UNIVERSITY OF ALBERTA
FACULTY OF ARTS
Department of Economics

Working Paper No. 2020-04

Residential Electricity Pricing in Texas's Competitive Retail Market

David P. Brown
University of Alberta

Chen-Hao Tsai
Midcontinent Independent System Operator

Chi-Keung Woo
Education University of Hong Kong

Jay Zarnikau
University of Texas at Austin

Shuangshuang Zhu
Frontier Energy

April 2020

Residential electricity pricing in Texas's competitive retail market

D.P. Brown[a,*], C.H. Tsai[b], C.K. Woo[c], J. Zarnikau[d], S. Zhu[e]

Abstract

Using a large sample of residential retail electricity plans advertised on the Public Utility Commission of Texas's Power-to-Choose website between during January 2014 to December 2018, our panel regression analysis finds changes in the projected wholesale price of electricity are not fully reflected as changes in these plans' price quotes. The estimated rates of wholesale price pass-through range from 43% to 45%. Retailers tend to charge risk premia that increase with wholesale price volatility. Prepayment and time-of-use plans likely contain price premia. The price premia associated with higher-than-average renewable energy contents in the early years of our sample have largely vanished by 2018. Longer contract terms come at a higher price. Finally, increased customer switching tends to reduce retail price quotes, implying that Texas's residential retail market can be made more price competitive through consumer education on plan choices and dissemination of credible price information.

[a] Department of Economics, University of Alberta, Edmonton, Alberta, Canada (dpbrown@ualberta.ca)

[b] Market and Grid Strategy, Midcontinent Independent System Operator, 2985 Ames Crossing Road, Eagan, MN 55121, USA (ctsai@misoenergy.org)

[c] Department of Asian and Policy Studies, Education University of Hong Kong, New Territories, Hong Kong (ckiwoo@eduhk.hk)

[d] Department of Economics, University of Texas at Austin, Austin, TX 78712, USA (jayz@utexas.edu)

[e] Frontier Energy, 1515 S. Capital of Texas Highway, Suite 110, Austin, TX 78746, USA (zsslucy@frontierenergy.com)

[*] Corresponding author

JEL Codes: D47, G12, Q31, Q41

Keywords: Retail electricity pricing, procurement cost pass-through, risk premium, renewable premium, ERCOT

1. Introduction

Over the last thirty years, the electricity industry has transformed considerably worldwide through market restructuring with the objective of fostering competition, reducing costs, and providing consumers with greater choices at lower prices (Sioshansi, 2013; Borenstein and Bushnell, 2015). A key feature of market restructuring in the U.S. has been the introduction of competition at the wholesale level and the formation of regional transmission organizations (RTOs) (Cramton, 2017). An often more controversial debate has been around the role and performance of retail market competition (e.g., Littlechild, 2002; Morey and Kirsch, 2016; Hortacsu et al., 2017).

Following the California electricity market crisis in 2000 – 2001, enthusiasm for retail competition waned, and much of the subsequent restructuring activity has focused on the establishment of competitive wholesale markets (Borenstein and Bushnell, 2015). That said, 14 states in the U.S. have retail competition despite 13 of them still keeps a default service for consumers without choosing a retail supplier (Littlechild, 2018). The only good case in fact is Texas, whose energy-only wholesale market design and limited oversight of retail prices have unleashed market forces to a greater extent than other regions of North America (Hortacsu et al., 2017). As a result, Texas is an ideal environment to analyse competitive retail electricity pricing, which is the focus of our analysis.

Retail price plans enable product differentiation (Woo et al., 2014). By offering plans with diverse attributes, competitive retailers satisfy choice preferences of consumers (Lancaster, 1990; Goett et al., 2000; Littlechild, 2002). In addition, a long-standing concern has been the absence of a close link between wholesale and retail markets due to cost-of-service regulation's lag in approving retail rate changes to reflect wholesale price changes (Kahn, 1978). In contrast, retailers serve as a link between wholesale market prices and retail consumption (Woo et al., 2019). As a result, retail competition is viewed as efficient, in part based on the degree to which wholesale price changes are passed down to consumers.

In this paper, we analyse retail price formation in Texas's retail electricity market for residential sales. To do so, we employ a large sample of over 5,000 retail price plans offered by 80 Retail Electric Providers (REPs) during January 2014 to December 2018. We explore how residential retail price quotes for monthly usage levels of 500 kWh, 1,000 kWh and 2,000 kWh respond to wholesale price changes and how the features of various retail plans may affect a REP's price quotes.

A key attribute of a retail price plan in Texas is the content of renewable energy that is emissions-free (e.g., solar and wind). If renewable energy is more costly to procure than conventional electricity generated by plants that burn fossil fuels, a retail plan for green energy tends to command a price premium (Woo and Zarnikau, 2019). We evaluate if Texas's retail price quotes for residential usage vary by renewable energy content.

To meet its delivery obligation, a REP may use electricity derivatives to manage its procurement cost risk because wholesale prices are highly volatile with occasional large price spikes (Eydeland and Wolyniec, 2003; Deng and Oren, 2006; Kleindorfer and Li, 2005; Woo et al., 2004a, 2004b, 2006). Electricity forward prices contain risk premia (Bessembinder and Lemmon, 2002; Longstaff and Wang, 2004; Woo et al., 2001, 2011; Zarnikau et al., 2015). As little known is about risk premia in retail price plans, we test if Texas's retail price quotes have risk premia that increase with wholesale price volatility.[1]

Our key findings are as follows. First, Texas's REPs do not fully pass wholesale market price changes through their retail price quote changes. The estimated rates of wholesale price pass-through range from 43% to 45%.

---

[1] A REP may also hedge against the wholesale price risk by owning generation assets or signing bilateral power purchase agreements. Because the forward price is the opportunity cost for future electricity delivery, this does not materially alter our theoretical analysis detailed in Section 2.2 that assumes a REP buying spot and forward electricity for resale to its customers.

Second, these REPs charge a risk premium that increases with wholesale price volatility. This premium is statistically significant (p-value < 0.05) at the 500-kWh monthly consumption level, though not at the 1,000- and 2,000-kWh levels.

Third, while REPs charged a statistically significant premium for retail price plans with an above-average renewable energy content at the beginning of our sample period, this premium had largely vanished by 2018, mirroring the declining cost of renewable energy in Texas.

Fourth, retail price quotes vary considerably by plan attributes such as contract term, time-of-use (TOU) pricing and payment method. These variations are all statistically significant. Plans with long contract terms tend to have higher price quotes than those with short contract terms because they increase retailers' wholesale price risk exposure (Eydeland and Wolyniec, 2003). TOU plans tend to have higher price quotes than non-TOU plans because when consumers with relatively low on-peak consumption can self-select TOU pricing, they likely reduce a REP's revenue (Woo et al., 1995). Prepayment plans contain price premia, plausibly due to higher administration costs of accounting and billing (Woo and Zarnikau, 2019) and their targeted customers who likely lack good credit (Eryilmaz and Gaffor, 2018).[2]

Finally, as the number of consumers who switch retailers increase, there is a statistically significant reduction in retail price quotes, consistent with retailers' reduced market power over inattentive or captive consumers with high switching and/or search costs (Giulietti et al., 2014; Hortacsu et al., 2017). This finding implies that Texas's residential retail market can be made more price competitive through consumer education on retail plan choices and dissemination of credible price information.

[2] Commonly used by lower-income households and college students, a prepayment plan does not require good credit to obtain electricity service from a retailer. This is because a prepayment customer adds money to his/her account in advance for settling the retailer's monthly bill. When the customer's account balance becomes zero, the retailer can stop service.

Our analysis contributes to the growing literature on the performance of retail electricity markets. Most relevant to our analysis is the work by Hartley et al. (2019) who provide important insights into retail pricing behavior in Texas during 2002 to 2016. The authors classify the state's retail market into competitive and non-competitive regions, finding that retail prices move more closely with wholesale prices in the competitive regions than the non-competitive regions.

Our analysis contributes to the findings provided by Hartley et al. (2019) by exploiting a larger sample of retail price plans marketed through the Public Utility Commission of Texas's (PUCT's) retail shopping website Power-to-Choose, whereas Hartley et al. (2019) consider a smaller set of plans from the PUCT's Retail Rate Survey. Importantly, our sample allows us to control for plan attributes that likely impact retailers' pricing decisions. Unlike their analysis which utilizes contemporaneous wholesale prices, we construct forward-looking wholesale price forecast levels and volatility, mirroring a REP's future delivery obligations during a retail price plan's contract term.

Looking beyond Hartley et al. (2019), our paper is related to a growing literature that estimates the degree and impact of search frictions and switching costs on consumer and firm behavior in retail electricity markets (e.g., Wilson and Waddams Price, 2010; Waddams Price et al, 2013; Giulietti et al., 2014; Hortacsu et al., 2017). These studies primarily focus on estimating frictions, finding evidence of search and/or switching frictions that help explain observed retail price dispersion and market power. Our analysis takes these frictions as given and empirically analyses a retailer's price quote decision.

Our paper contributes to an extensive literature that evaluates the degree of price pass-through resulting from a cost shock. In the electricity industry, there are a multitude of papers that assess the degree of wholesale price pass-through to retail prices in the United Kingdom (e.g., Ofgem, 2011), Netherlands (e.g., Mulder and Willems, 2019), and Norway (e.g., Mirza and Bergland, 2012). These studies often find evidence of imperfect or delayed wholesale price pass-through. Our analysis corroborates these studies by documenting Texas's retail price quotes' incomplete pass-through of the changes in wholesale price forecast level.

As a case study of wholesale price pass-through in Texas's competitive retail electricity market, our paper provides a contribution to a broader literature that analyses cost pass-through in an array of settings, ranging from retail gasoline (Borenstein et al., 1997; Eckert, 2013), carbon emissions from electricity generation (Fabra and Reguant, 2014), the coffee industry (Nakamura and Zerom, 2010), to exchange rates to prices of imported goods (Goldberg and Hellerstein, 2013).[3]

The rest of this paper proceeds as follows. Section 2 justifies our geographic choice of Texas, describes the retail plan data, presents an illustrative model of retail price quotation, sets up the retail price regressions, and discusses the estimation strategy. Section 3 presents our regression results. Section 4 concludes.

2. Materials and methods

2.1 Why Texas?

2.1.1 General overview

Texas's RTO, the Electric Reliability Council of Texas (ERCOT), is an important and interesting case study for the following reasons. First, ERCOT accounts for over 9% of the nation's total electricity generation. It serves 90% of the electric load in the nation's leading state in electricity generation and consumption, reaching a peak demand of 74,666 MW on August 12, 2019 (ERCOT, 2019). It has consistent load growth in recent decades due to a strong economy, unlike other U.S. RTOs with little growth.

[3] See Fabra and Reguant (2014) for a summary of the Industrial Organization literature and the analysis of pass-through. In particular, the authors provide a detailed literature review of the studies that document incomplete price pass-through for reasons varying from price rigidities to strategic adjustments of price markups in imperfectly competitive markets.

Second, ERCOT has limited interconnection with out-of-state grids, and thus operates with considerable independence. As a fully intrastate system, there is limited federal jurisdiction over the ERCOT market. With vibrant competition in both the generation and retail sectors of the market, ERCOT is generally recognized as one of the most successful electricity market reforms in North America (DEFG, 2015).

Third, Texas leads the U.S. in wind generation development, thanks to the state's enormous resource potential and favorable government policies and market rules (Zarnikau, 2011). After completing the Competitive Renewable Energy Zone in January 2014, it now has 3,600 miles of 345kv transmission line, accommodating an installed system-wide capacity 23.86 GW in 2019 and an expected addition of 12.6 GW by 2022.[4] Because of its weather dependence, however, the projected total wind generation capacity installed by 2022 can only provide ~9 GW of operation capacity at the annual firm peak load hour.[5]

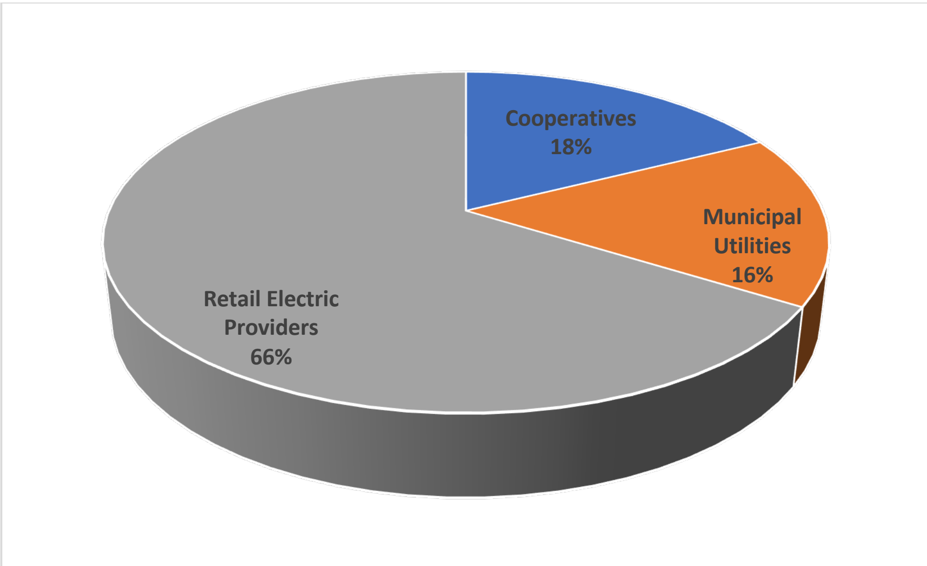
Finally, Texas has had retail competition since 2002. Efforts to introduce competition into the retail sector of the state's electricity market began in June 1999 with the Texas Legislature's passage of Senate Bill 7 (SB 7) (Adib and Zarnikau, 2006; Wood and Gülen 2009). Retail competition commenced on January 1, 2002, allowing REPs to serve retail customers in the service areas of investor-owned electric utilities within ERCOT.

During our estimation period of 2014-2018, 80 REPs appear on the PUCT's Power-to-Choose website. We use customer count data from the Energy Information Administration's 2018 Form 861 to establish a snapshot of the prevailing market structure in Texas's retail electricity market. Fig. 1 reports the market shares across ownership structures; REPs serve

[4] ERCOT Capacity Changes by Fuel Type Charts, February, 2020, available at: http://www.ercot.com/gridinfo/resource. A list of existing and planning wind and solar generation resources along with their capacities and on-line dates can be found in this report.

[5] ERCOT Capacity, Demand and Reserves (CDR) Report, December 2019. Available at: http://www.ercot.com/gridinfo/resource. ERCOT assumes its wind resource has the following Peak Average Capacity Contribution (% of installed capacity): Coastal Wind - 63% of installed capacity; Panhandle Wind-29% of installed capacity; Other Wind-16% of installed capacity.

66% of the market. It demonstrates that within this ownership category, over 50% of the market is served by three REPs: TXU, Reliant Energy, and Direct Energy. While over 50% of this market segment is served by three REPs: TXU, Reliant Energy, and Direct Energy, the standard four-firm concentration ratio equals 57%, demonstrating moderate market concentration in areas opened to retail competition.



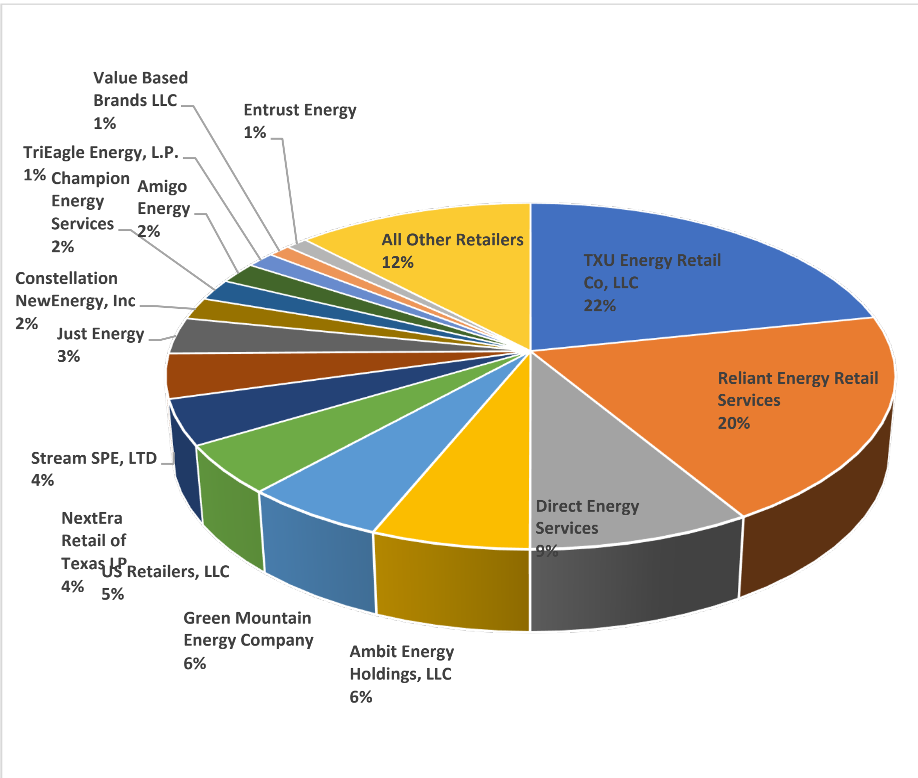


Fig. 1: Residential market shares of REPs based on customer counts

2.1.2 Texas's retail price plans

With frequent price updates, REPs in Texas offer retail plans with diverse attributes, including renewable energy content, contract term, fixed vs. variable pricing, TOU vs. non-TOU pricing, prepayment vs. no prepayment, and plan language: Spanish vs. English. Examples of retail price plans are available at http://powertochoose.org/.

Texas's renewable energy policies affect REPs by setting a minimum "greenness" or renewable energy content requirement for the electricity sold. The restructuring legislation, SB 7, set initial targets. SB 20 of 2005 increased the goal for renewable energy to 5,880 MW in 2015 and set a "voluntary" target of 10,000 MW of wind power for 2025, which Texas has already met. Further, each REP must have Renewable Energy Credits (RECs) equal to its share of the renewable energy goals in effect during a given year. It can procure more RECs to develop green energy price plans to target environmentally conscientious customers, potentially causing such plans to have a renewable energy premium.

2.1.3 Key research question

Competitive retail pricing arguably leads to efficiency gains by better matching prices to short-run locational marginal costs of electricity generation (Stoft, 2002). Regulatory delays are avoided, at least for the generation component of the final price. Further, customer choices made possible by diverse retail price plans offered by many REPs likely improve consumer welfare (Lancaster, 1990). Such benefits, however, cannot occur *sans* a close linkage between retail and wholesale prices. Hence, our key research question is: how do Texas's retail price quotes move with wholesale market prices?

2.2 Theory

We develop an illustrative model of retail price quotation for the sole purpose of setting up our retail price regression. As such, our model is not intended to accurately portray the reality that Texas have heterogenous REPs, each offering a menu of diverse retail price plans.

Our model development begins by assuming a hypothetical REP offering a fixed price plan with a specific contract term.[6] To match the plan data used in our retail price regression analysis, it further assumes each plan's price quote applies to a fixed MWh quantity, thus circumventing the thorny issue of quantity risk due to a REP's obligation to serve fluctuating retail consumption (Woo et al., 2004a, 2004b, 2006). For clarity and ease of exposition, it assumes the plan has a specific renewable energy content.[7]

To complete the model, we first define:

- R = retail price quote ($/MWh) of a plan with renewable energy content K (%) for delivery obligation of 1 MWh per month.
- P = wholesale market spot price ($/MWh) whose expected value is μ and variance σ^2.
- P_F = wholesale market forward price ($/MWh) whose expected value is $\mu + \phi\,\sigma$ where ϕ is a positive scalar, implying the forward price embodies a risk premium of $\phi\,\sigma$ that increases with the spot market price volatility σ (Woo et al., 2001, 2011a).
- C = renewable energy procurement cost ($/MWh) = per MWh cost of procuring renewable energy, which is assumed to be is known with certainty based on recently signed power purchase agreements.
- M = per MWh cost for marketing and operation, which is based on the REP's known cost before contract signing.

[6] We consider fixed pricing because of its popularity among Texas's REP, see Table 1 below in Section 2.3.1. We do not consider TOU pricing for the following reasons. First and foremost, our sample of price plan data only contains average prices by monthly usage level. Second, modelling TOU price quotes require on- and off-peak retail price regressions, a challenging estimation effort that entails producing wholesale price forecasts by TOU period. Finally, introducing TOU price plans in the presence of fixed price plans vastly complicates our theory's development due to consumers' adverse self-selection (Woo et al., 1995), an issue well beyond our paper's intent and scope. Finally, the materials in this section do not depend on the length of a contract term because they are qualitatively identical for terms of varying lengths. That said, our retail price regression recognizes the numerical impact of a contract term's length on the REP's price quotes.

[7] Expanding the menu of price plans with varying renewable energy contents requires introducing a subscript for plan type, which does not add material insights in the model's formulation and inferences.

- $G_i(R, K) = P(N = N_i \mid R, K)$ to be the probability mass function of the REP signing a discrete number (= N_i between 0 and N_{max} for $i = 0, 1, 2, \ldots, N_{max}$) of contracts with known attributes of R and K. We assume: (a) $\partial G_i / \partial R < 0$ for $i = 1, 2, \ldots, N_{max}$ because lowering the price quote improves the chance of contract signing; (b) $\partial G_i / \partial K > 0$ for $i = 1, 2, \ldots, N_{max}$ because raising the renewable content improves the chance of contract signing, as consumers are willing to pay more for cleaner energy (Woo and Zarnikau, 2019 and references thereof).

Using the above definitions, we define $Y_i = R\, N_i$ to be the revenue from serving N_i contracts. The cost of serving N_i contracts is $Z_i = \{C\, K + (1 - K)\, [\lambda\, P + (1 - \lambda)\, P_F] + M]\} N_i$, representing the sum of: (a) renewable procurement cost = $C\, K\, N_i$; (b) wholesale market procurement cost = $(1 - K)\, N_i$ at the per MWh cost of $[\lambda\, P + (1 - \lambda)\, P_F]$, where $\lambda \geq 0$ is the fraction of the REP's wholesale market procurement at spot P and $(1 - \lambda) \geq 0$ is the remaining fraction at forward price P_F (Woo et al., 2004a, 2006);[8] and (c) total marketing and operation cost = $M\, N_i$.

A REP's expected total profit is $E\{\pi\} = \sum_{i=1}^{N_{max}} G_i(R, K)\, E(Y_i - Z_i)$, the probability-weighted average of the expected profits from serving all possible numbers of contracts. The REP is assumed to set R to maximize expected profits, yielding the following first order condition for an interior solution for the optimal $R^* > 0$:

$$\partial \pi / \partial R = A - B = 0, \tag{1}$$

[8] The condition of $1 \geq \lambda \geq 0$ reflects that the hypothetical REP's wholesale procurement is solely for meeting its obligation of retail delivery. The remainder of this section treats λ as given, exogenously determined by the REP's portfolio management strategy in a real-world setting (Kleindorfer and Li, 2005; Woo et al., 2004a, 2006). The following two cases shows how λ financially affects the hypothetical REP:

- Case 1: If the hypothetical REP is risk-neutral and totally relies on spot purchases, $\lambda = 0$ and the REP's total expected profit is $E\{\Pi\} = \sum_{i=1}^{N_{max}} G_i(\cdot) N_i \times \{R - [C\, K + (1 - K)\, \mu + M]\}$ and total expected profit variance is $var(\mathrm{E}\{\Pi\}) = \left(\sum_{i=1}^{N_{max}} G_i(\cdot) N_i\right)^2 (1 - K)^2\, \sigma^2 > 0$ for $K < 1$.
- Case 2: If the hypothetical REP is highly risk-averse and only buys electricity forwards that guarantee wholesale price certainty, $\lambda = 1$ so that $E\{\Pi\} = \sum_{i=1}^{N_{max}} G_i(\cdot) N_i \times \{R - [C\, K + (1 - K)\, P_F + M]\}$ and $var(\mathrm{E}\{\Pi\}) = 0$.

where $A = \sum_{i=1}^{N_{max}} G_i(\cdot)N_i + \partial G_i/\partial R\ (R\ N_i)$; and $B = \sum_{i=1}^{N_{max}} H\ N_i\ \partial G_i/\partial R$ with $H = C\,K +$ $(1 - K)\ [\mu + (1 - \lambda)\ \phi\ \sigma] + M$. Using equation (1), the optimal retail price quote equals:

$$R^* = H + \frac{\sum_{i=1}^{N_{max}} G_i(\cdot)N_i}{\left|\sum_{i=1}^{N_{max}} \frac{\partial G_i}{\partial R} N_i\right|}. \tag{2}$$

Equation (2) yield the following inferences. First, the REP sets a mark-up above marginal cost H because the second right-hand-side term (RHS) of equation (2) is the positive mark-up that equals the expected sales divided by the expected marginal sales loss caused by a rising price quote. This mark-up shrinks as the size of $\partial G_i/\partial R$ increases, suggesting that R^* converges to H when consumers become increasingly price sensitive.

Second, the optimal retail price is increasing in its marginal cost parameters $\mu, C, \phi, \sigma,$ and M:

$$\frac{\partial R^*}{\partial M} = 1;\ \frac{\partial R^*}{\partial C} = K;\ \frac{\partial R^*}{\partial \mu} = 1 - K; \text{and } \frac{\partial R^*}{\partial \sigma} = (1 - K)(1 - \lambda)\phi. \tag{3}$$

Third, assuming the probability mass function $G_i(R, K)$ is additively separable in R and K (such that $\frac{\partial G_i}{\partial R}$ is independent of K for all $i = 1, 2, 3, \ldots, N_{max}$), equation (2) implies:

$$\frac{\partial R^*}{\partial K} = \{C - [\mu + (1 - \lambda)\ \phi\ \sigma]\} + \frac{1}{\left|\sum_{i=1}^{N_{max}} \frac{\partial G_i}{\partial R} N_i\right|} \sum_{i=1}^{N_{max}} \frac{\partial G_i(\cdot)}{\partial K} N_i. \tag{4}$$

The first RHS term in { } of equation (4) is the impact on the retailer's marginal cost due to increased renewable procurement. It is positive (negative) when renewable energy's per MWh procurement cost C is above (below) conventional electricity's expected per MWh procurement cost $[\mu + (1 - \lambda)\ \phi\ \sigma]$. The second RHS term is the impact of expanding K on the REP's mark-up. It is positive because raising K increases the chance of contract signing. Hence, $\partial R^*/\partial K > 0$ when $C > [\mu + (1 - \lambda)\ \phi\ \sigma]$, as later confirmed by our regression results.

In the analysis that follows, we will reference the equilibrium condition in equation (2) and derivatives in equations (3) and (4) to set up our regression analysis and interpret its ensuing findings.

2.3 Retail price plan data

2.3.1 Descriptive statistics

Our empirical exploration is made possible by a large sample of 5,171 retail price plans downloaded from the website www.powertochoose.com managed by the PUCT. These plans were offered in the 60-month period of Jan 2014 – Dec 2018.

These retail plans are diverse, as indicated by Panel A of Table 1 that presents the descriptive statistics of these plans' energy prices ($/MWh) for three monthly usage levels of 500 kWh, 1,000 kWh and 2,000 kWh.[9] With means of $52/MWh to $63/MWh and standard deviations of $16/MWh to $19/MWh, these prices are highly disperse. Fig. 2 presents box and whisker plots of the retail prices across the five transmission-distribution-utility (TDU) service areas and three monthly usage levels during our sample period.[10] It portrays considerable price dispersion across the retail plans in our sample, necessitating the need for an empirical analysis to understand the key drivers of these price differences.

Panel A of Table 1 also shows that the price plans have contract terms of one to 36 months and renewable energy content of 0 to 100%.[11] Further, 2% of the plans have TOU pricing, 85% fixed pricing and 5% prepayment. Finally, 10% of the plans have description in Spanish to target the state's Latino households.

---

[9] Each energy price is based on the difference between (a) a usage level's total bill and (b) charges for customer service and transmission and distribution. The 1,000-kWh level approximates the average monthly usage of a Texas household. Data of transmission and distribution charges of each transmission-distribution-utility (TDU) area is available at: https://www.puc.texas.gov/industry/electric/rates/TDArchive.aspx.

[10] The five TDU service areas in our sample are: AEP Central, AEP North, CenterPoint Energy (CenterPoint), Oncor, and Texas New Mexico Power Company (TNMP).

[11] We have excluded plans with: (a) contract terms of 48 months and 60 months due to limitation of our wholesale price forecast; (b) negative prices due to aggressive usage credit; or (c) extremely large prices that likely reflect data errors. For information about the total number of residential customers on TOU, real-time pricing, and other forms of dynamic pricing, see Raish (2020).

Table 1. Retail price plans

Panel A. Descriptive statistics of 5,171 plans offered in the 60-month period of Jan 2014 – Dec 2018

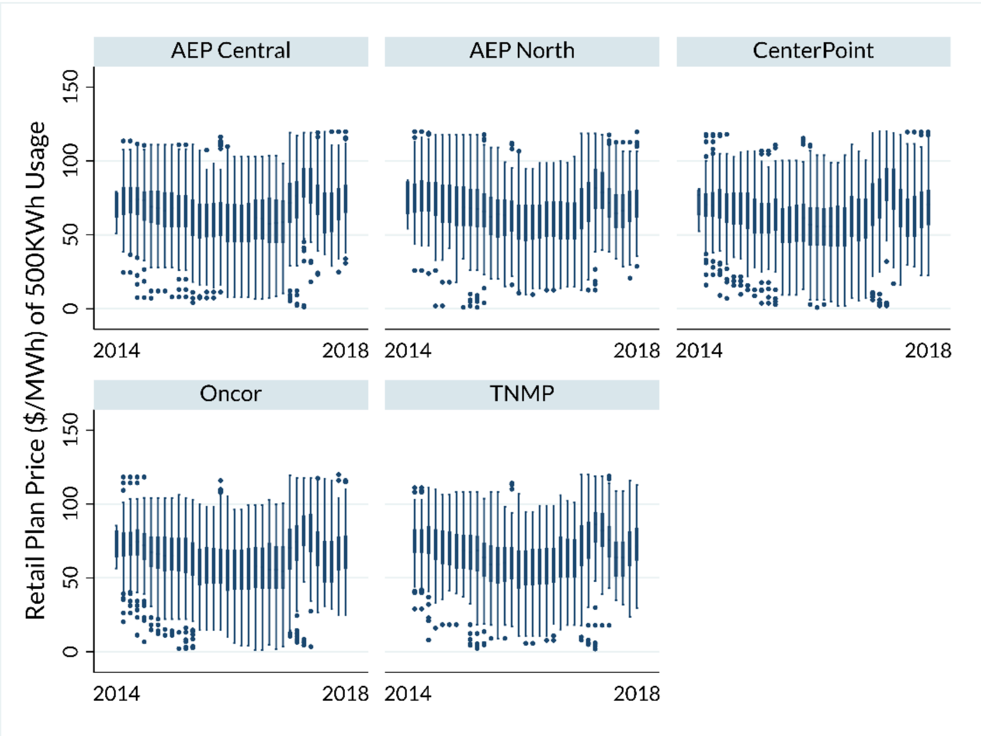
Variable	Mean	Standard deviation	Minimum	Maximum
Retail price ($/MWh) for 500 kWh per month	63.27	19.36	0.84	119.95
Retail price ($/MWh) for 1,000 kWh per month	52.33	19.36	0.09	119.57
Retail price ($/MWh) for 2,000 kWh per month	55.73	16.61	0.55	119.40
Contract term (month)	12.94	9.55	1	36
Renewable energy content (%)	29.99	38.12	0	100
TOU pricing indicator = 1 if yes, 0 otherwise	0.02	0.14	0	1
Fixed pricing indicator = 1 if yes, 0 otherwise	0.85	0.35	0	1
Prepayment indicator = 1 if yes, 0 otherwise	0.05	0.21	0	1
Spanish language indicator = 1 if Spanish, 0 otherwise	0.10	0.30	0	1

Panel B. Descriptive statistics of the monthly supplemental data for the retail price regressions

Variable	Mean	Standard deviation	Minimum	Maximum
Nominal weekly wage ($/week)	955.50	34.49	898	1,020
No. of move-in customers (thousands)	49.41	42.85	3.76	135.29
No. of move-out customers (thousands)	24.74	21.55	2.04	67.12
No. of switching customers (thousands)	17.81	15.65	1.16	82.40

Note: Nominal weekly wage proxies a retailer's operation costs (Hartley et al., 2019). A TDU area's numbers of move-in and move-out customers measure the area's changes in aggregate demand for retail service. The number of with-area switching customers measures local competition for customer sign-ups.

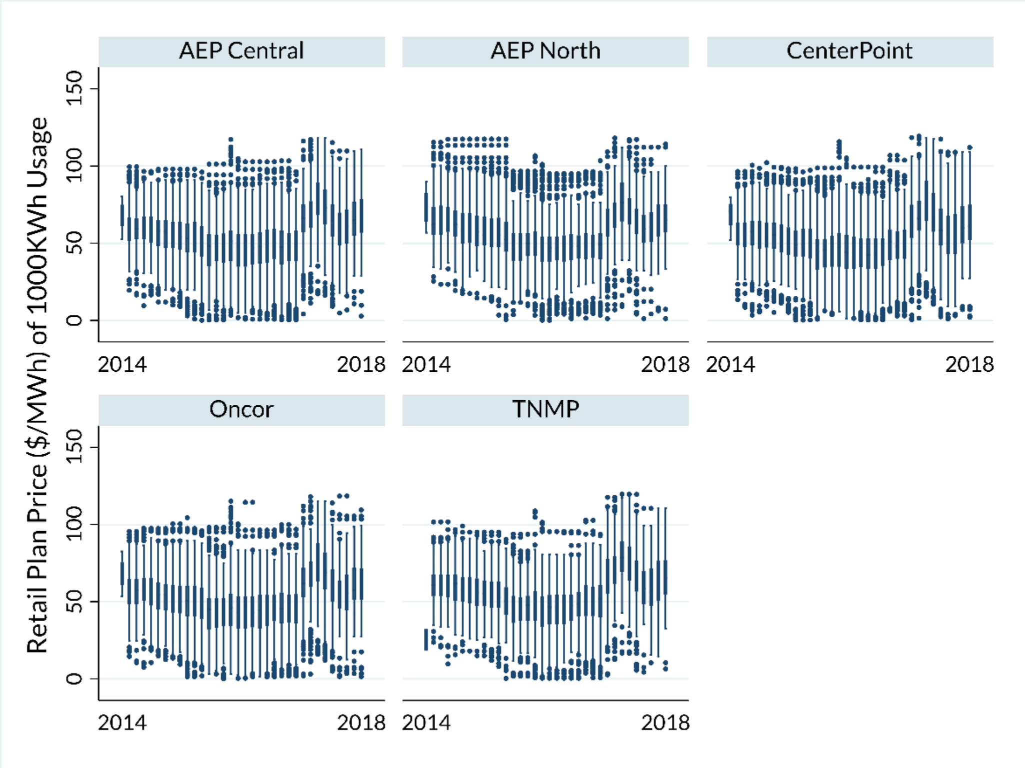
Panel B of Table 1 presents the descriptive statistics of the supplemental data for our retail price regression analysis. Following Hartley et al. (2019), we collect data from the U.S. Bureau of Labor Statistics on the nominal average weekly wage in the "Private Trade, Transportation, and Utilities" category to proxy for a REP's operating cost. A TDU area's market conditions are measured by (a) the numbers of move-in and move-out customers that measure the area's total demand for retail plans; and (b) the number of switching customers that measure the area's intra-market competition among REPs.[12] Chronologically matching a plan's offering months and observable customer numbers, both (a) and (b) are one-month lagged values.[13]



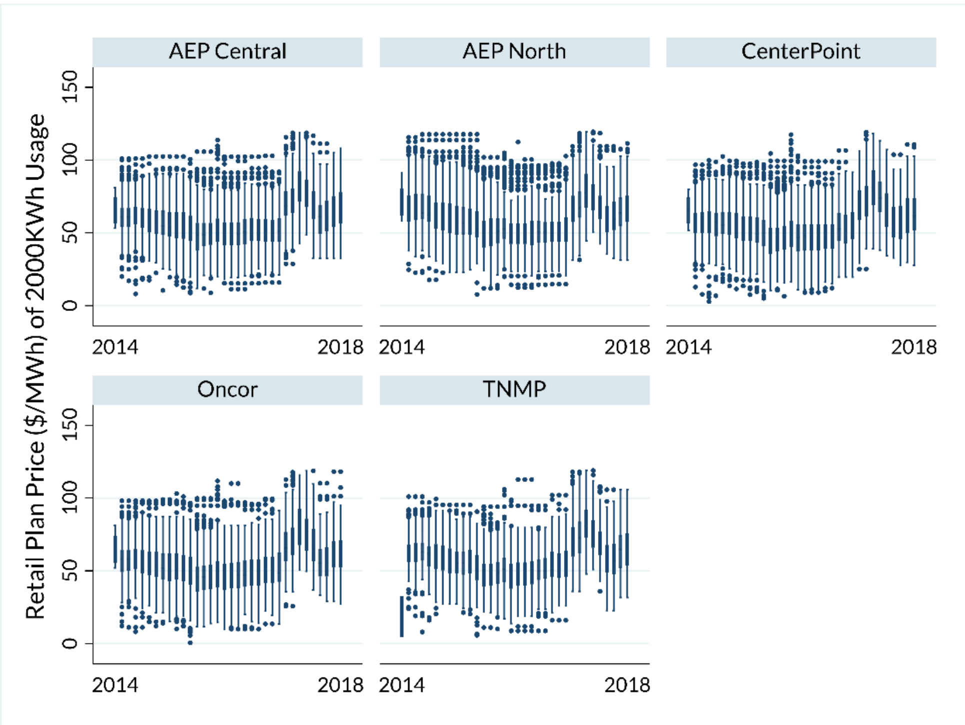
(a) 500-kWh usage level

[12] These data come from ERCOT "Retail Monthly Transaction Totals," available at http://www.ercot.com/mktinfo/retail. We utilize the following three main types of transactions recorded by ERCOT to proxy consumer movements and switching behavior within a TDU area: [814_01] Switch Request Received by ERCOT from new customer; [814_16] Move-In Request Received by ERCOT from new customer; and [814_24] Move-Out Request Received by ERCOT from current customer.

[13] Our regression analysis results in Table 3 below are virtually identical to those obtained using contemporaneous or three-month lagged values.



(b) 1,000-kWh usage level



(c) 2,000-kWh usage level

Fig.2: Retail price dispersions by TDU area and usage level.

2.3.2 Retail price correlations

The box plots in Fig. 3 suggest that nearly all retail price quotes in our sample are more than twice the wholesale price forecast levels developed in Appendix 1 that match the plans' contract terms. This suggestion, however, can be misleading because it ignores the retail price effects of other factors that enter a REP's quote determination.

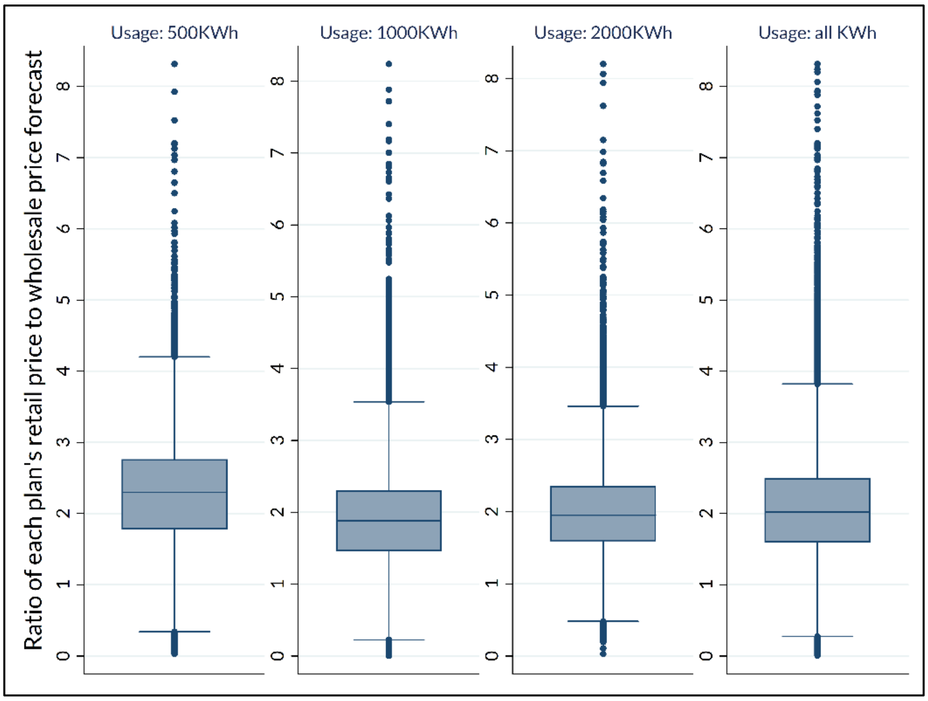


Fig. 3: Box plots of ratios of retail price quote to wholesale price forecast level

We use retail price correlations for the purpose of an initial exploration. Table 2 presents retail price correlations with the metric regressors in the retail price regression detailed below. Based on Section 2.2, the first two regressors are wholesale price forecast level and error, whose calculations are detailed in Appendix 1.

Table 2 shows all retail price correlations are weak ($|r| < 0.2$), incapable of convincingly establishing how retail prices move with wholesale price forecast level and error, plan attributes, nominal wage, and market conditions. Hence, the next section formulates a regression analysis to untangle the price effects of these regressors.

Table 2. Retail price correlations with metric regressors for the purpose of an initial exploration

Regressor	Monthly usage level			
	500 kWh	1,000 kWh	2,000 kWh	All levels
Wholesale price forecast level	0.0960	0.1362	0.1763	0.1295
Wholesale price forecast error	0.1395	0.1660	0.1446	0.1447
Contract term	0.0890	0.0828	0.0432	0.0706
Contract term squared	0.0873	0.1037	0.0490	0.0787
Renewable content	-0.0108	-0.0091	0.0467	0.0065
Nominal weekly wage	0.0730	0.1185	0.1501	0.1081
No. of move-in customers	-0.0524	-0.0746	-0.0690	-0.0629
No. of move-out customers	-0.0540	-0.0786	-0.0749	-0.0665
No. of switching customers	-0.0039	-0.0182	-0.0005	-0.0077

Note: All retail price correlations are weak ($|r| < 0.2$), necessitating a regression analysis to identify and quantify their retail price effects.

2.4 Retail price regression

For each plan j offered by retailer r in month t (= 1 for Jan 2014, …, T = Dec 2018), we assume the data generation process of the retail price quotes is characterized by the following panel regression with random error ε_{jrt}:

$$R_{jrt} = \alpha_t + \rho\, F_{jt} + \theta\, S_{jt} + \Sigma_k\, \beta_k\, X_{jkt} + \gamma\, W_t + \Sigma_q\, \varphi_q\, Q_{jqt} + \Sigma_r\, \gamma_r\, Z_r + \varepsilon_{jrt}; \tag{5}$$

where R_{jrt} is the retail price quote (converted from \$/kWh to \$/MWh) of plan j offered by retailer r in month t. The first regressor is α_t, a time-varying intercept which is assumed to be a linear function of monthly and yearly dummies.

The second regressor is F_{jt} (\$/MWh), which is month t's wholesale price forecast level for future delivery in plan j's contract period.[14] Its coefficient is $\rho > 0$, measuring the marginal price effect of F_{jt}. To better understand ρ, we recall from equation (3) that $\partial R^*/\partial\mu = (1 - K) \leq 1$, implying a retailer's optimal price quote increases by \$$(1 - K)$/MWh in response to a \$1/MWh increase in the expected wholesale price level. Hence, unless the REP is 100%

[14] Appendix 1 details how we calculate the wholesale price forecast level (F_{jt}) and error (S_{jt}) discussed below.

green at $K = 0$, $\partial R^*/\partial\mu$ presages that REPs may not fully pass a \$1/MWh change in the wholesale forecast level on a dollar-for-dollar basis to their retail price quotes. As the size of ρ is an empirical issue best settled by our regression analysis, the null hypotheses to be tested are: **H1**: $\rho < 1$ for incomplete pass-through; **H2**: $\rho = 1$ for 100% pass-through; and **H3**: $\rho = 1$ for over 100% pass-through.

The third regressor is S_{jt} (\$/MWh), the wholesale price forecast error. Its coefficient is θ, measuring the marginal price effect of S_{jt}. Using equation (3) that shows $\partial R^*/\partial\sigma = (1 - K)(1 - \lambda)\,\phi \geq 0$, the null hypotheses to be tested are: **H4**: $\theta = 0$ for risk neutrality;[15] and **H5**: $\theta > 0$ for risk aversion.

The next set of regressors are $\{X_{jkt}\}$, with X_{jkt} = attribute k of plan j offered in month t (e.g., fixed vs. variable pricing, contract term, renewable energy content, kWh level, TOU vs. non-TOU, …, etc.). We include a quadratic term on contract length to test for the presence of a nonlinear relationship between contract length and retail pricing decisions. In addition, we consider interactions between renewable energy content and year indicators to test if the impact of renewable energy content on retail pricing behaviour has changed over our sample period. The marginal price effect of X_{jkt} is given by coefficient β_k.

We use W_t, the hourly nominal wage in month t to proxy non-energy costs. The coefficient γ is the marginal price effect of W_t.

The next three regressors portray market activities in plan j's TDU service area in month t. They are denoted by Q_{jqt} for $q = 1$ for the number of move-in customers, 2 for the number of move-out customers, and 3 for the number of switching customers. Their marginal price effects are $\varphi_1 > 0$, $\varphi_2 < 0$, and $\varphi_3 < 0$ because as more (less) consumers are available in a region, market demand for a firm's product increases (decreases) and an

[15] See footnote 8 on the role of λ in determining the REP's expected profit and profit variance based on wholesale market procurement of spot and forward electricity.

increase in the incidence of customer switching is expected to mitigate a retailer's market power over inattentive/captive consumers.

The remaining set of regressors in $\{Z_r\}$ represent retailer and TDU service area fixed effects to control for time-invariant retailer and regional market characteristics. The corresponding set of marginal price effects is $\{\gamma_r\}$.

Finally, the random error ε_{jrt} is heteroskedastic robust and clustered at the retailer plan by usage level by TDU service area.

2.5 Estimation strategy

As many of the 5,171 retail price plans retail plans have multiple monthly observations in the sample period of Jan 2014 – Dec 2018, we use a panel regression analysis to estimate equation (5) (Wooldridge, 2010).

Since each retail price plan has three price quotes for usage levels of 500 kWh, 1,000 kWh and 2,000 kWh, we estimate three kWh-specific retail price regressions. We also pool the retail price data to estimate a single regression for all usage levels that includes usage level fixed effects.

We present two retail price regressions models. Our primary specification is equation (5) that includes fixed effects at the retailer and TDU service area. By assuming retailer plan-specific effects to be random, it permits us to quantify the retail price effects of time-invariant retailer plan characteristics (e.g., contract term, prepayment, and renewable energy content).

As a sensitivity check, we run an alternative specification that includes retailer plan by TDU service area fixed effects. While this specification controls for time-invariant factors beyond the observed retail plan covariates detailed above, this specification does not identify the retail price impacts of a plan's time-invariant attributes.

3. Regression results

Panel A of Table 3 presents the panel regression results from our primary specification. All regressions have empirically reasonable fit, as indicated by their relatively high R^2 values.

Across all usage levels, the wholesale price forecast level's coefficient estimates are between 0.43 and 0.45. As their 95% confidence intervals have lower bounds of ~0.39 and upper bounds of ~0.51, they lend support to **H1**: $\rho < 1$ for incomplete pass-through.[16]

The wholesale price forecast error' coefficient estimate is statistically significant when looking across all usage levels, lending support to **H5**: $\theta > 0$ for risk aversion. Decomposing this effect by usage level demonstrates that this effect is driven by price quotes for the 500-kWh usage level.

The positive and statistically significant coefficient estimates for contract term demonstrate that fixed-price plans with longer durations are associated with a considerable price premium. For example, when looking across all usage levels, a 36-month fixed-price plan comes at a retail price premium of $6.32/MWh compared to a 2-month fixed-price plan, holding all else constant.[17] This finding is likely driven by the higher wholesale price risk imposed on a retailer for providing the longer duration contracts.

The positive and significant coefficient estimates for renewable content capture the renewable energy price premium. In 2014, moving from 0 to 100% renewable energy content is associated with an approximate increase of $6.0/MWh in retail prices. However, the interaction terms' coefficient estimates demonstrate that the renewable energy premium has systematically decreased since 2014. The premium is no longer statistically different from

[16] We also performed a Wald test and verified that these coefficients are statistically different from 1.
[17] Using the All Levels results in Table 3, the difference in the contract term coefficients implies: $0.300 * 36 - 0.003 * 36^2 - (0.300 * 2 - 0.003 * 2^2) \approx 6.32$.

zero in 2018,[18] an outcome coincident with the observed reduction in the levelized cost of renewable energy and substantial growth in wind output during our sample period.

We find positive and statistically significant coefficient estimates for TOU price plans that offers free electricity consumed on weekends or during evening hours. This is expected because voluntary TOU pricing causes adverse self-selection, attracting consumers with relatively low usage during weekday daytime hours (Woo et al., 1995). To mitigate the potential revenue loss due to self-selection, a REP increases these plans' price quotes.

We find positive and statistically significant coefficient estimates for retail plans that offer prepayment. Consumers who sign up for prepayment accounts are subject to a significant premium ranging from \$9.11 to \$13.97/MWh, over a one standard deviation change in retail prices (see Table 1). In addition, we find that retail plans targeted at Spanish-speaking consumers are priced lower by a statistically significant amount of \$2.74 to \$4.68/MWh.

As expected, there is a positive relationship between nominal weekly wages and retail price quotes. However, this effect is modest. A one standard deviation increase in nominal weekly wages is estimated to cause a \$1.28 to \$1.41/MWh increase in retail price quotes, holding all else constant.[19]

The coefficient estimates for the 1-month lagged number of move-in and move-out customers have the expected signs and are statistically significant. As the number of consumers that move into (out of) a TDU service area increase, it tends to increase (decrease) in the retail price level.

---

[18] The renewable content's estimated price effects in 2018 are -0.01 for the 500-kWh usage level, -0.007 for the 1,000-kWh usage level, 0.014 for the 2,000-kWh usage level, and -0.002 for all usage levels. These estimated price effects are all statistically insignificant, corroborating the recent finding by Woo and Zarnikau (2019) of Texas's vanishing renewable price premium.

[19] Using the results in Table 3 for All Usage Levels and 500 kWh, a one-standard deviation increase in nominal weekly wage (34.49 from Table 1) implies: $34.49 \times 0.037 \approx 1.28$ and $34.49 \times 0.041 \approx 1.41$.

Finally, as the number of consumers switching retailers increases, retail price quotes decline by a statistically significant amount. This finding makes sense because equation (2) shows that an increase in the number of switching consumers increases the expected marginal sales loss caused by a rising price quote, thus causing downward pressure on retail price quotes. It is also consistent with the findings in the literature that retailers are able to exercise more market power over inattentive/captive consumers who face higher switching and/or search costs and are less likely to switch to lower-priced retailers (Giulietti et al., 2014; Hortacsu et al., 2017).

As a sensitivity analysis, Panel B of Table 3 presents results from our model specification where we include retailer plan by TDU service area fixed effects. It demonstrates that the results in Panel A are robust. Specifically, we continue to find statistically significant and incomplete wholesale price pass-through in the range of 0.42 to 0.45. Second, we detect retailer risk aversion across all usage levels; this is notwithstanding that this result is mainly driven by 500-kWh price quotes. We also find statistically significant evidence that retail prices rise as nominal wages increase and are lower for Spanish language plans.[20] Finally, the switching, move-in, and move-out variables remain statistically significant with the expected signs.

[20] We can identify the Spanish coefficient in this retailer-plan by TDU service area fixed effects model because within a retailer's plan, there is variation in whether the plan was offered in English or Spanish.

Table 3. Retail price regressions; sample period = Jan 2014 – Dec 2018; clustered robust standard errors used to determine statistically significant (p-value < 0.05) estimates in **bold**

Panel A: Plan-specific effects are assumed to be random

Variable	Monthly usage level			
	500 kWh	1,000 kWh	2,000 kWh	All levels
No. of observations	50,347	49,782	50,777	150,906
R^2: within	0.354	0.389	0.439	0.392
R^2: between	0.387	0.507	0.465	0.417
R^2: overall	0.396	0.480	0.482	0.430
Wholesale price forecast level	**0.430**	**0.453**	**0.448**	**0.442**
Wholesale price forecast error	**0.358**	0.128	0.086	**0.198**
Contract term	**0.286**	**0.372**	**0.367**	**0.300**
Contract term squared	-0.002	**-0.004**	**-0.006**	**-0.003**
Renewable content	**0.064**	**0.062**	**0.060**	**0.061**
Renewable content × 2015 indicator	**-0.017**	**-0.018**	**-0.017**	**-0.017**
Renewable content × 2016 indicator	**-0.030**	**-0.032**	**-0.030**	**-0.031**
Renewable content × 2017 indicator	**-0.025**	**-0.031**	**-0.030**	**-0.029**
Renewable content × 2018 indicator	**-0.074**	**-0.069**	**-0.046**	**-0.063**
Prepayment indicator	**9.111**	**13.970**	**12.430**	**11.850**
TOU pricing indicator	**4.987**	**12.100**	**6.480**	**7.735**
Fixed pricing indicator	-0.247	-1.418	-0.016	-0.292
Spanish language indicator	**-2.737**	**-3.851**	**-4.687**	**-3.733**
Nominal weekly wage	**0.037**	**0.047**	**0.037**	**0.041**
No. of move-in customers	**0.072**	**0.091**	**0.072**	**0.079**
No. of move-out customers	**-0.115**	**-0.133**	**-0.101**	**-0.118**
No. of switching customers	**-0.022**	**-0.031**	**-0.028**	**-0.026**
500 kWh indicator				**5.012**
1,000 kWh indicator				**-4.779**

Panel B: Plan-specific effects are assumed to be fixed

Variable	Monthly usage level			
	500 kWh	1,000 kWh	2,000 kWh	All levels
No. of observations	50,347	49,782	50,777	150,906
R^2: within	0.355	0.391	0.440	0.393
R^2: between	0.057	0.163	0.201	0.120
R^2: overall	0.112	0.184	0.248	0.161
Wholesale price forecast level	**0.429**	**0.455**	**0.433**	**0.439**
Wholesale price forecast error	**0.388**	0.177	0.183	**0.247**
Spanish language indicator	**-2.619**	**-3.823**	**-4.176**	**-3.554**
Nominal weekly wage	**0.040**	**0.049**	**0.041**	**0.043**
No. of move-in customers	**0.077**	**0.093**	**0.085**	**0.085**
No. of move-out customers	**-0.125**	**-0.138**	**-0.130**	**-0.131**
No. of switching customers	**-0.023**	**-0.031**	**-0.022**	**-0.025**

Notes: (1) Omitted from this table for brevity are the significant coefficient estimates for (a) the intercepts; and (b) the binary indicators for (i) 2015, 2016, 2017 and 2018; (ii) months of the year; (iii) retailer IDs; and (iv) TDU service areas.
(2) The coefficient estimates are mostly significant; and all have expected signs.
(3) Panels A and B have similar empirics for regressors listed in Panel B, attesting these empirics' insensitivity to the assumption on the plan-specific fixed effects.

4. Conclusion

Texas's competitive retail market provides residential energy consumers with retail price plans that have a vast array of features, including fixed pricing with varying contract terms, different levels of renewable energy content, prepayment option, and TOU pricing. Up to 80 retailers provide such plans, with highly disperse price quotes during our sample period.

Using a large sample of residential retail electricity plans advertised on the Power-to-Choose website between during January 2014 to December 2018, we find changes in the projected wholesale price of electricity over retail plans' contract terms not fully reflected as retail price quote changes in areas of Texas open to retail competition. Our panel regression analysis estimates wholesale price pass-through rates in the range of 43% to 45%. Further, these price quotes tend to increase with the wholesale price forecast errors because of REPs' risk aversion.

Our regression analysis also shows that retail plan attributes affect price quotes. Prepayment and TOU plans are available at a premium price. Longer contract terms come at a higher price. Increased customer switching leads to a reduction in retail prices, likely reflecting REPs' reduced ability to exercise market power over captive/inattentive consumers. While there are significant price premia associated with higher renewable energy content in the early years of our sample, such premia have largely vanished by 2018, supporting the contention that renewable energy is now cost-competitive with fossil-fuel generation traded in Texas's wholesale market (University of Texas at Austin Energy Institute 2020; EIA, 2020).

In summary, our empirics indicate that after accounting for factors that likely enter a REP's pricing decision, changes in Texas's retail price quotes incompletely pass through wholesale spot price changes. Nevertheless, retail price quotes tend to decrease as consumer switching increases. Hence, Texas's retail market for residential usage can be made more price competitive through consumer education on retail plan choices and dissemination of credible price information.[21]

We would be remiss had we ignored a possible limitation of this study, which is its reliance upon data which is "self-reported" by REPs on the PUCT's Power-to-Choose website. While the PUCT's website is the "richest" publicly available data source, some REPs have been accused of posting deceptive information about their price plans.[22] In response, the PUCT has taken positive steps to improve its website's data quality, including admonishing the offending retailers, removing the retailers from the website that refuse to

[21] These findings and policy implications are consistent with recent findings in Texas's retail electricity market (e.g., Hortacsu et al., 2017).
[22] For details, see Mosier (2018) and Lieber (2018).

provide accurate price information, and threatening to close the website (Davis, 2018; Sixel, 2018). As our data sample is large and we have taken steps to remove negative price quotes and other outliers, our regression results are deemed reasonably accurate.

Acknowledgements

This paper is based on David Brown's research funded by the Government of Canada's *Canada First Research Excellence Fund* at the University of Alberta and Jay Zarnikau's ongoing research at the University of Texas. C.K. Woo's research is funded by research grants (Grant No.: 4388 and 4400) from the Faculty of Liberal Arts and Social Sciences of the Education University of Hong Kong. Without implications, all errors are ours.

Appendix 1. Wholesale market price forecast level and error

This is an online appendix. Table A.1 presents the wholesale market data used to produce the wholesale market forecast price level and error variables. As an overview, Panel A reports the descriptive statistics. Panel B indicates that natural gas price and system load have relatively high positive price correlations ($r > 0.3$). Nuclear generation's correlation is oddly positive because rising nuclear generation is expected to reduce wholesale market prices. This could be driven by incentives to increase nuclear capacity utilization in high priced periods. Both solar and wind generation have negative correlations, mirroring their merit-order effects.

To construct the forecast price levels and errors, we use the following wholesale price regression with random error μ_n:

$$P_n = \phi_n + \Sigma_m \gamma_m Y_{mn} + \mu_n; \tag{A.1}$$

where P_n = Zone-specific wholesale energy price (\$/MWh) in month n = monthly MWh-weighted average of the 15-minute settlement prices. This regression's estimation period is the 36 months prior to a retail price plan's first delivery month.

In equation (A.1), ϕ_n = time-varying intercept = linear function of monthly dummies; and Y_{mn} = fundamental driver m in month n. Coefficient γ_m is the marginal price effect is of Y_{mn}. Based on Zarnikau et al. (2019), the two fundamental drivers are natural gas price (\$/MMBtu) and system net load (MWh) (= total load – non-dispatchable generation by nuclear, solar and wind).

We use net load for the following reasons. First, ERCOT's wholesale energy price determination is based on net load. Second, had we allowed natural gas price, total load, solar generation and wind generation to have individually separate coefficients, two empirically implausible outcomes would occur. First, the market-based heat rates based the natural gas price's coefficient estimates would vastly differ from natural-gas-fired generation's engineering-based heat rates of 7 to 10 MMBtu/MWh. Second, the forecast price levels could become negative, contradicting our sample of monthly wholesale price data.

ERCOT has eight wholesale price zones: North, South, Houston, West, AEN, CPS, LCRA, and Rayburn. The LCRA, Rayburn, AEN and CPS zones are not used in our analysis because they do not contain REPs that offered retail price plans in our retail data.

A given zone has 36 estimation samples, each with a sample period's beginning month that equals Jan 2011, Feb 2011, …, Dec 2013. As a result, the number of wholesale price regressions is 144 = 4 zones × 36 beginning months.

Figures A.1 summarizes these regressions' voluminous results. It shows that the average R^2 values are around 0.65. The averages of natural gas price's coefficient estimates are approximately 7 to 8 MMBtu per MWh, matching the engineering-base heat rates of natural-gas-fired generation. The averages of net load's coefficient estimates are around 0.001, indicating that a 1-GWh increase in system load tends to raise the wholesale market price by $1/MWh. By the same token, a 1-GWh increase in renewable generation tends to reduce the wholesale market price by $1/MWh.

Construction of wholesale price forecast data entails the following steps:

- Step 1: Use PROC ROBUSTREG in SAS to estimate a given zone's wholesale price regression for each of the following rolling 36-month samples: Jan – 2011 to Dec – 2013; Feb – 2011 to Jan 2014; …, etc. We use robust regression instead of OLS because the latter produce implausible coefficient estimates caused by the presence of outliers.

  Figure A.2 reports the mean bias estimates and their 95% confidence intervals by forecast period based on the differences between actual and forecast price levels. As all mean bias estimates are not statistically different from zero, the wholesale price forecasts generated through equation (A.1) are deemed accurate.

- Step 2: Produce the monthly wholesale price forecast's level f and standard error s for the next 36 months. For example, the first forecast period is Jan 2014 – Dec 2016. The second forecast period is Feb 2014 – Jan 2017.
- Step 3: For plan j offered in month t, create F_{jt} and S_{jt}, the averages of the f and s values that match plan j's contract term. Suppose plan j offered in Jan 2014 has a contract term of 12 months. Its F_{jt} and S_{jt} values are the averages of the 12 monthly price forecast levels and errors for Feb 2014 to Jan 2015.
- Step 4: Repeat Step 3 for all rolling subsamples to find F_{jt} and S_{jt} for all plans offered in Jan 2014 to Dec 2018.

We end this appendix by explaining how we construct the retail price regression's estimation sample. The retail data file contains the plan-specific data for price R_{jt} and attributes $\{X_{jkt}\}$. The wholesale data file contains the plan-specific forecast data for level F_{jt} and volatility S_{jt}. The supplemental data file contains the nominal weekly wage and each TDU area's customer activities. Merging these three files yields our estimation sample for the retail price regression. Finally, ERCOT's wholesale price zones do not always match TDU areas. Based on Table A.2, the AEP North TDU area's wholesale price forecasts are the average wholesale price forecasts for the North and West zones. The TNMP TDU area's wholesale price forecasts are the average wholesale price forecasts for the North, West and South zones.

Table A.1. Monthly data used for wholesale price regressions and forecasts; sample period = Jan 2011 – May 2019

Panel A: Descriptive statistics

Variable	Mean	Standard deviation	Minimum	Maximum
Wholesale price ($/MWh): North	31.86	15.86	15.83	158.47
Wholesale price ($/MWh): South	34.28	16.75	16.32	151.36
Wholesale price ($/MWh): Houston	32.82	14.98	15.20	155.14
Wholesale price ($/MWh): West	34.01	17.00	14.35	152.04
Natural gas price ($/MMBtu): Henry Hub	3.24	0.77	1.72	5.89
System load (MWh)	28,774,464	4,665,279	21,186,722	39,628,860
Nuclear generation (MWh)	3,300,207	478,211	1,844,380	3,846,057
Solar generation (MWh)	93,515	110,402	1,416	408,384
Wind generation (MWh)	3,819,433	1,520,492	1,509,672	7,148,327

Panel B: Wholesale price correlations with fundamental drivers

Driver	Wholesale price zone			
	North	South	Houston	West
Natural gas price	0.4885	0.4931	0.4670	0.4602
System load	0.3373	0.3245	0.3582	0.4125
Nuclear generation	0.1180	0.1042	0.0726	0.1469
Solar generation	-0.0796	-0.0048	-0.0377	-0.0712
Wind generation	-0.2468	-0.1529	-0.1938	-0.2920

Note: The wholesale market data include monthly observations in 2011 –2013 and 2019 for developing price forecasts for the retail pricing analysis's period of 2014 –2018.

Table A.2. Mapping between TDU areas and wholesale price zones

TDU area	Wholesale price zone
CenterPoint	Houston
AEP Central	South
Oncor	North
AEP North	Average of North and West
TNMP	Average of North, West, and South

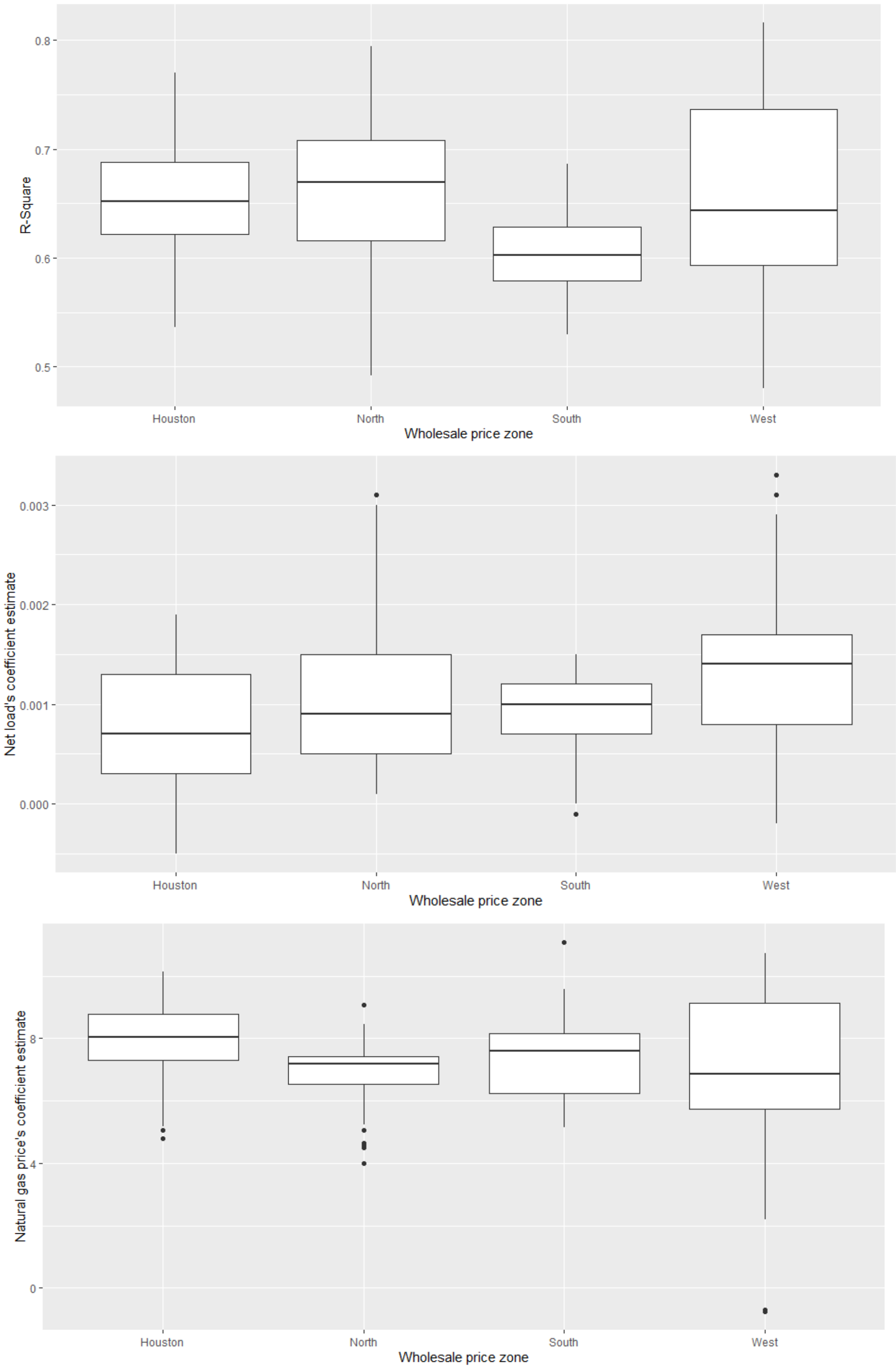


Fig. A.1: Box plots of wholesale price regression results: R^2 and coefficient estimates

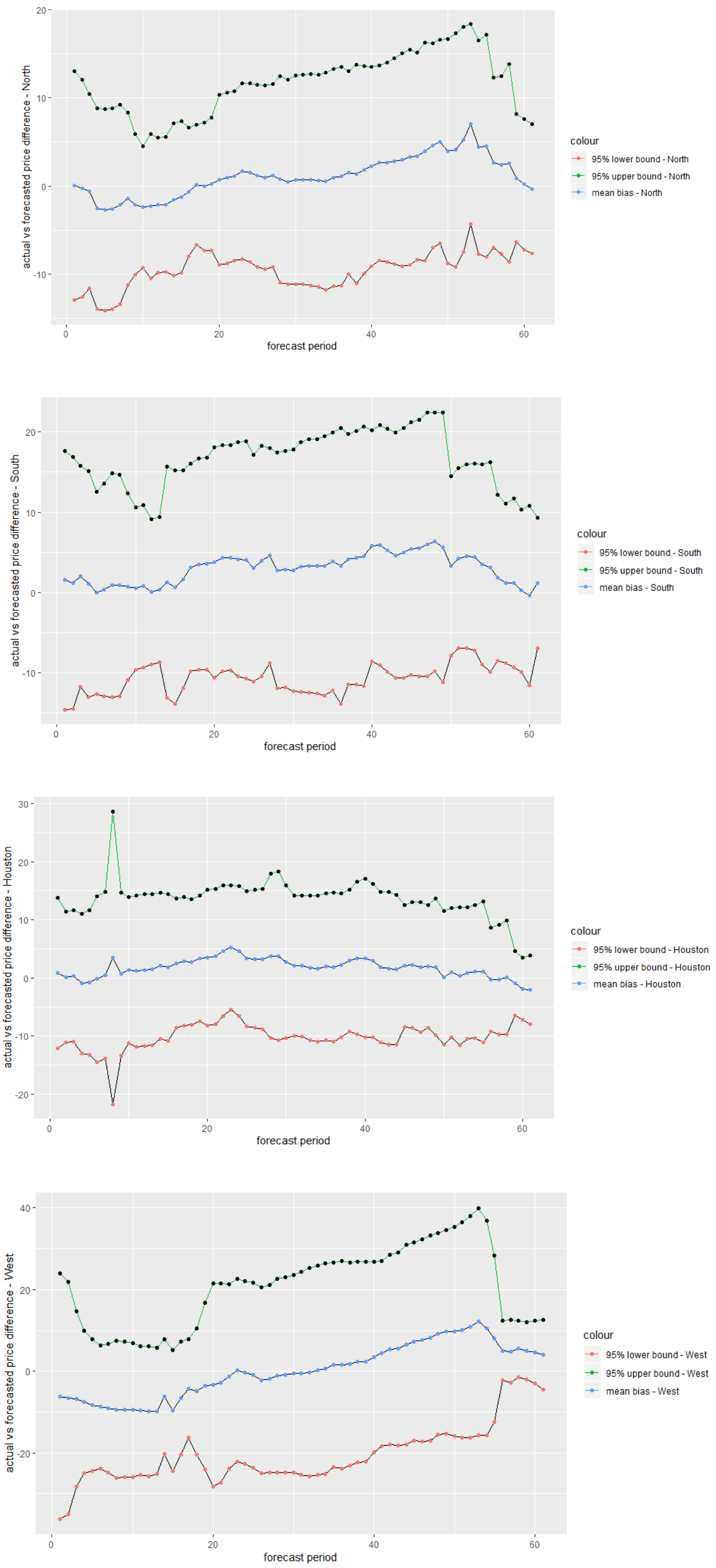


Fig. A.2: Mean bias of wholesale price forecast levels

References

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

Bessembinder, H., Lemmon, M., 2002. Equilibrium pricing and optimal hedging in electricity forward markets. Journal of Finance 57(3), 1347–1382.

Borenstein, S., Cameron, C., and R. Gilbert. 1997. Do gasoline prices respond asymmetrically to crude oil price changes? Quarterly Journal of Economics, 112(1): 305 – 339.

Borenstein, S., Bushnell, J., 2015. The US electricity industry after 20 years of restructuring. Annual Review of Economics 7, 437-463.

Cramton, P., 2017. Electricity market design. Oxford Review of Economic Policy 33(2), 589-612.

Davis, A., 2018. 'Power to Choose' website now gives you options to weed out tricky 'Tiered Plans'. Click2Houston, September 13, 2018.

Deng, S.J., Oren, S.S., 2006. Electricity derivatives and risk management. Energy 31, 940–953.

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

Eckert, A., 2013. Empirical studies of gasoline retailing: A guide to the literature. Journal of Economic Surveys, 27(1): 140 – 166.

EIA, 2020. Levelized Cost and Levelized Avoided Cost of New Generation Resources in the Annual Energy Outlook 2020. U.S. Energy Information Administration. Available at https://www.eia.gov/outlooks/aeo/pdf/electricity_generation.pdf (accessed on 21 March 2020).

ERCOT, 2019. ERCOT Summer 2019 Update. Available at: http://www.ercot.com/content/wcm/lists/172485/NERC_MRC_11.05.19_ERCOT_PUC.PDF (accessed on 21 March 2020).

Eryilmaz, D., Gafford, S. 2018. Can a daily electricity bill unlock energy efficiency? Evidence from Texas. The Electricity Journal. 31(3): 7 – 11.

Eydeland, A., Wolyniec, K., 2003. Energy and Power Risk management: New Development in Modeling, Pricing and Hedging. John Wiley, New York.

Fabra, N., Reguant, R., 2014. Pass-through of emissions costs in electricity markets. American Economic Review 104(9), 2872-2899.

Giulietti, M., Waterson, M., Wildenbeest, M. 2014. Estimating search frictions in the British electricity market. Journal of Industrial Economics 62(4), 555 – 590.

Goldberg, P., Hellerstien, R., 2013. A structural approach to identifying the sources of local currency price stability. Review of Economic Studies 80(1), 175 – 210.

Goett, A.A., Hudson, K., Train, K.E., 2000. Customers' choice among retail energy suppliers: the willingness-to-pay for service attributes. Energy Journal 21(4), 1–28.

Hartley, P.R., Medlock, K.B., Jankovska, O., 2019. Electricity reform and retail pricing in Texas. Energy Economics 80, 1-11.

Hortacsu, A., Madanizadeh, S., Puller, S., 2017. Power to choose? An analysis of consumer inertia in the residential electricity market. American Economic Journal: Economic Policy 9(4), 192 – 226.

Kahn, A.E., 1978. Can an economist find happiness setting public utility rates? Public Utilities Fortnightly 101:1.

Kleindorfer, P.R., Li, L., 2005. Multi-period VAR-constrained portfolio optimization with applications to the electric power sector. The Energy Journal 26(1), 1–26.

Lancaster, K., 1990. The economics of product variety: a survey. Marketing Science 9(3), 189-278.

Lieber, D., 2018. Your updated 2018 guide to shopping for electricity in Texas. The Dallas Morning News. April 9, 2018.

Littlechild, S., 2002. Competition in retail electric supply. Available at https://www.eprg.group.cam.ac.uk/wp-content/uploads/2014/01/ep09.pdf (accessed on 21 March 2020).

Littlechild, S., 2018. The regulation of retail competition in US residential electricity markets. Available at https://www.eprg.group.cam.ac.uk/wp-content/uploads/2018/03/S.-Littlechild_28-Feb-2018.pdf (accessed on 21 March 2020).

Longstaff, F.A., Wang, A.W., 2004. Electricity forward prices: a high-frequency empirical analysis. Journal of Finance 59(4), 1877–1900.

Mirza, F., Bergland, O., 2012. Pass-through of wholesale price to the end-user retail price in the Norwegian electricity market. Energy Economics 34, 2003 – 2012.

Morey, M., Kirsch, L., 2016. Retail choice in electricity: What have we learned in 20 years? Available at https://hepg.hks.harvard.edu/publications/retail-choice-electricity-what-have-we-learned-20-years (accessed on 21 March 2020).

Mosier, J., 2018. Texas regulators improve Power to Choose Website but threaten to scrap it if changes don't work. The Dallas Morning News, August 9, 2018.

Mulder, M., Willems, B., 2019. The Dutch retail electricity market. Energy Policy 127, 228 – 239.

Nakamura, E., Zerom, D., 2010. Accounting for incomplete pass-through. The Review of Economic Studies 77(3), 1192 – 1230.

Ofgem, 2011. Do energy bills respond faster to rising costs than falling costs? Available at https://www.ofgem.gov.uk/ofgem-publications/39712/priceasymmetry.pdf (accessed on 21 March 2020)

Raish, C., 2020. Analysis of Load Reductions Associated with 4-CP Transmission Charges and Price Responsive Load/Retail DR. Available at: http://www.ercot.com/content/wcm/key_documents_lists/189320/06._WMS_2019_4CP__Retail_DR_Analysis_Raish.pptx (accessed on 21 March 2020)

Sioshansi, F.P., 2013. Evolution of Global Electricity Markets: New paradigms, new challenges, new approaches. Elsevier, San Diego.

Sixel, L., 2018. Regulators Take Aim at Pricing Gimmicks on Power to Choose. Houston Chronicle, August 8, 2018.

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

University of Texas at Austin Energy Institute, 2020. Levelized Cost of Electricity. Available at: calculators.energy.utexas.edu/lcoe_map/#/county/tech (accessed on 20 March 2020.

Waddams Price, C., Webster, C., Zhu, M., 2013. Searching and switching: Empirical estimates of consumer behaviour in regulated markets. Available at http://competitionpolicy.ac.uk/publications/working-papers/working-paper-13-11 (accessed on 21 March 2020).

Wilson, C., Waddams Price, C., 2010. Do consumers switch to the best supplier? Oxford Economic Papers 63(4), 647 – 668.

Woo, C.K., Orans, R., Horii, B., Chow, P., 1995. Pareto-superior time-of-use rate option for industrial firms. Economics Letters 49, 267-272.

Woo, C.K., Horowitz, I., Hoang, K., 2001. Cross hedging and forward-contract pricing of electricity. Energy Economics 23, 1-15.

Woo, C.K., Horowitz, I., Horii, B., Karimov, R., 2004a. The efficient frontier for spot and forward purchases: An application to electricity. Journal of the Operational Research Society 55, 1130-1136.

Woo, C.K., Karimov, R., Horowitz, I., 2004b. Managing electricity procurement cost and risk by a local distribution company. Energy Policy 32(5), 635-645.

Woo, C.K., Horowitz, I., Olson, A., Horii, B., Baskette, C., 2006. Efficient frontiers for electricity procurement by an LDC with multiple purchase options. OMEGA 34(1), 70–80.

Woo, C.K., Horowitz, I., Olson, A., DeBenedictis, A., Miller, D., Moore, J., 2011. Cross-hedging and forward-contract pricing of electricity in the Pacific Northwest. Managerial and Decision Economics 32, 265-279.

Woo, C.K., Sreedharan, P., Hargreaves, J., Kahrl, F., Wang, J., Horowitz, I., 2014. A review of electricity product differentiation. Applied Energy 114, 262-272.

Woo, C.K., Milstein, I., Tishler, A., Zarnikau, J., 2019. A wholesale electricity market design *sans* missing money and price manipulation. Energy Policy 134, Article 110988.

Woo, C.K., Zarnikau, J., 2019. Renewable energy's vanishing premium in Texas's retail electricity pricing plans. Energy Policy 132, 764-760.

Wood, P., Gülen, G., 2009. Laying the groundwork for power competition in Texas. In Electricity Restructuring: The Texas Story, Edited by Kiesling, Lynne and Kleit, Andrew, American Enterprise Institute, (November), Washington, D.C.

Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data. MIT Press Cambridge.

Zarnikau, J., 2011. Successful renewable energy development in a competitive electricity market: A Texas case study. Energy Policy 39, 3906-3913.

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

Department of Economics, University of Alberta
Working Paper Series

2020-03: Competition in Higher Education – Kaganovich, M., Sarpca, S., **Su, X.**
2020-02: Misallocation across Establishment Gender – **Ranasinghe, A.**
2020-01: Does Locational Marginal Pricing Impact Generation Investment Location Decisions? An Analysis of Texas's Wholesale Electricity Market – **Brown, D.,** Zarnikau, J., Woo, C.
2019-16: A Unified Explanation of Trade Liberalization Effects Across Models of Imperfect Competition – **Alfaro, M.**, Lander, D.
2019-15: Analyzing Firm Behaviour in Restructured Electricity Markets: Empirical Challenges with a Residual Demand Analysis – **Brown, D., Eckert, A.**
2019-14: LinkedIn(to) Job Opportunities: Experimental Evidence from Job Readiness Training – **Wheeler, L.**, Garlick, R., Johnson, E., Shaw, P., Gargano, M.
2019-13: Entry Preemption by Domestic Leaders and Home-Bias Patterns: Theory and Empirics – **Alfaro, M.**
2019-12: How Much are Good Schools Worth? Evidence from School Acquisitions in Beijing – **Su, X.,** Yu, H.
2019-11: Enumerating Rights: More is Not Always Better – Ball, S., **Dave, C.,** Dodds, S.
2019-10: Motivating the Optimal Procurement and Deployment of Electric Storage as a Transmission Asset – **Brown, D.,** Sappington, D.
2019-09: Pricing Patterns in Wholesale Electricity Markets: Unilateral Market Power or Coordinated Behavior? – **Brown, D., Eckert, A.**
2019-08: Son Preference and Child Under Nutrition in the Arab Countries: Is There a Gender Bias Against Girls? – **Sharaf, M.,** Rashad, A., Mansour, E.
2019-07: How Local Economic Conditions Affect School Finances, Teacher Quality, and Student Achievement: Evidence from the Texas Shale Boom – **Marchand, J.,** Weber, J.
2019-06: Subjects in the Lab, Activists in the Field: Public Goods and Punishment – **Dave, C.,** Hamre, S., Kephart, C., Reuben, A.
2019-05: Fiscal Austerity in Emerging Market Economies – **Dave, C.,** Ghate, C., Gopalakrishnan, P., Tarafdar, S.
2019-04: Inequality and Trade Policy: Pro-Poor Bias of Contemporary Trade Restrictions – **Ural Marchand, B.**
2019-03: Determinants of Locational Patenting Behavior of Canadian Firms – **Eckert, A., Langinier, C., Zhao, L.**
2019-02: The Microeconomics of New Trade Models – **Alfaro, M.**
2019-01: Universal Childcare for the Youngest and the Maternal Labour Supply – Kunze, A., **Liu, X.**
2018-19: On the Benefits of Behind-the-Meter Rooftop Solar and Energy Storage: The Importance of Retail Rate Design – **Boampong, R., Brown, D.**
2018-18: The Value Premium During Flights – **Galvani, V.**
2018-17: Asymmetric Information, Predictability and Momentum in the Corporate Bond Market – **Galvani, V., Li, L.**
2018-16: The Momentum Effect for Canadian Corporate Bonds – **Galvani, V., Li, L.**
2018-15: Green Technology and Patents in the Presence of Green Consumers – **Langinier, C.,** Ray Chaudhuri, A.
2018-14: Subjective Performance of Patent Examiners, Implicit Contracts and Self-Funded Patent Offices – **Langinier, C.,** Marcoul, P.