Some Panel Aspects of the Objective Yield Survey

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I. Introduction

The Objective Yield Survey is a series of monthly measurements conducted by the United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) during the growing season for the purpose of forecasting end-of-season yield for crops such as corn, soybeans and wheat. In this paper, we discuss models for corn using data from the state of Iowa during the years 1979 to 1985. Thorough discussions of the survey design and current forecast methods can be found in Francisco, Fuller and Fecso (1987), and Reiser, Fecso and Taylor (1987), respectively. An abbreviated description follows.

An early season estimate for the number of acres planted or to be planted to corn is calculated by NASS from data collected during the June Enumerative Survey, a multistage stratified area sample. Objective Yield Surveys are conducted during the months of July through November, using fields that are subsampled from those visited during the June Enumerative Survey. In Iowa, approximately 240 fields are selected each year. For each selected field, a pair of randomly located units is established for data collection. Each unit is two rows (of corn) wide and fifteen feet long. In early July (month number one for the Objective Yield Survey), one half of the selected fields are visited, and data pertaining to number of stalks in each unit are collected. Starting in August (month two), all selected fields are visited monthly until the crop is either harvested or fully mature. No fields are visited after November (month five). During the visits in months two through five, data is collected on both number of ears and size of ears. Although 240 units are selected for the sample each year, some units are lost to refusals by owners, changes from intentions to plant as stated in June, and damage to crops. As a result, data is available each year on approximately 200 fields, or 200 pairs of units. For analysis purposes, each pair of units is treated as a single observation.

Even though the data represent observations over time, the number of time points is small, and, in the past, the data has been treated as essentially cross sectional. That is, data from July are used to develop a July forecasting model, data from August are used to develop an August forecasting model, etc. Trends over months within years are not presently used in forecasting models. In this paper we consider the use of panel models, which incorporate aspects of both cross sectional and time series data. Panel models are heavily used in the social sciences, where the emphasis is on the process of change over time -- i.e., which variables influence other variables over time. Here, the use of panel models has different purposes. First, month to month changes in variables could be monitored as a quality control process. Secondly, and to receive more attention here, panel models may be used for the purpose of identifying measurement error in the predictor variables, and, ultimately, to assess the impact of that measurement error on forecasts.

In the following section we will present a brief overview of the forecasting methods presently used by the USDA. Then, in Section III we consider a single indicator panel model for number of ears of corn, and in Section IV we will consider a two variable, two wave model for size of ears.

II. Present Methods

End of season yield is calculated for a selected field using total number of ears and average grain weight per ear:

$$Y_{ij} = Y_{wij} Y_{Nij} K S_{ij}^{-1} \qquad (1)$$

Y_{ij} = yield for field j in year i in bushels per acre

Y_{wij} = Average grain weight per ear, for field j in year i, measured on the ears in the selected units

Y_{Nij} = Number of ears of corn in the selected units for field j in year i

K = a constant that transforms pounds per unit into bushels per acre
= 103.714

S_{ij} = width of eight rows of corn, field ij.

During the growing season, the yield for the selected field is calculated from expression (1) using forecasted values for grain weight and/or number of ears. Forecast models for number of ears and grain weight are obtained using ordinary least squares on data from the five years previous to the present year. The model for predicting number of ears at the end-of-season includes number of stalks and number of ears measured earlier in the season.

$$Y_N = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon_{ij} \qquad (2)$$

where Y_N = end-of-season number of ears
X_1 = number of ears with kernels (P17) (months 2 and 3 only)
X_2 = number of stalks (P14)
X_3 = number of stalks with ears (P15)
X_4 = number of ears or ear shoots (P16)

The model for grain weight includes two measures of ear length

$$Y_W = \beta_0 + \beta_1 X_5 + \beta_2 X_6 + \varepsilon_{ij} \qquad (3)$$

where Y_W = average grain weight per ear, at end-of-season
X_5 = average length over husk (P18)
X_6 = total length of five kernel rows (P19)

III. Panel Model for Number of Ears

The model presented in this section is a single indicator panel model that will allow us to identify the measurement error in some of the predictor variables for the count of number of ears per sample unit. These predictor variables include number of stalks (P14), number of stalks with ears (P15), number of ears or ear shoots (P16), and number of ears with kernels (P17).

A consequence of the rapid growth of corn across a fairly short growing season is that not all variables are available in each month of the Objective Yield Survey, and even if one is available, it may not be available on all units. The longest span of time over which new observations are available for any of the predictor variables is, in fact, only three months, as shown in Table 1. An important variable for which data is available from months two, three and four is the count of ears with evidence of kernel formation, variable P17.

A model with measurements at three points in time is shown in Figure 1. The single X variable at each time point is sometimes referred to as a single indicator. We can write the model as follows:

$$\underset{\sim}{x} = \Lambda_x \underset{\sim}{\xi} + \underset{\sim}{\varepsilon} \qquad (6)$$

and $$\underset{\sim}{\xi} = \beta \underset{\sim}{\xi} + \underset{\sim}{\zeta} \qquad (7)$$

Expressions (6) and (7) specify relationships among the regressor variables over time, for the purpose of identifying measurement error. That is, in expressions (6) and (7), $\underset{\sim}{x}$ and $\underset{\sim}{\xi}$

contain a single regressor measured at different points of time:

X_1 = Measurement for number of ears with kernels at month two
X_2 = measurement for month three
X_3 = measurement for month four
ξ_1 = true value for number of ears with kernels at month two
ξ_2 = true value for month three
ξ_3 = true value for month four
$\underset{\sim}{\xi}$ = vector of measurement errors
$\underset{\sim}{\xi}$ = vector of equation errors

For the model shown in figure 1, the following specifications are also required.

$$V(\varepsilon_1)=V(\varepsilon_2)=V(\varepsilon_3)=V(\varepsilon)$$
$$\Lambda_x = I$$
$$\beta = \begin{pmatrix} 0 & 0 & 0 \\ \beta_{21} & 0 & 0 \\ 0 & \beta_{32} & 0 \end{pmatrix}$$
$$\xi_1 = \zeta_1$$

Using these specifications, the model is just identified, and the parameter estimates can be calculated directly from the covariance matrix, as given by Wiley and Wiley (1970). Under the assumption of multivariate normality, the estimators are maximum likelihood estimators. Estimates for model parameters are given in Figure 1. As is apparent from the figure, the magnitude of the measurement error variance, 2.21, is very small. Wiley and Wiley (1970) define the reliability ratio, ρ^2, as the ratio of variance of the true measure to the total variance:

$$\rho^2 = V(\xi)/[V(\xi)+V(\varepsilon)]$$

Under this definition, the reliability ratio of the measurements at times one, two and three are:

$$\rho_1^2 = 0.991$$
$$\rho_2^2 = 0.990$$
$$\rho_3^2 = 0.990$$

Although it is not necessarily the case that the reliabilities be equal across time points, it is clear that number of ears with kernels is measured virtually without error at months two, three and four.

We fit this simple model to other variables that are measured in months one, two and three. For the count of number of stalks, variable P14, the reliability ratio had the value 0.998 in each of the three months. However, the model was not successful for other variables, including counts of barren stalks, stalks with ears (P15) and ears or ear shoots (P16). For each of these three variables, the estimated error variance was negative by a substantial amount. We interpret this result as an indication that the assumption of constant error variance, and hence the model, is not appropriate. Number of ears and number of stalks with ears are stable from month two to month three, but are very unstable early in the season. When the early season measurements are apparently subject to much larger error, the model considered in this section is not appropriate.

Given the high reliability ratios for number of ears with kernels and number of stalks, it is clear that the measurement errors at month one in the counts of stalks with ears and ears or ear shoots are not simple counting errors. Instead, there appears to be a period of inherent unreliability in the growth of the ears, during which many ear shoots begin to form, but which ultimately die off. The inherent unreliability in the count is due to the difficulty in distinguishing ears that will survive from ears that will die off.

IV. A Two Variable, Two Wave Model for Size of Ears

Two variables are used as predictors of grain weight: average length over husk (P18), and total length of five kernel rows (P19). The size of an ear of corn should, of course, be represented by at least two dimensions - length and diameter or circumference, as if its shape was a cylinder. Using simple geometric shapes for modeling has worked well for fruit crops (Fecso, 1975). Recently Bigsby found that including diameter measures for corn reduced the mean square error by 30 to 50% from models with only length measures. However, there are no measures of diameter or circumference available in this data, thus we will examine only measures of length. For the analyses in this section, we use P19 divided by 5.0, to give average length over the five kernel rows. This transformation was done so that the metrics of the two X variables would be approximately in the same units. Neither of the X variables is an ideal measurement: we would like to have a measurement of grain weight at each month of the growing season, but obtaining it would destroy the ear being measured. So, the length of the cob, over the husk, is measured instead. To get a measurement that is closer to the actual grain weight, the length of the kernel row is measured for five ears. But again, since this measurement destroys the ear in terms of future growth, it is done on five ears that are <u>outside</u> the unit, and are on plants for which grain weight will not be determined at the end of the season. Thus, there may be substantial error in both the manifest variables as measures of the same underlying variable.

Neither of the two variables for grain weight are measured for three consecutive months, so the model given in the previous section cannot be used. However, since both variables are available in months two and three, the two variable-two wave model shown in Figure 8 can be used instead. The general form of this model is the same as the form of the model in Figure 1:

$$\underset{\sim}{x} = \underset{\sim}{\Lambda_x} \underset{\sim}{\xi} + \underset{\sim}{\varepsilon}$$

and $$\underset{\sim}{\xi} = \beta \underset{\sim}{\xi} + \underset{\sim}{\zeta} \quad ,$$

but now X_1 = average length over husk (P18), at month two

X_2 = average length of five kernel rows (P19) at month two

X_3 = average length over husk at month three

X_4 = average length of five kernel rows at month three

ξ_1 = true (average) length of corn cobs at month two

ξ_2 = true (average) length of corn cobs at month three

Identification conditions for this model are discussed by Wiley (1973). If we impose additional restrictions,

$$\Lambda_x = \begin{pmatrix} 1 & 0 \\ \lambda_{21} & 0 \\ 0 & 1 \\ 0 & \lambda_{42} \end{pmatrix}, \quad \xi_1 = \zeta_1,$$

then all parameters are identifiable in terms of the covariance matrix among the X variables. Since the covariance matrix among the X variables contains ten unique elements, and the model has only nine unknown parameters, there is 1 degree of freedom to test the constraint

$$\text{cov}(x_1x_4)\ \text{cov}(x_2,x_3) = \text{cov}(x_1x_3)\ \text{cov}(x_2x_4) \qquad (8)$$

Estimates of the parameters may be calculated directly from the sample covariance matrix, but if we adopt the assumption that

$$\begin{pmatrix} \underset{\sim}{x} \\ \underset{\sim}{\xi} \\ \underset{\sim}{\zeta} \\ \underset{\sim}{\varepsilon} \end{pmatrix} \sim N\left(\left(\begin{pmatrix} \underset{\sim}{\mu}_x \\ \underset{\sim}{\mu}_\xi \\ \underset{\sim}{0} \\ \underset{\sim}{0} \end{pmatrix}, \begin{pmatrix} \underset{\sim}{\Sigma}_{xx} & \underset{\sim}{\Sigma}_{x\xi} & 0 & 0 \\ \underset{\sim}{\Sigma}_{\xi x} & \underset{\sim}{I} & 0 & 0 \\ 0 & 0 & \underset{\sim}{\Psi} & 0 \\ 0 & 0 & 0 & \underset{\sim}{\Theta}_\varepsilon \end{pmatrix}\right)\right),$$

where $\underset{\sim}{\Psi}$ and $\underset{\sim}{\Theta}_\varepsilon$ are diagonal (i.e., all errors are uncorrelated), then maximum likelihood estimates, as well as estimated asymptotic standard errors, may be obtained from general purpose computer packages such as LISREL (Joreskog and Sorbom, 1984) or LISCOMP (Muthen, 1988). Under these distributional assumptions, we will also be able to perform a likelihood ratio test of the constraint given in expression (8).

Parameter estimates were obtained using data from the second and third months of the Objective Yield Survey. One aspect of the data that should be kept in mind is that

mind is that month three data regarding length of the cob is available only for the plants that were the slowest to mature. If the crop was already mature at month three, which was the case for just over one half of the sample locations, the corn would have been harvested and no measurements would have been taken regarding length of the cobs. For the model as specified above, the maximum likelihood estimate of $\Psi_{2,2}$, the error variance of ξ_2 was negative by a small amount, so the additional specification $\Psi_{2,2} = 0$ was added. This model shows a poor fit, since the likelihood ratio statistic is 104.39 on two degrees of freedom. Such a poor fit is usually taken as an indication that correlation of errors across occasions is present (Kessler and Greenberg, 1981). Residuals given by the LISREL program suggest that the covariance between length of five kernel rows (P19) at month two and at month three is not very well replicated under the model. Unfortunately, the model could not be identified if the covariance among the measurement errors from months two to month three were specified as a free parameter for both length over husk (P18) and length of five kernel rows (P19). However, the model is just identified if the second covariance, between the measurement errors for X_2 and X_4, is a free parameter to be estimated. The estimate of this parameter is 0.505, indicating a correlation among the errors of about 0.4. We refer to the model with this covariance as a free parameter as model B. With one degree of freedom for the likelihood ratio test obtained from restraining $\Psi_{22}=0$ to avoid a negative value for the estimated variance, the fit of this modified model is $G^2=0.703$, df=1. For the other parameter estimates, the new values show a slight increase in the error variance for X_2 and X_4, with a corresponding decrease in the path regression coefficients from Λ_x. The measurement error variances are large under either specification for $\underset{\sim}{\Theta}_\varepsilon$.

These error variances correspond to the following

reliabilities:

$$\rho_{x1}^2 = \rho^2(\text{P18m2}) = 0.73$$

$$\rho_{x2}^2 = \rho^2(\text{P19m2}) = 0.16$$

$$\rho_{x3}^2 = \rho^2(\text{P18m3}) = 0.78$$

$$\rho_{x4}^2 = \rho^2(\text{P19m3}) = 0.16$$

Clearly, P18, average length over husk, appears to be the preferable measure. In assessing these results, it is important to keep in mind that measurement error encompasses not only errors that literally occur with a tape measure in the field, but also components of the measured variable that are unrelated to the true value. That is, there appears to be some systematic variance in length of kernel rows (x_2 and x_4) that is unrelated to average length over husk (x_1 and x_3), and may be unrelated to end-of-season grain weight. Psychometricians use the term parallel measurements for two variables if their latent variables are linearly dependent and their measurement errors are independent. Clearly length of kernel rows and average length over husk are not parallel measurements. An important difference between these two variables is that length of kernel rows, since it is a destructive measure, is taken on the first five ears <u>outside</u> the unit. Also, since the ears used for the measurement in month two are destroyed, length of kernel row has to be measured on a different five ears in month three. Apparently, these features of the variable affect its reliability significantly, vis-a-vis length over husk which is measured inside the unit. The correlation among the errors from month two and month three is difficult to explain, but could be due to a possible bias in the selection of ears outside the unit for the measurement of kernel row length. Model B appears to fit the data well, with a likelihood ratio statistic of 0.703 on 1 degree of freedom. Nevertheless, it is not necessarily the correct model. The error covariance between length over husk and length of kernel rows within month one or month two appear as zeros simply because they are not identified. Similarly, there may be significant covariance between the errors for length over husk from month one to month two, but that parameter is not identified in this model, either.

One reason for examining measurement errors is to assess their effect on parameter estimates used in forecasting models discussed in Section II. One way to approach this question is to introduce the end-of-season grain weight as a variable into the panel model, as shown in Figure 2. We refer to the model including end-of-season grain weight as model C. Since end-of-season grain weight has only one measurement, we must assume that it is measured without error, or equivalently, that the measurement error is absorbed into the disturbance term. In this model, we are able to specify that the covariances between the disturbance term for grain weight and the measurement errors for length of kernel rows are free parameters to be estimated. We also calculated covariance matrices for each year separately, and found evidence that these within-year covariance matrices are not equal. For some of the years (1980, 1983 and 1984), there were not enough observations to estimate separate models, but for the years 1979, 1981, 1982, and 1985, we were able to estimate a model using the separate within-year covariance matrices simultaneously, with some constraints on parameters across years. If all parameters were constrained to equality across years, the model showed a poor fit (G^2=84.34, df=47). If we allowed only error variances and covariances to be free across years, then the fit was satisfactory (G^2=26.07, df=23). Parameter estimates are shown by year in Table 2 under Model C. The largest difference across years occurs in 1982, where $\theta_{\epsilon 42}$ is much smaller than in the other years. Changes in error variances across years implies changes in reliability ratios. Reliability ratios are shown by year in Table 3. Average length over husk, month three, appears to be the most reliable measurement.

The correlations among disturbance and error terms is important for the asymptotic properties of estimators based on ordinary least squares. Judging from the estimates and standard errors shown in Table 2, the error covariances are significant, although their magnitudes are small. We might want to compare estimates for the $\underset{\sim}{\beta}$ parameters from the structural equations in this model to estimates when the three error covariances are fixed at zero. Under such restrictions, the fit of the model is poor, with G^2=65.03 on 4 degrees of freedom, but the estimates for $\underset{\sim}{\beta}$ are affected only slightly: β_{21}=1.064 and β_{32}=0.057, as compared with the values 1.104 and 0.048 under model C. However, due to the identification conditions for the parameters in model C, the error covariances could not have a large effect on the beta parameters. For example, β_{32} is identified by $cov(x_1,x_5)/cov(x_1,x_3)$, which is not affected by serially correlated measurement error because the error covariances between variables x_1, x_3 and x_5 are not identified in the model. As we stated before, even though the model C fits well, it may still not be the correct model.

V. Conclusions

In this paper, we have used models of month to month changes to assess measurement errors in the Objective Yield Survey. Although measurement error incorporates errors made during data collection, such as miscounts, judging from the results for number of ears with kernels over months two to four, such errors appear to be minimal during the Objective Yield Survey. Measurement error can also incorporate other variability in an observed variable that is unrelated to the associated latent variable. During each month of the Objective Yield Survey, ideal measurements would be the number of ears that will have kernels at the end of the season and the average grain weight of these ears. Grain weight is inherently more difficult to measure, because the ear of corn must be destroyed to make the measurement, and so proxy variables must be used instead. Counting ears that will develop to full maturity is subject to large errors at the beginning of the season, because development of ears is very unstable at that time.

Indicators for size of ear were studied over months two and three, when month to month values are fairly stable. Length over cob, measured on the same plants over time, appears to have a reasonably high reliability ratio of 0.76. Length of kernel row is measured outside the unit, so variability of month to month changes in the panel model includes plant to plant variability, although it would still not include field to field variability. However, plant variability is apparently quite high, since the reliability ratio of length of kernel row is much lower.

When the objective is prediction, the deleterious effects of measurement error may not be severe. If the prediction is for X_{n+1}, a random element from the same distribution as the other X and Y values, and X and Y are bivariate normal, then the optimal prediction of Y_{n+1} is given by ordinary least squares estimators even in the presence of non-zero covariance between the equation error and the measurement error. However, sometimes when predicting to a new year, the new X observation could be considered to be from a different population. Severe weather conditions and technological changes can produce year to year differences. With a new population, there may be circumstances under which it is desirable to give a prediction which would be conditional on the predictor without error. (See Fuller, 1987, p. 74-79.) Under any circumstances, however, the measurement of length of kernel row would benefit if the monthly sample size per field was increased over the five ears presently used. A larger sample of ears would lead to a reduction in the standard error for the estimated regression coefficient, which would lead to a reduction in the standard error of the forecast.

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TABLE I
Availability of Variables
by Month
(Number of Observations)

Variable	Month 1	2	3	4
(P14)	702	1212	1405	NA
(P15)	714	1212	1405	NA
(P16)	714	1212	1405	NA
(P17)	NA	1196	1405	1405
(P18)	NA	1191	687	NA
(P19)	NA	1192	697	NA

TABLE 2

b) Parameter Estimates for Two Variable, Two Wave Models

Model C

	1979 Estimate	(s.e.)	1981
β_{21}	1.143	(0.086)	Constrained
β_{32}	0.043	(0.004)	to equality
λ_{21}	0.570	(0.083)	across
λ_{42}	0.488	(0.069)	years
$\Psi_{11}(=\Phi_{11})$	0.420	(0.047)	
Ψ_{22}	0.0	(fixed)	
$\theta_{\varepsilon 11}$	0.360	(0.061)	0.257 (0.052)
$\theta_{\varepsilon 22}$	1.275	(0.153)	1.869 (0.247)
$\theta_{\varepsilon 33}$	0.152	(0.057)	0.087 (0.051)
$\theta_{\varepsilon 44}$	1.115	(0.134)	1.105 (0.147)
$\theta_{\varepsilon 42}$	0.439	(0.109)	0.722 (0.151)
$\theta_{\varepsilon 52}$	0.022	(0.006)	0.013 (0.008)
$\theta_{\varepsilon 54}$	0.019	(0.006)	0.022 (.006)
Ψ_{33} $(=\theta_{\varepsilon 55})$	0.004	0.0005	0.004 (.0005)

	1982		1985	
$\theta_{\varepsilon 11}$	0.279	(0.048)	0.149	(0.041)
$\theta_{\varepsilon 22}$	0.883	(0.105)	1.406	(0.186)
$\theta_{\varepsilon 33}$	0.137	(0.049)	0.145	(0.051)
$\theta_{\varepsilon 44}$	0.990	(0.117)	1.006	(0.134)
$\theta_{\varepsilon 42}$	0.090	(0.079)	0.563	(0.124)
$\theta_{\varepsilon 52}$	0.000	(0.004)	0.022	(0.007)
$\theta_{\varepsilon 54}$	0.013	(0.005)	0.013	(0.005)
Ψ_{33} $(=\theta_{\varepsilon 55})$	0.003	(0.0004)	0.003	(.0004)

$G^2=26.07$
df=23

TABLE 3

c) Reliability Ratios by Year

	P18M2	P19M2	P18M3	P19M3
1979	0.488	0.066	0.746	0.056
1981	0.641	0.045	0.870	0.101
1982	0.560	0.107	0.798	0.095
1985	0.770	0.175	0.816	0.208

FIGURE 1

Single Indicator Model for Number of Ears with Kernels (P17)

n = 620

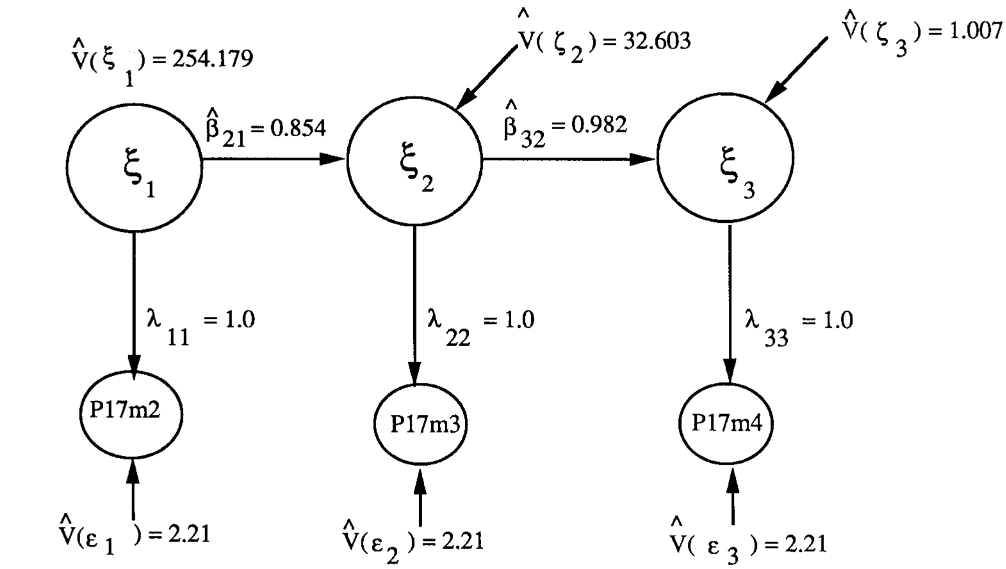

FIGURE 2

MODEL INCLUDING GRAIN WEIGHT (P42)

n = 604