An Unbalanced Nested Error Component Model for Estimating Pest Damage Functions and the Value of Rootworm Bt Corn

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Abstract

We apply Antweiler's (2001) double-nested unbalanced panel data model to estimate a western corn rootworm damage function using data from field trials in Illinois and Nebraska. Results imply that expected yield losses for a one unit difference in the node injury scale are 16.4%. Estimated random year and state effects are statistically significant, as is the estimated random experimental effect. The experimental effect is relatively large indicating the tremendous variability in yield losses at the small scale for plots with the same node injury scale measure of root damage. Using the estimated pest damage function to assess the value of Bt corn for farmers in Nebraska and Illinois, we find that, with a mean yield of 200 bu/ac, a yield CV of 25%, a corn price of $3.50/bu, and a Bt corn technology fee of $16/ac, the value of Bt corn for farmers is $173.35/ac and $156.14/ac under very high and high pest pressure respectively.

Pests have been a part of agriculture since its very beginnings, with crop damage and yield losses from pests a continual and serious problem even for modern producers. For example, Paoletti and Pimentel (2000) estimate that 40% of world crop production is annually lost due to weed, plant pathogen, and insect damage, with an additional 20% lost post-harvest. Annual spending by farmers to eliminate or reduce various types of pest losses is also large. In 2008, U.S. farmers spent $11.7 billion on non-fertilizer agricultural chemicals (both materials and application costs), primarily to control insects, weeds, and other pests, not including costs for chemical seed treatments and transgenic traits (USDA-NASS 2009).

When analyzing pest problems, in some cases pest damage functions are used to predict yield loss as a function of the pest density or some measure of pest damage. For example, a pest damage function can be used to evaluate the benefit of a new pest control technology (Alston et al. 2002; Hurley et al. 2004), to estimate the economic effect of an invasive species and policies to mitigate its impact (Song and Swinton 2009; Mitchell et al. 2004), or the benefit from suppressing or eliminating a pest species (Hutchison et al. 2010).

Data from field plots are a common source of data for estimating pest damage functions, such as yields from research trials testing new pest control technologies, or observations of measures of pest damage and yield from field sites. Such data—for various groups and/or from different sites through time—are panel data. Panel data from field experiments or field observations are commonly nested—collected for more than one year in different locations with different treatments, so that the data can be grouped (nested) by more than one index (e.g., year, location, treatment). Such panel data are also often unbalanced—locations and treatments change over the experimental or sampling period so that the number of observations by location and treatment changes. With unbalanced data, ordinary least squares (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. Estimation addressing both the nested and unbalanced nature of panel data would provide better estimates of pest damage functions and so improve economic analysis based on such functions.

Antweiler (2001) developed a double-nested unbalanced panel data method of estimation that can address these problems in estimating pest damage functions. An important strength of Antweiler's (2001) method is that the data can be nested by three or more indexes (e.g., year, location, hybrid, treatment), plus be unbalanced (have a different number of replicates or observations) within each index. Dun et al. (2010) recently applied Antweiler's (2001) double-nested unbalanced panel data model to estimate a western corn rootworm damage function using field plot data from Illinois and Italy. The first goal of our paper is to apply this method using additional data for this pest from more locations, and to compare our findings.

An additional advantage of the unbalanced nested panel data model is that it not only improves the accuracy of estimated standard errors relative to OLS, but also provides estimates of individual random effects. When using OLS to estimate a pest damage function with experimental data, a single error term attributes all variability in yield loss to the pest. However, the component error model used by unbalanced nested panel data models not only provides separate estimates of random location and year effects, but also estimates random effects from experimental errors and similar factors. As a result, after removing the effect of these experimental errors, the damage function is still stochastic due to the random location and year effects. A damage function estimated via OLS is only stochastic if it includes the error term, which is a mixture of all sources of variability. Thus an important advantage of the component error model is that it allows yield losses from the pest to be stochastic, without assigning all the variability to a single source, but rather decomposing it into variability arising from stochastic pest pressure and from environmental effects captured by random year and location effects. Hence, the economic analysis can incorporate uncertainty and risk aversion, an important advantage, since risk management is a significant aspect of pest control (e.g., Horowitz and Lichtenberg 1994; Hurley et al. 2004; Mitchell and Hutchison 2008).

The ability to separately estimate the magnitude of different variance components is an important advantage when using a pest damage function for economic analysis, as it allows the analysis to be stochastic without assigning all observed variability in field plot yields to the pest. Mitchell et al. (2004) adapted a mixed distribution used for estimating technical efficiency to develop a composed error model for this purpose—to separately estimate variability in losses from pest effects and from experimental errors. The unbalanced nested panel data model is an alternative to the method of Mitchell et al. (2004) that separately estimates variability from different sources. Dun et al. (2010) did not utilize this aspect of the composed error model—their analysis and discussion focused largely on the effect of pest damage on mean yield. Hence, another goal of this paper when developing an empirical application is to explore the ability of the unbalanced nested panel data model to incorporate stochastic pest damages.

In the remainder of this paper, we first present a general conceptual version of Antweiler's (2001) double-nested, unbalanced model adapted for estimating a pest damage function, and then describe its estimation via maximum likelihood. Because the data we use for the empirical illustration do not support the double-nested model, which may occur for other applications as well, we also present the single-nested version. We then describe the data and our estimation results. Next we develop an economic application using these results to assess the net benefit to farmers of using Bt corn for controlling western corn rootworm in Illinois and Nebraska.

Conceptual Model

Following Antweiler (2001) and Dun et al. (2010), the general form of the nested error component model to estimate a pest damage function is

(1) $$y_{stlr} = \sum_{j=1}^{J} \beta_j x_{jstlr} + u_{stlr} ,$$

where y is yield loss, x is an explanatory variable, β is a parameter to estimate, and u is a random error. The independent variable x_{jstlr} denotes the j^{th} explanatory variable, where j = 1 to J indexes the regressors. The unbalanced panel consists of s = 1 to S top level groups, each containing t = 1 to T_s second-level groups, with the second-level groups containing l = 1 to L_{st} subgroups, which in turn contain r = 1 to R_{stl} observations. For example, experiments could be conducted in s = 1 to S states, with experiments in each state s conducted for t = 1 to T_s years at l = 1 to L_{st} locations in each year t with replicates r = 1 to R_{stl} at each location l in each year t. Other designations for the index variables are possible, but we will continue with this example here.

The error term u is decomposed into several random components:

(2) $$u_{stlr} = \lambda_s + \mu_{st} + \nu_{stl} + \varepsilon_{stlr} ,$$

where λ_s, μ_{st}, ν_{stl}, and ε_{stlr} are independently and identically distributed errors with zero mean and respective variances σ_λ^2, σ_μ^2, σ_ν^2, and σ_ε^2. For this model, λ_s is the s^{th} unobserved random state effect, μ_{st} is the unobserved nested random effect in the t^{th} time period for the s^{th} state, ν_{stl} is the unobserved nested random effect of the l^{th} location in the t^{th} time period in the s^{th} state and ε_{stlr} is the random disturbance for the r^{th} replicate at the l^{th} location in the t^{th} time period in the s^{th} state. Maximum likelihood estimation assumes these random components have a normal distribution.

Preliminary analysis of the data used for the empirical application here indicated that the location effect (σ_{λ}^{2}) was not significant, as was the case for Dun et al. (2010). As comparable results may occur for other applications, we also present the single-nested unbalanced random effects model. In this case, the error term becomes:

(3) $$u_{tlr} = \mu_t + v_{tl} + \varepsilon_{tlr} ,$$

where the error components μ_t, v_{tl}, and ε_{tlr} are independently and identically distributed with zero mean and respective variances σ_{μ}^{2}, σ_{v}^{2}, and σ_{ε}^{2}. Now μ_t is the unobserved random year effect of the t^{th} year, v_{tl} is the unobserved nested random effect of the j^{th} state in the t^{th} year, and ε_{tlr} is the random disturbance of the r^{th} replicate at the l^{th} state in the t^{th} year.

Maximum Likelihood Estimation

The number of observations in the respective groups is the sum of R_{stl} over the lower sub-groups, or $N_{st} = \sum_{l=1}^{L_{st}} R_{stl}$ is the number of observations for each state s in year t, $N_s = \sum_{t=1}^{S_t} N_{st}$ is the number of observation for each state s and finally, $N = \sum_{s=1}^{S} N_s$ is the total number of observations. For notational convenience, define the following variables: $\theta_{stl} = 1 + \rho_v R_{stl}$, $\phi_{st} = \sum_{l=1}^{L_{st}} \frac{R_{stl}}{\theta_{stl}}$, $\theta_{st} = 1 + \rho_{\mu}\phi_{st}$, $\phi_s = \sum_{t=1}^{S_t} \frac{\phi_{st}}{\theta_{st}}$, and $\theta_s = 1 + \rho_{\lambda}\phi_s$, where $\rho_v = \sigma_v^2 / \sigma_{\varepsilon}^2$, $\rho_{\mu} = \sigma_{\mu}^2 / \sigma_{\varepsilon}^2$, and $\rho_{\lambda} = \sigma_{\lambda}^2 / \sigma_{\varepsilon}^2$ are variance ratios. Finally, define $V_{stl} = \sum_{l=1}^{R_{stl}} u_{stlr}^2$ and recursively define the following: $U_{stl} = \sum_{r=1}^{R_{stl}} u_{stlr}$, $U_{st} = \sum_{l=1}^{L_{st}} \frac{U_{stl}}{\theta_{stl}}$, and $U_s = \sum_{t=1}^{S_t} \frac{U_{st}}{\theta_{st}}$. Given these definition, the log-likelihood function is:

$$\ln\left(L(\boldsymbol{\beta},\sigma_\varepsilon^2,\rho_v,\ \rho_\mu,\ \rho_\lambda)\right) = -\frac{1}{2}\left[N\ln(2\pi\sigma_\varepsilon^2)\right]$$

(4)

$$-\frac{1}{2}\sum_{s=1}^{S}\left\{\ln\theta_s + \sum_{t=1}^{S_t}\left\{\ln\theta_{st} + \sum_{l=1}^{L_{st}}\left\{\ln\theta_{stl} + \frac{V_{stl}}{\sigma_\varepsilon^2} - \frac{\rho_v}{\theta_{stl}}\frac{U_{stl}^2}{\sigma_\varepsilon^2}\right\} - \frac{\rho_\mu}{\theta_{st}}\frac{U_{st}^2}{\sigma_\varepsilon^2}\right\} - \frac{\rho_\lambda}{\theta_s}\frac{U_s^2}{\sigma_\varepsilon^2}\right\},$$

where **β** is the J x 1 vector of β_j slope coefficients for the regressors.

Maximization of this likelihood function generally does not have an analytical solution, so numerical methods are needed to derive parameter estimates. The variance ratios ρ_v, ρ_μ, and ρ_λ must be constrained to be non-negative and the variance σ_ε^2 must be constrained to be strictly positive. As starting values for optimization algorithms, Antweiler (2001) recommends using OLS estimates for the vector of slope coefficients **β** and initial values for the variance ratios such that their sum is less than one. The square roots of the diagonal elements of the inverse Hessian (information) matrix, corrected for the degrees of freedom, estimate the standard errors:

(5) $$\mathbf{s_b} = \sqrt{\text{abs}\left(\left[\boldsymbol{\psi}^{-1}N/(N-G-J)\right]_{bb}\right)},$$

where $\boldsymbol{\psi}_{bb}$ are the diagonal elements of the Hessian matrix, $G = \sum_{s=1}^{S}\sum_{t=1}^{T_s} L_{st}$, and the elements of $\mathbf{s_b}$ approximately follow a t distribution with ($N - G - J$) degrees of freedom.

For the single-nested unbalanced panel model, the log-likelihood function is obtained from equation (4) by setting $S = 1$ and $\rho_\lambda = 0$:

$$\ln\left(L(\boldsymbol{\beta},\sigma_\varepsilon^2,\rho_v,\rho_\mu)\right) = -\frac{1}{2}\left[N\ln(2\pi\sigma_\varepsilon^2)\right]$$

(6)

$$-\frac{1}{2}\sum_{t=1}^{T}\left\{\ln\theta_t + \sum_{l=1}^{L_t}\left\{\ln\theta_{tl} + \frac{V_{tl}}{\sigma_\varepsilon^2} - \frac{\rho_v}{\theta_{tl}}\frac{U_{tl}^2}{\sigma_\varepsilon^2}\right\} - \frac{\rho_\mu}{\theta_t}\frac{U_t^2}{\sigma_\varepsilon^2}\right\} - \frac{\rho_\lambda}{\theta}\frac{U^2}{\sigma_\varepsilon^2},$$

where now $\theta_{tl} = 1 + \rho_v R_{tl}$, $\phi_t = \sum_{l=1}^{L_t} \dfrac{R_{tl}}{\theta_{tl}}$, $\theta_t = 1 + \rho_\mu \phi_t$, $\phi = \sum_{t=1}^{T} \dfrac{\phi_t}{\theta_t}$, $\rho_v = \sigma_v^2 / \sigma_\varepsilon^2$, $\rho_\mu = \sigma_\mu^2 / \sigma_\varepsilon^2$,

$V_{tl} = \sum_{l=1}^{R_{tl}} u_{tlr}^2$, $U_{tl} = \sum_{r=1}^{R_{tl}} u_{tlr}$ $U_t = \sum_{l=1}^{L_t} \dfrac{U_{tl}}{\theta_{tl}}$, $U = \sum_{t=1}^{T} \dfrac{U_t}{\theta_t}$, and $G = \sum_{t=1}^{T_s} L_{st}$.

Empirical Application

As an empirical illustration, we estimate a pest damage function for the western corn rootworm (*Diabrotica virgifera virgifera*). Corn rootworms are a group of four related insect species, with the western corn rootworm the most problematic species in the major corn growing regions of the U.S. (Spencer et al. 2009). The western corn rootworm has also invaded Europe and established widespread populations that cause economic damage in several European nations (Miller et al. 2005; Gray et al. 2009; Dillen et al. 2010a, 2010b).

Corn rootworm larvae hatch in the soil during the spring and feed almost exclusively on corn roots, with adults emerging from the soil in summer to lay eggs in the soil to continue the cycle (Spencer et al. 2009). Larval feeding causes yield loss by disrupting plant functions and making plants more likely to lodge (Godfrey et al. 1993; Gray and Steffey 1998; Spike and Tollefson 1991). Because corn rootworms typically lay eggs only in existing corn fields, crop rotation has been an effective and widely used control strategy in much of the U.S. Corn Belt (Spencer et al. 2009). For non-rotated corn, the most common control strategies are soil insecticides applied at planting to control larvae; aerial applications in summer to control adults, and more recently, transgenic corn (Fernandez-Cornejo and Jans 1999; Wilson et al. 2005; USDA 2009). Various types of biological control and resistant hybrids are also being evaluated for field control of western corn rootworm in Europe, though such methods have had limited use in the U.S. (Gray et al. 2009; Simic et al. 2007; Toepfer et al. 2005; Tollefson 2007). The western corn rootworm has developed resistance to various chemical insecticides (Ball and

Weekman 1963; Meinke et al. 1998; Miller et al. 2009). In addition, the western corn rootworm soybean variant has developed the behavioral adaptation of laying eggs in soybeans and other crops to adapt to crop rotation (Levine et al. 2002). 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; Gray et al. 2009).

Among the economic research regarding western corn rootworm are studies that estimate the economic impact of the pest, or the value of new control technologies (Alston et al. 2002; Demont et al. 2007; MacLeod 2007; Mitchell et al. 2004; Mellor et al. 2006; Yang et al. 2007; Dillen et al. 2010a, 2010b). An integral part of many of these economic analyses is a pest damage function that links the biological system with the economic system, for example, a function that estimates yield loss as a function of the population density or a measure of pest damage (Mitchell et al. 2004; O'Neal et al. 2001; Dun et al. 2010). Similar to Dun et al. (2010), we use a nested unbalanced panel data model to estimate a western corn rootworm damage function, and then use the estimated function for an economic analysis of the benefit of Bt corn to farmers.

Data

The data for this analysis are from small plot field experiments evaluating corn rootworm control technologies, including soil insecticides, insecticidal seed treatments, and Bt hybrids. Experiments were conducted in Illinois and Nebraska at seven different locations for all or some of the five years 2004-2008. Several roots from each replicated plot were evaluated for rootworm larval feeding damage using the 0-3 node injury scale of Oleson et al. (2005), which assigns a measure to each root indicating the amount of damage to the root caused by rootworm larval feeding. Yields were also collected for each replicated plot. See sources reported in Table 1 for a complete description of these experiments.

For each possible pairing of plots at a single site-year, we calculated the proportional yield difference and the associated node injury measure. Specifically, for two plots *a* and *b* at the same site-year (state *s*, location *l*, year *t*), each with yields Y_a and Y_b and node injury values N_a and N_b, the node injury scale difference and proportional yield difference are, respectively

(7) $$x = N_b - N_a$$

(8) $$y = (Y_a - Y_b)/Y_a.$$

Note that plots *a* and *b* are defined for our analysis so that the node injury scale is non-negative; the traditional benchmark for comparison is the untreated control (e.g., plot *b* is an untreated check). As a result of this definition for *x*, in most cases the associated proportional loss is positive (i.e., the plot with more root damage has a lower yield). Thus, if there are *k* treatments at a site-year, plus an untreated check, there are *k* observations of the node injury scale difference and paired proportional yield difference. However, we expanded observations at each site-year by comparing not only each treated plot to the untreated check, but also to all other treated plots in the same site-year (e.g., plots *a* and *b* can be two different replicates for different treatments). Plots are paired so that the node injury scale difference is always positive, though the associated proportional yield difference need not be, i.e., *a* and *b* are assigned such that $N_b > N_a$, but this does not imply that Y_a must be greater than Y_b. Thus, *z* replicated plots at a single site-year give $z(z + 1)/2$ unique pairings of the node injury scale difference and proportional yield difference. For the 7 locations in 2 states over 5 years, this method generates 3,146 observations of the node injury scale difference (*x*) and the associated proportional yield difference (*y*)—1,902 from 4 locations in Illinois and 1,244 from 3 locations in Nebraska. Table 1 further summarizes the number of observations for each state by year and location.

Results and Discussion

Preliminary analysis indicated that location effects were insignificant, so for this study, location effects were dropped from the nesting structure, leaving the single-nested unbalanced panel model as reported by equation (3). In addition, just as for Dun et al. (2010), the intercept was insignificant and dropped, which makes sense—if the observed node injury scale measures for two plots do not differ, on average, no difference in proportional yield loss is expected. Table 2 reports the final estimation results, while Figure 1 illustrates the model fit. For comparison, Table 2 also reports estimation results for a standard OLS regression:

(9) $$y_{tlr} = \beta x_{tlr} + \varepsilon_{tlr}.$$

Again, no intercept is included, so the R^2 is not reported, as it no longer has the standard range or interpretation (Greene 2003).

The estimated slope coefficient of 0.164 implies that a one unit difference in the node injury scale is, on average, associated with a 16.4% yield loss. This estimate is similar in magnitude to, but statistically different from, the estimate of 0.1788 reported by Dun et al. (2010). We derive the estimate reported here using some of the same data from Illinois as Dun et al. (2010) used, but added 78 observations for 2008 from Urbana, IL, plus all 1,244 observations from Nebraska. Expanding the geographic area and the number of observations implies a slightly smaller effect for rootworm larval feeding on yield loss.

Estimated random year and state effects reported in Table 2 are statistically significant. The experimental error component is by far the largest source of variability in yield loss. Using the standard deviations implied by the estimated variances reported in Table 2 as measures of loss variability, of the total variably obtained from summing over all three effects, about 10% is due to the year effect, almost 26% to the state effect, and 64% from the experimental error. Repeating this process using the results in Dun et al. (2010), almost 25% of the variability in yield loss is from the year effect, 14% from the (insignificant) location effect, and 62% from the experimental error.

The relatively large estimate for the random experimental error (σ_{ε}^{2}) and the data plotted in Figure 1 indicate the large amount of variability in yield losses. Substantial yield losses due to rootworm larval feeding damage can occur, even when the node injury scale difference is not large, and conversely, very little yield loss can occur, even if the node injury scale difference is quite large. For these data, the observed proportional yield losses range from –89.8% to +77.0% across all treatments. The implication is that many factors contribute to observed yield differences between plots near one another, not just rootworm larval feeding damage. Not only do soil conditions vary over such scales, but also availability of applied inputs (e.g., fertilizer). Furthermore, rootworm larvae are typically not uniformly distributed over a field, but clumped together in some places (Toepfer et al. 2007; Ellsbury et al. 2005). The substantial variability in yield losses for similar measures of rootworm larval feeding has also been noted for the 1-6 root rating scale of Hills and Peters (1971) (Gray and Steffey 1998; Urías-López and Meinke 2001; Mitchell et al. 2004) and for the 0-3 scale (Cox et al. 2008).

Experimental plots are relatively small (i.e., usually about 10 feet by 40 feet in both Illinois and Nebraska), so that in some sense the estimated experimental error can be interpreted as an estimate of the variability between smaller grids within a larger field. Following this interpretation, yield for the whole field would average over all these plots or grids so that these plot errors would on average cancel, but the random year and state effects would remain, as these would affect all parts of the field. Hence, for the economic analysis of field level impacts, we drop the experimental errors, but keep the variability from the random year and state effects.

For comparison, we used the same data to estimate a standard linear regression model, again not including an intercept, with estimation results reported in Table 2. The results indicate the nature of the error that would result from using a standard linear regression model—damages would be underestimated. The OLS slope coefficient implies a 14.3% yield loss for a one unit difference in the node injury scale, as opposed to the 16.4% difference for the nested unbalanced random effects model. This difference occurs because the random location and year effects are significant. However, note that the magnitude and direction of the difference is specific to these data and the differences reported here are not general results.

Economic Application

As an illustration, we use the estimated model for economic analysis of the value of Bt corn for farmers in Nebraska and Illinois. We first present a conceptual model and then describe parameterization of the model using the node injury scale data, and finally present the results of the economic analysis based on Monte Carlo simulations.

Returns (\$/ac) for untreated non-Bt corn and Bt corn are respectively, $\pi_{no} = PY_{no} - K$ and $\pi_{Bt} = PY_{Bt} - C_{Bt} - K$, where P is the price of corn (\$/bu), Y_{no} and Y_{Bt} are yield (bu/ac) for non-Bt corn and Bt corn, C_{Bt} is the extra cost for Bt corn (\$/ac) and K is the cost of production for corn for all costs other than seeds (\$/ac). Using these equations, the net increase in farmer returns for Bt corn relative to non-Bt corn is $\Delta\pi = \pi_{Bt} - \pi_{no} = P(Y_{Bt} - Y_{no}) - C_{Bt}$. Using equation (8), yield for non-Bt corn with no rootworm control can be expressed as $Y_{no} = Y_{Bt}(1 - y)$, where y is the proportional yield difference between Bt and non-Bt corn, or equivalently, the yield advantage of

Bt corn relative to untreated non-Bt corn expressed as a proportion of the observed Bt corn yield. Substituting this expression for Y_{no} into the expression for $\Delta\pi$ and simplifying gives:

(10) $$\Delta\pi = PY_{Bt}y - C_{Bt}.$$

Equations (1) and (3) for the estimated single-nested unbalanced panel data model imply that the yield advantage of Bt corn can be expressed as

(11) $$y = \beta(NIS_{no} - NIS_{Bt}) + \mu + \nu,$$

where μ and ν are the random year and state effects from equation (3) (indexes are dropped as they no longer pertain) and each is distributed normally with a zero mean and estimated variances σ_μ^2 and σ_ν^2 as reported in Table 2. Notice that equation (11) drops the experimental error as captured by ε and the estimated σ_ε^2 variance component, since yield at the field level averages over this "intra-plot" variability, but retains the random year and state effects. Finally, combining equations (10) and (11) gives

(12) $$\Delta\pi = PY_{Bt}[\beta(NIS_{no} - NIS_{Bt}) + \mu + \nu] - C_{Bt}$$

as an expression for the net increase in farmer returns for Bt corn relative to non-Bt corn.

In addition to the estimated parameters β, σ_μ^2 and σ_ν^2, empirically implementing equation (12) requires information for the remaining variables. To preserve the variability inherent in corn production and losses from corn rootworm larval feeding, we use random variables for more than just the year and state effects (μ and ν). For Bt corn yield (Y_{Bt}), we use a beta density, a common assumption for crop yields (Goodwin and Ker 2002; Mitchell and Knight 2008). Based on the average yields for Bt corn reported for the field plots and the county average yields for these areas (sources in Table 1; USDA-NASS 2010), we use a mean of 200 bu/ac for both states as a base case, but vary this assumption for sensitivity analysis. Following

Babcock et al. (2004), we use a coefficient of variation of 25% for both locations, varying it for sensitivity analysis, and use a minimum of zero and maximum of the mean plus two standard deviations. To focus on production risk, we use a non-random corn price (P) of \$3.50/bu and a non-random additional cost of Bt corn (C_{Bt}) of \$16/ac, but vary both for sensitivity analysis.

Corn rootworm larval pressure and damage each year is variable due to environmental factors such as weather impacts on female fecundity the previous summer/fall, over winter survival of eggs in the soil, and soil conditions during spring and early summer (Spencer et al. 2009). To capture this variability, we assume NIS_{no} is random, using the field plot data used for estimation of the nested unbalanced panel data model to develop its probability distribution. For the node injury scale without treatment, the Nebraska data included 24 observations from four locations, while the Illinois data included 65 observations from four locations. Following Mitchell et al. (2004), a beta distribution is used for the NIS_{no}, as the beta distribution is quite flexible, able to be J-, U-, or L-shaped, plus has a fixed maximum and minimum (Evans et al. 2000). For estimation, the minimum was set to 0, the maximum to 3, as these are the limits of the node injury scale by definition, and the density function was re-parameterized in terms of the mean and standard deviation. Table 3 reports maximum likelihood estimation results, pooling observations across years and locations for each state.

The results in Table 3 indicate that rootworm pressure is on average higher in Illinois than in Nebraska, as the mean node injury scale is almost 1.9 in Illinois versus 1.64 in Nebraska. In terms of variability in corn rootworm larval pressure, the standard deviation is also greater in Illinois, but variability is relatively higher in Nebraska, as the coefficient of variation is almost 45% in Nebraska, but not quite 35% in Illinois. These results indicate the potential for substantial root damage (and thus substantial yield loss) to occur in corn not receiving some form of rootworm control in these major corn producing states. The results also show the tremendous variability that occurs in this pressure—the mean and standard deviation for Nebraska imply that the 95% confidence interval for the untreated node injury scale ranges from 0.532 to 2.664, while in Illinois, the range is from 0.195 to 2.987. Reducing the impact of this variability in rootworm pressure is one of the benefits of Bt corn.

The data for Illinois are for plots planted in areas that had “trap crops” planted the previous season (corn planted late with pumpkins), which attracts adult western corn rootworm and thus increases female oviposition, resulting in a higher larval populations the next spring (e.g. Estes et al. 2008). The purpose is to ensure high rootworm pressure under which to evaluate rootworm control technologies. The implication is that the expected node injury scale without treatment is skewed to be higher than typical in Illinois. The sites in Nebraska did not use trap crops, but later planted corn, and so should be more representative of typical rootworm pressure. Hence, we use these results to develop 4 scenarios. The first is “very high pressure” with a mean NIS_{no} of 1.90 and a standard deviation of 0.855, implying a coefficient of variation (CV) of 0.45, based on the estimated results for Nebraska. The second is “high pressure” with a mean NIS_{no} of 1.65 and a standard deviation of 0.5775, implying a CV of 0.35. These two scenarios are based on estimation results for Illinois and Nebraska respectively. The third is “moderate pressure” with a mean of 1.20 and a standard deviation of 0.42, implying a CV of 0.35, and the fourth is “low pressure” with a mean of 0.80 and a standard deviation of 0.28, also implying a CV of 0.35. These scenarios represent a decrease in the mean NIS_{no} of approximately 25% and 50% from the high pressure scenario, keeping the same CV to maintain the same level of relative variability.

The node injury scale for Bt corn (NIS_{Bt}) is also variable due to environmental factors, plus it depends on the larval pressure. To capture this variability and dependence on larval pressure, we estimated a conditional beta distribution for the NIS_{Bt} using a smaller sub-set of the field plot data used to estimate the nested unbalanced panel data model. The Nebraska data included 18 observations of the node injury scale without treatment and with Bt corn for the same site-year from three locations over the five years, while the Illinois data included 98 such paired observations from four locations over the five years. Based on these data, a conditional beta distribution was estimated, with a Cobb-Douglas function for the mean: $m = \eta_1 NIS_{no}^{\eta_2}$, and an exponential function for the standard deviation: $s = \exp(\tau_0 + \tau_1 NIS_{no})$, with a minimum of 0 and maximum equal to the observed NIS_{no} (Mitchell et al. (2004) and Dillen et al. (2010a) use a similar model for the root rating with control conditional on the root rating without control). Table 3 reports maximum likelihood estimation results for the parameters η_1, η_2, τ_0 and τ_1, while Figure 2 illustrates the observations and the model fit for the mean and 95% confidence interval. Data were pooled across states as testing showed no significant difference between states.

The results in Table 3 and Figure 2 show that on average, Bt corn reduces root damage as measured by the node injury scale from what it would be without treatment. For example, the average node injury scale with Bt corn would be 0.07766 when the node injury scale without treatment is 1.0. The average would be 0.197 when the untreated node injury scale is 1.6437 (the Nebraska mean), with the 95% confidence interval ranging from 0.0231 to 0.518, while the average would be 0.257 when the untreated node injury scale is 1.8966 (the Illinois mean), with the 95% confidence interval ranging from 0.0305 to 0.670. These values indicate the tremendous efficacy of Bt corn to reduce rootworm larval feeding damage to corn roots, as well as the variability that remains, especially at higher larval pressure. For example, with an untreated node injury scale of 3.0 (the maximum possible), the node injury scale with Bt corn still has a 95% confidence interval ranging from 0.0134 to 1.892. Figure 2 illustrates the model fit, demonstrating the existence of this tremendous variability in the data, especially at higher node injury scales without treatment.

Monte Carlo Simulation Results

Empirical implementation of equation (12) with the probability distributions as specified does not allow for analytical expressions for even the expected benefit, nor its standard deviation or other such measures of variability. The problem arises because the node injury scale without treatment has a beta distribution and is transformed non-linearly to obtain the node injury scale for Bt corn. As a result, we use Monte Carlo integration to obtain numerical estimates for the expected benefit and its standard deviation. In addition, we use the simulations to develop histograms of the benefits to illustrate its distribution, plus calculate the probability that the benefit is negative (i.e., non-Bt corn generates higher net returns). Results are summarized in Tables 4 and 5 and Figure 3.

Tables 4 and 5 show Monte Carlo estimates of the expected benefit for Bt corn and the standard deviation of this benefit for the four western corn rootworm larval pressure scenarios. In Table 4, the mean Bt yield is varied for sensitivity analysis, while in Table 5, the Bt yield coefficient of variation (CV) is varied. Results for varying the corn price are not reported, since the effect is exactly the same as varying the mean Bt yield due to the way the corn price and the Bt yield enter equation (12). For results in both tables, other variables are held at their base case value—a mean Bt yield of 200 bu/ac, a Bt yield CV of 25%, a corn price of $3.50/bu, and a Bt corn technology fee of $16/ac.

Table 4 shows that, as expected, the benefit of Bt corn increases as the mean yield for Bt corn increases and as western corn rootworm larval pressure increases. With a low mean Bt yield of 100 bu/ac and low rootworm pressure, the expected benefit for Bt corn is only $28.66/ac and rises to $95.65/ac with a mean Bt yield of 250 bu/ac, which is an increase of 150%, the same as the increase in mean yield. The expected benefit is also sensitive to the rootworm larval pressure, more than doubling when moving from low to very high rootworm pressure. The variability of the Bt corn benefit also increases when rootworm pressure and mean Bt yield increase. The standard deviation of the benefit almost doubles when moving from low to very high larval pressure and, as expected, increases 150% when moving from a mean Bt yield of 100 bu/ac to 250 bu/ac.

Table 5 shows that, as expected, Bt yield variability has little effect on the expected benefit of Bt corn. Furthermore, the Bt yield variability does not have a large effect on the standard deviation of the benefit of Bt corn either. For example, under high larval pressure, the standard deviation of the base case is $82.24/ac, but only rises to $100.67 (a 22% increase) when the Bt yield CV increases from 25% to 40% (a 60% increase).

The mean Bt yield and the Bt yield CV affect the probability that the benefit is negative in a non-linear fashion. Tables 4 and 5 show how pest pressure affects the probability of a negative benefit. When moving from low to moderate to high pest pressure, the probability of a negative benefit decreases but at a decreasing rate—for example, with a 200 bu/ac mean Bt yield, the probability drops from 6.71% to 2.43% to 1.26% in Table 4. This decrease is due solely to the mean node injury scale without treatment increasing from 0.8 to 1.2 to 1.65, as the coefficient of variation remains constant at 35% for low, moderate and high pest pressure. However, moving from high to very high pest pressure, not only does the mean node injury scale increase from 1.65 to 1.9, but also the coefficient of variation increases from 35% to 45%. This shift causes the probability of a negative benefit to increase—the higher variability in pest pressure increase the probability of a negative benefit and dominates the decreasing effect of the increase in the mean node injury scale. For example, with a 200 bu/ac mean Bt yield, the probability drops from 6.71% to 2.43% to 1.26% in Table 4, then increases to 3.82% when moving form low to moderate to high and then very high pest pressure. These same trends are evident in Table 5.

Figure 3 illustrates these trends graphically. The intersections of the cumulative probability functions with the vertical axis are the probabilities reported in Table 4 for the base case, but Figure 3 shows the probabilities for other levels of benefits besides $0/ac. As expected, increasing pest pressure from low to moderate to high shifts the cumulative probability function to the right, and thus the probability density function as well. However, moving from high to very high pressure shows that the probability mass shifts to the right and spreads out, so that average benefits increase, but become more variable as well. This shift is due to the increase not only in the mean of the node injury scale without treatment, but also to the increases in its variability when moving from high to very high pressure.

Table 4 also shows how the mean Bt yield (and implicitly the price) affects the probability of negative benefits. Increasing the mean decreases the probability of negative benefits because the cumulative probability function shifts to the right, as the top plot in Figure 4 illustrates graphically, focusing on the lower end. Similarly, Table 5 shows how the coefficient of variation (CV) of Bt yield affects the probability of negative benefits. Increasing the Bt yield's CV increases the probability of negative benefits because the cumulative probability function shifts to the left, as the bottom plot in Figure 4 illustrates graphically, again focusing on the lower end.

Discussion and Conclusion

Economic assessments of insect pests commonly require a pest damage function to estimate yield loss based on some measure of plant damage or pest population density from field trials. A common occurrence for such data is that the number of locations and/or years (i.e., site-years) varies or the number of replicates differs across site-years, creating unbalanced nested panel data. We apply Antweiler's (2001) double-nested unbalanced panel data model in a manner similar to Dun et al. (2010), but use additional data from more locations to estimate a western corn rootworm damage function. As a random effects model, the method also estimates the contribution to the observed variability in yield losses from different variance components, such as location, year, and experimental noise. As an illustration, the model was applied to field trial data from seven locations in Illinois and Nebraska collected from 2004 to 2008.

Estimation results imply that expected yield losses for a one unit difference in the node injury scale are on average 16.4%, which is smaller than the estimate of 17.88% reported by Dun et al. (2010), with the difference apparently from expanding the number of observations. Estimated random year and state effects were much smaller than the random experimental effect, similar to results reported by Dun et al. (2010). The relatively large experimental error effect indicates the tremendous variability in yield losses at the smaller scale of plots (or smaller grids within fields) with the same node injury scale measure of corn rootworm larval feeding damage.

With the estimated pest damage function and its variance components, our analysis goes a step further than Dun et al. (2010) and assesses the value of Bt corn for farmers in Nebraska and Illinois, using Monte Carlo simulation to incorporate the randomness inherent in western corn rootworm damage. We find that Bt corn reduces root damage as measured by the node injury scale from what it would be without treatment, on average by about 90%-95%. With a mean Bt yield of 200 bu/ac, a Bt yield CV of 25%, a corn price of $3.50/bu, and a Bt corn technology fee of $16/ac, the expected value of Bt corn for farmers is $173.35/ac and $156.14/ac under very high and high pressure respectively. Varying parameters for sensitivity analysis changes these results in expected ways, but overall the expected values and the variably remain quite high. The large magnitudes of these values indicate the potential losses farmers face from western corn rootworm and are a key factor driving the high farmer demand for methods to control corn rootworm damage, and they indicate the economic incentives for farmers to not comply with Bt corn refuge requirements (e.g., Mitchell and Hurley 2006; Elmore et al. 2010; Jaffe 2009).

The Monte Carlo simulations also allow estimation of the variability of these benefits. Estimates are quite large—the standard deviation of the benefit of Bt corn is $105.06/ac for the Illinois base case and $82.24/ac for the Nebraska base case. As a result of this variability, even though expected benefits are quite large, the probability that the benefit is negative, i.e., that returns would have been larger without control, ranges from 1.3% to 3.8% for the base cases and can become much larger under different parameter assumptions. These values indicate the tremendous uncertainty in the benefits from controlling corn rootworm, largely due to the variability in corn rootworm pressure, in the efficacy of control, and in yield losses resulting form root damage. These values also indicate the importance of risk preferences when analyzing the benefits of pest control technologies (Mitchell and Hutchison 2008). However, the analysis of the benefits of western corn rootworm control summarized here does not include risk preferences, leaving this extension for future research.

Table 1. Number of observations by state, year and location.

State	Year	Location	Observations	Source
Illinois	2005	Dekalb	352	
	2005	Monmouth	253	
	2005	Urbana	190	
		Total for 2005	768	Estes et al. 2005
	2006	Urbana	91	
		Total for 2006	91	Estes et al. 2006
	2007	Dekalb	351	
	2007	Monmouth	253	
	2007	Perry	190	
	2007	Urbana	171	
		Total for 2007	965	Estes et al. 2007
	2008	Urbana	78	
		Total for 2008	78	Estes et al. 2008
		Total for Illinois	1,902	
Nebraska	2004	Clay Center	10	
	2004	Concord	190	
		Total for 2004	200	
	2005	Concord	378	
	2005	Mead	78	Meinke et al. 2005
		Total for 2005	456	
	2006	Clay Center	210	
	2006	Mead	36	Meinke et al. 2006
		Total for 2006	246	
	2007	Mead	66	Meinke et al. 2007
		Total for 2007	66	
	2008	Clay Center	276	DeVries and Wright 2008
		Total for 2008	276	
		Total for Nebraska	1,244	
		Total	3,146	

Table 2. Estimation results for the single-nested unbalanced panel data model and maximum likelihood estimation results for standard linear regression model.

Parameter	Estimate	Standard Error	t Statistic	p Value
---------- Single-Nested Unbalanced Panel Data Model ----------				
Slope (β)	0.164	0.00334	48.35	<0.001
Year Effect	0.000389	0.000300	1.296	0.0975
State Effect	0.00253	0.00182	1.389	0.0825
Experimental Error (σ_{ε}^{2})	0.0155	0.000401	38.71	<0.001
---------- Standard Linear Regression Model ----------				
Slope (β)	0.143	0.00240	59.54	<0.001
Variance (σ_{ε}^{2})	0.0166	0.000620	26.45	<0.001

Table 3. Estimation results for the beta distributions for the node injury scale without treatment in Illinois and Nebraska and for the node injury scale for Bt corn conditional on the node injury scale without treatment.

Parameter	Estimate	Standard Error	t Statistic	p Value
---------- Node Injury Scale without Treatment (NIS_{no}) ----------				
Mean (IL)	1.8966	0.1196	15.85	<0.001
Standard Deviation (IL)	0.8472	0.06165	13.74	<0.001
Mean (NE)	1.6437	0.1223	13.44	<0.001
Standard Deviation (NE)	0.5714	0.06518	8.78	<0.001
---------- Node Injury Scale with Bt Corn (NIS_{Bt}) ----------				
Slope (η_1)	0.07766	0.01086	7.15	<0.001
Exponent (η_2)	1.8723	0.1857	10.08	<0.001
Standard Deviation Intercept (τ_0)	-3.6909	0.3033	-12.17	<0.001
Standard Deviation Slope (τ_1)	1.0111	0.1378	7.34	<0.001

Table 4. Effect of expected Bt yield (bu/ac) (Yield Mean) on the expected benefit of Bt corn (Mean), the standard deviation of the benefit (St. Dev.), and the probability that the benefit is less than zero (Prob. $\Delta\pi < 0$) under different levels of western corn rootworm pressure.

	Very High Pressure			High Pressure			Moderate Pressure			Low Pressure		
Yield Mean	Mean ($/ac)	St. Dev. ($/ac)	Prob. $\Delta\pi < 0$	Mean ($/ac)	St. Dev. ($/ac)	Prob. $\Delta\pi < 0$	Mean ($/ac)	St. Dev. ($/ac)	Prob. $\Delta\pi < 0$	Mean ($/ac)	St. Dev. ($/ac)	Prob. $\Delta\pi < 0$
100	78.68	52.53	6.04%	70.07	41.12	2.68%	49.24	33.83	5.05%	28.66	27.40	13.64%
125	102.35	65.66	5.19%	91.59	51.40	1.97%	65.55	42.28	3.72%	39.82	34.25	10.27%
150	126.02	78.80	4.60%	113.11	61.68	1.63%	81.86	50.74	3.11%	50.99	41.10	8.54%
175	149.68	91.93	4.12%	134.62	71.96	1.43%	98.18	59.19	2.68%	62.15	47.96	7.42%
200	173.35	105.06	3.82%	156.14	82.24	1.26%	114.49	67.65	2.43%	73.32	54.81	6.71%
225	197.02	118.19	3.61%	177.66	92.53	1.22%	130.80	76.11	2.22%	84.48	61.66	6.10%
250	220.69	131.33	3.40%	199.18	102.81	1.12%	147.11	84.56	2.05%	95.65	68.51	5.63%

Table 5. Effect of the Bt yield coefficient of variation (Yield CV) on the expected benefit of Bt corn (Mean), the standard deviation of the benefit (St. Dev.), and the probability that the benefit is less than zero (Prob. $\Delta\pi < 0$) under different levels of western corn rootworm pressure.

	Very High Pressure			High Pressure			Moderate Pressure			Low Pressure		
Yield CV	Mean ($/ac)	St. Dev. ($/ac)	Prob. $\Delta\pi < 0$	Mean ($/ac)	St. Dev. ($/ac)	Prob. $\Delta\pi < 0$	Mean ($/ac)	St. Dev. ($/ac)	Prob. $\Delta\pi < 0$	Mean ($/ac)	St. Dev. ($/ac)	Prob. $\Delta\pi < 0$
10%	174.00	93.05	3.68%	156.77	70.15	1.21%	114.97	59.10	2.15%	73.65	49.60	6.19%
15%	173.78	96.06	3.68%	156.56	73.22	1.21%	114.81	61.25	2.20%	73.54	50.89	6.24%
20%	173.57	100.11	3.75%	156.35	77.31	1.25%	114.65	64.13	2.25%	73.43	52.64	6.35%
25%	173.35	105.06	3.82%	156.14	82.24	1.26%	114.49	67.65	2.43%	73.32	54.81	6.71%
30%	173.14	110.76	3.93%	155.93	87.86	1.40%	114.33	71.69	2.62%	73.21	57.33	7.13%
35%	172.92	117.12	4.16%	155.72	94.03	1.69%	114.16	76.17	3.04%	73.10	60.16	7.96%
40%	172.71	124.04	4.63%	155.52	100.67	2.18%	114.00	81.02	3.75%	72.98	63.27	8.85%

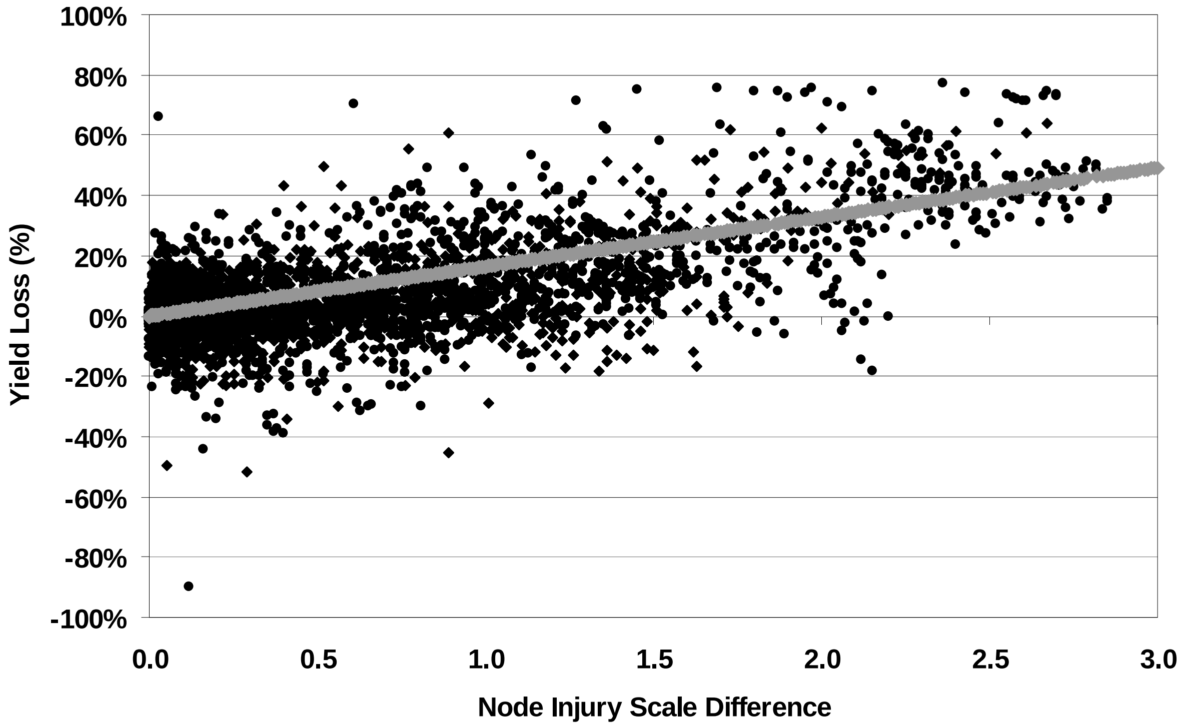

Figure 1. Observed node injury scale difference and associated yield loss (%) for all site-years (•) and estimated single-nested unbalanced panel model fit (gray line).

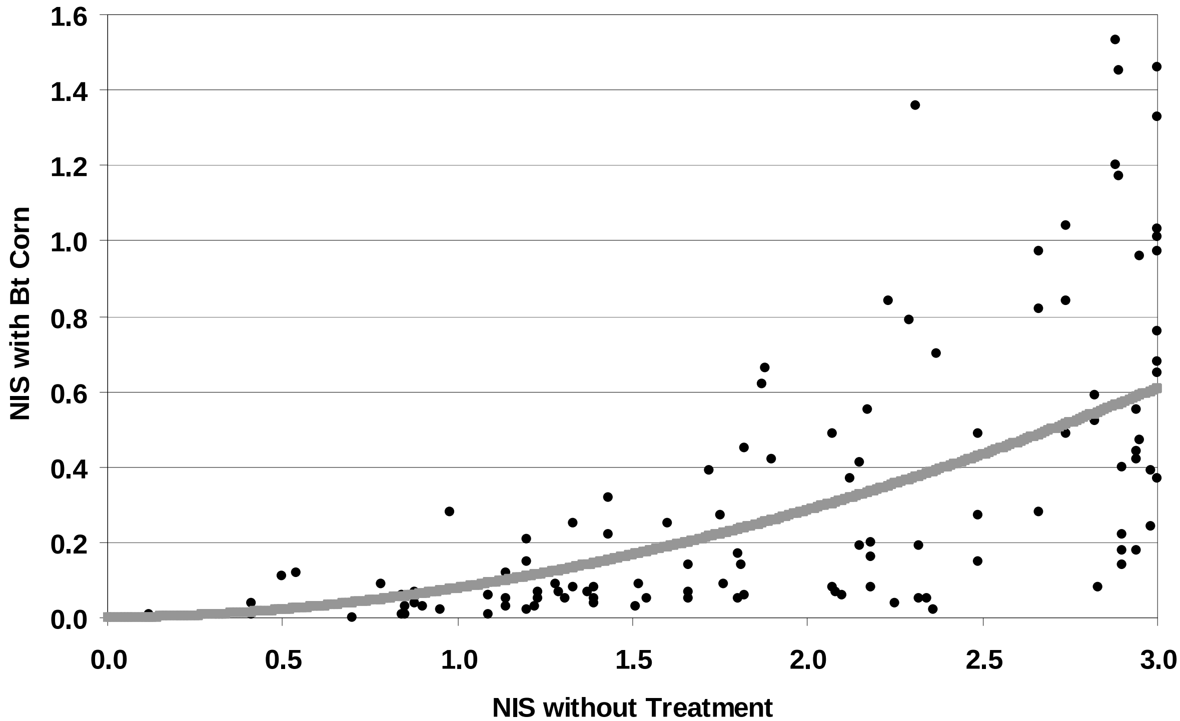

Figure 2. Observed node injury scale with Bt corn versus the node injury scale without treatment (•) and estimated model fit (gray line).

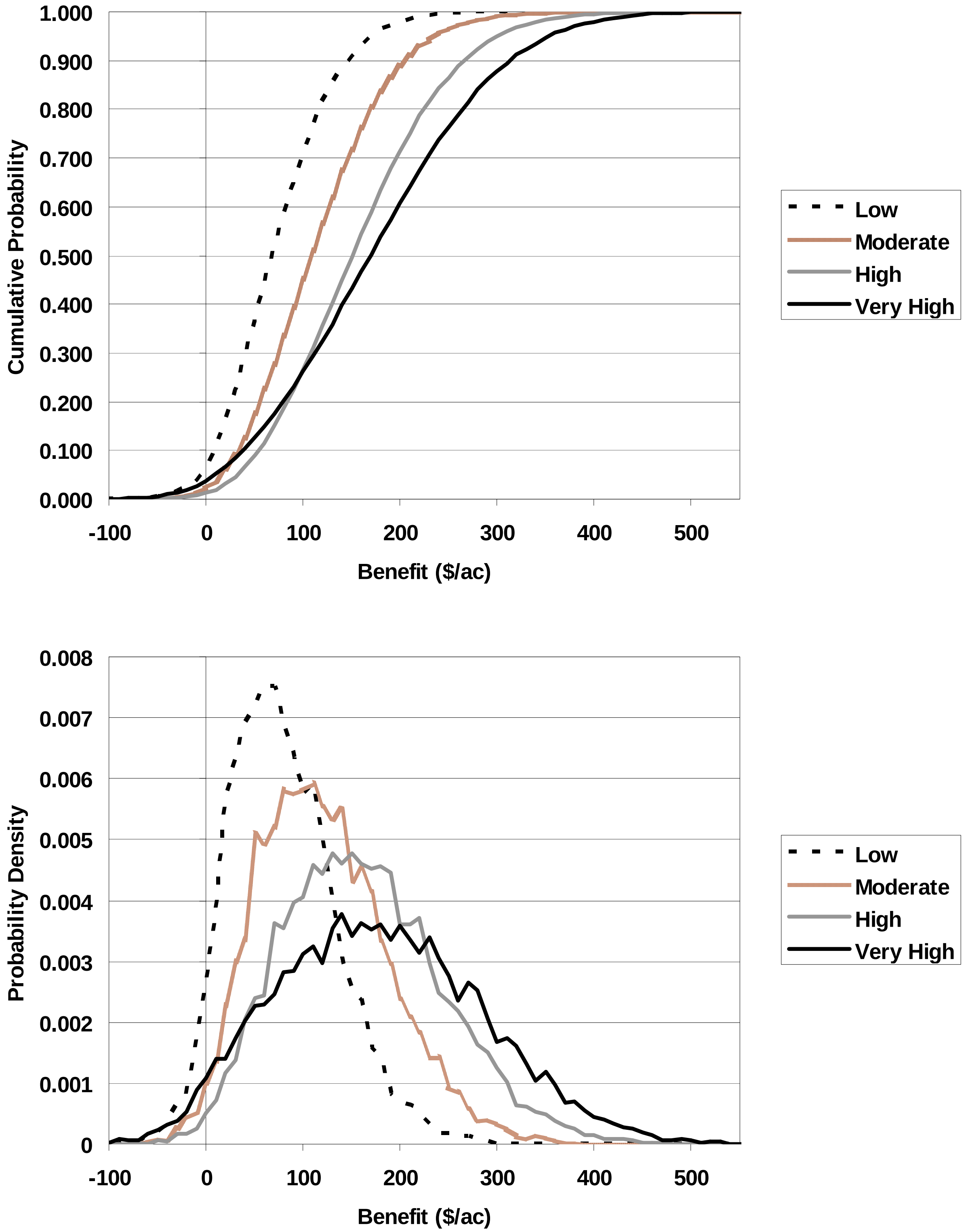

Figure 3. Plots of the empirical cumulative distribution functions and probability density functions from the Monte Carlo simulations for the base case under low, moderate, high and very high western corn rootworm larval pressure.

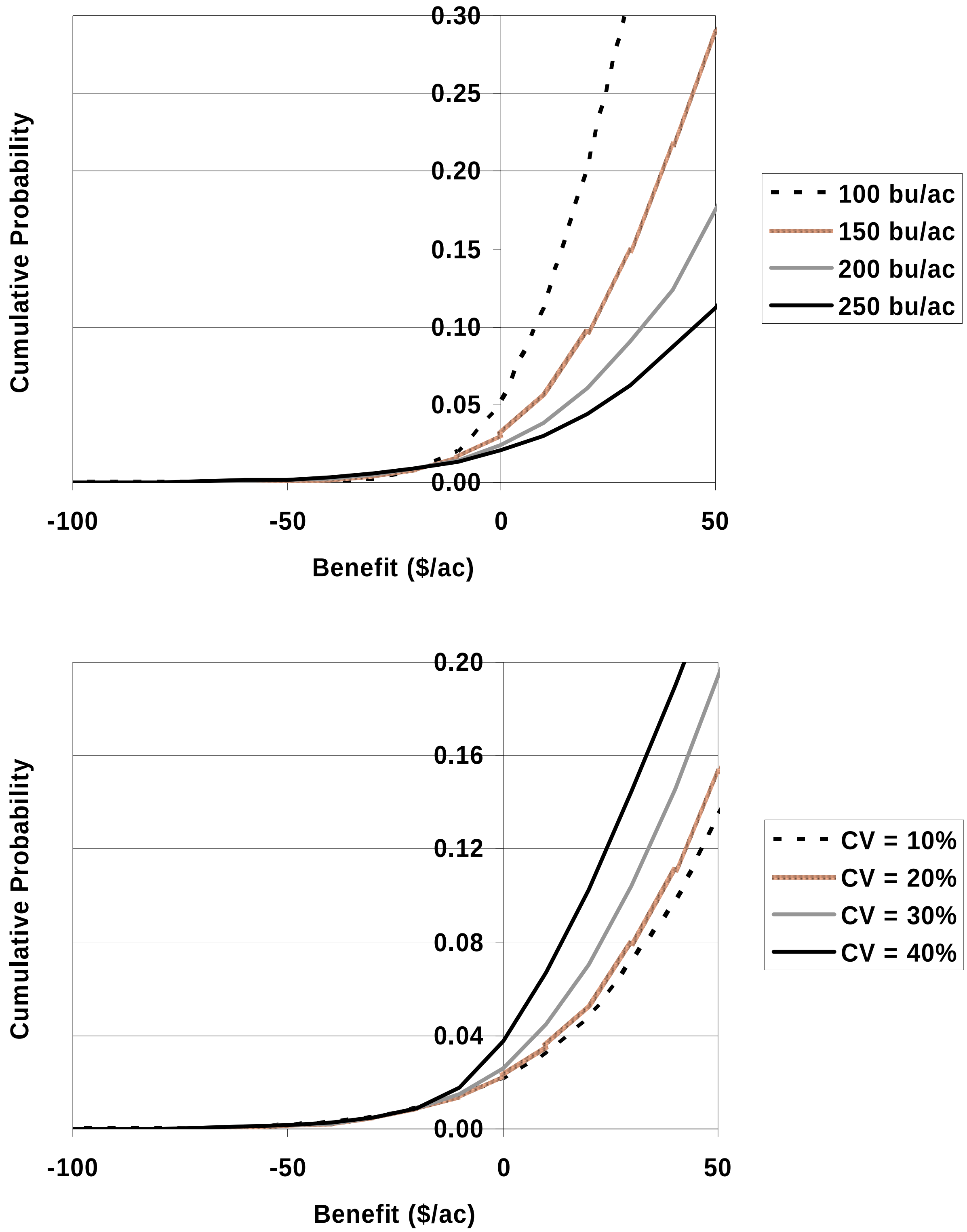

Figure 4. Plots of the empirical cumulative distribution functions from Monte Carlo simulations with varying mean yields (top) and varying yield coefficients of variation (CV) (bottom) under moderate western corn rootworm larval pressure.

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