PN-ABX-293

EAST-WEST CENTER WORKING PAPERS
ISN 97255

EAST-WEST CENTER

Pacific Islands Development Series

No. 7, July 1995

Distortional Effects of Measurement Error on Policy Inputs: Modeling Retail Demand for Electricity

Saia Kami

Saia Kami is a Research Project Fellow at the Pacific Islands Development Program.

East-West Center Working Papers: Pacific Islands Development Series present results of completed research and inform interested colleagues about work in progress. They are reviewed internally, edited, and distributed in limited numbers for comment and discussion. Single copies are available at no cost from the East-West Center's Distribution Office.

The Pacific Islands Development Program (PIDP) of the East-West Center serves as the regional Secretariat for the Pacific Islands Conference of Leaders. PIDP provides the research and training products based on the issues and problems identified by the heads of government in the region. The Conference, which meets every three years, selects the Leaders to serve on its Standing Committee. This Committee reviews PIDP's projects annually to ensure that they respond to the issues and challenges raised at each Pacific Islands Conference. This process enhances and provides focus for the East-West Center's mission in the Pacific islands region.

The U.S. Congress established the East-West Center in 1960 to foster mutual understanding and cooperation among the governments and peoples of the Asia-Pacific region, including the United States. Principal funding for the Center comes from the U.S. government, with additional support provided by private agencies, individuals, and corporations, and more than 20 Asian and Pacific governments.

The Center promotes responsible development, long-term stability, and human dignity for all people in the region and helps prepare the United States for constructive involvement in Asia and the Pacific.

East-West Center Working Papers are circulated for comment and to inform interested colleagues about work in progress at the Center. Working Papers are issued in the following subseries: Economics and Politics Series, Education and Training Series, Energy and Minerals Series, Environment Series, and Population Series.

For more information about the Center or to order publications, contact:

Publication Sales Office
East-West Center
1777 East-West Road
Honolulu, Hawaii 96848

telephone: (808) 944-7145
facsimile: (808) 944-7376

Distortional Effects of Measurement Error on Policy Inputs: Modeling Retail Demand for Electricity

Saia Kami*

July 1995

Background

The more informative quantitative inputs to policy formulation and analysis are usually in the form of behavioral statistics--*e.g.*, elasticity estimates. In the operationalized processes through which appropriate econometric models are constructed and estimated to yield such behavioral statistics, the use of derived "primary" data (data obtained from reconstructions of truly primary [independently collated] data) has been unduly common. Of much more concern, however, is the commonly accepted perception that such a practice is innocuous. The underlying notion--centrally tied to the concept of "measurement error"--as illustrated in this paper, is conveyed on the basis of a particular experience in a developed country (Donnelly and Saddler [1984]). Therefore, the kind of policy-linked problems it highlights has much wider and more significant implications in contexts similar to those of Pacific island nations--where their underlying national statistical/information systems are relatively much weaker and more underdeveloped.

This paper aims to warn policy analysts about a common pitfall; it illustrates through a particular case study how a seemingly innocuous data-handling procedure could lead to policy inputs that are distorting. In addition, the paper provides and encourages the use of a piece of practical methodology through which such distortional effects could be remedied. In fact, such a piece of methodology possesses many desirable statistical attributes, has wide practical applicability, and is straightforward to econometrically estimate.

* *The author is very grateful to Professor Dennis J. Aigner for valuable comments and discussions. Ms. Denise Hera's skilled word-processing input is thankfully acknowledged. The responsibility for the views expressed and any shortcomings is the author's alone.*

Introduction

The analytical capacity to unravel genuinely significant economic relationships relies, to a large extent, on accessibility to credible empirical materials. Thus, not surprisingly, some of the problems commonly encountered in empirical economics are consequences of limited/inadequate resources directed to the tasks of collecting, cleaning, and disseminating (relevant) empirical data and information. The problem of errors in measurement is essentially a symptom of this phenomenon. And as a matter of fact, it is not uncommon to encounter situations where the applied worker tends to pass over the problem of errors in measurement, hoping that these errors are too small to destroy the validity of the estimation procedure and invalidate the consequently generated estimates.

One technique that econometricians have devised to solve (at least in principle) the measurement error problem is the so-called "Errors-In-Variables" or "Latent Variables" modeling. This paper reports on a markedly improved policy-oriented result yielded from a particular application of such a technique--an application to a study of retail demand for electricity in Tasmania. In essence, this study attempts to highlight the serious consequences in terms of statistical biases of estimates, when errors in measurement are not adequately accounted for in model construction and estimation.

The paper first discusses the methodology and empirical results of Donnelly and Saddler (1984), which in fact account for the initial motivation behind this study. An errors-in-variables model abstracting from the work of Aigner (1974) is then proposed as a basis for effecting a substantial improvement over the results of Donnelly and Saddler. The paper concludes with a discussion of the empirical results flowing from the application of the proposed model to the *Tasmanian dataset*--the dataset utilized in Donnelly and Saddler (1984).

Selected Methodological Aspects of the Donnelly-Saddler Study

The study of Donnelly and Saddler (1984) focused on estimates and forecasts of the retail component of demand for electricity in Tasmania--a crucial issue given the significant public reactions and controversies induced by the proposal of the Tasmanian Hydro-Electric Commission (HEC) for a new generating capacity for Tasmania and a dam on the lower Gordon River.

The Donnelly-Saddler study adopted a static demand model of the form:

$$Q_E = \alpha + \beta_1 P_E + \beta_2 P_S + \beta_3 Y + \beta_4 T + u \quad , \tag{1}$$

where Q_E is retail per capita electricity consumption; P_E is price per kilowatt hour of electricity; P_S is price of a substitute fuel; T is a temperature variable; Y is income; and u is a stochastic error term.

Of principal interest to the present study are the ways the empirical counterparts of the variables, Q_E and P_E , were constructed from the available data. By focusing on this issue and in attempting to put it in context, we directly quote the following from Donnelly and Saddler (1984):

> *Retail electricity sales (Q_E)*
>
> The total retail sales of electricity in each financial year were obtained from the statistical section of the HEC Annual Report. The average population of Tasmania for each financial year, obtained from the Australian Bureau of Statistics (ABS), was used to construct the per capita sales figure for each year.
>
> *Electricity price (P_E)*
>
> Total retail electricity revenue for each year was taken from the HEC trading accounts, published in the Annual Report. This figure was divided by the total quantity of electricity sold, derived as described above, to obtain an average revenue per unit sold. This average revenue (price) per kilowatt hour (kWH) is one of the explanatory variables in the model.

In other words, the exogeneous "electricity price" variable, P_E , was empirically constructed by equating it to an "average revenue per unit sold"-type measure--a measure that relied fundamentally on the pre-constructed endogeneous "retail electricity sales" variable, Q_E. As a consequence of the way P_E was constructed, a statistically spurious relationship between the per capita electricity sales variable and its "price" has been induced. Thus, the use of this price measure, as constructed, would have inevitably biased the reported least squares coefficient estimates for the retail demand for electricity equation. Technically, this is the hypothesis this paper sets forth to examine and test.

Empirical Results of the Donnelly-Saddler Study and Others

Donnelly and Saddler (1984) used (and annexed as an appendix) the *Tasmanian Dataset*--a dataset consisting of annual data covering the twenty-year period, 1960/61-1979/80--to estimate the parameters of interest as contained in the linear and non-linear variants of equation (1). The "temperature variable" was found not to be statistically significant in both model variants, and hence it was omitted from the final model. Among the accessible candidates for the "substitute fuel" variable, heating oil (HO) was selected as the most meaningful.

The double logarithmic results were judged by the authors to be superior, and they were the ones they reported [equation (2)][1]

$$\ell n\, Q_E = \underset{(8.497)}{7.15} - \underset{(-3.580)}{0.56}\ \ell n\, P_E + \underset{(4.322)}{0.31}\ \ell n\, P_{HO} + \underset{(8.531)}{1.13}\ \ell n\, Y\ . \qquad (2)$$

The empirical results obtained from estimating some of the model variants, implied to have been examined by Donnelly and Saddler, have been reproduced by the present author using an identical dataset (the *Tasmanian dataset*) and are reported hereunder [equations (3)-(5)].

$$\ell n\, Q_E = \underset{(4.341)}{3.10} - \underset{(-3.423)}{0.55}\ \ell n\, P_E + \underset{(4.468)}{0.32}\ \ell n\, P_{HO} + \underset{(8.531)}{1.14}\ \ell n\, Y - \underset{(-0.307)}{0.03}\ \ell n\, T \qquad (3)$$

$$Q_E = \underset{(1.244)}{2198.1} - \underset{(-3.670)}{2136.3}\ P_E + \underset{(5.420)}{300.4}\ P_{HO} + \underset{(5.010)}{50.0}Y - \underset{(-0.836)}{78.7}T \qquad (4)$$

$$Q_E = \underset{(1.005)}{1617.1} - \underset{(-3.610)}{2040.5}\ P_E + \underset{(5.421)}{296.7}\ P_{HO} + \underset{(5.290)}{51.4}Y\ . \qquad (5)$$

Thus evidently, even with the above specific cases that were not explicitly reported in Donnelly and Saddler (1984), the (own) "electricity price" coefficient like the one these researchers reported has displayed consistently a statistically significant magnitude; moreover,

[1] *The respective "t" statistics appear in parentheses below the parameter estimates.*

its sign has implied consistently the prevalence of a negatively sloped "collapsed" Marshallian demand relationship.

In our present effort to put the hypothesis of interest into a perspective form of empirical testing, it is useful to have a closer look at estimates reported by Donnelly and Saddler (1984).

Table 1 reproduces estimates of electricity demand elasticities for the case of Tasmania obtained by Donnelly and Saddler, plus other estimates reported by them but obtained through the works of others. Belonging to the latter group is a set of estimates of demand elasticities obtained from a "similar" investigation but focused on the Australian Capital Territory (ACT).

Table 1[λ]

Electricity Demand Elasticities

Tasmania

	Tasmania			ACT	Australia	
Elasticity	*Donnelly and Saddler (1984)*	*Saddler et al. (1980)*			*DNDE#*	
	current	*original*	*replicated*		(1)	(2)
P_E	*-0.56*	*-0.54*	*-0.49*	*-0.74*	*-0.86*	*-0.19**
P_S	*0.31*	*0.30*	*0.21*	*0.38*	*0.25*	*0.11*
Y	*1.13*	*0.81*	*0.93*	*0.39*	*0.78*	*1.27*
D.W.	*1.696*	*1.32*	*1.771*	*1.702*	*N.R.*	*N.R.*
Reference Period of Data	*1960-61 to 1979-80*	*1961 to 1977*		*1963-64 to 1978-79*	*1967-68 to 1978-79*	
Number of Observations	*20*	*17*		*19*	*12*	

(1) – *substitute fuel-heating oil*
(2) – *substitute fuel-crude oil*
N.R. – *not reported*
– *Department of National Development and Energy*
*** – *not significant at 0.1 levels*

[λ]Source: Donnelly and Saddler (1984) [TABLE I].

The following comments, many of which did not escape the attention of Donnelly and Saddler (1984), are focused on the estimates of electricity demand elasticities shown in Table 1. Based on methodological criteria alone (*e.g.*, uniformities in the treatments of "reference period," constructions of "empirical counterparts" of model variables, and

adjustments for relevant influences of "serial correlation") the various sets of estimates reported are not comparable.

By way of illustration, notice that, *inter alia*, serial correlation (as empirically gauged by the Durbin-Watson (D.W.) statistic) was not present in the set (the "current" set) of estimates of Donnelly and Saddler (1984); but it was in fact detected in the set (the "original" set) of estimates of Saddler *et. al.* (1980). Once, however, an *ad hoc* serial correlation adjustment was applied to the latter set, the one consequently yielded (the "replicated" set) was found statistically not to be significantly different from the former set (the "current set") (Donnelly and Saddler 1984).

Statistically speaking, this result is essentially saying that, certain inherently differential effects of serial correlation apart, the stated "current" and "original" sets of estimates are quite insensitive (*i.e.*, robust) to other factors--considered methodologically, as significant stratifiers or discriminants of the two characterizing scenarios of conditions--*via* which the said two sets of estimates have been separately generated. Indeed, this implication, if it is genuinely durable, has great potential serviceability, especially when the yielded estimates are in heavy demand for forecasting purposes (Donnelly and Saddler 1984).

Of course, strictly speaking, in order to establish rigorously such a sense of genuine durability, the underlying econometric tasks or the implied relevant results need to be replicated under or abstracted from at least those varying conditions characterized by the principal members of the said stratifiers or discriminants. As in the experience of Donnelly and Saddler (1984), empirical efforts channeled in this direction may not go very far due to real practical constraints, *e.g.*, unavailability or paucity of quality (valid and reliable) data

However, the basic point that needs further emphasizing is this: Under the usual "non-controlled" domain of applied econometric analysis, "close likeness" between two sets of estimates does not necessarily mean factors that strictly manifest themselves differently in the two underlying generating conditions have effects that are innocuous and inconsequential. Alternatively stated, it is not a sufficient condition for the relevant *ceteris paribus* condition to have been fulfilled if the two exposed sets of estimates were judged as "closely alike."

In fact, the significance of the implied underlying phenomenon is further reflected in the somewhat commonly encountered situations where wide discrepancies are observed in

estimates; but the studies *via* which such estimates have been derived are known to have had adopted modeling approaches that are essentially the same.

Thus, it is apparent that by superimposing on the underlying phenomenon just emphasized the demand elasticity estimates derived from the works of others (Table 1), the scenario of electricity demand behavior consequently portrayed is indeed a diffused one. Donnelly and Saddler (1984) pointed out for instance that their estimates of electricity own-price elasticity differed significantly from those of the DNDE study (Table 1)--which in fact reported as a "most suitable equation" the specification that included the price of crude oil as the substitute good, even though the electricity own-price elasticity estimate in that equation was not significantly different from zero.

The direct permeation of this diffused effect to electricity demand forecasts simply follows as a corollary. This with little doubt must have played a non-trivial part on the observation by Donnelly and Saddler (1984)--that even on the basis of a 95 percent confidence limits on their so-regarded "most likely" scenario, their largest conditional forecast was still below the HEC projection!

The wide discrepancies in estimates/forecasts obtained in the different studies reported by Donnelly and Saddler (1984) must be disconcerting to those concerned decision makers who intend to use those estimates to assess the need for additional electrical power generating capacity in Tasmania. This point of view is particularly noteworthy and in fact vexatious because, as earlier deduced, the modeling approaches adopted by these studies are "understood" to be essentially the same.

Donnelly and Saddler (1984) explicitly acknowledged the fact that the data used in the estimation have limitations and that any attempt to significantly extend the pursued line of research would necessitate much improved data on energy consumption, income, and prices. With this spirit, we re-focus our attention and effort on the empirical counterparts of the variables, Q_E ("retail electricity sales") and P_E ("electricity price"), and recall how they had been constructed from the available data--thus, revealing potentially induced statistical biases in the estimation of the electricity demand equation, (1).

A number of empirical studies that focused on the estimation of labor-supply functions and for which (due to unavailabilities of independent wage measurements) measures of wages

had to be constructed from "earnings" and "hours of work"--with the latter variable representing a principal component of the measure of "labor supply." In such cases, biases had been consequently induced in the same way as we have indicated with respect to the Donnelly-Saddler study. Among these labor-supply studies, the relative magnitude and significance of the biasing factor (due to the particular construction of the wage measure used) may be clearly demonstrated by a comparison (as shown in Table 2) of appropriately selected wage coefficient estimates–ones that had been computed on the basis of very highly equivalent datasets.

Table 2

Differences in Estimates as a reflection of Differences in Approach to Estimation

Study	Wage Coefficient	Wage Measure/Estimation Approach
Greenberg-Kosters (1973)	*-78.55*	*"wages" = Earnings + Hours of Work*
Aigner (1974)	*+37.36*	*Modeled the wage variable as a latent variable (the resultant estimate was consistent, asymptotically efficient and asymptotically normal)*

The Modified Model

In presenting our proposed improvement to model construction and estimation of retail demand for electricity in Tasmania, we consider the basic functional form:

$$Q_{1t}^{E} = \beta_1 P_t^E + \beta_2 P_t^S + \beta_3 Y_t + \underline{X}_t^T \beta_4 + u_{1t} \qquad , \; t = 1,\ldots,T. \tag{6}$$

Q_{1t}^{E} is per capita electricity sale for year t; P_t^E is the price of electricity; P_t^S is the price of substitute fuel; Y_t is income; $\underline{X}_t$ is a vector of variables included as "controls" in the demand function (also included therein is a provision for an intercept term); and u_{1t} is a stochastic error term with the properties of zero mean, constant variance, and independence over time.[2]

[2] *This assumption appears reasonable in the context of the 1984 Tasmanian demand for electricity study because Donnelly and Saddler found that (first-order) serial correlation was not present in the Tasmanian dataset.*

We capitalize on the well-informed fact that P_t^E was not measured accurately and proceed to substantially remedy this deficiency by modeling P_t^E as a latent variable. In this regard, we develop our proposed model based on the methodology of Aigner (1974).

We setup the relationship,

$$Q_{2t} = P_t^E + u_{2t} \quad , \; t = 1,\ldots,T; \tag{7}$$

to represent the measured price (Q_{2t}) as a function of the true price (P_t^E) and an additive error (u_{2t}). We assume u_{2t} to be independent of P_t^E, with zero mean. P_t^E and u_{2t} are further supposed to have constant variances (σ_p^2 and σ_{u2}^2, respectively) and be independently distributed over time.

We also consider the relationship,

$$P_t^E = \underline{Z}_t^T \gamma + \varepsilon_t \quad , \; t = 1,\ldots,T; \tag{8}$$

where $\underline{Z}_t$ is a vector of certain auxiliary variables believed to determine/influence P_t^E, and an element that is one for all t corresponding to an intercept term. The error term, ε_t, is assumed to be well behaved (zero mean, constant variance, and independently distributed over time).

In summary, our "appropriate" model consists of three equations:

$$\begin{aligned} Q_{1t}^E &= \beta_1 P_t^E + \beta_2 P_t^S + \beta_3 Y_t + \underline{X}_t^T \underline{\beta}_4 + u_{1t} \\ Q_{2t} &= P_t^E + u_{2t} \quad ; \text{and} \\ P_t^E &= \underline{Z}_t^T \underline{\gamma} + \varepsilon_t \quad , \; t = 1,\ldots,T. \end{aligned}$$

We recall that all error terms are assumed to possess zero means and constant variances and to be independently normally distributed over time. We also do not impose (as we have no particular *a priori* reason to do so) the conditions:

$$E(u_{1t} u_{2t}) = 0 \;, \quad E(u_{1t} \varepsilon_t) = 0 \;\; and \;\; E(u_{2t} \varepsilon_t) = 0.$$

Upon substitution of (8) into (6) and (7), the full reduced form of the model appears as:

$$Q_{1t}^{E} = \underline{Z}_t^T \underline{\gamma} \beta_1 + \beta_2 P_t^S + \beta_3 Y_t + \underline{X}_t^T \beta_4 + u_{1t}^* \qquad (6)'$$

$$Q_{2t} = \underline{Z}_t^T \underline{\gamma} + u_{2t}^* \ , \qquad (7)'$$

where $u_{1t}^* = \beta_1 \varepsilon_t + u_{1t}$ *and* $u_{2t}^* = \varepsilon_t + u_{2t}$, $t = 1,\ldots,T.$

Now, if we assume that $\underline{Z}_t$ is (k x 1) and $\underline{X}_t$ is of dimension (r x 1) and that $\underline{X}_t$ is a sub-vector of $\underline{Z}_t$ (k > r), then $\underline{Z}_t$ can be partitioned into $\underline{Z}_t = (\underline{Z}_{1t}^T \underline{Z}_{2t})^T$, where $\underline{Z}_{1t} = \underline{X}_t$ and correspondingly, $\underline{\gamma} = (\underline{\gamma}_1^T \underline{\gamma}_2^T)^T$. Consequently, we may re-write equations (6)' and (7)' compactly (for all T observations) as:

$$(\underline{Q}_1 \ \underline{Q}_2) = (\underline{Z}_1 \underline{Z}_2 \underline{S}^*) \begin{pmatrix} \underline{\gamma}_1 \beta_1 + \underline{\beta}_4 & \underline{\gamma}_1 \\ \underline{\gamma}_2 \beta_1 & \underline{\gamma}_2 \\ \underline{\beta} & \underline{0} \end{pmatrix} + (\underline{\upsilon}_1 \underline{\upsilon}_2) \qquad (9)$$

where $\underline{S}^* = (P^S Y)$; $\underline{\beta}^* = \begin{pmatrix} \beta_2 \\ \beta_3 \end{pmatrix}$; and $(\underline{\upsilon}_1 \underline{\upsilon}_2)$ is a $(T \times 2)$ matrix of reduced form disturbances, defined by $\underline{\upsilon}_1 = (\upsilon_{11} \ldots \upsilon_{1T})^T$ with $\upsilon_{1t} = \beta_1 \varepsilon_t + u_{1t} = u_{1t}^*$ and $\underline{\upsilon}_2 = (\upsilon_{21} \ \ldots \upsilon_{2T})^T$ with $\upsilon_{2t} = u_{2t}^*$.

Model (9) is in the form of a multivariate regression system subject to certain parameter constraints. If we re-label the parameter matrix in (9) as it is partitioned there by:

$$\underline{\Pi} = \begin{bmatrix} \underline{\pi}_{11} \underline{\pi}_{12} \\ \underline{\pi}_{21} \underline{\pi}_{22} \\ \underline{\pi}_{31} \underline{\pi}_{32} \end{bmatrix}, \qquad (10)$$

the restrictions are: *(a)* $\underline{\pi}_{32} = \underline{0}$ and *(b)* $\underline{\pi}_{21} = \underline{\pi}_{22} \beta_1$.

There are no further restrictions to be observed in the estimation set-up of the model.

The Estimation Approach

It is well known that the efficiency of parameter estimates derived from the applications of methods, such as the 2SLS and IV estimation techniques, can be improved upon by using the technique of 3SLS--a natural extension to estimation of simultaneous-equation models of the approach of Zellner estimation developed for the estimation of seemingly unrelated regression (SUR) models. The 3SLS procedure takes into account cross-equation correlations and, like the LIML procedure, belongs to the category of estimation techniques that yield estimators belonging to the so-called k-class estimator. In fact, in a more general context, 3SLS and LIML become equivalent when the equation to be estimated is exactly identified.

The Empirical Model and Results

Of particular concern to any application of our methodology is the availability of more and better candidates for the auxiliary variables that constitute the z_t's. For the present application, we select components of $\underline{Z}_t$ as follows:

$$\underline{Z}_t = \begin{bmatrix} P_t^S \\ H_t^E \end{bmatrix}$$, where H_t^E is the supply of hydro-electricity for year, t.

Moreover, in consonance with (9), we posit $\underline{Z}_t$ and $\underline{X}_t$ to be mutually exclusive, *i.e.*, $\underline{X}_t \not\subset \underline{Z}_t$; and subsequently, we set $\underline{X}_t = X_t = T_t$ (a temperature variable).

Given the above operational specifications, we derive parameter estimates based on the following empirical variant of our model (written for each annual observation corresponding to the twenty-year reference period of the *Tasmanian dataset*)[3]:

$$\begin{aligned} Q_{1t}^E &= \beta_0 + \beta_1 P_t^E + \beta_2 P_t^S + \beta_3 Y_t + \beta_4 T_t + u_{1t} \\ Q_{2t} &= P_t^E + u_{2t} \quad \Rightarrow \quad P_t^E = Q_{2t} - u_{2t} \\ P_t^E &= \gamma_0 + \gamma_1 P_t^S + \gamma_2 H_t^E + \varepsilon_t \end{aligned} \tag{11}$$

That is, (11) implies the following:

[3] *The dataset used in the present empirical application is the Tasmanian dataset appropriately augmented with the 20 observations on the supply of hydroelectricity (H_t^E , $t = 1,\ldots, 20$) taken from the Department of Resources and Energy (1984).*

$$Q_{1t}^{E} = \beta_0 + \beta_1 Q_{2t} + \beta_2 P_t^S + \beta_3 Y_t + \beta_4 T_t + u_{1t}^*$$
$$Q_{2t} = \gamma_0 + \gamma_1 P_t^S + \gamma_2 H_t^E + u_{2t}^* , \qquad (12)$$

where $u_{1t}^* = u_{1t} - \beta_1 u_{2t}$ and $u_{2t}^* = \varepsilon_t + u_{2t}$

The parameters in the system of equation (12) are estimated using the 3SLS procedure.[4] Both linear and double logarithmic forms of (12) are fitted with/without the temperature variable T_t in the first equation, and with/without the P_t^S term in the second equation. We present herein our empirical results that could be directly compared with those published by Donnelly and Saddler (1984). In this particular empirical application, our main objective is to provide evidence in support of, or against, the appropriateness of, our proposed model in light of the *Tasmanian dataset.*

The relevant empirical results are as follows:

$$\ell n\, Q_1^E = -2.65 + 0.90 \ell n\, P^E + 0.62 \ \ell n\, P^S + 2.26 \ell n Y$$
$$(-0.674) \ (0.925) \qquad (2.725) \qquad (2.926)$$

$$\ell n\, Q_{2t} = 3.90 - 0.05 \ell n\, P^S - 0.41 \ell n\, H^E$$
$$(8.899)(-0.426) \qquad (-8.933)$$

Conclusion

Our results do not provide any evidence that the electricity own price elasticity is different from zero. This result is to be compared with the estimate of electricity own price elasticity of -0.56 (with an associated "*t*" value of -3.580) reported by Donnelly and Saddler (1984).[5] Our own price elasticity result is intuitively appealing on the grounds that the retail demand for electricity in Australia is "known" to be quite price inelastic.

[4] *The computer program, SHAZAM (White 1978) has facility for this procedure, and it is the one we use.*

[5] *Reproduced in equation (2).*

We also note that the supply of hydroelectric power (H^E) is shown to have a very significant influence on the price of electricity; moreover, the sign of the H^E coefficient is consistent with expectation. Such a variable, therefore, should be retained as one of the appropriate auxiliary variables to constitute $\underline{Z}_t$ in our future search (in this regard) for appropriate explanatory variables for our electricity price equation.

In any event, our results have served to highlight two basic arguments. The first is general--that uses of low quality empirical materials in pursuit of presumed working hypotheses, indeed do distort the true behavioral manifestations of the economic relationships/phenomena stylized by such hypotheses. The second argument--more specific in character--is that ignoring errors in measurement in econometric modeling and estimation could easily lead to substantial biases in the resultant estimates with obvious distortional implications on related projections and policy inputs.

References

Aigner, D.J.

1974 An Appropriate Econometric Framework for Estimating a Labor Supply Function from the SEO File, *International Economic Review*, Vol. 15, No. 1.

Department of Resources and Energy

1984 *Energy Demand and Supply 1960/61-1982/83,* Canberra: Australian Government Publishing Service, June.

Donnelly, W.A., and H.D.W. Saddler

1984 The Retail Demand for Electricity in Tasmania, *Australian Economic Papers,* Vol. 23, No. 42.

Greenberg, D.H., and M. Kosters

1973 Income Guarantees and the Working Poor: The Effect of Income Maintenance Programs on the Hours of Work of Male Family Heads, in: Gain, G. and Watts, H. (eds.), *Income Maintenance and Labor Supply: Econometric Studies*, Markham Press, 1973.

Pindyck, R.S., and D.L. Rubinfield

1981 *Econometric Models and Economic Forecasts,* New York: McGraw-Hill.

Saddler, H.D.W., and W.A. Donnelly

1982 *The Demand for Energy in Tasmania, with particular reference to electricity,* Submission to the Senate Select Committee on South-West Tasmania, Canberra: Official Hansard, 4 February.

Saddler, H.D.W., J. Bennett, I. Reynolds, and B. Smith

1980 *Public Choice in Tasmania: Aspects of the Lower Gordon River Hydro-electric Development Proposal.* Centre for Resource and Environmental Studies, CRES Monograph 2, Canberra: Australian National University.

White, K.J.

1978 A Generalized Computer Program for Econometric Methods-SHAZAM, *Econometrica,* Vol. 46.