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INTRA- AND INTER-COMMODITY PRICE RELATIONSHIPS IN ELECTRICITY AND NATURAL GAS SPOT AND FUTURES MARKETS

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By

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INTRA- AND INTER-COMMODITY PRICE RELATIONSHIPS IN ELECTRICITY AND NATURAL GAS SPOT AND FUTURES MARKETS

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Intra- and Inter-Commodity Price Relationships in Electricity and Natural Gas Spot and Futures Markets

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ABSTRACT

This dissertation explores the intra- and inter-commodity price relationships in the electricity and natural gas markets. It is composed of three empirical essays.

Essay 1 investigates the market evolution and integration in the electricity spot and futures markets in the context of electricity deregulation in the entire US. The application of market integration statistical tests provides evidence of increasing market integration in the spot markets but not in the futures markets. There is mixed evidence that market integration within the same area is stronger than across different areas.

Essay 2 examines why electricity futures contracts are failing despite apparent need for hedging instruments. Consistent with my hypothesis, empirical results find that the hedging protection provided by electricity futures contracts decreased and led to the decline of the futures market. I attribute the deterioration in hedging effectiveness to the mismatch between futures and spot prices, which arises from the non-storability of electricity, the futures contracts' delivery methods and the exceptional spot price volatility. The effectiveness of a cross hedge by using natural gas futures is also examined but turns out to be very weak.

Essay 3 studies the inter-commodity price relationships. The spread between electricity and natural gas prices is known as the "spark spread." This essay examines the time-series properties of this spread and determines whether it exhibits mean-reversion that traders can exploit. The study finds that there is both statistically and economically significant mean-reversion in electricity futures prices. And the profits generated in the simulation are mostly from the electricity side of the transactions.

Intra- and Inter-Commodity Price Relationships in Electricity and Natural Gas Spot and Futures Markets

Chapter 1 Introduction

Finance scholars and investors have become more interested in the electricity[1] markets than ever before. One of the most important reasons is the ongoing deregulation and the consequent increase in the volatility of electricity prices. The Federal Energy Regulatory Commission (FERC) Order 888 and 889 of 1996, along with the US Energy Policy Act of 1992, facilitated the price competition in the wholesale power markets by requiring utilities to open their transmission systems to wholesale power sales. Currently the fifty states in the U.S. are in different stages of preparation and legislation for electricity retail and wholesale market deregulation. Along with the release of market force came enormous volatility in spot electricity markets. For example, the spot price of electricity delivered to Cinergy switchyard varied from $50 to $7,500 per megawatt hour within the month of June in 1998. Such unprecedented volatility produces tremendous risks and opportunities for energy companies and traders. Secondly, the fact that electricity is difficult, if not impossible, to store basically removes any buffer for spot market and contributes to the spectacular price hikes. In the academic world, such a unique characteristic renders some popular finance theories, like the cash-and-carry theory, inapplicable and poses challenges to finance researchers. This motivates my study in this dissertation.

[1] In the electricity industry, the term "electricity" can be used to refer to electric energy, reserve power, ancillary power services, etc. In this dissertation, "electricity" only means electric energy.

To explore the electricity markets, it is essential to look into the natural gas prices because natural gas is an important input for the generation of electricity. Besides, when demand surges strike in summertime, utilities usually resort to natural gas fired generators because they take less preparation time so natural gas prices, to a certain extent, represent the marginal cost of electricity. The price relationship between electricity and natural gas, called the *spark spread*, is monitored both by power producers and by speculators. Power producers use it as a benchmark for production costs to help decide whether to produce the power or to buy it off the grid, whereas power market speculators usually interpret spark spread as an indicator of the directions in which electricity and natural gas prices will move. Another reason to study the natural gas prices is that natural gas market deregulation occurred in the mid-1980s, about a decade earlier than the electricity deregulation. Thus the behavior of natural gas prices can serve as a benchmark in studying electricity prices.

In this dissertation, the specific questions I address are: How has the deregulation process affected the electricity industry? Can electricity futures provide effective hedging protection against power price fluctuations? How do the prices of electricity and its most important generation resource, natural gas, interact?

To answer these questions, the dissertation explores the intra- and inter-commodity price relationships in the electricity and natural gas spot and futures markets. It consists of three essays which are all among the first to explore their respective areas. Figure 1.1 diagrams the structure of the research that includes studies of intra- and inter-commodity price relationships. Other researchers have studied spot market integration and futures market hedging effectiveness for natural gas (see King and Cuc (1996), and

Brinkmann and Rabinovitch(1995), for example). Therefore, this dissertation completes the study of the price relationship structure between these two commodities diagrammed in the figure.

Essay I explores the impact of the ongoing electricity market deregulation on the integration of regional electricity spot markets in the entire U.S. I apply a bivariate regression test, the Kalman Filter, and a price-difference test to the 1995 - 1999 on-peak and off-peak spot price series that cover 22 regional markets in four areas from coast to coast. I find evidence of increasing market integration for the on-peak electricity prices. But for off-peak electricity, the degree of market integration drops in the fourth year after consistent growth during the first three years. This might be due to the fact that the off-peak regional prices in the West area show signs of increasing independence from other markets in the fourth year. Furthermore, the test results indicate stronger market integration for on-peak prices than for off-peak prices. I also find some support for the hypothesis that market integration within the same area is stronger than across different areas.

The second essay studies the decline of the electricity futures market. I first examine their hedging effectiveness because hedging demand is vital to futures contracts' success. I hypothesize that the quality of the hedge provided by electricity futures contracts deteriorated and led to the decline of electricity futures markets. To test this, I compute the coefficient of determination (i.e., the R-square) from the minimum variance hedging models. Consistent with my hypothesis, the results find that the hedging effectiveness of electricity futures was relatively stable during the first two years, but declined after that. In view of the differences between natural gas and electricity in terms of hedging effectiveness and commodity characteristics, I argue that the decline of the electricity futures can be attributed to the mismatch between futures and spot prices arising from the non-storability of electricity, electricity futures contracts' delivery methods and the exceptional spot price volatility. Empirical tests show that the level of mismatch for electricity, measured by the basis, is statistically significant during each sub-period while that for natural gas is not. In addition, the mean and variance of the basis had a significant increase at the time when hedging effectiveness took a downturn, suggesting the mismatch between electricity futures and spot prices lowered the quality of the hedge. This change in hedging effectiveness caused the decline of the electricity futures market. Regarding the possibility of using natural gas futures to hedge spot electricity prices (the cross hedge), I examine its hedging effectiveness but it turns out to be very weak.

Essay III analyzes the relationship between electricity futures prices and natural gas futures prices. I find that the daily settlement prices of NYMEX's California-Oregon Border (COB) and Palo Verde (PV) electricity futures contracts and its natural gas futures contract are cointegrated. The coefficient of natural gas futures prices in my model of COB electricity futures is not significantly different from the coefficient of gas prices in my model of PV electricity even though there are differences in the production of electricity in these two service areas. However, the coefficients in my model do reflect differences in the consumption of electricity in the COB and PV service areas. My trading rule simulations show that the statistically significant mean-reversion I find in the relationship between electricity and natural gas futures prices is also economically significant in both in-sample and out-of-sample tests. A closer examination reveals that these profits are mostly generated by the electricity side of the trades. Adding the natural gas position neither increases the average profit nor lowers the standard deviation of the trading profits, but it is needed to determine the timing of the trades.

The remainder of this dissertation is organized as follows. Chapter 2, 3 and 4 present Essays I, II and III respectively. Chapter 5 summarizes the essays' implications.

Chapter 2 Essay I: Market Integration in the U.S. Spot and Futures Electricity Markets

2.1 Introduction

This dissertation investigates the risk management issues in the electricity spot and futures markets and the inter-commodity relationship between electricity and natural gas, so it is essential to lay out the groundwork by first studying the commodity markets themselves. Numerous papers, including De Vany and Walls (1993), Doane and Spulber (1994), King and Cuc (1996), and Serletis (1997), have studied the natural gas market. The evolution and integration of the electricity market, which are currently under deregulation, remains a less explored and understood area in financial economics. This is an important issue in my dissertation because there are numerous regional spot and futures electricity prices. If the electricity markets are not well integrated, then it is necessary to look into each regional market carefully in the ensuing studies.

Many economists believe that electricity produced in different regions is distinctively different commodities due to limited transmission capacity and the huge costs involved in transmitting power long distance. Others argue that, with the ongoing deregulation process, market forces would align the regional power prices and facilitate the integration of regional markets. The main reason is that, within the limits of market frictions and imperfections, the "Law of One Price" mandates that the spot prices of the same commodity in different locations be linked and the long-term price differences reflect the transaction and transportation costs.[2] This rule does not apply to regulated industries in which prices are set by authorities, usually by adding a certain percentage of margin to production costs that vary from location to location. Nevertheless, when deregulation of an industry is under way, competition from outsiders is introduced and prices are subject to more and more market pressure. Arbitrage activities serve to force the prices in different regions to converge and market integration among regional markets tends to grow over time. The natural gas market is exactly such a case.

The deregulation of the natural gas market and introduction of open access to pipeline transportation started in the mid-1980s. Since then, the natural gas market has seen a phenomenal increase in competition and integration among regional markets. In finance and economics literature, there have been numerous studies that focus on the integration of natural gas markets. De Vany and Walls (1993) apply cointegration techniques and show that more than 65% of the natural gas markets had been cointegrated by 1991. Doane and Spulber (1994) use monthly spot price data from 1984 to 1991 to test the hypothesis that the "Law of One Price" holds within the limits of transportation and transaction costs. They conclude that deregulation and open access increase integration among regional natural gas markets. King and Cuc (1996) employ time-varying parameter analysis (the Kalman Filter) to measure the degree of price integration in natural gas spot markets. They suggest that price integration is the strongest in the Gulf Coast region, and that there is an east-west split in natural gas

[2] In the electricity industry, transmission costs are on dollar basis while transaction costs are sometimes on percentage basis. Because the transmission costs are usually much higher than transaction costs across regions, I assume both costs are on dollar basis and the intercept term of the Bivariate model serves to capture their effects.

pricing. However, Serletis (1997) applies a maximum likelihood approach in cointegration analysis and finds that this east-west split does not exist.

Comparatively, the deregulation of the electricity markets is a newer event. It started after the Federal Energy Regulatory Commission (FERC) Order 888 of 1996, along with the US Energy Policy Act of 1992, required utilities to open their transmission systems to wholesale power sales. States then began legislation to introduce free competition in the electricity markets. As of March 2000, the fifty states are in different stages of electricity market deregulation. Due to issues such as recovery of stranded costs and pollution control, most states are still in a gradual process of deregulation, and most laws passed by state legislatures allow a certain period of time for this transition. As Figure 2.1 and Table 2.1 suggest, twenty-four states have enacted laws or issued relevant orders for deregulation while others are undergoing investigation or legislative debates. These laws or orders, passed since 1996, usually allow two to five years during which utilities can prepare for wholesale and/or retail competition.

In addition to the ongoing deregulation process, other factors also contribute to the uniqueness and complexity of the electricity markets. In contrast to natural gas and other commodities, electricity is different in that it cannot be stored. This means that in deregulated spot electricity markets, demand and supply have to be balanced instantly and continuously. A direct consequence is that spot electricity price shot up to thousands of dollars per megawatt hour during the past several summers, resulting in tremendous losses for some power marketers. Secondly, transmission lines, owned mostly by utility firms, have transmission constraints, which are especially serious during peak hours of the day (6am - 10pm weekdays in the West, 7am - 12am in other areas). The transmission constraints, along with the high cost associated with long-distance transmission, hinder price competition across regional markets. All these factors will affect the development and integration of electricity markets.

Electricity market integration remains a less explored area in comparison to the relatively abundant literature on natural gas price relationships. There are only three published papers. McCullough (1996) applies price correlation analysis to submarkets in the Western Systems Coordinating Council (WSCC) and finds significant correlations throughout WSCC with the exception at BC/US Border, Alberta Power Pool, and Palo Verde. Woo, Lloyd-Zannetti and Horowitz (1997) study the wholesale electricity submarkets in the Pacific Northwest region of WSCC using the 1996 on-peak electricity prices of four submarkets: Mid-Columbia, California-Oregon Border (COB), BC/US Border and Alberta Power Pool. Their tests suggest the first three submarkets are integrated and there is no price leadership among the three. De Vany and Walls (1999) use 1994-1996 on-peak and off-peak prices of 11 regional markets in the western United States and find evidence of efficient and stable electricity prices.

All these papers focused on the western and northwestern regions because California was among the first states to enact deregulation laws, establish an organized power exchange (California Power Exchange, or CALPX), and begin wholesale power trading. Price data for these regions are more readily available than for others. Figure 2.2 provides a picture of the area they study vis-a-vis other areas in the U.S based on the distribution of regional electric reliability councils. There have not been any published papers that investigate the integration of electricity spot or futures markets in the entire

United States or the integration of the electricity futures markets. This essay fills this void.

My spot price data covers the on-peak and off-peak daily electricity prices of 22 regional markets in 4 major areas—the East (4 regions), the Mid-Continent (8 regions), the Gulf/Southeast (4 regions), and the West (6 regions). And my futures data is the two longest running futures traded at New York Mercantile Exchange (NYMEX), California-Oregon-Border (COB) and Palo Verde (PV). Both the spot and futures data are between 3/29/1996 and 3/28/2000. Unit-root tests find that, contrary to the finding of De Vany and Walls (1999), nearly all spot electricity price series are stationary.

In this study, I divide the four-year data into four one-year sub-samples and apply to them a bivariate test, the Kalman Filter, and a price-difference test. I find that:

- The on-peak spot electricity prices exhibit clear and consistent patterns of increasing market integration.
- The on-peak regional markets in the East show integration only within the area, while those in the other three areas integrate across areas.
- Market integration for off-peak spot electricity grows during the first three years, but then takes a downturn in the fourth year.
- A closer examination of the test results reveals that the inconsistency in off-peak spot market integration might be due to the fact that the off-peak spot regional prices in the West show signs of increasing independence from other areas in the fourth year.
- From the values of the percentages of the market pairs that show market integration based on different criteria, on-peak spot prices display consistently stronger market integration than off-peak prices.

- The Kalman Filter results provide evidence that spot market integration is stronger within the same area than across different areas, though the two statistical tests do not show very strong support for this.
- As for the futures markets, there is at best weak evidence for increasing integration.

The remainder of the essay is organized as follows. Section II describes the characteristics of the data. Section III explains the tests and their respective results. Section IV summarizes and suggests future research areas.

2.2 Electricity Spot and Futures Price Series

I use the 1996 - 2000 on-peak and off-peak spot price series[3] and futures data from the Bloomberg™ terminal. For the spot data, Bloomberg™ divides the U.S. into four areas: East, Mid-Continent, Gulf/Southeast, and West, and then further divide the areas into regions. The price series are volume-weighted averages of spot power trades collected through surveys of brokers, traders, power marketers, and other market participants at the same trading post in the region. Since many spot markets are unorganized and over-the-counter, this averaging across different market participants provides relatively accurate price information for the regions and spurious correlation should not be a serious problem.

After the regions with missing data over certain periods are left out, I end up with four regions for the East area, eight regions for the Mid-Continent area, four regions

[3] I have firm on-peak, firm off-peak, non-firm on-peak, and non-firm off-peak price series. "Non-firm" refers to interruptible power. Because non-firm prices are calculated based on firm prices in many regions, and the firm and non-firm price series exhibit nearly identical properties, I use firm on-peak and firm off-peak price series in this essay. The word "firm" is skipped.

for the Gulf/Southeast area, and six regions for the West area. Table 2.2 gives a list of the areas/regions and descriptions for each region. The entire data period is exactly four years, from 3/29/96 to 3/28/00. I split the data sample into four one-year sub-samples, and these sub-samples have 250, 251, 250 and 251 observations respectively.

With regard to the futures data, there are currently 6 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. I use the two older contracts, California-Oregon Border (COB) and Palo Verde (PV), to obtain longer price series. The data represents the nearby futures contract's price at the close of each trading day.

Table 2.3 reports descriptive statistics for electricity spot prices by areas and by periods. In Panel 1, the means of the East, Mid-Continent and Gulf/Southeast areas are 38.54 and 36.02, significantly higher than the means of the East (30.17) and the West (24.58).[4] But the medians of the Mid-Continent and Gulf/Southeast areas, 22.97 and 23.95, are lower than the East's 27.00 and only slightly higher than the West's 22.75. This can be explained by the Mid-Continent and Gulf/Southeast's much higher standard deviations and their spectacular maximum values of 2041.67 and 1700. Figure 2.3 visually shows that during summers, especially the summers of 1998 and 1999, Mid-Continent and Gulf/Southeast have much greater upswings than the other two areas.

For off-peak prices, the East has the highest mean and median. But the West exhibits much greater volatility. Figure 2.4 gives a picture of this.

Given the West's traditionally higher electricity prices, I find it surprising that in Panel 1 the mean and median prices of the West are consistently the lowest among the

[4] The statistics for the mean comparisons are available upon request.

four areas. A possible reason is the West's early deregulation and establishment of wholesale markets. This invites further investigation.

Panel 2 of Table 2.3 shows the descriptive statistics for the data sample period by period. Each period is one year long. The means of Period 3 and 4, 40.12 and 42.31, are significantly greater than those of Period 1 and 2, 23.09 and 26.06. But the medians of all periods are similar. Like in Panel 1, this fact can also be explained by the differences in standard deviations and maximum values. As Figure 2.3 suggests, the summers of the last two years saw much more volatile pattern and greater upswings than the summers of the first two years.

Table 2.4 reports descriptive statistics by regions. Similar to Panel 1 of Table 2.3, the on-peak prices of the regions in the Mid--Continent and Gulf/Southeast areas exhibit higher means, standard deviations and maximum prices. And the off-peak prices of the regions in the West show higher standard deviations than other regions.

Table 2.5 gives the descriptive statistics for electricity futures prices. Similar to the spot prices, both COB and PV futures prices show steadily increase over the four-year sample period. There is a certain jump in the standard deviation between the first two years and the second two years. But the volatility, reflected by the value of standard deviation and the differences between minimum and maximum prices, is lower for futures than for spot prices. This is consistent with the fact that spot prices are directly subject to the ups and downs of demand and supply due to electricity's non-storability, while futures prices, facing the threat of delivery only days or months later, are not.

Table 2.6 provides the augmented Dickey-Fuller (ADF) unit root test results for electricity spot prices and their first differences. I use three lags, three lags and a time trend, the Akaike information criterion (AIC), and the Bayesian information criterion (BIC), respectively. All these tests give similar results. Except for New England Power Pool (NEPOOL) spot prices, all price series and their first differences reject the null hypothesis that the series have unit roots and are non-stationary. This is different from the finding of De Vany and Walls (1999), in which they study eleven regional price series in western United States between 1994 and 1996.

Table 2.7 presents the results of the same unit root tests on the futures price series and their first differences. Contrary to spot prices, the two futures prices cannot reject the null hypothesis they are non-stationary. But their first differences are stationary, which indicates that both futures price series are integrated of order one.

It appears perplexing that electricity spot prices are stationary but the futures prices are because futures prices are usually deemed as expected future spot prices. However, the non-storability of electricity, to a great extent, severs the relationship between the spot and futures prices. The futures electricity prices are "purely expectational", according to one analyst in the industry. This weak link between spot and futures markets makes the differences in time series properties possible. Essay II will further discuss this issue.

Because I reject the null hypothesis that the spot price series are non-stationary in all but one case, and all price series have equal numbers of observations, I argue that Ordinary Least Squares (OLS) regressions would not lead to spurious results. As for the non-stationary futures series, I will apply the OLS regressions on both the price levels and their first differences.

2.3 Market Integration Analysis

To show the changes in electricity market integration over time, three statistical methods are used: the bivariate regression test, the Kalman Filter, and the price-difference test. They are applied side by side to show different aspects of electricity market integration and facilitate a comparison of the results.

2.3.1 Bivariate Regression Test

In two integrated markets, the prices should track one another with unitary responses, and shocks at one location should be reflected in another market's price quickly. Along this line, I apply the following bivariate Ordinary Least Squares (OLS) regression test of market integration:

$$P_{j,t} = \alpha_{ij} + \beta_{ij} P_{i,t} + \varepsilon_{ij,t} \tag{1}$$

where $P_{j,t}$ and $P_{i,t}$ are the spot prices of regional market j and i at time t. I regress $P_{j,t}$ on a constant term and $P_{i,t}$. If the two markets are integrated, β should be equal to 1 and α should capture the transaction and transmission costs between the two markets. Because the regression results can be sensitive to the roles of the markets as dependent and independent variables, I estimate the regression both ways.[5]

Since almost all price series are stationary, I perform the traditional t-test on the hypothesis that the β coefficient is equal to 1. The R^2 values, ranging from 0.02 to 0.90, indicate different levels of goodness of fit and are consistent with the different volatility

[5] When I report market pairs that meet a certain criterion in Table 2.8, I only require one way. For instance, for a market pair of P_j and P_i, I both regress P_j on P_i and regress P_i on P_j. I say this market pair meets a criterion so long as one of the two regressions does. Table 2.12 does not have this problem because it deals with the differences in prices.

among regional markets. The β value and t-statistics for the four periods and the entire sample period are calculated and are available upon request. A summary of the bivariate regression results is presented in Table 2.8.

Panel 1 of Table 2.8 presents the percentages of market pairs with β coefficients that are not significantly different from 1, or in other words, β coefficients that do not reject the hypothesis that β is equal to one at the 10% confidence level.[6] For all 22 regions, the percentages for on-peak prices are 11.26%, 12.99%, 32.03%, 41.56% for period 1, 2, 3, 4 respectively, which clearly indicates increasing market integration. The percentages for off-peak prices, on the other hand, are 3.46%, 8.23%, 17.32%, 8.23% for the four consecutive years.[7] Market integration shows a rising trend during the first three years, but then make a dip in the fourth. In addition, for all four periods, the percentage for on-peak prices is 29.44% and for off-peak prices is 3.90%. And for each individual period the on-peak prices always have a bigger percentage than off-peak prices, suggesting that market integration is stronger in the on-peak markets than in the off-peak markets. This is in line with my expectation because of more competition and liquidity in the on-peak electricity transactions.

A closer examination of the β values and their t-statistics reveals that one possible cause of these trends may be the regional prices in the West area. As Panel 1 of Table 2.8 shows, market integration of the market pairs that involve the West exhibits exactly the same trends as the overall sample does. The West-related percentages are 2.70%, 7.21%, 56.76%, and 72.97% for on-peak prices and 5.41%, 15.32%, 28.83%, and 11.71%

[6] Similar to Woo et. al. (1997), I choose the 10% significance level to deflect the criticisms that I am too eager to find evidence of market integration.

[7] I use "year" and "period" interchangeably because each period is exactly one year.

for off-peak prices. The percentages for on-peak prices are at first lower than for off-peak prices, but then have big jumps during the third and fourth years, surpassing those for off-peak prices. The market pairs that do not involve the West do not show any clear trend of changes in market integration, nor do those from the same areas. But the market integration across different areas shows similar patterns to those of the overall sample in this test.

Under the criterion used by King and Cuc (1996) and Woo et al. (1997), β estimates between 0.93 and 1.01 indicate market integration. Panel 2 of Table 2.8 presents the percentages of market pairs with β coefficients between 0.93 and 1.01.

For all 22 regions, the percentages of β coefficients between 0.93 and 1.01 are 6.06%, 7.36%, 9.09%, and 12.99% for on-peak prices, and 2.16%, 2.16%, 4.76%, and 2.16% for off-peak prices. Although these percentages are smaller than those in Panel 1, they show the same trends: 1) Market integration grows along the entire period in on-peak markets; 2) In off-peak markets, integration develops during the first three years, but then drops in the fourth year; 3) On-peak markets exhibit stronger signs of integration than off-peak markets as indicated by the values of the percentages.

The West-related market pairs show similar trend patterns to those of the overall sample, so do the same-area market pairs. One thing to note is that the same-area percentages are consistently bigger than across-area percentages, providing support for the hypothesis that market integration is stronger within the same area than across different areas.

Table 2.9 reports the market pairs whose β coefficients are not significantly different from 1 or are between 0.93 and 1.01, or market pairs that meet the integration criteria, for the entire sample period. According to a Bloomberg™ representative, the four areas in the U.S. spot electricity market are defined based on geographic distributions and convenience rather than market integration. However, the on-peak results in Panel 1 indicate that the regions in the East area only integrate within the area and do not integrate with regions in other areas, suggesting that the East area is well-defined and independent. Nevertheless, the other three areas have numerous across-area integrated market pairs, especially between the West and the Mid-continent areas. For the off-peak markets in Panel 2, integration only occurs within the Mid-continent and West areas. This is expected because there is not much need to transmit power across regions during off-peak hours.

The bivariate regression test is also applied to COB and PV futures price series, and the results are presented in Table 2.10. I conduct the regression with COB or PV as the dependent variable and use the two criteria to determine whether the statistics show market integration. Table 2.10 shows only weak evidence for integration between these two futures contracts. Because the previous tests indicate that the two futures series are both non-stationary and integrated of order one over the entire sample, I apply the unit root tests on the bivariate regression residuals and find the existence of a unit root can be rejected at the 5% confidence level (though not at the 1% level). This suggests that the two futures price series are cointegrated. Therefore, the β coefficient values and the t-test results in this table are meaningful though the two price series are not stationary.

Since the first differences of the futures prices are stationary, I also estimate the following bivariate regression:

$$\Delta P_{j,t} = \alpha_{ij} + \beta_{ij} \Delta P_{i,t} + \varepsilon_{ij,t} \qquad (2)$$

The results are provided in Table 2.11. The Table 2.11 results are very similar to those of Table 2.10. Both tables indicate weak market integration in the futures markets.

In this bivariate regression analysis, the estimation of the β coefficients implicitly assumes a fixed structural relationship between regional market prices over the time period considered. It assumes that the responses to shocks between regional markets are identical over the four-year period. However, market integration and price convergence are a gradual and on-going process, especially in a regulated industry where states are loosening their reins one by one. Furthermore, Table 2.3 shows that the volatility of on-peak electricity spot prices increases drastically during the last two years. These changes within the sample can lead to the possibility that the β estimation, based on the assumption of structural stability, would reject the presence of market integration. For instance, two regional market prices that did not converge until the last year would possibly lead to a β and/or a t-statistic that rejects market integration. To address this issue, I will apply the Kalman Filter in the same way as in King and Cuc (1996).

2.3.2 Kalman Filter

Kalman filter is a recursive updating procedure popular with control engineers and other physical scientists. It has become more and more widely used in finance to produce time-varying parameter estimates. To apply Kalman Filter in my study, I first regress spot price in region Y on spot price in region X:

$$Y_t = \alpha + \beta * X_t + u_t \qquad (3)$$

α is an estimate of the arbitrage and transmission costs between region Y and X. Next, I estimate the following two equations using Kalman Filter techniques:

$$Y'_t = X_t * \beta_t + v_t \qquad (4)$$

$$\beta_t = \beta_{t-1} + w_t \qquad (5)$$

where $Y'_t = Y_t - \alpha$. Equation (4) is the observation equation while (5) is the system equation. v_t and w_t are assumed to be independent of each other and normally distributed with mean 0 and variance of V_t and W_t, respectively. A more detailed discussion can be found in Meinhold and Singpurwalla (1983).

By using the Kalman Filter, I compute optimal time-varying estimates of β_t and then plot them to see whether they meet my a priori expectations. Based on the Law of One Price, the β between two perfectly integrated markets should be equal to one. The closer β is to 1, the stronger the market integration between the two markets. If two regional markets are getting more and more integrated, the β should get closer and closer to one.

Each of Figures 2.5, 2.6, 2.7, and 2.8 presents one regional market price series from one area versus other three price series, acting as dependent and independent variables while passed through the Kalman Filter. I randomly choose the dependent variable series for each figure: Eastern New York Power Pool (SC) from the East, Western East-Central Area Reliability Council (WE) from the Mid-Continent, Entergy (SS) from the Gulf/Southeast, and Four Corners (FC) from the West.[8]

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[8] A complete set of Kalman Filter results is available upon request. All other results are similar to the ones presented in Figures 2.5, 2.6, 2.7 and 2.8.

Figure 2.5 shows the market integration from the perspective of Eastern New York Power Pool (SC) in the East, versus Florida/Georgia Border (FG) in the Gulf/Southeast, Palo Verde (PV) in the West and Pennsylvania/New Jersey/Maryland (PJ) in the East. From both the on-peak and off-peak prices I can see that the time-varying β_t exhibits a very clear trend to converge toward one, which is evidence of growing market integration. In the case of Florida/Georgia Border and Palo Verde, there are periods of exceptionally high volatility, especially around the summers of 1998 and 1999. This is expected because Figure 2.3 and 2.4 have shown similar patterns. But for the price series from the same area (the East), Pennsylvania/New Jersey/Maryland, β_t is a much smoother line over the entire period. This is especially evident during the summers of 1998 and 1999 when the other two fluctuate wildly, suggesting that during those high-volatility periods the regional prices within the same area shoot up and down in a more or less synchronous manner. Furthermore, this time-varying β_t line for the same area hovers much closer to one than the other two lines. This indicates stronger market integration between the regional markets in the same area than across-area market pairs.

Figures 2.6, 2.7, and 2.8 show similar results from the perspective of regional price series in the other three areas, which provide support for the way Bloomberg™ define the areas and shows the effect of the technical and cost barriers to long-distance power transmission. In Figure 2.8's off-peak chart, while the dependent variable price series is Four Corners (FC) in the West, the two across-area β_t lines seem to gradually converge to one during the first three years, but then displays fluctuations and wanders off one in the fourth year. I check other price series in the West area and most of them show similar patterns. This provides support for the Table 2.8 result that off-peak market integration takes a downturn in the fourth year, especially for the market pairs that involve regional prices in the West.

The Kalman Filter results for the futures price series are presented in Figure 2.9. Unlike what I have seen in Figure 2.5-2.8, this curve oscillates up and down and does not show a clear tendency to converge toward one. This finding is consistent with the weak integration evidence in Table 2.10 and 2.11.

The Kalman Filter results support many of Table 2.8, 2.9 and 2.10 findings. However, they do not show whether the market integration is stronger for on-peak markets than for off-peak markets. To further clarify this issue, I perform a price-difference test (Horowitz, 1981 and Woo et al., 1997).

2.3.3 Price-Difference Test

Under the Law of One Price, the difference between the prices of two integrated markets should converge rapidly to the average transmission and transaction costs between the markets in the long run. The convergence will not happen if the markets are not integrated. Hence, I can test the price differences between markets to measure the extent of market integration. Suppose I have two markets "j" and "k", their price difference is $D_t = P_{jt} - P_{kt}$, and their long-run equilibrium value of price difference is D_t^L. Given the above argument, I have

$$D_t - D_t^L = \lambda(D_{t-1} - D_t^L) \qquad (6)$$

where λ is the parameter indicating the speed of adjustment. Here the absolute value of λ should be less than 1 ($|\lambda| < 1$) in markets undergoing a partial adjustment process toward integration. If, on the contrary, $|\lambda| \geq 1$, then there is no evidence that markets j and k are integrated or moving toward integration.

Next I assume $D_t^L = \sigma + \tau t$. σ captures the long-run arbitrage profit between the markets, and τ represents the trending factors that affect both markets simultaneously, like weather, fuel cost changes, etc. Market integration requires that $\tau = 0$, because D_t^L will explode over time if $\tau \neq 0$. Substitute this into equation (6) and rearrange, I get

$$D_t = (1-\lambda)(\sigma + \tau t) + \lambda D_{t-1} = \phi_0 + \phi_1 \tau + \lambda D_{t-1} + \mu_t \tag{7}$$

where $\phi_0 = (1 - \lambda)\,\sigma$ and $\phi_1 = (1 - \lambda)\,\tau$. This is the model for the price-difference test. A more detailed discussion of the price-difference test can be found in Woo et al. (1997). To address the issue of possible serial correlation due to the lagged dependent variable, I add a serially correlated error term $\varepsilon_t = \rho\, \varepsilon_{t-1} + u_t$, where u_t is a white noise, to equation (7) and estimate the regression using maximum likelihood methods.

The above analysis suggests that market integration requires $\tau = 0$ and $|\lambda| < 1$. Therefore, three null hypotheses are to be tested in this price-difference model: 1) $\phi_1 = 0$; 2) $\lambda = 0$; 3) $|\lambda| \geq 1$. If hypothesis 1 is rejected, which means the long-term price difference explodes over time, I have evidence that the markets are not integrated. If this hypothesis is not rejected, then I can proceed to test hypothesis 2 and 3. If hypothesis 2 is not rejected, I have evidence that the markets are integrated because the second condition, $|\lambda| < 1$, is satisfied. If it is rejected, I then test hypothesis 3. If I reject the null hypothesis that $|\lambda| \geq 1$, I find evidence of market integration. The values of ϕ_1, λ and their respective t-statistics for the four periods and the entire sample period are calculated and are available upon request. The R^2 values of the regressions are similar to those in the bivariate tests and range from 0.10 to 0.70, which is expected given the considerable difference in volatility among regional markets. The integration test results are summarized in Table 2.12.

In Table 2.12, for all 22 regions, the percentages of market pairs that show market integration are 30.30%, 76.19%, 90.48%, 96.10% in period 1, 2, 3, 4 for on-peak prices, and 30.30%, 50.22%, 71.00%, *40.26%* for off-peak prices. This exhibits similar trend patterns to those in Table 2.8. For all periods, the percentage that shows market integration is 77.92% for on-peak markets and 12.55% for off-peak markets. Coupled with the fact that the percentage is consistently higher for on-peak markets than for off-peak markets in each separate period, I have evidence that on-peak electricity markets have stronger market integration.

For market pairs that involve regions in the West, the integration patterns are similar to those of the overall sample for both the on-peak and off-peak prices, including the drop in the fourth year for the off-peak markets. There is also a drop in the fourth-year off-peak prices in the sample not related to the West, but the drop is much smaller (from 66.67% to 55.00% versus from 75.68% to 24.32% in the West-related sample).

For the same-area sample, I can see clear trends of increasing market integration. The on-peak percentages are 58.18%, 63.64%, 83.64%, 89.09% and the off-peak percentages are 49.09%, 50.91%, 70.91%, 78.18%. The corresponding off-peak percentages are 21.59%, 80.11%m 92.61%, 98.30% and 24.43%, 50.00%, 71.02%, 28.41%. From the values of the percentages, there is no evidence that the same-area regional markets are more strongly integrated than the across-area markets. But the dip in the fourth-year off-peak prices is only evident in the across-area sample--the off-peak percentages go from 71.02% in period 3 to 28.41% in period 4. Since only the West-related and across-area samples show such a drop, I argue that the connection between the off-peak electricity markets of the west and the rest of the country becomes weaker between 1998 and 1999, and that the West's off-peak markets show signs of isolation in the fourth year.

Table 2.13 reports the market pairs that meet the integration criteria of the Price-Difference test for the entire sample period. Compare Panel 1 results with those in Panel 1 of Table 2.9, it can be concluded that the Price-Difference test is a more lenient measure of market integration. In Panel 2, the off-peak regional markets in the West area exhibit integration only within the area, in consistence with Table 2.12 results.

With regard to the futures market, I do not have to account for the unit root issue here since this test deals with the stationary price differences. Table 2.14 presents the price-difference test results for the COB and PV contracts. And similar to Table 2.10 and 11, only Period 2 results show signs of integration while the results from the overall sample and Periods 1, 3 and 4 do not.

The price-difference test and the previous bivariate regression test are based on different criteria of market integration, so I cannot directly compare their percentages. But in both tests, the on-peak prices show increasing integration over periods and have consistently bigger percentages than off-peak prices do for all periods. This provides evidence that the on-peak markets have growing integration and are more integrated than the off-peak markets.

2.4 Summary

The electricity marketplace has witnessed a wave of deregulation on a state-by-state basis since the passage of Federal Energy Regulatory Commission (FERC) Order 888 on April 24, 1996. Order 888, along with the Public Utility Regulatory Policies Act (PURPA) of 1978 and the Energy Policy Act of 1992, has allowed new market participants to enter the generation and wholesale power business. One of the most important goals of electricity market deregulation is to introduce price competition from other areas and thus reduce the power costs of consumers. If markets are integrated, power producers and marketers can come in and out of regional markets with ease and competition would force high power prices to go down. This motivates my study on the development of the market integration in the electricity spot markets while deregulation is under way. Furthermore, this essay serves to provide the context and foundation for the rest of the dissertation.

This essay applies a bivariate regression test, the Kalman Filter, and a price-difference test to 22 on-peak and off-peak regional electricity spot prices across the U.S and two futures price series between 3/29/1996 and 3/28/2000. Table 2.15 provides a summary of all the results from these three tests. In these tests, I find strong evidence of increasing market integration for the on-peak electricity prices, but market integration for off-peak prices drops in the fourth year after rising over the first three. A possible explanation is the finding that the off-peak prices in the West area demonstrate rising independence from other areas in the fourth year. On the other hand, the values of the percentages of market pairs that show market integration indicate stronger market integration for on-peak prices than for off-peak prices. In addition, the Kalman Filter curves suggest that market integration within the same area is stronger than across different areas, in support of the way Bloomberg^{TM} divide the areas. But this finding only receives partial support from the other two tests. Finally, there is only weak evidence for the integration in the futures markets.

A less important but surprising finding is that the spot electricity price series are stationary during the sample period. This finding is different from that of De Vany and Walls (1999), in which they find most of the 11 regional price series in the western United States between 1994 and 1996 are non-stationary. Because my sample covers the period from March of 1996 to March of 2000, my finding implies that the spot electricity markets became more stable after many states started deregulation processes around 1996.

Although the extent of integration is growing in the spot markets, the regional markets are still immature and far from becoming an integrated market. There is little evidence that the two longest running futures contracts, COB and PV, are getting more and more integrated, which might help explain why NYMEX has launched six different regional electricity futures contracts since 1996. As a result, when I investigate the hedging effectiveness of electricity futures contracts in Essay 2, it is essential to look into each regional market carefully.

Chapter 3 Essay II: Asset Mismatch, Hedging Effectiveness, and the Decline of Electricity Futures Market

3.1 Introduction

Futures exchanges launch contracts in hopes that that these contracts will attract sufficient trading volume for the exchanges to generate profit. On March 29, 1996, the New York Mercantile Exchange (NYMEX) initiated the first electricity futures contracts with delivery points at California-Oregon-Border (COB) and Palo Verde (PV). Many people believed that the contracts would become a huge success due to several reasons.

First, as I have addressed in Essay I, the spot wholesale electricity markets have experienced unprecedented volatility due to the non-storability of electricity, the ongoing deregulation, and other factors. On the other hand, the politically sensitive retail power prices are often protected by government-imposed caps. Therefore, the wholesale market volatility can translate into financial instability or even losses for spot market participants like electric utilities, independent producers, and power marketers. For example, when a heat wave hit the Midwest in June 1998, Chicago-based Commonwealth Edison Co. was forced to buy power on the spot market at $5,000 per megawatt-hour for eight hours -- more than 100 times the regular price. This price spike cost the company millions of dollars within one day. In another case, the electricity wholesale prices have been so high in California since June 2000 that Southern California Edison Co., the state's second largest utility, was on the brink of seeking bankruptcy protection by December. The effect of huge cost spikes on a company's bottom line can be very serious. As a result, there is great need for financial instruments like futures contracts that can help manage power transaction exposures. Second, the futures contract of another similarly deregulated energy commodity, the natural gas, turned out to be one of the fastest growing contracts in NYMEX history. The natural gas industry began the deregulation process in the mid-1980s, about ten years earlier than the power industry did. The first natural gas futures contract was initiated by NYMEX on April 3, 1990. Since then, the nearby contract's average daily trading volume has increased from below 100 to around 40,000, with a high of 79,552 contracts on September 2, 1999.[9] As Figure 3.1 shows, the trading volume growth has been steady and continuous over the ten-year span and the contract is now one of the most popular in NYMEX. This success story, according to a speech by NYMEX vice president Neal Wolkoff, helped NYMEX make the decision to launch electricity futures contracts when electricity deregulation was still in its early stages. Third, the size of the spot electricity market in the United States, at over $250 billion, is approximately four times that of the natural gas market. It is believed that a bigger spot market facilitates the development of a bigger futures market.

Overall, the market conditions appear to be in favor of electricity futures contracts. However, the trading volumes of the contracts have been disappointing.[10] Figure 2 presents the daily and monthly average trading volume of the two longest

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[9] The value of a natural gas futures contract is comparable to that of an electricity futures contract. For example, on March 28, 2000, the natural gas nearby futures price was $2.963 per MMBtu (million British thermal unit), and electricity $34.80 per megawatt hour. With a contract size of 10,000 MMBtu for natural gas and 736 megawatt hours for electricity, one natural gas futures contract was worth $29,630 while one electricity futures contract was worth $25,612.80. The electricity future contract size was cut in half later in 2000 but my sample only covers data up to March 28, 2000 before the change.

[10] The volumes in this study are nearby contracts' trading volumes because they represent approximately 90% of the total trading volume and other volumes are not readily available.

running futures contracts--COB and PV.[11] Over the four years since the launch in March 1996, the daily trading volume for nearby contracts has been around 200 contracts. The trading volume increased slightly during the first half of the sample period, but then dropped after that. This trend is especially conspicuous for the PV contract, whose monthly trading volume averages increased to above 600 contracts before October 1997 but then went all the way down to near zero by March 2000. The average daily trading volumes during the first three months in the year 2000 were 29 for COB and 21 for PV in sharp contrast to the approximately 40,000 contracts for natural gas futures.

The fact that the electricity futures market has become more and more inactive has been a puzzling issue to finance researchers, but there have not been any published papers that deal with it. My study fills this void. A number of previous papers have studied the rise and fall of futures contracts. For example, Brinkmann and Rabinovitch (1995) claim that the principal reasons a contract fails are a lack of hedging effectiveness due to low correlation between price changes of the futures and spot prices of the commodity, lack of trader interest, etc. They find that the approval of a second natural gas futures contract in 1995 was due to the lack of hedging effectiveness of the first futures contract (launched by NYMEX in 1990) for certain areas. And the lack of hedging effectiveness was a result of the limitations in the natural gas transportation system. Amundsen and Singh (1992) analyze the conditions for developing electricity futures contracts in Europe and find that, besides the adequate price uncertainty that warrants futures market development, the factors vital to the futures contracts' success also include: 1) whether the underlying spot markets are sufficiently competitive and

[11] Another four contracts with different delivery points were initiated in 1998, 1999 and 2000 and would be further discussed in Essay III. Similar to Essay III, I will only use COB and PV futures price series here.

well-functioning, 2) the neutrality of the futures exchange, and 3) complete open access to the transmission. Johnston and McConnell (1989) investigate the failure of GNMA CDR futures contract and find that the delivery options allowed by the futures contract reduced the contract's hedging effectiveness for current coupon mortgage securities and led to its downfall.

In these studies, the change in hedging effectiveness is a key issue in the development of the futures contracts. Following the same line, I investigate the decline of electricity futures contracts by first examining their hedging effectiveness. I hypothesize that the quality of the hedge provided by electricity futures contracts deteriorated and led to the decline of electricity futures markets. To test this hypothesis, I compute the coefficient of determination (i.e., the R-square) from the minimum variance hedging models. Consistent with my hypothesis, the results find that the hedging effectiveness of electricity futures was relatively stable during the first two years, but declined after that. In view of the differences between natural gas and electricity in terms of hedging effectiveness and commodity characteristics, I argue that the decline of the electricity futures can be attributed to the mismatch between futures and spot prices arising from the non-storability of electricity, electricity futures contracts' delivery methods and the exceptional spot price volatility. Empirical tests show that the level of mismatch for electricity, measured by the basis, is statistically significant during each sub-period while that for natural gas is not. In addition, the mean and variance of the basis had a significant increase at the time when hedging effectiveness took a downturn, suggesting the mismatch between electricity futures and spot prices lowered the quality of the hedge and the hedging effectiveness of futures contracts. This change in hedging effectiveness reduced the hedging demand for electricity futures contracts and caused the decline of the market.

A less important finding is that the two futures contracts appear to be regional because they provide better hedge for spot price series within the area than outside. This helps explain why NYMEX later launched electricity futures contracts with other delivery points.

The rest of the essay is organized as follows. Section 3.2 describes the data. Section 3.3 presents the hypothesis. Section 3.4 conducts the hedging effectiveness tests and present the results. Section 3.5 analyzes the mismatch between futures and spot prices and how it affects the hedging effectiveness and thus the trading volumes. Section 3.6 is the summary.

3.2 Data

In this essay, the data is also obtained from the Bloomberg™ terminal. For electricity futures, I use the California-Oregon-Border (COB) and Palo Verde (PV) futures prices between their launch on March 29, 1996 and March 28, 2000, a sample period of four years. The futures price series are nearby contract prices. The spot prices are from the same twenty-two regions as in Essay I.

Table 3.1 presents the descriptive statistics for the spot and futures price series. As I have noted in Essay 1, the medians of all the electricity price series are close to each other, mostly between 23 and 29, but the standard deviations vary substantially across areas. For example, the standard deviations in the mid-continent are mostly above 100, more than twice the standard deviations in the West, which are in turn more than twice those in the East. These substantial differences in volatility among areas suggest the high degree of segmentation in the electricity spot markets.

For the COB and PV electricity futures prices, the medians are 26.80 and 28.08, nearly identical with those of the COB and PV spot prices. However, the futures prices have lower means, standard deviations and maximum prices. The differences in standard deviations are significant at the 5% confidence level, suggesting that the spot markets are more volatile than the futures markets. For natural gas prices, the mean, median and standard deviation for futures are 2.38, 2.31 and 0.43, not significantly different from those for Henry Hub spot price, which are 2.34, 2.24, and 0.46. The differences between futures and spot prices, also called the basis, will be specifically addressed in Section 3.4.

One thing of concern is that all the spot and futures prices are time series and thus are prone to non-stationarity. Non-stationary series would lead to spurious results in regressions and other statistical tests. Therefore, I conduct augmented Dickey-Fuller (ADF) unit root tests on all price series and the results are provided in Table 3.2. To avoid possible errors that arise from the choice of ADF models, I use the model with three lags, the model with 3 lags and a time trend, and the models with number of lags determined by the Akaike and Bayesian Information Criteria (AIC and BIC). The spot unit root test results, which are similar to those in Essay I, show the electricity spot price series are mostly stationary. The natural gas spot price is non-stationary when using Akaike and Bayesian Information Criteria to choose the optimal numbers of lags. One the other hand, the two electricity futures price series cannot reject the existence of a unit root at the 5% confidence level, suggesting that they are not stationary over the sample period. The natural gas futures price is also non-stationary. With regard to the first differences of the price series, the presence of unit roots is rejected for all spot and futures price series by all augmented Dickey-Fuller tests. As a result, statistical analyses should be conducted on the first differences instead of the price levels.

3.3 Hypothesis

One of the most important functions of futures contracts is to provide hedgers with a financial instrument that can manage their risk exposures in the spot markets. The hedgers are futures traders who, planning to sell or buy an asset on a futures date, take positions in the futures markets to reduce their uncertainty regarding the future price of the asset. Since many futures traders enter the futures markets in order to hedge their risk exposure to the spot price variability of the underlying assets, it is generally believed that the hedging effectiveness of the futures contracts is an important determinant of their success, and that the changes in hedging effectiveness can lead to the rise or fall of futures contracts.[12]

In light of the way the electricity futures markets decline between March 1996 and March 2000, I hypothesize that the hedging effectiveness of the futures contracts declined and led to the lower demand by hedgers. This change in hedging demand resulted in lower liquidity, and thus reduced the contracts' attractiveness to other investors (like speculators) as well. To test this hypothesis, I estimate the hedging effectiveness of the electricity futures contracts over the four-year sample period.

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[12] See Brinkmann and Rabinovitch (1995) and Johnston and McConnell (1989) for similar discussions.

3.4 Hedging Performance of the Electricity Futures Contracts

In this section, I examine the hedging effectiveness of the electricity futures contracts over the four years in the sample using the minimum-variance hedging model. Ederington (1979) demonstrates that the percentage reduction in variation achieved by combining the variance-minimizing quantity of a futures contract (i.e., the optimal hedge ratio) with the asset to be hedged is the coefficient of determination, or the R-square. Because the first differences of spot and futures price series are all stationary, I employ the minimum-variance hedging model following Duffie and Jackson (1989), Johnston and McConnell (1989) and Figlewski (1985):

$$\Delta Spot\ \mathrm{Price}_t = \alpha + \beta \Delta Futures\ \mathrm{Price}_t + \varepsilon_t \qquad (1)$$

where t is the holding period of the hedge. The hedges are maintained for t trading days before being lifted at market close price, and then a new hedge is established on the first trading day following the close of the previous position. Hedging effectiveness, represented by the R-square of equation (1), is estimated for holding periods of 1, 5, and 10 trading days.

First I examine the overall hedging performance of the electricity futures contracts. Table 3.3 contains the R-square results for hedging the 22 spot price series with COB and PV futures contracts over the entire sample period, March 1996 through March 2000. Consistent with the results in similar studies, the hedging effectiveness is higher with longer holding periods. For example, when COB futures is used to hedge COB spot positions, the reduction in variation is 0.02, 0.12, and 0.22 for hedging periods of 1, 5, and 10 days. And the corresponding reductions in variation when hedging PV spot with PV futures are 0.02, 0.19, and 0.25.

Table 3.3 results also imply that there is a substantial degree of market integration within the West area because the hedging effectiveness of the futures contracts is similar across the different regions in the West area. For instance, the 10-day hedge R-squares for hedging regional spot markets in the West with COB futures contract are 0.18, 0.22, 0.24, 0.20, 0.22, and 0.22, and those with PV futures contract are 0.25, 0.27, 0.24, 0.21, 0.25, and 0.25. COB and PV regional spot prices do not seem to enjoy better hedging protection though they serve as the delivery points for the futures contracts. This is consistent with the Kalman Filter results in Essay I and provides support for the way the Bloomberg™ defines the West area.

On the other hand, these two electricity futures contracts with delivery locations in the West area seem to have little, if not zero, hedging effectiveness for spot price series in the East, Mid-Continent, and Gulf areas. Most of the R-squares for these other areas are close to 0. This helps explain why NYMEX decides to launch four more electricity futures contracts with delivery points in other areas after it had initiated COB and PV contracts in 1996, in comparison to the single natural gas futures contract with delivery point at Henry Hub in Erath, Louisiana. Table 4.1 gives a detailed description of all NYMEX electricity futures contracts.

Next I examine the evolution and development of the hedging effectiveness of the futures contracts in order to test my hypothesis about the causes of the decline of the electricity futures markets. To this end, I partition the sample into four comparable sub-periods. Each sub-period is one calendar year in length, with 252, 250, 250, and 250 observations respectively. I compare the hedging effectiveness of the futures contracts in these sub-periods to see how it evolves over the sample period.

Table 3.4 presents the R-squares for using the electricity futures contracts to hedge their underlying spot price series. Panel 1 is for hedging COB spot price with COB futures contract. Similar to Table 3.3, the 10-day hedge has higher R-squares than the 5-day hedge, which in turn has higher R-squares than the 1-day hedge. The R-squares for the four sub-periods are 0.10, 0.11, 0.02, 0.01 for the 1-day hedge; 0.25, 0.26, 0.08, 0.01 for the 5-day hedge; and 0.38, 0.37, 0.02, 0.02 for the 10-day hedge. These R-squares of different holding periods all exhibit a similar trend -- the R-squares are stable during the first two years, but then take a sharp drop in the third year and remain low in the fourth. Panel 2, which presents the R-squares for hedging PV spot price with PV futures contract, shows the same changes for all three holding periods. This suggests that the hedging effectiveness of the electricity futures contracts declined in the third sub-period, or between March 1998 and March 1999. Recall that Figure 3.2 shows the drop in trading volume also occurred during the second half of the sample period. This relationship in the changes between hedging effectiveness and trading volumes provides support for my hypothesis for the decline of the electricity futures contracts.[13]

3.5 The Mismatch Between Futures and Spot Prices

While the fall in hedging effectiveness is tied to the decline of electricity futures markets, another question inevitably arises: why did the hedging effectiveness of electricity futures contracts decrease, especially during the period between April 1998 and March 2000?

[13] There is the possibility that spot electricity market participants use natural gas futures to cross hedge their risks because natural gas is an important input for electricity and natural gas futures market provides high liquidity. However, correlation and hedging effectiveness tests show natural gas futures provides little hedging protection.

To address this issue, it would be helpful to compare the electricity and natural gas futures contracts. Natural gas is a good benchmark for two reasons. Firstly, natural gas is frequently viewed as a substitute for electricity because natural gas is an important resource used to generate power and many power companies store natural gas as a way to "store" electricity. And secondly, the electricity and natural gas futures contracts are both initiated and traded in NYMEX so they share similar trading mechanisms.

Table 3.5 contains the R-squares for hedging Henry Hub spot price with NYMEX natural gas futures contract. The R-squares for the four sub-periods are 0.20, 0.24, 0.19, 0.22 for the 1-day hedge; 0.59, 0.54, 0.58, 0.55 for the 5-day hedge; and 0.78, 0.86, 0.64, 0.70 for the 10-day hedge. In contrast to electricity futures' results in Table 3.4, the hedging effectiveness of the natural gas futures contract is stable over the four years in the sample. In addition, by comparing the corresponding cells between Table 3.4 and 3.5, I find that the natural gas futures contract invariably provides better hedging protection than the electricity futures contracts for their respective underlying asset, which helps explain the popularity of the contract in NYMEX.

Given the similarities between electricity and natural gas futures contracts, what are the factors behind the difference in hedging effectiveness? Since I am comparing the quality of the hedge futures contracts provide for their *underlying* spot markets, the fact that the natural gas spot markets are more integrated and developed than the electricity spot markets is irrelevant, then it is necessary to examine the characteristics of the two commodities themselves. As we know, between the two commodities, the most important difference is the fact that natural gas is storable whereas electricity is not. Along this line, I argue that the non-storability of electricity, along with the high spot market volatility and delivery methods of the futures contract, causes the mismatch between electricity futures and spot prices and thus weakens the effectiveness of the hedge.

3.5.1 The Formation of the Mismatch

In this study, the "mismatch" refers to the deviations of futures prices from their underlying assets' cash prices. Figure 3.3 and 3.4 plot the natural gas and COB, PV electricity futures and spot prices between March 1996 and March 2000. For the natural gas prices in Figure 3.3, the futures price closely follows the spot price except for a few occasions. Oftentimes the two prices are so close to each other that the two curves seem to overlap. In contrast, for the electricity prices in Figure 3.4, the electricity futures and spot prices deviate from each other more conspicuously and frequently. The electricity futures prices seem more stable while the spot prices sometimes fluctuate violently and depart from the futures price curves. Besides, there appears to be larger deviations in the last two years than in the first two years, which coincides with the change in hedging effectiveness.

To examine more closely the mismatch between electricity futures and spot prices, I compute the means and standard deviations of the futures and spot prices by sub-periods and test their differences. The results are presented in Table 3.6. As expected, most differences in means and variances between electricity futures and spot prices during sub-periods are statistically significant while those between natural gas futures and spot prices are mostly not. For example, in sub-period 3 (March 1998 -- March 1999), the mean and standard deviation of COB electricity spot prices are 28.81 and 14.81, significantly greater than those of COB futures prices, 26.97 and 7.25. This jump in spot electricity prices are consistent with the fact that more and more states began to implement deregulation in the electricity spot wholesale markets in the late 1990s. During the same sub-period, the mean and standard deviation of natural gas spot prices are 2.23 and 0.38, nearly identical with those of futures prices, 2.25 and 0.38. Other sub-periods have very similar results. Therefore, it can be concluded that the mismatch is significantly more serious for electricity than for natural gas.

This mismatch between electricity futures and spot prices is, first of all, due to the fact that electricity is difficult to store. Storability of a commodity is important to futures pricing because it establishes a link between spot and futures prices. Based on the Cost-of-Carry Model, storable commodities' futures prices depend on the cash price of a commodity and the cost of carrying the underlying good from the present to the delivery date of the futures contract. Large deviations of futures price from the spot price would create opportunities for cash-and-carry or reverse cash-and-carry arbitrage. Natural gas, because of its storability and relatively low carrying costs, has its futures and spot prices closely tied together. For electricity, however, the Cost-of-Carry Model breaks down because electricity's non-storability makes it impossible to conduct either the cash-and-carry or reverse cash-and-carry arbitrage strategies. Another popular model, the Expectations Model, is more relevant for electricity futures pricing. According to this view, the futures price today approximately equals the cash prices that traders expect to prevail for the underlying good on the delivery date of the futures contract, or the expected future spot price:

$$F_{0,t} \approx E_0(S_t) \qquad (2)$$

where:

$F_{0,t}$ = futures price at t = 0 for delivery at time t;

$E_0(S_t)$ = the expectation at t = 0 of the spot price at time t.

Too great a divergence between the futures price and the expected future spot price creates attractive speculative opportunities. Speculators who trade to take advantage of these opportunities will eventually shrink or even eliminate the divergence. Under such a framework, the delivery method of electricity futures contracts plays an important role in the mismatch between futures and spot prices. Electricity futures contracts specify delivery as 2 megawatts per peak hour (7am – 11pm) per peak-usage day (business day) over the entire delivery month at the delivery switchyard. Since the power is delivered evenly over all the peak hours during the month, the futures price should effectively reflect the market's expectations about the average on-peak spot price according to the model. To the extent that the futures price resembles an expected future monthly average spot price, it tends to be less affected by the large price spikes. Therefore, the futures prices should be more stable than the spot prices when spot prices become very volatile. When spot prices are volatile and the contemporary futures prices are relatively stable, the mismatch occurs and futures prices deviate from spot prices. On the contrary, if the spot prices are not as volatile, the futures prices should not deviate seriously from the spot prices, so it can be inferred that the spot market volatility is another cause of the mismatch and should be positively related to the degree of mismatch. An examination of the standard deviations of electricity prices in Table 3.6 reveals the pattern of changes in spot market volatility. The values of the standard deviations were 6.41, 4.92, 14.81, and 12.21 for the four sub-periods for COB spot price, and 6.95, 8.46, 16.21, and 13.34 for PV spot price. F-tests shows that all across-period volatility changes are significant, but the increase between Sub-periods 2 and 3 appears to be the largest, which could cause a substantial rise in the level of mismatch. These changes were consistent with the exceptionally hot summer of 1998 and the fact that more and more states began the deregulation process in the late 1990s.

For natural gas futures contract, the delivery method is more flexible. For instance, the delivery period can be of any number of days as long as it is in the delivery month and agreed upon by both parties. More importantly, the relatively easy storage of natural gas establishes no-arbitrage bounds for the futures price and links the futures and spot prices closely together, so mismatch is not an issue for the natural gas futures contract.

3.5.2 The Effect of Mismatch on Hedging Effectiveness

It is evident that there's more significant mismatch between electricity futures and spot prices. Nevertheless, how is the mismatch related to the hedging effectiveness of the futures contracts?

In order to illustrate this relationship, Table 3.7 provides a typical hedge example using real settlement prices. I assume that all trades are conducted at the settlement prices. Let us suppose that, on June 30, 1998, a power marketer makes the commitment to deliver 736 megawatt hours of electricity to its clients at the California-Oregon-Border (COB) switchyard on July 16, 1998. Since the power marketer does not produce electricity itself and electricity is not storable, it will need to buy electricity from the spot market. Fearing that the spot power price would go up and increase the costs, the marketer decided to place a futures hedge by buying one nearby futures contract and liquidating the position by shorting the contract. The delivery on the futures contract is not taken because it does not coincide with the spot delivery.

In this case, the spot power price went up from $39.03 to $48.50 between June 30 and July 16. Had the marketer not hedged, it would have incurred a loss of $6,969.92. However, the futures price also went up from $50.85 to $59.75, resulting in a gain of $6,550.40, which largely offset the loss in spot trades. Overall, the marketer actually delivered power at a price of $39.60 per megawatt hour, only slightly more than the June 30 spot price of $39.03. The electricity futures contract provided the power marketer with very good hedging protection and the hedge was successful. However, if the power marketer had committed to delivery on July 17, one day later than the previous case, the situation would have been very different. On July 17, the spot COB price shot up to $67.20, but the futures price was $57.85, barely different from the level on the previous day. As a result, the marketer suffered a bigger loss of $13,373.12 on the spot market, far above the gain on the futures trades. The net loss was $8,221.12, nearly twenty times the loss in the previous case. The hedging protection provided by the futures contract is severely weakened by the deviation of futures price from spot price, or the mismatch. The mismatch, as explained in the above analysis, caused the futures price to stay relatively stable while the spot price changed quickly, and thus lowered the quality of the hedge. It would be difficult for hedgers to use a relatively stable futures price series to hedge away the risks involved in their volatile spot positions. This helps explain why NYMEX has no maximum daily price fluctuation level for electricity futures contracts but has it for other commodities like crude oil, natural gas, gasoline, etc.

The mismatch between the futures and spot prices can be mathematically represented by the difference between contemporaneous futures and spot prices, or the basis:

$$\text{Basis}_t = \text{Spot Price}_t - \text{Futures Price}_t \qquad (3)$$

Because the basis quantifies the degree of mismatch, I can compare the basis means and volatility across sub-periods to see how the mismatch evolves between electricity futures and spot prices. In view of the cause-and-effect relationship between the mismatch and the decline in hedging effectiveness, and my finding that the hedging effectiveness took a significant downturn between the second and third sub-periods, I predict that there would be significant changes in the basis at the same time.

Figure 3.5 compares the basis of COB, PV electricity and natural gas (NG) over the entire sample period, March 1996 through March 2000. While the natural gas curve basically overlaps with the horizontal axis, the COB and PV basis curves oscillate up and down, and show periods of exceptional volatility. There appears to be larger spikes in the second half of the sample than in the first half.

To investigate more closely, I compute the descriptive statistics of the basis for COB, PV electricity and natural gas and present them in Table 3.8. The first thing to note is the difference in basis means between electricity and natural gas. Based on t-test results, all basis means for the two electricity contracts are significantly different from zero at the 1% confidence level for the four sub-periods. But for natural gas, the basis means for sub-period 2, 3 and 4 are not significantly different from zero, only the mean for the first sub-period is at the 5% confidence level. This supports Table 3.6 results in terms of the different levels of mismatch between electricity and natural gas prices.

The more interesting results in Table 3.8 are the basis changes across sub-periods. The basis means were 1.63, -0.67, 1.85, and 1.92 for the four sub-periods for COB, and 2.13, 2.27, 3.54, and 3.72 for PV electricity prices. There appears, especially for PV, to be a large increase in basis levels between sub-period 2 and 3. With regard to the volatility, measured by the standard deviation, the values were 3.85, 4.09, 10.15, and 9.07 for COB, and 5.01, 4.69, 11.01, and 10.24 for PV. Again, the volatility of the basis had a large jump between sub-period 2 and 3. The maximum values of the basis also exhibit the same trend.

To statistically compare these means and variances across the sub-periods, I conduct the t-test and F-test respectively. The results, given in Table 3.9, show the changes between sub-periods. Between Sub-periods 1 and 2, the basis means for COB are different at the 5% confidence level, but the t statistic is negative, suggesting a drop in the basis value rather than an increase; the variance difference is not significant. However, between Sub-periods 2 and 3, both the mean and variance differences are statistically significant at the 1% confidence level. The levels of mismatch increase significantly, as evident from the large positive t-values. A comparison between Sub-periods 3 and 4 also finds that the mean difference is not statistically significant.

Sub-period 3 represents the period between March 1998 and March 1999. This significant increase in basis level and volatility between electricity futures and spot prices coincided with the power price hikes reported in the media in the summer of 1998, and the large increase in spot price volatility shown in Table 3.6. These results are consistent with my prediction regarding the relationship between the changes in basis and the changes in hedging effectiveness. It can be concluded that the mismatch between electricity futures and spot prices, induced by the non-storability of electricity, the delivery method of electricity futures contracts, and the increase in spot price volatility, lowered the quality of the hedge provided by electricity contracts, and led to the decline of electricity futures markets.

3.6 Summary

The decline of the electricity futures market has been a puzzle to many people in electricity business. Numerous factors, including the size of the industry and the great need for hedging tools, are in favor of the contracts' success, but the trading volume has decreased since 1998 and dwindled to double digits in 2000. This study investigates this issue.

I hypothesize that the hedging effectiveness deteriorated and led to the decline of trading volume. To test this hypothesis, I use the coefficient of determination (i.e., the R-square) from the minimum-variance hedging models to examine the development of hedging effectiveness between March 1996 and March 2000. The results suggest that the hedging effectiveness was relatively stable during the first two years, but then declined after that.

I attribute the decline in hedging effectiveness to the mismatch between electricity futures and spot prices, which is caused by the non-storability of electricity, the futures contracts' delivery methods and the exceptional spot price volatility. The futures prices resemble a monthly average and are more stable than the spot prices. And the high volatility in spot power markets has served to worsen the mismatch. Empirical results show that the degree of mismatch for electricity, measured by the basis, is statistically significant while that for natural gas is not. Furthermore, the mean and variance of the basis had a significant increase at the time when hedging effectiveness dropped precipitously, suggesting the mismatch between futures and spot prices lowered the quality of the hedge provided by electricity futures contracts.

At present, the electricity forward markets are far more active than the futures market. One of the key factors is the more flexible design of forward contracts, which reduces the mismatch between forward and spot power prices and lowers the basis risk hedgers face. An analysis of the electricity forward contracts and market development would be an interesting topic for future research.

Chapter 4 Essay III: The Relationship between the Electricity and Natural Gas Markets: The Spark Spread

4.1 Introduction

The previous two essays investigate the issues concerning the spot and futures electricity markets. However, in order to fully understand how electricity markets work, it is essential to examine the relationship between electricity markets and other energy commodity markets. Electricity is not a stand-alone commodity. It is generated using resources like coal, natural gas, oil, hydro energy, nuclear energy, etc. Electricity prices are thus affected by, and related to, the prices of these resources through the generation process. Among these inter-commodity price relationships, the one between electricity and natural gas, also called the *spark spread*, has become the most well-known and most monitored indicator by electricity market participants.[14] A direct reason is that natural gas is the resource most used to meet demand surges during peak times because of the relatively short preparation time of natural gas-fired generators. By watching the movement of the spark spread, utilities can determine whether it is more cost-effective to generate electricity or buy it off the grid, and speculators can get clues about future movements of electricity prices. This essay studies this important inter-commodity spread in the futures markets.

Inter-commodity futures spreads are often 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, 1:1:0 crude, gasoline spread, and the 1:0:1 crude, heating oil spread. Simon (1999) examined the crush spread with similar results.[15]

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)

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[14] In view of its popularity, Bloomberg™ calculates and reports the spark spread alongside the electricity and natural gas prices.

[15] See Johnson, et. al. (1991), Rausser and Carter (1983), Rechner andPoitras (1993), and Tzang and Leuthold (1990) for other discussions of the crush spread.

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 indicated 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.

This study is most closely related to Girma and Paulson (1999) and Simon (1999) because the spark spread is an inter-commodity 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.

This essay examines the spark spread by analyzing the relationship between electricity futures prices and natural gas futures prices. The data are the daily settlement prices for the New York Mercantile Exchange's (NYMEX) two longest-running electricity futures contracts and its natural gas futures contract. The study finds 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 my 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 examined serves the southwestern US where the demand for electricity is highly dependent on the need for air conditioning. The other futures contract 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.

On the other hand, the coefficients of my models of the relationship between electricity and natural gas futures prices do not reflect differences in the production of electricity in the two regions. 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, I expected natural gas prices to play a more prominent role in my fitted model of the electricity futures prices for the contract that serves the southwest although they don't. This result suggests that differences in the costs of producing the underlying commodities are unimportant to the traders who buy and sell these futures contracts.

I also conducted in- and out-of-sample trading rule simulations to determine if the statistically significant mean-reversion in the spark spread that I found was economically significant. I found that traders who used my 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 variability of the profits.

This essay is organized as follows. Section 4.2 briefly describes NYMEX's electricity and natural gas futures contracts, the differences in the regions these contracts serve, and my data. Section 4.3 describes my analyses of the time-series properties of electricity and natural gas futures prices. This is where I report the results of the stationarity and cointegration tests and discuss the coefficients of the fitted models. Section 4.4 reports the results of the trading rule simulations. Section 4.5 is the summary.

4.2 Natural Gas and Electricity Futures Contracts

The New York Mercantile Exchange (NYMEX) initiated trading in natural gas futures on April 3, 1990. Each contract is for 10,000 million British thermal units (MMBtus), which is approximately 10,000 million cubic feet of gas. 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. 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 4.1 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 x 16 hours per day x 2 megawatts per hour = 800 megawatt hours (MWhs). Eighteen contracts, one for delivery in each of the next 18 calendar months, trade at any given time with more trading activity in the near-by ones. I use the two older contracts, California-Oregon Border (COB) and Palo Verde (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 4.2 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.

Similar to Essay 2, I collected daily settlement prices for the first nearby and second nearby COB and PV electricity futures contracts from the date the contracts were initiated, March 29, 1996, until March 31, 2000. I use the first nearby contracts' prices for my tests, switching to the second nearby contract five days prior to expiration of the first nearby contract. This approach is consistent with the practice of traders who use the nearby contract for its liquidity and rollover their positions into the second nearby contract as the first one approaches expiration. Traders tend to roll over a certain period earlier before expiration because they want to avoid the usually higher price volatility during the last days of trading of a futures contract. This rollover makes the simulations in this essay more consistent with real practices. In all, my sample comprises 1005 daily settlement prices for each series.

4.3 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 and 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.

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

I 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 percent 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 percent (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):

$$\text{Gross generation profit margin}_t = \text{Elec}_t - \beta_1 \text{Gas}_t \tag{1}$$

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 4.1 is a graph of the gross generation profit margin using the 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 percent, respectively. The gross generation profit margin has a positive trend during the sample period with wide variation around this trend.

Figures 4.2 and 4.3 provide graphs of the gas and electricity prices and the gross generation profit margin by 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 that 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 are also present in the average gross generation profit margins. The regional and seasonal differences depicted in Figure 4.2 and 4.3 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.

I added trend and seasonal terms to Equation (1) and rearranged it to obtain the 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. In subsequent sections, I will refer to the residual term in this equation as the "spark deviation," SPARKDEV.

$$\mathrm{Elec}_t = \beta_0 + \beta_1 \mathrm{Gas}_t + \beta_2 \mathrm{Trend} + \sum_{j=3}^{13} \beta_j X_j + \varepsilon_t \qquad (2)$$

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

I expect a positive coefficient of the trend term, β_2, and positive coefficients of the summer months dummy variables, β_js, given the patterns depicted in Figures 4.1 and 4.2. I also expect a positive coefficient of the natural gas futures price, the heat rate β_1, although I cannot be more precise about its value for three reasons. First, the heat rates of individual generators used in the US 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 percent 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 apparent heat rate 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 percent of its power will have an apparent 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, I 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, my data are futures prices rather than the prices of the actual natural gas and electricity that power companies buy and sell. These futures prices may reflect the apparent 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 percent 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, I predict that the coefficients of natural gas futures prices in my models are positive although I cannot predict the efficiency levels they imply or whether they are the same or different in the COB and PV service areas.

4.3.2 Stationarity and Cointegration Tests

Similar to Essay 2, I used the augmented Dickey-Fuller (1979) unit root test to determine whether each price series is stationary.[16] This test is conducted by fitting the regression given by Equation (3) to the futures prices. I included three lags of the dependent variable to eliminate autocorrelation. Under the null hypothesis that a series is non-stationary, the coefficient of the lagged level of the series, δ_1, is not significantly different from zero. If a series is non-stationary, 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.

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

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

The results of the augmented Dickey-Fuller unit root tests are displayed in Table 4.3. These results permit us to reject the hypothesis that natural gas prices are non-stationary at the 0.05 level but not at the 0.01 level. Neither COB nor PV electricity

[16]Different from Essay 2 data, the futures price series in this essay include 5-day rollovers in line with common trading practices.

futures prices are stationary at either level of significance. The first difference of all three price series are stationary, however, which is identical to the unit root test results in Essay 2.[17]

Based on these results, I could fit my model for the relationship between natural gas and electricity futures prices to the first differences of each series. However, I am primarily interested in the behavior of actual prices. In particular we'd like to know whether traders can earn profits when actual prices fall outside the boundaries established by the opportunity to burn natural gas to generate electricity. Therefore, I checked to see if electricity and natural gas prices are cointegrated so I can fit my model to the prices themselves.

I used the augmented Engle-Granger (1987) test to determine whether natural gas and electricity futures prices are cointegrated. This test is similar to the Dickey-Fuller test although it is applied to the spark deviations, the residuals from Equation (2), rather than to each separate time series. (I report and discuss the coefficients of the independent variables in Equation (2) later.) Under the null hypothesis that the spark deviations are non-stationary, i.e. that the prices are not cointegrated, the coefficient of the lagged level of the spark deviation in Equation (4), α_1, is not significantly different from zero.

$$\Delta SPARKDEV_t = \alpha_0 + \alpha_1 SPARKDEV_{t-1} + \sum_{j=2}^{4}\alpha_j \Delta SPARKDEV_{t-(j-1)} + v_t \tag{4}$$

Table 4.4 provides the results of the cointegration tests. The coefficient of the lagged level of the spark deviation, α_1, is significantly different from zero which means

[17]In consistence with Essay 2, I also examine the stationarity of each price series using 3 lags with a time trend, and number of lags determined by the Akaike information criterion (AIC) or the Bayesian information criterion (BIC), the results are all similar and available upon request.

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 9.6 and 7.9 days for COB and PV electricity, respectively. The short length of these half-lives implies deviations from the equilibrium level of the spread are temporary and that the spread returns to its equilibrium level quickly.

4.3.3 The Error Correction Model

Because the electricity and natural futures prices are cointegrated, I can use error correction models (5) and (6) to determine whether and how fast the cointegrating futures prices adjust to the deviations from the long-run equilibrium relationships, which are measured by the error correction term—Sparkdev$_{t-1}$, the lagged error term from the cointegration regression.

$$\Delta Elec_t = a_0 + a_1 Sparkdev_{t-1} + \sum_{i=1}^{m} \gamma_{i1} \Delta Elec_{t-i} + \sum_{j=1}^{n} \delta_{j1} \Delta Gas_{t-j} + \varepsilon_{1t} \tag{5}$$

$$\Delta Gas_t = b_0 + b_1 Sparkdev_{t-1} + \sum_{i=1}^{m} \gamma_{i2} \Delta Elec_{t-i} + \sum_{j=1}^{n} \delta_{j2} \Delta Gas_{t-j} + \varepsilon_{2t} \tag{6}$$

where m and n are chosen to avoid serial correlation in ε_{1t} and ε_{2t}. I choose the first-order error correction system (m = n = 1) and the Durbin-Watson d statistics do not indicate the presence of serial correction.

As Table 4.5 shows, in both the COB and PV cases, the coefficients of Sparkdev$_{t-1}$, a_1 and b_1, have the expected signs—negative for electricity and positive for natural gas, indicating that both futures prices have the tendency to return to their long-run equilibrium relationships. However, the absolute value of a_1 is much larger than that of b_1, and is significantly different from zero. This suggests that electricity futures prices return to the long-run equilibrium relationships at a more significant and greater speed than natural gas futures prices do.

4.3.4 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 given in Table 4.6.

The model fits both data sets very well with R^2s of 0.82 and 0.78 for COB and PV, respectively. All the coefficients have the predicted signs and nearly all are significant at conventional levels. The exceptions are the seasonal dummy variables for April, October, 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 arise because the air conditioning season begins earlier in the Palo Verde service area and is more intense.

The coefficient of natural gas prices is positive and significant in both series, as expected. Interpreted as heat rates, these coefficients imply efficiency levels of 100 percent in the COB service area and 108 percent in the PV service area. Of course, these coefficients are only *apparent* heat rates because power companies in both service areas use natural gas to generate less than 40 percent of their electricity.

PV's apparent heat rate is smaller than COB's heat rate, 3.16 vs. 3.41, even though power companies in the PV service area use more natural gas to generate electricity. However, the probability that this difference is due to chance is greater than 20 percent using either the F-test or the Wald test in Seemingly Unrelated Regression (SUR) models. This result, that COB and PV electricity futures prices have the same relationship to natural gas futures prices, implies that differences in methods of producing power in these two areas are unimportant to the process by which the futures prices are established.

4.3.5 A Naïve Alternative

Researchers studying other inter-commodity 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 (1991) and Simon (1999). Therefore, I replaced the lagged residual from Equation (2) that appears in Equation (4), SPARKDEV, with the deviation of the spark spread from its 5-day moving average, MA5DEV. The resulting model is given by Equation (7).

$$\Delta SPARKDEV_t = \alpha_o + \alpha_1 MA5DEV_{t-1} + \sum_{j=2}^{4}\alpha_j \Delta SPARKDEV_{t-(j-1)} + v_t \tag{7}$$

Table 4.7 provides the results of using the naïve moving-average model to explain the deviations from the spark spread. None of the coefficients of this model are significantly different from zero, indicating that the spark spread does not revert to its 5-day moving average. Consequently, my trading rule tests of the opportunity to earn profits in the spark spread are based on deviations from the equilibrium value rather than deviations from recent central tendency.

4.4 Trading Rule Simulations

The preceding section demonstrated 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. I found that trades based on my empirically determined apparent heat rates would have been profitable in both in- and out-of-sample tests.

4.4.1 The Trading Rules and Assumptions

The simulated trader opens a long position by purchasing electricity futures and selling natural gas futures when the electricity futures price is low. The trader opens a short position by selling electricity futures and buying natural gas futures when the electricity futures price is high. The trader closes a long (short) position by executing the opposite trades when the electricity futures price is high (low). All purchases and sales are in the first nearby contract. I assume that all transactions take place at the settlement price of the day when the trading rule is satisfied.

I considered an electricity futures price to be different from its equilibrium value when SPARKDEV, 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. Given the standard deviations of the residuals for the fitted models, the size of these filters ranges from \$0.50 to \$4.44 per Mwh depending on the electricity contract and heat rate that applies. My trading rules are summarized below.

Long positions

Buy 1 Mwh of electricity and sell β_1 MMBtus of natural gas when SPARKDEV < - $\phi\sigma$.

Close position when SPARKDEV ≥ 0.

Short positions

Sell 1 Mwh of electricity and buy β_1 MMBtus of natural gas when SPARKDEV > $\phi\sigma$.

Close position when SPARKDEV ≤ 0.

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

Open positions are rolled over in the nearby contract into the second nearby contract five days prior to the expiration of the nearby contract. This means a trade's total profit is the sum of the gain or loss on the original contract and the gain or loss on the one I rolled into.

There are two costs in implementing this trading scheme. The first cost is the commission paid to a broker. I used Simon's (1999) estimate of commission costs that 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. The 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 x (\$0.01 x 1 + \$0.001 x 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, this study omitted an adjustment for slippage costs when computing our trader's profits to avoid using an arbitrarily chosen amount. I compare the trader's profits to possible slippage costs later to assess their potential impact.

4.4.2 In-Sample Trading Rule Simulation Results

Table 4.8 provides the results of the 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.

The main feature to note in these results is that the trades were all profitable. First, the average profit was significantly greater than zero at the 1 percent level for every type of position, electricity contract, and trading filter. Second, the majority of all trades were profitable. The lowest percent profitable was 78.57% for short position based on COB contract with $\phi = 0.50$. Third, the profits were highly skewed to the right with the average maximum and minimum profits across all cells equal \$24.57 and \$-5.37, respectively.

Other features of the results in Table 4.8 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 4.8 but probably not eliminate them. 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 \$2.05 per Mwh. This average profit is nearly 70 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 8.5 percent (\$2.05/\$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 conclude that for reasonable estimate of slippage costs, these results indicate that the statistically significant mean reversion in the spark spread that we identified earlier was also economically significant.

These results indicate that the statistically significant mean reversion in the spark spread identified earlier was also economically significant. Traders could not actually earn the profits reported in Table 4.8, however, because I used the same data to estimate the coefficients of my model and to test it. A true test of the model's ability to produce trading profits requires an out-of-sample test that I describe next.

4.4.3 Out-of-Sample Trading Rule Simulation Results

I divided the sample in two and used the 503 observations from March 29, 1996 to March 31, 1998 to estimate the coefficients of my model of electricity futures prices. The coefficients of the fitted models for COB and PV, given in Table 4.9, are similar to those for the entire sample period, given in Table 4.6. The apparent heat rates are slightly lower although not significantly so and the COB and PV heat rates are not significantly different from each other.

I used the second half of my sample, the 502 observations from April 1, 1998 to March 31, 2000, to test the model's ability to produce trading profits. I followed the same procedures as I used in my 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 SPARKDEV is $\phi\sigma$ less its mean of zero. The trader closes this position by executing the opposite trades when SPARKDEV is greater than or equal to its mean of zero. The trader opens and closes short positions similarly.

The amount of natural gas to sell or buy, the β_1s, are the coefficients of natural gas prices or heat rates given in Table 4.9. These heat rates are 3.04 and 3.09 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 4.9. These standard deviations are 2.01 and 2.44 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, SPARKDEV, 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 4.9.

The results, given in Table 4.10, demonstrate that a trader who used data from March 29, 1996 to March 31, 1998 to estimate the parameters of my model would have earned significant trading profits by applying the model from April 1, 1998 to March 31, 2000. These results 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 PV contract. While all the long positions based on this contract produced average profits significantly greater than zero at the 5 percent level, none of the short positions did. However, the distribution of profits remained positively skewed for both the long and short positions, and the majority of trades are still profitable. Therefore, it can be concluded that, during the sample period, the tendency for the spark spread to revert to a mean that depended on the cost of producing electricity was persistent enough to provide significant trading profits.

Profits or losses on the electricity and natural gas components of the spread positions comprise the trading profits shown in Table 4.10. I computed the profits on these components separately to determine their contributions to the total. I also allocated the commission costs to each component: $0.02 per Mwh to electricity and $0.02 to natural gas. The results, given in Table 4.11, show that the average profit on electricity trades was significantly different from zero at the 5 percent level or better except for the short positions based on PV contract. In contrast, the average profit on natural gas trades was all negative and never significantly different from zero. Excluding the gas component actually improved the profitability of all the positions in both the COB and PV electricity contracts. The fact that the electricity component of the trades is profitable while the natural gas component isn't is not 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 equilibrium relationship, natural gas prices do not respond similarly. This apparent asymmetry may be due to the fact that natural gas is an important resource for generating electricity while generating electricity is only one of many uses for natural gas.

It can inferred from Table 4.11 that trading the spark spread is no more profitable than trading electricity futures contracts alone but I don't 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. I investigated this issue by comparing the profit and standard deviation of profit for trading the combination of electricity and natural gas (the spark spread) and electricity alone. The results are given in Table 4.12.

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 combination of entry and exit filters, confirming the inference from Table 4.11. 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 and no change in the percent of profitable trades in most cases. And trading the spread actually reduced the minimum profit in 12 of 16 situations. As a result, I conclude 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.

4.5 Summary

On the basis of the intra-commodity analyses of previous essays, this essay contributes to the study of electricity markets by examining an important inter-commodity relationship--the spark spread between electricity and natural gas futures prices. In this essay, I find that electricity and natural gas futures prices are cointegrated, which suggests the presence of a long-run equilibrium relationship between the two commodities. The ensuing error correction model results show that electricity prices adjust to deviations from the long-run equilibrium relationship faster and more significantly than natural gas prices.

I also find 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 significant 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 suggests that futures traders use the same apparent heat rate when pricing both contracts.

The trading rule simulations demonstrated that traders who used my model of the relationship between electricity and natural gas futures prices would have earned significant 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 standard deviation of the trading profits, but it is needed to determine the timing of the trades. This result is consistent with the difference in the two commodities' adjustment to deviations from the long-run equilibrium relationship found in the error correction model analysis.

One might argue that the efficient market hypothesis is violated because of the finding of significant in-sample and out-of-sample trading profits in the simulations. I do not agree with that. The reason is simple: the profits were generated by the illiquid side of the trades—electricity, but not by the liquid side—natural gas. Recall the comparison of the trading volumes between electricity and natural gas futures markets. The natural gas futures contract has become one of the most heavily traded contracts in NYMEX. Any opportunity to make easy profit would have been quickly taken in the liquid and efficient natural gas futures market. In contrast, there has been a dramatic decline in trading volumes in electricity futures markets where trading profits are balanced by the rising liquidity risk. In this essay I attempt to gauge the effect of the increased liquidity risk by comparing the slippage costs with the average profits of trades. Nevertheless, those who wish to make profits based on our findings should always bear in mind the substantial risks involved.

Chapter 5 Conclusion

The soaring power bills and occasional blackouts have put the electricity industry in national spotlight. The exceptional volatilities in electricity markets have resulted in huge losses for market participants and contributed to the rolling blackouts in California. As a result, investors and researchers strive to find answers to questions like: What is the status of the electricity deregulation process? How have the electricity industry evolved? Can electricity futures contracts provide effective hedging protection against the power price fluctuations? How do the prices of electricity and its most important generation resource, natural gas, interact? This dissertation explores these timely issues by studying the intra- and inter-commodity price relationships in the electricity and natural gas markets.

The dissertation mainly consists of three essays. Essay 1 explores the market development and integration in the electricity spot and futures markets in the U.S. Essay 2 investigates the causes for the decline of electricity futures markets. And Essay 3 studies the inter-commodity price relationships between electricity and natural gas futures, or the spark spread. Although the essays focus on different aspects of the intra- and inter-commodity relationships, overall they provide us with the following findings.

First, the electricity spot and futures markets are still immature and segmented though they show sign of increasing integration. The on-peak spot electricity markets are still far from becoming an integrated market despite the increasing number of market pairs that show integration. The off-peak spot markets exhibit increasing integration over the first three years but the trend is reversed during the fourth year. And the futures electricity markets show no sign integration at all. As the degree of integration is usually regarded as a measure of how mature a market is, these results suggest that all the electricity markets remain segmented and immature. In addition, the fact that the futures contracts provide much better hedging protection for spot prices in the same area than for spot prices in other areas in the U.S. is consistent with the segmentation of the markets.

Second, the electricity futures markets are declining due to the segmentation and immaturity of electricity futures markets, the exceptional spot market volatility and the non-storability of electricity itself. These factors contribute to the decline in hedging effectiveness of the electricity futures contracts and thus the dwindling trading volumes. And this helps explain the fact that the arbitrage profits in my spark spread trading simulations are from the electricity markets but not from the more mature natural gas markets.

Third, the electricity and natural gas futures prices are related through the production process. The finding that the price series are cointegrated indicates that there is a long-run equilibrium relationship between the two commodities. The error correction model results further suggest that electricity price responds to changes in natural gas price faster than natural gas price responds to electricity price. Therefore, higher natural gas price tends to prompt a jump in power price, but higher power price may not cause natural gas price to rise. This can help explain the synchronicity of the recent natural gas and electricity price hikes, and the fact that natural gas price was far more stable in the summers of 1998 and 1999 than electricity price.

Finally, the study finds significant economic profits in simulated transactions that take advantage of the mean-reverting cointegration relationship between electricity and natural gas price series. These profits can be, at least partially, attributed to the immature structure of electricity futures markets and investors should take precaution for the substantial liquidity and market risks involved.

All in all, the intra- and inter-commodity price relationship analyses in this dissertation would help investors better understand and manage their risk exposure in the electricity spot and futures markets.

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Table 2.1 Status of Deregulation Activities by States

#	State	Date of Legislation	State Law No.	Wholesale/Retail Competition By
1	Arizona	May-98	HB 2663	January, 2001
2	Arkansas	Apr-99	Senate Bill 791	January, 2002
3	California	Sep-96	AB 1890	March, 1998
4	Connecticut	Apr-98	RB 5005	July, 2000
5	Delaware	Mar-99	HB 10	April, 2001
6	Illinois	Dec-97	HB 362	May, 2002
7	Maine	May-97	LD 1804	March, 2000
8	Maryland	Apr-99	HB 703 (SB 300)	July, 2002
9	Massachusetts	Nov-97	HB 5117	March, 1998
10	Michigan	Aug-99	MPSC order	January, 2002
11	Montana	Apr-97	SB 390	July, 2002
12	Nevada	Jun-99	SB 438	March, 2000
13	New Hampshire	May-96	HB 1392	Originally 7/98 Pending due to litigation
14	New Jersey	Feb-99	A 10/S 5	November, 1999
15	New Mexico	Apr-99	SB 428	January, 2002
16	New York	May-96	PSC Order	3/2000 by a proposed bill
17	Ohio	Jul-99	SB 390	December, 2005
18	Oklahoma	Jun-98	SB 888	pending for studies
19	Oregon	Jul-99	SB 1149	July, 2002
20	Pennsylvania	Dec-96	HB 1509	January, 2000
21	Rhode Island	Aug-96	HB 8124	July, 1998
22	Texas	Jun-99	SB 7	January, 2002
24	Virginia	Mar-99	SB 1269	January, 2004

Source: Energy Information Administration, April 2000.

Table 2.2 Description of Regions for Electricity Spot Prices

Area/Region	Description
East	
NEPOOL (NU)	New England Power Pool, serves Connecticut, Massachusetts, Maine, New Hampshire, Rhode Island, Vermont
East of Cen. E. (SC)	Eastern part of New York Power Pool (NYPP), east of Central East Transmission System
West of Cen. E. (NW)	Western part of New York Power Pool (NYPP), west of Central East Transmission System
PJM (PJ)	Pennsylvania, New Jersey, Maryland
Mid-Continent	
Eastern ECAR (EA)	Eastern East Central Area Reliability Council (ECAR), serves western Pennsylvania
AEP (AE)	American Electric Power Co. (AEP), based in Columbus, Ohio, serves Ohio, Michigan, Indiana, Kentucky, Virginia and Tennessee
Western ECAR (WE)	Western ECAR, serves Indiana
Central ECAR (CE)	Central ECAR, serves Ohio and parts of Kentucky
Cinergy (CG)	Cinergy Corp., based in Cincinnati, Ohio, serves portions of Ohio, Indiana, and Kentucky
Southern ECAR (SO)	Southern ECAR, serves Tennessee, Kentucky, and West Virginia
Northern ECAR (NO)	Northern ECAR, serves Michigan, parts of northern Ohio and Indiana
MAPP (MP)	Mid-Continent Area Power Pool (MAPP), serves the Dakotas, Minnesota, Nebraska, Iowa, Wisconsin, and Saskatchewan, Manitoba

Table 2.2 Description of Regions for Electricity Spot Prices (Continued)

Area/Region	Description
Gulf /Southeast	
SPP (SP)	Southwest Power Pool (SPP), serves Kansas, Missouri, Oklahoma, Arkansas, Louisiana, and parts of Mississippi and Texas
ERCOT (ER)	Electric Reliability Council of Texas (ERCOT), serves Texas
Entergy (SS)	Entergy Corp., based in New Orleans, Louisiana, serves portions of Lousiana, Arkansas, Mississippi, and East Texas
Fla/Ga Border (FG)	Grid at Fiorida-Georgia Border, serves Florida, Georgia
West	
Mid-Columbia (MC)	Power traded for delivery at Mid-Columbia
COB (CO)	California-Oregon and Nevada-Oregon Borders
Midway/Sylmar (MW)	Power traded at Midway/Sylmar
Mead Substation (MD)	Power traded at Mead Substation
Palo Verde (PV)	Power traded at Palo Verde and West Wing, Arizona
Four Corners (FC)	Power traded at Four Corners

Source: Bloomberg™ Terminal, April 2000.

Table 2.3 Descriptive Statistics for Electricity Spot Prices by Areas

Panel 1: By Areas

			On-Peak					Off-Peak				
Areas	# Regions	# obs	Mean	Median	Std. Dev.	Minimum	Maximum	Mean	Median	Std. Dev.	Minimum	Maximum
East	4	4008	30.17	27.00	20.07	16.50	443.75	18.78	18.34	3.28	8.00	40.50
Mid-Continent	4	4008	36.02	23.95	86.34	13.50	1700.00	15.24	15.00	2.25	7.75	31.00
Gulf/Southeast	8	8016	38.54	22.97	117.99	12.80	2041.67	14.96	14.75	2.66	6.75	47.50
West	6	6012	24.58	22.75	11.50	5.50	140.00	13.63	13.00	6.13	1.75	54.00

Panel 2: By Periods

			On-Peak					Off-Peak				
Period	Dates	# Days	Mean	Median	Std. Dev.	Minimum	Maximum	Mean	Median	Std. Dev.	Minimum	Maximum
1	3/29/96 -- 3/27/97	250	23.09	22.50	7.53	5.50	64.50	15.31	16.00	4.43	4.00	47.50
2	3/31/97 -- 3/27/98	251	26.06	23.50	13.48	7.63	264.00	14.70	15.00	3.98	2.88	28.50
3	3/30/98 -- 3/26/99	250	40.12	24.50	115.40	7.38	2041.67	15.24	14.50	3.92	1.75	40.50
4	3/29/99 -- 3/28/00	251	42.31	26.00	113.30	12.80	1972.00	16.15	14.75	4.80	4.00	54.00

Table 2.4 Descriptive Statistics for Electricity Spot Prices by Regions

			On-Peak					Off-Peak				
Areas/Regions	Code	# obs	Mean	Median	Std. Dev.	Minimum	Maximum	Mean	Median	Std. Dev.	Minimum	Maximum
East:												
NEPOOL	NU	1002	31.46	29.67	12.97	17.50	214.00	21.47	21.00	2.79	14.75	31.25
East of Cen. E.	SC	1002	30.60	27.50	15.34	19.25	251.50	19.44	19.00	2.80	13.00	40.50
West of Cen. E.	NW	1002	28.18	25.00	18.83	16.50	293.17	17.98	17.50	2.49	12.00	28.50
PJM	PJ	1002	30.46	25.00	29.11	16.88	443.75	16.23	16.00	2.53	8.00	26.25
Mid-Continent:												
Eastern ECAR	EA	1002	42.27	24.25	133.67	15.50	1966.67	15.80	15.50	2.37	8.00	26.50
AEP	AE	1002	40.52	24.50	114.07	13.67	1900.00	16.26	15.71	3.68	6.75	39.50
Western	WE	1002	37.24	21.50	106.79	13.00	1800.00	14.94	14.75	2.05	10.00	47.50
Central	CE	1002	39.48	21.50	129.88	12.80	1972.00	15.10	14.75	2.34	8.00	29.00
Cinergy	CG	1002	39.89	21.63	130.00	12.80	1972.00	15.12	15.00	2.66	8.00	36.50
Southern	SO	1002	38.46	21.00	125.56	13.54	2041.67	14.81	14.63	1.92	10.50	34.50
Northern	NO	1002	39.75	24.00	117.10	15.50	1900.00	15.33	15.00	2.21	11.00	30.00
MAPP	MP	1002	30.71	22.00	76.47	14.25	1426.50	12.35	12.25	1.68	7.39	18.75
Gulf/Southeast:												
SPP	SP	1002	37.09	23.00	98.81	14.00	1550.00	14.36	14.25	1.90	8.00	29.50
ERCOT	ER	1002	29.83	24.25	29.93	15.08	500.00	14.94	14.50	2.74	7.75	31.00
Entergy	SS	1002	37.21	22.75	102.07	13.50	1700.00	15.00	15.00	1.66	10.25	27.00
Fla/Ga Border	FG	1002	39.96	25.50	93.30	17.67	1501.50	16.66	16.50	1.88	13.00	24.50
West:												
Mid-Columbia	MC	1002	20.87	18.25	10.96	5.50	85.90	13.76	12.50	7.91	2.88	54.00
COB	CO	1002	23.15	20.55	11.30	7.50	86.92	14.41	13.13	7.62	3.00	45.00
Midway/Sylmar	MW	1002	24.82	23.50	10.57	8.00	90.00	14.07	13.75	5.78	1.75	36.19
Mead Substation	MD	1002	26.37	24.75	11.35	9.25	115.50	13.11	12.63	4.76	4.50	37.50
Palo Verde	PV	1002	26.56	24.33	12.16	9.00	140.00	13.39	13.00	5.02	4.50	36.60
Four Corners	FC	1002	25.72	23.25	11.56	9.00	102.00	12.94	12.50	4.74	6.00	36.00

Table 2.5 Descriptive Statistics for Electricity Futures Prices

Futures Series	# Observations	Mean	Median	Std. Deviation	Minimum	Maximum
Entire Sample: 3/29/96 -- 3/28/00						
COB	1002	23.89	22.84	8.69	8.33	52.60
PV	1002	26.98	26.29	9.44	11.45	62.75
Period 1: 3/29/96 -- 3/27/97						
COB	250	15.80	15.43	5.34	8.33	29.73
PV	250	18.33	16.71	4.95	11.45	29.75
Period 2: 3/31/97 -- 3/27/98						
COB	251	20.99	22.13	4.25	10.68	31.83
PV	251	25.30	24.55	5.24	15.04	38.28
Period 3: 3/30/98 -- 3/26/99						
COB	250	26.97	25.98	7.25	16.83	45.28
PV	250	30.17	27.05	9.51	19.45	59.75
Period 4: 3/29/99 -- 3/28/00						
COB	251	31.80	31.30	7.57	16.74	52.60
PV	251	34.10	31.40	8.73	23.75	62.75

Table 2.6 Unit Root Test Results for Electricity Spot Prices by Regions

Areas/Regions	On-Peak								Off-Peak							
	3 Lags		3 Lags & Time		AIC		BIC		3 Lags		3 Lags & Time		AIC		BIC	
	ADF	ADF1	ADF	ADF1	ADF	ADF1	ADF	ADF1	ADF	ADF1	ADF	ADF1	ADF	ADF1	ADF	ADF1
East:																
NU	-8.19	-23.22	-8.28	-23.21	-2.71*	-9.53	-2.71*	-12.21	-5.14	-21.55	-5.13	-21.54	-4.26	-12.21	-5.14	-26.37
SC	-7.95	-21.78	-8.21	-21.77	-3.95	-13.93	-7.03	-16.31	-6.80	-19.71	-6.88	-19.71	-5.29	-11.50	-7.60	-19.36
NW	-8.32	-19.91	-8.63	-19.90	-4.12	-8.97	-3.67	-11.13	-5.41	-21.48	-5.62	-21.47	-3.01	-12.95	-5.62	-16.16
PJ	-7.43	-18.12	-7.59	-18.11	-4.20	-10.68	-4.20	-10.68	-6.17	-21.30	-7.03	-21.29	-3.66	-11.41	-7.61	-16.25
Mid-Continent:																
EA	-12.05	-23.29	-12.20	-23.28	-5.15	-17.57	-12.21	-17.57	-6.82	-21.30	-9.45	-21.29	-4.01	-13.20	-9.26	-17.72
AE	-11.92	-23.79	-12.05	-23.78	-5.44	-17.03	-11.92	-17.03	-7.57	-24.58	-10.38	-24.57	-3.23	-9.82	-6.13	-18.37
WE	-11.08	-22.33	-11.24	-22.32	-5.43	-13.68	-11.99	-16.92	-8.41	-23.10	-11.23	-23.09	-6.85	-13.91	-14.60	-16.52
CE	-12.27	-23.51	-12.42	-23.50	-5.22	-17.28	-12.27	-17.28	-5.27	-21.97	-8.39	-21.96	-3.65	-14.26	-6.96	-19.96
CG	-12.28	-23.51	-12.43	-23.50	-5.23	-17.27	-12.28	-17.27	-5.85	-21.55	-8.51	-21.54	-2.90	-11.95	-8.96	-16.46
SO	-11.93	-23.58	-12.10	-23.57	-5.29	-10.73	-12.33	-11.28	-9.16	-23.00	-9.98	-22.99	-7.99	-11.81	-9.71	-18.86
NO	-11.84	-23.33	-12.00	-23.32	-5.49	-16.97	-11.67	-16.97	-8.85	-21.38	-11.08	-21.37	-4.78	-11.02	-10.63	-17.10
MP	-11.44	-24.07	-11.61	-24.06	-12.81	-12.69	-12.81	-15.75	-7.46	-20.69	-7.54	-20.68	-5.76	-11.20	-8.60	-17.74

ADF and ADF1 are augmented Dickey-Fuller test results for electricity spot prices and their first differences, respectively. The tests use 3 lags, 3 lags and a time trend, the Akaike information criterion (AIC), and the Bayesian information criterion (BIC) respectively. The critical values are -3.45 and -4.04 at the 5% and 1% level for the test that includes a time trend, and -2.86 and -3.43 for all other tests.

* indicates t-value that is not significant at the 5% level, or equivalently, t-value that does not reject the null hypothesis that there is a unit root.

Table 2.6 Unit Root Test Results for Electricity Spot Prices by Regions (Continued)

	On-Peak								Off-Peak							
	3 Lags		3 Lags & Time		AIC		BIC		3 Lags		3 Lags & Time		AIC		BIC	
Areas/Regions	ADF	ADF1	ADF	ADF1	ADF	ADF1	ADF	ADF1	ADF	ADF1	ADF	ADF1	ADF	ADF1	ADF	ADF1
Gulf/Southeast:																
SP	-12.12	-23.86	-12.31	-23.85	-5.16	-10.70	-10.25	-17.03	-7.97	-20.45	-9.34	-20.44	-8.27	-11.17	-10.79	-17.99
ER	-7.79	-17.62	-7.99	-17.62	-5.61	-8.20	-5.40	-9.54	-7.52	-21.78	-7.60	-21.77	-4.86	-10.85	-10.26	-16.77
SS	-11.95	-23.60	-12.14	-23.59	-5.14	-10.65	-12.01	-11.58	-9.39	-19.65	-9.55	-19.64	-6.91	-12.03	-11.79	-17.61
FG	-11.42	-22.60	-11.63	-22.59	-5.19	-12.82	-11.88	-13.20	-6.49	-20.54	-6.75	-20.52	-5.83	-20.54	-6.75	-20.54
West:																
MC	-5.21	-19.58	-6.40	-19.57	-3.05	-11.49	-5.71	-23.07	-3.54	-18.92	-4.37	-18.91	-3.23	-18.92	-3.46	-28.02
CO	-4.98	-20.48	-6.54	-20.47	-2.86	-10.49	-6.46	-20.48	-3.45	-19.16	-4.41	-19.15	-3.11	-19.16	-4.13	-34.18
MW	-5.82	-21.28	-7.17	-21.27	-3.18	-13.75	-7.84	-16.96	-4.65	-19.49	-5.81	-19.48	-3.53	-7.23	-5.70	-15.17
MD	-6.64	-22.24	-8.01	-22.23	-2.93	-11.22	-8.25	-19.18	-4.27	-19.87	-5.58	-19.86	-3.13	-8.15	-4.44	-29.91
PV	-6.55	-21.40	-7.60	-21.39	-3.16	-11.39	-8.85	-14.97	-4.30	-20.76	-5.52	-20.75	-3.36	-11.95	-4.76	-20.76
FC	-6.13	-21.46	-7.31	-21.45	-3.36	-9.50	-7.28	-14.80	-4.19	-21.68	-5.58	-21.67	-3.65	-17.33	-3.65	-21.68

ADF and ADF1 are augmented Dickey-Fuller test results for electricity spot prices and their first differences, respectively. The tests use 3 lags, 3 lags and a time trend, the Akaike information criterion (AIC), and the Bayesian information criterion (BIC) respectively. The critical values are -3.45 and -4.04 at the 5% and 1% level for the test that includes a time trend, and -2.86 and -3.43 for all other tests.

* indicates t-value that is not significant at the 5% level, or equivalently, t-value that does not reject the null hypothesis that there is a unit root.

Table 2.7 Unit Root Test Results for Electricity Futures Prices

ADF and ADF1 are augmented Dickey-Fuller test results for electricity spot prices and their first differences, respectively. The tests use 3 lags, 3 lags and a time trend, the Akaike information criterion (AIC), and the Bayesian information criterion (BIC) respectively. The critical values are -3.45 and -4.04 at the 5% and 1% level for the test that includes a time trend, and -2.86 and -3.43 for all other tests.

	3 Lags		3 Lags & Time		AIC		BIC	
Futures Series	ADF	ADF1	ADF	ADF1	ADF	ADF1	ADF	ADF1
COB	-2.30*	-16.43	-2.98*	-16.42	-2.30*	-19.68	-2.58*	-28.22
PV	-2.61*	-16.74	-3.02*	-16.73	-2.61*	-19.35	-2.90	-28.59

* indicates t-value that is not significant at the 5% level, or equivalently, t-value that does not reject the null hypothesis that there is a unit root.

Table 2.8 A Summary of the Bivariate Regression Test Results for Electricity Spot Prices

This table reports the percentages of market pairs that show market integration according to the estimates of β coefficients and their t-statistics.

Panel 1: Percentages of Pairs of Markets with β Coefficients' t-statistics that do not reject the hypothesis that β is equal to 1 (p>10%).

All Regions

	Period 1	Period 2	Period 3	Period 4	All Periods
On-Peak	11.26%	12.99%	32.03%	41.56%	29.44%
Off-Peak	3.46%	8.23%	17.32%	8.23%	3.90%

West Related (market pair with at least one market in the West)

	Period 1	Period 2	Period 3	Period 4	All Periods
On-Peak	2.70%	7.21%	56.76%	72.97%	54.05%
Off-Peak	5.41%	15.32%	28.83%	11.71%	3.60%

Not West Related

	Period 1	Period 2	Period 3	Period 4	All Periods
On-Peak	19.17%	18.33%	9.17%	12.50%	6.67%
Off-Peak	1.67%	1.67%	6.67%	5.00%	4.17%

Same Area (maket pair that are both from the same area)

	Period 1	Period 2	Period 3	Period 4	All Periods
On-Peak	23.64%	32.73%	29.09%	21.82%	14.55%
Off-Peak	14.55%	12.73%	18.18%	16.36%	16.36%

Across Different Areas

	Period 1	Period 2	Period 3	Period 4	All Periods
On-Peak	7.39%	6.82%	32.95%	47.73%	34.09%
Off-Peak	0.00%	6.82%	17.05%	5.68%	0.00%

Table 2.8 A Summary of the Bivariate Regression Test Results for Electricity Spot Prices (Continued)

This table reports the percentages of market pairs that show market integration according to the estimates of β coefficients and their t-statistics.

Panel 2: Percentages of Pairs of Markets with β Coefficients between 0.93 and 1.01.

All Regions

	Period 1	Period 2	Period 3	Period 4	All Periods
On-Peak	6.06%	7.36%	9.09%	12.99%	9.96%
Off-Peak	2.16%	2.16%	4.76%	2.16%	3.90%

West Related (market pair with at least one market in the West)

	Period 1	Period 2	Period 3	Period 4	All Periods
On-Peak	4.50%	3.60%	7.21%	9.91%	11.71%
Off-Peak	3.60%	3.60%	8.11%	2.70%	3.60%

Not West Related

	Period 1	Period 2	Period 3	Period 4	All Periods
On-Peak	7.50%	10.83%	10.83%	15.83%	8.33%
Off-Peak	0.83%	0.83%	1.67%	1.67%	4.17%

Same Area (maket pair that are both from the same area)

	Period 1	Period 2	Period 3	Period 4	All Periods
On-Peak	20.00%	18.18%	30.91%	43.64%	25.45%
Off-Peak	9.09%	9.09%	12.73%	7.27%	16.36%

Across Different Areas

	Period 1	Period 2	Period 3	Period 4	All Periods
On-Peak	1.70%	3.98%	2.27%	3.41%	5.11%
Off-Peak	0.00%	0.00%	2.27%	0.57%	0.00%

Table 2.9 Integrated Market Pairs Based on Bivariate Tests

This table reports the market pairs whose β coefficients are not significantly different from 1 or are between 0.93 and 1.01 for the entire sample period (3/29/96 - 3/31/2000).

Panel 1: On-Peak Spot Markets

	East				Mid-Continent								Gulf				West					
	NU	SC	NW	PJ	EA	AE	WE	CE	CG	SO	NO	MP	SP	ER	SS	FG	MC	CO	MW	MD	PV	FC
NU																						
SC	*																					
NW		*																				
PJ		*	*																			
EA																						
AE																						
WE																						
CE					*																	
CG								*														
SO						*																
NO								*														
MP					*					*												
SP									*													
ER						*	*				*		*									
SS							*							*								
FG								*						*								
MC					*					*					*							
CO						*	*	*		*	*		*				*					
MW					*	*		*	*			*			*	*						
MD						*	*	*		*	*	*				*	*		*			
PV					*		*		*	*			*		*			*				
FC					*	*		*	*		*	*	*		*	*			*		*	

Table 2.9 Integrated Market Pairs Based on Bivariate Tests (Continued)

This table reports the market pairs whose β coefficients are not significantly different from 1 or are between 0.93 and 1.01 for the entire sample period (3/29/96 - 3/31/2000).

Panel 2: Off-Peak Spot Markets

	East				Mid-Continent								Gulf				West					
	NU	SC	NW	PJ	EA	AE	WE	CE	CG	SO	NO	MP	SP	ER	SS	FG	MC	CO	MW	MD	PV	FC
NU																						
SC																						
NW																						
PJ																						
EA																						
AE					*																	
WE																						
CE						*																
CG						*		*														
SO																						
NO						*																
MP																						
SP																						
ER																						
SS																						
FG																						
MC																						
CO																	*					
MW																						
MD																			*			
PV																			*			
FC																			*			

Table 2.10 Bivariate Regression Test Results for Electricity Futures Prices

This table reports the bivariate test results between COB and PV, and the augmented Dickey-Fuller unit root test results on the regression residuals using the Akaike information criterion (AIC) and Bayesian information criterion (BIC).

Criterion 1: β Coefficients' t-statistics that do not reject the hypothesis that b is equal to 1.
Criterion 2: β Coefficients between 0.93 and 1.01.

Entire Sample: 3/29/96 -- 3/28/00

Dependent Variable	Independent Variable	β Coefficient	t-test p-value	Integration? Criterion 1	Integration? Criterion 2
COB	PV	0.80	0.00%	NO	NO
PV	COB	0.94	0.07%	NO	YES

Unit Root Test Results on the Residuals:	ADF (AIC)	ADF (BIC)
	-3.00*	-2.86*

Period 1: 3/29/96 -- 3/27/97

Dependent Variable	Independent Variable	β Coefficient	p-value		
COB	PV	0.48	0.00%	NO	NO
PV	COB	0.73	0.00%	NO	NO

Period 2: 3/31/97 -- 3/27/98

Dependent Variable	Independent Variable	β Coefficient	p-value		
COB	PV	0.94	8.88%	NO	YES
PV	COB	0.81	0.00%	NO	NO

Period 3: 3/30/98 -- 3/26/99

Dependent Variable	Independent Variable	β Coefficient	p-value		
COB	PV	0.61	0.00%	NO	NO
PV	COB	1.06	9.01%	NO	NO

Period 4: 3/29/99 -- 3/28/00

Dependent Variable	Independent Variable	β Coefficient	p-value		
COB	PV	0.68	0.00%	NO	NO
PV	COB	0.91	4.35%	NO	NO

Table 2.11 Bivariate Regression Test Results for Electricity Futures Price Changes

This table reports the market pairs that show market integration in the bivariate regression test using first differences (price changes) according to the estimates of β coefficients and their t-statistics.

Criterion 1: β Coefficients' t-statistics that do not reject the hypothesis that b is equal to 1.
Criterion 2: β Coefficients between 0.93 and 1.01.

Entire Sample: 3/29/96 -- 3/28/00

Dependent Variable	Independent Variable	β Coefficient	t-test p-value	Integration? Criterion 1	Integration? Criterion 2
COB	PV	0.62	0.00%	NO	NO
PV	COB	0.93	3.79%	NO	YES

Period 1: 3/29/96 -- 3/27/97

Dependent Variable	Independent Variable	β Coefficient	p-value		
COB	PV	0.70	0.00%	NO	NO
PV	COB	0.94	2.31%	NO	YES

Period 2: 3/31/97 -- 3/27/98

Dependent Variable	Independent Variable	β Coefficient	p-value		
COB	PV	0.38	0.00%	NO	YES
PV	COB	0.74	0.03%	NO	NO

Period 3: 3/30/98 -- 3/26/99

Dependent Variable	Independent Variable	β Coefficient	p-value		
COB	PV	0.75	0.00%	NO	NO
PV	COB	1.03	4.25%	NO	NO

Period 4: 3/29/99 -- 3/28/00

Dependent Variable	Independent Variable	β Coefficient	p-value		
COB	PV	0.60	0.00%	NO	NO
PV	COB	1.05	4.95%	NO	NO

Table 2.12 A Summary of the Price-Difference Test Results for Electricity Spot Prices

This table reports the percentages of market pairs that show market integration based on the price-difference test results.

All Regions

	Period 1	Period 2	Period 3	Period 4	All Periods
On-Peak	30.30%	76.19%	90.48%	96.10%	77.92%
Off-Peak	30.30%	50.22%	71.00%	40.26%	12.55%

West Related (market pair with at least one market in the West)

	Period 1	Period 2	Period 3	Period 4	All Periods
On-Peak	13.51%	78.38%	85.59%	95.50%	82.88%
Off-Peak	7.21%	60.36%	75.68%	24.32%	6.31%

Not West Related

	Period 1	Period 2	Period 3	Period 4	All Periods
On-Peak	45.83%	74.17%	95.00%	96.67%	73.33%
Off-Peak	51.67%	40.83%	66.67%	55.00%	18.33%

Same Area (maket pair that are both from the same area)

	Period 1	Period 2	Period 3	Period 4	All Periods
On-Peak	58.18%	63.64%	83.64%	89.09%	69.09%
Off-Peak	49.09%	50.91%	70.91%	78.18%	29.09%

Across Different Areas

	Period 1	Period 2	Period 3	Period 4	All Periods
On-Peak	21.59%	80.11%	92.61%	98.30%	80.68%
Off-Peak	24.43%	50.00%	71.02%	28.41%	7.39%

Table 2.13 Integrated Market Pairs Based on Price-Difference Tests

This table reports the market pairs that meet integration criteria of the Price-Difference test for the entire sample period (3/29/96 - 3/31/2000).

Panel 1: On-Peak Spot Markets

	East				Mid-Continent								Gulf				West					
	NU	SC	NW	PJ	EA	AE	WE	CE	CG	SO	NO	MP	SP	ER	SS	FG	MC	CO	MW	MD	PV	FC
NU																						
SC	*																					
NW	*																					
PJ		*	*																			
EA		*	*	*																		
AE	*	*	*	*																		
WE					*	*																
CE	*	*	*	*	*		*															
CG	*	*	*	*	*	*	*															
SO			*	*	*		*	*	*													
NO	*	*		*			*	*	*													
MP	*	*	*	*	*	*	*	*	*	*	*											
SP	*		*	*	*	*		*	*		*	*										
ER	*	*	*	*	*		*	*		*	*	*	*									
SS		*	*			*		*	*	*		*	*	*								
FG		*			*	*	*		*		*	*	*	*	*							
MC		*	*	*	*	*	*	*	*	*	*	*	*	*	*	*						
CO				*	*	*			*	*		*	*		*	*						
MW			*	*	*		*	*	*	*		*	*		*	*	*					
MD				*	*					*	*	*		*		*	*	*	*			
PV				*	*	*	*	*		*	*	*	*		*		*	*	*	*		
FC				*	*	*	*	*	*	*	*	*	*	*	*	*	*		*	*	*	

Table 2.13 Integrated Market Pairs Based on Price-Difference Tests (Continued)

This table reports the market pairs that meet integration criteria of the Price-Difference test for the entire sample period (3/29/96 - 3/31/2000).

Panel 2: Off-Peak Spot Markets

	East				Mid-Continent								Gulf				West					
	NU	SC	NW	PJ	EA	AE	WE	CE	CG	SO	NO	MP	SP	ER	SS	FG	MC	CO	MW	MD	PV	FC
NU																						
SC																						
NW		*																				
PJ	*																					
EA																						
AE																						
WE				*																		
CE					*																	
CG					*			*														
SO																						
NO				*			*															
MP	*																					
SP				*																		
ER	*	*								*		*	*									
SS	*											*		*								
FG	*									*		*		*	*							
MC																						
CO																	*					
MW																						
MD																			*			
PV																			*	*		
FC																			*	*	*	

Table 2.14 Price-Difference Test Results for Electricity Futures Prices

This table reports the price-difference test results for the COB and PV futures price series.

Entire Sample: 3/29/96 -- 3/28/00

ϕ_1	p-value	λ	Std. Error	p-value1	p-value2	Integration?
0.00	58.20%	0.98	0.01	0.00%	10.17%	NO

Period 1: 3/29/96 -- 3/27/97

ϕ_1	p-value	λ	Std. Error	p-value1	p-value2	Integration?
0.00	98.63%	0.98	0.01	0.00%	12.82%	NO

Period 2: 3/31/97 -- 3/27/98

ϕ_1	p-value	λ	Std. Error	p-value1	p-value2	Integration?
0.00	16.71%	0.95	0.02	0.00%	1.40%	YES

Period 3: 3/30/98 -- 3/26/99

ϕ_1	p-value	λ	Std. Error	p-value1	p-value2	Integration?
0.00	66.26%	0.99	0.01	0.00%	22.01%	NO

Period 4: 3/29/99 -- 3/28/00

ϕ_1	p-value	λ	Std. Error	p-value1	p-value2	Integration?
0.00	58.19%	0.98	0.01	0.00%	9.62%	NO

Table 2.15 A Summary of the Integration Test Results

Bivariate Test: -Increasing percentages, suggesting growing integration. -The on-peak prices in the East area are relatively independent, while those in other areas integrate with each other. -On-peak percentages higher than off-peak. -Off-peak integration drops in the fourth year. -For futures, there's little evidence of market integration.
Kalman Filter: -β approaches 1, suggesting growing integration. -Same-area β's generally closer to 1 than across-area β's. -No clear trend for futures.
Price-Difference Test: -Increasing percentages, suggesting growing integration. -On-peak percentages higher than off-peak. -The West's off-peak markets show signs of independence from other areas. -Little evidence of integration for futures markets.

Table 3.1 Descriptive Statistics for Electricity Spot and Futures Prices

All electricity price series are between 3/29/1996 and 3/28/2000.

Price Series	Code	# obs	Mean	Median	Std. Dev.	Minimum	Maximum
Futures Prices:							
CA-OR-Border	COB	1002	35.93	26.80	30.73	9.22	174.00
Palo-Verde	PV	1002	38.20	28.08	29.17	12.40	180.00
Natural Gas	NG	1002	2.38	2.31	0.43	1.63	4.47
Spot Prices:							
East:							
NEPOOL	NU	1002	36.22	32.00	18.53	17.50	239.00
East of Cen. E.	SC	1002	35.95	29.75	19.88	19.50	251.50
West of Cen. E.	NW	1002	31.39	26.50	19.96	16.50	293.17
PJM	PJ	1002	32.70	25.89	30.35	14.25	443.75
Mid-Continent:							
Eastern ECAR	EA	1002	44.80	26.00	134.79	15.50	1966.67
AEP	AE	1002	42.07	25.50	115.09	13.67	1900.00
Western	WE	1002	39.48	23.50	107.69	13.00	1800.00
Central	CE	1002	41.64	23.35	130.96	12.80	1972.00
Cinergy	CG	1002	41.76	23.31	131.08	12.60	1972.00
Southern	SO	1002	41.82	23.63	126.58	13.54	2041.67
Northern	NO	1002	42.18	25.25	118.10	15.50	1900.00
MAPP	MP	1002	34.22	24.68	77.24	15.50	1426.50
Gulf/Southeast:							
SPP	SP	1002	40.89	25.50	99.69	14.00	1550.00
ERCOT	ER	1002	35.31	26.28	35.28	15.08	500.00
Entergy	SS	1002	41.86	25.00	103.15	13.50	1700.00
Fla/Ga Border	FG	1002	44.74	28.50	94.22	17.67	1501.50
West:							
Mid-Columbia	MC	1002	38.17	24.27	52.57	7.38	665.26
COB	CO	1002	41.14	26.83	52.64	8.13	625.00
Midway/Sylmar	MW	1002	41.56	29.00	47.71	8.00	484.21
Mead Substation	MD	1002	45.10	29.38	56.92	11.00	560.00
Palo Verde	PV	1002	44.40	28.97	54.36	9.00	522.78
Four Corners	FC	1002	44.05	28.50	56.21	9.00	600.00
Natural Gas Spot	NG	1002.00	2.34	2.24	0.46	1.03	4.60

Table 3.2 Unit Root Test Results for Electricity and Natural Gas Spot and Futures Prices

Price Series	Code	3 Lags		3 Lags & Time		AIC		BIC	
		ADF	ADF1	ADF	ADF1	ADF	ADF1	ADF	ADF1
Futures Prices:									
CA-OR-Border	COB	-0.89*	-18.28	-1.95*	-18.31	-0.90*	-6.06	-1.05*	-34.87
Palo-Verde	PV	-1.77*	-19.51	-2.42*	-19.50	-1.80*	-6.61	-1.62*	-14.24
Natural Gas	NG	-3.36	-15.40	-3.67	-17.65	-2.62*	-8.64	-2.53*	-12.69
Spot Prices:									
East:									
NEPOOL	NU	-8.19	-23.22	-8.28	-23.21	-2.71*	-9.53	-2.71*	-12.21
East of Cen. E.	SC	-7.95	-21.78	-8.21	-21.77	-3.95	-13.93	-7.03	-16.31
West of Cen. E.	NW	-8.32	-19.91	-8.63	-19.90	-4.12	-8.97	-3.67	-11.13
PJM	PJ	-7.43	-18.12	-7.59	-18.11	-4.20	-10.68	-4.20	-10.68
Mid-Continent:									
Eastern ECAR	EA	-12.05	-23.29	-12.20	-23.28	-5.15	-17.57	-12.21	-17.57
AEP	AE	-11.92	-23.79	-12.05	-23.78	-5.44	-17.03	-11.92	-17.03
Western	WE	-11.08	-22.33	-11.24	-22.32	-5.43	-13.68	-11.99	-16.92
Central	CE	-12.27	-23.51	-12.42	-23.50	-5.22	-17.28	-12.27	-17.28
Cinergy	CG	-12.28	-23.51	-12.43	-23.50	-5.23	-17.27	-12.28	-17.27
Southern	SO	-11.93	-23.58	-12.10	-23.57	-5.29	-10.73	-12.33	-11.28
Northern	NO	-11.84	-23.33	-12.00	-23.32	-5.49	-16.97	-11.67	-16.97
MAPP	MP	-11.44	-24.07	-11.61	-24.06	-12.81	-12.69	-12.81	-15.75
Gulf/Southeast:									
SPP	SP	-12.12	-23.86	-12.31	-23.85	-5.16	-10.70	-10.25	-17.03
ERCOT	ER	-7.79	-17.62	-7.99	-17.62	-5.61	-8.20	-5.40	-9.54
Entergy	SS	-11.95	-23.60	-12.14	-23.59	-5.14	-10.65	-12.01	-11.58
Fla/Ga Border	FG	-11.42	-22.60	-11.63	-22.59	-5.19	-12.82	-11.88	-13.20
West:									
Mid-Columbia	MC	-5.21	-19.58	-6.40	-19.57	-3.05	-11.49	-5.71	-23.07
COB	CO	-4.98	-20.48	-6.54	-20.47	-2.86	-10.49	-6.46	-20.48
Midway/Sylmar	MW	-5.82	-21.28	-7.17	-21.27	-3.18	-13.75	-7.84	-16.96
Mead Substation	MD	-6.64	-22.24	-8.01	-22.23	-2.93	-11.22	-8.25	-19.18
Palo Verde	PV	-6.55	-21.40	-7.60	-21.39	-3.16	-11.39	-8.85	-14.97
Four Corners	FC	-6.13	-21.46	-7.31	-21.45	-3.36	-9.50	-7.28	-14.80
Natural Gas Spot	NG	-3.20	-15.56	-3.75	-17.89	-2.60*	-8.86	-2.49*	-12.92

ADF and ADF1 are augmented Dickey-Fuller test results for electricity prices and their first differences. The tests use 3 lags, 3 lags and a time trend, the Akaike information criterion (AIC), and the Bayesian information criterion (BIC) respectively. The critical values are -3.45 and -4.04 at the 5% and 1% level for the test that has a time trend, and -2.86 and -3.43 for all other tests. * indicates that the existence of a unit root cannot be rejected at the 5% confidence level.

Table 3.3 R-Squares of Minimum Variance Hedging Models for All Electricity Spot Price Series

Spot Prices	1-day hedge COB	1-day hedge PV	5-day hedge COB	5-day hedge PV	10-day hedge COB	10-day hedge PV
East:						
NEPOOL	0.00	0.00	0.02	0.00	0.05	0.05
East of Cen. E.	0.00	0.00	0.01	0.00	0.00	0.00
West of Cen. E.	0.00	0.00	0.00	0.00	0.01	0.02
PJM	0.00	0.00	0.01	0.00	0.01	0.01
Mid-Continent:						
Eastern ECAR	0.00	0.00	0.00	0.00	0.00	0.00
AEP	0.00	0.00	0.00	0.00	0.00	0.00
Western	0.00	0.00	0.00	0.00	0.00	0.00
Central	0.00	0.00	0.00	0.00	0.00	0.00
Cinergy	0.00	0.00	0.00	0.00	0.00	0.00
Southern	0.00	0.00	0.00	0.00	0.00	0.00
Northern	0.00	0.00	0.00	0.00	0.00	0.00
MAPP	0.00	0.00	0.00	0.00	0.01	0.01
Gulf/Southeast:						
SPP	0.00	0.00	0.00	0.00	0.00	0.00
ERCOT	0.00	0.00	0.01	0.00	0.04	0.14
Entergy	0.00	0.00	0.00	0.00	0.00	0.01
Fla/Ga Border	0.00	0.00	0.00	0.00	0.00	0.00
West:						
Mid-Columbia	0.01	0.01	0.11	0.15	0.18	0.25
COB	**0.02**	0.01	**0.12**	0.18	**0.22**	0.27
Midway/Sylmar	0.02	0.01	0.09	0.19	0.24	0.24
Mead Substation	0.02	0.01	0.08	0.17	0.20	0.21
Palo Verde	0.03	**0.02**	0.10	**0.19**	0.22	**0.25**
Four Corners	0.02	0.02	0.09	0.18	0.22	0.25

Table 3.4 R-Squares of Minimum Variance Hedging Models for COB and PV Electricity Prices by Sub-periods

Periods	Mar/96 - Mar/97	Mar/97 - Mar/98	Mar/98 - Mar/99	Mar/99 - Mar/00	All
Panel 1: Hedging COB Spot with COB Futures					
1-day hedge	0.10	0.11	0.02	0.01	0.02
5-day hedge	0.25	0.26	0.08	0.01	0.22
10-day hedge	0.38	0.37	0.02	0.02	0.22
Panel 2: Hedging PV Spot with PV Futures					
1-day hedge	0.07	0.07	0.01	0.00	0.02
5-day hedge	0.39	0.42	0.20	0.00	0.19
10-day hedge	0.52	0.48	0.04	0.02	0.25

Table 3.5 R-Squares of Minimum Variance Hedging Models for Natural Gas Price by Sub-periods

Periods	Mar/96 - Mar/97	Mar/97 - Mar/98	Mar/98 - Mar/99	Mar/99 - Mar/00	All
Hedging Natural Gas Spot with Natural Gas Futures					
1-day hedge	0.20	0.24	0.19	0.22	0.17
5-day hedge	0.59	0.54	0.58	0.55	0.52
10-day hedge	0.78	0.86	0.64	0.70	0.78

Table 3.6 A Comparison between Futures and Spot Prices by Sub-periods

Price Series	# obs	Mean	t-statistic for Mean Diff. Tests	Standard Deviation	F-statistic for Variance Diff. Tests
Sub-period 1 (Mar/96 -- Mar/97):					
COB Futures	250	15.74		5.33	
COB Spot	250	17.37	3.10**	6.41	1.44**
PV Futures	250	18.30		4.95	
PV Spot	250	20.43	3.95**	6.95	1.97**
NG Futures	250	2.57		0.60	
NG Spot	250	2.60	0.16	0.64	1.46**
Sub-period 2 (Mar/97 -- Mar/98):					
COB Futures	251	21.03		4.16	
COB Spot	251	20.36	-1.70	4.92	1.40**
PV Futures	251	25.34		5.18	
PV Spot	251	27.61	3.44**	8.46	3.79**
NG Futures	251	2.26		0.34	
NG Spot	251	2.24	-0.89	0.31	0.75
Sub-period 3 (Mar/98 -- Mar/99):					
COB Futures	250	26.97		7.25	
COB Spot	250	28.81	1.99*	14.81	3.10**
PV Futures	250	30.17		9.51	
PV Spot	250	33.71	2.17*	16.21	6.84**
NG Futures	250	2.25		0.38	
NG Spot	250	2.23	-0.78	0.38	0.95
Sub-period 4 (Mar/99 -- Mar/00):					
COB Futures	251	31.79		7.58	
COB Spot	251	33.70	2.49*	12.21	1.55**
PV Futures	251	34.08		8.74	
PV Spot	251	37.80	2.40*	13.34	1.47**
NG Futures	251	3.53		1.00	
NG Spot	251	3.50	-0.40	1.00	0.96
Entire Sample (Mar/96 -- March/00):					
COB Futures	1002	35.93		30.73	
COB Spot	1002	41.14	2.10*	52.64	1.59**
PV Futures	1002	38.20		29.17	
PV Spot	1002	44.40	2.26*	54.36	1.50**
NG Futures	1002	2.38		0.43	
NG Spot	1002	2.34	-2.09*	0.46	1.16*

* and ** indicate significance at the 5%, and 1% confidence levels respectively.

Table 3.7 The Effect of Mismatch on Hedging: A Long Hedge Example

	Spot Market	Futures Market
June 30, 1998	Makes the commitment to deliver 736 megawatt hours of power to clients at COB switchyard Price: $39.03 / megawatt hour	Long one August contract at $37,425.60. Price: $50.85 / megawatt hour
If the delivery occurs on July 16, 1998		
	Purchases 736 megawatt hours from spot market. Price: $48.50 / megawatt hour	Short one August contract at $43,976. Price: $59.75 / megawatt hour
	Results:	
	Loss from delay on spot market:	$6,969.92
	Gain on the futures market:	$6,550.40
	Net loss:	$419.52
	Net delivery price per megawatt hour:	$48.50 - ($59.75 - $50.85) = $39.60
If the delivery occurs on July 17, 1998		
	Purchases 736 megawatt hours from spot market. Price: $67.20 / megawatt hour	Short one August contract at $42,577.60 Price: $57.85 / megawatt hour
	Results:	
	Loss from delay on spot market:	$13,373.12
	Gain on the futures market:	$5,152.00
	Net loss:	$8,221.12
	Net delivery price per megawatt hour:	$67.20 - ($57.85 - $50.85) = $60.20

Table 3.8 Basis Comparisons by Sub-periods

$Basis_t$ = Spot $Price_t$ - Futures $Price_t$

	Mean	Median	Std. Dev.	Minimum	Maximum
Sub-period 1 (Mar/96 -- Mar/97):					
COB Electricity	1.63**	1.27	**3.85**	-5.30	29.57
PV Electricity	2.13**	1.28	**5.01**	-7.26	39.65
Natural Gas	0.03*	0.03	**0.23**	-0.40	0.99
Sub-period 2 (Mar/97 -- Mar/98):					
COB Electricity	-0.67**	-1.02	**4.09**	-9.94	16.28
PV Electricity	2.27**	0.71	**4.69**	-9.05	29.13
Natural Gas	-0.02	-0.04	**0.21**	-0.49	0.20
Sub-period 3 (Mar/98 -- Mar/99):					
COB Electricity	1.85**	0.49	**10.15**	-17.22	59.54
PV Electricity	3.54**	-0.13	**11.01**	-25.84	72.65
Natural Gas	-0.02	-0.03	**0.17**	-0.95	0.13
Sub-period 4 (Mar/99 -- Mar/00):					
COB Electricity	1.92**	1.19	**9.07**	-22.70	46.06
PV Electricity	3.72**	0.57	**10.24**	-24.68	63.79
Natural Gas	-0.02	-0.03	**0.21**	-0.52	0.35
Entire sample (Mar/96 -- Mar/00):					
COB Electricity	5.21**	0.69	**16.20**	-22.70	59.54
PV Electricity	6.20**	0.54	**18.90**	-25.84	72.65
Natural Gas	-0.04*	-0.01	**0.29**	-0.95	0.99

* and ** indicates the mean is significantly different from zero at the 5%, and 1% confidence levels respectively.

Table 3.9 Basis Volatility Comparisons between Sub-periods

	t-statistic for Mean Diff. Tests	F-statistic for Variance Diff. Tests
COB Electricity		
Sub-period 1 vs. 2	-2.26*	0.88
Sub-period 2 vs. 3	6.57**	6.17**
Sub-period 3 vs. 4	1.22	1.45**
PV Electricity		
Sub-period 1 vs. 2	1.10	0.22
Sub-period 2 vs. 3	3.55**	5.89**
Sub-period 3 vs. 4	0.22	1.70**

* and ** indicates significance at the 5% and 1% confidence levels respectively.

Table 4.1 NYMEX Electricity Futures Contracts[*]

Name	Size (Mwhs)	Date Trading Initiated	Delivery Location	Service Area
California-Oregon Border Electricity[**]	432	3/29/96	California/Oregon boarder of the Pacific Northwest/Pacific Southwest AC Intertie.	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.

Table 4.2
Resources Used by Power Generators of the Western Systems Coordinating Council*

Resource	In the Vicinity of: Palo Verde[1]	California-Oregon Border[2]
Natural gas	36.7%	6.1
Conventional hydro	16.1	64.6
Coal	17.1	24.0
Nuclear	10.6	1.6
Other[3]	19.5	3.7
Total	100.0%	100.0%

[1]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).

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

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

*Information Summary published by the Western Systems Coordinating Council on its web-site, http://www.wscc.com, January 1999.

Table 4.3 Results of Augmented Dickey-Fuller Unit Root Tests

The Augmented Dickey-Fuller (1979) unit root test is used to determine whether a time-series is stationary. The 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 non-stationary 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 non-stationary, 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.

Series	Coefficient of Lagged Value of Series, δ_1	τ-statistic
Natural gas		
Prices	-0.026	-3.36*
1st difference of prices	-1.071	-15.40**
COB electricity		
Prices	-0.010	-2.33
1st difference of prices	-0.914	-14.67**
PV electricity		
Prices	-0.012	-2.53
1st difference of prices	-0.946	-14.90**

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

Table 4.4 Results of Cointegration Tests

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

$$\Delta SPARKDEVt = \alpha_0 + \alpha_1 SPARKDEV_{t-1} + \sum_{j=2}^{4} \alpha_j \Delta SPARKDEV_{t-(j-1)} + v_t$$

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.

Series	Coefficient of Lagged Value $SPARKDEV, \alpha_1$	τ-statistic	Half-life[1]
COB SPARKDEV	-0.0699	-5.91**	9.6 days
PV SPARKDEV	-0.0838	-6.50**	7.9 days

**Significant at 0.01 level.

[1]Half-life equals $\ln(0.50)/\ln(1 + \alpha_1)$.

Table 4.5 Results of Error Correction Models

The error correction model is used to determine whether and how fast the cointegrating variables (i.e., electricity and natural gas futures) adjust to the deviations from the long-run equilibrium relationships, which are measured by the coefficient of the error correction term, $Sparkdev_{t-1}$.

	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	0.0218	0.5313	0.0005	0.8715	0.0221	0.6169	0.0006	0.8479
$Sparkdev_{t-1}$	−0.0392	0.0001	0.0011	0.2066	−0.0401	0.0001	0.0002	0.8150
$\Delta Elec_{t-1}$	0.0566	0.0792	0.0082	0.0067	0.0238	0.4608	0.0039	0.1058
ΔGas_{t-1}	0.3743	0.2656	−0.1368	0.0000	0.6390	0.1349	−0.1307	0.0000
R^2	0.0192		0.0252		0.0180		0.0179	
Durbin-Watson d-statistic	2.0025		2.0153		2.0060		2.0118	

Table 4.6 Fitted Regression Models of the Spark Spread

Estimated values of the coefficients in $Elec_t = \beta_0 + \beta_1 Gas_t + \beta_2 Trend + \sum_{j=3}^{13} \beta_j X_j + \varepsilon_t$, the gross generation profit margin or spark spread. Data are daily settlement prices of NYMEX's 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.

	COB Electricity		PV Electricity	
	Coefficient	P-value	Coefficient	P-value
Intercept	4.10	0.0000	4.69	0.0000
Natural gas futures price	3.41	0.0000	3.16	0.0000
Trend	0.02	0.0000	0.02	0.0000
January	-4.05	0.0000	-2.32	0.0009
February	-6.09	0.0000	-3.29	0.0000
March	-5.38	0.0000	-1.75	0.0113
April	-4.54	0.0000	0.11	0.8760
May	-1.81	0.0018	5.47	0.0000
June	3.53	0.0000	13.72	0.0000
July	9.88	0.0000	19.12	0.0000
August	5.40	0.0000	8.45	0.0000
September	2.99	0.0000	2.37	0.0006
October	3.70	0.0000	1.09	0.1087
November	3.28	0.0000	1.06	0.1353
R^2	0.8215		0.7841	
Adjusted R^2	0.8191		0.7813	
Standard deviation of residuals	3.66		4.44	

Tests for equality of COB and PV apparent heat rates	Test Statistic	P-value
F	1.51	0.2196
Wald Chi-square	1.51	0.2195

Table 4.7 Results for Naïve Mean Reversion Model

The tendency for the spark spread to revert to its recent central tendency was tested by fitting the following model where SPARKDEV is the residual from Equation (2) and MA5DEV is deviation of the spark spread from its 5-day moving average.

$$\Delta SPARKDEV_t = \alpha_o + \alpha_1 MA5EV_{t-1} + \sum_{j=2}^{4} \alpha_j \Delta SPARKDEV_{t-(j-1)} + v_t$$

The coefficient of MA5DEV is not significantly different from zero under the null hypothesis that the spark spread does not revert to its short-term mean.

	COB-based Spark Spread			PV-based Spark Spread		
Coefficient	Value	Std. Error	P-value	Value	Std. Error	P-value
Intercept, α_0	0.0001	0.0420	0.9976	0.0020	0.0552	0.9715
$MA5DEV_{t-1}$, α_1	-0.0049	0.0416	0.9055	-0.0232	0.0399	0.5620
$\Delta SPARKDEV_{t-1}$	0.0126	0.0430	0.7691	0.0096	0.0402	0.8105
$\Delta SPARKDEV_{t-2}$	-0.0460	0.0388	0.2353	-0.0159	0.0373	0.6702
$\Delta SPARKDEV_{t-3}$	0.0106	0.0360	0.7675	0.0115	0.0350	0.7414

[1]Half-life equals $\ln(0.5)/\ln(\gamma_1 + \gamma_2)$.

Table 4.8 In-Sample Trading Rule Simulations

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 heat rate; $\beta_1 = 3.41$ for COB and 3.16 for PV. A position is closed by executing the opposite trades. SPARKDEV is the residual from Equation (2) computed using the coefficients given in Table 4.6. Commissions are $0.09 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.

Panel A: Long Positions

	Open Position When SPARKDEV			
	$< -0.25\sigma$	$< -0.50\sigma$	$< -0.75\sigma$	$< -1.00\sigma$
		California-Oregon Border Contract		
Number of trades	33	20	15	9
Average duration	14 days	18 days	20 days	30 days
Percent profitable	81.82%	95.00%	100.00%	100.00%
Maximum profit	$13.47	$13.47	$7.60	$7.60
Minimum profit	-2.05	-0.23	0.09	0.09
Average profit	2.76	3.82	3.74	4.90
Standard error	0.58	0.72	0.57	0.76
Probability	0.0000	0.0000	0.0000	0.0001
		PaloVerde Contract		
Number of trades	22	19	12	10
Average duration	20 days	20 days	27 days	29 days
Percent profitable	95.45%	100.00%	100.00%	80.00%
Maximum profit	$14.56	$15.48	$16.51	$16.51
Minimum profit	-0.26	1.04	2.74	-4.62
Average profit	4.99	5.81	7.38	6.84
Standard error	0.89	1.02	1.28	1.91
Probability	0.0000	0.0000	0.0001	0.0030

Panel B: Short Positions

	Open Position When SPARKDEV			
	$> 0.25\sigma$	$> 0.50\sigma$	$> 0.75\sigma$	$> 1.00\sigma$
		California-Oregon Border Contract		
Number of trades	27	14	12	11
Average duration	13 days	19 days	20 days	18 days
Percent profitable	85.19%	78.57%	83.33%	90.91%
Maximum profit	$14.12	$14.12	$14.12	$14.12
Minimum profit	-5.37	-3.19	-2.71	-1.62
Average profit	2.05	3.22	4.42	5.83
Standard error	0.65	1.07	1.35	1.31
Probability	0.0020	0.0051	0.0037	0.0006
		PaloVerde Contract		
Number of trades	29	14	12	9
Average duration	14 days	18 days	16 days	19 days
Percent profitable	79.31%	85.71%	100.00%	100.00%
Maximum profit	$18.57	$24.57	$24.57	$24.57
Minimum profit	-1.10	-0.62	1.78	2.14
Average profit	3.38	8.04	9.23	11.33
Standard error	0.92	2.31	2.49	3.02
Probability	0.0005	0.0020	0.0017	0.0028

Table 4.9 Fitted Regression Models of the Spark Spread for Out-of-Sample Tests

Estimated values of the coefficients in $Elec_t = \beta_0 + \beta_1 Gas_t + \beta_2 Trend + \sum_{j=3}^{13} \beta_j X_j + \varepsilon_t$, the gross generation profit margin or spark spread. Data are daily settlement prices of NYMEX's 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.

	COB Electricity		PV Electricity	
	Coefficient	P-value	Coefficient	P-value
Intercept	7.17	0.0000	5.52	0.0000
Natural gas futures price	3.04	0.0000	3.09	0.0000
Trend	0.02	0.0000	0.03	0.0000
January	-5.37	0.0000	-3.77	0.0000
February	-8.23	0.0000	-5.51	0.0000
March	-6.46	0.0000	-3.70	0.0000
April	-5.69	0.0000	-1.23	0.0435
May	-2.76	0.0000	2.90	0.0000
June	-0.72	0.1364	7.56	0.0000
July	2.12	0.0000	11.16	0.0000
August	1.35	0.0047	5.48	0.0000
September	1.11	0.0177	2.14	0.0002
October	0.58	0.1809	-0.34	0.5250
November	2.43	0.0000	1.29	0.0208
R^2	0.8622		0.8292	
Adjusted R^2	0.8585		0.8247	
Standard deviation of residuals	2.01		2.44	

Tests for equality of COB and PV apparent heat rates	Statistic	Test P-value
F	0.2685	0.6524
Wald Chi-square	0.2685	0.6523

Table 4.10 Out-of-Sample Trading Rule Simulations

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 heat rate given in Table 9; β_1 = 3.04 for COB and 3.09 for PV. A position is closed by executing the opposite trades. SPARKDEV is the difference between the actual electricity futures price on a particular day minus the price computed from Equation (2) using the coefficients given in Table 4.9. Commissions are $0.09 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.

Panel A: Long Positions

	Open Position When SPARKDEV			
	$< -0.25\sigma$	$< -0.50\sigma$	$< -0.75\sigma$	$< -1.00\sigma$
	California-Oregon Border Contract			
Number of trades	15	11	10	8
Average duration	17 days	21 days	22 days	27 days
Percent profitable	93.33%	90.91%	100.00%	100.00%
Maximum profit	$12.64	$11.40	$11.40	$11.40
Minimum profit	-0.02	-0.02	1.42	1.42
Average profit	3.49	3.80	4.25	4.86
Standard error	1.06	1.07	1.10	1.29
Probability	0.0027	0.0027	0.0019	0.0035
	PaloVerde Contract			
Number of trades	7	6	6	5
Average duration	36 days	36 days	37 days	41 days
Percent profitable	100.00%	100.00%	100.00%	100.00%
Maximum profit	$14.56	$14.56	$14.56	$15.26
Minimum profit	2.53	2.53	3.19	3.75
Average profit	6.97	7.16	7.38	8.56
Standard error	2.16	2.24	2.17	2.60
Probability	0.0117	0.0120	0.0096	0.0151

Panel B: Short Positions

	Open Position When SPARKDEV			
	$> 0.25\sigma$	$> 0.50\sigma$	$> 0.75\sigma$	$> 1.00\sigma$
	California-Oregon Border Contract			
Number of trades	16	12	10	8
Average duration	13 days	16 days	18 days	20days
Percent profitable	81.25%	83.33%	80.00%	75.00%
Maximum profit	$14.15	$14.15	$14.15	$14.15
Minimum profit	-2.44	-1.30	-1.23	-1.23
Average profit	1.97	2.83	3.39	3.86
Standard error	0.93	1.21	1.40	1.73
Probability	0.0260	0.0195	0.0196	0.0304
	PaloVerde Contract			
Number of trades	6	5	5	5
Average duration	18 days	20 days	20 days	20 days
Percent profitable	66.67%	60.00%	60.00%	60.00%
Maximum profit	$8.32	$8.32	$8.32	$8.32
Minimum profit	-4.41	-4.41	-3.55	-3.15
Average profit	1.65	1.86	2.49	2.73
Standard error	1.82	2.21	2.30	2.21
Probability	0.2024	0.2235	0.1699	0.1424

Table 4.11 Profitability of Separate Components of Spark Spread

Average profit and standard errors for the components of the spark spread trades described in Table 9. 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.

Panel A: Long Positions

	Open Position When SPARKDEV							
	< -0.25σ		< -0.50σ		< -0.75σ		< -1.00σ	
	Electricity	Gas	Electricity	Gas	Electricity	Gas	Electricity	Gas
	California-Oregon Border Contract							
Average profit	3.59	-0.09	3.87	-0.08	4.34	-0.09	4.95	-0.09
Standard error	1.16	0.23	1.25	0.29	1.30	0.31	1.57	0.39
Probability	0.0039	0.6538	0.0057	0.6021	0.0044	0.6092	0.0081	0.5842
	PaloVerde Contract							
Average profit	7.28	-0.31	7.49	-0.33	7.68	-0.30	8.81	-0.25
Standard error	2.05	0.15	2.17	0.14	2.10	0.14	2.52	0.20
Probability	0.0082	0.9532	0.0090	0.9654	0.0073	0.9541	0.0125	0.8545

Panel B: Short Positions

	Open Position When SPARKDEV							
	> -0.25σ		> -0.50σ		> -0.75σ		> -1.00σ	
	Electricity	Gas	Electricity	Gas	Electricity	Gas	Electricity	Gas
	California-Oregon Border Contract							
Average profit	2.03	-0.06	2.87	-0.04	3.43	-0.04	3.95	-0.10
Standard error	0.95	0.12	1.24	0.15	1.46	0.19	1.78	0.23
Probability	0.0251	0.6866	0.0206	0.6145	0.0217	0.5806	0.0309	0.6595
	PaloVerde Contract							
Average profit	1.98	-0.32	2.39	-0.53	3.02	-0.53	3.27	-0.54
Standard error	1.89	0.27	2.26	0.21	2.40	0.22	2.30	0.22
Probability	0.1718	0.8585	0.1742	0.9691	0.1384	0.9640	0.1140	0.9650

Table 4.12 Comparison of Spark Spreads and Electricity Trades

Average profit and standard deviation of profit of the spark spread trades and the electricity components of the spark spread trades described in Table 9. The probability that the two strategies have the same average profit is determined using an equality of means test with equal variances. The probability that the two strategies have the same standard deviation of profit is determined using an F-test for the equality of variances.

Panel A: Long Positions

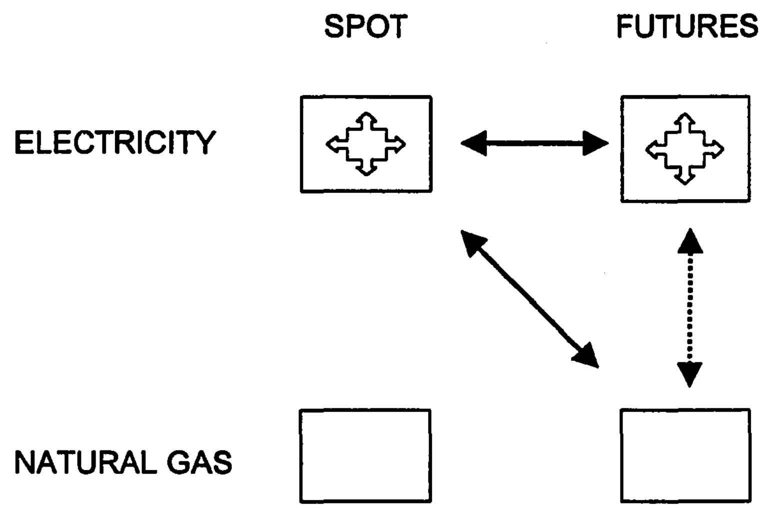
	Open Position When SPARKDEV											
	< -0.25σ			< -0.50σ			< -0.75σ			< -1.00σ		
	Spark Spread	Electricity Alone	Difference	Spark Spread	Electricity Alone	Difference	Spark Spread	Electricity Alone	Difference	Spark Spread	Electricity Alone	Difference
California-Oregon Border Contract												
Average profit	3.49	3.59	-0.09	3.80	3.87	-0.08	4.25	4.34	-0.09	4.86	4.95	-0.09
Standard deviation of profit	4.11	4.48	-0.37	3.55	4.16	-0.61	3.47	4.12	-0.65	3.66	4.44	-0.79
Min. Profit	-0.02	-0.69	0.67	-0.02	-0.69	0.67	1.42	0.54	0.88	1.42	0.54	0.88
Percent profitable	93.33%	93.33%	0.00%	90.91%	90.91%	0.00%	100.00%	100.00%	0.00%	100.00%	100.00%	0.00%
PaloVerde Contract												
Average profit	6.97	7.28	-0.31	7.16	7.49	-0.33	7.38	7.68	-0.30	8.56	8.81	-0.25
Standard deviation of profit	5.30	5.02	0.28	5.48	5.30	0.18	5.30	5.15	0.16	5.82	5.63	0.18
Min. Profit	2.53	2.90	-0.37	2.53	2.90	-0.37	3.19	3.36	-0.17	3.75	4.66	-0.91
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%

Table 4.12 Comparison of Spark Spreads and Electricity Trades (continued)

Panel B: Short Positions

	Open Position When SPARKDEV											
	> 0.25σ			> 0.50σ			> 0.75σ			> 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	1.97	2.03	-0.06	2.83	2.87	-0.04	3.39	3.43	-0.04	3.86	3.95	-0.10
Standard deviation of profit	3.74	3.81	-0.07	4.18	4.30	-0.12	4.44	4.61	-0.17	4.89	5.03	-0.15
Min. Profit	-2.44	-2.27	-0.17	-1.30	-1.27	-0.03	-1.23	-0.92	-0.31	-1.23	-0.92	-0.31
Percent profitable	81.25%	81.25%	0.00%	83.33%	75.00%	8.33%	80.00%	70.00%	10.00%	75.00%	75.00%	0.00%
PaloVerde Contract												
Average profit	1.65	1.98	-0.32	1.86	2.39	-0.53	2.49	3.02	-0.53	2.73	3.27	-0.54
Standard deviation of profit	4.45	4.63	-0.18	4.94	5.04	-0.10	5.14	5.36	-0.22	4.94	5.14	-0.19
Min. Profit	-4.41	-3.70	-0.71	-4.41	-3.70	-0.71	-3.55	-2.99	-0.56	-3.15	-2.38	-0.77
Percent profitable	66.67%	50.00%	16.67%	60.00%	60.00%	0.00%	60.00%	60.00%	0.00%	60.00%	60.00%	0.00%

Figure 1.1 Price Relationships Studied by the Dissertation

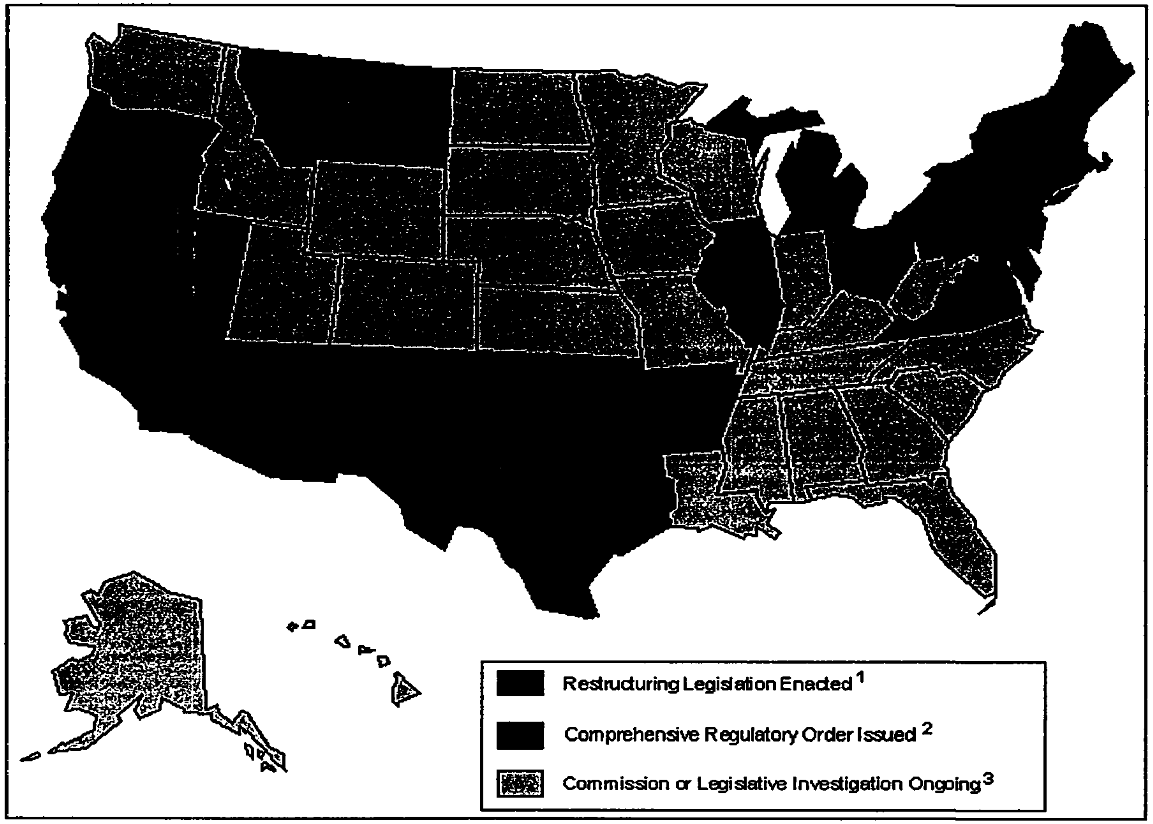


Essay 1: (Intra-Commodity Analysis)
Spot and futures electricity market integration

— Essay 2: (Intra- and Inter-Commodity Analysis)
Hedging effectiveness of direct hedge and cross hedge

····· Essay 3: (Inter-Commodity Analysis)
Spark spread in the futures markets

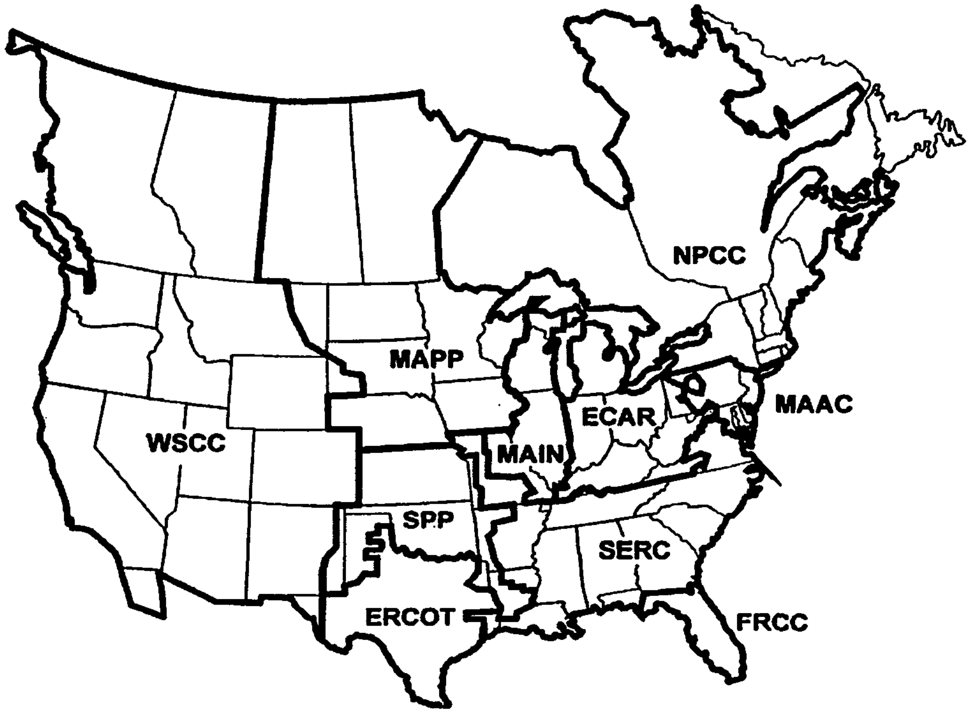
Figure 2.1 Status of State Electric Industry Restructuring Activity



1. Arizona, Arkansas, California, Connecticut, Delaware, Illinois, Maine, Maryland, Massachusetts, Montana, Nevada, New Hampshire, New Jersey, New Mexico, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, Texas, and Virginia.
2. Michigan, New York, and Vermont.
3. Alabama, Alaska, Colorado, District of Columbia, Florida, Georgia, Hawaii, Idaho, Indiana, Iowa, Kansas, Kentucky, Louisiana, Minnesota, Mississippi, Missouri, Nebraska, North Carolina, North Dakota, South Carolina, South Dakota, Tennessee, Utah, Washington, West Virginia, Wisconsin, and Wyoming.

Source: Energy Information Administration, April 2000.

Figure 2.2 Distribution of Regional Reliability Councils in North America

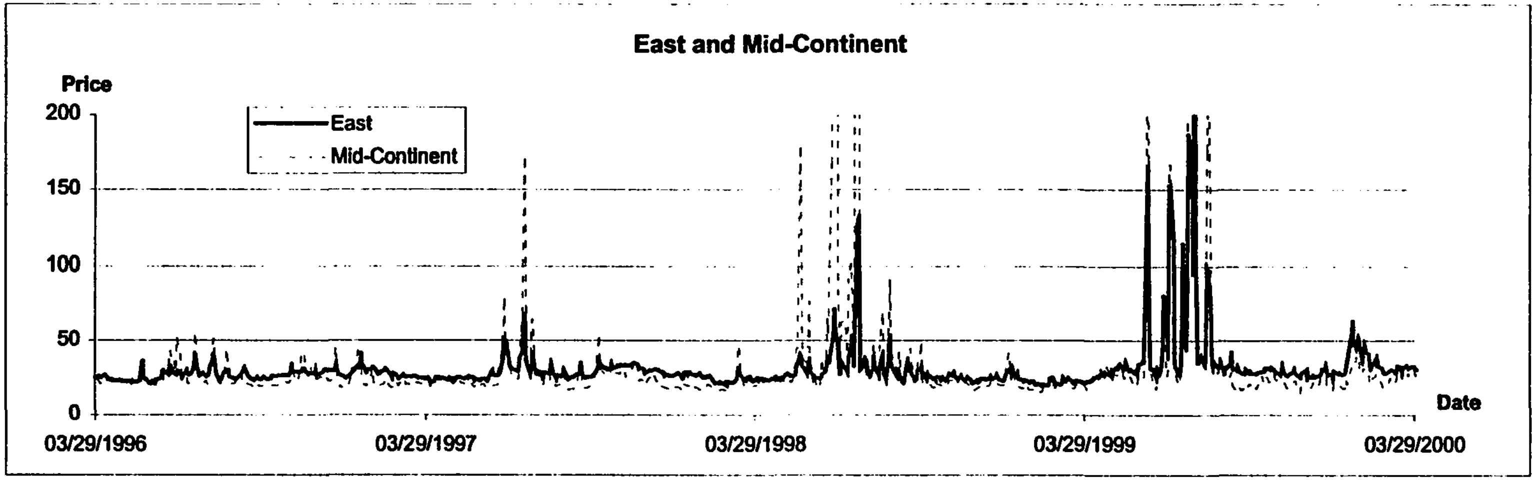


From left to right, top to bottom:

Western Systems Coordinating Council (WSCC), Mid-Continent Area Power Pool (MAPP), Northeast Power Coordinating Council (NPCC), Mid-America Interconnected Network, Inc. (MAIN), East Central Area Reliability Coordination Agreement (ECAR) Mid-Atlantic Area Council (MAAC), Southwest Power Pool (SPP), Southeastern Electric Reliability Council (SERC) Electric Reliability Council of Texas (ERCOT), Florida Reliability Coordinating Council (FRCC)

Source: North American Electric Reliability Council (NERC), April 2000.

Figure 2.3 Average On-Peak Electricity Spot Prices by Area



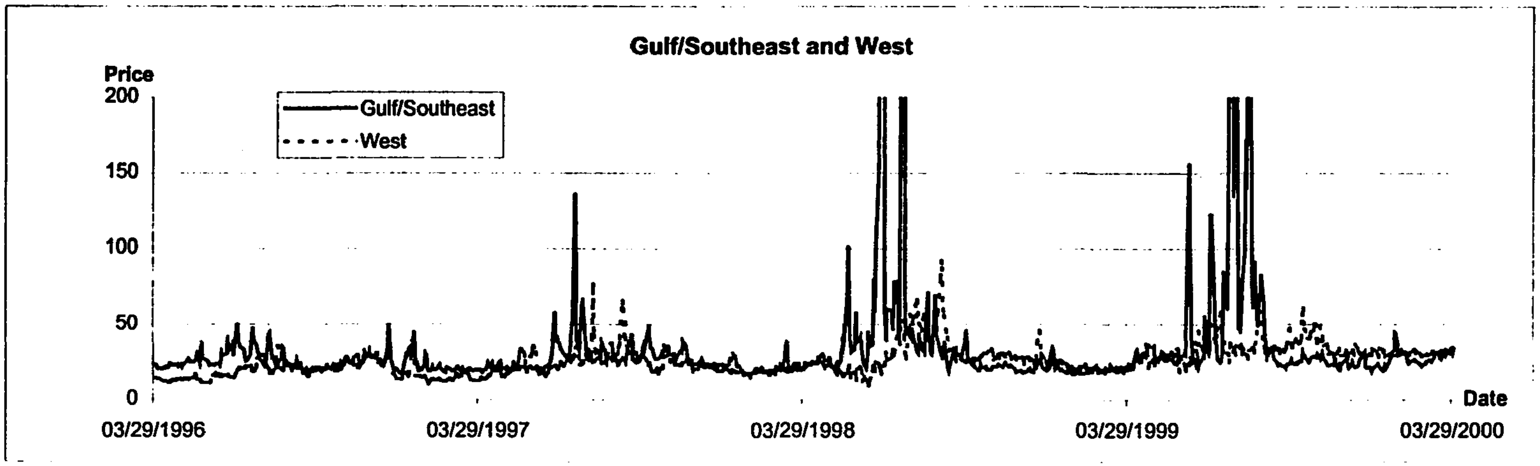
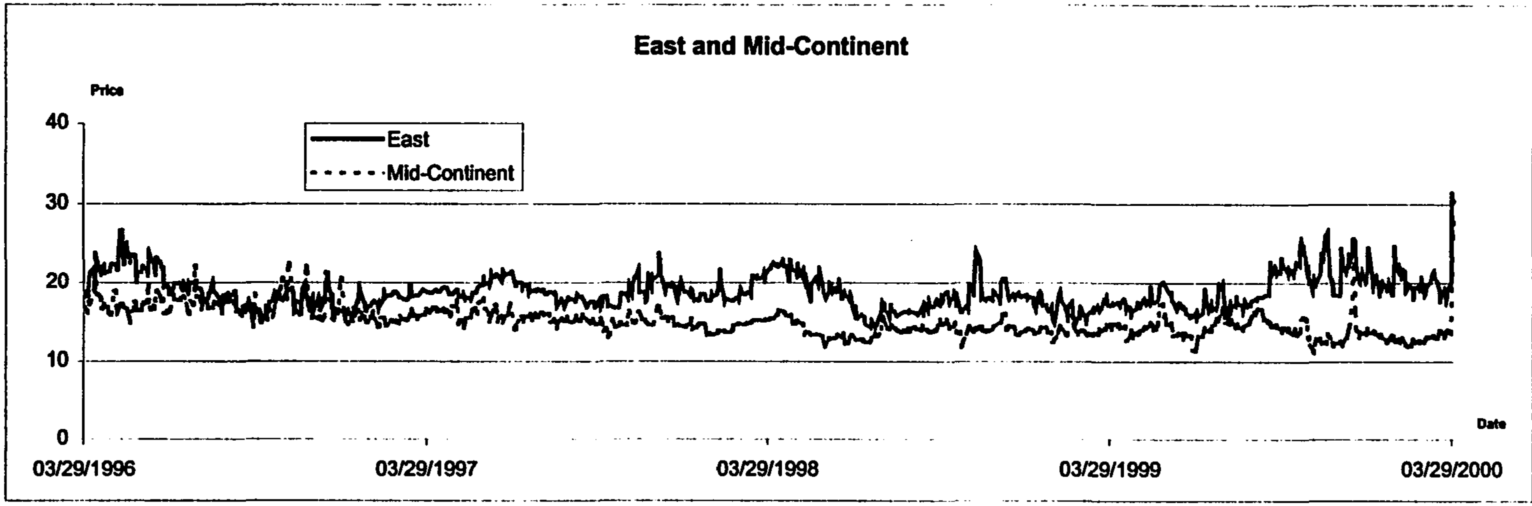


Figure 2.4 Average Off-Peak Electricity Spot Prices by Area



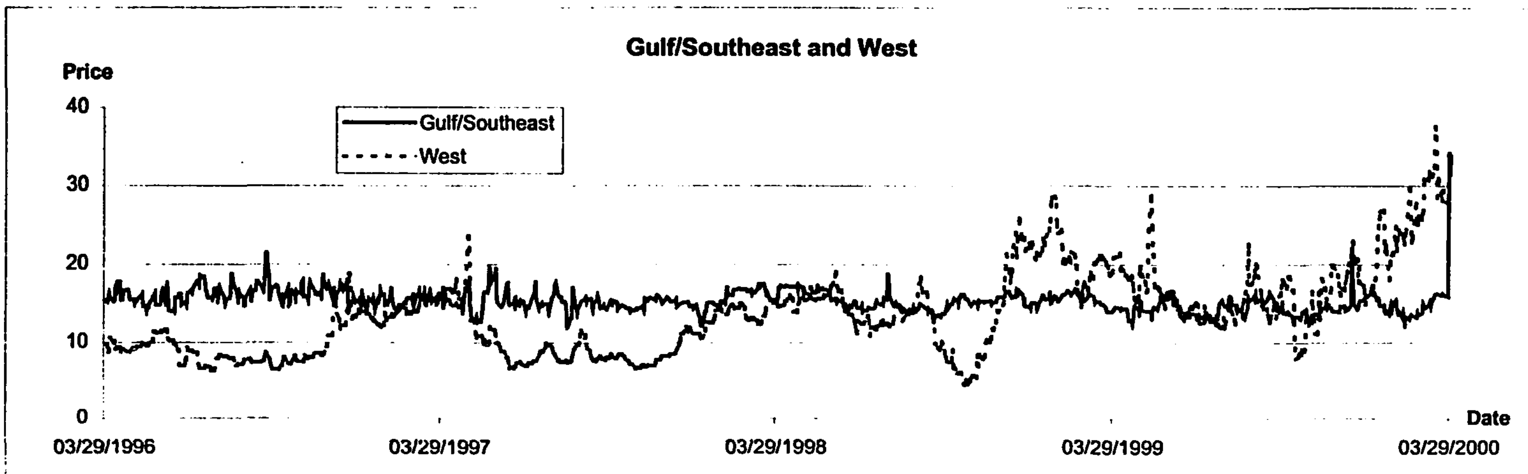


Figure 2.5 Kalman Filter Results for Eastern New York Power Pool (SC) in the East Area

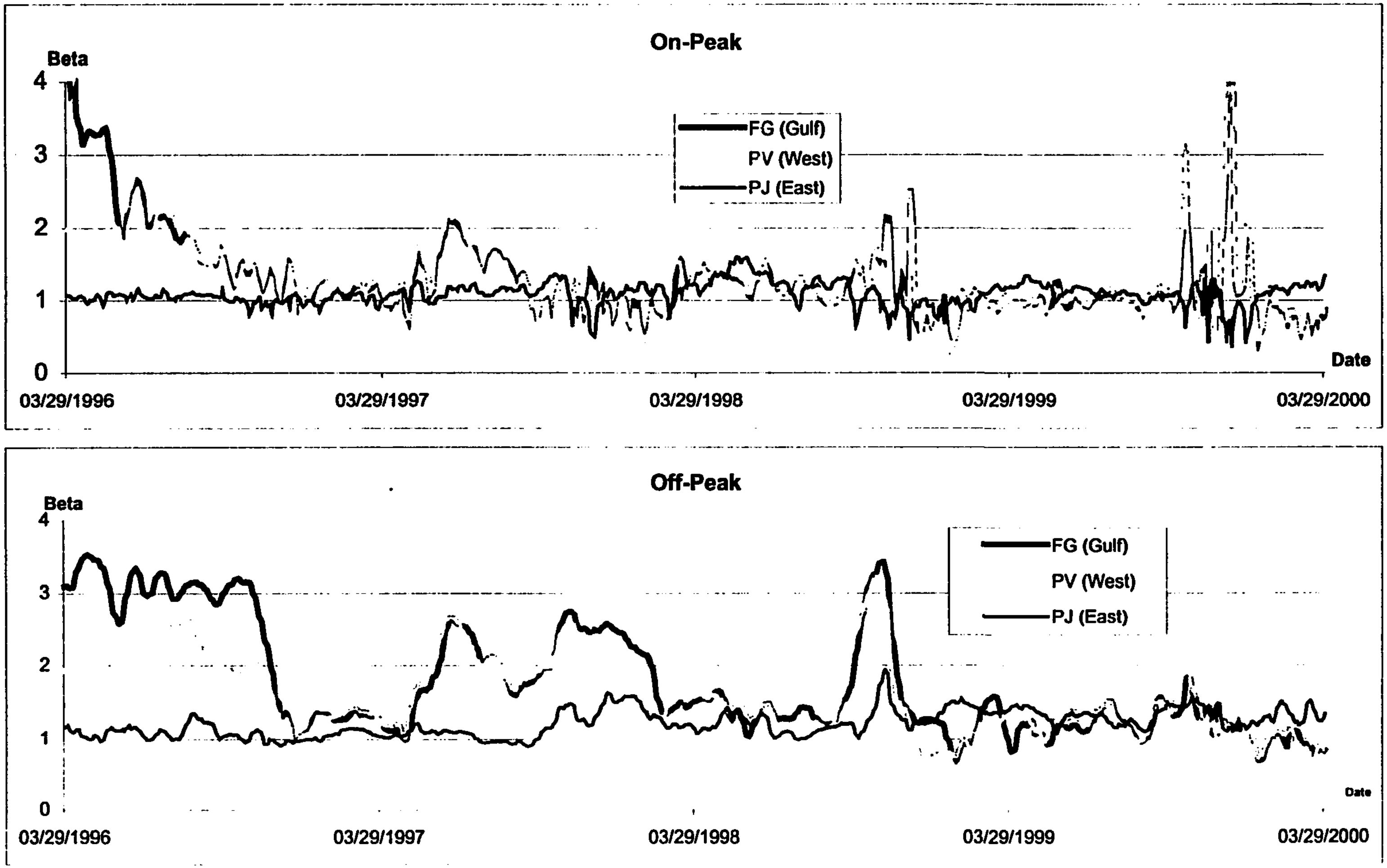


Figure 2.6 Kalman Filter Results for Western East-Central Area Reliability Council (WE) in the Mid-Continent Area

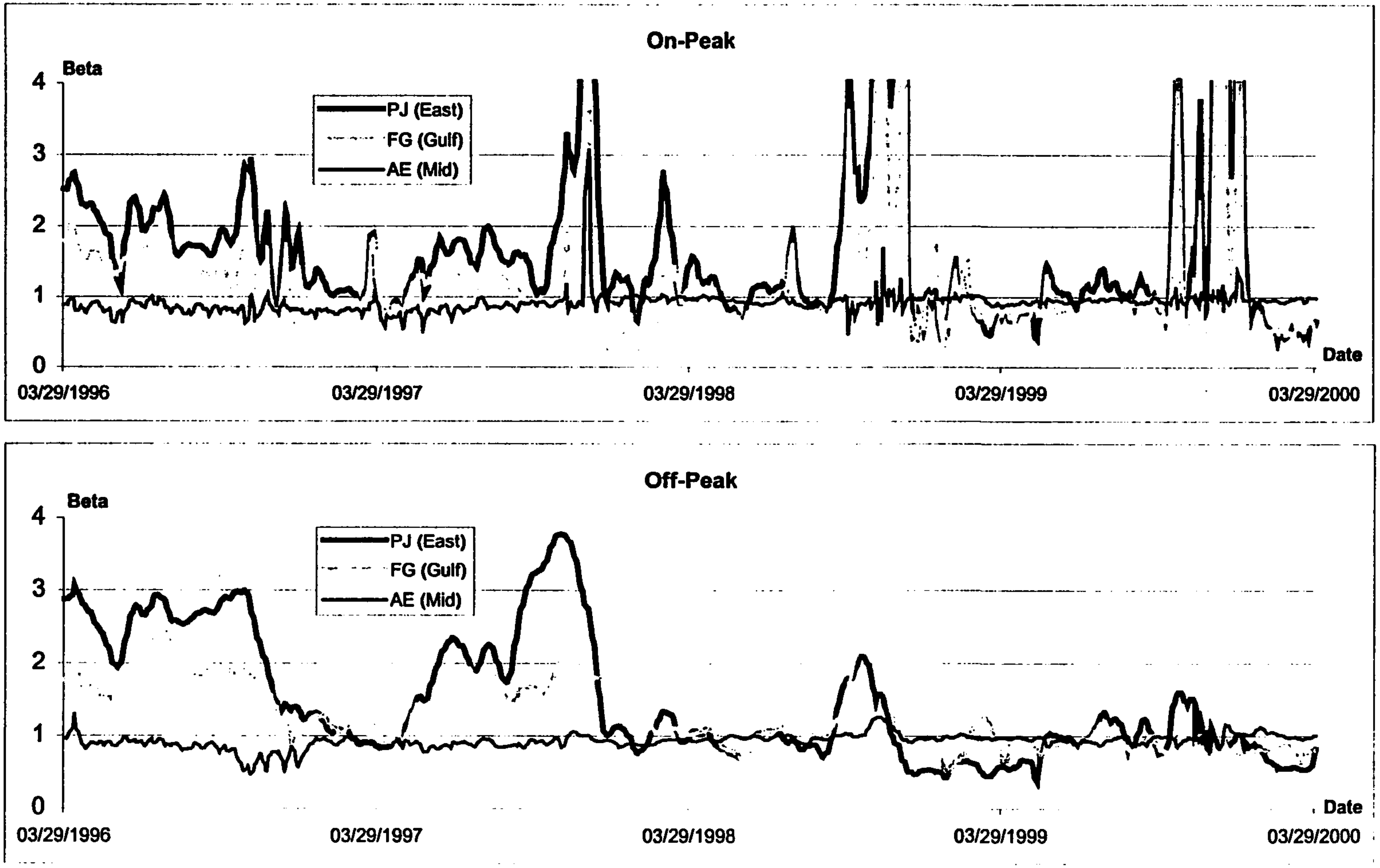


Figure 2.7 Kalman Filter Results for Entergy (SS) in the Gulf/Southeast Area

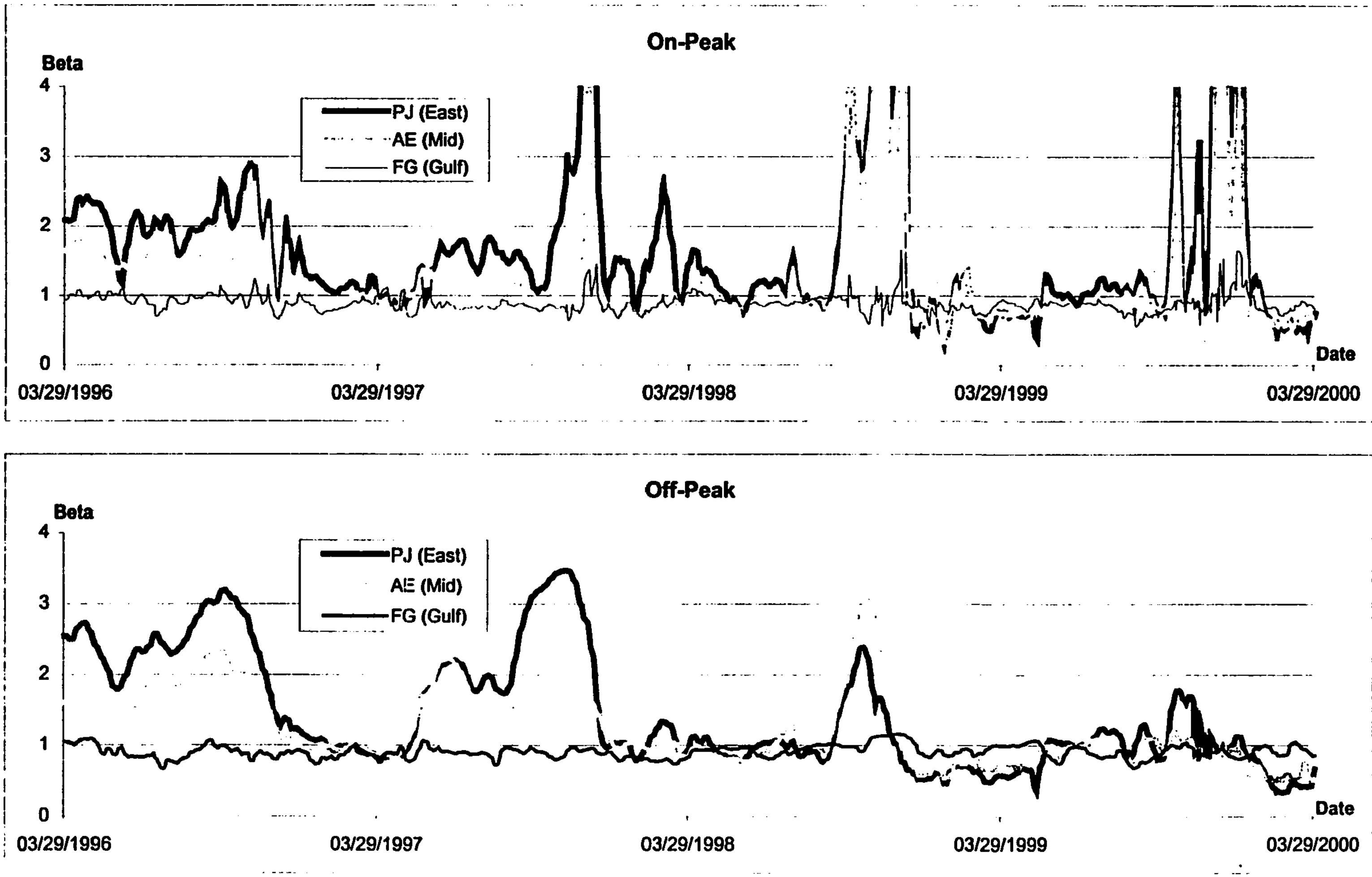


Figure 2.8 Kalman Filter Results for Four Corners (FC) in the West Area

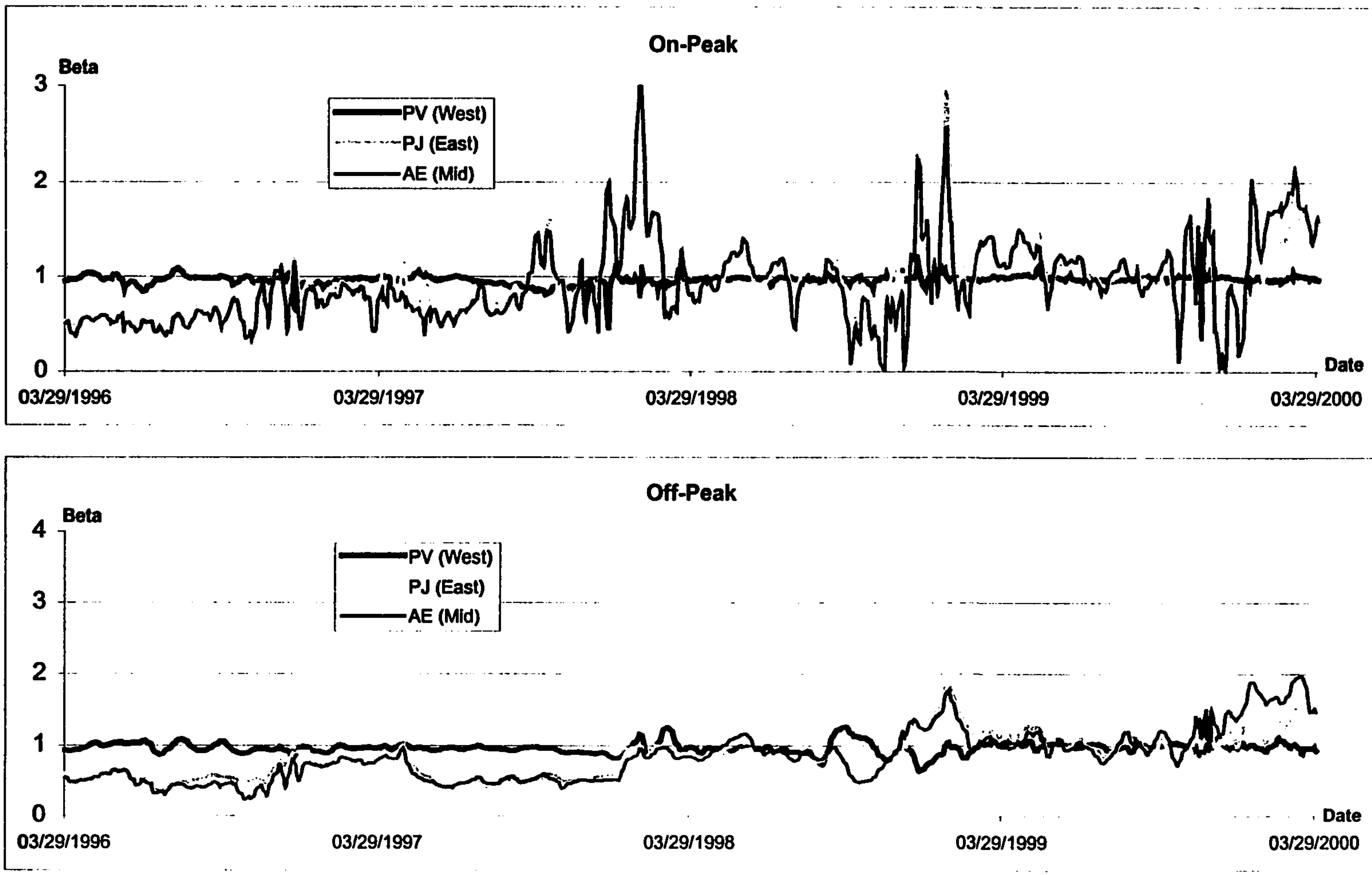


Figure 2.9 Kalman Filter Results for COB and PV Futures

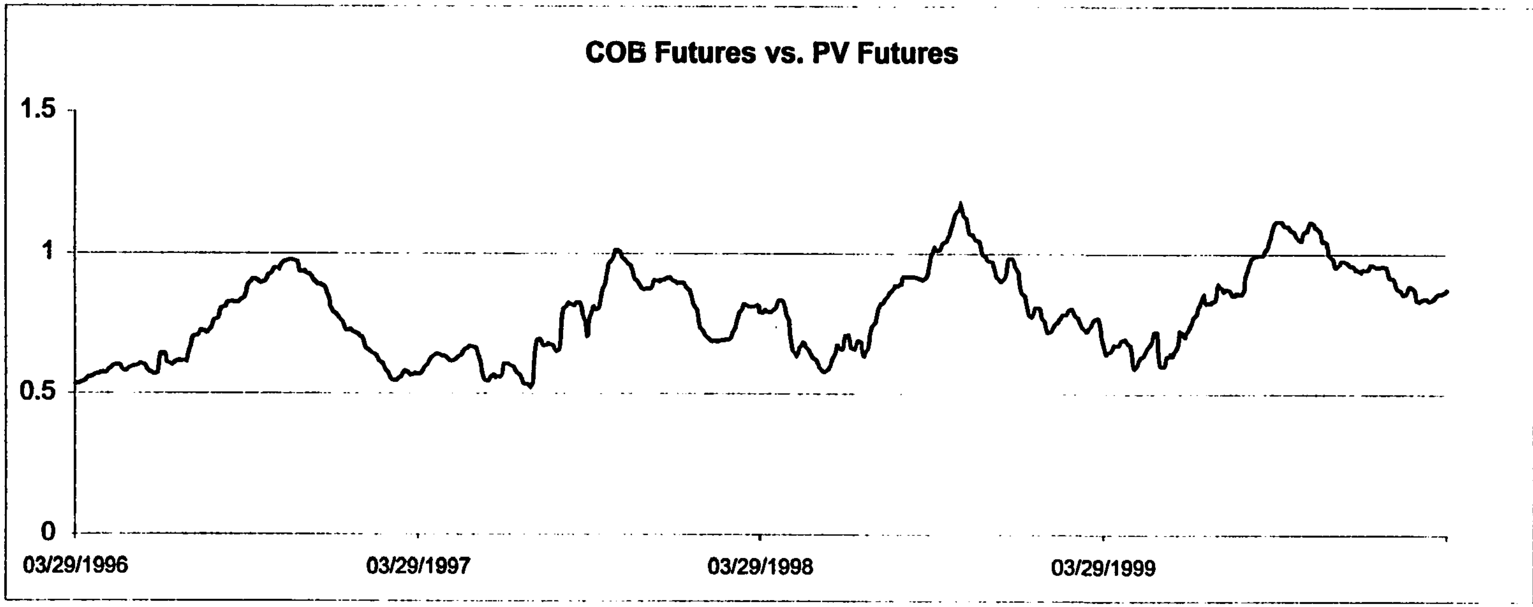


Figure 3.1 Natural Gas Futures Daily and Monthly Trading Volumes

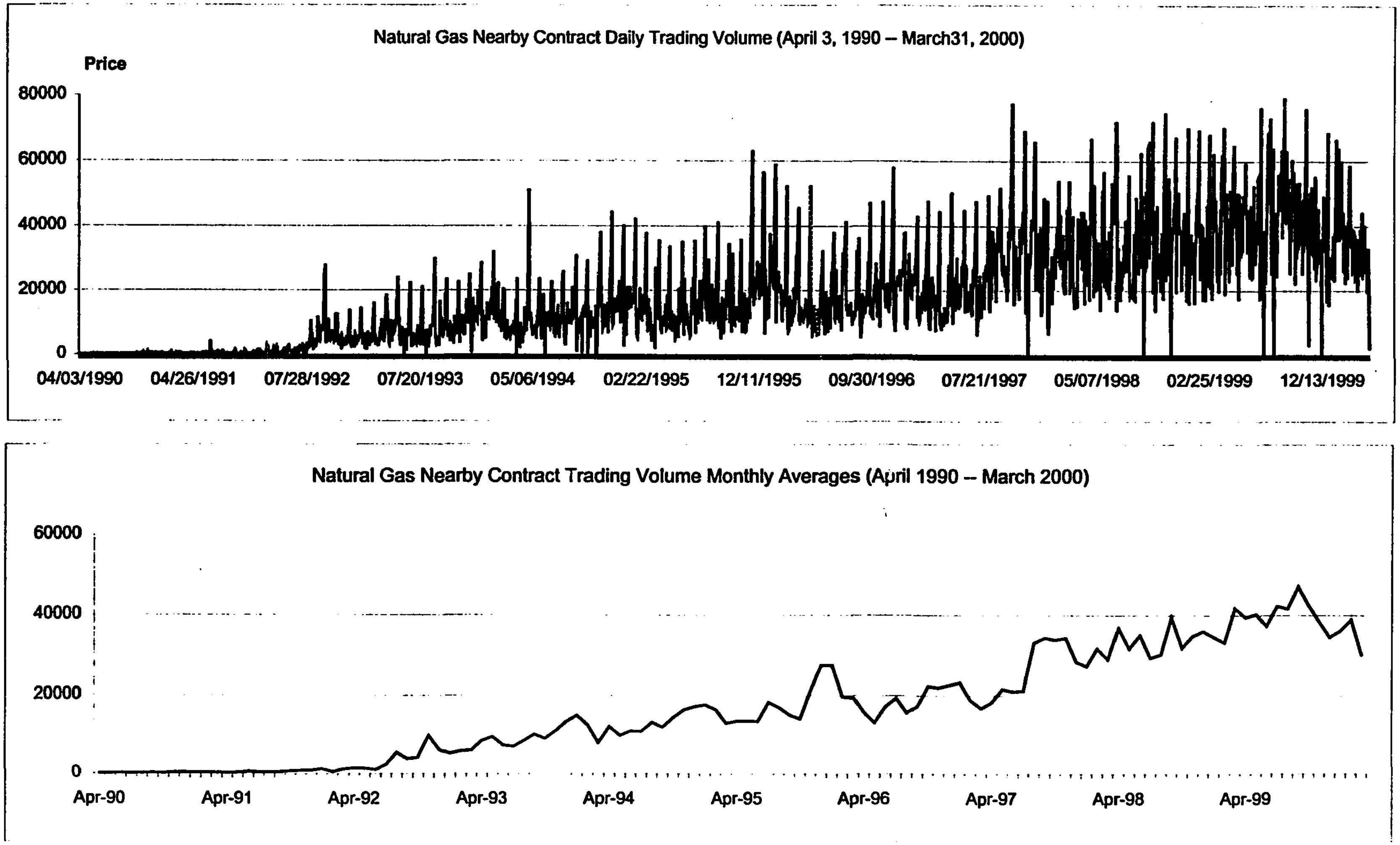


Figure 3.2 Comparisons of Daily Trading Volumes

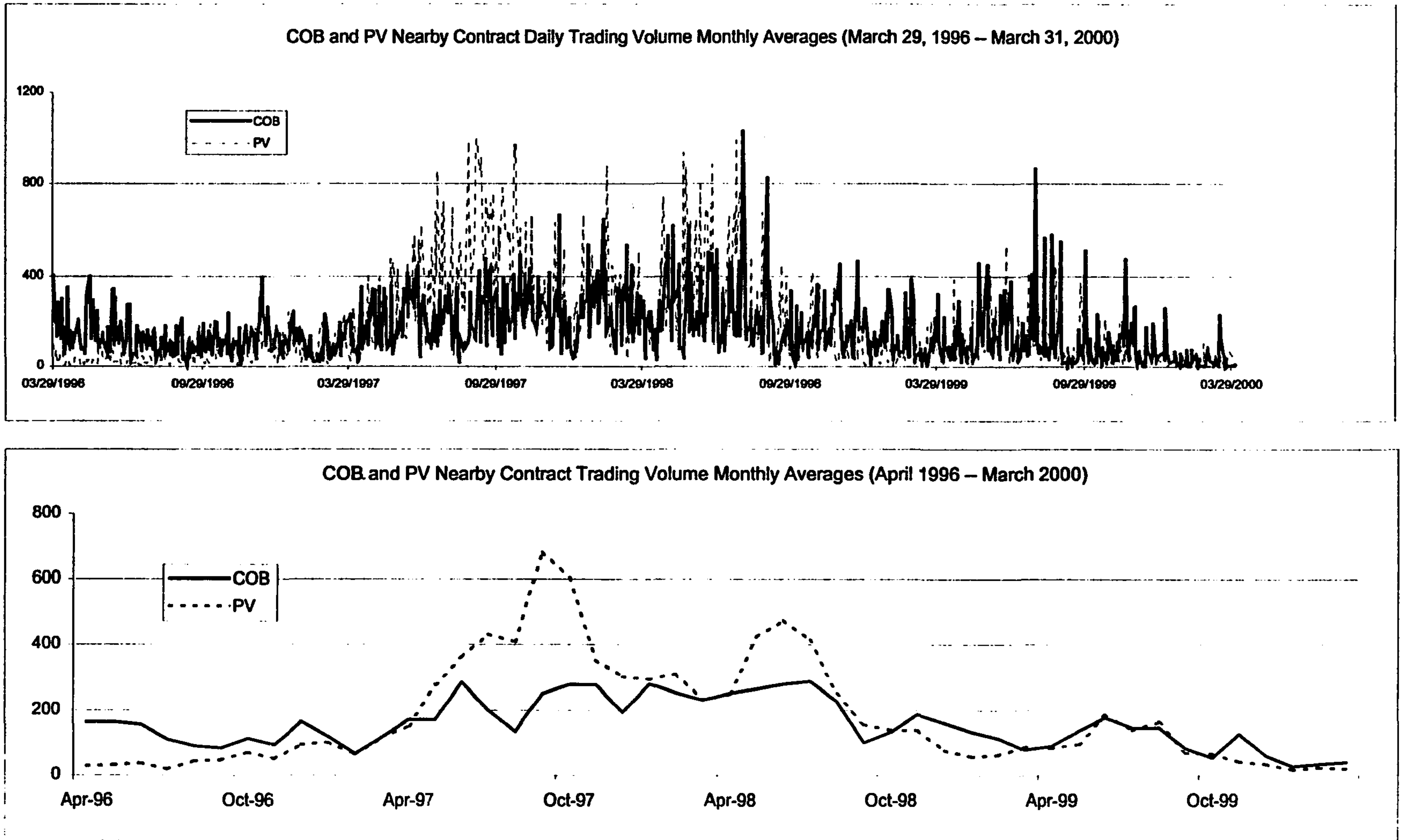


Figure 3.3 Natural Gas (NG) Futures and Spot Prices

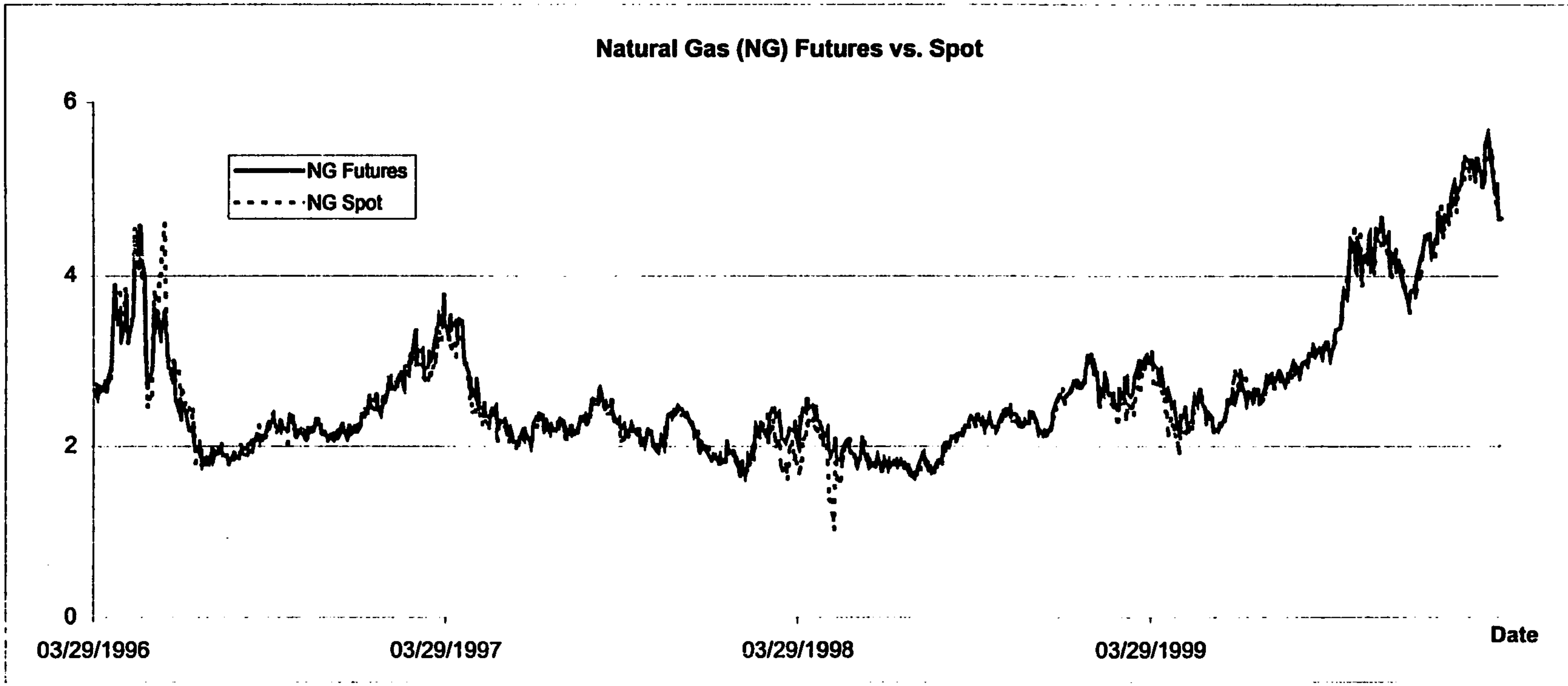


Figure 3.4 COB and PV Electricity Futures and Spot Prices

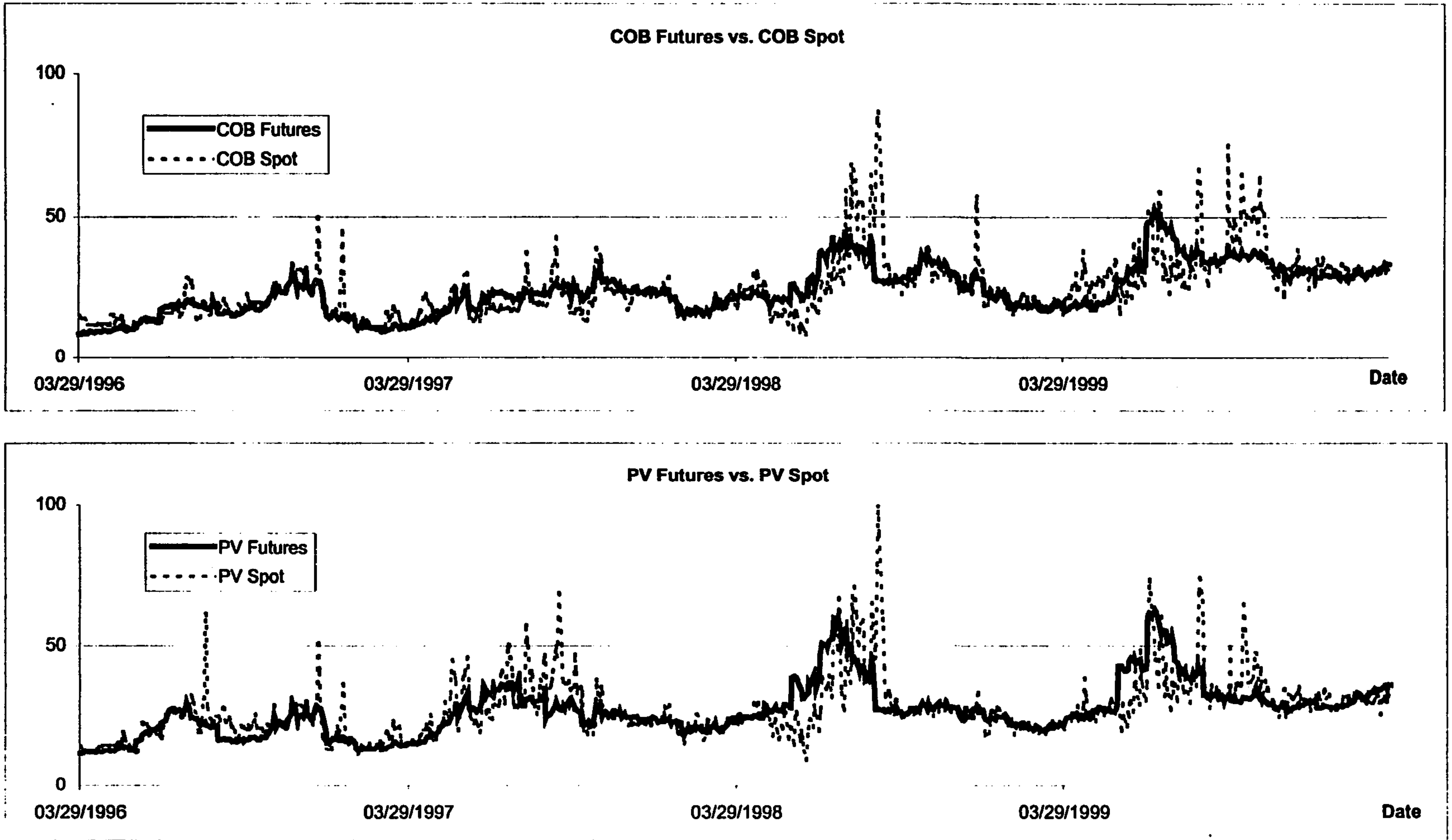
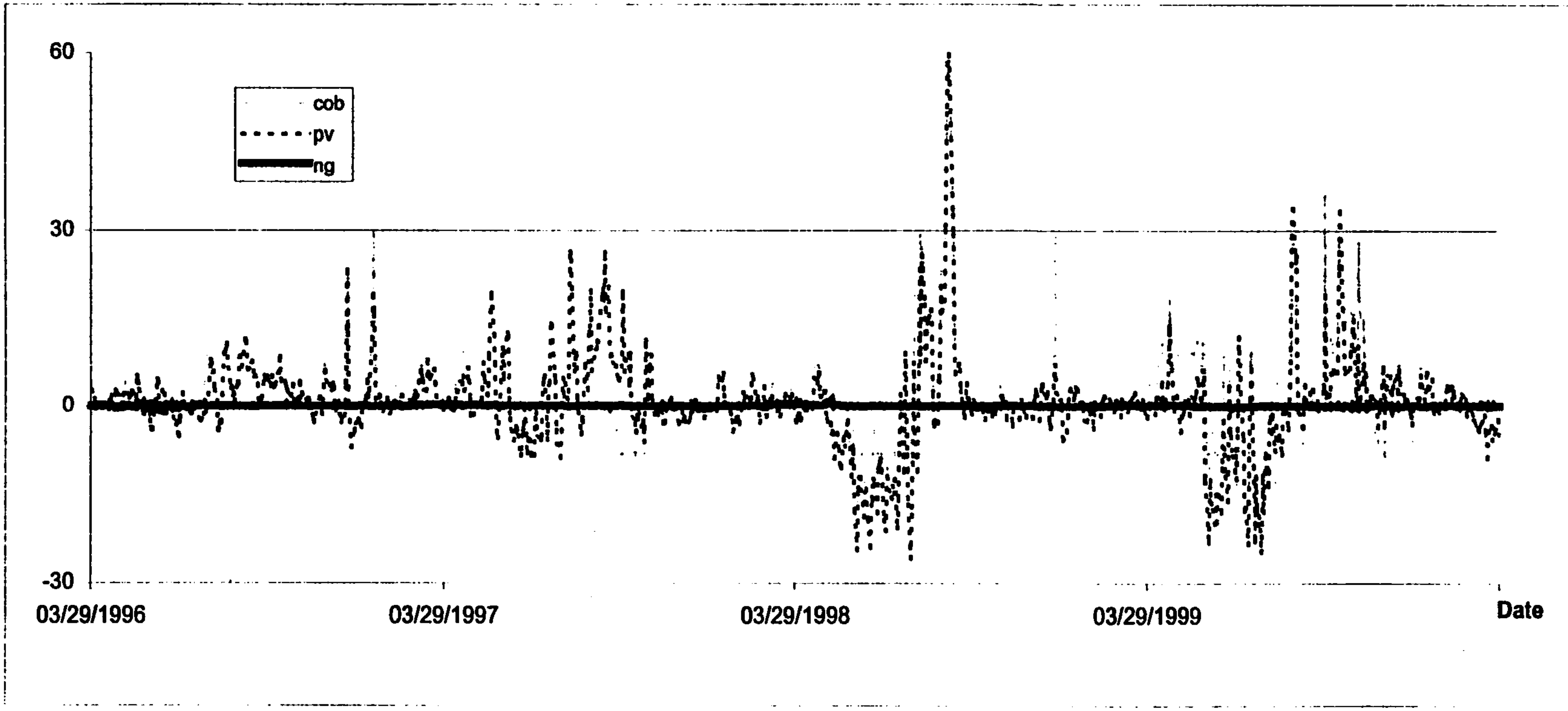
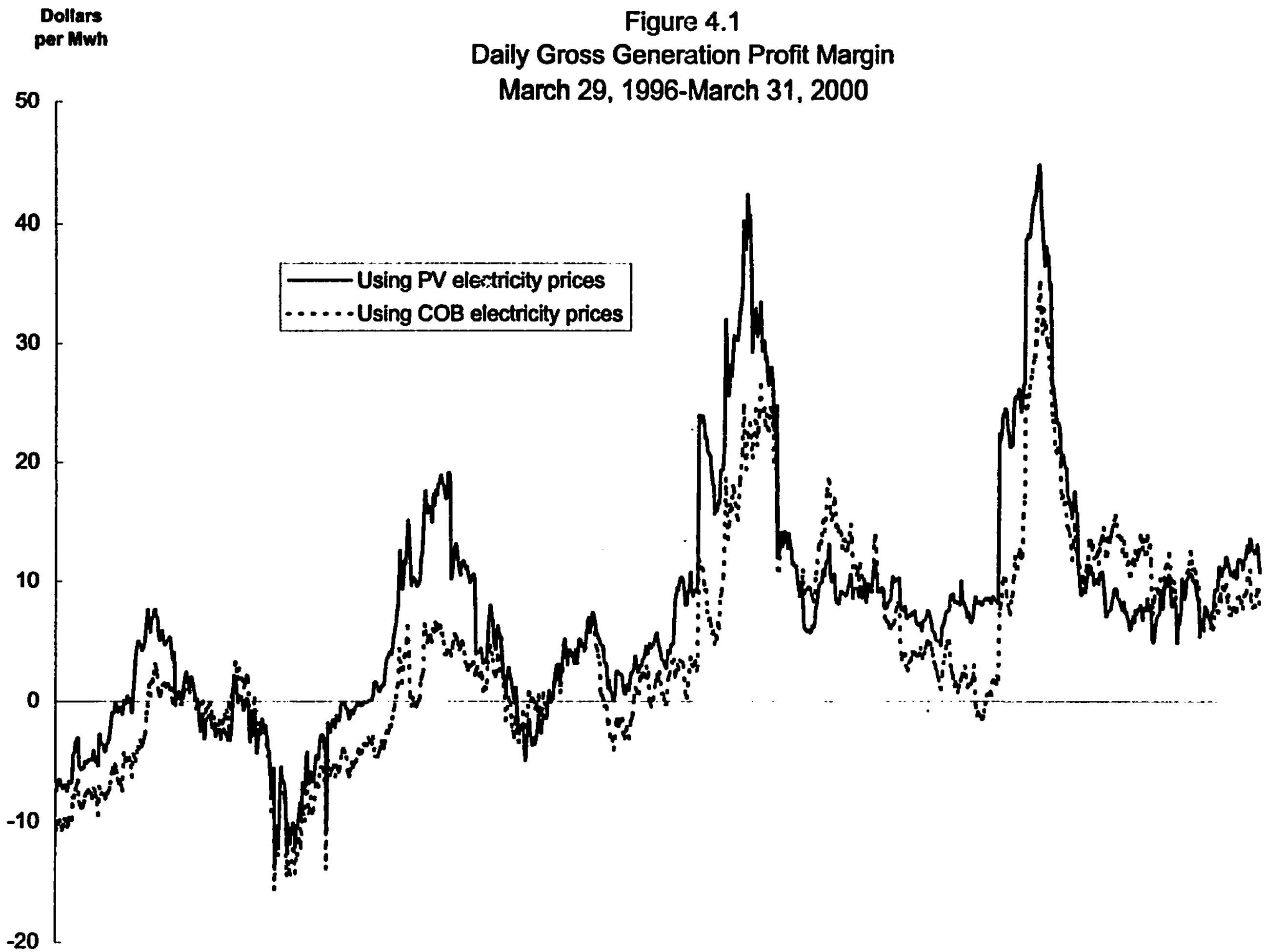


Figure 3.5 Basis Comparison between Natural Gas and Electricity

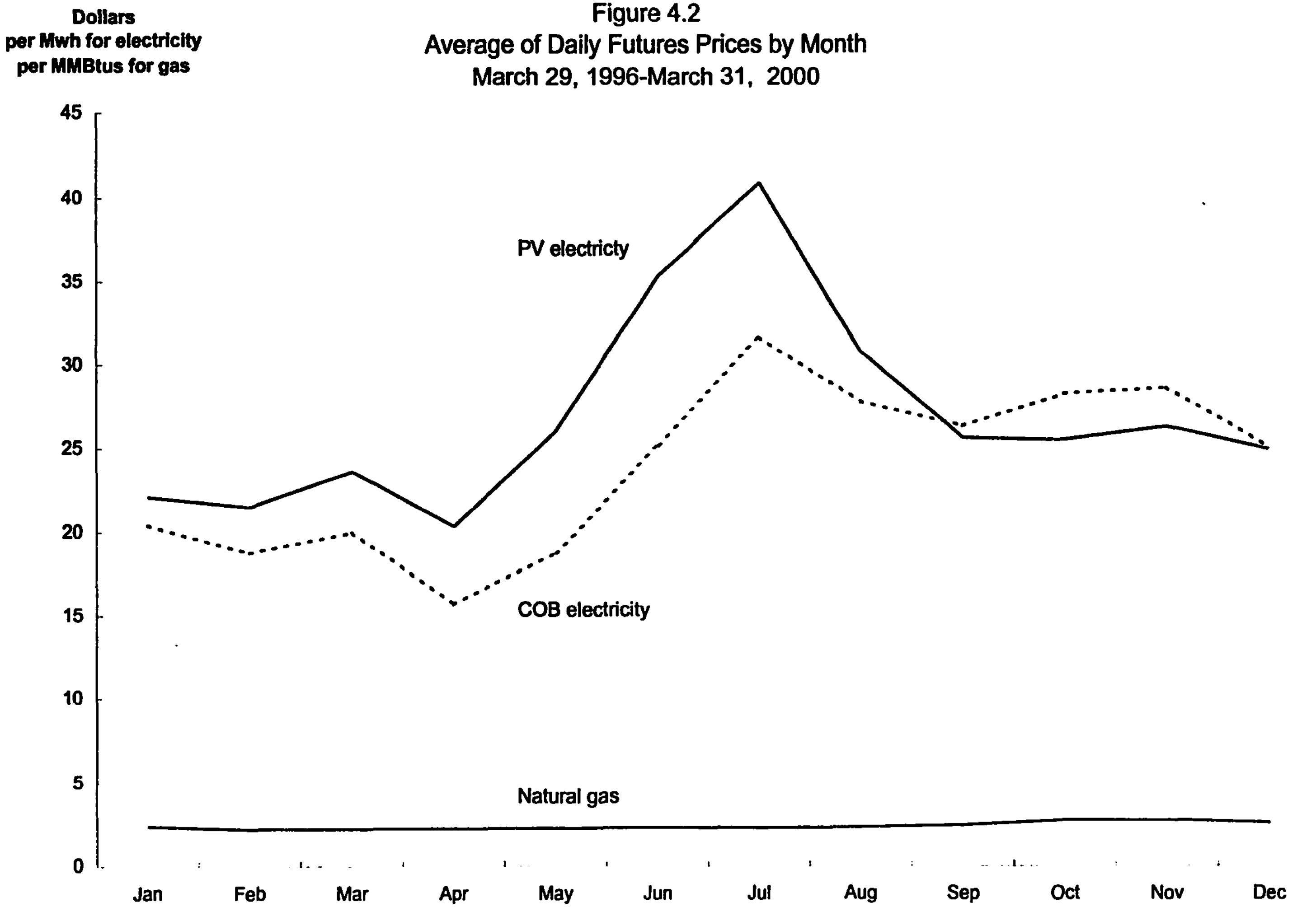
Basis Comparison ($Basis_t$ = Spot $Price_t$ - Futures $Price_t$)





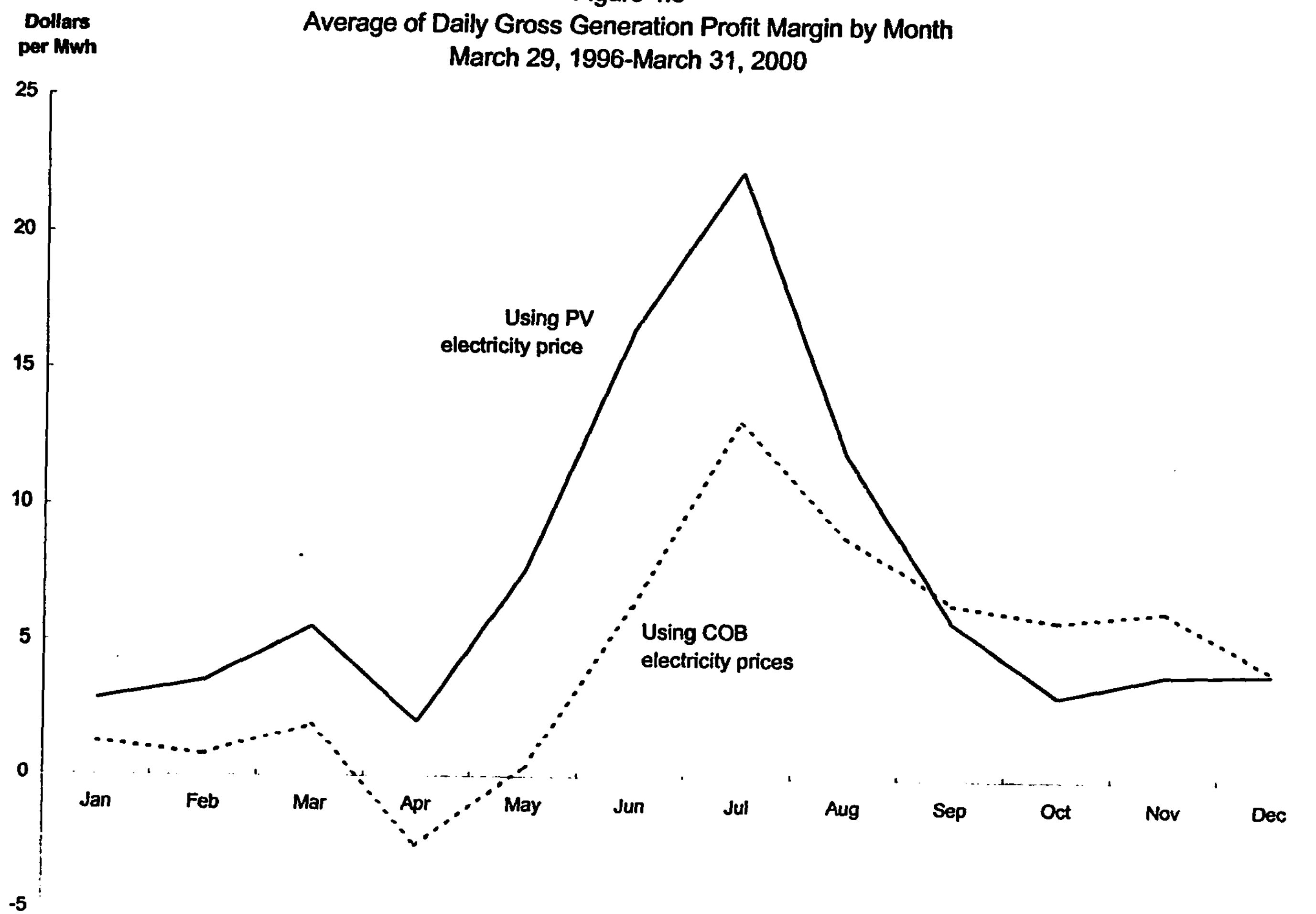
Daily gross generation profit margin is NYMEX's California-Oregon Border (COB) or Palo Verde (PV) electricity futures daily settlement price minus 8.15 times its Henry Hub natural gas futures daily settlement price where 8.15 is the heat rate implied by the 5:3 spread ratio commonly used in trading.

Figure 4.2
Average of Daily Futures Prices by Month
March 29, 1996-March 31, 2000



Prices are daily settlement prices for NYMEX's California-Oregon Border (COB) and Palo Verde (PV) electricity and Henry Hub natural gas futures contracts.

Figure 4.3
Average of Daily Gross Generation Profit Margin by Month
March 29, 1996-March 31, 2000



Daily gross generation profit margin is NYMEX's 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.