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A HISTORICAL OVERVIEW OF ESTIMATION OF HISTORICAL RISK COEFFICIENTS

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Estimation of risk parameters from historical data has been a perennial issue in agricultural economics. This research area began almost simultaneously with the emergence of expected utility theory. Heady undoubtedly provided a major stimulus by the discussion of the use of these coefficients in farm management in his seminal text in 1952. Estimation of risk coefficients and their use in elementary decision roles was a popular research activity over the next decade. Heady, Kehrberg, and Jebe was an early effort, and Carter and Dean is a widely cited source from this period. Walker and Lin review other similar research from this period.

The increased application of decision theory to agricultural risk management initially reduced the interest in historical risk coefficients. Decision theory has the perspective that only subjective probability distributions and parameters are relevant for management decisions. For example, Anderson, Dillon and Hardaker devote only minimal attention to this research area in the context of aiding elicitation of subjective distributions. However, shortcomings in estimation of subjective probabilities led to continued interest in historical measures (Young, 1984). As changes in policy areas led to more price variability in the 1970s, interest in risk management research increased. Simulation and math programming procedures were refined in this period and utilized variances and covariances or similar measures from historical data largely in a mean-

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variance decision framework. Concern about the theoretical assumptions of mean-variance framework led many researchers to adopt stochastic dominance approaches that analyze probability distributions rather than statistical parameters. However, subsequent empirical and theoretical developments (Levy and Markowitz; Meyer) have made mean-variance analysis and the use of statistical parameters once more an acceptable method of risk analysis. For example, Hazell (1984) used such risk coefficients in his influential analysis of increased risk in crop production.

Despite research on estimation of risk indices over a lengthy time period, considerable controversy still exists on procedures to calculate historical risk indices. A fundamental conceptual issue concerns the use of standard sampling estimates of variances and covariances of probability distributions in contrast to mean squared forecast error formulations. This issue is intertwined with the research purposes of the risk indices. A related issue that perhaps has received more attention is detrending methods. Another set of issues concerns appropriate data. Length of time series, level of aggregation, and inflation are among the data issues considered in estimation of risk indices. This paper discusses these issues in the approximate order outlined above. As a preliminary, a general definition of a risk index and a taxonomy of uses of risk indices are presented to provide pedagogical organization for the ensuing discussion.

A General Risk Index

Following Collins, Musser, and Mason, a general risk index can be written as a weighted moving average of historical errors from expected values:

$$(1)\ V(X, Y) = \sum_{t=1}^{n} w_t \, (X_t - E_t(X)) \, (Y_t - E_t(Y))$$

where V (X, Y) is the variance of X if X = Y and the covariance of X and Y if $X \neq Y$, $E_t(X)$ and E_t (Y) are expected values of X and Y in period t, w_t are weights on products of deviations, and n is the number of periods used to calculate V(X,Y). The adoption of a covariance framework is not meant to ignore the widespread use of absolute deviation measures of risk, especially in mathematical programming models. These measures can be interpreted as alternative estimates of variances (Hazell, 1971a). More importantly absolute deviation measures require decisions on all similar components defined in (1). The only mathematical difference is that the absolute value of deviations is used rather than the product of deviations. For both basic measures of risk, the issues concerning calculation of historical risk measures can be related to components of equation (1).

Taxonomy of Uses of Risk Indices

Various taxonomies of risk models could be developed. One approach could involve research methods such as simulation or mathematical programming and/or decision criteria such as stochastic dominance or safety-first. Since the topic of this paper is only a component of some of these general models, a more fruitful approach may be to consider purposes of the research. Young (1984) used the methodological distinction between positive and normative in discussing historical risk indices. McCarl and Nelson classified risk models into structural exploration of theoretical issues, prediction, and prescription, with the former two being roughly subsets of positive research. For this paper, it is helpful to further divide prediction into predicting decisions under risk and predicting the risk consequences of a decision (McCarl and Musser). Particularly at the firm level, much farm management activity is concerned with predicting risk consequences of a decision. For example, estimation of changes in income risk from crop enterprise diversification with crop insurance purchases is this form of prediction. In contrast, predicting participation in a particular crop insurance program is more likely to be analyzed at an aggregate level and is an example of predicting decisions under risk. Most policy analysis that includes risk probably involves predicting decisions. However, prediction of variability of income or stocks could also be concerned with the consequences of a risk-neutral decision.

Without devoting too much attention to these methodological issues, the position of McCarl and Nelson that very little, if any, research is concerned with prescription has merit. Much of what is seen as prescriptive or normative appears consistent with prediction of consequences. For example, Young (1984) considered the calculation of risk indices for farmers as normative while it could be considered as predicting consequences of decisions. Admittedly, no taxonomy is perfect. How would estimation of risk indices to set crop insurance rates be classified? This paper adopts a dual classification of behavioral and managerial. Behavioral includes structural exploration and predicting decisions while managerial includes prescription and predicting risk consequences of decisions. This classification precludes further discussion of the prescription versus prediction issue.

Sampling Variances Versus Mean Squared Errors

Most risk research has used the statistical theory concept of variance to calculate risk indices. Assuming the probability distribution of historical data is stationary, each observation on dispersion from predicted values is equally likely and equally relevant for consideration of risk. Under this view, estimates of dispersion are based on classical estimation under random sampling. Equation (1) is therefore simplified. The values of w_t are constant for all t, with $w_t = 1/(n-k)$, where k is the number of estimated parameters used to calculate $E_t(Y)$ and $E_t(X)$. In addition, all of the data (t=1,..n) are used to calculate $E_t(Y)$ and $E_t(X)$. If no systematic trends exist in the data, $\bar{Y}$ and $\bar{X}$ would be used. With linear trends in the data, $E_t(Y) = \hat{a} + \hat{b}\,t$, where $\hat{a}$ and $\hat{b}$ are estimated regression coefficients. Other detrending methods are used with more complex trends.

The alternative view of using forecast errors for risk indices is most widely identified with Young (1980). As this work was never published, it is probably useful to summarize his criteria for variability indices using equation (1):

(1) Variability indices should be weighted mean square forecast errors as in equation (1).

(2) $E_t(Y)$ and $E_t(X)$ should only use information available from previous periods--$n=t-1$.

(3) $V(X, Y)$ and $E_t(X)$ and $E_t(Y)$ should use information from a limited number of time periods--n is small.

(4) More recent information should be given greater weight so that $w_{t-1} > w_{t-h}$ where $h > 1$.

(5) $V(X,Y)$, $E_t(Y)$, and $E_t(X)$ should be updated each period.

(6) Methods of estimating $E_t(Y)$ and $E_t(X)$ should be updated if necessary each period.

(7) Methods of estimating $E_t(X)$, $E_t(Y)$ and $V(X, Y)$ should be simple and explicit.

This approach seemed quite radical in contrast to the sampling theory approach historically used in farm management. However, similar concepts had been previously used in analysis of hedging (Peck), supply response models (Just), and in several risk management studies reviewed in Young (1980). In retrospect, these criteria are also not as ad-hoc as they initially seemed. Psychological theories of risky behavior (Musser and Musser) can be used to rationalize these criteria. The basic proposition of these theories--people are not good intuitive statisticians--would suggest that criteria other than statistical sampling theory might be more useful in explaining human behavior. Subsequent behavioral studies that have adopted this approach have been concerned with structural exploration (Collins, Musser, and Mason) and predicting risk responses to marketing alternatives, policy, and changes in production technology (Berck; McSweeny, Kenyon and Kramer; Marra and Carlson). For these behavioral uses of risk indices, this approach seems to have merit.

In contrast, the sampling theory approach still seems appropriate for managerial uses which was the original intent of research in this area. In these cases, agricultural economists should incorporate their training in statistical theory into their estimates rather than use heuristic, naive methods. In fact, decision makers may implicitly expect agricultural economists to use such training in advising them. In addition, the use of standard statistical procedures can be supported for the behavioral uses of risk indices in certain cases. If the probability distribution is stationary, violation of Criterion 6 would not be a serious problem. In addition, the remainder of the Criteria likely would not have much influence on the estimates. In such a situation, the larger number of observations under the sampling approach would likely improve the accuracy of estimates. Furthermore, the sampling procedures are simpler in that updating need not occur each period. If the variable being modeled has structural shifts or periodic volatility in the time series, the mean forecast error approach would likely give substantially different results. Young (1980) demonstrated this effect in the contrast between dry peas and lentils in his discussion of these Criteria.

Detrending Methods

Detrending data is concerned with removing systematic components from a time series in order to isolate the random component of the data that is used to measure risk. Depending on the series chosen, the deterministic component could include secular trends, cyclical components, and seasonal influences. Formally, the detrending procedure assumes that $E_t(Y)$ is not a constant such as $\bar{Y}$ and varies over time due to deterministic influences. A number of detrending methods have been used--Young (1984) reviews a number of historical methods, and Moss and Boggess discuss more recent methods. This paper reviews the variate difference and regression methods, which have been widely used in past research.

The Variate Difference Method

As agricultural economists began to estimate risk indices in the 1970s, the variate difference method was one of the more commonly used techniques to detrend data (Young, 1984). Applications of the variate difference method in agricultural economics research include Mathia and Walker and Lin in presentations of risk indices and Adams, Menkhaus, and Woolery, Musser and Stamoulis, and Kramer, McSweeny, and Stavros in quadratic programming models. Because its use has declined, this discussion of the variate difference method is largely of historical interest.

Tintner (1940) was the leading proponent of the variate difference method. He included this method in his econometrics text (1952) which was an influential text in the 1950s. Carter and Dean used this method in a classic study which probably contributed to its subsequent popularity. The method involves calculating variances and covariances of successive differences of the time series. The process is terminated when the reduction in variance from the next difference is not significant. The major advantage of the method is that differences can approximate many functional forms, which do not need to be specified a priori. As Young (1984) points out, regression models with increasing powers of polynomials have similar approximation powers. In addition, such curve fitting procedures do require explicit mathematical decisions that can preclude removing variation which is actually consistent with risk. Furthermore, the variate difference method is not simple. Its mathematical and statistical properties are not as straightforward as regression, and students no longer regularly study the technique. This combination of reasons probably has contributed to its recent lack of use.

A technical limitation of the variate difference method is that an unconventional test criteria has usually been used. The null hypothesis that the variances of two subsequent differences are equal is tested with an error ratio that has an asymptotic standard normal distribution. The critical value of this statistic is generally 3.0, corresponding to a level of significance of 0.26 percent (Walker and Lin). Thus, a very low level of Type I error is allowed compared with usual practices. From standard statistical theory, one would expect a much higher Type II error than with more standard levels of significance. Therefore, the procedure is quite conservative in detrending--the data are not differenced again unless the probability that the variances of the two differences are not the same is very small. Therefore, estimated variances are likely biased upward with the variate difference method. If this method is used, a lower level of significance should probably be used.

Regression Methods

Regression methods are probably the most common method used to detrend data. Heady, Kehrberg, and Jebe used regression in their early work in this area. As Hazell (1971b) pointed out, regression models can also be used to detrend data from MOTAD models. Given the general familiarity of agricultural economists with regression, it is not surprising that it has been so extensively utilized. Most of the models presumably are estimated with ordinary least squares (OLS). Swinton and King recently demonstrated that this method is superior to some more robust procedures. However, very limited attention has been given to generalized least squares (GLS) estimators--Fackler and Young are one exception. Autocorrelation in time series data is likely to be a problem with simple time trend models due to specification error. In addition, heteroskedasticity will be present if risk is changing over time. Just and Pope demonstrated this result in the explicit inclusion of heteroskedasticity in risky response functions. The remainder of this section discusses problems in estimation of risk indices when GLS is not used.

It is well known that ordinary least squares estimates of regression coefficients are unbiased but not efficient if autocorrelation and/or heteroskedasticity are present. It is usually not emphasized as much that OLS estimates of variances, such as in most computer programs, are biased in these cases. The magnitudes of the bias is a complex issue depending on the data sample and unknown covariance matrix. Kmenta and Johnston concludes that OLS formulas are most likely to underestimate variances.

The increased efficiency of GLS estimation indicates that variances estimated with GLS will be smaller than OLS variances. This conclusion is easy to demonstrate for a simple autocorrelation model. Assume disturbances, ϵ_t, are first order autoregressive with $\epsilon_t = \rho\, \epsilon_{t-1} + u_t$ where ρ is an autocorrelation coefficient with absolute value less than one, and u_t is random variable which meets the OLS residual characteristics with a variance of σ_u^2. Kmenta demonstrates that the variance of ϵ_t, $\sigma^2 = \frac{\sigma_u^2}{1-\rho^2}$. Since the denominator is less than one, $\sigma^2 > \sigma_u^2$. Intuitively, accommodating autocorrelation allows estimation of the truly random components in σ_u^2 rather the larger random and deterministic components of σ^2. The situation with heteroskedasticity is more complex. Unlike with autocorrelation, the OLS errors do not have a predictable component but do have a structure. Recognition of this structure in GLS results in smaller variances than ignoring it in OLS.

Before further discussion of the econometric problems, discussion of their relevance for risk analysis may be helpful. In previous sections, it was argued that the best sampling estimators should be used to calculate managerial risk indices and that behavioral risk indices should be consistent with risk perceptions of producers. GLS procedures are therefore indicated in the former case and in the latter case only if producers regularly perceive autocorrelation and heteroskedasticity. Casual evidence would suggest that producers recognize these problems. Low (high) prices in one year result in high (low) ending stocks that can cause low (high) prices in the following year. Low (high) yields are accompanied by low (high) soil moisture levels at the end of the growing season that may result in low (high) yields next year. Similarly, producers probably recognize the effect of changes in input levels on variance of output. For example, increased fertilizer applications on dryland agriculture increases the range of possible output depending on weather conditions. Such knowledge of autocorrelation and heteroskedasticity among producers supports use of GLS for calculation of behavioral risk indices.

If this reasoning is not accepted, biases in variances from OLS remains a problem with less than satisfactory solutions. White developed a consistent estimation for OLS variances with heteroskedasticity ($\hat{\sigma}_H^2$):

$$2)\quad \hat{\sigma}_H^2 = \frac{1}{n} \sum_{t=1}^{n} \hat{e}_t^2 \underline{X}'_t \underline{X}_t$$

where $\hat{e}_t$ is the OLS residual for observation t, $\underline{X}_t$ is the (k x 1) vector of observations for the intercept and independent variables in t (p. 820). Consistent estimates of OLS variances with autocorrelation, $\hat{\sigma}_A^2$, are limited to first order autoregressive structures. Johnston presents such an estimator for k = 2:

$$3)\quad \hat{\sigma}_A^2 = \left(n - \frac{1 + \rho\lambda}{1 - \rho\lambda}\right)^{-1} \sum_{t=1}^{n} \hat{e}_t^2$$

where λ is the autoregressive coefficient for the independent variable. When k > 2, Neudecker presents upper and lower bounds for the bias in the OLS variance.

Several different approaches can be used to implement GLS. Engle assumed a particular structure for the errors that includes an autocorrelated, conditional, heteroskedastic (ARCH) stochastic process in estimating risk of inflation in the United Kingdom. Fackler and Young used a simpler combination of first order autoregression and a Glesjer structure on heteroskedasticity. Iterative procedures were used in both cases to estimate the final model. While generally supportive of iterative procedures for feasible GLS, Kmenta notes at one point that "This iterative procedure is quite laborious" (p. 291). Thus, these procedures may not be completely consistent with the Simplicity Criterion. As an alternative, standard tests for these problems could be implemented after OLS. Epps and Epps found that autocorrelation tests were quite robust in the presence of heteroskedasticity, but the reverse was not true. Thus, one could test for autocorrelation, correct that problem if it exists, and then test for heteroskedasticity and correct it if necessary. While this procedure may introduce pre-test bias, it does potentially simplify the estimation procedures, as autocorrelation and heteroskedasticity may not always be present. Judge, et al. indicate that pretest bias is not a serious problem for heteroskedasticity.

Issues in Appropriate Data Series

Issues in appropriate data series concern values of X_t and n in equation (1). A central underlying tradeoff in many of these issues concerns statistical efficiency versus decision relevance. Statistical theory suggests that longer time series will increase estimation efficiency, but decision theory suggests that the observations included in the calculations must be conceptually repeatable. Many of the data issues are related to this tradeoff. Using an econometric model to predict $E_t(Y)$, such as in Berck, has both theoretical and econometric appeal (Young, 1984). However, such an approach has not been often used because it is not simple and, more importantly, because relevant data such as costs are not available for a sufficient length of time to estimate the models. The aggregation issue for firm production risk, further discussed by Marra and Schurle, is related to the unavailability of firm production data.

Length of time series requires judgements about stability of economic and production environments. The pricing environment for agricultural products was fundamentally changed in the decade after the mid-1960s. First, agricultural income support policies were changed from a price support to a direct payment structure. In the early 1970s, international trade became much more important. Since the mean and the probability distributions of agricultural prices were considerably different after the early 1970s, risk analysis probably should truncate earlier prices (Musser, Mapp, and Barry). If one is interested in risk indices of revenue variables, one approach is to combine risk indices from longer time series of yields with shorter time series of prices (Tew, Musser and Smith) using statistical formulas adapted by Boggess, et al. and Tew and Boggess for risk management.

While previous studies have focused on changes in price distributions, yield distributions have also been evolving. In the 1950s, hybrid seed corn, fertilizers, and mechanized harvesting were widely adopted. In the 1960s, farmers increased use of pesticides, especially herbicides (Daberkow and Reichelderfer). Carlson found a definite risk response from pest management practices, so a similar argument to prices could be made to truncate yield trends in the 1970s. However, production technology has continued to evolve. Irrigation, which has definite risk management effects, increased dramatically in the 1970s (Musser). The 1980s had many firm failures associated with the farm financial crisis. Presumably, surviving firms have better managers who would be able to reduce production risk.

The above argument leads one to the decision theory perspective--historical yields have no decision relevance. However, the effects of these technological changes on yield risk is an empirical question. These changes were adopted gradually by individual farmers, so dramatic shifts in aggregate data are unlikely. More use of feasible GLS in trend analysis would be helpful in understanding the evolution of yield risk. Consideration of alternative functional forms for heteroskedasticity would especially be helpful in increasing understanding of shifts in yield risk. Given the current limited knowledge of evolution of yield risk, the errors associated with the incorrect maintained hypothesis on functional form for heteroskedasticity may be more of a problem than pretest errors.

A final data issue concerns deflation of price and revenue series. Carter and Dean recognized the possibility of deflating price data even though they used nominal data. The review of risk indices by Young (1980) found that some studies used deflated data and some did not. Given the importance of relative prices in neoclassical analyses, agricultural economists generally consider real data appropriate for analysis. However, inflation would increase risk unless inflation rates were perfectly forecasted. The implausibility of this result has led White and Musser and Brake to argue that inflation increases risk. Resolving this issue is beyond the scope of this paper. However, it is an important issue for historical price risk because of the increasing and decreasing inflation in the past 20 years.

Conclusions

Agricultural economists have been concerned with estimation of historical risk indices for at least 40 years. During that time, the popularity of this activity has increased with the early development of elementary risk theories, decreased with the emergence of decision theory, and then increased again as price risk became more important in the 1970s. Some issues, such as aggregation error, deflating data, and appropriate detrending methods have not been resolved. The variate difference method is not being used to detrend data as much as in the past. However, regression methods have retained their popularity throughout this period despite suggestions of several alternatives.

Several issues have emerged in the past 20 years that have not yet been resolved. One concerns the use of sampling versus forecast procedures in calculation of risk indices. This paper presented a general concept of a variability index that encompasses both concepts. In addition, the potential use of the indices was suggested as a method of resolving the issue. Sampling formulations seem appropriate for managerial applications in prediction of consequences of decisions and prescription, while forecast errors may be appropriate for behavioral applications involving testing theory and predicting decisions. The difference between the two estimates is likely to be larger with fluctuating than gradually evolving series. More research on the empirical consequences of the alternatives would be helpful to further resolve this issue.

Another issue related to statistical versus decision theory is the appropriate length of time series. The previous discussion of changes in pricing environment was reviewed, and similar trends in production technologies that would have changed level of production risk were identified. More research on trends in production risk seem necessary to further understand the appropriate length of yield series.

Increased use of feasible GLS for detrending historical data would allow an empirical evaluation of changes in price and yield risk. In situations where risk is evolving, heteroskedasticity may be present. Autocorrelation is also likely to be a problem with naive time trend models. In both these cases, OLS procedures gives biased estimates of variances. Inasmuch as heteroskedasticity and autocorrelation are recognized by producers, OLS estimates of variance will cause an upward bias on risk indices. Use of feasible GLS will alleviate these biases and allow an explicit evaluation of changes in risk over time. Given the limited knowledge of the structure of heteroskedasticity, exploratory analysis with alternative functional forms for heteroskedasticity rather than analysis with specific maintained hypotheses seems appropriate in increasing understanding of risk.

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