First, fields are chosen at random so that the probability of any given field being included in the sample is proportional to the size of that field. Larger fields have a higher probability of being selected and may be selected more than once in the sample. Selected fields are numbered from one to \( N \), where \( N \) is the total number of samples in the state.

In the second step in selecting the Objective Yield sample, selected fields are visited and two plots are randomly located within each field. The plots are estimated separately for the Objective Yield Survey and each will be fifteen feet long and will contain two rows of corn. The size of these sampling units depends on the amount of space between the two rows of corn.

A maturity stage is assigned to each sample field. Maturity stage ranges from one to seven and indicates the stage of growth of the corn. Maturity stage one indicates stalks without silked ear shoots, and maturity stage seven indicates corn ready for harvest.

### III. CURRENT METHODS - THE ORDINARY LEAST SQUARES MODEL

#### 3.1 Introduction

Estimation in corn yield surveys involves two components: number of ears and average grain weight per ear. As the corn grows through the season, it is classified into various maturity stages. For each maturity stage, the two components are estimated separately and then combined to give an estimate of gross yield. In the forecast for gross yield, number of ears and grain weight may be taken from either a historical average, a predicted value, or an actual value, according to maturity stage of the corn.

#### 3.4. Forecasting models

Let

\[
\hat{Y}_{ij}^N = \text{predicted number of ears for sample location } ij \text{ when the corn is at maturity stage } m, \\
\hat{Y}_{ij}^W = \text{predicted grain weight for sample location } ij \text{ when the corn is at maturity stage } m,
\]

A. Predicted number of ears \((m = 1 \text{ to } 4 \text{ only})\)

Two forecast models are used for number of ears:

\[
\hat{Y}_{ij}^N = a + b_{i,j}m_{ij} \quad (m = 1, 2, 3, 4)
\]

and

\[
\hat{Y}_{ij}^N = a' + b_{i,j}m_{ij}X_{2ij} \quad (m = 2, 3, 4)
\]

### II. THE JUNE ENUMERATIVE AND OBJECTIVE YIELD SURVEYS

The June Enumerative Survey (JES) is conducted by NASS every year in each of the forty-eight contiguous states during late May and early June. The purpose of the survey is to collect information on land use. Area sampling frames are developed individually for each state based on the land use, economy, and agricultural practices of that state.

From the JES data, the number of acres within a state planted to corn and to be planted to corn can be estimated and locations of sample acres can be determined. This information is then used to develop a sampling frame for the Objective Yield Survey. Selection of the Objective Yield sample is a two-step process. In the

1Now at Arizona State University
where

\[ X_1 = \text{number of stalks} \]
\[ X_2 = \text{number of ears and silked ear shoots} \]
\[ X_3 = \text{number of stalks with ears or silked ear shoots} \]

B. Predicted grain weight (M = 3 to 6 only).

Two forecast models are used for grain weight also:

\[ Y_{wijm} = \hat{a}_m + \hat{b}_m X_{4ijm} \quad (m = 3, 4, 5, 6) \]

and

\[ Y'_{wijm} = \hat{a}'_m + \hat{b}'_m X_{5ijm} \quad (m = 3, 4, 5, 6) \]

where

\[ X_4 = \text{total kernel row length.} \]
\[ X_5 = \text{average length over husk.} \]

When two forecast models exist for \( Y_N \) or \( Y_W \), a single value is obtained from a weighted combination. The final predictors for number of ears and grain weight for each sample location are as follows:

\[ \hat{Y}_{ijm} = \begin{cases} \hat{Y}_{Nijm} & \text{if } m = 1 \\ \frac{C_1\hat{Y}_{Nijm} + C_2\hat{Y}_{Wijm}}{C_1 + C_2} & \text{if } m = 2, 3, 4 \end{cases} \]

\[ \hat{Y}_{wijm} = \begin{cases} \hat{Y}_{Wijm} & \text{if } m = 1 \text{ or } 2 \\ \frac{C_1\hat{Y}_{Wijm} + C_2\hat{Y}_{Wijm}}{C_1 + C_2} & \text{if } m = 3, 4, 5 \text{ or } 6 \end{cases} \]

where \( C_1 \) is a function of \( R^2 \) for model 1, and \( C_2 = 1 - C_1 \).

Then the predicted gross yield per sample unit is calculated as

\[ \hat{Y}_{ijm} = \begin{cases} \hat{Y}_{Nijm} & \text{if } m = 1, 2 \\ \hat{Y}_{Nijm} \hat{Y}_{Wijm} & \text{if } m = 3, 4 \\ \hat{Y}_{Nijm} \hat{Y}_{Wijm} & \text{if } m = 5, 6 \end{cases} \]

and the predicted gross yield per sample field is given by

\[ \hat{Y}_{ijm} = Y_{ijm} S_{ij}^{-1} \quad \text{for } m=1, \ldots, 6 \]

where

\[ S_{ij} = \text{8-row space for field } ij \]

The 8-row space is unit 1 four row width plus unit 2 four row width. \( K \) is a constant conversion factor used to adjust gross yield for the sample units to "Bushels per acre":

\[ K = (CD)^{-1}AB = 103.714 \]

where

\[ A = \text{the number of square feet per acre} = 43560 \]
\[ B = \text{conversion for 1 60-foot row measurement to 8 row equivalent} \]
\[ C = \text{the combined length of 2 sample units} \]
\[ = (4 \text{ rows} \times 15 \text{ feet}) = 60 \]
\[ D = \text{bushels per pound} = 56 \]

C. Estimation

Under the procedures presently used by the National Agricultural Statistics Service, ordinary least squares is used to obtain the estimated intercept and slope parameters in the forecast equations. The forecasts for year \( i* \) are based upon the pooled data from the previous five years, years \( i^* - 5 \) to \( i^* - 1 \).

The ordinary least squares error structure is also assumed, which implies that the \( Y_{ijm} \) observation for year \( i \) and treated as independent. As will be discussed later, this is probably not a realistic assumption. We note the following points regarding the predictors for grain weight and number of ears:

(1) The predictor for \( Y_N \) under maturity classes 2, 3, and 4 is ill-advised because \( R^2 \) for \( Y_N \) is not comparable to \( R^2 \) for \( Y'_{N} \). The former is in units of number of ears, while the latter is in the units of the ratio of number of ears to number of stalks. A higher \( R^2 \) for one model does not mean it is a better predictor than the other.

(2) As mentioned previously, it is not realistic to assume that observations within years are independent, because they share many influences, such as weather, that are not shared by observations across years.

(3) \( \hat{Y}_{N} \) for maturity classes 2 to 4, and \( \hat{Y}_{W} \) for maturity classes 3 to 6 are not Best Linear Unbiased. The Best Linear Unbiased Estimator of grain weight from two predictors is
A Best Linear Unbiased Estimator of number of ears that corresponds to $Y_{N}^{(1)}$ would be

$$
\hat{Y}_{Wijm} = \hat{a} + \hat{b}_1 X_{4ijm} + \hat{b}_2 X_{54ijm} + \hat{b}_3 X_{3i} + \hat{b}_4 X_{1ijm} X_{3ijm}.
$$

A Best Linear Unbiased Estimator of number of ears that corresponds to $Y_{N}^{(1)}$ would be

$$
\hat{Y}_{Wijm} = \hat{a} + \hat{b}_1 X_{4ijm} + \hat{b}_2 X_{54ijm} + \hat{b}_3 X_{3i} + \hat{b}_4 X_{1ijm} X_{3ijm}.
$$

A Best Linear Unbiased Estimator of number of ears that corresponds to $Y_{N}^{(1)}$ would be

$$
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$$

A Best Linear Unbiased Estimator of number of ears that corresponds to $Y_{N}^{(1)}$ would be

$$
\hat{Y}_{Wijm} = \hat{a} + \hat{b}_1 X_{4ijm} + \hat{b}_2 X_{54ijm} + \hat{b}_3 X_{3i} + \hat{b}_4 X_{1ijm} X_{3ijm}.
$$

IV. COMPONENTS OF VARIANCE MODEL WITH NESTED ERROR

The forecasting models described in the previous sections assumed an ordinary least squares error structure for observations that are pooled from the five years preceding the current crop year. A more realistic model would specify that observations within years are correlated, since they are subject to many of the same influences such as weather.

In the preceding discussion, $Y_{W}$ was used as a symbol for grain weight, $Y_{N}$ was the symbol for number of ears, and $Y$ was the symbol for gross yield. We now use $Y$ as a generic dependent variable, so that it may represent grain weight, number of ears, or gross yield. A model with dependence among observations within years can then be written as follows:

$$
Y_{ijm} = X_{ijm} \beta + u_{ijm}, \quad i = 1, \ldots, h; \quad j = 1, \ldots, n_i
$$

$$
u_{ijm} = v_{im} + e_{ijm}
$$

where

$Y_{ijm}$ = the value for the dependent variable at sample location $ij$ when the corn is at maturity stage $m$.

$X_{ijm}$ = a row vector of independent variables for the $j$-th field in year $i$ at maturity stage $m$.

$\beta$ = a row vector of coefficients from a GLS regression and

$e_{ijm}$ = intrinsic error, and

$v_{im}$ = random effect for year $i$, maturity stage $m$.

The error in the equation for the $ij$-th observation is the sum of the random year effect, $v_{im}$, and the intrinsic error, $e_{ijm}$.

The $v_{im}$ are assumed to be distributed $\text{NID}(0, \sigma^2_{vm})$, the $e_{ij}$ are distributed $\text{NID}(0, \sigma^2_{em})$, and the $e_{ijm}$'s are independent of the $v_{im}$'s for all $ij$.

The covariance structure of the $u_{ijm}$'s has the form

$$
\text{E}(u_{ijm} u_{kjm}) = \begin{cases} 
\sigma^2_{vm} & \text{if } i=k \text{ and } j=k, \\
\sigma^2_{em} & \text{if } i=\ell \text{ and } j=k, \\
0 & \text{if } i=\ell.
\end{cases}
$$

Under the ordinary least squares models of the preceding sections, the $v_{im}$ are all assumed to be zero, which gives an error covariance matrix of $\sigma^2_{vm}. \text{ For the nested error model, it follows that the error covariance matrix for corn at maturity stage } m \text{ is block diagonal, with diagonal element } V_{im}(i=1, \ldots, h) \text{ given by:}

$$
V_{im} = \sigma^2_{vm} n_{im} + \sigma^2_{em} J_{n_{im}}
$$

where $I_{n_{im}}$ is an $n_{im} \times n_{im}$ identity matrix and $J_{n_{im}}$ is an $n_{im} \times n_{im}$ matrix of ones.

This nested error model is closely related to models developed by Battese and Fuller (1982) and Battese, Harter, and Fuller (1986) for small area estimation.

4.1. Prediction for Cluster Means

The prediction of cluster means is often of interest. For a particular time in year $i$ we may be interested in the prediction for corn that is at maturity stage $m$. The mean for such corn would be given by:

$$
\bar{Y}_{i,m} = \bar{X}_{i,m} \beta + v_{im}, \quad i = 1, 2, \ldots, h
$$

where

$\bar{X}_{i,m}$ = $n_{im}^{-1}(\sum_{j=1}^{n_{im}} X_{ijm})$ is a $k \times 1$ vector.

$n_{im}$ = number of sample locations at maturity stage $m$ at the particular time of interest

$\bar{X}_{i,m}$ = the $k \times 1$ vector of coefficients from a GLS regression and

$\bar{Y}_{i,m}$ = the year effect.

If $\bar{X}_{i,m}$, $\beta$, $\sigma^2_{vm}$ and $\sigma^2_{em}$ are assumed known,

$\bar{Y}_{i,m}$ can be written as

$$
\bar{Y}_{i,m} = \bar{X}_{i,m} \beta + v_{im} - \bar{v}_{i,m} \beta.
$$

where

$\bar{u}_{i,m} = \bar{Y}_{i,m} - \bar{X}_{i,m} \beta$. 

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The mean squared error for this predictor is

$$E[(\hat{y}_m - \bar{y}_m)^2] = (1 - \delta_m^2)\sigma_m^2 + \delta_m^2(\sigma_m^2/\nu_m).$$

Using this mean squared error and the usual method of differentiation, one obtains the following value of $\delta_m$ that will give the minimum mean squared error:

$$\delta_m = \frac{\sigma_m^2}{\nu_m + (\sigma_m^2/\nu_m)}.$$  

The preceding derivations assumed that $\sigma_m^2$ and $\nu_m^2$ were known. In practice, they usually are not known and must be estimated.

If we let $\bar{y}_m$ be the mean for corn that is observed at maturity stage $m$ at a certain time during the current year, then we know that

$$\bar{y}_m = \hat{\beta}_m X_m + \bar{v}_m.$$  

Since the mean of $\nu_m$ is assumed to be zero, the best linear predictor for $\bar{y}_m$ is given by

$$\hat{y}_m = \hat{\beta}_m X_m + \bar{v}_m,$$

where $\hat{\beta}_m$ is the best linear unbiased estimator of $\beta_m$.

The predictor has, approximately, the following mean squared error:

$$E[(\hat{y}_m - \bar{y}_m)^2] = \hat{\beta}_m^2 V(\hat{\beta}_m X_m) + \sigma_m^2.$$  

V. Results

Tables 3 and 4 show the generalized least squares estimates for the nested error model. There is little difference in the parameters or their standard errors under ordinary least squares estimation. Table 3 and 4 also show estimates for the components of variance. We can use these estimates to estimate the multiplier of $\nu_m$ that gives the year effect. These estimates are given in Table 2.

For grain weight, the multiplier is nearly 1.0 except in maturity category three, where frequencies are relatively low. For number of ears, the multiplier is lower, indicating less year to year variation in the equation error. The same information can be presented as the intraclass correlation, which gives the percent of the total error variance that is due to year to year variation:

$$\rho_m = \frac{\sigma_m^2}{\sigma_m^2 + \sigma_{\nu_m}^2}.$$  

The intraclass correlations are given in Tables 3 and 4. Once again, the year to year effect is much more substantial for grain weight than number of ears. $\rho_m$ ranges from 0.14 to 0.43 for grain weight, and from 0.02 to 0.10 for number of ears. They are directly comparable for maturity category four, where 2/3 of the equation error for grain weight is due to year variation, while only 2% is year variation for number of ears.

The error in a forecast for the current crop year is approximately,

$$E[(\hat{y}_m - \bar{y}_m)^2] = \hat{\beta}_m^2 V(\hat{\beta}_m X_m) + \sigma_m^2.$$  

Since we can always reduce $\hat{\beta}_m^2$ by including more years or more sample locations, $\sigma_m^2$ represents a lower bound on the error of the forecast. If we use $2\sigma_m^2$ has the half-width of an interval, we can compare the mean actual values to the mean predicted values given in Table 1. With this procedure, we find that the mean predicted value is already within this distance of the true value except for number of ears at both maturity values two and three. Although these forecasting results are for only one year, it appears that the sampling of additional locations would not improve the forecast for grain weight based on plant characteristics - the error of the forecast is already within the immutable limit determined by year to year variation.

In the forecast for number of ears from the August Objective Yield Survey, only one-half of the sample locations are visited (approximately 120). This means that there is a lower number of observations for maturity classes one and two, and since $Y_{N \hat{m}}$ is further than $2\sigma_{\nu_m}$ from $Y_{N \hat{m}}$, a significant improvement in the precision of the forecast at maturity stage two should result if the number of sample locations is increased.

REFERENCES


Table 1 Predicted and Actual Means by Maturity Class

<table>
<thead>
<tr>
<th>Grain weight</th>
<th>Number of ears</th>
<th>Gross yield</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual mean</td>
<td>Predicted mean</td>
<td>Actual mean</td>
</tr>
<tr>
<td>m n</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 26</td>
<td>$\bar{Y}_W = 0.30$</td>
<td>$\bar{Y}_N = 0.37$</td>
</tr>
<tr>
<td>2 71</td>
<td>$\bar{Y}_W = 0.34$</td>
<td>$\bar{Y}_N = 0.37$</td>
</tr>
<tr>
<td>3 4</td>
<td>$\bar{Y}_W = 0.29$</td>
<td>$\bar{Y}_N = 0.33$</td>
</tr>
<tr>
<td>4 104</td>
<td>$\bar{Y}_W = 0.33$</td>
<td>$\bar{Y}_N = 0.33$</td>
</tr>
<tr>
<td>5 71</td>
<td>$\bar{Y}_W = 0.33$</td>
<td>$\bar{Y}_N = 0.33$</td>
</tr>
<tr>
<td>6 79</td>
<td>$\bar{Y}_W = 0.33$</td>
<td>$\bar{Y}_N = 0.33$</td>
</tr>
</tbody>
</table>

Table 2 $\delta_{im}$ by year

<table>
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<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
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<tbody>
<tr>
<td>Grain Weight</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>m = 3</td>
<td>0.90</td>
<td>0.79</td>
<td>0.84</td>
<td>0.94</td>
<td>0.79</td>
<td>0.75</td>
</tr>
<tr>
<td>m = 4</td>
<td>0.98</td>
<td>0.96</td>
<td>0.98</td>
<td>0.96</td>
<td>0.96</td>
<td>0.96</td>
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<td>m = 5</td>
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<td>0.97</td>
<td>0.97</td>
<td>0.96</td>
<td>0.96</td>
<td>0.96</td>
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<tr>
<td>m = 6</td>
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<td>0.95</td>
<td>0.96</td>
<td>0.92</td>
<td>0.94</td>
</tr>
<tr>
<td>Number of Ears</td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>m = 1</td>
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<td>0.62</td>
<td>0.75</td>
<td>0.74</td>
<td>0.64</td>
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<td>m = 2</td>
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<td>0.90</td>
<td>0.88</td>
<td>0.88</td>
<td>0.87</td>
</tr>
<tr>
<td>m = 3</td>
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<td>0.90</td>
<td>0.90</td>
<td>0.88</td>
<td>0.88</td>
<td>0.87</td>
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<tr>
<td>m = 4</td>
<td>0.76</td>
<td>0.62</td>
<td>0.75</td>
<td>0.74</td>
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<td>0.72</td>
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666
Table 3 Nested error regression models for number of ears by maturity stage

<table>
<thead>
<tr>
<th>Maturity stage</th>
<th>Number of observations</th>
<th>( b_0 )</th>
<th>( x_1 )</th>
<th>( x_2 )</th>
<th>( x_3 )</th>
<th>( (x_1/x_3)x_2 )</th>
<th>( \hat{\sigma}_v^2 )</th>
<th>( \hat{\sigma}_e^2 )</th>
<th>( \hat{\rho} )</th>
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</thead>
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<td>1</td>
<td>84</td>
<td>15.3*</td>
<td>0.771*</td>
<td></td>
<td></td>
<td></td>
<td>5.7432</td>
<td>50.181</td>
<td>0.103</td>
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<td></td>
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<td>(4.1)</td>
<td>(0.048)</td>
<td></td>
<td></td>
<td></td>
<td>(2.39)</td>
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<tr>
<td>2</td>
<td>409</td>
<td>8.6*</td>
<td>0.655*</td>
<td>-0.016</td>
<td>0.05</td>
<td>0.148*</td>
<td>7.0824</td>
<td>80.201</td>
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<td></td>
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<td>(2.6)</td>
<td>(0.083)</td>
<td>(0.086)</td>
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<td>(0.067)</td>
<td>(2.6)</td>
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<tr>
<td>3</td>
<td>44</td>
<td>6.5*</td>
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<td>-0.10</td>
<td>0.99</td>
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<td>0</td>
<td>19.409</td>
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</tr>
<tr>
<td></td>
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<td>(0.85)</td>
<td>(0.75)</td>
<td>(0.90)</td>
<td>(0.71)</td>
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<tr>
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<td>0.59428</td>
<td>24.531</td>
<td>0.0236</td>
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<tr>
<td></td>
<td></td>
<td>(1.3)</td>
<td>(0.31)</td>
<td>(0.26)</td>
<td>(0.31)</td>
<td>(0.25)</td>
<td>(.77)</td>
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</table>

*Significant at the 5% level.

Table 4 Nested error regression models for grain weight per ear by maturity stage

<table>
<thead>
<tr>
<th>Maturity stage</th>
<th>Number of observations</th>
<th>( b_0 )</th>
<th>( x_4 )</th>
<th>( x_5 )</th>
<th>( (x_4)(x_5) )</th>
<th>( \hat{\sigma}_v^2 )</th>
<th>( \hat{\sigma}_e^2 )</th>
<th>( \hat{\rho} )</th>
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<td>1</td>
<td>967</td>
<td>0.3681</td>
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<td></td>
<td></td>
<td>0.0026808</td>
<td>0.0035247</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>(0.0029)</td>
<td></td>
<td></td>
<td></td>
<td>(0.0027)</td>
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<tr>
<td>2</td>
<td>967</td>
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<td>(0.095)</td>
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<td>(0.0035)</td>
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<td>(0.00040)</td>
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<td>0.0119*</td>
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<td>(0.014)</td>
<td>(0.00043)</td>
<td>(0.00043)</td>
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</tr>
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<td>6</td>
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<tr>
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<td>(0.13)</td>
<td>(0.0036)</td>
<td>(0.015)</td>
<td>(0.00043)</td>
<td>(0.00043)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Significant at the 5% level.