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Estimating a Social Accounting Matrix Using Cross Entropy Methods

Sherman Robinson
Andrea Cattaneo
Moataz El-Said
International Food Policy Research Institute

Trade and Macroeconomics Division
International Food Policy Research Institute
2033 K Street, N.W.
Washington, D.C. 20006 U.S.A.

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by

Sherman Robinson

Andrea Cattaneo

and

Moataz El-Said[1]

International Food Policy Research Institute

Washington, D.C., U.S.A.

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[1]Sherman Robinson, IFPRI, 2033 K street, N.W. Washington, DC 20006, USA. Andrea Cattaneo, IFPRI, 2033 K street, N.W. Washington, DC 20006, USA. Moataz El-Said, IFPRI, 2033 K street, N.W. Washington, DC 20006, USA.

Abstract

There is a continuing need to use recent and consistent multisectoral economic data to support policy analysis and the development of economywide models. Updating and estimating input-output tables and social accounting matrices (SAMs), which provides the underlying data framework for this type of model and analysis, for a recent year is a difficult and a challenging problem. Typically, input-output data are collected at long intervals (usually five years or more), while national income and product data are available annually, but with a lag. Supporting data also come from a variety of sources; e.g., censuses of manufacturing, labor surveys, agricultural data, government accounts, international trade accounts, and household surveys. The problem in estimating a SAM for a recent year is to find an efficient (and cost-effective) way to incorporate and reconcile information from a variety of sources, including data from prior years. The traditional RAS approach requires that we start with a consistent SAM for a particular year and "update" it for a later year given new information on row and column sums. This paper extends the RAS method by proposing a flexible "cross entropy" approach to estimating a consistent SAM starting from inconsistent data estimated with error, a common experience in many countries. The method is flexible and powerful when dealing with scattered and inconsistent data. It allows incorporating errors in variables, inequality constraints, and prior knowledge about any part of the SAM (not just row and column sums). Since the input-output accounts are contained within the SAM framework, updating an input-output table is a special case of the general SAM estimation problem. The paper describes the RAS procedure and "cross entropy" method, and compares the underlying "information theory" and classical statistical approaches to parameter estimation. An example is presented applying the cross entropy approach to data from Mozambique. An appendix includes a listing of the computer code in the GAMS language used in the procedure.

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Introduction

There is a continuing need to use recent and consistent multisectoral economic data to support policy analysis and the development of economywide models. A Social Accounting Matrix (SAM) provides the underlying data framework for this type of model and analysis. A SAM includes both input-output and national income and product accounts in a consistent framework. Input-output data are usually prepared only every five years or so, while national income and product data are produced annually, but with a lag. To produce a more disaggregated SAM for detailed policy analysis, these data are often supplemented by other information from a variety of sources; *e.g*., censuses of manufacturing, labor surveys, agricultural data, government accounts, international trade accounts, and household surveys. The problem in estimating a disaggregated SAM for a recent year is to find an efficient (and cost-effective) way to incorporate and reconcile information from a variety of sources, including data from prior years.

Estimating a SAM for a recent year is a difficult and challenging problem. A standard approach is to start with a consistent SAM for a particular prior period and "update" it for a later period, given new information on row and column totals, but no information on the flows within the SAM. The traditional RAS approach, discussed below, addresses this case. However, one often starts from an inconsistent SAM, with incomplete knowledge about both row and column sums and flows within the SAM. Inconsistencies can arise from measurement errors, incompatible data sources, or lack of data. What is needed is an approach to estimating a consistent set of accounts that not only uses the existing information efficiently, but also is flexible enough to incorporate information about various parts of the SAM.

In this paper, we propose a flexible "cross entropy" approach to estimating a consistent SAM starting from inconsistent data estimated with error. The method is very flexible, incorporating errors in variables, inequality constraints, and prior knowledge about any part of the SAM (not just row and column sums). The next section presents the structure of a SAM and a mathematical description of the estimation problem. The following section describes the RAS procedure, followed by a discussion of the cross entropy approach. Next we present an application to Mozambique demonstrating gains from using increasing amounts of information. An appendix includes a listing of the computer code in the GAMS language used in the procedure.

Structure of a Social Accounting Matrix (SAM)

A SAM is a square matrix whose corresponding columns and rows present the expenditure and receipt accounts of economic actors. Each cell represents a payment from a column account to a row account. Define T as the matrix of SAM transactions, where $T_{i,j}$ is a payment from column account j to row account i. Following the conventions of double-entry bookkeeping, the total receipts (income) and expenditure of each actor must balance. That is, for a SAM, every row sum must equal the corresponding column sum:

$$y_i = \sum_j T_{i,j} = \sum_j T_{j,i} \qquad \textbf{(1)}$$

where y_i is total receipts and expenditures of account i.

A SAM coefficient matrix, A, is constructed from T by dividing the cells in each column of T by the column sums:

$$A_{i,j} = \frac{T_{i,j}}{y_j} \qquad \textbf{(2)}$$

By definition, all the column sums of A must equal one, so the matrix is singular. Since column sums must equal row sums, it also follows that (in matrix notation):

$$y = Ay \qquad \textbf{(3)}$$

A typical national SAM includes accounts for production (activities), commodities, factors of production, and various actors ("institutions") which receive income and demand goods. The structure of a simple SAM is given in Table 1. Activities pay for intermediate inputs, factors of production, and indirect taxes, and receive payments for exports and sales to the domestic market. The commodity account buys goods from activities (producers) and the rest of the world (imports), and pays tariffs on imported goods, while it sells commodities to activities (intermediate inputs) and final demanders (households, government, and investment). In this SAM, gross domestic product (GDP) at factor cost (payments by activities to factors of production) or value added equals GDP at market prices (GDP at factor cost plus indirect taxes, and tariffs = consumption plus investment plus government demand plus exports minus imports).

Table 1. A national SAM

	Expenditure				
Receipts	Activity	Commodity	Factors	Institutions	World
Activity		Domestic sales			Exports
Commodity	Intermediate inputs			Final demand	
Factors	Value added (wages/rentals)				
Institutions	Indirect taxes	Tariffs	Factor income		Capital inflow
World		Imports			
Totals	Total costs	Total absorption	Total factor income	Gross domestic income	Foreign exchange inflow

The matrix of column coefficients, A, from such a SAM provides raw material for much economic analysis and modeling. For example, the intermediate-input coefficients (known as the "use" matrix) correspond to Leontief input-output coefficients. The coefficients for primary factors are "value added" coefficients and give the distribution of factor income. Column coefficients for the commodity accounts represent domestic and import shares, while those for the various final demanders provide expenditure shares. There is a long tradition of work which starts from the assumption that these various coefficients are fixed, and then develops various linear multiplier models. The data also provide the starting point for estimating parameters of nonlinear, neoclassical production functions, factor-demand functions, and household expenditure functions.

In principle, it is possible to have negative transactions, and hence coefficients, in a SAM. Such negative entries, however, can cause problems in some of the estimation techniques described below and also may cause problems of interpretation in the coefficients. A simple approach to dealing with this issue is to treat a negative expenditure as a positive receipt or a negative receipt as a positive expenditure. For example, if a tax is negative, treat it as a subsidy. That is, if $T_{i,j}$ is negative, we simply set the entry to zero and add the value to $T_{j,i}$. This "flipping" procedure will change row and column sums, but they will still be equal.

The RAS Approach to SAM estimation

The classic problem in SAM estimation is the problem of "updating" an input-output matrix when we have new information on the row and column sums, but do not have new information on the input-output flows. The generalization to a full SAM, rather than just the input-output table, is the following problem. Find a new SAM coefficient matrix, A^*, that is in some sense "close" to an existing coefficient matrix, $\bar{A}$ but yields a SAM transactions matrix, T^*, with the new row and column sums. That is:

$$T^*_{i,j} = A^*_{i,j} \, y^*_j \qquad \textbf{(4)}$$

$$\sum_j T^*_{i,j} = \sum_j T^*_{j,i} = y^*_i \qquad \textbf{(5)}$$

where y* are known new row and column sums.

A classic approach to solving this problem is to generate a new matrix A^* from the old matrix A by means of "biproportional" row and column operations:

$$A^*_{i,j} = R_i \, \bar{A}_{i,j} \, S_j \qquad \textbf{(6)}$$

or, in matrix terms:

$$A^{(} = \hat{R}\bar{A}\hat{S} \qquad \textbf{(7)}$$

where the hat indicates a diagonal matrix of elements of *R* and *S*. Bacharach (1970) shows that this "RAS" method works in that a unique set of positive multipliers (normalized) exists that satisfies the biproportionality condition and that the elements of *R* and *S* can be found by a simple iterative procedure.[1]

A Cross Entropy Approach to SAM estimation

The fundamental estimation problem is that, for an n-by-n SAM, we seek to identify n^2 unknown non-negative parameters (the cells of *T* or *A*), but have only 2n–1 independent row and column adding-up restrictions. The RAS procedure imposes the biproportionality condition, so the problem reduces to finding 2n–1 R and S coefficients (one being set by normalization), yielding a unique solution. The general problem is that of estimating a set of parameters with little information. If all we know is row and column sums, there is not enough information to identify the coefficients, let alone provide degrees of freedom for estimation.

In a recent book, Golan, Judge, and Miller (1996) suggest a variety of estimation techniques using "maximum entropy econometrics" to handle such "ill-conditioned" estimation problems. Golan, Judge, and Robinson (1994) apply this approach to estimating a new input-output table given knowledge about row and column sums of the transactions matrix — the classic RAS problem discussed above. We extend this methodology to situations where there are different kinds of prior information than knowledge of row and column sums.

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[1] For the method to work, the matrix must be "connected," which is a generalization of the notion of "indecomposable" [Bacharach (1970, p. 47)]. For example, this method fails when a column or row of zeros exists because it cannot be proportionately adjusted to sum to a non-zero number. Note also that the matrix need not be square. The method can be applied to any matrix with known row and column sums: for example, an input-output matrix that includes final demand columns (and is hence rectangular). In this case, the column coefficients for the final demand accounts represent expenditure shares and the new data are final demand aggregates.

Deterministic Approach: Information Theory

The estimation philosophy adopted in this paper is to use *all*, and *only*, the information available for the estimation problem at hand. The first step we take in this section is to define what is meant by "information". We then describe the kinds of information that can be incorporated and how to do it. This section focuses on information concerning non-stochastic variables while the next section will introduce the use of information on stochastic variables.

The starting point for the cross entropy approach is Information Theory as developed by Shannon (1948). Theil (1967) brought this approach to economics. Consider a set of n events $E_1, E_2, \ldots, E_n$ with probabilities $q_1, q_2, \ldots, q_n$ (prior probabilities). A message comes in which implies that the odds have changed, transforming the prior probabilities into posterior probabilities $p_1, p_2, \ldots, p_n$. Suppose for a moment that the message confines itself to one event E_i. Following Shannon, the "information" received with the message is equal to -ln p_i. However, each E_i has its own posterior probability q_i, and the "additional" information from p_i is given by:

$$-\ln\frac{p_i}{q_i} = -\left[\ln p_i - \ln q_i\right] \qquad \textbf{(8)}$$

Taking the expectation of the separate information values, we find that the *expected information* value of a message (or of data in a more general context) is

$$-I(p{:}q) = -\sum_{i=1}^{n} p_i \ln\frac{p_i}{q_i} \qquad \textbf{(9)}$$

where *I(p:q)* is the Kullback-Leibler (1951) measure of the "cross entropy" distance between two probability distributions (Kapur and Kenavasan, 1992).[2] The objective of the approach, which aims at utilizing all available information, is to minimize the cross entropy between the probabilities that are consistent with the information in the data and the prior information **q**.[3]

Golan, Judge, and Robinson (1994) use a cross entropy formulation to estimate the coefficients in an input-output table. They set up the problem as finding a new set of *A*

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[2]Kapur and Kenavasan, 1992 presents a description of the axiomatic approach from which this measure is obtained (Chapter 4).

[3] If the prior distribution is uniform, representing total ignorance, the method is equivalent to the "Maximum Entropy" estimation criterion (see Kapur and Kesavan, 1992; pp. 151-161).

coefficients which minimizes the entropy distance between the prior $\bar{A}$ and the new estimated coefficient matrix.[4]

$$\min \left[\sum_i \sum_j A_{i,j} \ln \frac{A_{i,j}}{\bar{A}_{i,j}} \right] \qquad \textbf{(10)}$$

subject to

$$\sum_j A_{i,j} y_j^{(} = y_i^{(} \qquad \textbf{(11)}$$

$$\sum_j A_{j,i} = 1$$

$$0 \leq A_{j,i} \leq 1 \qquad \textbf{(12)}$$

The solution is obtained by setting up the Lagrangian for the above problem and solving it.[5] The outcome combines the information from the data and the prior:

$$A_{ij} = \frac{\bar{A}_{ij} \exp(\lambda_i y_j^{(})}{\sum_{i,j} \bar{A}_{ij} \exp(\lambda_i y_j^{(})} \qquad \textbf{(13)}$$

where λ_i are the Lagrange multipliers associated with the information on row and column sums, and the denominator is a normalization factor.

The expression is analogous to Bayes' Theorem, whereby the posterior distribution (A_{ij}) is equal to the product of the prior distribution ($\bar{A}_{ij}$) and the likelihood function (probability of drawing the data given parameters we are estimating), dividing by a normalization factor to convert relative probabilities into absolute ones. The analogy to Bayesian estimation is that the approach can be seen as an efficient Information Processing Rule (IPR) whereby we use additional information to revise an initial set of estimates (Zellner, 1988, 1990). In this approach an "efficient" estimator is defined by Jaynes: "An acceptable inference procedure should have the

[4]Although the CE method can be applied to SAM coefficients, one must take care when interpreting the resulting statistics because the parameters being estimated are no longer probabilities, although the column coefficients satisfy the same axioms.

[5] The problem has to be solved numerically because no closed form solution exists.

property that it neither ignores any of the input information nor injects any false information." Zellner (1988) describes this as the "Information Conservation Principle."

Types of Information

Priors The matrix $\bar{A}$ from an earlier year provides information about the new coefficients. The approach is to estimate a new set of coefficients "close" to the prior.

Moment Constraints The most common kind of information to have is data on some or all of the row and column sums of the new SAM. This knowledge can be incorporated easily in the cross entropy framework by imposing a fixed value on y* in equation (11) in the same way as the RAS method (eq. (5)). While the RAS procedure is based on knowing all row and column sums, it is only one of several possible sources of information in CE estimation.

Economic Aggregates In addition to row and column sums, one often has additional knowledge about the new SAM. For example, aggregate national accounts data may be available for various macro aggregates such as value added, consumption, investment, government, exports, and imports. There also may be information about some of the SAM accounts such as government receipts and expenditures. This information can be summarized as additional linear adding-up constraints on various elements of the SAM. Define an n-by-n aggregator matrix, G, which has ones for cells in the aggregate and zeros otherwise. Assume that there are k such aggregation constraints, which are given by:

$$\sum_i \sum_j G_{i,j}^{(k)} \; T_{i,j} = \gamma^{(k)} \qquad \textbf{(14)}$$

where γ is the value of the aggregate. These conditions are simply added to the constraint set in the cross entropy formulation. The conditions are linear in the coefficients and can be seen as additional moment constraints.

Inequality Constraints While one may not have exact knowledge about values for various aggregates, including row and column sums, it may be possible to put bounds on some of these aggregates. Such bounds are easily incorporated by specifying inequality constraints in equations (11) and (14).

Stochastic Approach: Measurement Error

Most applications of economic models to real world issues must deal with the problem of extracting results from data or economic relationships with noise. In this section we generalize our approach to cases where: (i) row and column sums are not fixed parameters but involve errors in measurement, and (ii) the initial estimate, $\bar{A}$, is not based on a balanced SAM.

Consider the standard regression model:

$$Y = X\beta + e \qquad \textbf{(15)}$$

where β is the coefficient vector to be estimated, *Y* represents the vector of dependent variables, *X* the independent variables, and *e* is the error term. Consider the standard assumptions made in regression analysis from the perspective of information theory.

- There is lots of data providing degrees of freedom for estimation.

- The error *e* is assumed to be distributed with zero mean and constant variance. In practice the error distribution is usually assumed to be normally distributed. This represents a lot of information on the error structure. The only parameter that needs to be estimated is the error variance. Given these assumptions, we only need information in the form of certain moments, which summarize all the information needed from the data to carry out efficient estimation - $\hat{\beta} = (X'X)^{-1} X'Y$.

- On the other hand, no prior information is assumed about the parameters. The null hypothesis is β=0, and we assume that no other information is available about β.

- The independent variables are non-stochastic, meaning that it is in principle possible to repeat the sample with the same independent variables, excluding the possibility of errors in measuring these variables.

These assumptions are extremely constraining when estimating a SAM because little is known about the error structure and data are scarce. The SAM is not a model but a statistical framework where the issue is not specifying an error generating process but as a problem of measurement error.[6] Finally, data such as parameter values for previous years, which are often available when estimating a SAM, provide information about the current SAM, but this information cannot be put to productive use in the standard regression model. Compared to the standard regression model, we know little about the errors but have a lot of information in a variety of forms about the coefficients to be estimated.

We extend the cross entropy criterion to include an “errors in variables” formulation where the independent variables are assumed to be measured with noise as opposed to the “errors in equations” specification, where the process is assumed to include random noise.

Rewrite the SAM equation and the row/column sum consistency constraints as:

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[6]The problem is analogous to the distinction between errors in equations and errors in variables in standard regression analysis. See, for example, Judge *et al.* (1985). Golan and Vogel (1997) describe an errors in equations approach to the SAM estimation problem.

$$y = A\left[\bar{x} + e\right] = A\bar{x} + Ae$$
$$y = \bar{x} + e \qquad \textbf{(16)}$$

where y is the vector of row sums and x, measured with error e, is the initial known vector of column sums. Following Golan, Judge, and Miller (1994, chapter 6), we write the errors as a weighted average of known constants as follows:

$$e_i = \sum_w W_{i,w} \, \bar{v}_{i,w} \qquad \textbf{(17)}$$

subject to the weights summing to one:

$$\sum_w W_{i,w} = 1$$
$$\text{and} \qquad 0 \leq W_{i,w} \leq 1 \qquad \textbf{(18)}$$

where w is the set of weights, W. In the estimation, the weights are treated as probabilities to be estimated. The constants, v, define the "support" set for the errors and are usually chosen to yield a symmetric distribution with moments depending on the number of elements in the set w. For example, if the error distribution is assumed to be rectangular and symmetric around zero, with known upper and lower bounds, the error equation becomes:

$$e_i = W_i \, \bar{v}_i - (1 - W_i) \, \bar{v}_i \qquad \textbf{(19)}$$

In this case the variance is fixed. In general, one can add more v's and W's to incorporate more information about the error distribution (*e.g.*, more moments, including variance, skewness, and kurtosis).

Given knowledge about the error bounds, equations (17) and (18) are added to the constraint set and equation (16) replaces the SAM equation (equation 3). The problem is messier in that the SAM equation is now nonlinear, involving the product of A and e. The minimization problem is to find a set of A's and W's that minimize cross entropy including a term in the errors:

$$I(A,W:\bar{A}) = \left[\sum_i \sum_j A_{i,j} \ln A_{i,j} - \sum_i \sum_j A_{i,j} \ln \bar{A}_{i,j}\right] + \left[\sum_i \sum_w W_{i,w} \ln W_{i,w} - \sum_i \sum_w W_{i,w} \ln \frac{1}{n}\right] \quad \textbf{(20)}$$

subject to the constraint equations that column and row sums be equal, and that the *W*'s and *A*''s fall between zero and one, and any other linear known aggregation inequalities or equalities (where n is the number of elements in the set *W*,). Note that if the distribution is symmetric, then when all the *W*'s are equal, which is the default prior, all the errors are zero.[7]

We are minimizing equation 20 over the *A*'s (SAM coefficients) and *W*'s (weights on the error term), where the *W*'s are treated like the *A*'s. In the estimation procedure, the terms involving the *A*'s and *W*'s are assigned equal weights, reflecting an equal preference for "precision" (the *A*'s) in the estimates of the parameters, and "prediction" (the *W*'s) or the "goodness of fit" of the equation on row and column sums. Golan, Judge, and Miller (1996) report Monte Carlo experiments where they explore the implications of changing these weights and conclude that equal weighting of precision and prediction is reasonable.

Another source of measurement error may arise if the initial SAM, $\bar{A}$, is not itself a balanced SAM. That is, its corresponding rows and columns may not be equal. This situation does not change the cross entropy estimation procedure, but implies that it is not possible to achieve a cross entropy measure of zero because the prior is not feasible. The idea is to find a new feasible SAM that is "entropy-close" to the infeasible prior.

An Example: Mozambique

To illustrate the use of the proposed cross entropy estimator, we apply it to recover an already existing 1994 macro SAM for Mozambique (Table 3).[8] The original SAM is perturbed to be inconsistent, with some row and column sums not equal (Table 4). Starting from the perturbed inconsistent SAM as our prior, the problem is to estimate the coefficients of the original SAM.

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[7]When the error distribution is assumed to be rectangular between the upper and lower bounds, and is symmetric around zero (that is only two *W* s), equation (20) is written as:

$$\min\left[\sum_i \sum_j A_{i,j} \ln A_{i,j} - \sum_i \sum_j A_{i,j} \ln \bar{A}_{i,j} + \sum_i [\, W_i \ln W_i + (1 - W_i) \ln \frac{1}{2}\,]\right]$$

[8]Arndt, C. et al. (1997) describe the Mozambique SAM in detail.

We report the results and the efficiency gains from adding information to the estimation problem. The gains are evaluated according to how close the estimated SAM is to the initial SAM — the SAM in Table 3.

Three estimation results are reported. The first set of "Core" results are estimated under the assumption of no information and uses the core cross entropy method where only equations (11) and (12) are imposed as constraints (or equivalently, equations 1-8 in Appendix A with all error terms set to zero). The second set (Allfix) adds additional information assumed known from other sources. The additional information includes moment constraints on some row and column sums, inequality constraints, and knowledge of various economic aggregates like total consumption, exports, imports, and GDP at market prices. The third (Allfix plus error) extends the second estimation method to include the "errors in variables" formulation, adding information on additional row and column sums assumed to be measured with error. For the error term (e_i), we specify an error support set with three elements centered on zero, allowing a two-parameter symmetric distribution with unknown variance.

For each SAM estimation, Tables 5-7 report the new estimated balanced SAM along with the cell-by-cell deviation from the initial SAM. In addition, a set of estimation statistics relevant to each estimated SAM are reported in Table 2, which indicates the gains from adding information to the estimation problem.

Table 2. Estimation statistics

	Core	AllFix	Allfix plus error
Root Mean Square Error (RMSE)	2.4718	0.9406	0.7785
Coefficient RMSE	0.0112	0.0110	0.0072
CE* associated with SAM coefficients	0.0000	0.0007	0.0028
CE associated with error term	0.0000	0.0000	0.0010
Total CE	0.0000	0.0007	0.0038

Note:
Core = estimation under the assumption of no information added.
AllFix = estimation with additional information (moment constraints on some row and column sums, aggregate economic data on total consumption, exports, imports, and GDP at market prices).
AllFix plus error = AllFix + "errors in variables" formulation on remaining column sums.
* CE = cross entropy

The gains from adding information to the estimation problem are evaluated according to how close the estimated SAM is to the initial SAM, in terms of both flows and coefficients. From Table 2, the root mean square error (RMSE) for the SAM flows and the SAM coefficients, measured relative to the initial SAM, falls as we add more information to the Core estimation. A falling RMSE indicates that the estimated SAM coefficients have a smaller dispersion around their respective true values (represented by the initial SAM).

The Cross-Entropy measures reflect how much the information we have introduced has shifted our solution away from the inconsistent prior, and also accounting for the imprecision of the moments assumed to be measured with error. Intuition suggests that if the information constraints are binding the distance from the prior will increase; if none are binding then the cross entropy (CE) distance will be zero. That is, there exists a y, such that $\bar{A}y = y$. In our Core case without any constraints on the y other than that column and row sums must be equal, a solution can be found without changing the column coefficients, as indicated by a CE measure of zero.[9] We observe that, as more information is imposed, the CE measure increases as expected.

In the final estimation (AllFix with error), we impose a full set of column sums (information on y), but some are assumed to be measured with error. We end up with a CE measure associated with the error term that is larger, but the RMSE is smaller. The added information is significantly improving our estimate even when information is added in an imprecise way. The RMSE in Table 2 falls significantly as more information is used — by about 66 percent for the AllFix, and an additional 20 percent for the final estimation.

Conclusion

The cross entropy approach provides a flexible and powerful method for estimating a social accounting matrix (SAM) when dealing with scattered and inconsistent data. The method represents a considerable extension of the standard RAS method, which assumes that one starts from a consistent prior SAM and has knowledge only about row and column totals. The cross entropy framework allows a wide range of prior information to be used efficiently in estimation. The prior information can be in a variety of forms, including linear and nonlinear inequalities, errors in equations, measurement error (using an error-in-variables formulation). One also need not start from a balanced or consistent SAM. We have presented cross entropy estimation results applied to the case of a SAM for Mozambique, where we started from a perturbed inconsistent SAM as our prior. Then we measured the gains from incorporating a wide range of information from a variety of sources to improve our estimation of the SAM parameters.

[9] The CE measure associated with the error term is zero for the Core and AllFix cases because the error term is set to zero and the *column totals are free to vary*, so no constraint is imposed.

Table 3. Initial balanced 1994 Macro SAM for Mozambique (millions of 1994 meticais)

Receipts	Expenditure (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	Totals
(1) Agr. activity			25.14				30.49						55.63
(2) Non-agr. activity			12.46	206.28			2.14						220.88
(3) Agr. Commodity	1.58	13.42					20.12		0.00		0.09	8.58	43.79
(4) Non-agr. Commodity	7.24	98.86					86.72	16.78	0.00	33.94	33.03	24.13	300.69
(5) Factors	47.01	108.74											155.75
(6) Enterprises					62.86								62.86
(7) Households					91.63	58.96		1.33				3.46	155.38
(8) Rec. govt.*			0.94	9.88	1.26	2.41	2.48		5.55				22.53
(9) Indirect tax	-0.19	-0.14	0.24	5.64									5.55
(10) Govt. investment												22.94	22.94
(11) Private investment						1.49	13.42	4.43		-11.00		24.79	33.12
(12) Rest of the world			5.01	78.89									83.90
Totals	55.63	220.88	43.79	300.69	155.75	62.86	155.38	22.53	5.55	22.94	33.12	83.90	1163.02

Source: Arndt, C. et al., 1997.
* Recurrent government expenditures

Table 4. Perturbed unbalanced 1994 Macro SAM for Mozambique (millions of 1994 meticais)

	Expenditure												
Receipts	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	Totals
(1) Agr. activity			20.00 (-5.14)				30.49						50.49 (-5.14)
(2) Non-agr. activity			12.46	195.00 (-11.28)			2.14						209.60 (-11.28)
(3) Agr. Commodity	1.58	13.00 (-0.42)					20.12		0.00		0.09	8.58	43.37 (-0.42)
(4) Non-agr. Commodity	7.24	96.00 (-2.86)					86.72	16.78	0.00	32.00 (-1.94)	35.00 (-1.97)	24.13	297.86 (-2.82)
(5) Factors	47.01	108.74											155.75
(6) Enterprises					62.86								62.86
(7) Households					91.63	60.00 (-1.04)		1.33				3.46	156.42 (1.04)
(8) Rec. govt.*			0.94	9.88	1.26	2.41	2.48		5.55				22.53
(9) Indirect tax	-0.19	-0.14	0.24	5.64									5.55
(10) Govt. investment												22.94	22.94
(11) Private investment						1.49	12.00 (-1.42)	4.43		-11.00		24.79	31.70 (-1.42)
(12) Rest of the world			5.01	78.89									83.90
Totals	55.63	217.60 (-3.27)	38.65	289.41 (-11.28)	155.75	63.90 (-1.04)	153.96 (-1.42)	22.53	5.55	21.00 (-1.94)	35.09 (-1.97)	83.90	1163.02

Source: Arndt, C. et al., 1997.
* Recurrent government expenditures
Note: numbers in parenthesis represent the difference between the perturbed SAM and the true SAM of Table 3.

Table 5. Core Cross Entropy estimation for the 1994 Macro SAM for Mozambique (Core) (millions of 1994 meticais)

	Expenditure												
Receipts	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	Totals
(1) Agr. activity			21.77 (-3.37)				29.36 (-1.14)		0.00				51.13 (-4.50)
(2) Non-agr. activity			13.57 (1.11)	194.63 (-11.65)			2.06 (-0.08)		0.00				210.26 (-10.62)
(3) Agr. Commodity	1.45 (-0.13)	12.56 (-0.86)					19.37 (-0.75)		0.00		0.09 (-0.01)	8.61 (0.03)	42.08 (-1.71)
(4) Non-agr. Commodity	6.65 (-0.58)	92.76 (-6.09)					83.49 (-3.23)	16.61 (-0.17)	0.00	33.09 (-0.85)	32.04 (-0.98)	24.22 (0.08)	288.86 (-11.82)
(5) Factors	43.22 (-3.79)	105.07 (-3.67)											148.29 (-7.46)
(6) Enterprises					59.85 (-3.01)								59.85 (-3.01)
(7) Households					87.24 (-4.39)	56.20 (-2.76)		1.32 (-0.01)				3.47 (0.01)	148.22 (-7.15)
(8) Rec. govt.*			1.02 (0.08)	9.87 (-0.02)	1.20 (-0.06)	2.26 (-0.15)	2.39 (-0.09)		5.56 (0.01)				22.30 (-0.23)
(9) Indirect tax	-0.19	-0.14	0.26 (0.02)	5.63 (-0.01)									5.56 (0.01)
(10) Govt. investment											-0.93 (-0.92)	23.02 (0.08)	22.09 (-0.85)
(11) Private investment						1.39 (-0.09)	11.55 (-1.87)	4.38 (-0.05)		-11.00		24.88 (0.09)	31.20 (-1.92)
(12) Rest of the world			5.45 (0.44)	78.74 (-0.15)									84.19 (0.29)
Totals	51.13 (-4.50)	210.26 (-10.62)	42.08 (-1.71)	288.86 (-11.82)	148.29 (-7.46)	59.85 (-3.01)	148.22 (-7.15)	22.30 (-0.23)	5.56 (0.01)	22.09 (-0.85)	31.20 (-1.92)	84.19 (0.29)	

Source: Arndt, C. et al., 1997.
* Recurrent government expenditures
Note: numbers in parenthesis represent the difference between the estimated SAM and the initial SAM of Table 3.

Table 6. Cross Entropy and additional information estimation for the 1994 Macro SAM for Mozambique (AllFix) (millions of 1994 meticais)

	Expenditure												
Receipts	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	Totals
(1) Agr. activity			22.52				30.77		0.00				53.29
			(-2.62)				(0.28)						(-2.34)
(2) Non-agr. activity			14.02	203.10			2.15		0.00				219.27
			(1.55)	(-3.17)			(0.01)						(-1.61)
(3) Agr. Commodity	1.51	13.07					20.17		0.00		0.09	8.60	43.45
	(-0.07)	(-0.35)					(0.05)					(0.02)	(-0.35)
(4) Non-agr. Commodity	6.90	95.65					86.38	16.79	0.00	33.52	33.44	24.11	296.79
	(0.33)	(-3.20)					(-0.34)	(0.01)		(-0.42)	(0.41)	(-0.02)	(-3.89)
(5) Factors	45.07	110.68											155.75
	(-1.94)	(1.94)											
(6) Enterprises					62.94								62.94
					(0.08)								(0.08)
(7) Households					91.54	59.05		1.31				3.31	155.21
					(-0.08)	(0.09)		(-0.01)				(-0.15)	(-0.17)
(8) Rec. govt.*			1.05	9.78	1.27	2.38	2.52		5.55				22.53
			(0.11)	(-0.11)		(-0.03)	(0.03)						
(9) Indirect tax	-0.19	-0.14	0.27	5.61									5.55
			(0.03)	(-0.03)									
(10) Govt. investment											-0.49	23.01	22.52
											(-0.49)	(0.07)	(-0.42)
(11) Private investment						1.52	13.22	4.43		-11.00		24.87	33.04
						(0.03)	(-0.20)					(0.08)	(-0.09)
(12) Rest of the world			5.59	78.31									83.90
			(0.58)	(-0.58)									
Totals	53.29	219.27	43.45	296.79	155.75	62.94	155.21	22.53	5.55	22.52	33.04	83.90	
	(-2.34)	(-1.61)	(-0.35)	(-3.89)		(0.08)	(-0.17)			(-0.42)	(-0.09)		

Source: Arndt, C. et al., 1997.
* Recurrent government expenditures
Note: numbers in parenthesis represent the difference between the estimated SAM and the initial SAM of Table 3.

Table 7. Cross Entropy and additional column sums measured with error estimation for the 1994 Macro SAM for Mozambique (AllFix plus error) (millions of 1994 meticais)

	Expenditure												
Receipts	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	Totals
(1) Agr. activity			23.36				32.26		0.00				55.62
			(-1.78)				(1.77)						
(2) Non-agr. activity			13.40	202.98			1.68		0.00				218.06
			(0.94)	(-3.30)			(-0.46)						
(3) Agr. Commodity	1.58	13.14					19.96		0.00		0.09	8.60	43.37
		(-0.28)					(-0.16)					(0.02)	
(4) Non-agr. Commodity	7.24	96.30					85.57	16.64	0.00	33.93	33.18	24.11	296.97
		(-2.55)					(-1.15)	(-0.14)		(-0.01)	(0.16)	(-0.02)	
(5) Factors	47.00	108.76											155.75
	(-0.02)	(0.02)											
(6) Enterprises					62.86								62.86
(7) Households					91.61	58.95		1.35				3.30	155.21
					(-0.02)	(-0.01)		(0.02)				(-0.16)	
(8) Rec. govt.*			1.01	9.82	1.28	2.39	2.50		5.54				22.53
			(0.06)	(-0.06)	(0.02)	(-0.03)	(0.01)						
(9) Indirect tax	-0.19	-0.14	0.26	5.62									5.55
			(0.02)	(-0.02)									
(10) Govt. investment											0.11	22.82	22.93
												(-0.12)	
(11) Private investment						1.52	13.24	4.55		-11.00		25.07	33.38
						(0.04)	(-0.18)	(0.13)				(0.28)	
(12) Rest of the world			5.35	78.55									83.90
			(0.34)	(-0.34)									
Totals	55.62	218.06	43.37	296.97	155.75	62.86	155.21	22.53	5.55	22.93	33.38	83.90	
	(-0.02)	(-2.81)	(-0.42)	(-3.71)		(0.00)	(-0.17)			(-0.01)	(0.26)		

Source: Arndt, C. et al., 1997.

* Recurrent government expenditures

Note: numbers in parenthesis represent the difference between the estimated SAM and the initial SAM of Table 3.

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Appendix A: Mathematical Representation

Table A.1: Cross Entropy Equations

#	Equation	Description
1	$I(A,W:\bar{A}) = \left[\sum_i \sum_j A_{i,j} \ln A_{i,j} - \sum_i \sum_j A_{i,j} \ln \bar{A}_{i,j}\right] + \left[\sum_i \sum_w W_{i,w} \ln W_{i,w} - \sum_i \sum_w W_{i,w} \ln \frac{1}{n}\right]$	Cross-Entropy minimand
2	$T_{i,j} = A_{i,j}\ (\bar{X}_i + e_i)$	SAM equation
3	$Y_i = \bar{X}_i + e_i$	Row/column sum consistency
4	$e_i = \sum_w W_{i,w}\ \bar{v}_{i,w}$	Error definition
5	$\sum_j T_{i,j} = \bar{X}_i + e_i$	Row sum
6	$\sum_i T_{i,j} = Y_j$	Column sum
7	$\sum_i A_{i,j} = 1$ and $0 < A_{i,j} < 1$	Sum of Column coefficients
8	$\sum_w W_{i,w} = 1$ and $0 < W_{i,w} < 1$	Sum of weights on errors
9	$\sum_i \sum_j G_{i,j}^{(k)}\ T_{i,j} = \gamma^{(k)}$	Additional Constraints

Notation

Set

i and j	SAM accounts
w	weights on error support set

Variables

$A_{i,j}$	SAM coefficient matrix
e_i	Error variable
I	Cross Entropy measure (objective)
$T_{i,j}$	Transactions SAM
$W_{i,w}$	Error weights
Y_i	Row sum

Parameters

$\bar{A}_{i,j}$	Prior SAM coefficient matrix
$G_{i,j}^{(k)}$	k’th aggregator matrix
$\gamma^{(k)}$	k’th control total
n	number of elements in set w
$\bar{v}_{i,jwt}$	Error support values, including bounds
$\bar{X}_i$	fixed value of column sum

Appendix B: GAMS Code

Appendix B: GAMS code

What follows is a listing of the GAMS program used in illustrating the entropy difference method discussed above. A quick list of some of GAMS features are listed below. For additional information about GAMS syntax see Brooke, Kendrick, and Meeraus (1988).

In the GAMS language:

- Parameters are treated as constants in the model and are defined in separate "PARAMETER" statements.
- "SUM" is the summation operator, sigma.
- "$" introduces a conditional "if" statement.
- The suffix ".FX" indicates a fixed variable.
- The suffix ".L" indicates the level or solution value of a variable.
- The suffix ".LO" and ".UP" indicate the lower and upper bounds, respectively of a variable.
- An asterisk "*" in the first column indicates a comment. Alternative treatments in the model Code are shown commented out.
- An "ALIAS" statement is used to give another name to a previously declared set.
- A semicolon (;) terminates a GAMS statement.
- Items between slashes (/) are data or set elements.

```
$TITLE Entropy Difference. Mozambique Macro SAM
$OFFSYMLIST OFFSYMXREF OFFUPPER
*############################################################
############
*
*
* MOZAM101 start by aggregating the balanced micro SAM
reported in:
*  Arndt, Channing, et al. (1998) " Social Accounting
Matrices for
*     Mozambique 1994 and 1995" MERISSA projectworking paper
No. XX
*     IFPRI, Washington, D.C.
* The aggregated SAM is then perturbed and the Cross Entropy
Method
* is used under different assumptions about data
availability to
* re-estimate it.
*
* Programmed by Sherman Robinson, Andrea Cattaneo, and
Moataz El-Said,
* June 1998.
* Trade and Macroeconomics Division
* International Food Policy Research Institute (IFPRI)
* 2033 K St., N.W.
* Washington, DC 20006 USA
* Email: S.Robinson@CGIAR.ORG
*        A.Cattaneo@CGIAR.ORG
*        M.El-Said@CGIAR.ORG
*
* Method described in S. Robinson and M. El Said,
"Estimating a Social
* Accounting Matrix Using Cross Entropy Methods." September
1997.
* See also A. Golan, G. Judge, and D. Miller, Entropy
Difference
* Econometrics, John Wiley & Sons, 1996.
*
* Based on program used in C. Arndt, A. S. Cruz, H. T.
Jensen,
* S. Robinson, and F. Tarp, "A Social Accounting Matrix for
Mozambique:
* Base Year 1994." Institute of Economics, University of
Copenhagen,
* March 1997.
*
* Original version programmed by Sherman Robinson and Andrea
Cattaneo.
*
```

```
*################################################################
#######
SETS


i      macrosam accounts /  AGRA   Agricultural activities
                            NAGRA  Non agricultural activities
                            AGRC   Agricultural Commodities

                            NAGRC  Non agricultural Commodities

                            FAC    Factors
                            ENT    Enterprises
                            HOU    Households
                            GRE    Govt recurrent expenditures
                            ITAX   Indirect taxes
                            GIN    Govt investment
                            CAP    Capital account
                            ROW    Rest of world

                            TOTAL                /


ii(i)   all acounts in i except TOTAL

* For a uniform distribution, set jwt to only two entries. Error
* range set below with the vbar parameter.

jwt     weights on errors in variables     / 1*3 /

AA(i)   activity                            /AGRA
                                             NAGRA  /

CC(i)   Commodity                           /AGRC
                                             NAGRC  /

F(i)    Factors                             /FAC    /

H(i)    Households                          /HOU    /

G(i)    Government and Investment accounts  /GRE
                                             ITAX
                                             GIN
                                             CAP    /

FIX(i)  Accounts to be fixed when solving core with allfix
                                            / FAC, GRE, ITAX, ROW
/
;
```

```
ii(i)       = YES;
ii("Total") = NO;

ALIAS (AA,AAP), (CC,CCP), (F,FP), (H,HP) ;
ALIAS (i,j), (ii,jj);


*#########################    SAM DATABASE
#############################
*Initial balanced Macro SAM (aggregate of Micro SAM /
parameter SAM1)

Table SAM1(i,j)     Social accounting matrix

             AGRA       NAGRA        AGRC       NAGRC
FAC         ENT

AGRA                               25.140
NAGRA                              12.464     206.275
AGRC        1.578      13.419
NAGRC       7.235      98.855
FAC        47.012     108.740
ENT
62.860
HOU
91.629      58.961
GRE                                 0.941       9.885
1.263       2.414
ITAX       -0.194      -0.135       0.239       5.636
CAP
          1.485
ROW                                 5.007      78.892
TOTAL      55.631     220.879      43.792     300.687
155.752      62.860

    +         HOU         GRE        ITAX         GIN
CAP         ROW

AGRA       30.491
NAGRA       2.140
AGRC       20.120             -2.40000E-4
0.095       8.581
NAGRC      86.720      16.778 -2.20000E-4      33.942
33.027      24.131
HOU                     1.331
          3.457
GRE         2.485                   5.547
GIN
    22.942
CAP        13.422       4.426                 -11.000
    24.789
TOTAL     155.377      22.534       5.546      22.942      33.121
    83.899

    +       TOTAL

AGRA       55.631
NAGRA     220.879
AGRC       43.792
NAGRC     300.687
FAC       155.752
ENT        62.860
HOU       155.377
GRE        22.534
ITAX        5.546
GIN        22.942
CAP        33.121
ROW        83.899
TOTAL    1163.020
;

 SAM1("TOTAL",jj)          = sum(ii, SAM1(ii,jj));
 SAM1(ii,"TOTAL")          = sum(jj, SAM1(ii,jj));


*##########################  Parameters and Scalars
########################
PARAMETER

 SAM(i,j)          Base SAM transactions matrix (in 100 bn. of
1995 Meticais)
 SAM0(i,j)         Base SAM transactions matrix (used for
comparison reports)
 SAM2(i,j)         Base perturbed SAM transactions matrix (used
for comparison)
 DIFF(i,j)         Difference between SAM and SAM0
 PERCENT(i,j)      Percent change of SAM from SAM0
 T0(i,j)           Matrix of SAM transactions (flow matrix)
 T00(i,j)          Matrix of SAM transactions (flow matrix)
 T1(i,j)           Adjusted matrix of SAM transactions for
negative coefficients
 T2(i,j)           Adjusted original matrix of SAM transact for
(-)ve coefficients
 Abar0(i,j)        Prior SAM coefficient matrix
 Abar1(i,j)        Adjusted prior SAM coefficient matrix for
negative coefficients
```

```
 Abar00(i,j)      Prior SAM coefficient matrix
 Abar11(i,j)      Adjusted prior SAM coefficient matrix for
negative coefficients
 Target0(i)       Targets for macro SAM column totals
 Vbar(i,jwt)      Error bounds
 DELTA            Tolerance to allow zero entries in new SAM
;

SCALARS

 sumtarg0         sum of targets
 TM0              Total imports
 TX0              Total exports
 TC0              Total household consumption
 TVA0             total value added from true SAM
 GDPMP0           GDP at market prices

;
*############ Setting SAM to aggregated SAM1 then perturbing
it ############

 SAM(i,j)       = SAM1(i,j);
 SAM0(i,j)      = SAM(i,j);

* Perturbing Domestic sales
 SAM("AGRA","AGRC")    =  20.00;
 SAM("NAGRA","NAGRC")  = 195.00;

* Perturbing Intermediate demand
 SAM("AGRC","NAGRA")   = 13.00;
 SAM("NAGRC","NAGRA")  = 96.00;

* Perturbing Enterprise payment to Household
 SAM("HOU","ENT")      = 60.00;

* Perturbing Household Savings
 SAM("CAP","HOU")      = 12.00;

* Perturbing Government investment (Gov't Investment to
commodities)
 SAM("NAGRC","GIN")    = 32.00;

* Perturbing investment (Capital payment to commodities)
 SAM("NAGRC","CAP")    = 35.00;

* ############## calculating totals

SAM("TOTAL",jj)          = sum(ii, SAM(ii,jj));
SAM(ii,"TOTAL")          = sum(jj, SAM(ii,jj));

SAM2(i,j)              = SAM(i,j);
DIFF(i,j)              = SAM(i,j) - SAM0(i,j) ;
PERCENT(i,j)$SAM(i,j)  = 100*(SAM(i,j) - SAM0(i,j))/SAM0(i,j);


Display SAM, SAM0, DIFF, PERCENT;

*#################  Divide SAM entries by 10 for better scaling

 SAM(i,j)       = sam(i,j)/10;
 SAM1(i,j)      = sam1(i,j)/10;

*################# Initializing Parameters

 Abar0(ii,jj)$SAM(ii,jj)    = SAM(ii,jj)/SAM("TOTAL",jj) ;
 Abar00(ii,jj)$SAM1(ii,jj)  = SAM1(ii,jj)/SAM1("TOTAL",jj) ;

 T0(ii,jj)                 = SAM(ii,jj);
 T0("TOTAL",jj)            = SUM(ii, SAM(ii,jj));
 T0(ii,"TOTAL")            = SUM(jj, SAM(ii,jj));

 T00(ii,jj)                = SAM1(ii,jj);
 T00("TOTAL",jj)           = SUM(ii, SAM(ii,jj));
 T00(ii,"TOTAL")           = SUM(jj, SAM(ii,jj));

 DELTA                     = .000001;

 Display T0, Abar0, sam0 ;

*########################  CROSS ENTROPY
###############################


*########################  RED ALERT!!!
###############################

* The ENTROPY DIFFERENCE procedure uses LOGARITHMS: negative
flows in
* the SAM are NOT GOOD!!!
*
* The option used here is to detect any negative flows and net
them out
* of their respective symmetric cells, e.g.
*           negative flow ACT ---> GRE is set to zero
*           and ADDED  to GRE ---> ACT as a positive number.
* The entropy difference method can then be implemented.
* After balancing, the negative SAM values are returned to their
* original cells for printing.
```

```
SET
 red(i,j)            Set of negative SAM flows
;

Parameter
 redsam(i,j)         Negative SAM values only
 rtot(i)             Row total
 ctot(i)             Column total

 redsam1(i,j)        Negative SAM values only
 rtot1(i)            Row total
 ctot1(i)            Column total

;

 rtot(ii)                                   = sum(jj, T0(ii,jj));
 ctot(jj)                                   = sum(ii, T0(ii,jj));
 rtot1(ii)                                  = sum(jj, T00(ii,jj));
 ctot1(jj)                                  = sum(ii, T00(ii,jj));

 red(ii,jj)$(T0(ii,jj) LT 0)                = yes ;
 redsam(ii,jj)                              = 0;
 redsam(ii,jj)$red(ii,jj)                   = T0(ii,jj);
 redsam(jj,ii)$red(ii,jj)                   = T0(ii,jj);

 red(ii,jj)$(T00(ii,jj) LT 0)               = yes ;
 redsam1(ii,jj)                             = 0;
 redsam1(ii,jj)$red(ii,jj)                  = T00(ii,jj);
 redsam1(jj,ii)$red(ii,jj)                  = T00(ii,jj);


*Note that redsam includes each entry twice, in
corresponding row
*and column. So, redsam need only be subtracted from T0.
 T1(ii,jj)                                  = T0(ii,jj) -
redsam(ii,jj);
 T1("Total",jj)                             = sum(ii, T1(ii,jj));
 T1(ii,"Total")                             = sum(jj, T1(ii,jj));

 T2(ii,jj)                                  = T00(ii,jj) -
redsam1(ii,jj);
 T2("Total",jj)                             = sum(ii, T2(ii,jj));
 T2(ii,"Total")                             = sum(jj, T2(ii,jj));


 redsam("total",jj)                         = sum(ii,
redsam(ii,jj));
 redsam(ii,"total")                         = sum(jj, redsam(ii,jj));

 redsam1("total",jj)                         = sum(ii, redsam1(ii,jj));
 redsam1(ii,"total")                         = sum(jj, redsam1(ii,jj));

 sam(ii,"total")                            = sum(jj, T1(ii,jj));
 sam("total",jj)                            = sum(ii, T1(ii,jj));

 sam1(ii,"total")                            = sum(jj, T2(ii,jj));
 sam1("total",jj)                            = sum(ii, T2(ii,jj));

 rtot(ii)                                   = sum(jj, T1(ii,jj));
 ctot(jj)                                   = sum(ii, T1(ii,jj));

 rtot1(ii)                                   = sum(jj, T2(ii,jj));
 ctot1(jj)                                   = sum(ii, T2(ii,jj));

 Abar1(ii,jj)                               = T1(ii,jj)/sam("total",jj);
 Abar11(ii,jj)                              =
T2(ii,jj)/sam1("total",jj);

 display "NON-NEGATIVE SAM" ;
 display redsam, T1, T2, Abar0, Abar1, rtot, ctot ;


*##### Initializing Parameters after accounting for negative
values #######
*SR Note that target column sums are being set to average of
initial
*   row and column sums. Initial column sums could have been used
instead,
*   depending on data quality and prior knowledge.

  target0(ii)          = (sam(ii,"total") +  sam("total",ii))/2 ;
  target0(aa)          = sam("total",aa) ;
  target0(cc)          = sam(cc,"total") ;
  target0("ent")       = sam("ent","total") ;
  target0("gin")       = sam("gin","total") ;
  sumtarg0             = sum(ii, sam(ii,"total") );
  TM0                  = SUM(CC, T2("ROW",CC));
  TX0                  = SUM(CC, T2(CC,"ROW"));
  TVA0                 = T2("FAC","AGRA") + T2("FAC","NAGRA");
  TC0                  = SUM((AA,H), T2(AA,H)) + SUM((CC,H),
T2(CC,H));
  GDPMP0               = TC0 + TX0 + SUM((CC,G), T2(CC,G)) - TM0;

 Display TVA0, TC0, TX0, TM0, GDPMP0;
*###################### VARIABLES
########################################
```

```
VARIABLES
 A(i,j)          Post SAM coefficient matrix
 TSAM(i,j)       Post matrix of SAM transactions
 Y(i)            row sum of SAM
 X(i)            column sum of SAM
 ERR(i)          Error value
 W(i,jwt)        Error weight
 DENTROPY        Entropy difference (objective)

 TVA             Total value added or GDP at factor cost
 TC              Total consumption
 TX              Total exports
 TM              Total imports
 GDPMP           GDP at market prices

  ;

*######################### INITIALIZE VARIABLES
##########################

 A.L(ii,jj)          = Abar1(ii,jj) ;
 TSAM.l(ii,jj)       = T1(ii,jj);
 Y.L(ii)             = target0(ii) ;
 X.L(ii)             = target0(ii) ;
 ERR.L(ii)           = 0.0 ;
 W.L(ii,jwt)         = 1/card(jwt) ;
 DENTROPY.L          = 0;

 TVA.L               = TVA0;
 TC.L                = TC0;
 TX.L                = TX0;
 TM.L                = TM0;
 GDPMP.L             = GDPMP0;

Display TM.l;

*############ CORE EQUATIONS
 EQUATIONS

 SAMEQ(i)        row and column sum constraint
 SAMMAKE(i,j)    make SAM flows
 ERROREQ(i)      definition of error term
 SUMW(i)         Sum of weights
 ENTROPY         Entropy difference definition
 ROWSUM(i)       row target
 COLSUM(j)       column target
 COLSUM2(j)      column coefficients
```

```
*############ EQUATIONS IMPOSING KNOWN INFORMATION

 TOTVA           Total value added is known
 TOTC            Total Consumption
 TOTX            Total exports
 TOTM            Total Imports
 TOTGDP          GDP at market prices

 ;

*CORE
EQUATIONS======================================================


 SAMEQ(ii)..      Y(ii)       =E= X(ii) + ERR(ii) ;

 SAMMAKE(ii,jj)$(Abar1(ii,jj))..
                  TSAM(ii,jj) =E= A(ii,jj) * (X(jj) + ERR(jj)) ;

 ERROREQ(ii)..    ERR(ii)     =E= SUM(jwt,
W(ii,jwt)*vbar(ii,jwt)) ;

 SUMW(ii)..       SUM(jwt, W(ii,jwt)) =E= 1 ;

 ENTROPY..        DENTROPY    =E= SUM((ii,jj)$(Abar1(ii,jj)),
                                  A(ii,jj)*(LOG(A(ii,jj) + delta)
                                  - LOG(Abar1(ii,jj) + delta)))

                                  + SUM((ii,jwt), W(ii,jwt)
                                  * (LOG(W(ii,jwt) + delta)
                                  - LOG((1/card(jwt)) + delta)) )
;

 ROWSUM(ii)..     SUM(jj, TSAM(ii,jj)) =E= Y(ii) ;

 COLSUM(jj)..     SUM(ii, TSAM(ii,jj)) =E= (X(jj) + ERR(jj)) ;

 COLSUM2(jj)..    SUM(ii, A(ii,jj)) =E= 1;

*ADDITIONAL MACRO CONTROL-TOTAL
EQUATIONS===========================

TOTVA..            TVA   =E= TSAM("FAC","AGRA") +
TSAM("FAC","NAGRA");

TOTC..             TC    =E= SUM((AA,H), TSAM(AA,H))
                                + SUM((CC,H), TSAM(CC,H));

TOTX..             TX    =E= SUM(CC, TSAM(CC,"ROW"));
```

```
TOTM..             TM    =E= SUM(CC, TSAM("ROW",CC));

TOTGDP..           GDPMP =E= TC + TX + SUM((CC,G),
TSAM(CC,G)) - TM;


*################  Defining bounds for cell values
########################

 A.LO(ii,jj)$ABAR1(ii,jj)          = 0 ;
 A.UP(ii,jj)$ABAR1(ii,jj)          = 1 ;
 A.FX(i,j)$(NOT Abar1(i,j))        = 0;

 TSAM.lo(ii,jj)                    = 0.0 ;
 TSAM.up(ii,jj)                    = +inf ;
 TSAM.FX(ii,jj)$(NOT Abar1(ii,jj)) = 0 ;


*########################### Solve statenment
#############################

Scalars


Core     to solve model using core equations
     /1/
Colfix   to solve using core equations plus some column
total      /0/
hhldfix  colfix plus total household consumption known
     /0/
Expfix   hhldfix plus total exports known
     /0/
Impfix   Expfix plus total imports known
     /0/
Allfix   Impfix plus GDP at mkt prices known
     /0/
CoreER   to solve model using core equations
     /0/
AllfixER Impfix plus GDP at mkt prices known
     /0/
;

*###############  Define variables bounds on errors
#######################
* VBAR parameter defines upper and lower bounds on
rectangular error
* distribution on variable X. Here they are set at the
difference between
* the min and max column and row sums.
```

```
vbar(ii,"1")           =  .10*target0(ii) ;
vbar(ii,"3")           = -.10*target0(ii) ;
vbar(fix,"1")          = .0*target0(fix) ;
vbar(fix,"3")          = .0*target0(fix) ;
* vbar(ii,"1")          =  1*abs(rtot(ii)-ctot(ii)) ;
* vbar(ii,"3")          = -1*abs(rtot(ii)-ctot(ii)) ;
*SR to use only two weights, delete set element "2" in jwt and
*comment out next statement.
 vbar(ii,"2")          = 0.0 ;
 W.LO(ii,jwt)          = 0 ;
 W.UP(ii,jwt)          = 1 ;


*SR fix errors to zero by fixing weights at 1/3.
 W.FX(ii,jwt)          = 1/card(jwt) ;

 Display vbar ;

*########################### DEFINE MODEL
#################################


* Model with core equations only
 MODEL SAMENTRP0 /
                  SAMEQ
                  SAMMAKE
                  ERROREQ
                  SUMW
                  ENTROPY
                  ROWSUM
                  COLSUM
                  COLSUM2
                   /

 MODEL SAMENTROP / ALL /

*############################ SOLVE MODEL
################################

 OPTION ITERLIM = 5000;
 OPTION LIMROW  = 3000, LIMCOL = 3000;
 OPTION SOLPRINT = ON;

* SAMENTROP.holdfixed = 1 ;
* SAMENTROP.optfile   = 1 ;
  option NLP         = MINOS5 ;
* OPTION NLP         = CONOPT;
* SAMENTROP.WORKSPACE = 25.0;
```

```
*#################### Apply CE using core equations
######################

IF(Core,

* X.FX(ii)               = TARGET0(ii) ;
 SOLVE SAMENTRP0 using nlp minimizing dentropy ;
 display "CORE"
;

ELSE

);

*### Apply CE using core equations plus knowledge of some
column totals ###

IF(colfix,

*Set target column sums, X (assuming we know some column
totals)
* X.FX(ii)              = TARGET0(ii) ;
 X.FX("FAC")            = TARGET0("FAC") ;
 X.FX("GRE")            = TARGET0("GRE") ;
 X.FX("ITAX")           = TARGET0("ITAX") ;
 X.FX("ROW")            = TARGET0("ROW") ;

 SOLVE SAMENTROP using nlp minimizing dentropy ;
 display "colfix"
 ;

ELSE

);

*############ Apply CE using core equations + Colfix +
hhldfix ############

IF(hhldfix,

 X.FX("FAC")            = TARGET0("FAC") ;
 X.FX("GRE")            = TARGET0("GRE") ;
 X.FX("ITAX")           = TARGET0("ITAX") ;
 X.FX("ROW")            = TARGET0("ROW") ;
 TC.FX                  = TC0;

 SOLVE SAMENTROP using nlp minimizing dentropy ;
 display "colfix + hhldfix"
 ;
ELSE

);

*##### Apply CE using core equations + Colfix + hhldfix + expfix
#########

IF(expfix,

 X.FX("FAC")            = TARGET0("FAC") ;
 X.FX("GRE")            = TARGET0("GRE") ;
 X.FX("ITAX")           = TARGET0("ITAX") ;
 X.FX("ROW")            = TARGET0("ROW") ;
 TC.FX                  = TC0;
 TX.FX                  = TX0;

 SOLVE SAMENTROP using nlp minimizing dentropy ;
 display "colfix + hhldfix + expfix"
 ;

ELSE

);

*## Apply CE using core equations + Colfix + hhldfix + expfix +
impfix ####

IF(impfix,

 X.FX("FAC")            = TARGET0("FAC") ;
 X.FX("GRE")            = TARGET0("GRE") ;
 X.FX("ITAX")           = TARGET0("ITAX") ;
 X.FX("ROW")            = TARGET0("ROW") ;
 TC.FX                  = TC0;
 TX.FX                  = TX0;
* TM.FX                 = TM0;
 TM.LO                  = TM0 - 0.0001;
 TM.UP                  = TM0 + 0.0001;

 SOLVE SAMENTROP using nlp minimizing dentropy ;
 display "colfix + hhldfix + expfix + impfix"
 ;

ELSE

);

*## Apply CE using core eqns + Colfix + hhldfix + expfix + impfix
+ GDPMP ####
```

```
IF(allfix,

 X.FX("FAC")              = TARGET0("FAC") ;
 X.FX("GRE")              = TARGET0("GRE") ;
 X.FX("ITAX")             = TARGET0("ITAX") ;
 X.FX("ROW")              = TARGET0("ROW") ;
 TC.FX                    = TC0;
 TX.FX                    = TX0;
* TM.FX                   = TM0;
 TM.LO                    = TM0 - 0.0001;
 TM.UP                    = TM0 + 0.0001;
 GDPMP.FX                 = GDPMP0;

 SOLVE SAMENTROP using nlp minimizing dentropy ;
 display "colfix + hhldfix + expfix + impfix + GDPMP"
 ;

ELSE

);

*################# Apply CE using core eqns + ERROR
######################

IF(CoreER,

 X.FX(ii)                 = TARGET0(ii) ;
 W.LO(ii,jwt)             = 0 ;
 W.UP(ii,jwt)             = 1 ;

 SOLVE SAMENTRP0 using nlp minimizing dentropy ;
 display "CoreER"
 ;

ELSE

);

*# Apply CE using core eqns + Colfix + hhldfix + expfix +
impfix + GDPMP + ERROR ##

IF(AllfixER,

 W.LO(ii,jwt)             = 0 ;
 W.UP(ii,jwt)             = 1 ;
 X.FX(ii)                 = TARGET0(ii) ;
 TC.FX                    = TC0;
 TX.FX                    = TX0;
* TM.FX                   = TM0;
 TM.LO                    = TM0 - 0.0001;
 TM.UP                    = TM0 + 0.0001;
 GDPMP.FX                 = GDPMP0;

 SOLVE SAMENTROP using nlp minimizing dentropy ;
 display "colfix + hhldfix + expfix + impfix + GDPMP + Error";

);

*#################################################################
##########

*---------------- Parameters for reporting results
Parameters
 Macsam1(i,j)           Assigned new balanced SAM flows from
entropy diff
 Macsam2(i,j)           Balanced SAM flows from entropy diff x 10
 SEM                    Squared Error Measure
 percent1(i,j)          percent change of new SAM from original
SAM
 PosUnbal(i,j)          Positive unbalanced SAM
 PosBalan(i,j)          Positive balanced SAM
 Diffrnce(i,j)          Differnce btw original SAM and estimated
SAM in values
 Diffr(i,j)             Differnce btw PERTURBED SAM and estimated
SAM in values
 Percent1(i,j)          Differnce btw original SAM and estimated
SAM in values
 Percent2(i,j)          Differnce btw PERTURBED SAM and estimated
SAM in values
 Chisq                  Chi-squared staistic
 Chisq1                 Chi-squared staistic component1
 Chisq2                 Chi-squared staistic component2
 Chisq3                 Chi-squared staistic component3
 ChisqTot               Chisq1 * Chisq2 * Chisq3

 Count(i,j)

 RMSE                   Root Mean Square Error
 AAE                    Ave absolute error

 RMSEP                  Root Mean Square Error relative to
perturbed SAM
 AAEP                   Ave absolute error relative to perturbed
SAM

 CRMSE                  Coefficients Root Mean Square Error
 CAAE                   Coefficients Ave absolute error
```

```
 CRMSEP                  Coefficients Root Mean Square Error
relative to perturbed SAM
 CAAEP                   Coefficients Ave absolute error
relative to perturbed SAM


 DENTROPY0               CE metric (excluding the error term)
 DENTROPY1               CE metric including the error term
 DENTROPY2               CE metric for the error term
 DENTROPY3               DENTROPY0 + DENTROPY2

 ABAR10(i,j)
 ABAR110(i,j)
 ADOTL(i,j)
 CDIFF(i,j)              Coefficient Abar and A difference

* NormEntrop              Normalized Entropy a measure of
total uncertainty
 ;

 macsam1(ii,jj)          = TSAM.l(ii,jj);
 macsam1("total",jj)     = SUM(ii, macsam1(ii,jj)) ;
 macsam1(ii,"total")     = SUM(jj, macsam1(ii,jj)) ;
 macsam2(i,j)            = macsam1(i,j) * 10 ;
 SEM                     = Sum((ii,jj), SQR(A.L(ii,jj) -
Abar1(ii,jj)))/SQR(9);
 PosUnbal(i,j)           = T1(i,j) * 10;
 PosBalan(i,j)           = macsam2(i,j);
* NormEntrop              = SUM((ii,jj)$(Abar1(ii,jj)),
A.L(ii,jj)*
*                           LOG (A.L(ii,jj))) /
SUM((ii,jj)$(Abar1(ii,jj)),
*                           Abar1(ii,jj)* LOG (Abar1(ii,jj)))
 ;
 display macsam1, macsam2, sem, dentropy.l, PosUnbal,
PosBalan;
* display NormEntrop ;

*############ Return negative flows to initial cell position
##############

 macsam1(ii,jj)          = macsam1(ii,jj) + redsam(ii,jj) ;
 macsam1("total",jj)     = SUM(ii, macsam1(ii,jj)) ;
 macsam1(ii,"total")     = SUM(jj, macsam1(ii,jj)) ;
 macsam2(i,j)            = macsam1(i,j) * 10 ;
 Diffrnce(i,j)           = macsam2(i,j) - SAM0(i,j);
 Diffr(i,j)              = macsam2(i,j) - SAM2(i,j);
 PERCENT1(i,j)$SAM(i,j) = 100*(macsam2(i,j) -
SAM0(i,j))/SAM0(i,j);
 PERCENT2(i,j)$SAM(i,j) = 100*(macsam2(i,j) -
SAM2(i,j))/SAM2(i,j);

 Chisq                   =
-2*(sum((ii,jj)$(Abar1(ii,jj)),Abar1(ii,jj)
                                *log(Abar1(ii,jj) +
delta)))

                                *(1-   (
(sum((ii,jj),A.l(ii,jj)
                                       *log(A.l(ii,jj) +
delta)))
                                              /

((sum((ii,jj),(Abar1(ii,jj) + delta)
                                      *log(Abar1(ii,jj) +
delta))))  )     );
```

```
 Chisq1                  =
-2*(sum((ii,jj)$(Abar1(ii,jj)),Abar1(
                                 *lo
 ;

 Chisq2                  = ((sum((ii,j
                                 *lo
                                 ((s
delta)
                                 *lo
;

 Chisq3                  = (1-  ((sum(
                                 *lo
                                 ((s
delta)
                                 *lo
;

 ChisqTot                = Chisq1 * Ch

 Count(ii,jj)$SAM0(ii,jj)=1;

 RMSE                     = Sqrt(Sum((
sqr(diffrnce(ii,jj)))/

sum((ii,jj),count(ii,jj)))  ;

 AAE                      = sum((ii,jj

sum((ii,jj),count(ii,jj));

 CRMSE                    = Sqrt(Sum((
sqr(A.L(ii,jj)-Abar11(ii,jj)))/

sum((ii,jj),count(ii,jj)))  ;

 CAAE                     = sum((ii,jj
Abar11(ii,jj)) ))/

sum((ii,jj),count(ii,jj));

 RMSEP                    = Sqrt(Sum((

sum((ii,jj),count(ii,jj)))  ;

 AAEP                     = sum((ii,jj

sum((ii,jj),count(ii,jj));

 CRMSEP                   = Sqrt(Sum((
sqr(A.L(ii,jj)-Abar1(ii,jj)))/

sum((ii,jj),count(ii,jj)))  ;

 CAAEP                    = sum((ii,jj
Abar1(ii,jj)) ))/

sum((ii,jj),count(ii,jj));

 ABAR10(ii,jj)           = Abar1(ii,jj

 ABAR110(ii,jj)          = Abar11(ii,j

 ADOTL(ii,jj)            = A.L(ii,jj);

 CDIFF(ii,jj)            = A.L(ii,jj)-
```

```
 DENTROPY0    = DENTROPY.L - SUM((ii,jwt), W.L(ii,jwt)
                             * (LOG(W.L(ii,jwt) + delta)
                             - LOG(1/card(jwt)+ delta)) )  ;

 DENTROPY1    = DENTROPY.L;

 DENTROPY2    = SUM((ii,jwt), W.L(ii,jwt)*LOG(W.L(ii,jwt) +
delta)) -
                SUM((ii,jwt), W.L(ii,jwt)*LOG(1/card(jwt)+
delta))   ;

 DENTROPY3    =  DENTROPY0 + DENTROPY2;
;

 display macsam1, macsam2, Diffrnce,  Diffr, PERCENT1,
PERCENT2, count,chisq, RMSE,
         AAE, CRMSE, CAAE, DENTROPY0, DENTROPY1, DENTROPY2,
DENTROPY3,
         ABAR10, ABAR110, ADOTL, CDIFF;
```

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Copies can be obtained by calling
Maria Cohan at 202-862-5627
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