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Hedging-Effectiveness of Milk Futures Using Value-At-Risk Procedures

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Practitioner's Abstract

The effectiveness of the Class III Milk futures market is analyzed in terms of the reduction in Value-at-Risk (VaR) for milk producers located in four regions: Wisconsin, Northeast, Florida and California. Constant hedge ratios are estimated using Myers and Thompson's (1989) generalized conditional hedge ratio technique, and time-varying hedge ratios are estimated using an exponentially weighted moving average method. After defining milk price risk as the deviation of the actual milk price from its expected value, the effectiveness of uniform hedging strategies in the Class III milk futures market is assessed using three popular methods for VaR calculations: the parametric method, the historical method, and the Monte Carlo simulation method. The results suggest that uniform hedging strategies can reduce substantially the VaR of milk cash price for appropriately chosen hedge length and hedge signals. For example, a uniform hedge placed seven months prior to delivery and triggered at $11.00 cwt reduces the mailbox price tail risk more than the same uniform hedging established four months before delivery. As expected the higher the Class III utilization the more effective hedging seems. The magnitude of the hedging effectiveness seems to depend more on the hedge length and the hedge trigger than on the methodology used to obtain the hedge ratio or the VaR.

Keywords: Value-at-Risk, hedging effectiveness, price risk, milk

Introduction:

The dairy price support program and Milk Income Loss Contracts (MILC) are publicly funded risk management tools that offer limited protection against price risk. MILC is a target price-deficiency payment program with an annual production cap, but is scheduled to expire at the end of September 2005. The milk price support program effectively offers a free put option, but at a price floor below most producers' production costs. The trend toward market-based price determination in the dairy industry has coincided with increasing uncertainty in farm-level milk price. The coefficient of variation in Class III milk price rose from 9% during 1988-1995 to 18% during the 1996-2002 period, perhaps justifying privately funded hedging with Class III milk futures and options markets. The Dairy Options Pilot Program encouraged producers to embrace hedging, but active participation rates were low, partly due to a lack of solid information on how hedging would affect their risk profile. The objective of this article is to aid decision makers by providing intuitive measures of milk hedging effectiveness.

Due to sweeping milk pricing reforms in 2000, sufficient data to evaluate contemporary hedging effectiveness had not accumulated until recently. Existing hedging effectiveness measures are generally based on variance reduction, which does not isolate downside risk. Value-at-Risk (VaR) is defined as the worst expected losses over a given horizon under normal market condition at a given confidence level. VaR is typically measured by a lower quantile of the conditional distribution of the risk factor. By focusing on downside risk, VaR offers an intuitively appealing measure that has not previously been applied to milk markets.

Uniform futures hedging strategies and cash-only strategies are compared in terms of VaR reduction. A reduced VaR due to a straightforward uniform hedging activity should indicate that more sophisticated and information intensive hedging strategies have greater risk reduction potential for milk producers. In this article, we focus exclusively on milk price risk defined as the random deviation of the cash price (also called the mailbox price) from the expected price. Revenue risk and other type of risks are not addressed here. Using mailbox price data from Wisconsin, the Northeast, Florida and California, VaR is employed to evaluate the downside or tail risk reduction potential of hedges placed seven or four months prior to the Class III milk futures contract expiration. The uniform hedging strategies are triggered when the Class III futures reached $11.00 cwt or $12.00 cwt triggers. Wisconsin and Florida represent areas located at the both ends of the Class III milk utilization spectrum in the Federal Milk Marketing Orders while the Northeast is included to represent an intermediate case. California is included to illustrate the potential hedging effectiveness of the Class III futures for producers located in regions that are not in the Federal Milk Marketing Orders.

In the empirical investigation, constant hedge ratios are estimated using Myers and Thompson's (1989) generalized conditional hedge ratio technique, and time varying hedge ratios are estimated using an exponentially weighted moving average method. Finally, the hedging effectiveness of milk is assessed using three popular methods for VaR calculation, which are the parametric method, the historical method, and the Monte Carlo simulation method.

Data and Methods

The data cover the period January 1999 to October 2003. Monthly mailbox prices and daily futures price data were obtained from the University of Wisconsin Dairy Marketing and Risk Management Program. To match current marketing conditions, the analysis is designed to apply to federal milk marketing order regulations initiated in January 2000. The pre-reform year 1999 was included to accommodate producers' expectations for the year 2000. The role of producers' expectations is elaborated in the next section.

Price Changes Series and Deviation from Expected Price

VaR was established primarily for managing market risk in financial institutions where daily volatility is the cause for concern. To compute VaR, the standard data input in the financial industries is the daily price change or the daily price returns. The premise for the use of daily price change or price returns is that daily price variability is unpredictable and investors are concerned with limiting daily portfolio losses. Application of VaR for the purpose of managing market risk for agricultural commodity necessitates evaluation over a longer time horizon. Dairy producers receive a check every month and are assumed to be concerned with month-to-month price variability. In addition, due to the non-storable nature of milk, its continual production, and pricing structure, volatility forecasts are required over longer time horizon for parametric VaR calculation. Milk being a non-storable commodity, large price changes in reaction to changes in the expected market fundamentals is expected.

The longer time horizon and the existence of an active exchange market where Class III milk futures contracts are traded preclude the use of monthly price changes for VaR computation. Part of month-to-month milk price changes are predictable. Peck (1975, p. 412) stated that for agricultural producers, "the relevant concept of risk is that which surrounds the accuracy of producers' forecast." Because there is a price forecast underlying any production decision, the pertinent price change in our analysis is the deviation of the monthly milk price from its expected value. Therefore, VaR calculations for the cash-only strategy and the uniform hedging strategies are based on the deviation of mailbox price from the expected milk price. Milk price expectations were constructed using futures prices prior to expiration and expected basis.

$$r_{it} = MBP_{it} - E_{t-j}(MBP_{it})$$

where r_{it} is the deviation from expected mailbox price and $E_{t-j}(MBP)$ is the mailbox price expected *j* (*j* = four or seven) months prior to the expiration month.

The mailbox price expectation for each region *i* in time period *t* is formed by adding the basis expected in each region to the futures prices expiring in *t*. Anderson and Danthine (1981) claimed that the closer the relationship between cash and futures, the more the hedger could rely on futures price and his/her expectations of the basis. The basis is in this analysis equals the mailbox price minus the Class III futures price.

$$E_{t-7}(MBP_{it}) = F^{t}_{t-j} + E_{t-j}(Basis_{it})$$

Milk futures prices are publicly available information and it is often asserted in the literature that basis due to its relative stability is somewhat predictable (Peck, 1975; Anderson and Danthine, 1981).

The final price received by the producer is the mailbox price adjusted by the gains or losses, including commission costs from the futures hedge using the following equation:

$$net\ MBP_{it} = MBP_{it} + h(F^{t}_{t-j} - F^{t}_{t})$$

where *h* is the hedge ratio.

Basis Expectation Regression

Appropriate basis expectations are a key determinant in the success of a futures hedging strategy. The price that producers can lock in includes a known component, the price at which milk futures are sold, and a stochastic component, the basis. Milk production and milk demand are seasonal and basis behavior may reflect seasonality. Figure 1 illustrates the monthly variation of the Class III milk price. A characteristic of the milk industry is that the demand for milk increases in late summer when schools reopen and its supply peaks during the spring season. Demand jumps in late summer because children drink more milk through school lunch programs and the supply of milk peaks during the spring because of greener pasture and lower feed costs, all contributing to enhancing cows' milk production. In general, periods of increasing milk demand correspond to periods of decreasing milk supply. Drye and Cropp (2002) report that the milk components butterfat and protein decrease in summer and increase during the cooler seasons. Maynard, Wolf, and Gearhardt (2003) showed the existence of significant negative covariance between the Class III milk price and the basis, which they decomposed into the producer price differential (PPD), the butterfat premium and a residual accounting for other influences. In all marketing orders except Wisconsin, the PPD was found to be the principal source of negative covariance between the Class III price and the basis.

Basis expectations are derived with the following linear equation:

$$E_{t-j}(Basis_t) = \alpha_0 + \alpha_1\, F^t_{t-j} + \alpha_{21} Season1 + \alpha_{22} Season2 + \alpha_{23} Season3 + \alpha_3 Basis_{t-12}$$

where:

F_{t-j} is the futures price of the month in which the hedge was set

$Basis_{t-12}$ is the basis lagged one year

Season1 is a dummy variable for February, March, and April

Season1 is a dummy variable for May, June and July

Season3 is a dummy variable for August, September, and October.

Least Squares Regression Estimate of Basis Expectation

As expected for regions located in the Federal Milk Marketing Orders, the summary statistics of basis in Table 1 show that basis variability is higher in regions where Class III milk utilization is lower. Producers in Florida face a higher and a more variable basis compared to producers located in the other regions. The average basis in Florida, \$3.52, is two times larger than the average basis in Wisconsin, \$1.50. With 87% Class I utilization, producers located in Florida face higher basis risk because they attempt to cross-hedge their price risk with Class III milk futures, although Class I prices mirror their mailbox price more. The rate of Class I utilization in the Upper Midwest and Northeast orders is respectively 18% and 47%. The Class I milk price is based on the maximum of the "advanced" Class III and the Class IV milk prices, and is called the "Class I mover." Hedging with Class IV milk futures is not considered in this paper because the Class IV futures market depth is low. Market depth is a liquidity indicator that assesses the market ability to facilitate a large quantity of transactions without large price changes.

Hedging four months prior to the expiration of a Class III futures contract leads to a better expected basis equation fit than hedging seven months prior to the same Class III futures contract expiration. The coefficient of determination, R^2, for the expected basis linear equations for Wisconsin, Northeast, Florida and California for hedges placed four (seven) months before expiration are respectively 42.1% (38.6%), 43.9 % (35.3%), 24.38% (12.6%), and 33.57% (28.0%) (Table 2). Class III utilization appears to be inversely related to explanatory power of the basis regressions. The regression results confirm the seasonality of milk basis. In all three basis equations, the seasonality parameters are negative and highly significant, suggesting that basis is its highest level in the months of November, December, and January. Drye and Cropp (2002) found that basis peaks in November and is at its lowest level in July. Although the impact of futures price lagged seven months on the local basis is insignificant, the negative sign obtained for all regions confirms the Maynard, Wolf, and Gearhardt (2003) findings. The non-significance of the futures prices for the more distant delivery month (the seven month interval), might indicate that changes in basis are not explained by the futures price that prevailed when the hedge was set. Except in Wisconsin, futures prices have significant impacts on change in basis for hedges set four months to expiration.

Estimation of Hedge Ratios

The ultimate objective is to compute the hedging effectiveness using Value-at-Risk. Given that no analytically tractable method of finding the hedge ratio exists for the downside risk measure VaR, the hedge ratio is computed using techniques based on dispersion risk measures. The minimum variance hedge ratio, which is the ratio of the covariance between the cash and the futures price to the variance of the futures price, is determined using the generalized optimal hedge ratio of Myers and Thompson (1989) and an exponentially weighted moving average (EWMA) method is used to compute time-varying hedge ratios.

Least Squares Regression Hedge Ratio

The hedge ratios estimated for the four (seven) month hedge interval using the generalized least squares regression approach for Wisconsin, Northeast and Florida are respectively -84.6% (-84.4%), -64.7% (-66.9%), -43.5% (-40.9%)and -67.8% (-67.6). As expected, the higher the Class III utilization rate, the higher the hedge ratio. The variance reduction measure of hedging effectiveness is given by the adjusted coefficient of determination, R^2, which for Wisconsin, Northeast, Florida, and California are respectively 94.6% (94.8%), 65.5% (68.5%), 18.8% (24.5%) and 75.5% (76.1%) (Tables 3 and 4).

Exponentially Weighted Moving Average (EWMA)

Our original objective was to compute time-varying hedge ratios using multivariate GARCH models. Inconclusive results were obtained when the existence of ARCH effects in the price changes series were tested using the Lagrange Multiplier test and the Portmanteau Q-Statistic. We hypothesized that the inexistence of ARCH effects in the futures and mailbox price change series may be due the small size of our sample. Tests for ARCH effects are asymptotic tests whose small sample properties are still not well understood (Engle et al., 1985).

Unlike the test for ARCH effects, the yearly coefficient of variation (CV) of milk price changes indicate substantial variability. The CV of Class III futures price rose from 6.29% in 2000 to 16.65% in 2001, fell to 7.75% in 2002 and then rose to 18.33% in 2003.

To circumvent the large data requirements of GARCH, time varying hedge ratios were estimated using the exponentially weighted moving average (EWMA) recommended by JP Morgan Risk Metrics™. The EWMA is usually used for estimating the conditional variance for VaR purposes. Empirical studies by Alexander and Leigh (1997) and Boudoukh et al. (1997) found that the short-run estimate of volatility generated by EWMA is superior to volatility estimated using GARCH type models. The exponentially weighted moving average variance estimation method is actually a special case of the GARCH (1, 1) process.

Let $h_t = \alpha_0 + \alpha_1 r_{t-1}^2 + \beta h_{t-1}$ be a GARCH (1, 1) process where h_t is the conditional variance for period t and r corresponds to the absolute change in milk price. If $\alpha_0 = 0$ and $\beta = 1 - \alpha_1$, the GARCH model reduces to the EWMA which is also called the Integrated GARCH or IGARCH. By assuming an integrated covariance-variance matrix, shocks to the conditional variance in the EWMA are permanent, so that the estimated conditional variance does not revert to the unconditional variance as the forecast horizon increases. EWMA volatility forecasts necessitate the estimation of only one parameter.

The EWMA is expressed as:

$$\sigma_t^2 = \lambda \sigma_{t-1}^2 + (1-\lambda) r_{t-1}^2 \ .$$

To forecast monthly volatility[1], JP Morgan's Riskmetrics™ advocates a decay factor λ of 0.97. With that recommended magnitude for the decay factor, EWMA variance and covariance are easily computed in a spreadsheet. Specifically, the variance of change in Class III milk futures and the covariance between changes in futures prices and the changes in each series of mailbox price are calculated as follows:

$$\sigma_{s,t}^2 = \lambda \sigma_{s,t-1}^2 + (1-\lambda) r_{s,t-1}^2$$

$$\sigma_{sf,t} = \lambda \sigma_{sf,t-1} + (1-\lambda) r_{s,t-1} r_{f,t-1}$$

where s is the mailbox price, f is the class III futures prices and $\sigma_{s,t-1}^2 = \frac{1}{j}\sum_{i=0}^{h-1} r_{i-1}^2$ is the conditional variance with j = 6. For normally distributed price changes, $\sigma_{s,t-1}^2$ is an unbiased sample estimate of the variance when the mean price change is equal to zero.

[1] For daily data, Riskmetrics recommends setting λ= 0.94, and the decay factor of 0.97 is found to minimize on average the root mean squared error of monthly volatility forecasts.

To ensure that the estimated hedge ratios are consistent with the hedging decisions of risk averse producers, they are calibrated to equal a full cash position when the estimated hedge ratio is positive. The estimated time-varying hedge ratio is adjusted to rule out long positions.

Simulation of Pricing Strategies

The Class III milk used for hedging and the milk produced by farmers being different commodities, producers fundamentally engage in cross-hedging when trading Class III futures. The price received by farmers is based on the end use of milk in their corresponding regions. Without entering into the details of milk pricing, Class III milk is the input for cheese production. Other milk classes are Class I for fluid milk, Class II for soft dairy products, and Class IV for butter and nonfat dry milk. The blend price received by dairy farmers reflects the different products made from milk in their respective regions.

To evaluate the hedging effectiveness of milk price with VaR procedures, a uniform hedging strategy is simulated in an Excel spreadsheet. If a uniform hedging strategy is found to reduce substantially producers' risk, more sophisticated and information-intensive hedging strategies may present further potential for risk reduction.

Assuming that output is non-stochastic, a representative dairy producer located in one of four regions sells each month a futures contract expiring in four or seven months. The short hedge is placed if the futures quote is above \$11.00 (or \$12.00) per cwt. Otherwise the producer does not hedge her milk. For example, with the seven month hedging interval, the revenue expected for January 2002 milk is hedged by selling short a contract in June 2001. The contract is opened in the first business week of June if the prevailing futures price in greater than the \$11.00 (\$12.00) trigger. Class III milk contracts being cash settled, the hedge is lifted at contract expiration. Only one round turn is allowed over a given marketing period and the futures contract is closed only at its expiration date. With the national average operating cost of \$9.74 per cwt in 2002 (USDA-ERS), we assume that selling futures contracts when the \$11.00 per cwt or \$12.00 per cwt trigger is reached allows producers to at least cover their variable costs and perhaps earn a sustainable profit margin. The duration of the hedge, four months or seven months, is also arbitrary but matches our goal of having a sufficiently long time horizon where price uncertainty is substantial, without being so long that futures market liquidity becomes inadequate for practical hedging.

The existence of an active Class III futures market suggests that the incentives for hedging should be higher for regions with high Class III utilization (Maynard, Wolf, and Gearhardt, 2003). Wisconsin, Florida and the Northeast regions were chosen to reflect regional disparities in Class III utilization. Wisconsin and Florida represent the extremes of Class III milk utilization, while the Northeast represents an intermediate case. California is added to assess the hedging effectiveness of the Class III milk futures for a producer located outside the Federal Milk Marketing Orders. Milk production in California is regulated by a state-administered marketing order.

VaR Derivation

We consider the deviation of the mailbox price under each marketing strategy (cash-only and uniform hedging) from the expected mailbox price as the random component of milk price. The expected mailbox price is the sum of the futures price and the expected basis obtained from the basis linear regressions. For readability, deviation from expected mailbox price will be referred to as milk price change. The price change series obtained using the constant hedge ratio and the time-varying hedge ratios are used as inputs to calculate the Monte Carlo Simulation VaR, the historical simulation VaR, and the parametric VaR.

The parametric VaR method assumes that price changes are from a known distribution, usually the normal distribution. The normality assumption is, however, often violated. Asset and commodity price change distributions often display asymmetry and excess kurtosis. To incorporate some of the departures from the normality assumption, the Student's *t* distribution is used when excess kurtosis is suspected.

If the normal distribution is assumed, the parametric VaR procedures rest essentially on forecasting the variance and the mean. The Autogressive Conditional Heteroskedastic (ARCH) process introduced by Engle (1982) and extended by Bollerslev (1986) with the Generalized Autoregressive Conditional Heteroskedastic (GARCH) model are used to forecast the conditional variance.

Let $r_i = P_t - P_{t-i}$, denote the change in nominal asset price over the period *i*, and assume that price changes have a known parametric distribution with location parameter μ and a scale parameter σ^2. The Value at Risk is a number that satisfies the following relation:
$\text{Prob}\ (r_i < -VaR_{\alpha,h}) = \alpha$
where *h* is the time horizon and *α* is the confidence level.

Assuming a location-scale family of distributions, in which the location parameter is the expected return and the scale parameter is the standard deviation, can characterize the random price change distribution then, the following standard transformation holds for a parametric probability density function d (.):
$\text{Prob}\ \{(r_i - \mu)/\sigma_t\} < (-VaR_{\alpha,h} - \mu)/\sigma_t)\} = d(-VaR_{\alpha,h} - \mu)/\sigma_t) = \alpha$
For a standard normal variate Z_t, Prob ($Z_t < Z_\alpha$) = α, where Z_α represents the quantile α of the distribution. For holding horizon h=1, $VaR_{\alpha,h} = Z_\alpha\sigma_t - \mu$. In a large sample, $Z_{0.05} = -1.645$, for σ_t equal to one and μ equal to zero, we have $VaR_{0.05,\ 1}$ of -$1.645.

The parametric VaR was estimated using the short memory ARCH (1) with Student's *t* distribution for the conditional error. With ARCH (1) models, current period variance is a linear function of the previous period squared price change. The Student's *t* error distribution was found superior to the normal distribution in fitting the variance of milk price changes, as evidenced by a lower Akaike Information Criterion and Schwarz-Bayesian Information Criterion.

Simulation methods for VaR calculation are often called Monte Carlo simulation VaR. The Monte Carlo simulation method generates pseudo-random numbers over the entire range of possible values for a given distribution. Like the Monte Carlo simulation method, Latin Hypercube sampling is an alternative pseudo-random numbers generation procedure. The Latin Hypercube procedure permits one to replicate a certain probability distribution with a more limited number of iterations than the Monte Carlo simulation procedure (Richardson, 2002). The Latin Hypercube procedure divides the range of possible realizations into equal probability intervals within which the random numbers are generated. The software Simetar©[2] is employed to simulate milk price changes utilizing the Latin Hypercube sampling procedure.

Because Monte Carlo simulation methods can handle both parametric and non-parametric distributions, 5,000 milk price change observations are generated assuming alternatively the normal distribution and the empirical distribution. Simetar© permits one to estimate the parameters of the empirical distribution by finding the probability associated with each sorted price change, i.e., price changes are the random variables. With 5,000 iterations, the normal distribution might be a reasonable assumption. The price changes are simulated for each region under alternative minimum variance hedge ratios, hedge lengths and hedge triggers.

The historical VaR simulation method assumes that historical data accurately reflect future possible events. VaR with the historical simulation method is a certain quantile of the empirical distribution of the historical data set. We restrict our attention to the 10% and the 5% quantile of milk price change distributions.

VaR Results and Discussions

Given the large number of results obtained, we treat the constant hedge ratio, the $11.00 hedge trigger and the seven-month hedge length as the benchmark case. The four-month hedge interval, the $12.00 and the time-varying hedge ratios will be used to assess the robustness of the results derived from the benchmark case.

Table 4 presents the descriptive statistic of milk price change series with the constant hedge ratio. For all types of hedge ratios, hedge triggers, and hedge intervals considered, the standard deviation of milk price change with the uniform futures hedging is lower than the standard deviation of the cash-only strategy. Thus, uniform hedging seven months or four months prior to delivery reduces the dispersion of the mailbox price change distribution. The mean price change for the uniform hedging strategy tends to be higher or less negative than the mean price change for the cash-only strategy. This may suggest that hedging led to higher than expected price during the particular study period. However, if the assumption of efficient Class III futures market holds, one would not expect higher average price changes with uniform hedging.

The size of the data set does not allow reliable empirical comparisons of the three methods used to compute the VaR. We rely on past literature and logic to draw some

[2] Simetar is an Excel Add-In developed at Texas A&M by Dr. J. Richardson

conclusions on the validity of the methods utilized to calculate VaR. The Monte Carlo simulation method is touted as being flexible because of its ability to calculate the VaR of positions containing nonlinear payoffs such as options on futures. Jorion (1997) favors the parametric VaR methods for forecasting the tail risks of assets with linear payoffs. Mahoney (1995) found that the parametric VaR methods perform better than the historical VaR method for lower confidence levels, such as the 90% and 95% confidence interval while the historical VaR method is recommended for high confidence intervals above 99%.

The results for the benchmark case with a constant hedge ratio, $11.00 hedge trigger, and 10% VaR are presented in Table 7a and Table 7b. Seven months or four months prior to delivery for region members of the federal milk marketing order, Florida has the highest average absolute cash-only and uniform hedging VaR, the Northeast has the lowest average cash-only VaR and Wisconsin has the lowest average uniform hedging VaR. It appears that the absolute level of VaR is inversely related to Class III milk utilization. The absolute VaR for California resembles the absolute VaR for Northeast.

The cash-only VaR for milk hedged seven months before delivery tends to be larger than the cash-only VaR for milk hedged four months before delivery, but the uniform hedging VaR for the longer hedge interval tends to be smaller than the uniform hedging strategy VaR for the shorter hedge interval. This may imply that milk tail price risk reduction is greater for hedges placed using more distant futures contracts.

Hedging effectiveness in terms of change in VaR is measured by computing the rate of change in the cash-only VaR as:

$$\frac{\text{Cash VaR - Uniform Hedging VaR}}{\text{Cash VaR}}$$

Uniform hedging decreases milk price tail risk if the rate of change in VaR is positive. Table 8 presents the results for the rate of change in VaR for hedges placed seven months and four months prior to the futures contract expiration using the $11.00 trigger. As expected, uniform hedging leads to substantial reduction of VaR for Wisconsin and the Northeast. The various methodologies used to calculate VaR appear to yield consistent measures for Wisconsin and the Northeast. For Florida, mixed results are observed. According to the parametric VaR method, the four-month uniform hedge interval increases tail risk in Florida. The results for parametric VaR tend to deviate considerably from the other methods employed. They should be accepted with caution because they are based on a short-memory ARCH process. In the literature, parametric VaR is generally calculated using long-memory ARCH or GARCH process.

Using the $11.00 hedging trigger and the 10% significance level, the seven-month interval hedge is found to be more effective than the four-month interval hedge. The same pattern of results is observed when using time-varying hedge ratios (Table 11) and when VaR is measured at the higher 5% confidence level (Table 9).

Increasing the hedge trigger to $12.00 per cwt substantially diminishes the effectiveness of the uniform hedging strategy in terms of VaR reduction (Table 10). When hedging is triggered at $11.00 and the seven month hedge interval is used, the rate of change in the 10%VaR for Wisconsin ranges from 77% to 80% but for hedging triggered at $12.00 *ceteris paribus*, the rate of change in the 10% cash VaR ranges from 14% to 45%. At a higher trigger, the relative change in the cash VaR is lesser because producers engage less in the trade of futures contract and are more expose to the cash price risk. Also at the $12.00 trigger, there is no substantial difference between hedging seven months or four months prior to the delivery month. In the Florida region, the four-month hedge length does not appear to reduce price risk in Florida.

Summary and Conclusions

Milk price risk was defined as the deviation of the actual milk price from the expected milk price, and uniform hedges triggered at $11 per cwt or $12 per cwt were simulated using constant and time-varying minimum variance hedge ratios. The results indicated that uniform futures hedging has the potential to reduce substantially the VaR of milk producers' mailbox price in Wisconsin, the Northeast, and to a smaller extent in California. Ultimately the relative decrease in cash VaR with uniform hedging depends on producer preferences toward risk. A certain VaR reduction may be sufficient to justify hedging for some producers but not others.

For a dairy producer, a reduction in the VaR implies that the size of potential adverse price movement has diminished. Most of the VaR statistics computed at the 90% and 95% confidence intervals suggest that adverse large changes in mailbox price risk are lower when a uniform hedging strategy is performed than when a cash-only strategy is adopted. In this article, the hedging effectiveness measure with VaR seems to be more sensitive to the hedge length and the price that the producers choose to lock in than to the assumption regarding the hedge ratio. Consistent with most studies using alternative VaR methodologies, the results indicated some disparity in the VaR of milk mailbox price depending on whether the parametric method, the historical simulation method, or the Monte Carlo simulation method was used. The sensitivity of VaR estimates to the method used for its calculation is reported in Manfredo and Leuthold (1998), and in Mahoney (1995).

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Table 1. Descriptive Statistics for Basis

	Wisconsin	Northeast	Florida	California
Mean	1.5	1.78	3.51	0.85
std dev	0.64	1.35	2.36	1.14

Table 2a. Basis Regression for 4-Month Interval Hedge

	Wisconsin	Northeast	Florida	California
Constant	2.90**	3.82**	8.54**	3.15**
	(0.44)	(0.81)	(1.90)	(0.81)
$Futures_{t-4}$	-0.060	-0.180	-0.48**	-0.20**
	(0.04)	(0.06)	(0.15)	(0.06)
Season 1	-0.44*	-0.56	-0.94	-0.46
	(0.19)	(0.35)	(0.81)	(0.34)
Season 2	-0.48**	-0.46*	-0.71	-0.40*
	(0.11)	(0.17)	(0.42)	(0.17)
Season 3	-0.31**	-0.39**	-0.41	-0.37**
	(0.07)	(0.11)	(0.27)	(0.11)
ΔMBP_{t-12}	-0.03	0.17**	0.21	0.14
	(0.13)	(0.04)	(0.11)	(0.05)
	$R^2 = 0.42$	$R^2 = 0.44$	$R^2 = 0.24$	$R^2 = 0.41$

** Significance at 1% and * significance at 5%

Standard errors in parentheses

Table 2b. Basis Regression for 7-Month Interval Hedge

	Wisconsin	Northeast	Florida	California
Constant	2.44**	2.55**	6.07**	1.53
	(0.46)	(0.81)	(1.90)	(0.83)
$Futures_{t-7}$	-0.02	-0.07	-0.27	-0.06
	(0.04)	(0.06)	(0.15)	(0.07)
Season 1	-0.31	-0.15	-0.28	-0.02
	(0.21)	(0.37)	(0.87)	(0.38)
Season 2	-0.45**	-0.33	-0.37	-0.24
	(0.11)	(0.18)	(0.42)	(0.18)
Season 3	-0.29**	-0.34**	-0.29	-0.31
	(0.07)	(0.12)	(0.28)	(0.13)
ΔMBP_{t-12}	-0.09	0.14**	0.12	0.11
	(0.13)	(0.05)	(0.11)	(0.05)
	$R^2 = 0.39$	$R^2 = 0.35$	$R^2 = 0.12$	$R^2 = 0.28$

** Significance at 1% and * significance at 5%

Standard errors in parentheses

Table 3. Generalized Hedge Ratio Regression

4-M	Wisconsin MBP	Northeast MBP	Florida MBP	California MBP
Constant	3.98**	6.34**	11.04**	5.07**
	(0.43)	(1.01)	(2.02)	(0.83)
Class III	0.85**	0.66	0.44**	0.67**
	(0.03)	(0.07)	(0.15)	(0.06)
$Futures_{t-4}$	-0.03	0.01	0.07	-0.02
	(0.03)	(0.07)	(0.14)	(0.06)
Season 1	-0.40	-0.67	-1.18	-0.45
	(0.17)	(0.39)	(0.80)	(0.33)
Season 2	-0.39*	-0.48	-0.51	-0.28
	(0.08)	(0.19)	(0.39)	(0.16)
Season 3	-0.19**	-0.27*	-0.07	-0.18
	(0.06)	(0.14)	(0.29)	(-0.12)
	$R^2 = 0.95$	$R^2 = 0.65$	$R^2 = 0.18$	$R^2 = 0.75$

** Significance at 1% and * significance at 5%

Standard errors in parentheses

4-M for four-month hedge interval

Table 4. Generalized Hedge Ratio Regression

7-M	Wisconsin MBP	Northeast MBP	Florida MBP	California MBP
Constant	4.06**	7.43**	13.04**	5.51**
	(0.46)	(1.05)	(2.12)	(0.89)
Class III	0.84**	0.67**	0.41**	0.68**
	(0.03)	(0.07)	(0.14)	(0.06)
$Futures_{t-7}$	-0.03	0.12	0.25	-0.06
	(0.03)	(0.07)	(0.13)	(0.05)
Season 1	-0.29	-0.44	-0.62	-0.32
	(0.17)	(0.38)	(0.77)	(0.33)
Season 2	-0.35**	-0.45*	-0.59	-0.29
	(0.08)	(0.18)	(0.37)	(0.16)
Season 3	-0.18**	-0.28*	-0.03	-0.18
	(0.06)	(0.13)	(0.26)	(-0.11)
	$R^2 = 0.95$	$R^2 = 0.68$	$R^2 = 0.26$	$R^2 = 0.76$

** Significance at 1% and * significance at 5%

Standard errors in parentheses

7-M for four-month hedge interval

Table 5. Coefficients of Variation

	Class III	Wisconsin	Northeast	Florida	California
2000	6.29%	4.25%	3.55%	4.91%	5.14%
2001	16.65%	10.62%	9.29%	9.59%	10.01%
2002	7.75%	7.09%	5.63%	6.79%	6.28%
2003	18.33%	14.64%	13.85%	13.91%	12.26%

Table 6. Descriptive Statistics for Price Change Series with Constant Hedge Ratio

	Wisconsin		Northeast		Florida		California	
	Cash	Uniform	Cash	Uniform	Cash	Uniform	Cash	Uniform
Constant Hedge Ratio with 7-Hedge Length Triggered at $11								
Mean	-0.83	-0.14	-0.82	-0.36	-0.79	-0.60	-0.83	-0.37
Std Dev	2.03	0.42	1.81	0.78	1.96	1.71	1.76	0.74
Min	-3.82	-1.15	-3.40	-1.92	-4.69	-3.81	-3.52	-1.80
Max	3.76	0.75	3.27	0.96	3.08	2.48	3.15	1.07
Skewness	0.93	-0.06	0.87	-0.06	-0.10	-0.07	0.86	0.23
Constant Hedge Ratio with 7-Hedge Length Triggered at $12								
Mean	-0.83	-0.31	-0.82	-0.48	-0.79	-0.65	-0.85	-0.49
Std Dev	2.03	1.51	1.81	1.41	1.96	1.81	1.78	1.35
Min	-3.82	-2.41	-3.40	-2.50	-4.69	-3.81	-3.52	-2.50
Max	3.76	3.76	3.27	3.27	3.08	3.08	3.15	3.07
Skewness	0.93	0.89	0.87	0.92	-0.10	0.07	0.89	0.96
Kurtosis	-0.10	0.94	-0.14	0.47	-0.78	-0.96	0.02	0.54
Constant Hedge Ratio with 4-Hedge Length Triggered at $12								
Mean	-0.58	-0.33	-0.56	-0.40	-0.52	-0.44	-0.58	-0.41
Std Dev	1.57	1.22	1.35	1.11	1.76	1.65	1.37	1.14
Min	-3.49	-2.32	-2.80	-2.73	-4.48	-4.48	-2.98	-2.70
Max	3.52	3.52	2.73	2.73	2.51	2.66	2.80	2.80
Skewness	0.66	1.17	0.49	0.62	-0.58	-0.45	0.47	0.74
Kurtosis	0.17	2.41	-0.28	1.26	-0.40	-0.54	-0.10	1.36
Constant Hedge Ratio with 4-Hedge Length Triggered at $11								
Mean	-0.58	-0.12	-0.56	-0.26	-0.52	-0.38	-0.57	-0.27
Std Dev	1.57	0.87	1.35	0.86	1.76	1.60	1.36	0.87
Min	-3.49	-1.61	-2.80	-1.69	-4.48	-4.03	-2.98	-1.62
Max	3.52	3.52	2.73	2.73	2.51	2.66	2.80	2.80
Skewness	0.66	2.01	0.49	1.18	-0.58	-0.44	0.44	1.47

Table 7a. 10% VaR for 7-month Hedge Interval and trigger at $11

	Wisconsin		Northeast		Florida		California	
Methods	Cash	Uniform	Cash	Uniform	Cash	Uniform	Cash	Uniform
Historical	-$2.68	-$0.62	-$2.65	-$1.27	-$3.36	-$2.88	-$2.69	-$1.21
MC Norm	-$3.44	-$0.67	-$3.14	-$1.35	-$3.29	-$2.79	-$3.13	-$1.32
MC EMP	-$2.90	-$0.65	-$2.76	-$1.29	-$3.39	-$2.90	-$2.73	-$1.24
Parametric	-$2.91	-$0.57	-$2.46	-$1.31	-$3.49	-$3.16	-$2.08	-$2.09
Mean	-$2.98	-$0.63	-$2.75	-$1.31	-$3.39	-$2.93	-$2.66	-$1.46
Stdev	0.32	0.05	0.28	0.04	0.08	0.16	0.43	0.42

MC Norm is the Monte Carlo VaR with the Normal Distribution
MC EMP the Monte Carlo VaR with the Empirical Distribution

Table 7b. 10% VaR for 4-month Hedge Interval and trigger at $11

	Wisconsin		Northeast		Florida		California	
Methods	Cash	Uniform	Cash	Uniform	Cash	Uniform	Cash	Uniform
Historical	-$2.15	-$0.87	-$2.11	-$1.28	-$2.83	-$2.82	-$2.19	-$1.20
MC Norm	-$2.60	-$1.24	-$2.30	-$1.37	-$2.77	-$2.44	-$2.33	-$1.38
MC EMP	-$2.17	-$0.92	-$2.16	-$1.29	-$2.85	-$2.85	-$2.30	-$1.21
Parametric	-$2.37	-$0.68	-$2.01	-$1.43	-$3.10	-$3.19	-$2.16	-$1.93
Mean	-$2.32	-$0.93	-$2.15	-$1.34	-$2.89	-$2.83	-$2.25	-$1.43
Stdev	0.21	0.23	0.12	0.07	0.14	0.31	0.08	0.34

MC Norm is the Monte Carlo VaR with the Normal Distribution
MC EMP the Monte Carlo VaR with the Empirical Distribution

Table 8. Rate of Change of the 10% VaR for hedge triggered at $11

	Wisconsin		Northeast		Florida		California	
	7_M	4_M	7_M	4_M	7_M	4_M	7_M	4_M
Historical	0.77	0.60	0.52	0.39	0.14	0.00	0.55	0.45
MC Norm	0.80	0.52	0.57	0.41	0.15	0.12	0.58	0.41
MC EMP	0.78	0.58	0.53	0.40	0.14	0.00	0.54	0.47
Parametric	0.80	0.71	0.47	0.29	0.09	-0.03	0.00	0.11

7_M and 4_M denote the seven-month and the four-month hedge length

Table 9. Rate of Change of the 5% VaR for Hedge Triggered at $11

	Wisconsin		Northeast		Florida		California	
	7_M	4_M	7_M	4_M	7_M	4_M	7_M	4_M
Historical	0.76	0.50	0.44	0.45	0.18	0.19	0.53	0.51
MC Norm	0.80	0.51	0.57	0.40	0.15	0.12	0.58	0.40
MC EMP	0.76	0.51	0.41	0.45	0.19	0.20	0.54	0.51
Parametric	0.78	0.70	0.43	0.27	0.08	-0.04	-0.06	0.07

7_M and 4_M denote the seven-month and the four-month hedge length

Table 10. Rate of Change of the 10% VaR for Hedge triggered at $12

	Wisconsin		Northeast		Florida		California	
	7_M	4_M	7_M	4_M	7_M	4_M	7_M	4_M
Historical	0.14	0.21	0.24	0.28	0.08	0.00	0.28	0.32
MC Norm	0.34	0.27	0.27	0.21	0.10	0.08	0.29	0.20
MC EMP	0.20	0.19	0.26	0.24	0.07	0.00	0.27	0.28
Parametric	0.45	0.43	0.27	0.16	0.07	-0.05	0.22	-0.01

7_M and 4_M denote the seven-month and the four-month hedge length

Time-varying Hegde Ratios

Table 11. Rate of Change of the 10% VaR for Hedge triggered at $11

	Wisconsin		Northeast		Florida		California	
	7_M	4_M	7_M	4_M	7_M	4_M	7_M	4_M
Historical	0.62	0.35	0.27	0.10	0.33	0.09	0.38	0.21
MC Norm	0.66	0.30	0.32	0.13	0.27	0.14	0.39	0.20
MC EMP	0.63	0.35	0.26	0.11	0.31	0.14	0.39	0.19
Parametric	0.63	0.48	0.29	0.02	0.07	-0.10	0.42	0.26

7_M and 4_M denote the seven-month and the four-month hedge length

Figure 1. Monthly Variation of Class III Price

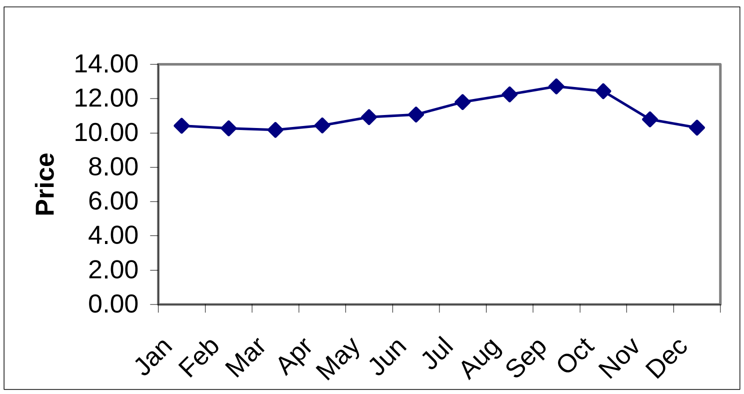

Figure 2. In-Sample Time-Varying Hedge Ratios