The database-modeling nexus in integrated assessment modeling of electric power generation

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Abstract:

Integrated assessment models (IAMs) are playing an increasingly important role in long-run sustainability analysis. At their core is a set of global economic and environmental accounts which capture a complete set of inter-industry and inter-regional relationships in the global economy in a consistent manner. While much attention is focused on the raw data and parameterization required to expand or add sectoral detail to IAMs, only rarely is there discussion of how different matrix balancing methods (i.e. translating disparate raw data sources into the consistent database) affect modeling results. This article offers an in-depth look into the database-modeling nexus in IAMs, focusing on the electric power sector which is both a major source of CO_2 emissions and a critical vehicle for climate change mitigation. Comparisons of the prevailing matrix balancing algorithms show how the choice of database reconciliation methodology affects modeling results using policy-relevant simulations in the context of the electric power sector. The resulting insights can be applied to the disaggregation of other, technology rich sectors in the economy. We conclude that appropriate selection of database reconciliation methodologies can reduce the deviation between bottom-up and top-down modeling.

Highlights:
- Database construction, particularly matrix balancing, is rarely well-documented in IAMs
- Database balancing alters key economic relationships in IAM
- These economic relationships affect modeling results
- Appropriate balancing methods help reconcile bottom-up and top-down models
- The ERP method is preferred for preserving bottom-up data in IAMs

Keywords: integrated assessment, computable general equilibrium, model validation, matrix balancing, cross-entropy, database-modeling nexus

JEL Classifications: C61, C68, D57, D58, Q47

1. Introduction

It is increasingly apparent that standalone economic, biophysical, atmospheric, or other data-driven numerical models cannot address long-run sustainability issues which cut across traditional academic boundaries. Such issues include, but are not limited to: anthropogenic climate change; environmental degradation; and energy, food, and water security. Integrated assessment models (IAMs) marry social, economic, and environmental modules within a single framework to offer a clearer picture of how sustainability issues might evolve in the future and how public policies might alter this trajectory. In light of the complex policy issues facing the world today, IAMs with increasing sector-level detail have grown in popularity (Tol, 2006). Correspondingly, it is useful to identify and characterize new sources of uncertainty in IAMs and how they affect uncertainties in policy impacts (Weyant, 2009).

The push of sector-level detail has not always the case. Early IAMs such as DICE (Nordhaus, 1992) and RICE (Nordhaus and Yang, 1996) included a single, aggregate economic sector. However, this stimulated interest in IAMs in policy circles which led to a demand for increased sector detail. This has brought the IAM community into intimate contact with the computable general equilibrium (CGE) modeling community. CGE models offer consistent theoretical underpinnings of inter-sectoral and inter-regional interactions across the entire global economy. Furthermore, adding sectoral detail is relatively straightforward and well-studied. As such, CGE models are becoming the preferred economic module in IAMs - especially for energy-related research. For example, 12 of the 18 models used in the EMF 27 study are CGE-based (Kriegler et al. 2014).

Sectoral extensions require disaggregating the largely aggregate sectors in an existing CGE database into detailed sub-sectors to analyze specific technologies and policy shocks (McFarland et al. 2004; Edmonds et al. 2004; Paltsev et al. 2004). For example, in the case of the electric power sector, many prevailing CGE databases (e.g. Narayanan et al. 2012) only include a single aggregate industry[1]; however, increasingly, policies are directed at specific generating technologies (e.g. solar investment tax credits, nuclear phase-out). Further, economic shocks may impact diverse generating technologies in different ways (e.g. a drop in the price of natural gas). Thus, several leading research groups independently disaggregate the electricity sector into electricity sub-sectors which include several generating technologies (Brenkert et al. 2004; Paltsev et al. 2005; Sue Wing, 2008; Burniaux and Chateau, 2010).

Greater sector-level detail allows IAMs to explore new (and reoccurring) research vistas such as energy policy (Bhattacharyya, 1996), agriculture/biofuel linkages (Kretschmer et al. 2009), and climate policy (Ciscar and Dowling, 2014). Introducing the detailed technologies involves two basic tasks: i) disaggregating an aggregate sector in a CGE database into sub-sectors or technologies (e.g. electric power into specific generating technologies) and ii) creating mathematical equations to represent supply and demand in the new sectors. Modelers typically devote the most attention and the greatest amount of documentation to the latter – that is, characterizing the supply and demand behavior in the detailed sub-sectors. Unfortunately, much less attention is placed on the constructing the disaggregate baseline database which defines key economic relationships in the economy and which, as this study demonstrates, can play a key role in determining model outcomes.

The disaggregation process consists of two basic steps: i) collecting technologically-rich, sector-detailed (often termed "bottom-up") data which, when price and quantity data are combined, imply some value flows in the new sub-sectors and ii) a method to allocate these estimated value flows across sub-sectors while meeting CGE accounting ("top-down") constraints. Unfortunately, the disaggregation process used

[1] The motivating example in this article is a disaggregation from an aggregate electricity sector into several generating technologies. However, the discussion of the database-modeling nexus is general to disaggregations of other sectors and extendable to estimating entire matrices.

in constructing the newly disaggregated database is often weakly or even wholly undocumented. When the disaggregation process is published, the focus is on the bottom-up data and less so on the construction method. Lenzen (2011) argues that models based on the disaggregation of sectors into individual activities generally perform better than modeling the aggregate sector, even when the information used to disaggregate is fragmentary. But how should this fragmentary information be combined and reconciled with the key economic relationships implied by the original top-down data?

This article shows that the choice of database reconciliation methodology has a significant impact on modeling results. Four commonly used disaggregation methods are compared: i) an *ad-hoc* method used by Marriott (2007), Lindner et al. (2014), and Arora and Cai (2014), ii) minimum sum of column cross-entropy (MSCCE) (Golan et al. 1994, Robinson et al. 2001), iii) RAS (e.g. Lahr and de Mesnard, 2004), and iv) economic relationship preserving with no column constraint (ERP) (Peters and Hertel, *in review*). The experiments use identical bottom-up data to create the balanced matrices and are then taken as input to a simple partial equilibrium (PE) model which allows us to analytically trace how economic relationships, which arise from the different disaggregation methods, impact modeling results.

The modeling analysis focuses on three contemporary economic shocks. The first is a technology-specific capital subsidy (e.g. an investment tax credit). This is useful since it will highlight the value of preserving the cost structure in the sub-sectors. The second example involves a shock to the price of natural gas (e.g. a result of the shale gas boom in the US). Finally, a sector-wide capital tax (e.g. removal of a sector-wide tax credit) is considered. This experiment illustrates the importance of preserving "row shares" in the reconciled database (i.e. the relative capital intensity of different technologies in the power sector). Model results are shown to be highly dependent on the balancing methods used to construct a CGE database and flow directly from the mathematical features of the algorithms.

In current practice the database construction methods used in IAMs are, at best, not adequately documented. This point will only increase in importance with the increasing demand for more highly resolved analysis of critical sectors in IAMs. The results shown in this article advocate for greater introspection at the database-modeling nexus. More broadly, the authors hope it will redirect attention back to the validation of new and innovative CGE and IAM extensions. Finally, the results provide evidence that the appropriate selection of matrix balancing methods can reduce the overall deviation between bottom-up and top-down modeling.

2. Database construction

This article focuses on the matrix balancing methods used to reconcile bottom-up data with the aggregate databases required by top-down IAM and CGE models. Schneider and Zenios (1990) provide the following description of the matrix balancing problem: "Given a rectangular matrix Z^0, determine a matrix Z that is close to Z^0 and satisfies a given set of linear restrictions on its entries. [Matrix names changed to conform to input-output (I-O) convention]" Matrix balancing for disaggregation of a sector in I-O, SAM, and CGE databases consists of the matrix Z^0, with elements z^0_{it}, where i is the input and t is the new sub-sector, constructed from the values implied by the bottom-up data for the disaggregate sectors. The linear restrictions, here, are the top-down economic accounting conditions (e.g. supply equals demand) and any other restrictions (e.g. non-negativity) required for modeling. Matrix balancing methods generally differ in the how they define the "closeness" of Z to Z^0 (e.g. an objective function) and the set of required constraints.

2.1. Bottom-up data and the Z^0 matrix

The example presented in this paper is a disaggregation of the electricity sector for the 129 regions in the Global Trade Analysis Project (GTAP) version 8 database (Narayanan et al. 2012). Here, the original power sector is disaggregated into seven new electricity sectors: nuclear, coal, gas, oil, hydroelectric, wind, and solar power. The data used for the disaggregation for this paper are:

i) q_t - electricity production (in GWh) by technology, t (IEA, 2010a; IEA, 2010b),

ii) o_i* - total value of inputs, i, (in US dollars) to the aggregate GTAP electricity sector , and

iii) l_{it} - levelized (i.e. annualized cost in US dollars per GWh) capital, operating and maintenance (O&M), fuel, and effective tax costs of electricity for generating technologies (IEA/NEA, 2010).

The data and formulations presented here are reduced to a single region; each regional database can be estimated independently. The elements of matrix Z^0, z^0_{it}, are thus the product of the levelized input costs, l_{it}, and the total production q_t scaled to the total value in the top-down data. The most important consistency requirement in the balanced database, Z, is that the total value of each input employed across the new sectors is equal to the total value of the corresponding input value employed in the original electricity sector, o_i*.

$$z_{it}^0 = \frac{l_{it} \cdot q_t}{\sum_i \sum_t l_{it} \cdot q_t} \cdot \sum_i o_i^* \tag{1}$$

$$\sum_t z_{it} = o_i^* \tag{2}$$

It is easy to see that the consistency requirement (Eq. 2) will not necessarily hold, since these data come from disparate sources (i.e. techno-economic data versus national accounts). In fact, Table 1 shows that the bottom-up data (Z^0) implies different allocations of levelized input costs, i, in the total electricity sector than the top-down data for this scenario.[2] Thus, it is important to analyze database reconciliation methods to minimize the effect in the model economy.

Table 1. Comparison of input employment implied by the bottom-up data and the total input employment in the top-down data (GTAPv8) of the total electricity sector ("ely") in the United States ("usa")

	Bottom-up (Z^0)		**Top-down (GTAP)**	
LCOE (*i*)	**Value (2007 USD)**	$s^V_{i,\text{"ely","usa"}}$	**Value (2007 USD) (o_i^*)**	$s^V_{i,\text{"ely","usa"}}$
Capital	143,679	38.3%	118,955	31.7%
O&M	58,560	15.6%	141,615	37.8%
Coal	63,625	17.0%	42,782	11.4%
Gas	84,065	22.4%	47,288	12.6%
Oil	24,823	6.6%	24,111	6.4%
Total	374,752	100%	374,752	100%

2.2. Matrix balancing methods

The methods for disaggregation fall into two broad categories: *ad-hoc* and constrained optimization. *Ad-hoc* methods employ straightforward algebraic rules to allocate the aggregate values

[2] Levelized costs try to capture the annualized cost of production while considering data such as overnight capital costs, depreciation rate, fuel costs averaged over the year, heat rate, and other technological factors. Top-down data comes from the reporting of final reported costs in broad categories which may encompass a wider breadth of costs than the bottom-up data (e.g. transmission and distribution, insurance services, customer service, litigation). These different perspectives offers some insight on the origin of the discrepancies between the two data types.

across the different technologies. Constrained optimization methods minimize a specific distance metric with respect to important economic relationships, such as: i) cost structure (i.e. the share of an input cost in total production cost of a sub-sector, c_{it}) and ii) relative input intensity (i.e. the row share corresponding to the relative employment of an input amongst the different sub-sectors, r_{it}). These relationships are expressed mathematically below where the super-script *0* refers to the relationship implied by the original matrix, Z^0. The relationships in the estimated matrix, Z, have no super-script.

$$c_{it}^0 = z_{it}^0 \Big/ \textstyle\sum_i z_{it}^0 \text{ and } r_{it}^0 = z_{it}^0 \Big/ \textstyle\sum_t z_{it}^0 \qquad \text{(3) and (4)}$$

$$c_{it} = z_{it} \Big/ \textstyle\sum_i z_{it} \text{ and } r_{it} = z_{it} \Big/ \textstyle\sum_t z_{it} \qquad \text{(5) and (6)}$$

Constrained optimization methods define the "closeness" metric explicitly via the objective function – seeking to find a new matrix Z which satisfies the column and/or row totals while coming as close as possible to the original column and/or row shares. *Ad-hoc* methods target these shares implicitly. The most relevant constrained optimization methods minimize entropy distance: i) MSCCE, ii) RAS, and iii) ERP.[3] The most popular *ad-hoc* method, and thus the one explored here, allocates value in the matrix based on row share alone. Other a*d-hoc* methods may be equally prevalent, but are rarely publicly documented. The term, a*d-hoc*, in this work always refers to the method described in Section 2.2.1. These four matrix balancing methods are explained in detail in the subsequent sections.

2.2.1. *Ad-hoc*

Despite the ubiquity of well-studied matrix balancing methods, *ad-hoc* approaches remain very popular in practice. The most prevalent of these is the row share-based allocation (Marriott, 2007; Lindner et al. 2014; and Arora and Cai, 2014). Here, the matrix Z^0 is comprised of the implied value from the bottom-up data (Eq. 1) and o_i* is the input employment in the original aggregate sector. The *ad-hoc* method allocates the original input value in the aggregate sector by the following equation:

$$z_{it} = \frac{z_{it}^0}{\sum_t z_{it}^0} \cdot o_i^* \qquad (7)$$

or equivalently, using the initial row share:

$$z_{it} = r_{it}^0 \cdot o_i^* \qquad (8)$$

Of course, this is a simplification of the *ad-hoc* methods used by Marriott (2007), Arora and Cai (2014), and Lindner et al. (2014). Their disaggregations include more detailed inputs than the illustrative ones presented here. Basic assumptions on fuel inputs (e.g. coal to coal-fired power) and even more detailed assumptions on other inputs (e.g. water transport is exclusive to coal-fired power and pipeline transport is split between gas and oil power) are easily made. However, the general intuition is the same: row share-based allocation in the cases where no *exact* assumption of values on Z can be made. Two key points are: i) cost structure is not specifically considered in the *ad-hoc* method and ii) there can be no total cost or any other informational constraint. These can be readily implemented in the context of constrained optimization methods to follow.

[3] In addition to entropy methods, Sue Wing (2008) provides a minimum of sum squared error approach specific to disaggregating the electricity sector. It is not clear how often this type of formulation is used in practice.

2.2.2. Minimum sum of column cross-entropy (MSCCE)

The minimum sum of column cross-entropy (MSCCE), as proposed by Golan et al. (1994) and extended by Robinson et al. (2001), focuses on cost structure, but does not specifically focus on row shares. The constrained optimization problem, in its most simplified form, is as follows:

$$\min_{c_{it}} \sum_i \sum_t c_{it} \ln \frac{c_{it}}{c_{it}^0} \tag{9}$$

subject to:

$$\sum_t c_{it} \cdot o_t^* = o_i^* \tag{10}$$

$$\sum_t c_{it} = 1 \tag{11}$$

$$0 \leq c_{it} \leq 1 \tag{12}$$

where c^0_{it} is the original cost structure implied by Z^0 and where o_i* and o_t* are the given row and column sums, respectively, which ensure consistency with the top-down data.[4] The optimal c_{it} result can be readily be transformed to z_{it} by multiplying them by the value of output for a given technology.

A key weakness of MSCCE is that the ordering of relative input intensities between technologies (i.e. row shares) is not always preserved (McDougall, 1999). This can have adverse consequences for economic modeling, as detailed in Section 3.

2.2.3. RAS

The biproportionate adjustment (RAS) method attempts to preserves both economic relationships (i.e. cost structure and row share) by targeting the elements of matrix Z^0, specifically. RAS is not always treated as a constrained optimization problem, but the problem can be written as follows (McDougall, 1999):

$$\min_{z_{it}} \sum_i \sum_t z_{it} \ln \frac{z_{it}}{z_{it}^0} \tag{13}$$

subject to:

$$\sum_t z_{it} = o_i^* \tag{14}$$

$$\sum_i z_{it} = o_t^* \tag{15}$$

This reflects a "true" cross-entropy formulation and is related to MSCCE as a *weighted* sum of column cross-entropy. While the distance between Z and Z^0 may be greater than in MSCCE, the basic RAS solution preserves the ordering of input intensity (McDougall, 1999). Robinson et al. (2001) acknowledges that the RAS approach may be better suited to cases where both cost structure and row shares are important, as is generally the case for CGEs and IAMs.

2.2.4. ERP

The MSCCE and RAS approaches both require column sum constraints (Eq. 10 and Eq. 15, respectively), whereas the *ad-hoc* approach has none. These constraints ensure a fit to an observed total

[4] The total cost constraint, o_t*, jointly considers the bottom-up and top-down data by first allocating the top-down value fuel to the corresponding sector (e.g. gas to gas power), then allocating the bottom-up values of O&M and capital in the same manner as in Eq. 1. This ensures a feasible solution for all the regions. The value of constraint is reflected in the total costs shown in *Table 3*.

cost for each sub-sector when such an observation exists. When data on the total cost associated with individual technologies does not exist, or where targeting relationships rather than totals is judged to be of more importance, the column sum constraint may unnecessarily restrict the problem (Peters and Hertel, *in review*). The economic relationship preserving (ERP) method is based on the RAS approach where the total cost constraint is relaxed. The result collapses to RAS when the constraint is included. It is formulated as follows:

$$\min_{z_{it}} \sum_i \sum_t \left({z_{it}} / {\sum_i \sum_t z_{it}} \right) \ln \left(\frac{c_{it} \cdot r_{it}}{c_{it}^0 \cdot r_{it}^0} \right) \quad (16)$$

$$\sum_t z_{it} = o_i^* \quad (17)$$

This objective explicitly balances both cost structure, c_{it}, and row share, r_{it}. The RAS row sum constraint remains (Eq. 14 and Eq. 17). This formulation is easily compared with both the *ad-hoc* and constrained optimization approaches because ERP does not require any assumption on total cost for the sub-sectors.

2.3. Comparison of construction methods

In summary, there are two primary considerations when selecting a matrix balancing method: i) an objective which seeks to preserve important economic relationships (i.e. row share and/or cost structure) and ii) required constraints (i.e. total input employment (row) and/or total cost (column) constraints). Here, the required constraints are independent of additional informational constraints and refer only to requirements of the method itself. Table 2 shows how MSCCE, RAS, ERP, and the *ad-hoc* approach fit into these categories.

Table 2. Mathematical considerations for comparing matrix balancing methods.

Consideration	MSCCE	RAS	ERP	Ad-hoc (Row Share)
Objective	-	- Row share	- Row share	- Row share
	- Cost structure	- Cost structure	- Cost structure	-
Required Constraints	- Total row	- Total row	- Total row	- Total row
	- Total column	- Total column	-	-

Because of the interdependent relationships between the objective, the constraints, and disparities in data sources, it is difficult to reach general conclusions about an algorithm's usefulness. However, some expectations from this investigation can be formed (all of which assume no additional informational constraints and required constraints are the identical if required).

If the total cost constraint values for RAS are the same as those implied by the *ad-hoc* method, then the RAS result is equivalent to the *ad-hoc* result. However, it is worth noting that, despite this equivalence, both the RAS and ERP allow for additional information via the constraint set. Also, as mentioned before, it is not necessary, but a total cost constraint can be imposed on ERP. If the optional total cost constraint on ERP is the same as the required constraint on RAS, the two methods are equivalent.

The objective function determines whether the balancing method preserves row share, cost structure, or both. The MSCCE objective considers only cost structure while sacrificing row share, and the *ad-hoc* method considers only row share, while neglecting cost structure. The RAS and ERP objectives attempt to preserve both, but in doing so sacrifice both (although likely to a lesser degree than MSCCE and *ad-hoc*).

Required constraints may prevent an algorithm from preserving economic relationships. The row total constraint is required in all cases for CGE consistency; however, the total cost constraint can be relaxed.[5] MSCCE and RAS require total cost constraints; *ad-hoc* and ERP do not. Imposing total cost constraints may prevent the algorithm from preserving the cost structure objective because the total cost is not flexible to preserve the economic relationship of the individual elements. The row constraints impact the overall possible "closeness" of the balanced top-down data to the unbalanced bottom-up data. These constraints increasingly prevent preserving economic relationships as the constraints become increasingly restrictive (i.e. increasing disparity between bottom-up and top-down data).

Assuming no additional constraints beyond those required, the objective and constraints imply a certain ordering of how well each algorithm preserves both row share and cost structure. Here, ordering is only relevant when viewing the entirety of the matrix; ordering may not hold for individual elements. First, the *ad-hoc* methodology perfectly preserves row share while MSCCE makes no consideration whatsoever of the row shares. Therefore, ERP and RAS lie somewhere in between. Second, ERP will preserve cost structure better than the *ad-hoc* method, given that ERP explicitly considers this in the objective function. Also, MSCCE should perform better than RAS with respect to cost shares, since there is no trade-off with preserving row share. These expectations are summarized later, along with the numerical results in the following sections, in Table 10.

2.4. Disaggregated matrices and numerical comparison

As mentioned previously, many researchers attempt to disaggregate CGE-consistent databases using detailed economic or technological data. If the bottom-up technical data and the aggregate economic data match perfectly, the balancing problem is moot; however, in practice the two data sources invariably differ, sometimes by a large margin. For example, the top-down GTAP data estimates less capital, coal, and gas employment and more O&M employment in the total electricity sector than the unbalanced matrix assembled directly from the bottom-up data, Z^0 (Table 1). Therefore, the ensuing differences between the matrix balancing algorithm results can be attributed to both the balancing method (the focus of this work) and the magnitude of discrepancy between the bottom-up data and the top-down economic data.

In this paper, *ad-hoc*, MSCCE, RAS, and ERP-based disaggregations are constructed for the 129 GTAPv8 regions using the data outlined in Section 2.1 (i.e. annual GWh production and levelized costs fit to the GTAP input employment data). Table 3 shows the results for the United States for each balancing method, and Table 4 shows the average deviation (in absolute value) from the bottom-up data for each matrix balancing method – again for the US.

The disaggregated electricity sector for the United States (Table 3) shows three main points. First, the unbalanced, bottom-up matrix, Z^0, has different total input employment values in the sector (row totals shown in Table 1) than the balanced matrices, all of which conform to the top-down data. However, as discussed in Section 2.1, the input employment for the balanced matrices must match that of the original electricity sector in the GTAP data. This is a major source of deviations shown in Table 4.

Second, expanding on the previous point, the total input employment of fuels from the bottom-up and top-down do not match. The fuel inputs are specific to a technology (i.e. coal to coal power, gas to gas power, and oil to oil power). This drives some of the deviations for the methods which attempt to preserve the cost structure of the technology because the fuel input value is inflexible.

[5] The total row constraint also constrains the total value in the balanced database to the original value in the top-down data (i.e. the sum of row constraints equals the original total sector value).

Table 3. Disaggregated electricity sector for the United States using different approaches (Z^0, Ad-hoc, MSCCE, RAS, and ERP) in 2007 USD.

Z^0

	Nuclear	Coal	Gas	Oil	Hydro	Wind	Solar	Total
Capital	33985	61938	9744	1313	33091	3103	504	143679
O&M	16487	27782	5816	2642	4936	855	43	58560
Coal	0	63625	0	0	0	0	0	63625
Gas	0	0	84065	0	0	0	0	84065
Oil	0	0	0	24823	0	0	0	24823
Total	50472	153345	99626	28778	38027	3958	546	

Ad-hoc

	Nuclear	Coal	Gas	Oil	Hydro	Wind	Solar	Total
Capital	28137	51280	8067	1087	27397	2569	417	118955
O&M	39869	67185	14066	6390	11936	2067	103	141615
Coal	0	42782	0	0	0	0	0	42782
Gas	0	0	47288	0	0	0	0	47288
Oil	0	0	0	24111	0	0	0	24111
Total	68007	161247	69422	31588	39333	4636	520	

MSCCE

	Nuclear	Coal	Gas	Oil	Hydro	Wind	Solar	Total
Capital	32641	32447	8901	1350	39017	3949	649	118955
O&M	32388	83151	11147	3746	9978	1150	55	141615
Coal	0	42782	0	0	0	0	0	42782
Gas	0	0	47288	0	0	0	0	47288
Oil	0	0	0	24111	0	0	0	24111
Total	65029	158380	67337	29207	48995	5100	704	

RAS

	Nuclear	Coal	Gas	Oil	Hydro	Wind	Solar	Total
Capital	25991	48392	7039	705	33517	2753	558	118955
O&M	39038	67206	13009	4391	15478	2347	146	141615
Coal	0	42782	0	0	0	0	0	42782
Gas	0	0	47288	0	0	0	0	47288
Oil	0	0	0	24111	0	0	0	24111
Total	65029	158380	67337	29207	48995	5100	704	

ERP

	Nuclear	Coal	Gas	Oil	Hydro	Wind	Solar	Total
Capital	34051	49088	6148	1081	25522	2707	358	118955
O&M	47776	63683	10614	6290	11010	2156	88	141615
Coal	0	42782	0	0	0	0	0	42782
Gas	0	0	47288	0	0	0	0	47288
Oil	0	0	0	24111	0	0	0	24111
Total	81827	155553	64051	31481	36532	4863	446	

Third, both MSCCE and RAS require a total cost constraint for each of the disaggregated technologies and are constrained to match the values in implied in Z^0. However, the *ad-hoc* and ERP methods do not require such a constraint and, in some cases, deviate greatly from the bottom-up data. This is especially true for the gas sector, a fuel-intensive technology, where the total costs of the sector are much lower for the unconstrained methods (*ad-hoc* and ERP). ERP has flexibility to preserve the cost structure where the value of gas input implied by the bottom-up data is higher than the gas input value in the GTAP data. Table 4 shows the deviations from cost structure and row share for the different methods.

Table 4. Percentage deviation (averaged absolute deviation across inputs and technologies) between the economic relationships before, Z^0, and after balancing for the United States. Ordering in parentheses.

	Cost structure error	**Row share error**	**Cell error**
$\mathbf{Z^0}$	0	0	0
Ad-hoc	0.344 *(4)*	0 *(1)*	0.341 *(3)*
MSCCE	0.201 *(1)*	0.129 *(4)*	0.232 *(1)*
RAS	0.336 *(3)*	0.072 *(3)*	0.378 *(4)*
ERP	0.315 *(2)*	0.044 *(2)*	0.326 *(2)*

The ordering of average absolute deviation between the bottom-up data and the data after balancing is consistent with the expectations outlined previously. MSCCE dominates RAS and ERP, which in turn dominate *ad-hoc* in cost structure preservation. The *ad-hoc* method perfectly preserves row share and both RAS and ERP dominate MSCCE on this metric. Also as expected, ERP outperforms RAS in both cases, because ERP does not require a possibly restrictive total cost constraint. The *ad-hoc* and ERP methods may outperform the MSCCE and RAS methods in either economic relationship if the total cost constraint is highly restrictive. As McDougall (1999) suggests, MSCCE generally preserves the original cell values better than the others.

The ordering shown for the United States in Table 4 generally holds for all 129 regions. Figure 1 shows percentage error for each region (averaged across inputs and technologies, in absolute values) between the row shares (1a) and cost structure (1b) in the balanced data and those implied by the bottom-up data for each method.

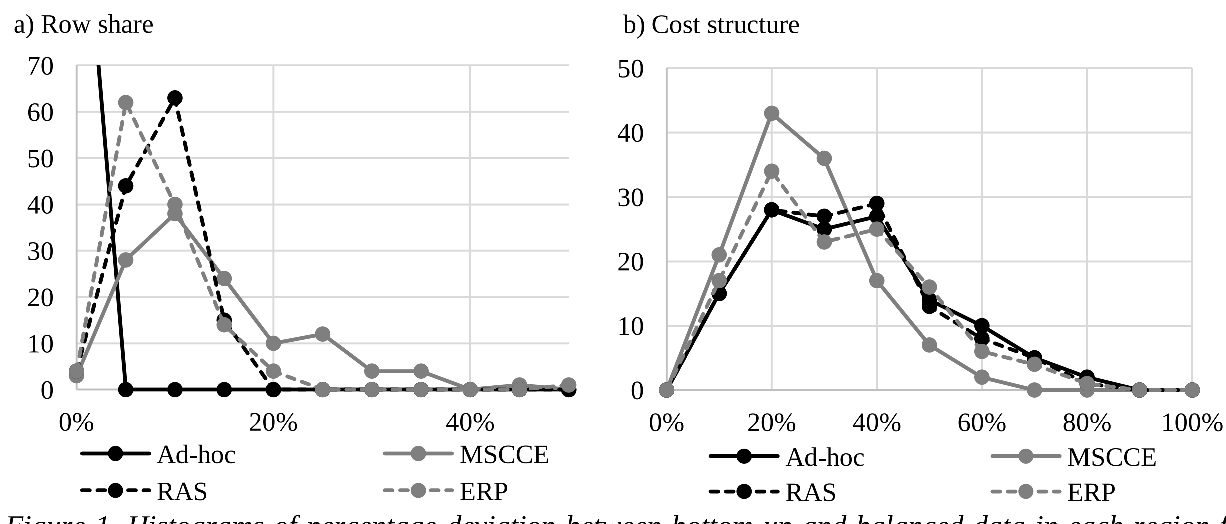


Figure 1. Histograms of percentage deviation between bottom-up and balanced data in each region for both row share (a) and cost structure (b) - where deviation is the absolute percentage deviation averaged across inputs and technologies in each region.

The results across the 129 regions show numerically that the deviation between row share, r_{it} and r^0_{it}, are generally ordered from least to greatest deviation as follows: *ad-hoc* (zero by definition), ERP, RAS, MSCCE. The ordering for the deviation between cost structures, c_{it} and c^0_{it}, is somewhat reversed: MSCEE, ERP, RAS, followed by *ad-hoc*. This ordering is not necessarily identical in each region, but indicates a general tendency that is again consistent with the expectation from the mathematical structure of the matrix balancing methods.

The specific example of the United States shows what the deviation between the bottom-up data and balanced data might look like in terms of values and magnitude of deviation. The ordering of the dominance between balancing methods across the 129 regions in GTAP shows that these results are consistent with the expectations from the mathematics of the methods.

The next section demonstrates how these deviations manifest in the ensuing economic analysis based on these diverse databases. It illustrates the importance of preserving both the cost and row share economic relationships in order to ensure the model results using balanced data are as consistent as possible with the model results using bottom-up data. The shocks chosen for the simulations represent the type of technological (e.g. shale gas extraction) and policy shocks (e.g. investment tax credits) prevalent in the electric power sector and commonly investigated using IAMs.

3. Economic implications of alternative database construction methodologies

This section explores common energy and environmental-related shocks in the context of a model which is broadly representative of those employed in IAMs, but tractable enough to follow how economic relationships in a database map to modeling results. Therefore, a simple partial equilibrium (PE) representation of the electricity sector is presented in this section. It is for illustration only and is not an adequate representation of the electricity sector for use in a full-blown IAM, nor is it representative of the current state of electricity research.[6] Rather this model is designed to clearly identify where and how differences in cost structure and row shares evidence themselves in modeling results for the electric power sector. The simple model implemented here assumes there is no trade in electricity, so the equations can be written for each region separately. Therefore, the regional index is dropped for clarity and conciseness without loss in generality. The simulations focus on the United States because of the availability of quality bottom-up data, but could be readily extended to other regions.

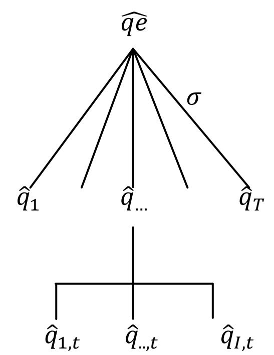
The model is represented in linearized form in order to highlight the role of key economic relationships, including key row and column shares. The ‘hat’ notation in Table 5 refers to percentage changes in the associated levels variables. It is solved as a non-linear, initial value problem using the GEMPACK software suite (Harrison and Pearson, 2006). The price responsiveness of electricity demand is represented via a single, aggregate demand elasticity, μ (Eq. 18), which aggregates the demand responses of retail, commercial and industrial activities. The electricity sector production process is characterized by a quantity-preserving constant elasticity of substitution (CES) production function which aggregates power generated from different technologies based on the CES parameter, σ, which yields a set of derived demands for electricity produced from specific technologies (Eq. 20). Each individual power generating technology demands fuel, O&M and capital in fixed proportion to generation (i.e. Leontief production) (Eq. 22).

Prices for electricity produced by each technology and the aggregate electricity good are assumed to cover costs, leaving no excess economic profits (Eq. 21 and Eq. 19, respectively) which is consistent with

[6] There are numerous studies on the electricity sector using partial equilibrium analysis which capture a vast quantity of engineering-economic interactions. The purpose here is to precisely show the interaction between the balancing methods and model results, rather than the precise sectoral interactions.

average cost pricing in a regulated market. Exogenous price shocks enter into the model by shifting the supply price of the input to electricity generation (Eq. 23). The supply of inputs to the generating technologies is assumed to be perfectly elastic in this simple model (Eq. 24).

Table 5. Production structure for the simple PE model of the representative electricity sector

Production Nest	Equation	Description	No.
	$\widehat{qe} = \mu \cdot \widehat{pe}$	Final electricity demand	(18)
	$\widehat{pe} = \sum_t s_t^Q \cdot \widehat{pt}_t$	Final electricity price – zero profit, average cost pricing	(19)
	$\widehat{qt}_t = \widehat{qe} - \sigma \cdot (\widehat{pt}_t - \widehat{pe})$	CES derived demand for individual technologies	(20)
	$\widehat{pt}_t = \sum_i s_{i,t}^V \cdot \widehat{ps}_{i,t}$	Price of generating technology – zero profit, average cost pricing	(21)
	$\hat{q}_{i,t} = \widehat{qt}_t$	Leontief derived demand for inputs	(22)
	$\widehat{ps}_{i,t} = \hat{p}_{i,t} + \hat{t}_{i,t}$	Supply price for generating technology	(23)
	$\hat{p}_{i,t} = 0$	Infinite factor supply elasticity	(24)
	$\widehat{qo}_i = \sum_t \hat{q}_{i,t}$	Total input employment in electricity sector	(25)

The hat accent designates a variable measured in percent change.
$\widehat{qe}$ is the percent change in total electricity production.
$\widehat{pe}$ is the percent change in price of electricity.
μ is the elasticity of demand for total electricity.
s_t^Q is the quantity share of production from technology *t* in the electricity sector.
$\widehat{pt}_t$ is the percent change in price of electricity from technology *t*.
$\widehat{qt}_t$ is the percent change in GWh production from technology *t*.
σ is the quantity-preserving CES parameter.
$s_{i,t}^V$ is the value share of input *i* in technology *t*.
$\widehat{ps}_{i,t}$ reflects the supply price for input *i* faced by technology *t*.
$\hat{q}_{i,t}$ is the percent change in input *i* used in technology *t*.
$\hat{p}_{i,t}$ is the percent change in price for input *i* for use in technology *t*.
$\hat{t}_{i,t}$ is an exogenous shock to price.
$\widehat{qo}_i$ is the total employment of input *i* in the electricity sector.

This simple framework is used to demonstrate the effect which different supply shocks, $\hat{t}_{i,t}$, have on the model economy. Again, the bottom-up data and the PE model (Eq. 18-25) are identical across the experiments. Therefore, all variation in results comes from the balancing method.

3.1 Simulation to highlight the role of cost structure in modeling

Cost structure preservation comes into play when there is a shock to a particular input to a particular technology (e.g. investment tax credit for a certain technology, fuel price). In order to show the importance of preserving cost structure within each individual technology, a price shock is applied to only one sector. Table 6 shows the capital intensity of each generating technology in the bottom-up data (Z^0) and after balancing using each method described above. The capital share in the cost structure of gas power is highlighted with a dashed box. The first simulation applies a -30% shock to the cost of capital for gas-fired power only ($\hat{t}_{i,\text{"}Gas\text{"}}$ = -30).[7]

Table 6. Capital intensity in the cost structure of technologies after matrix balancing procedures for the United States ($s^{V}_{\text{"}capital\text{"},t}$)

	$s^{V}_{\text{"}capital\text{"},t}$				
Technology	**Z^0**	**Ad-hoc**	**MSCCE**	**RAS**	**ERP**
Nuclear	0.673	0.414	0.502	0.400	0.416
Coal	**0.404**	0.318	**0.205**	0.306	0.316
Gas	**0.098**	**0.116**	**0.132**	**0.105**	**0.096**
Oil	0.046	0.034	0.046	0.024	0.034
Hydro	0.870	0.697	0.796	0.684	0.699
Wind	0.784	0.554	0.774	0.540	0.557
Solar	0.922	0.802	0.921	0.792	0.803

MSCCE is generally closer than the other methods to the capital share values implied by the bottom-up data with the exception of gas power and coal power where the deviation is comparatively large. This raises questions regarding the MSCCE method's ability to preserve cost structure despite (and probably a result of) focusing only on this in the objective.

Focusing on gas power, both the capital cost share in the RAS and ERP approaches are closer to the bottom-up data than the *ad-hoc* approach because the *ad-hoc* method has no specific objective to preserve cost structure. The ERP approach outperforms the RAS in this case because ERP does not require a total cost constraint which allows additional flexibility to conform to the bottom-up data.

Table 7 shows that the results flow directly from the deviations from the bottom-up data. The *ad-hoc*, MSCCE, and RAS methods overestimate capital intensity ($s^{V}_{\text{"}capital\text{"},\text{"}Gas\text{"}}$) in the gas power sector, thereby overestimating the price of gas power ($\widehat{pt}_{\text{"}Gas\text{"}}$) in Eq. 21 and overestimating production changes ($\widehat{qt}_t$) for all technologies in Eq. 20, while the ERP underestimates only slightly.

Table 7. Targeted technology policy: a -30% shock to the price of capital for gas power (Gas) in the US

	Percent change in production (GWh) by technology ($\widehat{qt}_t$)				
Technology	**Raw data**	**Ad-hoc**	**MSCCE**	**RAS**	**ERP**
Nuclear	-3.317	-3.957	-4.517	-3.55	-3.254
Coal	-3.317	-3.957	-4.517	-3.55	-3.254
Gas	**13.017**	**15.531**	**17.73**	**13.934**	**12.77**
Oil	-3.317	-3.957	-4.517	-3.55	-3.254
Hydro	-3.317	-3.957	-4.517	-3.55	-3.254
Wind	-3.317	-3.957	-4.517	-3.55	-3.254
Solar	-3.317	-3.957	-4.517	-3.55	-3.254

These results can be attributed to the deviation for this particular cell, ($s^{V}_{\text{"}capital\text{"},\text{"}Gas\text{"}}$) of the balanced matrices. The results may not deviate for shocks to other cells; however the implication is the same: deviations should be minimized for each cell in the matrix balancing method.

[7] This serves as the most straightforward example; a more relevant example in the context of IAM is presented subsequently (i.e. a negative price shock to gas as result of the shale gas extraction technology).

The shock to the price of capital in gas power in the United States is shown because the connection from cost structure to model results is transparent and tractable. However, the price of capital for gas is not terribly relevant in the context of energy, electricity, climate, and other policies that IAMs have proven useful for – although a similar shock on different sector might be more relevant (e.g. investment tax credit for renewables). Therefore, another relevant example is the glut of gas in the United States due to shale oil and gas extraction technology. Wellhead gas prices in the United States dropped roughly 67% from 2007 to 2012. If natural gas export terminals are constructed, then the rest of the world may also enjoy lower gas prices. A 40% decrease in gas price is applied to each of the 129 regions in the GTAP database ($\hat{t}_{"gas","Gas",r}$ = -40). Figure 2 shows a histogram of the absolute percentage deviation of each matrix balancing method result as compared to the bottom-up data (Z^0).[8]

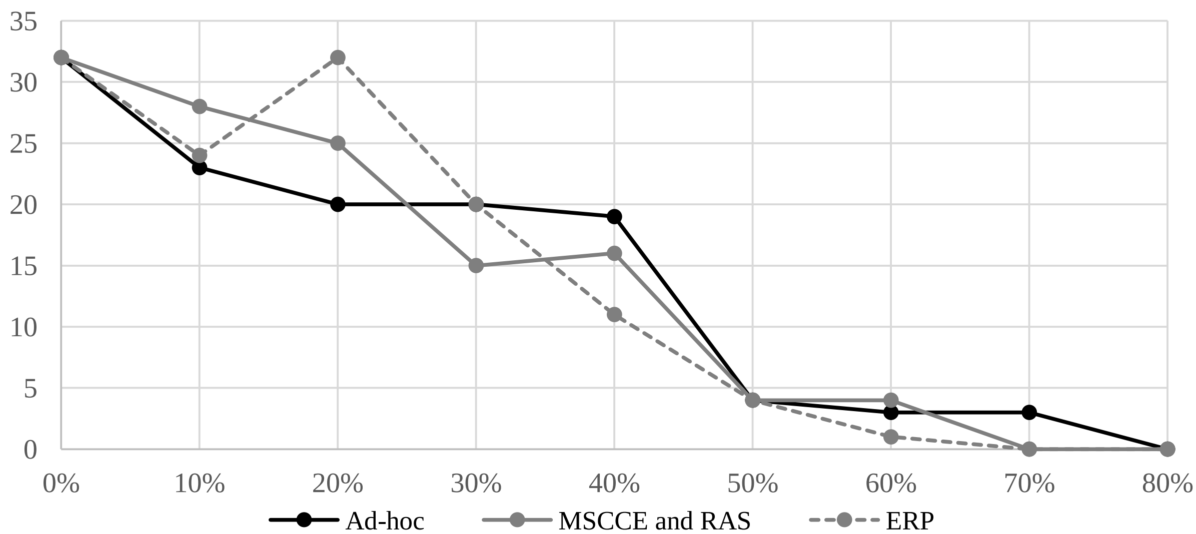


Figure 2. Histogram of absolute percentage deviation from bottom-up model results and balanced data model results from a -40% shock to the price of gas in each of the 129 GTAP regions.

The MSCCE and RAS results are identical because the share of fuel in gas power is given by the employment of gas in the total electricity sector and the total cost is constrained. The total cost is flexible for the *ad-hoc* and ERP methods, so the fuel shares may differ. The results clearly demonstrate that the ERP, RAS, and MSCCE, which consider cost structure in their objectives, dominate the *ad-hoc* method, which does not. However, it is difficult to discern any dominance between the ERP, RAS, and MSCCE methods. The average across technologies of the absolute percentage deviations for each balancing method are 22.83% for ad-hoc, 19.66% for RAS and MSCCE, and 18.47% for ERP. The same results (i.e. ERP, RAS, and MSCCE dominating *ad-hoc*) are found in other simulations, such as a capital subsidy for solar and wind power and a simple carbon-based tax on coal power and gas power, but to varying magnitudes. The general conclusion is that *ad-hoc* model results are less consistent with the bottom-up data model results than methods which explicitly preserve cost structure.

3.2 Simulation to highlight the role of row shares

Row share preservation primarily applies to a shock to an input shared by multiple technologies (e.g. investment tax credit across multiple technologies, labor taxes). Recall that Table 6 shows that

[8] Due to the simple nature of the PE model, the magnitude of the price shock does not have any significant impact on the percentage deviations between the balanced and bottom-up data (e.g. Figure 2). That is, the histogram looks almost identical regardless of the magnitude of the price shock applied in each region (regions are independent from one another).

MSCCE deviates from the bottom-up data for cost structure of capital in gas power and coal power. Another way to see this discrepancy for gas power and coal power is by capital employment across technologies (row share) in Table 8 below.

Table 8. Capital employment across technologies after matrix balancing procedures for the United States

	Share of total capital employment in electricity sector				
Technology	**Z^0**	**Ad-hoc**	**MSCCE**	**RAS**	**ERP**
Nuclear	**0.237**	0.237	**0.274**	0.218	0.286
Coal	**0.431**	0.431	**0.273**	0.407	0.413
Gas	0.068	0.068	0.075	0.059	0.052
Oil	0.009	0.009	0.011	0.006	0.009
Hydro	0.230	0.23	0.328	0.282	0.215
Wind	0.022	0.022	0.033	0.023	0.023
Solar	0.004	0.004	0.005	0.005	0.003
Total	1	1	1	1	1

As expected, the *ad-hoc* method perfectly preserves the row share relationship. RAS and ERP deviations are relatively similar which indicates the total cost constraint in RAS may not be overly restrictive in this particular case. Here, MSCCE shows a switch of ordering in row share between nuclear and coal power (shown in boxes in Table 8). A numerical simulation is provided in Table 9 by implementing a uniform capital price shock of 10% ($\hat{t}_{i,t}$ = 10). A capital price shock is representative of a tax or subsidy on electricity generation investment. Investment tax credits for renewable generation is a widely used policy tool to promote renewable energy and crowd-out investment in carbon-intensive generation. Here the policy is applied to all generation types to make the connection between matrix balancing and model results clear and tractable.

Table 9. Shared input policy simulation: 10% shock to the price of capital in the United States electricity sector

	Percent change in production (GWh) by technology ($\hat{q}_t$)				
Technology	**Z^0**	**Ad-hoc**	**MSCCE**	**RAS**	**ERP**
Nuclear	-13.607	-5.885	-11.3	-5.779	-6.231
Coal	**-0.951**	-1.298	**2.882**	-1.266	-1.417
Gas	14.476	8.730	6.511	8.723	9.511
Oil	17.217	12.933	10.886	12.854	12.683
Hydro	-22.307	-18.800	-24.318	-18.772	-19.107
Wind	-18.557	-12.419	-23.384	-12.300	-12.755
Solar	-24.517	-23.362	-29.535	-23.464	-23.638

The positive price shock, $\hat{t}_{i,t}$, increases, $\widehat{ps}_{i,t}$ (Eq. 23). The ensuing impact of $\widehat{ps}_{i,t}$ on $\widehat{pt}_t$ depends on the input share $s^V_{i,t}$ (Eq. 21) which is where the differences in matrix balancing method enter the model. The matrix balancing methods affect the result of interest, $\widehat{qt}_t$, via the substitution between technologies base on relative cost of technology, $\widehat{pt}_t$ (Eq. 20).

The results indicate that the large deviation in row share for coal power using the MSCCE method is translated directly to the deviation in model results. The direction of change is opposite those implied by the bottom-up data. The major implication is that, in the case of a uniform input price shock (e.g. tax break for capital investment for renewable power) with substitutability between sectors, MSCCE can lead to opposite interpretations of model results even with the simplest of models.

4. Discussion

Divergent results from bottom-up and top-down modeling are well-known (Grubb et al. 1993), and there is constructive research regarding the relative merits and reducing divergence between both approaches (e.g. Böhringer, 1998; McFarland et al. 2004). The important takeaways here pertain to the reasons the results of different top-down models might diverge even in the case of identical bottom-up data.[9] The divergence is the result of two primary factors: i) disparate bottom-up and top-down data and ii) the preservation of economic relationships (i.e. row share and cost structure) after the matrix balancing method which fits the bottom-up data to the top-down data. Of primary interest to this study are the discrepancies caused by the matrix balancing methods.

4.1 Disparate bottom-up and top-down data

Moving to a CGE/IAM framework requires that the engineering data conforms to data on the circular flow of the economy, which are important in certain analyses. For example, Hazilla and Kopp (1990) and Bergman (1991) conclude general equilibrium impacts, such as input prices, output prices, and allocation of resources in the economy, can be "significant and pervasive" in the context of environmental policy. Unfortunately, the two data sources tend to differ, sometimes by large margins. The bottom-up data is constructed from levelized (i.e. annualized) costs of electricity by technology and total production while the top-down data is constructed by targeting prices of electricity, cost structure, and production data (where available) in GTAPv8. The sources and type of data are disparate.

For example, Table 1 shows that the share of O&M is much higher in the top-down database which draws cost away from capital and fuels. Still, in moving to a CGE model, the balanced database must conform to the values in the top-down data via the total input employment constraint in the balancing methods described above. The constraint contributes to a large portion of the difference between the results, but is none-the-less necessary to move toward a CGE model which may be a more *holistic* representation of the economy as compared to the bottom-up representation.

4.2 Preservation of economic relationships

Section 3.1 simulated a technology-specific capital price shock and a shock to the price of gas. These simulations demonstrate that preserving the cost structure for individual technologies can be important. The *ad-hoc* model does not specifically consider cost structure; inputs are allocated solely based on row share. The RAS and ERP approaches, which specifically consider cost structure along with row share, conform closer to the bottom-up data and, therefore, the bottom-up model predictions. It is worth noting that the MSCCE may have large cost structure deviations for some technologies (e.g. coal-fired power in Table 6) which may be unattractive for policies targeting these technologies.

Section 3.2 simulated an electricity sector-wide shock to the price of capital. The MSCCE method implied an opposite result for one of the technologies. This can be attributed to the absence of consideration of the row share relationship in the MSCCE objective function (Eq. 9). MSCCE does not specifically preserve row share, so when a shock is applied which pertains to relative input employment between sectors an opposite result may occur. Even if the result does not turn out to be opposite, it is still less convincing after observing this simulation.

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[9] Another important determinant of modeling results are the different inherent assumptions in top-down and bottom-up models, which are (and should be) debatable. This work only focuses the differences in modeling results from the data and data construction process, which should be less flexible to debate. The simulations here all have identical assumptions and data. The data construction process solely reflects how the data is manipulated to conform to the top-down assumptions.

4.3 Selecting an appropriate matrix balancing method

The decision on which matrix balancing method is most appropriate for the research task at hand depends on several factors and is highly case-specific. The initial decision is whether to include a total cost constraint. This depends on the available bottom-up data and will drive the selection of matrix balancing method. Table 10 summarizes the insights from the mathematical structure discussed in Section 2 which then tie this to the modeling results from Section 3, and charts the path to selecting an appropriate matrix balancing method for CGE and IAMs (Table 11).

Table 10. Considerations for selecting an appropriate matrix balancing method – Insights from algorithms. These only hold when no additional informational constraints are present.

Equivalence		
E1	RAS = *ad-hoc*	- If total cost constraint for RAS is identical to total costs implied by *ad-hoc*, then the two are equivalent. - RAS still allows for information on total cost.
E2	ERP = RAS	- If total cost constraint is added as information to ERP, the two are equivalent.
Cost structure preservation		
C1	ERP > *ad-hoc*	- ERP considers cost structure in the objective.
C2	MSCCE > RAS	- RAS sacrifices some cost structure preservation for row share. - Individual elements may differ in ordering (e.g. RAS result may be closer than the MSCCE for certain elements), but as a whole MSCCE > RAS.
C3	ERP ~ MSCCE	- The level of restriction from the total constraint required by RAS and MSCCE will determine ordering.
Row share preservation		
R1	*Ad-hoc* > all others	- Ad-hoc perfectly preserves row shares.
R2	RAS and ERP > MSCCE	- MSCCE has no consideration of row shares.

Table 11. Considerations for selecting an appropriate matrix balancing method **-** *Insights from modeling. The corresponding insight from the algorithm (Table 10) are in parentheses.*

Total cost constraint?	**Restrictions and equivalence**	**Cost structure important?**	**Row share important?**	**Both relationships important?**
No	- RAS not possible - MSCCE not possible	- ERP > *ad-hoc* (C1)	- *ad-hoc* > ERP (R1)	ERP > all
Yes	- ERP = RAS (E2) - *ad-hoc* not possible	- RAS/ERP ~ MSCCE (E2, C3)	- RAS/ERP > MSCCE (R2)	RAS/ERP > all

If there are no data on input costs to technologies, then total cost may be the only way to differentiate sectors. Also, if the researcher wishes *only* to shock the outputs of the new sectors (e.g. subsidy on renewable technologies) rather than the input prices in the new sectors, perhaps total cost might be preserved while sacrificing some of the component cost detail. In this case, where a total cost constraint is desired, ERP and RAS are equivalent. A total cost constraint cannot be imposed on the *ad-hoc* method, thereby rendering it impotent for this particular information set. The numerical simulations of the RAS/ERP and MSCCE methods show that there is no clear dominance in method in the cost structure case. That is, RAS/ERP performs better for some sectors while MSCCE performs better for others (Table 6). However, RAS/ERP performs much better in the case of the row share relevant simulations (Table 8) which implies that the ERP/RAS might be the best selection when both relationships are relevant.

Alternatively, if technology specific input costs are available in the bottom-up data (e.g. levelized costs as is the case here) and the researcher wishes to shock input prices in the new sectors, the restrictive total cost constraint can be removed. In this case the applicable methods are the *ad-hoc* and the ERP approach, because the basic MSCCE and RAS approaches require a total cost constraint. The mathematical properties imply and the numerical simulations show that ERP performs better in terms of model results in the case of preserving cost structure (Table 7 and Figure 2) while the *ad-hoc* performs marginally better in preserving row share (Table 8). On balance, the ERP seems to outperform the *ad-hoc* method when both relationships are important. It is also worth noting that *ad-hoc* methods are unable to leverage the vast research on incorporating additional information and reliability of information in constrained optimization (Lahr and de Mesnard, 2004).

It is more than likely that both cost shares and row shares will eventually be of importance in most CGE/IAM projects. While researchers may have a particular shock or set of shocks in mind initially, the models are often subsequently used for simulations for which it was not originally designed. Given this, the ERP method is the most flexible method and preserves both economic relationships, thereby providing results which are the most consistent with the original bottom-up data over the largest set of shocks.

5. Conclusions and broader impacts

Using a simple partial equilibrium model, the deviation between results with bottom-up data and balanced data stem from two primary sources: i) differences between the bottom-up and top-down data and ii) the matrix balancing methodology used to conform the dataset when there are disparate data. If the database implied by the bottom-up data match that of the top-down data, there is no need for the matrix balancing method at all. Unfortunately, that is rarely, if ever, the case, and the data balancing methods are necessary. This work shows that the modeling differences can be quite large based on the selection of matrix balancing method which necessitates close consideration, justification, and documentation.

This article explores four matrix balancing methods which are commonly employed to create a consistent CGE/IAM database and the implications each has on economic modeling. Their mathematical constructions (i.e. the objective and constraints) provide some insight into how they might perform in relation to two important economic relationships (i.e. cost structure and row share). The analytical investigation is supported by numerical examples in a simple disaggregation of the electricity sector. Identical data is used for each method. The numerical results are generally consistent with their mathematical constructions regarding the economic relationships.

Numerical simulations showed the relevance of these economic relationships in modeling. The alternative balancing methods, despite identical original data, differed from the original bottom-up data results depending on their mathematical constructions and ability to preserve the economic relationships. In these experiments the original bottom-up data, partial equilibrium model, and simulations were control variables. The matrix balancing methods directly drove the modeling results.

Selecting an appropriate matrix balancing method will help decrease the divergence between bottom-up and top-down models. The ERP method outperforms the other methods both in flexibility (i.e. it is the only method which can be used with and without a total cost constraint) and where both economic relationships are important, which is the most likely case.

The implications for large-scale CGE and IAM modeling are straightforward. First, the best way to reduce deviation introduced by the matrix balancing methods is to inform the top-down data with the bottom-up data, and vice versa. Second, in cases of disparate bottom-up and top-down data, the balancing method matters. Finally, the database construction efforts, which includes the matrix balancing, should be considered closely, justified, and documented. Moving forward data construction elements of CGE and IAM modeling efforts should be publicly documented with data and methods posted online to promote continuous improvement at the data-database-modeling nexus. This is an under-researched, but critical, aspect of IAM research and critical to the long-run credibility of this important work.

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