THE FIRST ANNUAL INPUT-OUTPUT SERIES FOR THE REPUBLIC OF MOLDOVA UNDER THE CAEM REV.2 / NACE REV.2 CLASSIFICATION: METHODOLOGY AND STRUCTURAL DIAGNOSTICS

Andrian TATARU, PhD Candidate*

Abstract

The Republic of Moldova has no continuous, publicly available input-output (IO) series: the National Bureau of Statistics stopped compiling interindustry tables after 2014, and the country is absent from the main international IO databases. This paper reconstructs the first annual IO series for Moldova under the CAEM Rev.2/NACE Rev.2 classification, covering 2014-2023 at 20-sector detail. The method combines four steps: digitisation of the 2014 Supply-Use Table, a classification concordance with demographic reconciliation, sequential biproportional (RAS) updating to official marginals, and a five-criterion coherence audit. The resulting tables satisfy the Eurostat accounting balance and show stable technical coefficients. Structural diagnostics reveal an economy-wide Leontief multiplier of about 2.03 in 2023, four key sectors, and manufacturing as the dominant intermediate supplier. The main contributions are a reusable dataset and a transferable reconstruction protocol for other post-Soviet economies.

Keywords: RAS method, biproportional updating, Leontief multipliers, key sectors, post-Soviet economies

JEL Classification: C67, C82, E16, O52

DOI: https://doi.org/10.65672/fs.2026.2.6

1. Introduction

Input-output (IO) analysis has been, since Leontief (1941), one of the most enduring quantitative frameworks for understanding the

* *Department of Econometrics and Economic Statistics, Academy of Economic Studies of Moldova, Chişinău, Republic of Moldova. ORCID: https://orcid.org/0009-0003-6962-5156. Corresponding author, e-mail: andrian.tataru1@gmail.com*

structural linkages of an economy. For small open economies in particular, where domestic value chains are short, external exposure is high, and policy instruments are few, IO tables offer an indispensable evidence base (Miller & Blair, 2022). The expansion of international IO databases, WIOD (Timmer et al., 2015), FIGARO (Piñero et al., 2022), and OECD ICIO (OECD, 2023), has made this framework widely accessible, yet it has also produced a sharp asymmetry: economies that report their interindustry statistics to these consortia are well covered, while those that do not remain invisible to the global IO research community.

The Republic of Moldova sits squarely in this second group. Despite a functional statistical infrastructure that publishes detailed annual production, intermediate consumption, and gross value added series by activity, no input-output table constructed within an ESA 2010-compatible framework has ever entered the public domain. The National Bureau of Statistics (BNS) compiled interindustry tables under the earlier CAEM Rev.1 system but ceased this exercise after 2014 and has not resumed it under CAEM Rev.2; the country is absent from WIOD, OECD ICIO, and FIGARO. The only prior academic IO contribution for Moldova, Naval (2019), provided a single-year table at 19/16 aggregated branches in the legacy classification. An entire decade of structural change, spanning the 2015 banking crisis, the 2020 pandemic shock, and the 2022 energy crisis, has thus passed without a publicly available, replicable IO representation of the Moldovan economy.

This paper makes three contributions. First, it documents the first annual input-output series for the Republic of Moldova in the CAEM Rev.2 classification (the Moldovan implementation of NACE Rev.2 under ESA 2010), covering 2014-2023 at a 20-sector disaggregation. Second, it formalises a replicable four-step reconstruction protocol, analogue digitisation, classification concordance, biproportional RAS updating, and a five-criterion coherence audit (C1-C5), designed for the data-fragmentation conditions typical of post-Soviet statistical systems undergoing classification transitions. Third, it produces the first comprehensive structural diagnostic of the Moldovan economy at this level of disaggregation: Leontief output multipliers by sector and year, Rasmussen backward and forward linkage indices, and Dietzenbacher-Los structural decomposition of decadal output growth.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature on input-output analysis and reconstruction methods. Section 3 documents the data sources, classification concordance, RAS algorithm, and coherence audit. Section 4 reports convergence diagnostics and the technical coefficients of the reconstructed series. Section 5 presents the structural diagnostics. Section 6 discusses methodological caveats, and Section 7 concludes.

2. Related literature

2.1. Classical input-output analysis and table updating

The modern input-output framework originates with Leontief (1941), whose formalisation of an economy as a system of interconnected production accounts made it possible to trace the full direct-plus-indirect impact of a change in final demand. The accounting architecture, articulation of supply and use tables, distinction between products and industries, and derivation of symmetric IO tables were consolidated by Stone (1961) and codified in the System of National Accounts (United Nations et al., 2009) and the European System of Accounts (Eurostat, 2013). The contemporary reference is Miller and Blair (2022).

Two methodological developments are particularly relevant. The first is the RAS biproportional updating method, introduced by Stone (1961) and formalised by Bacharach (1970), which adjusts a known IO matrix to new marginal totals while preserving its internal structure as closely as possible. RAS has remained the workhorse method for updating and regionalising IO tables for half a century (Junius & Oosterhaven, 2003; Lahr & de Mesnard, 2004). Recent extensions include the multidimensional RAS of Holý and Šafr (2023) and entropy-optimising RAS-equivalent algorithms (Chlebus & Kasapu, 2023), while related work develops non-survey and gravity-based methods for interregional applications (Sargento et al., 2012). The second development is structural decomposition analysis (SDA), introduced in its modern form by Dietzenbacher and Los (1998), which partitions changes in output between a final-demand effect and a technology effect by comparing IO matrices across time periods. Recent work continues to refine and to compare these growth-decomposition techniques (Oosterhaven, 2024).

Both methods carry well-documented limitations. RAS by construction preserves the relative structure of intermediate flows, which means that subsequent SDA on an RAS-updated series will systematically under-attribute change to the technology channel (Dietzenbacher & Los, 1998, Section 4). This property is not a defect, but it requires explicit acknowledgement in any empirical application combining the two, an acknowledgement we return to in Section 6.

2.2. IO reconstruction under data fragmentation and classification transitions

Reconstructing IO tables under constraints is a recurrent methodological problem, particularly for economies that have undergone structural transformation. Three strands are directly relevant to the Moldovan case. The first addresses retrospective reconstruction across classification changes. Baranov et al. (2015) provide the most closely analogous reference point: they construct retrospective Russian IO time series spanning the OKVED → NACE/CPA transition, combining manual source reconciliation with RAS balancing. Their methodology, concordance matrix between old and new classifications, followed by biproportional adjustment to reported marginals, establishes the template we adopt. The second strand covers multi-dimensional and regional disaggregation: Holý and Šafr (2023) for the Czech Republic, Hutniczak (2022) for regional supply-use updates, Sargento et al. (2012) for interregional methods. The third strand concerns institutional and analytical uses of reconstructed IO series in fragile or disrupted economies: Haddad et al. (2023) reconstruct an interregional IO system for Ukraine, deployed to assess the territorial impact of the 2022 conflict. OECD (2023, 2025) codifies contemporary standards for input-output and extended supply-use frameworks within ESA 2010.

2.3. Input-output analysis and the Moldovan gap

Moldova has remained outside the main international IO data consortia. The most recent regional reconstructions have focused elsewhere: Haddad et al. (2022) on Ukraine, Holý and Šafr (2023) on the Czech Republic, and Baranov et al. (2015) on the Russian Federation. None addresses Moldova. Within the domestic literature, IO modelling has been confined to a single research line at the Institute of Mathematics and Computer Science, with Naval (2019) the most recent peer-reviewed contribution: a single-year (2014), 19/16-branch

CAEM Rev.1 table used as input to optimisation models. No subsequent work has produced a NACE Rev.2-compatible series, an annual panel of technical coefficients, or a structural diagnostic at 20-sector disaggregation. This paper addresses that gap directly using the methodological toolkit reviewed above.

3. Data and methodology

The reconstruction proceeds in four connected stages, each addressing a specific data constraint. The first digitises the 2014 Supply-Use Table, the only such table available for the country (Section 3.1). The second harmonises it from the legacy CAEM Rev.1 to the current CAEM Rev.2 classification and reconciles the population concept used in the national accounts (Section 3.2). The third propagates the base-year matrix through time by sequential biproportional (RAS) updating to official annual marginals (Section 3.3). The fourth submits every annual table to a five-criterion coherence audit (Section 3.4). In short, the first two stages build the base-year matrix, the third moves it through the decade, and the fourth validates the result. The full numerical series and the concordance matrix are available from the author on request.

3.1. Source data and digitisation of the 2014 Supply-Use Table

The reconstruction begins from the single Supply-Use Table (SUT) ever compiled by BNS for a post-independence period: the 2014 SUT in CAEM Rev.1. This table exists only in analogue form. Digitisation was performed manually, cell by cell, with four quality controls: (i) row total reconciliation with published total; (ii) verification of the accounting identity $VP_i = CI_i + GVA_i$ (where VP denotes gross output, CI intermediate consumption, and GVA gross value added) for each sector; (iii) column-level resource-use balance check; (iv) cross-check against published BNS macroeconomic aggregates within a tolerance of 0.001%. The digitised 2014 SUT covers 66 active rows (industries plus value-added components) and 78 columns, in current prices (thousand MDL).

3.2. Classification concordance and demographic reconciliation

Two substantive transformations were applied to the 2014 base matrix. The first is the classification transition from CAEM Rev.1 (35+ detailed sectors) to CAEM Rev.2 (20 sectors aligned with NACE Rev.2 under ESA 2010). It involves genuine sectoral remappings: Rev.1

detailed manufacturing subsectors D15-D37 are consolidated into a single section C in Rev.2; Rev.1 category K (real estate, renting, business activities) is split across four Rev.2 sections (L, M, N, and the financial component of K). We construct a 53-entry concordance matrix W that assigns each Rev.1 sector i to one or more Rev.2 sectors j with weights w_{ij} reflecting the relative gross value added of the constituent sub-activities. After applying the concordance, residual discrepancies with independently available 2014 Rev.2 sectoral aggregates were absorbed through a first, limited RAS pass.

The second transformation is demographic reconciliation. Moldovan national accounts underwent a concept transition from ”table population” to ”usually resident population” following the 2014 census revisions. The usually resident concept excludes long-term emigrants who maintain legal residence but live abroad for more than twelve months, a revision that reduces the estimated resident population by approximately 12-15% for Moldova. For sectors whose output is consumed proportionally to population, we apply sector-specific scaling factors derived from BNS methodological notes. The net aggregate effect is a 2.3% downward revision of 2014 GDP relative to the stable-population series, consistent with the BNS published revision.

3.3. The RAS biproportional updating algorithm

Annual updating from the 2014 base to target years 2015-2023 uses the biproportional RAS algorithm (Stone, 1961; Bacharach, 1970). RAS adjusts a known base matrix Z^o to new row totals u and column totals v through iterative row and column scalings, preserving relative structure. Intuitively, the procedure repeatedly rescales the rows and then the columns of the previous year’s table until both its row and its column totals match the new annual control totals, while changing the internal pattern of inter-sector flows as little as possible.

Formally, let Z^o be the 20×20 base matrix of intermediate flows. The RAS iteration aternates a row step $Z^{(k+½)} = \hat{R}^{(k+1)}Z^{(k)}$, with $\hat{R} = diag\left(\frac{u}{Z^{(k)}\mathbb{1}}\right)$ and a column step $Z^{(k+1)} = Z^{(k+½)}\hat{S}^{(k+1)}$, with $\hat{S} = diag\left(\frac{v}{\mathbb{1}^T Z^{(k+½)}}\right)$, terminating when $max_i|r_i - 1| < \varepsilon$ and $max_j|s_j - 1| < \varepsilon$, with $\varepsilon = 0.001$.

The resulting matrix Z^t satisfies both marginal constraints while minimising cross-entropy distance from Z^0. Here $\hat{R}$ and $\hat{S}$ are the diagonal row- and column-scaling matrices, $\mathbb{1}$ is the unit (summation) vector, r_i and s_j the row and column scaling factors, and ε the convergence tolerance.

The annual IO series is constructed by applying RAS sequentially along the time dimension: for each year t ∈ {2015, …, 2023}, the base matrix is the immediately preceding year $Z^{(t-1)}$, with marginal constraints (u^t, v^t) drawn from the BNS sectoral series. The sequential chain captures gradual structural change cumulatively: each year's adjustment starts from a matrix already incorporating the structural movements of the preceding period. Technical coefficients A^t are derived by element-wise division $a_{ij}^t = \frac{z_{ij}^t}{x_j^t}$, and the Leontief inverse $L^t = (I - A^t)^{-1}$ is computed by Gauss-Jordan elimination. We use the standard two-dimensional RAS rather than recent extensions (Holý & Šafr, 2023; Chlebus & Kasapu, 2023) because the additional marginal constraints they require - regional accounts, quarterly IO, and imported-component separation - are not available for Moldova at the 20-sector level.

3.4. A five-criterion coherence audit

Each of the ten annual matrices is subjected to an ex-post coherence audit comprising five criteria. C1 – Accounting identity: $VP_i^t = CI_i^t + GVA_i^t$ must hold within 0.001% of VP for every sector i and year t. C2 – Resource-use balance: total resources (production + imports) must equal total uses (intermediate + final + exports) within 2 MDL on a 2 × 10^{11} MDL base. C3 – Temporal coefficient stability: the coefficient of variation $CV(a_{ij})$ computed across 2014-2023 for each non-trivial coefficient (a_{ij} > 0.01) must fall below 0.3 for at least 90% of coefficients and below 0.5 for all coefficients. C4 – non-negativity: every element $z_{ij}^t \geq 0$. C5 – Convergence: RAS must converge to ε < 0.001 within fewer than 100 iterations for every year.

4. Results: The reconstructed IO series

4.1. RAS convergence and scaling diagnostics

Table 1 reports the RAS convergence diagnostics. For all nine extrapolated years (2015-2023), the algorithm converged in fewer than 10 iterations at ε = 0.001. Terminal row scaling factors fell within [0.85, 1.21] across all years and sectors, and column scaling factors within

[0.82, 1.18]. These ranges are narrow by RAS literature standards, which typically report terminal scaling factors in [0.5, 2.0] for economies undergoing comparable structural change over a decade (Miller & Blair, 2022).

Table 1

RAS convergence diagnostics, 2014-2023

Year	GO[1)]	CI[2)]	RAS iter.	Max scaling deviation	CI/GO	Status
2014	220.5	106.0	- (base)	-	0.481	Base
2015	236.5	108.4	< 10	< 0.001	0.458	✓ Converged
2016	253.9	114.8	< 10	< 0.001	0.452	✓ Converged
2017	275.2	123.3	< 10	< 0.001	0.448	✓ Converged
2018	294.9	131.8	< 10	< 0.001	0.447	✓ Converged
2019	316.6	137.7	< 10	< 0.001	0.435	✓ Converged
2020	304.5	131.5	< 10	< 0.001	0.432	✓ Converged
2021	379.0	171.2	< 10	< 0.001	0.452	✓ Converged
2022	441.9	205.6	< 10	< 0.001	0.465	✓ Converged
2023	494.7	232.8	< 10	< 0.001	0.471	✓ Converged

[1)]GO = gross output (in MDL bn); [2)]CI = intermediate consumption (in MDL bn).

Source: author's calculations based on BNS national accounts and the 2014 digitised Supply-Use Table

The intermediate-to-output ratio (CI/VP) oscillates within a narrow band [0.432, 0.481] across the decade, consistent with values reported for comparable emerging economies (Romania: 0.45-0.52; Bulgaria: 0.43-0.50, Eurostat national accounts series). Year-on-year movements are modest (|Δ| < 0.025 in all adjacent-year comparisons), indicating that the chained RAS updates track gradual structural change rather than absorbing large adjustment shocks. The 2020 observation (CI/VP = 0.432) lies at the lower bound, consistent with pandemic-induced contraction of intermediate trade. The 2021-2023 series exhibits monotonic recovery toward the pre-pandemic mean.

4.2. Technical coefficients and coefficient stability

The matrix of technical coefficients A^t captures the sectoral cost structure year by year. Significant coefficients $(a_{ij} > 0.10)$ and their decade-long evolution include: intra-manufacturing self-consumption a (C→C) declining from 0.398 to 0.362 (consistent with partial modernisation); agriculture-to-manufacturing integration a

(A→C) rising from 0.152 to 0.161 (reflecting increased domestic agricultural input use by food processing, plausibly a structural consequence of the 2014 Deep and Comprehensive Free Trade Area (DCFTA)); and energy intensity in manufacturing a (D→C) declining from 0.190 to 0.176 (consistent with equipment modernisation and energy price substitution effects).

The stability of the coefficient matrix across the decade is summarised by the coefficient of variation distribution. Across 297 non-trivial coefficients ($a_{ij} > 0.01$), the mean CV is 0.157, the median 0.142, with 94.6% of coefficients displaying CV < 0.3 and 100% displaying CV < 0.5. This indicates that the reconstructed series exhibits stable structural properties across the decade, a necessary precondition for the structural diagnostics developed in Section 5.

4.3. Coherence audit results

The five-criterion protocol introduced in Section 3.4 was applied to each of the ten annual matrices. All five criteria are satisfied on every year of the series. The accounting identity C1 holds with a maximum deviation of 2 MDL on a base of 232 × 10^9 MDL (below 0.001% of gross output). The resource-use balance C2 holds within the 2 MDL rounding tolerance for every product. Temporal coefficient stability C3 is satisfied with 94.6% of non-trivial coefficients below CV = 0.3 and 100% below CV = 0.5. Non-negativity C4 holds by construction (Lahr & de Mesnard, 2004) and is verified ex-post on every cell. Convergence C5 is achieved in fewer than 10 iterations every year, far below the 100-iteration upper bound. The joint satisfaction of C1-C5 on a 10-year series, combined with narrow scaling factors and coefficient stability, establishes the internal consistency of the reconstructed series.

In the regional context, the Moldovan intermediate-to-output ratio (0.432-0.481 across the decade) falls within the range typical for small post-communist economies; the Moldovan import-dependence ratio is substantially higher than for EU-27 member states at comparable development stages, a structural feature consistent with Moldova's small size, narrow industrial base, and high intermediate-input imports. A full quantitative comparison across Romania, Bulgaria, Georgia, and other post-Soviet economies is reserved for future work.

5. Structural diagnostics of the Moldovan economy

5.1. Leontief output multipliers across the decade

The diagnostics in this section describe the structure implied by the reconstructed series. Because that series is anchored to the 2014 benchmark and propagated by RAS (Section 6), the results are most reliable as a comparative, qualitative picture across sectors and over time, rather than as precise point estimates for any single year. For each annual matrix A^t we compute the Leontief inverse $L^t = (I - A^t)^{-1}$ and derive the output multiplier $m_j^t = \sum_i L_{ij}^t$.

Table 2 reports multipliers for 2014, 2020 and 2023, plus the change.

Table 2

Leontief output multipliers (Type I), selected years

Code	Sector	2014	2020	2023	Δ2014→23
A	Agriculture, forestry and fishing	2.011	1.976	2.292	+ 0.281
B	Mining and quarrying	2.097	1.965	2.287	+ 0.190
C	Manufacturing	2.647	2.508	2.683	+ 0.036
D	Electricity, gas, steam	2.401	2.285	2.785	+ 0.384
E	Water supply; waste mgmt	2.753	2.473	2.055	- 0.698
F	Construction	2.217	2.154	2.458	+ 0.241
G	Wholesale, retail trade	1.910	1.646	1.942	+ 0.032
H	Transportation, storage	2.588	2.238	2.372	- 0.216
I	Accommodation, food	2.387	2.189	2.283	- 0.205
J	Information, communication	2.019	1.777	1.540	- 0.479
K	Financial, insurance	1.556	1.600	1.700	+ 0.144
L	Real estate	1.418	1.349	1.481	+ 0.063
M	Professional, scientific	2.037	1.731	1.794	- 0.243
N	Administrative, support	2.438	1.991	2.594	+ 0.156
O	Public administration	1.790	1.759	1.655	- 0.135
P	Education	1.670	1.380	1.566	- 0.104
Q	Human health, social work	1.889	1.695	1.718	- 0.171
R	Arts, entertainment	2.371	1.653	2.396	+ 0.025
S	Other services	2.203	1.926	2.001	- 0.202
T	Households as employers	1.000	1.000	1.000	0.000
	Economy-wide mean	**2.070**	**1.865**	**2.029**	**- 0.041**

Source: author's calculations from the reconstructed 2014-2023 IO series

The economy-wide mean multiplier in 2023 is 2.029. Three sectors exhibit multipliers substantially above the mean: D - Electricity, gas and water (2.785), C - Manufacturing (2.683), and H - Transport (2.372). These represent infrastructural or productive cores of the economy, where a unit increase in final demand propagates through long supply chains of domestic intermediate inputs. The lowest multiplier is L - Real estate (1.481), reflecting the sector's low intermediate-input content.

Two decade-long movements warrant attention. The multiplier of J - ICT declines from 2.019 in 2014 to 1.540 in 2023 (-24%), the largest drop in the series, reflecting growing imported intermediate inputs (licensed software, cloud services, foreign equipment) in a sector whose nominal output has otherwise grown rapidly. Nominal growth in ICT thus masks structural weakening of domestic linkages, a pattern invisible in standard national accounts and detectable only through IO analysis. Conversely, the multiplier of D - Electricity rises from 2.401 to 2.785 (+0.384), reflecting both the growing cost share of imported energy inputs and cumulative network losses. The stability of the economy-wide mean (2.070 in 2014; 2.029 in 2023; decade range [1.865, 2.070]) indicates that overall interconnectedness has not changed dramatically, even as individual sectors have shifted meaningfully.

5.2. Rasmussen linkages and the identification of key sectors

Rasmussen (1956) introduced two standardised indices: the backward linkage index $BL_j = \frac{\frac{1}{n}\sum_i L_{ij}}{\mu}$ measuring the intensity of intermediate-input demand on the rest of the economy, and the forward linkage index $FL_i = \frac{\frac{1}{n}\sum_j L_{ij}}{\mu}$ measuring the intensity of the intermediate-input supply, where $\mu = \frac{1}{n^2}\sum_i \sum_j L_{ij}$. A sector with both $BL > 1$ and $FL > 1$ is classified as a key sector.

Table 3 reports the 2023 values.

Table 3

Rasmussen linkage indices and key-sector classification, 2023

Code	Sector	BL	FL	Classification
A	Agriculture, forestry and fishing	1.130	1.537	**KEY SECTOR**
B	Mining and quarrying	1.128	0.793	Backward-dependent
C	Manufacturing	1.323	5.629	**KEY SECTOR**
D	Electricity, gas, steam	1.373	1.296	**KEY SECTOR**
E	Water supply; waste mgmt	1.013	0.571	Backward-dependent
F	Construction	1.212	0.897	Backward-dependent
G	Wholesale, retail trade	0.957	0.598	Isolated
H	Transportation, storage	1.169	1.026	**KEY SECTOR**

Code	Sector	BL	FL	Classification
I	Accommodation, food	1.125	0.667	Backward-dependent
J	Information, communication	0.759	0.857	Isolated
K	Financial, insurance	0.838	0.793	Isolated
L	Real estate	0.730	0.933	Isolated
M	Professional, scientific	0.884	0.582	Isolated
N	Administrative, support	1.264	0.785	Backward-dependent
O	Public administration	0.816	0.493	Isolated
P	Education	0.772	0.519	Isolated
Q	Human health, social work	0.847	0.507	Isolated
R	Arts, entertainment	1.181	0.493	Backward-dependent
S	Other services	0.987	0.532	Isolated
T	Households as employers	0.493	0.493	Isolated

Source: author's calculations from the 2023 Leontief inverse matrix

Four sectors satisfy the joint BL > 1 AND FL > 1 condition: A - Agriculture (BL = 1.130; FL = 1.537), C - Manufacturing (1.323; 5.629), D - Electricity (1.373; 1.296), and H - Transport (1.169; 1.026). This is an increase from two key sectors in 2014, indicating measurable densification of interindustry linkages across the decade.

The most striking result is the forward linkage of manufacturing (FL = 5.629), more than three times the next-highest FL. Manufacturing output is absorbed as an intermediate input across virtually every other sector, placing sector C at the structural core of the Moldovan production system. A disruption to manufacturing from an external demand shock, an input cost shock, or a policy change would propagate through almost the entire sectoral network. No other sector exhibits this property. Agriculture, by contrast, has a high FL (1.537), driven by concentrated supply relationships with food processing rather than by economy-wide diffusion. The ICT sector (J) is classified as isolated (BL = 0.759; FL = 0.857). Combined with the multiplier decline in Section 5.1, this reinforces the picture of an ICT sector whose nominal growth has not translated into stronger domestic linkages.

5.3. Structural Decomposition: final demand vs. technology

Structural Decomposition Analysis (Dietzenbacher & Los, 1998) partitions the change in output between two endpoints into a final-demand effect and a technology effect.

We apply the polar form to decompose the 2014-2023 change in Moldovan output:

$$\Delta x \approx 0.5 \cdot (L_0 + L_{23}) \cdot \Delta f + 0.5 \cdot (f_0 + f_{23}) \cdot \Delta L$$

The aggregate result is striking: 99.98% of the decade's output growth is attributed to final-demand expansion, leaving only 0.02% to technology change. This result is partly genuine and partly methodological. Genuine: the decade's economic story for Moldova is dominated by demand-side dynamics, population dynamics, EU integration via DCFTA, energy and pandemic shocks affecting demand, rather than by deep restructuring of intermediate-input technology. Methodological: the structure-preserving property of RAS systematically under-attributes change to the technology channel (Dietzenbacher & Los, 1998, Section 4). Without independent IO benchmarks, the two cannot be cleanly separated. We discuss this in Section 6.

At the sectoral level, the technology-effect share varies more meaningfully. The energy sector D shows +20.0% technology-effect contribution to its output growth, plausibly reflecting compositional shifts in intermediate-input use during the energy crisis. The construction sector F shows a +8.8% technology effect. Other sectors show small or negative technology-effect contributions, the latter reflecting either genuine structural rationalisation or the under-attribution caveat noted above. These sectoral findings should be interpreted as suggestive rather than definitive.

6. Discussion

The reconstruction documented in this paper, to the best of our knowledge, constitutes the first publicly available annual IO series for the Republic of Moldova in the CAEM Rev. 2/NACE Rev. 2 classification. Three methodological aspects warrant discussion. First, the RAS-SDA interaction. The structure-preserving property of RAS produces the 99.98% finding for the demand effect documented in Section 5.3. This is not a defect of either RAS or SDA but a known interaction that requires explicit acknowledgement. The qualitative diagnostic, Moldova's decade was demand-dominated, is robust to this caveat; the precise quantitative attribution is not. Future work using independent IO benchmarks (alternative data sources and shorter observation intervals) could refine this attribution.

Second, data limitations. The reconstruction rests on a single 2014 base IO matrix, retained throughout the decade through RAS chaining. Genuine technological change between 2014 and 2023, driven by EU integration, the pandemic, and the energy crisis, cannot be detected by this method alone. The series should be understood as a structurally anchored extrapolation of the 2014 technology under the constraints of annual sectoral marginals, not as an independent reconstruction of each year's actual interindustry technology. This is an intrinsic limitation of any RAS-based annual reconstruction starting from a single base.

Third, methodological choices. We use standard two-dimensional RAS rather than recent extensions. The choice reflects data availability rather than methodological preference: multidimensional RAS (Holý & Šafr, 2023) requires regional or quarterly marginal constraints that are unavailable for Moldova; entropy-optimising variants (Chlebus & Kasapu, 2023) deliver gains over RAS at an additional computational cost that is not justified by the current data environment. The protocol established here is upward-compatible: as additional marginal data become available for Moldova, the RAS chain can be replaced or augmented without requiring complete reconstruction. The qualitative diagnostic developed in Section 5, three multiplier-leading sectors (D, C, H), four key sectors (A, C, D, H), and striking manufacturing FL, is robust to most plausible variations in the underlying RAS specification.

7. Conclusions

This paper documents the first annual input-output series for the Republic of Moldova in the CAEM Rev. 2/NACE Rev.2 classification, covering 2014-2023 with 20-sector disaggregation. The four-step protocol, analogue digitisation, classification concordance, biproportional RAS updating, and a five-criterion coherence audit produce a series satisfying the Eurostat balance identity within 2 MDL on a base of 232 billion, with 94.6% of technical coefficients displaying CV < 0.3 across the decade. Structural diagnostics reveal an economy-wide mean Leontief multiplier of 2.029 in 2023, four Rasmussen key sectors (agriculture, manufacturing, energy, transport), and a striking forward linkage for manufacturing (FL = 5.629).

The empirical contribution carries two implications. First, the structural picture of Moldova in 2023, manufacturing at the network core, ICT structurally isolated despite nominal growth, four key sectors driving the rest of the economy, provides a quantitative reference for industrial policy that has previously been unavailable. Second, the methodological protocol is transferable to other post-Soviet economies

(Armenia, Georgia, Kyrgyzstan) that face analogous statistical challenges: discontinuous IO series, classification transitions, and absence from international IO consortia. The protocol does not require quarterly disaggregated data, regional accounts, or imported-component separation, only annual sectoral marginals at the chosen disaggregation level. As more recent IO information becomes available for Moldova, the chain can be re-anchored to a more recent base; the structural diagnostic generated by the present series provides the empirical baseline against which future reconstructions can be compared.

The original contribution of the study is threefold. It delivers a new, internally consistent and openly documented dataset where none previously existed; it formalises a replicable reconstruction protocol that integrates analogue digitisation, classification concordance, biproportional updating and an explicit coherence audit into a single workflow; and it produces the first structural diagnostic of the Moldovan economy at this level of sectoral detail. These contributions should be read together with the study's limitations, set out in Section 6. Because the series is anchored to a single 2014 benchmark and updated by RAS, it preserves the relative input structure of the base year: it captures the cumulative effect of changing sectoral marginals rather than independently observed annual technologies, and, for the same reason, the structural decomposition under-attributes change to the technology channel. The series is therefore best understood as a structurally anchored, accounting-consistent extrapolation, reliable at the level of the qualitative diagnostics reported here but not a substitute for benchmark tables compiled from primary surveys.

Several directions for future research follow naturally. The most immediate is to re-anchor the series whenever the National Bureau of Statistics releases a new benchmark Supply-Use Table, which would allow the RAS chain to be split into shorter intervals and the technology effect to be identified more credibly. A second direction is to extend the framework toward applied uses: demand-driven impact and scenario analysis, price and energy-cost pass-through exercises, and the construction of a social accounting matrix for policy simulation. A third is comparative, placing the Moldovan multipliers and linkage structure alongside those of Romania, Bulgaria, Georgia and other regional economies, so that the diagnostics reported here can serve as the empirical baseline against which both future Moldovan reconstructions and cross-country comparisons are assessed.

References

1. Bacharach, M. (1970). Biproportional Matrices and Input-Output Change. *Cambridge: Cambridge University Press*.
2. BNS (2015). Conturile naționale ale Republicii Moldova 2014. *Chișinău: Biroul Național de Statistică*.
3. Cazcarro, I., Usubiaga-Liano, A., Roman, M. V., Pinero, P., Dietzenbacher, E., Rueda-Cantuche, J. M., & Arto, I. (2025). FIGARO-E3: A high-resolution extended multi-regional input-output database consistent with official statistics. Scientific Data, 12, Article 575. https://doi.org/10.1038/s41597-025-04431-z
4. Chlebus, E., & Kasapu, V. (2023). An Entropy-Optimizing RAS-Equivalent Algorithm for Iterative Matrix Balancing. *Comptes Rendus. Mathématique*, 361, pp. 737-746. https://doi.org/10.5802/crmath.398
5. Dietzenbacher, E., & Los, B. (1998). Structural Decomposition Techniques: Sense and Sensitivity. *Economic Systems Research*, 10(4), pp. 307-324. https://doi.org/10.1080/09535319800000023
6. Eurostat (2013). European System of Accounts - ESA 2010. *Luxembourg: Publications Office of the European Union*.
7. Haddad, E.A., Araújo, I.F., Rocha, A., & Sass, K.S. (2023). Input-Output Analysis of the Ukraine War: A Tool for Assessing the Internal Territorial Impacts of the Conflict. *Regional Science Policy & Practice*. https://doi.org/10.1111/rsp3.12582
8. Holý, V., & Šafr, K. (2023). Disaggregating Input-Output Tables by the Multidimensional RAS Method: A Case Study of the Czech Republic. *Economic Systems Research*, 35(1), pp. 95-117. https://doi.org/10.1080/09535314.2022.2091978
9. Hutniczak, B. (2022). Efficient Updating of Regional Supply and Use Tables with the National-Level Statistics. *Journal of Economic Structures*, 11(1), Article 16. https://doi.org/10.1186/s40008-022-00274-8
10. Junius, T., & Oosterhaven, J. (2003). The Solution of Updating or Regionalizing a Matrix with Both Positive and Negative Entries. *Economic Systems Research*, 15(1), pp. 87-96. https://doi.org/10.1080/0953531032000056954
11. Lahr, M.L., & de Mesnard, L. (2004). Biproportional Techniques in Input-Output Analysis: Table Updating and Structural Analysis. *Economic Systems Research*, 16(2), pp. 115-134. https://doi.org/10.1080/0953531042000219259
12. Leontief, W. (1941). The Structure of American Economy, 1919-1929. *Cambridge, MA: Harvard University Press*.

13. Miller, R.E., & Blair, P.D. (2022). Input-Output Analysis: Foundations and Extensions (3rd ed.). *Cambridge: Cambridge University Press*. ISBN:9781108636124
14. Naval, E. (2019). Experience of the Input-Output Models Application to the Moldovan Economy. *Economy and Sociology*, (1), pp. 36-52. https://doi.org/10.36004/nier.es.2019.1-03
15. OECD (2023). Development of the OECD Inter-Country Input-Output Database 2023. OECD Science, Technology and Industry Working Papers No. 2023/08. *Paris: OECD Publishing*.
16. OECD (2025). Handbook on Extended Supply and Use Tables and Extended Input-Output Tables. *Paris: OECD Publishing*. https://doi.org/10.1787/e9fdcf85-en
17. Oosterhaven, J. (2024). A Decomposition of Economic Growth Decompositions. The Annals of Regional Science, 73(4), pp. 1395-1408. https://doi.org/10.1007/s00168-024-01309-7
18. Piñero, P., Rueda-Cantuche, J.M., Arto, I., Amores, A.F., & Dietzenbacher, E. (2022). Experimental Full International and Global Accounts for Research in Input-Output Analysis (FIGARO Tables). *Eurostat Statistical Working Paper*.
19. Rasmussen, P.N. (1956). Studies in Inter-Sectoral Relations. *Amsterdam: North-Holland*.
20. Sargento, A.L.M., Ramos, P.N., & Hewings, G.J.D. (2012). Inter-Regional Trade Flow Estimation through Non-Survey Models: An Empirical Assessment. *Economic Systems Research*, 24(2), pp. 173-193. https://doi.org/10.1080/09535314.2011.574609
21. Stone, R. (1961). Input-Output and National Accounts. *Paris: Organisation for European Economic Co-operation*.
22. Timmer, M.P., Dietzenbacher, E., Los, B., Stehrer, R., & de Vries, G.J. (2015). An Illustrated User Guide to the World Input-Output Database: The Case of Global Automotive Production. Review of International Economics, 23(3), pp. 575-605. https://doi.org/10.1111/roie.12178
23. United Nations, Eurostat, IMF, OECD, & World Bank (2009). System of National Accounts 2008. *New York: United Nations*.