complete posterior conditional distributions can then be used to implement a Markov chain Monte Carlo (MCMC) algorithm—the Gibbs sampler in this case—to obtain posterior inference (Gelman et al. (2013)). Hence,

$$p(\beta_r | \Psi_{-\beta_r}, Y_r) \sim \text{Normal}(D_r d_r, D_r), \quad r = 1, \dots, R, \quad (7)$$

where

$$D_r = (X_r' X_r / \sigma_r^2 + \Sigma^{-1}) \quad (8)$$

$$d_r = (X_r Y_r / \sigma_r^2 + \Sigma^{-1} \mu). \quad (9)$$

Note that each β_r can be sampled in turn from its corresponding complete conditional distribution. These are the intercepts and slopes from the four interdependent regression equations—one for each zone—in the hierarchy. The slopes represent the marginal effects of each of the independent variables discussed earlier. Next, consider the population (or the top most) level of the layered model that corresponds to ERCOT as a whole. The conditional distributions of its parameters that represent each of the independent variables is given by:

$$p(\mu | \Psi_{-\mu}, Y) \sim \text{Normal}(D_\mu d_\mu, D_\mu), \quad (10)$$

where

$$D_\mu = (R \Sigma^{-1} + C^{-1}) \quad (11)$$

$$d_\mu = (R \Sigma^{-1} \bar{\beta} + m C^{-1}) \quad (12)$$

$$\bar{\beta} = \frac{1}{R} \sum_{r=1}^R \beta_r. \quad (13)$$

Finally, the zone-by-zone and ERCOT level differences in the volatility of demand—the heterogeneity factor—are encapsulated via the following con-

ditional distributions:

$$p(\sigma_r | \Psi_{-\sigma_r}, Y_r) \sim \text{IG} \left(T/2 + a_r, \left[\frac{1}{2} (Y_r - X_r \beta_r)' (Y_r - X_r \beta_r) + b_r^{-1} \right]^{-1} \right), \quad (14)$$

and

$$p(\Sigma | \Psi_{-\sigma}, Y_r) \sim \text{Wishart} \left(\left[\sum_{r=1}^R (\beta_r - \mu)(\beta_r - \mu)' + \rho S \right]^{-1}, R + \rho \right). \quad (15)$$

The above modeling framework nets us two groups of models, labeled Model-RTM and Model-DAM. The main differences between the two models are that the former contains RTM price as one of the regressors, while the latter contains DAM prices. Also, a two-hour moving average of RTM prices appear as a regressor in the DAM model; see discussion in the previous section for the rationale underlying this choice. All other independent variables (described earlier) are the same in both models.

Following the suggestions in Gelfand et al. (1990) and Gelman et al. (2013), to ensure diffuse prior beliefs in both models, we set $a_r = 0.00001$, $b_r = 0.00001$, $\rho = 100$. In the RTM model, $S = I_8$ and $C = (0.0001)I_8$, where I_8 denotes an 8×8 identity matrix. These choices render an extremely vague belief since the resulting prior variance selections are very large. Intuitively, this is akin to centering a normal distribution around zero with a very large variance, resulting in an almost flat normal curve. In the DAM model, since we have one additional covariate, the dimensionality of I increases by one.

One-day ahead predictions. Armed with the MCMC samples obtained

upon executing the above Gibbs sampler, it is straightforward to obtain samples from the following predictive distributions for each day. In our case, we set aside the last day in the historical sample, June 30th, 2016 to compare the actual 24-hour demands on this day with the model-based forecasts.

Consider the following MCMC-based estimate of the predictive distribution for each hour, Y_{rl} , for zones $r = 1, \dots, 4$ and hours $l = 1, \dots, 24$ using the corresponding stacked matrices X_r (comprising the covariates data for June 30th); and the β_r 's from the S MCMC simulations.

$$p(Y_{r,l}|Y) = \frac{1}{S} \sum_{j=1}^S N(Y_{rl} | X_r \beta_r^{(j)}, \sigma_r^{2(j)}). \quad (16)$$

A point estimate for the one-day ahead hourly forecast is now obtained as:

$$E(Y_{r,l}|Y) = \frac{1}{S} \sum_{j=1}^S X_r^{(j)} \beta_r^{(j)}. \quad (17)$$

Remark 2. The recursive estimation of probability distributions corresponding to zonal and population level parameters in equations 7 through 14 obviates structural estimation. The probability structure for the population level price parameters in equations 10 and 15 are functions of demand at the ERCOT level. Note also that these conditional distributions depend on the zonal level price parameters. Once the population level parameters are updated, then the zonal level dependence of demand on price is encapsulated in equations 7 and 14. Thus, to repeat a key point made under Remark 1, at the zonal level, demand is an *explicit* function of price. At the population

level, once all the zonal prices are known, the ERCOT level price distribution, viewed as a function of demand, is updated by *demands from all the zones*. In the subsequent Gibbs cycle, the zonal level price parameters are then functions of system level demand.

4 Results

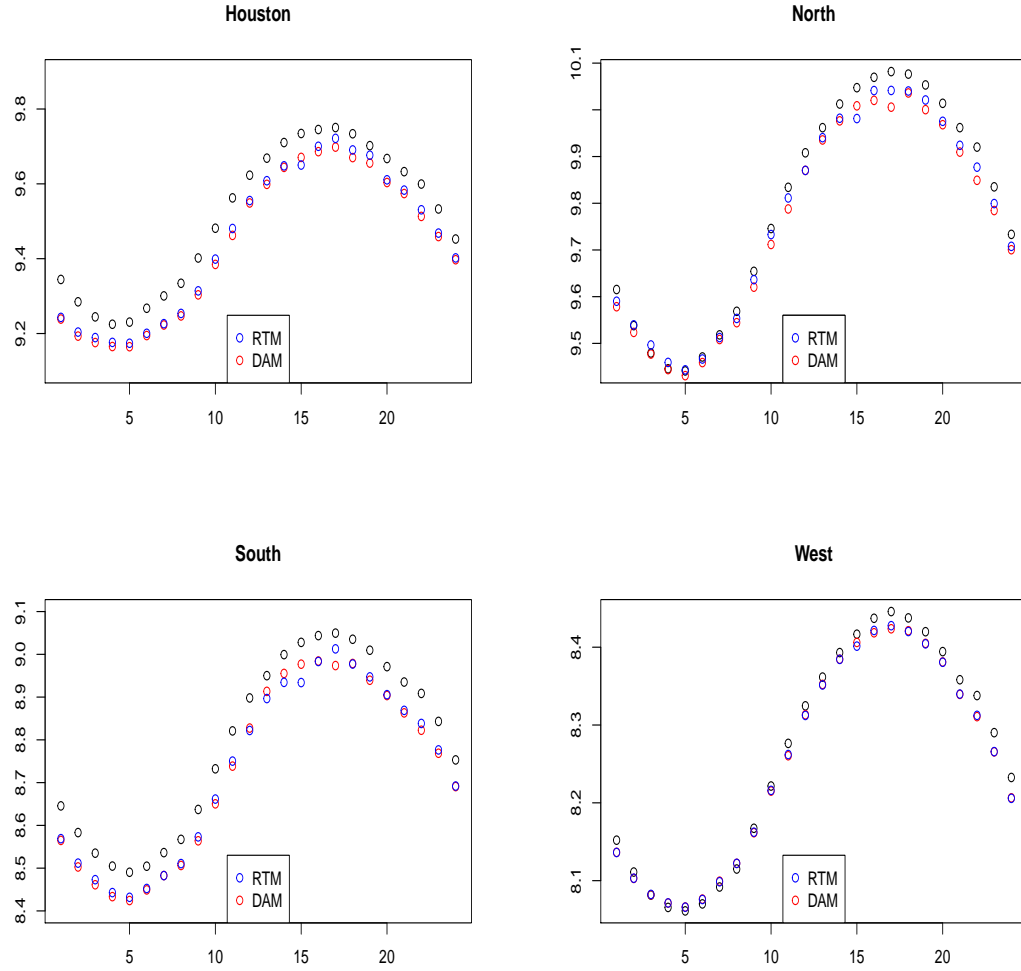
As shown in the previous section, all hyper-parameters in the hierarchical model are assumed to have diffuse prior distributions; see, Gelman et al. (2013) for details on selecting vague priors. The Gibbs sampler is run for 20,000 iterations with a burn-in period of 10,000. The chains mix well and convergence is attained within 20 minutes of run time. (Convergence plots are available as supplementary files.)

Table 1: DAM & RTM Average Root Mean Square Errors

Zone	RTM	DAM
Houston	0.063	0.073
North	0.026	0.035
South	0.064	0.067
West	0.012	0.013

One-day ahead load predictions. Consider the panel of graphs in Figure 3. The black circles are the actual data. Under both models, for each of the four regions, the panels depict the predictions under the DAM and RTM models. The corresponding root mean square errors (RMSEs) are reported in Table 1. The minimum and maximum forecast errors are 1.2% and 7.3%, respectively. It is encouraging to note that at peak demands during the day, the models do reasonably well in capturing the inflections in the demand

Figure 3: Day-ahead Forecasts for the 4 Zones



Notes. The black circles are the actual load. The Y-axis is the natural logarithm of load. The X-axis is in hours. The predictions under all the four zonal models are very close to the true values for both DAM and RTM prices.

distribution. It is these peak load values that could be used in a stochastic optimization model to better control the flow of electricity throughout ERCOT, especially under the DAM model where prices are known a day in advance. For RTM prices, one-day ahead forecasts serve to alert industrial customers on the maximum prices they could anticipate during summer months, since the effect of weather on load generally sustains over a few (even several) days. This type of anticipatory reactions could potentially lower RTM prices. The cut-off price points for these customer responses could vary by size of industrial customers; for instance, if RTM (or even DAM) prices exceed \$300 some plant operators are instructed to scale back on production.

Posterior distributions of population and zonal parameters. In the following, only the plots of the posterior distributions of some of the key parameters are shown. Also, in the interests of space, we only report the numerical posterior summaries for the ERCOT system and Houston in Tables 3 and 4, respectively. The posterior summaries for the remaining three zones are qualitatively similar albeit with some differences; where appropriate, these differences are discussed. However, the plots contain key information for all the zones. Table 2 provides a snapshot of the effects due to the key price variables; in this table, the summaries include all the four zones.

1. *Tables 3 and 4:* Under both the DAM and RTM models, the weather factor (CDH) coefficients are positive and virtually indistinguishable, as one would hope they should be. Also, the standard deviations are fairly small suggesting that there is not much fluctuation in the

parameter estimates.

2. *Tables 3 and 4:* Like the Houston and ERCOT summaries, the peak hours (5 to 7 pm) dummy variable, *Hour Dummy*, parameters exhibit variability in the other zones as well, except for West and North under the DAM model where the estimates are negative but with large variances. This may be partly due to cooler weather in West Texas and portions of North Texas.
3. *Tables 3 and 4:* As expected, under both models, the *Lagged Load* variables have a large positive impact on demand in Houston (and other zones)—all else fixed, high demand activity one day is likely to be followed by relatively high demand the following day.
4. *Tables 3 and 4:* The response to *transmission prices* should be independent of the response to DAM and RTM prices, unless a spike in RTM or DAM prices coincides with a transmission price. In the Houston summary, there are some differences in this parameter’s estimates under the two pricing models. However, as expected, at the ERCOT level there is no statistically meaningful difference in these costs under the two models. Generally, under DAM, transmission cost is negatively related to demand. In some regions, under the RTM model, they tend to be weakly positive. Of particular interest is the West region: here, under both the DAM and RTM models, the transmission costs parameters are negligible. There appears to be relatively little price-responsive demand in this zone.

5. *Figures 4, 5 and 6.* In all four regions, under both DAM and RTM models, the three price variables, marginally, exhibit similar relationships with load—the rates of change in *Price*, *Price Spike Dummy* and *Lagged Price* are positive, negative and negative, respectively. Recall that the price spikes correspond to values of \$2000 or more.
6. *Table 2: log price.* Focus on Houston’s DAM model. When price increases by, say 10% then price elasticity of demand is 0.0119; i.e., demand increases by roughly one percent. Likewise, for a 10% change in price, lagged price elasticity is -0.0194, namely a decrease in demand by almost two percent. Combined together, these elasticities reflect the gentle log-concave relationship between demand and price for Houston shown in Figure 2. In contrast, from the same table, the demand response to a 10% change in wholesale RTM price is even more inelastic. Examining these elasticities under the two pricing structures for all the zones, it is clear that demand for electricity is slightly more elastic under DAM than RTM.
7. *Table 2: price spike dummy.* Consider the effect of a spike of \$2000 or more in DAM and RTM prices for Houston. Under the former pricing model, the reduction in demand is 8.7%, whereas it is 2.2% under the latter. Comparing this for the remaining zones, it is clear that demand is highly price sensitive under DAM and less so under RTM for Houston, North and South. West is least affected by such spikes. This is consistent with the fact that pricing in the West region is tempered by wind generated power. Thus, a key empirical question posed at the

outset of this paper has an answer: For ERCOT, wholesale demand is significantly more sensitive to DAM than RTM prices during periods of very high prices. In normal periods, there are little to no differences in the price elasticities of demand under the two pricing markets. Figure 5 shows these posterior distributions.

8. *Table 2 and Figure 6: lagged log price.* From the table, once again, DAM prices tend to be more elastic than RTM prices. Consider Figure 6. In each zone, the impact of lagged price on demand is different under RTM and DAM pricing. However, at the ERCOT level, there is little or no difference in the impact of lagged price on demand under both pricing structures, as the posterior mass concentrates around zero under both distributions. This “borrowing strength” interdependence between zonal demand/price and ERCOT demand/price is one of the novel features of the modeling approach.
9. *Tables 3 and 4, and Figure 7: 2-month moving average RTM price (MA-RTM).* In the DAM model, the RTM cross-price elasticity, captured via the 2-month moving average regressor, has a very small but significant effect in each of the four zones; here the “word” significant implies that the approximate t-statistic obtained as the ratio of the parameter estimate to its standard deviation from the MCMC run is at least two. Thus, under the DAM model for Houston in Table 4, this ratio is roughly 20. Note, however, from Figure 7 that at the ERCOT level, the dependence of *MA-RTM* on system-wide demand is centered at zero values of the corresponding population level pa-

parameter. Also, from Table 3, at the ERCOT level, the approximate t-statistic for this parameter is 0.2. This is a nice illustration of how our approach captures the dependency of price on demand and vice-versa via probability distributions rather than structural estimation; see, also, Remarks 1 and 2.

10. *Figure 8: volatilities.* Zone-by-zone volatility in demand under the two pricing models is shown in this graph. Demand responses under both prices are more volatile in the North and South regions, whereas it is least volatile in the West. Moreover, the impacts of price volatility on demand under both pricing schemes are roughly the same.
11. *Tables 4: OLS estimates.* For comparison, OLS point estimates for the Houston DAM and RTM equations are shown. As expected, these are fairly close in magnitude to the Bayesian estimates since the latter uses highly non-informative priors. Thus, the least squares formula is roughly equivalent to the Bayesian estimator, as seen in the mean representations of the appropriate conditional probability distributions of the zonal slope parameters. There is no equivalent comparison at the ERCOT level since those estimates are draws from a probability distribution whose parameters are functions of the zonal level parameters in the hierarchy; see Remark 1 and Remark 2.

Table 2: Sensitivity to DAM & RTM Price Variables

Pricing Model	Log(Price)	Lag Log(Price)	Price Spike Dummy
Houston DAM	0.119	-0.194	-0.087
Houston RTM	0.044	-0.058	-0.022
North DAM	0.19	-0.209	-0.144
North RTM	0.071	-0.089	-0.036
South DAM	0.146	-0.186	-0.128
South RTM	0.045	-0.015	-0.031
West DAM	0.018	-0.097	-0.019
West RTM	0.006	-0.002	-0.005

Notes. Values are percentages. Example: In the table, columns 2 and 3 comprise continuous covariates while column 4 is a binary covariate in a log-log model. Hence, price and lagged price elasticities for Houston under the DAM pricing model are 0.119% and -0.194%. All else fixed, when price increases over \$2000, under Houston DAM, demand decreases by 8.7%.

Table 3: **ERCOT: posterior summaries of parameters**

DAM				RTM			
Variable	Mean	SD	90% Cred. Int.	Variable	Mean	SD	90% Cred. Int.
Price	0.12	0.01	(0.102,0.136)	Price	0.04	0.01	(0.027,0.059)
Price Dummy	-0.20	0.01	(-0.211,-0.179)	Price Dummy	-0.06	0.01	(-0.073,-0.041)
Lag(Price)	-0.09	0.10	(-0.249,0.074)	Lag(Price)	-0.02	0.01	(-0.184,0.14)
Transmission Cost	0.02	0.01	(0.004,0.037)	Transmission Cost	0.01	0.01	(-0.01,0.023)
Lag(Load)	0.62	0.01	(0.59,0.63)	Lag(Load)	0.66	0.01	(0.64,0.68)
CDH	0.01	0.01	(0.002,0.122)	CDH	0.01	0.01	(0.002,0.012)
Hour Dummy	-0.04	0.01	(-0.06,-0.03)	Hour Dummy	0.0001	0.01	(-0.016,0.017)
MA-RTM	0.002	0.01	(-0.0146,0.0185)				

Notes: (1) Price and Load are on the natural log scale in the dataset. (2) Lag corresponds to one whole day. (3) Price dummy is 1 if price exceeds \$2000, else 0. (4) Transmission cost dummy is 1 if system experiences abnormally high loads. (5) Hour dummy is 1 if time-of-day is 5 to 7 pm.

5 Discussion and Conclusion

A common concern regarding today’s wholesale electricity markets is that price formation fails to reflect the willingness or ability to pay for electricity from the demand side of the market. Most consumers are served through load-serving entities such as utilities or competitive retailers. They, in turn, re-sell electricity generation acquired via a wholesale market, based on fixed or average prices, or a usage block structure, thus removing the wholesale price signal. Metering infrastructure may pose an additional impediment to placing some consumers on real-time pricing. Moreover, few consumers may have an interest in monitoring and responding to dynamic prices, unless it can be done in an automated manner. Consequently, demand and prices may rise to inefficient levels. This had led to the imposition of wholesale price caps in all organized markets in North America. Thus, a better un-

Table 4: **Houston: posterior summaries of parameters**

DAM				
Variable	Mean	SD	90% Cred. Int.	OLS
Price	0.105	0.01	(0.103,0.108)	0.101
Price Dummy	-0.169	0.02	(-0.201,-0.136)	-0.171
Lag(Price)	-0.086	0.01	(-0.089,-0.084)	-0.080
Transmission Cost	-0.039	0.01	(-0.052,-0.025)	-0.041
Lag(Load)	0.662	0.01	(0.657,0.666)	0.660
CDH	0.007	0.01	(0.0069,0.0071)	0.006
Hour Dummy	0.002	0.01	(0.00076,0.0041)	0.002
MA-RTM	0.017	0.001	(0.0156,0.0184)	0.014
RTM				
Variable	Mean	SD	90% Cred. Int.	OLS
Price	0.0437	0.01	(0.0425,0.0449)	0.041
Price Dummy	-0.058	0.01	(-0.078,-0.038)	-0.061
Lag(Price)	-0.0216	0.01	(-0.0228,-0.0203)	-0.0210
Transmission Cost	0.0005	0.01	(-0.013,0.014)	0.0001
Lag(Load)	0.664	0.01	(0.659,0.668)	0.711
CDH	0.0073	0.01	(0.0072,0.0074)	0.0071
Hour Dummy	0.0078	0.01	(0.0061,0.0095)	0.0085

Notes: (1) Price and Load are on the natural log scale in the dataset. (2) Lag corresponds to one whole day. (3) Price dummy is 1 if price exceeds \$2000, else 0. (4) Transmission cost dummy is 1 if system experiences abnormally high loads. (5) Hour dummy is 1 if time-of-day is 5 to 7 pm. (6) OLS: Ordinary Least Squares

derstanding of the magnitude of demand response to price fluctuations is of critical importance in the design and refinement of markets. In markets where the demand side may face both a day-ahead and a real-time price, it is important to understand the effects of each.

Separating the response on the demand side of an electricity market resulting from a spike in DAM wholesale energy prices from a spike in RTM wholesale prices presents a challenging statistical problem. Yet, this is an

important topic for electricity grid operators striving to ensure that sufficient resources are available to meet fluctuating demand, as well as for policy-makers striving to design efficient markets. Moreover, participants in an electricity market may benefit from a better understanding of how price signals affect demand.

This analysis suggests that a spike in DAM prices prompts a greater reduction in demand than a spike in RTM prices of a similar magnitude in Texas' ERCOT electricity market. Presumably, the advance notice associated with a day-ahead price signal permits the demand side of this market more time to respond to the price signal—by rescheduling production at industrial facilities and dispatching demand response programs—thus resulting in greater demand response. Such information may be important in the design of more effective demand response programs. While the response to a real-time market price is somewhat muted—perhaps because the settlement price is not known with certainty until after the 15-minute settlement interval concludes—it is nonetheless important, since price spikes in the RTM occur with greater frequency and may reach higher levels. For researchers and forecasters faced with the decision of whether to use a DAM or RTM price to explain fluctuations in demand in an energy market, the trade-off is illuminated here.

The practical consequences of the above are several. The finding that demand is more-responsive to DAM prices might support the contention that demand response programs benefit from a day-long notice period. Yet, it might also lead a policy-maker to focus on opportunities to increase the responsiveness of the demand side to RTM prices, since RTM prices may

be a better signal of system conditions on an electricity grid, tend to be more volatile than DAM prices, and may reach higher levels. Opportunities to improve the response to RTM prices may include greater exposure of consumers to real-time prices; better communication with consumers regarding system conditions (e.g., text or email alerts); direct load control by a utility, retailer, or third-party of thermostats, water heaters, and industrial processes; and better automating the response to price signals.

Methodologically, the Bayesian model developed here is an appropriate way of handling the economic relationship between ERCOT’s demand and DAM and RTM prices. Acknowledging that no model is perfect, in the present context, the Bayesian hierarchical, population model appropriately captures key features in the data. This is because the Bayesian approach assigns probability distributions to all unknown parameters in the model. Thus, the need for a systems approach is replaced by a distributional approach to modeling price and demand; see, also, *Remark 1* and *Remark 2* in Section 3 that elaborates on these points. In this regard, it is worth mentioning that a series of Hausman tests with different instrumental variables (IVs) fails to detect endogeneity. This conclusion is not surprising for two reasons. First, endogeneity is likely not an issue for DAM pricing, as these prices are known in advance. For RTM price changes, barring rare instances, demand response is rarely simultaneous. Second, Crown et al. (2011) astutely note, “Just as we can never know the true magnitude of the endogeneity problem to begin with, we can never know exactly how contaminated our instrument really is (both quantities depend on the unobservable residuals of the outcome equation)...we urge caution in using IV methods at

even the merest suggestion of endogeneity.”

Then there are issues related to large samples. Convergence is problematic in IV-based estimation when sample sizes are large. Importantly, large samples are no guarantee of sound estimation using IV methods. Bound et al. (1995) state, “We find evidence that, despite huge sample sizes, [their] IV estimates may suffer from finite-sample bias and may be inconsistent as well. These findings suggest that valid instruments may be more difficult to find than previously imagined.” IVs also have significant problems in small scale models (Goldberger (1983)). Crown et al. (2011) advise that only under the most ideal circumstances are IV methods likely to produce estimates with less estimation error than ordinary least squares. Clearly, ERCOT’s demand system, with its attendant complexities, is far from such an ideal situation.

The full information maximum likelihood method to solve systems of dependent equations—a complex iterative procedure—is also infeasible for a variety of reasons, not the least of which are convergence issues in a problem of this scale. Importantly, as noted above and discussed elsewhere in the paper, there is no practical need for a simultaneous equations approach to model ERCOT’s wholesale demand.

We believe another useful methodological approach to try in this context is state-space models. In this paper, the marginal effects are fixed in time. While the lagged demand variables capture some autoregressive features in the demand data, what would be worth exploring is the time-varying nature of the slopes themselves; see, West and Harrison (1997). One way of capturing zone-by-zone heterogeneity in such a framework is to cast the seemingly

unrelated regression (SUR) model (Zellner (1971)) within a state-space representation; indeed, this is a viable approach than simultaneous equation models. State-Space SURs will allow one to monitor the evolutionary dynamics of price changes on demand. The challenges in this approach are one of scale and related problems of MCMC convergence. This will be pursued in future research.

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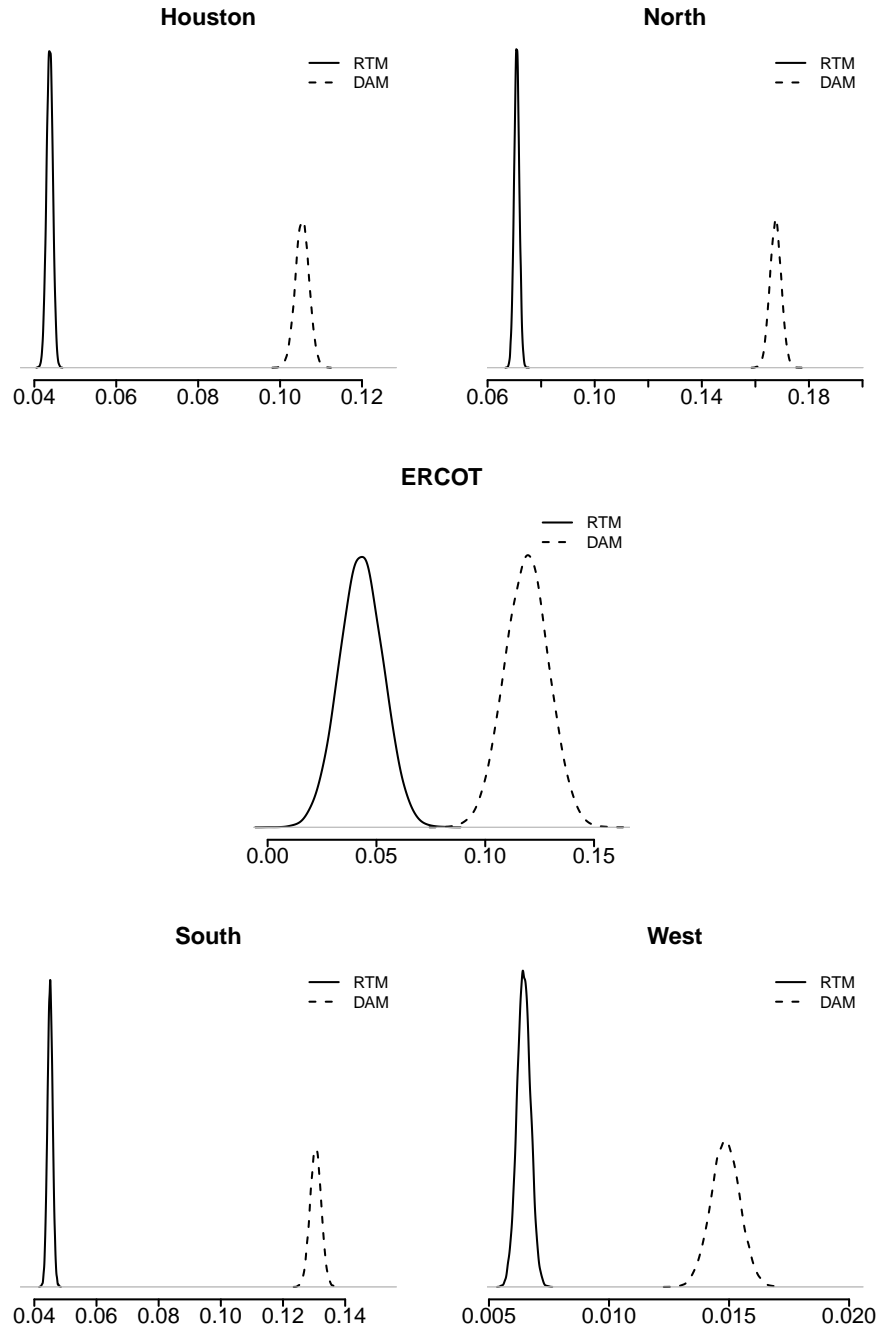
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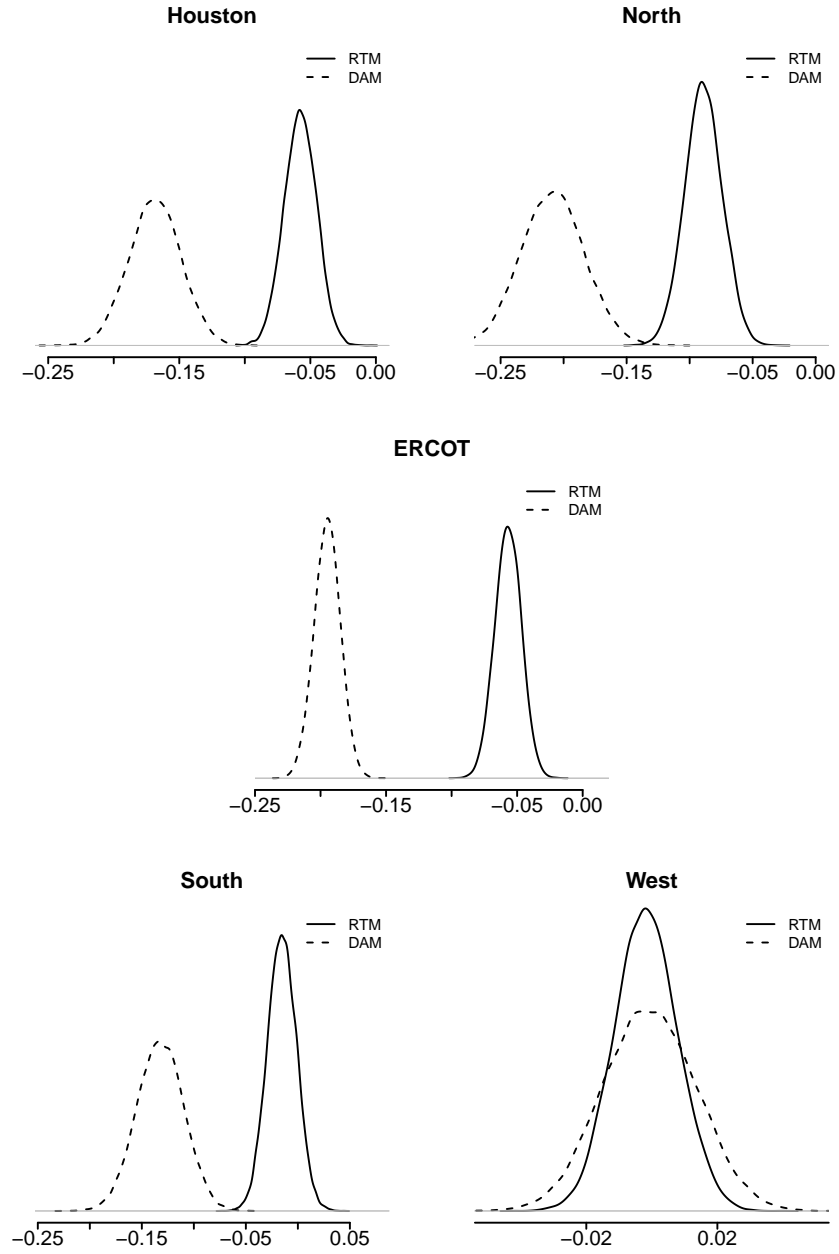
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Figure 4: Posterior distributions: log price



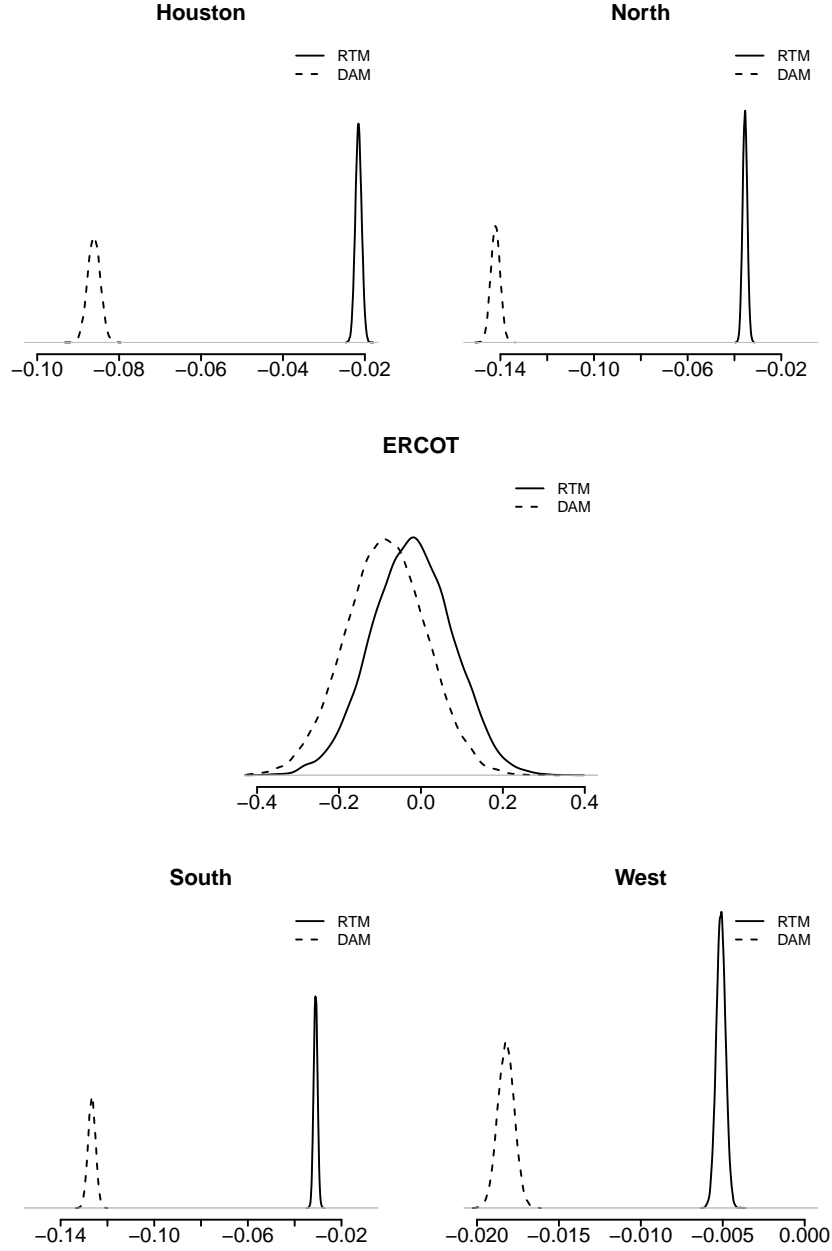
Notes. In every zone, the impact of DAM price on demand is greater than RTM price on demand. This also carries over to the ERCOT level. See Table 2 for corresponding numerical summaries.

Figure 5: Posterior distributions: price spike dummy



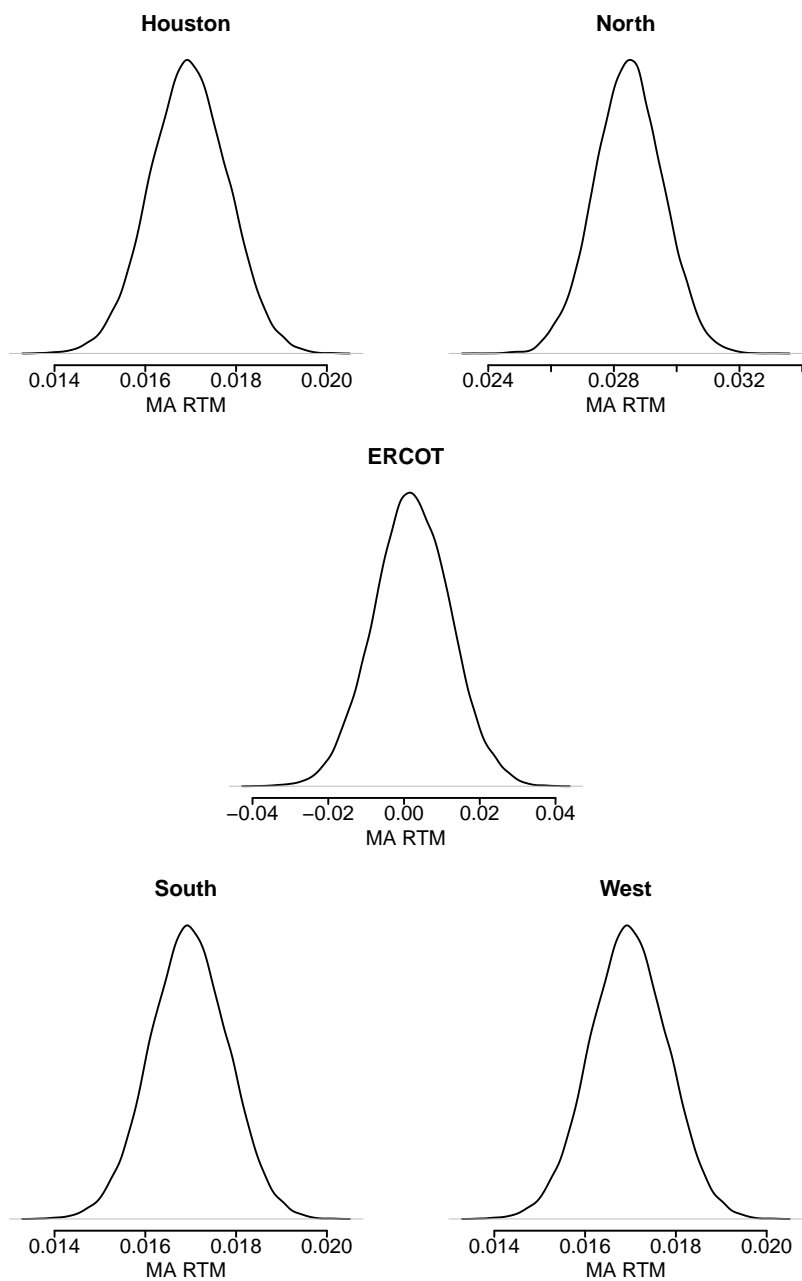
Notes. Except West, in all other zones and the ERCOT system demand decreases significantly more under DAM than RTM pricing. See Table 2 for corresponding zonal numerical summaries.

Figure 6: Posterior distributions: lagged log price



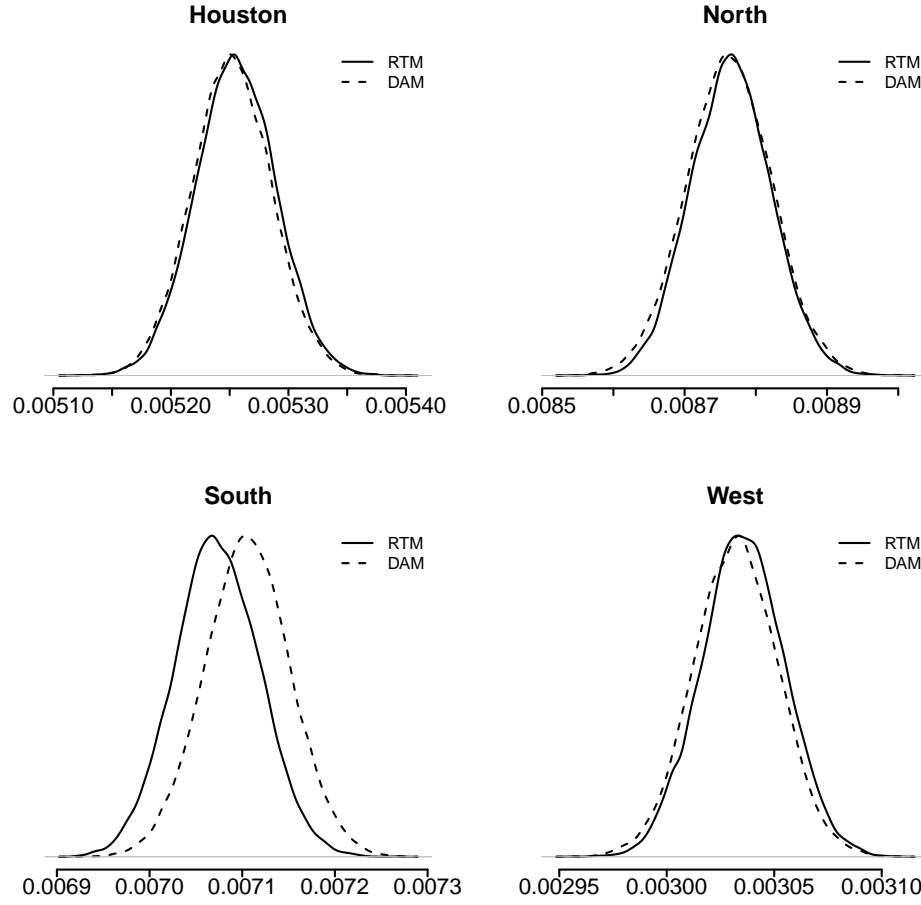
Notes. In all four zones, there are differences between lagged RTM and lagged DAM prices on load consumption. However, at the ERCOT level there is no difference on how these two prices from the previous day effect overall system demand. See Table 2 for corresponding numerical zonal summaries.

Figure 7: Posterior distributions: 2-month moving average RTM price



Notes. In all four zones under the DAM model, the RTM 2-hour moving average price weakly impacts demand. This carries over to the ERCOT level where this cross price variable has no effect on system-wide demand.

Figure 8: Posterior distributions of zonal variances



Notes. The variability in demand responses under both DAM and RTM pricing schemes are generally the same in all four zones. North and South tend to be more variable than the West and Houston zones, as seen by larger values along the X-axis for the former zones.