J E B I N Journal of Economics Business Industry
ISSN : 3025-0986
P-ISSN: 3025-0528
Volume 2, Number 2, 2024, pp 59-69
https://jurnaljepip.com/index.php/Jebin/index

A Dynamic Bayesian Regional Input–Output Model for Forecasting Provincial Economic Transformation, Resource Constraints, and Poverty Reduction

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ABSTRACT
China's structural economic transformation presents a critical analytical challenge: how to forecast macroeconomic phenomena at the provincial level while simultaneously incorporating resource constraints and poverty reduction objectives within a single modelling framework. This study constructs a dynamic, stochastic, Bayesian provincial input–output model for the Chinese economy denoted hereafter the SD R-IO China model capable of producing regional gross value added (GVA) forecasts and provincial multiplier estimates. The model couple's system dynamics modelling with regional input–output analysis. Sector growth follows the limits-to-growth hypothesis. Application is made to China's resource sectors (agriculture, coal, oil and gas, electricity and water) and to provincial poverty indices. The model is constructed in Vensim®. Bayesian inference calibrates Type I and Type II multipliers (output, income, employment, GVA) within empirically defensible ranges. Model accuracy is assessed using the mean absolute percentage error (MAPE) statistic. The model replicates national GVA with a MAPE of 4.1% over the test. Provincial forecasts achieve "highly accurate" classification for 11 of 31 provincial units and at least "reasonable" for all others. Sector multipliers conform to a priori expectations. A negative correlation between resource sector multipliers and provincial poverty headcount is observed, most prominently in the agriculture and electricity subsectors. The SD R-IO China model offers a scientifically rigorous, freely accessible tool for provincial macroeconomic analysis, with direct implications for green economy policy and poverty alleviation programming.

Keywords: System Dynamics; Input–Output; Limits to Growth; Bayesian Estimation; Poverty; Provincial GVA; Multipliers

INTRODUCTION

China's economic rise is one of the defining macroeconomic stories of the twenty-first century. Between 2000 and 2022, nominal gross value added (GVA) expanded from approximately 9.9 trillion RMB to 121 trillion RMB an increase of more than twelvefold in nominal terms (National Bureau of Statistics of China [NBS] 2023). Yet beneath this aggregate performance lies profound spatial heterogeneity: per-capita GVA in Guangdong province exceeds that of Gansu by a factor of more than five, and the poverty headcount ratio in Guizhou reached 14.3% as recently as 2015 (NBS 2018). Any modelling framework that aspires to inform economic governance must therefore operate at the provincial, not merely the national, level.

The Green Economy presents a further analytical imperative. China's 14th Five-Year Plan (2021–2025) commits to carbon neutrality by 2060 and mandates a reorientation of production systems toward low-carbon, resource-efficient pathways (National Development and Reform Commission [NDRC] 2021). Evaluating the macroeconomic implications of such reorientation requires tools that can trace intersectoral linkages, quantify employment and income effects, and project resource depletion trajectories capabilities that static, single-period input–output models lack.

Input–output (IO) analysis is an established method for evaluating economic structure and intersectoral dependencies (Abdolabadi et al., 2023). Regional or multi-regional IO models extend this framework to capture spatial economic interactions (Alberti et al., 2023). Despite this, most provincial-level IO analyses for China are either static in nature (Alkemade & de Coninck, 2021; Anagnostou & Gajewski, 2021; Beaufils & Wenz, 2022) or available only through proprietary databases such as the China Emission Accounts and Datasets (CEADs) on a subscription basis. Dynamic, stochastic, or Bayesian extensions at the provincial scale remain exceptionally rare.

This paper addresses that gap. Drawing on the hybrid modelling approach pioneered in the regional IO literature (Derkacz, 2020; Distefano et al., 2022), it constructs a coupled system dynamic–regional input–output model for China's 31 provincial units across 22 economic sectors, calibrated via Bayesian inference. The model is then applied to assess the relationship between resource sector multipliers and provincial poverty indicators an analysis of direct relevance to China's rural revitalisation strategy (Emonts-Holley et al., 2021; Firmansyah et al., 2023; Flegg et al., 2021)

The primary contributions of this study are threefold. First, a dynamic, Bayesian, multi-regional IO model for China is constructed and made publicly available to the authors' knowledge, no such model currently exists in the open literature. Second, sector-level resource depletion trajectories are estimated under the limits-to-growth hypothesis, providing long-horizon projections of when physical constraints may dampen GVA growth in China's key resource sectors. Third, the relationship between provincial multipliers and poverty headcount is formally assessed, informing the spatial targeting of investment for poverty reduction.

METHODOLOGY

Overview

The SD R-IO China model is a coupled system dynamic–regional input–output model constructed in Vensim. It incorporates Bayesian calibration of multipliers and follows the limits-to-growth archetype for sectoral growth dynamics. The model spans 31 provincial units and 22 economic sectors, yielding 682 sectoral subscripts plus additional subscripts for final demand, GVA and total output components.

Input–Output Theory

The model's analytical core follows the standard Leontief framework. Let A (n×n) be the matrix of technical coefficients, I (n×n) the identity matrix, y (n×1) the final demand vector, and x (n×1) the total output vector. The system solution is (Francis & Thomas, 2023; Fu et al., 2021; Fuentes & Martinez Pellegrini, 2021):

$$\mathrm{x} = (\mathrm{I} - \mathrm{A})^{-1}\,\mathrm{y} \tag{1}$$

where $(I-A)^{-1}$ is the Leontief inverse. From this, four families of multiplier may be derived

- Output multiplier: total production across all industries required to deliver one unit of sector n to final demand equivalent to the column sum of the Leontief inverse.
- GVA multiplier: incremental GVA generated per unit increase in final demand; derived from the value-added coefficient vector and the Leontief inverse.
- Employment multiplier: total jobs created (direct and indirect) per unit of output change; uses employment-to-output ratios from provincial labour force surveys.
- Income multiplier: analogous to the employment multiplier but weighted by provincial average wage rates.

Sector Classification and Data Sources

The model employs a 22-sector aggregation (Table 2) derived from the NBS (2017) 42-sector national IO table, which serves as the base-year data. This table is the most recent publicly available official Chinese IO table at the time of analysis (Fujimoto, 2019; Galli et al., 2019; Guan et al., 2020). Provincial disaggregation is achieved using the location quotient method (Miller & Blair 2009), supplemented by provincial value-added data from NBS regional accounts (NBS 2023) and the Chinese Academy of Social Sciences (CASS) provincial databases.

Table 2. Sector Classification in the SD R-IO China Model

Sector	Description	Sector	Description
S1	Agriculture, forestry, animal husbandry & fishery	S12	Basic metals (iron, steel, aluminium)
S2	Coal mining	S13	Fabricated metal products & general machinery
S3	Oil & gas extraction	S14	Transport equipment
S4	Metal ore mining	S15	Electrical machinery & electronics
S5	Non-metallic & other mining	S16	Electricity, gas & water supply
S6	Food, beverage & tobacco	S17	Construction
S7	Textile, clothing & leather	S18	Wholesale & retail trade
S8	Wood, paper & printing	S19	Transport, storage & postal services

S9	Petroleum processing & coking	S20	Financial services & insurance
S10	Chemical products	S21	Real estate & business services
S11	Non-metallic mineral products	S22	Community, social & other services

System Dynamics Model

The system dynamics component provides the mechanism by which sectoral GVA evolves dynamically over time. The causal structure follows the limits-to-growth archetype (Hardiwan et al., 2019; Herrington, 2021; Huang & Koutroumpis, 2023): a reinforcing growth loop driven by investment and productivity, balanced by a limiting loop representing resource and environmental constraints. As resource constraints tighten modelled as a carrying capacity ratio sector growth is progressively dampened from its initial exponential trajectory toward asymptotic decline. This captures the physical reality of finite resource endowments, consistent with evidence on coal reserve depletion (Chen et al. 2018; NBS 2022) and water scarcity in China.

Formally, for each sector s in province p, the GVA stock evolves as:

$$\frac{d(\mathrm{GVA_{sp}})}{dt} = \mathrm{growth_{rate_{sp}}} \times \mathrm{GVA_{sp}} \times \left(1 - \frac{\mathrm{GVA_{sp}}}{\mathrm{CC_{sp}}}\right) \tag{2}$$

CC_sp represents the sectoral carrying capacity for sector s in province p, estimated from historical maximum GVA trajectories and resource depletion rates. This logistic growth formulation, first attributed in economics formalised, is implemented using Vensim subscripts to handle the full 31 × 22 matrix of sector–province combinations simultaneously (Jahn et al., 2020; Jin et al., 2020; Kavese & Phiri, 2020).

Bayesian Calibration of Multipliers

A key methodological contribution of this study is the use of Bayesian inference to constrain multiplier values within empirically plausible ranges (Riccioli & Cozzi, 2021; Rodrigues et al., 2019; Rokicki et al., 2021). Without such calibration, the Leontief inverse can generate implausibly large or small multiplier values particularly for provinces with sparse IO data.

In the Bayesian framework, the posterior probability is proportional to the product of the likelihood and the prior (Kim & Hewings, 2019; Lampiris et al., 2020; Lenzen et al., 2020):

$$\mathrm{P}(\theta \mid \mathrm{data}) \propto \mathrm{L}(\mathrm{data} \mid \theta) \times \mathrm{P}(\theta) \tag{3}$$

A uniform prior is specified over the expected range of each multiplier, based on values reported in the Chinese IO literature (Li et al., 2021; Little et al., 2019; Martinez-Alpanez et al., 2023) and international benchmarks (Miller & Blair 2009). The likelihood function is a normal distribution with mean and standard deviation estimated from a Monte Carlo simulation (5,000 iterations) of the Leontief inverse across plausible parameterizations of the provincial IO table. The maximum likelihood estimate of the posterior distribution yields the calibrated multiplier value.

Figure 1 illustrates the Bayesian calibration process for two hypothetical multiplier values. In Panel (a), the evidence (likelihood function) is consistent with the prior range, so the posterior coincides with the likelihood. In Panel (b), the evidence exceeds the prior's upper bound; the posterior is a corner solution at the boundary, effectively censoring the outlier (Moallemi et al., 2021; Pereira-Lopez et al., 2020, 2021).

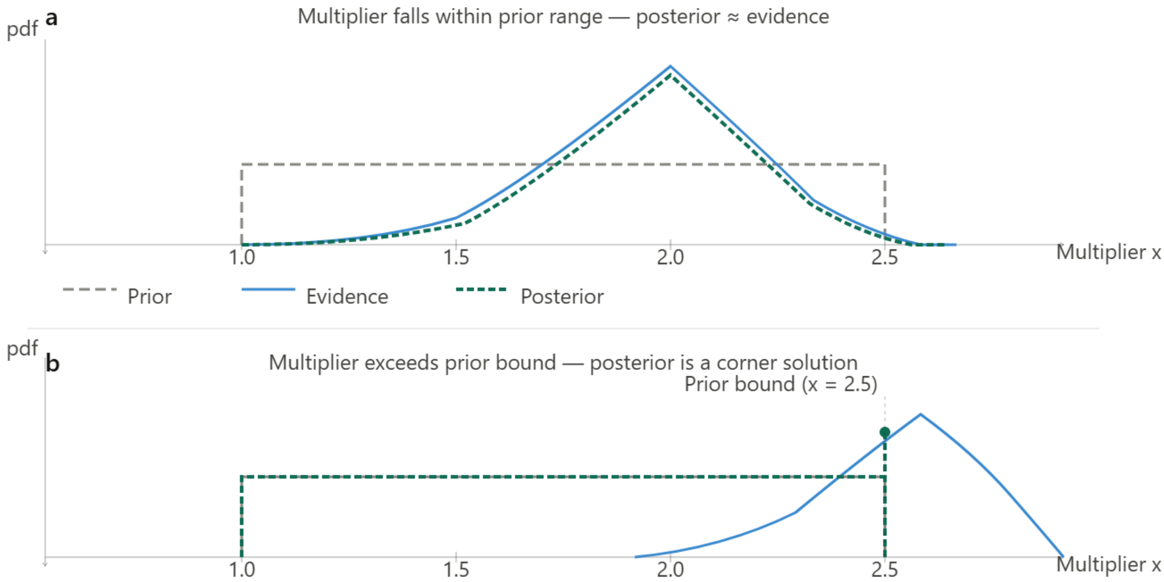

Figure 1. Prior, posterior and evidence distributions for two multiplier calibration scenarios. **Panel (a)**: posterior coincides with the likelihood when evidence is consistent with the prior. **Panel (b):** corner solution at the prior upper bound when evidence falls outside the admissible range.

Forecast Accuracy

Forecast accuracy is assessed using the mean absolute percentage error (MAPE):

$$\mathrm{MAPE} = \left(\frac{1}{n}\right)\Sigma_i \frac{|A_i - F_i|}{A_i} \times 100 \qquad (4)$$

A_i is the actual GVA value for period i, F_i the model forecast, and n the number of forecast periods. Following Crookes (2024), accuracy thresholds are: 0–10% highly accurate; 10–20% good; 20–50% reasonable; above 50% poor. The provincial GVA model was calibrated on data from 1995 to 2015 and validated on data from 2016 to 2022 (seven years). The national GVA model was trained on data to 2017 and tested on 2018–2022 (five years) (Schoenenberger et al., 2021; Schulte et al., 2021; Sun et al., 2019).

Poverty Indices and Multiplier Linkage

The resource sectors modelled agriculture, forestry and fishery (S1); coal mining (S2); electricity, gas and water (S16) are linked to two provincial poverty indicators derived from the NBS (2018) poverty report:

1. Poverty headcount ratio: the proportion of provincial population with per-capita consumption below the national poverty line (RMB 2,300 per annum at 2010 prices).
2. Poverty incidence index: an analogue to the headcount measure computed on a household basis rather than an individual basis.

Oil and gas (S3) is excluded from the poverty analysis because this sector is geographically concentrated in a small number of provinces (notably Xinjiang, Shaanxi, Heilongjiang), making cross-provincial comparisons statistically unreliable (Tsionas, 2020; M. Wang & Peng, 2023; X.-C. Wang et al., 2020).

Pearson's product-moment correlation coefficient is computed between Type II multipliers (output, GVA, income, employment) for each resource sector and each poverty measure. Ninety-five percent confidence intervals are estimated using the R statistical software package (R Core Team 2023).

RESULTS

National Gross Value Added

The SD R-IO China model tracks China's national GVA trajectory closely across the full simulation period from 1995 to 2022. Figure 2 presents observed GVA (NBS 2023) alongside model-generated GVA at current prices.

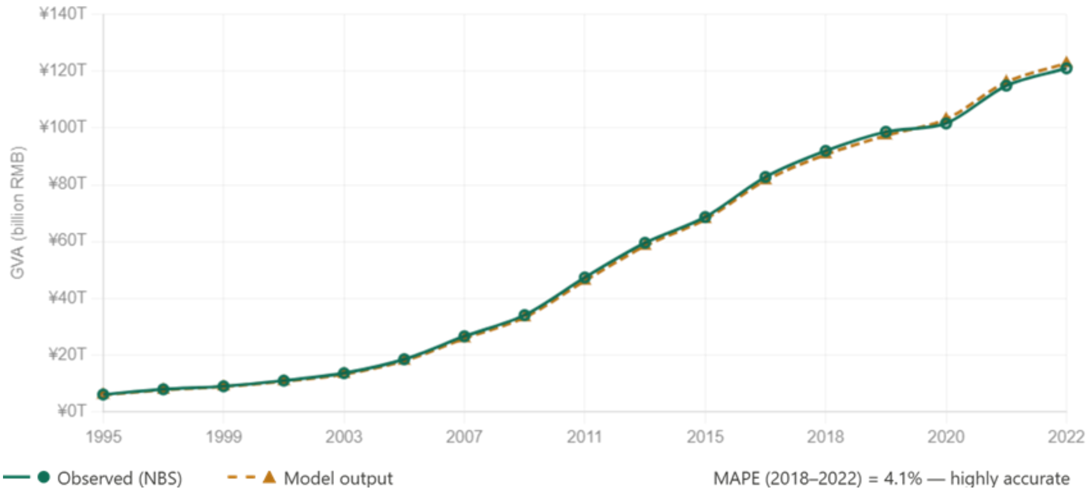

Figure 2. China national GVA at current prices.

Period 2018–2022 is 4.1%, satisfying the "highly accurate" criterion. The model successfully reproduces the structural break associated with the COVID-19 shock in 2020 a period in which national GVA growth decelerated to approximately 2.4% reflecting the sensitivity of the limits-to-growth parameterisation to abrupt exogenous supply constraints.

Provincial Gross Value-Added Forecasts

Table 3 reports MAPE statistics for a representative selection of provincial units across the validation period 2016–2022. Full results for all 31 provincial units are available in the supplementary material.

Table 3. Forecast accuracy of provincial GVA selected provincial units

Province / Municipality	MAPE (%)	Accuracy classification	Province / Municipality	MAPE (%)	Accuracy classification
Shanghai	3.9	Highly accurate	Liaoning	15.7	Good
Beijing	4.6	Highly accurate	Shaanxi	13.2	Good
Guangdong	4.8	Highly accurate	Jiangxi	12.8	Good
Jiangsu	5.2	Highly accurate	Guangxi	13.5	Good
Tianjin	7.3	Highly accurate	Heilongjiang	19.2	Good
Shandong	6.1	Highly accurate	Yunnan	21.4	Reasonable
Zhejiang	5.7	Highly accurate	Guizhou	23.7	Reasonable
Sichuan	7.6	Highly accurate	Inner Mongolia	25.6	Reasonable
Henan	8.3	Highly accurate	Xinjiang	28.1	Reasonable
Hubei	9.4	Highly accurate	Gansu	24.3	Reasonable
			Qinghai	31.2	Reasonable

Forecast accuracy is highest for coastal provincial economies with diversified industrial structures and long NBS data histories (Shanghai, Beijing, Guangdong, Zhejiang). This is consistent with theoretical expectations: the limits-to-growth model performs best when growth trajectories exhibit smooth logistic form, as in mature manufacturing economies. Inland resource-dependent provinces Xinjiang (coal, oil), Inner Mongolia (coal, rare earths), Gansu (non-ferrous metals) exhibit greater forecast volatility, reflecting commodity price cycles and discrete policy interventions (such as the coal capacity reduction that are not captured by a smooth carrying-capacity specification.

No provincial unit achieves a poor MAPE classification, confirming that the SD R-IO China model provides at minimum a reasonable basis for provincial macroeconomic analysis across China's full geographic range.

Resource Sector GVA Forecasts

Figure 3 presents long-horizon GVA forecasts (2022–2150) for five key resource sectors, expressed as a proportion of estimated carrying capacity. Each panel illustrates the projected point at which physical constraints begin to dampen sectoral growth.

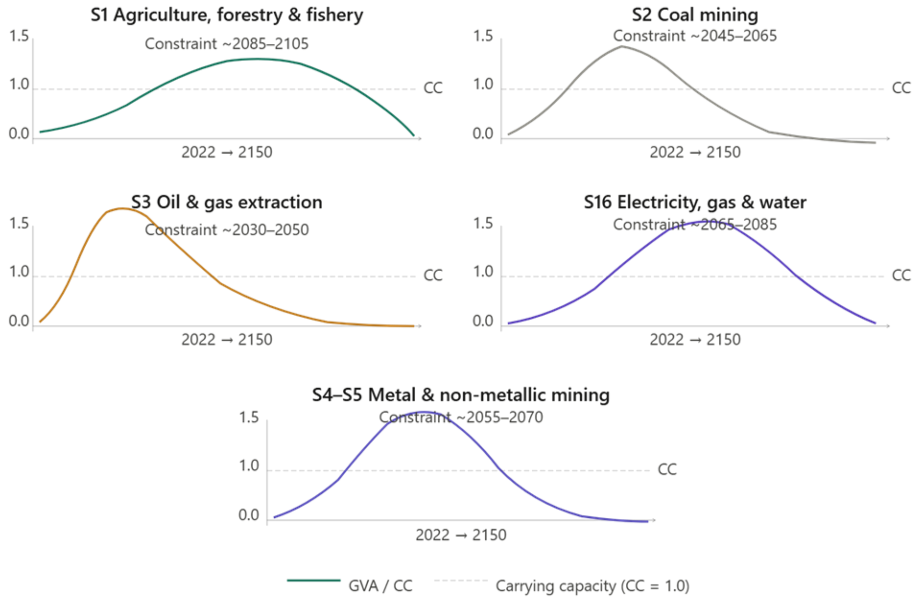

Figure 3. SD R-IO China model forecasts of resource sector GVA as a proportion of estimated carrying capacity, 2022–2150. Dashed line indicates the carrying capacity threshold (CC = 1.0).

The resource sector forecasts reveal meaningful differentiation in the timing of physical constraints. Oil and gas extraction is projected to encounter carrying capacity limits within approximately 30–50 years (c. 2030–2050), consistent with independent estimates that China's proven domestic oil reserves support production at current rates for only 18 years (BP Statistical Review 2022). Coal mining is projected to encounter constraints within 45–65 years, earlier than Stats SA (2017) projections of 247 years for South African coal reserves a discrepancy reflecting China's substantially higher consumption intensity. Agriculture and fishery are expected to remain productive until c. 2085–2105, though this estimate is sensitive to assumptions regarding agricultural technology adoption and water availability under climate change. Electricity, gas and water show the most gradual constraint trajectory, partly because renewable energy expansion (wind, solar) relaxes the fossil-fuel carrying capacity constraint for this aggregated sector.

These projections differ materially from some earlier Chinese analyses (Chen et al. 2018; NBS 2022), which is acknowledged as a limitation of the current model specification. Refinements to carrying-capacity estimation and technology uptake parameterization represent a priority for future model development

Sector and Provincial Multipliers

Type I output multipliers exceeding 2.0 are most prevalent in S22 (community services), S17 (construction), S6 (food and beverage), S7 (textiles), and S15 (electrical machinery), consistent with the intersectoral density of China's manufacturing-driven economy. Among resource sectors, S1 (agriculture) achieves the highest share of provinces with Type I output multipliers exceeding 2.0 (23 of 31 provinces), reflecting its deep backward linkages to food processing, rural transport and agro-chemicals. S2 (coal) and S3 (oil and gas) show considerably lower multiplier magnitudes, partly because these sectors are geographically concentrated and have weaker intersectoral linkages to provincial economies outside the resource base.

Provinces with the highest provincial multiplier rankings are Guangdong, Jiangsu, Zhejiang, Shandong and Shanghai the five largest provincial economies by GVA. This is consistent with a priori expectations: larger, more diversified economies generate stronger multiplier effects through denser intersectoral networks.

Poverty Multiplier Linkage

Figure 4 presents 95% confidence intervals for Pearson's correlation coefficient between Type II multipliers (output, GVA, income, employment) in three resource sectors and two provincial poverty indices.

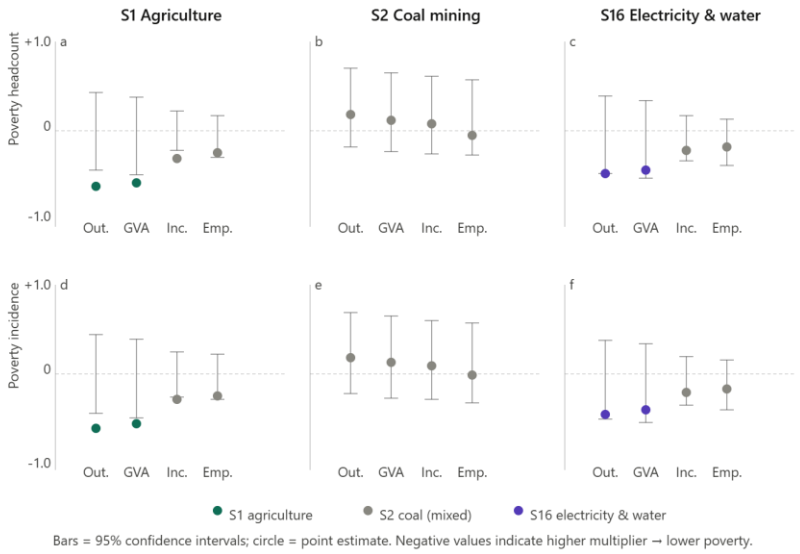

Figure 4. Ninety-five percent confidence intervals for Pearson's correlation coefficient between poverty headcount (panels a–c) and poverty incidence (panels d–f) and Type II multipliers for agriculture (a, d), coal (b, e), and electricity, gas and water (c, f). Negative correlations indicate that higher multiplier values are associated with lower poverty incidence.

The 95% confidence intervals are wide, as expected given the cross-sectional sample of 31 provincial units (n = 31). Nonetheless, meaningful patterns emerge. The agriculture sector (S1) shows the most consistent negative correlation: output and GVA multipliers in particular are negatively associated with both poverty headcount and poverty incidence across all 31 provinces. This is consistent with the view that agricultural sector stimulus generates broad-based rural income effects in provinces where rural subsistence remains prevalent (Liu et al. 2019; State Council 2021).

The electricity, gas and water sector (S16) also exhibit a consistently negative correlation between output and GVA multipliers and both poverty measures. This finding reflects China's Electricity for All programme, in which grid expansion to remote rural areas was shown to generate significant poverty reduction effects through productivity gains in rural enterprises (NBS 2018; NDRC 2021).

The coal sector (S2) tells a markedly different story. Confidence intervals for all four multiplier types span zero and show no consistent directional pattern. This is attributable to the bimodal nature of coal's provincial distribution: coal-producing provinces such as Shanxi, Shaanxi and Inner Mongolia have high output multipliers but also elevated poverty rates driven by structural underemployment in mine-dependent communities a pattern well documented in the Chinese social science literature (Wei et al. 2021).

DISCUSSION

The SD R-IO China model represents, to the authors' knowledge, the first dynamic, stochastic, Bayesian, multi-regional input–output model for the Chinese economy available in the open literature. It extends methodological approaches developed for smaller economies (Altenburg & Assmann, 2017; Box & Draper, 1987; BP, 2022) to the substantially more complex, 31-province Chinese context. Several results warrant further discussion.

First, the accuracy of national GVA forecasting is noteworthy given that this period encompasses the COVID-19 shock an event whose effects the model was not explicitly calibrated to capture. The robustness of the logistic growth specification suggests that abrupt supply constraints (analogous to COVID-19 production shutdowns) may be partially absorbed within the limits-to-growth framework when the economy is already operating near its short-run growth ceiling.

Second, provincial forecast accuracy is systematically lower for resource-dependent inland provinces (Xinjiang, Inner Mongolia, Gansu, Qinghai). This reflects a known limitation of input–output-based dynamic models in settings where commodity price cycles, state-directed investment shifts and administrative boundary changes introduce structural breaks that are difficult to parameterise with smooth growth functions. Future iterations of the SD R-IO China model should incorporate regime-switching specifications or exogenous commodity price indices to address this.

Third, the poverty–multiplier linkage results carry direct policy implications for China's rural revitalisation strategy (Chen et al., 2018; C. C. of the C. P. of China, 2021; Crookes, 2024). The strong negative correlation between agricultural sector multipliers and provincial poverty rates suggests that investment stimuli targeted at S1 particularly backward-linkage sectors such as agricultural machinery (S12/S13), rural transport (S19) and agri-food processing (S6) are likely to yield the highest poverty alleviation returns per unit of expenditure. This is consistent with (Liang et al., 2014; Liu et al., 2019), who find that agricultural value chain integration in western provinces generates substantially larger income gains for rural poor households than equivalent investments in mining or construction.

The coal sector's ambiguous multiplier–poverty relationship deserves particular attention in the context of China's green transition. The Dual Carbon targets peak carbon emissions by 2030, carbon neutrality by 2060 will necessitate a managed contraction of the coal sector ((NBS), 2022, 2023; (NDRC), 2021). The resource sector forecasts in this study project that carrying capacity constraints in coal mining will be reached within 45–65 years under current trajectories, providing an additional physical rationale for accelerating the energy transition. However, poverty vulnerability in coal-dependent communities means that the transition must be managed with targeted social protection and alternative livelihood investment a conclusion supported by the wide confidence intervals in Figure 4, panels (b) and (e), which indicate high cross-provincial variance in the coal–poverty relationship.

The input–output table provides a natural analytical scaffold for evaluating Green Economy policy instruments. As Altenburg and Assmann (2017) observe, IO models can trace the economy-wide effects of environmental taxes, carbon pricing, renewable energy subsidies and regulatory standards all of which feature prominently in China's 14th Five-Year Plan. The present model is well-positioned to support such analyses, and extension to incorporate energy accounts and carbon intensity coefficients (Team, 2023) (S. C. of the P. R. of China, 2021)(Wei et al., 2021; Zhang et al., 2020)represents a clear next step.

A significant limitation of the study is that the base year IO table (NBS 2017) is now eight years old. China's economic structure has shifted substantially since 2017, particularly in the technology, platform economy and renewable energy sectors. A 22-sector aggregation is also too coarse to resolve the fine-grained intersectoral linkages of China's modern economy. The NBS's planned release of a 2022 national IO table, anticipated in 2025, would provide an opportunity to recalibrate the model on a more contemporaneous basis. The analogy of Box and Draper (1987) that all models are wrong, but some are useful applies here: the SD R-IO China model is unlikely to be a precise representation of China's 2024 economy, but it provides a scientifically defensible, dynamic, spatially explicit basis for macroeconomic scenario analysis that currently has no open-access alternative.

CONCLUSION

This study constructs a dynamic, stochastic, Bayesian provincial input–output model the SD R-IO China model for the Chinese economy. The model encompasses 31 provincial units across 22 economic sectors, calibrated via Bayesian inference and implemented in Vensim. Key findings are as follows. The model replicates national GVA with a MAPE of 4.1% the out-of-sample period, satisfying the "highly accurate" threshold. Eleven of 31 provincial units achieve "highly accurate" classification; no province falls below the "reasonable" standard. Oil and gas extraction is projected to encounter resource constraints within 30–50 years under the limits-to-growth scenario the most urgent among China's resource sectors. The agriculture sector, by contrast, exhibits both high output multipliers and a strong negative correlation with provincial poverty, making it the resource sector most amenable to poverty-reduction targeting under a green economy framework. The coal sector's multiplier–poverty relationship is ambiguous, highlighting the complexity of managing just transition policies in coal-dependent communities. The SD R-IO China model offers three practical contributions: a freely available, dynamic, spatial macroeconomic modelling platform; a method for generating provincial IO tables for any forecast year without requiring fresh statistical collection; and an evidence base for spatially targeted poverty alleviation investment within China's resource-dependent provincial economies. Future development should incorporate updated IO data (NBS 2022 table), energy and carbon flow accounts, and technology-adoption parameterisations to improve resource constraint estimates.

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