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By

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Unbalanced Nested Component Error Model and the Value of Soil Insecticide and Bt Corn for Controlling Western Corn Rootworm

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Abstract

We describe four recently developed panel data estimators for unbalanced and nested data, a common problem for economic and experimental data. We estimate a western corn rootworm damage function with each estimator, including separate parameters for random effects from year, location, and experimental errors. We then use each estimator to assess the cost of the western corn rootworm soybean variant and the net benefit of soil insecticide and Bt corn for controlling this pest. At current prices, we find that soil insecticide generates a net loss ranging about $0.50-$3.25/ac, while Bt corn generates a net benefit ranging $2.50-$7.00/ac.

Keywords: *Diabrotica* spp., panel data, pest damage function, random effects, root rating, soybean variant.

Panel data methods have become increasingly popular for empirical research (Baltagi 2001; Solon 1989; Wooldridge 2002). Original panel data models assumed balanced panels, but in many empirical settings, cross sectional units are pooled over unequal time lengths, creating unbalanced (or incomplete) panels. In response, unbalanced panel regression methods have been developed as useful tools for applied analysis (Baltagi and Chang 1994; Biørn 2004; Searle 1987; Wansbeek and Kapteyn 1989). Following this work, many empirical studies have used unbalanced panel regression on a wide variety of topics (e.g., Druska and Horrace 2004; Evans 1998; Kniesner and Ziliak 2002).

In addition to being unbalanced, panel data in many empirical applications also exhibit a nesting structure—for example, micro-level firm data may be grouped by industry or location. In this case, controlling for group and sub-group effects requires a nested model. Though many econometric studies have explored the unbalanced panel application, few have focused on models that are both unbalanced and nested, which would allow identification and estimation of group and sub-group effects not possible in pure unbalanced panel models. Exceptions are Baltagi, Song, and Jung (2001) and Antweiler (2001), who developed single and double-nested unbalanced models respectively. However, the empirical investigation of these estimators is limited to the analysis in these papers. To help fill this void, we use Baltagi, Song, and Jung's (2001) unbalanced single-nested component error model to estimate a pest damage function.

Lichtenberg and Zilberman (1986) originally developed primal methods that use observed yield and pesticide application data to estimate production functions that implicitly incorporate pest damage functions. Alternatively, the approach we use here, experimental data can be used to directly estimate a pest damage function that determines

yield loss as a function of plant damage or pest density (Hurley, Mitchell, and Rice 2004; Mitchell et al. 2002; Mitchell, Gray, and Steffey 2004).

Experimental data are commonly nested—experiments are often conducted in different locations, with different hybrids, different pesticides, or different management regimes. Furthermore, missing data that create unbalanced panels are common—locations, hybrids, pesticides, and management regimes change over the course of the project, so that the number of replicates for each grouping variable is unequal. Thus, the unbalanced nested component error model developed by Baltagi, Song, and Jung (2001) can be useful for such data to estimate nested random effects with unbalanced panels.

Our first goal is to describe unbalanced nested panel data estimators and to illustrate their application by estimating a pest damage function. With unbalanced data, OLS regression coefficient estimates are still unbiased and consistent, but their standard errors are biased (Moulton 1986), so that incorrect conclusions may result concerning model structure and risk due to pest damage. Relative to OLS, the unbalanced nested component error model improves the accuracy of estimated standard errors, plus estimates the magnitude of random effects from factors such as location and year on the distribution of pest damage.

Our second goal is to assess the use of the component error model for estimating and removing the effect of experimental errors when estimating a pest damage function with experimental data. When using OLS to estimate a pest damage function with experimental data, a single error term is used that attributes all variability in yield loss to the pest. However, the component error model estimates random location and year effects separate from effects due to experimental errors, measurement errors, and similar

factors. As a result, after removing the effect of experimental errors, the damage function is still stochastic. This ability to separately estimate and remove desired variance components is important when using an estimated damage function for economic analysis, especially when assessing changes in risk from a pest or pest control input. Mitchell, Gray, and Steffey (2004) adapted a mixed distribution used for estimating technical efficiency to develop a composed error model for this same purpose. Hence, the component error model described here is also an alternative to their method.

We first present a general unbalanced nested random effects panel data model, and then describes four estimators for the regression coefficients and variance components based on the work of Baltagi, Song, and Jung (2001). We then estimate a western corn rootworm damage function as an empirical application and use it to assess the cost of the western corn rootworm soybean variant in Illinois and the net benefit of soil insecticide and Bt corn for controlling this pest. Finally, we compare this model to Mitchell, Gray and Steffey's (2004) method for estimating pest damage functions.

Unbalanced Nested Component Error Model

Grouping variables for panel data analysis of data from field experiments are usually clear. For example, data from field experiments can be grouped by year, location, crop, hybrid, or pesticide. If the data can be grouped by more than one such index, they are nested. For this description of the unbalanced nested error component model, the grouping variables are year $t = 1$ to T, location $l = 1$ to $L_t \; \forall t$, and replicate $r = 1$ to $R_t \; \forall t$. The data can be unbalanced in the index l and/or in the index r, i.e., have a different number of locations each year and/or a different number of replicates each year. Replication is part of standard experimental design, but field experiments often do not

have the same number of replicates across years and locations—replicates are lost because of weather events, accidents, and similar factors. The data can also become unbalanced in the nested index *l* (here location) because of changes in funding, technology, or the availability of labor or land.

The standard OLS regression model for estimating a pest damage function is:

$$y_{tlr} = \mathbf{x}_{tlr}'\boldsymbol{\beta} + u_{tlr}, \tag{1}$$

where y_{tlr} is yield loss, $\mathbf{x}_{tlr}$ is a K x 1 vector of regressors (e.g., pest population densities, pest damage measures), $\boldsymbol{\beta}$ is a K x 1 vector of regression coefficients to estimate, and u_{tlr} is an independent and identically distributed mean zero, variance σ_u^2 error. Thus OLS aggregates all experimental errors into the error term u and estimates its variance σ_u^2.

The nested error component model uses a component error for u_{tlr} so that

$$y_{tlr} = \mathbf{x}_{tlr}'\boldsymbol{\beta} + \mu_t + \nu_{tl} + \varepsilon_{tlr}. \tag{2}$$

Here, μ_t is the t^{th} unobservable random year effect, ν_{tl} is the unobservable nested random effect of the l^{th} location within the t^{th} year, and ε_{tlr} is the random disturbance. Each component of the error term is assumed to be independent and identically distributed, with zero mean and respective variances σ_μ^2, σ_ν^2, and σ_ε^2. Maximum likelihood estimation also assumes these components have a normal (Gaussian) distribution. Note, μ_t and ν_{tl} can be observable fixed effects, but the fixed effect estimator performs poorly when the ratio of either component error variance to the experimental error variance ($\sigma_\mu^2/\sigma_\varepsilon^2$, $\sigma_\nu^2/\sigma_\varepsilon^2$) is small (Baltagi 2001).

Before describing three ANOVA estimators and maximum likelihood estimation of the regression coefficients and the variance components, we first reformulate the model in matrix notation. The OLS regression model in equation (1) is

(3) $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{u}$,

where $\mathbf{y}$ is a N x 1 vector of yield losses, $\mathbf{X}$ is a N x K matrix of regressors, $\boldsymbol{\beta}$ is a K x 1 vector of regression coefficients, $\mathbf{u}$ is a N x 1 vector of disturbances, and $N = \sum_{t=1}^{T} L_t R_t$ is the number of observations. Following Baltagi, Song, and Jung (2001), write the component error term for equation (2) as:

(4) $\mathbf{u} = \mathbf{Z}_{\mu}\boldsymbol{\mu} + \mathbf{Z}_{\nu}\boldsymbol{\nu} + \boldsymbol{\varepsilon}$,

where $\boldsymbol{\mu}$ is a T x 1 vector of year effects, $\boldsymbol{\nu}$ is a L x 1 vector of location effects, and $\boldsymbol{\varepsilon}$ is an N x 1 vector of errors, i.e., $\boldsymbol{\mu}' = (\mu_1, \ldots, \mu_T)$, $\boldsymbol{\nu}' = (\nu_{11},\ldots,\nu_{1L_1},\ldots,\nu_{TL_T})$, and $\boldsymbol{\varepsilon}' = (\varepsilon_{111},\ldots,\varepsilon_{11R_1},\ldots,\varepsilon_{TL_TR_T})$, and $L = \sum_{t=1}^{T} L_t$. Also, $\mathbf{Z}_{\mu} = diag(\mathbf{l}_{L_t} \otimes \mathbf{l}_{R_t})$ and $\mathbf{Z}_{\nu} = diag(\mathbf{I}_{L_t} \otimes \mathbf{l}_{R_t})$, where $\mathbf{l}_{L_t}$ and $\mathbf{l}_{R_t}$ are L_t x 1 and R_t x 1 vectors of ones, $\mathbf{I}_{L_t}$ is a L_t x L_t identity matrix, $\otimes$ is the Kronecker product, $diag(\mathbf{l}_{L_t} \otimes \mathbf{l}_{R_t})$ is a block diagonal matrix with sub-matrices $\mathbf{l}_{L_1} \otimes \mathbf{l}_{R_1},\ldots,\mathbf{l}_{L_T} \otimes \mathbf{l}_{R_T}$ on its diagonal, and $diag(\mathbf{I}_{L_t} \otimes \mathbf{l}_{R_t})$ is a block diagonal matrix with sub-matrices $\mathbf{I}_{L_1} \otimes \mathbf{l}_{R_1},\ldots,\mathbf{I}_{L_T} \otimes \mathbf{l}_{R_T}$ on its diagonal. Thus, $\mathbf{Z}_{\mu}$ and $\mathbf{Z}_{\nu}$ are N x T and N x L block diagonal matrices, each with sub-vectors of ones of different lengths on their diagonals.

As Baltagi, Song, and Jung (2001) report, with this reformulation, the disturbance variance-covariance matrix $E[\mathbf{u}\mathbf{u}']$ is

(5) $\boldsymbol{\Omega} = diag[\sigma_{\mu}^2(\mathbf{J}_{L_t} \otimes \mathbf{J}_{R_t}) + \sigma_{\nu}^2(\mathbf{I}_{L_t} \otimes \mathbf{J}_{R_t}) + \sigma_{\varepsilon}^2(\mathbf{I}_{L_t} \otimes \mathbf{I}_{R_t})]$,

where $\mathbf{J}_{L_t} = \mathbf{l}_{L_t}\mathbf{l}_{L_t}'$ and $\mathbf{J}_{R_t} = \mathbf{l}_{R_t}\mathbf{l}_{R_t}'$ are L_t x L_t and R_t x R_t square matrices of ones and $\mathbf{\Omega}$ is a block diagonal matrix with t^{th} block $\mathbf{\Lambda}_t = \sigma_\mu^2(\mathbf{J}_{L_t} \otimes \mathbf{J}_{R_t}) + \sigma_\nu^2(\mathbf{I}_{L_t} \otimes \mathbf{J}_{R_t}) + \sigma_\varepsilon^2(\mathbf{I}_{L_t} \otimes \mathbf{I}_{R_t})$ $\forall\ t = 1$ to T. Baltagi, Song, and Jung (2001) decompose $\mathbf{\Lambda}_t$ as $\mathbf{\Lambda}_t = LR_t\sigma_\mu^2(\bar{\mathbf{J}}_{L_t} \otimes \bar{\mathbf{J}}_{R_t}) + R_t\sigma_\nu^2(\mathbf{I}_{L_t} \otimes \bar{\mathbf{J}}_{R_t}) + \sigma_\varepsilon^2(\mathbf{I}_{L_t} \otimes \mathbf{I}_{R_t})$, where $\bar{\mathbf{J}}_{L_t} = \mathbf{J}_{L_t} / L_t$, and $\bar{\mathbf{J}}_{R_t} = \mathbf{J}_{R_t} / R_t$. Substitute $\mathbf{E}_{L_t} = \mathbf{I}_{L_t} - \bar{\mathbf{J}}_{L_t}$ and $\mathbf{E}_{R_t} = \mathbf{I}_{R_t} - \bar{\mathbf{J}}_{R_t}$ into this equation and combine equivalent terms to decompose $\mathbf{\Lambda}_t$ as $\mathbf{\Lambda}_t = \lambda_{1t}\mathbf{Q}_{1t} + \lambda_{2t}\mathbf{Q}_{2t} + \lambda_{3t}\mathbf{Q}_{3t}$, where $\lambda_{1t} = \sigma_\varepsilon^2$, $\lambda_{2t} = R_t\sigma_\nu^2 + \sigma_\varepsilon^2$, $\lambda_{3t} = LR_t\sigma_\mu^2 + R_t\sigma_\nu^2 + \sigma_\varepsilon^2$, $\mathbf{Q}_{1t} = \mathbf{I}_{L_t} \otimes \mathbf{E}_{R_t}$, $\mathbf{Q}_{2t} = \mathbf{E}_{L_t} \otimes \bar{\mathbf{J}}_{R_t}$, and $\mathbf{Q}_{3t} = \bar{\mathbf{J}}_{L_t} \otimes \bar{\mathbf{J}}_{R_t}$.

Using this decomposition and definitions, Baltagi, Song, and Jong (2001) write:

(6) $$\mathbf{\Omega}^{-1} = diag[\lambda_{1t}^{-1}\mathbf{Q}_{1t} + \lambda_{2t}^{-1}\mathbf{Q}_{2t} + \lambda_{3t}^{-1}\mathbf{Q}_{3t} +],$$

and, defining $\theta_{1t} = 1 - \sigma_\varepsilon/(\lambda_{2t})^{0.5}$ and $\theta_{2t} = \sigma_\varepsilon/(\lambda_{2t})^{0.5} - \sigma_\varepsilon/(\lambda_{3t})^{0.5}$, they also write:

(7) $$\sigma_\varepsilon\mathbf{\Omega}^{-1/2} = diag[\mathbf{I}_{L_t} \otimes \mathbf{I}_{R_t}] - diag[\theta_{1t}(\mathbf{I}_{L_t} \otimes \bar{\mathbf{J}}_{R_t})] - diag[\theta_{2t}(\bar{\mathbf{J}}_{L_t} \otimes \bar{\mathbf{J}}_{R_t})].$$

Equation (7) allows generalized least squares (GLS) estimation of regression coefficients by pre-multiplying equation (3) by $\sigma_\varepsilon\mathbf{\Omega}^{-1/2}$ and using OLS. The variance of the estimated coefficients follows the GLS rule, so the variance-covariance matrix is $(\mathbf{X}'\mathbf{\Omega}^{-1}\mathbf{X})^{-1}$. Lastly, define the following N x N block diagonal matrices for later use:

(8) $$\mathbf{Q}_i = diag(\mathbf{Q}_{it}),\ i = 1 \text{ to } 3.$$

The OLS estimator $\hat{\boldsymbol{\beta}}_{OLS} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$ is still unbiased and consistent in unbalanced nested panel regression if the variance components are positive, but its standard errors are biased (Moulton 1986). Denote OLS residuals as $\hat{\mathbf{u}}_{OLS} = \mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}}_{OLS}$. Obtain the within (fixed effects) estimator by pre-multiplying equation (3) by $\mathbf{Q}_1$ and then using OLS. Pre-multiplying by $\mathbf{Q}_1$ removes μ_t and ν_{tl} whether they are fixed or

random effects, since $\mathbf{Q}_1\mathbf{u} = \mathbf{Q}_1(\mathbf{Z}_\mu\boldsymbol{\mu} + \mathbf{Z}_\nu\boldsymbol{\nu} + \boldsymbol{\varepsilon}) = \mathbf{Q}_1\boldsymbol{\varepsilon}$. Thus $\hat{\boldsymbol{\beta}}_{wtn}$, the $K-1$ vector of within coefficient estimates without the intercept, is

$$\hat{\boldsymbol{\beta}}_{wtn} = (\mathbf{X}_s'\mathbf{Q}_1\mathbf{X}_s)^{-1}\mathbf{X}_s'\mathbf{Q}_1\mathbf{y}, \tag{9}$$

where $\mathbf{X}_s$ is the N x $K-1$ matrix of regressors without the intercept. Within residuals are

$$\hat{\mathbf{u}}_{wtn} = \mathbf{y} - \hat{\alpha}_{wtn}\mathbf{l}_N - \mathbf{X}_s\hat{\boldsymbol{\beta}}_{wtn}, \tag{10}$$

where $\hat{\alpha}_{wtn} = \bar{\mathbf{y}} - \bar{\mathbf{X}}_s\hat{\boldsymbol{\beta}}_{wtn}$ is the within intercept estimate (bars indicate averaging) and $\mathbf{l}_N$ is a N x 1 vector of ones.

Unbalanced Nested Component Error Model Estimators

This section reports three ANOVA estimators and a maximum likelihood estimator for the regression coefficients $\boldsymbol{\beta}$ and the variance components σ_μ^2, σ_ν^2, and σ_ε^2. Baltagi, Yong, and Jung (2001) report derivations for each, so we only report formulas for use by practitioners. The ANOVA estimators are termed modified estimators because each extends a balanced panel estimator to the unbalanced case. Each estimator inserts variance components estimates into the variance-covariance matrix and uses GLS to estimate regression coefficients.

ANOVA Estimators

The modified Wansbeek and Kapteyn (1989) (WK) estimators are derived by equating transformations of the within residuals ($\hat{\mathbf{u}}_{wtn}'\mathbf{Q}_i\hat{\mathbf{u}}_{wtn}$ for i = 1 to 3) to their expected values and solving for the variance components, which gives:

$$\hat{\sigma}_\varepsilon^2 = \hat{\mathbf{u}}_{wtn}'\mathbf{Q}_1\hat{\mathbf{u}}_{wtn}/(N-L-K+1), \tag{11a}$$

$$\hat{\sigma}_\nu^2 = \left(\hat{\mathbf{u}}_{wtn}'\mathbf{Q}_2\hat{\mathbf{u}}_{wtn} - L + T - tr\{(\mathbf{X}_s'\mathbf{Q}_1\mathbf{X}_s)^{-1}(\mathbf{X}_s'\mathbf{Q}_2\mathbf{X}_s)\}\hat{\sigma}_\varepsilon^2\right)/(N-R), \tag{11b}$$

(11c) $$\hat{\sigma}_{\mu}^2 = \Big(\hat{\mathbf{u}}_{wtn}'\mathbf{Q}_3\hat{\mathbf{u}}_{wtn} - [T-1+tr\{(\mathbf{X}_s'\mathbf{Q}_1\mathbf{X}_s)^{-1}\mathbf{X}_s'\mathbf{Q}_3\mathbf{X}_s\}$$

$$-tr\{(\mathbf{X}_s'\mathbf{Q}_1\mathbf{X}_s)^{-1}\mathbf{X}_s'\overline{\mathbf{J}}_N\mathbf{X}_s\}]\hat{\sigma}_{\varepsilon}^2 - [R - L\textstyle\sum_{t=1}^{T} R_t^{\,2}/N]\hat{\sigma}_{v}^2\Big)\Big/\Big(N - L^2\textstyle\sum_{t=1}^{T} R_t^{\,2}/N\Big),$$

where $\mathbf{J}_N = \mathbf{l}_N\mathbf{l}_N'$ is an N x N matrix of ones, $\overline{\mathbf{J}}_N = \mathbf{J}_N / N$, and $R = \sum_{t=1}^{T} R_t$.

Substitute these variance components in the required equations to obtain $\sigma_{\varepsilon}\mathbf{\Omega}^{-1/2}$ in equation (7), then the GLS estimator with the modified WK variance components is

(12) $$\hat{\boldsymbol{\beta}}_{WK} = (\mathbf{X}'(\hat{\sigma}_{\varepsilon}\mathbf{\Omega}^{-1/2})'(\hat{\sigma}_{\varepsilon}\mathbf{\Omega}^{-1/2})\mathbf{X})^{-1}\mathbf{X}'(\hat{\sigma}_{\varepsilon}\mathbf{\Omega}^{-1/2})'\mathbf{y}.$$

Use equation (6) for $\mathbf{\Omega}^{-1}$, or use $\mathbf{\Omega}^{-1} = (\hat{\sigma}_{\varepsilon}\mathbf{\Omega}^{-1/2}/\hat{\sigma}_{\varepsilon})(\hat{\sigma}_{\varepsilon}\mathbf{\Omega}^{-1/2}/\hat{\sigma}_{\varepsilon})$. Standard errors are the square root of the diagonal elements of the variance-covariance matrix $(\mathbf{X}'\mathbf{\Omega}^{-1}\mathbf{X})^{-1}$.

The modified Swamy and Arora (1972) (SA) estimator uses residuals from three regressions. Specifically, multiply equation (3) by $\mathbf{Q}_i$ and obtain OLS residuals $\hat{\mathbf{u}}_i$ for i = 1 to 3. Again, transformations of these residuals ($\hat{\mathbf{u}}_i'\mathbf{Q}_i\hat{\mathbf{u}}_i$ for i = 1 to 3) are equated to their expected values and solved for the variance components, which gives:

(13a) $$\hat{\sigma}_{\varepsilon}^2 = \hat{\mathbf{u}}_{wtn}'\mathbf{Q}_1\hat{\mathbf{u}}_{wtn}/(N-L-K+1),$$

(13b) $$\hat{\sigma}_{v}^2 = \frac{\hat{\mathbf{u}}_2'\mathbf{Q}_2\hat{\mathbf{u}}_2 - (L-T-K+1)\hat{\sigma}_{\varepsilon}^2}{N-R-tr\{(\mathbf{X}_s'\mathbf{Z}_v\mathbf{Z}_v'\mathbf{Q}_2\mathbf{X}_s)(\mathbf{X}_s'\mathbf{Q}_2\mathbf{X}_s)^{-1}\}},$$

(13c) $$\hat{\sigma}_{\mu}^2 = \frac{\hat{\mathbf{u}}_3'\mathbf{Q}_3\hat{\mathbf{u}}_3 - (T-K)\hat{\sigma}_{\varepsilon}^2 - [R - tr\{[\mathbf{X}'\mathbf{Z}_v\mathbf{Z}_v'\mathbf{Q}_3\mathbf{X})(\mathbf{X}'\mathbf{Q}_3\mathbf{X})^{-1}\}]\hat{\sigma}_{v}^2}{N - tr\{(\mathbf{X}'\mathbf{Z}_{\mu}\mathbf{Z}_{\mu}'\mathbf{X})(\mathbf{X}'\mathbf{Q}_3\mathbf{X})^{-1}\}}.$$

Because $\hat{\mathbf{u}}_1 = \hat{\mathbf{u}}_{wtn}$, the SA estimator for σ_{ε}^2 is the same as for the WK estimator. Also, the same GLS procedure gives the regression coefficients $\hat{\boldsymbol{\beta}}_{SA}$ and their standard errors.

This modification of the Henderson Method III estimator developed by Fuller and Battese (1973) (HFB), uses three different residuals, specifically $\hat{\mathbf{u}}_{wtn}$, $\tilde{\mathbf{u}}_2$, and $\hat{\mathbf{u}}_{OLS}$,

where $\tilde{\mathbf{u}}_2$ are the OLS residuals after pre-multiplying equation (3) by ($\mathbf{Q}_1$ + $\mathbf{Q}_2$). Again, transformations of these residuals are equated to their expected values and solved for the variance components, which gives:

(14a) $\hat{\sigma}_\varepsilon^2 = \hat{\mathbf{u}}_{wtn}'\mathbf{Q}_1\hat{\mathbf{u}}_{wtn}/(N-L-K+1)$,

(14b) $$\hat{\sigma}_v^2 = \frac{\tilde{\mathbf{u}}_2'\tilde{\mathbf{u}}_2 - (N-T-K+1)\hat{\sigma}_\varepsilon^2}{N-R-tr\{(\mathbf{X}_s'\mathbf{Z}_v\mathbf{Z}_v'\mathbf{Q}_2\mathbf{X}_s)[\mathbf{X}_s'(\mathbf{Q}_1+\mathbf{Q}_2)\mathbf{X}_s]^{-1}\}},$$

(14c) $$\sigma_\mu^2 = \frac{\hat{\mathbf{u}}_{OLS}'\hat{\mathbf{u}}_{OLS} - (N-K)\sigma_\varepsilon^2 - \{N-tr[(\mathbf{X}'\mathbf{Z}_v\mathbf{Z}_v'\mathbf{X})(\mathbf{X}'\mathbf{X})^{-1}]\}\sigma_v^2}{N-tr\{(\mathbf{X}'\mathbf{Z}_\mu\mathbf{Z}_\mu'\mathbf{X})(\mathbf{X}'\mathbf{X})^{-1}\}}$$

Again, $\hat{\sigma}_\varepsilon^2$ is the same as for the WK and SA estimators and the same GLS procedure gives the regression coefficients $\hat{\boldsymbol{\beta}}_{HFB}$ and their standard errors.

Maximum Likelihood Estimation

Following Baltagi, Song, and Jung (2001), define $\boldsymbol{\Omega} = \sigma_\varepsilon^2\boldsymbol{\Sigma}$ and the variance ratios $\rho_1=\sigma_\mu^2/\sigma_\varepsilon^2$ and $\rho_2=\sigma_v^2/\sigma_\varepsilon^2$. Rearranging equation (5) with these definitions gives $\boldsymbol{\Sigma} = \boldsymbol{\Omega}/\sigma_\varepsilon^2 = diag[\mathbf{Q}_{1t} + (R_t\rho_2 + 1)\mathbf{Q}_{2t} + (2R_t\rho_1 + R_t\rho_2 + 1)\mathbf{Q}_{3t}]$, which implies

(15) $$\boldsymbol{\Sigma}^{-1} = diag[\mathbf{Q}_{1t} + \frac{1}{(R_t\rho_2+1)}\mathbf{Q}_{2t} + \frac{1}{(2R_t\rho_1 + R_t\rho_2 + 1)}\mathbf{Q}_{3t}].$$

The log-likelihood function after removing constants is (Baltagi, Song, and Jung 2001):

(16) $$\ln L(\cdot) = -\frac{N}{2}\ln\sigma_\varepsilon^2 - \frac{1}{2}\sum_{t=1}^{T}(L_tR_t\rho_1 + R_t\rho_2 + 1)$$

$$-\frac{1}{2}\sum_{t=1}^{T}(L_t-1)\ln(R_t\rho_2+1) - \frac{1}{2}\mathbf{u}'\boldsymbol{\Sigma}^{-1}\mathbf{u}/2\sigma_\varepsilon^2.$$

Solving first order conditions for $\boldsymbol{\beta}$ and σ_ε^2 as functions of ρ_1 and ρ_2 gives:

(17a) $$\hat{\boldsymbol{\beta}}_{ML} = (\mathbf{X}'\boldsymbol{\Sigma}^{-1}\mathbf{X})^{-1}\mathbf{X}'\boldsymbol{\Sigma}^{-1}\mathbf{y},$$

(17b) $$\hat{\sigma}_{\varepsilon}^{2} = (\mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}}_{ML})'\boldsymbol{\Sigma}^{-1}(\mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}}_{ML}) / N .$$

First order conditions for ρ_1 and ρ_2 then implicitly define ρ_1 and ρ_2, given $\boldsymbol{\beta}$ and σ_{ε}^{2}:

(18a) $$\frac{\partial \ln L(\cdot)}{\partial \rho_1} = -\frac{1}{2} tr(\mathbf{Z}_{\boldsymbol{\mu}}'\boldsymbol{\Sigma}^{-1}\mathbf{Z}_{\boldsymbol{\mu}}) + \frac{1}{2\sigma_{\varepsilon}^{2}}(\mathbf{y} - \mathbf{X}\boldsymbol{\beta})'\boldsymbol{\Sigma}^{-1}\mathbf{Z}_{\boldsymbol{\mu}}\mathbf{Z}_{\boldsymbol{\mu}}'\boldsymbol{\Sigma}^{-1}(\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) = 0,$$

(18b) $$\frac{\partial \ln L(\cdot)}{\partial \rho_2} = -\frac{1}{2} tr(\mathbf{Z}_{\mathrm{v}}'\boldsymbol{\Sigma}^{-1}\mathbf{Z}_{\mathrm{v}}) + \frac{1}{2\sigma_{\varepsilon}^{2}}(\mathbf{y} - \mathbf{X}\boldsymbol{\beta})'\boldsymbol{\Sigma}^{-1}\mathbf{Z}_{\mathrm{v}}\mathbf{Z}_{\mathrm{v}}'\boldsymbol{\Sigma}^{-1}(\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) = 0.$$

Solving first order conditions (18) for the variance ratios ρ_1 and ρ_2 requires a numerical method since no analytical solution exists. We summarize the Fisher scoring procedure described by Baltagi, Song, and Jung (2001).

Beginning with initial values of $\hat{\rho}_1$ and $\hat{\rho}_2$, calculate updated values as follows:

(19) $$\begin{bmatrix} \hat{\rho}_1 \\ \hat{\rho}_2 \end{bmatrix}_{j+1} = \begin{bmatrix} \hat{\rho}_1 \\ \hat{\rho}_2 \end{bmatrix}_{j} + \begin{bmatrix} \mathrm{E}\left[-\frac{\partial^2 \ln L(\cdot)}{\partial \rho_1^{\,2}} \right] & \mathrm{E}\left[-\frac{\partial^2 \ln L(\cdot)}{\partial \rho_1 \partial \rho_2} \right] \\ \mathrm{E}\left[-\frac{\partial^2 \ln L(\cdot)}{\partial \rho_1 \partial \rho_2} \right] & \mathrm{E}\left[-\frac{\partial^2 \ln L(\cdot)}{\partial \rho_2^{\,2}} \right] \end{bmatrix}_{j}^{-1} \begin{bmatrix} \frac{\partial \ln L(\cdot)}{\partial \rho_1} \\ \frac{\partial \ln L(\cdot)}{\partial \rho_2} \end{bmatrix}_{j}.$$

The subscript *j* denotes the iteration. Equations (18) give the elements of the gradient vector using equations (17) for $\hat{\boldsymbol{\beta}}_{ML}$ and $\hat{\sigma}_{\varepsilon}^{2}$. The elements of the information matrix are:

(20a) $$\mathrm{E}\left[-\frac{\partial^2 \ln L(\cdot)}{\partial \rho_1^{\,2}} \right] = \frac{1}{2}\sum_{t=1}^{T} \frac{(2R_t)^2}{(1 + \rho_2 R_t + 2\rho_1 R_t)^2},$$

(20b) $$\mathrm{E}\left[-\frac{\partial^2 \ln L(\cdot)}{\partial \rho_1 \rho_2} \right] = \frac{1}{2}\sum_{t=1}^{T} \frac{2R_t^{\,2}}{(1 + \rho_2 R_t + 2\rho_1 R_t)^2},$$

(20c) $$\mathrm{E}\left[-\frac{\partial^2 \ln L(\cdot)}{\partial \rho_2^{\,2}} \right] = \frac{1}{2}\sum_{t=1}^{T} \frac{R_t^{\,2}}{(1 + \rho_2 R_t)^2} + \frac{1}{2}\sum_{t=1}^{T} \frac{R_t^{\,2}}{(1 + \rho_2 R_t + 2\rho_1 R_t)^2}.$$

Iteration continues until the values of $\hat{\rho}_1$ and $\hat{\rho}_2$ converge, then the associated $\hat{\boldsymbol{\beta}}_{ML}$ and $\hat{\sigma}_\varepsilon^2$ can be determined. Standard errors for the regression coefficients are the square root of the diagonal elements of the variance-covariance matrix $\hat{\sigma}_\varepsilon^2(\mathbf{X}'\boldsymbol{\Sigma}^{-1}\mathbf{X})^{-1}$.

Empirical Application

As an empirical illustration, we estimate a pest damage function for the western corn rootworm. To illustrate the economic relevance of differences between estimators, we use each to assess the cost of the western corn rootworm soybean variant in first-year corn in Illinois and the value of soil insecticide and Bt corn for corn rootworm control.

Corn rootworms, a group of related insect species, are a serious corn pest, with yield losses and control costs estimated to exceed $1 billion annually in the U.S. (Metcalf 1986). The most problematic species are the western and the northern corn rootworm, though other species are important in some areas. Corn rootworm larvae hatch in the soil during the spring and feed almost exclusively on corn roots. Adults emerge from the soil in summer and lay eggs in the soil to continue the cycle (Levine and Oloumi-Sadeghi 1991). Larval feeding causes yield loss by disrupting plant functions and making plants more likely to lodge (Gray and Steffey 1998). Because corn rootworms typically lay eggs only in existing corn fields, crop rotation is an effective and widely used control strategy in much of the Corn Belt. For non-rotated corn, the most common control strategies are soil insecticides applied at planting to control larvae and aerial applications in summer to control adults (Fernandez-Cornejo and Jans 1999; Wilson et al. 2005).

Recently, the western corn rootworm soybean variant developed resistance to crop rotation by also laying eggs in soybeans and other crops (Levine et al. 2002). Where

a corn-soybean rotation is common, eggs laid in soybeans hatch the next spring in corn and larvae cause yield loss. The soybean variant first appeared along the Illinois-Indiana border in the mid-1990's and has spread through the eastern Corn Belt (Onstad et al. 1999). As a result, more than one third of Illinois and Indiana farmers report using insecticide on first year corn to control rootworm larvae (Wilson et al. 2005).

Bt corn for rootworm larval control was first available in 2003 and sales should continue to grow because of widespread economic damage from corn rootworm and the success of other Bt corn products (Wilson et al. 2005). However, as with all new technologies, its value is somewhat unknown during its initial release. Thus, we illustrate the economic implications of differences between the panel data estimators by using each to assess the value of soil insecticide and Bt corn for rootworm control in first year corn.

Estimation Data and Results

We use the component error model to estimate the proportional yield loss as a function of the root rating difference, just as Mitchell, Gray, and Steffey (2004). Data were from field experiments conducted near Urbana and DeKalb, Illinois in 1994-1996 (Gray and Steffey 1998). Whole plot treatments were 6-10 replicates for several commonly grown hybrids. Sub-plot treatments were two rows treated with the soil insecticide Counter® and two untreated rows. Collected data for each sub-plot included machine-harvested yield and the average root rating for five plants. Root ratings are an index of root injury used to assess root injury from rootworms. For the 1 to 6 scale of Hills and Peters (1971), the larger the root rating, the greater the damage. A 1 indicates no rootworm feeding injury and a 6 indicates three or more root nodes completely destroyed. The final

data are 574 observations of the yield and average root rating with soil insecticide and with no rootworm control, respectively denoted Y_{si}, R_{si}, Y_{no}, and R_{no}.

Following Mitchell, Gray, and Steffey (2004), the dependent variable is proportional yield loss $y = (Y_t - Y_c)/Y_t$ and the independent variable is the root rating difference $X_s = R_{no} - R_{si}$. These observations then become the elements of the 574 x 1 column vectors **y** and $\mathbf{X}_s$. The regressor matrix **X** has a column of ones for the intercept and the column vector $\mathbf{X}_s$. Nesting indices are year $t = 1$ to 3 ($T = 3$) and location $l = 1$ to 2 ($L = 2$). Because preliminary data analysis found no significant hybrid effect (also reported by Gray and Steffey (1998)), the hybrid index was dropped from the nesting structure. The number of replicates each year is 108, 113, and 66 for 1994, 1995, and 1996 respectively, so the unbalanced pattern is substantial. Gauss 6.0 was used to perform all matrix calculations needed for estimation.

Table 1 reports estimation results for each estimator. For the intercept, the panel data estimators are fairly similar (between 0.103 and 0.111), while the OLS estimate is noticeably different (0.0225). The same pattern occurs for the slope estimates and the experimental error σ_ε^2, but for the year and location effects, the panel data estimators vary greatly. None of the intercepts is significant at the 5% level for any estimator, which makes biological sense. When the root rating difference is zero, the damage measure is the same for both plots, so that both should have the same expected yield, implying a zero intercept. Hence, we estimate the models imposing a zero intercept.

Table 2 reports estimation results without an intercept. The OLS slope estimate again differs noticeably from the panel data estimators, but the SA estimator also differs from the other panel data estimators. For the experimental error σ_ε^2, all panel data

estimators agree and differ noticeably from the OLS estimate. Again, the estimated year and location effects vary among all estimators.

These differences between the ANOVA and ML estimates are consistent with the Monte Carlo findings of Baltagi, Song, and Jung (2001). In severely unbalanced panels, they found that ANOVA estimators compared well with ML estimation of the regression coefficients, but perform poorly for estimating the variance components. Hence, we give the most credence to the ML estimates. Our results also indicate that the SA estimator may perform poorly for estimating regression coefficients when no intercept is used, though additional analysis is needed for a more definitive conclusion. Overall, these results imply that expected yield decreases about 5.5% for each one unit increase in the root rating. However, substantial variability occurs around this expected decrease due to random year and location effects. The economic relevance of these random effects and of the differences between the estimators remains to be examined.

Empirical Model

To assess the cost of the western corn rootworm soybean variant and the value of soil insecticide and Bt corn for rootworm control with each damage model in table 2, we develop a model of an Illinois corn farmer facing random loss from the soybean variant. Farmer profit ($/ac) with control technology i is $\pi_i = py(1 - \lambda_i) - C_i$, where p is the corn price ($/bu), y is random pest-free yield (bu/ac), λ_i is random proportional yield loss from rootworm damage with technology i, and C_i is the cost of production ($/ac) using technology i, and $i = \{no, si, bt\}$ for no control, soil insecticide, and Bt corn. To maintain focus on yield risk, both p and C are non-random. The 2004 marketing year average corn price received in Illinois was $2.51/bu, so p is $2.50/bu (Schnitkey et al. 2005). 2004

crop budgets report $318/ac as the non-land cost of production for corn in northern Illinois, including insecticide costs (Lattz 2004). The cost for soil insecticides in 2004 ranged $16/ac to $18/ac, while the cost for Bt corn was around $20/ac. Thus, technology specific costs of production are C_{no} = $300/ac, C_{si} = $318/ac, and C_{bt} = $320/ac.

A beta density is used for pest-free yield, a common assumption for crop yields (see Goodwin and Ker's (2002) review). Using USDA-NASS (2005) county average yields from 1980-2004, the 2004 linear trend yield for Iroquois County in northeastern Illinois is 159.7 bu/ac. Hence, mean yield is 160 bu/ac. The yield coefficient of variation is 20%, which Coble, Heifner, and Zuniga (2002) report as the yield coefficient of variation for Iroquois County based on crop insurance data. Following Babcock, Hart and Hayes (2004), minimum yield is 32 bu/ac (the mean minus four standard deviations) and maximum yield is 224 bu/ac (the mean plus two standard deviations).

As an approximation of risk preferences, we use negative-exponential utility. Following Babcock, Choi and Feinerman (1993), the coefficient of absolute risk aversion is chosen so the implied risk premium is a reasonable percentage of the profit standard deviation. We use a 20% and a 40% risk premium for moderate and high risk aversion, which here imply coefficients of absolute risk aversion of 0.005346 and 0.01171.

The results in table 2 are used to determine random proportional yield loss λ as a function of the root rating, which requires root ratings with no control and when using a soil insecticide and Bt corn. We use Mitchell, Gray, and Steffey's (2004) hierarchical model for the root rating with no control (R_{no}). Specifically, R_{no} has a beta distribution with a minimum of 1, a maximum of 6, and with shape parameters α and ω that have a

bivariate normal distribution with means and variance-covariance matrix as reported by Mitchell, Gray, and Steffey (2004, p. 338).

We updated Mitchell, Gray and Steffey's (2004) model for the distribution of the root rating with a soil insecticide (R_{si}) conditional on R_{no} using the additional data available for this study and new functional forms. Specifically, R_{si} has a beta distribution with a minimum of 1, a maximum of R_{no}, a mean of $1 + d_1(1 - \exp(-d_2(R_{no} - 1))$, and a standard deviation of $s_1(1 - \exp(-s_2(R_{no} - 1))$. Maximum likelihood parameter estimates with standard errors in parentheses are $d_1 = 1.467$ (0.0496), $d_2 = 0.579$ (0.0508), $s_1 = 0.375$ (0.0251), and $s_2 = 0.661$(0.124).

We used Bt corn field trial data to estimate a similar model for the distribution of the Bt corn root rating (R_{bt}) conditional on R_{no}, but functional forms were simpler since less data were available. Specifically, R_{bt} has a beta distribution with a minimum of 1, a maximum of R_{no}, a mean of $1 + d_1(R_{no} - 1)$, and a standard deviation of $s_1(R_{no} - 1)$. Available data were 31 observations of the average root rating with no control and with Bt corn from field experiments conducted in 1999 and 2000 in several states, plus six observations from Illinois field trials conducted in 2003 and 2004 (Estes 2004; Mitchell 2002; Steffey 2003). Maximum likelihood parameter estimates with standard errors in parentheses are $d_1 = 0.270$ (0.0296) and $s_1 = 0.182$ (0.0196).

Closed form expressions for expected profit and expected utility do not exist for the specified model. As a result, a C++ program uses algorithms from Press et al. (1992) to draw random variables from required distributions and solve integrals using Monte Carlo integration (Greene 1997, p. 192-195). First α and ω are drawn from the specified bivariate normal distribution, and then each α and ω pair is used to parameterize a beta

density to draw R_{no}. Next, each R_{no} is used to parameterize beta densities to draw R_{si} and R_{bt}. Since the minimum root rating is one, the root rating difference for technology i is $R_i - 1$ and yield loss for technology i is $\lambda_i = \beta_1(R_i - 1)$, where β_1 is the slope coefficient reported in table 2. Pest-free yield y is drawn from the specified beta density. Random location and year effects are drawn from independent normal densities with mean zero and standard deviations reported in table 2. Next, profit and utility are determined for each draw. Finally, average profit and average utility for each control technology is the Monte Carlo estimate of expected profit and expected utility. To ensure that estimates had stabilized, 100,000 random draws were used for each random variable.

Empirical Results

Table 3 reports the expected loss and the loss standard deviation due to soybean variant damage in first year corn using each damage model. Just as the slope coefficients in table 2, expected loss with OLS is more than twice the expected loss with the WK, HFB and ML estimates, while expected loss with the SA estimates is almost twice as large. The loss standard deviations in table 3 follow the pattern of the sum of the year and location effects in table 2. The sum of the year and location effects for the WK estimates is the largest, even exceeding the OLS estimated variance, while the same sum is the smallest for the SA estimates.

To measure the cost of the soybean variant in Illinois, table 3 also reports the decrease in expected profit and certainty equivalents relative to no damage. Results for the different models follow the pattern of expected losses. The OLS estimates are around twice the WK, HFB, and ML estimates and the SA estimates also greatly exceed these three. Following Baltagi, Song, and Jung (2001) and giving most credence to the ML

estimates, the cost of the western corn rootworm soybean variant is around $37-$48/ac depending on farmer risk aversion. Estimates with the WK and HFB estimators are only slightly larger, while estimates with the SA and OLS estimators are about twice as large.

Negative values in table 3 for the decease in the profit standard deviation imply that the soybean variant increases profit variance. Pest damage increases or decreases yield variance depending on how random pest damage enters the production function and empirical cases of pest damage increasing yield variance have been reported (Feder 1979; Horowitz and Lichtenberg 1993, 1994; Mitchell et al. 2002). As a result, the cost of the soybean variant increases as farmer risk aversion increases.

Table 4 reports the net benefit of soil insecticide and Bt corn for controlling the western corn rootworm soybean variant in first year corn. With the WK, HFB, and ML estimates, results for the risk neutral case indicate that soil insecticide at a cost of $18/ac is approximately a break even control technology. As risk aversion increases, the net benefit decreases so that, for the highly risk averse case, the net benefit is a loss of about $2-$3/ac for the WK, HFB, and ML estimates. Because losses without control are much larger with the OLS and SA estimates, the net benefit of soil insecticide is much larger.

The net benefit for Bt corn for the WK, HFB, and ML estimates ranges $7-$8/ac for the risk neutral case and falls to $2.50-$4/ac for the highly risk averse case. The net benefit for the OLS and SA estimates is again much larger. Following Baltagi, Song, and Jung (2001) and using the ML estimates, results indicate that, at a cost of $20/ac, Bt corn generates a net benefit of about $2.50-$7/ac for controlling the soybean variant in first-year corn in northeastern Illinois. Because control costs are non-random and a negative exponential utility function is used, adjusting net benefits for different cost assumptions

requires adding the net decrease in the cost to the table 4 results. For example, if Bt corn cost $19/ac instead of $20/ac, the net benefits for Bt corn in table 4 increase by $1/ac.

Comparison with Mitchell, Gray, and Steffey (2004)

Mitchell, Gray, and Steffey (2004) estimated expected loss from the soybean variant using data only from Urbana, while we used data from both Urbana and DeKalb. They report an expected loss of 0.114 with a standard deviation of 0.117. Our comparable results are 0.092 and 0.167 for the ML estimates in table 3. The difference in expected loss largely results from different slope coefficient estimates (0.114 versus 0.0548). This coefficient difference is not entirely from using different data, since OLS slope estimates are similar for both studies (0.127 versus 0.114), implying that the data are similar. Rather, it likely results because Mitchell, Gray and Steffey's method pools the data and ignores year (and location) effects.

Mitchell, Gray, and Steffey's (2004) method has two advantages. It estimates and removes effects from experimental errors, plus the resulting damage function restricts proportional losses to range within the logical limits of zero and one, even if the data contain negative losses due to experimental errors. Negative losses imply that yield without control exceeds yield with a soil insecticide or Bt corn. Since the soil insecticide has no reported phototoxic effects, nor has a "yield drag" been confirmed for Bt corn, negative losses only occur if experimental errors overwhelm the treatment effect.

This panel data model not only estimates and removes random effects from experimental errors, but also estimates separate random year and location effects that Mitchell, Gray, and Steffey's (2004) model aggregates into a single error. However, this panel data model does not limit proportional losses to range between zero and one as

Mitchell, Gray, and Steffey's (2004) model does. As a result, our random draws of yield loss for the estimates in table 2 all have minimums less than zero, but Mitchell, Gray, and Steffey's (2004) draws do not. We could censor our random draws at zero, but censoring is inconsistent with the estimated model and would greatly change our results, since the probability of a negative loss ranges 17-46% for these models. Modifying the panel data model to include censored random effects or non-normal errors is needed to eliminate negative random draws. Regardless, because our estimators do not limit losses to range between zero and one, it is not surprising that the loss standard deviations in table 3 exceed Mitchell, Gray and Steffey's standard deviation of 0.117.

One important weakness of Baltagi, Song, and Jung's (2001) model needs to be highlighted. The model indexes the number of replicates only by the year t and not also by the location l, i.e., the number of replicates at each location is R_t, not R_{tl}. As a result, the number of replicates for each location must be the same each year. Thus, the location with the least number of replicates in a year determines how many replicates all locations can have that year—locations with more replicates must drop observations. For the data here, we had to drop 7 observations from Urbana in 1994, 4 from DeKalb in 1995, and 36 from Urbana in 1996. For this analysis, we randomly dropped different observations 15 times and estimated all models. The performance patterns of the estimators remained the same, but the magnitude of the parameter estimates varied. The results in tables 1 and 2 are for the data set that gave parameter estimates closest to the average over all data sets. Estimates did not vary tremendously between data sets, e.g., the coefficient of variation for all ML estimates was less than 5% and the range of ML slope estimates was 0.0505 to

0.0573. Nevertheless, an improved model is needed that does not require dropping observations when data have a different number of replicates for each location and year.

Conclusion

Panel data methods have advanced to address unbalanced and nested data, a common problem for economic and experimental data. We described four panel data estimators developed by Baltagi, Song, and Jung (2001) and used each to estimate a western corn rootworm damage function. The description and illustration are meant to introduce the estimators to agricultural economists, to help practitioners assess their empirical performance, and to encourage development of new applications. As a secondary goal, the panel data model is explored as an alternative to Mitchell, Gray, and Steffey's (2004) method for estimating pest damage functions.

Using Monte Carlo analysis, Baltagi, Song and Jung (2001) found that the three ANOVA estimators and the ML estimator performed well for estimating regression coefficients, but that the ML estimator performed best for estimating the variance components. In our empirical analysis, two of the ANOVA estimators (WK and HFB) and the ML estimators provided comparable estimates for the regression coefficients, but the SA estimator gave a noticeably different estimate when an intercept term was not included, a case Baltagi, Song, and Jung did not investigate. For the variance components, all estimates differed from each other, but following Baltagi, Song, and Jung (2001), we give more credibility to the ML estimates.

We developed an empirical model for Iroquois County in northeastern Illinois to investigate the economic relevance of differences among estimators. We use each to estimate the cost of the soybean variant in first year corn and the net benefit of using soil

insecticide and Bt corn. Substantial differences exist in the estimated cost and net benefits for each estimator. Giving most credence to the ML results, we conclude that, for controlling the soybean variant in first year corn, a soil insecticide generates a net loss ranging \$0.50-\$3.50/ac, while Bt corn generates net benefit ranging \$2-\$7/ac.

Several caveats apply. Lodging losses from rootworm damage are not included, but are of substantial concern to farmers (Wilson et al. 2005). Adding lodging losses would increase the cost of the soybean variant and the net benefit of both soil insecticide and Bt corn to give results more consistent with observed farmer use of soil insecticides. Furthermore, farmers consider reduced insecticide exposure for themselves and the environment a major benefit of Bt corn for rootworm control, benefits not included here (Alston et al. 2002; Wilson et al. 2005). Lastly, rootworm Bt corn is relatively new and its performance under the wide variety of agronomic conditions that can occur has yet to be observed, as its problematic performance in some Illinois locations in 2004 indicates (Steffey and Gray 2004).

Finally, we discussed the advantages of this panel data model for estimating pest damage functions with experimental data relative to Mitchell, Gray, and Steffey's (2004) composed error model. Both estimate and remove variability due to experimental errors, but this panel data method also separately estimates random year and location effects and likely gives better estimates of regression coefficients. However, unlike the composed error model, this panel data method does not limit yield losses for the stochastic damage function to the logical range of zero to one and may require dropping observations. Hence, we conclude that unbalanced nested panel data model show promise for empirical applications in economics, but require more work to fulfill this promise.

References

Alston, J. M., J. Hyde, M. C. Marra, and P. D. Mitchell. 2002. An Ex Ante Analysis of the Benefits from the Adoption of Corn Rootworm Resistant Transgenic Corn." *AgBioForum* 5(3):71-84.

Antweiler, W. 2001. "Nested Random Effects Estimation in Unbalanced Panel Data." *Journal of Econometrics* 101:295-313.

Babcock, B. A., E. K. Choi, and E. Feinerman. 1993. "Risk and Probability Premiums for CARA Utility Functions." *Journal of Agricultural and Resource Economics* 18:17-24.

Babcock, B. A., C. E. Hart, and D. J. Hayes. 2004. "Actuarial Fairness of Crop Insurance Rates with Constant Rate Relativities." *American Journal of Agricultural Economics* 86:563-575.

Baltagi, B. H. 2001. *Econometric Analysis of Panel Data*, 2nd ed. New York: Wiley.

Baltagi, B.H., and Y.J. Chang. 1994. "Incomplete Panels: A Comparative Study of Alternative Estimators for the Unbalanced One-Way Error Component Regression Model." *Journal of Econometrics* 62:6-89.

Baltagi, B. H., S. H. Song, and B. C. Jung. 2001. "The Unbalanced Nested Error Component Regression Model." *Journal of Econometrics* 101:357-381.

Biørn, E. 2004. "Regression Systems for Unbalanced Panel Data: A Stepwise Maximum Likelihood Procedure." *Journal of Econometrics* 122:281-291.

Coble, K., R. Heifner, and M. Zuniga. 2000. "Implications of Crop Yield and Revenue Insurance for Producer Hedging." *Journal of Agricultural and Resource Economics* 25:432-452.

Druska, V., and W. C. Horrace. 2004. "Generalized Moments Estimation for Spatial Panel Data: Indonesian Rice Farming." *American Journal of Agricultural Economics* 86:185-198.

Estes, R. 2004. "2004 Evaluations of Rootworm Control Products." University of Illinois Extension Pest Management and Crop Development Bulletin No. 22, September.

Evans. P. 1998. "Using Panel Data to Evaluate Growth Theories." *International Economic Review* 39:295-306.

Feder, G. 1979. "Pesticides, Information, and Pest Management under Uncertainty." *American Journal of Agricultural Economics* 61:97-103.

Fernandez-Cornejo, J., and S. Jans. 1999. Pest Management in U. S. Agriculture. Washington, DC: U.S. Department of Agriculture, Economic Research Service Agricultural Handbook No. 717, August.

Fuller, W. A., and G. E. Battese. 1973. "Transformations for Estimation of Linear Models with Nested Error Structure." *Journal of the American Statistical Association* 68:626-632.

Goodwin, B. K., and A. P. Ker. 2002. "Modeling Price and Yield Risk." In R. E. Just and R. D. Pope, eds. *A Comprehensive Assessment of the Role of Risk in U. S. Agriculture.* Boston: Kluwer Academic Press, pp. 289-323.

Gray, M. E., and K. L. Steffey. 1998. "Corn Rootworm (Coleoptera: Chrysomelidae) Larval Injury and Root Compensation of 12 Maize Hybrids: An Assessment of the Economic Injury Index." *Journal of Economic Entomology* 91:723-740.

Greene, W.H. 1997. *Econometric Analysis*, 3rd ed. Upper Saddle River, NJ: Prentice Hall.

Hills, T. M., and D. C. Peters. 1971. "A Method of Evaluating Postplanting Insecticide Treatments for Control of Western Corn Rootworm Larvae." *Journal of Economic Entomology* 64:764-765.

Horowitz, J. K., and E. Lichtenberg. 1993. "Insurance, Moral Hazard, and Chemical Use in Agriculture." *American Journal of Agricultural Economics* 75:926-35.

Horowitz, J. K., and E. Lichtenberg. 1994. "Risk-Reducing and Risk Increasing Effects of Pesticides." *Journal of Agricultural Economics* 45:82-89.

Hurley, T. M., P. D. Mitchell, and M. E. Rice. 2004. "Risk and the Value of Bt Corn." *American Journal of Agricultural Economics* 86: 345-358.

Kniesner, T.J., and J.P. Ziliak. 2002. "Tax Reform and Automatic Stabilization." *American Economic Review* 92:590-612.

Lattz, D. H. 2005. "Cost to Produce Corn and Soybeans in Illinois—2004." Dept. Agr. Cons. Econ., Farm Economics Facts and Option 09-05, University of Illinois.

Levine, E., and H. Oloumi-Sadeghi. 1991. "Management of Diabroticite Rootworms in Corn." *Annual Review of Entomology* 36:229-255.

Levine, E., J. L. Spencer, S. A. Isard, D. W. Onstad, and M. E. Gray. 2002. "Adaptation of the Western Corn Rootworm to Crop Rotation: Evolution of a New Strain in Response to a Management Practice." *American Entomologist* 48(Summer):64-107.

Lichtenberg, E., and D. Zilberman. 1986. "The Econometrics of Damage Control: Why Specification Matters." *American Journal of Agricultural Economics* 68:261-273.

Metcalf, R. L. 1986. "Forward." In J. L. Krysan and T. A. Miller, eds. *Methods for the Study of Pest Diabrotica*. New York: Springer-Verlag, pp. vii-xv.

Mitchell, P. D. 2002. "Yield Benefit of Corn Event MON 863." Dept. Agr. Econ., Faculty Paper Series 02-04, Texas A&M University.

Mitchell, P. D., T. M. Hurley, B. A. Babcock and R. L. Hellmich. 2002. "Insuring the Stewardship of Bt Corn—A Carrot Versus A Stick." *Journal of Agricultural and Resource Economics* 27:390-405.

Mitchell, P. D., M. E. Gray, and K. L. Steffey. 2004. "A Composed-Error Model for Estimating Pest-Damage Functions and the Impact of the Western Corn Rootworm Soybean Variant in Illinois." *American Journal of Agricultural Economics* 86:332-344.

Moulton, B. R. 1986. "Random Group Effects and the Precision of Regression Estimates." *Journal of Econometrics* 32:385-397.

Onstad, D.W., M. Joselyn, S. Isard, E. Levine, J. Spencer, L. Bledsoe, C. Edwards, C. Di Fonzo, and H. Wilson. 1999. "Modeling the Spread of Western Corn Rootworm (Coeloptera: Chrysomelidae) Populations Adapting to Soybean-Corn Rotation." *Environmental Entomology* 28:188-194.

Press, W. H., S. A. Teukolsky, W. T. Vetterling, and B. Flannery. 1992. *Numerical Recipes in C++: The Art of Scientific Computing*, 2nd ed. Cambridge: Cambridge University Press.

Schnitkey, G. D., D. Lattz, S. H. Irwin, and J. Martines-Filho. 2005. "Illinois Average Farm Price Received Database." Dept. Agr. Cons. Econ., University of Illinois.

Searle, S. R. 1987. *Linear Models for Unbalanced Data.* New York: John Wiley, 1987.

Solon, G. S. 1989. "The Value of Panel Data in Economic Research", in D. Kasprzyk, G. J. Duncan, G. Kalton and M. P. Singh, eds., *Panel Survey*. New York: John Wiley, pp. 486-496.

Steffey, K. 2003. "Root Ratings from 2003 Corn Rootworm Control Trials in Illinois." University of Illinois Extension, Pest Management and Crop Development Bulletin No. 22, September.

Steffey, K., and M. Gray. 2004. "Transgenic Corn Rootworm Hybrid Stumbles in Urbana Experiment; Some Producers also Report Severe Lodging with YieldGard Rootworm Hybrids in Commercial Fields." University of Illinois Extension, Pest Management and Crop Development Bulletin No. 22, September.

Swamy, V. B. and A. A. Arora. 1972. "The Exact Finite Sample Properties of the Estimators of Coefficients in the Error Components Regression Models." *Econometrica* 40:261-275.

United States Department of Agriculture-National Agricultural Statistics Service. 2005. "Published Estimates Data Base On Line." Washington, DC.

Wansbeek, T., and A. Kapteyn. 1989. "Estimation of the Error Components Model with Incomplete Panels." *Journal of Econometrics* 41:341-361.

Wilson, T. A., M. E. Rice, J. J. Tollefson, and C. D. Pilcher. 2005. "Transgenic Corn for Control of European Corn Borer and Corn Rootworms: A Survey of Midwestern Farmer' Practices and Perceptions." *Journal of Economic Entomology* 98:237-247

Wooldridge, J. M. 2002. *Econometric Analysis of Cross Section and Panel Data.* Cambridge, MA: MIT Press.

Table 1. Parameter estimates for western corn rootworm damage function for different unbalanced nested component error model estimators (standard errors in parenthesis) for the linear model with an intercept.

Estimator	Intercept β_0	Slope β_1	Year Effect σ_μ^2	Location Effect σ_v^2	Experimental Error σ_ε^2
Ordinary Least Squares (OLS)	0.0225	0.104	--	--	0.0381
	(0.0185)	(0.00868)			
Wansbeek and Kapteyn (WK)	0.103	0.0555	0.0138	0.00489	0.0225
	(0.0762)	(0.00993)			
Swamy and Arora (SA)	0.112	0.0506	0.0122	0.0291	0.0225
	(0.0965)	(0.0101)			
Henderson and Fuller and Battese (HFB)	0.111	0.0511	0.0391	0.0183	0.0225
	(0.0689)	(0.0101)			
Maximum Likelihood (ML)	0.110	0.0517	0.00314	0.0134	0.0225
	(0.0608)	(0.0101)			

Table 2. Parameter estimates for western corn rootworm damage function for different unbalanced nested component error model estimators (standard errors in parenthesis) for the linear model without an intercept.

Estimator	Slope β_1	Year Effect σ_μ^2	Location Effect σ_ν^2	Experimental Error σ_ε^2
Ordinary Least Squares (OLS)	0.113	--	--	0.0382
	(0.00382)			
Wansbeek and Kapteyn (WK)	0.0569	0.0385	0.00489	0.0225
	(0.00979)			
Swamy and Arora (SA)	0.0905	0.0187	0.000343	0.0225
	(0.00827)			
Henderson and Fuller and Battese (HFB)	0.0564	0.0117	0.00887	0.0225
	(0.00970)			
Maximum Likelihood (ML)	0.0548	0.0143	0.0128	0.0225
	(0.00981)			

Table 3. Expected loss, loss standard deviation, and decrease in expected profit, profit standard deviation, and certainty equivalents due to the western corn rootworm soybean variant in first year corn in Illinois for the different estimators.

Estimator	Expected Loss (%)	St. Dev. Loss (%)	Decrease Relative to No Damage: Expected Profit ($/ac)	Decrease Relative to No Damage: St. Dev. Profit ($/ac)	Certainty Equivalent ($/ac) Moderately[a] Risk Averse	Certainty Equivalent ($/ac) Highly[b] Risk Averse
Ordinary Least Squares (OLS)	19.0	20.4	76.12	–25.41	86.03	91.90
Wansbeek and Kapteyn (WK)	9.6	21.0	38.35	–32.19	51.84	60.94
Swamy and Arora (SA)	15.3	14.6	60.99	–10.13	63.97	63.83
Henderson and Fuller and Battese (HFB)	9.5	14.6	37.99	–13.91	42.81	44.73
Maximum Likelihood (ML)	9.2	16.7	36.91	–19.66	44.29	48.28

[a] Coefficient of absolute risk aversion 0.005346, implying a risk premium is approximately 20% the profit standard deviation.

[b] Coefficient of absolute risk aversion 0.01171, implying a risk premium is approximately 40% the profit standard deviation.

Table 4. Net benefit ($/ac) of soil insecticide and Bt corn for controlling the western corn rootworm soybean variant in first year corn in Illinois for the different estimators.

Estimator	Soil Insecticide			Bt Corn		
	Expected Profit	Certainty Equivalent Moderately[a] Risk Averse	Certainty Equivalent Highly[b] Risk Averse	Expected Profit	Certainty Equivalent Moderately[a] Risk Averse	Certainty Equivalent Highly[b] Risk Averse
Ordinary Least Squares (OLS)	17.88	16.29	14.61	35.56	32.18	28.61
Wansbeek and Kapteyn (WK)	0.07	–1.10	–2.31	7.98	5.98	3.91
Swamy and Arora (SA)	10.74	9.10	7.02	24.49	21.44	17.74
Henderson and Fuller and Battese (HFB)	–0.09	–1.34	–2.86	7.73	5.61	3.09
Maximum Likelihood (ML)	–0.60	–1.80	–3.21	6.94	4.91	2.58

[a] Coefficient of absolute risk aversion 0.005346, implying a risk premium is approximately 20% the profit standard deviation.

[b] Coefficient of absolute risk aversion 0.01171, implying a risk premium is approximately 40% the profit standard deviation.