"Cross-Hedging and Forward-Contract Pricing of Electricity in the Pacific
Northwest," Managerial and Decision Economics, 32, 265-279.

ABSTRACT
This paper develops a linear regression model for using actively-traded NYMEX natural
gas futures as a cross-hedge against electricity spot-price risk in the Pacific Northwest
and for pricing the forward contracts in the presence of temperature and hydro risks. Our
approach comports with reality and provides power purchasers with an effective
instrument through which they can hedge their electricity bets through natural gas
futures. It also demonstrates the sharp month-to-month variations in the natural gas
futures’ optimal hedge ratios and hedge effectiveness. Finally, it finds significant risk
premiums in the Pacific Northwest forward prices, supporting the hypothesis that
forward-contract buyers are relatively more risk-averse than sellers.
INTRODUCTION

The restructuring of electricity markets to introduce wholesale-generation market competition has taken place in North America, Europe, Australia/New Zealand, and Asia (Xu, 2004; Sioshansi and Pfaffenberger, 2006; Woo et al., 2006a). 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; weather-dependent demands with intra- and inter-day fluctuations to be met in real time by generation and transmission already in place; capacity change caused by planned and forced outages of electrical facilities; and lumpy capacity additions that occur with a long lead times (Li and Flynn, 2006; Tishler et al., 2008). Poor market designs and market-power abuse by generators exacerbate this volatility (Borenstein, 2002; Borenstein et al., 2002; Woo et al., 2003, 2006c; Trebilcock and Hrab, 2005).

Volatile electricity spot prices and their occasional sharp spikes, have sparked extensive research into their behavior and dynamics, and subsequent applications of this research.¹ This rich research, however, says little about using natural gas futures to cross-hedge against electricity spot-price risk, even though natural gas is often the marginal fuel used by the last dispatched generation unit.² Hence, this paper provides a first look at two related questions: How may the actively-traded NYMEX natural gas futures for Henry Hub delivery in Louisiana be used to cross-hedge against electricity spot-price risk in the Pacific Northwest, and how should a forward contract be priced in the presence of temperature and hydro risks? Our answers enrich the literature on natural gas cross-hedging, whose main focus has been mitigating natural gas spot-price risk at a delivery
location different from the Henry Hub (e.g.: Woo et al., 2006d; Ederington and Salas, 2008).

The two questions posted above are timely and relevant because North American electricity futures are thinly traded, with delivery only at the Pennsylvania-Jersey-Maryland (PJM) Interconnection (http://www.cmegroup.com/trading/energy/electricity/pjm-western-hub-peak-calendar-month-real-time-Imp.html). The lack of actively-traded electricity futures with geographically dispersed delivery points hinders efforts to hedge against the spot-price risk. A trade publication such as Platts MegaWatt Daily reports forward prices at major hubs across North America. It is doubtful, however, that these prices are an outgrowth of active trading among many market participants. Thus, we investigate whether a cross-hedge based on NYMEX natural gas futures can reduce electricity spot-price risk in a future delivery period in the Pacific Northwest, a North American region endowed with vast hydro resources.

Our choice of NYMEX futures is motivated by the well-documented high spot-price correlation between its Henry Hub delivery point and other points across North America, including the west coast (Woo et al., 2006d and references thereof). Our interest in the Pacific Northwest is attributable to the influence of hydro conditions on the spot price at the Mid-Columbia (Mid-C) market hub. This weather risk is difficult to hedge due to the lack of suitable instruments (Lee and Oren, 2009). Our investigation also compares the forward price based on cross-hedging and the one reported in Platts MegaWatt Daily, thus enabling an assessment of the latter’s risk premium above a Mid-C spot-price expectation.
We answer these questions through the ordinary-least-squares (OLS) parameter estimates of 12 monthly regression equations whose regressand is the daily Mid-C electricity price and whose explanatory regressors are: the weather; the hydro flow; and most saliently for our study the Henry Hub (HH) natural gas price on that day. Our monthly regressions use seven years of daily data, rather than a single equation or seven yearly equations because a forward contract typically has monthly delivery. This has two virtues. First, it comports with reality and provides power purchasers with an effective instrument through which to hedge their electricity bets via natural gas futures. Second, it demonstrates the sharp differences that the instrument implies for the optimal hedge ratios from one month to the next, with no readily detected connection between them. By the same token, careful analysis of the underlying price data raises a flag of caution as to how confident one should be in the specific parameter estimates, although not to the broader message they convey and the guidance they provide to market agents.

THE MID-COLUMBIA HUB

To presage our analytical model, we describe the Mid-C hub, a major wholesale spot electricity market in the Pacific Northwest. Physically located at several substations along the Columbia River in central Washington, the Mid-C hub is an intersection point for several regional transmission systems, the most prominent of which is the federal Bonneville Power Administration (BPA). The area houses several large hydroelectric dams, including the Grand Coulee (6,089 MW) and Dalles (1,780 MW) dams.

The Mid-C hub is an important pricing point in the Western Electricity Coordinating Council (WECC). With close to 200,000 MW of generation to meet about
160,000 MW of system load in 2009, the WECC encompasses the western part of the continental United States, the two Canadian provinces of British Columbia and Alberta, and portions of one Mexican state, Baja California (NERC, 2009).

Electricity trading for day-ahead delivery at the Mid-C hub is bilateral, primarily through telephone calls among such diverse market participants as independent power producers and marketers, investor-owned, municipal, and Canadian utilities, cooperatives, and the BPA. The resulting spot prices partly reflect hydro dominance in the Northwest Power Pool (NWPP) of the WECC. In 2009, the NWPP had 81,357 MW of generating capacity, 56% of which was hydro (NERC, 2009, p.181). Below-normal precipitation can severely impede hydro generation and increase the dispatch of the more costly thermal generation (e.g., natural-gas-fueled turbines) to meet demand, subsequently raising the electricity spot-market price.

The price influence of hydro production mainly occurs during on-peak hours, defined in the Western Systems Power Pool Agreement as 06:00AM to 10:00PM, Monday through Saturday (excluding WECC holidays), when hourly electricity demands are relatively high and the fast-ramping capability of hydro facilities can effectively satisfy fluctuating demands. The off-peak period comprises low-demand hours when the hydro system is ramped down, which allows the reservoirs to replenish for the next day’s on-peak production. And Mid-C prices are weather-dependent because river flows are highest during the spring runoff and water release for salmon spawning, and rising (falling) summer (winter) temperatures in the Pacific Northwest increase its aggregate demand and therefore price.
Finally, prices exhibit seasonality beyond weather effects, chiefly because the Pacific Northwest system is interconnected with California, Arizona and New Mexico to the south. These linkages enable the system’s surplus hydro power to flow south during the summer when its air-conditioning loads are high, and enable surplus thermal power in the south to flow north during the winter months when its heating loads are high.

**THE DAILY SPOT-PRICE REGRESSIONS**

Our sample comprises 2,256 daily observations for the on-peak Mid-C electricity price ($/MWH), degree-day, hydro flow, and HH natural gas price, for the seven-year period from January 2003 through December 2009. We measure degree-days by cooling degree-day = max(daily maximum temperature - 65°F, 0) for May through September, which are dominated by air-conditioning needs; otherwise heating needs prevail and it is measured by heating degree-day = max(65°F - daily minimum temperature, 0). Hydro flow is measured by the daily river flow (in 00000 ft.³ per second) at The Dalles Dam on the Washington-Oregon border, the most closely-watched indicator of the Federal Columbia River Power System's energy potential, and is the subject of forecasts published by the Northwest River Forecast Center during the winter.

The descriptive statistics of Table 1 show the wide-ranging values of the variables. As one would expect, the electricity price is positively correlated with degree-day and the natural gas price, but negatively correlated with hydro flow. Finally, the Phillips-Perron unit-root test statistics indicate that these series are stationary at the 1% level (α = 0.01), except for the HH price series that is stationary at α = 0.05. The test is
implemented through the AUTOREG procedure of SAS, which automatically determines the optimal number of lags.

Our focus on the cross-hedging option available to west coast power purchasers through HH futures contracts that typically have monthly delivery, impels us to analyze our data on a month-by-month basis. We thus divide our sample into 12 sub-samples, the first comprising 187 daily observations for January 2003 through January 2009, and the last comprising 193 daily observations for December 2003 through December 2009.

Figures 1 to 4 portray the four daily data series. The Mid-C prices are seasonal and volatile due to the seasonality and volatility of hydro flow and degree-day. The HH natural gas prices are volatile but do not have a clear seasonal pattern because natural gas can be stored and is required for winter heating in the colder regions of North America and for electric generation to serve summer air-conditioning-driven loads in warmer regions. Insofar as natural gas prices are a major driver of electricity prices, eliminating natural gas price volatility via cross-hedging can substantially reduce the Mid-C price risk. Figure 5 presents the monthly correlations between the Mid-C price and each of its drivers. Taken together, these figures suggest that the Mid-C price moves with the underlying drivers and that their relationship varies across months.

Let \( y_{tm} \) denote the daily on-peak Mid-C price ($/MWH) on day \( t \) (\( t = 1, 2, ..., T_m \)) of month \( m \) (\( m = 1 \) (January), \( \ldots \), 12 (December)). Our model hypothesizes that the Mid-C price depends upon three independent variables: \( x_{1tm} \) which denotes the degree-day at Portland, on day \( t \) of month \( m \), which we use to proxy the region’s cooling and heating loads; \( x_{2tm} \) which denotes the Columbia River flow at The Dalles Dam (in 00000 ft.\(^3\)/sec) on day \( t \) of month \( m \); and \( x_{3tm} \) which denotes the HH natural gas price on day \( t \) of month
Finally, let $\varepsilon_{tm}$ denote an i.i.d. random-error term with zero mean and finite variance $\sigma_m^2$. With minimal risk of confusion, the $tm$ subscript is henceforth suppressed and we specify the following linear regression model for each month, $m$:

$$y = \beta_{0m} + \beta_{1m}x_1 + \beta_{2m}x_2 + \beta_{3m}x_3 + \varepsilon.$$  \hspace{1cm} (1)

The OLS parameter estimates are denoted $b_{im}$ ($i = 0, 1, \ldots, 3$), where $b_{3m}$ determines the estimated minimum-variance (MV) hedge ratio for month $m$ (Anderson and Danthine, 1981; Chen et al., 2003; Alexander and Barbosa, 2007; Ederington and Salas, 2008), which is our ultimate goal. Concurrently, however, we want to compare these $b_{3m}$-estimated MV hedge ratios with those in adjacent months to see whether they suggest inter-month stability or instability.

Estimating 12 regressions, rather than a single regression with 12 binary indicators as in Goto and Karolyi (2003) and Woo et al. (2007) and perhaps as many as 36 interaction terms of the indicators with each of the three regressors, obviates the possibility of multi-collinearity issues that might compromise our results. The Mid-C-hub discussion guides the selection of the regressors. Exogenous variable $x_1$ aims to capture the hypothesized daily degree-day's marginal effect of $\beta_{1m} > 0$ on the Mid-C price. Variable $x_2$ is daily river flow at Dalles, with a hypothesized marginal effect of $\beta_{2m} < 0$ on the price. While hydro-generation dispatch may respond to spot-market prices (Johnsen, 2001; Bushnell, 2003), we contend that the Columbia River flow is largely exogenous, as water release in the Pacific Northwest serves several competing purposes, including salmon spawning, flood control, recreation, irrigation, and navigation (WECC, 2005, p. 5).
With a hypothesized marginal effect of $\beta_{3m} > 0$ on the Mid-C price, $x_3$ is the HH natural gas price rather than the local natural gas price at Sumas (Washington). Using the NYMEX natural gas futures to cross-hedge the Mid-C price risk requires that $x_3$ be the HH price. Moreover, the Sumas price may be endogenous, driven by local thermal generation. For the HH price to be a reasonable proxy for the potentially endogenous Sumas price, however, the two should be highly correlated, as indeed they are at $r = 0.97$ for the sample period. Comparably, the statewide precipitation index in Washington and Oregon is highly correlated with the Columbia flow. To minimize multi-collinearity concerns, we do not include Sumas prices and the precipitation index in the model.

Since Equation (1) has explanatory variables postulated to be uncorrelated with the error term, at first blush its coefficients can be consistently estimated using OLS, which is the most common approach for obtaining the MV hedge ratio (e.g., Chen et al., 2004). We choose not to use estimation methods that recognize that the error term may follow a complicated process such as AR(1)/GARCH(1, 1) with regime switching, because there is no clear evidence that such methods consistently yield better hedging performance (Alexander and Barbosa, 2007). Moreover, our focus is not estimation sophistication. Rather, it is a first look to illustrate how to practically solve the twin problems of cross-hedging and forward-contract pricing. Finally, the OLS results aid easy computation of a Mid-C price forecast and its variance for a future delivery month, one that inevitably has stochastic degree-day and river flow. We shall, however, eventually qualify our results through a second look at the underlying assumptions regarding our data and the specter of spurious regression, which may impact our confidence in the specific estimates although not the inferences and conclusions we draw from them.
ELECTRICITY PRICE FORECASTS

Letting $e$ denote a residual and after suppressing the monthly subscript, the estimate of Equation (1) is written:

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + e.$$  \hspace{1cm} (2)

Here, $b^T = (b_0, b_1, b_2, b_3)$ is the OLS estimate of $(\beta_0, \beta_1, \beta_2, \beta_3)$.

To see how cross-hedging may reduce the Mid-C spot-price risk in a future delivery month, define $z = (1, z_1, z_2, z_3)$ as the forecast values for the exogenous variables. For example, the degree-day and river-flow forecasts are based on historical averages. The natural gas price forecast is based on NYMEX price futures.

The daily Mid-C price forecast is:

$$F = zb.$$  \hspace{1cm} (3)

Since the forecast values are stochastic, the variance of $F$ without cross-hedging is:

$$v_1^2 = (s^2 + z\Omega z^T) + b^T \Lambda b + \text{tr}(\Omega \otimes A),$$  \hspace{1cm} (4)

where $\Omega = \text{var}(b)$ and $\Lambda = \text{var}(z)$ (Feldstein, 1971). The first term on the right-hand side of Equation (4), $(s^2 + z\Omega z^T)$, is the forecast variance when $z$ has zero variance. The second term, $b^T \Lambda b$, comprises the variances and co-variances of the forecast values magnified by the associated coefficient estimates. The last term, $\text{tr}(\Omega \otimes A)$, comprises the variances of forecast values magnified by the variances of the coefficient estimates.

As $s^2$ and $\Omega$ come from OLS estimation, $\Lambda$ is the remaining information required to compute $v_1^2$. The variance for degree-day or hydro flow is based on the historical data of Figures 2 and 3. The standard deviation of the natural gas price forecast is estimated as the NYMEX futures price multiplied by the coefficient of variation of the HH price history. Figure 6 shows the NYMEX futures prices and their daily standard deviations for
monthly delivery in 2011. Each off-diagonal element of $\mathbf{A}$ is an estimate of the co-
variance between two forecast values, found as the product of their standard deviations
for the forecast period and their historical correlation coefficient.

**CROSS-HEDGING**

Consider an electricity buyer (e.g., a local distribution company) that wishes to mitigate
the Mid-C spot-price volatility. The buyer purchases $b_3$ MMBTU of natural gas futures at
$z_3$ per on-peak MWH delivered in the forecast month. Taking natural gas delivery and
reselling the delivered amount at $x_3'$ in the HH spot market yields a daily profit of $b_3(z_3 -
x_3')$ per MWH in the delivery month. Denote by $(x_1', x_2', x_3', e')$ the actual values for $(x_1,$
$x_2, x_3, e)$ in the forecast period, which are unknown at the time of the cross-hedging
decision. Then, including the daily profit in a Mid-C spot-market purchase results in an
effective price of:

$$y' = b_0 + b_1 x_1' + b_2 x_2' + b_3 x_3' + e' + b_3(z_3 - x_3').$$

While the price forecast is still $F = zb$, cross-hedging locks in the natural gas price
for future delivery, implying that the natural-gas-related elements in $\mathbf{A}$ become zero.

Hence, cross-hedging shrinks the size of $\mathbf{b}^T \mathbf{A} \mathbf{b}$ and $\text{tr}(\mathbf{Q} \otimes \mathbf{A})$.

Let $v_2^2$ denote the variance of $F$ with cross-hedging. We measure the effectiveness
of the cross-hedge by the percent reduction in the variance of the price forecast.

$$E = 1 - \left( \frac{v_2^2}{v_1^2} \right).$$

We use $E$, instead of the $R^2$ of the spot-price regression to measure the NYMEX natural
gas futures' hedge effectiveness, because $R^2$ only shows the percent reduction in the
regression's sum of squared errors for the estimation sample, rather than the relative reduction in the Mid-C price forecast variance, when the forecast month's degree-day and river-flow values are stochastic.

FORWARD-CONTRACT PRICING
The forecast and its variance described thus far apply to a daily price. As the typical forward contract has monthly delivery, the price forecast is the monthly average of the daily forecasts, or \( F = \bar{z}b \), whose variance \( \nu^2 \) is the daily variance divided by the number of delivery days that month (i.e., 25 delivery days for January 2011). Under the Central Limit Theorem, the monthly average of the daily forecasts is normally distributed.

The price forecast and its variance can help construct a two-tail 90% confidence interval for forward-contract pricing. For example, a seller might profitably set its asking price at the interval’s upper bound of \( F_U = F + 1.65\nu \), knowing that the probability is 0.95 for \( F_U \) to be above the monthly average of daily spot prices that might be realized in the delivery period. Alternatively, a buyer could guard against overpaying by making a price offer of \( F_L = F - 1.65\nu \), or the interval's lower bound, comforted in the knowledge that the probability is 0.95 for \( F_L \) to be below the monthly average of the realized spot prices. If both agents act conservatively as described here, the spread between \( F_U \) and \( F_L \) can be as large as 3.3\( \nu \), a potential cause for thin trading of electricity forward contracts.

When the observed forward price is close to \( F_U \), the forward-contract seller extracts a positive risk premium from the buyer in exchange for absorbing the spot-price risk. As entry into a forward market for far ahead delivery is relatively easy, market-
power abuse is not a primary concern. The premium's presence supports the hypothesis that the forward-contract seller is less risk-averse than the buyer.

**RESULTS**

Our results consist of the estimated regressions and their price forecasts, and the implied optimal hedge ratios. Each aspect is discussed in turn below.

**Monthly Mid-C Electricity-Price Regressions**

Table 2 reports the OLS estimates of Equation (1), which we refer to here as Model 1. The table also reports the results of a restricted regression, Model 2, with $\beta_{1m} = \beta_{2m} = 0$, and the HH natural gas price as the only Mid-C price driver. Model 2 reflects a pragmatic view that it is unproductive to model the Mid-C price effects of daily degree-day and river flow when these two variables cannot be accurately forecast months ahead for the purpose of forward-contract pricing. That being said, the findings below yield the following observations. First, degree-day and river flow matter in modeling electricity spot-price behavior at the Mid-C hub. Second, ignoring these weather-related variables tends to reduce the MV hedge-ratio estimates, especially those for June and July, the months with high hydro runoff. Finally, the hedge-ratio estimates have large month-to-month variations.

Panel A of Table 2 shows the OLS estimates for the cold winter months of January through March that likely have natural gas as the marginal generation fuel. As is the case with all months other than April, shown in Panel B, the Phillips-Perron statistics below the "Model ID" row indicate stationary residuals ($\alpha = 0.01$), mitigating concerns
of spurious regression (Davidson and MacKinnon, 1993, pp.715-719). As to goodness-of-fit, Model 1 has adjusted $R^2$ (Adj. $R^2$) values of 0.70, 0.80, and 0.85 that exceed their Model 2 counterparts of 0.54, 0.75, and 0.70. The mean squared error (MSE) of Model 1 can be 50% of that of Model 2 (e.g., 36.6 vs. 73.7 for March), reflecting that degree-day and river flow are highly statistically-significant drivers of Mid-C prices. Model 1 has monthly MV hedge-ratio estimates for those winter months of $b_{3,1} = 8.55$, $b_{3,2} = 6.44$, and $b_{3,3} = 7.81$ that are similar to their counterparts of 7.68, 6.08, and 7.59 of Model 2. Finally, all coefficient estimates exhibit large month-to-month variations.

Panel B shows the OLS estimates for April through June, the months with rising spring runoff. Excluding degree-day and river flow can greatly reduce the regression’s goodness-of-fit, as demonstrated by June's Model 1 where Adj. $R^2 = 0.46$ and MSE = 146.6 are drastically different from Model 2’s Adj. $R^2 = 0.05$ and MSE = 256.8. The MV hedge-ratio estimates for April and May are $b_{3,4} = 8.06$ and $b_{3,5} = 5.67$ for Model 1, comparable to Model 2's estimates of 9.16 and 4.95. June's MV hedge-ratio estimate for Model 1, however, is $b_{3,6} = 2.97$, almost twice the 1.51 estimate for Model 2. This shows that an optimal hedge-ratio estimate can be highly sensitive to model specification. Finally, the coefficient estimates continue to vary across months.

Panel C shows the results for the summer months of July through September that likely have hydro-power exports and Mid-C prices that are influenced by thermal generation and electricity prices to the south. The July regression has a poor fit: Adj. $R^2 = 0.33$ and MSE = 340 for Model 1, and 0.23 and 391, respectively, for Model 2. Model 1’s MV hedge-ratio estimate is $b_{3,7} = 5.77$, which is about 30% larger than Model 2’s estimated 4.44. The goodness-of-fit improves for the next two months. Both models have
Adj. $R^2 \approx 0.75$ for August and above 0.85 for September. The corresponding MSE values are between 52 and 56 for August and 23 and 29 for September. The August MV hedge-ratio estimates are $b_{3,8} = 6.15$ for Model 1 and a comparable 6.04 for Model 2, indicating that excluding degree-day and river flow does not materially alter the August estimates and that these excluded variables do not contribute to the regressions either substantively or to a statistically-significant extent. The same can be said about the September MV hedge-ratio estimates of $b_{3,9} = 4.80$ and 4.65.

Panel D reports the results for October through December, which are the late-fall and early-winter months with low river flow and power import from the south. The models have similarly good fits: $0.72 \leq \text{Adj. } R^2 \leq 0.88$. Model 1, however, has a lower MSE than Model 2, especially for December (96 vs. 165). The models’ MV hedge-ratio estimates are similar: $b_{3,10} = 5.28$ and 4.90 for October; $b_{3,11} = 5.58$ and 5.61 for November; and $b_{3,12} = 7.75$ and 7.79 for December.

**Hedge Effectiveness**

Consider a Mid-C buyer that procures NYMEX futures according to the MV-ratio estimates in Table 2. An immediate question arises: is the cross-hedge effective?

Figure 7 shows the cross-hedge's effectiveness according to Equation (5) that computes the percent reduction in the Mid-C price-forecast variance. The effectiveness of the hedge, based on Model 1’s MV-ratio estimates, varies substantially across months, ranging from 10% for June to 80% for December, with an average of 64.9%.

The effectiveness of the hedge based on Model 2 also varies substantially across months, ranging from 10% for June and 75% for April. The average effectiveness of
56.9%, is less than that based on Model 1. This suggests that modeling weather risks can matter when making a Mid-C price forecast, but that using simple monthly models based exclusively on natural gas prices can still substantially reduce Mid-C electricity-price volatility.

**Mid-C Price Forecasts**

An electricity-price forecast requires NYMEX HH futures prices and daily standard deviations. For illustration, we use Figure 6 which displays these prices from March 26, 2010, the trading day for the delivery months of January through December 2011.

Figure 8 shows the Model 1 forecast of the monthly average of daily on-peak Mid-C prices and the 90% confidence intervals for the monthly forecast results, based on the historic average of degree-day and river flow over the seven-year sample period, as we cannot forecast their patterns for the forecast period. It also shows the quarterly forward prices published in Platts MegaWatt Daily on March 26, 2010 for the 12 delivery months in 2011. Despite the unavailability of monthly forward prices, this figure yields two observations. First, the quarterly forward prices track but are above the upper bound of the 90% confidence interval. Thus, these forward prices imply almost certain *ex ante* profitability for a forward seller that may meet its delivery obligation using spot-market purchases. Second, these forward prices contain an average premium of 6.5% above the price forecast. The presence of a relatively large premium corroborates the electricity-price literature (e.g., Woo et al., 2001; Bessembinder and Lemmon, 2002; Longstaff and Wang, 2004) and supports the hypothesis that a forward-contract seller is relatively less risk averse than a buyer.
Figure 9, which shows the Model 2 forecast results and the quarterly forward prices of Figure 8, yields similar observations. In particular, the forward prices track the upper bounds of the 90% confidence intervals, with an average premium of 5.4%.

The similarity between the Figures suggest that not modeling weather conditions because of an inability to credibly forecast them well in advance does not materially alter the price forecast. This is not totally unexpected because the Model 1 forecast in Figure 8 assumes historical average weather conditions. By not considering weather conditions, the Model 2 forecast in effect also assumes average weather conditions. Thus, a forward-contract seller may rely on the simple Model 2 for a quick forward price quote for a delivery period at least six months into the future.

STATISTICAL CAVEATS

The fact that the time series for the entire sample are stationary, as shown in Table 1, could easily mislead one into believing the same to be true for the monthly sub-samples. Unfortunately, this is not the case for both the Mid-C and HH price series’, which the Philips-Perron tests reveal to be non-stationary for 11 of the 12 months. Moreover, in eight of the 12 regressions $R^2$ exceeds the Durbin-Watson statistic, which signals the strong likelihood of a spurious regression (Granger and Newbold, 1974). Fortunately, we can reject the null hypothesis that the residuals have a unit root, $\alpha = 0.01 (0.05)$ for 11 (12) of the regressions, implying that the two series do not drift apart without limit.

We have considered alternative specifications, found either by including a lagged Mid-C price as an additional regressor or by turning to first differences. But neither of these alternatives is appropriate when, for example, the January data for 2003 are
immediately followed by the January data for 2004. Yet a third alternative would be a logarithmic transformation, but that would negate the ready determination of the MV hedge ratio from the estimated parameters, which is a fundamental objective of the paper. These alternative specifications complicate the calculation of the price forecast variances when the weather variables are inevitably stochastic in the forecast horizon. Moreover, the linear model is a first-order approximation of the unknown regression form, one that has reasonable performance in light of the relatively good fits to the data and by comparison with the actual forward price.

In any event, the darkest implications of our possible misspecification is that our \( t \) statistics are artificially high and “over-reject” the \( \beta_{3m} = 0 \) hypotheses (Davidson and McKinnon, 1993, pp. 671-672). It would also be the case that our confidence intervals are too narrow. In our regressions, however, the \( t \) statistics of the MV hedge ratios range between 8.0 and 9.0 for June and July; in all other months, these \( t \) statistics exceed 19.0. Thus, even allowing for considerable exaggeration of these statistics, we can march confidently forward with the inferences that the monthly MV hedge ratios range from about 3.0 to 8.5, tend to be lower in the summer, and vary from month to month.

**FINAL REMARKS**

Dealing with electricity spot-price risk presents decision makers engaged in our restructured and newly-competitive wholesale energy markets with a considerable challenge. This paper provides a readily implementable means for electricity-market managements to profitably mitigate risk, most notably through cross-hedging in the natural gas futures market. We also provide insight into why the optimal monthly hedge
ratios vary from one month to the next. The significant risk premiums in the Mid-C forward market support the hypothesis that forward-contract sellers are less risk averse than buyers. Finally, we show that modeling weather conditions in a notoriously unpredictable future delivery period does not improve an electricity price forecast, at least for our Mid-C case. Hence, a forward-contract seller can rely on a simple regression model to prepare its profitable price quote.

Our analysis also raised some statistical issues whose resolution and broader implications we are now only beginning to explore. In particular, we are presently studying whether and the extent to which the salient parameter estimates change when, say, we deal with the serial-correlation issues through the use of AR, ARCH, and GARCH estimation procedures, or with the stationarity issues through an error-correction procedure. Those statistical concerns, however, would take us far afield, beyond the scope of the present paper with its relatively modest, if important, practical objectives.
NOTES

1. Some examples of this research are: Johnsen (2001); Bessembinder and Lemmon (2002); Goto and Karolyi (2003); Longstaff and Wang (2004); Knittel and Roberts (2005); Haldrup and Nielsen (2006); Mount et al. (2006); Park et al. (2006); Guthrie and Videbeck (2007); Woo et al. (2007); Benth and Koekebakker (2008); Karakatsani and Bunn (2008; Marckhoff and Wimschulte (2009); and Redl et al. (2009). Useful applications of this research include: risk management (Woo et al., 2004a, 2004b, 2006b; Kleindorfer and Li, 2005; Deng and Oren, 2006; Huisman et al., 2009), pricing of electricity options, futures, forwards, and generation assets (Deng et al., 2001; Woo et al., 2001; Kamat and Oren, 2002; Lucia and Schwartz, 2002; Eydeland and Wolyniec, 2003; Fleten and Lemming, 2003; Keppo and Lu, 2003); evaluation of power contracts (Woo et al., 2004c); detection of market-power abuse and price manipulation (Borenstein et al., 2002; Joskow and Khan, 2002; Helman, 2006); investigation of generation-investment behavior (Neuhoff and De Vries, 2004); assessment of wholesale market integration (De Vany and Walls, 1996; Woo et al., 1997; Park et al., 2006); and assessment of how retail competition may affect forward-contract pricing (Green, 2003).

2. An internet search on April 12, 2010 at scholar.google.com using the key words cross-hedge, natural gas, electricity, and futures, yielded 30 hits, none of which is related to the subject at hand.
REFERENCES


Tishler A, Milstein I, Woo CK. 2008. Capacity commitment and price volatility in a


Woo CK, Lloyd D, Tishler A. 2003. Electricity market reform failures: UK, Norway,


Table 1: Descriptive statistics for the 2003-2009 sample of 2256 daily observations.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Correlation with Mid-C price</th>
<th>Phillips-Perron unit root τ test statistics (lags)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mid-C on-peak price ($/MWH)</td>
<td>50.6</td>
<td>18.7</td>
<td>4.0</td>
<td>197.4</td>
<td>1.0</td>
<td>-7.80 (9)</td>
</tr>
<tr>
<td>Portland degree-day</td>
<td>20.1</td>
<td>10.3</td>
<td>0.0</td>
<td>49.0</td>
<td>0.25</td>
<td>-13.95 (9)</td>
</tr>
<tr>
<td>Columbia River flow at The Dalles Dam (00000 ft.³/sec.)</td>
<td>1.64</td>
<td>0.66</td>
<td>0.66</td>
<td>4.25</td>
<td>-0.35</td>
<td>-5.50 (9)</td>
</tr>
<tr>
<td>Natural gas price at Henry Hub ($/MMBTU)</td>
<td>6.64</td>
<td>2.29</td>
<td>1.83</td>
<td>18.4</td>
<td>0.65</td>
<td>-3.35 (9)</td>
</tr>
</tbody>
</table>

Data sources: (a) Mid-C and Henry Hub prices: Intercontinental Exchange; (b) Columbia River flow at The Dalles Dam: US Geological Survey; and (c) Portland degree days: National Oceanic and Atmospheric Administration.
Table 2: Monthly OLS regression results for the period January 2003-December 2009, standard errors in ( ), and "*" = "significant at the 1% level".

### Panel A: January - March

<table>
<thead>
<tr>
<th>Variable</th>
<th>January</th>
<th>February</th>
<th>March</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample size</td>
<td>187</td>
<td>177</td>
<td>194</td>
</tr>
<tr>
<td>Mean Mid-C price</td>
<td>51.5</td>
<td>51.8</td>
<td>46.5</td>
</tr>
<tr>
<td>Model ID</td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 1</td>
</tr>
<tr>
<td>Phillips-Perron (zero mean with 2 lags) statistic to test random walk regression residuals</td>
<td>-5.13*</td>
<td>-3.10*</td>
<td>-5.11*</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.70</td>
<td>0.54</td>
<td>0.80</td>
</tr>
<tr>
<td>MSE ($s^2$)</td>
<td>53.1</td>
<td>79.9</td>
<td>29.5</td>
</tr>
<tr>
<td>Intercept</td>
<td>-13.93*</td>
<td>(4.31)</td>
<td>15.41*</td>
</tr>
<tr>
<td>Portland degree-day</td>
<td>0.838*</td>
<td>(0.088)</td>
<td>0.343*</td>
</tr>
<tr>
<td>Columbia River flow at The Dalles Dam (00000 ft.$^3$/sec.)</td>
<td>-9.49*</td>
<td>(2.06)</td>
<td>-11.70*</td>
</tr>
<tr>
<td>Natural gas price at Henry Hub ($/MMBTU)</td>
<td>8.55*</td>
<td>(0.431)</td>
<td>6.44*</td>
</tr>
</tbody>
</table>

### Panel B: April - June

<table>
<thead>
<tr>
<th>Variable</th>
<th>April</th>
<th>May</th>
<th>June</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample size</td>
<td>187</td>
<td>177</td>
<td>188</td>
</tr>
<tr>
<td>Mean Mid-C price</td>
<td>44.7</td>
<td>41.5</td>
<td>36.4</td>
</tr>
<tr>
<td>Model ID</td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 1</td>
</tr>
<tr>
<td>Phillips-Perron (zero mean with 2 lags) statistic to test random walk regression residuals</td>
<td>-5.77*</td>
<td>-2.55</td>
<td>-5.75*</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.86</td>
<td>0.65</td>
<td>0.61</td>
</tr>
<tr>
<td>MSE ($s^2$)</td>
<td>74.3</td>
<td>180.3</td>
<td>119.7</td>
</tr>
<tr>
<td>Intercept</td>
<td>17.27*</td>
<td>(4.31)</td>
<td>35.45*</td>
</tr>
<tr>
<td>Portland degree-day</td>
<td>0.392*</td>
<td>(0.132)</td>
<td>0.403*</td>
</tr>
<tr>
<td>Columbia River flow at The Dalles Dam (00000 ft.$^3$/sec.)</td>
<td>-16.75*</td>
<td>(1.04)</td>
<td>-13.02*</td>
</tr>
<tr>
<td>Natural gas price at Henry Hub ($/MMBTU)</td>
<td>8.06*</td>
<td>(0.323)</td>
<td>5.67*</td>
</tr>
</tbody>
</table>
Table 2 continued: Monthly OLS regression results for the period January 2003-December 2009, standard errors in ( ), and "*" = "significant at the 1% level".

Panel C: July - September

<table>
<thead>
<tr>
<th>Variable</th>
<th>July</th>
<th>August</th>
<th>September</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample size</td>
<td>186</td>
<td>194</td>
<td>182</td>
</tr>
<tr>
<td>Mean Mid-C price</td>
<td>56.8</td>
<td>56.8</td>
<td>51.7</td>
</tr>
<tr>
<td>Model ID</td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 1</td>
</tr>
<tr>
<td>Phillips-Perron (zero mean with 2 lags) statistic to test random walk regression residuals</td>
<td>-6.91*</td>
<td>-6.24*</td>
<td>-5.20*</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.33</td>
<td>0.23</td>
<td>0.75</td>
</tr>
<tr>
<td>MSE ($s^2$)</td>
<td>340.4</td>
<td>391.2</td>
<td>52.7</td>
</tr>
<tr>
<td>Intercept</td>
<td>30.47*</td>
<td>27.96*</td>
<td>22.30*</td>
</tr>
<tr>
<td>(8.02)</td>
<td>(4.12)</td>
<td>(4.24)</td>
<td>(1.74)</td>
</tr>
<tr>
<td>Portland degree-day</td>
<td>0.692*</td>
<td>0.219*</td>
<td>0.281*</td>
</tr>
<tr>
<td>(0.159)</td>
<td>(0.062)</td>
<td>(0.062)</td>
<td>(0.062)</td>
</tr>
<tr>
<td>Columbia River flow at The Dalles Dam (00000 ft.³/ sec.)</td>
<td>-14.09*</td>
<td>-6.31*</td>
<td>-9.11*</td>
</tr>
<tr>
<td>(4.65)</td>
<td>(3.22)</td>
<td>(2.25)</td>
<td>(2.25)</td>
</tr>
<tr>
<td>Natural gas price at Henry Hub ($/MMBTU)</td>
<td>5.77*</td>
<td>4.44*</td>
<td>6.03*</td>
</tr>
<tr>
<td>(0.644)</td>
<td>(0.594)</td>
<td>(0.259)</td>
<td>(0.123)</td>
</tr>
</tbody>
</table>

Panel D: October - December

<table>
<thead>
<tr>
<th>Variable</th>
<th>October</th>
<th>November</th>
<th>December</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample size</td>
<td>195</td>
<td>185</td>
<td>193</td>
</tr>
<tr>
<td>Mean Mid-C price</td>
<td>54.2</td>
<td>52.0</td>
<td>63.1</td>
</tr>
<tr>
<td>Model ID</td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 1</td>
</tr>
<tr>
<td>Phillips-Perron (zero mean with 2 lags) statistic to test random walk regression residuals</td>
<td>-5.56*</td>
<td>-3.10*</td>
<td>-4.95*</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.88</td>
<td>0.83</td>
<td>0.76</td>
</tr>
<tr>
<td>MSE ($s^2$)</td>
<td>29.4</td>
<td>41.8</td>
<td>45.8</td>
</tr>
<tr>
<td>Intercept</td>
<td>25.82*</td>
<td>21.33*</td>
<td>15.92*</td>
</tr>
<tr>
<td>(2.65)</td>
<td>(1.14)</td>
<td>(1.71)</td>
<td>(6.35)</td>
</tr>
<tr>
<td>Portland degree-day</td>
<td>0.490*</td>
<td>0.465*</td>
<td>1.319*</td>
</tr>
<tr>
<td>(0.066)</td>
<td>(0.090)</td>
<td>(0.117)</td>
<td>(1.171)</td>
</tr>
<tr>
<td>Columbia River flow at The Dalles Dam (00000 ft.³/ sec.)</td>
<td>-15.65*</td>
<td>-7.74*</td>
<td>-20.10*</td>
</tr>
<tr>
<td>(2.51)</td>
<td>(3.38)</td>
<td>(3.76)</td>
<td>(3.76)</td>
</tr>
<tr>
<td>Natural gas price at Henry Hub ($/MMBTU)</td>
<td>5.28*</td>
<td>4.90*</td>
<td>5.61*</td>
</tr>
<tr>
<td>(0.141)</td>
<td>(0.156)</td>
<td>(0.254)</td>
<td>(0.282)</td>
</tr>
</tbody>
</table>
Figure 1: Monthly means and standard deviations of Mid-C daily on-peak electricity prices from 2003 to 2009, exhibiting both seasonality and wide price dispersion.
Figure 2: Monthly means and standard deviations of degree-days at Portland from 2003 to 2009, showing a seasonal pattern of high heating-degree-days during the winter months and high cooling-degree-days during the summer months.
Figure 3: Monthly means and standard deviations of daily Columbia River hydro flow at The Dalles Dam from 2003 to 2009, showing a seasonal pattern of high hydro flow occurring during the spring months of April through June.
Figure 4: Monthly means and standard deviations of daily Henry Hub natural gas spot prices from 2003 to 2009, showing wide price dispersion but no distinct seasonal pattern.
Figure 5: Monthly correlations of daily Mid-C prices with daily degree-day, daily hydro flow, and daily Henry Hub natural gas prices from 2003 to 2009.
Figure 6: NYMEX Henry Hub natural gas futures prices on March 26, 2010, for monthly delivery in 2011, as shown by the solid line. The upper (lower) dashed line is the futures price plus (minus) one estimated daily standard deviation.
Figure 7: Cross-hedge effectiveness by model, as measured by the reduction in the monthly price-forecast variance due to locking-in the Henry Hub natural gas price for delivery months in 2011.
Figure 8: Model 1 forecast of monthly average of daily on-peak Mid-C prices with a 90% confidence interval and premium percentage of MegaWatt Daily's quarterly forward prices. Both the Henry Hub natural gas futures and the quarterly forward prices are taken from March 26, 2010. The average forward price premium is 6.5%.
Figure 9: Model 2 forecast of monthly average of daily on-peak Mid-C prices with 90% confidence interval and premium percentage of MegaWatt Daily's quarterly forward prices. Both the Henry Hub natural gas futures and the quarterly forward prices are taken from March 26, 2010. The average forward-price premium is 5.4%.