AN ANALYSIS OF THE RELATIONSHIP BETWEEN ELECTRICITY AND NATURAL-GAS FUTURES PRICES

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This article analyzes the relationship between electricity futures prices and natural-gas futures prices. We find that the daily settlement prices of New York Mercantile Exchange's (NYMEX's) California–Oregon Border (COB) and Palo Verde (PV) electricity futures contracts are cointegrated with the prices of its natural-gas futures contract. The coefficient of natural-gas futures prices in our model of COB electricity futures prices is not significantly different from the coefficient of gas prices in our model of PV electricity although there are differences in the production of electricity in these two service areas. The coefficients in our model do reflect differences in the consumption of electricity in the COB and PV service

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areas, however. Our trading-rule simulations indicate that the statistically significant mean reversion found in the relationship between electricity and natural-gas futures prices also is economically significant in both in-sample and out-of-sample tests. Jrl Fut Mark 22: 95–122, 2002

INTRODUCTION

Intercommodity futures spreads often are constructed from futures contracts on commodities that are related to one another through a production process. For example, refiners buy crude oil, process it in a catalytic converter, and sell the resulting products, including gasoline and heating oil. A long (short) position in crude-oil futures, coupled with short (long) positions in gasoline and heating-oil futures, is known as the crack spread. The crush spread is constructed similarly using soy-bean futures contracts and the futures contracts for soy oil and soy meal, the products obtained by crushing the beans. Refiners and processors use these spreads to manage operating risk, while speculators use them to obtain profits when the commodity prices fall outside the no-arbitrage boundaries established by the production process.

Researchers have examined the crack and crush spreads to determine whether each price series is stationary, whether related price series are cointegrated, and whether traders can earn profits when the related futures contracts are mispriced relative to one another. Girma and Paulson (1999) found that crude oil, unleaded gasoline, and crude-oil futures prices are cointegrated and that the spread between them is stationary. Furthermore, they documented the presence of profits from trading three popular spreads in these contracts: the 3:2:1 crude, gasoline, heating-oil spread, the 1:1:0 crude, gasoline spread, and the 1:0:1 crude, heating-oil spread. Simon (1999) examined the crush spread with similar results.[1]

Other researchers examined the individual contracts that make up the crack spread. Peroni and McNown (1998) concluded that spot and futures prices in the crude-oil, gasoline, and heating-oil markets require differencing to become stationary, and that corresponding spot and futures price series are cointegrated. Similarly, Serletis (1992) found that the crude-oil, unleaded-gasoline, and heating-oil prices in his sample were stationary after allowing for a one-time break in the intercept and slope of the trend function. Ng and Pirrong's (1996) error-correction models indi-

[1]See Johnson, Zulauf, Irwin, and Gerlow (1991), Rausser and Carter (1983), Rechner and Poitras (1993), and Tzang and Leuthold (1990) for other discussions of the crush spread.

cated that informed trading takes place in the gasoline and heating-oil futures markets and spills over to the corresponding spot markets. Focusing on spot prices, Borenstein, Cameron, and Gilbert (1997) found that gasoline prices respond more quickly to increases than to decreases in crude-oil prices. Finally, Ma (1989) and Schwarz and Szakmary (1994) found that crude-oil, gasoline, and heating-oil futures provided better forecasts of future spot prices than the alternative they considered.

Our study is related most closely to Girma and Paulson (1999) and Simon (1999) because we examine the *spark spread*, a relatively new intercommodity spread based on the generation of electricity. This spread, which is constructed from natural-gas and electricity futures contracts, became available when the New York Mercantile Exchange (NYMEX) initiated trading in electricity futures in March 1996. The availability of the spark spread roughly coincided with the beginning of deregulation in the electric-energy industry. Consequently, there was immediate interest in using this spread to hedge, to estimate the value of generating assets, and to speculate.

We examine the spark spread by analyzing the relationship between electricity futures prices and natural-gas futures prices. Our data are the daily settlement prices for the NYMEX's two longest-running electricity futures contracts and its natural-gas futures contract. We find that each series is stationary after first-differencing and that there is a cointegration relationship between each electricity futures price series and the natural-gas futures price series.

The coefficients of our models of the relationship between electricity and natural gas futures prices reflect differences in the demand for electricity in the two regions. One of the futures contracts we examine serves the southwestern US, where the demand for electricity is highly dependent on the need for air conditioning. The other futures contract we examine serves the Pacific Northwest, where there is less need for cooling. Not surprisingly, seasonal factors play a more prominent role in our fitted model of the electricity futures prices for the contract that serves the southwest.

The coefficients of our models of the relationship between electricity and natural-gas futures prices do not reflect differences in the production of electricity in the two regions, however. Natural gas and coal are the primary fuels used to generate electricity in the southwestern US, while hydro is the primary resource used in the Pacific Northwest. Consequently, we expected natural-gas prices to play a more prominent role in our fitted model of the electricity futures prices for the contract that serves the southwest; they don't.

We also conducted in- and out-of-sample trading-rule simulations to determine if the statistically significant mean reversion in the spark spread we found was economically significant. We found that traders who used our models would have earned profits on long and short positions in spark spreads based on both electricity contracts. Furthermore, these profits were generated by the electricity side of the trades. Trading the spark spread rather than electricity alone did not increase the average profit or reduce the risk.

Our paper is organized as follows. In the next section, Natural Gas and Electricity Futures Contracts, a brief description is offered of NYMEX's electricity and natural-gas futures contracts, the differences in the regions these contracts serve, and our data. We follow up this discussion with our analyses of the time-series properties of electricity and natural-gas futures prices. This is where we report the results of our stationarity and cointegration tests and discuss the coefficients of our fitted models. We then report the results of our trading rule simulations, and close with a summary.

NATURAL GAS AND ELECTRICITY FUTURES CONTRACTS

The NYMEX initiated trading in natural-gas futures on April 3, 1990. Each contract is for 10,000 million British thermal units (MMBtus). Thirty-six contracts, one for delivery in each of the next 36 calendar months, trade at any given time, although near-by contracts are the more active ones. At any given time, the contract for delivery in the following month is known as the first near-by contract. Trading in this contract terminates three business days prior to the first calendar day of the delivery month. The following day, the contract for delivery in the next month begins trading as the first near-by contract. Delivery takes place at the Sabine Pipe Line Company's Henry Hub in Louisiana, simply called Henry Hub.

There are currently six electricity futures contracts traded on NYMEX. The only differences among them are their sizes and the locations on the national power grid where delivery takes place. Table I gives each contract's name, size, the date trading was initiated, delivery location, and service area. Although each contract's size is fixed, the delivery unit depends on the number of peak-usage days in the delivery month. For example, the delivery unit in a month with 25 peak days is 25 days $\times$ 16 hours per day $\times$ 2 megawatts per hour = 800 megawatt hours (MWhs). Eighteen contracts, one for delivery in each of the next

TABLE I
NYMEX Electricity Futures Contracts*

Name	*Size (Mwhs)*	*Date Trading Initiated*	*Delivery Location*	*Service Area*
California–Oregon Border Electricity**	432	3/29/96	California/Oregon border of the Pacific Northwest/Pacific Southwest AC	California, Oregon, Nevada
Palo Verde Electricity**	432	3/29/96	Palo Verde high-voltage switchyard	Arizona, California
Cinergy Electricity	736	7/10/98	Into Cinergy transmission system at any interface designated by the seller	Ohio, Indiana, Kentucky
Entergy Electricity	736	7/10/98	Into Entergy transmission system at any interface designated by the seller	Louisiana, Arkansas, Mississippi, Texas
PJM Electricity	736	3/19/99	PJM western hub	Pennsylvania, New Jersey, Maryland
Mid-Columbia Electricity	432	9/15/00	Mid Columbia River bus	

*From the New York Mercantile Exchange web site at http://www.nymex.com/, October 2000.
**The California–Oregon Border and Palo Verde contracts were originally for 736 Mwhs, although their sizes were changed to 864 Mwhs in October 1999 and 432 Mwhs in December 1999.

18 calendar months, trade at any given time, with more trading activity in the near-by ones. Trading in the first near-by electricity futures contracts terminates four business days prior to the first calendar day of the delivery month. We use the two older contracts, COB and PV, to obtain longer price series.

NYMEX offers electricity futures contracts based on delivery in different regions of the US because there are regional differences in the production of electricity. Table II shows the generating resources used by power companies in the three western-most regions of the Western System Coordinating Council. Power companies in the vicinity of NYMEX's COB delivery point primarily use hydro to generate electricity, while companies in the vicinity of the PV delivery point primarily use natural gas and coal. Although California has power plants near each delivery point, its hydroelectric plants are concentrated in the northern part of the state, served by the COB contract, while its natural-gas- and coal-fired plants are in the southern part, served by the PV contract.

We collected daily settlement prices for the first near-by natural gas and COB and PV electricity futures contracts from the date the electricity contracts were initiated, March 29, 1996, until March 31, 2000. Our sample comprises 1005 daily settlement prices for each series. We calculated price changes where required by taking the settlement price for a particular contract on day *t* and subtracting from it the settlement price

TABLE II

Resources Used by Power Generators of the Western Systems Coordinating Council Average for 1997–2000*

	In the Vicinity of	
Resource	*Palo Verde***	*California-Oregon Border*†
Natural gas	37.0%	6.7
Conventional hydro	16.5	64.6
Coal	17.1	23.9
Nuclear	10.6	1.6
Other‡	18.8	3.1
Total	100.0%	99.9%

*Information Summaries for 1997–2000 published by the Western Systems Coordinating Council on its web site, http://www.wscc.com. Obtained from the web site in April 2001.

**California–Mexico Power Area (all of California and a small part of northern Mexico) plus Arizona–New Mexico–Southern Nevada Power Area (all of Arizona, most of New Mexico, and small parts of Nevada and Texas).

†Northwest Power Pool Area (all of Oregon, Washington, Idaho, Utah, British Columbia, and Alberta; most of Montana and Nevada; part of Wyoming).

‡Other fuels are pumped storage hydro, fuel oil, geothermal, internal combustion, cogeneration, and unclassified.

for the same contract on day $t - 1$. This approach ensures that the price change on the day after a contract expires reflects only the effect of market changes and not the effect of switching contracts.

THE TIME-SERIES PROPERTIES OF THE SPARK SPREAD

This section describes a production-based model of the relationship between electricity and natural-gas futures prices. It uses daily settlement prices from NYMEX's COB and PV electricity futures contracts and natural-gas futures contract to estimate the coefficients in this model.

A Model of the Relationship Between Natural-Gas and Electricity Futures Prices

We begin by defining the spark spread as the gross-generation profit margin earned by buying natural gas and burning it to produce electricity. The size of this profit margin depends on energy prices and the generator's efficiency. A generator operating at 100% efficiency requires 3.41 million Btus of natural gas to produce 1 Mwh of electricity. The amount of energy required, 3.41 million Btus in this example, is called the generator's heat rate. A generator with a heat rate of 8.0 operates at slightly less than 43% (3.41/8.0) efficiency. The gross-generation profit margin per Mwh of electricity written in terms of the heat rate is given by Equation (1).

$$\text{Gross generation profit margin}_t = \text{Elec}_t - \beta_1 \text{Gas}_t, \qquad (1)$$

where Elec_t = price of 1 Mwh of electricity at time t.
Gas_t = cost of 1 million Btus of natural gas at time t.
β_1 = generator's heat rate

Figure 1 is a graph of the gross-generation profit margin using our daily futures prices and the heat rate implied by a popular spark-spread trading strategy. This strategy is implemented by buying five electricity futures contracts and selling three natural-gas futures contracts. At this 5:3 spread ratio, 30,000 million Btus of natural gas will produce 3,680 Mwhs of electricity. The corresponding heat and efficiency rates are 8.15 and 41.8%, respectively. The gross-generation profit margin has a positive trend during the sample period with a wide variation around this trend.

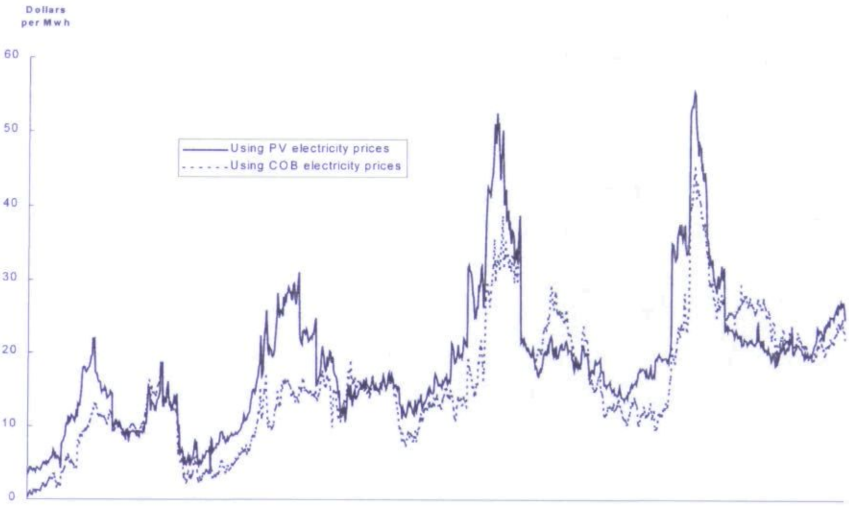

FIGURE 1
Daily gross generation profit margin, March 29, 1996–March 31, 2000. Daily gross-generation profit margin is NYMEX's 1st nearby California–Oregon Border (COB) or Palo Verde (PV) electricity futures daily settlement price minus 8.15 times its Henry Hub natural-gas futures daily settlement price, where 8.15 is the heat rate implied by the 5:3 spread ratio commonly used in trading.

Figure 2 shows graphs of the gas and electricity prices and the gross-generation profit margin by contract month. There is a strong seasonal pattern to the electricity prices, reflecting the demand for cooling in the summer. This seasonal variation is greater in the Palo Verde contract that serves southern California and Arizona, which have greater demands for air conditioning. In contrast, there is very little seasonal variation in natural-gas futures prices. The seasonal differences in electricity prices also are present in the average gross-generation profit margins. The regional and seasonal differences shown in Figure 2 persist and are reflected in prices and the spark spread because electricity cannot be stored and because there are physical barriers to transporting it long distances.

We added trend and seasonal terms to Equation (1) and rearranged it to obtain our model of the equilibrium relationship between electricity and natural-gas futures prices. The result is given by Equation (2), where the intercept term, β_0, includes the gross-generation profit margin. We will refer to the residual term in this equation as the abnormal price of electricity at time t, AP_t, in subsequent sections.

$$\text{Elec}_t = \beta_0 + \beta_1 \text{Gas}_t + \beta_2 \text{Trend} + \sum_{j=3}^{13} \beta_j X_j + \varepsilon_t \tag{2}$$

where $X_3 = 1$ if contract month is January and 0 otherwise, etc.

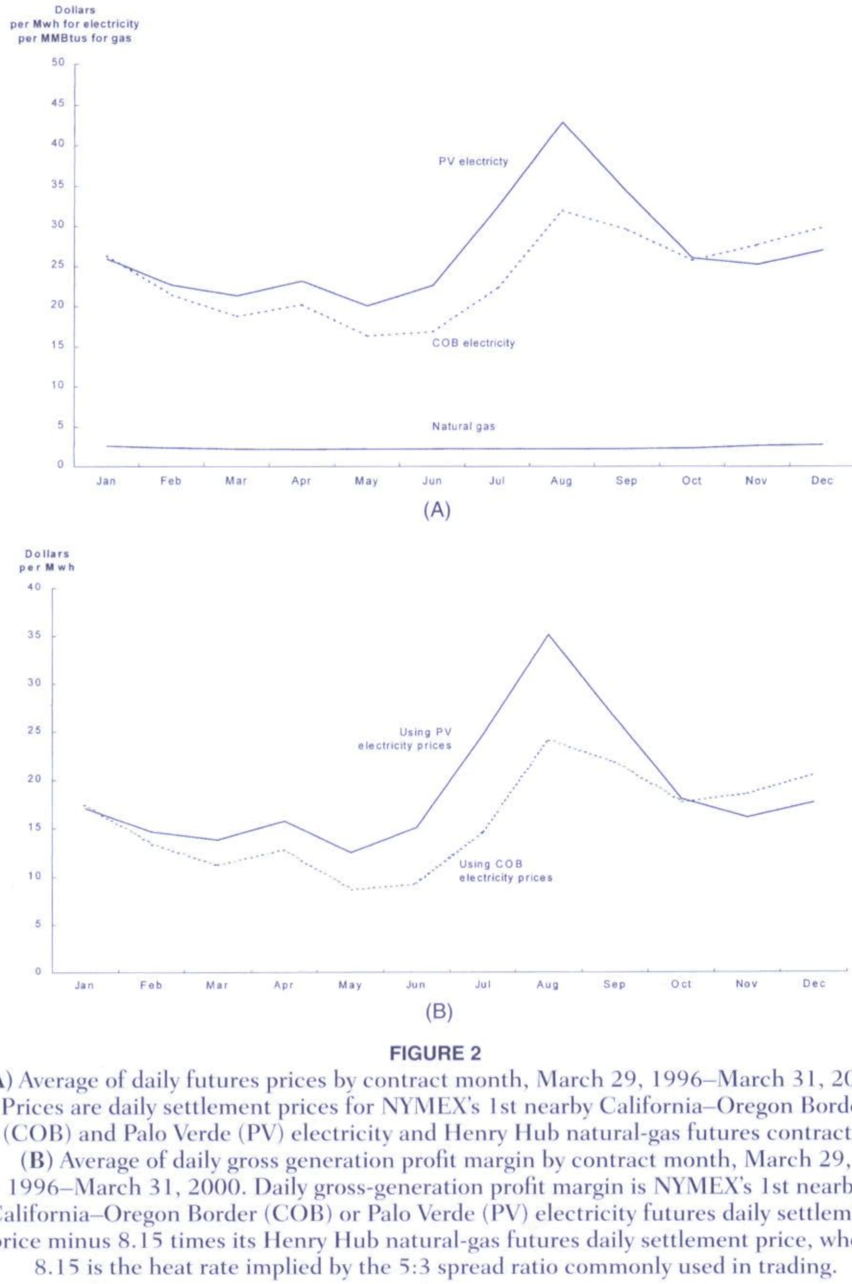

FIGURE 2

(**A**) Average of daily futures prices by contract month, March 29, 1996–March 31, 2000. Prices are daily settlement prices for NYMEX's 1st nearby California–Oregon Border (COB) and Palo Verde (PV) electricity and Henry Hub natural-gas futures contracts. (**B**) Average of daily gross generation profit margin by contract month, March 29, 1996–March 31, 2000. Daily gross-generation profit margin is NYMEX's 1st nearby California–Oregon Border (COB) or Palo Verde (PV) electricity futures daily settlement price minus 8.15 times its Henry Hub natural-gas futures daily settlement price, where 8.15 is the heat rate implied by the 5:3 spread ratio commonly used in trading.

We expect a positive coefficient of the trend term, β_2, and positive coefficients of the summer-months dummy variables, β_js, given the patterns shown in Figures 1 and 2. We also expect a positive coefficient of the natural-gas futures price, β_1, although we cannot be more precise about its value for three reasons. First, the heat rates of individual generators used in the U.S. and Canada vary from about 12.0 for old equipment to 5.0 for new, combined-cycle generators. These heat rates correspond to approximately 28–68% efficiency. The average heat rate in a particular service area depends on the mix of old and new equipment operated by the power companies in that area and their policies for using the equipment to produce reserve, off-peak, and peak power.

Second, power companies use fuels other than natural gas to generate electricity, causing their heat rate to appear to be less than the actual heat rate of their gas-fired generators. For example, a company that uses its gas-fired generators to produce 50% of its power will appear to have a heat rate of 3.0 if those generators have an actual heat rate of 6.0. Taken together, these two effects imply the relationship between natural-gas and electricity prices depends on the aggregate mix of generators, policies, and fuels used by power companies in the service area. Ideally, we would control for the second effect by including the prices of other fuels when computing the gross-generation profit margin, but there are no price series for hydro and nuclear, two of the more important sources of energy in these service areas.

Third, our data are futures prices rather than the prices of the actual natural gas and electricity power companies buy and sell. These futures prices may reflect the heat rate of the virtual generators implicit in the traders' models rather than the heat rates of the actual generators employed in the two service areas. For example, if traders assume that generators are 100% efficient and that COB and PV electricity *futures* are interchangeable (even though COB and PV electricity are not), then the heat rate implicit in both data sets should be approximately 3.41.

For these reasons, we predict that the coefficients of natural-gas futures prices in our models are positive although we cannot predict the efficiency levels they imply or whether they are the same or different in the COB and PV service areas. Henceforth, we will refer to the β_1s in Equation (2) as *apparent heat rates* to emphasize that they are estimated from futures prices and not calculated from information about power companies' generators, policies, and fuels.

Stationarity and Cointegration Tests

We used the augmented Dickey–Fuller (1979) and Pantula, Gonzalez-Farias, and Fuller's (1994) weighted symmetric unit root tests to determine whether each price series is stationary. The Dickey–Fuller test is conducted by fitting the regression described by Equation (3) to the futures prices. We included three lags of the dependent variable to eliminate autocorrelation. Under the null hypothesis that a series is nonstationary, the coefficient of the lagged level of the series, δ_1, is not significantly different from zero. If a series is nonstationary, its values are replaced by their first differences and the test is conducted again. This process is repeated until each series has been differenced enough times to achieve stationarity.

$$\Delta Y_t = \delta_0 + \delta_1 Y_{t-1} + \sum_{i=2}^{4} \delta_i \Delta Y_{t-(i-1)} + u_t \tag{3}$$

where Y_t = daily natural gas, COB electricity, or PV electricity futures prices.

Pantula et al. (1994) found that the weighted symmetric (ws) unit root test is more powerful than the augmented Dickey–Fuller tests. This test is applied by determining the value of ρ_{ws} that minimizes the value of Equation (4) with weights, the w_ts, equal to $n^{-1}(t-1)$ rather than 1.0 as implied by Dickey–Fuller's OLS approach. The test statistic, τ_{ws}, is calculated using Equation (5).[2] Critical values for the test statistic were published by Fuller (1996).

$$Q_w(\rho) = \sum_{t=2}^{n} w_t(y_t - \rho y_{t-1})^2 + \sum_{t=1}^{n-1} (1 - w_{t+1})(y_t - \rho y_{t+1})^2 \tag{4}$$

$$\tau_{ws} = (\rho_{ws} - 1)\left(\sum_{t=2}^{n-1} y_t^2 + n^{-1}\sum_{t=1}^{n} y_t^2\right)^{0.5} \sigma_{ws}^{-1} \tag{5}$$

The results of both tests are shown in Panel A of Table III. These results permit us to reject the hypothesis that natural-gas prices are nonstationary at the 0.05 level, but not at the 0.01 level. Neither COB nor PV electricity futures prices are stationary at either level of significance. The first differences of all three price series are stationary, however.

Electricity futures prices have a strong seasonal pattern, as shown in Figure 2. In this situation, Enders (1995) suggested applying the unit root tests to the deseasonalized series, y_t, defined by Equation (6).

$$Y_t = \beta_0 + \sum_{j=1}^{11} \beta_j X_j + y_t \tag{6}$$

where Y_t = daily COB electricity or PV electricity futures prices.
X_j = 1 if contract month is January and 0 otherwise, etc.

The results, presented in Panel B of Table III, are similar to those in Panel A; electricity futures prices are not stationary, although their first differences are.

Based on these results, we could fit our model for the relationship between natural-gas and electricity futures prices to the first differences

[2]See Pantula et al. (1994) for the expressions to calculate ρ_{ws} and σ_{ws}.

TABLE III
Results of Unit Root Tests

Series	*Coefficient of Lagged Value of Series, δ_1*	*τ-statistic*	*Weighted Symmetric τ_{ws}*
Panel A: Test Applied to Original Series			
Natural gas			
Prices	−0.026	−3.36*	−2.93*
1st difference of prices	−1.071	−15.40**	−35.85**
COB electricity			
Prices	−0.010	−2.33	−1.91
1st difference of prices	−0.914	−14.67**	−28.32**
PV electricity			
Prices	−0.012	−2.53	−2.35
1st difference of prices	−0.946	−14.90**	−28.67**
Panel B: Test Applied to Deseasonalized Series			
COB electricity			
Prices	−0.015	−2.43	−2.32
1st difference of prices	−1.18	−17.63**	−27.68**
PV electricity			
Prices	−0.021	−2.79	−2.41
1st difference of prices	−1.28	−17.96**	−28.02**

Note. The Augmented Dickey–Fuller (1979) unit root test is conducted by fitting the following regression to the series, Y_t, with lagged values of the dependent variable included to eliminate autocorrelation.

$$\Delta Y_t = \delta_0 + \delta_1 Y_{t-1} + \sum_{i=2}^{4} \delta_i \Delta Y_{t-(i-1)} + u_t$$

The null hypothesis that a series is nonstationary is rejected at the 0.05 and 0.01 levels if the τ-statistic is less than −2.86 and −3.43, respectively. If a series is nonstationary, its values are replaced by their first differences and the test is conducted again. This process is repeated until each series has been differenced enough times to achieve stationarity.

The weighted symmetric unit root test is applied by determining the value of ρ_{ws} that minimizes $Q_w(\rho)$ with weights, the wts, equal to $n - 1$ $(t - 1)$ rather than 1.0, as implied by Dickey–Fuller's OLS approach. Critical values for the test statistic, τ_{ws}, are from Fuller (1996). These critical values are −2.50 and −2.98 for rejecting the null hypothesis at the 0.05 and 0.01 levels, respectively.

$$Q_w(\rho) = \sum_{t=2}^{n} w_t (y_t - \rho y_{t-1})^2 + \sum_{t=1}^{n-1} (1 - w_{t+1})(y_t - \rho y_{t+1})^2$$

$$\tau_{ws} = (\rho_{ws} - 1)\left(\sum_{t=2}^{n-1} y_t^2 + n^{-1} \sum_{t=1}^{n} y_t^2\right)^{0.5} \sigma_{ws}^{-1}$$

*Significant at 0.05 level.
**Significant at 0.01 level.

of each series. However, we are interested primarily in the behavior of actual prices. Therefore, we determined whether electricity and natural-gas prices are cointegrated in advance of fitting our model to the prices themselves.

We used the augmented Engle–Granger (1987) test to determine whether natural-gas and electricity futures prices are cointegrated. This

TABLE IV
Results of Cointegration Tests

Series	*Coefficient of Lagged Value of AP, α_1*	*τ-statistic*	*Half Life**
COB Abnormal price	−0.0451	−4.37**	15.0 days
PV Abnormal price	−0.0460	−4.50**	14.7 days

Note. The Augmented Engle–Granger (1979) test is used to determine whether two time series are cointegrated. The test is conducted by fitting the following regression where AP_t is the residual from Equation (2). Lagged values of the dependent variable are included to eliminate autocorrelation.

$$\Delta AP_t = \alpha_0 + \alpha_1 AP_{t-1} + \sum_{j=2}^{4} \alpha_j \Delta AP_{t-(j-1)} + V_t$$

The null hypothesis that the series are not cointegrated is rejected at the 0.05 and 0.01 levels if the τ-statistic is less than −3.34 and −4.32, respectively.

*Half life equals $\ln(0.50)/\ln(1+\alpha_1)$.
**Significant at 0.01 level.

test is similar to the Dickey–Fuller test, although it is applied to the abnormal prices, the residuals from Equation (2), rather than to each separate time series. (We report and discuss the coefficients of the independent variables in Equation (2) later.) Under the null hypothesis that the electricity and natural-gas prices are not cointegrated, the coefficient of the lagged level of the abnormal price in Equation (7), α_1, is not significantly different from zero.

$$\Delta AP_t = \alpha_0 + \alpha_1 AP_{t-1} + \sum_{j=2}^{4} \alpha_j \Delta AP_{t-(j-1)} + v_t \qquad (7)$$

Table IV shows the results of the cointegration tests. The coefficient of the lagged level of the abnormal price, α_1, is significantly different from zero, which means the residuals are stationary or, equivalently, the natural-gas and electricity futures prices are cointegrated. The half-lives of shocks to the spark spread are short, at 15.02 and 14.72 days for COB and PV electricity, respectively. The relatively short length of these half-lives implies that deviations from the equilibrium level of the spread are temporary and that the spread returns to its equilibrium level quickly.[3]

[3]Researchers studying other intercommodity futures spreads have examined the behavior of deviations of a spread from its recent central tendency, as well as from its long-run equilibrium; see Johnson et al. (1991) and Simon (1999). Therefore, we replaced the lagged residual from Equation (2) that appears in Equation (7) with the deviation of the electricity price from its 5-day moving average. None of the coefficients of this model were significantly different from zero, indicating that electricity prices do not revert to their 5-day moving average.

Error-Correction Models

Error-correction models of the relationship between electricity and natural-gas futures prices show how the prices adjust to departures from the long-run equilibrium. The models are described by Equations (8) and (9), where the error-correction term, AP_{t-1}, is the lagged error term from the cointegration regression, Equation (2).

$$\Delta\text{Elec}_t = a_0 + a_1 AP_{t-1} + \sum_{i=1}^{m} \gamma_{i1} \Delta\text{Elec}_{t-i} + \sum_{j=1}^{n} \delta_{j1} \Delta\text{Gas}_{t-j} + \varepsilon_{1t} \quad (8)$$

$$\Delta\text{Gas}_t = b_0 + b_1 AP_{t-1} + \sum_{i=1}^{m} \gamma_{i2} \Delta\text{Elec}_{t-i} + \sum_{j=1}^{n} \delta_{j2} \Delta\text{Gas}_{t-j} + \varepsilon_{2t} \quad (9)$$

In these models, m and n are chosen to avoid serial correlation in ε_{1t} and ε_{2t}. We chose the first-order error-correction system, $m = n = 1$, and the Durbin–Watson d statistics do not indicate the presence of serial correlation. The results of fitting the error-correction models are given in Table V.

The coefficient of the lagged abnormal price of electricity (AP_{t-1}) is significantly less than zero, as expected, in the model of the change in electricity prices in both COB and PV electricity. In contrast, the coefficient of AP_{t-1} is positive, but not significantly different from zero in the models of the change in natural-gas prices. These results indicate that electricity prices respond to departures from the equilibrium relationship, but natural gas prices do not. The fact that the response is confined to the electricity prices was somewhat surprising at first because a curtailment of electricity production when prices are low (which prompts the opening of a long position in electricity and a short position in gas) should prompt a reduction in the demand for natural gas and a decrease in its price. However, an asymmetric response makes sense, considering that natural gas is an important resource for generating electricity, while generating electricity is only one of many uses for natural gas.

The Fitted Model

The conclusion that natural-gas and electricity futures prices are cointegrated means that the regression of electricity prices on natural-gas prices in Equation (2) is meaningful and that the standard significance tests apply. The results of fitting this model to the COB and PV electricity prices are shown in Table VI.

The model fits both data sets very well, with R^2s of about 0.85 for both COB and PV. All the coefficients have the predicted signs, and

TABLE V
Error Correction Models

	COB Electricity				*PV Electricity*			
	Dependent Variable $\Delta Elec_t$		*Dependent Variable* ΔGas_t		*Dependent Variable* $\Delta Elec_t$		*Dependent Variable* ΔGas_t	
	Coefficient	*P-value*	*Coefficient*	*P-value*	*Coefficient*	*P-value*	*Coefficient*	*P-value*
Intercept	0.0196	0.5940	0.0008	0.8140	0.0194	0.6760	0.0008	0.8110
AP_{t-1}	−0.0390	0.0000	0.0009	0.3720	−0.0416	0.0001	0.0001	0.9550
$\Delta \mathrm{Elec}_{t-1}$	0.1133	0.0000	0.0034	0.2400	0.0961	0.0030	0.0023	0.3160
$\Delta \mathrm{Gas}_{t-1}$	0.7654	0.0240	−0.1096	0.0000	0.8355	0.0520	−0.1097	0.0000
R^2	0.0297		0.0142		0.0246		0.0127	
Durbin–Watson *d*-statistic	1.9989		2.0513		1.9941		2.0496	

Note. The error-correction model describes how fast the cointegrating variables (i.e., electricity and natural-gas futures) adjust to the deviations from the long-run equilibrium relationships. The speed of adjustment is measured by the coefficient of the error-correction term, AP_{t-1}, in the equations given below.

$$\Delta \mathrm{Elec}_t = a_0 + a_1 AP_{t-1} + \sum_{i=1}^{m} \gamma_{i1} \Delta \mathrm{Elec}_{t-i} + \sum_{j=1}^{n} \delta_{j1} \Delta \mathrm{Gas}_{t-j} + \varepsilon_{1t}$$

$$\Delta \mathrm{Gas}_t = b_0 + b_1 AP_{t-1} + \sum_{i=1}^{m} \gamma_{i2} \Delta \mathrm{Elec}_{t-i} + \sum_{j=1}^{n} \delta_{j2} \Delta \mathrm{Gas}_{t-j} + \varepsilon_{2t}$$

The Durbin–Watson *d*-statistics indicate that our choice of $m = n = 1$ eliminated serial correlation in ε_{1t} and ε_{2t}.

TABLE VI
Fitted Regression Models of the Spark Spread

	COB Electricity		*PV Electricity*	
	Coefficient	*P-value*	*Coefficient*	*P-value*
Intercept	9.60	0.0000	7.09	0.0000
Natural gas futures price	3.03	0.0000	3.06	0.0000
Trend	0.02	0.0000	0.02	0.0000
January	−3.27	0.0000	−0.80	0.1719
February	−7.53	0.0000	−3.43	0.0000
March	−10.68	0.0000	−5.17	0.0000
April	−9.78	0.0000	−3.90	0.0000
May	−9.15	0.0000	−2.63	0.0000
June	−8.22	0.0000	0.30	0.6199
July	−3.77	0.0000	9.05	0.0000
August	5.50	0.0000	19.27	0.0000
September	2.69	0.0000	10.13	0.0000
October	−1.94	0.0004	1.19	0.0468
November	−1.15	0.0290	−0.78	0.1796
R^2	0.8523		0.8490	
Adjusted R^2	0.8504		0.8470	
Durbin–Watson statistics	1.8354		1.8865	
Standard deviation of residuals	3.34		3.67	
Tests for Equality of COB and PV Apparent Heat Rates	*Test Statistic*	*P-value*		
F	0.0367	0.8480		
Wald χ^2	0.0367	0.8480		

Note. Estimated values of the coefficients in $\text{Elec}_t = \beta_0 + \beta_1\text{Gas}_t + \beta_2\text{Trend} + \sum_{j=3}^{13} \beta_j X_j + \varepsilon_t$. Data are daily settlement prices of NYMEX's 1st nearby California–Oregon Border and Palo Verde electricity futures contracts and Henry Hub natural-gas futures contract from March 29, 1996 to March 31, 2000.

nearly all are significant at conventional levels. The exceptions are the seasonal dummy variables for January, June, and November in PV electricity. The coefficient of the trend term is positive and significant in both data sets, and the seasonal dummy variables reflect the summer peak that begins earlier and is higher in PV prices. This pattern in both series is a consequence of the demand for electricity for air conditioning. The difference between the COB and PV seasonal patterns arises because the air-conditioning season begins earlier in the Palo Verde service area and is more intense.

As expected, the coefficient of natural-gas prices is positive and significant in both series. Interpreted as heat rates, these coefficients imply efficiency levels of about 112% in both service areas. Of course, these coefficients are only *apparent* heat rates because power companies in both service areas use natural gas to generate less than 40% of their electricity. PV's apparent heat rate is only slightly larger than COB's heat rate, 3.06 versus 3.03, although power companies in the PV service area use more natural gas to generate electricity. Furthermore, the probability that this difference is due to chance is greater than 84% under either the F-test or the Wald test. A possible reason that the apparent heat rates are the same in both regions is that all power companies tend to use natural gas as their marginal fuel for generating peak power.

TRADING-RULE SIMULATIONS

The preceding section showed that there is a statistically significant tendency for the spark spread to revert to the equilibrium value given by Equation (2). This section presents the results of trading-rule simulations that examine the *economic* significance of mean reversion in the spark spread. We found that trades based on our empirically determined apparent heat rates would have been profitable in both in- and out-of-sample tests.

The Trading Rules and Assumptions

Our simulated trader opens a long (short) position by purchasing (selling) electricity futures and selling (buying) natural-gas futures when the electricity futures price is low (high). Our trader closes these positions by executing offsetting trades when the electricity futures price returns to its equilibrium value. All purchases and sales are in the first near-by contract. A position that is open when the first near-by contract stops trading is closed that day and reopened the following day when the new first near-by contract starts trading. We assumed that all purchases and sales took place at the settlement price of the day the appropriate trading rule is satisfied.

We considered an electricity futures price to be different from its equilibrium value when the abnormal price of electricity, the residual from Equation (2), was more than ϕ standard deviations away from its mean of zero with ϕ equal to 0.25, 0.50, 0.75, and 1.00.[4] Given the standard deviations of the residuals for our fitted models, the size of these filters ranged from about \$0.50 to \$3.50/Mwh depending on the electricity contract and apparent heat rate that applies. Our trading rules are summarized below.

[4]Note that the results of trades using different sized filters are not independent because the trades entered into when $\phi = 1.00$ is a subset of the trades entered into when $\phi = 0.75$, which in turn is a subset of the trades entered into when $\phi = 0.50$, etc.

Long positions

Buy 1 Mwh of electricity and sell β_1 MMBtus of natural gas when $\mathrm{AP} < -\phi\sigma$.

Close position when $\mathrm{AP} \geq 0$.

Short positions

Sell 1 Mwh of electricity and buy β_1 MMBtus of natural gas when $\mathrm{AP} > \phi\sigma$.

Close position when $\mathrm{AP} \leq 0$.

$\phi = 0.25, 0.50, 0.75$, and 1.00; β_1 = the apparent heat rate estimated from our data.

We recognized two costs of implementing this trading scheme. The first cost is the commission paid to a broker. We used Simon's (1999) estimate-of-commission costs, which were \$15.50 per round trip per contract. A spark-spread trade requires 4 contracts (1 electricity and 3 natural-gas contracts), so the total commission is \$62.00 or approximately \$0.08 (\$62.00/736) per megawatt hour. Our trader's profits are net of this \$0.08 per Mwh commission cost.

The second cost of implementing this trading scheme is the inability to transact at the settlement price. Simon (1999) called this cost a slippage cost and assumed that it equals two price ticks per round trip in each contract. The price ticks for electricity and natural gas are \$0.01 per Mwh and \$0.001 per MMBtus, so based on Simon's approach, the slippage cost for a spark-spread trade is $2 \times (\$0.01 \times 1 + \$0.001 \times 3) = \$0.026$, or approximately \$0.03 per Mwh. Two price ticks per round trip may underestimate electricity futures slippage costs, however, because these markets are not as active as the natural-gas futures market and the soy-bean futures market Simon studied. Therefore, we omitted an adjustment for slippage costs when computing our trader's profits to avoid using an arbitrarily chosen amount. We later compared the trader's profits to possible slippage costs to assess their potential impact.

In-Sample Trading-Rule-Simulation Results

Table VII shows the results of our tests of the economic significance of mean reversion in the spark spread. Panel A contains the results for long positions, constructed by purchasing an electricity futures contract and selling natural-gas futures contracts, while Panel B contains the results for short positions, constructed by selling an electricity futures contract and purchasing natural-gas futures contracts. Profits are net of commissions, but not slippage costs.

TABLE VII

In-Sample Trading-Rule Simulations

Panel A: Long Positions

	Open Position When			
	$AP < -0.25\sigma$	$AP < -0.50\sigma$	$AP < -0.75\sigma$	$AP < -1.00\sigma$
	California–Oregon Border Contract			
Number of trades	30	16	11	6
Average duration	15 days	22 days	26 days	43 days
Percent profitable	73.33%	68.75%	54.55%	66.67%
Maximum profit	$12.25	$12.25	$12.95	$13.68
Minimum profit	−3.69	−3.69	−3.69	−3.69
Average profit	1.26	1.68	2.30	2.98
Standard error	0.50	0.87	1.34	2.45
Probability	0.0092	0.0361	0.0581	0.1390
	Palo Verde Contract			
Number of trades	21	12	7	5
Average duration	20 days	32 days	43 days	58 days
Percent profitable	90.48%	91.67%	100.00%	100.00%
Maximum profit	$16.29	$17.27	$17.39	$18.28
Minimum profit	−4.91	−4.91	2.46	5.47
Average profit	2.91	4.26	7.12	8.63
Standard error	0.90	1.53	1.96	2.42
Probability	0.0021	0.0087	0.0055	0.0118

Panel B: Short Positions

	Open Position When			
	$AP > 0.25\sigma$	$AP > 0.50\sigma$	$AP > 0.75\sigma$	$AP > 1.00\sigma$
	California–Oregon Border Contract			
Number of trades	31	19	15	10
Average duration	13 days	17 days	17 days	21 days
Percent profitable	77.42%	68.42%	73.33%	70.00%
Maximum profit	$5.12	$7.92	$7.92	$7.92
Minimum profit	−7.25	−5.75	−5.75	−4.91
Average profit	0.57	1.26	1.77	1.76
Standard error	0.44	0.71	0.84	1.10
Probability	0.1047	0.0475	0.0273	0.0722
	Palo Verde Contract			
Number of trades	20	14	10	9
Average duration	20 days	23 days	28 days	26 days
Percent profitable	65.00%	64.29%	60.00%	77.78%
Maximum profit	$21.19	$21.19	$21.19	$10.90
Minimum profit	−5.00	−4.14	−3.17	−2.39
Average profit	1.23	2.31	3.32	3.91
Standard error	1.18	1.61	2.23	1.43
Probability	0.1552	0.0877	0.0856	0.0128

Note. A long (short) position is opened by purchasing (selling) 1 Mwh of electricity and selling (buying) β_1 MMBtus of natural gas, where β_1 is the apparent heat rate; $\beta_1 = 3.03$ for COB and 3.06 for PV. A long (short) position is closed by executing the opposite trades when $AP \geq (\leq)$ zero. *AP* is the residual from Equation (2) computed using the coefficients given in Table VI. Commissions are $0.08 per Mwh for COB and PV. The probability that the average profit is different from zero by chance is computed from the *T*-distribution with $n - 1$ degrees of freedom and the standard error of the mean equal to the sample standard deviation divided by the square root of n, where n is the number of trades.

The main feature to note in these results is that the trades generally were profitable. First, the average profit was significantly greater than zero at the 10% level for every type of position, electricity contract, and trading filter except long positions based on the COB contract with $\phi = 1.00$ and short positions based on either contract with $\phi = 0.25$. Second, the majority of the trades were profitable, including more than 90% of long positions based on the PV contract. Third, the profits were skewed highly to the right with the average maximum and minimum profits across all cells equal to \$13.09 and −\$4.37, respectively.

Other features of the results in Table VII are that long positions were always more profitable than short positions (compare a cell in Panel A with the corresponding cell in Panel B) and that trades based on the PV-based spark spread were always more profitable than trades based on the COB-based spark spread (compare corresponding cells in Panel A and Panel B). Finally, requiring the electricity futures price to be further from its equilibrium value before opening a long or short position (by increasing the size of the trading filter) decreased the number of trades, generally increased the duration of the trades, and increased the average profit.

A trader's inability to transact at the settlement price would reduce the profits shown in Table VII, but probably would not eliminate them. Let us consider the worst case, a short position in the COB-based spark spread with a trading filter of 0.25σ that produced an average profit of \$0.57 per Mwh. This average profit is nearly 20 times larger than the \$0.03 estimate of slippage costs based on Simon's approach. For a different perspective on the impact of these costs, note that the average price of COB electricity over the sample period was a little less than \$24. Slippage costs would have to be about 2.4% (\$0.57/\$24) to reduce the trader's average profit to zero in this worst case, and even higher to eliminate it in the other, more profitable cases. Therefore, we concluded that for reasonable estimate of slippage costs, these results indicate that the statistically significant mean reversion in the spark spread we identified earlier also was economically significant.

Of course, traders actually could not earn the profits reported in Table VII, with or without slippage costs, because we used the same data to estimate and test the coefficients of our model. A true test of the model's ability to produce trading profits requires an out-of-sample test, which is describe next.

Out-of-Sample Trading-Rule-Simulation Results

We divided our sample in two and used the 503 observations from March 29, 1996 to March 31, 1998 to estimate the coefficients of our models of electricity futures prices. The coefficients of the fitted models for COB and PV, given in Table VIII, are similar to those for the entire sample period given in Table VI. The apparent heat rates in both regions are lower, but the COB and PV apparent heat rates still are not significantly different from each other.

We used the second half of our sample, the 502 observations from April 1, 1998 to March 31, 2000 to test the model's ability to produce trading profits. We followed the same procedures used in our in-sample tests: the trader opens a long position by purchasing 1 Mwh of electricity futures and selling β_1 MMBtus of natural-gas futures when the abnormal price of electricity is $\phi\sigma$ less its mean of zero. The trader closes this position by executing the offsetting trades when the abnormal price of electricity is greater than or equal to zero. The trader opens and closes short positions similarly.

TABLE VIII

Fitted Regression Models of the Spark Spread for Out-of-Sample Tests

	COB Electricity		*PV Electricity*	
	Coefficient	*P-value*	*Coefficient*	*P-value*
Intercept	11.93	0.0000	8.17	0.0000
Natural gas futures price	2.62	0.0000	2.86	0.0000
Trend	0.02	0.0000	0.03	0.0000
January	−2.10	0.0000	−0.85	0.0798
February	−7.78	0.0000	−5.17	0.0000
March	−11.71	0.0000	−7.59	0.0000
April	−10.24	0.0000	−6.52	0.0006
May	−9.64	0.0000	−4.06	0.0007
June	−7.50	0.0000	−0.80	0.1350
July	−5.39	0.0000	4.65	0.0000
August	1.92	0.0000	10.31	0.0000
September	1.71	0.0002	5.73	0.0002
October	−3.07	0.0000	0.44	0.3943
November	−3.35	0.0000	−2.38	0.0000
R^2	0.8878		0.8810	
Adjusted R^2	0.8848		0.8778	
Durbin–Watson statistics	1.9826		1.9234	
Standard deviation of residuals	1.83		2.13	
Tests for Equality of COB and PV Apparent Heat Rates	*Test Statistic*	*P-value*		
F	1.5730	0.2101		
Wald χ^2	1.5730	0.2098		

Note. Estimated values of the coefficients in $\text{Elec}_t = \beta_0 + \beta_1\text{Gas}_t + \beta_2\text{Trend} + \sum_{j=3}^{13}\beta_j X_j + \varepsilon_t$. Data are daily settlement prices of NYMEX's 1st nearby California–Oregon Border and Palo Verde electricity futures contracts and Henry Hub natural-gas futures contract from March 29, 1996 to March 31, 1998.

The amount of natural gas to sell or buy, the β_1s, are the coefficients of natural-gas prices or apparent heat rates given in Table VIII. These apparent heat rates are 2.62 and 2.86 for COB and PV, respectively. Commission costs are still \$0.08 per Mwh. The standard deviations that form the basis of the trading filters, σ, are the standard deviations of the residuals of the fitted models described in Table VIII. These standard deviations are 1.83 and 2.13 for COB and PV, respectively. The indicator that the electricity futures price is too low or too high on a particular day during the test period, AP_t, is the difference between the actual electricity futures price on that day and the price computed from Equation (2) using the parameter estimates given in Table VIII.

The results, given in Table IX, are similar to, although not as strong as, those for the in-sample test. The weakening of the results occurred in the trades based on the COB contract. While all the long positions based on this contract produced average profits significantly greater than zero at the 5% level, none of the short positions did. Furthermore, although the distribution of profits remained skewed positively for the long positions, the distribution became symmetric or even skewed negatively for the short positions.

The out-of-sample results for the PV-based trades actually were stronger than the in-sample results. One hundred percent of the long and short positions based on this contract were profitable no matter what the size of the trading filter. The minimum profit on long positions when the trading filter was 1.00σ was positive at \$3.25 per Mwh. More importantly, the average profit in this situation was not significantly different from zero.

Profits or losses on the electricity and natural-gas components of the spread positions comprise the trading profits shown in Table IX. We separately computed the profits on these components to determine their contributions to the total. We also allocated the commission costs to each component; \$0.02 per Mwh electricity and \$0.06 to natural gas. The results, given in Table X, show that the electricity component provided the trading profits reported in Table IX. The electricity trades were profitable at about the 10% level or better except for short positions in the COB-based spark spread.[5] Excluding the gas component actually improved the profitability of the short positions in both the COB and PV electricity contracts. These results—that the electricity component of the trades is profitable while the natural gas component is not—are not

[5]The average profit on the electricity component of a long position based on the PV contract with a filter of 1.00σ was not significantly different from zero, but all the electricity trades in this situation were profitable, as suggested by the results in Table IX and shown in Table XI.

TABLE IX
Out-of-Sample Trading-Rule Simulations

Panel A: Long Positions

	Open Position When			
	$AP < -0.25\sigma$	$AP < -0.50\sigma$	$AP < -0.75\sigma$	$AP < -1.00\sigma$
California–Oregon Border Contract				
Number of trades	11	11	8	6
Average duration	21 days	21 days	27 days	34 days
Percent profitable	90.91%	90.91%	87.50%	83.33%
Maximum profit	$7.70	$7.70	$7.78	$9.63
Minimum profit	−2.62	−2.62	−2.01	−1.74
Average profit	2.83	2.84	2.73	3.91
Standard error	0.86	0.85	1.12	1.73
Probability	0.0040	0.0039	0.0221	0.0367
Palo Verde Contract				
Number of trades	8	6	4	3
Average duration	29 days	37 days	54 days	67 days
Percent profitable	100.00%	100.00%	100.00%	100.00%
Maximum profit	$29.81	$29.81	$29.81	$29.81
Minimum profit	1.39	1.39	3.25	3.25
Average profit	7.34	7.80	10.84	12.46
Standard error	3.37	4.44	6.35	8.68
Probability	0.0330	0.0698	0.0931	0.1439

Panel B: Short Positions

	Open Position When			
	$AP > 0.25\sigma$	$AP > 0.50\sigma$	$AP > 0.75\sigma$	$AP > 1.00\sigma$
California–Oregon Border Contract				
Number of trades	12	11	10	10
Average duration	17 days	18 days	19 days	19 days
Percent profitable	58.33%	72.73%	80.00%	80.00%
Maximum profit	$8.62	$8.62	$8.62	$8.76
Minimum profit	−11.76	−11.76	−7.97	−7.97
Average profit	0.58	0.81	1.50	1.72
Standard error	1.53	1.68	1.56	1.54
Probability	0.3566	0.3199	0.1809	0.1470
Palo Verde Contract				
Number of trades	7	5	5	5
Average duration	14 days	18 days	18 days	18 days
Percent profitable	100.00%	100.00%	100.00%	100.00%
Maximum profit	$17.13	$17.13	$17.13	$26.91
Minimum profit	0.40	2.42	2.42	3.11
Average profit	8.74	9.17	9.17	12.63
Standard error	2.56	2.89	2.89	4.49
Probability	0.0071	0.0168	0.0168	0.0240

Note. A long (short) position is opened by purchasing (selling) 1 Mwh of electricity and selling (buying) β_1 MMBtus of natural gas, where β_1 is the apparent heat rate; $\beta_1 = 2.62$ for COB, and 2.86 for PV. A long (short) position is closed by executing the opposite trades when $AP \geq (\leq)$ zero. *AP* is the residual from Equation (2) computed using the coefficients given in Table VIII. Commissions are $0.08 per Mwh for COB and PV. The probability that the average profit is different from zero by chance is computed from the *T*-distribution with $n - 1$ degrees of freedom and the standard error of the mean equal to the sample standard deviation divided by the square root of *n*, where *n* is the number of trades.

TABLE X
Profitability of Separate Components of Spark Spread

Panel A: Long Positions

	Open Position When							
	$AP < -0.25\sigma$		$AP < -0.50\sigma$		$AP < -0.75\sigma$		$AP < -1.00\sigma$	
	Electricity	*Gas*	*Electricity*	*Gas*	*Electricity*	*Gas*	*Electricity*	*Gas*
			California–Oregon Border Contract					
Average profit	2.66	0.17	2.63	0.21	2.51	0.23	3.61	0.30
Standard error	0.87	0.29	0.88	0.29	1.21	0.39	1.98	0.53
Probability	0.0062	0.2912	0.0067	0.2439	0.0386	0.2872	0.0640	0.2941
			Palo Verde Contract					
Average profit	7.23	0.11	7.61	0.19	10.43	0.41	12.26	0.19
Standard error	3.28	0.15	4.33	0.20	6.23	0.32	8.42	0.33
Probability	0.0316	0.2436	0.0696	0.1871	0.0963	0.1453	0.1412	0.3109

Panel B: Short Positions

	Open Position When							
	$AP > 0.25\sigma$		$AP > 0.50\sigma$		$AP > 0.75\sigma$		$AP > 1.00\sigma$	
	Electricity	*Gas*	*Electricity*	*Gas*	*Electricity*	*Gas*	*Electricity*	*Gas*
			California–Oregon Border Contract					
Average profit	0.72	−0.14	1.04	−0.22	1.79	−0.29	2.01	−0.29
Standard error	1.42	0.21	1.56	0.22	1.41	0.24	1.82	0.25
Probability	0.3112	0.7410	0.2605	0.8304	0.1177	0.8692	0.0913	0.8583
			Palo Verde Contract					
Average profit	9.06	−0.32	9.57	−0.40	9.57	−0.40	13.04	−0.42
Standard error	2.66	0.35	3.11	0.50	3.11	0.50	4.48	0.48
Probability	0.0072	0.7981	0.0184	0.7633	0.0184	0.7633	0.0218	0.7831

Note. Average profit and standard errors for the components of the spark-spread trades described in Table IX. The probability that the average profit is different from zero by chance is computed from the *T*-distribution with $n - 1$ degrees of freedom and the standard error of the mean equal to the sample standard deviation divided by the square root of *n*, where *n* is the number of trades.

surprising for two reasons. First, positions are opened and closed when the *electricity* futures price differs from our estimate of its equilibrium value. Second, our error-correction model revealed that although electricity futures prices respond to changes in the long-run equilibrium relationship, natural-gas futures prices do not.

We can infer from Table X that trading the spark spread is no more profitable than trading electricity futures contracts alone, but we do not know the effect on risk. Spread trades are thought to entail less risk, so it may have been worthwhile to trade natural gas as well as electricity to obtain risk reduction, if not an increase in profit. We investigated this issue by comparing the outcomes of trading the combination of electricity and natural gas (the spark spread) and electricity alone. The results are given in Table XI.

There was no significant difference between the average profit from trading the spark spread and electricity futures contracts alone for any type of position, electricity contract, or entry filter, confirming the inference from Table X. More importantly, trading the spark spread rather than electricity alone did not reduce the risk. There was no significant difference in the standard deviation of profit, there was no change in the percent of profitable trades in most cases, and trading the spread actually reduced the minimum profit in 9 of 16 situations. We concluded that, using our trading rules during this test period, there was no return or risk advantage to trading the spark spread rather than the electricity futures contract alone. This is not to say that it is safe to ignore natural-gas prices because the electricity trades were opened when there was a violation of the long-run equilibrium relationship between electricity and natural-gas futures prices.

SUMMARY

We found that electricity and natural-gas futures prices are cointegrated and that the characteristics of the relationship between them depend on when and why electricity is consumed. Palo Verde electricity futures prices exhibit more seasonality than California–Oregon Border electricity prices due to the region's greater demand for air conditioning. There was no difference in sensitivity of electricity futures prices to natural-gas prices in the two service areas, even though power companies use more natural gas to generate electricity in the southwest than in the northwest. This result may reflect the fact that many power companies use natural gas as their marginal fuel to generate peak power.

Our trading rule simulations demonstrated that traders who used our model of the relationship between electricity and natural-gas futures prices would have earned profits in both in- and out-of-sample tests. Long positions were more profitable that short positions, and trades in the Palo Verde contract were more profitable than those in the California–Oregon Border contract. Closer examination revealed that these profits were generated by the electricity side of the trades. Adding the natural-gas position neither increased the average profit nor lowered the risk of the trades. These results demonstrate that traders could have profited from the persistent tendency for the spark spread to revert to a mean, which depends on the cost of producing electricity.

TABLE XI
Comparison of Spark-Spread and Electricity Trades

Panel A: Long Positions

	Open Position When											
	$AP < -0.25\sigma$			$AP < -0.50\sigma$			$AP < -0.75\sigma$			$AP < -1.00\sigma$		
	Spark Spread	*Electricity Alone*	*Difference*	*Spark Spread*	*Electricity Alone*	*Difference*	*Spark Spread*	*Electricity Alone*	*Difference*	*Spark Spread*	*Electricity Alone*	*Difference*
	California–Oregon Border Contract											
Average profit	2.83	2.66	0.17	2.84	2.63	0.21	2.73	2.51	0.23	3.91	3.61	0.30
Standard deviation of profit	2.84	2.90	−0.06	2.83	2.91	−0.08	3.16	3.42	−0.27	4.24	4.85	−0.61
Minimum profit	−2.62	−1.65	−0.97	−2.62	−1.65	−0.97	−2.01	−1.20	−0.81	−1.74	−1.55	−0.19
Percent profitable	90.91%	81.82%	9.08%	90.91%	81.82%	9.08%	87.50%	75.00%	12.50%	83.33%	66.67%	16.66%
	Palo Verde Contract											
Average profit	7.34	7.23	0.11	7.80	7.61	0.19	10.84	10.43	0.41	12.46	12.26	0.19
Standard deviation of profit	9.53	9.27	0.26	10.89	10.61	0.28	12.69	12.46	0.24	15.04	14.58	0.46
Minimum profit	1.39	1.29	0.10	1.39	1.29	0.10	3.25	3.00	0.25	3.25	3.00	0.25
Percent profitable	100.00%	100.00%	0.00%	100.00%	100.00%	0.00%	100.00%	100.00%	0.00%	100.00%	100.00%	0.00%

Panel B: Short Positions

	Open Position When											
	AP > 0.25σ			*AP > 0.50σ*			*AP > 0.75σ*			*AP > 1.00σ*		
	Spark Spread	*Electricity Alone*	*Difference*	*Spark Spread*	*Electricity Alone*	*Difference*	*Spark Spread*	*Electricity Alone*	*Difference*	*Spark Spread*	*Electricity Alone*	*Difference*
California–Oregon Border Contract												
Average profit	0.58	0.72	−0.14	0.81	1.04	−0.22	1.50	1.79	−0.29	1.72	2.01	−0.29
Standard deviation of profit	5.31	4.92	0.39	5.59	5.16	0.43	4.94	4.45	0.49	4.88	4.40	0.49
Minimum profit	−11.76	−10.37	−1.39	−11.76	−10.37	−1.39	−7.97	−6.51	−1.46	−7.97	−6.51	−1.46
Percent profitable	58.33%	58.33%	0.00%	72.73%	63.64%	9.09%	80.00%	80.00%	0.00%	80.00%	80.00%	0.00%
Palo Verde Contract												
Average profit	8.74	9.06	−0.32	9.17	9.57	−0.40	9.17	9.57	−0.40	12.63	13.04	−0.42
Standard deviation of profit	6.77	7.05	−0.27	6.45	6.95	−0.49	6.45	6.95	−0.49	10.03	10.01	0.02
Minimum profit	0.40	0.69	−0.29	2.42	1.91	0.51	2.42	1.91	0.51	3.11	2.55	0.56
Percent profitable	100.00%	100.00%	0.00%	100.00%	100.00%	0.00%	100.00%	100.00%	0.00%	100.00%	100.00%	0.00%

Note. Average profit and standard deviation of profit of the spark-spread trades and the electricity components of the spark-spread trades described in Table IX. The probability that the two strategies have the same average profit is determined using an equality of means test. The probability that the two strategies have the same standard deviation of profit is determined using an *F*-test for the equality of variances.

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