Why Are Estimates of Agricultural Supply Response so Variable?

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Abstract: Estimates of the response of agricultural supply to movements in expected price display curiously large variation across crops, regions and time periods. We argue that this anomaly may be traced, at least in part, to the statistical properties of the commonly-used econometric estimator, which has infinite moments of all orders and may have a bimodal distribution. We propose an alternative minimum-expected-loss estimator, establish its improved sampling properties, and argue for its usefulness in the empirical analysis of agricultural supply response.

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1. Introduction

The Nerlove model of agricultural supply response (e.g., Nerlove and Addison, 1958) is one of the most successful in applied econometrics, as evidenced by the hundreds of subsequent studies that use it productively. A nagging and recurring problem, however, concerns the variability of estimated supply response. In their extensive English-language survey, for example, Askari and Cummings (1977) document this variability and ascribe it to differences in the "quality" of estimates, due to differences in definitions of price and output measures, as well as data measurement errors. They note, however, that:

> "Still unexplained is why, if these results reasonably reflect the responsiveness of the cultivators concerned, considerable differences in elasticity exist for the same crop in different regions, or why, in the same country, the degree of supply responsiveness may vary widely from crop to crop." (p. 263)

One suspects, then, that factors other than data quality may be relevant, including model specification, sample period, true underlying differences in response parameters across regions, countries and commodities, and so on.[1] We shall elaborate on one such factor, the properties of the commonly-used econometric estimator. Specifically, we argue in sections 2 and 3 that its sampling properties are poor, which may explain (at least in part) the high dispersion of reported estimates.[2] We show that the standard supply response estimator

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[1] See for example Braulke (1982), Gardner (1993), Just (1993), and Tomek and Myers (1993).

[2] A related paper, of which we became aware after completing ours, is Bewley and Fiebig (1990). As will become clear shortly, however, the two papers are very different. Ours, in particular, focuses entirely on the agricultural supply question and treats it in depth.

possesses infinite moments of all orders and may have a bimodal distribution. We propose an alternative estimator with better sampling properties, which we document using Monte Carlo methods in section 4. We conclude in Section 5.

2. The Sampling Properties of Estimates of Supply Response

The standard structural form of the Nerlove model is

$$A_t^* = \alpha_0 + \alpha P_t^e + u_t \tag{1}$$

$$P_t^e = P_{t-1}^e + \gamma (P_{t-1} - P_{t-1}^e) \tag{2}$$

$$A_t = A_{t-1} + \theta (A_t^* - A_{t-1}) \tag{3}$$

$$u_t \overset{iid}{\sim} (0, \sigma_u^2), \tag{4}$$

where A denotes crop acreage under cultivation, P is crop price, A^* is desired acreage, P^e is expected future price, and α_0, α, γ, θ, and σ_u^2 are parameters.

Equation (1) describes the relationship between desired acreage and expected price. Economic theory predicts that $\alpha \geq 0$, and there are economic reasons to expect $\alpha_0 > 0$ as well, due to subsistence farming. Equations (2) and (3) represent a simple adaptive-expectations partial-adjustment mechanism linking P^e and A^* to observable P and A values. The adjustment parameters γ and θ are expected to be positive. As shown by Muth (1960), the adaptive expectations (2) are in fact fully rational if prices follow an integrated moving average process, and the partial adjustment mechanism (3) has been advocated for approximating economic dynamics at least since Samuelson (1947).

The reduced-form equation relating acreage and price is found by solving equations (1)-(4) for acreage in terms of the observable variables of the system, yielding

$$A_t = b_1 + b_2 P_{t-1} + b_3 A_{t-1} + b_4 A_{t-2} + e_t, \tag{5}$$

where

$$b_1 = \alpha_0 \gamma \theta$$

$$b_2 = \alpha \gamma \theta$$

$$b_3 = (1 - \gamma) + (1 - \theta)$$

$$b_4 = -(1 - \gamma)(1 - \theta)$$

$$e_t = \theta u_t - [\theta(1-\gamma)]u_{t-1}.$$

The parameter of interest, α, is expressed in terms of the reduced-form parameters as

$$\alpha = \frac{\delta_1}{\delta_2}, \tag{6}$$

where

$$\delta_1 \equiv b_2$$

$$\delta_2 \equiv (1 - b_3 - b_4).$$

In practice, of course, the reduced form must be *estimated*. Least squares (LS) may not be strictly appropriate, however, because the reduced-form disturbance is potentially serially correlated and the regressors include lagged dependent variables. We nevertheless focus on LS estimation and an improvement obtained via Bayesian shrinkage techniques. Our focus is entirely appropriate in certain cases. If, for example, expectations adapt quickly (that is, if γ is close to 1), then the reduced-form disturbance is approximately white noise. Alternatively, if the supply-response equation's disturbance is serially correlated, and if that serial correlation is approximately first-order autoregressive with parameter $1-\gamma$, then the reduced-form disturbance is again approximately white noise. Much more important than any such special cases, however, is the recognition that regardless of whether LS is entirely appropriate, it has nevertheless been used regularly in the applied agricultural economics literature. Because we want to mimic what's done in practice, our research strategy is to follow suit, and to ask whether improvements are nevertheless possible within the LS framework via Bayesian shrinkage techniques. As we shall show, our strategy yields important insights, even if it leaves certain other issues unaddressed.

Let "^" denote the LS estimator of the reduced-form parameter vector. The estimate of α is formed as

$$\hat{\alpha} = \frac{\hat{\delta}_1}{\hat{\delta}_2} = \frac{\hat{b}_2}{(1 - \hat{b}_3 - \hat{b}_4)} \,. \tag{7}$$

Note in particular that $\hat{\alpha}$ is formed as the ratio of two random variables, $\hat{\delta}_1$ and $\hat{\delta}_2$. Under very general conditions, ratios or reciprocals of random variables have Cauchy tails and hence no finite moments.[3] Moreover, as shown by Zellner (1978) for the normal case and Lehmann and Popper Shaffer (1988) for more general cases, the distributions of reciprocals or ratios will, in general, be multimodal (typically bimodal). Both the non-existence of moments and the multimodality may contribute to high variability in estimates of agricultural supply response.[4]

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[3] See Zellner (1978, 1985, 1986), Zellner and Park (1979), Zaman (1981) and Piegorsch and Casella (1985), *inter alia*.

[4] Problems of non-existence of moments and multimodality are not likely to be solved through various "improved" structural specifications, leading to different reduced forms. As

(continued...)

3. An Improved Estimator

In contrast, for problems of ratio estimation such as ours, the minimum-expected-loss (MELO) estimator of Zellner (1978) has been shown to have (at least) finite first and second moments, and hence finite risk with respect to generalized quadratic loss in small as well as large samples. Furthermore, the MELO estimator is consistent, asymptotically efficient and asymptotically normal.

The generalized quadratic loss function for our problem is

$$GQL = (\delta_1 - \delta_2\alpha^*)^2 = \delta_2^2(\alpha - \alpha^*)^2, \tag{8}$$

where α^* is any estimate of $\alpha \equiv \frac{\delta_1}{\delta_2}$. Let $\beta = (b_1, b_2, b_3, b_4)'$ and let prior information regarding β and σ (the standard deviation of the disturbances of the reduced form (5)) be represented by the density function $f(\beta, \sigma)$. [5] The information contained in the data is summarized by the likelihood $L(A \mid X, \beta, \sigma)$, where A is a (Tx1) vector with t-th entry A_t, X is a (Tx4) matrix with t-th row $(1, P_{t-1}, A_{t-1}, A_{t-2})$, and T is sample size. Then, by Bayes' theorem,

$$g(\beta, \sigma \mid A, X) \propto L(\beta, \sigma \mid A, X)\, f(\beta, \sigma), \tag{9}$$

where the posterior density $g(\cdot)$ summarizes posterior beliefs. For any prior and likelihood, the estimator that minimizes posterior expected loss (that is, the MELO estimator) is given by

[4](...continued)
long as the supply-response parameter is constructed as a ratio of estimated reduced-form parameters, such problems will arise.

[5] From the Bayesian vantage point β, and hence δ_1 and δ_2, are viewed as subjectively random variables.

$$\hat{\alpha}_{MELO} = \frac{E(\delta_1)}{E(\delta_2)} \cdot \frac{1 + \mathrm{cov}(\delta_1, \delta_2) / E(\delta_1)\, E(\delta_2)}{1 + \mathrm{var}(\delta_2) / E^2(\delta_2)} \tag{10}$$

$$\equiv \frac{E(\delta_1)}{E(\delta_2)} \cdot F,$$

where $E(\cdot)$ denotes posterior expectation, $\mathrm{var}(\cdot)$ denotes posterior variance and $\mathrm{cov}(\cdot)$ denotes posterior covariance (that is, expectation, variance, and covariance with respect to $g(\cdot)$), and F denotes the shrinkage factor.

If the reduced-form disturbance e_t is approximately white noise, and if the likelihood is normal and the prior is diffuse, then the marginal posterior density $g(\beta)$ has a multivariate Student-t distribution with 4-dimensional mean vector[6]

$$E(\beta) = (X'X)^{-1}X'A = (\hat{b}_1, \hat{b}_2, \hat{b}_3, \hat{b}_4)', \tag{11}$$

which is equal, of course, to the LS estimator. Immediately,

$$E(\delta_1) = \hat{b}_2 \tag{12a}$$

and

$$E(\delta_2) = (1 - \hat{b}_3 - \hat{b}_4). \tag{12b}$$

Furthermore, the posterior covariance matrix is given by

$$(X'X)^{-1} \frac{\nu}{\nu - 2} s^2, \tag{13}$$

where $\nu = T - 4$ and[7]

$$\nu s^2 = (A - XE(\beta))' (A - XE(\beta)), \tag{14}$$

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[6] See Zellner (1971) for the derivation.

[7] For the present application, we require T > 6, so that the posterior covariance matrix is well defined.

the LS residual sum of squares. Then

$$\mathrm{cov}(\delta_1,\ \delta_2) = \mathrm{cov}(\beta_2,\ (1 - \beta_3 - \beta_4)) \tag{15}$$

$$= E[(\beta_2 - E(\beta_2))(1 - \beta_3 - \beta_4 - (1 - E(\beta_3) - E(\beta_4)))].$$

Simple manipulations enable us to write this as

$$\mathrm{cov}(\delta_1,\ \delta_2) = -\ [\mathrm{cov}(\beta_2,\ \beta_3) + \mathrm{cov}(\beta_2,\ \beta_4)] \tag{16}$$

$$= \frac{\nu}{\nu - 2} s^2\ [(X'X)^{-1}_{23} + (X'X)^{-1}_{24}], \tag{17}$$

where $(X'X)^{-1}_{ij}$ denotes the ij-th element of $(X'X)^{-1}$. Furthermore,

$$\mathrm{var}(\delta_2) = \mathrm{var}(1 - \beta_3 - \beta_4) \tag{18}$$

$$= \mathrm{var}(\beta_3) + \mathrm{var}(\beta_4) + 2\ \mathrm{cov}(\beta_3,\ \beta_4), \tag{19}$$

so that

$$\mathrm{var}(\delta_2) = \frac{\nu}{\nu - 2} s^2\ [(X'X)^{-1}_{33} + (X'X)^{-1}_{44} + 2\ (X'X)^{-1}_{34}]. \tag{20}$$

Given these quantities, $\hat{\alpha}_{MELO}$ may be constructed at once from equation (10).

Some insight into the properties of the MELO estimator may be gained by considering special cases, such as that arising when $E(\delta_1) > 0$, $E(\delta_2) > 0$, and $\mathrm{cov}(\delta_1,\ \delta_2) > 0$, in which

$$F > 1 \text{ if } \frac{\mathrm{Cov}(\delta_1,\ \delta_2)}{\mathrm{var}(\delta_2)} > \frac{E(\delta_1)}{E(\delta_2)} = \hat{\alpha}$$

$$F = 1 \text{ if } \frac{\mathrm{Cov}(\delta_1,\ \delta_2)}{\mathrm{var}(\delta_2)} = \frac{E(\delta_1)}{E(\delta_2)} = \hat{\alpha} \tag{21}$$

$$F < 1 \text{ if } \frac{\mathrm{Cov}(\delta_1,\ \delta_2)}{\mathrm{var}(\delta_2)} < \frac{E(\delta_1)}{E(\delta_2)} = \hat{\alpha}\ .$$

These expressions show how the MELO estimator "shrinks" $\hat{\alpha}$ in the direction of $\frac{\text{cov}(\delta_1, \delta_2)}{\text{var}(\delta_2)}$. Note, however, that as T gets large, $F \rightarrow 1$ and $\hat{\alpha}_{MELO} \rightarrow \hat{\alpha}$, given in (7). Thus, it's in *small* samples, precisely the case where the performance of LS is expected to be poor and precisely the case relevant for the analysis of agricultural supply response, that MELO estimation is expected to yield the most improvement.

We obtain the estimated long-run elasticity evaluated at price P and acreage A as $\hat{\Psi} = \hat{\alpha}_{MELO} \frac{P}{A}$, where P and A are the selected values of price and acreage at which the elasticity is to be evaluated. Note that $\hat{\Psi}$ is also a MELO estimator if we treat $\frac{P}{A}$ as a nonstochastic entity to be selected by the investigator, which is the view adopted in this paper and typically adopted in practice. Alternatively, assuming stationarity of the price and acreage series, one might attempt to evaluate the elasticity at the true but unknown means μ_P and μ_A. Then the ratio $r = \frac{\mu_P}{\mu_A}$ can be estimated by the MELO approach outlined above, with the requisite posterior variances and covariance obtained from an application of the normal-likelihood diffuse-prior Bayesian multivariate regression model. The MELO estimator $\hat{r}_{MELO}$ for the ratio of means will have at least finite first and second moments, and by the Cauchy-Schwartz inequality for random variables (e.g., Rao, 1973, p. 149) the elasticity estimator $\hat{\alpha}_{MELO} \cdot \hat{r}_{MELO}$ will have finite second moment if $\hat{\alpha}_{MELO}$ and $\hat{r}_{MELO}$ have finite fourth moments.[8]

In closing this section, we sketch how the MELO procedure could be extended to

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[8] To see this, let $\tilde{\tilde{\alpha}} = \hat{\alpha}^2_{MELO}$ and $\tilde{\tilde{r}} = \hat{r}^2_{MELO}$. Then the Cauchy-Schwartz inequality gives $[E|\tilde{\tilde{\alpha}}\tilde{\tilde{r}}|]^2 \leq E(\tilde{\tilde{\alpha}}^2)\, E(\tilde{\tilde{r}}^2)$, but by positivity of $\tilde{\tilde{\alpha}}$ and $\tilde{\tilde{r}}$, we can write this as $E(\tilde{\tilde{\alpha}}\tilde{\tilde{r}}) \leq [E(\tilde{\tilde{\alpha}}^2)E(\tilde{\tilde{r}}^2)]^{1/2}$, or $E(\hat{\alpha}_{MELO}\hat{r}_{MELO})^2 \leq [E(\hat{\alpha}^4_{MELO})\ E(\hat{r}^4_{MELO})]^{1/2}$.

handle explicitly a reduced form that contains a lagged dependent variable and serially-correlated errors. Zellner and Geisel (1970) give a Bayesian treatment of such models and provide expressions for the posterior density function, from which the posterior moments could be computed numerically and then used as inputs to MELO estimation. Such an approach, however, loses the attractive simplicity of the LS and MELO procedures explored in this paper. Recent work by Zellner (1994, 1995) on Bayesian method-of-moments instrumental-variables estimation goes a long way toward recapturing that simplicity, however, and represents a very promising direction for future research.

4. A Monte Carlo Experiment

Here we report on a Monte Carlo experiment designed to contrast the sampling properties of the least-squares and MELO estimators of supply response.

4a. Experimental Design

We generate 1000 samples of data from each of various parameterizations of the restricted reduced form (5). Certain of the parameters are kept at fixed values; we set $\theta = .5$, $\alpha_0 = .25$, and $\alpha = 2$. The supply adjustment parameter $\theta = .5$ implies a moderate adjustment speed. The small but positive value of α_0 reflects subsistence farming. Setting $\alpha = 2$ (and $E(P) = 100$, as is done below) implies a supply elasticity of approximately 1.[9]

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[9] To compute the elasticity, take expectations of both sides of the reduced form (5), yielding $E(A) = \alpha_0 + \alpha\, E(P)$, which satisfies the behavioral relationship (1) exactly. Thus, $E(P)/E(A) = E(P)/(\alpha_0 + \alpha E(P))$. For the present example this yields

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Other parameters are varied. In particular, we examine

$T = 25, 50, 100$

$\gamma = .5, .75, 1.0$

$\rho = .500, .625, .750, .900$

$\sigma_u = 1, 2, 3, 5$

$\sigma_\varepsilon = 1, 2, 3, 5,$

where

$$(P_t - 100) = \rho\ (P_{t-1} - 100) + \varepsilon_t, \tag{22}$$

$$\varepsilon_t \sim \text{IID } N(0, \sigma_\varepsilon^2),\ t = 1, 2, ..., T.$$

First let us discuss the choice of sample sizes (T) explored. A sample size of 25 (or even less) is typical in empirical work using annual time series of acreage and price. It is our hope, of course, that the MELO estimator will perform well in this important small-sample situation. As sample size increases, MELO estimation should yield progressively less noticeable improvements, because sample information will eventually dominate prior beliefs. Inclusion of sample sizes of 50 and 100 allows us to see the speed and patterns with which such effects transpire.

The values $\gamma = .5, .75, 1.0$ are associated with varying speeds of expectations adaptation. The standard deviations σ_ε and σ_u are varied within ranges designed to capture a variety of relative shock volatility patterns. The three values of ρ explored span a range of moderate persistence through high persistence. We set all initial conditions at their expected

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$E(P)/E(A) = 100/200.25 \approx 1/2,$ so that the elasticity is approximately $2 \cdot 1/2 = 1.$

values; that is, $P_0 = 100$ and $A_0 = A_{-1} = \alpha_0 + \alpha E(P) = 200.25$.

4b. Results

Table 1 provides an easily-digested summary of certain of the Monte Carlo results, focusing on T = 25 and $\gamma = 1$. The entries in the table are the percent reductions in mean-squared error (MSE) due to the use of MELO rather than LS, under a variety of values of σ_ε, σ_u, and ρ. MELO is always best, often by a large margin. The relative efficiency of the MELO estimator depends significantly on σ_ε^2, σ_u^2, and ρ and tends to be greatest when the variability of price relative to acreage is small. This is particularly evident in the way in which the relative efficiency of the MELO estimator is decreasing in ρ. The intuition for the result is straightforward. The likelihood function contains relatively little information about the location of the reduced-form coefficients when variability of the reduced-form regressors is small, which is precisely the case in which the shrinkage induced by MELO estimation will be beneficial. Moreover, the *amount* of shrinkage varies inversely with the precision of the reduced-form parameter estimates, as evidenced by the expression for the shrinkage factor F in (10).

Note that, although one of the estimators (LS) is known to have infinite MSE in population, it does not follow that examination of MSE across Monte Carlo replications is inappropriate. If MSE is considered to be an appropriate loss function, as it is in this paper and throughout the econometrics and statistics literatures, then estimators should be judged in terms of it and not some other loss function. We could of course change the loss function, but then the optimal estimator would change as well (e.g., absolute-error loss and 0-1 loss lead to posterior median and mode estimators, respectively).[10] For any fixed number of Monte Carlo replications, MSE provides a legitimate summary of the sampling variability of both the LS and MELO estimators.

The results are presented in a different way in Tables 2 through 5, in which we fix $\sigma_\varepsilon = 1$ and $\sigma_u = 5$, but vary T, γ, and ρ. We present various statistics indicating distributional shape, including mean, variance, MSE, and several percentiles. First consider the effects of varying sample size. Like the LS estimator, the MELO estimator displays some bias, but the variability of the MELO estimator is substantially less than that of the LS estimator.[11] This variance reduction results in overall MSE-superiority of the MELO estimator, which is what one expects from a "shrinkage" estimator: variance reductions are achieved at the cost of possible bias increases, but the tradeoff is favorable, and the result is an MSE decrease. For example, for T = 25, MELO estimation reduces MSE from 5.93 to 3.10. This is quite a dramatic reduction in variability of the estimator, and it should be remembered that this small-sample case is the one relevant in typical applications. As expected, however, the reduction in MSE decreases as sample size increases.

Now consider the effects of varying γ and ρ. MELO estimation continues to yield

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[10] See Zellner (1971, p. 276). It's interesting to note that 0-1 loss and use of the resulting posterior mode may be particularly attractive when the posterior is bimodal, as can happen in models such as the one studied here, but additional research along those lines is beyond the scope of the present paper.

[11] This finding parallels that of Park (1982) for the MELO estimator in the simultaneous-equations model.

improvements, and as seen before, the improvements are decreasing in ρ. Interestingly, the improvement afforded by MELO estimation appears robust to the value of γ, and in particular, it remains when γ is less than one. This is fortunate in light of the revealed preference in applied work for LS estimation, even though it is not strictly appropriate when γ is less than one.

In closing this subsection, we conjecture that, even if one were to use classical and Bayesian estimators that explicitly account for serial correlation in the presence of a lagged dependent variable, the relative superiority of the Bayesian estimator would remain. Previous studies that bear on the conjecture include Fomby and Guilkey (1978), who study classical and Bayesian approaches to regression with AR(1) errors and find that a Bayesian estimator dominates others, as well as the impressive contributions of Park (1982) and Tsurumi (1990), who compare classical and Bayesian estimators of simultaneous-equations models and document good relative performance of the Bayesian estimators. Tsurumi, in particular, notes that the relative performance of the Bayesian estimators increases with the degree of simultaneity.

4c. Additional Discussion

The Monte Carlo results show clearly that MELO estimation improves upon LS. Moreover, they highlight two characteristics of the data important for determining the relative efficiency of the MELO estimator--the sample size and the relative variability of price and acreage.

Although the smallest sample size in our Monte Carlo study is 25, the Nerlove model is often applied when even less data are available. A review of the studies summarized by

Askari and Cummings (1977) indicates that sample sizes of eight are not unheard of, and numerous estimates have been made on the basis of sample sizes of ten or eleven. Indeed, of the 602 different crops and regions for which Askari and Cummings catalog supply response estimates, approximately 85 percent were obtained from samples of size 25 or less. Thus, on this ground alone, it appears advantageous to use the MELO estimator.

Concerning the relative variability of prices and acreage, one might expect low relative variability of prices. For export crops, whose prices are determined in the world market, prices are less subject to variability from country-specific factors such as weather. For crops produced for domestic consumption, government price controls are frequently imposed, which reduces price variability.

The empirical issue remains, however, as to the *relative* variability of price and acreage. Here we attempt to shed some light on the issue by focusing on one very important, well-known and representative dataset, that used in Behrman's (1966, 1968) study of the supply response of total production and the marketed surplus of four major crops in Thailand.[12]

Behrman used annual data to estimate the Nerlove model for various regions of the Thai kingdom. We examine 64 of Behrman's crop/region combinations, 32 of which involve a sample size of 13, 28 of which involved a sample size of 9, and four of which involved a sample size of 8. Such small sample sizes are typical of the literature, and they are in the

[12] For one crop, rice, a significant portion of output is consumed by the family farmer, making significant modifications to the model necessary. For this reason, we do not include rice in the subsequent discussion.

region for which the Monte Carlo analysis indicated superior performance of the MELO estimator.

In order to assess the relative variability of acreage and price, we computed their coefficients of variation (CV) for each of the 64 datasets, the distributions of which are summarized in Table 6. The acreage CV is rather widely dispersed, with the bulk of the probability mass above unity. In contrast, the price CV is much less dispersed, with most of its probability mass between .1 and .4. The median acreage CV is about six times the median price CV.

Finally, we estimated the first-order serial correlation coefficient for each of the 64 price series, the distribution of which is also summarized in Table 6. The estimates are rather widely dispersed, as expected in such small samples, but most of the probability mass appears in the low to moderate range -- the vast majority of the 64 estimates are below .75.

The upshot is clear: the conditions under which the MELO estimator performs best may well be satisfied in the data.

5. Conclusion

Accurate assessment of agricultural supply response is of key importance both to academic economists and policy makers. Unfortunately, an oft-cited but little-understood problem plagues such assessments: supply-response estimates display curiously large variation across crops, regions, and time periods. We identified one suspect, the commonly-used econometric estimator, which has infinite moments of all orders in small samples. We proposed an alternative and simple minimum-expected-loss estimator, and we evaluated its sampling properties, which were consistently superior. Moreover, an examination of Behrman's well-known and representative agricultural data indicated accordance with the conditions under which minimum-expected-loss estimation yields improvements.

In closing, we stress that the supply model we study is restrictive in many respects.[13] It is potentially limited by its aggregative nature, *ad hoc* expectations and adjustment schemes, partial equilibrium perspective, lack of institutional detail, and so forth. We hasten to add that our improved estimator is not a panacea for these and other potential limitations of the model. But we also hasten to add that the model's immense popularity is not accidental. It is discretely sophisticated and highly parsimonious. It has emerged as a great workhorse of agricultural supply analysis, and its popularity shows no signs of waning. It will remain in widespread use, and it appears that improvements in estimates of the key supply response parameter can be attained through minimum-expected-loss estimation.

[13] See also Nerlove (1979) and Zellner (1985).

References

Askari, A. and T. Cummings, 1977, Estimating agricultural supply response with the Nerlove model: a survey, International Economic Review, 18, 257-329 .

Behrman, J.R., 1966, Price elasticity of the marketed surplus of a subsistence crop, Journal of Farm Economics 48, 875-893.

Behrman, J.R., 1968, Supply response in underdeveloped agriculture: a case study of four major annual crops in Thailand, 1937-1963 (North-Holland, Amsterdam).

Bewley, R. and D.G. Fiebig, 1990, Why are long-run parameter estimates so disparate?, Review of Economics and Statistics 72, 345-349.

Braulke, M., 1982, A note on the Nerlove model of agricultural response, International Economic Review 23, 241-244.

Fomby, T.B. and D.K. Guilkey, 1978, On choosing the optimal level of significance for the Durbin-Watson test and the Bayesian alternative, Journal of Econometrics 8, 203-213.

Gardner, B., 1992, How the data we make can unmake us: annals of factology, American Journal of Agricultural Economics 74, 1066-1075.

Just, R., 1993, Discovering production and supply relationships: present status and future opportunities, Review of Marketing and Agricultural Economics 61, 11-40.

Lehmann, E.L. and J. Popper Shaffer, 1988, Inverted distributions, American Statistician 42, 191-194.

Muth, J., 1960, Optimal properties of exponentially weighted forecasts, Journal of the American Statistical Association 55, 299-305.

Nerlove, M., 1979, The dynamics of supply: retrospect and prospect, American Journal of

Agricultural Economics 61, 874-888.

Nerlove, M. and W. Addison, 1958, Statistical estimation of long-run elasticities of supply and demand, Journal of Farm Economics 40, 861-880.

Park, S.B., 1982, Some sampling properties of minimum-expected-loss (MELO) estimators of structural coefficients, Journal of Econometrics 18, 295-312.

Piegorsch, W.W. and G. Casella, 1985, The existence of the first negative moment, American Statistician 39, 60-62.

Rao, C.R., 1973, Linear statistical inference and its applications (John Wiley and Sons, New York).

Samuelson, P.A., 1947, Foundations of economic analysis (Harvard University Press, Cambridge, Mass.).

Tomek, W. and R. Myers, 1993, Empirical analysis of agricultural commodity prices: a viewpoint, Review of Agricultural Economics 15, 181-202.

Tsurumi, H., 1990, Comparing Bayesian and non-Bayesian limited information estimators, in: S. Geiser, J.S. Hodges, S.J. Press and A. Zellner, eds., Bayesian and likelihood methods in statistics and econometrics: essays in honor of George Barnard. (North-Holland, Amsterdam) 179-207.

Zaman, A., 1981, Estimators without moments, Journal of Econometrics 15, 289-298.

Zellner, A., 1971, An introduction to Bayesian inference in econometrics (John Wiley and Sons, New York).

Zellner, A., 1978, Estimation of functions of population means and regression coefficients including structural coefficients: a minimum expected loss approach, Journal of

Econometrics 8, 127-158.

Zellner, A., 1985, Bayesian econometrics, Econometrica 53, 253-269.

Zellner, A., 1986, Further results on Bayesian minimum expected loss estimates and posterior distributions for structural coefficients, in D.J. Slottje, ed., Advances in econometrics (JAI Press, Greenwich, Connecticut) 171-182.

Zellner, A., 1994, Bayesian method of moments / instrumental variables analysis of mean and regression models, Manuscript, Graduate School of Business, University of Chicago.

Zellner, A., 1995, The finite sample properties of simultaneous equations estimates and estimators: Bayesian and non-Bayesian approaches, Manuscript, Graduate School of Business, University of Chicago.

Zellner, A. and M.S. Geisel, 1970, Analysis of distributed lag models with applications to consumption function estimation, Econometrica 38, 865-888.

Zellner, A. and S.B. Park, 1979, Minimum expected loss (MELO) estimators for functions of parameters and structural coefficients of econometric models, Journal of the American Statistical Association 74, 185-193.

Table 1

Minimum Expected Loss Estimation, T = 25, γ = 1
Mean-Squared Error Reduction Relative to Least Squares

	ρ = .50	ρ = .625	ρ = .75	ρ = .90
$\sigma_\varepsilon = 1, \sigma_u = 5$	52%	45%	39%	35%
$\sigma_\varepsilon = 3, \sigma_u = 3$	37%	31%	21%	12%
$\sigma_\varepsilon = 2, \sigma_u = 2$	32%	24%	17%	6%
$\sigma_\varepsilon = 3, \sigma_u = 5$	32%	12%	17%	6%
$\sigma_\varepsilon = 5, \sigma_u = 5$	32%	29%	17%	6%

Table 2
Empirical Distributions of Estimated Supply Response
$\sigma_\varepsilon = 1,\ \sigma_u = 5,\ \rho = .5$

T = 25

	$\gamma = .5$		$\gamma = .75$		$\gamma = 1.0$	
	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$
MEAN	1.93	1.48	1.95	1.58	1.88	1.55
VAR	35.30	15.17	17.21	6.49	5.92	2.89
MSE	35.36	15.44	17.18	6.66	5.94	3.09
1 %	-12.39	-7.49	- 6.62	-4.09	-3.21	-2.09
5 %	- 5.79	-4.43	- 2.78	-2.25	-1.13	-0.96
50%	1.60	1.33	1.70	1.44	1.69	1.49
95%	10.42	7.82	7.67	5.95	5.37	4.29
99%	19.83	13.58	14.43	9.25	10.33	6.62

T = 50

	$\gamma = .5$		$\gamma = .75$		$\gamma = 1.0$	
	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$
MEAN	2.04	1.81	2.10	1.91	1.98	1.84
VAR	13.10	9.45	5.47	3.90	2.18	1.75
MSE	13.10	9.49	5.48	3.91	2.18	1.78
1 %	- 6.03	- 5.42	-2.60	-2.40	-0.98	-0.97
5 %	- 3.00	- 2.77	-1.17	-1.07	-0.13	-0.15
50%	1.75	1.62	1.86	1.74	1.84	1.74
95%	7.59	6.87	5.76	5.14	4.34	4.02
99%	12.23	10.72	9.25	7.71	6.50	5.62

T = 100

	$\gamma = .5$		$\gamma = .75$		$\gamma = 1.0$	
	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$
MEAN	1.93	1.85	2.01	1.94	1.93	1.87
VAR	5.34	4.86	2.03	1.87	0.84	0.78
MSE	5.34	4.88	2.03	1.87	0.84	0.80
1 %	-3.23	-3.10	-1.01	-0.99	0.06	0.06
5 %	-1.68	-1.56	-0.14	-0.14	0.57	0.54
50%	1.71	1.65	1.89	1.82	1.86	1.80
95%	5.81	5.56	4.48	4.23	3.51	3.40

99%   8.03   7.63   6.01   5.85   4.39   4.25

Table 3

Empirical Distributions of Estimated Supply Response

$\sigma_{\varepsilon} = 1, \ \sigma_{u} = 5, \ \rho = .625$

	$\gamma = .5$		$\gamma = .75$		$\gamma = 1.0$	
	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$
T = 25						
MEAN	1.89	1.49	1.95	1.60	1.89	1.60
VAR	34.12	14.63	16.19	6.26	5.23	2.74
MSE	34.13	14.89	16.19	6.42	5.24	2.90
1 %	−12.89	− 7.47	− 5.91	−3.58	−2.91	−1.85
5 %	− 5.58	− 4.23	−2.64	−2.10	−1.03	−0.87
50%	1.60	1.32	1.73	1.50	1.73	1.54
95%	10.06	7.81	7.52	5.86	5.46	4.39
99%	21.32	12.92	14.94	8.94	10.36	6.68
T = 50						
MEAN	2.00	1.80	2.07	1.90	1.98	1.87
VAR	12.53	8.54	4.79	3.50	1.83	1.53
MSE	12.57	8.58	4.80	3.51	1.83	1.55
1 %	−4.69	−4.37	−2.17	−2.05	−0.77	−0.83
5 %	−2.90	−2.64	−0.96	−0.89	0.13	−0.00
50%	1.66	1.56	1.85	1.72	1.88	1.80
95%	7.16	6.51	5.40	4.92	4.12	3.89
99%	11.23	9.95	8.25	7.43	5.76	5.32
T = 100						
MEAN	1.85	1.79	1.97	1.91	1.93	1.89
VAR	4.47	4.12	1.69	1.57	0.70	0.66
MSE	4.49	4.16	1.69	1.57	0.70	0.67
1 %	−2.72	−2.72	−0.86	−0.90	0.13	0.11
5 %	−1.54	−1.49	−0.03	−0.03	0.70	0.68
50%	1.76	1.70	1.93	1.89	1.92	1.87
95%	5.37	5.14	4.19	4.01	3.33	3.24

99%   7.27   6.84   5.62   5.47   4.26   4.13

Table 4
Empirical Distributions of Estimated Supply Response
$\sigma_\varepsilon = 1,\ \sigma_u = 5,\ \rho = .75$

T = 25

	$\gamma = .5$		$\gamma = .75$		$\gamma = 1.0$	
	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$
MEAN	1.77	1.53	1.88	1.64	1.89	1.67
VAR	33.41	13.77	16.28	5.85	4.27	2.52
MSE	33.46	13.99	16.29	5.98	4.28	2.63
1 %	−12.87	− 7.47	− 5.91	−3.58	− 2.34	−1.64
5 %	− 5.58	− 4.23	− 2.64	−2.10	− 0.83	−0.68
50%	1.60	1.32	1.74	1.49	1.71	1.59
95%	10.06	7.81	7.52	5.86	5.22	4.35
99%	21.32	12.92	14.94	8.94	9.16	6.38

T = 50

	$\gamma = .5$		$\gamma = .75$		$\gamma = 1.0$	
	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$
MEAN	1.95	1.79	2.03	1.91	1.98	1.90
VAR	9.91	7.29	3.60	2.90	1.38	1.21
MSE	9.91	7.33	3.60	2.91	1.38	1.22
1 %	−4.23	−4.07	−1.71	−1.63	−0.45	−0.45
5 %	−2.47	−2.43	−0.66	−0.65	0.24	0.22
50%	1.68	1.58	1.84	1.75	1.90	1.82
95%	6.65	6.03	5.13	4.74	3.91	3.73
99%	9.81	8.96	7.58	6.66	5.23	4.86

T = 100

	$\gamma = .5$		$\gamma = .75$		$\gamma = 1.0$	
	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$
MEAN	1.79	1.75	1.93	1.89	1.94	1.90
VAR	3.42	3.22	1.28	1.21	0.52	0.50
MSE	3.46	3.28	1.28	1.22	0.53	0.51
1 %	−2.52	−2.44	−0.66	−0.64	0.32	0.31
5 %	−1.12	−1.10	0.22	0.21	0.85	0.82
50%	1.76	1.73	1.92	1.88	1.92	1.89
95%	4.92	4.74	3.84	3.70	3.13	3.06

99%	6.57	6.28	5.03	4.94	3.86	3.80

Table 5
Empirical Distributions of Estimated Supply Response

$\sigma_\varepsilon = 1,\ \sigma_u = 5,\ \rho = .9$

T = 25

	$\gamma = .5$		$\gamma = .75$		$\gamma = 1.0$	
	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$
MEAN	0.94	1.59	2.05	1.70	1.88	1.74
VAR	566.58	11.57	32.65	4.85	3.27	2.06
MSE	566.59	11.74	32.65	4.94	3.28	2.13
1 %	-8.61	-6.35	-4.59	-3.53	-2.01	-1.76
5 %	-4.66	-3.69	-1.99	-1.75	-0.58	-0.46
50%	1.49	1.44	1.72	1.59	1.78	1.65
95%	8.26	6.86	6.21	5.13	4.64	4.08
99%	16.96	12.07	10.78	7.93	7.15	6.04

T = 50

	$\gamma = .5$		$\gamma = .75$		$\gamma = 1.0$	
	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$
MEAN	1.90	1.81	1.99	1.91	1.98	1.92
VAR	5.45	4.79	2.04	1.82	0.81	0.74
MSE	5.46	4.84	2.04	1.83	0.81	0.75
1 %	-3.47	-3.40	-1.35	-1.36	-0.13	-0.14
5 %	-1.59	-1.57	-0.16	-0.18	0.61	0.61
50%	1.82	1.75	1.94	1.88	1.96	1.89
95%	5.59	5.39	4.25	4.15	3.45	3.33
99%	8.30	6.98	5.76	5.25	4.32	4.25

T = 100

	$\gamma = .5$		$\gamma = .75$		$\gamma = 1.0$	
	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$	$\hat{\alpha}_{LS}$	$\hat{\alpha}_{MELO}$
MEAN	1.78	1.75	1.91	1.89	1.95	1.93
VAR	1.92	1.86	0.70	0.68	0.28	0.27
MSE	1.97	1.92	0.79	0.69	0.28	0.27
1 %	-1.61	-1.51	-0.10	-0.09	0.64	0.64
5 %	-0.53	-0.50	0.55	0.53	1.08	1.07
50%	1.75	1.7	1.88	1.86	1.93	1.91

95%	4.04	3.97	3.33	3.28	2.83	2.80
99%	5.06	5.04	4.02	3.85	3.20	3.15

Table 6
Distributions of Acreage, Price and Price Persistence,
Sixty Four Behrman Datasets

	Price CV	Acreage CV	Price Persistence
1%	.07	.50	-0.36
5%	.08	.50	-0.25
10%	.09	.71	-0.21
25%	**.15**	**.85**	**0.03**
50%	**.19**	**1.24**	**0.25**
75%	**.25**	**1.53**	**0.37**
90%	.31	1.84	0.56
95%	.34	1.96	0.68
99%	.44	1.96	1.89

Figure 1
Distribution of Coefficient of Variation, Acreage

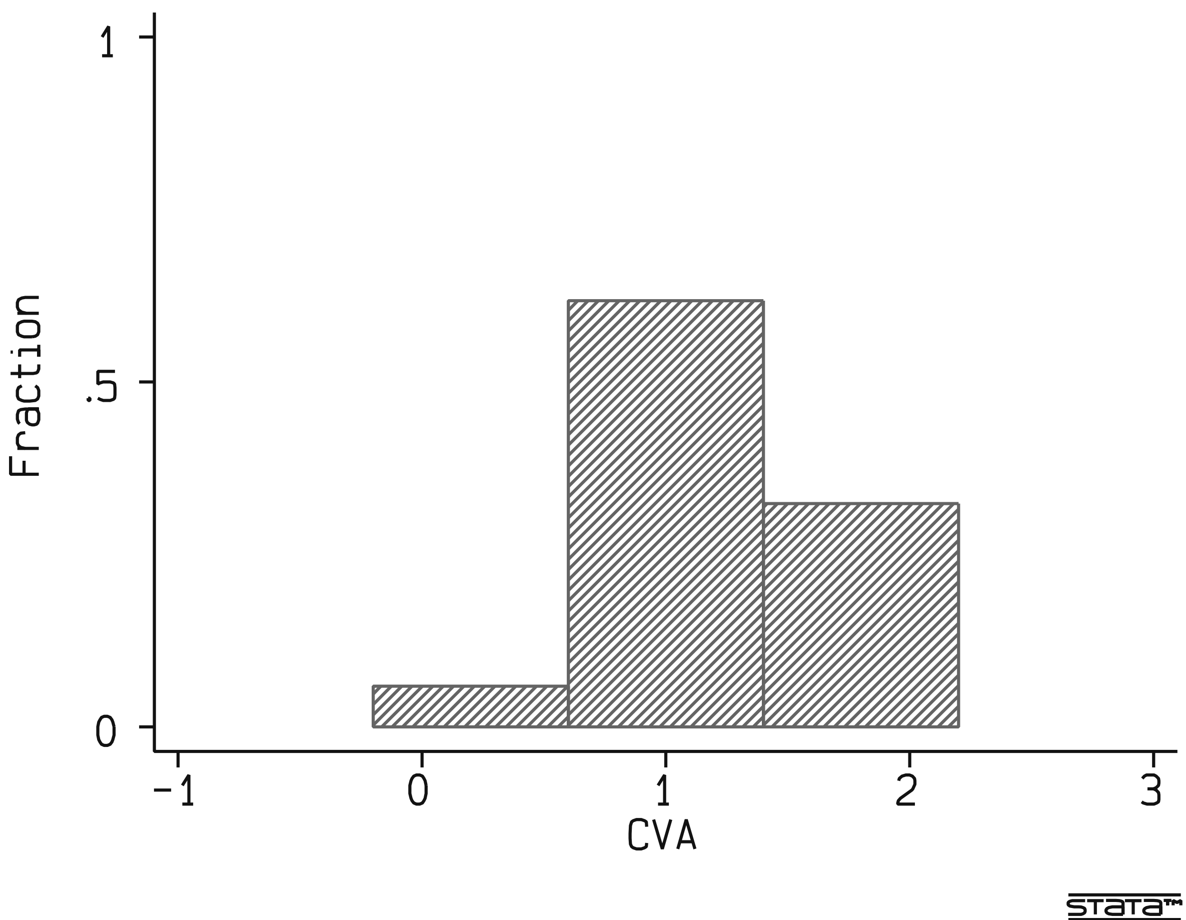


Figure 2
Distribution of Coefficient of Variation, Price

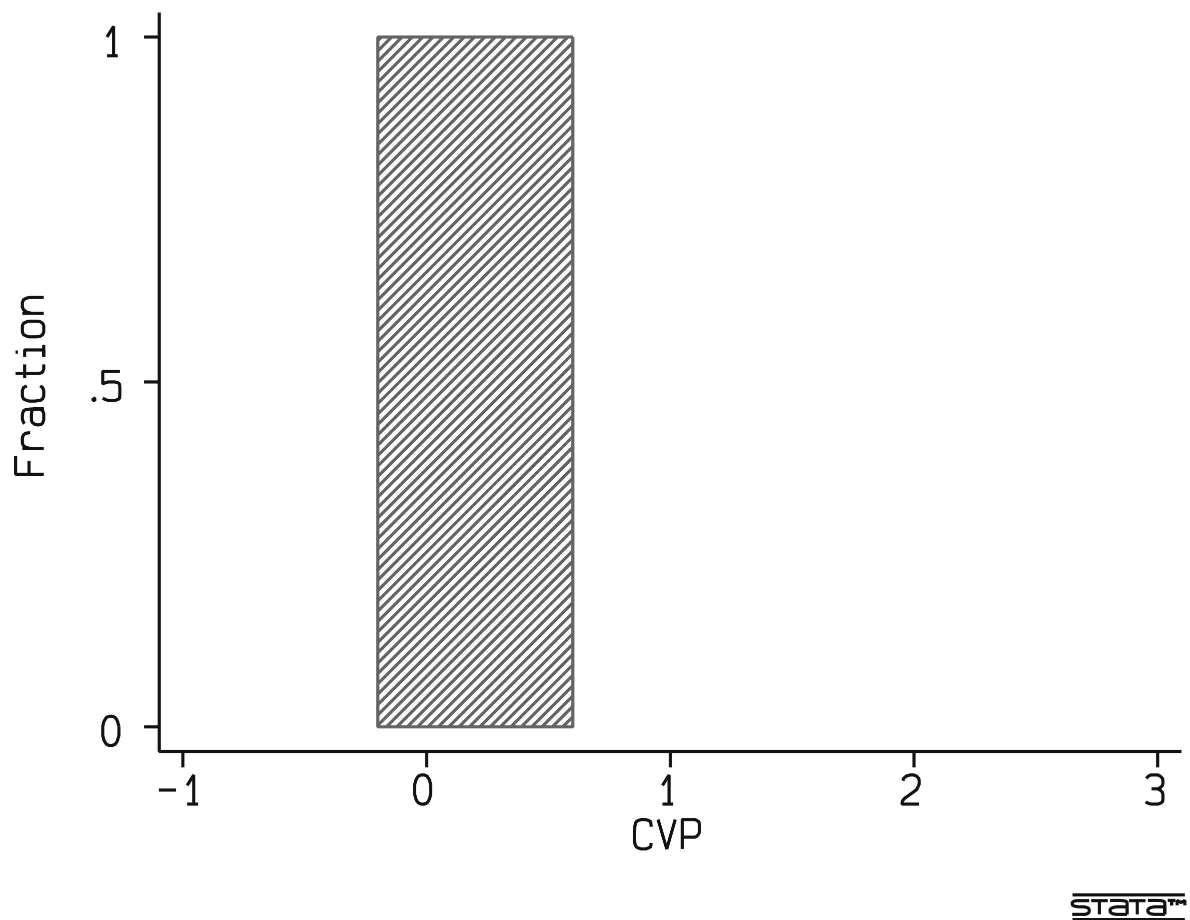
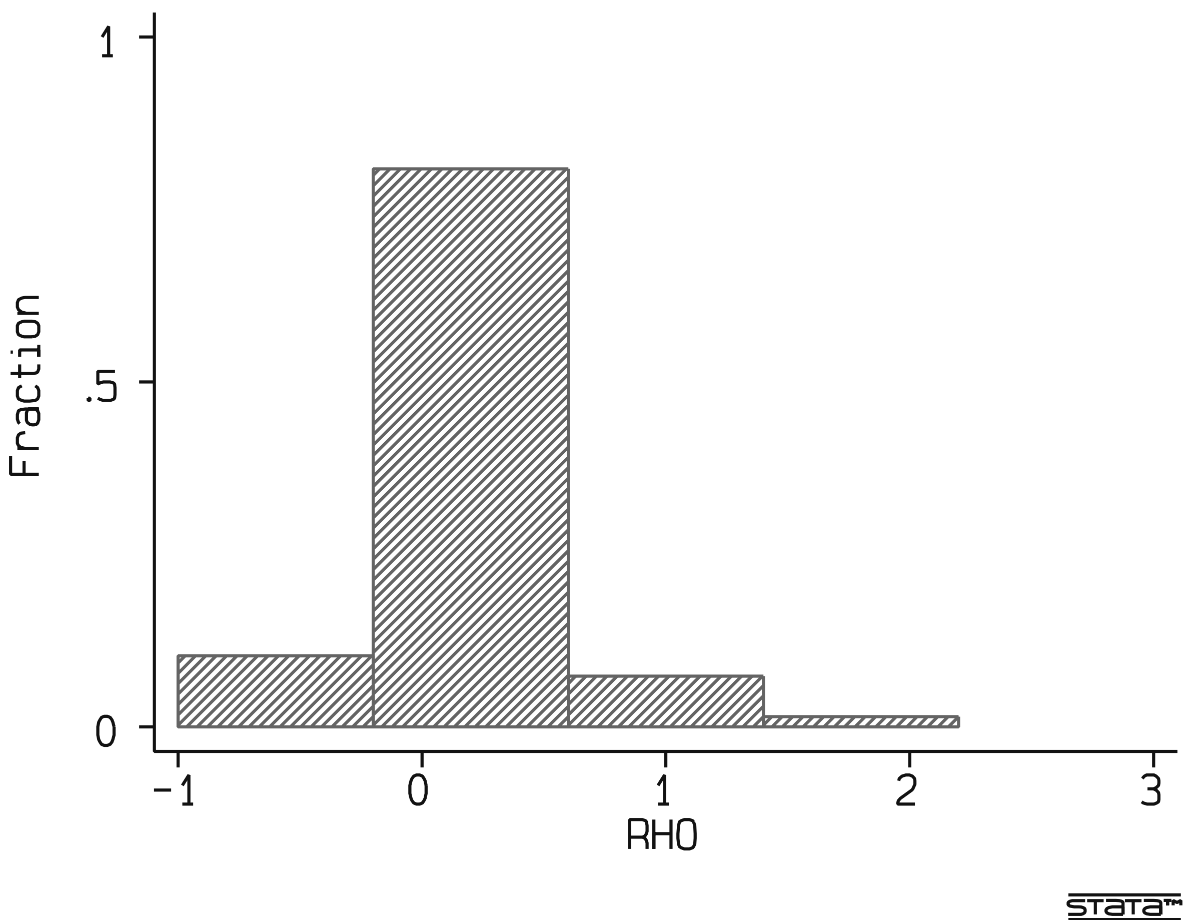


Figure 3
Distribution of ρ Estimates



Notes to tables and figures:

Table 1: σ_{ε}^{2} is the variance of the price innovation, given in equation (22) in the text, and σ_{u}^{2} is the variance of the disturbance in the structural equation for desired acreage, given in equation (1) in the text. ρ is the first-order autoregressive coefficient governing price dynamics, given in equation (22) in the text.

Tables 2 - 5: σ_{ε}^{2} is the variance of the price innovation, given in equation (22) in the text, and σ_{u}^{2} is the variance of the disturbance in the structural equation for desired acreage, given in equation (1) in the text. ρ is the first-order autoregressive coefficient governing price dynamics, given in equation (22) in the text. T is sample size. γ is the expectations-adjustment parameter given in equation (2) in the text. $\hat{\alpha}_{LS}$ and $\hat{\alpha}_{MELO}$ denote the least-squares and minimum-expected-loss estimators. For each parameter configuration, we report the mean (MEAN), variance (VAR), mean-squared error (MSE), and five percentiles of the sampling distribution of each estimator.

Table 6: We provide nine percentiles of the distributions of the coefficient of variation of acreage ("Acreage CV"), the coefficient of variation of price ("price CV"), and the serial correlation coefficient of price ("price persistence") across 64 crop/region combinations. For visual reference, the 25th, 50th and 75th percentiles are shown in boldface.

Figure 1: The coefficients of variation for acreage (CVA) are ratios of its sample standard deviation to the sample mean, for each of 68 crop/region combinations, as discussed in the text. We graph the distribution of the 68 values of CVA, as estimated by a histogram. The area in each bin is the proportion of the 68 observations falling in that bin. The position of the leftmost bin is an artifact of the algorithm used to select histogram bin width; all of the coefficients of variation underlying the histogram are positive.

Figure 2: The coefficients of variation for price (CVP) are ratios of its sample standard deviation to the sample mean, for each of 68 crop/region combinations, as discussed in the text. We graph the distribution of the 68 values of CVP, as estimated by a histogram. All observations fell in the one bin graphed. The position of the bin is an artifact of the algorithm used to select histogram bin width; all of the coefficients of variation underlying the histogram are positive.

Figure 3: ρ is the first-order autoregressive coefficient governing price dynamics, given in equation (22) in the text. We graph the distribution, as estimated by a histogram, of estimates of ρ for 68 crop/region combinations.