Measuring Historical Risk in Quarterly Milk Prices

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Various methods have been used to estimate risk indices with historical data. An industry perception of increasing milk price risk over time provides a standard for evaluating several techniques used to measure historical risk. Risk measures from a regression model and an ARIMA model were consistent with the perception of increasing risk.

The use of historical data to estimate the level of risk for output, prices, and income is a continuing research topic in agricultural economics. Previous literature has considered various risk measures and detrending methods for estimating firm-level risk (Young, 1984). Defining sample variance as a measure of risk, Carter and Dean used the variate difference method pioneered by Tintner to detrend California crop price, yield, and gross return data. Other studies have used the variate difference method to detrend gross returns for use in quadratic programming models of firm behavior under risk (Adams, Menkhaus, and Woolery; Kramer, McSweeny, and Stavros; Musser and Stamoulis). Despite its popularity during the 1970's and early-1980's, the variate difference method is no longer widely used in agricultural economics applications. A weakness of the method is its inapplicability to series which exhibit substantial zig-zag patterns (Young, 1980).

As Young (1984) noted, ordinary least squares regression of a data series on polynomial functions of time is equivalent to the variate difference method. Time polynomials have been widely used and can be adapted to include cycles, seasonality, and secular trends (Franzmann). Swinton and King demonstrated that this standard method is superior to more robust regression methods. Additional advantages of using time polynomials include empirical simplicity and applicability to large amounts of data. Because simple regression models are naive, alternative detrending methods have also been suggested. Fackler recently proposed a stochastic trend method for detrending crop yields, and Hammida and Eidman used non-linear filters to detrend livestock and poultry production data.

Mean squared forecast errors are often used rather than sample variance as a measure of historical risk. Young (1980, 1984) was an early advocate of the use of forecast errors. Several methods for generating forecasts are autoregressive integrated moving average (ARIMA) models (Bessler), futures prices (McSweeny, Kenyon, and Kramer), weighted moving averages of historical data (Collins, Musser, and Mason), and combinations of futures prices and weighted moving averages of yield (Marra and Carlson). ARIMA models and moving averages are appealing for empirical application because of their computational simplicity. However, Fackler notes that there are no standard criteria available for determining the optimal number of terms to include in moving average calculations. In addition, weights are often assigned arbitrarily in weighted moving average procedures (Young, 1980). Berck suggested using econometric equations to generate forecasts for the series of interest. However, econometric forecasting equations often require data which are difficult to obtain for firm-level analyses, thus limiting their applicability.

As indicated in the previous discussion, a considerable number of choices exist for calculating risk indices from historical data. This study compares linear filters, least squares regression, and ARIMA methods to calculate historical risk measures for quarterly milk prices for the 1960–90 period. A perception of increasing milk price risk faced by producers over the 1960–1990 time period (Fraher; Hamm) provides an opportunity to test the performance of these methods in quantifying objective risk. The choice of these methods is somewhat arbitrary. However, the above review of literature suggests that these methods are currently

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widely used for calculating risk indices. In addition, the three methods are appealing for their explicit specification, computational simplicity, and applicability to a wide range of problems involving firm-level risk.

Data and Methods

A thirty-one-year period (1960–90) of quarterly milk prices received by farmers (USDA, NASS) was used in the analysis of historical risk.[1] While some studies deflate nominal data to create real series for risk analysis, unexpected inflation may also be a source of risk.[2] The observed nominal milk prices for 1960–90 appear consistent with industry perceptions of increasing risk over time (Figure 1). This consistency of nominal data patterns with industry perceptions provides an opportunity to compare the performances of the previously discussed methods in quantifying objective risk. For these reasons, nominal data were used in this analysis.

Based on the data patterns in Figure 1 and historical economic and policy environments, three sub-periods were delineated to examine the hypothesis of increasing risk: 1960–72, 1973–80, and 1981–90. The 1960–72 sub-period was characterized by relatively stable economic and policy conditions. Increasing inflation rates and changes in federal policy during the 1972–80 sub-period contributed to higher support price levels. A substantial upward trend resulting from higher energy prices and increased crop export demand (Musser, Mapp, and Barry) appears to contribute significantly to the variance in milk prices observed during the 1972–80 sub-period. In addition, large, persistent increases in input prices occurred during the 1972–80 sub-period. If producers include these price increases into expectations about the future, these price changes would not represent risk. Detrending will allow measurement of the true random variation associated with this sub-period. The 1981–90 sub-period was characterized by significant changes in the structure of dairy policy during the early-1980's, followed by increased export demand for dairy products and unusual crop weather conditions in 1988–89 which significantly affected the supply of milk (USDA, ERS). The variation observed for the 1981–90 sub-period appears to be random, with no obvious trend in the data.

Two measures of risk used in this analysis are the variance of the price series and the mean squared forecast error calculated from a series of one-step ahead forecasts. Variance (VAR) is used as an *ex post* measurement of risk:

$$VAR = E(z_t - Ez_t)^2, \tag{1}$$

where E is the expectation operator and z_t denotes the detrended price series. Mean squared forecast error (MSE) is used as an *ex ante* measurement of price risk:

$$MSE = E(y_t - \hat{y}_t)^2, \tag{2}$$

where y_t is observed data and $\hat{y}_t$ is the one-step ahead forecast for period t.

Ex Post Risk Measurement

Several detrending methods were used to eliminate seasonal and trend components from the price series in order to measure the remaining random variation. Linear filters were applied to the series following techniques outlined by Granger and Newbold. The data were deseasonalized using a quarterly moving average before applying the linear filters to estimate the trend. The difference between the trend and the actual series is an estimate of the random component (Hammida and Eidman). The five-period symmetric moving average (SMA5) filter and the three-period asymmetric moving average (AMA3) filter used by Hammida and Eidman were calculated, where

$$\begin{aligned} SMA5_t &= \frac{1}{5}\sum_{j=-2}^{2} y_{t+j}; \\ AMA3_t &= \sum_{j=0}^{2} w_j y_{t-j}. \end{aligned} \tag{3}$$

The subscript t indexes time. Following Young (1980), weights (w_j) used with the asymmetric moving average (AMA3) decline over time, with the most recent observation being assigned the

[1] Monthly prices could also have been used in the analysis. However, variances calculated for monthly prices were nearly identical to those calculated for quarterly prices for 1960–72, 1973–80, and 1981–90. This similarity in variances is observed because milk prices tend to be most variable during months comprising the second and fourth quarters. In addition, seasonal effects are easily handled in a linear regression model with quarterly prices, without using as many degrees of freedom as monthly data.

[2] The issue of using real versus nominal prices in calculating historical risk indices has not been adequately addressed in the literature. An examination of the studies reviewed by Young (1980) reveals that both nominal and real prices have been used in calculating risk indices. Furthermore, choices between the use of nominal versus real prices appear to have been made arbitrarily. Neoclassical economic theory suggests that real data should be used to measure the profitability implications of prices faced by farmers. However, inflation can affect the risk associated with profits if the inflation rate is uncertain (White and Musser). Resolution of this issue is beyond the scope of this paper. The use of nominal data has a conceptual basis and is consistent with several past risk measurement studies.

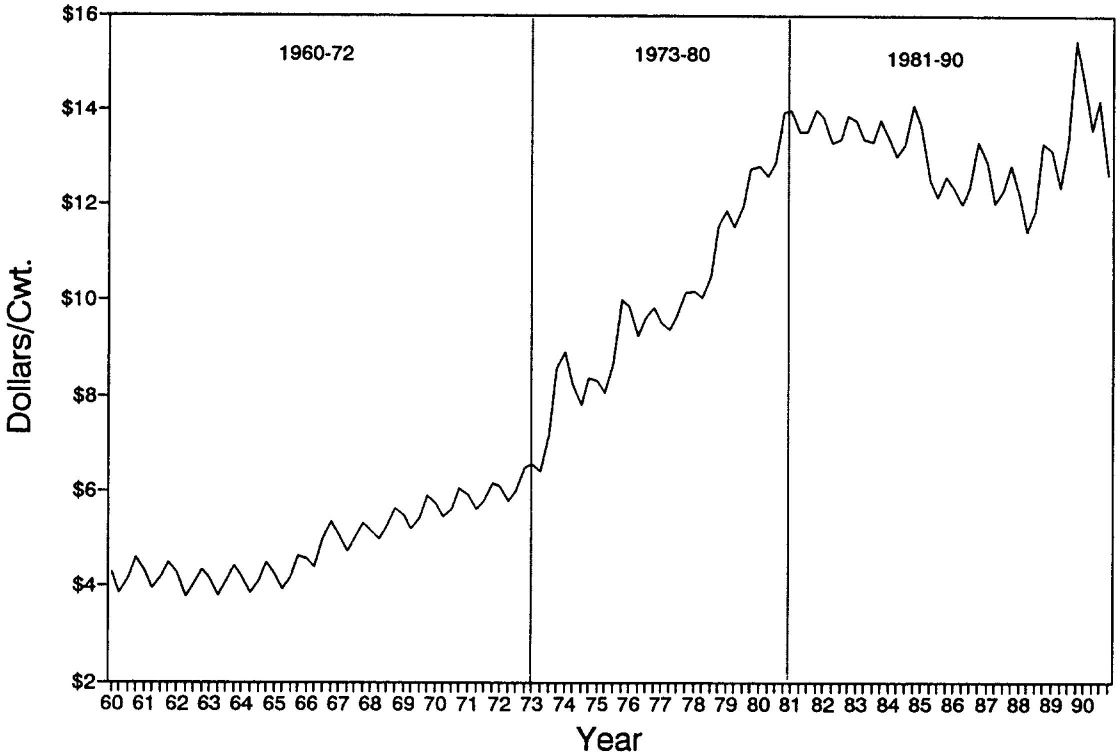

Figure 1. Quarterly Nominal Milk Prices, 1960–1990

heaviest weight. Numerical values for the weights were chosen arbitrarily, with $w_0 = .5$, $w_1 = .3$, and $w_2 = .2$. These weights have been used in previous risk studies, e.g. Persaud and Mapp. Variances of the estimated random components were calculated for the three sub-periods (1960–72, 1973–80, 1981–90), and the entire period (1960–90).

Regression techniques were also used to estimate deterministic components of the milk price series. Milk prices were regressed on a time trend and quarterly dummies, using the first quarter as the base. Model parameters were initially estimated using ordinary least squares (OLS). Except for Fackler and Young, limited attention has been given to generalized least squares (GLS) estimates in trend analyses. When autocorrelation is present, OLS estimates are inefficient. Most importantly, an often overlooked consequence is that the OLS estimate of variance is biased in the presence of autocorrelation (Kmenta). This reasoning suggests that models corrected for autocorrelation should be used for calculating unbiased risk measures.

Ordinary least squares residuals were checked for first-order autocorrelation using the Durbin-Watson statistic. If significant autocorrelation was present, models were re-estimated with feasible GLS (Judge, et al.). The feasible GLS method uses OLS residuals to provide an initial estimate of the autocorrelation coefficient (p). This estimated coefficient is then used to transform the dependent and independent variables. The transformed model is re-estimated with least squares. The resulting residuals provide a second estimate of p, which is used to transform the model again for re-estimation with least squares. The process continues until either (1) the Durbin-Watson statistic indicates white noise (random) residuals; or (2) successive estimates of model parameters differ by less than a set convergence criterion (Johnston). Residuals from the feasible GLS model were used to calculate the *ex post* variance for the selected time periods.

Ex Ante Risk Measurement

An ARIMA model was developed to measure risk using mean squared forecast errors from one-step ahead forecasts. The model was estimated using a stationary price series, which has the property that the covariance between two adjacent observations depends only on their distance in time. A stationary series is desirable for obtaining reliable forecasts (Judge, et al.). In order to achieve stationarity, the natural logarithm was first applied to the price series. The log transformed data were then seasonally differenced. Goodness of fit for the estimated ARIMA model was determined by the minimization of Akaike's information criterion (Harvey). One-step ahead forecasts from the ARIMA model were first adjusted to account for the differencing transformation using the methods outlined in Granger and Newbold. Final forecast values were then obtained by taking antilogs using the following equation (Pankratz):

$$F_{t+T} = \exp(F_{t+T}) * \exp(std * \text{std}/2), \tag{4}$$

where $\exp(F_{t+T})$ is the antilog of the forecast for time $t + T$, and std denotes the estimated standard error of the forecast. The second term in the equation is a correction factor for forecasts with large standard errors. When estimated standard errors of the forecasts are small, the correction factor approaches unity. Mean squared forecast errors were calculated for the selected periods using the final forecast values.

Results

Regression estimates of trends in quarterly milk prices are presented in Table 1. The OLS model had a high R^2, with the constant and time coefficients significant at the one percent level. The Durbin-Watson statistic of 0.10 indicates significant first-order autocorrelation in the OLS model. The initial estimate of the autocorrelation coefficient ($\hat{\rho}$) using OLS residuals is significant at the one percent level. Estimates for the constant, time, and quarterly dummy coefficients in the feasible GLS model are significant at the one percent level. In addition, the R^2 value improved to 0.99. A large reduction in standard errors for the quarterly dummies in the feasible GLS model is consistent with the correction for autocorrelation. However, the Durbin-Watson statistic for the feasible GLS model still indicates the presence of autocorrelation, as the lower critical value for four regressors and 100 observations at the one percent level is 1.462; however, the statistic is considerably smaller than the OLS value. The rejection of the hypothesis of no autocorrelation in the feasible GLS model is disturbing. However, the specification error inherent in naive time trend models may be difficult to accommodate with standard GLS procedures. Nevertheless, the GLS model appears superior to the OLS model and should provide less biased estimates of variance.

Table 1. Regression Estimates of Trends in Quarterly Milk Prices.[a]

Coefficients	Ordinary Least Squares	Feasible Generalized Least Squares
Constant	2.795*	3.525*
	(.287)	(.732)
Time	0.099*	0.086*
	(.003)	(.010)
Quarter2	−0.536	−0.502*
	(.308)	(.061)
Quarter3	−0.353	−0.286*
	(.309)	(.070)
Quarter4	0.134	0.233*
	(.309)	(.061)
R^2	0.90	0.99
Durbin-Watson	0.10	1.32
Autocorrelation	−0.925*	
Coefficient ($\hat{\rho}$)	(.035)	

[a]Standard errors of estimated coefficients are in parentheses.
*Denotes significance at the .01 level.

The estimated ARIMA model is presented in Table 2. Chi-square statistics listed for the ARIMA model indicate that the residuals follow a white noise process, as none are significant at the five percent level. Estimates of the moving average process in the ARIMA model are consistent with the significance of the quarterly dummy variables in the feasible GLS model. In addition, the estimated first-order autoregressive process in the ARIMA model is consistent with first-order autocorrelation in the GLS regression model.

Variances for the original and detrended series are presented in Table 3.[3] Prices for production inputs such as feed, fuel, and labor were quite volatile during the 1973–80 period due to the energy crisis, changes in the structure of U.S. feed grain markets, and an accelerating level of overall inflation. These events contributed to a large upward trend in milk prices during this period. Not surprisingly, the variance of the original price series was highest during the 1973–80 period. In addition, values for relative changes in risk indicate that risk increased approximately 500 percent from the first to the second sub-period, but decreased around 80 percent from the second to the third sub-period. These inconsistencies of the variances calculated from the original series with the perception of increasing risk over time supports the use of detrending procedures to isolate random components.

Variances calculated using linear filters fol-

[3] Differences in estimated variances from one sub-period to another represent absolute changes in risk. Relative changes in risk are calculated as percentage changes from one sub-period to the adjacent sub-period.

Table 2. ARIMA Estimated Equation and Residual Autocorrelation.[a]

$$z_t = \underset{(.034)}{0.01} + \underset{(.108)}{0.547z_{t-1}^*} - \underset{(.055)}{0.798\epsilon_{t-1}^*} - \underset{(.067)}{0.703\epsilon_{t-2}^*} - \underset{(.051)}{0.857\epsilon_{t-3}^*}$$

Akaike Information Criterion = −468.76

Lag	χ^2	Prob.	Autocorrelations					
6	4.62	0.099	0.084	−0.076	−0.074	−0.082	−0.109	0.008
12	6.46	0.596	0.059	0.025	0.060	−0.006	−0.013	0.007
18	7.95	0.892	−0.018	0.041	0.032	−0.000	−0.065	−0.058
24	11.78	0.924	−0.008	0.062	0.088	0.116	0.016	0.021

[a]Standard errors of estimated coefficients are in parentheses.
*Denotes significance at the .01 level.

lowed patterns similar to those observed for the original price series, as variances were larger for 1973–80 than for 1981–90. Similarly, measures of relative risk increased from the first to the second sub-period, but decreased from the second to the third sub-period. The filters appear to have over-smoothed the price series, as the variances are substantially smaller than the variances of the original series and the estimated variances from the regression. For short time periods such as those being considered here, the most obvious problem associated with applying these smoothing techniques to the deseasonalized milk price series is the loss of critical observations at the end of the time series, where random variation is hypothesized to have increased relative to the rest of the series. An entire year (four observations) of data was lost at the end of the series after applying the quarterly moving average and linear filters. Thus, the variances calculated with these smoothing procedures may not fully reflect the random variation associated with the 1981–90 period.

Variance estimates for the OLS and feasible GLS regression models in Table 3 support the hypothesis that milk price risk has increased, as variances are higher in 1973–80 than in 1960–72, and variances in 1981–90 are higher than in 1973–80 and 1960–90. Mean squared forecast errors from the ARIMA model are similar in magnitude to the variances for the feasible GLS model for 1960–90 and 1981–90. An identical variance pattern exists between periods for the regression and ARIMA models. However, the ARIMA mean squared forecast error estimate is much lower than the feasible GLS variance estimate for 1960–72. This difference in magnitude may be a result of the influence that outlying observations at the end of the data series have on the location of the trend line in the feasible GLS model. The ARIMA model therefore suggests a much larger increase in risk between the earliest and latest sub-periods than the regression model. Variances and mean squared forecast errors calculated for the feasible GLS and ARIMA models, respectively, are substantially smaller in magnitude than variances calculated using the OLS model. This difference in magnitudes illustrates the bias of OLS variance estimates in the presence of autocorrelation. The hypothesis that milk price risk has increased over time is also supported in percentage terms, as measures of relative risk for the OLS, GLS and ARIMA models indicate increases from the first to the second sub-period, and from the second to the third sub-period.

Table 3. Milk Price Variance Estimates.[a]

	1960–90	1960–72	1973–80	1981–90
Original Series	14.290	0.570	3.560 (525)	0.670 (−81)
SMA5	0.006	0.001	0.011 (1000)	0.007 (−36)
AMA3	0.017	0.002	0.038 (1800)	0.018 (−53)
Ordinary Least Squares	1.420	0.740	0.980 (32)	2.280 (133)
Feasible GLS	0.140	0.030	0.090 (200)	0.270 (200)
ARIMA	0.133	0.009	0.123 (1267)	0.288 (134)

[a]Numbers in parentheses are percentage changes from the previous sub-period.

Conclusions

An industry perception that risk in milk prices has been increasing over time provides an opportunity to evaluate three methods used for detrending historical data to calculate risk indices for the 1960–90 period. Simple linear filters appeared to perform poorly as measures of historical risk, as variance estimates calculated using linear filters were inconsistent with both the hypothesis of increasing risk and industry perceptions about risk. Use of linear filters may be more appropriate for longer, less volatile, time series than the series used in this research. However, given the poor performance of the filters observed in this study, application of linear filters to other data series should be made with careful consideration of the prescriptive and/or descriptive nature of the study undertaken, and of the nature of the available data.

Variances calculated from the ordinary least squares and feasible generalized least squares regression models of milk prices on time and seasonal dummies were consistent with the hypothesis of increasing risk over the 1960–90 period. Misspecification in naive time trend models often results in violations of assumptions about the error covariance matrix. Violations of these assumptions have important implications for model estimates. In particular, variance estimates calculated using autocorrelated and/or heteroskedastic models will be biased. This bias is evidenced by the differences in magnitudes between variances calculated using the ordinary least squares model versus the generalized least squares model. Therefore, generalized least squares should be used rather than ordinary least squares in risk analysis when these problems are present.

Mean squared forecast errors obtained with the ARIMA model were also consistent with the research hypothesis of increasing risk over time. One potential advantage of using time series models rather than naive time trend models is that misspecification error may be more easily accommodated in the moving average and autoregressive parameters. Use of univariate time series techniques is often simpler and more reliable than attempting to correct for autocorrelation and/or heteroskedasticity in naive time trend models. When the objective is to provide unbiased measures of risk, these advantages may be particularly appealing to the researcher.

Future research on estimation of risk indices also may benefit from use of some of the general procedures applied in this paper. If only several risk indices are being calculated, comparison of the results from several detrending procedures may be helpful. A comparison of results could be made by examining differences in risk estimates for different sub-periods if a priori hypotheses concerning magnitudes of estimates are available. However, many studies estimate large numbers of risk indices as parameters for firm and policy models. Comparison of estimates with different methods is likely to be beyond the scope of the research in those cases. When large numbers of risk indices are to be estimated, the results of this study suggest that the use of generalized least squares or ARIMA methods would be appropriate for detrending data. However, a general recommendation of the best detrending procedure for all types of data would not be wise.

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