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MEASURING HISTORICAL RISK IN QUARTERLY MILK PRICES

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Abstract

Various methods have been used to detrend historical data to estimate risk indices. A perception of increasing milk price risk over time allows evaluation of several techniques to detrend data. Risk measures from a least squares regression model and an ARIMA model were consistent with the hypothesis of increasing risk.

Use of historical data to estimate the level of risk for output, prices, and income is a continuing research topic in agricultural economics. Two issues explored in previous literature include choice of risk measure and appropriate detrending method (Young, 1984). Defining variance as a measure of risk, Carter and Dean used the variate difference method pioneered by Tintner to detrend data series. This method was adopted in subsequent risk measurement studies (Adams, Menkhaus, and Woolery; Musser and Stamoulis; Kramer, McSweeny, and Stavros). Young (1984) noted that 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 seasonal and cyclical components in addition to secular trends (Franzmann). Swinton and King demonstrated that this standard method is superior to more robust regression methods. However, alternatives to time polynomials are often suggested -- Fackler recently proposed a stochastic trend method and Hammida and Eidman used non-linear filters.

Mean squared forecast errors are often used rather than variance as a measure of risk. Young (1980, 1984) was an early advocate of the use of forecast errors. Among the methods used for forecasting are ARIMA models (Bessler), futures prices (McSweeny, Kramer, and Kenyon), econometric forecasting equations (Berck), weighted moving averages of historical data (Collins, Musser, and Mason), and combinations of futures prices and weighted moving averages of yield (Marra and Carlson). Thus, considerable choices exist for the appropriate method to calculate risk indices from historical data.

This study reports a comparison of several methods to calculate historical risk measures for quarterly milk prices for the 1960-1990 period. Structural changes affecting the dairy sector during the 1960-90 period have resulted in the perception of increasing price risk over time (Fraher; Hamm). The performance of the above described procedures in quantifying this perception is therefore an interesting test of these methods. All of the methods previously discussed could not be used in this analysis due to the length of components of the time series and the complexity of the research required for some of the methods, such as econometric forecasting models. Rationale for the procedures applied are further considered in the next section.

Data and Methods

The milk price series used in the analysis of historical risk covers a thirty-one-year period from 1960 to 1990. Monthly observations of prices received by farmers measured in dollars per hundredweight (USDA, NASS) were used to calculate quarterly averages weighted by monthly milk production. The observed milk prices for 1960-90 appear consistent with the hypothesis that price risk has been increasing over this time period (Figure 1). 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. Higher energy prices and increased export demand (Musser, Mapp, and Barry) increased the cost of producing milk in the early-1970's. Rapidly increasing inflation rates and changes in federal policy during the 1972-80 sub-period led to higher support price levels. The 1981-90 sub-period was characterized by significant changes in the structure of dairy policy during the early-1980's, later 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).

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:

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

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

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

The subscript t indexes time, while k indexes observations used in calculating the updated moving average. Weights (w_j) used with AMA3 were .5, .3, and .2. Variance of the estimated random component was calculated for each of the four time periods.

Regression techniques were also used to estimate deterministic components of the milk price series. Milk prices were regressed on a trend and quarterly dummies, using the first quarter as the base. Model parameters were estimated using ordinary least squares (OLS), and residuals checked for first-order autocorrelation using the Durbin-Watson statistic. If significant autocorrelation was present, models were re-estimated with feasible generalized least squares (FGLS) using the Yule-Walker (YW) method (Gallant and Goebel). Residuals from the models were used to calculate the *ex post* variance for the four time periods.

Except for Fackler and Young, limited attention has been given to FGLS 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 in the presence of autocorrelation is biased (Kmenta), which suggests that the YW model should be used for calculating unbiased risk measures.

Ex Ante Risk Measurement. An ARIMA model was developed to measure risk using mean squared forecast errors from one-step ahead forecasts. A covariance stationary series was obtained by applying the natural logarithm to the price series and seasonally differencing the log transformed data. Residuals were tested for autocorrelation using a chi-square statistic. Goodness of fit was determined by the minimization of Akaike's information criterion (Harvey). One-step ahead forecasts of the stationary data were adjusted to account for the differencing transformation using the methods outlined in Granger and Newbold. Final forecast values were obtained by taking antilogs of the resulting series. Optimal forecasts were generated using the following equation (Pankratz):

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

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. Mean squared forecast errors were calculated for four periods using the optimal one-step ahead forecasts.

Results

Variances for the original series are presented in Table 1. Not surprisingly, the variance of the original price series was highest during the 1973-80 period. Input prices, especially feed, fuel costs, and wage rates were quite volatile during this period due to the energy crisis, changes in the structure of U.S. feed grain markets, and an accelerating level of overall inflation. The observed variance pattern is inconsistent with the basic hypothesis of this research, supporting the use of detrending procedures to isolate true random components.

Regression estimates for the trend analysis are reported in Table 2. The most prominent result is that OLS does not perform as well as the YW method. This result is particularly apparent in comparing the Durbin-Watson statistics. The Durbin-Watson value for the OLS model indicates significant first-order autocorrelation. After applying the YW method to correct for autocorrelation, the Durbin-Watson statistic falls within the inconclusive range at the 1% level of significance. The estimated equation and residual autocorrelations for the ARIMA model are presented in Table 3. Estimates of the moving average and autoregressive processes are consistent with the significance of the seasonal dummy variables and the one-period autocorrelation pattern for the YW model in Table 2.

Variances for the linear filters and regression models and mean squared forecast errors for the ARIMA model are reported in Table 1. Variances calculated using linear filters followed a pattern similar to that observed for the original price series, as the variance was higher for 1973-80 than for 1981-90. The filters appear to have oversmoothed the price series, as the variances are substantially smaller than the variances of the original series and the estimated variances from the regressions. 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 do not fully reflect the random variation associated with the 1981-90 period.

Variance estimates for the OLS and YW models 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 YW model, and an identical pattern exists between periods. However, the mean squared forecast error estimate is much lower than the YW variance estimate for 1960-72. Thus, the ARIMA model suggests a much larger increase in risk between the earliest and latest sub-periods than the YW model. Variances and mean squared forecast errors calculated for the YW and ARIMA models, respectively, are substantially smaller than variances calculated using the OLS model. The difference in magnitudes illustrates the bias of OLS variance estimates in the presence of autocorrelation.

Conclusions

The hypothesis that risk in milk prices has been increasing provides an opportunity to evaluate methods used for detrending historical data to calculate risk indices. Variance estimates calculated using simple linear filters were inconsistent with the hypothesis of increasing risk. Use of linear filters may be more appropriate for longer, less erratic, time series than the series used in this research. Mean squared forecast errors obtained with the ARIMA model were consistent with the research hypothesis, as were variances calculated from regression models on time and seasonal dummies. However, OLS models, which have often been used for detrending in previous risk research, did not perform as well as YW models which accommodated autocorrelation. Variance estimates from the OLS models showed substantial bias relative to the YW and ARIMA estimates, a consequence of ignoring autocorrelation in the OLS residuals. Thus, regression analysis of trends should consider use of generalized least squares methods in order to obtain unbiased estimates of risk indices.

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Figure 1. Quarterly Milk Prices
Received by Farmers, 1960-90

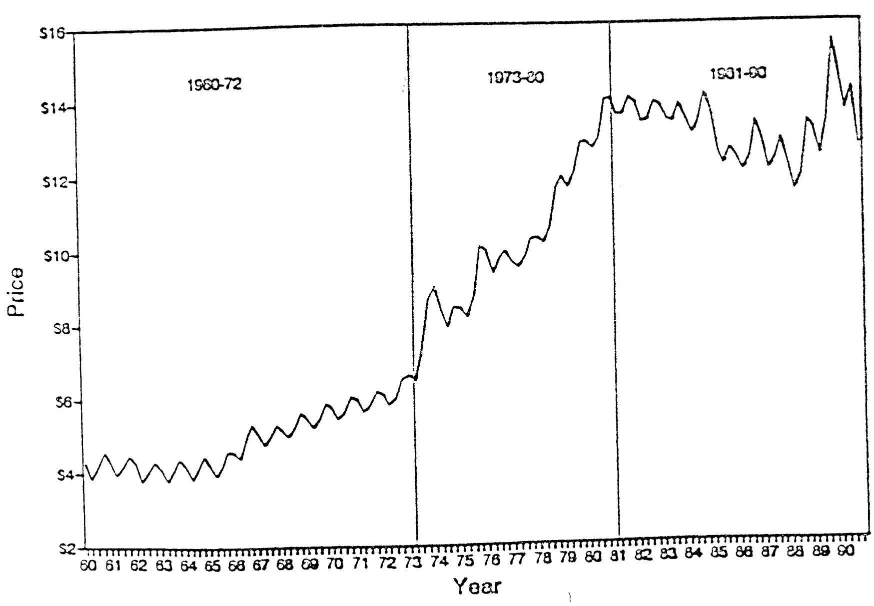

Table 1. Milk Price Variance Estimates.

	1960-90	1960-72	1973-80	1981-90
Original Series	14.290	0.570	3.560	0.670
SMA5	0.006	0.001	0.011	0.007
AMA3	0.017	0.002	0.038	0.018
Ordinary Least Squares	1.420	0.740	0.980	2.280
Yule-Walker	0.140	0.030	0.090	0.270
ARIMA	0.133	0.009	0.123	0.288

Table 2. Regression Estimates of Trends in Quarterly Milk Prices.

Models	Ordinary Least Squares	Yule-Walker
Constant	2.80*	3.53*
	(.287)	(.732)
Time	0.10*	0.09*
	(.003)	(.010)
Quarter2	-0.54	-0.50*
	(.308)	(.061)
Quarter3	-0.35	-0.29*
	(.309)	(.070)
Quarter4	0.13	0.23*
	(.309)	(.061)
LAG1		-0.93*
		(.035)
R^2	.90	.99
Durbin-Watson	0.10	1.32

[a]Standard errors of estimated coefficients are in parentheses.

*Denotes significance at the .05 level of confidence.

Table 3. ARIMA Estimated Equation and Residual Autocorrelation.

$$z_t = \underset{(.034)^a}{0.01} + \underset{(.108)}{0.54z_{t-1}^{*}} - \underset{(.055)}{0.80\epsilon_{t-1}^{*}} - \underset{(.067)}{0.70\epsilon_{t-2}^{*}} - \underset{(.051)}{0.86\epsilon_{t-3}^{*}}$$

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	0.077
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 .05 level of confidence.