Blowing in the wind: Vanishing payoffs of a tolling agreement for natural-gas-fired generation of electricity in Texas

Chi-Keung Woo[a,b,*,**], Ira Horowitz[c], Brian Horii[a], Ren Orans[a], and Jay Zarnikau[d,e]

[a] Energy and Environmental Economics, Inc., 101 Montgomery Street, Suite 1600, San Francisco, California USA, 94104.

[b] Hong Kong Energy Studies Centre, Hong Kong Baptist University, Kowloon Tong, Hong Kong, China.

[c] Information Systems and Operations Management, Warrington College of Business Administration, University of Florida, Gainesville, Florida USA, 32611.

[d] Frontier Associates LLC, 1515 S. Capital of Texas Highway, Suite 110, Austin, Texas 78746, USA.

[e] The University of Texas at Austin, LBJ School of Public Affairs and Division of Statistics, Austin, Texas 78713, USA.

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** Corresponding author. Phone: +1 415 391 5100; fax: +1 415 391 6500; Email address: ck@ethree.com (C.K. Woo)

Abstract

We use a large Texas database to quantify the effect of rising wind generation on the payoffs of a tolling agreement for natural-gas-fired generation of electricity. We find that while a 20% increase in wind generation may not have a statistically-significant effect, a 40% increase can reduce the agreement's average payoff by 8% to 13%. While natural-gas-fired generation is necessary for integrating large amounts of intermittent wind energy into an electric grid, a large expansion of wind energy may reduce the incentives for further investment in natural-gas-fired capacity. Our finding contributes to the policy debate of capacity adequacy and system reliability in a restructured electricity market that will see large-scale wind-generation development.

1. Introduction

The oil price spike of over US$100/barrel in 2011 is an unkind reminder of the worldwide dependence on oil, much of which comes from the politically unstable Middle East. Global warming and pollution due to fossil fuel consumption and environmental damages of fossil fuel extraction (e.g., deep-sea drilling, oil sand hydro-processing and shale-gas fracking) lend support to the development of renewable energy resources (e.g., wind and solar) that do not have emissions and severe environmental impacts. Caused by a 9.0 earthquake and the ensuing tsunami, the nuclear plant failures of 2011 along Japan's east coast further heighten the need for renewable energy resources that are preferably widely dispersed over a large geographic region. And nowhere in the states has the response been more proactive than in Texas, which despite its wealth of oil and natural gas has led the way in the development of wind generation. Indeed, although wind generators account for perhaps 2% of electric power in the United States, about 25% of that power is housed in Texas. The state's growth of wind generation will continue, accommodated by a US$4.9 billion transmission construction initiative designed to better interconnect competitive renewable energy zones (CREZ) to the state's major load centers.[1]

The goal of this paper is to explore the effect of rising wind generation on the expected payoff of a tolling agreement for natural-gas-fired generation in Texas. Such an agreement is attractive to a generation owner because it provides stable known cash inflow, critical for the owner to obtain financing at relatively low costs (Stern, 1998).

After making an upfront lease payment to a generator, the agreement's buyer, assumed to be a local distribution company (LDC) or a retail electric provider (REP) that

[1] http://www.texascrezprojects.com/

serves retail loads, gains the right, but not the obligation, to use the generator's capacity when it is less costly than buying from the wholesale spot electricity market (Eydeland and Wolyniec, 2003; Deng and Xia, 2006).[2] Since the buyer's willingness-to-pay (WTP) tracks the agreement's expected payoff, our exploration sheds light on how rising wind generation reduces the generator's lease revenue, which in turn diminishes the incentive to invest in natural-gas-fired generation.

Our exploration is motivated by two transforming events taking place over the past two decades in the electricity industry. The first event is restructuring designed to introduce wholesale-market competition in Australia, New Zealand, parts of North and South America, and Europe (Sioshansi and Pfaffenberger, 2006; Woo et al., 2006). The second event is the large-scale development of wind generation due to its abundance (Hoogwijk et al., 2004; Lu et al., 2009) and government policies in North America and Europe (Haas et al., 2008; Schmalensee, 2009; Pollitt, 2010; Woo et al., 2011a; Alagappan et al., 2011).

Related to the first event is the empirical fact that wholesale electricity spot-market prices are inherently volatile, thanks to: daily fuel-cost variations, especially for the natural gas now widely used in combined-cycle gas turbines (CCGT) and combustion turbines (CT); weather-dependent seasonal demands with intra-day and inter-day fluctuations that must be met in real time by generation and transmission already in place; limited economic viability of energy storage systems; changes in available capacity caused by planned and forced outages of electrical facilities; precipitation and river flow

[2] In areas of the Electric Reliability Council of Texas (ERCOT) market that have been opened to retail competition, retail electric providers or "REPs" compete to make retail sales to energy consumers. In areas of this market not open to customer choice, municipal utilities or rural electric cooperatives sell electricity at the retail level.

for a system with significant hydro resources; carbon price fluctuations that affect thermal generation that uses fossil fuels; transmission constraints that cause transmission congestion and generation redispatch; lumpy capacity additions that can only occur with a long lead time (Li and Flynn, 2006; Bunn and Fezzi, 2007; Woo et al., 1998, 2007; Tishler et al., 2008; Newcomer et al., 2008; Milstein and Tishler, 2011).

The price volatility, accompanied by occasional sharp spikes, has encouraged extensive research on two related areas of electricity finance.[3] The first area encompasses the data-generation process (DGP) of electricity spot prices,[4] as well as locational price spreads and electricity trading gains.[5] The second area is the pricing of electricity derivatives, such as forward contracts[6] and capacity options,[7] which are useful for electricity risk management (Kleindorfer and Li, 2005; Deng and Oren, 2006; Huisman et al., 2009).

The second event is the large-scale development of wind generation. Since wind generation has zero fuel cost, it is economically dispatched to displace high-fuel-cost marginal generation (EWEA, 2010), unless curtailed to resolve grid congestion and instability (Kumar et al., 2005). Hence, rising wind generation tends to reduce wholesale spot electricity prices (Sensfuß et al., 2008; Trotsher and Korpas, 2008; Nicholson et al.,

[3] We would be remiss if we failed to acknowledge a particularly important line of inquiry: notably, the use of electricity price data to detect market-power abuse and price manipulation (e.g., Wolfram, 1999; Borenstein et al., 2002; Joskow and Khan, 2002). That line, however, is tangential to the primary focus of the present paper.

[4] See e.g., Johnsen (2001), Haldrup and Nielsen (2006), Knittel and Roberts (2005), Mount et al. (2006), Weron (2006), Guthrie and Videbeck (2007), Karakatsani and Bunn (2008), Fanone and Prokoczuk (2010), and Janczura and Weron (2010).

[5] See e.g., De Vany and Walls (1996), Woo et al. (1997, 2011c), Bessembinder and Lemmon (2006), Park et al. (2006), Marckhoff and Wimschulte (2009), and Douglas and Popova (2011).

[6] See e.g., Bessembinder and Lemmon (2002), Longstaff and Wang (2004), Benth and Koekebakker (2008), and Redl et al. (2009).

[7] See e.g., Deng et al. (2001), Lucia and Schwartz (2002), Eydeland and Wolyniec (2003), Burger et al. (2004), and Deng and Xia (2006).

2010; Woo et al., 2011b), diminishing the incentive for generation investment (Steggals et al., 2011; Traber and Kemfert, 2011).[8]

The incentive to invest in a generation unit can be measured by the expected payoff of a tolling agreement, with the payoff being the positive difference between the wholesale spot electricity price and the unit's per MWH fuel cost. When rising wind generation suppresses the wholesale spot electricity price, it also suppresses the tolling agreement's expected payoff for the generation unit.

We contribute to the literature in two ways. First, we introduce a regression-based approach to valuate a tolling agreement. It differs from an option pricing formula based on an assumed DGP (e.g., Brownian motion) (Deng et al., 2001; Eydeland and Wolyniec, 2003). It uses market data to directly estimate the agreement's payoffs, without first modeling spot price behavior as done by Burger et al. (2004), Deng and Xia (2006) and Trabert and Kemfert (2011).[9]

Second, we find that while a 20% increase in wind generation in Texas may not have a statistically-significant effect, a 40% increase can reduce the tolling agreement's expected payoff by 8% to 13%. Even though our 8% to 13% estimates are based on an econometric analysis of historical data for Texas, they corroborate the 12% to 33% estimates based on market simulation for the 100% increase in wind generation in

[8] When wind generation capacity becomes a very large portion of a grid's total installed generation (e.g., Demark, Germany and Spain), this price reduction effect may not prevail because of the loss in the grid's flexibility to integrate wind generation (Pérez-Arriaga, 2011). Investigating market price behavior via simulation for a future scenario of very high wind generation is an area that has attracted recent research attention (e.g., Troy et al., 2010). Such an investigation, however, is well beyond the scope of the current paper.

[9] As noted by an insightful referee, our empirical results are based on Texas-specific historical data. A substantial increase in wind generation development could exhaust the state's flexibility in integrating wind-generation output and exacerbate its transmission congestion. This could be a structural change unseen in the historical data, causing concerns over our results' usefulness and relevance. Such concerns, however, are tempered by the large amount of natural-gas generation in Texas and on-going transmission expansion to accommodate wind generation (Alagappan et al., 2011; Woo et al., 2011c; Zarnikau, 2011).

Germany (Trabert and Kamfert, 2011, Table 5, bottom rows RW and AW). Hence, both sets of estimates offer similar insight into the policy debate on capacity adequacy and system reliability. Since natural-gas-fired generation is necessary for integrating intermittent wind energy into an electric grid (Parson et al., 2009; Jacobsen and Zvingilaite, 2010), our findings contribute to the policy debate of capacity adequacy and system reliability in a restructured electricity market that will see large-scale wind-generation development (Neuhoff and De Vries, 2004; Roques et al., 2005; Newberry, 2010; Milstein and Tishler, 2011).

2. Data

2.1 ERCOT zonal markets

Our estimation of the effects of rising wind generation on an LDC's WTP for a tolling agreement is made possible by a unique and rich ERCOT database of electricity prices for 15-minute intervals over 24-hour days, in each of the four ERCOT zonal markets of Houston, North, South and West. These prices were observed over the 41-month period of January 2007 through May 2010.

This database has five distinct features that help us to determine the effects of wind generation on the payoffs of a tolling agreement (Sioshansi and Hurlbut, 2010; Zarnikau, 2011). First, the installed capacity of wind generation grew during 1997 to 2009 from under 500 MW to over 7,500 MW, and accounts for about 10% of ERCOT's total generation capacity of approximately 80,000 MW. When combined with the intermittence of wind generation, this feature leads to widely-dispersed levels of wind-

energy output, a requisite for statistically-precise detection of its effect on a tolling agreement's payoffs.

Second, generators in ERCOT make supply bids used by ERCOT for its least-cost dispatch decisions and determination of the market-clearing price of energy (MCPE) (ERCOT, 2004). All dispatched generators receive the MCPE, which is the marginal bid price of the last dispatched generator. Since wind generators have intermittent output at almost zero variable cost, they often make a zero supply- price bid. At times they make negative supply-price bids due to the presence of a tax-credit incentive. As a result, wind generators are essentially treated as must-run units by the ERCOT independent system operator. This feature helps unmask the price effects of wind generation, not confounded by the wind generators' bidding behavior.

Third, ERCOT's marginal generation is likely to be natural-gas fired and dispatchable, offering ample opportunity for spot-price reductions through its displacement by wind generation. Had the marginal generation been must-run and non-dispatchable (e.g., nuclear generation or run-of-river hydro generation), the zonal market prices would have been low due to close-to-zero marginal supply bids. As a result, wind generation could not have a detectable effect on the value of a tolling contract, because natural-gas-fired generation would not have been profitable anyway.

Fourth, ERCOT's 15-minute zonal loads can be used as exogenous variables to delineate market price movements due to fluctuating demands (ERCOT, 2004). This feature leads us to suggest that a detected price effect of wind generation could not have been biased by the possible price response of zonal loads.

Finally, there is negative correlation between wind generation and zonal loads, with *R* between -0.15 and -0.22. Hence, when wind generation peaks, zonal loads tend to be low, a phenomenon also observed in non-Texas markets (e.g., California and Western Europe). This feature helps make our findings relevant to those markets.

2.2 Descriptive statistics

Table 1 presents descriptive statistics for the approximately 116,000 15-minute observations comprising our database. The data reveal the high volatility of 15-minute zonal prices that are prone to have large spikes of up to $4,500 per megawatt hour (MWH) for the North zone, and that can be negative (e.g., -$1,536/MWH for the Houston zone). Reflecting capacity growth and output intermittency, the 15-minute wind-generation output has a range of zero to 1,703 MWH, with an average of 444 MWH. Fifteen-minute nuclear generation tends to be close to full capacity, as evidenced by the average output of 1,159 MWH and maximum output of 1,298 MWH. The daily Henry Hub natural-gas price data have a wide range of $1.8 to $13.3 per million British thermal units (MMBTU), with an average of $6.4/MMBTU. Finally, like the zonal prices, the 15-minute zonal loads are volatile with large spikes. For example, the North zone's maximum load of 6,555 MWH is almost twice the average load of 3,357 MWH.

Table 2 reports the 15-minute payoffs of a tolling agreement by zonal market and heat rate (*HR* in MMBTU/MWH), which is the natural-gas-to-electricity conversion ratio. Assuming a zero operation and maintenance (O&M) cost, a 15-minute payoff is given by max(15-minute spot-market price - *HR* x Houston Ship Channel natural-gas price, 0). The payoffs in Table 2 assume two real-world heat rates: (a) *HR* = 7 MMBTU/MWH which

approximates the heat rate of a CCGT; and (b) *HR* = 9 MMBTU/MWH which approximates the heat rate of a CT (CEC, 2010; EIA, 2010).

Panel A of Table 2 shows that for the full sample, the average payoffs are about $11/MWH at *HR* = 7 MMBUT/MWH and $7/MWH at *HR* = 9 MMBUT/MWH for the North and West zones, which are lower than the corresponding averages of about $14/MWH and $10/MWH for the Houston and South zones. The correlations between zonal payoffs and wind generation are weak, between -0.027 to -0.106, presaging the challenge in our identification and estimation of wind generation's effect on payoffs.

The weak correlation between payoffs and wind generation stems in part from the many zero payoffs in the full sample. Panel B of Table 2 shows that a tolling agreement with *HR* = 7 MMBTU/MWH is "in-the-money" with strictly positive payoffs about half the time. When the *HR* is 9 MMBTU/MWH, the agreement is "in-the-money" only a quarter of the time.

Panel B also reports mean values of strictly positive payoffs (e.g., $38.34/MWH for Houston at *HR* = 9) that are several times the median values (e.g., $6.72/MWH for Houston at *HR* = 9). Thus, the distributions of these payoffs are highly skewed with long right tails, as further confirmed by their 75-percentile, 95-percentile and maximum values.

3. Model

3.1 A tolling agreement's payoffs

Since the generator plant's variable O&M cost is small when compared to the electricity spot-market price, we assume zero variable O&M cost, implying that the plant's, or equivalently the agreement's, per MWH payoff in any 15-minute interval t (t = 1, ..., 96) on day d (d = 1, ..., D), denoted Y_{td}, may be written as:

$$Y_{td} = \text{Max}(P_{td} - HR \times G_d, 0), \quad (1)$$

where P_{td} is the spot price ($/MWH) in interval t on day d, HR is the contracted heat rate, and G_d is the natural-gas spot price ($/MMBTU) on day d. It may be seen as the payoff of an European spark-spread call option that expires in time interval t on day d.

The specification of the DGP for our sample of 15-minute payoffs is guided by four empirical facts. First, as Table 2 shows, over half of the sample time periods have zero payoffs at HR = 7 MMBTU/MWH and about three quarters have zero payoffs at HR = 9 MMBTU/MWH. The presence of many zero values precludes applying ordinary least squares (OLS) to the entire sample in order to fit a regression that reveals the marginal effect of wind generation on the profitability of a tolling agreement, because the estimate of the marginal effect will be biased (Maddala, 1983).

Second, Table 2 shows that the distribution of strictly positive payoffs within any zonal market is skewed with a long right-hand tail. Thus, a log-linear specification is better suited for modeling the size of these payoffs than a linear specification.

Third, a random factor such as, equipment failure, which affects whether a strictly positive payoff would occur, can be expected to influence the size of the payoff.

Finally, zonal-market spot prices in the ERCOT zones have been found to move with a set of seven fundamental factors (Woo et al., 2011), notably: X_1, which measures the 15-minute wind generation; X_2, which measures the 15-minute nuclear generation; X_3, which measures the daily natural-gas price at the Henry Hub; and X_4 through X_7, which respectively measure the 15-minute loads of the Houston, North, South and West zonal markets.

For notational simplicity, we suppress the time subscripts t and d when specifying the DGP for the 15-minute payoffs:

$$\begin{aligned} Y &= \exp(B + \mu) > 0 \text{ if } (A + \eta) > 0; \\ &= 0, \text{ otherwise.} \end{aligned} \tag{2}$$

In equation (2), $B = \beta_0 + \beta_1 \ln X_1 + ... + \beta_7 \ln X_7$, μ = white noise, $A = \alpha_0 + \alpha_1 X_1 + ... + \alpha_7 X_7$, and η = logistically distributed random-error term. To allow for the residual time-dependence of Y, the intercepts of β_0 for B and α_0 for A are assumed to be linear functions of binary indicators for hour-of-day, day-of-week, and month-of-year effects.

Useful for analyzing a data sample with many zero values for the dependent variable (e.g., outage cost estimation in Munasinghe et al. (1988)), equation (2) generalizes the standard Tobit model, allowing the drivers (X_1, ..., X_7) to have different impacts on whether a strictly positive payoff would occur, than on the size of the payoff.[10]

We estimate the coefficients in two stages.

Stage 1: Apply the maximum likelihood method to the full sample to estimate the following binary logit model:

[10] We applied the maximum likelihood method to the full sample of about 116,000 observations to estimate a standard Tobit model for each zonal market. The model, however, failed to converge after 500 iterations.

$$S \equiv \text{Prob}(Y > 0) = \exp(\alpha_0 + \alpha_1 X_1 + ... + \alpha_7 X_7) / [1 + \exp(\alpha_0 + \alpha_1 X_1 + ... + \alpha_7 X_7)] \quad (3)$$

Stage 2: Apply the OLS method to the subsample of strictly positive payoffs to estimate the following log-linear regression:

$$\ln Y = \beta_0 + \beta_1 \ln X_1 + ... + \beta_7 \ln X_7 + \theta C + \varepsilon \quad (4)$$

In equation (4), the white noise μ in equation (2) has been decomposed into its conditional mean θC and a heteroskedastic disturbance term ε. Intended to correct sample- selection bias, the term C is $[(1 - S) \ln(1 - S)/S + \ln S]$, a negative number whose size increases in S (Dubin and McFadden, 1984). If $\theta < 0$, it can be inferred that an unobserved random factor that increases the probability of a strictly positive payoff will tend to enlarge the size of the payoff.

3.2 Testable hypotheses

To help interpret our regression results, we formulate a set of hypotheses that can be tested via the coefficient estimates. These hypotheses reflect our expectations as to the effects of each driver on the spot-market price and the cost of burning natural gas to produce electricity.

3.2.1 Probability of strictly positive payoffs

We hypothesize that rising wind generation will tend to reduce spot-market prices and therefore the probability of a strictly positive payoff. This translates into our first hypothesis: $\alpha_1 < 0$.

We do not use the 15-minute data on dispatchable generation (i.e., hydro, coal, and natural gas), because they are endogenous as a result of ERCOT's least-cost dispatch

decisions (ERCOT, 2004). Nuclear generation is baseload and non-dispatchable. Reducing nuclear output due to maintenance, repair or refuel is expected to raise the market price and therefore the probability of a strictly positive payoff. This translates into our second hypothesis: $\alpha_2 < 0$.

Because of a vast thermal-generation fleet in Texas, we use the exogenous Henry Hub price, which is almost perfectly correlated with the Houston Ship Channel price (R = 0.99), to quantify what we hypothesize to be the positive price effect of the marginal fuel (natural gas) on the electricity spot-market price. An increase in the natural-gas price, however, also raises the cost of the natural gas used to generate electricity. Hence, our third hypothesis is: $\alpha_3 < 0$. This hypothesis reflects our conjecture that the cost effect, on average, dominates the price effect.

Finally, we postulate that rising loads will tend to raise market prices and therefore the probability of a strictly positive payoff. Hence, our fourth through seventh hypotheses are: $\alpha_4, ..., \alpha_7 > 0$.

3.2.2 Size of a strictly positive payoff

As rising wind generation reduces the market price and therefore the size of a strictly positive payoff, our eighth hypothesis is: $\beta_1 < 0$.

Since reducing nuclear output is expected to raise the electricity spot-market price and therefore the size of a strictly positive payoff, our ninth hypothesis is: $\beta_2 < 0$.

An increase in the natural-gas price raises both the spot price and the cost of natural gas. Conditional on the tolling agreement already being in the money for the

particular 15-minute interval, we conjecture that the price effect dominates the cost effect. Hence, our tenth hypothesis is: $\beta_3 > 0$.

As rising loads tend to raise spot-market prices and therefore the size of any strictly positive payoffs, our next four hypotheses are: $\beta_4, ..., \beta_7 > 0$.

Our 15th and final hypothesis is $\theta < 0$, reflecting our intuition that an unobserved random factor that increases the probability of a strictly positive payoff also tends to magnify the size of the payoff.

3.3 Impact of rising wind generation on a tolling agreement's payoffs

We have postulated a highly non-linear DGP. To estimate the effect of rising wind generation on the 15-minute payoffs, we simulate the payoffs at various hypothetical levels of wind generation. Our simulation uses the following steps (Woo and Train, 1988):

- Step 1: For each zonal-market subsample we compute the equally-weighted average of actual strictly positive payoffs, which is the mean value in Panel B of Table 2.
- Step 2: For each observation in the same subsample, we compute $Y_{hat} = \exp[b_0 + b_1 \ln X_1 + ... + b_7 \ln X_7 + qC]$ where $(b_0, b_1, ..., b_7, q)$ are the OLS estimates for $(\beta_0, \beta_1, ..., \beta_7, \theta)$.
- Step 3: We compute the equally-weighted average value of Y_{hat} from Step 2.
- Step 4: We determine an adjustment factor, which is the mean payoff from Step 1, divided by the mean Y_{hat} from Step 3. Motivated by the skewed distributions of the actual payoffs and the nonlinearity of Y_{hat}, this factor ensures that the actual and predicted means of the subsample are equal.

- Step 5: We then scale the historical wind-generation output by $\phi = 1.0$, 1.1, 1.2, 1.3, or 1.4. At $\phi = 1.0$, the historical wind generation is unchanged for the purpose of model validation, as explained in Step 8 below. When $\phi = 1.1$ (1.4), we are provided with a test of whether a 10% (40%) increase in wind generation has a statistically-significant effect on the payoffs.
- Step 6: The coefficient estimates of the logit regression are applied to each 15-minute observation in the *full* sample to estimate that observation's probability of a strictly positive payoff for a given ϕ value.
- Step 7: The data are now available to allow us to estimate the unconditional payoff for each observation in the *full* sample. This is done by multiplying the estimated probability of a positive profit from Step 6 by the estimated positive profit for that observation based upon the scaled wind-generation level, and then multiplying this product by the adjustment factor from Step 4.
- Step 8: In the final step, we compute the average difference between the estimated and the actual payoffs for each observation in the *full* sample.

The results from Step 8 allow us to estimate the effects of rising wind generation on the profitability of a tolling agreement. When the average difference at $\phi = 1.0$ is not statistically significant, say at the $\alpha = 0.01$ level of statistical significance, which is the standard to which we adhere throughout the paper, our simulation process is said to be unbiased and useful for computing the effects of rising wind generation. When the average difference at $\phi = 1.1$ is not statistically significant, we may infer that a 10% increase in wind generation does not have a statistically-significant impact on the agreement's payoffs. Finally, if the average difference at $\phi = 1.4$ is statistically

significant, a 40% increase in wind generation can be said to have a statistically-significant impact on the payoffs to a tolling agreement.

4. Results

4.1 Binary logit estimates

Table 3 presents the parameter estimates for the binary logit regression of equation (3). Presented in Panels A and B of the table, the parameters are estimated, by zonal market, for both CCGT and CT generation with heat rates of 7 and 9 MMBTU/MWH, respectively. The estimates for the binary hourly, daily, and monthly indicators, which vary in both sign and statistical significance, are not reported, as they are too numerous and are only included in the regressions to reflect and account for any residual time-dependence. As one would expect, the percentage of strictly positive payoffs in the estimation sample is much larger, here about twice as large, for the lower heat rate. In that case, too, the fit to the data is somewhat better, with R^2s in the neighborhood of 0.42 as opposed to 0.36.

The statistically-significant estimates for parameters α_1 through α_3 support our first three hypotheses for all four zonal markets: notably, regardless of the agreement's heat rate, the probability of a positive payoff is reduced by (1) increased wind or (2) nuclear generation, and (3) increases in the price of natural gas. When statistically significant, the estimates for parameters α_4 through α_7 are all positive, supporting our hypotheses that rising zonal loads tend to improve the probability of strictly positive payoffs.

In the overwhelming main, then, the binary logit results are intuitively plausible and support our hypotheses.

4.2 OLS estimates

Using the same basic two-panel format as in Table 3, the estimates for the OLS regression of equation (3), by zonal market and with the parameter estimates for the time-dependent indicators not reported, are presented in Table 4.

With two minor exceptions, both related to the direction of the correction bias, hypotheses (8) through (14) are supported for CCGT generation with $HR = 7$ MMBTU/MWH. That is, strictly positive payoffs will decrease in response to (8) increases in wind or (9) nuclear generation, and will increase in response to (10) increases in the natural-gas price wherein the price effect of the increase dominates the cost effect, or increased zonal loads in (11) Houston, (12) the North, (13) the South, or (14) the West.

Although the first three parameter estimates for θ have the hypothesized negative sign – or (15) a randomly-induced increase in the probability of a positive payoff will tend to magnify its size – the hypothesis receives statistically-significant support only in the Houston and South zonal markets.

The estimate for θ in the West zone is 0.0341 and statistically significant (p = 0.0064). While small in size, this positive estimate would suggest that when an unobserved random factor reduces the likelihood of a strictly positive payoff in the West zone, it also tends to reduce the size of that payoff, which is the only counter-intuitive result from our regression analysis of a large and noisy database.

As equation (3) is a double-log specification, the parameter estimates may be interpreted as elasticities. Thus, for example, the first of the estimates in Table 3, Panel A, or b_1 = -0.1028 for Houston, indicates that a positive payoff in Houston is relatively inelastic with respect to wind generation, although responsive in the hypothesized direction. The inelasticity of the positive payoffs also holds with respect to nuclear output and the natural-gas price. All zonal loads have the expected effects on strictly positive payoffs. Some of the positive payoffs are elastic with respect to the zone loads. For example, with b_4 = 2.0229 for Houston, a 1% increase in its zonal load is estimated to result in a 2% increase in the positive payoffs realized through a Houston tolling agreement. The positive payoffs in the other three zonal markets are also quite elastic with respect to changes in the Houston zonal load.

The OLS results for CT generation and *HR* = 9, as reported in Panel B of Table 4, are generally supportive of our hypotheses. The statistically-significant estimates for β_1 and β_2 support hypotheses (8) and (9) of the negative impact on a positive payoff of an increase in either wind or nuclear generation. As to hypothesis (10) - the price effect of an increase in the natural-gas price dominates the cost effect - both estimated coefficients with the hypothesized positive sign, for the Houston and South zonal markets, are statistically insignificant, while the two statistically-significant estimates, for the North and West markets, have signs that would disconfirm the hypothesis. There is, however, a rather straight-forward explanation: at the higher heat rate of 9 MMBTU/MWH the cost effect of an increase in the natural-gas price tends to overcome the price effect.

Fourteen of the 16 positive-payoff elasticities with respect to zonal loads are statistically significant and have the hypothesized signs, in support of hypotheses (11)

through (14). The two exceptions are for the South zonal load and neither exception lends statistically-significant support to contradict the hypothesis. By contrast with the estimates for the lower heat rate, however, and particularly for the Houston and West zonal loads, the positive payoffs in all four zonal markets are highly elastic with respect to the loads. That is, if a tolling agreement is not going to be profitable, it will *really* be unprofitable with a high-heat-rate CT generator and when the Houston or West zones have low loads.

Finally, in support of our bias-correction hypothesis (15), all four estimates of θ are negatively signed and statistically significant.

4.3 Effect of rising wind generation on a tolling agreement's payoffs

We undertook this research in order to explore the valuation of a tolling agreement in the presence of increased wind generation. Based upon the parameter estimates presented in the Tables 3 and 4, the estimated payoffs as presented in Panels A through D of Table 5, are computed through our eight-step simulation process. Each panel shows the average payoff, for that zonal market, for no change in wind generation, $\phi = 1.0$, through a 40% increase in wind generation, $\phi = 1.4$.

Absent an increase in wind generation, there should be no change to a tolling agreement's payoffs. This is borne out by the statistically-insignificant estimates in the row labeled $\phi = 1.0$, in the average-payoff column, in each of the four panels, which supports the notion that our estimation process is unbiased.

When $\phi = 1.1$, the payoff difference of a tolling agreement that is estimated to occur due to rising wind generation is statistically insignificant; or, a 10% increase in

wind generation is not expected to have an impact on the value of an extant or contemplated tolling agreement.

The situation takes a modest turn when $\phi = 1.2$. A 20% increase in wind generation and an *HR* = 7 MMBTU/MWH results in a statistically-significant reduction of an LDC management's WTP for a tolling agreement in the North or West zonal markets, and the same holds for the West market when *HR* = 9 MMBTU/MWH.

The situation takes a more radical turn in all four zonal markets when $\phi = 1.4$. A 40% increase in wind generation would reduce the average payoff of a tolling agreement to a statistically-significant extent.

In sum, Table 5 indicates that a 40% increase in wind generation would reduce payoffs by 8% to 13%, as shown in the bottom rows of Panels A-D. Unless an owner of natural-gas-fired generation could receive compensation elsewhere, the decline in the LDC's WTP could be a serious disincentive for investment in thermal generation.

5. Conclusion

With some 36 GW of installed capacity, or a little more than 20% of the world's total, the United States is at the forefront of wind generation, with second-place China rapidly closing a very narrow gap and the United Kingdom in eighth place at approximately the same level as Texas. Indeed, for several years "wind power has been the fastest-growing source of new electric power generation" in the states (EIA, 2011, p. 2). Even though new installations have recently declined, wind generators still account for 16% of *all planned* capacity additions for the five-year period from 2010 to 2014.

Rising wind generation can benefit electricity consumers by reducing wholesale market prices, but it can also discourage natural-gas-fired generation investment, as we have demonstrated using the ERCOT 15-minute database. Even though CCGT and CT are required to integrate large amounts of intermittent wind energy into an electricity grid, there may not be sufficient investment in CCGT and CT to maintain system reliability.

Besides Texas, there are other restructured markets (e.g., Germany, Denmark, Spain, UK, Ontario, and California) that have or will have significant wind-generation development (Alagappan et al., 2011; Yatchew and Baziliauskas, 2011). Our finding of vanishing investment incentives for natural-gas-fired generation corroborates that of Traber and Kemfert (2011) for Germany and Steggals et al. (2011) for UK. Hence, the policy debate over market design and generation investment incentives should account for the large-scale wind generation that will occur in a restructured market (Neuhoff and De Vries, 2004; Roques et al., 2005; Newberry, 2010; Milstein and Tishler, 2011).

In closing, we acknowledge three important changes in ERCOT that will command future attention by researchers studying the relationship between large-scale wind-generation development and the investment incentive for conventional generation. First, ERCOT will likely see more wind-generation expansion, beyond the 40% assumed here. Infrastructure upgrades are underway to accommodate the transmission of over 18 GW of wind generation.[11] Hence, ERCOT's future wholesale spot-market price behavior and dynamics may differ from that in the past. Second, as of December 2010 ERCOT switched from zonal to nodal pricing. Even though ERCOT continues to have zonal prices for bill settlement of zonal loads, such zonal prices may behave differently from

[11] http://www.texascrezprojects.com/

those in the past. Lastly, ERCOT continues to build new transmission to interconnect its CREZ. It is difficult to accurately predict at the present time how the new transmission will impact ERCOT's wholesale spot electricity prices in the future. Notwithstanding these changes, our econometric approach remains valid as it is equally applicable to model the impact of rising wind generation on the investment incentive for natural-gas-fired generation, using the zonal-price data that will be forthcoming over the next two to three years.

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Table 1: Descriptive statistics for the sample period of 01/01/2007 - 05/31/2010.

Variable	Mean	Standard deviation	Minimum	Maximum
15-minute Houston zonal price ($/MWH)	50.9	95.4	-1536.0	3806.0
15-minute North zonal price ($/MWH)	47.2	73.2	-999.0	2383.0
15-minute South zonal price ($/MWH)	51.0	110.1	-2293.0	4515.0
15-minute West zonal price ($/MWH)	42.5	77.7	-1982.0	2321.0
15-minute wind-generation output (MWH)	444.7	339.1	0.0	1703.0
15-minute nuclear output (MWH)	1159.0	201.6	0.0	1298.0
Daily Henry Hub natural-gas price ($/MMBTU)	6.4	2.4	1.8	13.3
15-minute Houston zonal load (MWH)	2413.0	558.4	1278.0	4416.0
15-minute North zonal load (MWH)	3397.0	859.2	1714.0	6555.0
15-minute South zonal load (MWH)	2379.0	589.3	1344.0	4491.0
15-minute West zonal load (MWH)	589.0	99.1	382.7	974.1

Data sources: Zonal price and load data were downloaded on 06/22/2010 from www.ercot.com. Generation data by fuel type were provided by ERCOT on 07/01/2010.

Table 2: 15-minute payoffs = max(15-minute spot market price - *HR* x Houston Ship Channel natural-gas price, 0) of a tolling agreement by zonal market and heat rate (*HR* in MMBTU/MWH) for the sample period of 01/01/2007 - 05/31/2010.

Panel A: Average payoffs ($/MWH) and correlation based on full sample

Variable	Zonal market							
	Houston		North		South		West	
	HR = 7	*HR* = 9	*HR* = 7	*HR* = 9	*HR* = 7	*HR* = 9	*HR* = 7	*HR* = 9
Average payoff	14.47	9.81	11.25	6.90	14.75	10.22	11.60	7.44
Correlation with wind generation	-0.051	-0.034	-0.070	-0.046	-0.041	-0.027	-0.106	-0.078

Panel B: Distribution of payoffs ($/MWH). This panel does not report the minimum positive payoffs, which are less than $0.01/MWH. The mean, percentiles and maximum are based on the subsample of strictly positive payoffs.

Variable	Zonal market							
	Houston		North		South		West	
	HR = 7	*HR* = 9	*HR* = 7	*HR* = 9	*HR* = 7	*HR* = 9	*HR* = 7	*HR* = 9
Percent of sample with a strictly positive payoff	48.6	25.6	46.6	23.8	47.9	24.7	44.3	23.2
Number observations with strictly positive payoffs	56,592	29,781	54,271	27,752	55,709	28,810	51,545	27,034
Mean	29.75	38.34	24.11	28.95	30.81	41.27	26.18	32.04
5-percentile	1.08	0.63	1.03	0.59	1.05	0.62	1.05	0.62
25-percentile	5.81	3.25	5.65	3.07	5.64	3.21	5.77	3.18
50-percentile	11.88	6.72	11.49	6.45	11.59	6.75	11.76	6.64
75-percentile	20.45	13.58	19.73	12.64	20.11	13.81	20.13	13.12
95-percentile	61.97	118.68	50.00	89.22	62.64	124.87	60.23	41.72
Maximum	3,732	3,711	2,321	2,304.13	4,441	4,420	2,247	2,227

Table 3: Binary logit regressions for the probability of strictly positive payoffs of a tolling agreement. Values in ( ) are standard errors of the coefficient estimates and "*" denotes significance at $\alpha = 0.01$.

Panel A: Heat rate = 7 MMBTU/MWH

Variable: coefficient	Zonal market			
	Houston	North	South	West
Number of strictly positive payoffs	56,589	54,271	55,706	51,545
Percent of estimation sample	48.64	46.65	47.88	44.30
R^2	0.43	0.42	0.43	0.41
15-minute wind-generation output (MWH): α_1	-0.0023* (0.00003)	-0.0024* (0.00003)	-0.0023* (0.00003)	-0.0032* (0.00003)
15-minute nuclear output (MWH)): α_2	-0.0014* (0.00005)	-0.0014* (0.00005)	-0.0015* (0.00005)	-0.0016* (0.00005)
Daily Henry Hub natural-gas price ($/MMBTU): α_3	-0.0474* (0.00520)	-0.1301* (0.00522)	-0.0491* (0.00516)	-0.1456* (0.00526)
15-minute Houston zonal load (MWH): α_4	0.0028* (0.00006)	0.0026* (0.00006)	0.0027* (0.00006)	0.0022* (0.00005)
15-minute North zonal load (MWH)) α_5	0.0015* (0.00004)	0.0019* (0.00004)	0.0013* (0.00004)	0.0017* (0.00004)
15-minute South zonalload (MWH)): α_6	0.0012* (0.00006)	0.0003* (0.00005)	0.0014* (0.00006)	0.0004* (0.00005)
15-minute West zonal load (MWH)): α_7	-0.0004 (0.00025)	-0.0004 (0.00025)	-0.0002 (0.00025)	-0.0006 (0.00025)

Panel B: Heat rate = 9 MMBTU/MWH

Variable: coefficient	Zonal market			
	Houston	North	South	West
Number of strictly positive payoffs	29,781	27,752	28,809	27,034
Percent of estimation sample	25.60	23.85	24.76	23.24
R^2	0.37	0.35	0.37	0.36
15-minute wind-generation output (MWH): α_1	-0.0020* (0.00003)	-0.0022* (0.00003)	-0.0020* (0.00003)	-0.0030* (0.00004)
15-minute nuclear output (MWH)): α_2	-0.0018* (0.00006)	-0.0017* (0.00006)	-0.0017* (0.00006)	-0.0018* (0.00006)
Daily Henry Hub natural-gas price ($/MMBTU): α_3	-0.1004* (0.00577)	-0.1965* (0.00605)	-0.1027* (0.00579)	-0.1881* (0.00615)
15-minute Houston zonal load (MWH): α_4	0.0027* (0.00006)	0.0024* (0.00006)	0.0024* (0.00006)	0.0023* (0.00006)
15-minute North zonal load (MWH)) α_5	0.0014* (0.00004)	0.0018* (0.00004)	0.0012* (0.00004)	0.0017* (0.00004)
15-minute South zonal load (MWH)): α_6	0.0006* (0.00005)	-0.0001 (0.00005)	0.0008* (0.00005)	0.00004 (0.00005)
15-minute West zonal load (MWH)): α_7	0.0008* (0.00026)	0.0004 (0.00026)	0.0017* (0.00026)	0.0007* (0.00027)

Note: For brevity, this table does not report the coefficient estimates for the intercept and the binary indicators to capture the hour-of-day, day-of-week and month-of-year effects, even though these estimates indicate the probability's statistically-significant time-dependence (α = 0.01). The R^2 value is $[1 - (L_0 / L_1)^{2/N}]$, where L_0 = log-likelihood with intercept only, L_1 = log-likelihood of the estimated model, and N = sample size (Cox and Snell, 1989, pp.208-209).

Table 4: OLS log-linear regressions for the natural logarithm of the size of the payoff of a spark-spread call option. Values in ( ) are standard errors of the coefficient estimates based on the consistent covariance matrix (White, 1980) and "*" denotes significance at $\alpha = 0.01$.

Panel A: Heat rate = 7 MMBTU/MWH

Variable: coefficient	Zonal market			
	Houston	North	South	West
Number of observations	56,515	54,197	55,632	51,471
Mean of natural log of positive payoffs	2.34	2.28	2.32	2.32
RMSE	1.08	1.07	1.09	1.11
Adjusted R^2	0.30	0.27	0.30	0.26
Natural log of 15-minute wind-generation output (MWH): β_1	-0.1028* (0.00427)	-0.1126* (0.0043)	-0.1041* (0.0044)	-0.1246* (0.0051)
Natural log of 15-minute nuclear output (MWH): β_2	-0.6810* (0.03212)	-0.5332* (0.0354)	-0.6269* (0.0363)	-0.4581* (0.0379)
Natural log of daily Henry Hub natural-gas price ($/MMBTU): β_3	0.5921* (0.01921)	0.4335* (0.0195)	0.5494* (0.0193)	0.4638* (0.0209)
Natural log of 15-minute Houston zonal load (MWH): β_4	2.0229* (0.08178)	1.7064* (0.0836)	1.7188* (0.0852)	1.6431* (0.0870)
Natural log of 15-minute North zonal load (MWH): β_5	1.0610* (0.08061)	1.3462* (0.0857)	0.8575* (0.0830)	1.0481* (0.0894)
Natural log of 15-minute South zonal load (MWH): β_6	0.9636* (0.07325)	0.4809* (0.0732)	1.1746* (0.0754)	0.3895* (0.0766)
Natural log of 15-minute West zonal load (MWH): β_7	1.2280* (0.08698)	1.1381* (0.0890)	1.5259* (0.0901)	1.3147* (0.0953)
OLS bias correction: θ	-0.0579* (0.01303)	-0.0117 (0.0143)	-0.0502* (0.0150)	0.0341* (0.0137)

Panel B: Heat rate = 9 MMBTU/MWH

Variable: coefficient	Zonal market			
	Houston	North	South	West
Number of observations	29,735	27,704	28,764	26,986
Mean of natural log of positive payoffs	1.95	1.86	1.96	1.93
RMSE	1.39	1.37	1.40	1.41
Adjusted R^2	0.19	0.15	0.20	0.14
Natural log of 15-minute wind-generation output (MWH): β_1	-0.1562* (0.0081)	-0.1532* (0.0083)	-0.1534* (0.0084)	-0.1763* (0.0095)
Natural log of 15-minute nuclear output (MWH): β_2	-1.4662* (0.0694)	-1.1532* (0.0682)	-1.4541* (0.0719)	-1.0009* (0.0717)
Natural log of daily Henry Hub natural-gas price ($/MMBTU): β_3	0.0242 (0.0363)	-0.2225* (0.0388)	0.0325 (0.0374)	-0.1746* (0.0403)
Natural log of 15-minute Houston zonal load (MWH): β_4	3.4915* (0.1731)	2.4127* (0.1671)	3.0613* (0.1743)	2.4201* (0.1722)
Natural log of 15-minute North zonal load (MWH): β_5	1.7989* (0.1559)	2.2192* (0.1718)	1.2681* (0.1581)	1.3011* (0.1707)
Natural log of 15-minute South zonal load (MWH): β_6	1.2667* (0.1325)	0.1227 (0.1353)	1.8826* (0.1364)	-0.0792 (0.1415)
Natural log of 15-minute West zonal load (MWH): β_7	2.8697* (0.1620)	2.3805* (0.1662)	3.3120* (0.1677)	2.7159* (0.1748)
OLS bias correction: θ	-0.4614* (0.0261)	-0.2859* (0.0243)	-0.4784* (0.0271)	-0.2130* (0.0242)

Note: The regressions are based on 15-minute strictly positive payoffs in the period from 01/01/2007 to 05/31/2010. The number of observations is slightly less than the one in the second row of Table 3 due to missing values for the metric variables. For brevity, this table does not report the coefficient estimates for the intercept and binary indicators that capture the hour-of-day, day-of-week and month-of-year effects, even though these estimates indicate statistically-significant time-dependence of the natural logarithm of payoff size (α = 0.01).

Table 5: Effects of rising wind generation on the expected payoff of a tolling agreement in the ERCOT's zonal markets. Values in ( ) are standard errors and "*" denotes significance at $\alpha = 0.01$.

Panel A: Houston zonal market

Variable	Heat rate = 7 MMBTU/MWH		Heat rate = 9 MMBTU/MWH	
	Relative frequency	Average payoff	Relative frequency	Average payoff
Actual value	0.4863* (0.0015)	14.4681* (0.2670)	0.2559* (0.0013)	9.8127* (0.2631)
Estimated difference at ϕ = 1.0	-0.0003 (0.0011)	0.0184 (0.2555)	-0.0003 (0.0010)	-0.0272 (0.2530)
Estimated difference at ϕ = 1.1	-0.0133* (0.0011)	-0.3138 (0.2555)	-0.0077* (0.0010)	-0.2491 (0.2530)
Estimated difference at ϕ = 1.2	-0.0258* (0.0011)	-0.6285 (0.2556)	-0.0147* (0.0010)	-0.4559 (0.2531)
Estimated difference at ϕ = 1.3	-0.0378* (0.0011)	-0.9280* (0.2556)	-0.0213* (0.0010)	-0.6501* (0.2531)
Estimated difference at ϕ = 1.4	-0.0492* (0.0011)	-1.2139* (0.2556)	-0.0276* (0.0010)	-0.8336* (0.2531)
Estimated difference at ϕ = 1.4 ÷Actual value	-0.1012	-0.0839	-0.1079	-0.0850

Panel B: North zonal market

Variable	Heat rate = 7 MMBTU/MWH		Heat rate = 9 MMBTU/MWH	
	Relative frequency	Average payoff	Relative frequency	Average payoff
Actual value	0.4664* (0.0015)	11.2431* (0.2018)	0.2384* (0.0012)	6.9012* (0.1983)
Estimated difference at ϕ = 1.0	-0.0003 (0.0011)	-0.0110 (0.1960)	-0.0002 (0.0009)	-0.0034 (0.1945)
Estimated difference at ϕ = 1.1	-0.0138* (0.0011)	-0.3126 (0.1960)	-0.0079* (0.0009)	-0.2005 (0.1945)
Estimated difference at ϕ = 1.2	-0.0267* (0.0011)	-0.5967* (0.1960)	-0.0151* (0.0009)	-0.3899 (0.1945)
Estimated difference at ϕ = 1.3	-0.0391* (0.0011)	-0.8653* (0.1960)	-0.0219* (0.0009)	-0.5668* (0.1945)
Estimated difference at ϕ = 1.4	-0.0508* (0.0011)	-1.1200* (0.1960)	-0.0283* (0.0009)	-0.7327* (0.1946)
Estimated difference at ϕ = 1.4 ÷Actual value	-0.1055	-0.1080	-0.1158	-0.1208

Panel C: South zonal market

Variable	Heat rate = 7 MMBTU/MWH		Heat rate = 9 MMBTU/MWH	
	Relative frequency	Average payoff	Relative frequency	Average payoff
Actual value	0.4787* (0.0015)	14.7527* (0.3110)	0.2475* (0.0013)	10.2182* (0.3075)
Estimated difference at ϕ = 1.0	-0.0003 (0.0011)	-0.0279 (0.2990)	-0.0003 (0.0009)	-0.0078 (0.2957)
Estimated difference at ϕ = 1.1	-0.0133* (0.0011)	-0.3728 (0.2990)	-0.0075* (0.0009)	-0.2338 (0.2958)
Estimated difference at ϕ = 1.2	-0.0259* (0.0011)	-0.6994 (0.2991)	-0.0144* (0.0009)	-0.4447 (0.2958)
Estimated difference at ϕ = 1.3	-0.0379* (0.0011)	-1.0099* (0.2991)	-0.0209* (0.0009)	-0.6429 (0.2959)
Estimated difference at ϕ = 1.4	-0.0493* (0.0011)	-1.3060* (0.2992)	-0.0270* (0.0009)	-0.8305* (0.2959)
Estimated difference at ϕ = 1.4 ÷Actual value	-0.1030	-0.0885	-0.1091	-0.0813

Panel D: West zonal market

Variable	Heat rate = 7 MMBTU/MWH		Heat rate = 9 MMBTU/MWH	
	Relative frequency	Average payoff	Relative frequency	Average payoff
Actual value	0.4429* (0.0015)	11.5913* (0.2012)	0.2322* (0.0012)	7.4399* (0.1974)
Estimated difference at ϕ = 1.0	-0.0003 (0.0011)	0.0243 (0.1957)	-0.0003 (0.0009)	0.0039 (0.1938)
Estimated difference at ϕ = 1.1	-0.0172* (0.0011)	-0.3933 (0.1956)	-0.0094* (0.0009)	-0.2835 (0.1938)
Estimated difference at ϕ = 1.2	-0.0330* (0.0011)	-0.7818* (0.1956)	-0.0179* (0.0009)	-0.5470* (0.1937)
Estimated difference at ϕ = 1.3	-0.0477* (0.0011)	-1.1444* (0.1955)	-0.0257* (0.0009)	-0.7896* (0.1937)
Estimated difference at ϕ = 1.4	-0.0614* (0.0011)	-1.4834* (0.1955)	-0.0330* (0.0009)	-1.0139* (0.1937)
Estimated difference at ϕ = 1.4 ÷Actual value	-0.1386	-0.1280	-0.1421	-0.1363