

**Reconciling the System of U.S. Accounts and Distribution of the
Aggregate Statistical Discrepancy
(First Draft. Please do not circulate)**

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Abstract

This paper describes and illustrates a generalized least squares (GLS) method that systematically incorporates all available information on relative reliability of initial data in reconciling a disaggregated system of accounts. The GLS method is applied to reconciling the 2002 U.S. Input-Output accounts, GDP-by-industry accounts, and final expenditures from National Income and Product Accounts. The results show that using estimated relative reliabilities of initial data to remove inconsistencies in different sets of accounts produces a statistically meaningful balanced system of accounts. The estimated distribution of the statistical discrepancies by industry and by expenditure category traces the aggregate statistical discrepancy to its sources. The study demonstrates the empirical feasibility and computational efficiency of using a relative reliability-based GLS method to reconcile a large system of national accounts.

1. Introduction

Systems of national accounts are constructed using data from a variety of sources, and, thus, typically contain various types of measurement errors. Initial estimates of national accounts items rarely satisfy all accounting identities and restrictions of the system. The usual balancing procedure is to use accounting identities from different parts of the system to reduce measurement errors as much as possible and to record the residual between the major aggregates. For example, the Bureau of Economic Analysis (BEA) publishes estimates of U.S. Gross Domestic Product (GDP) and Gross Domestic Income (GDI). Although the two estimates are conceptually equivalent, the actual estimates are inconsistent. The residual between estimated GDP and estimated GDI is the aggregate statistical discrepancy. Currently there are no estimates of statistical discrepancy by industry and by expenditure category. Lack of such information hinders a good understanding of the sources of aggregate inconsistency and makes it difficult to identify improvements in source data and estimation methods needed to minimize the statistical discrepancy.

Traditional balancing procedures are purely numerical and often conducted manually. Automatic balancing using numerical procedures, such as the Iterative Proportional Fitting (Raking) method (Deming and Stephan, 1940), are sometimes done in the final stage. Stone et al. (1942) proposed a generalized least squares (GLS) method for reconciling national accounting matrices according to data reliabilities which are determined by measurement errors. The GLS reconciliation method has two empirical advantages. First, it has a firm Bayesian foundation and allows information on relative reliabilities of initial data to be used efficiently in the reconciliation process. Using this method, reconciliation is achieved by trading off relative degrees of uncertainty of data items in the system in order to adjust initial estimates to satisfy accounting constraints. Second, it provides flexibility to the balancing process by allowing, for example, reconciliation to be conducted hierarchically (Dagum and Cholette, 2006) and additional constraints to be easily imposed (Barker et al., 1984).

However, it was not practical to implement the GLS method (Stone et al., 1942) in large systems of accounts due to its large

computational requirement. Thus, the RAS method (Bacharach, 1965) became very popular for balancing input-output matrices. The RAS method, however, does not allow varying degrees of uncertainty in initial estimates and constraints, provides dubious economic interpretation of the balancing results, and requires a large number of iterations for convergence. Byron (1978) introduced a more efficient alternative based on the conjugate gradient algorithm and, thus, made it empirically feasible to implement the GLS method in large accounting systems. The GLS reconciliation method has since been further developed (Stone, 1982; van der Ploeg, 1982a, b; Bartholdy, 1991; Weale, 1992), and its feasibility has been demonstrated by van der Ploeg (1982a, 1988) and Barker et al. (1984).

Despite these developments, the GLS reconciliation method has not been widely adopted by national accounting systems since its first inception by Byron (1978) for two reasons. The first obstacle, which has been overcome, was the large required computer memory for reconciling large systems of accounts. The second obstacle was, and still is, insufficient objective information on reliability of initial data. In previous applications, reliability of initial data was set subjectively (van der Ploeg, 1982a; Barker et al, 1984; Beaulieu and Bartelsman, 2004). Reconciliation based on subjectively set reliabilities may lead to incorrectly reconciled accounts and an inaccurately estimated distribution of the aggregate statistical discrepancy. The difficulty in obtaining sufficient information on measurement errors in initial data largely explains why the GLS reconciliation method has not been implemented widely by national accounting systems more than six decades after it was first introduced. The few countries (e.g. Australia, Canada, and UK) that publish reconciled annual estimates of GDP derive it as an average of GDP estimated via production, expenditures, and income approaches.

In a recent study (Chen, 2006) a generalized least squares (GLS) method was applied to reconciling, using the 1997 data, the U.S. industry accounts with GDP estimated via expenditure approach according to the estimated reliabilities of initial estimates in the industry accounts. The study made a first attempt to systematically collect all available objective information on the reliability of initial data and to use that information to reconcile the accounts. In that study, the GLS method produced a balanced system of industry accounts and

estimated distribution of statistical discrepancy by industry. However, in that study, initial estimates of final expenditures were considered final and were not adjusted. Consequently, the aggregate statistical discrepancy was distributed entirely to the income side of the industry accounts. Although there were institutional justifications for not adjusting initial estimates of final expenditures, not allowing them to be adjusted implied zero measurement errors in initial estimates of final expenditures. This is an assumption not supported by empirical statistics.

The objective of this study is to extend the GLS method to reconcile the system of U.S. national accounts by allowing all initial data items to be adjusted according to their estimated reliabilities and to estimate distribution of the aggregate statistical discrepancy by industry and by final expenditure category. The GLS method is applied to reconciling the 2002 benchmark U.S. Input-Output (IO) accounts, the GDP-by-industry accounts, and final expenditures from the national income and product accounts at the level of detail of 65 industries (See Appendix) 69 commodity groups, 3 value-added (VA) components, 13 final expenditure categories including exports and imports. Before reconciliation, initial estimates in the IO accounts were not balanced; initial estimates of VA from the IO and the GDP-by-industry accounts were not consistent; and initial estimates of VA from neither set of industry accounts were consistent with the expenditure-based GDP.

The GLS method produced a balanced system of U.S. national accounts. The results show that using estimated relative reliabilities of initial data to reconcile different sets of accounts produces statistically meaningful balanced estimates. The distribution of the statistical discrepancy by industry and by expenditure category properly reflects the sources of the aggregate discrepancy. Moreover, this study demonstrates the empirical feasibility and computational efficiency of implementing the GLD method in a large system of national accounts according estimated relative reliabilities of initial data.

The plan for the paper is as follows. Section 2 discusses the major problems in the 2002 U.S. data. Section 3 describes the GLS method and a sensitivity analysis of the method. Section 4 discusses the reliability of initial data. Section 5 reports and discusses the balanced results. Section 6 concludes the paper.

2. Major Problems in the 2002 Data

U.S. industry accounts measure GDP by industry using production and income data. In the IO accounts, GDP produced by an industry is the VA of that industry, measured as the residual between industry gross output and intermediate inputs. VA of all industries from production must sum to GDP measured via the expenditure approach. In the GDP-by-industry accounts, VA of an industry measures the total income of that industry, and VA estimates of all industries sum to GDI. In theory, GDP estimated from production and income data should be equivalent to expenditure-based GDP. However, actual estimates are not. The presence of inconsistencies in GDP estimated via production, income and expenditure approaches are due to various sources of errors in initial data. There are four major sources of errors identified in initial estimates in the 2002 IO and GDP-by-industry accounts.

The first major source of errors was inconsistencies caused by differences in definitions and classifications of variables, data collection and estimation methods used by different statistical agencies. For the 2002 benchmark IO accounts, initial data on gross output and intermediate inputs were compiled mostly from the 2002 Economic Census and Census related surveys. The GDP-by-industry accounts contain estimates of VA by industry using data on compensation, taxes and subsidies, and gross operating surplus (GOS). The primary source data on compensation, taxes and subsidies were from the Bureau of Labor Statistics (BLS) and BEA. A major portion of data on GOS was from Statistics of Income (SOI) of the IRS. Data from the Federal Reserve Board, other government and regulatory agencies, and private trade companies were also used in both sets of the accounts.

The second major source was sampling and non-sampling errors in the source data. The Census Bureau and SOI provided information on sampling errors for their published estimates in terms of coefficients of variation (CV), computed as the ratio of the standard deviation to the mean. In addition, source data in both sets of the accounts also suffered from non-sampling errors such as double counting, misreporting, omission, misallocation, misspecification, and simple mistakes (ARS, 2005). Non-sampling errors were either due to inconsistencies in definition and classification of variables between

statistical agencies and national accounts or the result of problems in data collection and estimation methods used for compiling initial data.

The third major source was errors in various adjustments made by the national accounts to correct non-sampling errors in source data. Adjustments, however, introduced additional uncertainty in initial estimates, because some adjustments were based on studies conducted some years ago and some were estimated judgmentally.

The fourth major source was the official residual errors, i.e., the aggregate statistical discrepancy. Recorded as a separate item in the GDP-by-industry accounts, the aggregate statistical discrepancy was a major inconsistency to be removed.

3. Generalized Least Squares Method for Reconciling National Accounts

Following Byron (1996), this section describes a GLS method for reconciling a set of national accounts. Subsection 3.1 describes the GLS method in general. The three inputs to the method are initial estimates of variables to be adjusted, covariances which measure their accuracy, and variables to be held at their initial values and not to be adjusted. Subsection 3.2 discusses available sample information, in the application with the U.S. data in Section 5, for setting the measurement-accuracy covariances. Subsection 3.3 develops a sensitivity analysis of the method with respect to the measurement-accuracy covariances.

3.1 The General GLS Problem

Let α denote the $n \times 1$ vector of true, nonstochastic, and unknown values of variables in a linear system of national accounts. The system and α are said to be reconciled when they satisfy the linear accounting system

$$H\alpha = \beta, \tag{1}$$

which imposes m ($< n$) independent linear constraints on the n variables in α , for a given $m \times n$ matrix H and a given $m \times 1$ vector β . Independence of the constraints means that H has full row rank m , the elements of H are either 0 or ± 1 , and in the overall accounting there is usually one more

constraint not included in (1) so as to keep H from being singular, so that the overall number of variables is $n+1$. See Byron (1996, p. 134).

Let α^0 denote an initial, unreconciled, estimate of α , produced by a statistical agency, so that $e_0 = H\alpha^0 - \beta \neq 0$. Following Byron (1996), suppose that α^0 is considered a stochastic and unbiased estimate of true α , with positive definite covariance matrix Σ . The GLS method computes an adjusted and reconciled estimate denoted by α^* , which is as close as possible to α^0 in the sense that the weighted sum of squared adjustments, $(\alpha^* - \alpha^0)' \Sigma^{-1} (\alpha^* - \alpha^0)$, is minimal. Given α^0 , β , H, and Σ , the GLS problem minimizes

$$S(\alpha^*) = (\alpha^* - \alpha^0)' \Sigma^{-1} (\alpha^* - \alpha^0) \quad (2)$$

with respect to α^* , subject to $H\alpha^* = \beta$. If indeed H has full row rank and Ω is positive definite, then, the problem has the unique solution

$$\alpha^* = \alpha^0 - \Sigma H' (H\Omega H')^{-1} (H\alpha^0 - \beta). \quad (3)$$

If true α is reconciled and initial α^0 is unbiased, then, revised α^* is also an unbiased estimate of true α (Byron, 1996). The idea of weighting by Ω^{-1} in objective function (2) is to induce small adjustment of presumably accurate initial estimates with small variances in an adjusted and reconciled accounting system and vice versa for inaccurate initial estimates. Optimal adjustment rule (3) has the Bayesian interpretation of being drawn from a posterior distribution of α (van der Ploeg, 1982).

Because (3) is based on α^0 being unbiased, one would like to statistically test this assumption. Supposing α^0 is normally distributed, Byron (1996) proposed testing this assumption with the quadratic form $g = (\alpha^* - \alpha^0)' H' (H\Omega^{-1}H')^{-1} H (\alpha^* - \alpha^0)$, distributed chi-squared with m degrees of freedom. As usual, a large and significant value of g rejects the null hypothesis that α^0 is unbiased. Normality is a reasonable assumption for initial estimates in national accounts (Byron, 1996). In the application in Section 5, $g = 159.9$ and $m = 134$ imply that g has a p value of .937, which does not reject unbiasedness of α^0 at the 5% significance level.

3.2 Setting Ω for U.S. National Accounts Data

In the application in Section 5 with U.S. data, there are 134 independent accounting constraints (rows of H) and 10062 variables (columns of H and elements of α). The variables to be adjusted in α are gross output, intermediate inputs, VA, and final expenditures, including exports and imports. Since all variables are included in α to be adjusted, β is zero. The GLS method is applied to the 2002 benchmark input-output, GDP-by-industry, and final expenditures data, with 134 independent accounting constraints in equation (1), reflecting 65 industry and 69 commodity constraints. As usual, there is one more overall constraint equating total industry VA with total expenditure-based GDP, which is excluded from (1) in order to keep H nonsingular, so that α excludes one variable of the overall accounting.

In the application in Section 5, Σ is restricted to be diagonal, with positive diagonal elements. Following Dagum and Cholett (2006), the covariance matrix can be decomposed as

$$\Sigma = \Omega^\lambda \Phi \Omega^\lambda, \quad (4)$$

where Ω is $n \times n$ diagonal matrix with positive diagonal elements, Φ is $n \times n$ identity matrix, and $\lambda = \frac{1}{2}$ or 1. If $\lambda = 1$, Σ is diagonal matrix with positive diagonal elements, $\sigma_{ii}^2 > 0$, set to be estimated variances of elements in α^0 ; if $\lambda = \frac{1}{2}$, Σ is diagonal matrix with positive diagonal elements, $\sigma_{ii} > 0$, set to be estimated standard errors of elements in α^0 .

Ideally, survey data would provide enough information to estimate all elements in Σ . However, U.S. survey data underlying the data used in Section 5 provided only information to estimate variances in Σ . In particular, only CV for IO data from the Census Bureau and CV for VA data from SOI were available and were converted to estimated variances by multiplying them by sample means and squaring. Accordingly, in the application, data were considered inaccurate according to their estimated variances. Restricting Σ to be a diagonal matrix of estimated variances or standard errors is standard practice in reconciliation using data from surveys (Dagum and Cholette, 2006). The sensitivity

analysis in the next subsection suggests that specifying Σ to be diagonal is not overly restrictive.

3.3. Sensitivity Analysis for the GLS Method

The following sensitivity analysis provides an upper bound on the size of the adjustment or revision vector, $r = \alpha^* - \alpha^0$, in terms of the size of the initial-nonreconciliation-error vector, $e = H\alpha^0 - \beta$, for diagonal Σ and any H . The following mathematical notions needed in the analysis are standard in numerical mathematics and are reviewed in, for example, Golub and Van Loan (1989, ch. 2, pp. 49-85).

For $p \geq 1$, let $\|x\|_p$ denote the p -norm of $n \times 1$ vector $x = (x_1, \dots, x_n)'$, defined by $\|x\|_p = (|x_1|^p + \dots + |x_n|^p)^{1/p}$; and let $\|A\|_p$ denote the p -norm of $m \times n$ matrix A induced by the vector p -norm and defined by $\|A\|_p = \text{maximum of } \|Ax\|_p \text{ with respect to } x, \text{ subject to } \|x\| = 1$. For $p = 1$, $\|A\|_1 = \text{maximum of } \sum_{i=1}^m |a_{ij}| \text{ over } j = 1, \dots, n$; for $p = 2$, $\|A\|_2 = \text{square root of the maximum (positive and real) eigenvalue of } A'A$; for $p = \infty$, $\|A\|_\infty = \text{maximum of } \sum_{j=1}^n |a_{ij}| \text{ over } i = 1, \dots, m$. Because the elements of H are either 0 or ± 1 , $\|H\|_1 = \text{maximum number of nonzero elements in any column of } H$ and $\|H\|_\infty = \text{maximum number of nonzero elements in any row of } H$. If A and B are compatible with product AB , then, for $p \geq 1$, (i) $\|AB\|_p \leq \|A\|_p \cdot \|B\|_p$. The p -norm condition number of a matrix A , denoted by $k_p(A)$ and defined by $k_p(A) = \|A\|_p \cdot \|A^{-1}\|_p$, satisfies $k_p(A) \geq 1$. Also, (ii) $\|A\|_2 \leq \sqrt{\|A\|_1 \|A\|_\infty}$.

The 2-norms, inequality (i), and optimal adjustment rule (3) imply that (iii) $\|r\|_2 \leq k_2(\Sigma) \cdot \|H'\|_2 \cdot \|e_0\|_2$. For r and e_0 viewed as sample vectors, $s_r^2 = \sum_{i=1}^n r_i^2 / n = \|r\|_2^2 / n$ and $s_e^2 = \sum_{i=1}^n e_{0i}^2 / n = \|e_0\|_2^2 / n$ are sample second moments. If, as in the application, Σ is diagonal, with positive diagonal elements, and (after permutation, if necessary, without loss of generality) σ_{11}^λ and σ_{nn}^λ are the largest and smallest diagonal elements, then, $k_2(\Sigma) = \sigma_{11}^\lambda / \sigma_{nn}^\lambda$. After combining inequalities (ii) and (iii), we obtain the desired inequality

$$s_r / s_e \leq \sqrt{\frac{m}{n} \cdot \|H\|_1 \cdot \|H\|_\infty} \cdot k_2(\Sigma), \quad (5)$$

which implies the following about the sensitivity of r to Σ .

First, inequality (5) gives a worst case analysis: for the given norms of H and condition number of Σ , the relative size of the adjustment, s_r/s_e , at most equals the right-side of (5), but could actually be much smaller. Second, optimal r given by (3) is invariant to the size of Σ in the sense of Σ being multiplied by a positive constant. Third, consequently, any diagonal or nondiagonal Σ can be scaled down without changing the GLS problem, so that its implied normal-distribution confidence region of a given probability fits into the normal-distribution confidence region of the same probability implied by the diagonal Σ being considered. In other words, in the GLS problem, any degree of absolute uncertainty of a Σ can be fit into the absolute uncertainty of the diagonal Σ being considered. Finally, in the application in Section 5, $m = 134$, $n = 9165$, $\|H\|_1 = 2$, and $\|H\|_\infty = 93$ imply $s_r/s_e \leq 1.64 \cdot (\omega_{11}/\omega_{nn})$. In sum, the key implication of inequality (4) of the sensitivity analysis is that the adjustments are expected to be smaller if variables to be adjusted have equal uncertainties and larger if they have very differing degrees of relative uncertainties.

4. Reliability of Initial Data

This section discusses how reliability of initial estimates was determined. Because initial data come from various sources, an initial estimate consists of two parts, source data and adjustments, where source data are from official data collection agencies and adjustments aim to correct non-sampling errors in source data.

In the 2002 data, initial source and adjustment data items were identified by a reliability indicator, denoted, in a decreasing order of reliability, by $\theta = (1, 2, 3, 4, 5)$ (Table B in the appendix defines the 5 categories of reliability indicator). Distributions of initial data items in the 5 reliability categories, as shown in Table 1, vary among the variables. Initial source data items fall mostly into reliability categories 1 and 2, and adjustment data items fall largely into reliability categories 3, 4 and 5.

Reliability of source data is usually measured by estimated variances based on published estimates and CVs, when available, from

statistical agencies. Data from the Economic Census have no assigned sampling errors, and, thus, have zero assigned CVs. Administrative data, such as salaries, wages, taxes, and subsidies are provided by regulatory agencies and, thus, are treated like the data from the Economic Census. Initial data from Economic Census and administrative data fall in category 1 of reliability.

Estimating reliability of adjustment data, however, is less straightforward, because there is inadequate information about the uncertainty in these data items. Stone et al. (1942) addressed this issue and suggested that, in the absence of standard errors, margins of error may be set judgmentally by experienced analysts. In this application, subjective margins of errors were systematically assigned based on information reflected from reliability indicators.

Let α_{i,A_0}^0 denote an initial estimate of the i^{th} element in α^0 of category θ that has no CV, and let c denote the average CV of detailed initial data items from surveys conducted by data collection agencies. The subjective CV of α_{i,A_0}^0 is, then, computed as

$$CV(\alpha_{i,A_0}^0) = c \cdot (\theta - 1). \quad (6)$$

For data in the IO accounts, c is the average CV of detailed data items from Economic Census related surveys, and in the GDP-by-industry accounts, c is the average CV of SOI estimates. The subjective standard error of an initial data item is, thus, the product of the subjective CV and the estimate of the data item. Based on the reliability indicator values assigned by experienced analysts, equation (6) is used to differentiate varying degrees of uncertainty in initial adjustment items. Here, the computed subjective CVs are 0, c , $2c$, $3c$ and $4c$. However, because adjustment data fall into reliability category 2 to 4, the computed subjective CVs for adjustments are effectively c , $2c$, $3c$ and $4c$.

Thus, reliability of an initial estimate in α^0 , in the sense of its diagonal element of Σ , is measured by the sum of variances of the source data and the adjustments,

$$\sigma_{ii}^{2\lambda} = \sigma_{ii}^{2\lambda} (\alpha_{i,S}^0 + \alpha_{i,A}^0) = (CV(\alpha_{i,S}^0) \cdot \alpha_{i,S}^0)^{2\lambda} + \sum_{\theta=1}^5 (c \cdot (\theta - 1) \cdot \alpha_{i,A_0}^0)^{2\lambda}, \quad (6)$$

where $\alpha_{i,S}^0$ and $\alpha_{i,A}^0$ refer to the source data and adjustment components of the i^{th} item in α^0 , and $\alpha_{i,A}^0 = \sum_i^5 \alpha_{i,A_0}^0$. Table 1-b contains simple statistics of the estimated CVs by variable. The average CV for gross output in the IO accounts is the lowest, and that of GOS and final expenditures is much larger. Standard deviation for intermediate inputs and final expenditures is much larger than that for gross output and GOS, reflecting some large outliers in those components.

In Section 5, we contrast the uncertainty measures based on estimated variances and standard errors of initial estimates with a so-called neutral variant, defined as the square of an initial estimate, $\omega_{ii} = (\alpha_i^0)^2$ (Barker et al, 1984). The neutral variant, motivated by the idea that large initial estimates imply large discrepancies in the accounts, has been used previously to reconcile accounts (Beaulieu and Bartelsman, 2004). Reconciling different accounts using neutral variants is equivalent to assuming that all initial estimates have the same degree of uncertainty.

5. A Balanced System of Accounts

This section discusses the application using the 2002 U.S. initial estimates from the IO accounts, GDP-by-industry accounts, and initial estimates of final expenditures from NIPA. Accounts were reconciled according to three weighting schemes: relative reliabilities measured by estimated variances and standard errors of initial estimates, and neutral variants of initial estimates. Subsection 5.1 compares the three sets of balanced estimates at the aggregate level. 5.2 compares balanced estimates at the industry and commodity levels. Subsection 5.3 Discusses adjustments of the variables and the estimated distribution of statistical discrepancy by industry and by expenditure category. Subsection 5.4 discusses the implications of balanced results.

5.1 Balanced Estimates at the Aggregate Level

Tables 2-a and 2-b contain initial and three sets of balanced estimates at the aggregate industry and commodity levels. The first row of Table 2-a shows initial aggregate industry estimates of gross

output, intermediate inputs and VA, and initial gap, in level and in percentages, between total industry gross output and total inputs measured as the sum of intermediate inputs and VA. Correspondingly, the first row of Table 2-b shows initial aggregate commodity estimates and initial gap between total commodity gross output and total commodity inputs measured as the sum of intermediate and final uses of commodities. Because initial estimates of final expenditures from NIPA were quite close to initial estimates of final uses in the IO accounts, the initial aggregate commodity gap of .57% is much smaller than the initial aggregate industry gap of 1.52%. Rows 2-4 in both tables show the three sets of balanced estimates at the aggregate level with the percentage adjustments of the variables in the parentheses.

Table 2-a and 2-b are here

We observe three features from balanced estimates at the aggregate. First, reconciliation based on relative reliabilities of initial estimates allows larger adjustments to less reliable components in the system; whereas reconciliation based on neutral variants tend to distinguish adjustments according to their relative sizes. For example, initial estimates of gross output were considered most reliable because they were compiled mostly from Economic Census data, and initial VA estimates, on the other hand, were considered much less reliable, because the GOS component of VA was compiled using a combination of SOI data which had larger CVs and various adjustments which were significant portions of the total GOS estimate. Thus, balanced estimates based on relative reliabilities reflect smaller percentage adjustments in gross output and much larger adjustments in VA. However, balanced estimates based on neutral variants reflect similar absolute percentage adjustments in gross output and VA, and the percentage adjustment in total intermediate inputs is the smallest because it is smallest component of all variables.

Second, compared with reconciliation based on estimated standard errors, reconciliation based on estimated variances generates, in this data set, smaller total adjustments in gross output, intermediate inputs and final uses, but higher adjustment in VA.

Third, allowing initial estimates of final uses to be adjusted, aggregate statistical discrepancy is distributed between final

expenditures and VA estimates. Table 2-c shows that using relative reliabilities to reconcile the accounts, the aggregate statistical discrepancy is mostly distributed to VA in the GDP-by-industry accounts. Furthermore, if accounts were reconciled according to estimated variances, statistical discrepancy, in absolute value, distributed to VA is more than 11 times of that distributed to final expenditures. This relative distribution ratio drops to 3.3 if accounts were reconciles using estimated standard errors, and drops to 1.3 if accounts were reconciled using neutral variants.

Table 2-c is here

5.2 Balanced Estimates at Industry and Commodity Levels

Table 3-a and 3-b contain initial and balanced estimates at the 65-industry and 69-commodity levels. In both tables, Panel A shows, respectively, initial estimates of the variables and percentage gaps between initial estimates of gross output and total inputs by industry and by commodity. Panels B, C and D show, respectively, balanced estimates based on neutral variants of initial estimates and relative reliabilities of initial estimates derived from estimated variances and standard errors. As seen at the aggregate level, initial gaps by commodity are much smaller in general than initial gaps by industry, because initial estimates of final uses from NIPA were quite close to those of final uses in the IO accounts.

Table 3-a is here

Initial estimates of each variable are compared with balanced estimates based on the three weighting schemes. Sums of balanced estimates of gross output and intermediate inputs of all industries shown in Table 3-a match those of balanced estimates of gross output and intermediate inputs shown in Table 3-b; sum of balanced estimates of VA shown in Table 3-a matches that of balanced estimates of final uses shown in Table 3-b, indicating that the IO accounts are balanced and that the IO accounts, GDP-by-industry accounts, and final expenditures from NIPA are reconciled.

Table 3-b is here

We observe two significant features of the balanced estimates at the industry and commodity levels from Table 3-a and 3-b. First, if an industry or a commodity has a large initial gap, adjustments will be large for some variables (e.g. industry 334 and 532R; commodity 212 and 335). Second, the sizes of adjustments can be disproportional in gross output, intermediate inputs, and VA or final uses from reconciliation based on relative reliabilities; whereas adjustments tend to be more proportional among the variables for reconciliation based on neutral variants (e.g. industry 335 and 532R; commodity 335 and 482).

5.3 Adjustments in Variables and Distribution of Statistical Discrepancy by Industry and by Expenditure Category

The second feature of balanced estimates at industry and commodity levels are clearly depicted in Figure 1 and Table 4 on percentage adjustments in the variables. In accounts reconciled by relative reliabilities, the absolute means and standard deviations of percentage adjustments are much smaller for gross output and intermediate inputs than for VA and final uses. This is because initial estimates of gross output and intermediate inputs, compiled mostly from surveys from the Economic Census, and a smaller portion of initial estimates were in reliability categories of 3-5, are more reliable; whereas initial estimates of GOS in VA, compiled using SOI estimates which had larger sampling errors, and a larger portion of initial estimates were in reliability categories of 3-5, are less reliable. Similarly, initial estimates of final uses, compiled using data from various sources with most of initial estimates in reliability category 3, were also less reliable than those of gross output and intermediate inputs. By contrast, in accounts reconciled by neutral variants, relative sizes of initial estimates affect sizes of adjustments. Despite large varying degrees of relative reliabilities, differences are much smaller in absolute means and standard deviations of percentage adjustments from reconciliation based on neutral variants.

Table 4 is here

By allowing initial estimates of final expenditure to be adjusted, the aggregate statistical discrepancy is allocated between VA and final expenditures. Tables 5-a and 5-b show, respectively, estimated statistical discrepancy by industry and by final expenditure category. Panel A of Table 5-a shows initial gaps, in levels and percentages, between estimates of VA from IO and VA from the GDP-by-industry accounts. Statistical discrepancies based on neutral variants, relative reliability measured by relative variances and relative standard errors are respectively shown in panels B, C and D in Table 5-a. Two notable features echo those observed from Tables 3-a and 3-b. First, sizes of initial gaps in VA estimates between the two accounts affect sizes of statistical discrepancies distributed by industry (e.g. industry 324 and 532R). Second, if accounts are reconciled according to relative reliabilities, relative variances or relative standard errors of initial estimates determine statistical discrepancies by industry (e.g. 311F and 42); whereas if reconciliation is based on neutral variants, relative sizes of industry VA of total GDP determine the distributions (e.g. industry 313T and 531). Furthermore, statistical discrepancy distributed to each industry tends to be proportional to the estimated variances if reconciliation is based on relative variances; whereas statistical discrepancy tends to be proportional to the estimated standard errors if reconciliation is based on relative standard errors.

Table 5-a is here

Correspondingly, panels A, B and C of Table 5-b show, by expenditure category, distributed statistical discrepancy; statistical discrepancy as a percentage of final expenditure; and statistical discrepancy as a percentage of aggregate GDP, from reconciliation based on the three weighting schemes. The fourth column in panel A displays final expenditure of each category as a percentage of aggregate GDP, and the fourth column of panel C contains CVs of initial estimates by final expenditure category as a reference of their reliabilities. The distribution results in panel A show that if reconciliation is based on neutral variants, statistical discrepancy is distributed largely according to the sizes of final expenditure categories (e.g. F010, F030). By contrast, the results in panels B and C show that statistical

discrepancy is distributed largely according to the relative reliabilities of initial estimates, if reconciliation is based on relative variances or relative standard errors (e.g. F030, F06C).

5.4 Significance of Balanced Estimates

The greatest value of the reliability-based GLS method is that it produces a statistically meaningful balanced system of accounts, and, thus, enhances the credibility of national accounts estimates. Balanced results from the reliability-based GLS method should improve the credibility of further data derived from the balanced estimates. For example, estimates of intermediate inputs data are used by BEA to compile annual industry KLEMS data and by the Federal Reserve Board to produce industry productivity indexes. Balanced estimates of intermediate inputs represent more accurate allocations of intermediate inputs across industries, and, hence, should help improve the accuracy of industry KLEMS data and productivity data compiled from them.

Degrees of impact on data derived from balanced estimates may vary. For example, BLS produces industry output and employment projections using estimates of gross output from annual IO accounts at BEA. Because initial estimates of gross output are considered reliable, using balanced estimates of gross output should not significantly affect industry output projections. However, because initial VA estimates are less reliable, the impact should be more significant on statistics compiled using balanced estimates of VA.

Another significant value of the GLS-based reconciliation method is that it helps identify the improvements needed in source data collection and in estimation methods used to compile initial estimates. Furthermore, it should enable a time series of distribution of the aggregate statistical discrepancy to be constructed. Such a time series could track the distribution of the aggregate statistical discrepancy over time and provide information on the improvements in the reliability of source data by industry and by expenditure category.

6. Conclusion

In this paper, a GLS method is applied to reconcile a disaggregated system of accounts using the 2002 U.S. data by allowing

all initial data items to be adjusted. The results demonstrate that using estimated relative reliabilities of initial data to remove inconsistencies in different sets of accounts produces statistically meaningful balanced estimates. The distribution of the statistical discrepancies by industry and by final expenditure category properly traces the aggregate statistical discrepancy back to its sources. Moreover, the study also demonstrates that using a GLS method to reconcile a large system of national accounts according to estimated relative reliabilities of initial data is empirically feasible and computationally efficient.

In this study, the GLS method is applied to reconciling the system of U.S. national accounts of a benchmark year. Because Economic Census is conducted only for benchmark years, objective information on the reliability of source data is more available for benchmark years than for off-benchmark years. A future extension of this study is to combine time series analysis methods with the GLS method to balance the system of U.S. national accounts for multiple years.

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Table 1-a: Distribution of Quality Index by Variable

Quality Index	Gross output	Inter. Inputs	Final Uses	Compensation	Taxes
$\theta=1$	65.78	25.15	52.45	15.90	0.02
$\theta=2$	9.72	30.39	2.78	81.17	0.00
$\theta=3$	7.23	22.51	44.50	2.87	99.98
$\theta=4$	14.01	10.46	0.20	0.03	0.00
$\theta=5$	3.25	11.49	0.07	0.02	0.00

Table 1-b: Simple Statistics of CV by Variable

	Gross Output	Intermediate Inputs	GOS	Final Uses
Statistics	$CV(x_{ij})$	$CV(z_{ij})$	$CV(VA_{i3})$	$CV(y_{dj})$
Mean	0.016	0.070	0.091	0.199
Max	0.562	13.029	0.608	1.772
Min	0.000	0.000	0.002	0.000
Stdv	0.041	0.240	0.092	0.492

Table 2-a: Balanced Estimates of Industry Aggregates and Percentage Adjustments in Initial Estimates (Million dollars)

Model	Total Industry Gross Output	Total Industry Intermediate Inputs	Total Industry Value-Added	Total Industry Gap	Total Industry Gap (%)
Initial Estimates	19180034.33	8398244.5	10490589.9	291199.93	1.52
M1 (w=1/NV)	19003230.18 (-0.92)	8410057.06 (0.14)	10593173.11 (0.98)	0	0
M2(w=1/var)	19141485.85 (-0.20)	8484435.61 (1.03)	10657050.24 (1.59)	0	0
M3 (w=1/se)	19120561.11 (-0.31)	8491880.02 (1.11)	10628681.09 (1.32)	0	0

Table 2-b: Balanced Estimates of Commodity Aggregates and Percentage Adjustments in Initial Estimates (Million dollars)

Model	Total Commodity Gross Output	Commodity Intermediate Inputs	Total Final Expenditures	Total Commodity Gap	Total Commodity Gap (%)
Initial Estimates	19180034.33	8398244.5	10671888.8	109901.03	0.57
M1 (w=1/NV)	19003230.18 (-0.92)	8410057.06 (0.14)	10593173.11 (0.98)	0	0
M2(w=1/var)	19141485.85 (-0.20)	8484435.61 (1.03)	10657050.24 (1.59)	0	0
M3 (w=1/se)	19120561.11 (-0.31)	8491880.02 (1.11)	10628681.09 (-0.40)	0	0

Table 2-c: Distribution of Aggregate Statistical Discrepancy between VA and Final Uses (Million dollars and %)

Model	Total Industry Value-Added	Total Final Expenditures	Aggregate Statistical Discrepancy	Change in Total Value-Added	Change in Total Final Uses	%Change in Total Value-Added	%Change in Total Final Uses
Initial Estimates	10490589.9	10671888.8	181298.9	-	-	-	-
M1 (w=1/NV)	10593173.11	10593173.11	0	102583.21	-78715.69	0.98	-0.74
M2(w=1/var)	10657050.24	10657050.24	0	166460.34	-14838.56	1.59	-0.14
M3 (w=1/se)	10628681.09	10628681.09	0	138091.19	-43207.71	1.32	-0.40

Table 4: Summary Statistics of Percentage Adjustments by Variable

Statistics	(w=1/NV)	(w=1/var(.))	(W=1/Stdv)
% Adjustment in Gross Output			
Mean	-1.54	-0.53	-0.66
Max	5.87	7.00	5.44
Min	-20.53	-16.31	-15.41
Stdv	4.40	3.34	2.92
% Adjustment in Intermediate Inputs			
Mean	1.03	1.27	2.45
Max	31.46	35.25	48.75
Min	-10.20	-25.68	-22.18
Stdv	6.56	8.34	11.29
% Adjustment in Value Added			
Mean	2.33	4.71	3.08
Max	32.11	49.82	35.87
Min	-13.27	-52.93	-42.51
Stdv	7.50	16.00	10.91
% Adjustment in Final Use by Category			
Mean	-0.37	3.46	1.47
Max	1.25	42.16	18.88
Min	-2.00	-0.74	-0.71
Stdv	1.09	11.67	5.28

Table 5-a: Estimates of Statistical Discrepancy by Industry
(Million dollars)

	A		B			C			D		
	Initial VA Estimates		Estimated SD (w=1/NV)			Estimated SD (w=1/var)			Estimated SD (w=1/se)		
Ind ID	Initial VA Gap	Initial VA Gap (%)	Industry SD	Ind. SD as % of VA ⁰	VA' as % of GDP	Industry SD	Ind. SD as % of VA ⁰	Relative Variance	Industry SD	Ind. SD as % of VA ⁰	Relative Std. Error
111C	-7	-0.01	823	1.17	0.67	-3533	-5.31	0.48	-908	-1.31	0.70
113F	-8286	-48.85	-2857	-11.31	0.21	-3577	-16.50	0.01	-1778	-7.58	0.10
211	-5538	-10.19	-1955	-3.26	0.55	7046	10.53	0.39	2237	3.60	0.63
212	-2941	-10.57	-2611	-8.48	0.27	-1605	-5.50	2.82	-794	-2.65	1.68
213	5585	28.78	1694	12.26	0.15	4698	25.37	3.82	3265	19.11	1.95
22	-8595	-4.48	523	0.26	1.9	3021	1.48	0.99	-645	-0.32	1.00
23	-62781	-13.19	-21934	-4.07	4.88	-21312	-4.12	0.03	-6410	-1.20	0.17
311F	71287	32.13	15471	10.27	1.57	64960	30.14	7.15	42903	22.17	2.67
313T	6772	24.95	1058	5.20	0.2	6393	23.89	15.57	4013	16.46	3.95
315A	-3839	-23.06	-859	-4.19	0.19	-3275	-19.02	5.99	-1510	-7.95	2.45
321	-597	-2.01	-385	-1.27	0.28	-436	-1.46	2.89	-72	-0.24	1.70
322	14926	23.98	4136	8.74	0.49	12772	21.25	5.16	8830	15.72	2.27
323	1244	2.52	1834	3.81	0.47	906	1.85	1.41	701	1.44	1.19
324	-30988	-185.90	-4845	-10.17	0.4	-25224	-112.43	5.13	-20261	-73.95	2.27
325	34326	20.11	8096	5.94	1.36	24448	15.20	1.16	14747	9.76	1.08
326	13886	19.20	3015	5.16	0.58	10264	14.94	2.42	6338	9.79	1.55
327	5775	12.69	1497	3.77	0.39	5560	12.27	16.36	4101	9.35	4.05
331	2457	5.40	679	1.58	0.41	2444	5.38	13.92	2033	4.51	3.73
332	8346	7.59	2592	2.55	0.98	7641	6.99	8.17	4552	4.29	2.86
333	14311	13.58	3472	3.81	0.89	13273	12.72	9.63	8145	8.21	3.10
334	86518	55.46	17832	25.66	0.82	15395	18.14	13.92	75	0.11	3.73
335	-13695	-31.84	-4465	-7.87	0.49	-13235	-30.45	45.87	-9799	-20.89	6.77
3361	11370	9.01	2197	1.91	1.1	10477	8.36	2.42	7016	5.76	1.56
3364	519	0.81	725	1.15	0.6	1883	2.89	4.59	1773	2.72	2.14
337	8631	24.10	2156	7.93	0.28	3083	10.19	0.55	1505	5.25	0.74
339	-726	-1.17	-98	-0.16	0.59	-468	-0.75	4.54	125	0.20	2.13
42	-100835	-19.07	-41542	-6.60	5.55	-86923	-16.02	8.50	-58756	-10.29	2.92
44RT	-150531	-26.95	-54860	-7.74	6.18	-62909	-9.73	0.72	-29681	-4.37	0.85
481	-12365	-32.30	-3224	-6.36	0.45	-2346	-4.86	0.05	-1293	-2.62	0.21
482	5987	25.17	1464	8.23	0.18	272	1.50	0.01	640	3.47	0.11
483	4222	34.25	765	9.45	0.08	220	2.64	0.05	340	4.03	0.21
484	-2385	-2.51	-1754	-1.80	0.9	-2862	-3.02	0.37	-806	-0.83	0.61
485	1717	8.73	663	3.69	0.18	518	2.80	0.34	474	2.57	0.58
486	223	3.02	-10	-0.14	0.07	61	0.84	0.20	88	1.21	0.45
487O	-2868	-3.98	-649	-0.87	0.7	-1727	-2.36	2.45	-526	-0.71	1.57
493	-231	-0.88	-58	-0.22	0.25	-49	-0.19	0.41	-51	-0.19	0.64
511	48303	31.24	15434	14.52	1.15	40233	27.45	4.50	21998	17.14	2.12
512	15817	30.49	5304	14.71	0.39	15513	30.08	52.43	11292	23.85	7.24
513	3902	1.37	4208	1.50	2.69	1384	0.49	0.18	1846	0.65	0.42
514	12119	19.68	4103	8.29	0.51	10352	17.30	6.35	6477	11.58	2.52
521C	-1953	-0.42	919	0.20	4.44	1002	0.21	1.64	2450	0.52	1.28
523	-6437	-3.89	-4926	-2.87	1.58	-5168	-3.10	1.89	-1114	-0.65	1.38
524	-11604	-4.61	-5465	-2.08	2.43	-6656	-2.59	0.04	-3675	-1.42	0.20
525	-15168	-121.59	-3669	-13.27	0.23	-3771	-15.80	0.04	-3075	-12.52	0.20
531	97934	7.47	49448	4.08	11.92	35678	2.86	0.27	47337	3.76	0.52
532R	88567	50.39	27994	32.11	1.09	43428	33.25	0.34	31267	26.40	0.59
5411	10454	6.74	5300	3.67	1.41	6678	4.42	1.57	4333	2.91	1.25
5412	45852	10.01	21543	5.23	4.09	40988	9.05	7.33	18971	4.40	2.71
5415	764	0.69	1037	0.94	1.05	640	0.58	65.90	1884	1.68	8.12
55	30433	10.98	14363	5.82	2.47	0	0.00	0.00	39	0.02	0.00
561	15464	5.13	7581	2.65	2.77	3105	1.07	0.18	2961	1.02	0.42
562	5001	16.06	1936	7.41	0.26	4591	14.94	9.44	2812	9.71	3.07
61	5744	6.44	2403	2.88	0.81	102	0.12	0.00	462	0.55	0.04
621	-27883	-8.23	-11118	-3.03	3.35	-7887	-2.20	0.75	-6473	-1.80	0.87
622H	14406	4.63	6770	2.28	2.87	940	0.32	0.01	1361	0.46	0.09
624	-6953	-12.00	-2443	-3.77	0.59	-914	-1.43	0.12	-697	-1.09	0.35
711A	3963	7.56	1139	2.35	0.47	673	1.37	0.14	1399	2.81	0.38
713	5144	10.46	2100	4.77	0.44	277	0.63	0.00	952	2.12	0.06
721	7986	8.18	3811	4.25	0.88	3854	4.12	0.70	2336	2.54	0.84
722	12737	5.82	4713	2.28	1.99	2552	1.22	0.15	2679	1.28	0.39
81	51113	19.06	15780	7.27	2.2	13015	5.66	0.31	9655	4.26	0.56
GFE	-457	-0.71	1030	1.60	0.62	0	0.00	0.00	1	0.00	0.00
GFG	-1	0.00	1596	0.45	3.35	0	0.00	0.00	1	0.00	0.00
GSL E	-5732	-9.16	-709	-1.04	0.64	0	0.00	0.00	0	0.00	0.00
GSLG	793	0.09	3814	0.45	8.05	0	0.00	0.00	5	0.00	0.00
Sum	291200	2.78	102583		100	166460			138091		

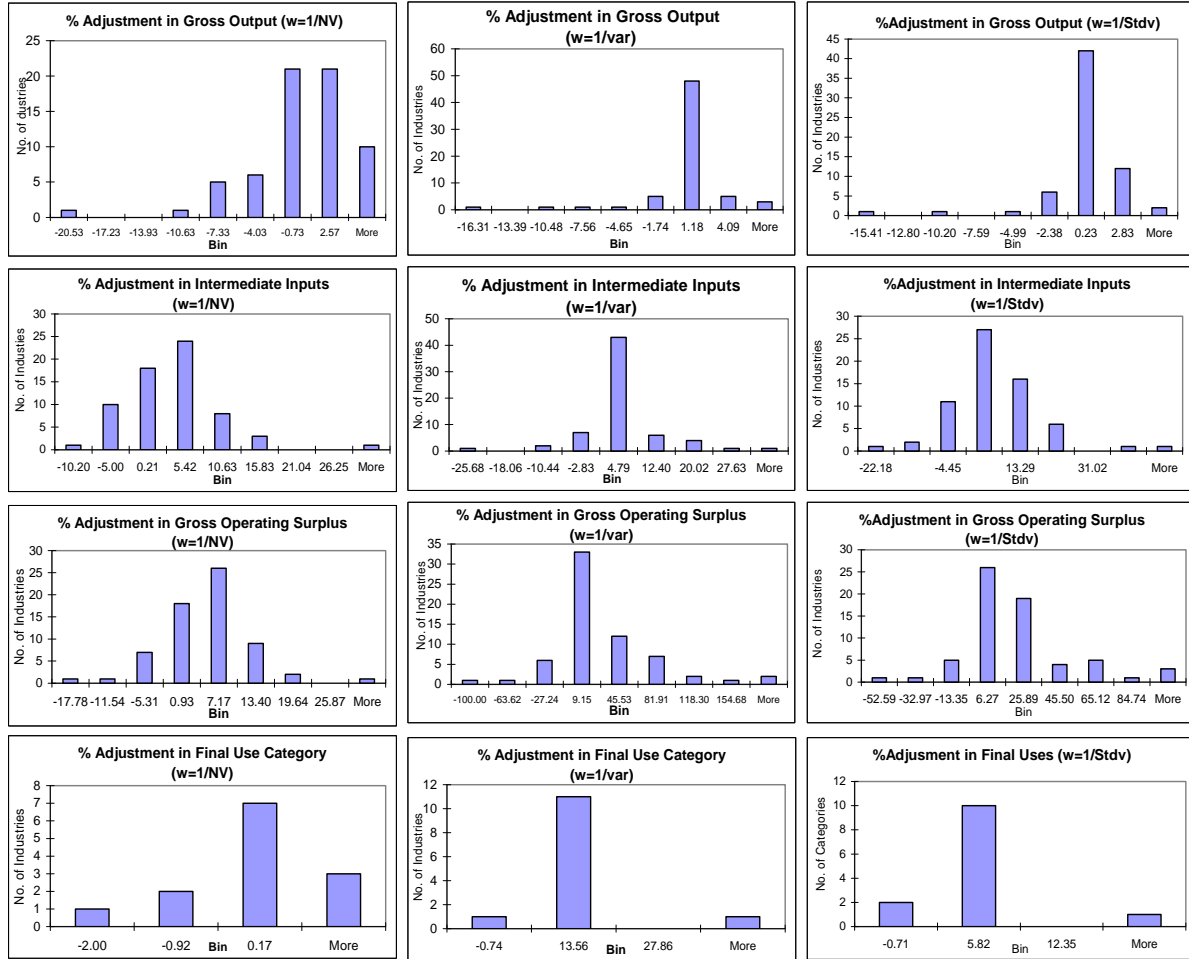
Table 5-b: Estimates of Statistical Discrepancy by Final Expenditure Category
(Billion dollars)

Exp Cat. Code	Balanced Estimates (w=1/abs(a ⁰))				Balanced Estimates (w=1/var)			Balanced Estimates (w=1/se)			Reliability
	$SD_d^E = \frac{y_d^E - y_d^0}{y_d^0}$	$SD_d^{E\%} = \frac{(y_d^E - y_d^0)/y_d^0}{(y_d^E - y_d^0)/y_d^0}$	$(SD_d^E/SD^E)\%$	$(y_d^E/GDP)\%$	$SD_d^E = \frac{y_d^E - y_d^0}{y_d^0}$	$SD_d^{E\%} = \frac{(y_d^E - y_d^0)/y_d^0}{(y_d^E - y_d^0)/y_d^0}$	$(SD_d^E/SD^E)\%$	$SD_d^E = \frac{y_d^E - y_d^0}{y_d^0}$	$SD_d^{E\%} = \frac{(y_d^E - y_d^0)/y_d^0}{(y_d^E - y_d^0)/y_d^0}$	$(SD_d^E/SD^E)\%$	$CV(y_d^E)(\%)$
F010	-42.5	-0.57	83.4	70.02	-41.1	-0.55	276.67	-49.92	-0.67	115.55	1.78
F020	-4.0	-0.25	7.86	15.11	23.5	1.44	-158.41	8.92	0.55	-20.65	5.52
F030	-0.3	-2.04	0.54	0.13	5.8	29.65	-38.85	2.58	15.88	-5.98	213.73
F040	-0.9	-0.23	1.69	8.56	-1.6	-0.41	10.53	-2.69	-0.71	6.23	0.25
F050	-1.1	-1.91	2.07	-12.40	0.0	0.00	0.01	-0.12	-0.22	0.28	0.21
F06C	-0.5	-0.23	0.93	3.58	-1.6	-0.75	10.53	-1.48	-0.71	3.44	20.00
F06I	-0.3	-0.84	0.53	0.53	0.0	0.04	-0.08	0.00	-0.02	0.01	2.41
F07C	-1.1	-0.23	2.17	1.97	-2.7	-0.55	18.24	-2.23	-0.45	5.17	20.00
F07I	0.8	1.12	-1.57	0.32	1.4	1.90	-9.2	1.22	1.70	-2.83	2.38
F08C	-1.2	-0.23	2.42	4.64	-2.7	-0.50	18.24	-1.41	-0.26	3.26	16.12
F08I	2.3	1.24	-4.52	0.69	3.9	2.05	-26.01	1.82	0.98	-4.22	9.64
F09C	-16.1	-1.81	31.65	5.01	0.0	0.00	-0.16	-0.30	-0.03	0.69	9.16
F09I	13.9	-1.04	-27.18	1.86	-0.2	0.02	-1.5	0.41	0.03	-0.94	6.24
Sum	-51.0	-0.54	100	100	-15.3		100	-43.21		100	

Table 5-c: Summary Statistics of Statistical Discrepancy
(Million Dollars)

Statistics	w=1/NV	w=1/var	w=1/SE
Distribution of Statistical Discrepancy by Industry			
Mean	1578	2561	2124
Max	49448	64960	47337
Min	-54860	-86923	-58756
Stdv	12914	19950	13362
Distribution of Statistical Discrepancy by Expenditure Category			
Mean	-705	-1141	-3324
Max	13859	23506	8924
Min	-16139	-41053	-49924
Stdv	6561	13816	14308

Figure 1: Histograms of Percentage Adjustments by Variable



Appendix A: NAICS Industry Codes and Industry Description

Industry	Industry description	Indcode	Industry description
111CA	Farms	486	Pipeline transportation
113FF	Forestry, fishing, and related activities	487OS	Other transportation and support activities
211	Oil and gas extraction	493	Warehousing and storage
212	Mining, except oil and gas	511	Publishing industries (includes software)
213	Support activities for mining	512	Motion picture and sound recording industries
22	Utilities	513	Broadcasting and telecommunications
23	Construction	514	Information and data processing services
311FT	Food and beverage and tobacco products	521CI	Federal Reserve banks, credit intermediation, and related activities
313TT	Textile mills and textile product mills	523	Securities, commodity contracts, and investments
315AL	Apparel and leather and allied products	524	Insurance carriers and related activities
321	Wood products	525	Funds, trusts, and other financial vehicles
322	Paper products	531	Real estate
323	Printing and related support activities	532RL	Rental and leasing services and lessors of intangible assets
324	Petroleum and coal products	5411	Legal services
325	Chemical products	5412OP	Miscellaneous professional, scientific and technical services
326	Plastics and rubber products	5415	Computer systems design and related services
327	Nonmetallic mineral products	55	Management of companies and enterprises
331	Primary metals	561	Administrative and support services
332	Fabricated metal products	562	Waste management and remediation services
333	Machinery	61	Educational services
334	Computer and electronic products	621	Ambulatory health care services
335	Electrical equipment, appliances, and components	622HO	Hospitals and nursing and residential care facilities
3361MV	Motor vehicles, bodies and trailers, and parts	624	Social assistance
3364OT	Other transportation equipment	711AS	Performing arts, spectator sports, museums, and related activities
337	Furniture and related products	713	Amusements, gambling, and recreation industries
339	Miscellaneous manufacturing	721	Accommodation
42	Wholesale trade	722	Food services and drinking places
44RT	Retail trade	81	Other services, except government
481	Air transportation	GFE	Federal government enterprises
482	Rail transportation	GFG	Federal general government
483	Water transportation	GSLE	State and local government enterprises
484	Truck transportation	GSLG	State and local general government
485	Transit and ground passenger transportation		

Appendix B: Description of Quality Index in IO Accounts

0	Description
1	2002 Economic Census or USDA data; regulatory data
2	Economic Census related Surveys, Business Expenditure Survey; SOI data; Economic Census data with adjustments
3	Non-Economic Census data from BEA or trade companies
4	Adjusted Census data, Misreporting, etc
5	Analysts judgments, other adjustments, data extrapolated from 1997 benchmark