Hedging Energy Price Risk Using Artificial Neural Networks

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Abstract

This paper provides an empirical study of the effectiveness of hedging energy prices using a neural network model. The hedging effectiveness of the model is investigated using daily crude oil, natural gas, and unleaded gasoline futures prices. Empirical results show that the neural network hedging model is effective in reducing commodity price risks.

I. Introduction

The demand for natural gas in the United States is projected to increase by 1.5 percent per year, on average, through 2025, and consumption to reach 31 trillion cubic feet. Similarly, world crude oil demand is predicted to reach more than 120 million barrels per day by 2025.[1] Increasing world demand for gas and crude oil, along with recent wars and political tensions in the Middle East, have led the price of these resources to fluctuate widely. For example, the price of crude oil has fluctuated between $1.70 and $78.00 per barrel from 1970 to 2006.

Various hedging models have been introduced in the literature to manage energy price risks. Mahul (2002), Routledge, Seppi, and Spatt (2000), Pirrong (1997), Newbery (1988), and McKinnon (1967) have employed minimum-variance models to minimize the variance of a firm's payoffs by selecting the optimal unit of commodity to hedge. Studies by Brennam and Schwartz (1985), Ross (1997), and Schwartz (1997) show that futures prices are not driven by spot prices and the costs and benefits of storage alone, but are also a function of the expected spot price at maturity of the futures contract. Brinkman and Rabinovich (1995) examined the extent to which the transportation system for natural gas in the United States narrows the effectiveness of the New York Mercantile Exchange natural gas futures contract as a hedging instrument. Linn and Zhu (2004) studied the short-term volatility of natural gas prices by examining the intraday prices of nearby natural gas futures contracts traded on the New York Mercantile Exchange. They found that the weekly gas storage announcement had considerable effect on the volatility of gas prices. In an empirical study, Rahgozar and Najafi (2003a, 2003b) showed that while a minimum-variance model effectively reduces price risk, it negatively affects revenue. Using an *ad hoc* approach to hedging, they showed that this approach reduced crude oil price risk without having an adverse and strong effect on revenue. More recently, Olaf (2005) presented a two-factor model on commodity price derivatives. Using crude oil prices to test the model, he found that the two-factor model not only worked well for short-term contracts but led to major improvements for long-term contracts.

Over the past two decades, several learning networks have been developed for modeling nonlinear statistical relationships. In particular, Projection Pursuit Regression (Friedman and Stuetzle (1981)), Multiplayer Perception (Rumelhart (1986), Werbos (1974)), Radial Basis Functions (Poggio and Girosi (1990)), and Support Vector Machine (Vapnik et. al. (1992)) are

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1 Annual Energy Outlook, 2005.

examples of such techniques. Many researchers (Hutchinson, Andrew and Poggio (1994), Gençay and Qi (2001), Carelli et al (2000)) have used these techniques for pricing and hedging derivative securities as alternatives to the Black and Scholes (1973) and Merton (1973) models. Applying a neural network model to hedge crude oil price risk, Najafi and Rahgoza (2005), demonstrated that their approach outperforms the other models in terms of price risk reduction. This study expands the application of the neural network hedging model and investigates its effectiveness in reducing price risk for natural gas and unleaded gasoline.

The remainder of this article is organized as follows: Section II describes the neural network hedging model used in this study; Section III provides performance results of the model in the energy sector; Section IV offers concluding comments and evaluations.

II. The Neural Network Hedging Model Development

To develop the neural network model, Najafi and Rahgozar (2005) first identified a set of input and output variables that were considered relevant to the hedging. Then using historical data on these variables, three training, test, and validation sets were generated. Each set was made of feature vectors that represented one day of historical data, with each feature vector composed of a set of input values and a single output value. To improve the performance of the network model, as was done by Kaastra and Boys (1995), deviations from short, medium and long-term norms, instead of the actual value of the variables were employed as inputs to the network. The short, medium, and long-term z-scores of the corresponding variables in the data set were calculated and employed in this study. The process we employed is outlined in Figure 1.

It is assumed that during the training phase, information regarding futures prices and their maturity values are available and can be used to generate desired hedge ratios. More specifically, for a given day, the futures prices with different maturity dates e.g., $F_1, F_2, \ldots, F_n$ and their corresponding spot prices into the future e.g., $Fs_1, Fs_2, \ldots, Fs_n$ are known to the hedger.

For any given day **i,** the target hedge ratio, $h_\tau(i)$, is computed as the weighted sum of the revenue maximizing hedge ratio $h_\alpha(i)$ and the risk minimizing hedge ratio $h_\beta(i)$.

$$h_\tau(i) = (1-\gamma)*h_\alpha(i) + \gamma*h_\beta(i)$$

where the value for γ varies between 0 and 1. For example, a γ equal to 1 leads to a hedge ratio that only minimizes risk, whereas, a γ equal to 0 indicates a hedge ratio that only maximizes revenue, while a γ equal to 0.5 indicates a hedge ratio that optimizes risk and revenue simultaneously.

The revenue maximizing ratio, $h_\alpha(i)$, is computed based on the relationship between F_i and Fs_i. When the futures prices are higher than their maturity values, hedging is performed using futures. Otherwise, commodities are sold at spot prices.

$$h_\alpha(i) = \begin{cases} 1 & if \quad F_i \geq Fs_i \\ 0 & otherwise \end{cases}$$

The risk minimizing ratio, $\boldsymbol{h_\beta (i)}$, is calculated to keep the hedged revenue $\boldsymbol{hr_i}$ as close as possible to its long-term norm[2]. That is,

$$hr_i = \overline{hr}$$

where

$$\overline{hr} = \frac{\sum_{j=1}^{j=n} hr_{i-j}}{n} \quad \text{and}$$

$$hr_i = h_\beta (i) * F_i + (1 - h_\beta (i)) * Fs_i$$

Limiting the hedge ratio to values between 0 and 1 leads to a risk-minimizing factor of

$$h_\beta (i) = \begin{cases} (\overline{hr} - Fs_i)/(F_i - Fs_i) & \\ 0 & if \quad (\overline{hr} - Fs_i)/(F_i - Fs_i) < 0 \\ 1 & if \quad (\overline{hr} - Fs_i)/(F_i - Fs_i) > 1 \end{cases}$$

After generating the feature vector sets, they were sampled to produce the training, test, and validation sets. The most recent contiguous set of observations were selected and used for the validation set and the remaining feature vectors were randomly sampled to produce the training and test set.

III. Model Performance

Data considered under this study included daily spot and futures prices on U.S. crude oil, natural gas, and unleaded gasoline traded on the NYMEX over the 1991 – 2003 period. In addition, the daily North American average temperature, Consumer Price Index (CPI), and short-term interest rates[3] were considered relevant variables that influence energy prices. These variables were added as input variables to the network. To create the training, test, and validation sets all data were first tested, cleaned, and preprocessed. Using the resulting sets, the performance of the designed neural network-hedging model was tested extensively and the performance of the model was compared with alternative hedging approaches.

One hundred networks were trained and tested and the average performance of the trained networks in terms of risk and revenue was studied. The network with the best performance in terms of maximizing revenue and minimizing risk was then selected and its performance was tested using the validation set as depicted in Figure 1.

[2] This reflects the concept of mean reversion that has been considered important in deciding futures prices (E. Schwartz, 1997, Gibson and Schwartz 1990, Ross 1997).

[3] Interest rates were measured by 3-month T-Bill rates.

About 60 percent of the data set was used to train the networks for estimating the target hedge ratios, about 20 percent of the data set was used to evaluate the effectiveness of the network, and the remaining 20 percent of the data set was employed in validation of the trained networks.

The hedging effectiveness of the networks, i.e., their average effect on revenues and risks were measured on the test set. The effectiveness of each network was investigated by calculating changes in revenue (i.e., price) and risks. Changes in revenue, **Δr**, and changes in risk, **Δs**, were computed using the following formulas.

$$\Delta r = 1 - \overline{y^{o}} \Big/ \overline{y^{h}}$$

and

$$\Delta s = 1 - sd(y^{0}) \Big/ sd(y^{h})$$

where

$\overline{y^{0}}$, $\overline{y^{h}}$, $sd(y^{0})$ and $sd(y^{h})$ are the mean and standard deviation of unhedged and hedged revenue positions respectively. Note that if $sd(y^{h})$ were smaller than $sd(y^{0})$, and then Δs will be negative, indicating risk reduction.

Table I includes the empirical results of the network model. It contains hedge ratios plus the changes on the risk and revenue for crude oil, unleaded gasoline and natural gas. As is apparent from Table I, the estimated hedge ratios vary for each year under each futures prices. On average, ratios were generally above 50 percent during the 1991-2000 (last column of Table I).

The performance of the networks in terms of their effect on risk is also presented in Table I. The results suggest that the neural network hedging model reduces price risk. Overall, the nearby futures contracts reduced risk less than the distant futures contracts. As shown in the last column of Table I, during 1991-2000, the average risk reduction for hedging crude oil ranged from 7 to 58 percent, for natural gas from 12 to 72 percent, and for unleaded gasoline it ranged from 13 to 63 percent respectively.

The neural network model not only reduced risk but at the same time increased or had a minimal effect on revenue. For example, using the fourth-month futures contract, the revenue, on average, increased by 3, 4, and 3 percentage respectively for all three commodities during the period 1991-2000. The annual plot of the networks' effectiveness on revenue and risk for the fourth-month futures is depicted in Figure 2.

A comparison of the neural network results with previous hedging models, (Rahgozar and Najafi (2003a), Mahul (2002), Routledge, Seppi, and Spatt (2000), Pirrong (1997), Newbery (1988), and McKinnon (1967)), shows that the neural network model performed remarkably well. For example, using fourth-month futures prices, the neural network model reduced risk by

57.58 percent and improved revenue by 2.89 percent while the minimum-variance hedging models tested by Rahgozar and Najafi (2003a) reduced average risk by almost 18 percent but caused revenue to decline about 2 percent.

Hedging effectiveness of the network on the validation set is presented in Table II The last three years of the data set (2001-2003) were used to further investigate the results. Out of the 100 trained networks, the one with the least mean square error on the test set was selected and used for this purpose. Although performance of the network was expected to drop, for all three commodities the network's outputs on the validation set were fairly comparable to the performances on the test set. There was some performance degradation, but the effect of network's hedging on risk reduction was still considerable for all three commodity prices and its effect on revenue was minimal.

IV. CONCLUSION

This study examined and compared the performance of a new neural network hedging model using crude oil, natural gas, and unleaded gasoline prices. It estimated performance in terms of its ability to reduce price risk and improve revenue. Overall, the empirical results confirmed that, for the three commodities considered in this study, the neural network model not only reduced price risk, but increased or had no effect on revenue.

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Figure 1
Process Involved in Producing the Neural Network Hedging Model

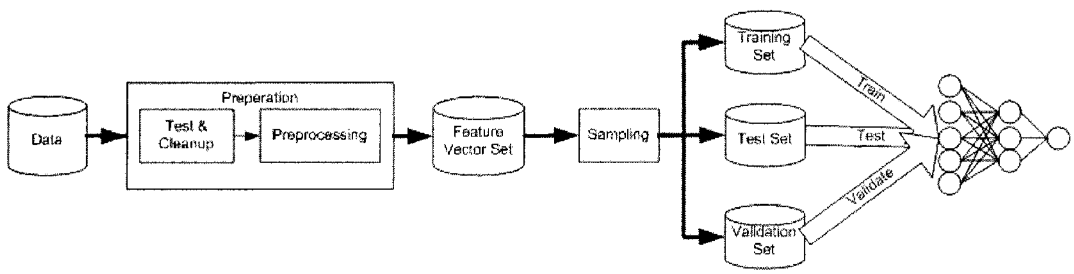
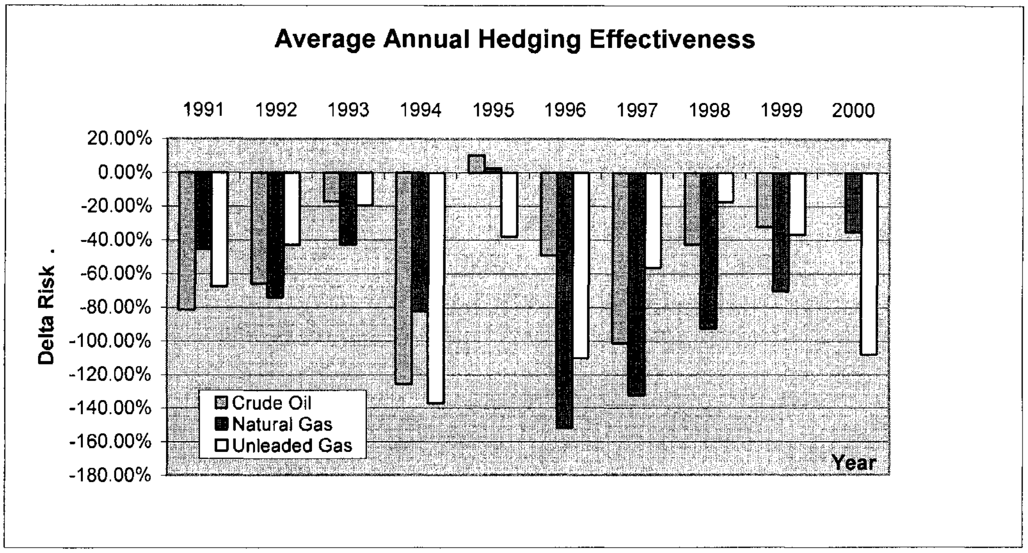
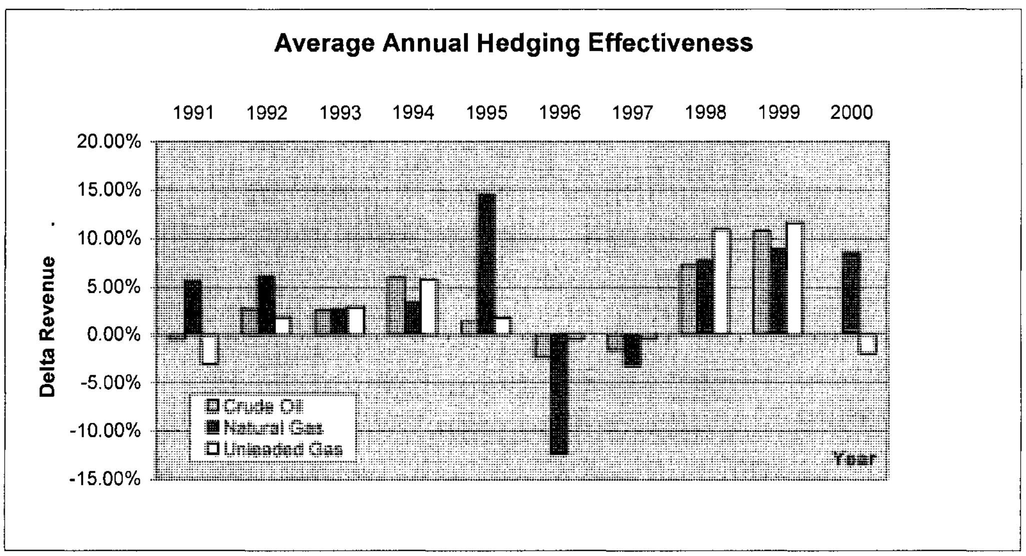


Figure 2

Plot of Model's Effectiveness on Revenue and Risk for Fourth-Month Futures





Delta Revenue, $\mathbf{\Delta r}$, and Delta Risk, $\mathbf{\Delta s}$, are measured as $\Delta r = 1 - \overline{y^o} / \overline{y^h}$ and $\Delta s = 1 - sd(y^0) / sd(y^h)$ where $\overline{y^0}$, $\overline{y^h}$, $sd(y^0)$ and $sd(y^h)$ are the mean and standard deviation of unhedged and hedged unit-revenue respectively.

Table I

Average Hedge Ratios and Measure of Hedging Effectiveness of Network Models Using Futures Prices of Different Maturity Dates

			1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	Avg 91-00
Average Hedge Ratio	Crude Oil	F1	55%	58%	63%	46%	49%	50%	49%	60%	47%		53%
		F2	51%	59%	74%	48%	52%	51%	65%	74%	47%		58%
		F3	40%	49%	84%	44%	41%	50%	66%	76%	43%		55%
		F4	40%	50%	84%	37%	47%	51%	71%	82%	43%		56%
	Natural Gas	F1	57%	45%	50%	71%	49%	50%	50%	55%	50%	51%	53%
		F2	58%	40%	50%	79%	48%	51%	45%	57%	48%	51%	53%
		F3	65%	37%	50%	81%	47%	51%	47%	72%	44%	51%	55%
		F4	64%	38%	50%	82%	55%	52%	48%	69%	39%	50%	55%
	Unleaded Gas	F1	59%	57%	68%	42%	57%	53%	70%	82%	55%	53%	60%
		F2	49%	52%	67%	40%	56%	52%	68%	81%	49%	52%	57%
		F3	44%	63%	83%	45%	54%	51%	72%	87%	44%	51%	59%
		F4	46%	66%	86%	47%	58%	51%	70%	87%	43%	51%	60%
Average Change in Risk	Crude Oil	F1	-13%	-5%	-3%	-10%	-4%	-11%	-14%	-5%	0%		-7%
		F2	-31%	-20%	-3%	-39%	-25%	-28%	-44%	-17%	-4%		-23%
		F3	-52%	-42%	-9%	-81%	-13%	-37%	-64%	-17%	-17%		-38%
		F4	-81%	-66%	-17%	-126%	10%	-49%	-101%	-43%	-32%		-58%
	Natural Gas	F1	-9%	-3%	-6%	-5%	13%	-63%	-18%	-38%	0%	4%	-12%
		F2	-14%	-20%	-44%	-48%	4%	-102%	-47%	-28%	-15%	-3%	-32%
		F3	-31%	-46%	-59%	-95%	-1%	-152%	-82%	-46%	-28%	-16%	-56%
		F4	-45%	-74%	-43%	-82%	3%	-152%	-132%	-92%	-70%	-35%	-72%
	Unleaded Gas	F1	-2%	-9%	-2%	-15%	-24%	-30%	-31%	5%	-5%	-20%	-13%
		F2	-6%	-7%	-7%	-47%	-44%	-72%	-48%	5%	-21%	-63%	-31%
		F3	-23%	-16%	-9%	-131%	-46%	-119%	-41%	8%	-35%	-89%	-50%
		F4	-68%	-43%	-20%	-137%	-38%	-110%	-56%	-17%	-37%	-108%	-63%
Average Change in Revenue	Crude Oil	F1	0%	0%	0%	1%	0%	1%	0%	1%	2%		1%
		F2	0%	1%	1%	3%	0%	0%	0%	3%	6%		2%
		F3	0%	2%	2%	5%	0%	-1%	-1%	5%	9%		2%
		F4	-1%	3%	2%	6%	1%	-2%	-2%	7%	11%		3%
	Natural Gas	F1	0%	2%	1%	-1%	4%	-5%	0%	5%	2%	4%	1%
		F2	3%	3%	2%	1%	8%	-5%	-1%	7%	5%	7%	3%
		F3	4%	4%	3%	3%	11%	-9%	-2%	7%	7%	9%	4%
		F4	6%	6%	3%	3%	15%	-13%	-3%	8%	9%	9%	4%
	Unleaded Gas	F1	0%	0%	0%	1%	3%	2%	2%	6%	3%	3%	2%
		F2	0%	1%	1%	3%	2%	2%	1%	8%	7%	1%	2%
		F3	-2%	2%	2%	4%	1%	1%	0%	9%	10%	-1%	3%
		F4	-3%	2%	3%	6%	2%	-1%	-1%	11%	12%	-2%	3%

Table II

Average Hedge Ratios and Measure of Hedging Effectiveness of the Best Network Models on the Validation Set Using Futures Prices with Different Maturity Dates

			2001	2002	2003	Avg 01-03
Average Hedge Ratio	Crude Oil	F1	54%	49%	69%	57%
		F2	70%	67%	58%	65%
		F3	43%	61%	43%	49%
		F4	86%	79%	48%	71%
	Natural Gas	F1	63%	59%	70%	64%
		F2	70%	60%	61%	64%
		F3	56%	44%	49%	49%
		F4	41%	47%	53%	47%
	Unleaded Gas	F1	75%	60%	53%	62%
		F2	74%	76%	56%	69%
		F3	65%	69%	44%	59%
		F4	69%	62%	39%	57%
Average Change in Risk	Crude Oil	F1	-8%	-3%	5%	-2%
		F2	-12%	-6%	-5%	-8%
		F3	-20%	-9%	-10%	-13%
		F4	-17%	-26%	-75%	-39%
	Natural Gas	F1	-17%	10%	-135%	-47%
		F2	-40%	10%	-166%	-65%
		F3	-55%	-3%	-230%	-96%
		F4	-93%	-8%	-355%	-152%
	Unleaded Gas	F1	7%	-8%	-55%	-18%
		F2	-6%	-24%	-75%	-35%
		F3	-13%	-77%	-74%	-55%
		F4	-35%	-61%	-11%	-36%
Average Change in Revenue	Crude Oil	F1	0%	-1%	1%	0%
		F2	-3%	-2%	2%	-1%
		F3	-1%	-4%	5%	0%
		F4	-7%	-2%	6%	-1%
	Natural Gas	F1	-2%	4%	-1%	0%
		F2	-4%	8%	-4%	0%
		F3	-11%	13%	-7%	-1%
		F4	-14%	15%	-6%	-2%
	Unleaded Gas	F1	4%	3%	1%	3%
		F2	2%	3%	-2%	1%
		F3	1%	5%	-1%	2%
		F4	1%	4%	0%	2%