UC Davis

Agriculture and Resource Economics Working Papers

Title

Efficient Estimates of a Model of Production and Cost

Permalink

https://escholarship.org/uc/item/4tw149s5

Authors

Paris, Quirino Caputo, Michael R.

Publication Date

2004-08-01

Department of Agricultural and Resource Economics University of California, Davis

Efficient Estimates of a Model of Production and Cost

by

Quirino Paris and Michael R. Caputo

Working Paper No. 04-016

August 2004



Copyright @ 2004 by Quirino Paris and Michael R. Caputo All Rights Reserved.

Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

Giannini Foundation of Agricultural Economics

Efficient Estimates of a Model of Production and Cost

Quirino Paris* University of California, Davis

Michael R. Caputo University of Central Florida

Abstract

In 1944, Marschak and Andrews published a seminal paper on how to obtain consistent estimates of a production technology. The original formulation of the econometric model regarded the joint estimation of the production function together with the first-order necessary conditions for profit-maximizing behavior. In the seventies, with the advent of duality theory, the preference seemed to have shifted to a dual approach. Recently, however, Mundlak resurrected the primal-versus-dual debate with a provocative paper titled "Production Function Estimation: Reviving the Primal." In that paper, the author asserts that the dual estimator, unlike the primal approach, is not efficient because it fails to utilize all the available information. In this paper we argue that efficient estimates of the production technology can be obtained only by jointly estimating all the relevant primal and dual relations. Thus, the primal approach of Mundlak and the dual approach of McElroy become nested special cases of our general specification. The theory of the price-taking cost-minimizing, risk-neutral firm is based upon the expectation of prices and quantities as the relevant information used by the entrepreneur in making her decisions. The econometrician intervenes later on and collects information about those quantities and prices. In so doing, measurement errors creep into the econometric specification. A two-phase procedure is suggested to implement the primal-dual approach. A Monte Carlo analysis indicates that our primal-dual approach produces estimates that exhibit a smaller variance of the estimates than those obtained from either the traditional primal or the dual specification separately implemented. A bootstrapping approach is used to compute the standard errors of the model's estimates.

JEL Classification: D0, C3.

Keywords: Primal, Dual, Cobb-Douglas, Nonlinear errors-in-variables.

* Corresponding author

We thank Art Havenner and Richard Green for stimulating discussions on the subject. All errors are our responsibility. Quirino Paris is a member of the Giannini Foundation of Agricultural Economics.

Efficient Estimates of a Model of Production and Cost

I. Introduction

Marschak and Andrews (1944), Hoch (1958, 1962), Nerlove (1963), Mundlak(1963, 1996), Zellner, Kmenta and Dreze (1966), Diewert (1974), Fuss and McFadden (1978), McElroy (1987) and Schmidt (1988) are among the many distinguished economists who have dealt with the problem of estimating production functions, first-order conditions, input demand functions, and cost and profit functions in the environment of price-taking firms. Some of these authors (e.g., Marschak and Andrews, Hoch, Mundlak, Zellner, Kmenta and Dreze, and Schmidt) used a primal approach in the estimation of a production function and the associated first-order necessary conditions corresponding to either profit-maximizing or cost-minimizing behavior. Their concern was to obtain consistent estimates of the production function parameters even in the case when output and inputs can be regarded as being determined simultaneously. This group of authors studied the "simultaneous equation bias" syndrome extensively. Nerlove (1963) was the first to use a duality approach in the estimation of a cost function for a sample of electricity-generating firms. After the seminal contributions of Fuss and McFadden (1978) (a publication that was delayed at least for a decade) and Diewert (1974), the duality approach seems to have become the preferred method of estimation.

In reality, the debate whether the duality approach should be preferred to the primal methodology has never subsided. As recently as 1996, Mundlak published a paper in *Econometrica* that is titled "*Production Function Estimation: Reviving the Primal.*" To appreciate the strong viewpoint held by an influential participant in the debate, it is con-

venient to quote his opening paragraph (1996, p. 431): "Much of the discussion on the estimation of production functions is related to the fact that inputs may be endogenous and therefore direct estimators of the production functions may be inconsistent. One way to overcome this problem has been to apply the concept of duality. The purpose of this note is to point out that estimates based on duality, unlike direct estimators of the production function, do not utilize all the available information and therefore are statistically inefficient and the loss in efficiency may be sizable."

Our paper contributes the following fundamental point: Efficient (in the sense of using all the available information) estimation of the technical and economic relations involving a sample of price-taking firms requires the joint estimation of all the primal and dual relations. This conclusion, we suggest, ought to be the starting point of any econometric estimation of a production and cost system. Whether or not it may be possible to reduce the estimation process to either primal or dual relations is a matter of statistical testing to be carried out within the particular sample setting. Therefore, the debate as to whether a primal or a dual approach should be preferred is moot. We will show that *all* the primal and dual relations are necessary for an efficient estimation of a production and cost system.

Section II describes the firm environment adopted in this study. Initially, we focus our attention on the papers by McElroy (1987) and Mundlak (1996) because their additive error specifications are the exact complement to each other. In order to facilitate the connection of our paper with the existing literature, we adopt much of the technological and economic environments described by them. Our model, therefore, is a general ap-

proach for the estimation of a production and cost system of relations which contains McElroy's and Mundlak's models as special cases.

Section III describes the generalized additive error (GAE) nonlinear specification adopted in our study and the estimation approach necessary for a consistent and efficient measurement of the cost-minimizing risk-neutral behavior of the sample firms. The pricetaking and risk neutral entrepreneurs are assumed to base their cost-minimizing input decisions on their planning expectations concerning quantities and prices. Expectations are known to the decision makers but not to their accountants, let alone the outside econometrician. The resulting generalized additive error (GAE) model corresponds to a nonlinear errors-in-variables (EIV) system of equations. The literature about errors-in-variables models is vast and points to two rather general results: consistent estimates may be obtained if either the ratio of the error variances is known or if replicate measurements of the sample variables are available. The literature does not discuss nonlinear systems of equations where all the variables are measured with error. For this reason, we conduct a Monte Carlo analysis in order to gauge the performance of the primal-dual procedure suggested in this paper and to contrast it with the performance of the traditional primal and dual estimators separately implemented. Section III also describes in details the twophase procedure used in this paper for estimating the production and cost system of equations. The objective of the phase I nonlinear least-squares problem is to obtain estimates of the expected quantities and prices which are assumed to be used by the entrepreneurs in making their planning decisions. The objective function of Phase I is weighted by the ratios of the error variances. The estimated expected quantities and prices are then used in a nonlinear seemingly unrelated (NSUR) equation system of phase

II. Section IV presents an empirical application of the methodology using the sample information of 84 firms as a basis for a Monte Carlo analysis of the suggested procedure. This analysis shows that the proposed primal-dual estimator is robust even in the case of significant mis-specification of the error variances' ratio. It also supports the initial conjecture that primal-dual estimates of the model's parameters exhibit smaller variances than the estimates of either the traditional primal or dual estimators.

II. Production and Cost Environments

In this paper we postulate a static context. Following Mundlak (1996), we assume that the cost-minimizing firms of our sample make their output and input decisions on the basis of expected quantities and prices and that the entrepreneur is risk neutral. That is to say, a planning process can be based only upon expected information. The process of expectation formation is characteristic of every firm. Such a process is known to the firm's entrepreneur but is unknown to the econometrician. The individuality of the expectation process allows for a variability of input and output decisions among the sample firms even in the presence of a unique technology and measured output and input prices that appear to be the same for all sample firms.

Let the expected production function $f^{e}(\cdot)$ for a generic firm have values

$$y^e \le f^e(\mathbf{x}),\tag{1}$$

where y^e the expected level of output for any strictly positive $(J \times 1)$ vector \mathbf{x} of input quantities. After the expected cost-minimization process has been carried out, the input vector \mathbf{x} will become the vector of expected input quantities \mathbf{x}^e that will satisfy the

firm's planning target. The expected production function $f^e(\cdot)$ is assumed to be twice continuously differentiable, quasi-concave, and non-decreasing in its arguments.

We postulate that the cost-minimizing risk-neutral firm solves the following problem:

$$c^{e}(y^{e}, \mathbf{w}^{e}) \stackrel{\text{def}}{=} \min_{\mathbf{x}} \{ \mathbf{w}^{\prime e} \mathbf{x} \mid y^{e} \le f^{e}(\mathbf{x}) \}, \tag{2}$$

where $c^e(\cdot)$ is the expected cost function, \mathbf{w}^e is a $(J \times 1)$ vector of expected input prices and "' is the transpose operator.

The Lagrangean function corresponding to the minimization problem of the risk neutral firm can be stated as

$$L = \mathbf{w}^{\prime e} \mathbf{x} + \lambda [y^e - f^e(\mathbf{x})]. \tag{3}$$

Assuming an interior solution, first-order necessary conditions are given by

$$\frac{\partial L}{\partial \mathbf{x}} = \mathbf{w}^e - \lambda \mathbf{f}_{\mathbf{x}}^e(\mathbf{x}) = \mathbf{0},
\frac{\partial L}{\partial \lambda} = y^e - f^e(\mathbf{x}) = 0.$$
(4)

The solution of equations (4), gives the expected cost-minimizing input demand functions $\mathbf{h}^{e}(\cdot)$, with values

$$\mathbf{x}^e = \mathbf{h}^e(\mathbf{y}^e, \mathbf{w}^e). \tag{5}$$

In the case where equations (4) have no analytical solution (as with flexible functional forms), the input derived demand functions (5) exist via the duality principle.

The above theoretical development corresponds precisely to the textbook discussion of the cost-minimizing behavior of a price-taking firm. The econometric representation of that setting requires the specification of the error structure associated with the observation of the firm's environment and decisions.

Mundlak (1996) deals with two types of errors: a "weather" error associated with the realized (or measured) output quantity that, in general, differs from the expected (or planned) level. This is especially true in agricultural firms, where expected output is determined many months in advance of realized output. Hence, measured output y differs from the unobservable expected output y^e by a random quantity u_0 according to the additive relation $y = y^e + u_0$. Furthermore, and again according to Mundlak (1996, p. 432): "As \mathbf{w}^e is unobservable, the econometrician uses \mathbf{w} which may be the observed input price vector or his own calculated expected input price vector." The additive error structure of input prices is similarly stated as $\mathbf{w} = \mathbf{w}^e + \mathbf{v}$. Mundlak (1996, p. 432) calls \mathbf{v} "the optimization error, but we note that in part the error is due to the econometrician's failure to read the firm's decision correctly rather than the failure of the firm to reach the optimum." We will continue in the tradition of calling \mathbf{v} the "optimization" error although it is simply a measurement error associated with input prices. Mundlak, however, does not consider any error associated with the measurement of input quantities.

To encounter such a vector of errors we need to refer to McElroy (1987). To be precise, McElroy (1987, p. 739) argues that her cost-minimizing model of the firm contains "... parameters that are known to the decision maker but not by the outside observer." Her error specification, however, is indistinguishable from a measurement error on the input quantities (McElroy, [1987], p. 739). In her model, input prices and output are (implicitly) known without errors. The measured vector of input quantities \mathbf{x} bears an additive relation to its unobservable expected counterpart \mathbf{x}^e , that is $\mathbf{x} = \mathbf{x}^e + \mathbf{\epsilon}$. The vector $\mathbf{\varepsilon}$ represents the "measurement" errors on the expected input quantities.

We thus identify measurement errors with any type of sample information in the production and cost model of the firm. For reason of clarity and for connecting with the empirical literature on the subject, we maintain the traditional names of these errors, that is, u_0 is the "weather" error associated with the output actually produced, ε is the vector of "measurement" errors associated with the measured input quantities, and \mathbf{v} is the vector of "optimization" errors associated with the measured input prices.

The measurable GAE model of production and cost can now be stated using the theoretical relations (1), (4), (5) and the error structure specified above. The measurable system of relations is thus the following set of primal and dual equations:

Primal

production function
$$y = f^e(\mathbf{x} - \mathbf{\epsilon}) + u_0,$$
 (6)

input price functions
$$\mathbf{w} = c_{v}^{e}(y - u_{0}, \mathbf{w} - \mathbf{v})\mathbf{f}_{x}^{e}(\mathbf{x} - \mathbf{\epsilon}) + \mathbf{v}, \tag{7}$$

Dual

input demand functions
$$\mathbf{x} = \mathbf{h}^e(y - u_0, \mathbf{w} - \mathbf{v}) + \mathbf{\varepsilon},$$
 (8)

where $c_y^e(y - u_0, \mathbf{w} - \mathbf{v}) \stackrel{\text{def}}{=} \frac{\partial c^e}{\partial y^e}$ is the measurable marginal cost function.

Several remarks are in order. Relations (6) through (8) form a system of nonlinear equations that can be regarded as an EIV model with substantive unobservable variables (see Zellner [1970], Theil [1971], Goldberg [1972], Griliches [1974], Klepper and Leamer [1984, 1987]).

Although relations (7) and (8) may be regarded as containing precisely the same information, albeit in different arrangements, the measurement of their error terms requires, in general, the joint estimation of the entire system of primal and dual relations.

This means that, in a general setting, all the primal and dual relations are necessary, and the debate about the "superiority" of either a primal or dual approach is confined to simplified characterizations of the error structure.

Consider, in fact, McElroys' (1987) model specification in which the "weather" and "optimization" errors are identically zero, that is, $u_0 = 0$ and $\mathbf{v} = \mathbf{0}$. Therefore, $y = y^e$ and $\mathbf{w} = \mathbf{w}^e$. In her case, the measurable GAE model (6)-(8) collapses to

$$y = f^{e}(\mathbf{x} - \mathbf{\varepsilon}),\tag{9}$$

$$\mathbf{w} = c_{y}^{e}(y, \mathbf{w}) \mathbf{f}_{\mathbf{x}}^{e}(\mathbf{x} - \mathbf{\varepsilon}), \tag{10}$$

$$\mathbf{x} = \mathbf{h}^{e}(y, \mathbf{w}) + \mathbf{\varepsilon}. \tag{11}$$

McElroy (1987) can limit the estimation of her model to the dual side of the cost-minimizing problem because she implicitly assumes that the primal relations, namely the output levels and input prices, are measured without errors. Consequently, it is more convenient to estimate the dual relations (11) because the errors ε are additive in those relations while they are nonlinearly nested in equations (9) and (10).

An analogous but not entirely similar comment applies to Mundlak's (1996) specification. In his case the "measurement" errors are identically equal to zero, that is, $\varepsilon = 0$. Therefore, $\mathbf{x} = \mathbf{x}^e$, so the measurable GAE model (6)-(8) collapses to

$$y = f^{e}(\mathbf{x}) + u_0, \tag{12}$$

$$\mathbf{w} = c_{\mathbf{y}}^{e}(\mathbf{y} - u_{0}, \mathbf{w} - \mathbf{v})\mathbf{f}_{\mathbf{x}}^{e}(\mathbf{x}) + \mathbf{v}, \tag{13}$$

$$\mathbf{x} = \mathbf{h}^e (y - u_0, \mathbf{w} - \mathbf{v}). \tag{14}$$

We notice that, traditionally, Mundlak's approach to a cost-minimizing model requires the elimination of the Lagrange multiplier (equivalently, marginal cost) by taking the ratio of the last (J-1) of the first-order necessary conditions to, say, the first (see, for ex-

ample, Schmidt, 1987, p. 362). As a result, the error term of the first equation is confounded into the disturbance term of every other equation. Under these conditions, it may be more convenient to follow Mundlak's recommendation and estimate the primal relations (12) and (modified) (13) because the two types of errors appear in additive form. No such a loss of information is required in the model presented here and under the more general structure of GAEM presented in equations (6)-(8) (where no ratios of (J-1) equations to the first equation is necessary), this "advantage" no longer holds.

III. Estimation of the GAE Model of Production and Cost

The structure of the production and cost system developed above assumes the structure of a nonlinear EIV system of equations for which no easily implementable estimator seems to exist. The literature on errors in variables is vast and growing. The practical conclusion appears to be centered upon two aspects of the sample information: Consistent estimators require either knowledge of the ratio of the error variances or the availability of replicate measurement of the latent variables. In general, it is difficult to meet these conditions. For this reason, we assess the primal-dual estimator proposed herein by performing a Monte Carlo analysis using a sample of real data that we assume as the benchmark observations of the latent variables, and then compare the estimates obtained with the specification of the true ratio of the error variances with those obtained with mis-specified ratios. The interesting conclusion is that the estimator is robust to mis-specification of the true ratio of the error variances. We then return to the original sample of data and estimate the primal-dual model proposed in this paper using a bootstrapping approach to estimate the standard error of the estimates.

We assume a sample of cross-section data on N cost-minimizing firms, i = 1,...,N. The empirical GAE model in its most general specification can thus be stated as

$$y_i^e = f^e(\mathbf{x}_i^e, \mathbf{\beta}_v), \tag{15}$$

$$\mathbf{w}_{i}^{e} = c_{v}^{e}(y_{i}^{e}, \mathbf{w}_{i}^{e}, \boldsymbol{\beta}_{c})\mathbf{f}_{x}^{e}(\mathbf{x}_{i}^{e}, \boldsymbol{\beta}_{w}), \tag{16}$$

$$\mathbf{x}_{i}^{e} = \mathbf{h}^{e}(y_{i}^{e}, \mathbf{w}_{i}^{e}, \mathbf{\beta}_{\mathbf{x}}), \tag{17}$$

$$y_i = y_i^e + u_{0i}, (18)$$

$$\mathbf{W}_i = \mathbf{W}_i^e + \mathbf{V}_i, \tag{19}$$

$$\mathbf{x}_i = \mathbf{x}_i^e + \mathbf{\epsilon}_i. \tag{20}$$

Constraints (15)-(17) represent the theory of production and cost, while constraints (18)-(20) specify the error structure of the sample information. The vectors of technological and economic parameters $\boldsymbol{\beta}_y.\boldsymbol{\beta}_w.\boldsymbol{\beta}_x.\boldsymbol{\beta}_c$ may be of different dimensions, characterize the specific relations referred to by their subscript and, in general, enter those relations in a nonlinear fashion.

The vector of error terms $\mathbf{e}_i' = (u_{0i}, \mathbf{v}_i', \mathbf{\epsilon}_i')$ is assumed to be distributed according to a multivariate normal density with zero mean vector and variance matrix Σ . We thus assume independence of the disturbances across firms and contemporaneous correlation of them within a firm. If the expected quantities and prices were known, the above system of equations would have the structure of a traditional nonlinear seemingly unrelated equations (NSUR) estimation problem. In that case, consistent and efficient estimates of the parameters could be obtained using commercially available computer packages for econometric analysis. Unfortunately, the recording of planning information and decisions is not a common practice. However, if we could convince a sample of entrepreneurs to

record expected quantities and prices at planning time, the direct estimation of system (15)-(20) would be feasible and efficient. Hence, lacking the "true" expected quantities and prices, the next best option is to obtain estimates of them.

To confront the estimation challenge posed by the system of relations (15)-(20), we envision a two-phase procedure that, in phase I, produces estimates of the unobservable substantive variables, represented by the expected quantities and prices and the vector of $\beta = (\beta_y, \beta_w, \beta_x, \beta_c)$ parameters, and then uses those estimates of expectations in phase II to estimate a traditional NSUR model.

In phase I, the nonlinear least-squares estimation problem consists in minimizing the weighted residual sum of squares

$$\min_{\boldsymbol{\beta}, y_i^e, x_{ij}^e, w_{ij}^e, e_i} \sum_{i=1}^{N} u_{0i}^2 / \sigma_{u_0}^2 + \sum_{j=1}^{J} \sum_{i=1}^{N} v_{ij}^2 / \sigma_{v_j}^2 + \sum_{j=1}^{J} \sum_{i=1}^{N} \varepsilon_{ij}^2 / \sigma_{\varepsilon_j}^2$$
(21)

or

$$\min_{\boldsymbol{\beta}, y_i^e, x_{ij}^e, w_{ij}^e, \mathbf{e}_i} \sum_{i=1}^N u_{0i}^2 + \sum_{j=1i-1}^J \sum_{i=1}^N v_{ij}^2 / \lambda_{v_j} + \sum_{j=1i-1}^J \sum_{i=1}^N \varepsilon_{ij}^2 / \lambda_{\varepsilon_j}$$

with respect to the residuals and all the parameters, including the expected quantities and prices for each firm, subject to equations (15)-(20), where $\sigma_{u_0}^2, \sigma_{v_j}^2, \sigma_{\varepsilon_j}^2$ are the variances of the respective error terms, j = 1,...,J. The weights of the objective function (21) are specified as the ratios of the error variances using the variance of the output quantity as the normalizing factor

$$\lambda_{v_j} = \frac{\sigma_{v_j}^2}{\sigma_{u_0}^2}, \lambda_{\varepsilon_j} = \frac{\sigma_{\varepsilon_j}^2}{\sigma_{u_0}^2}.$$

We assume that an optimal solution of the phase I problem exists and can be found using a nonlinear optimization package such as, for example, GAMS (see Brooke *et al.* [1988]).

With the estimates of the expected quantities and prices obtained from phase I, a traditional NSUR problem can be stated and estimated in phase II using conventional econometric packages such as SHAZAM (Whistler *et al.* [2001]). For clarity, this phase II estimation problem can be stated as

$$\min_{\boldsymbol{\beta}, \mathbf{e}_i} \sum_{i=1}^{N} \mathbf{e}_i' \hat{\Sigma}^{-1} \mathbf{e}_i$$
 (22)

subject to

$$y_i = f^e(\hat{\mathbf{x}}_i^e, \boldsymbol{\beta}_v) + u_{0i}, \tag{23}$$

$$\mathbf{w}_{i} = c_{y}^{e}(\hat{\mathbf{y}}_{i}^{e}, \hat{\mathbf{w}}_{i}^{e}, \boldsymbol{\beta}_{c}) \mathbf{f}_{x}^{e}(\hat{\mathbf{x}}_{i}^{e}, \boldsymbol{\beta}_{w}) + \boldsymbol{v}_{i}, \tag{24}$$

$$\mathbf{x}_{i} = \mathbf{h}^{e}(\hat{\mathbf{y}}_{i}^{e}, \hat{\mathbf{w}}_{i}^{e}, \mathbf{\beta}_{\mathbf{v}}) + \mathbf{\varepsilon}_{i}, \tag{25}$$

where $(\hat{y}_i^e, \hat{\mathbf{w}}_i^e, \hat{\mathbf{x}}_i^e)$ are the expected quantities and prices of the *i*-th firm estimated in phase I and assume the role of instrumental variables in phase II. The matrix $\hat{\Sigma}$ can be updated iteratively to convergence. Given the complexity of the nonlinear EIV system of equations specified above, the standard errors of the estimates will be computed by a bootstrapping approach, as discussed in details further on.

The specification of the functional form of the production function constitutes a further challenge toward the successful estimation of the above system of production and cost functions. In the case of self-dual technologies such as the Cobb-Douglas and the constant elasticity of substitution (CES) production functions, the corresponding cost function has the same functional form and no special difficulty arises. For the general case of more flexible functional forms, however, it is well known that the functional form

can be explicitly stated only for either the primal or the dual relations. The associated dual functions exist only in an implicit, latent state. The suggestion, therefore, is to assume an explicit flexible functional form for the cost function and to represent the associated implicit production function as a second-degree Taylor expansion. Alternatively, one can use an appealing approach to estimation of latent functions presented by McManus (1994) that fits a localized Cobb-Douglas function to each sample observation.

IV. An Application of the GAE Model of Production and Cost

The model and the estimation procedure described in section III have been applied to a sample of 84 California cooperative cotton ginning firms. These cooperative firms must process all the raw cotton delivered by the member farmers. Hence, the level of their output is exogenous and their economic decisions are made according to a cost-minimizing behavior. This is a working hypothesis that can be tested during the analysis.

There are three inputs: labor, energy and capital. Labor is defined as the annual labor hours of all employees. The wage rate for each gin was computed by dividing the labor bill by the quantity of labor. Energy expenditures include the annual bill for electricity, natural gas, and propane. British thermal unit (BTU) prices for each fuel were computed from each gin's utility rate schedules and then aggregated into a single BTU price for each gin using BTU quantities as weights for each energy source. The variable input energy was then computed by dividing energy expenditures by the aggregate energy price.

A gin's operation is a seasonal enterprise. The downtime is about nine months per year. The long down time allows for yearly adjustments in the ginning equipment

and buildings. For this reason capital is treated as a variable input. Each component of the capital stock was measured using the perpetual inventory method and straight-line depreciation. The rental prices for buildings and ginning equipment was measured by the Christensen and Jorgenson (1969) formula. Expenditures for each component of the capital stock were computed as the product of each component of the capital stock and its corresponding rental rate and aggregated into total capital expenditures. The composite rental price for each gin was computed using an expenditure-weighted average of the gin's rental prices for buildings and equipment. The composite measure of the capital service flow is computed by dividing total yearly capital expenditure by the composite rental price.

Ginning cooperative firms receive the raw cotton from the field and their output consists of cleaned and baled cotton lint and cottonseeds in fixed proportions. These outputs, in turn, are proportional to the raw cotton input. Total output for each gin was then computed as a composite commodity by aggregating cotton lint and cottonseed using a proportionality coefficient. For more information on the sample data see Sexton *et al.* (1989).

We assume that the behavior of the ginning cooperatives of California can be rationalized with a Cobb-Douglas production function. Hence, the system of equations to specify the production and cost environments is constituted of the following eight primal and dual relations:

Cobb-Douglas production function

$$y_i = A \prod_{j=1}^{3} (x_{ij}^e)^{\alpha_j} + u_{0i},$$
 (26)

Input price functions

$$w_{ik} = \alpha_k [A_{i=1}^3 \alpha_j^{\alpha_j}]^{-1/\eta} (y_i^e)^{1/\eta} \prod_{j=1}^3 (w_{ij}^e)^{\alpha_j/\eta} / (x_{ik}^e) + v_{ik},$$
(27)

Input derived demand functions

$$x_{ij} = \alpha_j \left[A \prod_{k=1}^3 \alpha_k^{\alpha_k} \right]^{-1/\eta} (y_i^e)^{1/\eta} (w_{ij}^e)^{-(\sum_{k \neq j} \alpha_k)/\eta} \prod_{k \neq j=1}^3 (w_{ik}^e)^{\alpha_k/\eta} + \varepsilon_{ij},$$
 (28)

where $\eta = \sum_{j} \alpha_{j}$, j = 1,2,3, and k = 1,2,3.

As discussed in previous sections, the consistent estimation of an errors-in-variables model requires a priori knowledge of the ratio of the error variances. Since this kind of information cannot be derived from the sample observations, we conducted a Monte Carlo analysis of the model developed in section III in order to gauge the performance of the primal-dual estimator under a misspecification of the ratio of the error variances. Since the estimator is robust (as determined by the mean squared error statistics reported in Table 1), we estimate the primal-dual model using the available sample information and compute the standard errors of the estimates by a bootstrapping procedure.

The system of Cobb-Douglas relations (26)-(28) was estimated by using the twophase procedure described in section III using the computer package GAMS (Brooke *et al.* [1988]) for phase I and phase II. We must point out that with technologies (such as the Cobb-Douglas production function) admitting an explicit analytical solution of the firstorder necessary conditions, either the input derived demand functions (28) or the input price functions (27) are redundant in the phase I estimation problem, and thus either set of equations can be eliminated as constraints. They are not redundant, however, in the phase II NSUR estimation problem because, as noted earlier, all the primal and dual relations convey independent information in the form of their errors and the corresponding probability distributions. Furthermore, neither the primal nor the dual relations would be redundant in phase I if the specified technology were of the flexible form type.

The Monte Carlo analysis of the primal-dual estimator was performed with the choice of the following "true" parameter values of the Cobb-Douglas specification: Efficiency parameter A = 0.81, production elasticities $\alpha_K = 0.43$, $\alpha_L = 0.48$, $\alpha_E = 0.27$, and returns to scale $\eta = 1.18$. The input quantities were generated as $x_{ij} = x_{ij}^e + N(0,0.5)$, where the latent expected quantities were taken as the original sample data. The input prices were generated as $w_{ij} = w_{ij}^e + N(0,0.6)$, where the latent expected prices were taken as the original sample data. The choice of the normal error's standard deviation was related to the scale of the corresponding latent variable and the desire to minimize negative values of the associated observed variable. The output quantity was generated as $y_i = A \prod_{j=1}^3 (x_{ij}^e)^{\alpha_j} + N(0,1.5)$. In each specification, the normal error has a zero mean and σ standard deviation, and is signified by $N(0,\sigma)$. Hence, for the input quantities, the true variance is $\sigma_{\varepsilon_i}^2 = 0.25$ while the true variance of the input prices is $\sigma_{v_i}^2 = 0.36$, j = K, L, E. Thus, the weights of the sum of squared residuals are $\lambda_{\varepsilon j} = \sigma_{\varepsilon_j}^2 / \sigma_{u_0}^2 = 0.25/(1.5)^2 = 0.111 \quad \text{and} \quad \lambda_{\nu j} = \sigma_{\nu_j}^2 / \sigma_{u_0}^2 = 0.36/2.25 = 0.16, \quad j = K, L, E.$ Three hundred samples were drawn for the Monte Carlo analysis, whose results are reported in Table 1.

Table 1 is divided in three sub-tables relating to primal-dual, Mundlak and McElroy's models. The first three sections of Table 1 deal with the results of the primal-dual estimator: In the first section, the lambda parameters were chosen with the true value

of the error variance ratios. Hence, the corresponding estimates are consistent and the mean squared error statistics are relatively low, with the squared bias values also pretty small. In the second section of Table 1 the lambda parameters' (ratios of error variances) values are three times as large as the true values. Yet, the mean squared error statistics are of the same level as those for the true values of the lambda parameters. In particular, the squared bias of the efficiency parameter A is much lower than the corresponding statistic of the true model. In the third section of Table 1 the lambda parameters' values are between seven and ten times as large as the corresponding values of true model. Yet, this gross mis-specification of the error variances induces only a relatively small (30 percent) increase in the mean squared error statistics as compared to those of the true lambda ratios.

In all the three cases, the mean values of the production elasticities are within a remarkable narrow range of the true values and the corresponding standard deviations of the estimates are small and stable. Therefore, the empirical evidence presented in Table 1 suggests that even a large mis-specification of the true values of the error variances induces only a relatively small bias into the estimates.

The second section of Table 1 deals with Mundlak's primal model. Given the structure of the production and cost model presented in this paper, Mundlak's primal model comes in two versions. The first version assumes that there are no measurement errors (the usual assumption) and the estimated model is similar to that exposed by Mundlak (1996). The second version assumes an errors-in-variables specification with $\varepsilon = 0$ and the model to be estimated reduces to equations (12) and (13) in section II.

Table 1. Results of the Monte Carlo analysis: 300 samples

Dained Deed Torre	286 61	Standard De-	E-4:4-/	MCE	C1 D:
Primal-Dual. True	286 Samples Mean Estimate	viation	Estimate/ Std Dev	MSE	Squared Bias
$\lambda_{\epsilon_i} = .111, \lambda_{\nu_i} = .16$				0.0161012	0.0005702
A, efficiency 0.81 α_K , capital 0.43	0.8341 0.4207	0.1249 0.0314	6.678 13.398	0.0161913	0.0005793
	0.4207				
α_L , labor 0.48 α_E , energy 0.27	0.4829	0.0347	13.916		
ь. С.	0.2773	0.0205	13.527	0.0027574	0.0001405
all inputs η, scale 1.18	1.1809	0.0850	13.893	0.0027564 0.0072246	0.0001485 0.0000008
η, scale 1.18	1.1809	0.0830	15.895	0.0072240	0.0000008
Primal-Dual					
Misspecified	284 Samples	Standard	Estimate/		Squared Bias
$\lambda_{\rm ei} = .333, \lambda_{\rm vi} = .40$	Mean Estimate	Deviation	Std Dev	MSE	. 1
A, efficiency	0.8070	0.1202	6.714	0.0144611	0.0000088
α _κ , capital	0.4293	0.0319	13.457		
$\alpha_{\rm L}$, labor	0.4928	0.0345	14.284		
$\alpha_{\rm E}$, energy	0.2836	0.0206	13.767		
all inputs				0.0029331	0.0003477
η, scale	1.2056	0.0846	14.251	0.0078109	0.0006559
,,					
Primal-Dual					
Misspecified	285 Samples	Standard	Estimate/		Squared Bias
$\lambda_{i}=1, \lambda_{i}=1$	Mean Estimate	Deviation	Std Dev	MSE	
A, efficiency	0.7545	0.1126	6.701	0.0157617	0.0030752
α_{K} , capital	0.4467	0.0312	14.317		
α_L , labor	0.5139	0.0343	14.982		
$\alpha_{\rm E}$, energy	0.2966	0.0209	14.191		
all inputs				0.0047143	0.0021343
η, scale	1.2572	0.0843	14.913	0.0130659	0.0059551
Mundlak Primal	300 Samples	Standard	Estimate/		
True λ_{v_i} =.16	Mean Estimate	Deviation	Std Dev	MSE	Squared Bias
True λ_{v_i} =.16 A, efficiency	Mean Estimate 1.5848	Deviation 0.9521	Std Dev 1.665	MSE 1.5067987	Squared Bias 0.6002639
True λ_{vi} =.16 A, efficiency α_{K} , capital	Mean Estimate 1.5848 0.3748	Deviation 0.9521 0.1413	Std Dev 1.665 2.653		
True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor	Mean Estimate 1.5848 0.3748 0.5165	Deviation 0.9521 0.1413 0.1720	Std Dev 1.665 2.653 3.003		
True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy	Mean Estimate 1.5848 0.3748	Deviation 0.9521 0.1413	Std Dev 1.665 2.653	1.5067987	0.6002639
True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy all inputs	Mean Estimate 1.5848 0.3748 0.5165 0.1734	Deviation 0.9521 0.1413 0.1720 0.1018	Std Dev 1.665 2.653 3.003 1.703	0.0797794	0.6002639
True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy	Mean Estimate 1.5848 0.3748 0.5165	Deviation 0.9521 0.1413 0.1720	Std Dev 1.665 2.653 3.003	1.5067987	0.6002639
True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy all inputs η , scale	Mean Estimate 1.5848 0.3748 0.5165 0.1734 1.0647	Deviation 0.9521 0.1413 0.1720 0.1018 0.3086	Std Dev 1.665 2.653 3.003 1.703	0.0797794	0.6002639
True λ_{v_l} =.16 A, efficiency α_K , capital α_L , labor α_E , energy all inputs η , scale Mundlak Primal	Mean Estimate 1.5848 0.3748 0.5165 0.1734 1.0647 242 Samples	Deviation 0.9521 0.1413 0.1720 0.1018 0.3086	Std Dev 1.665 2.653 3.003 1.703 3.450	0.0797794 0.1085206	0.6002639 0.0198745 0.0132898
True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy all inputs η , scale Mundlak Primal True λ_{v_i} =.16	Mean Estimate 1.5848 0.3748 0.5165 0.1734 1.0647 242 Samples Mean Estimate	Deviation 0.9521 0.1413 0.1720 0.1018 0.3086 Standard Deviation	Std Dev 1.665 2.653 3.003 1.703 3.450 Estimate/ Std Dev	1.5067987 0.0797794 0.1085206 MSE	0.6002639 0.0198745 0.0132898 Squared Bias
True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy all inputs η , scale Mundlak Primal True λ_{v_i} =.16 A, efficiency	Mean Estimate 1.5848 0.3748 0.5165 0.1734 1.0647 242 Samples Mean Estimate 0.9002	Deviation 0.9521 0.1413 0.1720 0.1018 0.3086 Standard Deviation 0.1279	Std Dev 1.665 2.653 3.003 1.703 3.450 Estimate/ Std Dev 7.038	0.0797794 0.1085206	0.6002639 0.0198745 0.0132898
$True \ \lambda_{v_i} = .16$ $A, efficiency$ $\alpha_K, capital$ $\alpha_L, labor$ $\alpha_E, energy$ $all inputs$ $\eta, scale$ $Mundlak Primal$ $True \ \lambda_{v_i} = .16$ $A, efficiency$ $\alpha_K, capital$	Mean Estimate 1.5848 0.3748 0.5165 0.1734 1.0647 242 Samples Mean Estimate 0.9002 0.4080	Deviation 0.9521 0.1413 0.1720 0.1018 0.3086 Standard Deviation 0.1279 0.0308	Std Dev 1.665 2.653 3.003 1.703 3.450 Estimate/ Std Dev 7.038 13.246	1.5067987 0.0797794 0.1085206 MSE	0.6002639 0.0198745 0.0132898 Squared Bias
$\begin{aligned} & \text{True } \lambda_{v_i} \!\!=\! .16 \\ & \text{A, efficiency} \\ & \alpha_{K}, \text{capital} \\ & \alpha_{L}, \text{labor} \\ & \alpha_{E}, \text{energy} \\ & \text{all inputs} \\ & \eta, \text{scale} \\ & \\ & \text{Mundlak Primal} \\ & \text{True } \lambda_{v_i} \!\!=\! .16 \\ & \text{A, efficiency} \\ & \alpha_{K}, \text{capital} \\ & \alpha_{L}, \text{labor} \end{aligned}$	Mean Estimate 1.5848 0.3748 0.5165 0.1734 1.0647 242 Samples Mean Estimate 0.9002 0.4080 0.4683	Deviation 0.9521 0.1413 0.1720 0.1018 0.3086 Standard Deviation 0.1279 0.0308 0.0375	Std Dev 1.665 2.653 3.003 1.703 3.450 Estimate/ Std Dev 7.038 13.246 12.488	1.5067987 0.0797794 0.1085206 MSE	0.6002639 0.0198745 0.0132898 Squared Bias
True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy all inputs η , scale Mundlak Primal True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy	Mean Estimate 1.5848 0.3748 0.5165 0.1734 1.0647 242 Samples Mean Estimate 0.9002 0.4080	Deviation 0.9521 0.1413 0.1720 0.1018 0.3086 Standard Deviation 0.1279 0.0308	Std Dev 1.665 2.653 3.003 1.703 3.450 Estimate/ Std Dev 7.038 13.246	1.5067987 0.0797794 0.1085206 MSE 0.0245102	0.6002639 0.0198745 0.0132898 Squared Bias 0.0081314
$\begin{aligned} & \text{True } \lambda_{v_i} \text{==} .16 \\ & \text{A, efficiency} \\ & \alpha_{K}, \text{capital} \\ & \alpha_{L}, \text{labor} \\ & \alpha_{E}, \text{energy} \\ & \text{all inputs} \\ & \eta, \text{scale} \end{aligned}$ $& \text{Mundlak Primal} \\ & \text{True } \lambda_{v_i} \text{==} .16 \\ & \text{A, efficiency} \\ & \alpha_{K}, \text{capital} \\ & \alpha_{L}, \text{labor} \\ & \alpha_{E}, \text{energy} \\ & \text{all inputs} \end{aligned}$	Mean Estimate 1.5848 0.3748 0.5165 0.1734 1.0647 242 Samples Mean Estimate 0.9002 0.4080 0.4683 0.2496	Deviation 0.9521 0.1413 0.1720 0.1018 0.3086 Standard Deviation 0.1279 0.0308 0.0375 0.0220	Std Dev 1.665 2.653 3.003 1.703 3.450 Estimate/ Std Dev 7.038 13.246 12.488 11.345	1.5067987 0.0797794 0.1085206 MSE 0.0245102	0.6002639 0.0198745 0.0132898 Squared Bias 0.0081314 0.0187866
True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy all inputs η , scale Mundlak Primal True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy	Mean Estimate 1.5848 0.3748 0.5165 0.1734 1.0647 242 Samples Mean Estimate 0.9002 0.4080 0.4683	Deviation 0.9521 0.1413 0.1720 0.1018 0.3086 Standard Deviation 0.1279 0.0308 0.0375	Std Dev 1.665 2.653 3.003 1.703 3.450 Estimate/ Std Dev 7.038 13.246 12.488	1.5067987 0.0797794 0.1085206 MSE 0.0245102	0.6002639 0.0198745 0.0132898 Squared Bias 0.0081314
True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy all inputs η , scale Mundlak Primal True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy all inputs α_K , scale	Mean Estimate 1.5848 0.3748 0.5165 0.1734 1.0647 242 Samples Mean Estimate 0.9002 0.4080 0.4683 0.2496 1.1249	Deviation 0.9521 0.1413 0.1720 0.1018 0.3086 Standard Deviation 0.1279 0.0308 0.0375 0.0220 0.0797	Std Dev 1.665 2.653 3.003 1.703 3.450 Estimate/ Std Dev 7.038 13.246 12.488 11.345	1.5067987 0.0797794 0.1085206 MSE 0.0245102	0.6002639 0.0198745 0.0132898 Squared Bias 0.0081314 0.0187866
True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy all inputs η , scale Mundlak Primal True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy all inputs η , scale	Mean Estimate 1.5848 0.3748 0.5165 0.1734 1.0647 242 Samples Mean Estimate 0.9002 0.4080 0.4683 0.2496 1.1249 300 Samples	Deviation 0.9521 0.1413 0.1720 0.1018 0.3086 Standard Deviation 0.1279 0.0308 0.0375 0.0220 0.0797 Standard	Std Dev 1.665 2.653 3.003 1.703 3.450 Estimate/ Std Dev 7.038 13.246 12.488 11.345 14.114 Estimate/	1.5067987 0.0797794 0.1085206 MSE 0.0245102 0.0216267 0.0092844	0.6002639 0.0198745 0.0132898 Squared Bias 0.0081314 0.0187866 0.0029282
True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy all inputs η , scale Mundlak Primal True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy all inputs η , scale	Mean Estimate 1.5848 0.3748 0.5165 0.1734 1.0647 242 Samples Mean Estimate 0.9002 0.4080 0.4683 0.2496 1.1249 300 Samples Mean Estimate	Deviation 0.9521 0.1413 0.1720 0.1018 0.3086 Standard Deviation 0.1279 0.0308 0.0375 0.0220 0.0797 Standard Deviation	Std Dev 1.665 2.653 3.003 1.703 3.450 Estimate/ Std Dev 7.038 13.246 12.488 11.345 14.114 Estimate/ Std Dev	1.5067987 0.0797794 0.1085206 MSE 0.0245102 0.0216267 0.0092844 MSE	0.0198745 0.0132898 Squared Bias 0.0081314 0.0187866 0.0029282 Squared Bias
True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy all inputs η , scale Mundlak Primal True λ_{v_i} =.16 A, efficiency α_K , capital α_L , labor α_E , energy all inputs η , scale	Mean Estimate 1.5848 0.3748 0.5165 0.1734 1.0647 242 Samples Mean Estimate 0.9002 0.4080 0.4683 0.2496 1.1249 300 Samples Mean Estimate 0.5645	Deviation 0.9521 0.1413 0.1720 0.1018 0.3086 Standard Deviation 0.1279 0.0308 0.0375 0.0220 0.0797 Standard Deviation 0.1034	Std Dev 1.665 2.653 3.003 1.703 3.450 Estimate/ Std Dev 7.038 13.246 12.488 11.345 14.114 Estimate/ Std Dev 5.459	1.5067987 0.0797794 0.1085206 MSE 0.0245102 0.0216267 0.0092844	0.6002639 0.0198745 0.0132898 Squared Bias 0.0081314 0.0187866 0.0029282
$True \ \lambda_{v_i} = .16$ $A, efficiency$ $\alpha_K, capital$ $\alpha_L, labor$ $\alpha_E, energy$ $all inputs$ $\eta, scale$ $Mundlak Primal$ $True \ \lambda_{v_i} = .16$ $A, efficiency$ $\alpha_K, capital$ $\alpha_L, labor$ $\alpha_E, energy$ $all inputs$ $\eta, scale$ $McElroy Dual$ $True \ \lambda_{\varepsilon_i} = .111$ $A, efficiency$ $\alpha_K, capital$	Mean Estimate 1.5848 0.3748 0.5165 0.1734 1.0647 242 Samples Mean Estimate 0.9002 0.4080 0.4683 0.2496 1.1249 300 Samples Mean Estimate 0.5645 0.5265	Deviation 0.9521 0.1413 0.1720 0.1018 0.3086 Standard Deviation 0.1279 0.0308 0.0375 0.0220 0.0797 Standard Deviation 0.1034 0.0395	Std Dev 1.665 2.653 3.003 1.703 3.450 Estimate/ Std Dev 7.038 13.246 12.488 11.345 14.114 Estimate/ Std Dev 5.459 13.329	1.5067987 0.0797794 0.1085206 MSE 0.0245102 0.0216267 0.0092844 MSE	0.0198745 0.0132898 Squared Bias 0.0081314 0.0187866 0.0029282 Squared Bias
$True \ \lambda_{v_i} = .16$ $A, efficiency$ $\alpha_K, capital$ $\alpha_L, labor$ $\alpha_E, energy$ $all inputs$ $\eta, scale$ $Mundlak Primal$ $True \ \lambda_{v_i} = .16$ $A, efficiency$ $\alpha_K, capital$ $\alpha_L, labor$ $\alpha_E, energy$ $all inputs$ $\eta, scale$ $McElroy Dual$ $True \ \lambda_{\epsilon_i} = .111$ $A, efficiency$ $\alpha_K, capital$ $\alpha_L, labor$	Mean Estimate 1.5848 0.3748 0.5165 0.1734 1.0647 242 Samples Mean Estimate 0.9002 0.4080 0.4683 0.2496 1.1249 300 Samples Mean Estimate 0.5645 0.5265 0.6046	Deviation 0.9521 0.1413 0.1720 0.1018 0.3086 Standard Deviation 0.1279 0.0308 0.0375 0.0220 0.0797 Standard Deviation 0.1034 0.0395 0.0444	Std Dev 1.665 2.653 3.003 1.703 3.450 Estimate/ Std Dev 7.038 13.246 12.488 11.345 14.114 Estimate/ Std Dev 5.459 13.329 13.617	1.5067987 0.0797794 0.1085206 MSE 0.0245102 0.0216267 0.0092844 MSE	0.0198745 0.0132898 Squared Bias 0.0081314 0.0187866 0.0029282 Squared Bias
$True \ \lambda_{v_i} = .16$ $A, efficiency$ $\alpha_K, capital$ $\alpha_L, labor$ $\alpha_E, energy$ $all inputs$ $\eta, scale$ $Mundlak Primal$ $True \ \lambda_{v_i} = .16$ $A, efficiency$ $\alpha_K, capital$ $\alpha_L, labor$ $\alpha_E, energy$ $all inputs$ $\eta, scale$ $McElroy Dual$ $True \ \lambda_{\epsilon_i} = .111$ $A, efficiency$ $\alpha_K, capital$ $\alpha_L, labor$ $\alpha_E, energy$ $\alpha_K, efficiency$ $\alpha_K, capital$ $\alpha_L, labor$ $\alpha_E, energy$	Mean Estimate 1.5848 0.3748 0.5165 0.1734 1.0647 242 Samples Mean Estimate 0.9002 0.4080 0.4683 0.2496 1.1249 300 Samples Mean Estimate 0.5645 0.5265	Deviation 0.9521 0.1413 0.1720 0.1018 0.3086 Standard Deviation 0.1279 0.0308 0.0375 0.0220 0.0797 Standard Deviation 0.1034 0.0395	Std Dev 1.665 2.653 3.003 1.703 3.450 Estimate/ Std Dev 7.038 13.246 12.488 11.345 14.114 Estimate/ Std Dev 5.459 13.329	1.5067987 0.0797794 0.1085206 MSE 0.0245102 0.0216267 0.0092844 MSE 0.0709756	0.0198745 0.0132898 Squared Bias 0.0081314 0.0187866 0.0029282 Squared Bias 0.0602833
$True \ \lambda_{v_i} = .16$ $A, efficiency$ $\alpha_K, capital$ $\alpha_L, labor$ $\alpha_E, energy$ $all inputs$ $\eta, scale$ $Mundlak Primal$ $True \ \lambda_{v_i} = .16$ $A, efficiency$ $\alpha_K, capital$ $\alpha_L, labor$ $\alpha_E, energy$ $all inputs$ $\eta, scale$ $McElroy Dual$ $True \ \lambda_{\epsilon_i} = .111$ $A, efficiency$ $\alpha_K, capital$ $\alpha_L, labor$	Mean Estimate 1.5848 0.3748 0.5165 0.1734 1.0647 242 Samples Mean Estimate 0.9002 0.4080 0.4683 0.2496 1.1249 300 Samples Mean Estimate 0.5645 0.5265 0.6046	Deviation 0.9521 0.1413 0.1720 0.1018 0.3086 Standard Deviation 0.1279 0.0308 0.0375 0.0220 0.0797 Standard Deviation 0.1034 0.0395 0.0444	Std Dev 1.665 2.653 3.003 1.703 3.450 Estimate/ Std Dev 7.038 13.246 12.488 11.345 14.114 Estimate/ Std Dev 5.459 13.329 13.617	1.5067987 0.0797794 0.1085206 MSE 0.0245102 0.0216267 0.0092844 MSE	0.0198745 0.0132898 Squared Bias 0.0081314 0.0187866 0.0029282 Squared Bias

The empirical results of the first version of the Mundlak model indicate very large mean squared error statistics for all the parameters. The squared bias statistics are also orders of magnitude larger than the corresponding biases of the primal-dual model. The mean estimates of the parameters are very different from the true value and the corresponding standard deviations are very large. The results of the second version of the Mundlak model are considerably better but one must recall that nobody has ever estimated such a primal model. Yet, the mean squared error statistics of this partial EIV model are also orders of magnitude larger than any of the corresponding statistics of the primal-dual model.

The third and final section of Table 1 reports the results of McElroy's dual model as specified in equations (9)-(11) of section II. In this model the assumption is that $y = y^e$ and $\mathbf{w} = \mathbf{w}^e$ and, thus the relevant system of equations to estimate are the derived demand functions as expressed by equation (11). The empirical results reported in the last section of Table 1 indicate that the mean estimates of the parameters are way off as compared to the true values, the mean squared error statistics are much larger that the corresponding statistics of the primal-dual model, as are the squared biases.

The summary conclusion of the Monte Carlo analysis performed in this paper suggests that the primal-dual model is a robust estimator even under large misspecification of the error variances' ratios. This result is a novel finding that has not been previously reported in the econometric literature. When compared to either the primal (Mundlak) or dual (McElroy) results, the estimates of the primal-dual model are considerably closer to the true values of the parameters. On the strength of this finding we now proceed to estimate the primal-dual model using exclusively the available sample infor-

mation and two specifications of the error variances' ratios. The empirical results are reported in Table 2.

Table 2. Estimates of the Primal-Dual Model of Production and Cost. Standard Deviations computed by bootstrapping on 300 samples.

Primal-Dual		Standard	Estimate/
$\lambda_{\varepsilon j}$ =.5, $\lambda_{v j}$ =.5	Estimate	Deviation	Standard Deviation
A, efficiency	0.8284	0.0537	15.426
α_{K} , capital	0.4098	0.0395	10.375
α_L , labor	0.4796	0.0651	7.367
$\alpha_{\rm E}$, energy	0.2696	0.0709	3.802
η, scale	1.1590	0.0324	35.377
Primal-Dual		Standard	Estimate/
Primal-Dual $\lambda_{\epsilon i}$ =1.0, $\lambda_{\nu i}$ =1.0	Estimate	Standard Deviation	Estimate/ Standard Deviation
	Estimate 0.8087		
$\lambda_{\epsilon j}=1.0, \lambda_{\nu j}=1.0$		Deviation	Standard Deviation
$\lambda_{\epsilon_i}=1.0, \lambda_{\nu_i}=1.0$ A, efficiency	0.8087	Deviation 0.0585	Standard Deviation 13.824
$\lambda_{\epsilon i}$ =1.0, λ_{vi} =1.0 A, efficiency α_{K} , capital	0.8087 0.4141	Deviation 0.0585 0.0417	Standard Deviation 13.824 9.930
$\begin{aligned} &\lambda_{\epsilon j} = 1.0, \lambda_{\nu j} = 1.0 \\ &A, efficiency \\ &\alpha_{K}, capital \\ &\alpha_{L}, labor \end{aligned}$	0.8087 0.4141 0.4862	Deviation 0.0585 0.0417 0.0729	Standard Deviation 13.824 9.930 6.669

The estimates and their bootstrap standard errors are not very different between the two sets of estimates even though they depend on two different ratios of the error variances. This result mimics the findings of the Monte Carlo analysis.

V. Conclusion

We tackled the 60-years old problem of how to obtain efficient estimates of a Cobb-Douglas production function when the price-taking firms operate in a cost-minimizing environment. The simplicity of the idea underlying the model presented in this paper can be re-stated as follows. Entrepreneurs make their planning, optimizing decisions on the basis of expected, non-stochastic information. When econometricians intervene and desire to re-construct the environment that presumably led to the realized decisions, they have to measure quantities and prices and, in so doing, commit measurement errors. This background seems universal and hardly deniable. The challenge, then, of how to deal with a nonlinear errors-in-variables specification was solved by a two-phase estimation procedure. In phase I, the expected quantities and prices are estimated by a nonlinear least-squares method. In phase II, this estimated information is used in a NSUR model to obtain efficient estimates of the Cobb-Douglas technology. It is well known that consistent estimates of an EIV model require the a priori knowledge of the ratio of the error variances. A Monte Carlo analysis, however, has revealed that even a gross misspecification of these ratios is associated with estimates that are remarkably close to those obtained under the choice of the true ratios.

In the process, the debate whether a primal or a dual approach is to be preferred for estimating production and cost relations was put to rest by the demonstration that a more efficient system is composed by both primal and dual relations that must be jointly estimated. Only under special cases it is convenient to estimate either a primal (Mundlak's) or a dual (McElroy's) environment.

In connection with this either-primal-or-dual debate, it is often said (for example, Mundlak 1996, p. 433): "In passing we note that the original problem of identifying the production function as posed by Marschak and Andrews (1944) assumed no price variation across competitive firms. In that case, it is impossible to estimate the supply and factor demand functions from cross-section data of firms and therefore (the dual estimator) $\hat{\gamma}_p$ cannot be computed. Thus, a major claimed virtue of dual functions---that prices

are more exogenous than quantities--- cannot be attained. Therefore, for the dual estimator to be operational, the sample should contain observations on agents operating in different markets."

After many years of pondering this non-symmetric problem, the solution is simpler than expected and we can now refute Mundlak's assertion. The key to the solution is the assumption that individual entrepreneurs make their planning decisions on the basis of their expectation processes, an assumption made also by Mundlak (1996, p. 431). The individuality of such information overcomes the fact that econometricians measure a price that seems to be the same across firms. In effect, we know that this uniformity of prices reflects more the failure of our statistical reporting system rather than a true uniformity of prices faced by entrepreneurs in their individual planning processes. The model proposed in this paper provides an operational dual estimator, as advocated by Mundlak, by decomposing a price that is perceived as the same across observations into an individual firm's expected price and a measurement error.

The GAE model of production and cost presented here can be extended to a profit-maximization environment and also to the consistent estimation of a system of consumer demand functions.

References

- Brooke, Anthony, Kendrick, David and Meeraus, Alexander. *GAMS*, *A User's Guide*,
 Boyd and Fraser Publishing Company. Danvers, MA, 1988.
- Christensen, Lauritis R. and Jorgenson, Dale W. "The Measurement of U.S. Real Capital Input 1929-1967." *Review of Income and Wealth*, Series 15 (September 1969): 135-151.
- Diewert, W. Erwin. "Application of Duality Theory." In *Frontiers of Quantitative Economics*, Contributions to Economic Analysis, Vol. 2, pp. 106-171, edited by Intrilligator, Michael D. and Kendrick. David A. Amsterdam: North Holland, 1974.
- Fuss, Melvyn and McFadden, Daniel, eds. *Production Economics: A Dual Approach to Theory and Applications*, Amsterdam: North Holland, 1978.
- Goldberg, Arthur S. "Maximum Likelihood Estimation of Regressions Containing
 Unobservable Independent Variables." *International Economic Review*13 (February 1972):1-15.
- Griliches, Zvi. "Errors in Variables and Other Unobservables" *Econometrica* 42 (November 1974):971-998.
- Hoch, Irving. "Simultaneous Equation Bias in the Context of the Cobb-Douglas Production Function." *Econometrica* 26 (October 1958):566-578.
- _____. "Estimation of the Production Function Parameters Combining

 Time-Series and Cross-Section Data." *Econometrica* 30 (January 1962):4-53.
- Klepper, Steven and Leamer, Edward E. "Consistent Sets of Estimates for Regression With Errors in All Variables." *Econometrica* 52 (January 1984):163-183.

- Leamer, Edward E. "Errors in Variables in Linear Systems." *Econometrica* 55 (July 1987):893-909.
- Marschak, Jacob and Andrews, William H. Jr. "Random Simultaneous Equations and the Theory of Production." *Econometrica* 12 (January 1944):143-206.
- McElroy, Marjorie B. "Additive General Error Models for Production, Cost, and Derived Demand or Share Systems." *J. Political Economy* 95 (August 1987):737-757.
- McManus, Douglas A. "Making the Cobb-Douglas Functional Form an Efficient

 Nonparameteric Estimation Through Localization." Paper 94-31, Monetary and

 Financial Studies. Board of Governors of the Federal Reserve. Washington D.C.,

 September 1994.
- Mundlak, Yair. "Estimation of the Production and Behavioral Functions from a

 Combination of Cross-Section and Time-Series Data." Pp. 138-166 in: Christ,

 Carl F. et al., Measurement in Economics. Standford University Press, Stanford,

 CA, 1963.
- . "Production Function Estimation: Reviving the Primal." *Econometrica* 64 (March 1996):431-438.
- Nerlove, Marc. "Returns to Scale in Electricity Supply." pp. 167-198, in Christ, Carl F. *et al.*, *Measurement in Economics*. Stanford, California, Stanford University Press, 1963.
- Schmidt, Peter. "Estimation of a Fixed-Effect Cobb-Douglas System Using Panel Data." *Journal of Econometrics*. 37 (March 1988):361-380.
- Sexton, Richard J., Wilson, Brooks M. and Wann, Joyce J. "Some Tests of the

- Economic Theory of Cooperatives: Methodology and Application to Cotton Gin ning." Western Journal of Agricultural Economics 4 (July 1989):56-66.
- Theil, Henry. Principles of Econometrics, John Wiley, New York, 1971
- Whistler, Diana, White, Kenneth J., Wong, S. Donna and Bates, David. SHAZAM, The

 Econometric Computer Program, User's Reference Manual, Version 9.

 Northwest Econometrics Ltd. Vancouver, B.C. Canada, 2001.
- Zellner, Arnold, Kmenta, Jan and Dreze, Jacques. "Specification and Estimation of Cobb-Douglas Production Function Models." *Econometrica*, 34 (October 1966):784-795.
- Zellner, Arnold. "Estimation of Regression Relationships Containing Unobservable Independent Variables." *International Economic Review* 11 (October 1970):441-454.