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Micro versus Macro Acreage Response Models: Does Site-Specific Information Matter?

JunJie Wu and Richard M. Adams

Because requisite micro data frequently are unavailable, it is common practice to use aggregate data to estimate economic relationships representing the behavior of individual agents. A substantial body of literature has examined conditions under which inferences between micro and aggregate specifications can be made. Less attention has been focused on the relative accuracy of predictions for each scale of model. In an empirical application, we compare the goodness-of-fit measures of eight sets of acreage response models, varying in aggregation from field- (micro-) level to regional- (macro-) level models. Results suggest aggregate models are superior to the micro model in predicting acreage response, even though the micro models contain substantially more data on site-specific characteristics.

Key words: acreage response model, aggregation, macro models, micro models, prediction accuracy, site-specific information

Introduction

Applied economists must wrestle with the tradeoff between a theoretically consistent model specification and tractability constraints imposed by data. For example, microeconomic relationships representing the behavior of individual economic agents are frequently estimated using aggregate or "macro" data. These empirical macro relationships are then used for making inferences about individual behavior and for making aggregate predictions. This practice of using macro or aggregate data to estimate what are inherently micro relationships is often necessary because micro-level data are unavailable (Grunfeld and Griliches).

Two problems arise from this practice. One, which is often referred to as the aggregation problem, concerns the connections between micro and macro behavior (Chambers and Pope). If aggregate relationships are used to make inferences about individual behavior, one must consider the conditions under which the distribution of individual characteristics can be ignored so the results can be treated as if they are the outcome of the decision of a single "representative" firm or consumer. If these conditions are met, the relationships derived from micro theory can be estimated with aggregate data and behavioral interpretations can be drawn from the estimated parameters.

The second problem, which is the focus of this study, concerns the relative accuracy of predictions made by micro and macro models. With the advance of data collection and

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JunJie Wu is associate professor and Richard M. Adams is professor, both in the Department of Agricultural and Resource Economics at Oregon State University, Corvallis. The authors thank two anonymous referees for their helpful comments and suggestions.

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management technologies, such as Geographic Information Systems (GIS) and satellite imaging, more micro-level, spatially articulated data are now available. With these data, it is increasingly possible to estimate micro models and then statistically aggregate the micro-level predictions to the aggregate level by using distributions of micro-level characteristics. The question is whether the micro approach, facilitated by the availability of those micro data, will provide better predictions of aggregate outcomes than traditional aggregate models.

A large body of literature has focused on the aggregation problem in general, and two lines of inquiry in particular. The first seeks the requisite conditions on micro behavior to guarantee existence of a representative producer or consumer for any distribution of individual characteristics (Gorman; Muellbauer), or on the distribution of individual characteristics that guarantee the existence of macro functions which share some or all properties of the corresponding micro functions (Klein; Theil; Hildenbrand; Chiappori; Stoker; Blackorby and Schworm). These conditions are found to be quite stringent. The second line of inquiry focuses on the problem of "aggregation bias," defined by the derivation of the macro parameters from the average of the corresponding micro parameters (e.g., Theil; Gupta; Sasaki; Lee, Pesaran, and Pierse), or tests the consistency between theory and empirical evidence (Shumway 1995; Love).

In contrast to the aggregation problem, the issue of prediction accuracy has received less attention. In a 1960 paper, Grunfeld and Griliches (GG) examined the relative power of micro and macro models for explaining the variability of the aggregate dependent variable and found the aggregate equation may explain the aggregate data better than a combination of micro equations, if the micro equations are not correctly specified. Sasaki reexamined the issue using data from four Japanese industries and concluded the explanatory power of the macro models is not necessarily higher than that of micro models.

Pesaran, Pierse, and Kumar (PPK) developed a more general criterion for choosing between micro and macro models and applied it to labor demand in UK industries. They found that for manufacturing industries, the prediction criterion marginally favors the aggregate model, but over all industries the disaggregate models are strongly preferred. Building upon the work by PPK, Thompson developed a joint test for spatial and temporal aggregation; Thompson and Lyon developed a generalized test of perfect aggregation which accommodates the case where the full rank conditions required for conducting the PPK test are not satisfied or where linear models estimated with time-series data display serially correlated error terms.

The primary objective of this study is to compare the prediction accuracy of micro and macro models, using crop acreage projections as an example. As with other types of economic predictions, acreage projections are typically based on "macro" models estimated from aggregate time-series data. However, substantial site-specific data [e.g., the National Resources Inventory (NRI) and similar GIS-based land use data systems] are becoming available for estimating micro-level relationships. The availability of such data now allows estimation of more disaggregate models of acreage response and on-farm behavior. The question is whether the micro approach, facilitated by the availability of micro data, will provide better predictions of aggregate outcomes than traditional aggregate models.

To explore this issue, we estimate eight sets of crop choice/acreage response models for the Corn Belt (Iowa, Illinois, Indiana, Ohio, and Missouri) and then compare their

goodness-of-fit measures. Five of the models, which are specified at the field, county, state, and regional levels, were estimated using the National Resources Inventory, the most comprehensive resource and land use survey ever conducted in the United States. The other three models, specified at the county, state, and regional levels, were estimated using county crop acreage data from the U.S. Department of Agriculture's (USDA's) National Agricultural Statistics Service (NASS). Although the NASS data are more aggregate than the NRI data, they encompass a much longer time series.

This article makes two contributions to the literature. First, we show that the GG criterion for discriminating between micro and macro models may lead to the choice of the macro model even if the micro models are correctly specified. This goodness-of-fit criterion, which is based on the sum of squared residuals, may fail simply because even when the sums of squared residuals are very large, the aggregate prediction can be accurate if over-predictions for some units are offset by under-predictions for others. The PPK criterion, which is more general than the GG criterion, will not lead to the choice of a "wrong" model. However, in some special cases (see the next section), the PPK criterion cannot be used to discriminate between micro and macro models even if the variance of prediction errors of the micro model is smaller.

Second, this study focuses on acreage prediction, an area where aggregate models are most commonly used but where disaggregate data are now becoming available. Previous studies on prediction issues, however, have not examined acreage projections.

Aggregation and Prediction Accuracy

In this section, we present a statistical model to examine the relative accuracy of micro and macro models in terms of aggregate prediction. We show that even in the context of linear prediction models, the issue of whether one should choose micro or macro models to make aggregate predictions cannot be generally resolved by a priori reasoning. The issue must be settled with empirical analysis.

Assume a set of sample observations on a "panel" of N decision units over T time periods. Let Y_{it} be the dependent variable for unit i in period t, and let $\mathbf{X}_{it} = (x_{1it}, x_{2it}, \ldots, x_{kit})$ be the independent variables for unit i in period t. We wish to use these data to develop a model to predict the total value of Y for all units associated with an estimate of independent variables $\mathbf{X}_i^0$ $(i = 1, 2, \ldots, N)$. There are several approaches for making such a prediction. A simple approach is to use the pooled time-series and cross-sectional data to estimate the following micro model:

$$H_d\colon\ Y_{it} = \mathbf{X}_{it}\beta + u_{it},\ u_{it} \sim N(0, \sigma^2), \tag{1}$$

and then use the model to make predictions for each micro unit. Summing the predictions for all micro units provides an aggregate prediction. Model (1) is a very restrictive specification, but one that allows us to illustrate the problem with the GG and PPK criteria.[1]

[1] A more general specification of the micro model is $H_d\colon Y_{it} = \mathbf{X}_{it}\beta_i + u_{it}$, which allows parameter β to vary across micro units. In the empirical study, both (1) and the more general specification were estimated, and their prediction accuracies were compared.

Alternatively, we can first add Y_{it} and $\mathbf{X}_{it}$ for all units in each time period to get

$$Y_t^a = \sum_i Y_{it} \quad \text{and} \quad \mathbf{X}_t^a \equiv \left(\sum_i x_{1it}, \sum_i x_{2it}, \ldots, \sum_i x_{kit} \right),$$

and use aggregate, time-series data to estimate a macro model:

$$H_a\colon\ Y_t^a = \mathbf{X}_t^a \beta^a + v_t^a,\ \ v_t^a \sim N(0, \sigma_a^2), \tag{2}$$

and then use the macro model to make aggregate predictions. Following GG and PPK, we consider the question as to which approach provides a more accurate prediction.

The GG and PPK prediction (or, more accurately, the within-sample goodness-of-fit) criteria for choosing between micro and macro models are based on the sums of squared residuals from the micro and macro models. Specifically, the GG prediction criterion is:

$$\text{Choose the micro model if } \mathbf{e}_d'\mathbf{e}_d < \mathbf{e}_a'\mathbf{e}_a, \tag{3}$$

where $\mathbf{e}_d$ and $\mathbf{e}_a$ are vectors of residuals from (1) and (2), respectively. The estimates employed by GG for $\mathbf{e}_d$ and $\mathbf{e}_a$ are based on the ordinary least squares (OLS) method and are given by:

$$\mathbf{e}_d = \left[\mathbf{I}_{NT} - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\right]\mathbf{u} \quad \text{and} \quad \mathbf{e}_a = \left[\mathbf{I}_T - \mathbf{X}^a(\mathbf{X}^{a'}\mathbf{X}^a)^{-1}\mathbf{X}^{a'}\right]\mathbf{v}^a, \tag{4}$$

where $\mathbf{I}_{NT}$ is an $\{NT \times NT\}$ identity matrix; $\mathbf{X} = (\mathbf{X}_{11}', \ldots, \mathbf{X}_{1T}'; \mathbf{X}_{21}', \ldots, \mathbf{X}_{2T}'; \ldots; \mathbf{X}_{N1}', \ldots, \mathbf{X}_{NT}')'$ is $\{NT \times k\}$; and $\mathbf{X}^a = (\mathbf{X}_1^{a'}, \mathbf{X}_2^{a'}, \ldots, \mathbf{X}_T^{a'})'$ is $\{T \times k\}$.

As noted by PPK, like the justification for Theil's $\bar{R}^2$ criterion, the rationale behind the use of the GG criterion lies in the fact that if the micro equations are correctly specified, the fit of the macro equation should not be any better than the fit of the micro equations. Specifically, we should have

$$E_d(\mathbf{e}_d'\mathbf{e}_d) \leq E_d(\mathbf{e}_a'\mathbf{e}_a), \tag{5}$$

where $E_d(\cdot)$ is the mathematical expectation operator under H_d. However, from (4),

$$E_d(\mathbf{e}_d'\mathbf{e}_d) - E_d(\mathbf{e}_a'\mathbf{e}_a) = (NT - k)\sigma^2 - (T - k)N\sigma^2 = (N - 1)k\sigma^2 > 0. \tag{6}$$

Thus, even if the micro model is correctly specified, under the GG prediction criterion the macro model will be chosen.

The PPK prediction criterion is also based on the sums of squared residuals. In the context of the micro and macro models specified in (1) and (2), the PPK adjusted goodness-of-fit criterion is:

$$\text{Choose the micro model if } s_d^2 = \frac{N\mathbf{e}_d'\mathbf{e}_d}{NT - k} < s_a^2 = \frac{\mathbf{e}_a'\mathbf{e}_a}{T - k}. \tag{7}$$

This criterion, however, cannot be used to discriminate between the macro and micro models in (1) and (2) because

$$E_d(s_d^2) - E_d(s_a^2) = 0. \tag{8}$$

Thus, like the GG criterion, the PPK does not lead to the choice of the micro model even if it is correctly specified. However, this does not mean the micro model has no

advantage over the macro model in terms of aggregate prediction. Below, we show that the variance of prediction errors from the micro model at an out-of-sample point is always smaller than that from the macro model if the micro model in (1) is correctly specified.

To demonstrate this result, consider the aggregate prediction from the micro model (1) at an out-of-sample point, $\mathbf{X}_i^0 = (x_{1i}^0, x_{2i}^0, \ldots, x_{ki}^0)'$:

$$\sum_{i=1}^{N} \hat{Y}_i^0 = \sum_{i=1}^{N} \mathbf{X}_i^0 \hat{\beta}, \tag{9}$$

which implies the prediction error is

$$e_d^0 \equiv \sum_{i=1}^{N} Y_i^0 - \sum_{i=1}^{N} \hat{Y}_i^0 = \sum_{i=1}^{N} u_i^0 + \sum_{i=1}^{N} \mathbf{X}_i^0(\beta - \hat{\beta}). \tag{10}$$

The variance of the prediction error is found by squaring equation (10) and taking expectations:

$$V(e_d^0) = N\sigma^2 + \left(\sum_{i=1}^{N} \mathbf{X}_i^0\right)' \left[\sigma^2(\mathbf{X}'\mathbf{X})^{-1}\right] \left(\sum_{i=1}^{N} \mathbf{X}_i^0\right). \tag{11}$$

By using a similar procedure, the variance of prediction errors from the aggregate model can be derived as

$$V(e_a^0) = N\sigma^2 + \left(\sum_{i=1}^{N} \mathbf{X}_i^0\right)' \left[N\sigma^2(\mathbf{X}^{a'}\mathbf{X}^a)^{-1}\right] \left(\sum_{i=1}^{N} \mathbf{X}_i^0\right). \tag{12}$$

A comparison of (11) and (12) indicates the disaggregate model makes better predictions [i.e., $V(\varepsilon_d^0) \leq V(\varepsilon_a^0)$] if and only if

$$(\mathbf{X}'\mathbf{X})^{-1} \leq N(\mathbf{X}^{a'}\mathbf{X}^a)^{-1} \quad \text{or} \quad N(\mathbf{X}'\mathbf{X}) \geq (\mathbf{X}^{a'}\mathbf{X}^a), \tag{13}$$

in the sense that the difference between the two matrices is positive semi-definite. This condition always holds because

$$N(\mathbf{X}'\mathbf{X}) - (\mathbf{X}^{a'}\mathbf{X}^a) = N \sum_i (\mathbf{X}_i - \bar{\mathbf{X}})(\mathbf{X}_i - \bar{\mathbf{X}})' \geq 0, \tag{14}$$

where $\mathbf{X}_i = (X_{i1}', X_{i2}', \ldots, X_{iT}')'$, and $\bar{\mathbf{X}} = \Sigma_i \mathbf{X}_i/N$. Thus, if the micro model is correctly specified, the micro model makes more reliable (smaller variance) out-of-sample predictions than the macro model. The intuition behind this result is that when the micro model (1) is correctly specified, it provides a more accurate prediction of β than the macro model (i.e., the variance is smaller) because it uses more observations than the macro model. As a result, the second component of the variance of prediction errors from the micro model is smaller than that for the macro model. This result is important because it demonstrates PPK's goodness-of-fit criterion may fail to discriminate between the micro and macro models even in the context of linear models.

The above results suggest the out-of-sample prediction error has two components: the random disturbance term and the error term which occurs due to the incorrect estimation of the model coefficients. The GG criterion fails to select the micro model even if it provides more reliable predictions because (*a*) it provides biased estimates of the first component of the variances of the prediction errors, and (*b*) it ignores the second component of prediction errors. Although the PPK criterion provides unbiased estimates

of the first components of the variances of prediction errors, it ignores the second component of the prediction error. Thus, although the PPK criterion does not lead to the choice of a "wrong" model, it may not be able to discriminate between the micro and macro models under some circumstances.

In addition to the above problem, there are several other issues that make the choice between micro and macro models difficult. First, aggregate or macro data for estimating economic relationships are often available for a longer time series than disaggregated data. Other things being equal, this tends to favor the macro model because the longer the time series, the smaller the variance of the prediction error. Thus, there is a tradeoff between a longer time series and more detailed data in terms of prediction accuracy. A longer time series tends to favor prediction accuracy of macro models.

Second, the result that the prediction error for the micro model has a smaller variance than the prediction error variance for the aggregate model depends on the assumption the micro models are correctly specified—an unlikely event. GG argue that as long as micro models are not correctly specified, there can be a gain from aggregation, due to the elimination of the specification errors. In such a circumstance, the issue of whether disaggregation is useful for the study of macro phenomena and the extent of the gain which may be expected from micro models depends on the relative importance of the micro specification errors in the micro model and the aggregation errors in the macro model (Pesaran, Pierse, and Kumar).

Third, one may not be able to include some variables typically contained in micro models in the estimation of macro models. For example, we can include land quality variables in a micro acreage response function to examine their impact on land allocation, but cannot include these variables in a macro model that uses time-series data because land quality generally does not change over time. Furthermore, the type and format of variables in macro and micro data are often different. For example, survey-based data frequently focus on whether an economic agent produces or consumes a certain product, whereas in aggregated data, total production and consumption are reported. As a result, different methods may be required to estimate micro and macro models.

Finally, nonlinear specification complicates the choice between micro and macro models. The GG and PPK criteria, which are based on the coefficient of variation or sums of squares of residuals, may not be meaningful for a nonlinear specification or a discrete choice model. The perfect aggregation test developed by PPK, and subsequently generalized by Thompson and by Thompson and Lyon in the context of linear models, cannot be applied to nonlinear models.[2] For these reasons, we use the Theil U-statistic and the root mean squared error (RMSE) of aggregate predictions to discriminate between the micro and macro models. Specifically, the root mean squared errors of prediction from the micro and macro models equal:

$$(15) \qquad RMSE_d = \left[\frac{1}{T}\sum_{t=1}^{T}\left(\sum_{i=1}^{N}\left(Y_{it} - \hat{Y}_{it}\right)\right)^2\right]^{1/2}, \quad RMSE_a = \left[\frac{1}{T}\sum_{t=1}^{T}\left(Y_t^a - \hat{Y}_t^a\right)^2\right]^{1/2}.$$

[2] We could make the same arguments as made by PPK when they apply their criterion to the log of the dependent variable, but if this argument is made, then comparisons of predictions from a nonlinear field-level model with predictions from "linear" models are not legitimate.

In our empirical application, Y_{it} and $\hat{Y}_{it}$ represent the reported and predicted crop acreage from micro models, and Y_t^a and $\hat{Y}_t^a$ represent the reported and predicted crop acreage from macro models. Theil's U-statistics are defined as:

$$(16) \qquad U_d = \frac{RMSE_d}{\left[\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N} Y_{it}^2\right]^{1/2}}, \quad U_a = \frac{RMSE_a}{\left[\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N} Y_{it}^2\right]^{1/2}}.$$

In the remainder of this study, we apply these measures to evaluate eight sets of crop choice and acreage response models.

Crop Choice and Acreage Response Models

The crop choice and acreage response models are specified at four different levels of aggregation: field, county, state, and regional levels. Each model is used to predict crop acreage at the regional level, and the results are compared with the reported acreage to calculate the Theil U-statistic and RMSEs. The specification and estimation of each model are discussed below.

The Field-Level Crop Choice Models

The crop choice problem at the field level is modeled as a multinomial logit model:

$$(17) \qquad P_{ijt} = \frac{\exp(\mathbf{X}_{ijt}'\beta_j)}{\sum_{k=1}^{N}\exp(\mathbf{X}_{ikt}'\beta_k)}, \quad (i = 1, 2, \ldots, N;\ j = 1, 2, \ldots, M;\ t = 1, 2, \ldots, T),$$

where P_{ijt} is the probability of field i being used to grow crop j in year t. The multinomial logit model has been widely used in economic applications, including the choice of transportation modes, occupations, asset portfolios, and the number of automobiles demanded. In agriculture, it has been used to model farmers' land allocation decisions (Lichtenberg; Wu and Segerson; Hardie and Parks; Plantinga, Mauldin, and Miller) and the choice of irrigation technologies and alternative crop management practices (Caswell and Zilberman).

The coefficients in a multinomial logit model are difficult to interpret, so the marginal impacts of independent variables are often calculated using the following:

$$(18) \qquad \frac{\partial P_{ijt}}{\partial x_{ijt}^k} = P_{ijt}\left(\beta_j^k - \sum_{j=1}^{M} P_{ijt}\beta_j^k\right),$$

where x_{ijt}^k and β_j^k are the kth element of vectors $\mathbf{X}_{ijt}$ and β_j, respectively. In policy analysis, it is also useful to estimate the acreage elasticity for a region. With the multinomial logit model, the total acreage of crop j in year t in the region, A_{jt}, can be estimated by:

$$(19) \qquad A_{jt} \equiv \sum_{i=1}^{N} P_{ijt}E_i,$$

where E_i is the acreage of field i. Using equations (18) and (19), the acreage elasticity of crop j for the region can be obtained as follows:

$$(20) \qquad \zeta_{jt} \equiv \frac{\partial A_{jt}}{\partial x_{jt}^k}\frac{\bar{x}_{jt}^k}{A_{jt}} = \frac{\bar{x}_{jt}^k}{A_{jt}}\sum_{i=1}^{N}\left(E_i\frac{\partial P_{ijt}}{\partial x_{jt}^k}\right) = \frac{\bar{x}_{jt}^k}{A_{jt}}\sum_{i=1}^{N}\left[E_i P_{ijt}\left(\beta_j^k - \sum_{j=1}^{M} P_{ijt}\beta_j^k\right)\right],$$

where $\bar{x}_{jt}^k$ is the average of x_{ijt}^k across all N fields.

Two types of multinomial logit models are estimated. One is estimated with parameters β_j restricted to be the same across fields in the study region. The other is estimated with the restriction relaxed to allow different β_j in each state. Both are estimated using the Times Series Processor's LOGIT procedure (Hall). The logistic procedure is used because our micro-level survey data indicate the type of crop grown in each field (see the discussion of data in the next section).

Multinomial logit models predict the probability of choosing each crop at each field and the results can be aggregated to the county, state, or regional levels based on the acreage of individual fields as determined by the survey. The acreage elasticities are calculated using (20), with all variables evaluated at their means. The t-statistics and standard errors are estimated using Times Series Processor's ANALYZ procedure for the null hypothesis that the acreage elasticities are zero (Hall, pp. 26–27).

The County-Level Acreage Response Models

Because of a lack of disaggregate data, most acreage response models are estimated using regional or national data (e.g., Houck and Ryan; Lidman and Bawden; Chavas and Holt; Chavas, Pope, and Kao). More recently, several studies have estimated acreage response models using county-level data. Lichtenberg estimated a county-level acreage response model to examine the interaction among land quality, cropping patterns, and irrigation development. Wu and Segerson estimated a similar model to examine the effect of government commodity programs and land characteristics on groundwater pollution in Wisconsin. Hardie and Parks used county-level data to analyze the impact of land quality on land allocation between agriculture and forests.

In these county-level analyses, P_{ijt} is estimated as the share of potential cropland allocated to crop j in county i in year t, and the beta parameters are estimated using the following logistic regression equations, which are derived by taking the log of the ratio of P_{ijt} and P_{iMt} in (17):

$$(21) \qquad \ln\left(\frac{P_{ijt}}{P_{iMt}}\right) = \mathbf{X}_{ijt}'\beta_j + v_{ijt}, \quad (j = 1, \ldots, M-1),$$

where i is the index of the county, and β_M is normalized to zero to reduce the indeterminacy in the model (Greene 1990, p. 697). The acreage elasticity of crop j with respect to x_{ijt}^k for the whole region is specified as:

$$(22) \qquad \zeta_{jt} \equiv \frac{\partial A_{jt}}{\partial x_{ijt}^k}\frac{\bar{x}_{jt}^k}{A_{jt}} = \frac{\bar{x}_{jt}^k}{A_{jt}}\sum_{i=1}^{N}\frac{\partial A_{ijt}}{\partial x_{ijt}^k} = \frac{\bar{x}_{jt}^k}{A_{jt}}\sum_{i=1}^{N}A_{ijt}\left(\beta_j^k - \sum_{j=1}^{M}P_{ijt}\beta_j^k\right)$$

$$= \bar{x}_{jt}^k\left[\beta_j^k - \sum_{j=1}^{M}\left(\sum_{i=1}^{N}w_{ijt}P_{ijt}\right)\beta_j^k\right],$$

where $w_{ijt} = A_{ijt}/A_{jt}$ is the percentage of total acreage of crop j in county i in year t.

The county-level model is estimated using panel data. Because county size, cultivation history, and other disturbance factors differ across counties, heteroskedasticity may exist in the county-level model. Heteroskedasticity was tested using the Lagrange multiplier test (Greene 1990, p. 467). Also, because the disturbances affecting one crop in one year may affect the same crop in other years, autocorrelation was tested using the Durbin test. Finally, with land allocation imposing joint production decisions and disturbances for different crops reflecting common factors (e.g., climate and the general state of the economy), contemporaneous correlation (i.e., correlation between error terms for different crops) may be present. Contemporaneous correlation was tested using the Lagrange multiplier test suggested by Breusch and Pagan (Greene 1990, p. 515). All these standard problems were present in the county-level model.

Several approaches can be used to specify the error structure for the county-level model (Baltagi and Raj). Our specification follows Kmenta's cross-sectionally heteroskedastic and timewise autoregressive model for panel data (Kmenta, pp. 509–12). In addition, we allow the error terms for the different equations to be contemporaneously correlated. Thus, this specification accounts for groupwise heteroskedasticity, autocorrelation, and contemporaneous correlation. To correct these econometric problems, the county-level equation system was estimated using SUR-HEAR—a procedure that combines the Seemingly Unrelated Regression technique with Kmenta's method of handling heteroskedasticity and autocorrelation problems (Wu and Brorsen). The procedure was implemented using SAS.

The State- and Regional-Level Acreage Response Models

To determine the effect of aggregation on prediction accuracy, two models representing higher levels of aggregation were estimated. One was at the state level, and the other at the regional level. For each state, we specify the following acreage response system:

$$\ln\left(\frac{P_{jt}^{s}}{P_{Mt}^{s}}\right) = \mathbf{Z}_{jt}^{s}\gamma_{j}^{s} + \varepsilon_{jt}^{s}, \quad (j = 1, \ldots, M-1), \tag{23}$$

where s is the index of state, P_{jt}^{s} is the percentage of potential cropland allocated to crop j in year t in state s, $\mathbf{Z}_{jt}^{s}$ is a vector of independent variables including input and output prices and government commodity program provisions in the state. The acreage elasticity of crop j with respect to an independent variable for the whole region is:

$$\zeta_{jt} = \sum_{s=1}^{S} w_{jt}^{s}\zeta_{jt}^{s}, \tag{24}$$

where ζ_{jt}^{s} is the acreage elasticity of crop j in state s in year t, and w_{jt}^{s} is the percentage of total acreage of crop j in state s in year t. The state model differs from the county-level model in that only time-series data are used in the estimation (as opposed to panel data in the county model). In addition, the parameters are restricted to be the same across the states in the county-level model, but are not in the state-level model.

The state-level model is estimated in a two-step procedure. First, the Prais-Winsten transformations based on OLS estimates are applied to individual equations to correct for autocorrelation (Greene 1990, p. 443). Then the equations for all states are estimated simultaneously using the seemingly unrelated regression (SUR) estimator.

The most aggregated (macro) acreage response model estimated in this study is a regional-level (Corn Belt) acreage response model, which is also specified as a logit regression model:

$$\ln\left(\frac{P_{jt}}{P_{Mt}}\right) = \mathbf{Z}_{jt}\gamma_j + \varepsilon_{jt}, \quad (j = 1, \ldots, M-1), \tag{25}$$

where P_{jt} is the percentage of potential cropland allocated to crop j in year t in the region. The regional-level model is estimated using the same procedure as the state-level model.

Acreage elasticities were estimated using (24) for the state-level model. All elasticities were evaluated at the mean values of variables. Since these elasticities were calculated from a number of the estimated parameters, it is important to test their statistical significance. F-statistics are calculated to test the null hypothesis that the elasticities are zero, and standard errors for the elasticities are then calculated using the F-statistics.

The Data

Acreage and Land Characteristic Data

The field-level crop choice model was estimated using data from the 1982, 1987, and 1992 Natural Resources Inventory (NRI) for the Corn Belt. The NRI is conducted every five years by the USDA's Natural Resource Conservation Service (NRCS) to determine the status, condition, and trend in the nation's soil, water, and other related resources at more than 800,000 sites (fields) across the continental United States. Each NRI site is assigned a weight (called the expansion factor) to reflect the acreage each site represents. For example, the summation of expansion factors for all sites planted to corn in a region gives an estimate of corn acreage in the region.

For each NRI site, information on nearly 200 attributes is collected. The information includes land use and cover, cropping history, tillage and conservation practices, topography, hydrology, and soil type. In the Corn Belt, over 55,000 NRI sites fall into the cropland, rangeland or pastureland categories. Three NRI surveys are currently available (1982, 1987, and 1992). (The 1997 NRI survey has been conducted, but has not yet been released.) Each NRI survey has crop choice information for four years (the current year plus the previous three years). Thus, we have land use/crop choice information for 12 years at each NRI site. Pooling these time-series and cross-sectional data results in 660,000 observations (55,000 NRI sites × 12 years).[3]

To make our estimation computationally feasible, 10% of the NRI sites were randomly selected and used in the estimation of the crop choice model. Specifically, we first divided the NRI sites in each Major Land Resource Area (MLRA) defined by the USDA into different groups according to crop, crop rotations, irrigation, and tillage and conservation practices; we then drew 10% of sample sites from each group. This procedure guarantees the subsamples are representative of the whole sample in terms of crop acreage and management practices. To ensure the subsamples are also representative in terms of soil properties, the frequency distribution of four important soil properties

[3] The lack of a continuous time series from the NRI data makes correction of autocorrelation more difficult. Instead of multiplying only the first observation by $\sqrt{1-\rho^2}$ in continuous time series, we must multiply the first observation by $\sqrt{1-\rho^2}$ in each time interval.

for the selected sample (clay percentage, bulk density, pH, and organic matter percentage) was compared to that of the population. The two distributions were found to be essentially identical, indicating the subsamples were also representative in terms of soil properties.

Each NRI sample site is linked to the NRCS's SOILS5 database, providing detailed soil profile information from soil surveys. From the data, average measures of soil properties for top soil layers were calculated. These include average organic matter percentage, clay percentage, soil pH, and permeability. The data also include information about soil texture and land capability class. Historical weather data from 1975–1992 were obtained from the Midwestern Climate Center. The mean and variance of maximum monthly temperature and precipitation during corn and soybean growing seasons were estimated from these weather data and included in the crop choice model.

The county-level acreage response model was estimated by aggregating the NRI data to the county level. Instead of using dummy variables to indicate soil texture, we now use the percentage of land with different textures as independent variables. We estimated the average values of slope, organic matter percentage, permeability, and soil pH for potential cropland (defined as cropland, pastureland, and rangeland) in each county based on land characteristics at each NRI site and the number of acres each NRI site represents. In the field-level model, dummy variables were included to indicate the MLRA to which each NRI site belongs. The percentage of potential cropland in each county that falls into each MLRA was also estimated and included in the county-level model. The state- and regional-level models were estimated by aggregating the NRI data to the state and regional levels. Only time-series data were used in the state and regional models because land characteristics of potential cropland do not change much over the relatively short time period involved here. The data include a sample for the 12 years.

Three of the four models (the county, state, and regional models) were also estimated using the NASS's county crop history data. The advantage of these data is that they cover a much longer time series than the NRI data. For this study, county crop acreage data from 1975–1994, along with land quality variables from NRI and the SOILS5 database, were used to estimate the county-level acreage response model. All other independent variables were constructed in the same manner as in the NRI-based models, although they cover a longer time series. The state- and regional-level acreage response models were then estimated by aggregating the data to the state and regional levels. Table 1 provides details about the number of cross-sectional units and the length of each time series for both data sets, along with the estimation procedures for each model.

Prices and Government Commodity Programs

Much research has focused on the effect of government commodity programs on acreage responses (e.g., Lidman and Bawden; Houck and Ryan; Chavas, Pope, and Kao; Chavas and Holt; Shumway 1983; Wu and Segerson). Based on most recent studies, the following approach was used to incorporate government commodity programs.

The expected market price for corn was specified as a weighted average of target price and lagged market price, and the weights were selected to minimize the sum of the prediction error. The higher of the expected market price and the weighted target price was specified as the farmers' expected price for corn, where the weighted target price is calculated by multiplying the target price by the portion of corn base permitted for

Table 1. Sample Details and Estimation Procedures for the Eight Sets of Crop Choice and Acreage Response Models

Models	Number of Cross-Sectional Units	Time Series Length (years)	Procedure/ Program[d]
Estimated with NRI Data:			
Field Model[a]	5,924[c]	12	LOGIT/TSP
Field Model–Restricted[b]	5,924	12	LOGIT/TSP
County Model[b]	439	12	SUR-HEAR/SAS
State Model	0	12	SUR-AR/SAS
Regional Model	0	12	SUR-AR/SAS
Estimated with NASS Data:			
County Model[b]	439	20	SUR-HEAR/SAS
State Model	0	20	SUR-AR/SAS
Regional Model	0	20	SUR-AR/SAS

[a] Estimation allows different coefficients for each state (i.e., different models for different states).
[b] Coefficients are restricted to be the same across states.
[c] The number of cross-sectional units in Iowa, Illinois, Missouri, Indiana, and Ohio are, respectively, 1,569, 1,611, 899, 903, and 942, for a total of 5,924.
[d] See Wu and Brorsen for a discussion of the SUR-HEAR and SUR-AR procedures.

corn planting [i.e., 1-Acreage Reduction Program (ARP) rate for corn]. In contrast to corn, soybeans is not a program crop. The expected price for soybeans was specified as the average futures price in the planting season, which was estimated as the average of the first and second Thursday closing prices in March at the Chicago Board of Trade (CBOT) for November soybeans.

Government commodity program data, such as target prices and the ARP rates, were taken from Green and other USDA publications. Input prices including farmer wage rates and prices paid by farmers for agricultural chemicals, seeds, and fuel (index number) were taken from the USDA. All prices were normalized by the index of prices paid by farmers for all inputs including interest, taxes, and wages (USDA).

Results and Implications

This section presents results from the estimation of the four acreage response models, as applied to the NRI (field-level) and NASS (county-level) data for corn and soybeans. Using two data sets provides a more comprehensive test of the relative performance of the various models; comparisons within a given data set ensure consistency with respect to specifications and time periods.

The models are first evaluated relative to their ability to predict actual (reported) acreages of each crop. This type of comparative evaluation, performed with the two statistical measures (Theil *U*-statistic and RMSE), can test for model superiority when the primary goal is to predict acreage. The other form of comparative evaluation reported here evaluates the performance of each model in terms of statistical properties and estimates of structural parameters, including resulting elasticities. These characteristics are important when addressing specific policy issues, such as the effect of government programs on land use and off-site environmental consequences.

Table 2. The Theil *U*-Statistic and the Root Mean Squared Error of Predictions, by Model and Crop

	Theil's *U*-Statistic		RMSE	
Models	Corn	Soybeans	Corn	Soybeans
Estimated with NRI Data:				
Field Model[a]	0.022	0.025	830	733
Field Model–Restricted[b]	0.027	0.029	1,000	856
County Model[b]	0.033	0.068	1,243	1,981
State Model	0.057	0.067	2,120	1,961
Regional Model	0.021	0.023	837	669
Estimated with NASS Data:				
County Model[b]	0.039	0.048	853	1,003
State Model	0.047	0.062	1,019	1,276
Regional Model	0.033	0.041	724	849

[a] Estimation allows different coefficients for each state (i.e., different models for different states).
[b] Coefficients are restricted to be the same across states.

The predictive ability of each model is evaluated statistically in table 2, which reports the Theil *U*-statistic and the root mean squared errors for each model's predictions based on comparisons of reported and predicted regional crop acreages. The results in table 2, for both statistical measures, indicate the aggregate or macro model performs best for both the NRI and NASS data and for each crop. Specifically, the regional model performs better than the restricted field-, county-, and state-level models for the NRI data and better than the county and state models for the NASS data, for both corn and soybeans. For the less restricted field model, the predictive ability is similar to the most aggregated model (as measured by the RMSE), although the Theil *U*-statistics for the most aggregated model are superior.

The fact that the most aggregated model in general performs better than the least aggregated models for each data set (i.e., the county-level NASS model and the field-level NRI model) seems counterintuitive, given that the micro model contains more information. As Grunfeld and Griliches report, this finding can be explained in the nature of the estimation required for each type of model. Specifically, "perfect" micro relationships will perform better, as evidenced by a comparison between the restricted and less restricted field-level models. Because the null hypothesis that parameter vectors are the same between any two states (i.e., H_0: $\beta_i = \beta_j$, $i \neq j$) is rejected at the 1% level of significance, the less restricted field-level model is likely a better approximation to the real micro relationship, and thus provides better predictions than the restricted field-level model.

In practice, however, we do not know the real micro relationships. Estimating an aggregate measure may favor the aggregate model, simply because there is less aggregation required to obtain the measure used here (total crop acreage). The other models used here require aggregation of hundreds to thousands of predictions to obtain an annual aggregate acreage response. In the process, prediction errors across micro units will be accumulated. In addition, the quality of micro data may be another source of aggregation gain (Grunfeld and Griliches; Gardner).

Figures 1–4 compare reported and predicted regional corn and soybean acreages for models of different levels of aggregation estimated using NRI and NASS data. The total

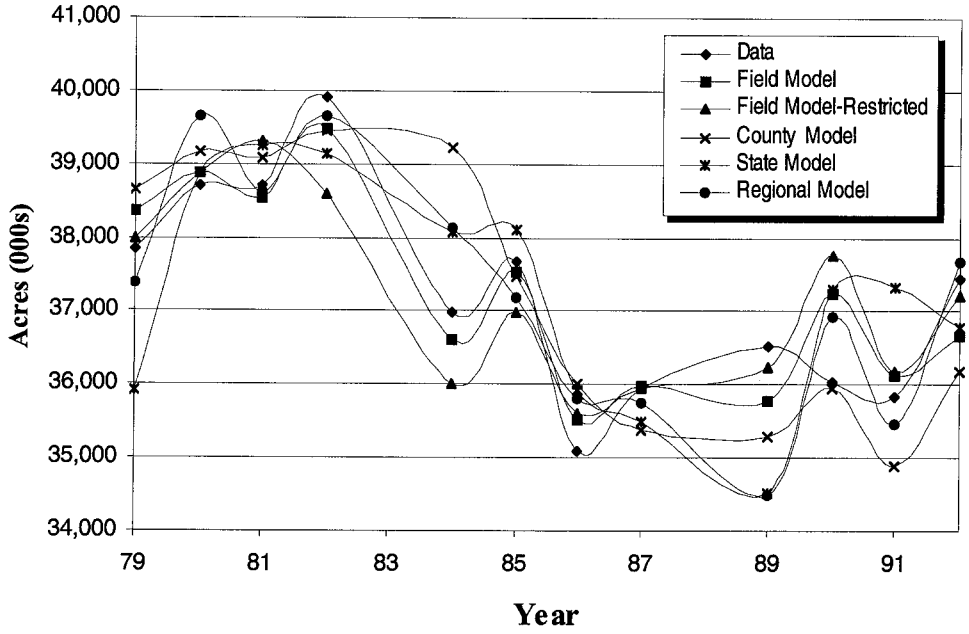

Figure 1. Reported versus predicted corn acreage, by models of different levels of aggregation, estimated with NRI data

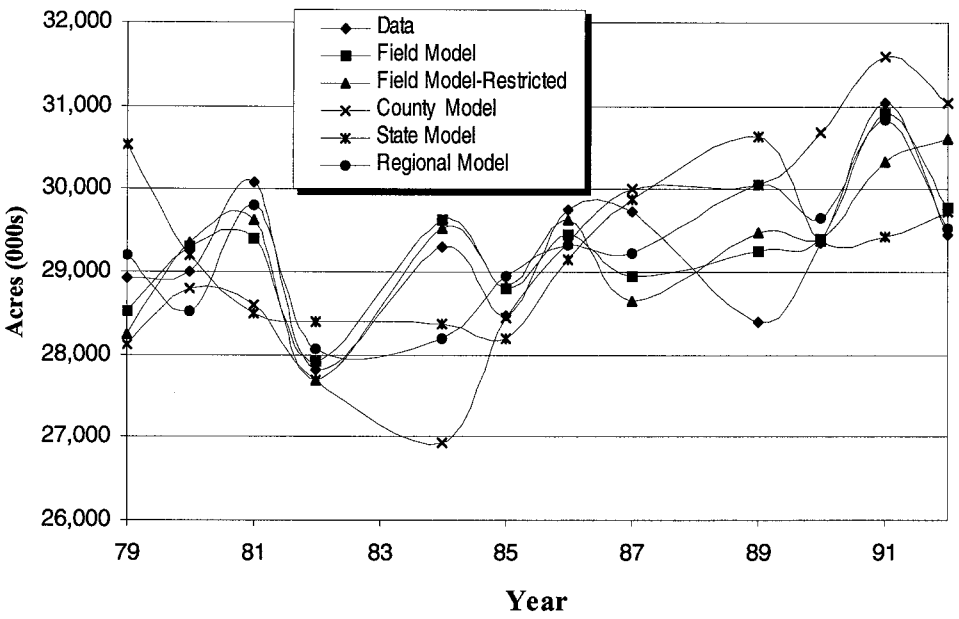

Figure 2. Reported versus predicted soybean acreage, by models of different levels of aggregation, estimated with NRI data

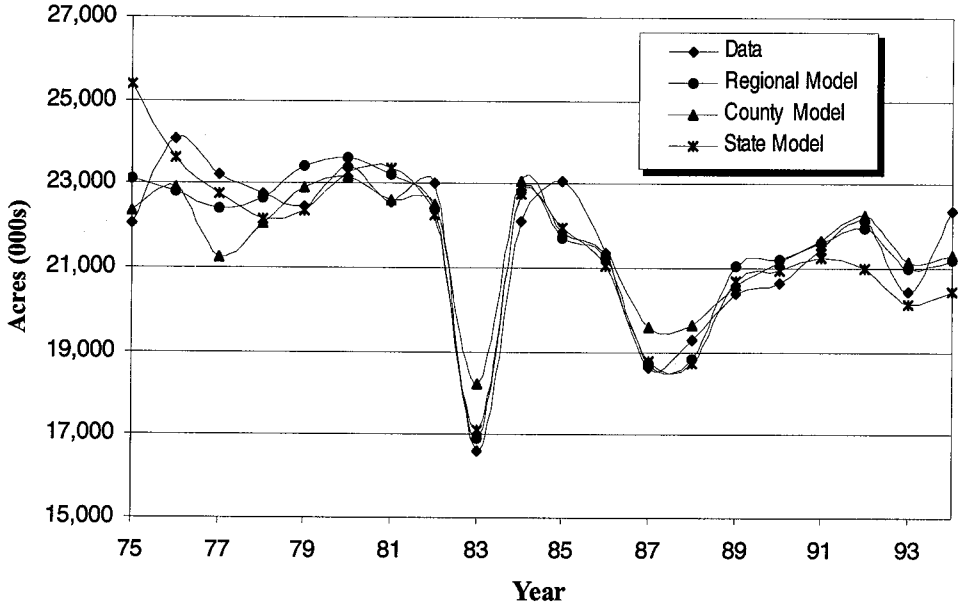

Figure 3. Reported versus predicted corn acreage, by models of different levels of aggregation, estimated with NASS data

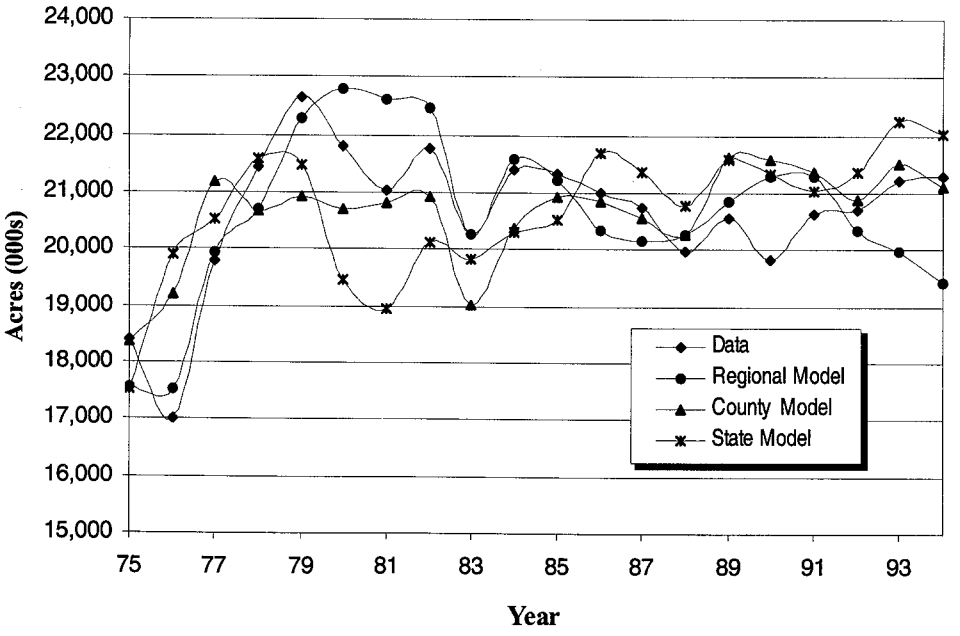

Figure 4. Reported versus predicted soybean acreage, by models of different levels of aggregation, estimated with NASS data

acreages from the NASS data are much lower than those from the NRI data because counties with no land quality data are not used in the estimation and their acreages are not included in the total acreage.

Two noticeable points are demonstrated by the figures and elasticities. First, the models estimated with NASS data (with a longer time series) fit the data better than the models estimated with NRI data. This result is consistent with statistical expectations derived earlier in the paper. Second, the predictions of corn models are more stable across models as evidenced by the figures and the number of significant elasticities. This finding is partially explained by the fact that corn, as the more profitable crop, tends to respond more directly to economic incentives than soybeans, which has a shorter growing season and tends to be a residual claimant on acreage (often planted when weather conditions prevent timely planting of corn). In addition, government programs for corn could be a source of stabilization. For example, under acreage reduction programs, farmers had incentive to maintain their acreage "base."

It is interesting to note that while the most aggregate models perform best (as measured by both statistical tests and across crops and data sources), the next best performance is by the most micro-level models (the less restricted field-level model using NRI data and the county-level model using NASS data). The mid-range models are consistently the worst performers. Thus, the inclusion of site-specific, field-level data in models without few restrictions in model coefficients may improve prediction performance.

The results from table 2 and figures 1–4 address the predictive performance of each model. The implication is that if aggregate acreage predictions are the primary interest, then a more highly aggregated (macro) model is generally superior to a series of micro relationships. This result is consistent with Grunfeld and Griliches's argument: "Aggregation is not necessarily bad if one is interested in the aggregates." It has the advantage of simplicity in specification and estimation because fewer variables are required to estimate such a model.

However, for many policy analyses, there is a need to understand how changes in inputs may affect acreage planted. Increasingly, there is also interest in understanding the link or relationship between physical characteristics of land and acreage responses. For example, solutions to many environmental issues related to agriculture require information on the interaction between physical or environmental variables and land use. In this case, the simpler, more aggregate models may not be as useful, given they abstract from many of the variables of interest.

To explore the performance of the various models in this regard, table 3 reports the acreage elasticities with respect to input and output prices.[4] The statistical properties of each model, as measured by statistical significance of each explanatory variable, present a different picture than observed in table 2. Specifically, the micro models have the highest number of statistically significant variables. For example, five of the six price elasticities in the NRI-based field-level model (restricted) for corn are statistically significant at least at the 5% level. Similarly, all six price elasticities in the NASS-based micro (county) model for corn are significant at the 5% level. However, the aggregate model for corn has only three statistically significant variables in the NRI-based model

[4] The general statistical results for each model are summarized in an appendix and are available from the authors upon request.

Table 3. Acreage Elasticities Estimated with Models of Different Levels of Aggregation and Different Data

Models	Acreage of:	Acreage Elasticities with Respect to: Expected Price for Corn	Expected Price for Soybeans	Chemical Price	Seed Price	Fuel Price	Wage Rate
Estimated with NRI Data:							
Field Model [a]	Corn	0.03	-0.18*	-0.46*	-0.16	0.19*	-0.15
	Soybeans	-0.05	0.24*	0.51*	-0.10	0.01	0.21
Field Model–Restricted [b]	Corn	0.14*	-0.15*	-0.52*	-0.23*	0.15*	0.12
	Soybeans	0.09	0.10	0.34*	-0.22	-0.03	0.29*
County Model [b]	Corn	0.20	-0.18	-0.48	-0.33	-0.07	-0.24
	Soybeans	-0.13	0.14	0.35	-0.14	0.20	0.54*
State Model	Corn	0.10	-0.14	-0.07	-0.26	0.36*	-0.09
	Soybeans	-0.09	0.12	-0.16	-0.06	-0.21	0.11
Regional Model	Corn	0.20	-0.28*	-0.59*	-0.68	0.002*	-0.11
	Soybeans	-0.02	0.15	0.34	0.26	0.19	0.35
Estimated with NASS Data:							
County Model [b]	Corn	0.22*	-0.10*	-0.09*	-0.61*	-0.06*	-0.12*
	Soybeans	-0.24*	0.14*	-0.11*	0.50*	0.14*	0.04
State Model	Corn	0.25*	-0.12*	0.00	-0.32	-0.08	-0.13
	Soybeans	-0.17*	0.06	-0.32*	0.34*	-0.08	0.00
Regional Model	Corn	0.17	-0.03	0.03	-0.45	-0.07	0.04
	Soybeans	-0.17	0.07	-0.24	0.31	0.14	-0.17

Notes: All elasticities are evaluated at the mean of variables for the sampling period. An asterisk (*) denotes statistical significance at the 5% level.

[a] Estimation allows different coefficients for each state (i.e., different models for different states).

[b] Coefficients are restricted to be the same across states.

and none in the NASS model. For soybeans, the micro models again have more statistically significant variables than do the most aggregate (the regional) models. In general, the corn models perform better than the soybean models across all levels of aggregation.

Table 4 presents the elasticities and standard errors for the physical variables used in the field and county models (the state and regional models do not contain these variables). The differences between these four models are not as striking as those shown in table 3 when measured by the numbers of statistically significant variables. For example, both the restricted and unrestricted field models have similar numbers of significant variables. However, the signs of the elasticities for the field-level model are more consistent with agronomic expectations. For instance, corn is more likely to be planted on high-quality land with low slope. This is consistent with the sign of the elasticities for the first-class land and the slope variables in the field-level models, but not with the sign of the elasticities for these variables in the two county-level models. Field- or farm-level acreage and planting decisions should be more responsive to site-specific data, such as soil characteristics. Thus, it seems plausible the effects of physical variables on planting decisions are likely to be captured with the field-level models.

Overall, the performance of the aggregate models, as measured by significance of estimated elasticities, is inferior to that for the micro (field or county) models. In terms of signs of acreage elasticities for the economic variables, all models perform about equally well. As shown in table 3, all own-price elasticities have the expected sign. Elasticities

Table 4. Estimates of Acreage Elasticities with Respect to Physical Variables from Disaggregated Models

	Field Model[a] (NRI Data)		Field Model–Restricted[b] (NRI Data)		County Model[b] (NRI Data)		County Model[b] (NASS Data)	
Physical Variables	Corn	Soybean	Corn	Soybean	Corn	Soybean	Corn	Soybean
First-Class Land	0.03*	0.08*	0.05*	0.04*	-0.31*	0.63*	-0.27*	0.60*
	(3.99)	(7.32)	(5.74)	(3.15)	(-8.76)	(9.77)	(-32.10)	(42.11)
Land Slope	-0.03*	-0.13*	-0.02*	-0.11*	0.15*	-0.33*	2.94*	-6.66*
	(-5.28)	(-18.36)	(-4.14)	(-18.54)	(5.90)	(-7.51)	(39.44)	(-51.81)
Organic Matter %	0.07*	0.00	0.00	-0.01	0.22*	-0.19*	0.00	0.03*
	(7.52)	(0.14)	(0.78)	(-1.64)	(4.18)	(-3.04)	(0.05)	(2.63)
Soil pH	0.24*	0.27*	0.22*	0.14*	1.47*	0.07	3.05*	-0.87*
	(3.69)	(3.25)	(4.59)	(2.48)	(3.66)	(0.16)	(25.21)	(-7.14)
Soil Permeability	0.01*	-0.02*	0.02*	-0.02*	0.10*	-0.14*	0.16*	-0.34*
	(3.72)	(-4.19)	(5.52)	(-5.21)	(4.16)	(-4.79)	(19.82)	(-39.24)
Medium Textured Soil	-0.002	-0.09*	-0.01	0.02	0.15*	-0.34*	0.44*	0.31*
	(-0.21)	(-9.40)	(-1.29)	(1.34)	(2.61)	(-5.37)	(25.36)	(18.63)
Fine Textured Soil	-0.004*	0.00	-0.04*	-0.05	-0.01	0.02	-0.02*	0.10*
	(-2.33)	(-0.82)	(-2.39)	(-1.94)	(-0.46)	(1.18)	(-6.86)	(32.23)
Mean Max. Temp.	-1.70*	1.87*	-2.99*	2.37*	-6.45*	2.42*	2.60*	2.49*
	(-6.41)	(5.50)	(-16.30)	(11.03)	(-6.49)	(2.40)	(14.28)	(13.02)
Std. Dev. of Max. Temp.	-0.27*	0.26*	-0.75*	0.40*	-1.70*	0.48	-1.06*	0.72*
	(-3.17)	(2.39)	(-11.92)	(5.42)	(-5.76)	(1.50)	(-17.91)	(11.91)
Mean Precipitation	-0.07	-0.19	-0.12	-0.12	0.44	-0.80*	-2.92*	-0.40*
	(-0.77)	(-1.72)	(-1.79)	(-1.62)	(1.38)	(-2.24)	(-35.58)	(-4.85)
Std. Dev. of Precip.	-0.21*	0.38*	-0.16*	0.24*	-1.13*	0.68*	1.73*	0.45*
	(-2.29)	(3.35)	(-2.36)	(3.06)	(-3.62)	(1.96)	(23.28)	(5.96)

Notes: All elasticities are evaluated at the mean of variables for the sampling period. An asterisk (*) denotes statistical significance at the 5% level. Numbers in parentheses are *t*-statistics.

[a] Estimation allows different coefficients for each state (i.e., different models for different states).

[b] Coefficients are restricted to be the same across states.

with respect to the competing crop for all models except the field-level soybean equation also have the expected sign. However, the signs of the acreage elasticities for the physical variables are more consistent with agronomic information in the field-level models than in the county-level models.

The results are consistent with the arguments provided in this article. With a disaggregated model, a large number of data points are used to estimate a few coefficients, and the standard errors of the estimates are smaller due to higher degrees of freedom. Yet, the one set of estimated coefficients arising from the restricted models may not be representative of land-use responses of a particular state, and hence the resulting predictions may be poor. Conversely, the coefficients can be selected to closely fit the macro data and provide good predictive power, but the variances of the parameter estimates are relatively large because of the smaller size of the aggregated sample.[5] These results suggest that the choice of level of aggregation depends on the intended use of the results. If data are available, then estimation of micro relationships may warrant the effort when specific parameters are needed. Otherwise, aggregate models, given their relative ease of estimation, are a preferred alternative.

[5] We thank an anonymous referee for this observation.

Conclusions

The increasing availability of physical and natural science data describing land characteristics allows economists to specify and estimate increasingly complex micro relationships concerning land-use decisions. To the extent these relationships meet certain, stringent conditions, it is generally assumed that the aggregation of these individual micro relationships will yield better predictions than more aggregate models.

In this study, we examine the performance of a field- (micro-) level model of land use (crop choice) relative to more common (and aggregated) specifications of the land-use decision. Specifically, models of county-, state-, and regional-level acreage responses are also evaluated. This comparison allows for an exploration of the question of whether the availability of such micro data, and hence the ability to conduct detailed micro-level analysis, matters for improving predictions of aggregate changes in land use.

Based on our results, if the measure of interest is aggregate crop acreage predictions, then the micro model is inferior to the most aggregated class of models, despite the greater informational content embedded in the micro model. This conclusion holds across two data sets evaluated here. The greater number of variables and the more detailed spatial resolution represented in the micro model make it much more complex.

In the case of the crops and regions studied here, econometric complications increase the variance of the estimates, and consequently the root mean square error of model predictions. However, the micro model did perform better than the two intermediate models (county and state models). Also, when emphasis is on a limited set of characteristics, such as elasticities derived for a particular variable, the micro model does perform better than the most aggregate models. This finding is encouraging, given that detailed site-specific information and land use data are needed when one is interested in the impact of land use changes on nonpoint-source pollution and other environmental quality indicators.

The results of this study may not hold for other crops and settings, but they do corroborate findings of earlier theoretical inquiries contending that aggregation is not necessarily "bad." Within the context of contemporary problems associated with aggregate land use decisions, the results provide evidence to suggest economic analysis of land-use issues need not await the availability of data on every conceivable geographic variable; economic reasoning and simple aggregates of data can be useful tools for predictions. However, the fact that micro models perform better in terms of other statistical measures clearly indicates the choice of model must reflect the intended use of these models.

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References

Baltagi, B. H., and B. Raj. "A Survey of Recent Theoretical Developments in the Econometrics of Panel Data." *Empirical Econ.* 17(1992):85–109.

Blackorby, C., and W. Schworm. "The Existence of Input and Output Aggregates in Aggregate Production Functions." *Econometrica* 56(May 1988):613–43.

Caswell, M., and D. Zilberman. "The Choice of Irrigation Technologies in California." *Amer. J. Agr. Econ.* 67(May 1985):224–34.

Chambers, R. G., and R. D. Pope. "Testing for Consistent Aggregation." *Amer. J. Agr. Econ.* 73(August 1991):808–18.

Chavas, J.-P., and M. T. Holt. "Acreage Decisions Under Risk: The Case of Corn and Soybeans." *Amer. J. Agr. Econ.* 72(August 1990):529–38.

Chavas, J.-P., R. D. Pope, and R. S. Kao. "An Analysis of the Role of Future Prices, Cash Prices, and Government Programs in Acreage Response." *West. J. Agr. Econ.* 8(July 1983):27–33.

Chiappori, P.-A. "Distribution of Income and the 'Law of Demand.'" *Econometrica* 53(January 1985): 109–27.

Gardner, B. L. "How the Data We Make Can Unmake Us: Annals of Factology." *Amer. J. Agr. Econ.* 74 (December 1992):1066–75.

Gorman, W. M. "Community Preference Fields." *Econometrica* 21(January 1953):63–80.

Green, R. C. "Program Provisions for Program Crops: A Database for 1961–90." Staff Rep. No. AGES 9010, USDA/Economic Research Service, Agriculture and Trade Analysis Div., Washington DC, March 1990.

Greene, W. H. *Econometric Analysis.* New York: Macmillan, 1990.

———. *LIMDEP: User's Manual and Reference Guide, Version 6.0.* New York: Econometric Software Inc., 1991.

Grunfeld, Y., and Z. Griliches. "Is Aggregation Necessarily Bad?" *Rev. Econ. and Statis.* XLII(February 1960):1–13.

Gupta, K. L. "Aggregation Bias in Linear Economics Models." *Internat. Econ. Rev.* 12(1971):293–305.

Hall, B. H. *Times Series Processor, Version 4.3: User's Guide.* Palo Alto CA: TSP International, March 1995.

Hardie, I. W., and P. J. Parks. "Land Use with Heterogeneous Land Quality: An Application of an Area Base Model." *Amer. J. Agr. Econ.* 79(May 1997):299–310.

Hildenbrand, W. "On the 'Law of Demand.'" *Econometrica* 51(July 1983):997–1020.

Houck, J. P., and M. E. Ryan. "Supply Analysis for Corn in the United States: The Impact of Changing Government Programs." *Amer. J. Agr. Econ.* 54(May 1972):184–91.

Klein, H. A. J. "Macroeconomics and the Theory of Rational Behavior." *Econometrica* 14(January 1946): 93–108.

Kmenta, J. *Elements of Econometrics.* New York: Macmillan, 1986.

Lee, K. C., M. H. Pesaran, and R. G. Pierse. "Testing for Aggregation Bias in Linear Models." *Econ. J.* 100(Conference 1990):137–50.

Lichtenberg, E. "Land Quality, Irrigation Development, and Cropping Patterns in the Northern High Plains." *Amer. J. Agr. Econ.* 71(February 1989):187–94.

Lidman, R., and D. L. Bawden. "The Impact of Government Programs on Wheat Acreage." *Land Econ.* 50(November 1974):327–35.

Love, H. A. "Conflicts Between Theory and Practice in Production Economics." *Amer. J. Agr. Econ.* 81(August 1999):696–702.

Muellbauer, J. "Aggregation, Income Distribution, and Consumer Demand." *Rev. Econ. Stud.* 42(October 1975):525–43.

Pesaran, M. H., R. G. Pierse, and M. S. Kumar. "Econometric Analysis of Aggregation in the Context of Linear Prediction Models." *Econometrica* 57(July 1989):861–88.

Plantinga, A. J., T. Mauldin, and D. J. Miller. "An Econometric Analysis of the Cost of Sequestering Carbon in Forests." *Amer. J. Agr. Econ.* 81(November 1999):812–24.

Sasaki, K. "An Empirical Analysis of Linear Aggregation Problems: The Case of Investment Behavior in Japanese Firms." *J. Econometrics* 7(1978):313–31.

Shumway, C. R. "Supply, Demand, and Technology in a Multiproduct Industry: Texas Field Crops." *Amer. J. Agr. Econ.* 65(November 1983):749–60.

———. "Recent Contributions in Production Economics." *J. Agr. and Resour. Econ.* 20(July 1995): 178–94.

Stoker, T. M. "Completeness, Distribution Restrictions, and the Form of Aggregate Functions." *Econometrica* 52(July 1984):887–907.

Theil, H. *Principles of Econometrics.* Amsterdam: North-Holland Publishing Co., 1971.

Thompson, G. D. "A Test for Spatial and Temporal Aggregation." *Econ. Letters* 36(1991):391–96.

Thompson, G. D., and C. C. Lyon. "A Generalized Test for Perfect Aggregation." *Econ. Letters* 40(1992): 389–96.

U.S. Department of Agriculture. *Agricultural Statistics.* USDA/Statistical Reporting Service, National Agricultural Statistics Service, Washington DC. Various years, 1971–97.

Wu, J. J., and B. W. Brorsen. "The Impact of Government Programs and Land Characteristics on Cropping Patterns." *Can. J. Agr. Econ.* 43(March 1995):87–104.

Wu, J. J., and K. Segerson. "The Impact of Policies and Land Characteristics on Potential Groundwater Pollution in Wisconsin." *Amer. J. Agr. Econ.* 77(November 1995):1033–47.