A First Look at Estimating the Relation between Spot and Futures Electricity Prices in the US

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Abstract

In this study we investigate the statistical properties of wholesale electricity spot and futures prices traded on the New York Mercantile Exchange for delivery at the California-Oregon Border. Using daily data for the years 1998 and 1999, we find that many of the characteristics of the electricity market can be viewed to be broadly consistent with efficient markets. The futures risk premium for six-month futures contracts is estimated to be about .1328 percent per day or 4 percent per month. Using a GARCH specification, we estimate minimum variance hedge ratios for electricity futures. Finally, we model the dynamic relation between spot and futures prices using both an Exponential GARCH model and a vector autoregression representation.

1 Introduction and Background

The recent deregulation of the electric utility industry in many parts of the United States has created a competitive wholesale power market that exhibits a level of price volatility unparalleled in traditional commodity markets. The reason

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for this price behavior is attributed to the nature of how electricity is produced and consumed, inelastic demand, seasonal effects and most importantly, the non-storability of electricity. These unique characteristics of the supply and demand for electricity are reflected in the behavior of wholesale power prices as well as in the dynamic relation between the spot and futures prices.

At about the same time deregulation was taking place, the market for *electricity futures* was emerging. The New York Mercantile Exchange (NYMEX) introduced electricity futures in March 1996. Standardized futures contracts for delivery at Palo Verde (Arizona), California-Oregon Border, Cinergy (Midwest), Entergy (South-Central), and PJM are now traded on NYMEX. Trading of futures contracts allows generators and consumers the opportunity to hedge the price risk and minimize the impact of large price fluctuations. However, as pointed out by Eydeland and Geman (1999) and Pirrong and Jermakyan (1999), the inability to store electricity means that the well known cost-of-carry relationship that links spot and forward prices cannot be used to price futures or establish optimal hedge ratios.[4]

Bessembinder and Lemmon (2002) present an equilibrium pricing model of forward electricity contracts. Their model implies that the relationship between forward power price and the future spot price is a function of both expected demand and demand variance. More specifically, they indicate that the forward price will generally be a biased forecast of the future spot price, with the forward premium being a decreasing function of the expected variance of the wholesale spot price and an increasing function of the expected skewness of wholesale spot prices.

This study investigates the empirical relationship between spot and futures electricity prices traded on the New York Mercantile Exchange and delivered at the California-Oregon Border (COB).[5] We examine the characteristics of the market using daily data for the years 1998 and 1999 and document its behavior to be consistent with efficient markets. The futures risk premium for six-month futures contracts is estimated to be about .1328 percent per day or 4 percent per month.

[4]Routledge, Seppi and Spatt (2000) develop an equilibrium model of forward prices for storable commodities. They use a competitive rational expectations model of storage to study the impact of the embedded timing option on commodity spot and futures pricing. Unfortunately their results do not necessarily extend to electricity futures.

[5]The COB location has emerged as a major market center for electricity futures. This particular region has an active wholesale market and utilities in California have started operating under a performance based rate-making policy. This futures market provides a price reference and risk management tool to the market participants.

Using a GARCH specification, we estimate minimum variance hedge ratios. Finally, we study the dynamic relation between spot and futures prices using both an Exponential GARCH model and a vector autoregression representation.

The literature on corporate risk management suggests that firms can benefit from hedging market risk. For instance, Smith and Stultz (1985) show that risk hedging can reduce expected tax liabilities and expected bankruptcy costs. Bessembinder (1991), Froot, Scharfstein and Stein (1993) and Stultz (1990) present models that show that a policy of hedging market risks can lead to more efficient capital investment results.

Forward hedging in the power industry is likely to lead to even greater benefits. The extreme volatility of wholesale power prices suggest that most power producers and retailers have significant price exposures that may lead to serious financial difficulties.[6] Futures contracts provide a way to transfer risk between agents who have different risk preferences. Keynes (1930) claimed that highly risk averse individuals, the hedgers, would transfer the risk of carrying an asset to less risk-averse individuals, the speculators. Also, individuals with different endowments of a commodity can transfer price risk when the owners of large endowments go short while those with future requirements go long.[7]

The remainder of this paper is organized in five sections. In section 2 we describe the data and present its statistical properties. In section 3 we examine the characteristics of the spot and futures electricity markets and estimate the forward risk premium. Implications for efficiency in the electricity markets are also discussed. In section 4, we estimate the dynamic relation between spot and futures markets and derive estimates for optimal hedge ratios. A vector autoregression of the spot and futures electricity prices is estimated in section 5. Further implications derived from impulse response functions are discussed. A brief summary and some concluding remarks are presented in the final section.

2 Data Description

Daily spot and futures electricity prices for the period March 1996 to January 2000 were obtained from the New York Mercantile Exchange. The same dataset

[6] A recent example in California are Southern California Edison and Pacific Gas and Electric, both companies experiencing financial problems stemming from the high costs of purchasing power on the wholesale spot markets.

[7] For further details on hedging and risk behavior, see Hicks (1946), Working (1953) and more recently Cornell (2000).

included daily data on trading volume as well as on open interest for all contracts traded on NYMEX. The dataset included daily observations for all five electricity futures contracts traded on NYMEX, where the only differences between these contracts are in the size and delivery location.[8]

Similar to futures markets for other commodities, electricity futures rarely require physical delivery of electricity.[9] In most instances, the contract is closed by entering into an offsetting trade. NYMEX offers electricity futures contracts for different delivery locations because of the regional differences in the production of electricity.[10] In this study we focus only on electricity futures contracts that are delivered at the California-Oregon Border (COB).

The COB futures contract trades in units of 432 MWh delivered over a one month period. The exchange sets a minimum price fluctuation of 1 cent per MWh, with no limits on maximum price fluctuation. Trading in any given futures contract terminates on the fourth business day prior to the first day of the delivery month. For the COB futures, the delivery location is the Interconnection point at the COB of the pacific northwest/pacific southwest AC inter-tie, including the California Oregon Trans Mission project.

Two important reasons prompted us to omit data for the years 1996 and 1997 and consider only the years 1998 and 1999 for the present study. First, because the market for electricity futures started only in March 1996, it is likely that in the beginning years, observed futures prices will reflect the inexperience of industry participants, and may not represent the true equilibrium pricing structure.[11] Second and perhaps more importantly, futures trading in the early years (1996 and 1997) was not very active, and the financial contracts used for trading these futures was constantly developing.

The spot price series represented the daily wholesale closing price at COB. Figure 1, displays daily spot electricity prices posted on the California-Oregon Border market for the period January 2, 1998 through January 1, 2000. As evident from the graph, the behavior of electricity prices is characterized by temporary upward spikes, high volatility and frequent extreme values. Moreover, the

[8] For a complete description of the various futures electricity contracts traded on NYMEX, see Emery and Liu (2002) and the NYMEX website.

[9] According to NYMEX, less than 2% of electricity futures result in actual delivery.

[10] For example, California-Oregon Border (COB) delivery point primarily uses hydro, Palo Verde uses natural gas, PJM uses nuclear etc.

[11] Figlewski (1984) reports that market prices for stock index futures initially (at inception) deviated significantly from theoretical values, but converged toward predicted values after a few months of trading.

price series exhibits significant positive skewness. These features are generally attributed to the fact that electricity cannot be economically stored.[12]

Figure 1 to go about here.

Data for futures prices included several different series for each of the contracts traded. All of the electricity futures contracts ran for six consecutive months. Limiting our sample period for the years 1998 and 1999 resulted in a total of 16 overlapping six months contracts; the first began on April 6, 1998 and expired on September 25, 1998. The next contract starts one month later (May 5, 1998) and ends one month later (October 27, 1998), and so on. The last contract starts on July 6, 1999 and expires on January 1, 2000. While the futures price for each contract is independent of other contracts, spot prices overlap. Since there is more than one and half years of data (and less than two full years) in our sample period, we have three non-overlapping six-months contracts.

It is important to point out that in this study, we conduct empirical testing on three different sets of data. The first set represents the 16 futures contracts with their corresponding spot prices. The second dataset is the forward premium series which is derived from synchronizing these 16 contracts with respect to maturity. Finally, we conduct some tests on a subset of the contracts that are non-overlapping. These contracts are the 1st, 7th, and 13th contracts from the original sequence of 16 contracts.

3 General Characteristics of Spot and Futures Electricity Markets

Descriptive statistics for daily spot and futures prices for each of the 16 electricity futures contracts are presented in Table 1. The same statistics for daily spot and futures returns are presented in Table 2. Several important features of the electricity price series stand out. Both the spot returns and the futures returns have means that are not significantly different from zero. The volatility in the spot price series is five to fifteen times higher than the volatility in the futures price series. Similar differences are observed for the returns of the two series. All of the spot price as well as the spot return series exhibit a significant level of positive skewness whereas the futures price and return series do not exhibit such behavior.

[12]Market prices are volatile because inventories cannot be used to smooth supply and demand and positive skewness is the result of expected demand being higher than or more volatile than capacity.

Tables 1 and 2 to go about here.

Bessembinder and Lemmon (2002) point out that positive skewness in the wholesale electricity prices reflects the possibility of large upward swings in the marginal production costs. Given the relative fixed retail prices, this may cause industry profits to decline. To counter this effect, the industry as a whole will have an incentive to hedge against production cost hikes by purchasing power at fixed futures prices. This demand for fixed forward prices is likely to result in a positive forward premium as well as an active market in electricity futures.

We test for the stationarity of the price series using the Augmented Dickey Fuller (1979) unit root test. Consider the following AR(1) process:

$$p_t = c + \rho p_{t-1} + e_t$$

If the parameter ρ is 1, then the series p_t is non-stationary which is tested against the one sided hypothesis, $\rho < 1$, that is, the series is stationary. This approach requires estimation of the following equation:

$$\Delta p_t = \mu + \gamma p_{t-1} + \delta_1 \Delta p_{t-1} + \delta_2 \Delta p_{t-2} + \cdots + \delta_p \Delta p_{t-n} + \epsilon_t \tag{1}$$

where p_t is the spot and future price series, $\gamma = \rho - 1$, ρ is the autocorrelation between p_t and p_{t-1} and ϵ_t is the error term. The higher order correlations are controlled by adding lagged difference terms of the dependent variable to the right hand side of the equation. In this procedure, the null hypothesis is taken as the unit root and tested via:

$$H_0 : \gamma = 0$$

against the one sided alternative:

$$H_1 : \gamma < 0$$

Unit root test results for the spot and futures price series are presented in Table 3. The results indicate that all the series, except S_{13}, are non-stationary and follow a random walk. The spot and futures returns series tests exhibit similar results.[13] Together, these tests indicate that we cannot reject the notion of weak form efficiency in the electricity market.

[13] The results for the returns series are identical to those for the price series and are therefore not shown here.

Table 4 records the autocorrelation results for the first differenced series of the three non-overlapping contracts. As the results in table 4 show, there is no significant autocorrelation present and none appears to be persistent in the spot return series. The futures return series however, exhibits some level of autocorrelation for only one of the contracts examined. Once again, the lack of any significant serial correlation in the daily spot returns is consistent with an electricity market that is at the very least, weak-form efficient.[14]

Tables 3 and 4 to go about here.

3.1 The Forward Premium in Electricity Futures contracts

We employ a research design that is commonly used in the literature to test forward and futures pricing theories in equity, commodities, fixed income derivatives and foreign exchange markets. Essentially, we calculate the ex-ante premium in the forward price by measuring the ex-post differential between futures prices and realized delivery date spot prices.[15] For each of the sixteen futures contracts in our sample, we calculate the daily futures premium (or discount) as follows:

$$(Premium)_t = (F_t - S_t)/S_t, \quad t = 1, 2, \cdots, 180\ days$$

Where F_t is the futures price and S_t is the spot price at time period t. For all of the 16 contracts, we have a total of 2880 independent daily futures premium observations. A common problem in the literature with studying forward premiums is that random shocks to asset prices are large relative to any premium in the futures price, causing tests conducted in small samples to lack statistical power.[16]

As a way of working around the problem of small samples, we employ a technique that is similar in spirit to the well-known event-study methodology. Essentially, we synchronize the start and the expiration dates for each of the 16

[14]A competitive electricity market is necessary but not sufficient condition for market efficiency. The competitive nature of the wholesale power markets has been the subject of much debate. Green and Newbery (1992), Newbery (1995) and Wolfram (1999) conclude that there are an insufficient number of suppliers in the British power markets. Borenstein and Bushnell (1999) find that California electricity markets have some potential for market power. Joskow and Kahn (2001) indicate that recent electricity prices in California "far exceeded competitive levels".

[15]It is important to note that in this paper, we do not distinguish between futures premium and forward premium. Both terms are used interchangeably and are only referring to traded futures prices relative to the spot price.

[16]Fama and French (1987) test whether futures risk premiums are nonzero using 9 to 18 years of data on 22 commodity markets. They conclude that "the evidence is not strong enough to resolve the long-standing controversy about the existence of nonzero expected premiums."

contracts. This procedure allows us to document the behavior of the forward premium over the life of a standard 6-months futures contract. Figure 2 plots the mean forward risk premium for all 16 futures contracts traded during our sample period. Note that each point on the graph represents the mean value of approximately sixteen independent observations. The futures premium is shown to be an increasing function of time to maturity and reaches zero at expiration date.[17]

Figure 2 to go about here.

Before we estimate the slope of the trend line in Figure 2, which gives the mean forward premium for electricity prices, it is important to first confirm that the premium decays in a linear trend toward a zero mean at expiration. That is, the premium does not follow a quadratic or any other nonlinear pattern. While this behavior is evident from the graph in Figure 2, we attempt to fit the futures premium series to a number of nonlinear specifications without much success. Thus, we proceed to estimate the slope of the trend line using ordinary least squares regression of the futures premium series against a linear time trend. The average daily futures premium is estimated from the following regression:

$$Premium = -0.01 + .001328(Trend)$$

The coefficient of trend is found to be positive and highly significant at 1% level with a t-statistic of 9.75. The estimated forward premium value of .1328 percent per day or approximately 4 percent per month is robust to a variety of other model specifications.[18]

The estimated forward premium appears to be large relative to similar premia documented in the literature for other commodities. There are two possible explanations for observing such a large premium. It may indeed be the case that the unique features of electricity as a commodity require a high premium to bring equilibrium to a market where supply and demand conditions are volatile. That is, the value obtained from hedging price risk in electricity markets is perhaps worth much more than in other more stable commodities. On the other hand, such a large premium also suggests that the power markets may suffer from limited industry outsider participation and thus are not sufficiently integrated with the broader financial markets. Only the passage of time will affirm either of these explanations.

[17] Due to the NYMEX rule of no trading 4 days prior to contract expiration, we observe a slight negative premium two or three days prior to contract expiration.

[18] To confirm the linearity of the forward premium over time, we smooth the premium series using the Hodrick-Prescott (1997) filter. This method provides a good estimate of the long-term trend in a series. Using their filter we obtain an identical estimate for the estimated premium with a t-statistic of 463 and an R-squared of 99.9 percent.

3.2 Trading Patterns in Electricity Futures

Using the same event-study methodology with respect to synchronizing the contract period, we examine trading volume and the number of open interest contracts for that same time period. Figure 3 depicts the volume of trading in COB electricity futures. It is worth noting that volume of trading gradually increases over the life of the sixth months contracts. There is a sharp increase in trading volume as we approach the 30-day mark and into the days before the contract closes. The behavior of trading volume over the six-months contract period is found to be well represented by an exponential function of time to maturity.

Figure 3 to go about here.

Figure 4 shows the volume of open interest in electricity futures contracts throughout the six-months contracts. Consistent with the previous graph depicting trading volume, open interest volume is shown to gradually increase as the contracts approach maturity. Note the significant drop in the volume of open contracts beyond the 30-day mark and towards the expiration date, where the vast majority of these contracts are closed out.

Figure 4 to go about here.

4 The Relation between Spot and Futures Markets

4.1 Estimating the Hedge Ratio

The hedge ratio is the ratio of the position taken in the futures contracts that will exactly offset the size of the exposure in the spot market. An optimal hedge ratio is derived by minimizing the variance of the investor's (hedger) hedged portfolio returns. Let r_{t+1} represent the return, s_{t+1}, the spot price, f_{t+1}, the futures price in period $t+1$ and h_t be the hedge ratio in period t. An investor's return who is going long in the spot market and short in the futures market would be:

$$r_{t+1} = s_{t+1} - h_t f_{t+1}$$

The variance on the return can be written as:

$$var_t(r_{t+1}) = var_t(s_{t+1}) + h_t^2 var_t(f_{t+1}) - 2h_t cov_t(s_{t+1}, f_{t+1})$$

The minimum variance hedge ratio is calculated by taking the derivative of the above expression with respect to h_t and setting it to zero, which gives:

$$h_t = \frac{cov_t(s_{t+1}, f_{t+1})}{var_t(f_{t+1})} \tag{2}$$

The minimum variance hedge ratio given in equation (2) can generally be estimated by regressing futures returns on spot returns. However, estimating hedge ratios using ordinary least squares provides static estimates that are not very useful given the volatile behavior of electricity prices.

Sudden spikes and periods of increased volatility characterize most spot and futures electricity time series. Moreover, the change in the volatility of forward prices at different horizons is important for both derivative pricing as well as dynamic hedging. Most commodities exhibit a pattern of forward price volatility which is declining with contract horizon. This effect is attributed to the smoothing of expectations over the life of the futures contract. Under such circumstances, the assumption of a constant variance over time is clearly not appropriate. In order to capture the potential changes in the variance, the conditional variance can be modeled as a function of past errors as well as its own lags. This is best accomplished by using an ARCH type model introduced by Engle (1982) and generalized as GARCH by Bollerslev (1986).

To estimate the hedge ratio using a GARCH specification, spot and futures daily returns are modeled using a standard GARCH (1,1) specification.[19] Specifically, we estimate the following:

$$r_t^S = \alpha r_t^F + \epsilon_t \tag{3}$$

$$\sigma_t^2 = \beta_1 + \beta_2 \epsilon_{t-1}^2 + \beta_3 \sigma_{t-1}^2 \tag{4}$$

The mean equation (3) shows spot returns (r_t^S) as a function of future returns (r_t^F) and the error term. The conditional variance (σ_t^2) equation (4) is specified as a function of three terms; the mean (β_1), the news about volatility from the previous period (ϵ_{t-1}^2) and the previous period's forecast variance (σ_{t-1}^2).

Table 5 presents the estimated hedge ratios for each of the 16 futures contracts. The coefficient for the hedge ratio is found to be positive and statistically significant at the 1$\%$ confidence level in 10 of the 16 contracts. The mean hedge

[19] Bystrom (2000) examines several alternative specifications for estimating hedge ratios for electricity futures traded on the Nordic Power Exchange Nord Pool. He finds that a standard GARCH model works better than more elaborate specifications.

ratio for the 10 significant values is 1.629. This estimate of the hedge ratio may appear high relative to hedge ratios for other commodities. However, due to the uniqueness of electricity as a non-storable commodity, the price volatility in the spot market is typically many times higher than the price volatility in the futures market. This characteristic is unparalleled in any other futures market.

Table 5 to go about here.

Equally important to the estimation procedure are the significance of the conditional variance estimates. The estimated coefficients for last period's forecast variance (the GARCH term) are significant in every regression. This is consistent with a price behavior that is subject to sudden spikes in one period which causes sudden increases in volatility in the next period. The ARCH term is also significant in 11 of the 16 contracts. These results are consistent with those obtained by Bystrom (2000) for the Nordic Power Pool, and suggest that a GARCH representation might be a reasonable assumption for the process generating returns in the electricity market.[20]

4.2 Estimating the Dynamic Relation between Spot and Futures Prices

In this section we attempt to model the relation between the spot and futures electricity prices. As alluded to earlier, wholesale electricity prices are characterized by periods of tranquility that are often followed by periods of sudden increases in the levels of volatility. This behavior is consistent with the *asymmetric ARCH* type models developed by Engle and Ng (1993), which allows for asymmetric shocks to volatility. Among the specifications that allow for asymmetric shocks to volatility, we estimate the EGARCH or the *exponential GARCH* model which was proposed by Nelson (1991). The mean equation is modeled as:

$$f_t = \delta_1 + \delta_2 s_t + \delta_3 \sigma_t + \epsilon_t \tag{5}$$

where f_t represents the futures price and s_t the spot price. σ_t is the conditional standard deviation. The specification for the conditional variance is given by:

$$\log(\sigma_t^2) = \gamma_1 + \gamma_2 \log(\sigma_{t-1}^2) + \gamma_3 \mid \frac{\epsilon_{t-1}}{\sigma_{t-1}} \mid + \gamma_4 \frac{\epsilon_{t-1}}{\sigma_{t-1}} \tag{6}$$

[20]The standard approach to choosing a particular return generating process is to test the results against alternative specifications. We tested this model against other higher order ARCH and GARCH models including Asymmetric ARCH type specifications. None performed better than the simple first order GARCH model.

The left-hand side is the log of the conditional variance implying that the leverage effect as shown by γ_4 is exponential and that the forecasts of the conditional variance are non-negative. Given the standard formulation between futures and spot prices, this specification appears particularly attractive for modeling the behavior of such derivative securities. We use this conditional variance specification to study the dynamic relation between spot and futures electricity prices.

For this estimation we use three consecutive but non-overlapping futures contracts.[21] As indicated before, the first contract, denoted as 1, starts on April 6, 1998 and matures on September 25, 1998. The second contract, denoted as contract 2, starts on October 25, 1998 and ends on March 26, 1999. The third contract, denoted as 3, starts on April 15, 1999 and matures on September 27, 1999. Table 6 presents the estimated coefficients for the EGARCH model applied to these three futures contracts.

Table 6 to go about here.

The results in Table 6 indicate that the relation between spot and futures electricity prices can be reasonably captured by the exponential GARCH specification described by Nelson (1991). All of the estimated coefficients are found to be significant at the 95$\%$ confidence level with an average R-squared above 80$\%$. In the mean equation, the slope coefficient is highly significant in all three contracts. More importantly, the GARCH term (σ_{t-1}^2) is very significant not only in the variance equation, but also in the mean equation. This indicates that conditional volatility is a major determinant of the dynamic relation between spot and futures electricity prices.

The "leverage effect" is estimated by the coefficient γ_4 in Table 6. In all three contracts this coefficient is highly significant indicating that the impact of a leverage effect will be asymmetric. In the first contract this estimate is negative while in contracts 2 and 3 this estimate is positive. Moreover, the EGARCH term in the variance equation, represented as (γ_2) in equation 6, is shown to be not very close to one in all three contracts. This result indicates that volatility shocks are not likely to be very persistent. This behavior will be further examined using impulse response functions in the next section.

[21] It should be noted that to characterize the behavior of spot and futures prices, overlapping observation can obscure the true structure of the relation. However, in the previous section we estimated hedge ratios using the full sample of 16 contracts since each futures contract and its corresponding spot prices is unique with respect to its start and expiration dates.

5 Vector Autoregression of the Spot and Futures Returns

As pointed out before, the traditional no-arbitrage cost-of-carry models of pricing forward contracts do not readily apply to power markets. Thus it may be difficult to theoretically establish the usual link between spot and forward prices. An alternative, non-structural approach is to use a vector autoregression (VAR) to model the relationship between spot and futures prices. This methodology is particularly useful in analyzing the dynamic impact of random disturbances on the estimated relationship.

We estimate a VAR model to assess the time-series behavior of spot and futures electricity return series based on the following general model:

$$x_t = A_0 + \Sigma_{l=1}^{g} A_l x_{t-l} + \eta_t \tag{7}$$

$$x_t = \begin{pmatrix} f_t \\ s_t \end{pmatrix}$$

where s_t and f_t are the spot and futures daily return series for each of the 16 futures contracts in our sample period. Since there is no theoretically justified method of choosing the lag length for the VAR, we employ the Bayesian estimation criterion function suggested by Geweke and Reese (1981), which is minimized for a VAR of order one. Table 7 presents results for the VAR(1) estimation.

Table 7 to go about here.

As expected, there is a positive relation between current and future values of both the spot and futures prices. In every statistically significant estimate in the VAR system, the coefficient is positive. Moreover, in every one of the 16 contracts estimated, the spot equation is found to be more significant than the futures equation. This finding is consistent with an electricity market in which spot prices are significantly more impacted by current events than futures electricity prices.

To assess further the implications of the estimated VAR(1) for the time-series properties of the spot and futures returns, we conduct what amounts to a numerical simulation of the VAR system. Specifically, an impulse-response function traces the response of one of the variables to a change in one of the model's innovations. For instance, we trace the effect on current and future values of both the spot and futures returns resulting from a one-standard deviation-shock to one of the innovations. If the residuals are not correlated, the impulse response function for one innovation measures the effect of one standard deviation shock today on current and future values of the spot and futures returns.

To account for potential correlation between the innovations, we orthogonalize the two process using a Cholesky decomposition of the covariance matrix of the errors. Assuming that both the spot and futures returns are at their long-run averages, Figure 4, shows the effect of two impulse vectors on VAR(1), where the solid line and dashed lines represent the spot returns and the futures returns respectively. These vectors correspond to a shock of magnitude 1 to the process as the basis for the orthogonalization, where in the first case the spot return is used as the basis, and in the second case the futures returns is used as the basis.

Figure 5 to go about here.

The graph at the top of Figure 5 shows that the positive shock to the spot price dies out after eight days with a half-life of about four days. This shock results in a positive shock to the futures price series, which peaks out at two to three days, and dies out gradually over the next nine to ten days. Moreover, the shock causes both the spot and the futures prices to move in the same direction as they reach their steady state, with a much smaller impact on the futures price during the first two days.

The bottom part of Figure 5 shows that a positive shock to the futures price has a much less impact on both the spot and futures prices. This is evident when we compare the magnitude of the scales between the two graphs. The movement in the spot price series tends to be insignificant in relative magnitude. Interestingly, regardless of the impact of the shock, both the spot and futures returns seem to converge to their long-run steady state within about nine to ten days.

In general, the VAR(1) estimation and the impulse response analysis provides more insight into the behavior of spot and futures prices. Positive shocks to spot prices have significantly more impact on both current and future values of electricity than shocks to futures prices. Moreover, shocks to both spot and futures prices appear to be relatively short-lived with a half-life of about four to five days before they converge to their long-run equilibrium.

6 Summary and Conclusions

The recent deregulation of the electric utility industry in many parts of the United States has created a competitive wholesale power market that exhibits a level of price volatility unparalleled in traditional commodity markets. The reason for this price behavior is attributed to the nature of how electricity is produced and consumed, inelastic demand, seasonal effects and most importantly, the non-storability of electricity. These unique characteristics of the supply and demand for electricity are reflected in the behavior of wholesale power prices as well as in the dynamic relation between the spot and futures prices.

This study investigates the empirical relation between spot and futures electricity prices traded on NYMEX that are for delivery at the California-Oregon Border. We examine the characteristics of the market using daily data for the years 1998 and 1999. Unit root tests and autocorrelation results on the spot and futures price series indicate that the behavior of the electricity market is generally consistent with efficient markets.

The forward risk premium for six-month futures contracts is estimated to be about .1328 percent per day or 4 percent per month. The estimated forward premium is large relative to similar premia documented in the literature for other commodities. However, because of the unique features of electricity as a non-storable commodity this large premium may be in fact be required in order to bring equilibrium to a futures market where supply and demand conditions are so volatile. In other words, the value of hedging price risk in electricity markets may perhaps be worth much more than in other more stable commodities. On the other hand, such a large premium may also suggest that the power markets may presently suffer from limited industry outsider participation and thus may not be sufficiently integrated with the broader financial markets. Only the passage of time will affirm either of these explanations.

Using a GARCH specification, we estimate minimum variance hedge ratios. The mean hedge ratio for the 16 futures contracts traded during the period April 6, 1998 through January 1, 2000 is estimated to be 1.629. Once again the hedge ratio is high relative to its value for other commodities. However, due to the uniqueness of electricity as a non-storable commodity, the price volatility in the spot market is typically many times higher than the price volatility in the futures market.

Finally, we study the dynamic relation between spot and futures prices using both an Exponential GARCH model and a vector autoregression representation. Given the behavior of the spot and futures price series, the EGARCH model appears to be a reasonable description of the dynamic relation between spot and futures electricity prices. The vector autoregression of spot and futures prices reveals that positive shocks to spot prices have significantly more impact on both current and future values of electricity than shocks to futures prices. Moreover, shocks to both spot and futures prices appear to be relatively short-lived with a half-life of about four to five days before they converge to their long-run equilibrium.

Future research into this relatively new market should explore a variety of unresolved issues. For instance, the magnitude of the forward risk premium in electricity prices may significantly change over time as more industry outsiders are attracted into trading in spot and futures electricity markets. More research into the behavior of the futures market and its relation with the spot price is needed to better understand the effectiveness of hedging in this market. Modeling the theoretical relation between spot and futures prices for non-storable commodities will shed new light on the behavior of this highly volatile electricity market.

Acknowledgement The authors would like to thank Jerome Huhman of the *Commodity Futures Trading Commission* for helping us obtain the data used in this study.

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Table 1: Summary statistics of the daily spot and futures price series for all of the sixteen futures contracts

Series	Mean	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.
S1	31.11	17.25	1.27	4.23	39.95	0.00
S2	31.95	16.98	1.17	4.17	35.23	0.00
S3	34.66	15.33	1.28	4.94	52.71	0.00
S4	37.21	14.31	1.69	5.20	82.27	0.00
S5	34.72	14.59	1.83	5.86	107.40	0.00
S6	29.17	11.15	3.15	14.80	880.65	0.00
S7	25.98	8.31	2.76	14.60	818.88	0.00
S8	24.91	7.78	3.52	20.33	1751.06	0.00
S9	24.66	7.72	3.72	21.65	2001.22	0.00
S10	24.11	5.12	1.13	4.43	35.76	0.00
S11	27.28	8.95	1.71	6.27	114.48	0.00
S12	29.88	9.86	1.67	6.08	105.61	0.00
S13	32.29	8.85	1.82	6.72	136.75	0.00
S14	36.66	11.09	1.09	3.72	26.91	0.00
S15	38.76	11.37	0.81	3.00	13.42	0.00
S16	38.41	10.80	1.07	3.53	24.65	0.00
F1	28.56	1.03	-0.26	1.91	7.30	0.02
F2	29.82	1.64	1.74	7.86	182.47	0.00
F3	32.02	1.60	0.79	4.10	19.04	0.00
F4	28.88	2.77	0.74	2.63	11.82	0.00
F5	25.30	2.65	0.15	2.03	5.10	0.07
F6	21.22	1.85	-0.39	1.88	9.14	0.01
F7	19.54	1.51	0.36	2.42	4.34	0.11
F8	17.65	1.31	0.37	2.22	5.82	0.05
F9	17.81	1.47	1.76	7.67	170.33	0.00
F10	27.10	2.11	1.69	6.12	106.24	0.00
F11	43.79	3.40	0.79	2.42	14.40	0.00
F12	41.89	2.86	-0.18	3.48	1.91	0.38
F13	31.84	1.90	0.26	2.06	5.76	0.05
F14	33.36	2.05	0.44	2.20	7.19	0.02
F15	35.37	1.47	-0.68	3.98	14.41	0.00
F16	31.27	1.53	-0.17	2.65	1.22	0.54

Table 2: Summary statistics of the daily spot and futures return series for all of the sixteen futures contracts

Series	Mean	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.
S1	0.0193	0.1956	0.84	5.04	33.55	0.00
S2	0.0256	0.1913	0.85	5.32	39.87	0.00
S3	0.0231	0.1804	1.11	6.12	70.50	0.00
S4	0.0153	0.1469	0.74	4.84	26.87	0.00
S5	0.0027	0.1409	0.54	7.61	107.63	0.00
S6	-0.0009	0.1208	0.54	11.63	363.29	0.00
S7	0.0046	0.1174	0.60	12.55	444.39	0.00
S8	0.0068	0.1303	0.34	9.24	188.95	0.00
S9	0.0104	0.1301	0.29	9.29	191.55	0.00
S10	0.0128	0.1315	1.44	9.30	230.36	0.00
S11	0.0154	0.1587	0.75	6.04	55.34	0.00
S12	0.0209	0.1764	0.79	5.24	36.23	0.00
S13	0.0193	0.1848	0.82	4.88	30.09	0.00
S14	0.0231	0.2022	1.27	6.42	87.08	0.00
S15	0.0170	0.2027	1.34	6.53	94.83	0.00
S16	0.0122	0.1786	1.47	8.58	190.79	0.00
F1	-0.0002	0.0165	-0.09	4.82	16.17	0.00
F2	0.0021	0.0181	1.06	6.69	87.13	0.00
F3	0.0004	0.0197	0.34	4.54	13.74	0.00
F4	0.0009	0.0254	0.66	5.87	48.10	0.00
F5	-0.0010	0.0265	-0.32	3.97	6.60	0.03
F6	-0.0004	0.0239	-0.30	3.08	1.75	0.41
F7	0.0004	0.0235	-0.13	2.78	0.55	0.76
F8	0.0000	0.0235	0.17	2.70	1.01	0.60
F9	0.0019	0.0233	0.19	4.65	13.83	0.00
F10	0.0029	0.0220	0.92	4.94	34.45	0.00
F11	-0.0008	0.0182	-0.08	3.07	0.17	0.91
F12	-0.0009	0.0194	-0.61	3.51	8.42	0.01
F13	0.0014	0.0138	-0.65	6.14	55.75	0.00
F14	0.0013	0.0147	0.07	3.84	3.52	0.17
F15	-0.0006	0.0161	-0.37	4.49	13.39	0.00
F16	0.0002	0.0173	-0.40	3.16	3.21	0.20

Table 3: Results of augmented Dickey-Fuller unit root test. The estimated coefficients are as shown in equation (1). An asterisk ($*$) indicates that the ADF statistic is significant at the 95% confidence level and the series has a unit root.

Price Series	γ	ADF-stat	DW stat
Future Contract 1	-0.09*	-2.19	2.00
Future Contract 2	-0.04*	-1.55	2.00
Future Contract 3	-0.01*	-0.54	2.00
Spot Series 1	-0.08*	-2.47	1.94
Spot Series 2	-0.17*	-2.90	2.00
Spot Series 3	-0.29	-4.55	2.02

Table 4: Autocorrelation estimates of the first difference in futures and spot price series for three consecutive non-overlapping contracts.

First Difference in Futures Price Series									
	04/06/98 to 09/25/98			10/25/98 to 03/26/99			04/15/99 to 09/27/99		
Lag	AC	Q-stat	Prob.	AC	Q-stat	Prob.	AC	Q-stat	Prob.
1	-0.07	0.60	0.43	-0.06	0.45	0.49	-0.11	1.55	0.21
2	-0.17	4.30	0.11	-0.11	2.01	0.36	-0.10	3.01	0.22
3	-0.005	4.30	0.23	0.07	2.67	0.44	0.13	5.39	0.14
4	0.15	7.20	0.12	0.03	2.80	0.59	0.02	5.45	0.24
5	-0.04	7.42	0.19	-0.05	3.24	0.66	-0.16	9.01	0.10
6	-0.20	12.60	0.05	0.06	3.84	0.69	-0.12	10.94	0.09
7	0.01	12.62	0.08	0.06	4.40	0.73	0.12	12.89	0.07
8	0.02	12.69	0.12	-0.05	4.77	0.78	-0.19	18.06	0.02
9	-0.02	12.74	0.17	-0.09	5.97	0.74	0.11	19.86	0.01
10	-0.19	17.49	0.06	-0.005	5.98	0.81	-0.10	19.87	0.03
11	-0.005	17.49	0.09	-0.14	8.75	0.64	-0.03	20.07	0.04
12	0.05	17.93	0.11	0.02	8.84	0.71	0.10	21.62	0.04
First Difference in Spot Price Series									
1	0.10	1.40	0.23	0.15	2.91	0.08	0.02	0.07	0.77
2	-0.20	6.57	0.03	-0.18	7.05	0.02	-0.07	0.84	0.65
3	-0.08	7.47	0.05	-0.25	14.98	0.002	-0.27	10.53	0.01
4	-0.006	7.48	0.11	-0.13	17.34	0.002	-0.22	16.62	0.002
5	-0.10	8.77	0.11	0.001	17.34	0.004	0.07	17.37	0.004
6	0.08	9.75	0.13	-0.08	18.22	0.006	-0.13	19.64	0.003
7	0.10	11.24	0.12	-0.03	18.38	0.01	0.18	24.29	0.001
8	-0.10	12.61	0.12	-0.01	18.41	0.01	0.11	26.15	0.001
9	-0.13	14.83	0.09	0.08	19.27	0.02	-0.08	27.03	0.001
10	-0.10	16.23	0.09	0.01	19.29	0.03	0.02	27.12	0.002
11	-0.16	19.84	0.04	-0.005	19.29	0.05	-0.21	33.55	0.00
12	-0.03	20.05	0.06	-0.06	19.80	0.07	0.08	34.54	0.001

Table 5: GARCH(1,1) Estimation of the hedge ratio for all of the sixteen futures Contracts. The estimated coefficients are as shown in equation (3) and (4). An asterisk ($*$) indicates that the coefficient is significant at the 95% confidence level.

Contract	α	β_2	β_3	Durbin-Watson	Std. Error	AIC
1	2.08*	0.07	0.90*	2.08	0.19	-0.57
	(2.37)	(1.30)	(17.74)			
2	0.61*	0.65*	0.61*	2.05	0.19	-0.76
	(3.36)	(4.05)	(10.16)			
3	0.82*	0.35*	0.70*	1.94	0.18	-1.01
	(4.67)	(2.77)	(12.03)			
4	0.41*	0.54*	0.54*	1.48	0.16	-1.30
	(2.62)	(4.14)	(7.12)			
5	0.01	0.60*	0.46*	1.43	0.14	-1.50
	(0.04)	(3.78)	(7.06)			
6	0.26	0.54*	0.37*	1.51	0.12	-1.85
	(1.47)	(3.39)	(3.43)			
7	0.56*	0.51*	0.34*	1.60	0.12	-1.91
	(2.10)	(2.12)	(2.22)			
8	1.00*	0.42*	0.46*	1.77	0.13	-1.66
	(3.29)	(2.12)	(2.98)			
9	0.62	0.43*	0.43*	1.76	0.13	-1.58
	(1.75)	(1.94)	(2.83)			
10	0.79	0.27	0.70*	2.39	0.13	-1.48
	(1.74)	(1.72)	(4.66)			
11	2.56*	0.15*	0.86*	2.28	0.16	-1.19
	(4.89)	(2.22)	(17.96)			
12	1.43	0.08*	0.91*	2.29	0.18	-0.74
	(1.83)	(2.45)	(34.69)			
13	-0.78	0.45*	0.60*	2.20	0.18	-0.67
	(0.57)	(3.49)	(6.46)			
14	2.95*	0.01	0.93*	2.29	0.19	-0.44
	(2.37)	(0.56)	(23.78)			
15	3.17*	-0.02	1.03*	2.30	0.19	-0.53
	(4.70)	(0.21)	(4.31)			
16	2.13*	0.19	-0.35*	2.43	0.17	-0.71
	(3.35)	(1.16)	(2.03)			

Table 6: Modeling the relation between the spot and futures electricity prices using an Exponential GARCH specification for three consecutive non-overlapping futures contracts. The estimated coefficients are as shown in equation (5) and (6). An asterisk($*$) indicates that the coefficient is significant at the 95% confidence level.

Contract	δ_1	δ_2	δ_3	γ_1	γ_2	γ_3	γ_4	R^2
1	3.38*	0.02*	-5.92*	-0.95*	0.87*	-0.11*	-0.31*	0.77
	(149.05)	(3.46)	(9.05)	(2.30)	(16.96)	(2.02)	(5.88)	
2	2.63*	0.04*	6.84*	-0.75*	0.89*	-0.01	0.30*	0.86
	(59.28)	(3.14)	(11.33)	(2.24)	(19.96)	(0.19)	(7.19)	
3	3.29*	0.01*	5.35*	-0.62*	0.91*	-0.14*	0.38*	0.82
	(125.40)	(2.11)	(20.24)	(2.40)	(30.81)	(2.30)	(7.79)	

Table 7: VAR(1) Estimation of the spot and futures price series as represented by the system in equation (7): Contracts from 1 through 8. An asterisk ($*$) indicates that the coefficient is significant at the 95% confidence level.

S_{it}/F_{it}	$S_{i,t-1}$	$F_{i,t-1}$	R^2	Std. Error	AIC
S_{1t}	-0.06	4.09*	0.11	0.18	-0.53
	(0.71)	(3.88)			
F_{1t}	-0.004	-0.06	0.008	0.01	-5.34
	(0.50)	(0.71)			
S_{2t}	-0.03	2.05*	0.04	0.18	-0.51
	(0.36)	(2.22)			
F_{2t}	0.005	0.12	0.016	0.018	-5.09
	(0.55)	(1.26)			
S_{3t}	.01	2.74*	0.09	0.17	-0.67
	(0.10)	(3.39)			
F_{3t}	0.0006	0.17	0.03	0.02	-5.04
	(0.06)	(1.91)			
S_{4t}	0.25*	1.26*	0.10	0.15	-0.89
	(2.88)	(2.27)			
F_{4t}	-0.02	0.23*	0.08	0.02	-4.55
	(1.86)	(2.57)			
S_{5t}	0.28*	0.09	0.8	0.13	-1.12
	(3.14)	(0.18)			
F_{5t}	-0.03	0.22*	0.07	0.02	-4.45
	(1.79)	(2.41)			
S_{6t}	0.23*	0.23	0.05	0.12	-1.35
	(2.59)	(0.48)			
F_{6t}	-0.03*	0.08	0.04	0.02	-4.63
	(2.09)	(0.88)			
S_{7t}	0.17	0.01	0.03	0.11	-1.41
	(1.85)	(0.02)			
F_{7t}	-0.03	-0.03	0.02	0.02	-4.65
	(1.61)	(0.40)			
S_{8t}	0.10	0.10	0.01	0.13	-1.23
	(1.05)	(0.19)			
F_{8t}	-0.01	-0.01	0.003	0.02	-4.60
	(0.62)	(0.09)			

Continued VAR(1) estimation of the spot and futures price series as represented by the system in equation (7): Contracts from 9 through 16. An asterisk ($*$) indicates that the coefficient is significant at the 95% confidence level.

S_{it}/F_{it}	$S_{i,t-1}$	$F_{i,t-1}$	R^2	Std. Error	AIC
S_{9t}	0.10	0.16	0.01	0.13	-1.22
	(1.13)	(0.32)			
F_{9t}	-0.01	0.11	0.01	0.02	-4.65
	(0.61)	(1.15)			
S_{10t}	-0.32*	2.24*	0.17	0.12	-1.34
	(3.51)	(4.45)			
F_{10t}	-0.05*	0.29*	0.12	0.02	-4.66
	(3.39)	(3.03)			
S_{11t}	-0.23*	1.77*	0.06	0.16	-0.75
	(2.43)	(2.06)			
F_{11t}	-0.03*	0.21*	0.08	0.01	-5.18
	(2.87)	(2.29)			
S_{12t}	-0.19*	2.09*	0.07	0.17	-0.62
	(2.14)	(2.54)			
F_{12t}	-0.02*	0.09	0.04	0.02	-5.02
	(2.30)	(0.99)			
S_{13t}	-0.10	2.55*	0.05	0.17	-0.58
	(1.13)	(2.19)			
F_{13t}	-0.003	-0.11	0.01	0.01	-5.65
	(0.47)	(1.24)			
S_{14t}	-0.18*	2.50*	0.05	0.19	-0.41
	(1.96)	(2.03)			
F_{14t}	-0.01	0.02	0.02	0.01	-5.56
	(1.57)	(0.25)			
S_{15t}	-0.20*	2.98*	0.07	0.19	-0.40
	(2.23)	(2.69)			
F_{15t}	-0.01	0.13	0.03	0.01	-5.30
	(1.82)	(1.42)			
S_{16t}	-0.25*	3.22*	0.13	0.16	-0.73
	(2.87)	(3.54)			
F_{16t}	-0.01	0.01	0.03	0.01	-5.23
	(1.91)	(0.15)			