APO
PRODUCTIVITY OUTLOOK 2026

Energy Efficiency, Productivity Impacts, and Composite Indicator Development

The Asian Productivity Organization (APO) is an intergovernmental organization that promotes productivity as a key enabler for socioeconomic development and organizational and enterprise growth. It promotes productivity improvement tools, techniques, and methodologies; supports the National Productivity Organizations of its members; conducts research on productivity trends; and disseminates productivity information, analyses, and data. The APO was established in 1961 and comprises 21 members.

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APO Productivity Outlook 2026
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FOREWORD

Productivity growth remains a key issue for the Asia-Pacific region, where rising energy uncertainty, climate pressures, and structural transformation are putting pressure on economies. Against this backdrop, the efficient use of energy has become paramount for sustaining productivity and economic resilience. Therefore, understanding the implications of energy efficiency for productivity is a critical policy priority for APO member economies.

The *APO Productivity Outlook 2026* was undertaken to respond to this need by examining the relationship between energy efficiency and productivity across different APO member economies and sectors. Building on the previous edition's focus on climate change and productivity, this edition takes a more targeted analytical approach, examining how changes in energy efficiency impact productivity outcomes at both macroeconomic and sectoral levels. Drawing on empirical analysis, the report provides evidence-based insights relevant to policy design and implementation.

This research presents a comprehensive assessment of productivity trends and energy efficiency patterns across APO member economies, supported by comparative data analysis and sector-specific examination, particularly in agriculture and manufacturing. It also highlights the importance of robust data and measurement frameworks, drawing on international practices and institutional experiences to strengthen the foundation for energy efficiency indicators and productivity analysis.

Conducted in collaboration with the Chungnam National University (CNU) of the Republic of Korea, this study is a valuable joint effort to deepen understanding of the impact of energy efficiency on productivity. We hope that the findings and policy implications presented in the APO Productivity Outlook 2026 will support the development of strategies to enhance productivity while advancing energy-efficient, sustainable, and resilient growth across the Asia-Pacific region.

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EXECUTIVE SUMMARY

In recent years, the pursuit of sustainable productivity has become a central priority across the Asia–Pacific region, as APO member economies confront rising energy costs, intensifying climate risks, and growing pressure to maintain economic competitiveness. In this context, improving energy efficiency has emerged as a critical strategy linking productivity enhancement with environmental sustainability. Energy efficiency—defined as the ability to achieve equal or greater output with less energy input—offers dual benefits: it lowers production costs while simultaneously reducing greenhouse gas emissions, thereby supporting both economic and climate objectives. Recognizing this strategic importance, the APO Productivity Outlook 2026 examines how energy efficiency shapes productivity outcomes across APO members and how they can strengthen their pathways toward more resilient, high-performing, and energy-efficient economies.

Building on the 2025 edition, which explored climate-related impacts on productivity across agriculture, manufacturing, and services, the 2026 edition adopts a more focused, sectorally grounded approach centered on the productivity implications of energy efficiency. While energy efficiency affects all sectors, its impacts are far from uniform. Differences in energy intensity, technological capability, capital structure, and resource dependence result in varying efficiency–productivity dynamics across economies and industries. Manufacturing remains the most energy-intensive sector and therefore offers the greatest opportunities for productivity gains through process optimization, equipment upgrades, digital control systems, and industrial automation. Agriculture also benefits significantly from improvements in irrigation systems, mechanization, input management, and cold-chain logistics, especially in economies where agriculture continues to account for a large share of employment and GDP. Meanwhile, the ability to measure, monitor, and benchmark these improvements depends heavily on the quality of national energy statistics.

A major challenge in assessing energy efficiency across APO member economies is the limited availability of direct and reliable efficiency indicators. As highlighted in global and regional reviews, many economies, particularly lower-income and ASEAN members, face persistent gaps in Energy Balance reporting, inconsistencies in calorific values, limited sectoral disaggregation, and substantial statistical discrepancies between total energy supply and demand. These limitations reduce the accuracy of energy intensity measures and complicate cross-economy comparisons. To address this challenge, the APO Productivity Outlook 2026 advances a refined framework for developing Energy Efficiency Indicators (EEIs), grounded in international standards and informed by case studies from the Republic of Korea (ROK) and Japan. By combining thermodynamic principles with economic data, this framework provides a more coherent basis for monitoring energy efficiency improvements at national and sectoral levels.

Against this backdrop, the APO Productivity Outlook 2026 is organized around three analytical pillars.

First, a macro-level analysis examines the relationships among energy efficiency, productivity, and environmental outcomes across APO member economies, identifying structural patterns and income-level heterogeneity.

Second, the agricultural analysis investigates how improvements in energy efficiency influence agrarian productivity, with particular attention to irrigation, mechanization, climate-related stresses, and differences between high- and low-efficiency economy groups.

Third, the manufacturing analysis examines process-level efficiency improvements, technological upgrading, and income-differentiated strategies needed to raise productivity in energy-intensive industries.

Finally, the report proposes a harmonized, data-driven EEI construction framework to improve measurement quality and support cross-economy benchmarking.

Ultimately, the APO Productivity Outlook 2026 positions energy efficiency as a foundational driver of sustainable productivity growth. By integrating empirical evidence, sector-specific analysis, and a strengthened statistical framework, the report provides actionable insights that can guide APO member economies in designing effective regulatory, technological, and institutional strategies. Strengthening energy efficiency will not only enhance productivity outcomes but also support the broader transition toward low-carbon, resilient, and future-ready economic systems across the Asia–Pacific region.

CHAPTER 1

OVERVIEW OF THE IMPACTS OF ENERGY EFFICIENCY ON PRODUCTIVITY AND SUSTAINABILITY IN APO MEMBER ECONOMIES

Introduction

Enhancing energy efficiency has become a central pathway for sustaining productivity while advancing environmental sustainability across APO member economies. As global challenges such as climate change, energy insecurity, and rising energy costs intensify, economies must find ways to achieve higher output with lower energy input. This chapter provides a macro-level overview of how improvements in energy efficiency contribute to productivity growth and sustainable development in the Asia–Pacific region. It also establishes a conceptual foundation for sector-specific analyses presented in subsequent chapters.

Energy efficiency is generally defined as the ability to produce a desired level of output with less energy input. At the macroeconomic level, it is typically measured by energy intensity, defined as energy consumption per unit of GDP. A decline in energy intensity indicates that an economy produces more output with less energy, thereby improving efficiency and reducing environmental burden. In this study, the term "energy efficiency" refers to this relationship. For analytical purposes, the reciprocal of EE (1/EE) is used only in the empirical analysis to simplify the interpretation of regression results. Another complementary indicator is carbon productivity, or GDP per unit of CO_2 emissions, which reflects how effectively an economy creates value while minimizing environmental impact.

Recent global evidence indicates that energy intensity has declined steadily, with annual efficiency gains of approximately 2% during the 2010s. Within the APO region, advanced economies such as Japan and the Republic of Korea (ROK) maintain high efficiency levels through advanced technologies and stringent energy management, while emerging member economies are gradually transitioning from energy-intensive growth patterns toward more efficient, technology-driven production systems. These developments highlight the increasing role of innovation, industrial upgrading, and policy interventions in promoting efficiency-oriented growth.

A macro-level perspective is essential for understanding how energy efficiency influences aggregate productivity dynamics. By analyzing the linkages between energy usage, economic output, and emissions, this chapter provides insights into how efficiency gains contribute to both productivity enhancement and environmental sustainability. The indicators introduced here, namely, energy intensity (EE), carbon productivity, and energy-adjusted total factor productivity (TFP), provide the analytical foundation for subsequent chapters that examine the sectoral dynamics of agriculture, manufacturing, and services.

Ultimately, improving energy efficiency is not only an environmental imperative but also a strategic economic policy for achieving long-term productivity growth and competitiveness. Integrating energy efficiency into productivity analysis enables APO member economies to design development pathways that are both efficient and sustainable, align with the Green Productivity (GP) framework, and advance the region's transition toward low-carbon, resilient growth.

2. Definition of Energy Efficiency

Energy efficiency refers to the ability to obtain the same or higher level of output, such as goods, services, and useful energy, with less energy input. In economic terms, it measures how effectively an economy converts energy into productive output, while serving as a key link between resource usage, technological progress, and sustainable growth.

This conceptualization aligns with definitions provided by leading international organizations, as follows:

(1) The European Union's Energy Efficiency Directive (EU 2023/1791) defines energy efficiency as "the ratio of output of performance, service, goods, or energy to input of energy."

(2) The Intergovernmental Panel on Climate Change (IPCC, AR6) similarly describes it as "the ratio of useful energy services or other physical outputs obtained from a system to the energy input."

(3) The International Energy Agency (IEA) views energy efficiency as a "pillar of clean energy transitions," improving when less energy is required to produce the same needs."

Although each definition emphasizes a different aspect—technical, economic, or environmental—they converge on a common principle, i.e., achieving more output with less energy consumption.

At the macroeconomic level, energy efficiency is commonly represented by energy intensity (EI), measured as the amount of energy used per unit of GDP. A lower energy intensity indicates higher efficiency, as it implies that less energy is required to produce the same level of output. Accordingly, throughout this chapter, visual analyses and trend comparisons are expressed in terms of energy efficiency (EE), with lower EE values indicating improved efficiency.

For empirical analysis, however, this study also employs the reciprocal measure (1/EE) to facilitate a more intuitive interpretation within the econometric framework. Using 1/EE allows for positive coefficients to directly indicate improvements in energy efficiency and their association with productivity gains. In other words, while graphical illustrations present energy efficiency trends as EE, the empirical model interprets an increase in 1/EE as a positive efficiency advancement.

It is important to note that EI (and by extension, EE) is a proxy rather than a direct technical measure of efficiency. As highlighted by the IEA, intensity values can also reflect external factors, such as changes in industrial structure, climatic conditions, exchange rates, or behavioral patterns, that may not correspond to genuine efficiency improvements. Therefore, energy intensity should be interpreted cautiously, and ideally complemented by sectoral or technological indicators to provide a more comprehensive picture of energy performance.

Within this conceptual framework, EE serves as a bridge between productivity and sustainability. Improvements in efficiency lower production costs, enhance competitiveness, and simultaneously contribute to climate change mitigation by reducing greenhouse gas emissions. These benefits underscore its strategic importance for the Asia–Pacific region, where economies seek to balance industrial expansion with environmental responsibility.

Finally, although the detailed methodology for constructing sectoral energy efficiency indicators is presented in the next chapter, the conceptual approach established here provides the analytical foundation for interpreting the subsequent empirical results. Energy efficiency, whether represented through EE in descriptive analysis or 1/EE in econometric modeling, remains a core element of the APO's pursuit of Green Productivity (GP) and sustainable economic transformation.

3. Productivity and Energy Efficiency Data

Given the absence of harmonized sectoral energy-efficiency data across APO member economies, this study constructs a consistent and comparable dataset using a multistep estimation approach. The objective is to approximate the level of EE at both aggregate and sectoral levels, thereby enabling cross-economy comparison and empirical analysis of its relationship with productivity. At the same time, sector-specific productivity indicators, derived from the APO Productivity Databook and the APO Productivity Database, are systematically processed to align with the analytical framework of this study.

3.1. Construction of Sectoral Productivity Indicators

To ensure full consistency between sectoral productivity and EE indicators constructed in this study, labor productivity measures were recalculated using standardized industry-level data from the APO Productivity Databook and the APO Productivity Database. These sources provide internationally comparable series for industry value added and employment, enabling harmonized productivity estimation across APO member economies. Sectoral labor productivity for industry j in country i and year t is defined as:

$$LP_{j,i,t} = \frac{GDP_{j,i,t}}{Emp_{j,i,t}}$$

To ensure comparability across economies and over time, value-added data have been converted into constant-price series, and employment data have been harmonized by adjusting for missing observations and aligning industry classifications. All productivity indicators have been normalized, where necessary, to match the coverage and frequency of the EE dataset. This approach ensures that the constructed productivity measures are consistent with the sectoral structure used to estimate energy efficiency and provide a solid empirical basis for analyzing energy–productivity linkages across APO member economies.

3.2. Data Sources

The dataset integrates information from multiple international sources:

- Energy use per GDP and sectoral energy-use ratios were obtained from the International Energy Agency (IEA).

- GDP (in constant 2021 PPP) and sectoral value added were drawn from the APO Productivity Database and the World Bank.

- Employment data for agriculture, manufacturing, and services were sourced from the APO Productivity Databook to compute industry-level labor productivity.

This combination allows for consistent estimation of total and sectoral energy consumption and productivity across the APO region over the study period.

3.3. Estimation Framework

Because direct observations of sectoral energy efficiency are unavailable for most APO member economies, a three-stage indirect estimation procedure was applied to construct comparable indicators.

Step 1 (Estimation of Total Energy Consumption). For each economy, total energy consumption was computed as:

$$\text{Total energy use} = \text{Energy use per GDP} \times \text{GDP (PPP)} \tag{1}$$

where energy use per GDP (kg of oil equivalent per USD1,000 GDP) was sourced from the IEA, and GDP values were expressed in constant PPP terms.

Step 2 (Allocation of Energy Consumption by Sector). Using global average sectoral energy-use ratios from the IEA, total national energy consumption was distributed across agriculture, manufacturing, and services as follows:

$$\text{Energy use by sector} = \text{Sectoral ratio} \times \text{total energy use} \tag{2}$$

These ratios capture structural differences in energy use patterns across industries. While they are based on global averages due to limited economy-specific data, adjustments were made where supplementary national information was available.

Step 3 (Derivation of Sectoral Energy Efficiency Indicators). Sectoral EE was then calculated as the ratio of energy consumption per unit of sectoral GDP:

$$EE_{i,s,t} = \frac{Energy\ Use_{i,s,t}}{GDP_{i,s,t}} \tag{3}$$

where i denotes the country, s the sector, and t the year.

A lower EE value indicates higher efficiency, that is, less energy required per unit of economic output.

In empirical regression analyses, the reciprocal of this measure (1/EE) was used to express improvements in energy efficiency as a positive change, enabling direct interpretation of coefficients. However, for descriptive and visual analyses, EE values were retained to illustrate the actual trend in energy consumption relative to output.

3.4. Interpretation and Limitations

The resulting dataset provides a harmonized view of energy efficiency trends across the APO region. It enables both cross-economy comparison and sectoral assessment of energy–productivity linkages.

Nonetheless, some caveats remain:

- The use of global sectoral ratios introduces potential bias in economies with distinctive industrial structures.
- Energy-use patterns can also be influenced by climatic, behavioral, and exchange-rate factors that are not captured by aggregate measures.
- Limited data availability in certain developing APO member economies constrains the precision of historical estimates.

Despite these limitations, this approach provides the most comprehensive and internally consistent measure currently feasible for APO member economies. It establishes the empirical foundation for subsequent analysis of how changes in energy efficiency, interpreted through both EE and 1/EE, affect productivity across income groups and sectors.

3.5. Analytical Application

The constructed energy efficiency dataset serves the following two purposes in this report:

- It supports visual and descriptive analysis of long-term energy efficiency trends (using EE), enabling comparisons across APO income groups.
- It provides the quantitative basis for econometric modeling (using 1/EE) to estimate the impact of efficiency improvements on productivity indicators such as total factor productivity (TFP) and labor productivity (LP).

By integrating these perspectives, the analysis offers both structural and dynamic understanding of energy efficiency performance across the APO region. The data framework presented here thus serves as a bridge between the conceptual discussion and the empirical investigation, guiding the interpretation of results in the subsequent chapters.

4. Productivity and Energy Efficiency

Improving energy efficiency is increasingly recognized as a strategic pathway for enhancing productivity while advancing environmental sustainability. In the context of APO member economies, this chapter aims to provide a macro-level overview of the relationship between energy efficiency and productivity. The analysis provides a conceptual foundation for sector-specific investigations in subsequent chapters.

Energy efficiency is the production of greater output with reduced energy input. At a macro level, it is commonly measured by energy intensity, defined as energy consumption per unit of GDP. A decline in energy intensity, rather than being a negative outcome, signifies an improvement in efficiency, that is, an economy is generating more output with less energy use, thereby enhancing productivity and reducing its environmental burden. Another relevant measure is carbon productivity, or GDP per unit of CO_2 emissions, which reflects how effectively an economy produces value while minimizing its carbon footprint.

Recent global trends indicate a steady decline in energy intensity, averaging approximately 2% annually during the 2010s. This trend represents a continuous improvement in global energy efficiency. Within APO member economies, advanced members such as Japan already demonstrate high efficiency levels, while emerging members are making strong progress, shifting from energy-intensive industrial structures toward more efficient and technology-driven production systems. These developments underscore the growing importance of technological innovation, sectoral transformation, and policy interventions in shaping energy-use patterns.

A macro-level perspective is essential for understanding the systemic effects of energy efficiency across economies. It provides critical insight into how aggregate productivity gains are shaped by energy-related factors, and sets the stage for evaluating sector-specific contributions. The indicators introduced here—energy intensity, carbon productivity, and energy-adjusted TFP—will serve as the analytical foundation for subsequent chapters on agriculture, manufacturing, and services.

This chapter highlights that improving energy efficiency is not only environmentally beneficial but also economically strategic. By embedding energy considerations into productivity analysis, APO member economies can design more effective and sustainable development strategies.

5. Productivity Trends in APO Member economies

To analyze productivity dynamics in APO member economies, we computed TFP, LP, and capital productivity (CP) growth over two horizons: a long-term period (1970–2022) and a short-term period (2018–22). Group averages were calculated according to APO classifications of low- and middle-income economies (LMIEs), upper-middle-income economies (UMIEs), and high-income economies (HIEs). The empirical results are summarized in Table 1.1.

TABLE 1.1

PRODUCTIVITY GROWTH TRENDS IN APO MEMBER ECONOMIES BY INCOME GROUP (CAGR, %).

Group	Long-term TFP (1970–2022)	Short-term TFP (2018–22)	Long-term LP (1970–2022)	Short-term LP (2018–22)	Long-term CP (1970–2022)	Short-term CP (2018–22)
LMIE	0.218	–0.964	2.44	1.63	–0.476	4.23
UMIE	0.218	–0.577	2.37	1.03	0.215	–1.01
HIE	1.51	0.505	3.55	1.33	0.380	–0.0895

Note: CAGR = $\left(\frac{\text{END}}{\text{START}}\right)^{\frac{1}{n}} - 1$, with the long-term period defined as 1970–2022 (52 years) and the short-term period defined as 2018–22 (four years).
Source: Author's calculations (2025), based on the APO Productivity Dataset (1970–2022).

From 1970 to 2022, productivity indicators in APO member economies demonstrated moderate long-term improvements, while short-term patterns (2018–22) exhibited mixed results. The long-term average annual growth rate of TFP was 0.65%, compared with –0.35% in the short term. LP has demonstrated the most significant and consistent gains among the three indicators, with an average of 2.79% over the period 1970–2022 and 1.33% during 2018–22. CP remained almost unchanged in the long term (0.04%) but increased to 1.04% in the short term.

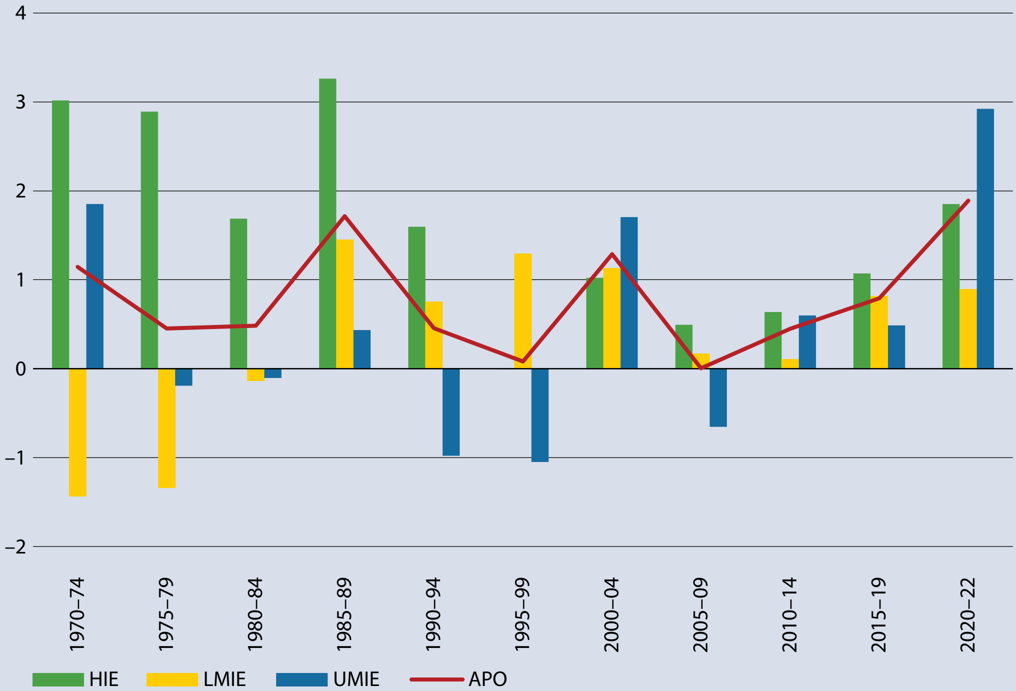
Across all income brackets, data reveal consistent but varied trends. For HIEs, long-term TFP growth was 1.51%, LP was 3.55%, and CP was 0.38%. In the short term, the same group experienced lower growths, with TFP being 0.51%, LP 1.33%, and CP –0.09%, thereby indicating an overall slowdown.

UMIEs showed lower long-term averages, with TFP at 0.22%, LP at 2.37%, and CP at 0.22%. All three indicators declined during 2018–22, reaching –0.58%, 1.03%, and –1.01%, respectively. For LMIEs, TFP was modestly positive in the long term at 0.22% but turned negative in the short term at –0.96%. LP growth remained relatively strong at 2.44% and 1.63%, while CP increased sharply from –0.48% to 4.23%, marking the largest short-term improvement among all groups.

Overall, the long-term results suggest steady but uneven productivity performance across groups, with LP consistently contributing the most to growth. Short-term data (2018–22) show a broad slowdown in TFP and LP, alongside a temporary improvement in CP, particularly within LMIEs.

FIGURE 1.1

FIVE-YEAR AVERAGE ANNUAL GROWTH RATE OF TFP BY INCOME GROUP IN APO MEMBER ECONOMIES.



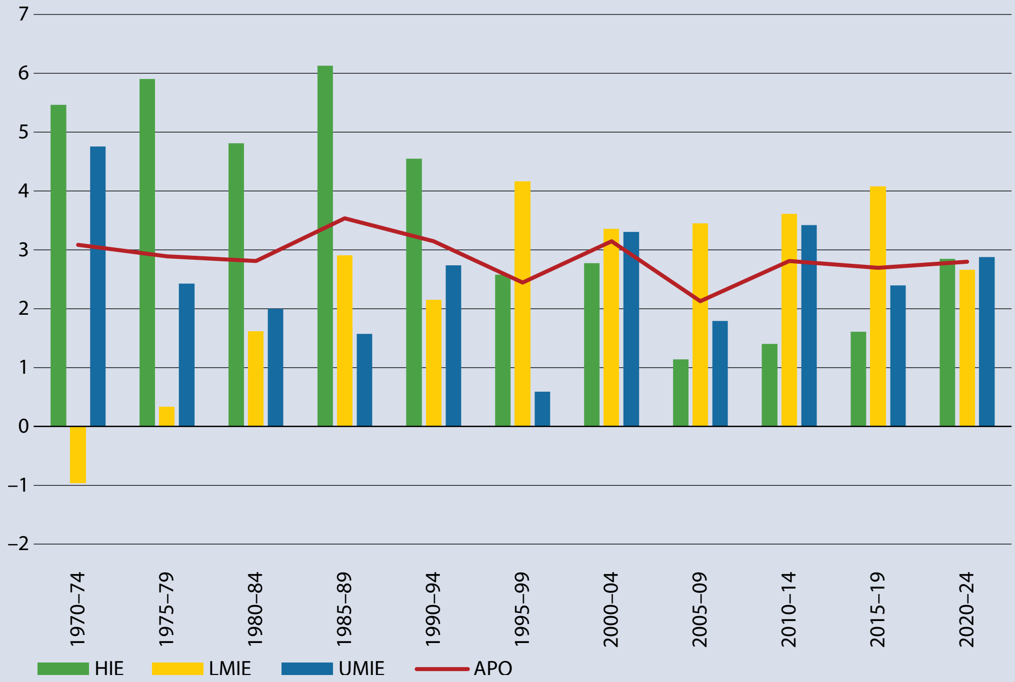
Note: APO = Average of APO member economies; LMIE = low-middle-income economy; UMIE = upper-middle-income economy; HIE = high-income economy.
Source: Author's calculations (2025), based on the APO Productivity Database.

This dataset in Figure 1.1 provides the five-year average annual growth rate from 1970 to 2022. Between 1970 and 2024, the overall TFP growth rate of APO member economies remained low, ranging from 1.14% in 1970–74 to 0.46% in 1990–94, and increasing to 1.89% in 2020–24. For HIEs, TFP growth declined from 3.02% in 1970–74 to 1.60% in 1990–94, and fluctuated between –0.01% and 1.85% after 2000. LMIEs experienced negative growth during the 1970s (–1.44%) and transitioned to positive growth rates following the 1990s, reaching 0.89% in the 2020–24 period. UMIEs maintained rates close to zero or slightly negative before 2000, then rose from 1.71% in the 2000–04 period to 2.92% in the 2020–24 period. Across all income brackets, average TFP growth for APO member economies increased from below 1% before 2000 to between 1% and 2% after 2000.

Figure 1.2 summarizes key findings from the report on LP productivity in APO member economies between 1970 and 2022. The overall average annual growth rate of LP ranged from 1.14% in the

FIGURE 1.2

FIVE-YEAR AVERAGE ANNUAL GROWTH RATE OF LP BY INCOME GROUP IN APO MEMBER ECONOMIES.



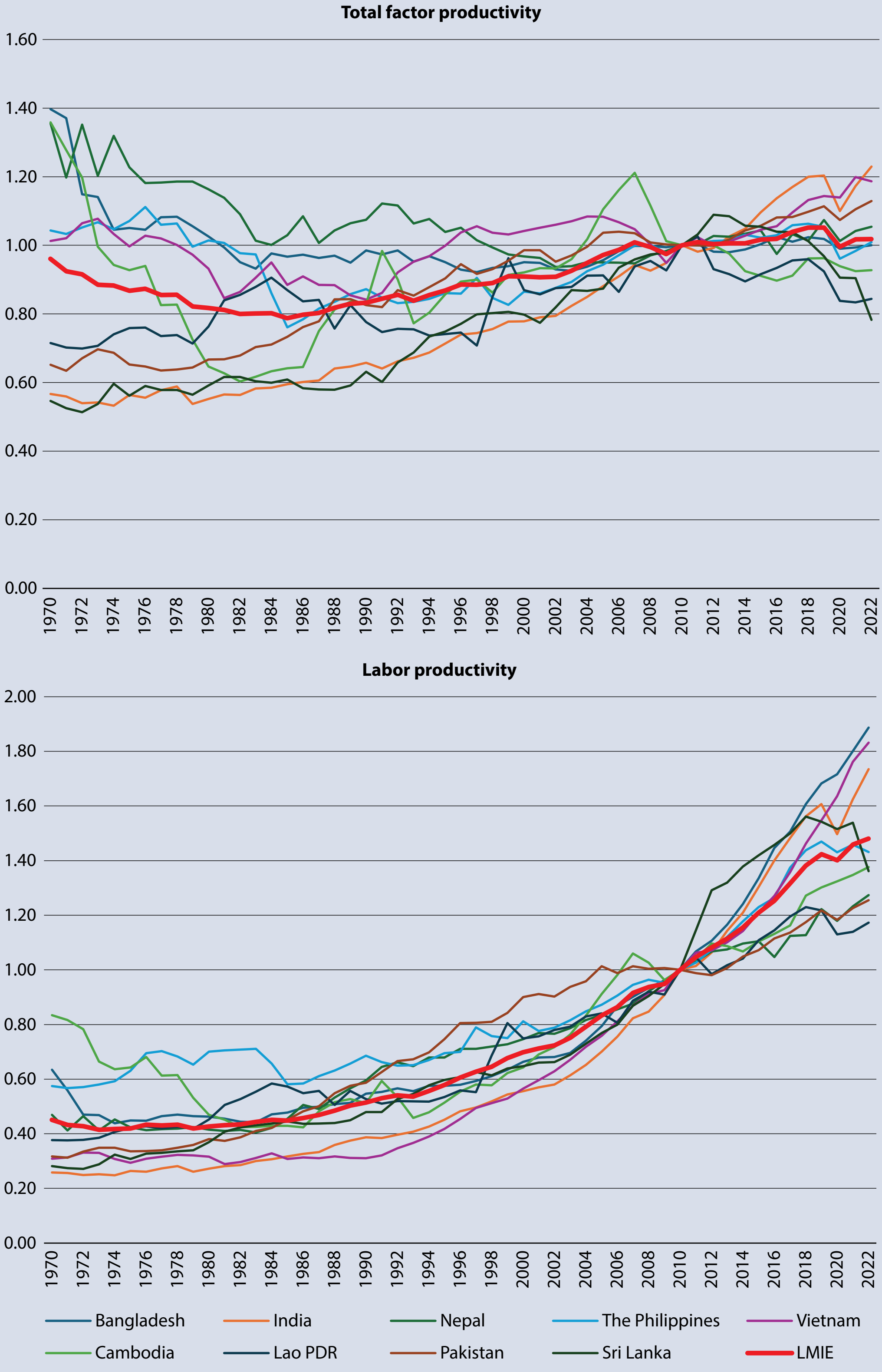
Note: APO = Average of APO member economies; LMIE = low-middle-income economy; UMIE = upper-middle-income economy; HIE = high-income economy.
Source: Author's calculations (2025), based on the APO Productivity Database.

period 1970–74 to 0.45% in 1975–79. It remained below 1% through most of the 1980s and 1990s. The average rate increased from 1.29% in the 2000–04 period to 1.89% in the 2020–22 period. For HIEs, LP growth declined from 3.02% in 1970–74 to 1.59% in 1990–94, with a temporary negative of –0.01% in 1995–99, and then remained between 0.5% and 1.9% after 2000. For LMIEs, growth rates were negative in the 1970s (–1.44% and –1.33%), turned positive in the 1980s (1.45% in 1985–89), and stabilized between 0.8% and 1.3% after 1995. For UMIEs, LP growth fluctuated between positive and negative values before 2000, including –0.98% in 1990–94 and –1.05% in 1995–99, then improved to 1.70% in 2000–04 and 2.92% in 2020–22. Across all income groups, LP growth remained moderate before 2000 (mostly below 1%) and increased to 1–2% during the 2000s and 2010s, with the highest average of 1.89% observed in 2020–22.

Figure 1.3 illustrates LP trends in lower-middle-income APO member economies. Across LMIEs as a group, long-term productivity growth was limited. From 1990 to 2020, average TFP growth was close to zero (0.02% annually), while LP growth was substantially higher at 3.88% annually. This indicates that efficiency gains did not strongly support improvements in LP. In the short-term period of 2018–22, the trend weakened further: TFP growth turned negative (–0.57%), and LP growth also slowed sharply to just 0.42%. Within this overall pattern, a few economies stood out. India demonstrated the strongest gains, with TFP rising by 1.73% annually and LP by 4.61% over a long term, more than doubling its LP between 2000 and 2020. Vietnam also recorded robust growth, with TFP at 1.01% and LP at 5.69%. By contrast, economies such as Nepal and Lao PDR displayed stagnant or slightly negative TFP performances, despite some modest LP improvements.

FIGURE 1.3

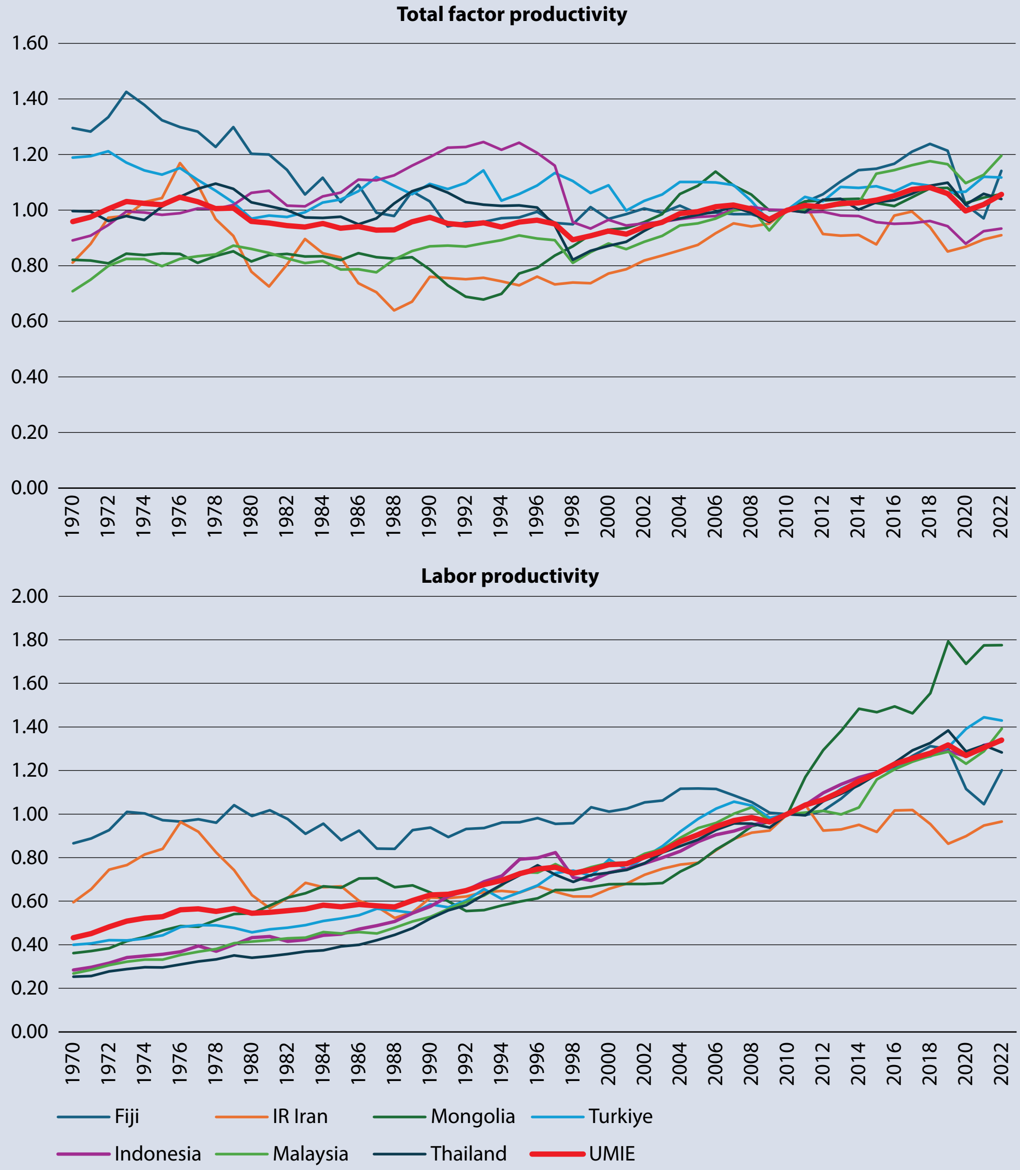
TREND OF TOTAL FACTOR PRODUCTIVITY AND LABOR PRODUCTIVITY IN LMIEs.



Source: Author's calculations (2025) based on the APO Productivity Database.

FIGURE 1.4

TREND OF TOTAL FACTOR PRODUCTIVITY AND LABOR PRODUCTIVITY IN UMIEs.

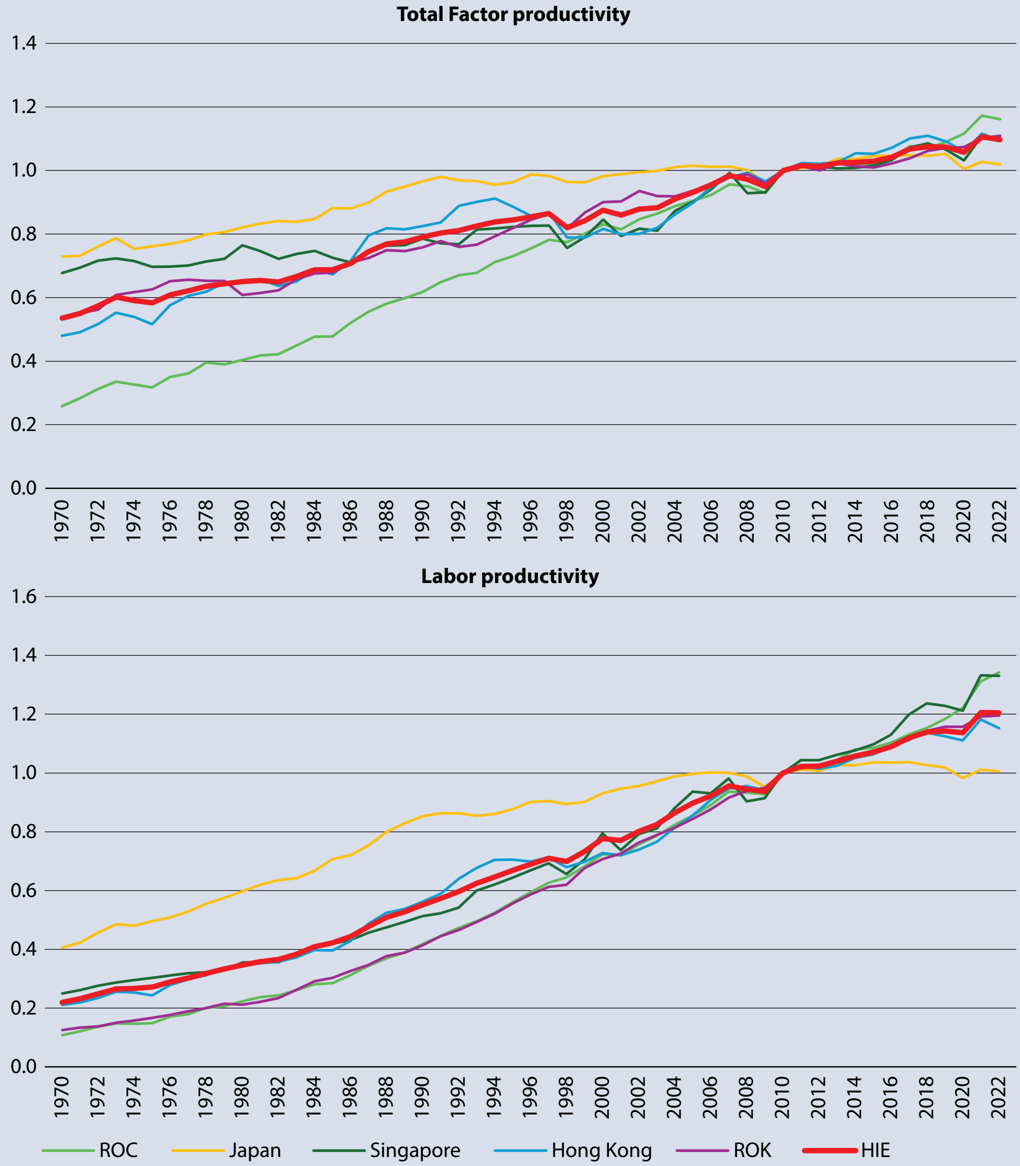


Source: Author's calculations (2025) based on the APO Productivity Database.

For UMIEs as a whole, productivity performance was weaker (Figure 1.4). Between 1990 and 2020, the group recorded slightly negative TFP growth (–0.04%) and very modest LP gains (0.58%). In the recent short-term period (2018–22), the decline became more pronounced, with TFP falling by –2.03% annually and LP turning negative (–0.45%). This indicates that productivity pressures intensified in recent years. Some UMIEs performed relatively better. Malaysia and Mongolia achieved steady progress, combining moderate TFP growth (between 0.8% and 0.9%) with LP growth above 2.8%. On the other hand, Indonesia and Thailand both experienced negative TFP growth (–1.00% and –0.22% annually, respectively), though their LP growths remained positive. Turkiye showed stable LP growth (2.93%) but essentially flat TFP, while Fiji remained stagnant across both dimensions.

FIGURE 1.5

TREND OF TOTAL FACTOR PRODUCTIVITY AND LABOR PRODUCTIVITY IN HIEs.



Source: Author's calculations (2025) based on the APO Productivity Database.

As a group, HIEs maintained steady productivity gains over a long term (Figure 1.5). Between 1990 and 2020, average TFP rose at an annual rate of 1.99%, while LP increased by 3.64%, indicating sustained improvements in both efficiency and output per worker. In the short-term period of 2018–22, TFP growth in HIEs remained positive (2.08%), although LP growth decelerated to 2.83%, showing a mild slowdown compared to the longer horizon.

At the economy level, the Republic of Korea (ROK) achieved the strongest advances, with long-term TFP growth of 1.99% and LP growth of 3.64%, accompanied by further gains in the recent short-term period (2.08% for TFP and 2.83% for LP). Singapore also demonstrated robust long-term performance, with TFP expanding by 0.91% and LP by 2.91% annually. By contrast, Japan recorded very modest growth, with TFP increasing by only 0.13% and LP by 0.47% per year, and even experienced a slight contraction in TFP during 2018–22 (–0.65% annually). Hong Kong and the Republic of China (ROC) fell in between, with moderate long-term productivity gains but weaker momentum in the most recent years.

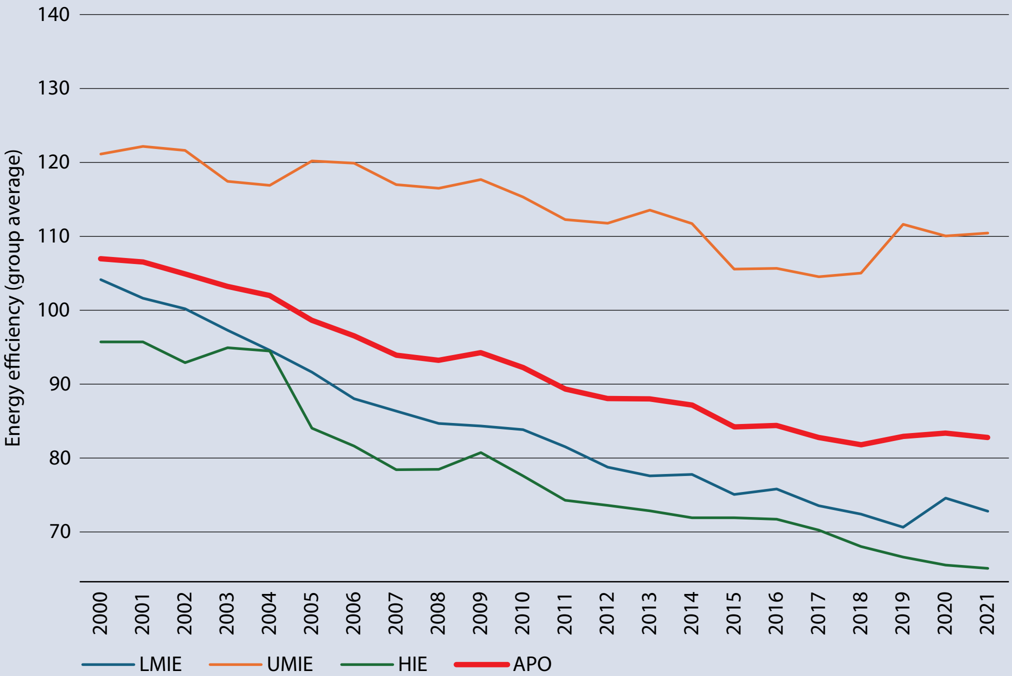
6. Relationship between Energy Efficiency and Productivity

6.1. Energy Efficiency Trends in APO Member Economies

Over the two decades from 2000 to 2020, EE declined consistently across all income groups, though the extent of this deterioration varied substantially (Figure 1.6). HIEs experienced the sharpest decline, with the group average falling from 110 in 2000 to 78.3 in 2020. This corresponds to an average annual reduction of –1.68%, reflecting a persistent erosion in efficiency levels over the long term. LMIEs followed a nearly identical trajectory, decreasing from 104 to 74.6, equating to a –1.66% per-year decline. In both groups, therefore, EE losses were widespread and sustained, falling to significantly lower levels by the end of the period. UMIEs also recorded a reduction, though the pace of decline was notably slower. Their EE decreased from 121 to 110 between 2000 and 2020, corresponding to a –0.48% per-year decline, indicating that while efficiency fell, the downturn was much less severe than for HIEs and LMIEs.

FIGURE 1.6

TREND OF ENERGY EFFICIENCY BY INCOME LEVEL IN APO MEMBER ECONOMIES.



Source: Author's calculations (2025) based on the APO Productivity Database. Fiji and Singapore were not included in certain parts of the analysis due to the lack of energy-related data required to compute energy efficiency.

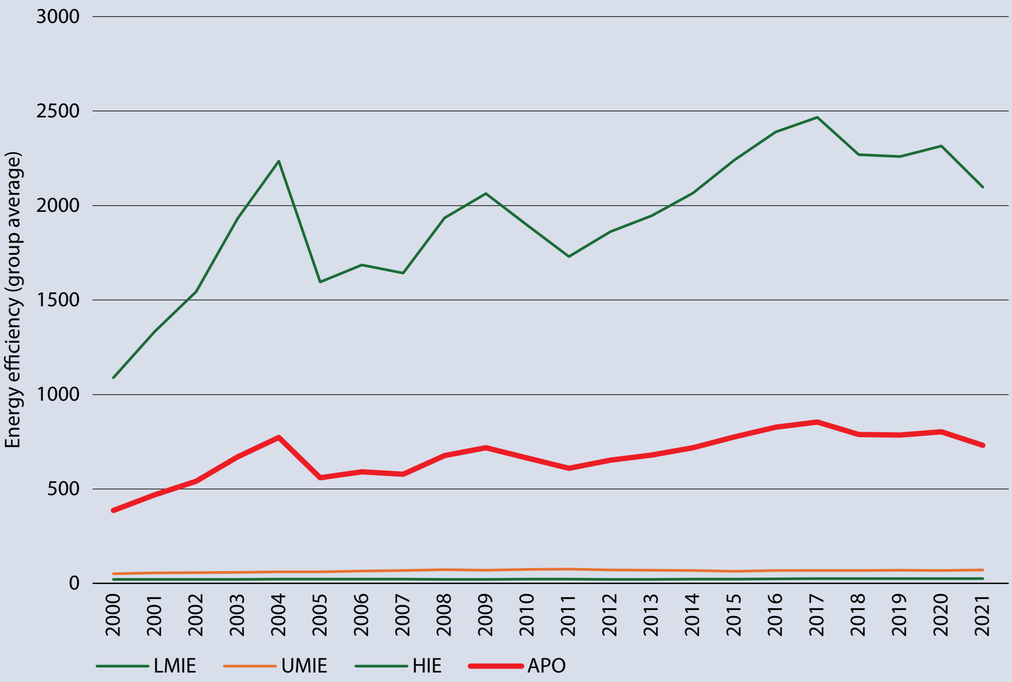
When shifting attention to the more recent short-term period of 2018–21, a more diverse set of dynamics emerges. HIEs continued to experience a decline, with EE contracting at an average rate of –1.18% per year, suggesting that their earlier long-term deterioration had not been reversed. In contrast, LMIEs recorded a slight positive shift, registering a marginal improvement of 0.20%

annually. Although small in magnitude, this change marked a departure from two decades of continuous decline. The most striking development occurred in UMIEs, which displayed a clear rebound. Their EE rose at 1.69% per year during 2018–21, representing a temporary reversal of the long-term downward trend observed from 2000 to 2020.

Taken together, the evidence indicates a general long-term decline in EE across all income groups, with the sharpest reductions found in HIEs and LMIEs. However, short-term developments reveal emerging divergence: while HIEs continued to decline, LMIEs stabilized, and UMIEs moved into recovery. This contrast suggests that the recent years have witnessed a modest but noticeable differentiation in group-level EE trajectories, compared with the more uniformly negative patterns seen in earlier decades.

FIGURE 1.7

TREND OF ENERGY EFFICIENCY FOR AGRICULTURE BY INCOME LEVEL IN APO MEMBER ECONOMIES.

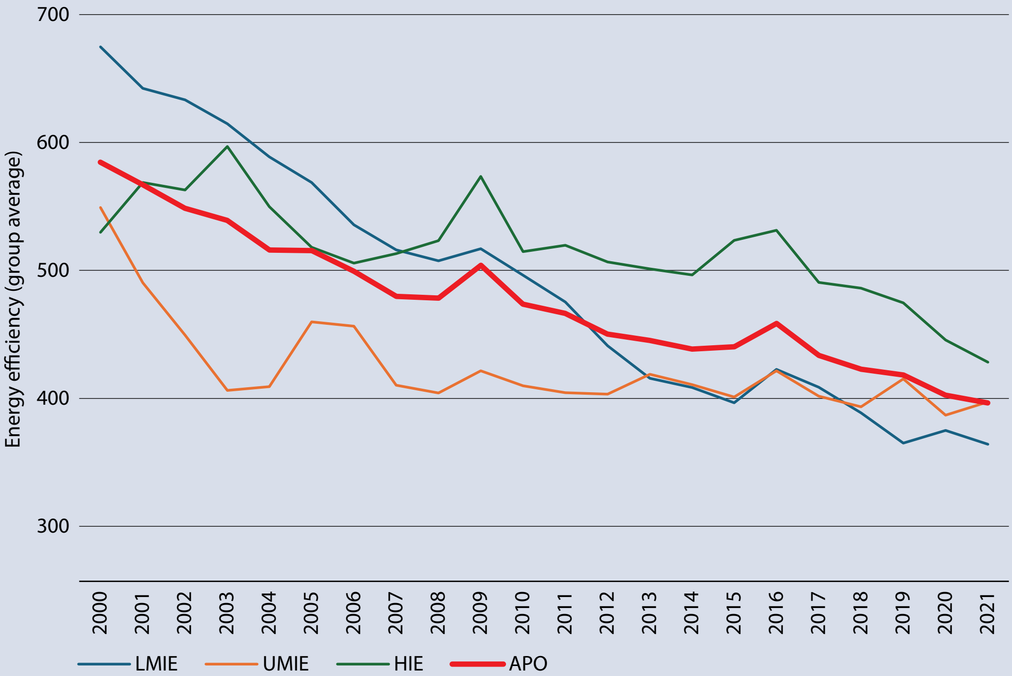


Source: Author's calculations (2025) based on the APO Productivity Database. Fiji and Singapore were not included in certain parts of the analysis due to the lack of energy-related data required to compute energy efficiency.

There is a significant disparity in agricultural energy efficiency across income groups (Figure 1.7). The APO average increased from 297 in 2000 to 557 in 2021, representing a rise of 87.8%. HIEs demonstrated the highest levels throughout the period under review, rising from 1,088 in 2000 to 2,098 in 2021, with values ranging between 1,088 and 2,467 in the period. LMIEs demonstrated an increase from 20.5 to 25.1 over the same period, while UMIEs exhibited an uptick from 51.2 to 71.4. The numerical ranges also differed substantially by group. LMIEs remained within the specified range of 20.5–25.4; UMIEs within the range of 51.2–74.9, and HIEs within the range of 1,088–2,467. The standard deviation of the variables was measured as follows: 1.62 for LMIE, 6.45 for UMIE, and 354 for HIE. These figures indicate that the numerical variation was largest in the HIE group and smallest in the LMIE group.

FIGURE 1.8

TREND OF ENERGY EFFICIENCY FOR MANUFACTURING BY INCOME LEVEL IN APO MEMBER ECONOMIES.



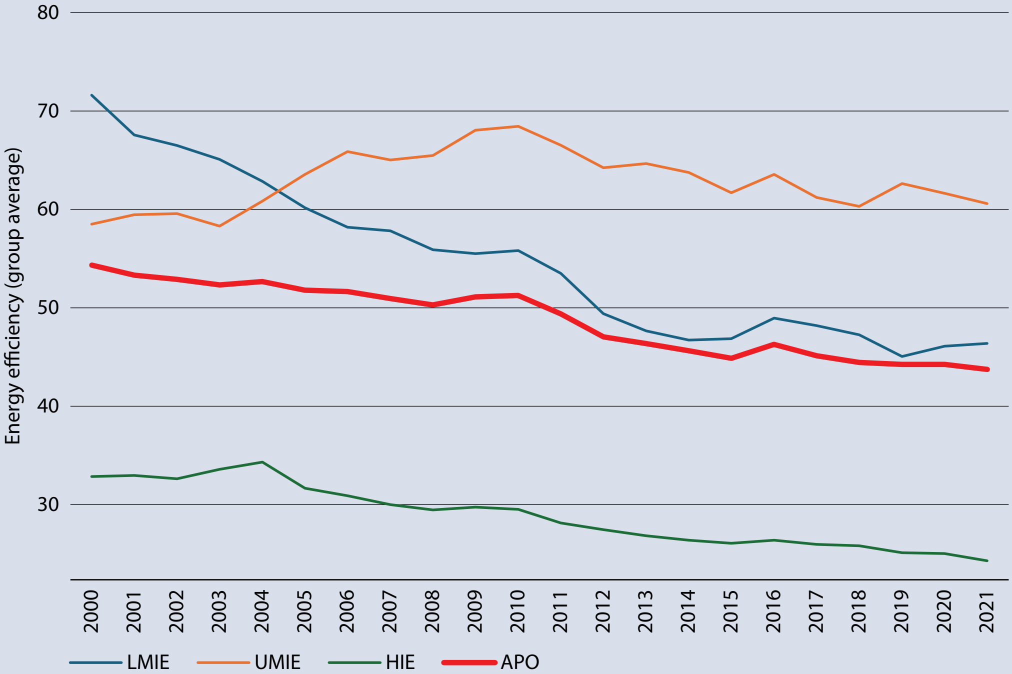
Source: Author's calculations (2025) based on the APO Productivity Database. Fiji and Singapore were not included in certain parts of the analysis due to the lack of energy-related data required to compute energy efficiency.

Manufacturing energy efficiency (EE_MFR) has shown a clear downward trend across all income groups over the observed period (Figure 1.8). On average, for APO member economies, EE_MFR declined from approximately 601 in 2000 to 390 in 2021, representing a 35.1% reduction. Among the income groups, LMIEs experienced the steepest decline, falling from 675 to 364 (–46.1%), reflecting constraints in industrial upgrading and slower transitions toward energy-efficient technologies. UMIEs and HIEs also exhibited noticeable decreases, with UMIEs declining from 549 to 397 (–27.7%) and HIEs from 530 to 428 (–19.2%). When comparing absolute levels, HIEs consistently maintained the highest efficiency across the period (range of 428–597), followed by LMIEs and UMIEs. Year-on-year fluctuations continue to reveal predominantly negative values, thereby confirming a consistent decline in manufacturing efficiency. In terms of volatility, LMIEs displayed the highest standard deviation (98.3), suggesting that these economies experienced the most unstable trends in manufacturing efficiency, while UMIEs and HIEs exhibited more stable patterns.

Energy efficiency in the services sector shows a more modest pattern, with smaller fluctuations than in manufacturing (Figure 1.9). The APO average decreased slightly from 58.0 to 45.1 (–22.2%), indicating mild efficiency deterioration. Group-specific trends differ significantly. While HIEs have shown the largest decline, from 32.9 to 24.3 (–26.1%), LMIEs have fallen from 71.6 to 46.4 (–35.2%), though they still maintain relatively high absolute efficiency values. In contrast, UMIEs are the only group to have recorded an improvement, rising from 58.5 to 60.6 (3.56%), suggesting structural shifts and a growing role of services in their economies. Efficiency levels have been generally higher in LMIEs and UMIEs, whereas HIEs have consistently shown lower levels in the services sector (range of 24.3–34.3). The most volatile index is that of LMIEs

FIGURE 1.9

TREND OF ENERGY EFFICIENCY FOR SERVICE BY INCOME LEVEL IN APO MEMBER ECONOMIES.



Source: Author's calculations (2025) based on the APO Productivity Database. Fiji and Singapore were not included in certain parts of the analysis due to the lack of energy-related data required to compute energy efficiency.

(8.14), indicating greater instability in service-sector efficiency. In contrast, UMIEs and HIEs maintain stability with standard deviations below 3.5. Overall, the services sector is characterized by gradual changes rather than sudden shifts, with distinct group-wise differences in both the level and direction of efficiency trends.

6.2. Relationship between Energy Efficiency and Total Factor Productivity

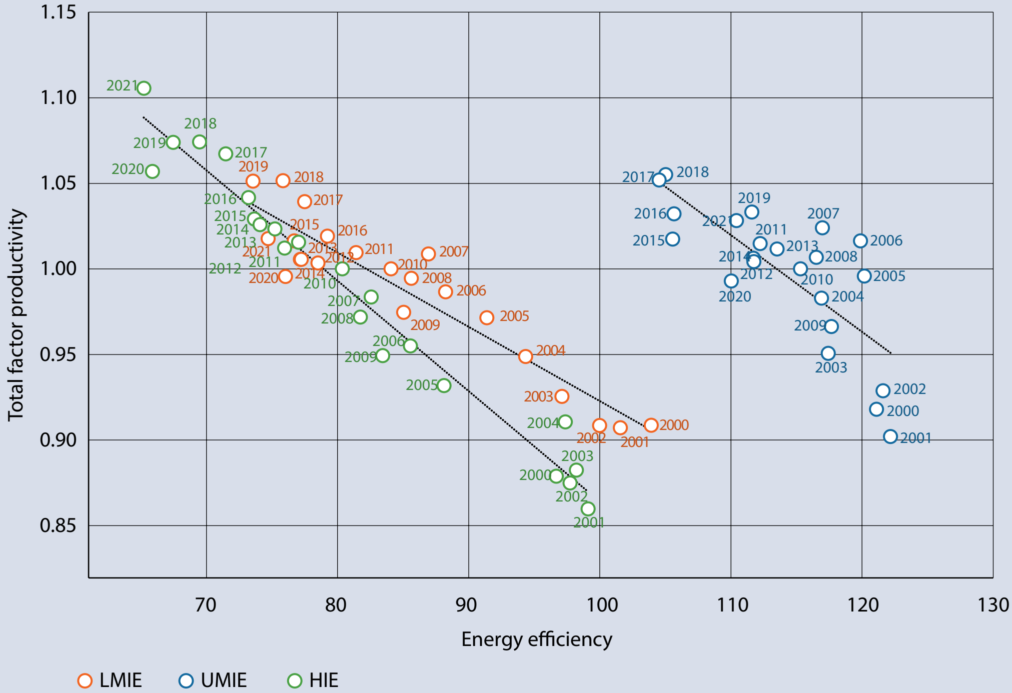
Figure 1.10 illustrates the temporal evolution of the relationship between EE and TFP across APO member economies, categorized by income groups, from 2000 to 2021. Each point on the graph indicates the average position of a group in a specific year, with the dotted regression lines representing the overall direction of movement over time. Across all income groups, a clear negative relationship between EE and TFP is observed, suggesting that more efficient economies tend to exhibit higher productivity. This pattern indicates that productivity gains generally accompany improvements in EE. However, the extent and pace of progress differ markedly by the income level.

For HIEs, the EE fell from 95.7 in 2000 to 65.1 in 2021, while the TFP increased from 0.875 to 1.106. This pattern clearly indicates a shift toward higher energy efficiency, coupled with consistent productivity gains. The data points are concentrated in the upper-left region of the figure, consistent with high efficiency and productivity.

For UMIEs, there was a moderate decrease in EE from 121.1 to 110.4, and an increase in TFP from 0.925 to 1.020. The trajectory appears less pronounced than that of HIEs, indicating a more gradual progression in both indicators, albeit in a similar overall direction.

FIGURE 1.10

COMPARISON OF ENERGY EFFICIENCY AND TOTAL FACTOR PRODUCTIVITY BY INCOME GROUP AMONG APO MEMBER ECONOMIES, 2000–21.



Source: Author's calculations (2025) based on the APO Productivity Database. Fiji and Singapore were not included in certain parts of the analysis due to the lack of energy-related data required to compute energy efficiency.

For LMIEs, the EE fell from 104.1 to 72.8, while TFP increased from 0.909 to 1.018. The LMIE trajectory is characterized by a stronger reduction in EF and a relatively small rise in TFP, indicating a more gradual productivity response to efficiency improvement.

This data indicates that across all income brackets, efficiency and productivity have increased consistently from 2000 to 2021. However, the extent of improvement varies by the income level. HIEs achieved the largest combined gains, followed by UMIEs and LMIEs. These results suggest a persistent gap in efficiency and productivity across income groups within the APO grouping.

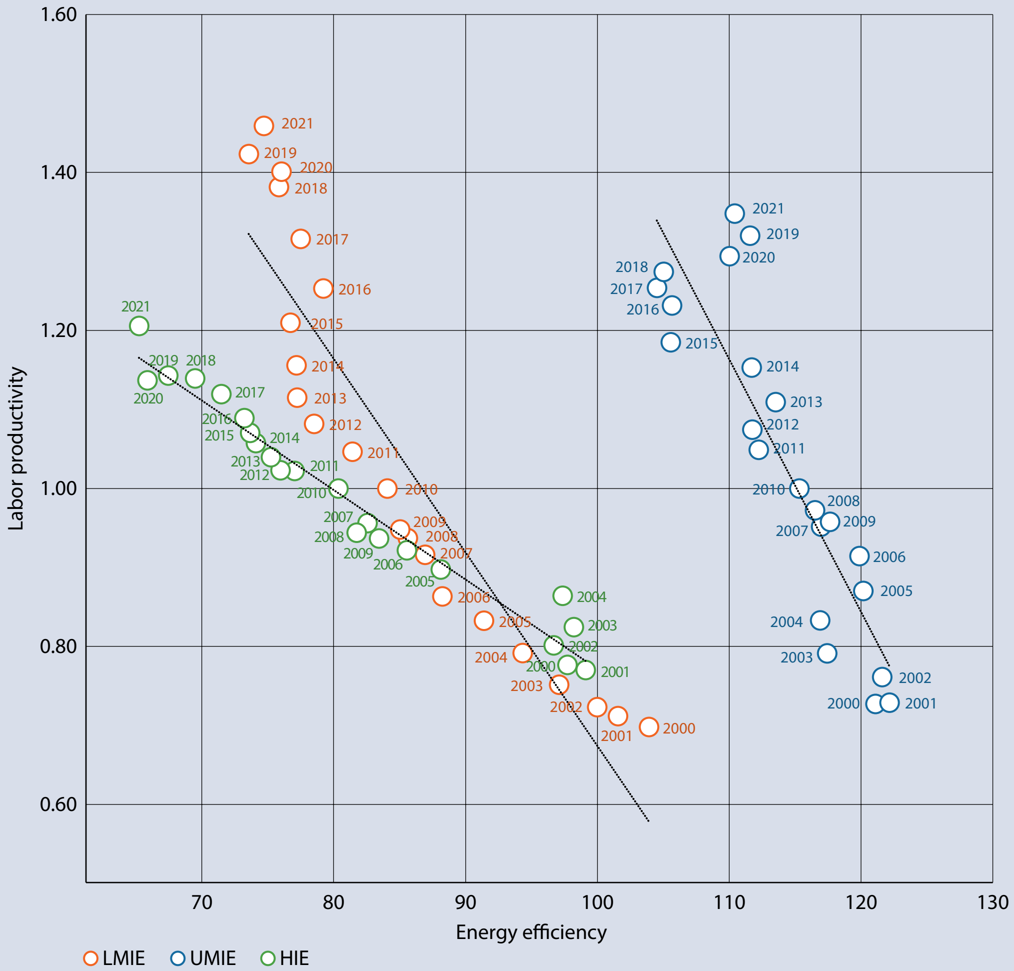
6.3. Relationship between Energy Efficiency and Labor Productivity

Figure 1.11 illustrates the correlation between EE and LP across APO member economies, categorized by the income level, during 2000–21. Each point on the graph represents the average EE and LP values of a given income group in a specific year, with the dotted lines showing the overall trends within each group. A consistent negative correlation between EE and LP is observed, indicating that more efficient economies tend to exhibit higher LP. All income groups have shown improvements in both indicators over time, but the size of these improvements and the speed at which they have been achieved vary considerably between groups.

For HIEs, average EE declined from 95.7 in 2000 to 65.1 in 2021, while LP increased from 0.777 to 1.206. This pattern demonstrates a clear shift toward greater energy efficiency accompanied by

FIGURE 1.11

COMPARISON OF ENERGY EFFICIENCY AND LABOR PRODUCTIVITY BY INCOME GROUP AMONG APO MEMBER ECONOMIES, 2000–21.



Source: Author's calculations (2025) based on the APO Productivity Database. Fiji and Singapore were not included in certain parts of the analysis due to the lack of energy-related data required to compute energy efficiency.

steady productivity gains. The HIEs form a cluster in the upper-left region of the plot, reflecting persistently high productivity levels and continuous efficiency improvement.

For UMIEs, EE decreased moderately from 121.1 to 110.4, and LP rose from 0.768 to 1.305. Although the overall trajectory is less steep than that of HIEs, UMIEs show a gradual upward movement, indicating steady gains in productivity alongside moderate efficiency improvement.

For LMIEs, EE fell markedly from 104.1 to 72.8, while LP increased from 0.698 to 1.459. This group recorded the largest relative improvement in productivity among the three, but starting from a lower initial base. The LMIE trajectory moves substantially upward and to the left, reflecting rapid growth in labor productivity concurrent with an increase in EE.

Overall, the figure shows that all income groups have advanced toward higher efficiency and productivity, though from different starting points and at varying speeds. The negative slope across all groups confirms that lower energy intensity is associated with higher productivity levels. Between 2000 and 2021, HIEs maintained the highest productivity with the lowest energy intensity, while LMIEs exhibited the fastest productivity growth, narrowing part of their gap with higher-income groups.

7. Impact of Energy Efficiency on Productivity in APO Member Economies

7.1. Theoretical and Empirical Literature Review

The relationship between energy efficiency and productivity is largely explored within the theoretical frameworks of growth and structural transformation. In the neoclassical growth model (Solow, 1956), productivity growth is driven by technological progress. Conversely, improvements in energy efficiency can lead to factor-augmenting innovations that allow economies to achieve higher output per unit of energy. Endogenous growth models extend this framework by demonstrating how energy-saving technological change can promote long-term growth through spillovers, research and development (R&D) dynamics, and complementarities like human and physical capital (Aghion & Howitt, 2009).

As numerous macro studies demonstrate, energy efficiency is a significant contributor to TFP. For instance, Stern (2011) posits that energy services are fundamental inputs into production, and efficiency improvements enhance the productivity of capital and labor by enabling more effective use of energy resources. In a similar vein, a Burke and Csereklyei (2016) study provides cross-economy evidence of a correlation between energy efficiency and income growth as well as structural change, particularly in economies transitioning from energy-intensive to knowledge- and service-based structures.

However, the macro literature also acknowledges that transitional costs can accompany efficiency gains. As Basu et al. (2006) emphasize, adjustment costs, learning delays, and capital–labor substitution effects may mitigate the initial impact of technological shocks, including energy-saving innovations, on productivity. Long-term gains frequently succeed these short-term contractions as economies adapt and diffuse new technologies. Another strand of macroeconomic evidence is derived from the study of rebound effects and the so-called Jevons' paradox. Sorrell (2009) and Gillingham et al. (2016) demonstrate that while energy efficiency can reduce energy intensity, macro-level rebound effects may negate the anticipated productivity benefits if efficiency gains result in increased overall energy consumption or alterations in production patterns. This finding indicates that the impact of energy efficiency on productivity is contingent on the prevailing macroeconomic and institutional environment.

In emerging and developing economies, including many APO members, the productivity impacts of energy efficiency are contingent on structural transformation. Csereklyei et al. (2016) demonstrate that improvements in energy efficiency are closely linked with rising income levels and changes in sectoral composition as economies first industrialize and later transition toward services. This perspective is particularly relevant to APO member economies as energy-intensive growth strategies evolve into service-oriented economies. The ability to embed efficiency gains into national growth trajectories is, therefore, becoming decisive for the sustained productivity of these economies.

A comprehensive review of the extant literature on macroeconomics indicates that energy efficiency is both a catalyst and an outcome of productivity growth. The short-term impacts of such measures may be ambiguous due to adjustment costs. Still, in the long run, efficiency improvements are a fundamental ingredient of growth, particularly when supported by structural transformation and institutional frameworks. This macro perspective directly informs the empirical framework employed in this chapter.

7.2. Energy Efficiency Effects on Productivity: An Empirical Framework

The empirical framework presented below, as formalized in the subsequent equations, is inspired by both theoretical and empirical literature. Its main objective is to quantify the impact of energy efficiency on various productivity measures, while accounting for the moderating roles of institutional membership and macroeconomic conditions. Specifically, the analysis employs a two-way panel regression model covering both APO and non-APO member economies over the study period.

Let i denote the economy (or country) index and t the time index. Equation (1) uses a two-way fixed-effects estimator to address potential endogeneity biases, whereas Equation (2) extends the framework by incorporating an autoregressive term to capture individual fixed-effects heterogeneity among economies.

$$y_{ijt} = a_{ijt} + \lambda_{ijt} + \beta_{1j} lnEE_{it} + \beta_{2j} lnGDP_{it} + \beta_{3j} lnZ_{it} + \beta_{kj}(lnEE_{it} \times INS_i) + \varepsilon_{ijt} \quad (4)$$

$$y_{ijt} = a_{ijt} + \theta_j y_{ij,t-1} + \beta_{0j} lnEE_{it-1} + \beta_{1j} lnEE_{it} + \beta_{2j} lnGDP_{it} + \beta_{3j} lnZ_{it} + \beta_{kj}(lnEE_{it} \times INS_i) + \mu_{ijt} \quad (5)$$

where y_{ijt} denotes the productivity indicator (with $j \in \{TFP, LP\}$, $lnEE_{it}$ represents the energy efficiency and $lnGDP_{it}$ is the natural log of gross domestic product. lnZ_{it} stands for trade openness and INS_i captures the economy's institutional membership, defined as either APO_i (a time-invariant dummy equal to one if the economy is an APO member) or as a categorical variable identifying low-, upper-middle-, and high-income economies. The parameters a_{ijt} and λ_{ijt} represent the economy and year fixed effects, respectively. The error terms ε_{ijt} and μ_{ijt} denote the disturbance components of the within-estimation procedure, with standard errors clustered at the economy level.

Moreover, the model captures both short- and long-term effects of energy efficiency on productivity. The contemporaneous coefficient of the energy efficiency indicator ($lnEE_{it}$) reflects the short-term marginal effect, measuring the immediate impact of improvements in energy efficiency on productivity. To account for dynamic adjustment mechanisms, the model also includes the lagged energy efficiency term ($lnEE_{it-1}$), whose coefficient captures any delayed or persistent influence on productivity outcomes. The inclusion of the lagged dependent variable ($y_{ij,t-1}$) allows us to estimate dynamic responses over time and provides the basis for computing the long-term effect. The long-term elasticity of productivity with respect to energy efficiency is derived as:

$$LR_j = (\beta_{0j} + \beta_{1j})/(1 - \theta_j), \text{ with } 0 < \theta_j < 1 \quad (6)$$

7.3. Data

The analysis included 45 economies, including 22 APO member economies (see the attached Appendix for the full list). Due to the lack of reliable variables for some APO member economies, this study limited the dataset to a few macroeconomic control variables, indices, and other controls (Table 1.2). Based on the literature, the analysis used the GDP variable, the Energy Efficiency Index estimated as the ratio of energy use to GDP per capita, and the Trade Openness Indicator from 2000 to 2021. These variables mainly came from the World Bank dataset, while the main APO productivity variables were obtained from the APO Productivity Database.

TABLE 1.2

DESCRIPTIVE STATISTICS.

Variable	Description	Obs.	Mean	Std. Dev.	Min	Max
EE	Energy efficiency	990	4.57	1.01	3.13	9.03
GDP	Gross domestic product	990	6.32	1.63	1.03	10.30
OPEN	Trade openness	990	4.31	0.57	2.97	6.09
APO	APO dummy	22	0.44	0.49	0	1
OECD	OECD economy dummy	25	0.56	0.49	0	1
LIE	Low-income economies	13	27	0.44	0	1
UMIE	Upper-medium-income economies	5	0.11	0.31	0	1
HIE	High-income economies	27	0.58	0.49	0	1
TFP	Total factor productivity	990	0.0002	0.04	–0.38	0.26
LP	Labor productivity	990	0.0007	0.12	–1.27	0.18

Hausman specification tests were conducted for each productivity model to compare fixed effects (FE) and random-effects (RE) estimators. According to the Total Factor Productivity model, the test yielded a borderline p-value of 0.057, failing to reject the null hypothesis of RE consistency at the 5% level. However, the proximity to the threshold suggests caution. For LP and CP regressions, the Hausman test was highly significant ($p < 0.001$), strongly rejecting the RE assumption and indicating that unobserved economy-specific effects are correlated with the regressors. In the light of these findings, the FE estimation approach remains the preferred approach for LP, while the RE approach appears more appropriate for TFP regression. However, to ensure methodological coherence and mitigate potential bias, given the borderline TFP result, the FE specification has been used across all models. This approach ensures that estimates are robust to unobserved time-variant heterogeneity and that the empirical strategy remains consistent across productivity indicators.

7.4. Results

7.4.1. Energy efficiency and Productivity by Regional Integration

In Table 1.3, the positive, highly significant coefficient for 1/EE on TFP confirms that improvements in energy efficiency are strongly associated with higher productivity. In other words, economies that use less energy per unit of output, and therefore are more energy efficient, allocate resources more effectively, reduce waste, and foster technological upgrading, which together enhance aggregate productivity. This finding is consistent with Filippini and Hunt (2016), who demonstrated that efficiency gains led to measurable productivity improvements at both firm and macro levels. Similarly, the positive coefficient of 1/EE on LP suggests that greater energy efficiency tends to enhance worker performance by enabling more effective use of energy inputs within production processes. This relationship implies that energy-efficient production structures reduce redundancy and improve process optimization, ultimately fostering LP. Conversely, in highly energy-intensive industries, the initial output gains from higher energy use are often offset by technological rigidity, energy waste, and operational inefficiencies, thereby underscoring the importance of efficiency-oriented policies.

TABLE 1.3

ENERGY EFFICIENCY IMPACT OF PRODUCTIVITY BY ECONOMY'S REGIONAL INTEGRATION.

	Dependent Variables			
	TFP	TFP	LP	LP
1/EE	0.135***	0.193***	0.208***	0.498***
OPEN	–	0.005	–	0.008
POP	–	0.158***	–	0.253*
(1/EE)×APO	–	–0.072***	–	–0.196***
(1/EE)×OECD	–	0.079***	–	–0.602***
R square	0.267	0.304	0.104	0.396
F test	335.997	80.187	107.513	120.271
Obs.	990	990	990	990

* p < 0.1.
** p < 0.05.
*** p < 0.01.
Source: Author (2025).

The interaction terms between energy efficiency (1/EE) and institutional frameworks reveal important nuances in how regional integration moderates these relationships. The negative and significant coefficients for (1/EE × APO), for both TFP (–0.07) and LP (–0.20), do not imply that higher efficiency reduces productivity. Instead, they indicate that while energy efficiency generally enhances productivity, this positive effect is slightly weaker among APO members compared with non-members. These results suggest that APO member economies may already be near an intermediate efficiency frontier, where marginal productivity gains from additional efficiency improvements are smaller. However, the negative interaction continues to demonstrate the institutional resilience of APO members, who experience less fluctuation in productivity amid changing energy-use scenarios, driven by improved regional coordination, technology dissemination, and learning effects. These findings are consistent with Azhgaliyeva et al. (2020), who highlight the role of institutional cooperation in promoting energy-efficient practices across Asian industrial systems.

By contrast, the (1/EE × OECD) interaction shows a positive coefficient for TFP (0.08) but a strongly negative one for LP (–0.60), implying a divergence between aggregate and labor productivity channels in advanced economies. While energy efficiency continues to improve overall productive performance in OECD economies through capital deepening, digital innovation, and clean-technology integration, it appears to exert downward pressure on LP, possibly due to automation and substitution of labor by technology. Hence, advanced economies derive productivity gains primarily through capital and process efficiency, whereas APO members benefit more from institutional and collective resilience to energy-related productivity shocks.

Building on these results, which highlight the differentiated effects of energy efficiency across institutional memberships, a more extensive analysis follows, classifying economies by their income levels. This differentiation enables a more refined understanding of whether the productivity impact of energy efficiency varies not only across institutional frameworks but also across structural and developmental stages of economic growth.

7.4.2. Energy Efficiency and Productivity by APO Members' Income Differentiation

Table 1.4 presents the results of the energy–productivity regressions restricted to APO member economies. The coefficient on 1/EE is positive and highly significant for TFP (0.145), showing that improvements in energy efficiency substantially enhance TFP in APO member economies. This result supports the view that energy-saving technologies, when integrated into production, promote overall efficiency and technological upgrading—an essential mechanism for productivity growth within the APO framework that explicitly targets "productivity-led industrial policies."

Conversely, the coefficient on 1/EE for LP (0.731) is positive and statistically strong, but its economic interpretation is nuanced. While at first glance this positive sign could indicate that energy efficiency raises output per worker, it is more likely a labor-saving effect: APO members adopting cleaner, more automated technologies may experience increases in output per worker due to capital deepening and digitalization, rather than pure efficiency-driven labor utilization. As found by Zhao et al. (2023), efficiency-driven technological changes often first benefit aggregate productivity and then LP through reallocation channels.

TABLE 1.4

ENERGY EFFICIENCY EFFECT ON PRODUCTIVITY BY AN ECONOMY'S INCOME LEVEL.

	Dependent Variable	
	TFP	LP
1/EE	0.145***	0.731***
OPEN	–0.017*	–0.005
POP	0.067	0.125
(1/EE)×LME	–0.136***	–0.634***
(1/EE)×UMIE	–0.033	–0.882***
(1/EE)×HIE	–0.034	–0.897***
R square	0.169	0.47
F test	13.072***	58.907***
Obs.	440	440

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Source: Author (2025).

The coefficients for trade openness (OPEN) are slightly negative for both specifications, implying that external exposure alone does not guarantee productivity gains without corresponding domestic efficiency improvements. Similarly, population (POP) has a positive but insignificant effect, suggesting that productivity in APO member economies depends less on population size and more on resource efficiency and innovation capacity.

Moreover, the interaction terms (1/EE × LME, 1/EE × UMIE, 1/EE × HIE) reveal strong heterogeneity across income levels. For low-income economies, the negative and significant coefficients (TFP = –0.136; LP = –0.634) suggest that productivity benefits of energy efficiency are weaker or constrained by structural bottlenecks such as outdated technologies and limited absorptive capacity (Pao & Tsai, 2010). For upper-middle-income and high-income APO members, the interaction terms remain negative and significant for LP (–0.882 and –0.897), reflecting diminishing marginal returns to additional efficiency gains once technological maturity is reached (Sorrell, 2018).

In essence, energy efficiency remains a core determinant of productivity among APO members, but its marginal benefits vary across stages of development. While early industrializers gain substantially in aggregate efficiency (TFP), advanced APO members face an efficiency plateau, requiring deeper innovation, green investment, and digital transformation to sustain productivity growth.

7.4.3. Short- and Long-term Effects of Energy Efficiency on Productivity

Tables 1.5 and 1.6 jointly investigate how energy efficiency influences productivity dynamics across APO member economies, distinguishing between aggregate (TFP) and LP effects. Across both dimensions, the lagged dependent variables (lag(TFP) ≈ 0.68-0.74; lag(LP) ≈ 0.95) are positive and highly significant, confirming the strong persistence of productivity performance. This finding suggests that past productivity improvements—driven by technological learning, institutional coordination, and energy management—continue to shape current outcomes, consistent with theories of cumulative growth and path dependence (Arellano & Bond, 1991; Roodman, 2009).

The short-term coefficients of energy efficiency (1/EE) are positive and significant in both models (TFP: 0.25–0.43; LP: 0.17–0.19), indicating that efficiency improvements immediately enhance productivity across APO member economies. In the short term, reductions in energy intensity likely free up resources, lower production costs, and improve input allocation, translating directly into performance gains. These short-term effects are stronger for TFP, suggesting that aggregate efficiency, rather than labor alone, responds faster to technological and energy optimization.

TABLE 1.5

DYNAMIC IMPACTS OF ENERGY EFFICIENCY ON TFP AMONG APO MEMBER ECONOMIES.

	Dependent Variable		
	TFP	TFP	TFP
lag(TFP)	0.741***	0.678***	0.737***
1/EE	0.247**	0.431	0.245*
lag(1/EE)	–0.216**	–0.364	–0.215*
POP	0.018	0.044	0.189
OPEN	0.011	–0.013	0.011
(1/EE)×LME	–0.002	–	–
(1/EE)×UMIE	–	0.208	–
(1/EE)×HIE	–	–	–0.002
LR(1/EE)	0.086	0.779	0.085
Sargan test	0.990	0.001	0.987
AR(1) test	–2.308**	–2.032*	–2.006**
AR(2) test	–2.538*	–1.862*	–2.551*
Wald test (coefs)	350.7753***	255.162***	362.165***

* $p < 0.05$.
** $p < 0.01$.
$p < 0.001$.
Source: Author (2025)

However, the lagged coefficients of 1/EE are negative in both models (TFP ranging from –0.21 to –0.36; LP ranging from –0.15 to –0.18), suggesting temporary adjustment effects or diminishing short-term returns to prior efficiency gains. This lagged decline could reflect investment or learning costs, in which firms initially incur reorganization expenses and technological adaptation, lags before stabilizing at a new efficiency frontier (Sorrell, 2018). Despite these short-term corrections, the long-term elasticities denoted by LR(1/EE) remain positive, with TFP (≈ 0.08 to 0.78) and LP (≈ 0.03 to 0.20) indicating that sustained energy efficiency ultimately yields cumulative productivity benefits across both levels.

The difference in magnitudes between the two models underscores an important asymmetry that energy efficiency exerts a stronger and more persistent effect on TFP than on LP. This divergence suggests that efficiency gains materialize first through aggregate technological and organizational channels—such as energy management systems, industrial restructuring, and capital upgrading—before translating into LP improvements. The relatively smaller long-term coefficient for LP implies that while workers benefit indirectly from improved energy use, the direct effects are mediated by automation, digitalization, and skill-biased technological changes (Zhao et al., 2023).

TABLE 1.6

DYNAMIC IMPACTS OF ENERGY EFFICIENCY ON LABOR PRODUCTIVITY AMONG APO MEMBER ECONOMIES.

	Dependent Variable		
	LP	LP	LP
lag(LP)	0.958***	0.955***	0.951***
1/EE	**0.185****	**0.192****	**0.168***
lag(1/EE)	–0.167	–0.181	–0.156
POP	0.005	0.010	0.007
OPEN	0.008	–0.06	0.009
(1/EE)×LME	–0.009	–	–
(1/EE)×UMIE	–	–0.038	–
(1/EE)×HIE	–	–	–0.009*
LR(1/EE)	**0.196**	**0.099**	**0.033**
Sargan test (Chisqr)	2.239	1.901	2.186
AR(1) test (Chisqr)	–2.286	–2.315*	–2.260
AR(2) test (Chisqr)	–1.193	–1.977	–1.916
Wald test (coefs)	1440.317***	1547.039***	1353.565***

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Source: Author (2025)

Income-level interactions (1/EE×LME, ×UMIE, ×HIE) remain weak across both models, reinforcing the idea that the energy–productivity nexus is relatively homogeneous within the APO framework, where shared policies and training systems promote convergence. Yet, the slightly negative coefficients for HIEs (–0.002 for TFP; –0.009 for LP) suggest an efficiency plateau: in technologically advanced APO members, additional improvements in energy efficiency yield smaller productivity returns, consistent with marginal convergence dynamics (Filippini & Hunt, 2016).

8. Relationship between Energy Efficiency and Key Factors

8.1. Energy Efficiency and CO_2

Economic Growth and CO_2 Emissions: A Comparative Analysis between 2000 and 2021. The comparative analysis of 2000 and 2021 (Figure 1.12) confirms a clear positive association between GDP and CO_2 emissions. The correlation coefficient between the logarithms of GDP and CO_2 emissions was 0.614 in 2000 and 0.670 in 2021, suggesting that the linkage between economic scale and emissions has slightly strengthened over time. The regression slope remained relatively stable, at 0.835 in 2000 and 0.800 in 2021, indicating that the structural relationship between economic growth and increases has persisted.

FIGURE 1.12

TREND OF ENERGY EFFICIENCY AND CO_2 EMISSIONS IN 2000 AND 2021.

Source: Author's calculations based on the APO Productivity Database. Energy Efficiency for Fiji are missing due to data availability.

From 2000 to 2021, the majority of economies experienced a decline in energy efficiency (EE) while concurrently increasing CO_2 emissions. The Islamic Republic of Iran has seen a significant increase in energy efficiency (31.4%), accompanied by a substantial rise in CO_2 emissions (112%). The ROC's EE declined by 37.8%, while CO_2 emissions increased by 214%. In India, the EE decreased by 34.2%, while CO2 emissions rose by 171%. Indonesia's EE also declined by 33.2%, while CO_2 emissions increased by 120%. Japan recorded –30.9% in EE and –16.0% in CO_2, and Hong Kong recorded –52.3% in EE with –16.3% in CO_2. Vietnam's EE decreased by 6.8%, while its CO_2 emissions increased by 482%. In Malaysia, the EE fell by 17.4%, while CO_2 emissions rose by 463%. Similarly, in Cambodia, EE dropped by 43.3%, while CO_2 emissions grew by 862%. Overall, among the 20 APO member economies analyzed, 17 recorded efficiency declines and 18 recorded increases in emissions, while only Japan and Hong Kong exhibited simultaneous reductions in both the indicators.

8.2. Energy Efficiency and Renewable Energy

FIGURE 1.13

TREND OF ENERGY EFFICIENCY AND RENEWABLE ENERGY SHARE BY INCOME GROUP.

Source: Author's calculations based on the APO Productivity Database. Energy Efficiency for Fiji are missing due to data availability.

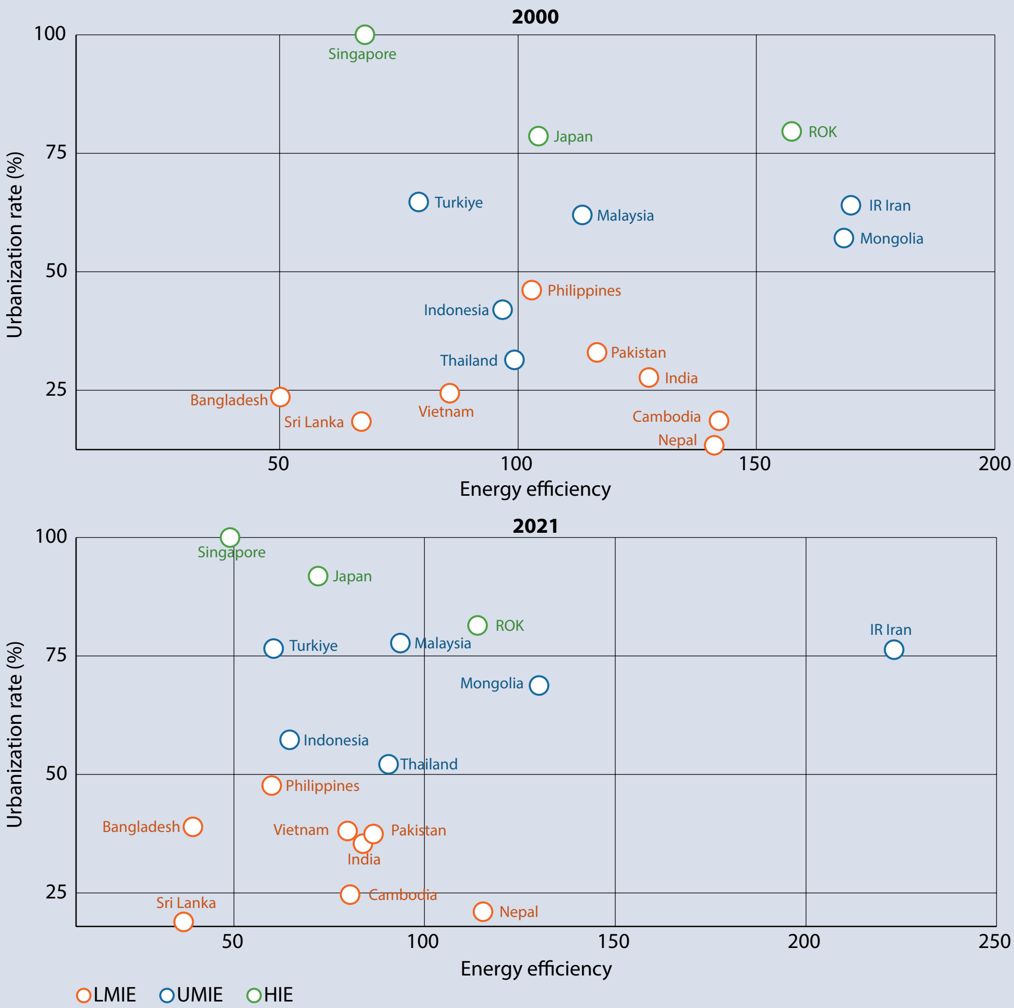
Figure 1.13 presents the relationship between EE and the share of renewable energy by income groups (LMIEs, UMIEs, and HIEs), for the years 2000 and 2021. Both the variables are plotted on logarithmic scales with identical axis ranges to allow comparison across years. In 2000, correlation coefficients were 0.094 for LMIEs, –0.737 for UMIEs, and –0.037 for HIEs. By 2021, these values changed to 0.085, –0.879, and 0.216, respectively. In the course of the study, it was found that average energy efficiency had decreased for all groups (from 97.7 to 65.2 for HIEs; from 121 to 110 for UMIEs; and from 104 to 74.7 for LMIEs), while the share of renewable energy had increased (from 1.71 to 4.49 for HIEs; from 4.09 to 8.52 for UMIEs; and from 12.2 to 12.6 for LMIEs). At the economy level, Japan and Hong Kong (both HIEs) increased their renewable energy shares while maintaining consistent efficiency levels. It is evident that the ROK has experienced a decline in efficiency and maintained a low share of renewable energy. The ROC and India (UMIE) have increased their shares of renewable energy, but efficiency has also decreased. Vietnam and Nepal (LMIEs) had comparatively higher renewable shares but efficiency levels close to the group average.

On the whole, energy efficiency declined, while the use of renewable energy increased across all income groups. HIEs demonstrated a shift from negative to positive correlation between the two indicators. In contrast, UMIE and LMIE groups exhibited only marginal changes in correlation values.

8.3. Energy Efficiency and Urbanization

FIGURE 1.14

TREND OF ENERGY EFFICIENCY AND URBANIZATION RATE BY INCOME GROUP.



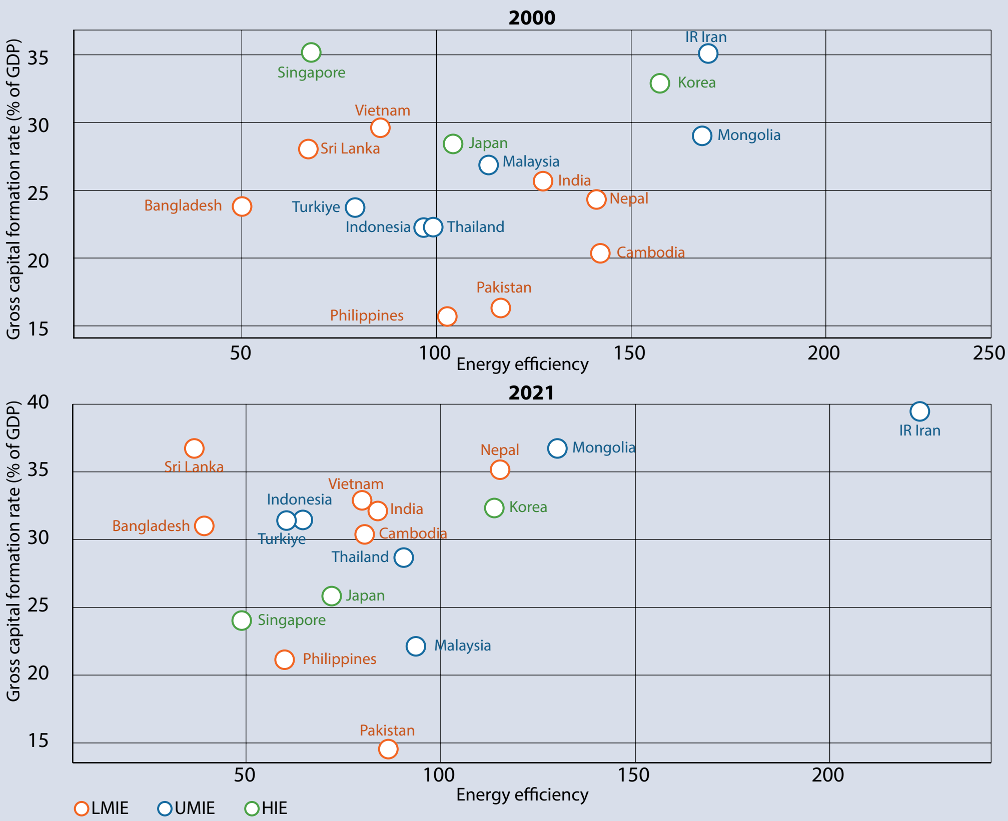
Source: Author's calculations based on the APO Productivity Database (2024), World Bank (2024). Energy Efficiency for Fiji are missing due to data availability.

Figure 1.14 compares the relationship between urbanization rate (UR) and EE in APO member economies in 2000 and 2021. The descriptive statistics demonstrate a decline in average EE across all income groups, while UR increased steadily over the same period. In the period between 2000 and 2021, the average UR across all economies increased from 46.2% to 55.5%, representing a 9.3 percentage point rise. Conversely, the average EE declined from 111.0 to 87.0, indicating a decrease of 24.0 units. By income group, HIEs recorded a decline in average EE from 110.0 to 78.3, alongside an increase in UR from 86.1% to 91.1%. The correlation coefficient between the two variables was –0.783 in 2000 and –0.996 in 2021. For UMIEs, average EE fell from 121.0 to 110.0, and UR from 53.5% to 68.1%, with correlation coefficients of 0.343 and 0.352, respectively. In LMIEs, EE decreased from 104.0 to 72.8, while UR increased from 25.6% to 32.8%. The corresponding correlation coefficients were –0.085 in 2000 and –0.178 in 2021. The scatterplots show that most economies moved toward right between 2000 and 2021, reflecting higher urbanization, while many also moved downward, indicating lower efficiency levels. HIEs such as Japan, Singapore, and the ROK have maintained relatively high UR levels while operating at moderate efficiency. In contrast, several lower-income economies have shown greater dispersion between the two indicators. Overall, the data indicate that UR expanded significantly across APO member economies during the past two decades, but EE did not exhibit parallel improvements.

8.4. Energy Efficiency and Gross Capital Formation

FIGURE 1.15

TREND OF ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION BY INCOME GROUP.



Source: Author's calculations based on the APO Productivity Database (2024), World Bank (2024). Energy Efficiency for Fiji are missing due to data availability.

Figure 1.15 presents the relationship between gross capital formation (GF, % of GDP) and EE in APO member economies for the years 2000 and 2021. As shown in the descriptive statistics, the average GF increased from 25.9% in 2000 to 29.8% in 2021 (3.9 percentage points), while the average EE decreased from 111.0 to 87.0 (–24.0 units). These changes indicate that, during this period, higher investment shares in output were recorded alongside an overall decline in efficiency levels. By income group, HIEs recorded a decrease in average EE from 110.0 to 78.3, while their average GF declined slightly from 32.2% to 27.4%. The correlation between the two variables shifted from –0.229 in 2000 to 0.989 in 2021. For UMIEs, average EE fell from 121.0 to 110.0, whereas GF increased from 26.5% to 31.6%. The correlation coefficients were 0.879 and 0.659, respectively. In LMIEs, EE decreased from 104.0 to 72.8, while GF rose from 23.0% to 29.2%, with correlation coefficients of –0.340 in 2000 and 0.080 in 2021. The scatterplots further illustrate these patterns. In 2000, economy observations were widely dispersed, with the fitted regression lines showing weak or inconsistent slopes across income groups. By 2021, the points for most economies had become more aligned with a positive relationship, particularly among higher-income economies, reflecting a clearer statistical association between GF and EE.

9. Strategies for Enhancing Energy Efficiency

Empirical analysis shows that improving energy efficiency yields sustained productivity gains. In response, APO members should integrate energy efficiency into productivity strategies under the Green Productivity (GP) framework. Green Growth policies explicitly target both “energy efficiency and emission control” through technical upgrades and economic incentives. For example, the APO (2020) notes that low-carbon development relies on improved energy management systems and complementary fiscal instruments (taxes/subsidies) to curb wasteful fossil-fuel use. Building on these insights, governments can adopt multipronged GP strategies to lock in long-term efficiency benefits (APO, 2020; APO, 2024).

9.1. Policy Instruments

Grants, Subsidies, and Tax Incentives. Governments can offer grants and tax breaks explicitly for energy-saving investments. The APO GP 2.0 roadmap (2024) calls for capacity-building grants and subsidies to support industrial upgrades and efficiency retrofits. For example, Japan’s SDG Action Plan requires manufacturers to set and meet energy-efficiency targets (APO, 2020), while India has enacted stringent fuel standards (leapfrogging to BS VI) and levies on polluting vehicles, together with incentives for electric and hybrid vehicles. Such fiscal policies can be extended to services (e.g., tourism, IT) through green bonds or green loans, thereby lowering financing costs for energy-efficient projects.

Regulations and Standards. Mandatory standards and audits ensure compliance. For instance, the APO recommends broad adoption of ISO 50001 energy management systems and periodic energy audits (APO, 2020). Governments can institute or tighten building and appliance efficiency standards (e.g., LEED/Green Building criteria) and require regular reporting of energy use and GHG inventories. In the transport sector, incentives and regulations, such as fuel-economy norms or EV mandates, complement energy policies (APO, 2024).

Green Public Procurement. Public agencies can lead by example. Embedding energy-efficiency criteria into government procurement—from office equipment to infrastructure projects—creates demand for green products. The APO 2.0 report highlights “green procurement” for buildings and services as a key approach. For example, requiring LEED-certified public buildings or efficient street lighting drives market uptake of efficient technologies (APO, 2024).

Examples of National Action. Several APO members already illustrate these instruments. Japan's Green Purchasing Law mandates that government bodies buy eco-labeled products, helping scale up efficient technologies (APO, 2020). Vietnam's National Green Growth Strategy (2021–30) and its COP26 net-zero pledge explicitly emphasize enterprise energy-efficiency improvements. These cases show how fiscal measures and standards can be woven into broader national plans to reinforce GP gains.

9.2. Technological Tools and Innovations

Energy Management Systems. Implementing ISO 50001 and similar EMS frameworks helps firms systematically reduce energy wastage. APO training programs (e.g., self-learning courses on energy auditing) underscore the need for certified energy auditors to identify efficiency opportunities. Regular audits and energy monitoring software can pinpoint inefficiencies in real time.

Smart Manufacturing (Industry 4.0). Advanced digital technologies can dramatically cut energy use. The APO advises leveraging Industry 4.0 practices such as internet of things (IoT) sensors, cloud computing, artificial intelligence (AI), and cyber-physical systems, to optimize production processes. For example, IoT-enabled motor controls and AI-driven scheduling reduce idle running time, while real-time data analytics support predictive maintenance (reducing unplanned shutdowns). The 2023 Smart Green Manufacturing report shows that integrating smart recycling and circular practices into factories yields both productivity and energy gains (APO, 2023).

Resource-efficient Production Techniques. Tools such as Material Flow Cost Accounting (MFCA), life-cycle assessment (LCA), and ecodesign help industries minimize waste. The APO (2020) notes that addressing waste streams and adopting MFCA are critical GP levers. Ecodesign, i.e., designing products for durability, reusability, and recyclability, lowers the energy needed per unit output by avoiding raw-material wastage (APO, 2024). Clean production methods (e.g., closed-loop water systems, high-efficiency furnaces) are also promoted for both cost savings and pollution control.

Sector-specific Technologies. Different sectors require tailored tools. In manufacturing, process controls and high-efficiency motors/pumps are key. The APO suggests ecodesign of industrial machinery and smart supply-chain tracking. In agriculture, precision irrigation systems and solar-powered pumps conserve water and reduce fuel use. The APO's GP 2.0 roadmap highlights innovations such as agrivoltaics (solar panels over farmland) and on-farm biogas from organic waste. For services and buildings, smart energy management (building automation, LEDs, smart thermostats) combined with certification schemes (e.g., Green Building Index) delivers big gains.

9.3. Institutional Arrangements

National Coordination Bodies. These establish or empower agencies to champion GP. For example, India's Bureau of Energy Efficiency and Japan's Eco-Management Program coordinate industry-wide initiatives. The APO (2024) recommends adopting formal GP management systems, akin to ISO 9001, so that enterprises institutionalize efficiency improvements. National GP councils or committees can set cross-sectoral targets and monitor progress.

Green Public Procurement Offices. These create dedicated units to implement green procurement policies. Institutionalizing procurement guidelines (e.g., energy-performance criteria for vehicles or appliances) ensures continuity beyond single programs. This approach was urged in APO studies to "foster green procurement" in both public- and private-sector organizations.

Centers of Excellence and Partnerships. These leverage APO networks to build capacity. The APO's Center of Excellence on Green Productivity (hosted in Taipei, ROC since 2013) provides training and shares best practices. In 2023, the ROC's productivity center led a Green Productivity study mission for Vietnam, demonstrating technologies and policies for net-zero energy efficiency. Such institutional collaborations, with international donors, industry chambers, and non-government organizations (NGOs), can accelerate adoption.

Finance and Incentive Programs. The objective is to develop green financing platforms (green banks, ESCO models) linked to GP goals. The APO notes the need for "green financial markets" and specialized lending standards (environmental taxonomies) to mobilize private capital. Granting low-interest loans or credit guarantees for energy-efficient projects helps overcome upfront cost barriers, especially for SMEs.

9.4. Sectoral Strategies

Agriculture. GP in farming combines efficient resource use with circularity. Strategies include precision agriculture (to minimize fuel/power per yield); solar irrigation and cold storage (to replace diesel generators); and on-site renewables (e.g., biogas digesters for animal waste). The APO's Climate-Smart Agriculture initiatives and CE studies urge the use of organic waste for energy and the production of locally produced biofertilizers, thereby reducing dependence on energy-intensive chemical inputs.

Manufacturing. Industries should integrate GP tools in production lines. Lean production, clean technology, and smart automation together increase output per unit of energy. For example, Japanese and Korean firms have long used Total Productive Maintenance (TPM) and MFCA to cut downtime and energy leaks. Governments can support this by subsidizing industrial energy audits and mandating ecolabels on equipment.

Services (Buildings and Transport). The service sector's productivity is heavily tied to energy in buildings and logistics. Key GP interventions include green building standards (APO, 2024) and efficient facility management. For example, many APO member economies now offer LEED or equivalent certification to encourage high-performance offices. In transport and logistics, policy measures (such as EV incentives and optimized freight networks) combine with GP tools, such as route-optimization algorithms, to reduce fuel use. In hotels and hospitals, energy audits often reveal easy retrofits (e.g., LED lighting and heat recovery) that cut operating costs and boost service productivity.

GP and Circular Economy Synergies. GP strategies naturally complement circular economy (CE) approaches. Both frameworks emphasize resource efficiency and closed-loop thinking. As an APO research notes, a systems view is key: organizations must be "interdependent," and improvements in one part (e.g., waste recycling) require parallel changes elsewhere for overall gains. In practice, this means adopting circular practices (e.g., product takeback, remanufacturing, and industrial symbiosis) alongside GP measures. For instance, designing products for reuse not only conserves materials but also reduces the energy used per unit value added, thereby achieving dual GP/CE benefits (APO, 2022). By aligning GP policy with CE principles, member economies can multiply productivity gains while moving toward sustainability (APO, 2022).

10. Conclusion and Policy Implications

This chapter has provided a comprehensive overview of the relationship between energy efficiency and productivity across APO member economies. Using both descriptive and empirical evidence, the analysis confirmed that while productivity has generally improved over the past two decades, energy efficiency has deteriorated across most income groups. The divergence between rising productivity and declining energy efficiency underscores a structural imbalance in growth patterns, where short-term output gains have often been achieved through energy-intensive processes rather than sustainable efficiency improvements.

Empirical findings indicate that improvements in energy efficiency are positively associated with TFP, suggesting that more efficient energy use enables economies to allocate resources more effectively, reduces production costs, and supports technological upgrading. In contrast, the short-term negative relationship with LP indicates transitional effects of technology adoption, in which labor-saving innovations temporarily weaken employment-based output before stabilizing through technological diffusion and learning by doing. Over the long term, however, efficiency gains remain a structural driver of productivity, particularly when supported by institutional coordination under the APO framework.

From a policy perspective, these findings reaffirm that energy efficiency must be treated as a core productivity policy, not merely as an environmental goal. Within the GP framework, five strategic directions are emphasized:

(1) **Institutional integration:** Establish national coordination bodies or GP councils to align energy efficiency and productivity objectives. APO member economies should institutionalize energy management through ISO 50001 systems, national audit frameworks, and transparent performance reporting to ensure policy consistency and accountability.

(2) **Technological transformation:** Promote digitalization and clean technologies, such as smart manufacturing, precision agriculture, and intelligent building management, to achieve both energy savings and productivity improvements. Cross-economy collaboration and technology transfer within the APO network can accelerate adoption and diffusion of best practices.

(3) **Green finance and incentives:** Expand fiscal and financial instruments, such as grants, tax incentives, green bonds, and public procurement, to stimulate energy-efficient investment and innovation. Special attention should be given to supporting SMEs and local industries facing high upfront costs associated with energy transition.

(4) **Sector-specific strategies:** Develop tailored policies that reflect each sector's energy profile and productivity potential. In agriculture, energy efficiency can be enhanced through precision irrigation, renewable-powered equipment, and low-carbon logistics. In manufacturing, the focus should be on process optimization, clean production systems, and upgrades to high-efficiency machinery. In services, energy management in buildings and transportation should be strengthened through digital monitoring and green certification programs.

(5) **Data-driven energy governance:** Establish economy-specific and disaggregated energy efficiency databases to support evidence-based policymaking. Aggregate measures such

as energy use per unit of GDP are useful but insufficient for targeted policy design. Building robust data systems at sectoral and regional levels will enable policymakers to track efficiency performance, identify bottlenecks, and evaluate the effectiveness of GP initiatives across the APO region.

In conclusion, energy efficiency represents the essential bridge between productivity growth and environmental sustainability in the Asia–Pacific region. For APO member economies, achieving sustainable productivity requires embedding energy efficiency into each layer of economic planning, supported by sector-specific strategies, robust data systems, and institutional collaboration. By aligning national productivity agendas with data-driven energy governance under the Green Productivity vision, APO members can secure long-term competitiveness, energy security, and climate resilience.

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Appendix

This section lists different groups of economies used for all the regressions made among the 45 economies selected. The classification of economies by income group follows the World Bank's official methodology, which is based on gross national income (GNI) per capita, calculated using the Atlas method. This measure serves as the foundation for grouping economies into lower-middle-income, upper-middle-income, and high-income categories. Fiji and the ROC were not included in certain parts of the analysis due to lack of energy-related data required to compute energy efficiency and productivity indicators.

APO Member Economies

Bangladesh, Cambodia, Fiji, Hong Kong, India, Indonesia, the Islamic Republic of Iran, Japan, the ROK, Lao PDR, Malaysia, Mongolia, Nepal, Pakistan, the Philippines, Singapore, Sri Lanka, the ROC, Thailand, Turkiye, and Vietnam.

Non-APO Member Economies

Australia, Austria, Belgium, Bhutan, Canada, Chile, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Mexico, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom (UK), and the United States of America (USA).

OECD Economies

Australia, Austria, Belgium, Canada, Chile, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, the ROK, Mexico, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the UK, and the USA.

Low-income APO Member Economies

Bangladesh, Cambodia, India, Indonesia, Islamic Republic of Iran, Lao PDR, Mongolia, Nepal, Pakistan, the Philippines, Sri Lanka, and Vietnam.

Upper-medium-income APO Member Economies

The ROC, Fiji, Malaysia, Thailand, and Turkiye.

High-income APO Member Economies

Hong Kong, Japan, the ROK, and Singapore.

Energy Efficiency Indicators by APO Member Economy

Economy	Energy Efficiency	2000	2005	2010	2015	2021
Bangladesh	Total	50.2	49.5	47.5	44.5	39.4
	Agriculture	12.2	14.3	14.8	16.2	17.2
	Manufacturing	259.7	220.3	172.5	126.3	91.9
	Service	21.9	23.9	25.4	24.3	21.8
Cambodia	Total	142.1	103	87.1	76.5	80.6
	Agriculture	18	17	15.4	15.5	21.7
	Manufacturing	886.5	513.2	389.3	261.6	258.9
	Service	111.8	85.4	74.5	56.5	68.6
ROC	Total	106	104.4	91.6	80.7	65.9
	Agriculture	107.8	139.5	71.9	83.2	85.7
	Manufacturing	457.7	385.9	279.4	220	154.8
	Service	15.5	18.7	18.1	15.7	15.9
Hong Kong	Total	53.3	38.9	34.2	32.4	25.4
	Agriculture	1,343.2	1,375.3	1,937.5	2,391.3	2,218.6
	Manufacturing	1,166.2	1,316.9	1,500.1	1,634.4	1,326.9
	Service	16.1	12.2	11.2	10.6	8.3
India	Total	127.5	109.6	105.2	95.8	83.9
	Agriculture	20	22.7	26.7	30.1	26.6
	Manufacturing	638.1	549.4	472.3	402	341.9
	Service	69.4	61.9	59.8	51	45.5

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Economy	Energy Efficiency	2000	2005	2010	2015	2021
Indonesia	Total	96.8	89.3	79.2	63.6	64.7
	Agriculture	27.9	29	28.4	24.6	25.9
	Manufacturing	270	235.3	215.2	172.1	177.7
	Service	51.9	54.4	55.4	41.9	42.3
IR Iran	Total	169.8	184.2	179.1	196.9	223.2
	Agriculture	67.3	95.1	120.5	110.4	130.3
	Manufacturing	801.2	678.6	561.4	671.3	704.2
	Service	90.2	104.7	113.6	108.2	111.8
Japan	Total	104.3	99	95.5	78.4	72.1
	Agriculture	169.8	213.3	197.3	193.7	212.3
	Manufacturing	378.6	351.5	324.6	272.7	239.2
	Service	37.2	35.9	35.1	28.4	27.8
ROK	Total	157.4	138.1	130.9	123.4	113.9
	Agriculture	275.3	252.3	229.3	185.6	214
	Manufacturing	460.3	370.9	336.8	325.9	299.7
	Service	71.7	69.7	62.9	54.4	49.1
Lao PDR	Total	102.4	89.5	86.1	89.9	90.1
	Agriculture	15.2	18.9	20.2	21.8	22.5
	Manufacturing	1,315.5	1,249	1,020.4	680.5	544.9
	Service	164.8	96.3	86.9	78.7	73.6
Malaysia	Total	113.5	121.2	108.6	97.8	93.7
	Agriculture	39.9	49.2	49.6	54.7	62.3
	Manufacturing	264.5	271.4	259.8	248	215.4
	Service	67.4	72.9	61.9	56.1	51.8
Mongolia	Total	168.4	153.6	148.5	108.6	130.1
	Agriculture	44.7	60.4	77.3	49.5	60.5
	Manufacturing	1,336.7	1,048.6	938.1	872.2	880
	Service	79.7	73.9	88	76.2	90.2
Nepal	Total	141.2	134.6	121.1	113.9	115.4
	Agriculture	23.8	23.1	22.2	21.8	23.5
	Manufacturing	1,234.4	1,293.9	1,270.8	1,136.3	1,158.7
	Service	76.4	80.2	69.2	58.2	57.7

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Economy	Energy Efficiency	2000	2005	2010	2015	2021
Pakistan	Total	116.6	107.9	101.6	94.1	86.7
	Agriculture	18.7	20.5	21	20.5	21.1
	Manufacturing	851.7	588.2	506.7	448.8	414
	Service	62.2	59.7	56.4	51.1	46.4
Philippines	Total	102.9	80.7	68.8	64.9	60
	Agriculture	31.9	27.4	26.1	29.6	32.9
	Manufacturing	273.9	212.8	193.2	183.5	166.8
	Service	50	40.7	35.3	31.8	28.8
Singapore	Total	67.9	60.2	49.9	53.6	49
	Agriculture	3,546.3	5,998.8	7,044.9	8,350.7	7,757.8
	Manufacturing	186.7	165.2	132.8	164.5	120.6
	Service	24	22.1	20.5	21.4	20.5
Sri Lanka	Total	67.2	59.8	47.6	37.7	36.9
	Agriculture	27.4	31.3	25.4	22.1	24.7
	Manufacturing	207.5	189.3	148	135.5	121.4
	Service	32	30.8	26.5	20.4	19
Thailand	Total	99.3	104.4	102.8	102.8	90.6
	Agriculture	38.8	49	54.7	63.3	54.4
	Manufacturing	222.5	213.4	195.1	212.5	177.1
	Service	49.3	56.4	60	56.3	45.7
Turkiye	Total	79.2	68.6	73.9	64	60.5
	Agriculture	89.1	87.7	117	82.6	95.3
	Manufacturing	401.1	312.1	289.2	229.8	229.3
	Service	12.9	19.4	32.2	31.9	22.1
Vietnam	Total	85.7	88.2	92.2	73.5	79.9
	Agriculture	17.4	23.4	30.3	27.1	36.4
	Manufacturing	407.7	302.8	293.6	195.4	178
	Service	56.6	63.2	69	50.2	56.5

CHAPTER 2

ENERGY EFFICIENCY AND AGRICULTURAL PRODUCTIVITY: CHALLENGES AND POLICY OPTIONS

1. Introduction

The agricultural sector in Asia is at a critical juncture, confronted by a confluence of escalating challenges, including population growth, climate change (e.g., shifts in temperature and precipitation), and resource depletion. Consequently, the imperative to enhance agricultural productivity has become increasingly pronounced. In this context, energy efficiency is widely recognized as a pivotal determinant of agricultural productivity. The efficient use of energy not only reduces production costs but also mitigates environmental impacts by curtailing greenhouse gas emissions and conserving finite resources.

Previous studies have suggested that improvements in energy efficiency can enhance both total factor productivity (TFP) and labor productivity (LP) in agriculture (Jeong, 2024; Liu et al., 2021; Shang et al., 2023). However, numerous prior studies have shown that this relationship yields different outcomes depending on factors such as income and region (Fei and Lin, 2016; Li et al., 2019). This suggests that the relationship has not yet been fully studied and that its dynamics remain unclear. To address this research gap, this study aims to analyze the impact of energy efficiency on agricultural productivity empirically. Elucidating these relationships will enable policymakers to formulate sustainable agricultural development strategies that optimize energy use and enhance food security. The findings of this study are anticipated to contribute to the relevant academic literature as well as policymaking across APO member economies by providing robust empirical evidences.

The primary objective of this study is to conduct a comprehensive analysis of the impact of energy efficiency on agricultural productivity using panel data from APO member economies. The analysis also explores effective strategies for addressing the identified challenges. To achieve these objectives, the research is structured into the following four distinct steps:

First, a baseline model is developed to identify the main factors affecting agricultural productivity using traditional economic theory. The explanatory variables are broadly divided into economic factors (such as labor, capital, human capital, government policies, and land area) and non-economic factors (such as average annual temperature and precipitation) to reflect the unique characteristics of the agricultural sector.

Second, building upon the baseline model, the study assesses the effect of energy efficiency on agricultural productivity, measured by LP. Energy efficiency is proxied by energy productivity (agricultural GDP per agricultural energy use). The analysis also considers interaction effects to capture the indirect impacts of energy efficiency.

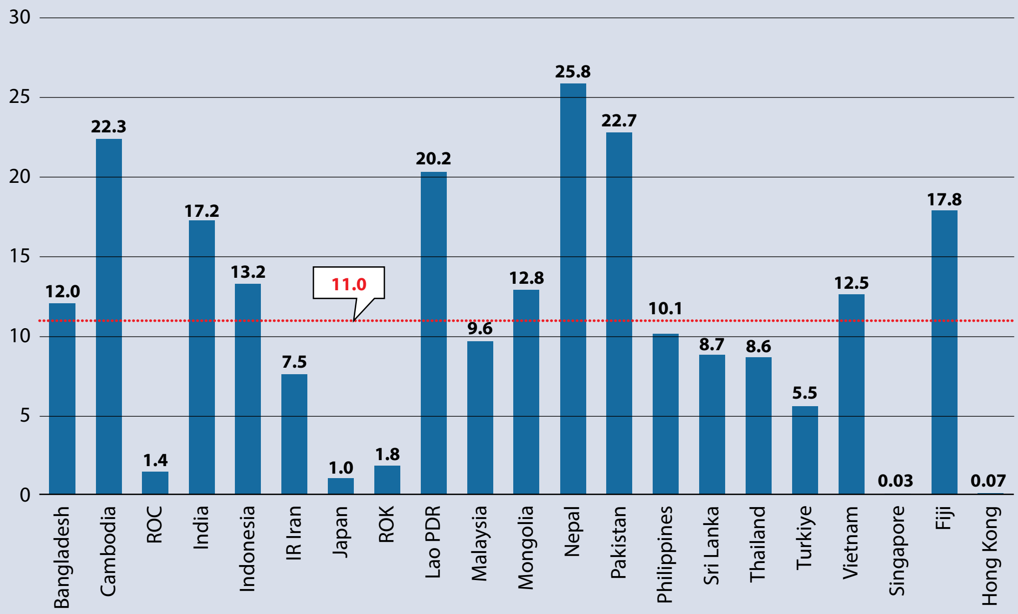
Third, the model accounts for regional heterogeneity by dividing APO member economies into two subregions: (1) Central and West Asia; and (2) South Asia, East Asia, and the Pacific, to examine differences in the energy–productivity relationship. This regional classification aligns with the framework established by the International Assessment of Agricultural Knowledge, Science, and Technology for Development (IAASTD, 2009), which categorized global regions based on climate and crop characteristics. Furthermore, the relationship between energy efficiency and LP in the agricultural sector is likely to be heterogeneous depending on factors such as energy efficiency levels (Fei and Lin, 2016; Li et al., 2019) and each economy's industrial structure. Therefore, we analyze these potential differences by dividing the economies into groups with relatively high and relatively low energy-efficiency levels, and groups with high and low agricultural GDP contributions. Consequently, the economies under analysis are grouped into high- and low-energy-efficiency categories to examine this potential variation.

Lastly, this study examines the response strategies adopted by APO member economies and derives comprehensive policy implications based on the empirical findings, to provide actionable insights for policymakers.

2. Trends of the Agriculture Sector in APO Member Economies

FIGURE 2.1

AGRICULTURAL SECTOR'S GDP SHARE BY APO MEMBER ECONOMIES IN 2021 (%).



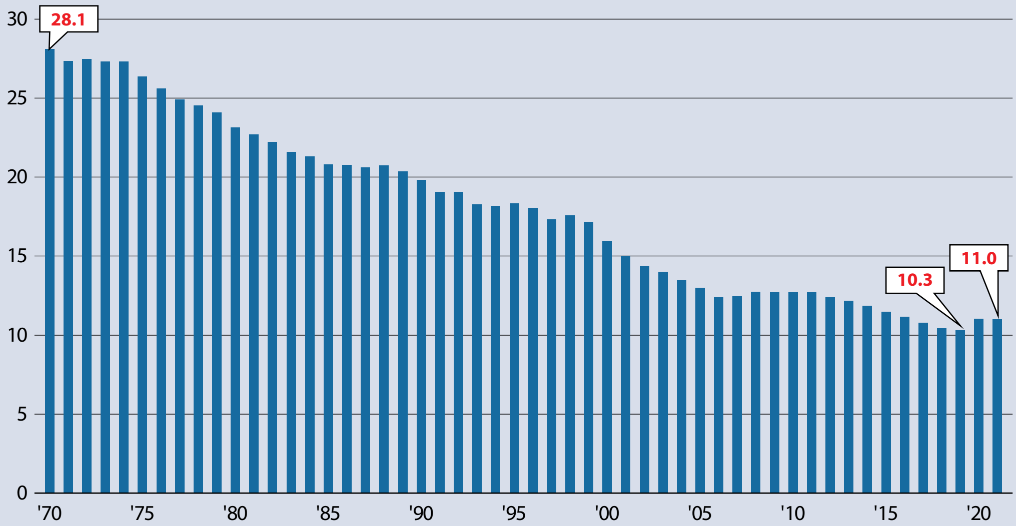
Source: APO (2024).

This section examines the structural characteristics of the agricultural sector in APO member economies by analyzing its share of GDP and employment trends. Figure 2.1 presents the share of agriculture in GDP (%) in 2021. On average, agriculture accounted for 11.0% of GDP across APO member economies, highlighting notable differences in economic structures. Nepal (25.8%), Pakistan (22.7%), Cambodia (22.3%), and Lao PDR (20.2%) rely on agriculture for more than one-fifth of their GDP, whereas Japan (1.0%), the ROC (1.4%), and the ROK (1.8%) record shares below 2%. City-economies such as Singapore (0.03%) and Hong Kong (0.07%) report agricultural contributions below 1%.

The agricultural share of GDP has declined rapidly over time. As shown in Figure 2.2, the average share decreased from 28.1% in 1970 to 11.0% in 2021, reflecting the shift from agriculture to manufacturing and services as industrialization advanced. The pace of decline was sharp in the 1970s and 1990s but slowed after the 2000s, stabilizing at 10–11% since 2019.

FIGURE 2.2

TREND OF AGRICULTURAL SECTOR'S SHARE OF GDP IN APO MEMBER ECONOMIES (%).



Source: APO (2024).

TABLE 2.1

AGRICULTURAL SECTOR'S SHARE OF GDP IN APO MEMBER ECONOMIES, 1970–2021 (%).

APO Member Economy	1970	1980	1990	2000	2010	2020	2021
Nepal	60.70	50.70	45.80	35.23	33.16	25.15	25.79
Pakistan	35.22	27.82	23.27	25.42	22.71	21.88	22.69
Cambodia	41.27	42.73	49.27	35.74	33.68	22.15	22.28
Lao PDR	68.52	65.72	60.60	52.03	28.53	20.97	20.24
Fiji	24.93	19.35	15.28	14.90	10.11	17.80	17.82
India	40.60	33.12	26.69	21.40	17.11	18.61	17.18
Indonesia	42.32	21.79	17.32	14.84	13.90	13.63	13.21
Mongolia	14.32	8.09	9.42	21.85	11.73	12.82	12.83
Vietnam	40.28	44.44	37.87	20.87	15.35	12.63	12.54
Bangladesh	34.00	31.34	28.75	23.16	16.91	12.35	11.98

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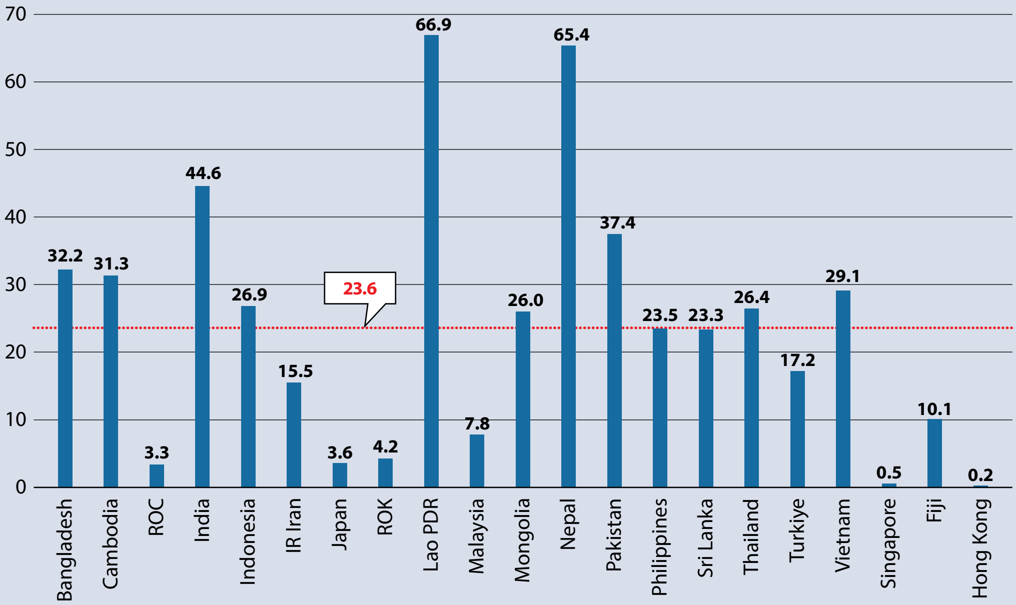
APO Member Economy	1970	1980	1990	2000	2010	2020	2021
Philippines	28.98	24.54	20.69	13.94	13.75	10.19	10.07
Malaysia	25.71	19.84	14.82	8.50	10.09	8.17	9.59
Sri Lanka	17.53	16.77	14.64	10.30	9.17	8.18	8.74
Thailand	21.84	19.88	9.95	8.48	10.50	8.60	8.61
IR Iran	14.69	12.57	14.71	10.99	5.89	7.38	7.52
Turkiye	27.32	19.12	12.67	10.03	8.97	6.67	5.54
ROK	26.49	14.27	7.61	3.86	2.14	1.77	1.79
ROC	16.12	7.81	4.01	2.02	1.61	1.57	1.43
Japan	5.87	3.49	2.43	1.54	1.16	1.03	0.99
Hong Kong	0.72	0.77	0.24	0.07	0.05	0.09	0.07
Singapore	2.56	1.51	0.32	0.09	0.04	0.03	0.03

Source: APO (2024).

While most economies experienced steady declines, the pace varied by development stage (Table 2.1). For instance, the ROK, the ROC, and Japan reduced their agricultural shares from 10–20% in 1970 to below 2% in 2021, reflecting rapid industrialization. In contrast, Nepal and Pakistan still rely on agriculture for more than 20% of their GDP. Some member economies, such as Cambodia (from 42.7% in 1970 to 49.3% in 1990), Mongolia (from 9.4% in 1990 to 21.9% in 2000), and Fiji (from 10.1% in 1990 to 17.8% in 2010), experienced temporary increases, likely due to economic shocks or policy shifts.

FIGURE 2.3

AGRICULTURAL SECTOR'S EMPLOYMENT SHARE IN APO MEMBER ECONOMIES IN 2021 (%).

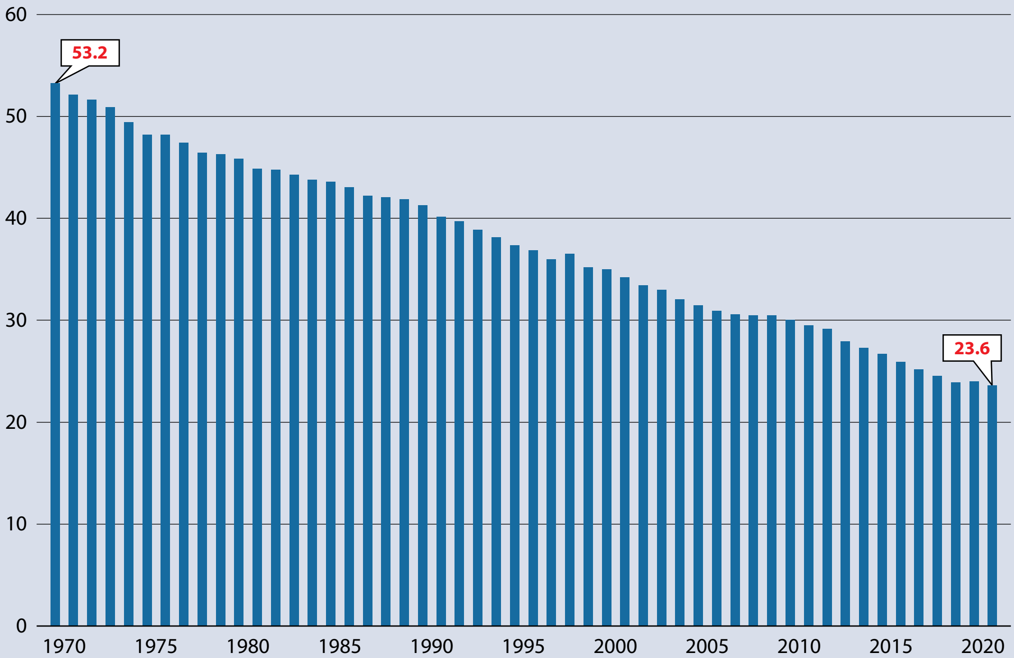


Source: APO (2024).

Agricultural employment shows a similar pattern. Figure 2.3 illustrates the share of agriculture in total employment in 2021. In Lao PDR (66.9%) and Nepal (65.4%), more than two-thirds of the labor force remains in agriculture, while India (44.6%), Bangladesh (32.2%), and Cambodia (31.3%) also exhibit high levels of agricultural dependence. By contrast, Singapore (0.5%), Hong Kong (0.2%), the ROC (3.3%), Japan (3.6%), and the ROK (4.2%) record very low agricultural employment shares, reflecting substantial labor reallocation to non-agricultural sectors.

FIGURE 2.4

TREND OF AGRICULTURAL SECTOR'S EMPLOYMENT SHARE IN APO MEMBER ECONOMIES (%).



Source: APO (2024).

Over time, the decline in agricultural employment has been even more pronounced. Figure 2.4 shows that the average share fell from 53.2% in 1970 to 23.6% in 2021, indicating massive labor outflows from agriculture to industry and services. Table 2.2 confirms that all APO member economies experienced declines, though at varying speeds. The ROK reduced its agricultural employment from 50.3% in 1970 to 4.2% in 2021, while in the ROC, the share fell from 40.9% to 3.3%. These sharp declines illustrate rapid industrialization. By contrast, Pakistan and Bangladesh, despite decreases, still maintain agricultural employment shares of 30–40%, indicating slower structural transformation. Lao PDR and Nepal, although also showing declines, remain highly dependent on labor-intensive agriculture.

TABLE 2.2

TRENDS OF AGRICULTURAL SECTOR'S EMPLOYMENT SHARE BY ECONOMY (%).

APO Member Economy	1970	1980	1990	2000	2010	2020	2021
Lao PDR	78.2	77.3	85.2	82.2	71.3	67.5	66.9
Nepal	94.1	92.6	82.4	64.6	71.2	65.9	65.4

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APO Member Economy	1970	1980	1990	2000	2010	2020	2021
India	69.5	63.4	63.5	55.1	52.2	44.9	44.6
Pakistan	58.0	52.8	48.7	48.4	45.0	39.2	37.4
Bangladesh	60.9	63.6	49.5	46.5	42.0	33.0	32.2
Cambodia	80.5	80.0	79.4	73.5	57.4	30.9	31.3
Vietnam	66.8	67.5	71.9	64.4	49.5	33.1	29.1
Indonesia	72.9	56.0	56.0	45.2	38.5	28.1	26.9
Thailand	76.9	70.8	56.8	37.2	32.3	26.1	26.4
Mongolia	49.7	37.6	31.7	42.0	33.6	23.9	26.0
Philippines	46.3	45.9	40.1	32.9	33.6	23.9	23.5
Sri Lanka	55.6	50.4	48.3	37.2	27.6	23.1	23.3
Turkiye	65.6	55.5	45.9	36.0	23.3	17.6	17.2
IR Iran	46.4	32.1	26.6	21.3	19.2	16.7	15.5
Fiji	40.9	22.9	18.6	12.1	10.1	10.3	10.1
Malaysia	40.5	32.4	26.0	16.7	10.3	8.1	7.8
ROK	50.3	34.1	18.0	8.3	5.2	4.3	4.2
Japan	19.5	12.8	8.7	5.9	4.6	3.7	3.6
ROC	40.9	13.5	8.8	5.4	3.7	3.4	3.3
Singapore	2.5	1.0	0.3	0.2	0.2	0.5	0.5
Hong Kong	1.5	0.9	0.6	0.3	0.2	0.2	0.2

Source: APO (2024).

A comparison of GDP and employment shares yields three important insights. First, the agricultural sector's economic importance has diminished across APO member economies, both in terms of production and employment. Second, industrialization has driven structural transformation, though the pace has varied considerably by economy. Third, discrepancies between GDP and employment shares reflect differences in productivity. Economies such as Lao PDR (employment 66.9% vs. GDP 21.1%) and Nepal (employment 65.4% vs. GDP 25.9%) employ large agricultural workforces but generate relatively low value added, suggesting labor-intensive, low-productivity agriculture. In contrast, the ROK (employment 4.2% vs. GDP 1.7%) and Japan (employment 3.6% vs. GDP 1.1%) have achieved higher productivity with small agricultural populations through capital- and technology-intensive farming.

3. Theoretical Background and Literature Review

Energy use constitutes a critical input in modern agriculture, underpinning the operation of machinery, irrigation, and greenhouse management (FAO, 2017). Enhancing energy efficiency has been widely recognized as a means to reduce production costs, strengthen competitiveness, and ultimately improve agricultural productivity (Andriushchenko et al., 2025; Benedek et al., 2023; IEA, 2014; Liu et al., 2021; Shang et al., 2023). Despite this theoretical consensus, empirical evidence for directly addressing the productivity effects of energy efficiency remains limited, with the literature presenting mixed findings.

Several studies provide evidence in favor of a positive relationship (Table 2.3). The OECD (2019), analyzing data from 1995 to 2017 across OECD economies using a panel model, showed that improvements in energy efficiency promoted faster growth in LP. This was largely driven by mechanization, precision agriculture, and energy optimization, which enabled larger production areas to be managed with fewer workers. Their findings highlight energy efficiency as a central driver of agricultural modernization and labor-saving technological progress.

Other empirical studies, however, report weaker or inconclusive links. Wysokiński et al. (2020), drawing on Eurostat data for Poland and EU member economies from 2000 to 2018, found no consistent correlation between agricultural productivity and energy efficiency. Nevertheless, they stressed that efficiency gains remained vital for reducing greenhouse gas (GHG) emissions and enhancing long-term sustainability. Similarly, Boczar and Błażejczyk-Majka (2024) analyzed 30 farms across 11 EU member economies (2019–21) using Data Envelopment Analysis (DEA) and stepwise regression. Their results indicated no strong relationship between productivity and energy efficiency, suggesting that heterogeneity at the farm level may obscure broader aggregate trends. A comparable line of inquiry by Zhu et al. (2023) extended the DEA framework to EU economies (2003–19), incorporating GHG emissions and structural inefficiencies into productivity measurement. Their findings revealed that high energy and structural efficiency mitigated productivity decline, whereas energy intensity and structural inefficiency exacerbated both environmental degradation and productivity losses. This approach underscored the importance of integrating environmental performance into assessments of agricultural productivity.

Beyond these empirical assessments, some studies posit a bidirectional relationship between energy efficiency and productivity. Hasanov and Mikayilov (2021), through panel cointegration analysis of 49 economies (1990–2019), reported that higher TFP reduced energy consumption, suggesting that productivity itself could enhance efficiency. In the Korean context, Jeong (2024) applied an autoregressive distributed lag (ARDL) model using data from 1987 to 2021 and found that increases in agricultural TFP reduced long-run energy consumption by 0.021%. Moreover, his findings supported the environmental Kuznets curve hypothesis, which posits that agricultural energy consumption initially rises with economic growth but subsequently declines as economies mature.

Taken together, the literature suggests that the nexus between energy efficiency and agricultural productivity is multifaceted. While some studies demonstrate a direct positive relationship, others highlight weak or context-specific associations, and yet others suggest reverse causality through productivity-driven efficiency improvements. These divergent findings indicate that energy efficiency should be analyzed not only as a potential driver of productivity but also as a variable that interacts dynamically with broader structural, technological, and environmental factors. Against this backdrop, the current study establishes a baseline model of factors influencing agricultural productivity, while explicitly including energy efficiency, to analyze its specific impact on LP.

TABLE 2.3

LITERATURE ON THE IMPACT OF ENERGY EFFICIENCY ON AGRICULTURAL PRODUCTIVITY.

Author	Data	Finding
Liu et al. (2021)	1995–2014 12 emerging economies DEA and Panel Tobit Model	Energy efficiency in agriculture varies across economies, but improvements in energy efficiency increase agricultural productivity.
Shang et al. (2023)	1995–2019 / OECD Panel Fixed Effect Model	Improving energy efficiency in agriculture has positive spillover effects on agricultural productivity.
Andriushchenko et al. (2025)	Europe and Ukraine / Case Study	Advances in energy efficiency technologies have a positive impact on agricultural industry growth and enhance sustainability.
Benedek et al. (2023)	2000~2022 / World Bibliometric Analysis (820 papers)	It emphasizes that energy efficiency significantly improves agricultural productivity.
Wysokiński et al. (2020)	2000–2018 Poland and EU / OLS	Higher energy efficiency leads to improved agricultural productivity, and its elasticity appears to be more sensitive in large-scale farms.
Jeong (2024)	1990–2022 The Republic of Korea / ARDL Model	TFP appears to significantly reduce energy consumption in the long run, but the relationship between technological progress and energy consumption is weak or insignificant in the short run.
FAO (2017)	Literature review of TFP Global	Energy efficiency is a critical component of TFP in agriculture. By reducing the energy intensity of production processes, farms can lower operational costs and reallocate labor toward higher-value activities, thereby increasing output per worker.
OECD (2019)	1995–2017 OECD/ Panel data analysis	Economies with higher energy efficiency in farm operations saw faster labor productivity growth; mechanization and optimized energy use were key drivers.
Zhu et al. (2023)	2003–19 EU / DEA	Energy use in agriculture is essential for modernization and productivity growth. However, productivity gains achieved without considering energy efficiency and environmental performance are unlikely to be sustainable in the long term.
Błażejczyk-Majka (2024)	2019–21 EU / DEA, OLS	No strong correlation was found between productivity and energy efficiency.

Source: Author (2025).

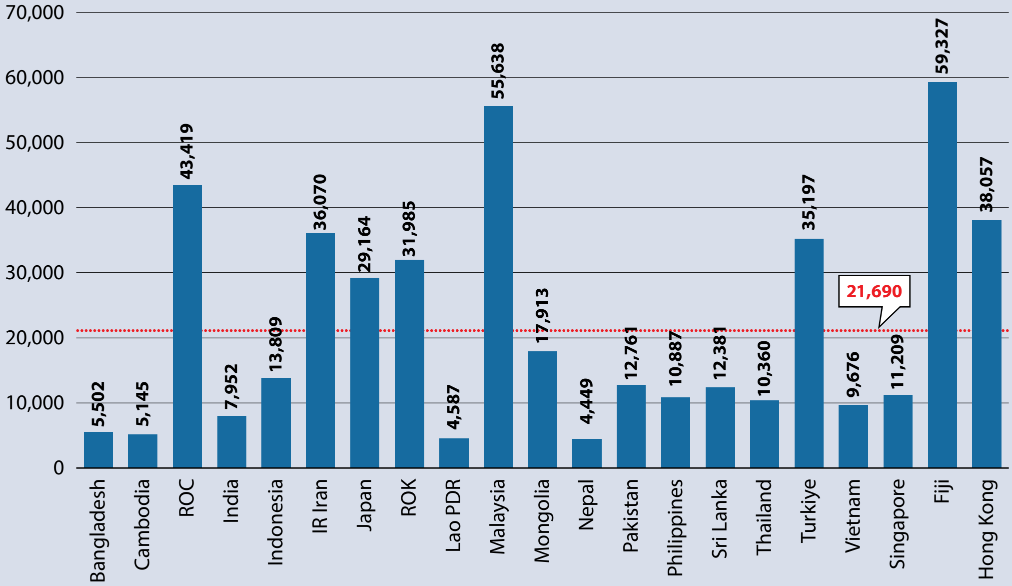
4. Data Description in APO Member Economies

The dependent variable in this study is the agricultural labor productivity index. The primary data sources are the APO Productivity Databook and the APO Productivity Database, published by the APO. However, alternative datasets from international organizations are also used where appropriate. For a more detailed analysis, macro-level data from APO member economies are used to calculate agricultural LP by industry classification. Agricultural LP is measured as the value of GDP in agriculture, hunting, forestry, and fishing at constant prices, divided by employment in the same sectors, as follows:

$$Agriculture\ Labor\ Productivity_{it}(LP_{i,t}) = \frac{Agricutre\ GDP_{it}}{Agricutre\ Employment_{it}} \quad (1)$$

FIGURE 2.5

LABOR PRODUCTIVITY IN THE AGRICULTURAL SECTOR, 2021.



Source: APO (2024).

Building on these variables, Figure 2.5 illustrates LP in the agricultural sector across APO member economies in 2021, with higher values indicating greater productivity. The figure reveals substantial cross-economy disparities and suggests that agricultural LP does not necessarily correspond to economic development.

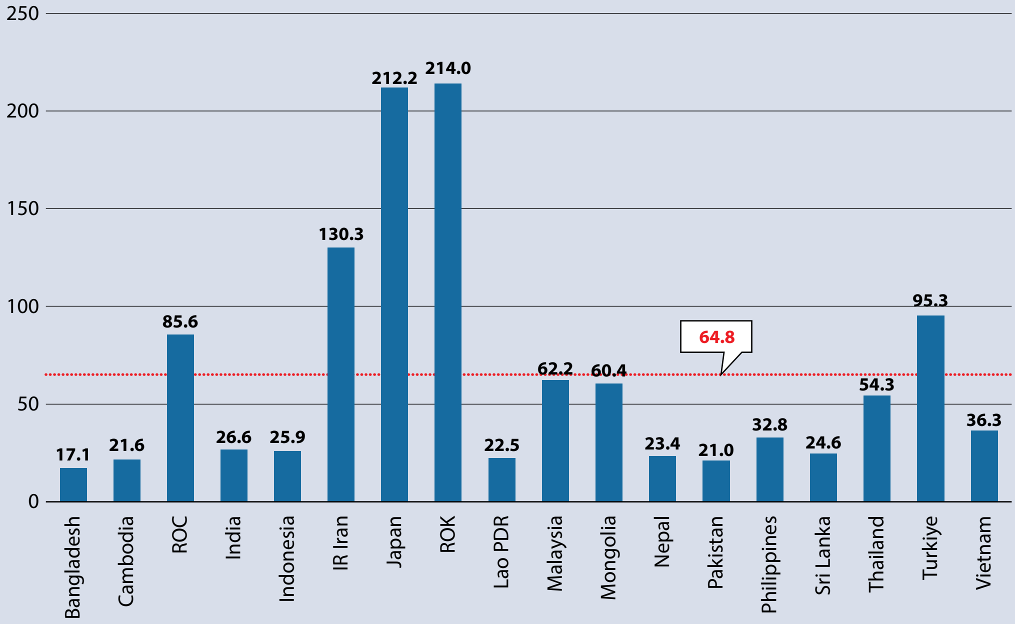
The main explanatory variable of interest is the energy efficiency index in the agricultural sector. Since no direct data on energy efficiency in the agricultural sector are available, it is constructed as a proxy variable through a two-step procedure. First, agricultural energy use is estimated by combining economy-level energy use per GDP data from the World Bank with industry-specific energy use shares from the IEA. Second, energy efficiency in the agricultural sector is calculated as agricultural energy use divided by industry-specific GDP, as reported by the APO.

$$Agriculture\ Energy\ Efficiency_{it}\ (EE_{i,t}) = \frac{Energy\ Use\ by\ Agriculture_{it}}{Agricuture\ GDP\ _{it}} \quad (2)$$

Figure 2.6 presents the energy efficiency of the agricultural sector in APO member economies in 2021, where lower values represent higher efficiency. The figure highlights substantial differences in energy efficiency by economy and reveals a lack of consistency with economic development levels. For instance, Japan, the ROK, and the ROC, i.e., economies with the highest levels of economic development, exhibit the lowest energy efficiency. At the same time, Bangladesh, with one of the lowest levels of economic development, demonstrates the highest efficiency. These

FIGURE 2.6

ENERGY EFFICIENCY IN THE AGRICULTURAL SECTOR, 2021.



Note: Fiji and Singapore were not included in certain parts of the analysis due to the lack of energy-related data required to compute energy efficiency.
Source: APO (2024).

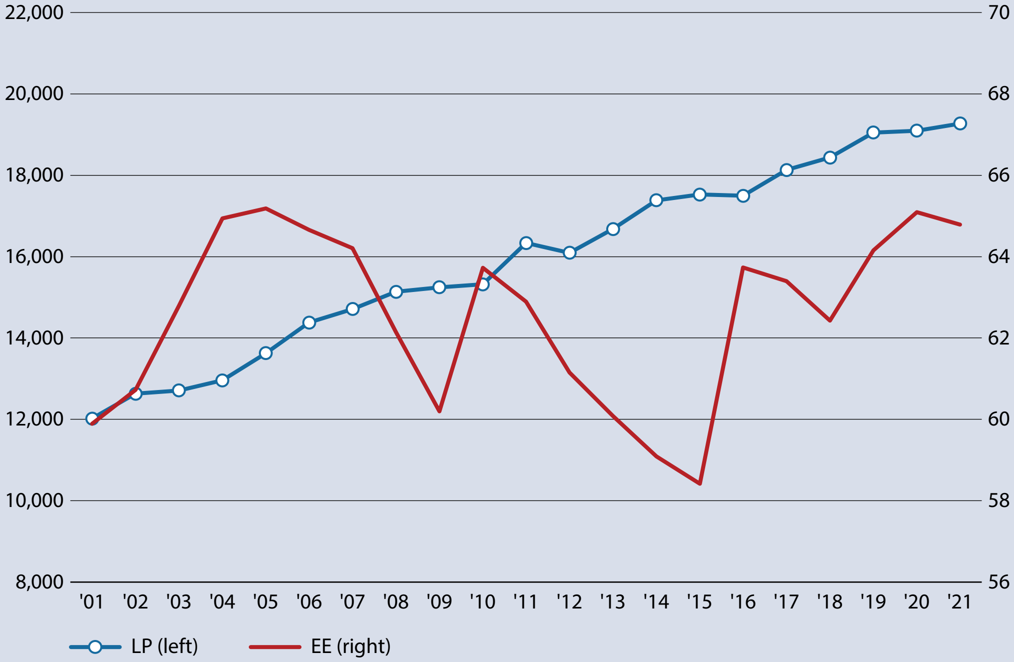
results may be due to the type of energy used in agricultural production. For example, agriculture in developing economies still relies heavily on human and animal labor, as well as traditional energy sources (e.g., firewood and livestock manure). In contrast, agriculture in developed economies relies heavily on commercial energy. This includes chemical fertilizers (especially nitrogen fertilizers, which are energy-intensive to manufacture); pesticides; large agricultural machinery (diesel fuel); large irrigation pumps; greenhouse heating and cooling; and electricity used for post-harvest processing and refrigeration systems. Nevertheless, developing economies are considered 'highly energy efficient" because their commercial energy inputs (oil and electricity) are much lower than those in developed economies.

Taken together, Figure 2.6 and Figure 2.7 indicate that neither agricultural LP nor energy efficiency aligns consistently with the stage of economic development. This suggests that structural characteristics of agriculture, resource endowments, and production methods may play a more decisive role than income level alone in shaping both productivity and efficiency outcomes.

The empirical model incorporates several control variables, which, based on theory and prior research, are expected to affect agricultural productivity, directly or indirectly. These include physical capital (CAP), human capital, government policy, trade openness (OPEN), and farmland coverage (ALC). Specifically, physical capital is measured using net capital stocks in the agriculture, forestry, and fishing sectors, obtained from Food and Agriculture Organization (FAO)'s FAOSTAT. Human capital is proxied by the Human Capital Index (HCI), derived from years of schooling and returns to education, as provided by the Penn World Table (PWT 10.01). Government policy is measured using the Agriculture Orientation Index (AOI), which reflects the level of government

FIGURE 2.7

TRENDS OF LABOR PRODUCTIVITY AND ENERGY EFFICIENCY IN THE AGRICULTURAL SECTOR.



Note: Fiji and Singapore were not included in certain parts of the analysis due to the lack of energy-related data required to compute energy efficiency.
Source: APO (2024).

expenditure on agriculture and is available from FAOSTAT. This index is calculated by dividing the share of government spending directed at agriculture by the share of total GDP. OPEN is captured by the ratio of trade volume to GDP (%), serving as a proxy for the structural characteristics of each economy. Finally, farmland coverage is measured through Agricultural Land Classification (ALC) as hectares of arable land per person, based on the World Bank's World Development Indicators (WDI).

Furthermore, climate change generally has a significant impact on agricultural production. To understand how natural conditions influence agriculture, climate variables are included in the analysis. The main climate indicators used are average annual temperature and yearly precipitation, obtained from the Climate Research Unit (CRU). According to the APO (2024), the analysis shows that agricultural productivity is more responsive to sudden changes in temperature and precipitation than to their annual averages. Therefore, this study uses meteorological anomalies as climate variables, defined as the difference between observed annual weather data and the long-term averages for the period 1961–90. A larger anomaly indicates a greater deviation, either positive or negative, from the historical climate baseline.

Except for trade openness, all explanatory variables are expressed as indices or monetary values, which may introduce distortions due to differences in scale across economies. To address this issue, these variables are transformed into natural logarithms before estimation. Descriptive statistics are presented in Table 2.4, and pairwise correlations among the variables are summarized in Table 2.5.

TABLE 2.4

DATA DESCRIPTION.

	LLP	LEE	LCAP	LHCI	LAOI	OPEN	LALC	ANO _PRE	ANO _TMP
Mean	9.28	3.76	4.43	0.87	−1.11	73.72	2.34	33.13	0.75
Median	9.16	3.38	4.48	0.88	−1.02	56.68	2.24	9.55	0.66
Max.	10.96	5.65	5.15	1.36	0.94	210.37	3.87	849.81	2.79
Min.	7.75	2.60	3.26	0.33	−4.61	19.56	0.90	−668.67	−0.24
Std. Dev.	0.89	0.83	0.34	0.25	1.02	42.09	0.81	204.95	0.46
Skew.	0.26	0.65	−0.77	−0.02	−0.19	0.98	0.05	0.40	0.90
Kurt.	1.77	2.22	3.73	1.99	2.97	3.13	1.92	5.08	4.46
J.–B. (Prob.)	28.13 (0.00)	36.20 (0.00)	45.71 (0.00)	16.05 (0.00)	2.19 (0.34)	60.51 (0.00)	18.55 (0.00)	77.72 (0.00)	84.20 (0.00)
Obs	378	378	378	378	378	378	378	378	378

Note: ( ) denotes the P-value.
Source: FAO's FAOSTAT, PWT 10.01, WDI.

TABLE 2.5

CORRELATION.

Variable	LLP	LEE	LCAP	LHCI	LAOI	OPEN	LALC	PRE
LEE	0.79 (24.88)	1						
LCAP	0.38 (7.87)	0.24 (4.78)	1					
LHCI	0.68 (18.12)	0.72 (19.87)	0.35 (7.24)	1				
LAOI	0.47 (10.42)	0.66 (16.97)	0.23 (4.67)	0.66 (17.15)	1			
OPEN	−0.04 (−0.68)	−0.05 (−0.97)	−0.22 (−4.41)	0.16 (3.17)	−0.14 (−2.79)	1		
LALC	−0.27 (−5.42)	−0.18 (−3.55)	−0.20 (−3.91)	−0.46 (−9.93)	−0.52 (−11.79)	0.10 (1.87)	1	
PRE	0.22 (4.27)	0.11 (2.20)	0.05 (1.01)	0.23 (4.58)	0.01 (0.12)	0.15 (2.95)	−0.13 (−2.50)	1
TMP	0.37 (7.75)	0.39 (8.10)	0.26 (5.21)	0.22 (4.38)	0.10 (2.00)	−0.10 (−2.00)	0.15 (3.00)	−0.12 (−2.41)

Note: ( ) denotes the t-value.
Source: Author (2025).

5. Estimation Methodology

Based on the above discussion and data, the basic estimation equation for understanding the impact of changes in energy efficiency on LP in the agricultural sector of APO member economies is as follows.

$$LP_{it} = \beta_0 + \beta_1 EE_{it} + \sum_{k=1}^{n} \gamma_k X_{it} + \varepsilon_{it} \quad (3)$$

where LP_{it} represents the productivity (value-added per worker) in the agricultural sector of country i in year t; β_0 is a constant term; EE_{it} and β_1 denote energy efficiency indicators (energy intensity, energy productivity) and its coefficient values; X_{it} and γ_k represent the determinants of productivity and their estimated coefficients (e.g., physical capital, human capital, government policy, trade openness, and cultivated land area); and ε_{it} is the error term.

We also consider climate factors (non-economic factors) that can have a decisive impact on agricultural productivity in Equation (1).

$$LP_{it} = \beta_0 + \beta_1 EE_{it} + \beta_2 Temp_{it} + \beta_3 Prec_{it} + \sum_{k=1}^{n} \gamma_k X_{it} + \varepsilon_{it} \qquad (4)$$

where $Temp_{it}$ and $Prec_{it}$ represent the temperature and precipitation of country i in year t. β_2 and β_3 represent the coefficient values of climate conditions. The remaining notations are as in Equation (1).

The estimations in Equations (1) and (2) use the traditional panel analysis method, that is, the fixed-effect or random-effect model. The t-values for statistical inference account for heteroscedasticity using the White (1980) method. The optimal model is selected between the fixed-effect and random-effect models using the Hausman test. A more specific estimation equation can be expressed as follows:

$$LP_{it} = \beta_0 + \beta_1 EE_{it} + \beta_2 Temp_{it} + \beta_3 Prec_{it} + \sum_{k=1}^{n} \gamma_k X_{it} + \mu_i + \varepsilon_{it} \qquad (5)$$

In Equation (3), μ_i represents the unobserved economy-specific effect, and the remaining notations are identical to Equations (1) and (2).

Meanwhile, the impact of changes in energy efficiency on LP in the agricultural sector may vary depending on factors such as climate and crop characteristics, the level of energy efficiency, and the share of agriculture in GDP. Therefore, to examine whether this regional heterogeneity exists among APO member economies, we conduct additional analyses by dividing the economies into subgroups based on climate and crop characteristics, energy efficiency, and the agricultural share of GDP. The first subgroups are divided into (1) Central and West Asia and (2) South Asia, East Asia, and the Pacific according to the criteria of IAASTD (2009) share (Table 2.6). IAASTD (2009) classified the world into five regions considering climate and crop characteristics (food production type), and APO member economies are included in two of these regions: (1) Central and West Asia, and (2) South Asia, East Asia, and the Pacific. The second subgroup is divided into nine economies with relatively high energy efficiency and nine with relatively low energy efficiency (Table 2.7). The third subgroup is divided into nine economies with a relatively high share of agriculture in GDP and nine economies with a relatively low share (Table 2.8).

TABLE 2.6

CLASSIFICATION BY CLIMATE AND CROP PRODUCTION CHARACTERISTICS.

Type	APO Member Economies
Central and West Asia	Islamic Republic of Iran, Nepal, Pakistan, and Turkiye
South Asia, East Asia, and the Pacific	Bangladesh, Cambodia, India, Indonesia, Japan, ROK, Lao PDR, Malaysia, Mongolia, Philippines, Sri Lanka, ROC, Thailand, and Vietnam

Note: IAASTD (2009) classified the world into five regions based on climate and crop characteristics (food production types), and APO member economies are included in two of these regions (Central and West Asia, South Asia, East Asia, and the Pacific).
Source: Author (2025)

TABLE 2.7

CLASSIFICATION BY HIGH- AND LOW-ENERGY-EFFICIENCY GROUPS.

Type	APO Member Economies
High energy efficiency (EE) group (9)	Bangladesh, Cambodia, India, Indonesia, Lao PDR, Nepal, Pakistan, Philippines, and Sri Lanka
Low EE group (9)	Islamic Republic of Iran, Japan, ROK, Malaysia, Mongolia, Thailand, ROC, Turkiye, and Vietnam

Source: Author (2025)

TABLE 2.8

CLASSIFICATION BY HIGH AND LOW-SHARE GROUPS.

Type	Member Economies
High-share group (9)	Bangladesh, Cambodia, India, Indonesia, Lao PDR, Mongolia, Nepal, Pakistan, and Vietnam
Low-share group (9)	Islamic Republic of Iran, Japan, ROK, Malaysia, Philippines, Sri Lanka, ROC, Thailand, and Turkiye

Source: Author (2025)

6. Empirical Results

6.1. Energy Efficiency and Labor Productivity in the Agricultural Sector

Table 2.9 reports the estimation results of Equation (2), which examines the impact of changes in energy efficiency on LP in the agricultural sector. The Hausman test rejects the null hypothesis that unobserved member-economy-specific effects are uncorrelated with the explanatory variables, thereby validating the use of the fixed-effects estimator. Accordingly, this study presents and interprets only the results based on the fixed-effects model.

The empirical analysis proceeds through four specifications, sequentially introducing explanatory variables. Model (A-1) constitutes the baseline specification, including physical capital, human capital, government policy, and trade openness as determinants of LP, in line with standard economic theory. Model (A-2) augments the baseline with the energy efficiency variable, which is the principal focus of this study. It should be noted that the energy efficiency measure adopted here is inversely scaled, such that lower values indicate higher efficiency (see Figure 2.7). If this variable were used directly, a positive estimated coefficient would suggest that improved energy efficiency reduces LP, potentially leading to misinterpretation. To address this, the reciprocal of the energy efficiency variable is employed. Consequently, a positive coefficient indicates that improved energy efficiency enhances LP.

TABLE 2.9

EFFECT OF ENERGY EFFICIENCY ON LABOR PRODUCTIVITY IN THE AGRICULTURAL SECTOR, DEPENDENT VARIABLE BEING LABOR PRODUCTIVITY.

Variable	M(A-1)	M(A-2)	M(B-1)	M(B-2)
Constant	6.508*** (0.115)	7.365*** (0.206)	6.733*** (0.371)	7.531*** (0.394)
Log(CAP)	0.534*** (0.039)	0.516*** (0.038)	0.542*** (0.041)	0.522*** (0.040)

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Variable	M(A-1)	M(A-2)	M(B-1)	M(B-2)
Log(HCI)	0.377** (0.176)	0.634*** (0.178)	0.273 (0.239)	0.556** (0.238)
Log(AOI)	–0.018 (0.016)	–0.018 (0.015)	–0.019 (0.016)	–0.018 (0.015)
OPEN	0.001 (0.001)	0.001* (0.001)	0.001* (0.001)	0.001* (0.001)
Log(ALC)	–	–	–0.076 (0.119)	–0.057 (0.116)
Log(1/EE)	–	0.268*** (0.054)	–	0.267*** (0.054)
R2	0.697	0.716	0.697	0.716
Hausman Test	11.83** [0.019]	66.680*** [0.000]	10.99* [0.052]	74.63*** [0.000]
Obs.	378	378	378	378

Notes: The numbers in ( ) and [ ] for each variable indicate the standard error and p-value, respectively.
Significance codes:
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Source: Author (2025).

Models (B-1) and (B-2) extend Models (A-1) and (A-2), respectively, by including per capita cultivated land area. This stepwise approach not only controls for potential macroeconomic fluctuations but also allows for assessing multicollinearity, a common issue in regression analysis. Across all specifications, the estimated coefficient for energy efficiency is positive and statistically significant at conventional levels. The results indicate that a 1 percentage point improvement in energy efficiency is associated with an average annual increase of approximately 0.268 percentage points in LP, ceteris paribus. This estimate closely aligns with the findings of OECD (2019) for OECD economies. The results support the argument that improved energy efficiency directly enhances technical efficiency, thereby maximizing output per unit of input. This improvement modifies the cost structure of farms, enhances economic efficiency, and generates resources for reinvestment, ultimately raising LP (Jaffe et al., 2004).

The results for the control variables are broadly consistent with the economic theory. Physical capital exerts a statistically significant positive effect on LP across all models, reinforcing prior evidence (Adamopoulos & Restuccia, 2014; FAO, 2017; Martin & Mitra, 2001). These findings suggest that physical capital investment in agriculture promotes productivity through mechanization (e.g., agricultural machinery and irrigation systems), infrastructure development, labor substitution, improved efficiency, and economies of scale.

Similarly, human capital is positively and significantly associated with LP in most specifications. This result aligns with classical human capital theory (Becker, 1962; Barro, 1990; Hanushek & Woessmann, 2009), indicating that higher human capital investment enhances technological adoption and utilization capacity, thereby improving LP.

Trade openness is also found to exert a positive effect, with statistical significance at approximately 10% level. This is consistent with the findings of McMillan and Rodrik (2011) and Rena et al.

(2009), who argue that international integration fosters productivity through intensified competition, economies of scale, and technology diffusion.

By contrast, both government-sector concentration in agriculture and per capita cultivated land area show negative, but statistically insignificant, effects on LP. This suggests that their direct impact remains ambiguous, possibly due to the complexity of structural and institutional dynamics in agriculture.

Finally, it should be emphasized that the results may be affected by heterogeneity across economies, including differences in geographical conditions (climate, crop characteristics), efficiency levels, and industrial structures. To account for this possibility, the subsequent analysis incorporates climate variables (precipitation and temperature). Further, it explores cross-economy heterogeneity by dividing the sample, as shown in Tables 2.6, 2.7, and 2.8.

6.2. Considering the Impact of Climate Change

Table 2.10 presents models (C-1) and (C-2), which incorporate precipitation and temperature deviations from the long-term average as additional variables to control for climate change in models (B-1) and (B-2). Even after accounting for these climate-related factors, the estimated effects of energy efficiency on LP remain consistently positive, closely aligning with the results reported in Table 2.9. This indicates that including variables reflecting agricultural and climatic characteristics does not substantially alter the main findings. However, the impact of climate variables on agricultural productivity varies depending on temperature and precipitation. While temperature deviations from the long-term average have a statistically significant positive effect on agricultural productivity, the impact of precipitation deviations is unclear. Moreover, the coefficients of other economic variables, such as physical capital and human capital, are largely consistent with those in Table 2.9.

TABLE 2.10

IMPACT OF CLIMATE CHANGE ON LABOR PRODUCTIVITY IN THE AGRICULTURAL SECTOR, DEPENDENT VARIABLE BEING LABOR PRODUCTIVITY.

Variables	M (C-1)	M (C-2)
Constant	7.341*** (0.205)	7.463*** (0.393)
Log(CAP)	0.519*** (0.038)	0.523*** (0.040)
Log(HCI)	0.536*** (0.182)	0.480** (0.205)
Log(AOI)	−0.017 (0.015)	−0.018 (0.015)
OPEN	0.001** (0.001)	0.001** (0.001)
Log(ALC)		−0.042 (0.115)
Log(1/EE)	0.254*** (0.054)	0.254*** (0.054)
Ano_pre	0.000 (0.000)	0.000 (0.000)

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Variables	M (C-1)	M (C-2)
Ano_tmp	0.044** (0.019)	0.044** (0.019)
R2	0.721	0.721
Hausman Test	59.280*** [0.000]	60.500*** [0.000]
Obs.	378	378

Notes: The numbers in ( ) and [ ] for each variable indicate the standard error and p-value, respectively.
Significance codes:
* p < 0.05.
** p < 0.01.
*** p < 0.001.
Source: Author (2025).

6.3. Comparison by Climate and Crop Production Characteristics

Table 2.11 examines the regional heterogeneity of the impact of energy efficiency on LP in the agricultural sector. This analysis is based on Model (C-2) presented in Table 2.10 and incorporates the regional crop production type classification proposed by IAASTD (2009).

The first column of Table 2.11 examines potential regional differences by employing an interaction term between the energy efficiency variable and a regional dummy variable. Specifically, the dummy variable is coded as 1 for economies in Central and West Asia and 0 otherwise. The estimation results indicate a statistically significant positive effect of energy efficiency on LP in South Asia, East Asia, and the Pacific. At the same time, the impact remains inconclusive in Central and West Asia. These findings align with the estimation results (columns 2 and 3) obtained by splitting the sample into two regional groups. This suggests that the effect of energy efficiency on LP in the agricultural sector may differ across regions, potentially depending on the predominant crop production type. Furthermore, the results show that one percentage point improvement in agricultural energy efficiency in South Asia, East Asia, and the Pacific is associated with an increase of 0.259% to 0.298% in agricultural LP, ceteris paribus.

Crucially, the estimation results for Central and West Asia do not include the Hausman test results. Random effects estimation requires that the number of cross-sections exceed the number of coefficients. However, since Central and West Asia include only four APO member economies, random effects could not be estimated in this model. Therefore, caution is warranted when interpreting these results, as the fixed-effects model was estimated without the standard Hausman test.

TABLE 2.11

COMPARISON OF FOOD PRODUCTION TYPES, DEPENDENT VARIABLE BEING LABOR PRODUCTIVITY.

Variables	Total	Food Production Types	
		Central and West Asia	South Asia, East Asia, and the Pacific
Constant	7.457*** (0.395)	8.019*** (1.252)	7.113*** (0.485)
Log(CAP)	0.526*** (0.041)	0.570*** (0.163)	0.455*** (0.051)

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Variables	Total	Food Production Types	
		Central and West Asia	South Asia, East Asia, and the Pacific
Log(HCI)	0.462* (0.248)	−0.283 (0.378)	1.062*** (0.347)
Log(AOI)	−0.017 (0.015)	−0.025 (0.017)	−0.022 (0.022)
OPEN	0.001** (0.001)	0.004* (0.002)	0.001 (0.001)
Log(ALC)	−0.044 (0.116)	−0.319 (0.195)	0.049 (0.146)
Log(1/EE)	0.259*** (0.058)	0.061 (0.117)	0.298*** (0.064)
Log(1/EE)×Region	−0.039 (0.140)	–	–
Ano_pre	0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)
Ano_tmp	0.044** (0.019)	−0.021 (0.025)	0.041* (0.024)
R2	0.721	0.708	0.731
Hausman Test	41.072*** [0.000]	–	23.984*** [0.000]
Obs.	378	84	294

Notes: The numbers in ( ) and [ ] for each variable indicate the standard error and p-value, respectively.
Significance codes:
* p < 0.05.
** p < 0.01.
*** p < 0.001.
Source: Author (2025).

6.4. Comparison by High- and Low-energy-efficiency Groups

Table 2.12 presents the estimation results for economies based on Model (C-2) in Table 2.10, grouped by relatively high- and low-energy-efficiency (EE) categories. The estimation reveals heterogeneous effects for the core variable: the impact of energy efficiency on LP in the agricultural sector appears to differ significantly across levels of EE. Specifically, in the low-energy-efficient group, enhanced energy efficiency is associated with a discernible increase in agricultural LP. In contrast, in the high-energy-efficient group, the effect is statistically non-significant and ambiguous. These findings underscore the need to adopt a differentiated policy framework to enhance agricultural LP, one that explicitly accounts for cross-economy variation in EE levels and economic development stages.

A more granular examination reveals that the low-EE group, comprising predominantly advanced economies such as the ROK, Japan, and the ROC, exhibits considerable potential for productivity gains derived from improvements in energy efficiency. Despite their high endowments of capital and technological capability, these economies may still exhibit pockets of inefficiency in the agricultural sector or retain substantial scope for deploying high-efficiency technologies in energy-intensive production systems (e.g., controlled-environment agriculture). At this developmental juncture, incremental improvements in EE are likely to translate directly into cost reductions and concomitant gains in LP.

Conversely, the marginal effect of EE is statistically insignificant in the High EE Group, which consists primarily of developing economies such as Bangladesh and India. This outcome may indicate that these economies have already reached a threshold level of energy efficiency beyond which additional improvements yield diminishing returns, or that alternative structural determinants—such as capital accumulation, human capital quality, or technological adoption—exert a comparatively greater influence on productivity outcomes. The negative coefficient associated with the human capital index (HCI) further supports the interpretation that deficiencies in human capital quality, institutional inefficiencies, and capital scarcity bind productivity enhancement. Moreover, the comparatively larger coefficient on capital (CAP) suggests that capital deepening exerts a more pronounced effect on productivity than incremental improvements in EE within these economies. Taken together, these results emphasize the need for context-sensitive policy interventions that address structural bottlenecks rather than uniform, efficiency-driven strategies.

TABLE 2.12

COMPARISON OF HIGH- AND LOW-EE GROUPS, DEPENDENT VARIABLE BEING LABOR PRODUCTIVITY.

Variables	Low EE Group	High EE Group
Constant	9.998*** (0.621)	6.234*** (0.452)
Log(CAP)	0.443*** (0.053)	0.759*** (0.055)
Log(HCI)	0.188 (0.343)	−0.972*** (0.335)
Log(AOI)	−0.072*** (0.022)	0.047*** (0.017)
OPEN	0.004*** (0.001)	−0.002*** (0.001)
Log(ALC)	−0.720*** (0.197)	0.150 (0.120)
Log(1/EE)	0.227*** (0.067)	0.119 (0.083)
Ano_pre	−0.000 (0.000)	0.000 (0.000)
Ano_tmp	0.021 (0.023)	−0.026 (0.028)
R2	0.738	0.825
Hausman Test	325.51*** [0.000]	112.120*** [0.000]
Obs.	189	189

Notes: The numbers in ( ) and [ ] for each variable indicate the standard error and p-value, respectively.
Significance codes:
* p < 0.05.
** p < 0.01.
*** p < 0.001.
Source: Author (2025).

6.5. Comparison by High- and Low-share Groups

Table 2.13 presents the estimation results for economies categorized by a relatively high versus a relatively low share of agriculture in GDP, using Model (C-2) from Table 2.10. The findings indicate that improvements in energy efficiency (EE) in the agricultural sector significantly enhance agricultural LP, irrespective of the agricultural sector's share of GDP. This outcome suggests that increased EE in agriculture promotes capital investment, which, in turn, facilitates labor substitution and maximizes the remaining labor force's qualitative input time (effective work time) (Jaffe et al., 2004; OECD, 2019). However, the mechanism underlying this enhancement is anticipated to differ across the two groups. For instance, in APO member economies with a high agricultural share, such as Bangladesh and Cambodia, EE improvements are expected to lead to the direct replacement of labor by agricultural machinery (e.g., tractors and combine harvesters). Conversely, in economies with a low agricultural share, such as Japan and the ROK, which are already highly mechanized, the efficiency gains are more likely to drive the adoption of advanced mechanization and automation systems.

TABLE 2.13

COMPARISON OF HIGH- AND LOW-SHARE GROUPS, DEPENDENT VARIABLE BEING LABOR PRODUCTIVITY.

Variables	Low-share Group	High-share Group
Constant	7.421*** (0.758)	7.197*** (0.487)
Log (CAP)	0.375*** (0.077)	0.752*** (0.063)
Log (HCI)	1.306*** (0.343)	−0.811** (0.370)
Log (AOI)	0.029 (0.031)	−0.011 (0.019)
OPEN	0.001 (0.001)	0.001 (0.001)
Log (ALC)	0.191 (0.172)	−0.180 (0.154)
Log (1/EE)	0.217*** (0.083)	0.298*** (0.083)
Ano_pre	−0.000 (0.000)	0.000 (0.000)
Ano_tmp	0.012 (0.032)	0.045** (0.022)
R2	0.555	0.838
Hausman Test	422.38*** (0.000)	745.05*** (0.000)
Obs.	189	189

Notes: The numbers in ( ) and [ ] for each variable indicate the standard error and p-value, respectively.
Significance codes:
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Source: Author (2025).

Meanwhile, a notable finding derived from Table 2.13 concerns the heterogeneous impact of human capital on agricultural LP across the two groups. Specifically, in economies with a low agricultural share of GDP, higher human capital is positively correlated with higher LP. Conversely, in economies with a high agricultural share of GDP, increases in human capital are negatively correlated with LP. These divergent results suggest that distinct mechanisms are at play. In economies with a low agricultural share (typically advanced economies), a positive coefficient implies that human capital accumulation (e.g., higher education and specialized skills) complements existing advanced technology, thereby directly enhancing LP in the agricultural sector. Highly skilled labor is critical for the adoption and operation of complex, capital-intensive farming systems. In contrast, the negative coefficient observed in the high-agricultural-share group (typically developing economies) suggests a labor-outflow effect. This suggests that the agricultural sector in these economies may experience brain drain, as individuals with higher levels of education and skills migrate from agriculture to other sectors offering higher returns or greater opportunities. As a result, the remaining workforce has a lower average skill level, which negatively affects the economy's human capital and agricultural LP.

7. Conclusion and Policy Implications

7.1. Summary

This chapter empirically analyzed the impact of EE on LP in the agricultural sector across APO member economies for the period 2001–21. The methodology involved an initial assessment of the macroscopic characteristics of the agricultural sector—utilizing GDP and employment statistics for trend analysis—followed by an empirical study using a fixed-effects model.

The findings of the trend analysis reveal two crucial heterogeneities that necessitate consideration in the formulation of energy efficiency and productivity enhancement policies. First, there is a structural disparity in agriculture among APO members, evident in the pronounced differences in the sector’s share of GDP and employment. Developed economies, such as Japan and the ROK, possess capital- and technology-intensive, high-productivity agricultural structures, with agriculture contributing less than 5% to both GDP and employment. Conversely, economies such as Nepal and Lao PDR maintain labor-intensive, low-productivity agricultural systems, in which the agricultural sector accounts for over two-thirds of the total workforce. This structural contrast implies substantial variation in the characteristics and efficiency of energy inputs, and consequently, in their impact on productivity, across economies.

Second, the analysis highlights the paradoxical nature and implications of EE measurement. EE, calculated as agricultural GDP divided by agricultural commercial energy consumption, shows little correlation with economic development. Specifically, developing economies, such as Bangladesh, exhibited numerically higher EE than advanced economies, such as the ROK and Japan. This phenomenon is attributable to the structural reliance of agriculture in developing economies on noncommercial, traditional energy sources, including manual labor, firewood, and animal manure, rather than on commercial energy (electricity, petroleum).

Consequently, the empirical analysis using the fixed-effects model sought to quantify these heterogeneous relationships through a subgroup analysis. Table 2.14 summarizes the effects of EE on LP in the agricultural sector.

TABLE 2.14

SUMMARY OF EFFECTS (ELASTICITY) OF ENERGY EFFICIENCY ON LABOR PRODUCTIVITY IN THE AGRICULTURAL SECTOR.

<table>
<tr><th>Type</th><th>Total</th><th>Climate and Crop Characteristics</th><th>Level of EE</th><th>Agriculture's Share of GDP</th></tr>
<tr><td>Central and West Asia or High Group</td><td rowspan="2">0.254–0.267</td><td>–</td><td>–</td><td>0.298</td></tr>
<tr><td>South Asia, East Asia, and the Pacific or Low Group</td><td>0.259–0.298</td><td>0.227</td><td>0.217</td></tr>
</table>

Source: Author (2025)

The analysis using the full sample of APO member economies revealed a statistically significant positive correlation between improvements in EE and LP across all conditions, including those controlling for climate variables. Specifically, a 1% improvement in EE was associated with an increase of 0.254% to 0.268% in LP. This finding supports the traditional economic theory that efficiency gains strengthen technological capacity, optimize cost structures, and facilitate resource generation for reinvestment. However, subsequent subgroup analyses revealed important differences in the mechanisms and effects of EE. The results for the groups categorized by EE level and agricultural share were particularly insightful.

The analysis segmented by EE level revealed inter-group differences. The positive impact of EE on LP was statistically significant only in the low-EE group (including advanced economies such as the ROK and Japan). Conversely, this effect was either statistically insignificant or ambiguous in the high-EE group (comprising primarily developing economies such as Bangladesh and Nepal). These findings indicate that policies aimed at enhancing agricultural LP should adopt a differentiated approach that reflects the structural heterogeneity in EE across the agricultural sector and at different stages of economic development. Advanced economies in the low-EE group demonstrate significant potential to improve productivity through the adoption of high-efficiency technologies in energy-intensive agricultural systems, whereas developing economies in the high-EE group show statistically insignificant marginal effects of EE due to binding constraints such as limited capital, low-quality human capital, and institutional inefficiencies.

Furthermore, an analysis based on the agricultural share of GDP indicated that an improvement in EE robustly increased LP, irrespective of the sample division. However, the HCI played a perplexing role in this analysis. In economies with a low agricultural share (i.e., developed economies), HCI showed a positive correlation with LP, consistent with standard economic predictions. In marked contrast, in economies with a high agricultural share (developing economies), HCI demonstrated a negative correlation with LP. This finding is indicative of a potential "brain drain" effect, in which skilled labor may be relocating from the agricultural sector to more lucrative non-agricultural sectors.

In conclusion, this study demonstrates that while EE enhancement is an essential and universal catalyst for boosting agricultural productivity, its ultimate effectiveness and operational mechanism are highly contingent on an economy's underlying structural characteristics. These findings provide substantive empirical justification for abandoning a "one-size-fits-all" policy paradigm and underscore the imperative to implement structurally differentiated, customized EE policies that account for the stage of agricultural modernization and the intricate dynamics of capital and human resource flows within the APO member economies.

7.2. Policy Implications

Empirical findings from the analysis of APO member economies demonstrate that the effectiveness of interventions to enhance EE and LP in the agricultural sector is fundamentally shaped by structural heterogeneity. The substantial disparities observed across APO member economies—particularly in the agricultural sector's share of GDP and employment, productivity levels, and energy efficiency metrics—necessitate a shift from uniform policy frameworks toward approaches grounded in structural differentiation. The estimation results, which verify that the impact of EE improvements on LP growth varies across national groupings, form the basis for evidence-based policy recommendations intended to support tailored national strategies and strengthen multilateral cooperation.

7.2.1. A Dual-track EE Enhancement Strategy Based on Structural Disparity

A key implication of this research is the need to establish a dual-track strategy to improve energy efficiency in the agricultural sector, calibrated to heterogeneous stages of economic and agricultural development. For advanced, technology-intensive economies such as Japan and the Republic of Korea, which comprise the Low EE Group, the marginal returns to improvements in EE are statistically significant, suggesting untapped efficiency potential. Accordingly, resource allocation should be intensified toward technological and knowledge-intensive innovation that complements these gains, including precision agriculture, AI-assisted analytics for optimized cultivation practices, and the international diffusion of smart farming systems. The overarching objective is to maximize output per unit of input and per unit of land area through the deployment of advanced technologies.

By contrast, the effect of energy efficiency on labor productivity in the High EE Group—consisting primarily of developing, labor-intensive economies such as Bangladesh, Nepal, and Lao PDR—is statistically insignificant, indicating that EE is not the binding constraint on labor productivity growth in these contexts. Policy priorities in these economies should therefore be reoriented toward structural and capital-deepening interventions, rather than focusing exclusively on accelerating the energy transition. Notably, high EE values in these economies are paradoxically attributable to dependence on traditional, noncommercial energy sources, such as manual labor and biomass. When pursuing EE policies, they should prioritize conditional subsidies for high-efficiency machinery and other technologies as an entry point for introducing modern capital and rationalizing commercial energy use.

TABLE 2.15

EXAMPLES OF A DUAL-TRACK EE ENHANCEMENT STRATEGY.

EE Group	Goal	Concrete Implementation Program
Low-EE Group (ROK, Japan)	To maximize output per unit of input and land area through advanced technological deployment	**"Precision Energy Optimization (PEO) Mandate"** Policy funding for energy-intensive farming (e.g., controlled-environment agriculture) is conditional on integrating AI-assisted analytics to ensure efficiency gains translate to faster LP growth.
High-EE Group (Bangladesh, Nepal, Lao PDR)	To reorient policy priorities toward structural and capital-deepening interventions.	**"Capital-EE Conditional Subsidy"** The subsidy is linked to the adoption of certified high-efficiency equipment. It requires farmers to attend training on transitioning from traditional to commercial energy sources, marking an entry point for introducing modern capital.

Source: Author (2025).

7.2.2. Human Capital Development and Skilled Labor Retention

The observed "brain drain" effect in high-agricultural-share economies necessitates targeted policies to enhance the sector's professional appeal and profitability. The first step is to establish value-chain-linked smart agriculture education programs. These programs (Table 2.16) must move beyond primary production skills to focus on high-value activities such as processing, logistics, and e-commerce platform integration (e.g., training young professionals in online marketing). To address the "push factors" of out-migration, strategic investments are required to create rural non-farm employment opportunities—such as in processing plants, agri-IT support centers, and tourism—in proximity to agricultural areas, providing diverse job prospects for agricultural households. Finally, to directly combat skilled labor exodus, targeted skilled personnel retention incentives must be offered, such as low-interest startup loans or land rental subsidies, to make the agricultural sector competitive with non-agricultural sectors.

TABLE 2.16

EXAMPLES OF HUMAN CAPITAL DEVELOPMENT AND SKILLED LABOR RETENTION.

APO Member Economy	Goal	Concrete Implementation Program
Nepal, Philippines	To establish enabling environments that alleviate key push factors associated with skilled labor outflow.	**Agri-Tech Pioneer Grant** This program provides subsidized land access and seed funding to university graduates who establish IT/robotics-integrated smart farming enterprises in rural areas, thereby increasing the profitability and professional attractiveness of the sector.
Vietnam	To promote the transition toward a technology- and knowledge-intensive sector.	**Agri-value-chain Modernization Certifications** These certifications train young farmers in advanced areas like post-harvest processing, logistics, and e-commerce platform integration. Graduates receive priority linkage to high-value export markets, ensuring that human capital investment yields better returns within agriculture.

Source: Author (2025).

7.2.3. Integrated Policy Platforms and Regional Collaboration

Given that EE effectiveness is shaped by complex and interacting variables, integrated policy platforms and enhanced regional cooperation are indispensable (Table 2.17). APO member economies should institutionalize comprehensive financial, technical, and educational support packages. For instance, low-interest credit for adopting EE technologies should be complemented by mandatory training in system operation and maintenance. In Indonesia, for example, financial assistance for irrigation system upgrades must be accompanied by compulsory training in digital technologies and maintenance to ensure the long-term viability of capital investments. Furthermore, advanced member economies such as Japan and the ROK should reconceptualize their technology transfer models by providing not only the underlying technologies but also localized implementation methodologies, sustained technical assistance, and continuous education to recipient economies, including Cambodia and Lao PDR. This holistic approach fosters the internalization and effective utilization of imported technologies, ultimately promoting balanced LP growth across the region.

TABLE 2.17

EXAMPLES OF INTEGRATED POLICY PLATFORMS AND REGIONAL COLLABORATION.

Economy	Goal	Concrete Implementation Program
Indonesia–APO Cooperation	To ensure the long-term viability of capital investments	Technology + Training + Financing Package Low-interest credit for adopting EE technologies must be complemented by mandatory training in system operation and maintenance to ensure capital investments are effective.
ROK/Japan–Cambodia/ Lao PDR Cooperation	To foster the internalization and effective utilization of imported technologies	Localized Implementation Methodology Model Advanced member economies must provide not only the underlying technologies but also localized implementation methodologies, sustained technical assistance, and continuous education to recipient economies, moving beyond simple technology transfer.

Source: Author (2025).

7.2.4. Establishment of Joint R&D Hubs

APO member economies span a very wide area, from Fiji, a Pacific island nation in Oceania, to Turkiye. The significant geographical and climatic diversity among APO member economies necessitates the establishment of joint R&D hubs (Table 2.18). These hubs would focus on developing customized control algorithms and low-cost smart farming solutions tailored to local climate conditions and crop characteristics, thereby systematically narrowing the technological gap. The smart farming sector, which offers substantial potential for carbon neutrality through agrivoltaics and generates high-value employment opportunities in IT and robotics, represents an optimal policy domain for initiating such strategic collaboration models.

TABLE 2.18

EXAMPLES OF ESTABLISHMENT OF JOINT R&D HUBS.

APO Member Economy	Goal	Concrete Implementation Program
ROK–Cambodia Joint R&D	To develop customized control algorithms and low-cost smart farming solutions adapted to local climate and crop characteristics	**Rice-agrivoltaics Climate Adaptation Center** This hub pools the ROK's IT/robotics expertise with Cambodian rice production data to codevelop customized, low-cost smart sensors and energy management algorithms, specifically for the Mekong Delta climate, maximizing both energy efficiency and yield.
Turkiye–Central and West Asia Group	To address the specific challenges (e.g., water scarcity) of the Central and West Asia region	**EE Water Management R&D Hub** This hub focuses on developing energy-efficient, climate-adapted solutions (e.g., solar-powered drip irrigation combined with optimized soil sensors) relevant to the region's climate and crop production type.

Source: Author (2025).

7.2.5. Cooperation on Agricultural Data Governance and Standardization

Promoting cooperation in agricultural data governance and standardization is also critical. The success of agricultural technology cooperation ultimately depends on the availability of accurate and interoperable agricultural data. However, discrepancies in data collection methodologies and standards across APO member economies frequently undermine the effectiveness of technological collaboration. Accordingly, establishing an APO-wide framework for agricultural data standardization and interoperability merits serious consideration. For example, by leveraging precision agriculture data standardization technologies developed in the ROK and Japan, member economies could collaborate to collect and share sensor, soil, and meteorological data from Vietnamese farms under a unified APO protocol (Table 2.19). Such cooperation would enable the joint development of data-driven models for optimizing agricultural energy consumption and facilitate more efficient technology transfer across member economies. Moreover, integrated data governance frameworks are essential for quantifying the impacts of improvements in EE and LP as well as for rigorously evaluating associated policy outcomes. In addition, this cooperative approach may help create new high-value-added service markets based on agricultural data, such as precision agriculture consulting, which could indirectly support human capital policies aimed at attracting young professionals to the agricultural sector.

TABLE 2.19

EXAMPLES OF COOPERATION ON DATA GOVERNANCE AND STANDARDIZATION.

APO Member Economy	Goal	Concrete Implementation Program
Japan/ROK–Thailand/ Philippines Cooperation	To establish an APO-wide agricultural data standardization and interoperability framework	**Unified APO Protocol Pilot** Japan or the ROK provides its precision agriculture data standardization technologies, and the recipient economy (e.g., Thailand) implements them to collect and share sensor, soil, and meteorological data under a unified APO protocol.
APO-wide Initiative	To quantify the impacts of improvements in EE and LP and rigorously evaluate associated policy outcomes	**Common Reporting Standards (CRS) for EE/LP Metrics** This framework ensures that all APO member economies measure and report agricultural GDP, energy use, and labor hours consistently, providing the accurate and interoperable data necessary for effective policy evaluation.

Source: Author (2025).

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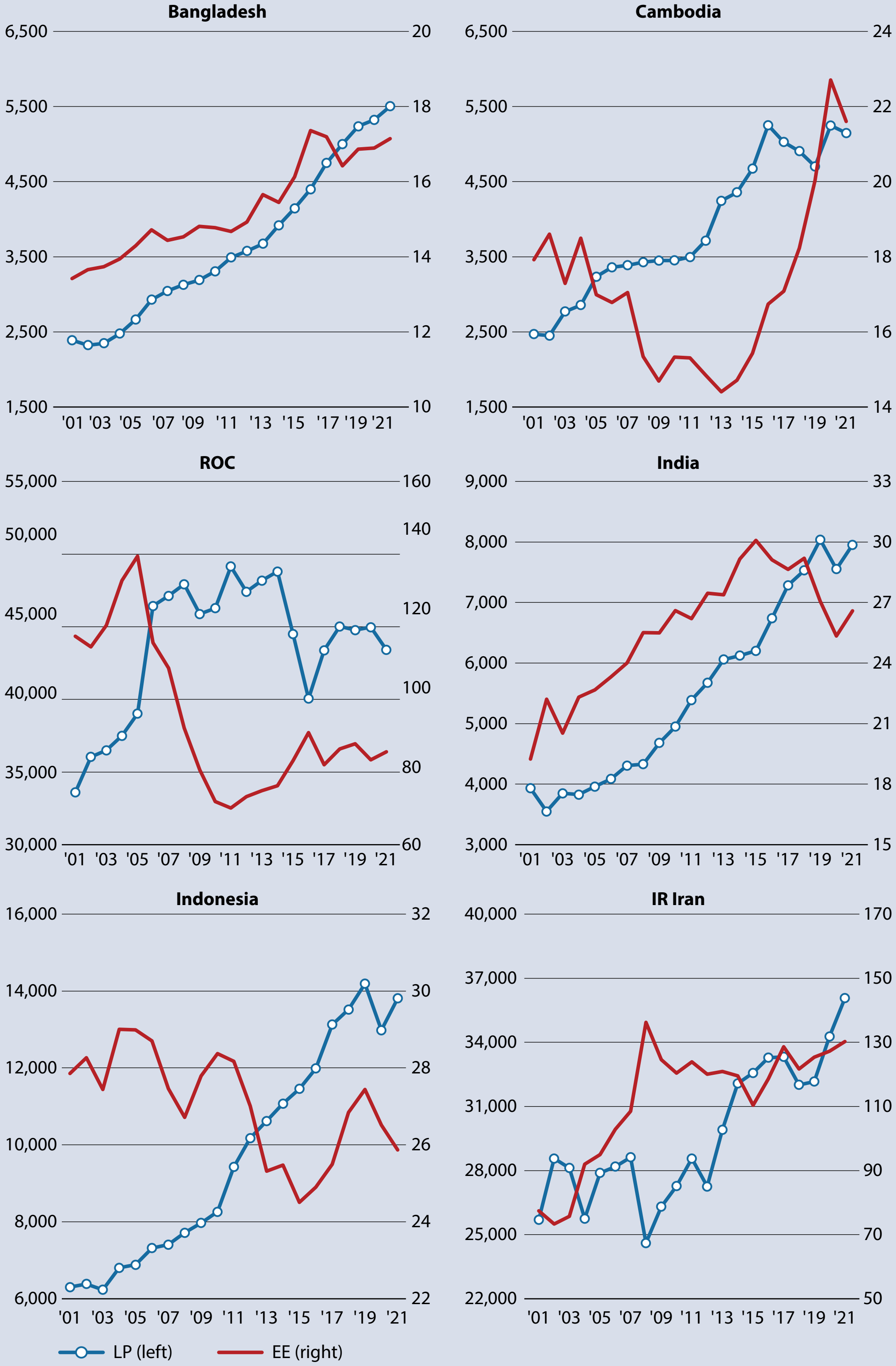
Appendix

FIGURE A1

LABOR PRODUCTIVITY AND ENERGY EFFICIENCY IN THE AGRICULTURAL SECTOR.



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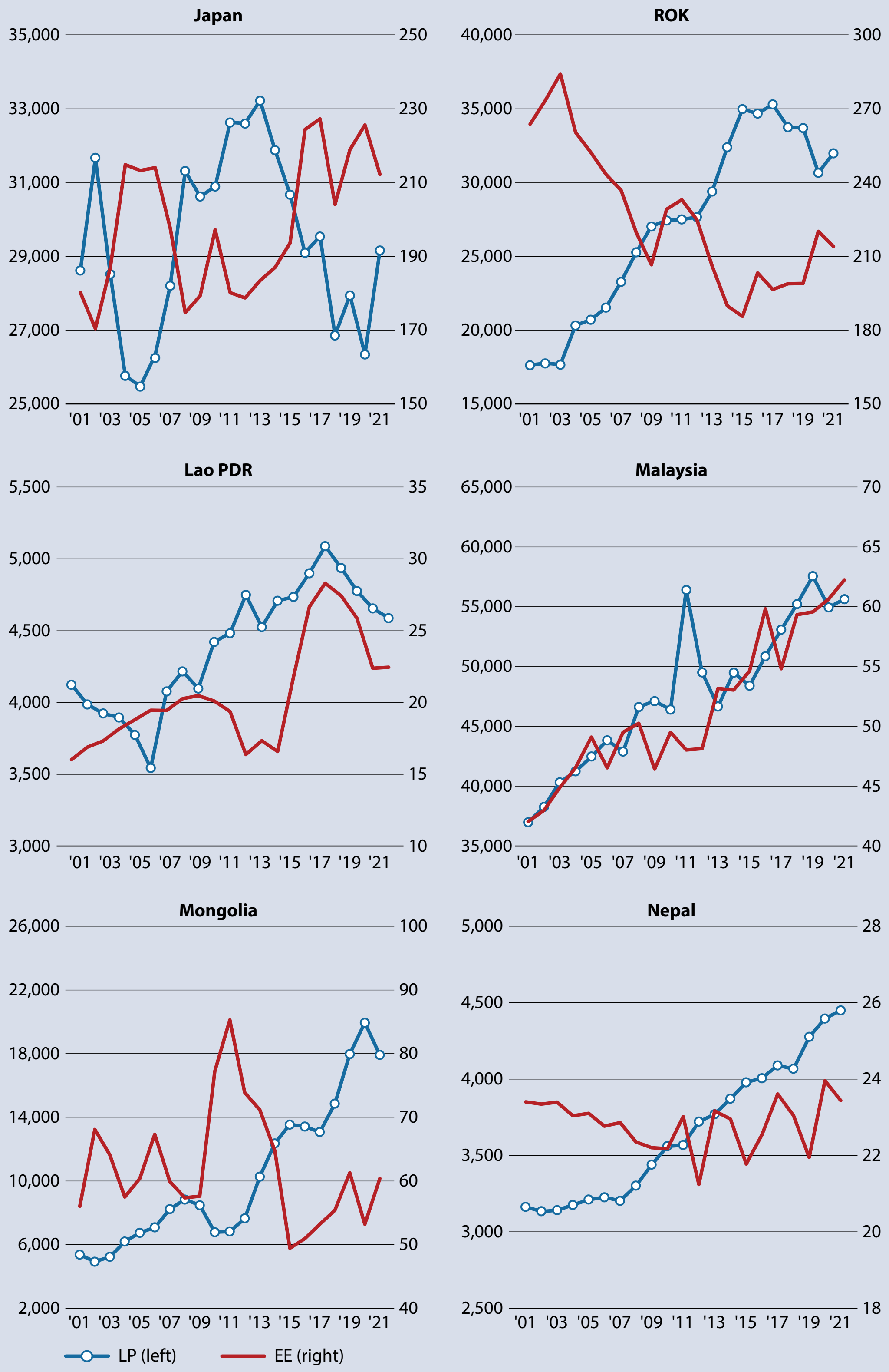

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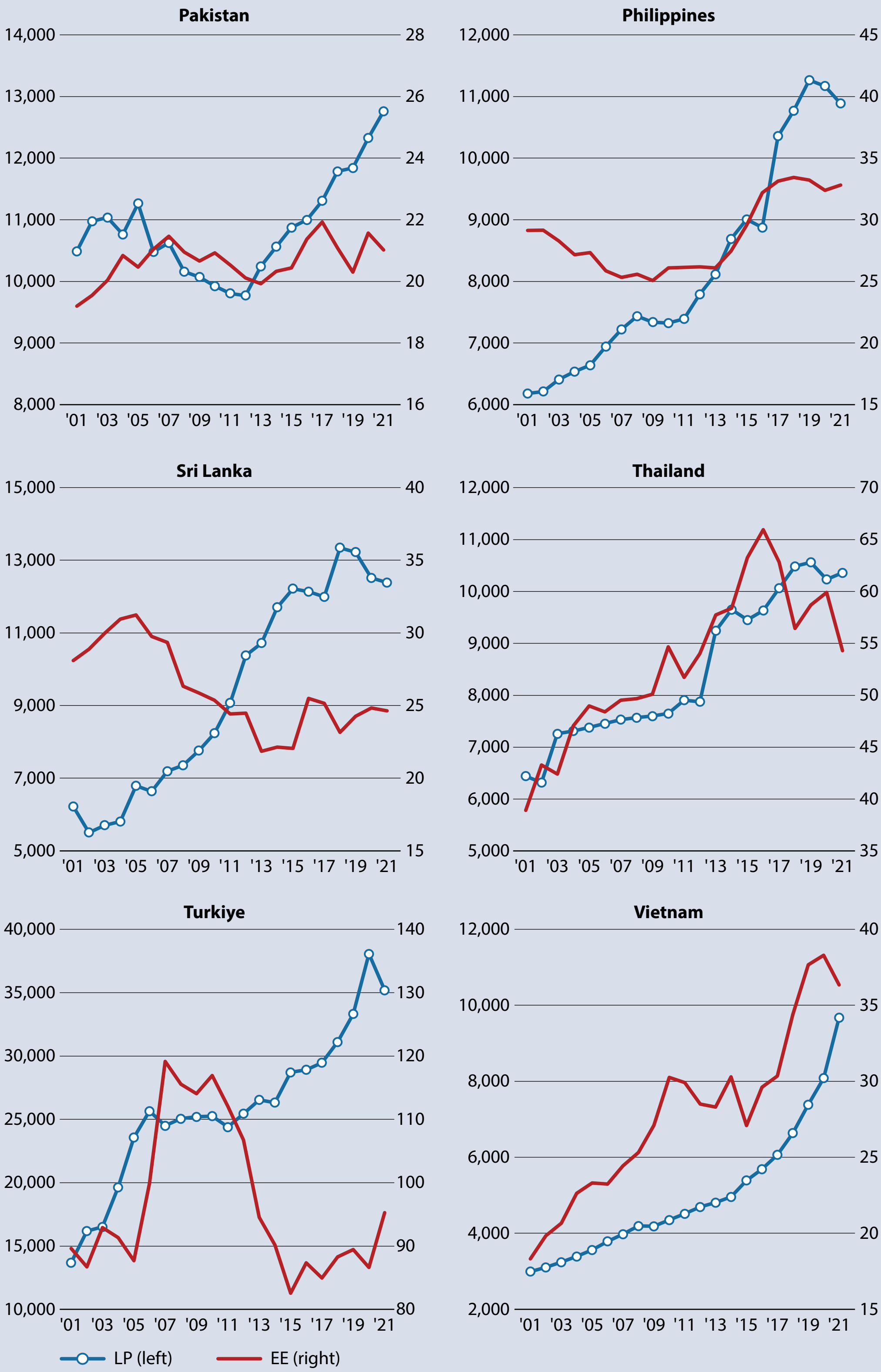


Note: Fiji and Singapore were not included in certain parts of the analysis due to the lack of energy-related data required to compute energy efficiency.

CHAPTER 3

ENERGY EFFICIENCY AND PRODUCTIVITY IN THE MANUFACTURING SECTOR

1. Introduction

The manufacturing sector continues to serve as a cornerstone of economic development, contributing substantially to GDP, employment, and productivity growth. Recent USA reshoring policies have brought renewed attention to manufacturing's strategic importance. Following the 2008 financial crisis, the USA has implemented reshoring policies to expand its manufacturing base and create jobs, continuing through the Trump administration's efforts to rebuild manufacturing and create employment through domestic production expansion, particularly in core industries such as semiconductors, shipbuilding, and batteries. Movements toward reshoring and nearshoring aim to ensure national security and economic stability while building resilient supply chains. The USA government's legislative interventions, including the Creating Helpful Incentives to Produce Semiconductors (CHIPS) Act and the Inflation Reduction Act (IRA), provided substantial financial support for domestic manufacturing investment and helped create hundreds of thousands of manufacturing jobs.

Manufacturing is highlighted not only by the USA's reshoring and industrial policies but also by its stronger economic spillover effects than other industries. Manufacturing serves not merely as an industrial sector but as a fundamental infrastructure for innovation, productivity, and employment across the entire economy. The USA's reshoring policies represent typical industrial restructuring strategies based on manufacturing's strategic value, and the reason economies worldwide emphasize a "manufacturing renaissance" lies precisely in this growth multiplier effect. However, the USA's reshoring and nearshoring movements create both opportunities and pressures for APO member economies. Manufacturing-intensive economies face competitive challenges as production networks reorganize. Some economies attract investments through friend-shoring and participation in regional supply chains. Others experience reduced exports or the risk of hollowing out in manufacturing. This restructuring demands that APO member economies enhance manufacturing competitiveness through supply chain adaptation, productivity improvements, and operational efficiency gains.

Energy costs account for a substantial share of manufacturing operational expenses, with energy-intensive industries, such as steel, chemicals, cement, and aluminum, facing particularly high energy costs. According to 2022 data from the U.S. Energy Information Administration (EIA), manufacturing accounts for approximately 76% of industrial sector's final energy consumption, followed by mining (12%), construction (7%), and agriculture (4%). Within manufacturing, energy consumption is concentrated in specific subsectors, with six energy-intensive industries (chemicals, petroleum and coal products, paper, primary metals, food, and nonmetallic minerals) accounting for 87% of manufacturing energy consumption in 2018.

In developing Asia, industrial energy use accounts for about 60% of total national energy use. Under these circumstances, rising energy prices and expanding carbon-pricing mechanisms are fundamentally altering manufacturing cost structures. The European Union (EU) has implemented the Carbon Border Adjustment Mechanism (CBAM) since October 2023, imposing reporting obligations on imports, with mandatory carbon content payments beginning in 2026. The IEA projects that under current policies, international carbon prices could reach USD140 per ton by 2030. Carbon pricing mechanisms such as carbon taxes and emissions trading systems (ETS) impose direct costs on greenhouse gas emissions, increasing firms' production costs, which cascade through entire supply chains and are reflected in final product prices. Carbon-neutrality policies implemented across major advanced-economy alliances worldwide are driving up supply chains and fundamentally transforming their structures.

In response to these cost pressures, governments and firms are pursuing carbon neutrality and energy efficiency improvements through international cooperation, domestic policies, and technology development. Following the 2015 Paris Agreement, economies have established voluntary greenhouse gas reduction targets through Nationally Determined Contributions (NDCs). At the 28th UN Climate Change Conference (COP28), parties agreed to double the global annual energy efficiency improvement rate from 2% to over 4% by 2030. The Republic of Korea (ROK) has confirmed its 2050 Carbon Neutrality Scenario and enhanced 2030 NDC, pursuing strategies including realigning the energy mix through harmonization of nuclear power and renewable energy, optimizing energy efficiency through ICT, strengthening building energy efficiency standards, and promoting the deployment of zero-emission vehicles and ecofriendly mobility. In technology development, Carbon Capture, Utilization, and Storage (CCUS) technologies are attracting attention as core technologies, with the ROK announcing plans to reduce 11.2 million tons annually through CCUS in its 2030 NDC. AI-based grid operation technologies, sensor networks, and digital twin technologies are also contributing to refining carbon-emission calculations for products and processes and in improving energy efficiency.

The Asia–Pacific region comprises diverse economies with varying levels of economic development and industrial structures, resulting in significant gaps in energy efficiency. While developed economies consistently demonstrate high energy efficiency, developing economies remain at relatively lower levels. This gap signifies substantial untapped potential in manufacturing processes. Most Asian economies view manufacturing-based industries as current and future sectors driven by low-wage competitive advantages. Therefore, improving energy efficiency is essential for achieving international environmental standards and participating in global markets. Particularly since 2000, amid trends of globalization, technological advancement, and strengthened environmental regulations, energy efficiency improvement has become essential not merely for cost reduction but also for industrial competitiveness, profit structures, and national competitiveness. As one of the most energy-intensive industries, manufacturing faces increasing pressure to balance industrial competitiveness with sustainability goals while maintaining cost-effective operations.

The relationship between energy efficiency and productivity extends beyond simple cost savings. Efficient energy use often correlates with optimized production processes, reduced waste, improved equipment utilization, and enhanced operational reliability, with all these factors directly contributing to labor productivity (LP) gains. This research examines the extent to which improvements in energy efficiency within the manufacturing sector affected LP across APO member economies from 2000 to 2021. The analysis builds on established theoretical foundations that industrial energy efficiency measures generate significant productivity benefits beyond simple energy cost savings.

The methodology employs a panel fixed-effects regression model using comprehensive datasets from the APO Productivity Database and energy-efficiency indicators from internationally recognized sources, such as the IEA. This approach controls for economy-specific and time-invariant characteristics while capturing both within-economy changes over time and cross-economy variations in manufacturing practices, thereby isolating the true effect of energy efficiency on manufacturing productivity.

2. Background and Conceptual Review

2.1 Manufacturing and Economic Growth

Manufacturing serves as a critical engine for economic transformation, providing pathways that catalyze and mediate productivity enhancement and structural change. Szirmai and Verspagen (2015), through comparative analysis across developing economies from 1950 to 2005, demonstrate that manufacturing's economies of scale; technological accumulation and diffusion; and linkage and spillover effects operate as structural foundations that underpin sustained productivity growth. Su and Yao (2017) demonstrate that manufacturing drives growth in other sectors in a statistically significant and economically substantial manner, further emphasizing manufacturing as the key engine of economic development for middle-income economies. Haraguchi, Cheng, and Smeets (2017), while acknowledging that many developing economies have experienced premature deindustrialization in recent decades, confirm that manufacturing's importance as an engine of economic growth has not diminished. They suggest that the decline in manufacturing's share stems not from the manufacturing sector's weakened potential, but rather from the concentration of manufacturing activities in a small number of populous economies. Therefore, despite concerns about deindustrialization, developing economies should continue and strengthen their manufacturing-based industrialization strategies.

Beyond direct production, manufacturing underpins productivity growth across industries and broader macroeconomic expansion through sequential interactions with raw-material and capital-equipment inputs, as well as with the supply of components and intermediate goods (Gabriel & de Santana Ribeiro, 2019). Wang (2009) provides evidence from Asian economies showing that manufacturing FDI significantly contributes to economic growth, while Cantore, Clara, Lavopa, and Soare (2017) decompose manufacturing growth into structural transformation components (productivity and manufacturing employment share) and employment-scale components to empirically verify what serves as a more effective fuel for GDP growth.

The post-2000 period witnessed manufacturing's evolution toward higher-value-added activities, with emerging economies climbing up global value chains while advanced economies focused on technology-intensive production. This transformation fundamentally altered traditional manufacturing patterns, making energy efficiency a strategic competitive factor rather than merely an operational concern.

2.2 Energy Efficiency and Economic Output in the Manufacturing Sector

Energy efficiency in manufacturing represents the inverse of energy intensity, measured as economic output per unit of energy consumed. Improvements in energy efficiency directly translate to cost reductions, enhanced competitiveness, and reduced environmental footprint. Kang and Lee (2016) demonstrate that efficiency improvements that achieve both energy conservation and environmental burden reduction simultaneously generate positive effects on final industrial output growth rates. They emphasize that sustaining and expanding these achievements requires investments in energy technologies and establishment of efficient production structures.

The relationship between energy efficiency and productivity operates through multiple channels: technological modernization, process optimization, and reallocation of resources toward higher-value activities. Kalantzis and Niczyporuk (2022) provide empirical evidence from European firms showing that energy efficiency investments yield substantial LP improvements, extending benefits beyond simple energy cost savings. Worrell, Laitner, Ruth, and Finman (2003) identify multiple pathways through which industrial energy efficiency measures generate productivity improvement effects, including reduced maintenance and replacement costs, improved product quality and yield, reduced cycle time, and enhanced operational flexibility and productivity.

Modern manufacturing systems integrate energy management with production optimization, thereby creating synergies that enhance overall productivity performance. Otsuka (2016) analyzes the relationship between energy efficiency and productivity in Japanese manufacturing, demonstrating that technological adoption makes manufacturing particularly responsive to improvements in energy efficiency. The manufacturing sector's capacity for technological adoption makes it particularly responsive to energy efficiency improvements.

2.3 Research Gap: Energy Efficiency and Productivity in the Manufacturing Sector

Despite extensive literature on manufacturing productivity and growing attention to energy efficiency, limited research examines their integrated relationship during the crucial 2000–21 period of transformation. This study addresses this gap by analyzing how energy efficiency improvements contribute to manufacturing productivity growth while incorporating employment dynamics as a critical dimension of sectoral performance.

3. Trends in Manufacturing: Energy Efficiency and Economics

3.1 Data

In this study, we define energy efficiency as the inverse of energy intensity, which is the ratio of energy consumption to GDP in the manufacturing sector. Energy intensity measures how much energy is required to produce one unit of output (a higher intensity indicates greater energy consumption per unit of GDP). By inverting this measure, we obtain energy efficiency, which directly captures the productive output generated per unit of energy consumed. This transformation allows us to interpret improvements in energy performance more intuitively: an increase in energy efficiency indicates that the manufacturing sector is producing more output with the same amount of energy, reflecting enhanced energy productivity.

$$Energy\ Efficiency = (Energy\ Intensity)^{-1} = \left(\frac{Final\ Goods\ Produced}{Energy\ Use}\right)^{-1}$$

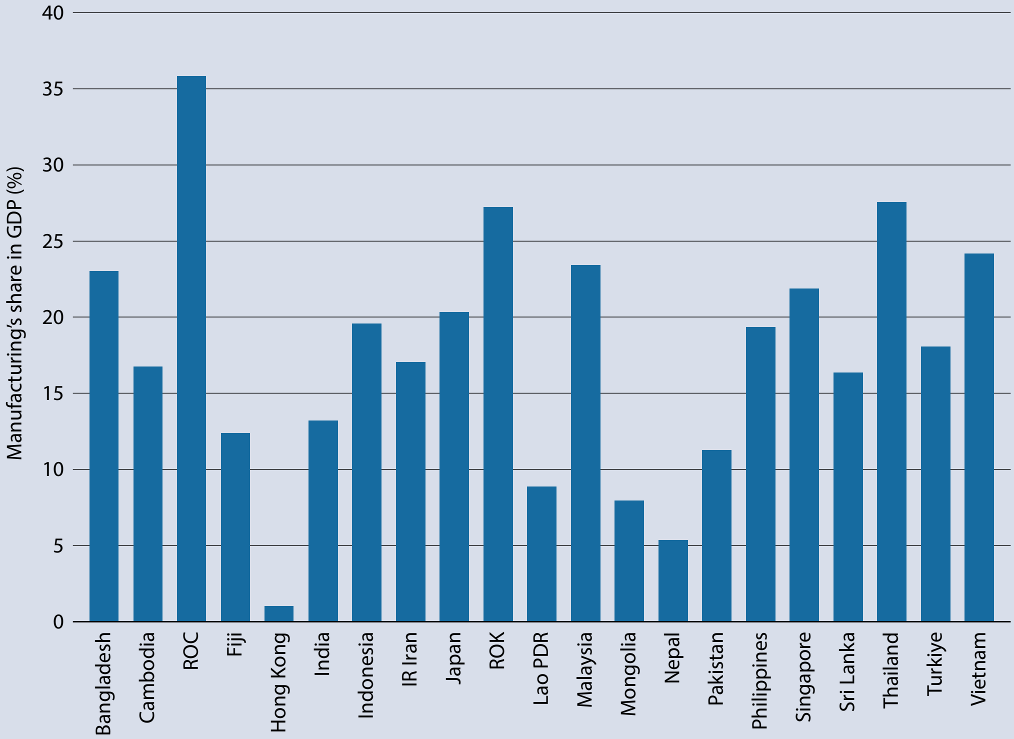
3.2 Stylized Facts

The manufacturing sector demonstrates substantial variations in economic importance across APO member economies as of 2021. Figure 3.1 illustrates that manufacturing's contribution to GDP ranges dramatically across economies, reflecting different stages of industrialization and economic structural transformation. This pattern reveals significant heterogeneity in industrial development strategies and manufacturing capabilities across the region.

The importance of the manufacturing sector varies considerably across the region. At the upper tier, East Asian manufacturing powerhouses dominate the landscape, with the ROC (35.8%) standing as the clear leader, followed by Thailand (27.6%) and the ROK (27.2%). These economies demonstrate manufacturing shares exceeding 25%, reflecting their roles as major global manufacturing hubs with well-established industrial infrastructure and export-oriented production capabilities.

FIGURE 3.1

MANUFACTURING'S SHARE OF GDP OF 2021.



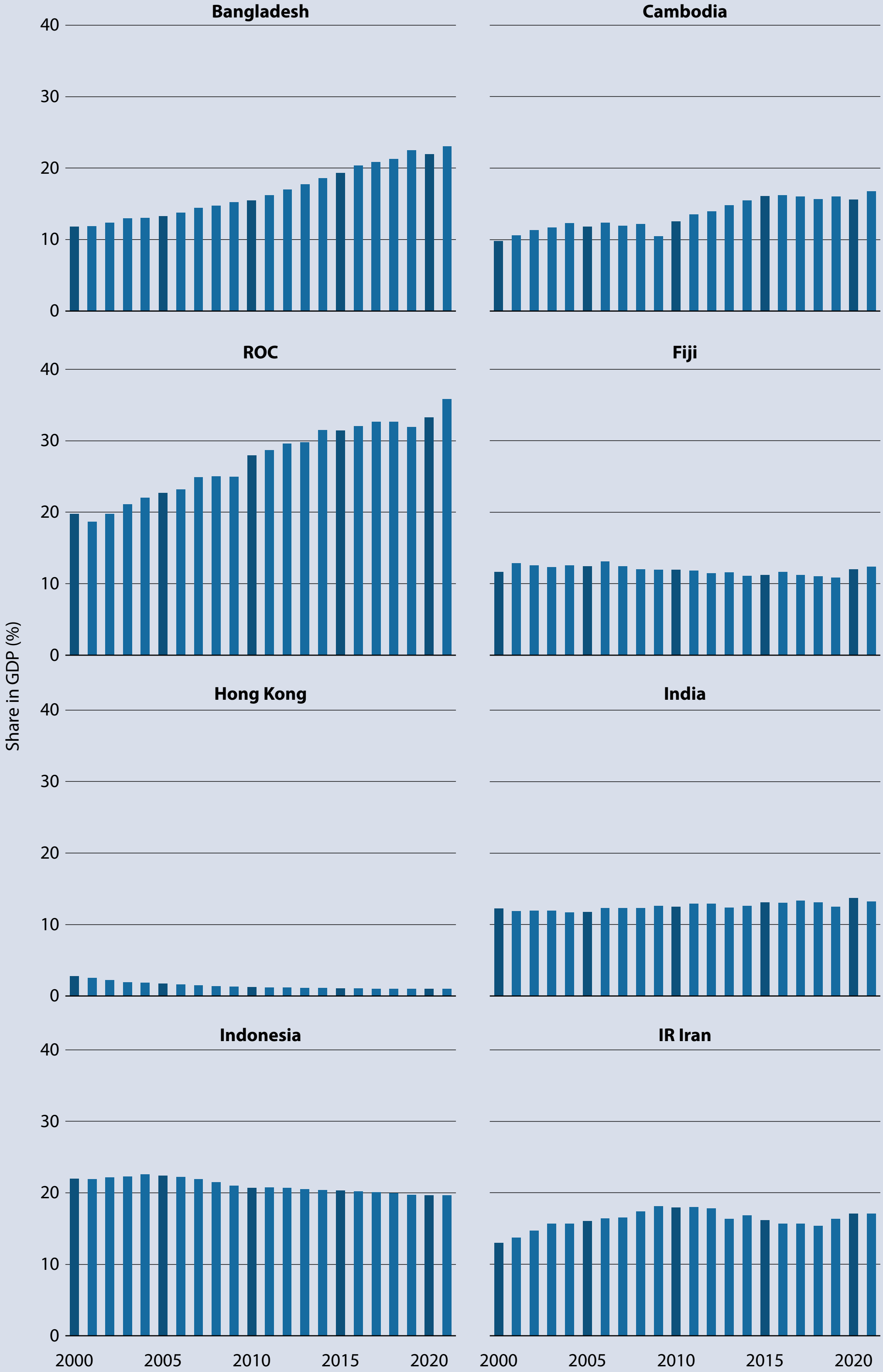
Source: APO (2024).

Figure 3.1 also shows that economies such as Vietnam (24.2%), Malaysia (23.4%), and Bangladesh (23.0%) form an upper-middle tier, with manufacturing shares of 23–24%, indicating successful integration into global manufacturing value chains. Singapore (21.9%) and Japan (20.3%) occupy a distinct middle ground, with Singapore's substantial manufacturing presence demonstrating that even advanced service-oriented economies maintain significant industrial capacity. In comparison, Japan's 20.3% share reflects a mature, technology-intensive manufacturing structure.

At the lower end, economies such as India (13.2%), Pakistan (11.3%), and Nepal (5.4%) have more limited manufacturing bases. In comparison, Hong Kong (1.0%) represents the extreme case of complete structural transformation toward services and finance.

FIGURE 3.2

MANUFACTURING'S SHARE OF GDP IN APO MEMBER ECONOMIES, 2000–20.



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Source: APO (2024).

Despite these variations, long-term trends from 2000 to 2021, as depicted in Figure 3.2, reveal divergent trajectories of manufacturing development across APO member economies. The figure shows varied patterns across economies, with some demonstrating sustained industrial growth while others exhibiting structural transitions.

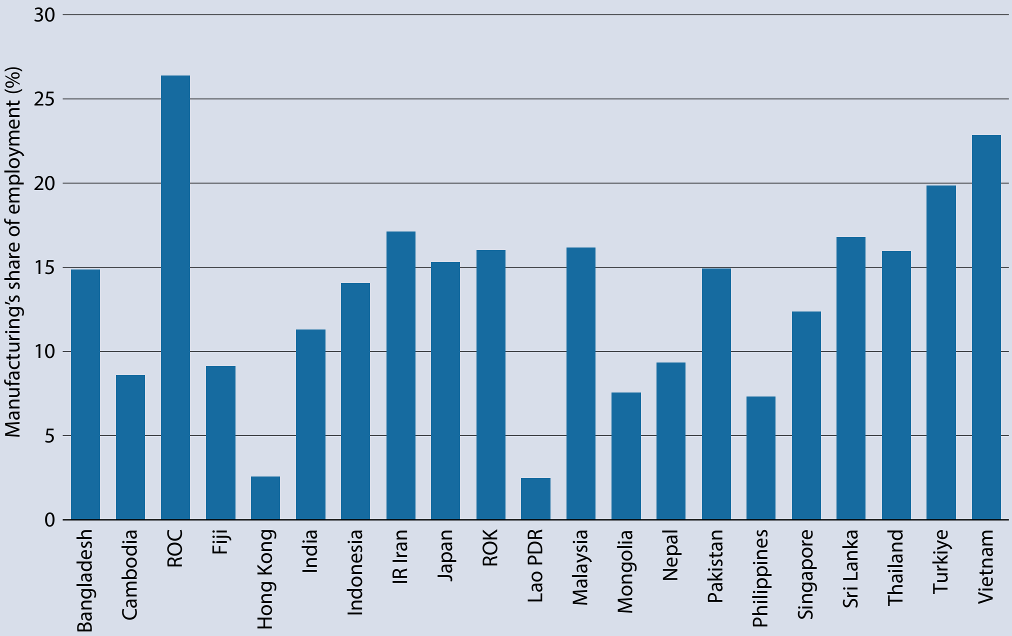
Several economies show pronounced upward trajectories in manufacturing intensity. Bangladesh and Vietnam exhibit particularly notable increases since the 2000s, with Vietnam demonstrating accelerated growth after 2005, coinciding with WTO accession and enhanced global integration. These patterns suggest successful implementation of export-oriented industrialization strategies and integration into global manufacturing networks.

Advanced manufacturing economies such as the ROK and Japan hold relatively steady manufacturing shares over time, reflecting established industrial systems. The ROK shows modest fluctuations in the range of 25–27%, while Japan demonstrates gradual stabilization of 20–22%. This stability reflects established industrial foundations and technological sophistication. Meanwhile, Hong Kong maintains a consistently minimal manufacturing presence throughout the entire period, reinforcing its role as a financial and services hub.

The temporal patterns suggest that manufacturing development follows distinct pathways: emerging economies pursuing rapid industrialization, mature economies maintaining stable industrial bases, and advanced service economies completing deindustrialization transitions.

FIGURE 3.3

MANUFACTURING'S SHARE OF EMPLOYMENT ACROSS APO MEMBER ECONOMIES IN 2021.



Source: APO (2024).

Manufacturing employment patterns exhibit dynamics distinct from GDP contributions, highlighting varying degrees of labor intensity and productivity across economies (Figure 3.3). The employment share analysis demonstrates that manufacturing remains a crucial job creator, though with significant cross-economy variations.

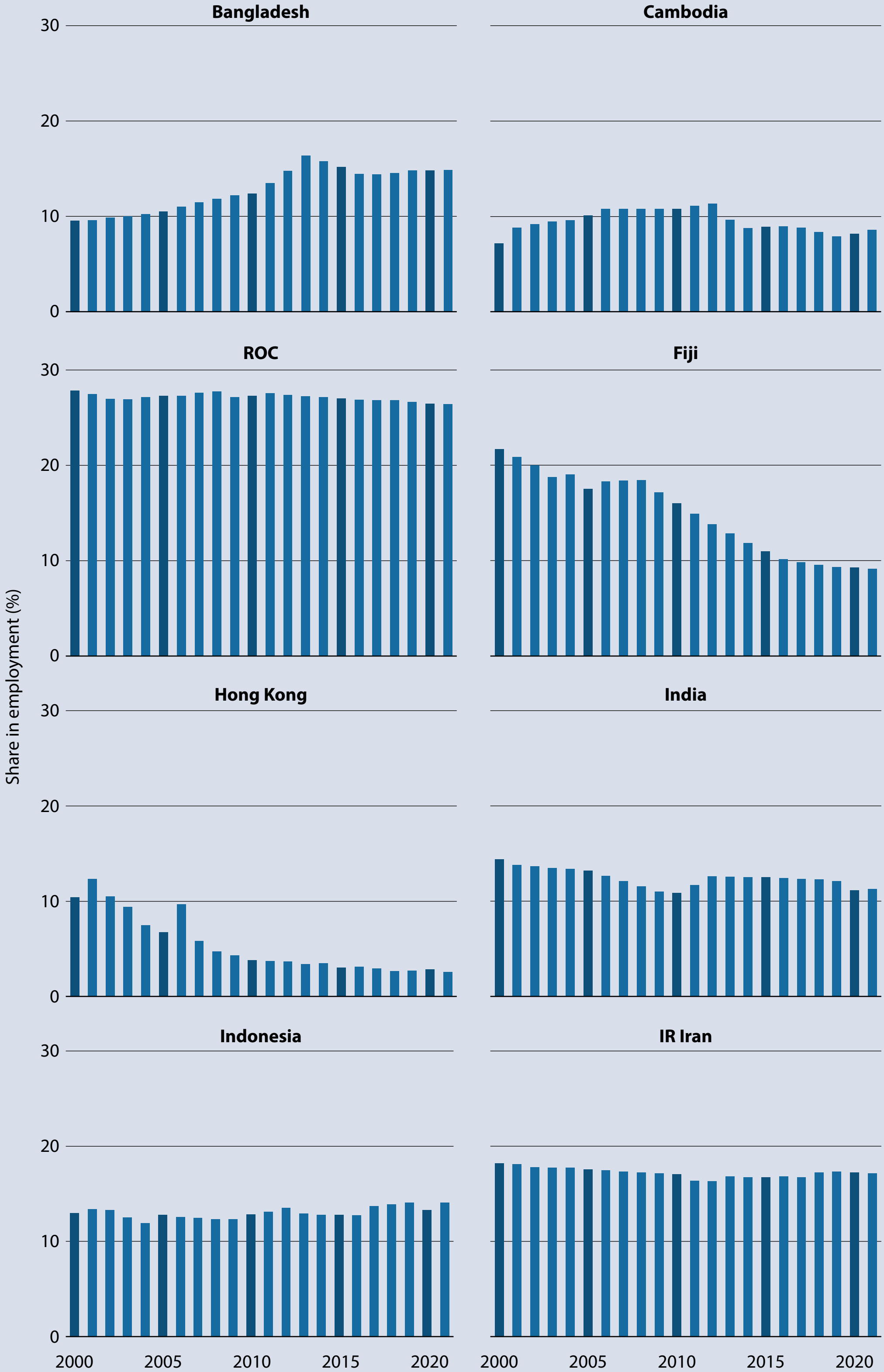
The ROC leads in manufacturing employment (26.4%), closely followed by Vietnam (22.8%) and Turkiye (19.9%). This top tier suggests labor-intensive manufacturing structures that generate substantial employment opportunities. The prominence of Vietnam reflects its emerging role as a manufacturing hub with significant job creation capacity.

Middle-tier manufacturing employers include the Islamic Republic of Iran (17.1%), Sri Lanka (16.8%), Malaysia (16.2%), and the ROK (16.0%), demonstrating manufacturing sectors that balance employment generation with productivity considerations. Thailand (15.9%) and Japan (15.3%) complete this group, with Japan's relatively modest employment share contrasting notably with its higher GDP contribution, suggesting more capital-intensive, technologically sophisticated manufacturing operations.

Interestingly, when we compare employment shares with GDP contributions from Figure 3.1, contrasting patterns emerge. Thailand demonstrates a higher GDP share (27.6%) relative to an employment share (15.9%), indicating high manufacturing productivity. Similarly, Singapore contributes substantially to GDP (21.9%) while employing a smaller workforce (12.4%), reflecting highly efficient, technology-intensive manufacturing operations. In contrast, economies like Turkiye exhibit higher employment shares (19.9%) relative to their GDP contributions (18.1%), suggesting more labor-intensive manufacturing structures and lower productivity per worker.

FIGURE 3.4

MANUFACTURING'S SHARE OF EMPLOYMENT ACROSS APO MEMBER ECONOMIES, 2000–20.



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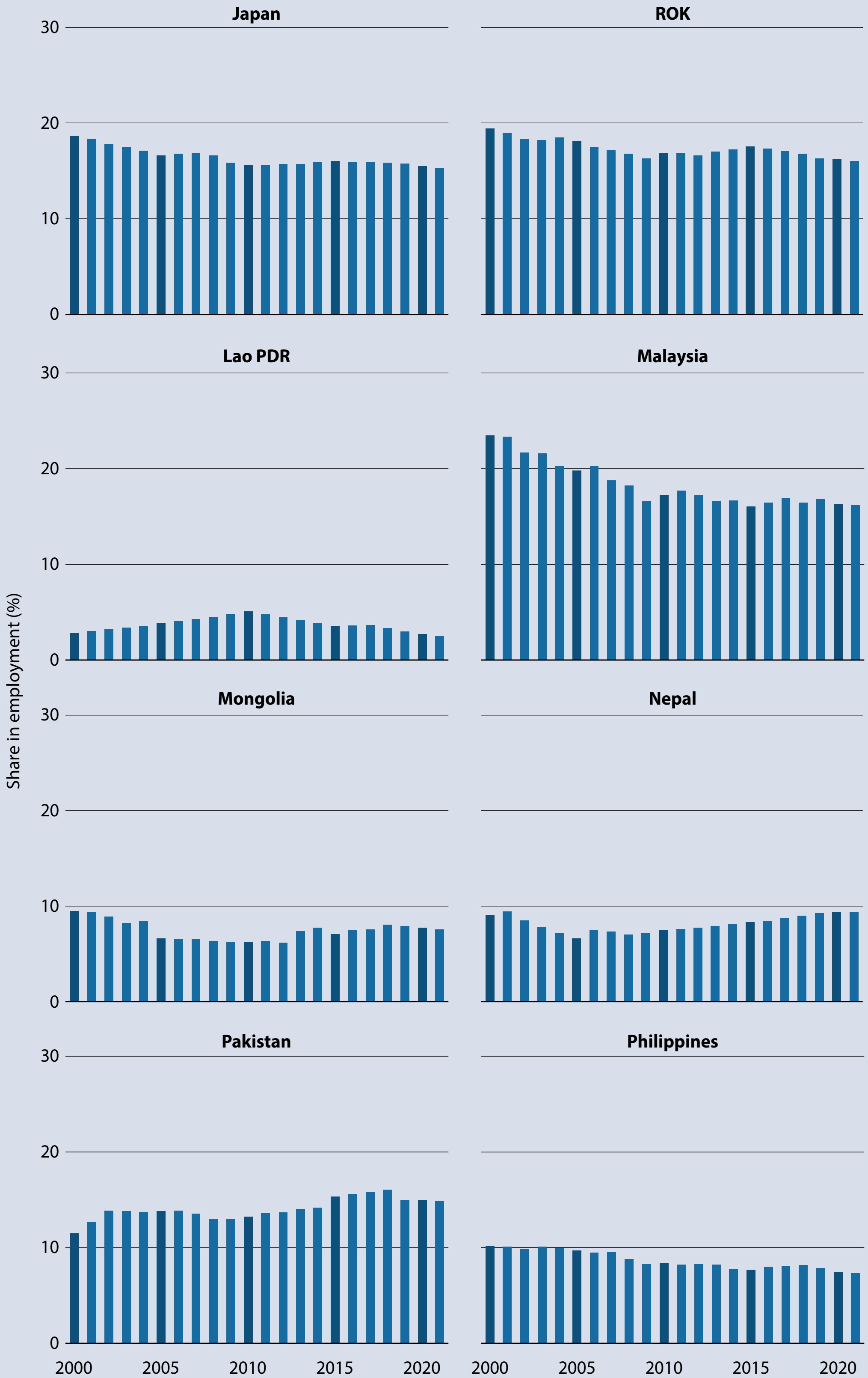

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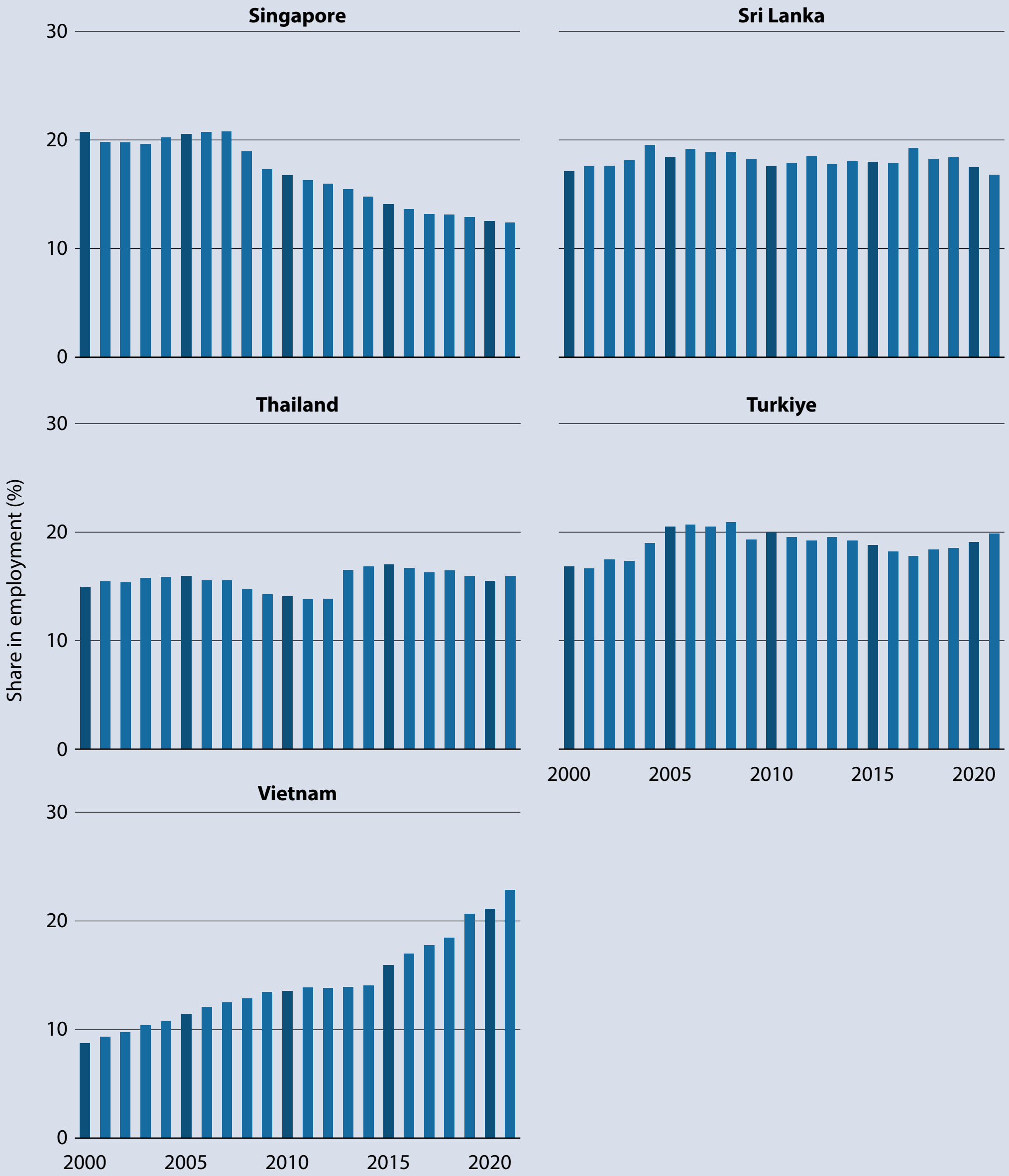


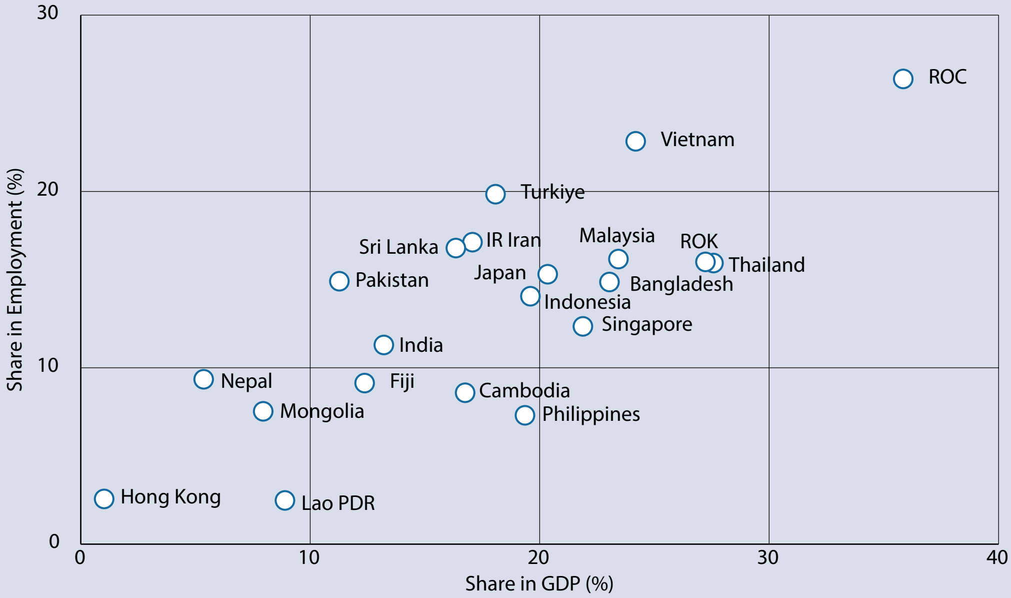
Source: APO (2024).

The temporal evolution shown in Figure 3.4 reveals varied employment development trajectories from 2000 to 2021. Several economies demonstrate sustained increases in manufacturing employment intensity, with Vietnam showing particularly pronounced growth throughout the period, reflecting successful labor-intensive industrialization strategies. The ROC maintains consistently high employment levels, reinforcing its position as a major manufacturing employer.

Conversely, some advanced economies exhibit gradual moderation in manufacturing employment shares, consistent with structural transitions toward higher productivity operations and service-sector development, while maintaining or increasing their manufacturing output contributions to GDP.

FIGURE 3.5

MANUFACTURING'S SHARE OF GDP AND EMPLOYMENT ACROSS APO MEMBER ECONOMIES, 2021.



Source: APO (2024).

The relationship between the manufacturing sector's share of GDP and its share of employment shows a clear positive correlation across APO member economies, as illustrated in Figure 3.5. Generally, economies with a higher manufacturing contribution to GDP tend to have a larger proportion of their workforce employed in manufacturing. This trend is particularly evident across most of the sample economies.

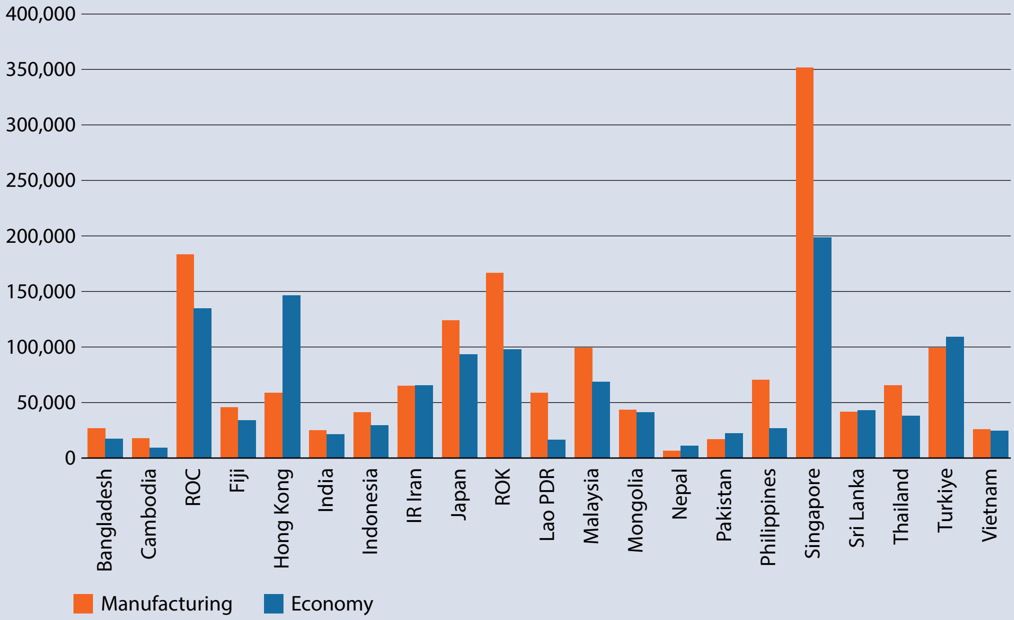
Thailand, the ROK, and the Philippines show higher GDP shares relative to employment shares, with the Philippines demonstrating a particularly pronounced gap (19.4% GDP share versus 7.3% employment share). These productivity gaps suggest above-average value added per worker, indicating manufacturing structures characterized by higher capital intensity and technological sophistication rather than labor-dependent production processes.

Conversely, economies like Turkiye, Pakistan, Nepal, and Hong Kong have higher employment shares relative to GDP shares. Notably, Nepal exhibits the most pronounced disparity with an employment share of 9.4% compared with a GDP contribution of only 5.4%. Pakistan too shows a similar pattern (14.9% employment share versus 11.3% GDP contribution). Both economies exhibit highly labor-intensive manufacturing structures, with employment shares outpacing their value-added contributions. This setup indicates relatively low LP, meaning there is significant job creation compared with economic output, which implies that productivity improvements usually fall behind the overall economy's average.

LP in the manufacturing sector, defined as manufacturing value added per manufacturing employee, varies markedly across economies (Figure 3.6). Singapore stands out as the clear outlier at the top end, with manufacturing productivity far above that of any other economy. High-productivity performers also include the ROC, the ROK, and Japan.

FIGURE 3.6

MANUFACTURING LABOR PRODUCTIVITY IN 2021.



Note: Labor productivity = GDP/Employment (GDP = GDP by industry at constant prices, using 2017 PPPs, reference year 2021)
Source: APO (2024).

Comparing manufacturing productivity with economy-wide productivity reveals distinct patterns. In Singapore, the ROC, the ROK, Japan, Malaysia, and the Philippines, manufacturing productivity substantially exceeds economy-wide productivity, consistent with more capital- and technology-intensive industrial bases.

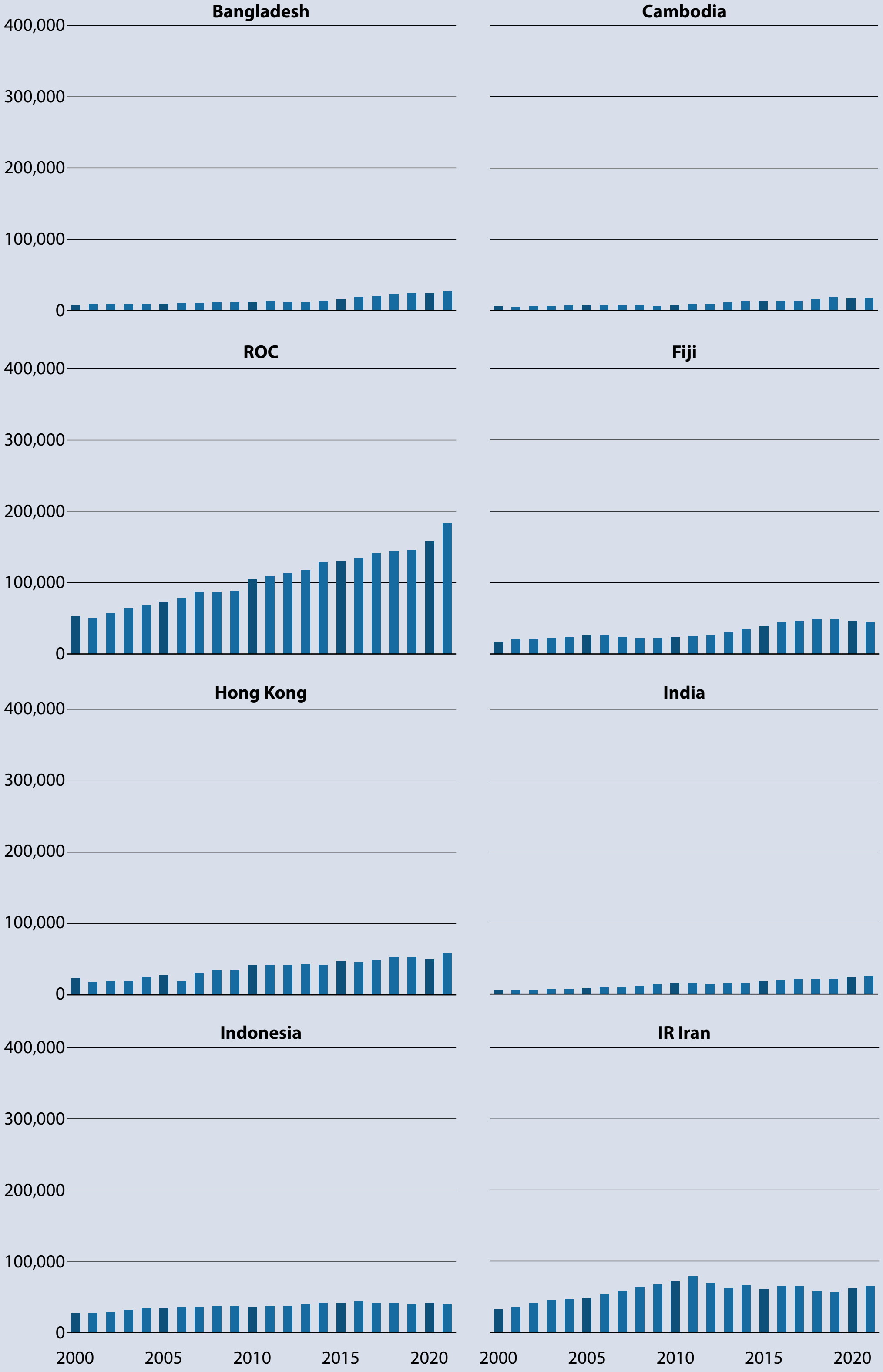
Conversely, some economies show manufacturing productivity levels that fall short of their broader economic performance, such as Hong Kong, Nepal, Pakistan, Sri Lanka, and Turkiye, suggesting that manufacturing sectors underperform other sectors of the economy. These economies display manufacturing productivity gaps that suggest other sectors—particularly high-value services, resource extraction, or capital-intensive industries—drive overall national productivity upward. At the same time, manufacturing remains constrained by technological limitations, infrastructure deficits, or structural inefficiencies that prevent it from achieving economy-wide productivity benchmarks.

A few economies, including India and Vietnam, display manufacturing productivity levels that closely align with their overall economic productivity, suggesting that their manufacturing sectors reflect broader national productivity characteristics rather than serving as productivity leaders.

Taken together, these results indicate pronounced cross-economy heterogeneity in manufacturing LP, consistent with varying degrees of technological sophistication, capital intensity, and industrial upgrading. As economies continue to develop their manufacturing capabilities, productivity enhancement is likely to play an increasingly crucial role in their industrial competitiveness and economic growth strategies. However, the path to high-productivity manufacturing is not uniform, and each economy's journey reflects its unique industrial structure, technological capacity, and development priorities.

FIGURE 3.7

LABOR PRODUCTIVITY IN MANUFACTURING ACROSS APO MEMBER ECONOMIES, 2000–20.



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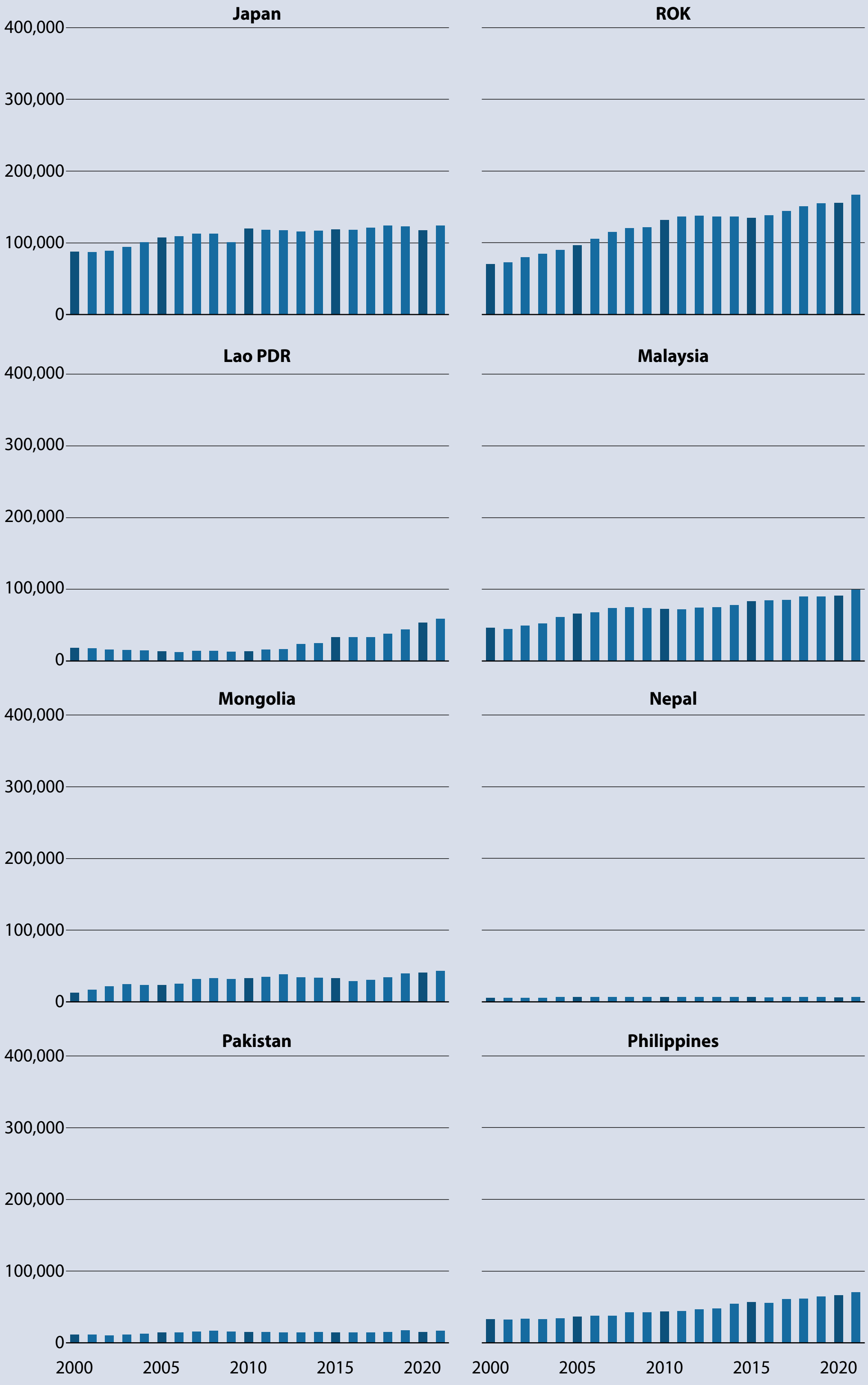

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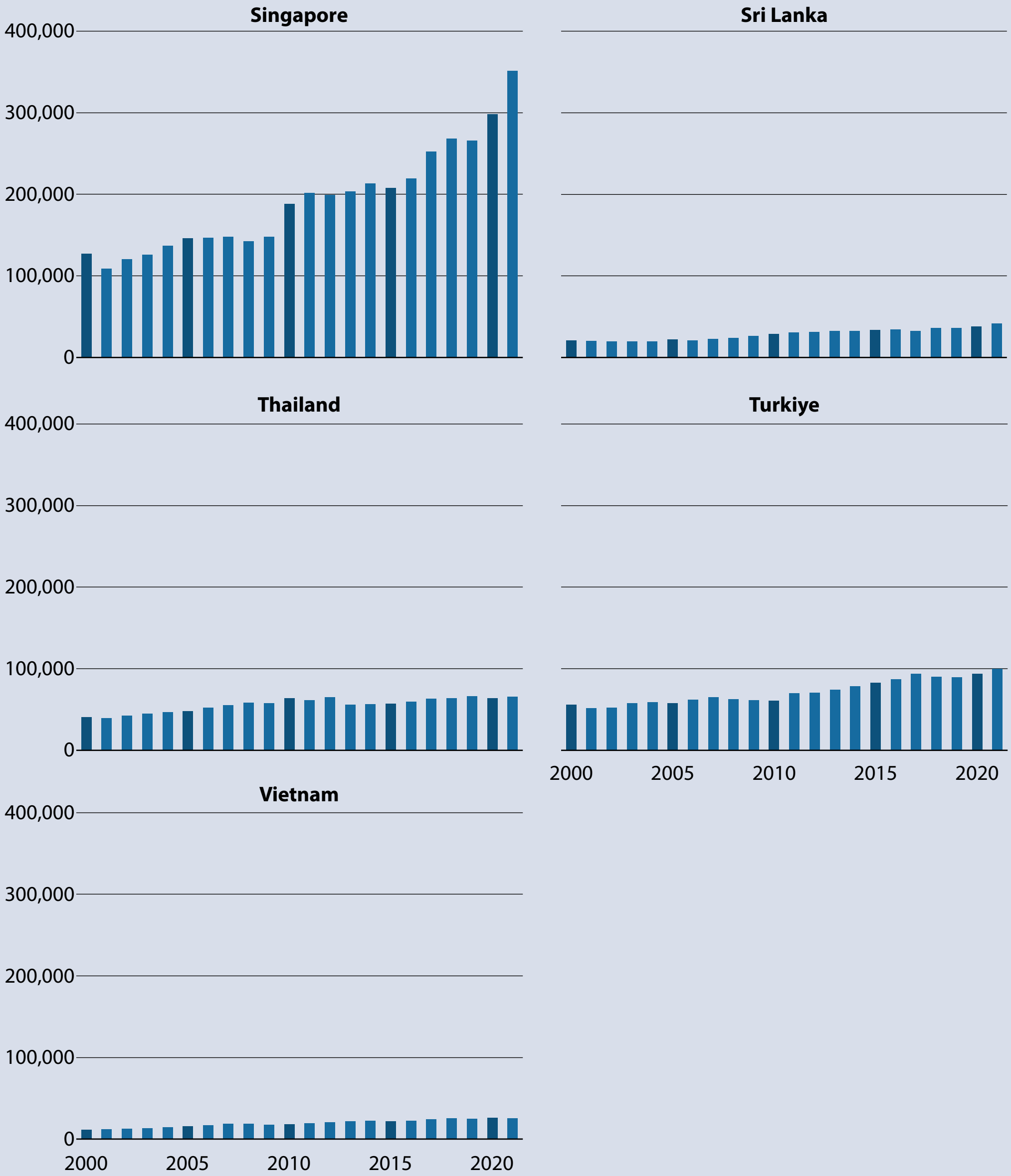


Source: APO (2024).

LP in the manufacturing sector over the period 2000–21, defined as manufacturing value added divided by manufacturing employment, reveals distinct temporal trajectories and development patterns across economies in Figure 3.7. The time series analysis demonstrates significant heterogeneity in productivity growth paths, with some economies achieving sustained improvements while others exhibit stagnation or volatility.

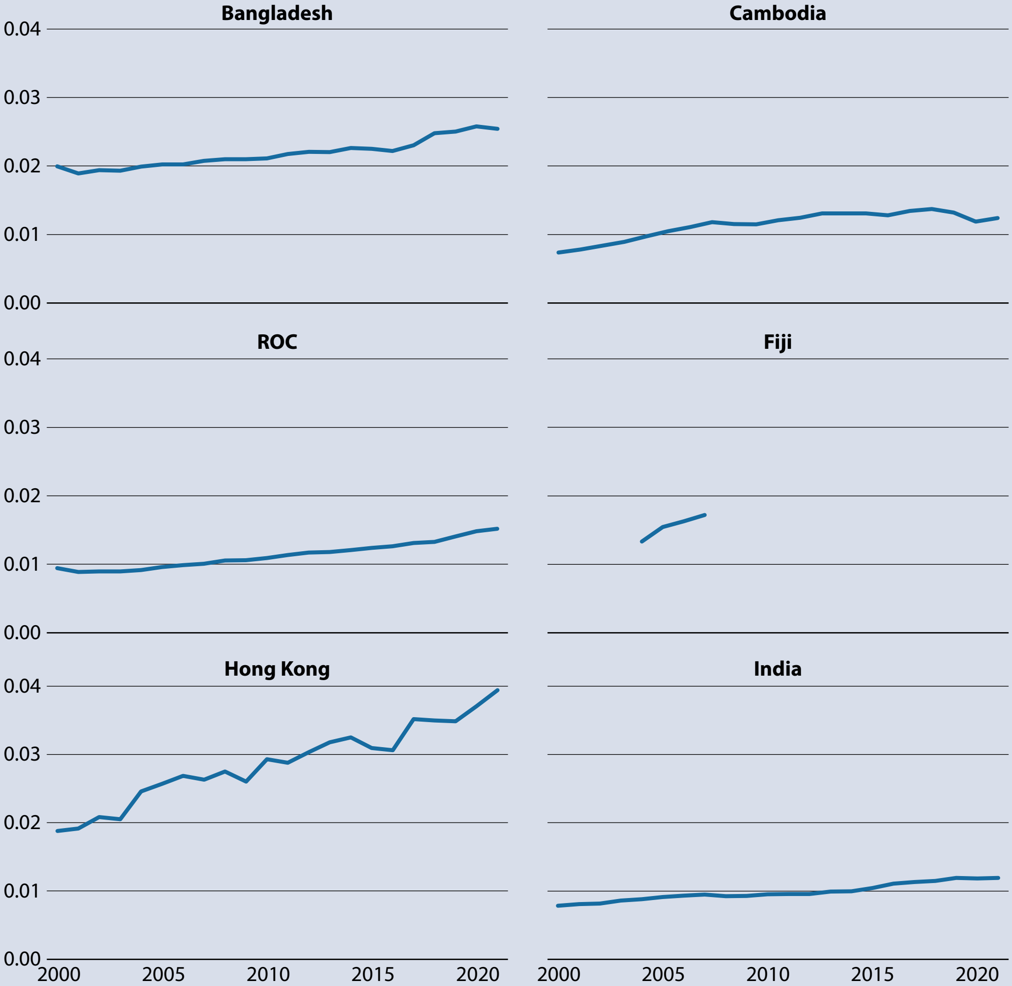
Several economies demonstrate pronounced upward productivity trajectories over the two-decade period. Singapore displays exceptional productivity growth, reaching levels substantially above those of other economies by 2021. The ROC displays sustained high productivity levels and continues to grow, reinforcing its position as a major manufacturing hub. The ROK, Japan, and Malaysia also show notable productivity improvements, though with varying degrees of consistency and pace. These patterns suggest successful industrial upgrading and technological advancement processes.

Conversely, some economies, including Bangladesh, Cambodia, and several South Asian economies, show stable but low productivity growth during this period, suggesting that manufacturing sectors have maintained employment-generating capacity without significant efficiency improvements or technological upgrading. Meanwhile, other economies, including Vietnam and Thailand, show moderate but steady productivity improvements, reflecting gradual industrial development and integration into global value chains.

Taken together, these temporal patterns reveal that manufacturing productivity enhancement is neither automatic nor uniform across developing economies. The divergent trajectories suggest that sustained productivity growth requires deliberate industrial policies, technological upgrading, and institutional capabilities that enable continuous improvement in manufacturing efficiency and sophistication over extended periods.

FIGURE 3.8

ENERGY EFFICIENCY ACROSS ALL SECTORS OF APO MEMBER ECONOMIES, 2000–20.



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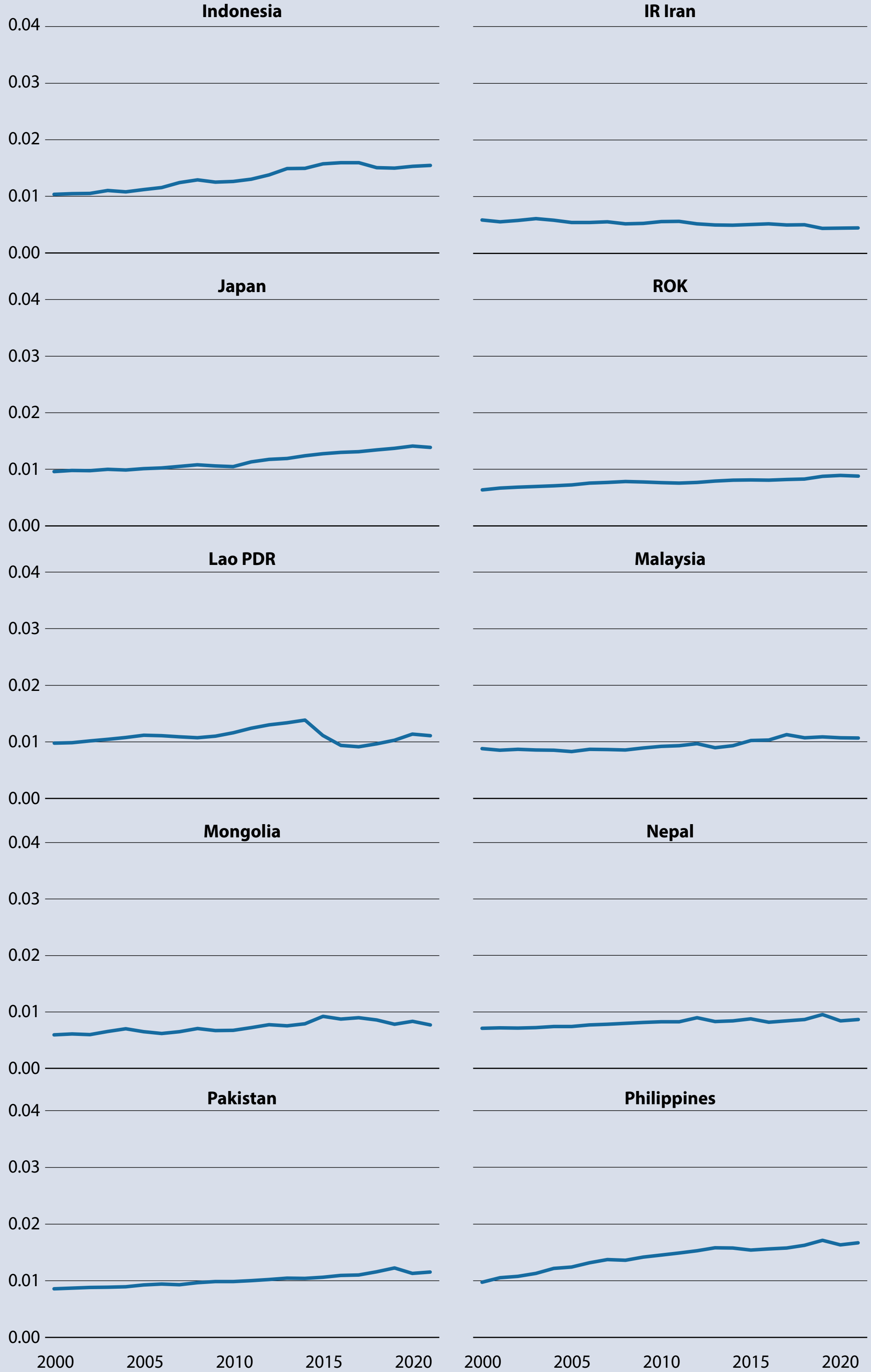

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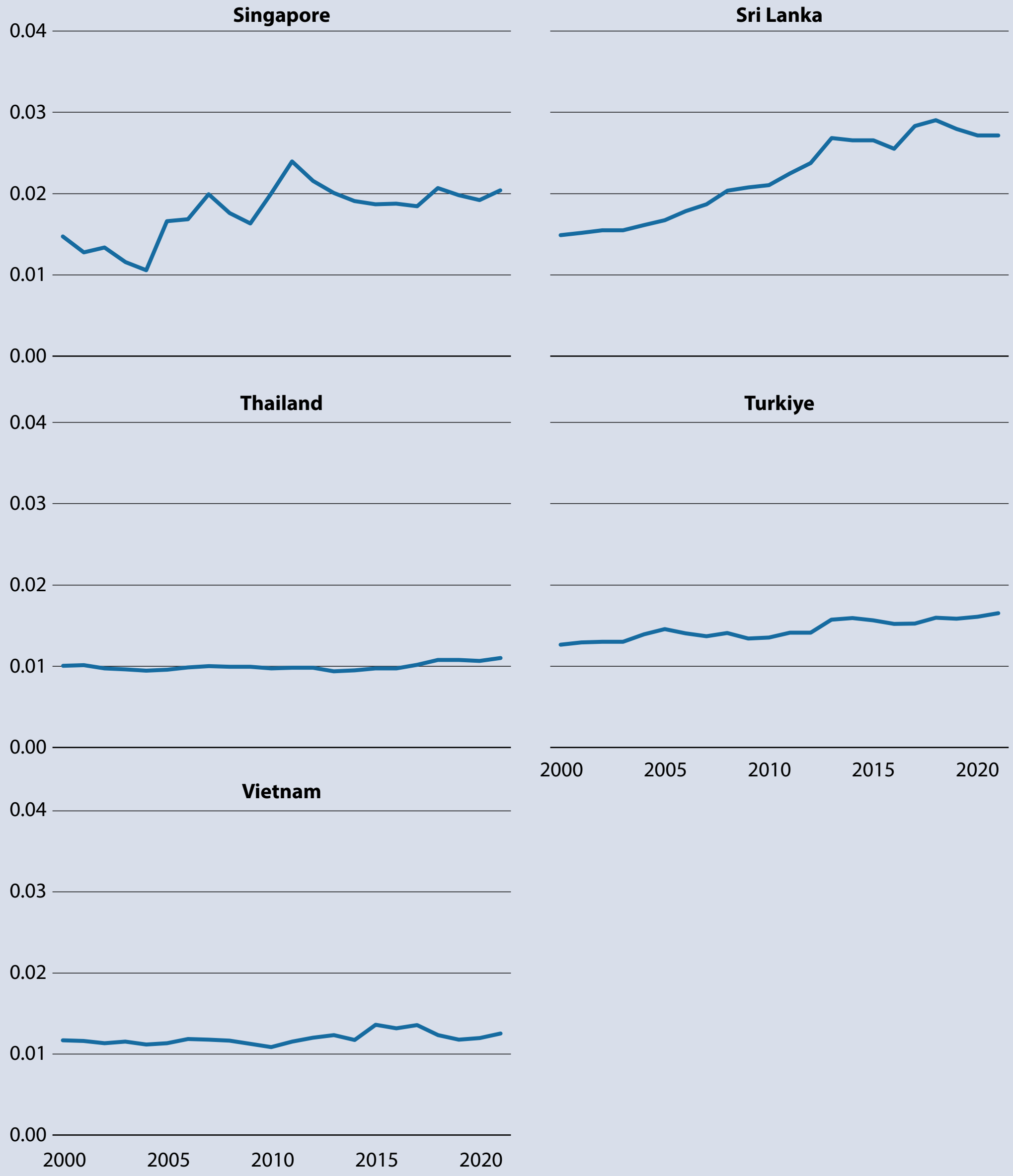
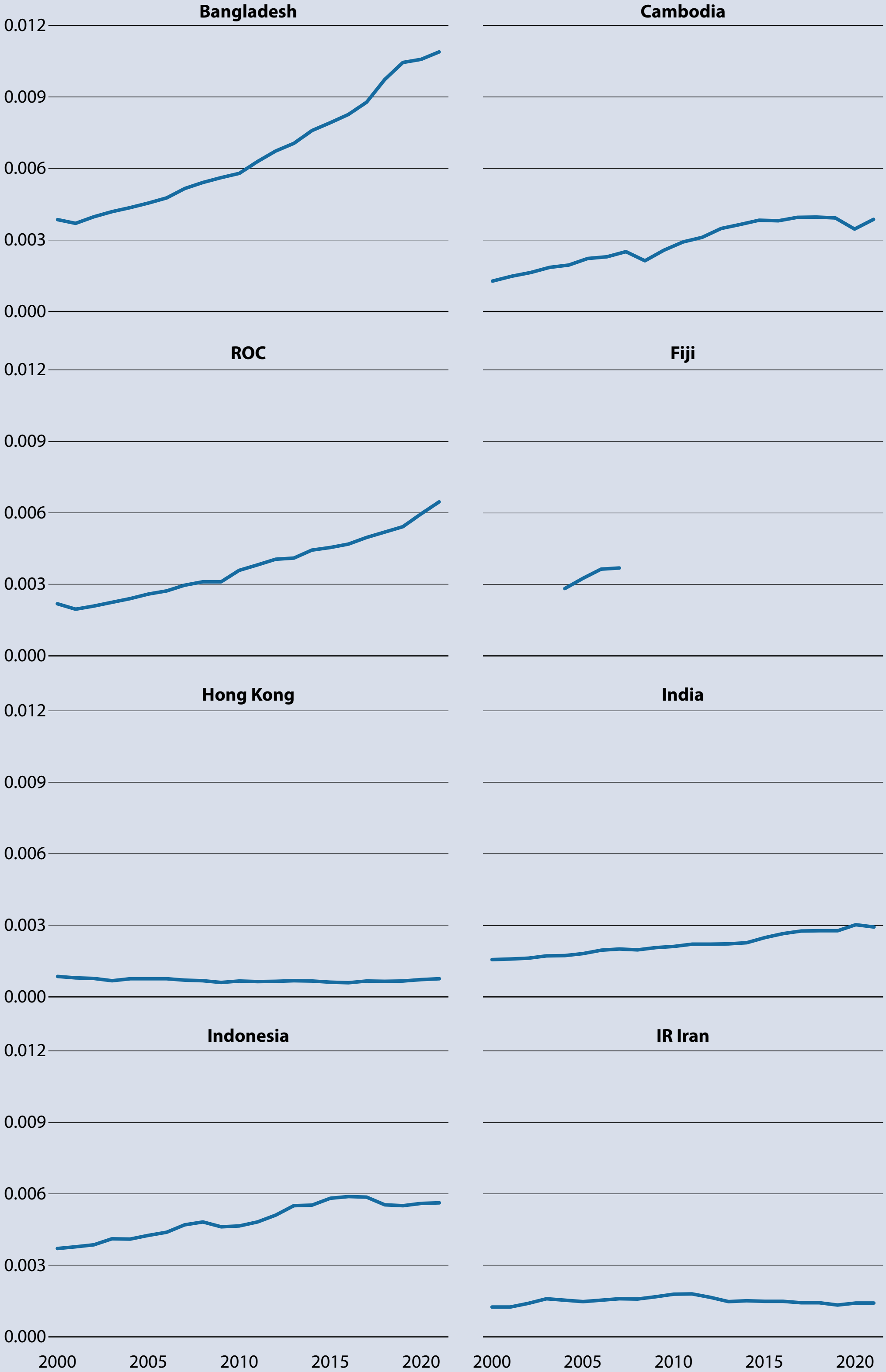


Source: APO (2024).

Figure 3.8 reveals significant heterogeneity in energy efficiency trends across all economic sectors, with most economies showing gradually increasing energy efficiency—indicating improved performance as the sectors produce more output per unit of energy consumed. While the overall patterns suggest modest efficiency gains across the sample, the pace and consistency of improvements vary considerably among economies. For example, economies such as the ROC, the ROK, and the Philippines demonstrate steady upward trajectories in energy efficiency, suggesting sustained improvements in efficiency across their economic activities. Conversely, several economies such as Vietnam, Nepal, and Bangladesh exhibit relatively stable or only slightly changing levels, suggesting limited progress in increasing output per unit of energy consumed.

FIGURE 3.9

ENERGY EFFICIENCY OF THE MANUFACTURING SECTOR ACROSS APO MEMBER ECONOMIES, 2000–20.



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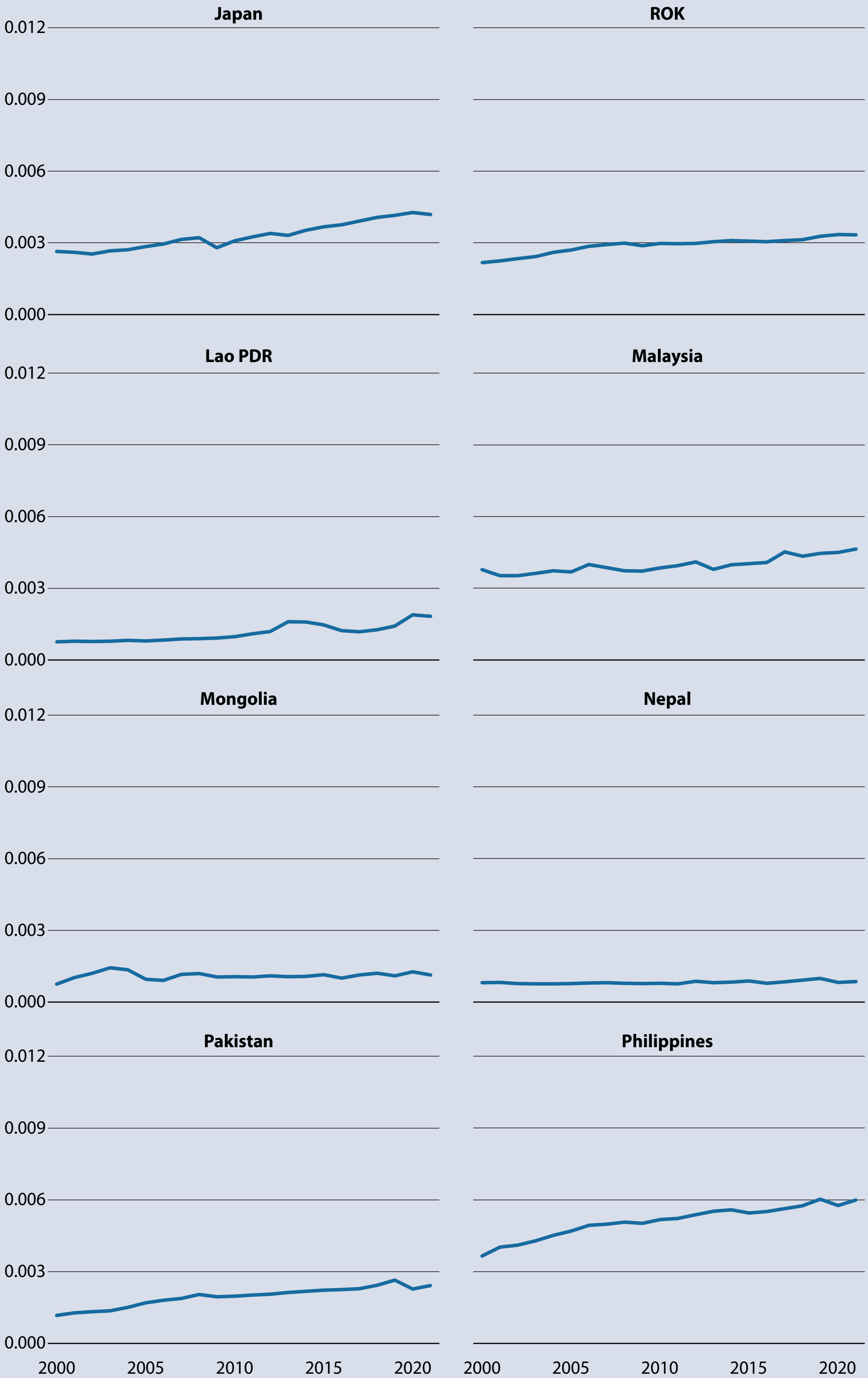

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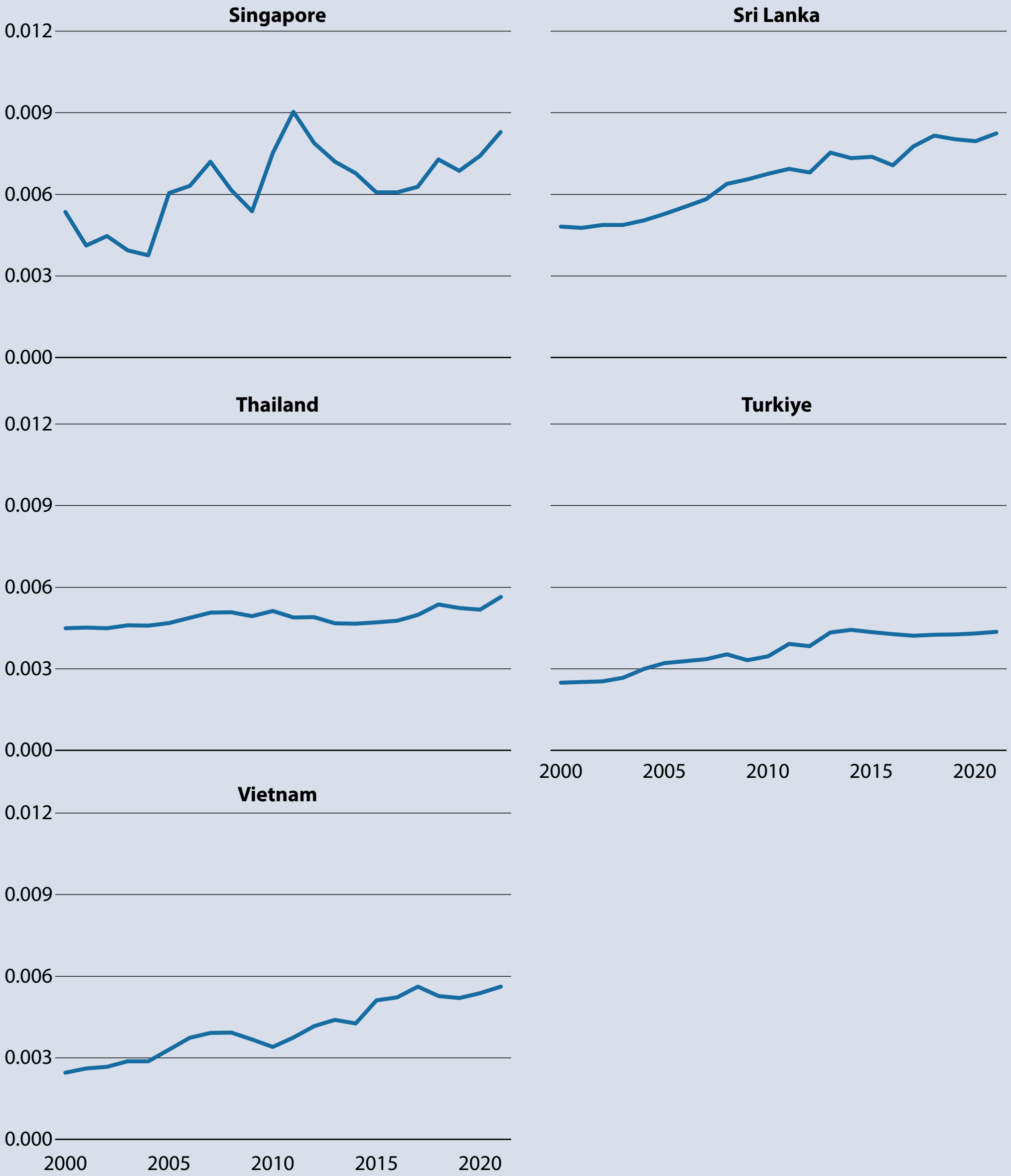


Source: APO (2024). Fiji is included in certain parts of the analysis due to the lack of energy-related data required to compute energy efficiency.

The manufacturing sector's energy efficiency patterns, as shown in Figure 3.9, exhibit more pronounced variations than economy-wide trends. The manufacturing-specific analysis reveals that several economies achieved notable efficiency improvements in their industrial sectors, with steeper increasing trends than observed across all sectors. Economies such as India and Vietnam show a gradual yet steady increase in manufacturing energy efficiency over the period, consistent with ongoing industrial modernization and technology adoption. However, some economies, including Hong Kong and several South Asian economies, show more volatile patterns in manufacturing energy efficiency, with periodic fluctuations that may reflect varying industrial policies, economic cycles, or technological adoption rates.

Comparing energy efficiency trends between all sectors and manufacturing reveals important sectoral dynamics in efficiency improvements. Manufacturing sectors in some economies appear to drive overall national energy efficiency gains, often showing steeper improvement trajectories than economy-wide averages. This pattern suggests that industrial modernization and technological upgrading in manufacturing may serve as key drivers of national energy efficiency enhancement. The manufacturing sector's role as an efficiency leader likely reflects the sector's greater exposure to international competition, technology transfer, and targeted policy interventions aimed at industrial upgrading and environmental compliance.

3.3 Relationship between Energy Efficiency and Productivity in Manufacturing

FIGURE 3.10

CORRELATIONS BETWEEN GDP, LABOR PRODUCTIVITY, AND ENERGY EFFICIENCY IN MANUFACTURING.

Source: APO (2024).

The relationships between economic growth, LP, and energy efficiency in the manufacturing sector are interconnected, as revealed by our correlation analysis across economies from 2000 to 2021. Figure 3.10 presents a correlation matrix examining the relationships between GDP growth, LP growth, and improvements in energy efficiency in the manufacturing sector. The results suggest that these key performance indicators demonstrate statistically significant relationships, though with varying strengths and directions that require careful interpretation.

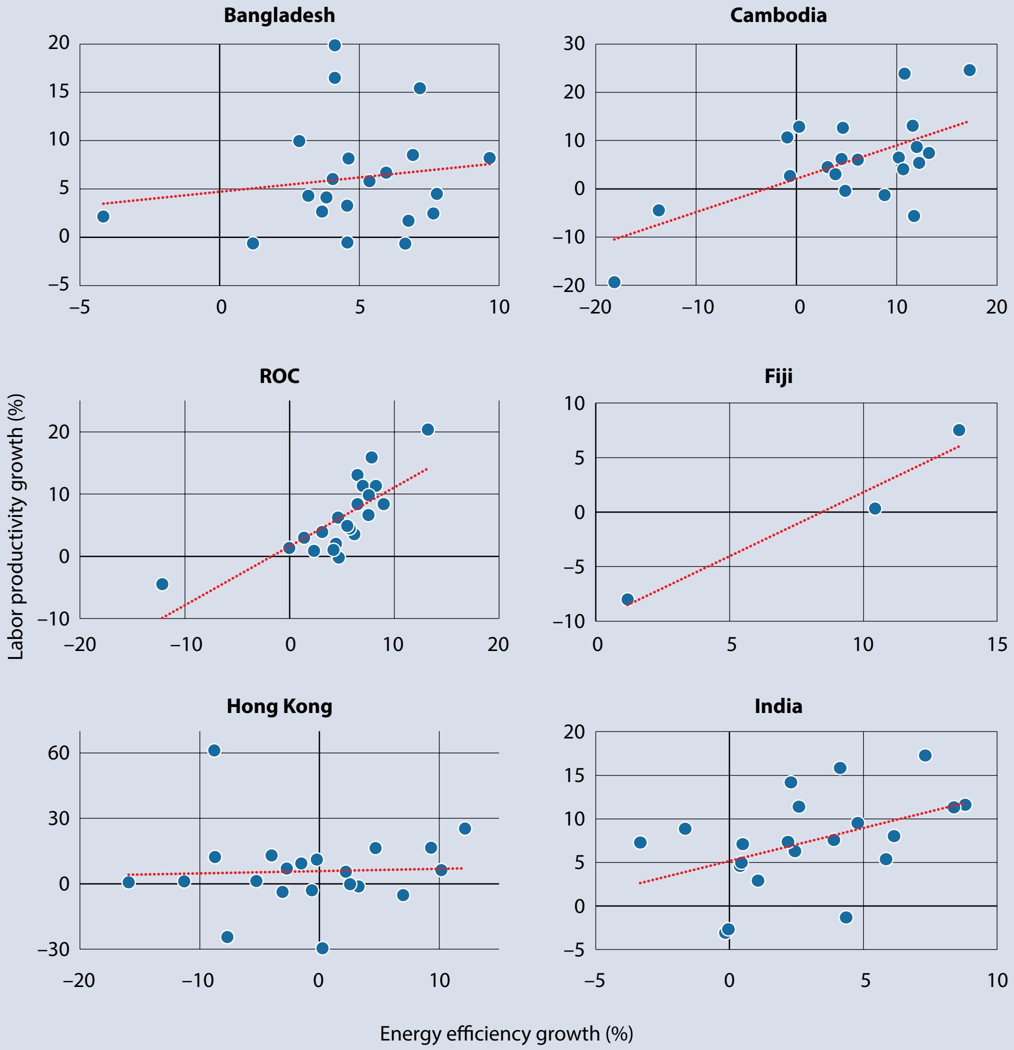
GDP growth and LP growth exhibit a moderate positive correlation (0.34), suggesting that productivity improvements contribute meaningfully to economic expansion in manufacturing. This relationship indicates that manufacturing growth strategies emphasizing productivity enhancement generate sustained economic benefits.

Energy efficiency demonstrates positive correlations with both GDP growth (0.24) and LP growth (0.44). These positive correlations indicate that economic and productivity growth tend to occur alongside energy efficiency improvements, suggesting that economies experiencing higher growth and productivity also tend to produce more output per unit of energy consumed.

Interestingly, the strongest relationship is observed between LP growth and improvements in energy efficiency, rather than between economic growth and other variables. This finding may indicate that technological upgrading and process optimization in manufacturing contribute to simultaneous gains in productivity and sustainability. However, it is equally plausible that improvements in energy efficiency drive increases in LP, thereby fostering overall economic growth. In this sense, the relationship is likely to be bidirectional, and the precise causal pathway warrants further empirical investigation.

FIGURE 3.11

ENERGY EFFICIENCY AND LABOR PRODUCTIVITY IN MANUFACTURING ACROSS APO MEMBER ECONOMIES.



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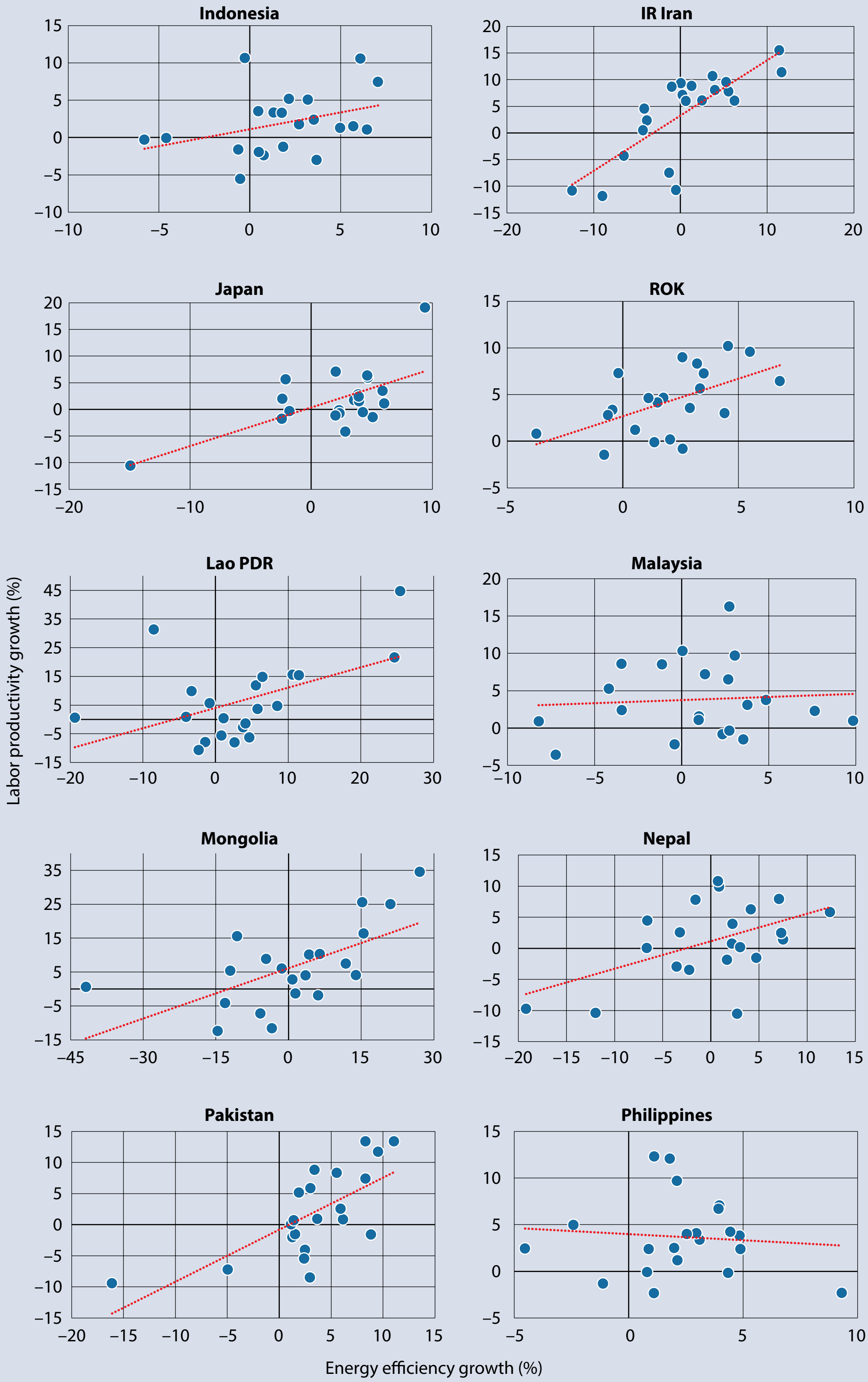

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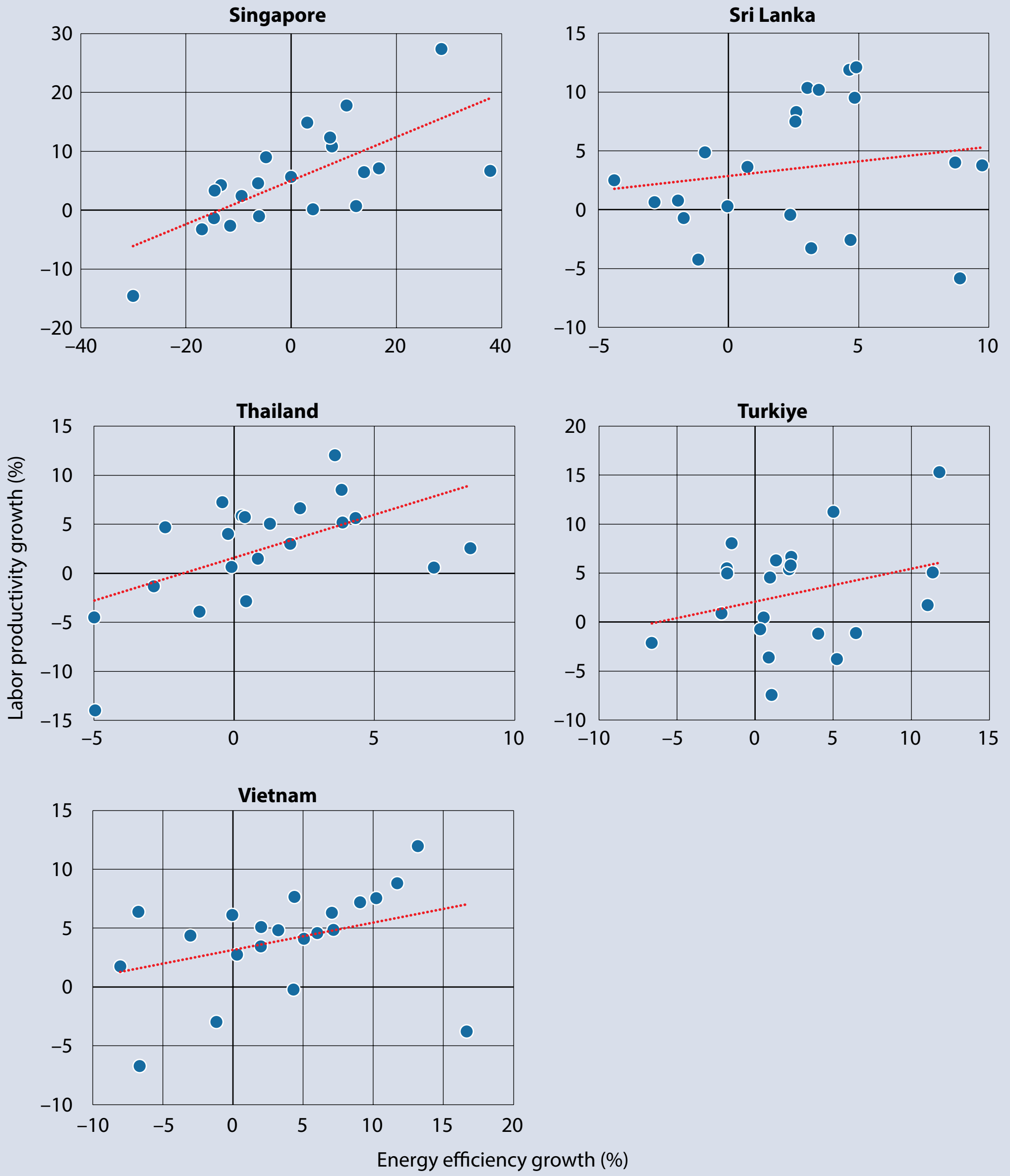

Note: Fiji is not included in certain parts of the analysis due to the lack of energy-related data required to compute energy efficiency.
Source: APO (2024).

The relationship between energy efficiency improvements and LP growth in manufacturing exhibits complex, nonlinear patterns across APO member economies, as shown in Figure 3.11. While simple correlations may suggest straightforward relationships, scatter plots reveal more nuanced, economy-specific dynamics in which productivity and efficiency improvements do not always move in lockstep. For example, economies such as Singapore and the ROK show strong positive relationships between productivity gains and improvements in energy efficiency, with higher productivity growth coinciding with greater increases in energy efficiency. By contrast, some economies display more varied patterns. For example, Bangladesh and Vietnam show different trajectories that may reflect varying stages of industrial development, technology adoption, or structural transformation. These findings highlight the importance of considering economy-specific contexts when analyzing the relationship between productivity enhancement and environmental efficiency, as the pathways to achieving simultaneous economic and environmental gains appear to be highly dependent on industrial structure, technological capacity, and policy frameworks.

4. Effects on the Manufacturing Sector

4.1 Empirical Methodology

The methodology employs a panel-fixed-effects regression model to control for economy-specific and time-invariant characteristics, thereby isolating the true effect of energy efficiency on manufacturing productivity. Panel data analysis combines time-series and cross-sectional data, allowing observation of the same entities (APO member economies) over multiple time periods. This approach provides analytical advantages in capturing both within-economy changes over time and cross-economy variations in manufacturing practices. The empirical model is expressed as follows:

$$LP_{it} = \mu_i + v_t + \beta EE_{it} + \gamma X_{it} + \varepsilon_{it}$$

where the indexation consists of two components: i for an economy and t for a year. The model includes economy- and year-fixed effects to control for unobservable heterogeneity across economies and over time. Specifically, the economy-specific argument, μ_i, reflects the invariant properties of socioeconomic, geographic, and cultural determinants. v_t captures the common global effect, such as the sudden breakdown of the world business cycle. X_{it} is a matrix of control variables including population, human capital, capital investment, and total factor productivity (TFP). All variables are transformed into growth rates by first taking the log difference of the levels to remove nonstationary components.

We employ three model specifications to assess the robustness of our estimates. Model 1 is related to only one variable of our interest: energy efficiency. Model 2 combines energy efficiency with other control variables and examines whether these variables affect the sole interaction between energy efficiency and LP. Model 3 adds TFP to the set of previously considered variables. Incorporating TFP into the model enables the model to explain how exogenous technological advancement can influence endogenous productivity.[1] However, the control variables sourced from Penn World Table 10.01 are available only through 2019. Therefore, it is an unbalanced panel.

4.2 Estimation Results

4.2.1 Baseline Results: Full Sample Analysis

The estimation results presented in Table 3.1 indicate significant impacts of energy efficiency improvements on manufacturing productivity growth across APO member economies. The dependent variable represents the growth rate of LP in the manufacturing sector (measured as manufacturing value added per worker). In contrast, energy efficiency is measured as manufacturing output per unit of energy consumption (the inverse of energy intensity). Since higher energy efficiency values indicate better performance, the positive coefficients indicate a positive relationship between efficiency improvements and productivity gains.

The estimated coefficients on energy efficiency are consistently positive and statistically significant at the 0.1% level across all three model specifications. The coefficient magnitude remains relatively

[1] Since our study defines the productivity as GDP per employment, it differs to the exogenous productivity such as total factor productivity, which is the modified Solow residuals from growth accounting.

stable across models (ranging from 0.4311 to 0.4371), demonstrating the robustness of this relationship even when additional control variables are introduced.

TABLE 3.1

ESTIMATED RESULTS OF PANEL ANALYSIS.

	Model 1	Model 2	Model 3
Energy efficiency	0.4349***	0.4371***	0.4311***
Population	–	−1.6786	−1.6660
Human capital	–	0.5637	0.5585
Capital investment	–	0.0138	0.0036
Total factor productivity	–	–	0.4673**

Note: All variables are transformed into growth rates by log difference.
Significance codes:
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Source: Author (2025).

In Model 1, the basic specification shows that energy efficiency improvements alone explain a substantial portion of the variations in manufacturing productivity. The coefficient of 0.4349 indicates that a 1% improvement in energy efficiency is associated with approximately 0.43% increase in LP growth, representing an economically meaningful relationship.

Model 2 introduces additional control variables to capture other determinants of productivity growth. The population growth coefficient is negative but not statistically significant, suggesting that demographic changes do not significantly impact manufacturing productivity in the short term. Human capital shows a positive coefficient (0.5637), indicating that improvements in workforce skills and education contribute to productivity enhancement, though the effect is not statistically significant at conventional levels. Capital investment shows a small positive coefficient (0.0138) but is not statistically significant, suggesting a complex relationship between physical capital accumulation and immediate productivity gains in manufacturing operations.

Model 3 represents the most comprehensive specification, incorporating TFP as an exogenous variable that captures productivity, efficiency, and an economy's level of technology. The energy efficiency coefficient remains positive and significant at 0.4311, confirming the persistent relationship between efficiency improvements and productivity gains even after controlling for broader technological progress. Notably, the TFP coefficient is positive and highly significant (0.4673**), indicating that technological advancement and efficiency improvements in factor utilization contribute substantially to manufacturing productivity growth.

The stability of the energy efficiency coefficient across all specifications suggests that the relationship between energy efficiency and LP in manufacturing is robust to different model configurations. This consistency shows that energy efficiency improvements work through channels beyond just technological progress, highlighting the multiple benefits of using energy efficiently in manufacturing operations.

The estimated results suggest four fruitful implications. First, the magnitude of the estimated coefficients reveals economically substantial effects. With elasticities ranging from 0.43 to 0.44, a

10% improvement in energy efficiency is associated with approximately 4.3–4.4% increase in LP growth. This magnitude is comparable to, or exceeds, the impact of other traditional productivity drivers, suggesting that energy efficiency should be considered a first-order determinant of manufacturing competitiveness rather than a secondary concern. The persistence of this effect across different model specifications, including when controlling for TFP, indicates that energy efficiency captures productivity-enhancing mechanisms that are distinct from general technological progress.

Second, the complementarity between energy efficiency and TFP in Model 3 provides additional insights into the pathways through which efficiency improvements affect manufacturing performance. Both variables exhibit positive and significant coefficients (0.4311 for energy efficiency and 0.4673 for TFP), suggesting that they operate through partially independent channels. Energy efficiency improvements may enhance productivity through direct cost-reduction mechanisms—lower energy expenditures per unit of output free up resources for other productive investments, thereby improving overall operational efficiency. Additionally, the pursuit of energy efficiency often requires process optimization, equipment modernization, and organizational improvements that generate productivity spillovers beyond energy use alone. Manufacturing firms that invest in energy-efficient technologies usually experience collateral benefits, including reduced waste, improved product quality, enhanced worker safety, and better environmental compliance—all of which contribute to overall productivity.

Third, the relatively weak and insignificant effects of population and capital investment variables, compared with the strong energy-efficiency effects, suggest important policy implications for manufacturing development strategies, especially in the short term. Traditional growth models emphasize capital accumulation and labor force expansion as primary drivers of productivity growth. However, our results indicate that, in the short run, energy efficiency improvements may offer more immediate and measurable productivity gains than simple increases in physical capital or workforce size. This finding is particularly relevant for developing and emerging APO member economies, where resource constraints may limit the scale of capital investment. The results suggest that targeted investments in energy efficiency—through technology adoption, process improvements, and organizational changes—can generate substantial productivity returns even in the absence of large-scale capital accumulation.

Lastly, the positive relationship between energy efficiency and productivity also has implications for the environmental sustainability of manufacturing growth. Conventional economic thinking sometimes posits a tradeoff between environmental performance and economic competitiveness, suggesting that pollution control and resource efficiency impose costs that reduce profitability and productivity. Findings challenge this narrative by demonstrating that energy efficiency improvements are positively associated with productivity gains. This suggests the possibility of a "double dividend" from energy efficiency policies: manufacturing sectors can simultaneously achieve environmental objectives (reduced energy consumption and associated emissions) while enhancing economic performance (higher LP and competitiveness). This complementarity between environmental and economic goals may help explain why many successful manufacturing economies have pursued aggressive energy efficiency standards and investments as part of their industrial development strategies.

4.2.2 Heterogeneous Effects by Income Level

While the baseline results establish a robust positive relationship between energy efficiency and manufacturing productivity, the aggregate estimates may mask important heterogeneity across economies at different stages of economic development. To investigate whether the productivity benefits of energy efficiency vary systematically across income groups, we extend the empirical model to include interaction terms between energy efficiency and income-group dummies. This approach allows us to test whether economies at different income levels experience differential returns to energy efficiency investments.

We partition APO member economies into three income groups following the World Bank classification: high-income economies (HIEs); upper-middle-income economies (UMIEs); and lower-middle-income economies (LMIEs). The extended model specification is as follows:

$$LP_{it} = \mu_i + v_t + \beta_1 EE_{it} + \beta_2(EE_{it} \times UMIE_i) + \beta_3(EE_{it} \times LMIE_i) + \gamma X_{it} + \varepsilon_{it}$$

where $UMIE_i$ and $LMIE_i$ are dummy variables indicating UMIE and LMIE economies, respectively. HIE serves as the reference group. The coefficient β_1 captures the effect of energy efficiency in HIEs, while β_2 and β_3 represent the differential effects (relative to HIEs) for UMIEs and LMIEs, respectively. The total effects by income group are therefore β_1 for HIEs, $\beta_1 + \beta_2$ for UMIEs, and $\beta_1 + \beta_3$ for LMIEs.

TABLE 3.2

ESTIMATED RESULTS BY INCOME LEVELS OF APO MEMBER ECONOMIES.

Model	Income Group	Estimates	Total Effect	*t*-value (coefficient)	*t*-value (Total)
1	HIE (Reference)	0.2383**	0.2383**	3.2585	3.2585
	UMIE	0.3300**	0.5682***	2.9300	4.2318
	LMIE	0.3187**	0.5569***	2.9547	4.2741
2	HIE (Reference)	0.2465**	0.2465**	3.1869	3.1869
	UMIE	0.3379**	0.5844***	2.7776	4.0538
	LMIE	0.3318**	0.5783***	2.6989	3.9815
3	HIE (Reference)	0.2130**	0.2130**	2.7734	2.7734
	UMIE	0.3475**	0.5605***	2.8998	3.9379
	LMIE	0.3462**	0.5591***	2.8579	3.8988

Note: All variables are transformed into growth rates by log difference.
Significance codes:
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Source: Author (2025).

Table 3.2 presents the estimation results with income-level interactions. The findings reveal a striking pattern: productivity gains from energy efficiency improvements are substantially larger in middle-income economies than in high-income economies. Focusing on Model 3, which includes the full set of control variables, the total effect of energy efficiency on LP is 0.2130 for HIEs, 0.5605 for UMIEs, and 0.5591 for LMIEs. This implies that a 1% increase in energy efficiency generates approximately 0.21% productivity growth in high-income economies, but 0.56% in middle-income economies (nearly 2.6 times).

Importantly, the interaction coefficients for both UMIEs (0.3475**) and LMIEs (0.3462**) are statistically significant and of similar magnitude, indicating that the differential effect relative to HIEs is not merely a statistical artifact. Moreover, the similarity between the UMIE and LMIE coefficients suggests that the distinction between upper-middle- and lower-middle-income economies matters less than the broader gap between middle- and high-income economies.

This pronounced heterogeneity can be explained by the pattern reflecting diminishing marginal returns to energy efficiency investments in economies that have already achieved relatively high levels of energy efficiency. High-income economies in the sample—the ROC, Hong Kong, Japan, the ROK, and Singapore—are characterized by advanced manufacturing sectors that have undergone decades of technological upgrading and capital deepening. These economies likely operate closer to the technological frontier in energy efficiency, having already implemented many available energy-saving technologies and management practices. As a result, further improvements in energy efficiency yield progressively smaller productivity gains.

In contrast, middle-income economies retain substantial scope for catching up to the efficiency frontier. Their manufacturing sectors typically feature a mix of modern and older, less efficient production facilities. Energy efficiency improvements in these contexts often involve adopting proven technologies and practices already standard in high-income economies, generating large productivity dividends through multiple channels: direct cost savings from reduced energy consumption, indirect benefits from equipment modernization, improved production processes, and organizational learning. This "technology gap" or "catch-up" dynamic is well documented in development economics literature and appears to extend to the domain of energy efficiency.

An alternative, but complementary, explanation concerns the capital intensity of manufacturing. HIEs in our sample generally have higher capital-to-labor ratios and more advanced levels of physical and human capital. In such capital-rich environments, energy represents a smaller share of total production costs, and marginal improvements in energy efficiency may have limited effects on overall cost structures and productivity. Middle-income economies, where energy costs account for a larger share of manufacturing costs, stand to gain more from efficiency improvements.

It is worth noting that while the productivity effect is smaller in HIEs, the coefficient remains positive and statistically significant (0.2130**). This indicates that energy efficiency continues to contribute to productivity growth even in advanced manufacturing contexts, though the magnitude is more modest. From a policy perspective, energy efficiency remains a relevant objective for high-income economies, albeit with potentially lower economic returns compared to middle-income economies.

4.2.3 Evidence from Manufacturing Intensity Groups

To further explore the diminishing returns hypothesis, this analysis investigates whether variation in energy-efficiency effects is linked to the structural significance of manufacturing across different economies. If high-income economies experience smaller productivity gains from energy efficiency partly because their manufacturing sectors are already highly developed and efficient, a similar pattern should be observed when grouping economies by manufacturing intensity rather than income level. Economies with larger manufacturing sectors (as a share of GDP) are likely to have invested more heavily in industrial capital, technology, and energy management systems, potentially exhibiting characteristics similar to high-income economies regardless of their income classification.

An alternative grouping is constructed based on the share of manufacturing value added in GDP (measured in 2021). Economies are classified into three groups: Group 1 comprises economies with manufacturing shares of 20% or above (ROC, Thailand, ROK, Vietnam, Malaysia, Bangladesh, Singapore, and Japan); Group 2 includes economies with manufacturing shares between 10% and

20% (Indonesia, Philippines, Turkiye, Islamic Republic of Iran, Cambodia, Sri Lanka, India, Fiji, and Pakistan); and Group 3 consists of economies with manufacturing shares below 10% (Mongolia, Nepal, and Hong Kong). Notably, most high-income economies (except Hong Kong) fall into Group 1, reflecting their strong manufacturing bases.

The modified empirical model is specified as:

$$LP_{it} = \mu_i + v_t + \beta_1 EE_{it} + \beta_2(EE_{it} \times S_M) + \beta_3(EE_{it} \times S_L) + \gamma X_{it} + \varepsilon_{it},$$

where S_M and S_L are dummies on the groups having medium (Group 2) and low (Group 3) shares of manufacturing in GDP. The reference group is the high-share group, which exceeds 20% of GDP (Group 1).

TABLE 3.3

ESTIMATED RESULTS BY MANUFACTURING INTENSITY.

Model	Income Group	Estimates	Total Effect	*t*-value (coefficient)	*t*-value (Total)
1	Group 1 (=20%, Ref)	0.2473***	0.2473***	3.5202	3.5202
	Group 2 (10–20%)	0.3561**	0.6034***	2.8323	4.1894
	Group 3 (<10%)	0.3139**	0.5612***	3.0705	4.5242
2	Group 1 (=20%, Ref)	0.2484***	0.2484***	3.3646	3.3646
	Group 2 (10–20%)	0.3824**	0.6308***	2.7193	3.9718
	Group 3 (<10%)	0.3444**	0.5928***	3.0593	4.4035
3	Group 1 (=20%, Ref)	0.2209**	0.2209**	3.0158	3.0158
	Group 2 (10–20%)	0.3419*	0.5628***	2.4568	3.5788
	Group 3 (<10%)	0.3656**	0.5866***	3.2892	4.4060

Note: All variables are transformed into growth rates by log difference.
Significance codes:
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
Source: Author (2025).

Table 3.3 presents the estimation results using manufacturing share groups. The pattern that emerges is remarkably consistent with the income-level analysis. In Model 3, economies with high manufacturing intensity (Group 1) exhibit a productivity elasticity with respect to energy efficiency of 0.2209, while economies in Groups 2 and 3 show substantially larger effects: 0.5628 for Group 2 and 0.5866 for Group 3. These magnitudes are strikingly similar to those observed in Table 3.2, despite the different classification criterion.

The similarity between Tables 3.2 and 3.3 provides strong support for the “diminishing returns” interpretation. Economies classified by income level or manufacturing intensity consistently show that those with less developed manufacturing sectors—or those farther from the efficiency frontier—experience larger productivity gains from energy efficiency improvements. The fact that this pattern holds across two independent classification schemes reduces concerns that idiosyncratic features of particular economy groupings drive the results.

Interestingly, Groups 2 and 3 show nearly identical total effects (0.5628 vs. 0.5866), and the difference between their interaction coefficients is not statistically significant (interaction coefficient for Group 2 is 0.3419* and for Group 3 is 0.3656**). This suggests that once manufacturing intensity falls below 20% of GDP, the marginal effect of energy efficiency plateaus. The key distinction is between manufacturing-intensive economies (Group 1) and the rest, rather than among different levels of lower manufacturing intensity.

One notable observation is that Hong Kong, classified as a high-income economy but with a very low manufacturing share (Group 3), exhibits the characteristics of Group 3 rather than other high-income economies. This suggests that manufacturing structure may be as important as overall economic development in shaping the productivity returns to energy efficiency. It also implies that as high-income service-oriented economies reduce their manufacturing bases, they may exhibit different patterns of productivity responses to energy efficiency investments than manufacturing-centered high-income economies.

4.2.4 Synthesis and Implications

The evidence from both income-level and manufacturing-intensity classifications points to a coherent interpretation: the productivity benefits of energy-efficiency improvements are largest in economies with less developed manufacturing, less capital-intensive manufacturing, or manufacturing farther from the technological frontier. This heterogeneity has important implications for policy design and international cooperation on energy efficiency.

For middle-income and less manufacturing-intensive economies, the results suggest that energy efficiency represents a high-return investment opportunity. The elasticities of 0.56 imply that a 10% improvement in energy efficiency could boost manufacturing productivity by approximately 5.6%—an economically substantial effect. Policymakers in these economies should prioritize energy efficiency as a core element of their industrial development strategy, recognizing that efficiency gains can serve as both a driver of competitiveness and a means of achieving environmental objectives. The “double dividend” appears particularly large for these economies.

For high-income, manufacturing-intensive economies, the more modest elasticity of 0.21–0.22 suggests that, while energy efficiency remains beneficial, the economic returns are more limited. This does not imply that these economies should neglect energy efficiency—environmental considerations alone may justify continued efforts—but calibrate their expectations for productivity gains accordingly. High-income economies may need to focus on frontier innovation in energy technologies and processes, where returns remain higher, rather than simply adopting existing best practices.

The consistency of results across different classification schemes also strengthens confidence in the diminishing-returns interpretation and reduces concerns about alternative explanations, such as measurement error or omitted variables. Convergent evidence from multiple angles indicates that the observed heterogeneity reflects genuine differences in the marginal productivity of energy-efficiency investments across economies at various stages of industrial development.

5. Policy Implications: Scaling Energy Efficiency for Productivity in Manufacturing

Chapter 4 provides rigorous evidence quantifying the energy efficiency-productivity relationship in APO manufacturing. The baseline elasticity of 0.43 indicates that a 1% improvement in efficiency generates 0.43% productivity growth (Section 4.2.1). Critically, this relationship varies systematically by development stage: HIEs exhibit elasticities of 0.21, while UMIEs and LMIEs demonstrate elasticities of 0.56—a differential exceeding 2.6 times (Section 4.2.2). For middle-income economies, a 1% efficiency improvement yields approximately 0.56% productivity gain, establishing energy efficiency as a first-order determinant of manufacturing competitiveness.

This chapter translates these findings into concrete policy recommendations structured along three dimensions: intervention type (direct versus indirect measures); time horizon (short-term versus long-term); and development context (differentiated by income level). All recommendations derive directly from the established empirical relationships discussed in Chapters 1-4.

5.1 Direct Measures to Raise Energy Efficiency

Direct regulatory and programmatic interventions establish the foundational policy architecture through which energy efficiency improvements translate systematically into productivity gains. These measures address market failures, including information asymmetries, split incentives, and coordination problems that prevent firms from capturing efficiency opportunities.

5.1.1 Priority Short-term Direct Measures (0–2 Years): Three measures are discussed below:

(1) Mandatory energy audits for large manufacturing facilities: Energy audits systematically identify efficiency improvement opportunities (EMOs) and provide implementation roadmaps. Section 2 demonstrates that industrial energy-efficiency measures improve productivity by reducing maintenance costs, enhancing product quality, and increasing operational flexibility. Given that energy costs account for 10–30% of manufacturing operating expenses (Section 1), audit-driven improvements directly reduce production costs.

Implementation: Legal mandates require periodic energy audits (every 3–4 years) for facilities above defined consumption thresholds (typically 1,000–5,000 toe). Establish accredited auditor certification programs and require EMO implementation reports linked to subsequent incentive eligibility. Japan and the ROK achieve 10–20% reductions in energy consumption through such programs.

(2) Minimum energy performance standards (MEPS) for key industrial equipment: MEPS prevents the entry of inefficient equipment, ensuring that capital stock replacement automatically improves fleet efficiency. Modern high-efficiency equipment incorporates advanced controls and optimized designs, enhancing operational reliability beyond energy savings. The USA's manufacturing experience documents a USD79 billion increase in revenue and a USD12.8 billion reduction in costs over 25 years, attributable to industrial MEPS.

Implementation: Prioritize high-impact equipment (industrial motors, boilers, compressors). Set initial MEPS at the current market median performance with scheduled increases every 3–5 years. Implement market surveillance, including import controls and field testing. Target 70%+ market transformation within 3–5 years.

(3) Accelerated equipment retrofit and replacement programs: Subsidizing the early retirement of obsolete equipment mitigates capital constraints, which are particularly acute for SMEs. Section 4.2.2 demonstrates that middle-income economies exhibit elasticities of 0.56 (equipment modernization programs yield particularly strong productivity benefits). Modern equipment not only lead to energy savings but also improve process control, reduce downtime, and enhance integration with digital systems.

Implementation: Establish tiered subsidies (20–50% of incremental costs), prioritizing deeper efficiency improvements and SMEs. Mandate independent technical verification of baselines and projected savings. Combine SME grants with preferential financing for larger firms. Germany and USA programs achieve 20–40% reductions in manufacturing energy consumption through blended, direct-enabling approaches.

5.1.2 Priority Long-term Direct Measures (3–7 Years). The measures are discussed below:

(1) **Progressive MEPS roadmaps with multistage stringency increases:** Building on initial MEPS, long-term strategies require pre-announced stringency trajectories that provide regulatory certainty while driving continuous innovation. Schedule standard increases occur at 3–5-year intervals, with levels announced 5–7 years in advance, enabling manufacturers to plan R&D investments. Japan's MEPS integration with Industry 4.0 demonstrates evolution toward smart, connected systems with embedded monitoring capabilities. This leverages the complementarity between energy efficiency and TFP documented in Section 4.2.1.

(2) **Comprehensive digital energy management infrastructure:** Scaling from pilots to comprehensive infrastructure requires: (a) industrial internet connectivity and sensor networks enabling real-time data collection; (b) open-source energy management platforms with standardized interfaces reducing vendor lock-in; (c) data governance frameworks balancing confidentiality with collective learning; (d) systematic capacity building through educational integration and professional certification; and (e) ESCO evolution toward digital service delivery models addressing SME capital constraints. Real-time monitoring, integrated with AI optimization, enables 20–30% efficiency gains while enhancing overall operational performance.

(3) **Sector-specific technology upgrading programs:** Manufacturing subsectors exhibit distinct energy-intensity profiles, requiring tailored interventions. Target major energy-consuming sectors (steel, chemicals, cement, and paper) with: sectoral benchmarking for establishing performance distributions; Best Available Technology (BAT) assessments documenting state-of-the-art processes; technology demonstration projects for derisking adoption; sectoral roadmaps with quantitative targets; and industry-specific technical assistance. This recognizes that productivity elasticities vary across sectors, reflecting sector-specific technological opportunities.

5.2 Indirect and Enabling Measures

Indirect instruments address underlying barriers related to financing, information, capacity, and coordination, amplifying the effectiveness of direct measures. The evidence that energy efficiency effects remain robust when controlling for TFP (Section 4.2.1) suggests that efficiency operates through multiple complementary channels that require adequate enabling infrastructure.

5.2.1 Priority Short-term Enabling Measures (0-2 Years). The measures are discussed below:

(1) **Green finance instruments and credit guarantee schemes:** Capital constraints constitute a primary barrier to efficient investment, particularly for SMEs in middle-income economies, where elasticities are highest (Section 4.2.2: elasticity of 0.56 for middle-

income economies versus 0.21 for HIEs). Energy efficiency projects typically feature favorable economics but face financing obstacles due to small transaction sizes and unfamiliarity among financial institutions.

Implementation: Establish dedicated credit lines through development banks providing preferential interest rates (2–4 percentage points below commercial rates). Implement partial-credit guarantee programs covering 50–70% of the loan amount. Design loan products with flexible terms aligned with energy savings cash flows. Germany's KfW program achieves leverage ratios of 1:3 to 1:5 (public-to-private funding), contributing to 20–40% reductions in manufacturing energy consumption.

(2) **Energy Efficiency Networks (EENs) and learning collaboratives:** Structured peer learning networks overcome information barriers through systematic benchmarking and knowledge sharing. European EENs document energy consumption reductions of 15–25% among participating firms, substantially exceeding the improvements among non-participants.

Implementation: Facilitate formation of 8–12 firm networks within similar manufacturing subsectors or geographic clusters. Provide initial technical support, including benchmarking and opportunity identification. Structure activities around regular data sharing, collective target setting, site visits, and joint problem-solving on 2–3-year cycles. Networks particularly benefit middle-income economies (with high baseline elasticities) by rapidly diffusing proven technologies.

(3) **Standardized Measurement, Reporting, and Verification (MRV) templates:** Credible performance measurement underpins all efficiency policies by establishing baselines, tracking progress, and verifying claims. Lack of standardized methodologies creates uncertainty and increases transaction costs.

Implementation: Develop sector-specific MRV protocols balancing rigor with practicality. Establish energy consumption measurement hierarchies (direct metering preferred, engineering calculations acceptable). Create reporting templates standardizing data collection. Develop verification protocols for independent assessment. Given substantial heterogeneity in elasticities across economy groups (Sections 4.2.2–4.2.3), MRV systems must capture sufficient contextual detail to support differentiated policy calibration.

5.2.2 Priority Long-term Enabling Measures (3–7 Years). The measures are discussed below:

(1) **Industrial energy and emissions data infrastructure:** Building upon short-term MRV, comprehensive infrastructure requires (a) universal energy consumption and emissions reporting for facilities above thresholds, integrated with environmental permitting; (b) anonymized benchmarking databases enabling statistical analysis of performance distributions; (c) public access balancing confidentiality with accountability; and (d) integration with research infrastructure enabling sophisticated analysis beyond the Section 4 baseline.

This infrastructure transforms energy efficiency from a compliance exercise into a data-driven, continuous-improvement system.

(2) **Carbon pricing integration and competitiveness transition support:** As carbon pricing becomes central to climate policy, manufacturing sectors face competitiveness challenges requiring coordinated responses: (a) domestic carbon pricing (ETS or tax) with manufacturing coverage and revenue recycling toward efficiency investments; (b) border carbon adjustment participation, ensuring domestic manufacturers compete on a level playing field; (c) regional coordination among APO members on pricing approaches; and (d) targeted assistance for trade-exposed sectors structured to reinforce efficiency incentives.

Carbon pricing integration directly aligns with the "double dividend" framework (Section 4.2.4) by ensuring that environmental improvements generate economic returns.

(3) **Just transition and workforce development programs:** Productivity transformations associated with efficiency improvements (Sections 4.2.1–4.2.3) involve employment transitions requiring proactive management, including (a) integration of energy management and digital manufacturing competencies into technical education curricula; (b) worker transition assistance, including retraining and income support, particularly critical in middle-income economies where efficiency improvements enable substantial output increases with smaller employment growth; (c) regional economic development ensuring manufacturing productivity gains contribute to broad-based prosperity; and (d) social dialogue mechanisms ensuring worker participation in efficiency policy design.

5.3 Differentiated Strategies by Income Level

The empirical heterogeneity documented in Sections 4.2.2 and 4.2.3 mandates tailored policy approaches. HIEs with elasticities around 0.21 face different optimization problems than middle-income economies with elasticities around 0.56 (approximately 2.6 times higher).

5.3.1 High-income Economies

They have advanced manufacturing sectors with established energy management infrastructure, mature regulatory frameworks, and high capital intensity. Each 1% improvement in efficiency yields a 0.21% productivity gain, reflecting positions near the efficiency frontier where marginal returns diminish.

Their long-term priorities would be:

(1) Comprehensive industrial decarbonization pathways integrating efficiency, electrification, and renewable energy—system-level perspective maximizes value from efficiency improvements by connecting to broader transformation;

(2) Global technology development leadership positioning HIEs as developers and exporters of efficiency technologies;

(3) Regional capacity building leveraging HIEs' technical expertise to support middle-income APO members through technology transfer and joint demonstrations; and

(4) Circular economy integration emphasizing material efficiency and waste heat utilization, where additional gains remain available.

5.3.2 Middle-income Economies

Each 1% improvement in energy efficiency generates 0.56% increase in productivity, indicating a substantial return, thereby justifying aggressive efficiency investment programs emphasizing rapid diffusion of proven technologies.

Their short-term priorities would be:

(1) Foundational regulatory infrastructure—establishing mandatory audit requirements and EnMS frameworks targeting large energy consumers initially, and leveraging international technical assistance (IEA, APO) for rapid institutional development;

(2) MEPS for priority equipment using international reference standards to accelerate implementation; coordinating across multiple APO members, creating larger harmonized markets; major retrofit program investment with 30–50% public cofinancing justified by high productivity returns; combining with green finance instruments, maximizing private capital mobilization; and

(3) Capacity building investment in auditor training, EnMS practitioners, and program administrators; and SME access through simplified compliance pathways and subsidized group audits.

Long-term priorities would be:

(4) Systematic frontier-closing through multi-year programs targeting convergence with best practices—sustained efficiency improvements generate substantial cumulative productivity gains, justifying persistent policy effort given the high productivity return rate (0.56% gain per 1% efficiency improvement);

(5) Manufacturing upgrading integration connecting energy efficiency to broader agendas, including quality management and workforce skills—integrated approaches maximize returns by reinforcing multiple improvement pathways;

(6) South–South technology transfer among middle-income APO members, enabling shared learning and joint procurement, achieving scale economies; and

(7) Domestic green finance ecosystem development, reducing dependence on external finance, and enabling sustainable scaling.

5.3.3 Manufacturing Intensity Considerations

Analysis by manufacturing intensity (Section 4.2.3) provides complementary insights:

- High intensity (≥20% GDP, productivity return 0.22) should integrate efficiency policies with industrial competitiveness strategies;
- Medium intensity (10–20% GDP, productivity return 0.56–0.59) should view efficiency as a pathway to increasing manufacturing's economic contribution; and
- Low intensity (<10% GDP, productivity return 0.59) requires targeted approaches focusing on existing operations where efficiency improvements yield high returns without overinvesting in manufacturing-specific infrastructure.

5.4 Illustrative Policy Packages

Package A: High-income Manufacturing Leader (Productivity Return Rate 0.21).

- **Representative economies:** Japan, the ROK, and the ROC.
- **Components:** (1) Digital energy management platform deployed across large manufacturers within 18 months; (2) MEPS progression roadmap through 2035 with smart equipment requirements; (3) sector-specific technology roadmaps for energy-intensive industries with R&D support; (4) national energy-productivity database operational by second year; (5) regional technology transfer program supporting middle-income APO members; and (6) carbon pricing strengthening with revenue recycling to productivity investments.
- **Financing:** Government R&D funding (0.05–0.1% GDP annually), development bank credit lines (mobilizing 3–5x private capital), and carbon pricing revenue recycling.
- **Expected outcomes:** 15–20% manufacturing energy intensity reduction by 2030; 3–4% cumulative productivity contribution (0.21 elasticity × 15–20% efficiency gain); and global technology leadership positioning.

Package B: Middle-income Rapid Industrializer (Productivity Return Rate 0.56).

- **Representative economies:** Vietnam, Bangladesh, Cambodia, Thailand, and Malaysia.
- **Components:** (1) Mandatory energy audit requirements for facilities 1,000 toe within 12 months, expanding to 500 toe by third year; (2) ISO 50001 EnMS incentive program with subsidized certification; (3) MEPS for motors, pumps, fans, compressors with three-year phase-in; (4) equipment retrofit program with 40% subsidy for replacement exceeding 20% efficiency improvement; (5) rapid auditor training targeting 500 certified auditors within 24 months; (6) green finance credit facility (USD200–500M) with partial guarantees; (7) and Energy Efficiency Network pilot covering 50 facilities.
- **Financing:** Blended finance combining multilateral development bank loans (40%); government cofinancing (30%); and private-sector contributions (30%). Heavy frontloading of public resources with declining public share as markets mature.
- **Expected outcomes:** 25–35% manufacturing energy intensity reduction by 2030; 14–20% cumulative productivity contribution (0.56 elasticity × 25-35% efficiency gain); and enhanced competitiveness in global supply chains.

5.5 Implementation Roadmap and Governance

Robust governance structures, clear institutional assignments, and adaptive management systems are essential for translating policy packages into realized productivity gains.

- **Lead agency designation:** Establish or designate a lead energy efficiency authority with a clear statutory mandate, adequate resources, and coordination powers. Agency functions include policy development, standard-setting, program design, data collection, enforcement, and stakeholder engagement. Authority requirements include legal foundation through primary legislation, budget security, enforcement powers, and coordination authority across government agencies.

- **Interagency coordination:** Core coordinating group (lead efficiency authority plus ministries of industry, finance, environment, trade, and employment) meeting quarterly. Technical working groups addressing standards, financing, capacity building, and international cooperation. Regional/local coordination connecting national policies with provincial implementation.

- **Platform development:** National efficiency knowledge platform providing technology information, best practice documentation, performance data, program information, and training resources. Technology demonstration network providing hands-on learning venues. Regional collaboration platform facilitating knowledge exchange among APO members.

- **Data governance:** Standardized methodologies ensuring consistency; quality assurance through independent verification; data security protecting commercially sensitive information; public access balancing confidentiality with accountability; and data-driven management using collected data for program evaluation and policy refinement.

- **Capacity building:** Government capacity through training programs for administrators and inspectors; technical service provider capacity through auditor and ESCO professional development; manufacturing sector capacity through energy manager training; academic capacity through university programs and research funding; and financial sector capacity through training on efficiency project evaluation.

- **Adaptive management:** Annual performance reviews informing budget allocations; structured pilots testing alternative designs; stakeholder feedback mechanisms identifying practical obstacles; international peer learning; and sunset provisions triggering program continuation, modification, or termination decisions.

5.6 Monitoring and Evaluation Framework

Systematic monitoring and rigorous evaluation ensure policy accountability and enable evidence-based refinement.

- **Primary Outcome Indicators:**

  (1) Manufacturing energy intensity (toe per million GDP)—target annual reduction 2–3% for HIEs, 3-5% for middle-income economies;

  (2) Manufacturing labor productivity growth—target attributable contribution based on efficiency improvements and relevant elasticity (0.21 for HIEs, 0.56 for UMIEs/LMIEs);

  (3) CO2 emissions intensity; and

  (4) Manufacturing competitiveness metrics, including trade balance and unit labor costs.

- **Intermediate Outcome Indicators:**

  (1) Facility audit coverage—target 80%+ compliance within two years;

  (2) EnMS certification levels—target 30–50% of large manufacturers within five years;

  (3) High-efficiency equipment market share—target 70%+ within 3–5 years of MEPS implementation; and

  (4) Efficiency investment volumes—target 0.5–1.5% of manufacturing GDP.

- **Implementation Indicators:**

  (1) Program participation rates—target 40–60% participation among eligible entities;

  (2) Incentive utilization rates—target 80%+ utilization; and

  (3) Technical capacity metrics—sufficient certified auditors and consultants.

- **Baseline-to-target Approach:** Comprehensive baseline data collection documenting pre-policy conditions. Quantitative performance targets for short-term (two years); medium-term (five years); and long-term (seven or more years) horizons, differentiated by economy context and evidence-based from elasticity estimates.

- **Data Collection:** Administrative data from program implementation; mandatory/voluntary facility reporting; periodic sample surveys; and independent verification through third-party audits.

- **Evaluation Design:** Process evaluation assessing implementation fidelity; outcome evaluation measuring program effects through before–after comparisons and quasi-experimental designs; impact evaluation isolating causal effects; and cost-effectiveness analysis comparing costs to achieved outcomes.

- **Feedback Loops:** Performance dashboards for real-time monitoring; quarterly implementation reviews; annual performance assessments; mid-term comprehensive evaluations (year 3–4) to inform major adjustments; and policy adjustment mechanisms to modify programs based on evidence.

6 Conclusion

The empirical evidence from Chapter 4 establishes that energy efficiency improvements generate substantial manufacturing productivity gains across APO member economies, with elasticities averaging 0.43 overall and reaching 0.56 in middle-income contexts. A 10% efficiency improvement translates into 4–6% productivity growth—an economically significant effect that justifies energy efficiency as a core industrial policy rather than a peripheral environmental concern.

The pronounced heterogeneity in productivity returns, with middle-income economies achieving roughly 2.6 times the gains of high-income economies, mandates differentiated policy approaches. Middle-income economies should pursue aggressive investment in efficiency, leveraging high returns to accelerate industrial development. High-income economies should emphasize frontier innovation and system integration where marginal returns to conventional measures diminish.

Effective policy requires combining direct regulatory measures (audits, MEPS, and EnMS) with enabling instruments (finance, capacity building, and networks) to capture synergies and maximize productivity gains. Implementation success depends on robust governance, including designated lead agencies, effective coordination, capacity building, comprehensive data infrastructure, and adaptive management systems.

The "double dividend" framework, i.e., achieving productivity gains and environmental improvements simultaneously, operates most powerfully in middle-income economies pursuing industrial development while facing environmental constraints. For these economies, energy efficiency offers a rare policy opportunity aligning economic and environmental objectives. Realizing this potential requires sustained political commitment, adequate resources, institutional capacity development, and evidence-based management over multiyear horizons.

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CHAPTER 4

DEVELOPING COMPOSITE INDICATORS FOR ENERGY EFFICIENCY AND PRODUCTIVITY BENCHMARKING

1. Introduction

Within this broader context, energy efficiency has served as a cornerstone of the APO's Green Productivity (GP) strategy, providing a foundation for both sustainable economic development and environmental responsibility. The development of GP is important for setting the APO's GP initiative on a new trajectory aligned with the increasing global awareness and actions to achieve sustainability. Measuring energy efficiency contributes to reducing emissions, enhancing industrial competitiveness, and ensuring long-term energy security. However, at the macro and micro (sectoral) levels, it requires robust and reliable indicators. This endeavor requires confronting the complexities of contemporary sustainability frameworks, such as net-zero emissions policies and the UN Sustainable Development Goals (SDGs), thereby making the project inherently challenging. GP plays a vital role in achieving sustainability, a shared global goal.

Energy efficiency is closely linked to energy use. The patterns of energy use evolve alongside different phases of economic development. Several researchers have argued that the energy intensity of an economy follows an inverted U-shaped trajectory as per capita income rises, where energy intensity is defined as the amount of energy consumed per unit of economic output (Medlock and Soligo, 2001). This relationship can be explained by both inter-industry structural changes and intra-industry improvements in energy efficiency during the course of development. In the early stages of industrialization, energy consumption increases sharply as industrial activity expands. In the post-industrial phase, however, the service sector grows faster than manufacturing, leading to slower growth in energy demand relative to GDP. At the same time, technological progress introduces more energy-efficient capital, thereby reducing the energy required to produce a given level of output. In such a context, energy efficiency serves as a source of competitive advantage for both economies and firms.

Here, Energy Efficiency Indicator (EEI) is defined as the inverse of energy intensity, that is, the amount of GDP (or value added) produced per unit of real energy input.

$$EEI = \frac{Units\ of\ the\ Value\ Added\ (or\ GDP)}{Units\ of\ energy} \tag{1}$$

Energy intensity—the ratio of energy consumption to economic output—provides a straightforward measure of aggregate energy savings across macroeconomic and industrial sectors. Still, it has clear limitations in capturing actual changes in energy efficiency. For example, an increase in energy efficiency (a decline in energy intensity) may reflect a shift from energy-intensive industries to service sectors rather than genuine technological improvements. Moreover, the discrepancy between actual micro-level efficiency and the economic variables embedded in energy-efficiency formulas may hinder proper aggregation, potentially leading to misleading efficiency trends driven by external economic factors rather than true technological or process-level improvements. Due to these issues, energy intensity is limited in explaining improvements in specific technological processes. However, when used with control variables in regression models or subjected to robustness checks, it remains a useful indicator of temporal trends in overall energy efficiency at the national or sectoral level.

To obtain a more accurate understanding of changes in national energy efficiency, it is essential to use metrics that overcome EEI's inherent limitations. This requires the development of a clearer EEI grounded in the first-law thermodynamic definition of efficiency. However, such an approach is more suitable for evaluating specific projects (such as cost–benefit analyses of particular R&D programs) than for constructing aggregate national-level variables. The divergence between economic and engineering definitions of energy efficiency will be discussed later. At this stage, the most feasible option is to develop detailed energy consumption data to construct sector-level EEI. In doing so, not only economic expertise but also a deep understanding of energy engineering is crucial. The case of building the Republic of Korea (ROK)'s Energy Balance dataset illustrates the importance of integrating engineering knowledge into the process.

In this chapter, we introduce the procedure for compiling micro-level statistical data and aggregating them into macro-level indicators, using the ROK and Japan as case studies. The rest of the paper proceeds as follows: Section 2 presents the background for a refined EEI framework; Section 3 presents strategies to address the limitations of traditional measures of energy intensity; Sections 4 and 5 cover the cases of the ROK and Japan, respectively; and Section 6 provides the conclusion.

2. The Need for Refined EEI Frameworks

To gain a more accurate understanding of changes in national energy efficiency, it is essential to adopt metrics that go beyond EEI's inherent limitations. Precise measurement of energy efficiency requires a structured framework that accounts for complex industrial facilities and energy flows, multiple products and fuels, and the influence of production rates on efficiency. However, capturing these dynamics at the macro level is challenging.

The problem is the lack of a reliable indicator of macroeconomic progress in energy efficiency. An appropriate framework must be grounded in a clear definition of "energy efficiency." Despite the definition varying, energy efficiency is often used as a general term for achieving the same level of service or useful output with less energy. The International Energy Agency (IEA), which is the most prominent source of energy sector statistics, defines energy efficiency as, "a way of managing and restraining the growth in energy consumption. A company is called more energy efficient if it delivers more services for the same energy input or the same services for less energy input." [1]

In energy statistics and econometrics, it is often assumed that energy intensity and energy efficiency are interchangeable measures of an economy's energy performance. It challenges this assumption by underscoring the discrepancy between energy efficiency as an engineering concept and energy intensity as defined in macroeconomic statistics. Engineering-based energy efficiency is rooted in

[1] International Energy Agency; 2014 http://www.iea.org/topics/energyefficiency [accessed 03.02.14]

thermodynamic principles, whereas energy intensity incorporates economic elements. From a practical standpoint, energy intensity captures technical and engineering efficiency only indirectly and with a delay, thereby limiting its value for management and policymaking.

From a national perspective, relying solely on EEI as a metric poses significant challenges in capturing true energy efficiency. Although energy intensity is closely correlated with efficiency at the end-use level, this relationship weakens at higher levels of aggregation, where structural and economic factors beyond efficiency influence outcomes. Although EEI remains the most widely used aggregate indicator of national energy use, it has been criticized for oversimplifying complex dynamics.

One possible approach is to construct a more refined proxy variable, which requires detailed data on energy consumption flows by sector and end use. It begins with a reference to energy consumption. It then introduces the idea of "restraining the growth in energy consumption," which, mathematically, corresponds to the time derivative of consumption—a dynamic characteristic. To make this measure meaningful and policy-relevant, it is essential to establish detailed, consistent datasets across sectors, fuels, and activities, thereby enabling the construction of precise energy-intensity metrics. Such data-driven approaches not only strengthen the analytical foundation of energy efficiency policies but also facilitate benchmarking, cross-economy comparisons, and the design of targeted strategies that align with global sustainability goals.

2.1 Strategies to Overcome the Limitations of Traditional EEI

This section reviews strategies proposed in the literature for overcoming the limitations of traditional EEI measures.

2.1.1 Relative EEI

Choi et al. (2017) present firm-level evidence on how the productive use of energy across industries affects economic growth. Using firm-level data from 21 manufacturing industries in France, Germany, Japan, the ROK, the UK, and the USA for the period 1991–2005, they estimate the impact of improvements (or deteriorations) in industry-level EEI (or energy intensity) on a firm's growth. To construct industry-level energy intensity measures for the sample economies, the authors draw on the EU KLEMS and IEA databases. Energy intensity is defined as the ratio of real energy use (measured in tons of oil equivalent, i.e., toe) to real value added, where real energy use is derived by recalculating IEA final energy consumption data in toe using the EU KLEMS energy input volume indices.

A key challenge in measurement is distinguishing industrial energy intensity from natural energy demand rather than from industry-specific energy dependence and usage patterns. As energy intensity declines, energy-intensive industries benefit disproportionately from efficiency gains, as they can achieve greater cost savings from reduced energy inputs. Moreover, energy-use patterns differ substantially across industries, and technologies applied in one sector are often not transferable to others. Industry-specific factors do not solely drive changes in energy intensity; they can also reflect economy-specific conditions, such as resource availability and regulatory frameworks. For example, rising energy intensity may stem from market inefficiencies if energy price regulations distort price mechanisms, thereby limiting input substitution (Parker and Liddle, 2016). Given that these influences vary across economies, the data collected from different economies may potentially be biased. Therefore, using aggregate measures without accounting for differences across industries or economies can lead to inaccurate conclusions.

One effective approach to addressing this issue is to measure the relative distance of an industry's energy intensity from that of a reference industry in an economy with open, resource-abundant, and market-friendly energy environments. This reference case is assumed to reflect the level of energy intensity naturally dictated by technology, since firms in such environments face minimal barriers to using their preferred levels of energy consumption. Choi et al. (2017) introduced the concept of relative energy efficiency (REE), which is the ratio of a USA industry's energy intensity to the economy's industry energy intensity to correct for improvements in the industry's own specific energy use. The distance from the reference case of the industry k and the country c is defined as:

$$REE_{k,c} = \frac{EI_{k,US}}{EI_{k,c}} \tag{2}$$

where $EI_{k,c}$ and $EI_{k,US}$ are the industry k's energy intensity of country c and the USA, respectively. With respect to the USA, the value of REE is equal to 1. For economies that use energy less intensively than in the USA, the value of REE is greater than 1. In contrast, for economies that consume energy more intensively than in the USA, the value of REE is less than 1.

Choi et al. (2017) developed a new measure that captures common industry-specific technological traits while remaining independent of economy-level characteristics, thereby ensuring cross-economy comparability. This approach, which designates the USA as the benchmark, is not entirely novel. Similar strategies have been employed in the finance literature, where industry-specific natural measures independent of national factors have been constructed. Example include measures of external finance dependence (Rajan and Zingales, 1998); opaqueness (Durnev, Morck, and Yeung, 2004); growth opportunities (Fisman and Love, 2007); and the share of small firms (Beck et al., 2008). Consistent with these precedents, our new index of energy intensity is well supported by prior literature.

Figure 4.1 shows that while energy efficiency (EE) declined in France, Germany, Japan, and the USA, it remained relatively stable in the UK and the ROK. Notably, REE in the USA improved rapidly during the 2000s. From a comparative perspective, Europe's productivity slowdown is particularly disappointing, given that the USA's productivity growth accelerated from the mid-1990s, driven by substantial gains in high-productivity industries producing information and communications technology (ICT) equipment as well as capital-deepening effects from widespread ICT investments across the economy. By 2005, the USA recorded the lowest EE among all sample economies, reflecting its position as a technological frontier with a market-friendly environment for energy use. In contrast, a comparison of REE with the USA's reference industries reveals no clear patterns for France, Germany, or Japan. However, the ROK and the UK exhibit an overall upward trend in REE since 1991. Although both the UK and the USA had high ratios of natural resource rents to population, the ROK's ratio was exceptionally low, underscoring the scarcity of natural resources in the ROK. Indeed, the ROK's trends appear distinctive—unlike other economies, its REE rose more sharply and persistently throughout most of the sample period.

To construct industry-level EEI and REE, we draw on the EU KLEMS and IEA databases. The EU KLEMS database, covering the period 1970–2005, provides annual time-series data on industry-level real value added and energy input volume indices (base year 1995) for EU member economies and several other economies. EEI is defined as real value added divided by real energy use (in toe). However, because EU KLEMS provides only indices of real energy use rather than quantities, we estimate quantities in three steps. First, we set 2005 as the reference year and obtain industrial real energy use from the IEA Energy Balances database. Since the EU KLEMS (based on NACE Rev.

FIGURE 4.1

EEI AND PER CAPITA NATURAL RESOURCE RENTS OF SELECT ECONOMIES.

Notes: EE (right axis) = the ratio of total real value added in the manufacturing sector to the total energy used in that sector. REE (left axis) = the energy intensity of an economy relative to that of the USA; resource rents per capita are the ratio of total natural resource rents to the population aged 15 or older.
Sources: Choi et al. (2017); IEA, EU KLEMS, and the World Bank.

1) is more disaggregated than the IEA classification, we align the two by redistributing the IEA's 2005 industry-level energy data to NACE Rev. 1, using industry energy shares derived from EU KLEMS nominal energy-use data. This yields energy use quantities disaggregated to the two-digit industry level. Second, we extend the time series of industrial energy use by applying the EU KLEMS energy input indices to the 2005 benchmark quantities. Third, because EU KLEMS measures real value added in national currencies, we convert these figures into a common reference currency (USD) using purchasing power parity (PPP) exchange rates to ensure international comparability of EEI across economies.

TABLE 4.1

MANUFACTURING SECTORS IN ENERGY BALANCE AND RU KLEMS DATABASES.

	EU KLEMS	
Energy Balance	**Code**	**Industry Description**
Food and tobacco	15–16	Food, beverages, and tobacco
Textile and leather	17–19	Textiles, wearing apparel, leather, and footwear
Wood and wood products	20	Wood and cork
Paper, pulp, and printing	21–22	Pulp, paper, printing, publishing, and reproduction
Chemical and petrochemical	24–25	Chemical and rubber
Non-metallic minerals	26	Non-metallic minerals
Iron and steel	27–28	Basic metal and fabricated metal products
Non-ferrous metal		
Machinery	29	Machinery
	30–33	Office, accounting, computing machinery; electrical machinery Radio, television, and communication equipment; Medical, precision, and optical instruments
Transport equipment	34–35	Motor vehicles; trailers; semi-trailers; other transport equipment
Non-specified	36	Furniture, manufacturing n.e.c.

Source: Choi et al. (2017); IEA and EU KLEMS.

2.1.2 Price Elasticities

Recent studies have demonstrated that both the economic structure and technology-driven efficiency are key determinants of an economy's EEI. Structural differences, in particular, play a significant role in explaining variations in observed energy intensity. Yet these differences extend beyond those observed energy efficiencies, and this work examines differences in price response. Given manufacturing's economic significance, diversity, and, in many cases, high dependence on energy, it is crucial to understand the effects of rising energy prices on manufacturing's energy consumption, particularly on changes in EEI. While higher energy prices are often assumed to negatively affect economic performance—by reducing output or encouraging the relocation of manufacturing activities—these are not the only drivers of changes in EEI.

To account for such heterogeneity and interdependence, Parker and Liddle (2016) examined the role of energy prices in shaping efficiency within the OECD manufacturing sector between 1980 and 2009. Their analysis employed a flexible, robust econometric approach to estimate the price elasticities of the factors driving EEI. Using a Logarithmic Mean Divisia Index (LMDI) framework, they first decomposed changes in EEI into two components—efficiency change and structural change—for 14 OECD economies over the period. In the second stage, they investigated cross-economy differences in price responses to these two drivers, i.e., efficiency change and structural change. Consistent with expectations, the results highlighted that structural differences across OECD manufacturing sectors significantly affect estimated price elasticities.

The decomposition results reaffirm prior findings that efficiency improvements are the primary driver of observed improvement in EEI. Moreover, the second-stage analysis suggests that rising energy prices can enhance efficiency, though the magnitude and direction of these effects vary across economies. Parker and Liddle's (2016) finding that structural change is highly sensitive to price fluctuations underscores the importance of controlling for structural change when analyzing variations in EEI. This underscores the importance of accounting for heterogeneity and cross-sectional dependence in EEI research.

Parker and Liddle (2016) also illustrate the use of the decomposed components of energy efficiency and structural change, derived from the LMDI methodology, as control variables in regression analysis. Using a similar approach, Choi et al. (2017) also controlled for the structural change component in their regression models.

3. Building Industry-level EEI Data Using Energy Balances

3.1 Background

Accurately evaluating an economy's energy efficiency requires a systematic framework that links physical energy flows with economic performance. While EEI is widely used as a proxy for energy efficiency, the reliability of such indicators depends on the consistency and depth of the underlying energy statistics. In particular, the construction of industry-level EEI data—expressed as the ratio of real value added to energy use—requires harmonizing two distinct types of information: physical energy data from national energy statistics and economic data from national accounts.

The key data required to construct EEI statistics are: detailed energy supply and consumption data disaggregated by demand and supply categories, which are provided in the Energy Balances database, which is a key database that includes detailed information on energy consumption flows. The Energy Balances provides a complete overview of an economy's energy supply and demand chain, showing where energy comes from, how it is transformed, and where it is consumed. Since the IEA and other organizations standardize balances, they allow for cross-economy comparisons of energy systems. Policymakers use them to evaluate energy security, energy efficiency trends, and import dependence, and to design measures for decarbonization and integration of renewables. Energy balances are the foundation for calculating key indicators, such as energy intensity, CO_2 emissions, and efficiency metrics, at both national and sectoral levels. By showing transformation efficiencies and sectoral consumption patterns, they support energy modeling, long-term projections, and infrastructure planning.

Rows (flows). These represent the stages of the energy system, from supply (domestic production, imports, exports, and stock changes) through transformation processes (refining, power generation, and heat production), energy industry's own use, distribution losses, and finally final consumption (by sectors such as industry, transport, households, services, and non-energy use).

Columns (commodities). These represent the different energy products, both primary (e.g., coal, crude oil, natural gas, and renewables) and secondary (e.g., petroleum products, electricity, and heat). Each column traces the flow of that commodity through the entire system.

Industry-level energy intensity is calculated as the ratio of real energy use to real value added. Real energy use (measured in toe) can be obtained from national energy balance statistics. An energy balance is a matrix that organizes all energy flows within an economy over a given period (usually one year).

3.2 Five Steps of the Procedure

We present a comprehensive explanation of how such data can be compiled, drawing on the standardized methodologies used by the Korea Energy Economics Institute (KEEI) and Japan's Institute of Energy Economics (IEEJ). The process consists of five sequential stages:

(1) compiling the commodity balance;

(2) constructing the energy balance;

(3) extracting industrial energy consumption;

(4) integrating economic and energy datasets; and

(5) calculating industry-level energy intensity.

Each step contributes to improving the methodological consistency and comparability of national and sectoral energy indicators.

Step 1: Compiling the Commodity Balance. The process begins with constructing a commodity balance for each energy product, such as coal, oil, natural gas, electricity, heat, and renewable energy. This table describes, in physical terms, how each energy commodity is supplied and used within an economy over a given period. The commodity balance identifies the total supply (including domestic production, imports, and stock changes) and the total use, which comprises energy transformation processes (such as power generation or refining), energy industry own use, transmission losses, and final consumption across various sectors, including industry, transport, households, commerce, and the public sector.

To ensure comparability, each energy product must be expressed in its appropriate natural unit, such as tons for coal, cubic meters for gas, kiloliters for oil, and kilowatt-hours (kWh) for electricity. After harmonizing measurement units and classifications, the total supply and demand for each energy commodity are reconciled. Any discrepancy between the two sides is recorded as a statistical difference. The resulting Commodity Balance Table serves as the foundation for all subsequent steps, providing a clear, internally consistent representation of national energy flows that enables analysts to identify where energy originates, how it is transformed, and which sectors ultimately consume it.

Step 2: Constructing the Energy Balance. Once the commodity balances for all major energy products are completed, the next stage is to integrate them into a single framework known as the Energy Balance. This process converts all commodities—originally expressed in different physical units—into a common energy unit, such as toe or terajoules (TJ). The conversion is achieved by applying official calorific conversion factors, typically those published by the Korea Energy Agency or the International Energy Agency (IEA). For example, 1 ton of coal is approximately 0.7 tow, and 1,000 kWh of electricity is about 0.086 toe.

By converting all fuels to a common unit, the energy balance enables direct comparison and aggregation of energy flows across different energy sources. The integrated Energy Balance Matrix is structured as follows: the rows represent the stages of energy flow (production, imports, transformation, final consumption, and losses), while the columns represent the energy commodities (coal, oil, gas, electricity, heat, and renewables). In this matrix, the transformation efficiency of each process, such as electricity generation, oil refining, or coking, is also incorporated by applying input–output ratios that reflect actual conversion performance.

Energy transformation processes convert one form of energy into another (for example, coal to electricity, oil to petroleum products, or gas to heat). These processes incur inherent efficiency losses that must be accounted for in the Energy Balance for accuracy.

The formula for the calculation is:

$$\text{Final Energy Output (toe)} = \text{Input Energy (toe)} \times \text{Conversion Efficiency (\%)}$$

Example calculations are as follows:

- Thermal power plant: 100 toe of coal input → 38 toe of electricity output (62 toe lost as heat)
- Oil Refinery: 100 toe of crude oil input → 90 toe of refined products (10 toe loss)

Additionally, energy industry’s own consumption (e.g., by refineries and power plants) is recorded under “Energy Industry Own Use,” whereas distribution losses (e.g., electricity transmission losses, or gas leakage) are recorded under “Losses.” This ensures that the accounting identity “Supply = Demand” holds.

The final product is a national energy balance table (Figure 4.3) that consolidates the economy’s entire energy system into a single, coherent picture. It shows not only how much energy is produced and consumed, but also how efficiently energy is converted from one form to another. This table provides the empirical basis for analyzing national energy efficiency and for deriving sector-specific consumption indicators.

Step 3: Extracting Industrial Energy Consumption. Within the energy balance, one of the most policy-relevant categories is the final energy consumption by sector, particularly in the industrial sector. Extracting industrial energy consumption data enables researchers to evaluate how energy-use patterns vary across industries and how structural or technological changes affect the overall efficiency. The industrial sector is typically divided into detailed sub-industries, such as food and tobacco; textiles; wood and paper; chemicals and petrochemicals; non-metallic minerals; basic metals (iron and steel, non-ferrous metals); machinery; transport equipment; and other manufacturing activities.

Energy consumption for each sub-industry is converted into toe using the calorific conversion factors described earlier. At this stage, data classification and consistency are crucial. Industrial definitions must align with national standard classifications (e.g., KSIC in the ROK or NACE Rev.1 in Europe), ensuring that each industry's energy use can subsequently be matched to the corresponding economic output data. The resulting dataset provides the foundation for estimating industry-level energy intensity.

Step 4: Integrating with Economic Data. To evaluate energy efficiency, energy consumption data must be linked to economic performance indicators. Therefore, the next step is to integrate the energy consumption dataset with industry-level real value-added data from national accounts or central bank statistics. The value-added figures are expressed in constant prices to remove the effects of inflation and, when necessary, are converted into a common currency (e.g., USD) using purchasing power parity (PPP) exchange rates to ensure international comparability.

This integration requires careful alignment between the industrial classifications of the energy and economic datasets. Each industry's energy consumption (in toe) is matched to its real value added for the same year and industry code. The resulting merged dataset provides a consistent basis for quantifying energy intensity at the industry level. By combining physical and economic data, analysts can examine how energy consumption scales with production output, enabling the identification of both technological improvements and structural changes in industrial composition.

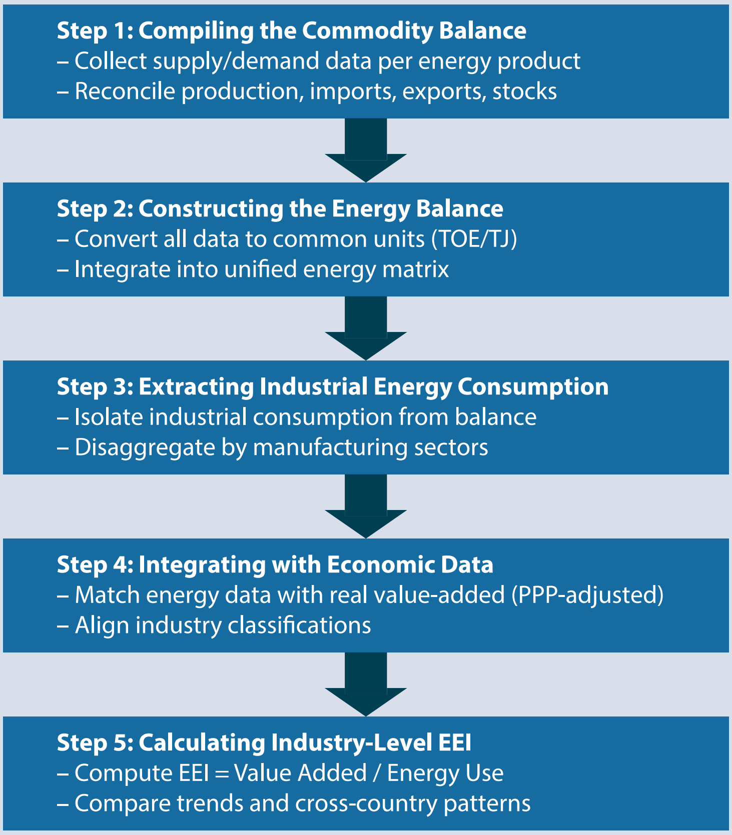
Step 5: Calculating Industry-level EEI. The final step is to calculate the EEI of each industry. EEI (EEI_i) is defined as the ratio of real value added (VA_i) to total energy use (E_i) in that industry. This indicator represents the energy required to produce one unit of economic output and serves as a direct measure of energy performance. Once calculated, the values can be compared across industries, over time, or between economies.

The resulting time-series data reveal whether improvements in energy efficiency are driven by technological innovation, structural shifts toward less energy-intensive industries, or other macroeconomic factors. Cross-validation with IEA and OECD data ensures that the constructed indicators are robust and consistent with international standards.

The five-step procedure described above provides a comprehensive, replicable framework for constructing industry-level energy intensity indicators from national energy statistics. Beginning with commodity balances and culminating in internationally comparable intensity measures, the process bridges the gap between engineering-based energy data and macroeconomic efficiency analysis. By linking the physical flow of energy with its economic output, this approach enables policymakers, engineers, and researchers to understand the structural and technological drivers of energy efficiency. Moreover, it supports evidence-based policymaking by providing a consistent statistical foundation for monitoring industrial energy performance, designing targeted efficiency programs, and benchmarking national progress toward sustainability and net-zero goals.

FIGURE 4.2

FLOWCHART FOR BUILDING INDUSTRY-LEVEL EEI DATA.



Source: Author (2025)

3.3 Basic Concepts

The fundamental concepts for constructing the Commodity Balance, the foundational database, are introduced here. We present the basic concepts of energy statistics—what fuels and energy are, the distinction between primary and secondary energy products, how energy products are classified and measured, and the relationship between product balances and the overall energy balance—to provide a foundation for energy statistics.

For this purpose, much of the report draws on and organizes material from the IEA's Energy Statistics Manual, which serves as the standard reference for energy balance revisions, and from the Study on the Reform of National Energy Statistics, published by the Korea Energy Economics Institute during earlier revision efforts. Where relevant, the report also incorporates information from Eurostat and the USA's EIA, allowing for comparisons of differences and diversity across statistical systems. In addition, following the overview of basic concepts, the report provides a detailed explanation of the main ideas of the revised balance, the structure of energy flows and energy products, and a comparison between the revised and previous balances, to enhance understanding of the new framework.

In its dictionary definition, energy is the capacity to do work. Energy exists in various forms, such as mechanical energy (potential and kinetic), thermal energy, radiant (light) energy, electrical energy, chemical energy, and nuclear energy, and can be readily converted from one form to another. Energy can be categorized into two types: stored energy and working energy (EIA). Fuel is a substance that generates energy through combustion. Combustion is the process in which the carbon and hydrogen components of a fuel combine with oxygen to release heat, thereby providing thermal and electrical energy in physical or electrical form. In the strict sense of energy statistics, the term energy refers only to heat and power, and does not include fuel. When fuel, heat, and power are combined, they are referred to as energy commodities (IEA, 2005). Other related terms in use include energy carrier, energy vector, energy ware, and energy source. These terms are often defined as materials or natural phenomena that can be consumed or transformed to provide energy. For example, the EIA uses the term energy sources to refer to substances that supply energy. While understanding the physical, chemical, and mechanical properties of energy can be helpful, energy statistics are primarily concerned not with energy as it exists in time and space, but with energy commodities that carry or may carry economic meaning, along with their flows.

In practice, however, the terms energy and energy commodities are often used interchangeably. Under the ROK's Energy Act, the term "energy" refers specifically to energy commodities. Similarly, when people use terms such as "petroleum energy" or "nuclear energy," they refer to energy commodities or energy sources. A similar overlap occurs with electricity-related terminology, where electricity, electric energy, power, and electricity volume are often used interchangeably. In this report, the term electricity refers to the commodity that delivers electric energy. When necessary, the terms power and electricity volume are also used: power is the rate at which electric energy is supplied per unit of time (measure in kW), and electricity volume is the total amount of power consumed over a period (measured in kilowatt-hours or kWh). It should also be noted that in energy statistics, both energy use for energy purposes and energy use for non-energy purposes (e.g., as feedstock) are included.

3.3.1 Primary and Secondary Energy Commodities

There are various criteria for classifying energy commodities, but one of the most commonly used distinctions is between primary and secondary energy commodities. Primary energy commodities refer to those extracted directly from natural resources, such as crude oil, solid fuels, and natural gas. Secondary energy commodities are all forms of energy derived from primary energy commodities and, in some cases, from other secondary commodities. Examples include producing petroleum products (secondary) from crude oil (primary), converting coking coal (primary) into coke (secondary), or generating electricity (secondary) from petroleum fuels (secondary).

Both electricity and heat can be produced as either primary or secondary forms. Primary electricity comes directly from natural resources such as hydropower, wind, solar, tidal, and wave power. Secondary electricity is produced by converting heat generated from nuclear fuels, geothermal sources, solar thermal energy, or the combustion of combustible fuels. Primary heat is generated by geothermal reservoirs, nuclear reactors, or solar thermal panels, which convert solar radiation into heat. Because primary electricity and primary heat are obtained directly from natural resources, they are considered "new" additions to an economy's energy supply.

In contrast, secondary electricity and secondary heat do not constitute a new supply because they are produced from energy commodities already accounted for in national energy statistics. Accordingly, primary electricity and heat are entered into energy flow accounts as domestic production. However, because the raw materials for nuclear fuels and certain bioenergy commodities are largely imported, it is necessary to identify their sources when assessing energy import dependence.

When energy is obtained from devices driven by air or water flows (e.g., wind turbines, hydropower, wave power, tidal power), almost all of the mechanical power is ultimately converted into electricity. Thus, the energy form for hydropower, wind, and tidal energy is the electricity they produce; there is no intermediate representation of the mechanical power before its conversion to electricity. Since mechanical energy is not considered a primary energy commodity, it is not classified as such. Primary electricity generated from such devices is called non-thermal electricity, as it is produced without the need for heat. Electricity generated by photovoltaic (PV) panels, which directly convert sunlight into electricity, is also considered a primary energy source and is classified among non-thermal sources.

In contrast, thermal electricity is generated from primary or secondary heat sources, such as nuclear or geothermal processes. The classification of atomic energy is complex. Rather than using the total heat content of the nuclear fuel, the calorific value of the steam transferred from the reactor to the turbine is treated as the primary energy commodity.

The EIA, for example, classifies energy sources as renewable, nonrenewable, and secondary. Renewable and nonrenewable sources are used either to produce useful energy directly or to generate secondary energy, such as electricity. Useful energy refers to energy that can be directly utilized. In the EIA framework, secondary energy sources are limited to electricity and hydrogen. If energy is produced from a secondary commodity derived from a primary source (e.g., synthetic gas from coal), it is sometimes referred to as a tertiary energy source. Unlike the International Energy Agency (IEA) classification, the EIA's classification of renewable and nonrenewable sources includes both primary and secondary energy commodities. Conversely, the IEA's distinction between primary and secondary energy commodities encompasses both renewable and non-renewable sources.

3.3.2 Fossil Fuels and Renewables

Primary energy commodities can be classified as renewable or nonrenewable. Non-renewable energy includes fossil fuels, nuclear energy, and certain forms of waste-to-energy. Fossil fuels are natural resources formed from ancient biomass in geological layers, while secondary fuels derived from primary fossil fuels are also considered fossil fuels. Except for geothermal energy, renewables are defined as energy extracted directly or indirectly from current or recent flows of solar and gravitational energy that are continuously available. For example, the energy content of biomass originates from sunlight absorbed during plant growth.

In the ROK, the Act on the Promotion of the Development, Use, and Diffusion of New and Renewable Energy (hereafter the New and Renewable Energy Act) defines "new energy" as the energy obtained by converting conventional fossil fuels or by using chemical reactions such as hydrogen–oxygen to produce electricity or heat, and "renewable energy" as energy converted from renewable sources such as sunlight, water, geothermal heat, precipitation, and biological organisms. Since new energy is a secondary energy commodity derived from fossil fuels, double-counting issues arise when it is added to the national energy supply. Therefore, in energy statistics, new energy must be treated appropriately to avoid such duplication. A similar issue arises in hydroelectric pumped storage.

For renewable energy sources obtained directly from nature—such as geothermal, solar thermal, solar PV, wind, ocean, and hydro—the amount of primary heat or primary electricity produced is recorded as renewable energy supply. In the case of waste or bioenergy, however, the actual calorific value of the input cannot be measured accurately. Hence, rather than using the material's chemical calorific value, the calorific value of the output is treated as the renewable energy supply. In the ROK, the renewable energy supply is calculated based on either output or the estimated calorific value of the input. Specifically, for heat production, the actual heat produced is counted; for power generation, the renewable energy supply is calculated by back-estimating the heat required to generate the electricity. This approach, known as the partial substitution method, is described in more detail below. An exception is made for coal gas and refinery gas, for which both the physical volume and the calorific value of the input are known. So, in such cases, the production volume is recorded directly as renewable energy output.

3.3.3 Partial Substitution Method and Physical Energy Content

As previously discussed, energy statistics must define the form of primary energy commodities and determine the specific point at which primary energy production is measured for statistical purposes. The partial substitution method and the physical energy content method are two distinct approaches for assigning energy values to the outputs of primary energy commodities. The choice of method in energy statistics is, to some extent, a matter of international agreement. Such methodological decisions have significant implications for both the characterization of primary energy commodities and the reported production volumes.

3.3.4 Partial Substitution Method

The partial substitution method assigns an imputed energy value to primary electricity production equal to the amount of fuel required to generate the same amount of electricity in a conventional thermal power plant. This method is used in the ROK to calculate calorific conversion factors and is also applied in the USA to estimate primary energy production.

The advantage of the partial substitution method is that it reduces fluctuations in total national energy supply that may arise from variations in primary electricity production. Such fluctuations are especially common in economies where fossil-fuel-based power generation represents a large share of the electricity supply. For instance, when drought reduces hydropower generation, an economy may need to increase thermal power generation or import electricity. However, due to the lower efficiency of thermal power plants, significantly more fossil fuel is required to replace the lost hydropower. This imbalance can be partially corrected by using the partial substitution method.

Nonetheless, this method is not without drawbacks. In economies where hydropower accounts for a large share of electricity generation, the difference is negligible. Moreover, the imputed substitution value assigned to primary electricity is arbitrary and lacks a firm basis. For these reasons, the IEA no longer applies this method. At the same time, recording primary electricity as domestic production under the partial substitution method inflates the share of primary energy commodities in the total national energy supply.

3.3.5 Physical Energy Content Method

The method currently adopted by the IEA is the physical energy content method, which records the actual physical energy content of primary energy forms at the point of production. For example, in the case of primary electricity, the physical energy content is simply the total amount of electricity generated. When applying this method, caution should be exercised when presenting the share of primary electricity in the national electricity production mix. Since primary electricity does not involve a conversion process within the balance, the share of thermal versus primary electricity cannot be calculated based on input fuels. Instead, generation data disaggregated by fuel type in thermal power plants must be used to determine contributions.

For electricity produced from primary heat sources such as nuclear reaction heat or geothermal energy, the heat generated is considered a primary energy. However, because it is difficult to measure the exact amount of heat transferred into the turbine, it is often estimated as heat input. Recording steam from nuclear reactors as a primary energy source in national statistics significantly increases dependence on imported nuclear fuel, as most economies rely heavily on imported nuclear fuel.

3.3.6 Quantities and Energy Values

In handling energy flows at major points of production, transformation, and consumption, the characteristics of each energy commodity must remain consistent throughout its lifecycle, and its quantities must be expressed in uniform units regardless of the source or usage. At specific points of production, trade, or consumption, the most appropriate natural unit is used depending on the fuel's physical state: weight for solid fuels, volume for liquids and gases, kWh for electricity, and calories (cal) or joules (J) for heat contained in steam flows. Except for the heat contained in steam, heat flows are not measured directly; they are estimated from the fuel input used to generate heat. Because volume varies with pressure or temperature, quantities are expressed in mass or energy units whenever possible.

Fuel quantities expressed in natural units can be converted into energy units, allowing comparisons between fuels and estimates of efficiency. Energy units also allow aggregation across energy commodities in different physical states. This conversion is a fundamental step in compiling an energy balance from product balances. The IEA and Eurostat use toe as the standard energy unit, whereas the EIA primarily uses the British thermal unit (Btu).

To convert natural or intermediate units to energy units, calorific conversion factors are required, which represent the amount of heat released by one unit of an energy commodity. In the ROK, official calorific conversion factors are published every five years. The official calorific tables announced by the government are used in national energy statistics to convert commodity quantities into energy values. The IEA recommends applying economy-specific calorific values whenever available.

3.3.7 Gross and Net Calorific Values

Most fuels are compounds of carbon and hydrogen, and combustion is the process by which these elements combine with oxygen. When hydrogen combines with oxygen, water vapor is produced, which exits with the fuel gases from combustion. When these gases cool, the vapor condenses into liquid, releasing latent heat. Gross calorific value (GCV) includes this latent heat and represents the total heat released by fuel combustion. Net calorific value (NCV) excludes the latent heat of vaporization. Typically, NCV is about 5–6% lower than GCV for solid and liquid fuels and about 10% lower for natural gas (IEA, 2005). In the ROK, both official calorific conversion factors and the national energy balance are based on GCVs.

3.3.8 Energy Calorific Standards in the Republic of Korea

According to Article 15(1) of the Enforcement Decree of the Energy Act and Article 5 of its Enforcement Rules, the ROK publishes official calorific conversion factors every five years through the Korea Energy Agency. When compiling the energy balance, if an energy commodity is not included in the official tables, the most recent values are used. For commodities still not covered, the IEA's average density and calorific values are used.

4. Institutional Experiences

4.1 The Republic of Korea's Case

The ROK began compiling its energy balance in 1983, thereby establishing nearly four decades of data. Although there have been a few revisions during this period, they have largely focused on the inclusion of additional energy products—such as natural gas and district heating—and on a more detailed classification of non-energy-use petroleum products. This indicates that the current energy balance may be insufficient to capture the complexity and diversity of energy markets that have evolved significantly over the past several decades.

As more energy products are produced, traded, and consumed, energy dependence grows. At the same time, greenhouse gas emissions have become a central international issue, making it increasingly important to understand energy markets quickly and accurately. Furthermore, concerns about energy dependence, security, efficiency, and the environment require a deeper understanding of energy supply and demand. To gain a clear understanding of the situation, detailed and accurate data are needed for each part of the energy supply and consumption chain. The important task in the ROK's energy statistics is to revise energy supply and demand statistics so that not only energy products but also energy flows are classified in greater detail, in line with current realities. This would enable a more accurate understanding of energy supply and demand. The core of supply and demand statistics lies in the product balances of individual energy products and the combined energy balance, through which the completeness and accuracy of national energy statistics can be assessed.

A turning point in the fundamental development of the ROK's energy statistics came with its accession to the IEA in 2001. Subsequently, the government strengthened the legal foundation for statistical systems. In 2006, the enactment of the Basic Energy Act included Article 19, which mandated the compilation, analysis, and management of energy supply and demand statistics; and in 2008, the government issued official regulations titled Rules on the Compilation of Energy Statistics through a ministerial notification. While these legal and institutional changes were accompanied by attempts to improve the development and quality of energy statistics, most efforts did not yield concrete results and were limited to presenting research outcomes. This report draws on those experiences and presents results from building energy supply and demand statistics with strong linkages to international energy statistics.

Another key priority is to enhance expertise in the fundamentals of energy statistics. To this end, this report not only explains the revisions to the energy balance but also presents definitions and methodologies for supply and demand energy statistics. Terms and concepts related to energy are often used with different meanings in broader society, and even at the statistical level, such inconsistencies hinder an accurate understanding of national energy statistics. Occasionally, even experts in the energy field make the mistake of directly comparing statistical figures from the ROK's energy balance with those from the IEA's energy balance without understanding the structural and conceptual differences. Therefore, to communicate about such issues in a common language and jointly address and improve them, it is essential to share the underlying definitions and methodologies.

FIGURE 4.3

STRUCTURE OF ENERGY BALANCE TABLE.

Energy Balance (UNIT: 1,000 toe or TJ, gross)	Coal	Gas	Oil	Nuclear	Hydro	Electricity	Heat	Renewable (Solar, Wind ...)	Biofuels and waste	Total
Production										
Imports										
Exports										
International bunkers										
Stocks changes										
Total primary energy supply										
Statistical differences										
Total primary energy consumption										
Transformation processes										
Energy industry's own use										
Losses										
Total final consumption										
Final energy consumption										
Industry										
Transport										
Residential										
Commercial										
Public services										
Final non-energy consumption										
of which in petrochemical feedstock										
Electricity Output										
Heat output										

Source: Author's own compilation based on the IEA Energy Balance Table format from IEA (2024), World Energy Balances, 2024 Edition.

A commodity balance is a statistical table (Figure 4.3) that shows how much of each energy commodity is supplied and where it is consumed within a specific time and spatial scope. When individual commodity balances, expressed in natural units, are converted to energy units and arranged in a single matrix after appropriate adjustments, the result is an energy balance. In general, an energy balance refers to a table that presents the supply and consumption of all energy commodities in an economy over the course of one year.

In an energy balance, energy commodities are listed along the horizontal axis. In contrast, commodity flows are shown along the vertical axis, indicating which sources supply which energy, how they change through transformation pathways, and where they are ultimately consumed.

4.1.1 Commodity Flow

Economies use fossil fuels extracted from natural deposits and biofuels obtained from the biosphere, while importing energy commodities when domestic supply is insufficient and exporting surpluses when available. Primary energy commodities are often converted into secondary energy commodities to facilitate usage, storage, or trade. Commodity flow refers to the key points at which energy commodities are generated or extinguished throughout their lifecycles.

In energy statistics, energy commodity flows can generally be divided into three categories: supply, transformation, and final consumption. Similar flows apply to heat and electricity. From a statistical perspective, a key principle in handling commodity flows is that the characteristics of an energy commodity should remain consistent throughout its lifecycle and be expressed in uniform units regardless of its source or usage. As a result, both the supply and the consumption of a single energy commodity are shown in one column. The movement of energy from one commodity to another is called energy transformation.

The characteristics of an energy commodity affect its productive capacity. For instance, freshly mined coal contains impurities that must be removed before sale, so the coal as mined is not the same as the coal that is used. Therefore, coal production reported in energy statistics refers to coal after washing and preparation.

4.1.2 National Boundary Considerations

The definition of a "nation" generally aligns with national borders but does not necessarily coincide in every case. Imports and exports of energy commodities are recorded at the time of customs clearance. Fuel used for international aviation and marine transport is deducted in advance as international bunkering and excluded from domestic energy consumption, leaving a balance that is effectively defined by reference to the geographic border. In some cases, commodity flows may also be recorded by subdividing domestic regions according to specific criteria. In the ROK's case, although Democratic People's Republic of Korea is treated as a separate economy under international law, it is considered to have a special relationship under domestic law, thereby necessitating a clear definition of the nature of energy trade with it.

4.1.3 Harmonization of Commodity and Energy Balances

In the revised Korean energy balance, the commodity and energy balances use the same structure and definitions for commodity flows. Details on the commodity flows as applied in the balance are explained in the section "Row Structure of the Balance." Here, we clarify the key terms, concepts, and methodologies used to describe commodity flows.

4.1.4 Total Primary Energy Supply and Total Primary Energy Demand

Total primary energy supply (TPES) refers to the sum of energy commodity flows from domestic natural resource production and from imports from outside the economy. Here, “primary” denotes the initial supply of energy and therefore encompasses both primary and secondary energy commodities. In contrast, total primary energy demand (TPED) refers to the sum of energy commodity flows that occur within the economy. The distinction between TPES and TPED depends on how the total amount of national energy use is calculated. Energy commodities are supplied to an economy through sources of supply such as domestic production, external trade, international bunkering, and stock changes. The sum of these constitutes TPES, where domestic production refers specifically to the production of primary energy commodities. These “sources of supply” represent energy quantities before any domestic transformation processes. TPED, by contrast, is the sum of energy inputs and outputs for transformation, energy consumption across all sectors, including the energy industry itself, and losses occurring between supply and consumption. The difference between the sum of TPES plus “intercommodity transfers” and TPED is recorded as the statistical difference.

For each energy commodity, the total quantity supplied domestically should be identified not only from “sources of supply” but also from secondary fuel production through transformation and intercommodity transfers. Although not explicitly shown in the balance, the total supply is the sum of the sources of supply, secondary fuel output, and intercommunity transfers. Similarly, total demand is defined as the sum of transformation inputs, the energy industry’s own use, losses, and final consumption. The statistical difference calculated between total supply and total demand is identical to that between TPES and TPED.

Users may be confused about whether to use TPES/TPED or total supply/total demand. Generally, TPES (or total supply) is used when referring to national total energy use or for international comparisons, as statistical discrepancies are an accounting issue for which the reporting economy is responsible. However, for analyzing and forecasting national energy consumption, TPED (total demand) may be used.

4.1.5 Transformation Processes

Transformation processes refer to the physical or chemical conversion of primary or secondary energy commodities into other secondary commodities. Typical examples include producing coke from coal and generating electricity by burning fuels to produce steam. While both fall under the category of transformation, they are fundamentally different. In coke production, coal undergoes a separation process in which most of the carbon remains in the coke, while hydrogen and some carbon form gases and byproducts. Both inputs and outputs are fuels, but no combustion occurs during this process. By contrast, electricity generation from combustion converts the heat released by fuel combustion into electrical energy. The carbon and hydrogen in the fuel are released into the atmosphere as CO_2 and water vapor, while the electricity produced does not carry over the fuel’s original chemical elements.

Heat production in heat plants also results from combustion. When heat is produced for sale, it is treated as a transformation activity: the fuel consumed is recorded in the transformation sector. In contrast, the heat generated is recorded as final consumption. This differs from electricity generation, in which all production is treated as a transformation. The distinction arises because energy statistics are applied to commodities. While burning fuel to obtain heat for direct use is considered an activity, heat sold as a commodity must be recorded as a transformation output. Without this, fuel consumption would be overstated and consumer heat use understated.

Commodity flows in electricity and heat production are subdivided by energy source (e.g., kinetic energy such as hydropower or wind, thermal energy such as nuclear or geothermal, and fuels), plant type (electricity-only, combined heat and power or CHP, heat-only), and producer type (main activity producers versus autoproducers). Details are presented in the section on the balance’s row structure.

4.1.6 Allocation of Input Fuels

In CHP plants, it is necessary to allocate the fuel consumed between electricity and heat production. This requirement is also consistent with IEA recommendations. When part of the heat produced is sold, and the remainder is consumed in-house, the same method applies to allocate fuel use between transformation input and final consumption (i.e., the energy industry’s own use).

4.1.7 Final Consumption

Final consumption refers to the use of energy commodities for economic and social activities other than transformation processes, whether for energy or nonenergy purposes. At this stage, energy commodities are assumed to disappear from the energy accounts, as they are not further transformed into other commodities. In practice, energy is not destroyed but converted into different forms. As with the treatment of primary electricity and heat, the physical or chemical energy resulting from final consumption is not recorded statistically and thus appears to leave the flow.

Final consumption is classified into final energy consumption (for energy purposes) and non-energy use. Statistics on final consumption are generally derived from energy suppliers' sales data, and consumer classifications follow standard industry classifications. However, supplier classifications do not always align with the standard and may reflect internal business purposes, necessitating detailed verification where possible.

Energy commodities are also used for nonenergy purposes, such as raw material inputs for petrochemical processes, the physical properties of lubricants and greases, or solvent use. For example, naphtha and ethane derived from natural gas are key feedstocks in steam cracking for petrochemical production. Byproducts from this process may be recycled back into refining or used as fuel. These returns are referred to as backflows. To avoid double-counting in oil statistics, backflows included in transformation processes must be accurately identified. Naphtha used exclusively for petrochemical production is recorded as nonenergy use.

4.1.8 Importance of Commodity Balances

A commodity balance is an energy statistical table, expressed in natural units, that records the supply and use of each energy commodity, enabling verification of completeness and facilitating the extraction of key data. For each commodity, it shows quantities in their original units for each flow over a specified period. As explained earlier, because an energy commodity is homogeneous from production to the end of the supply chain, its supply and consumption are shown in a single column.

Each economy should compile individual commodity balances for all energy commodities used at the national or regional level, although for practical reasons, some commodities may be aggregated. Commodity balances underpin national energy statistics and are essential accounting tools for compiling the energy balance.

The magnitude of the statistical difference can be used to assess the quality of commodity balance statistics. Large discrepancies should prompt an investigation into which data are problematic or incomplete. However, not all statistical data can be corrected; in such cases, the statistical difference may be left as is, indicating the magnitude of uncertainty. Whether to resolve discrepancies is ultimately a matter of judgment.

The IEA recommends tolerances for statistical differences based on commodity importance: for major commodities, less than 1% of supply; for others, approximately 10%. A closed balance is one in which the statistical difference is zero. Still, such cases often suggest that some figures have been artificially adjusted to enforce consistency, typically when a single entity reports all data. To gain a realistic understanding of the reporting challenges businesses face, it is important to identify which figures have been estimated solely to balance the accounts.

4.1.9 Energy Balances

The primary reason for using fuels is their ability to generate heat. Since fuels can be converted into other fuels, expressing supply and consumption data for energy commodities in energy units is advantageous in several ways. An energy balance is a table that combines commodity balances expressed in energy units. By compiling an energy balance from commodity balances, one can further validate data accuracy and reveal relationships among data that are not visible in the commodity tables alone. Energy balances allow users to identify fuel conversion efficiencies and the relative importance of fuels to the national economy. They are also the starting point for calculating various energy-use indicators such as per-capita consumption and energy intensities. As noted earlier, unusually large energy gains or losses within transformation processes signal data issues, enabling higher-level validation of accuracy.

An energy balance is prepared by converting commodity balances—originally expressed in natural units—into energy units and then reorganizing the structure. This restructuring involves properly ordering the converted commodity balances, regrouping certain rows, and assigning signs within the transformation section. In practice, however, the construction of commodity balances and energy balances is not a sequential process but occurs concurrently. This is because the more finely commodity flows are disaggregated, the more the entries must be crosschecked against multiple data sources in energy statistics.

Depending on established practice or purpose, different agencies may compile energy balances in various formats. When new types of energy commodities or new patterns of energy production/consumption emerge, the balance can be revised to accommodate them. There is no single, internationally fixed format for energy balances; each economy reflects its own characteristics. The IEA, however, applies a consistent compilation method across member economies and publishes a harmonized balance format that enables international comparison.

A prominent difference between the IEA and Eurostat balances concerns how primary and secondary fuel production is shown in commodity balances. Eurostat restricts the production item to primary (domestic) production and classifies secondary production as transformation output, thereby making the commodity and energy balances identical in this respect. The IEA, by contrast, shows both primary and secondary production in the commodity balance, but records only primary production in the energy balance, while showing secondary energy output as a positive entry in the transformation section. Consequently, the IEA undertakes a modest reformatting when deriving the energy balance from the commodity balance. This conceptual difference also manifests in the layout: Eurostat separates the transformation section (the "transformation matrix") into separate inputs and outputs, whereas the IEA uses a single integrated matrix and distinguishes inputs and outputs by sign.

In the ROK, the production item in both the commodity and energy balances is defined as primary production, as in Eurostat. The overall table layout, however, follows the IEA's single-transformation-matrix approach. Thus, the ROK's commodity and energy balances share a structure similar to that of the IEA, but—unlike the IEA—the ROK's two balances are identical to each other. In the ROK, the legal authority to compile basic energy statistics, and, in some cases, commodity balances for each commodity rests with relevant private associations or public institutions. As detailed in the section "Basic Data," the Korea Coal Association (coal); The Korea National Oil Corporation (oil); The Korea Gas Corporation and the City Gas Association (gas); KEPCO (electricity); and The Korea Energy Agency (new and renewable energy) produce basic statistics. While some institutions prepare commodity balances, most collect, collate, and provide basic statistics, even those balances are not compiled using a common definition and format. Therefore, the Korea Energy Economics Institute (KEEI)—which holds the mandate to compile the national energy balance, constructs separate commodity balances and, on that basis, the national energy balance, using statistics reported by these institutions and other survey data.

4.1.10 Types of the Revised Balance

The ROK's revised balance is produced in two forms: Simple Balance and Extended Balance. The Simple Balance aggregates data monthly to provide a timely view of supply–demand trends. The Extended Balance covers one year and, using supplementary survey data, describes national energy flows in greater detail and with higher accuracy. Official annual supply–demand figures are finalized based on the Extended Balance.

4.1.11 Simple Balance

The Simple Balance is compiled monthly to provide supply–demand statistics and is prepared in a format similar to the previous energy balance. It comprises 48 commodity flows and 48 energy commodities. Flows are grouped into supply, transformation, and final consumption. Supply includes domestic production, imports/exports, international bunkering, and stock changes. Transformation covers generation-only, CHP, heat-only, oil refining, and gas manufacturing, as well as the transformation sector's own use and losses. Final consumption is divided into industry (13 manufacturing branches, plus agriculture, fisheries, mining, and construction); transport (four transport modes); households; commerce; and the public sector.

Energy commodities are grouped—as in the previous balance—into coal, oil, gas, nuclear, hydro, electricity, heat, and renewables. Unlike the previous format, coal is subdivided into sub-bituminous coal, lignite, peat, solid fuels, and coke; while oil products are subdivided into five categories, including crude oil, refinery feedstocks, and refinery gas. Renewables are grouped into bio and waste, geothermal, and solar and others. Because some "new and renewable" items overlap with fossil categories, a memorandum item is added to reflect the total defined under the New & Renewable Energy Act.

A key feature of the Simple Balance is that the transformation sector is simplified and narrower in scope than in the Extended Balance. Monthly statistics are insufficient to aggregate autoproducer generation and heat production, and major enterprise surveys are conducted annually. Energy commodities consumed by autoproducer are therefore captured under final consumption, so total primary energy demand (or supply) matches that in the Extended Balance. However, because electricity/heat production and consumption are limited to data from KEPCO, The Korea District Heating Corporation, SH Corporation, and GS Power, the scope is narrower than the actual nationwide production/consumption. These issues regarding electricity and heat are resolved in the Extended Balance, which incorporates autoproducer and renewable energy statistics.

Although similar in appearance to the legacy balance, the Simple Balance differs substantially in its compilation. Previously, the oil imports line included refinery output, while omitting interindustry inflows and product transfers within refining and petrochemicals and thereby double-counting final oil product consumption. The Simple Balance addresses this by moving refinery output from "oil imports" into the transformation section and recording only the quantities finally supplied after all product conversions. A fundamental limitation shared by both Simple and legacy balances is the inconsistency between electricity generation and input fuels: KEPCO's generation statistics include output from community energy providers, classified as autoproducers, while the fuels they consume are largely recorded under final consumption. This issue is discussed further in "Basic Data" and is resolved in the Extended Balance.

4.1.12 Extended Balance

The Extended Balance is the benchmark annual balance that represents national energy supply–demand flows. It includes 87 commodity flows and 61 energy commodities. Flows are grouped into supply, transformation processes, energy industry's own use, and final consumption. Unlike the Simple Balance, the transformation section and energy industry's own use are more detailed: generation-only, CHP, and heat-only are each subdivided into main activity producers and autoproducers. In addition to electricity and heat, coal-related conversions (e.g., coking plants, blast furnaces, and briquette manufacturing) are included, and oil-product conversions are separated into refining and petrochemical processes.

The Extended Balance treats the energy industry's own use as a separate sector, encompassing not only its own use by power and heat producers but also by the fuels consumed to operate coking plants and blast furnaces, as well as those used in oil refining. In coking and blast furnace transformation processes, coal inputs and outputs of coal products and byproduct gases are recorded as energy transformations, whereas own-use records the fuels required to operate these plants. Most energy industry uses correspond to transformation activities, with additional energy-producing industries including coal mining and crude oil/natural gas extraction.

Compared with legacy and Simple balances, the Extended Balance adds coal gases and provides greater detail for renewables. Coal gases, such as coke oven gas, blast furnace gas, and converter/other gases, are byproducts of coal transformation. Renewables are divided into bio and waste (11 categories, including biofuels/biomass, municipal waste, and industrial waste) and renewables (five categories, including solar thermal, solar PV, wind, and hydropower, which is listed separately). As in the Simple Balance, a memorandum item indicates the total "new and renewable" volume defined by the New & Renewable Energy Act.

4.1.13 Basic Data

In the ROK, data produced by various institutions—such as the Korea Coal Association, The Korea Gas Corporation, Korea National Oil Corporation, Korea Electric Power Corporation (KEPCO), The Republic of Korea District Heating Corporation, and the Korea Energy Agency—are officially recognized as energy statistics for their respective commodities. However, differences in classification standards among these institutions make it difficult to consolidate the data into a single table. Simply summing the energy statistics across institutions can lead to double-counting or omissions. For example, under the New and Renewable Energy Act, the ROK previously treated byproduct gases from coal and petroleum as renewable energy (before October 2019). However, petroleum byproduct gases were also included in oil statistics. Thus, if oil statistics and renewable energy statistics were added together, an artificial increase in total primary energy supply would appear. Therefore, compiling the national energy balance requires verifying consistency and accuracy across institutional data, eliminating overlaps in accordance with clear rules, and supplementing missing information with additional sources.

Another important issue is the inconsistency in producer classifications for major users. This reflects a practical difficulty in establishing statistical standards and compiling data, and is also a reason that the Simple Balance differs from the Extended Balance. For example, KEPCO's statistics on electricity production and sales include electricity purchased from community energy providers, particularly those operating in industrial complexes or as combined operators. By contrast, fossil fuel statistics classify the fuels supplied to these providers as final consumption. Even when detailed data are available, ensuring consistency is difficult unless producers are clearly classified as either main-activity producers or autoproducers. In principle, the fuel consumed by community energy providers should be allocated between electricity sold to the KEPCO, electricity consumed internally, and electricity sold directly to consumers. However, given the current statistical reporting framework and the obligations of reporting entities, such allocations cannot be made on a monthly basis.

As a result, in the Simple Energy Balance, the fuel consumed by these providers is recorded as final consumption, while their electricity production is recorded as transformation. This leads to errors in efficiency indicators for the transformation sector. The problem is addressed in the annually compiled Extended Balance.

Commodity balances for each energy commodity primarily rely on supply statistics. Among these, trade statistics from the Korea International Trade Association (KITA) are used first, followed by data from the Korea Coal Association, Korea National Oil Corporation, Korea Gas Corporation (and direct natural gas importers), the City Gas Association, the KEPCO, the Korea District Heating Corporation, and the Korea Energy Agency. These data form the basis of the commodity balances used in compiling the Simple Balance.

Where supply statistics are insufficient, supplementary data from company reports or surveys are used to ensure consistency and accuracy. Next, survey data on energy consumption are used to fill the remaining gaps. For example, coal consumption data by use category from companies such as POSCO and Hyundai Steel are employed to describe in detail the coal transformation processes in integrated steelmaking. Survey data from major coal users is also incorporated to ensure accurate identification of consumption purposes.

For electricity and heat statistics, the KEPCO's electricity statistics are used as the primary source. In contrast, data from the Korea Power Exchange (on independent power producers) and statistics from the Korea Energy Agency (on community energy and renewables) serve as supplementary or adjustment data. Conversely, for renewable energy statistics, the Korea Energy Agency's commodity-level statistics serve as the base, with KEPCO and Korea Power Exchange data being supplementary sources.

4.1.14 Row Structure of the Balance

Flows of energy commodities trace their path from initial appearance to disappearance through final consumption and are shown on the vertical axis of the energy balance. These flows are grouped into supply, transformation processes, energy industry own use, and final consumption.

4.1.15 Supply

"Supply" corresponds to total primary energy supply sources plus transfers between commodities, and represents the total quantity of energy products made available domestically. While this follows the IEA's commodity-flow structure, there are differences in the definitions of domestic production and other sources.

4.1.16 Domestic Production

Domestic production includes the extraction of primary fossil fuels from onshore, offshore, and Exclusive Economic Zone (EEZ) deposits; the capture of renewable energy from water, wind, and solar; and the extraction of biofuels. Energy commodities that are transformed domestically from domestically produced or imported inputs are not counted as domestic production; they are recorded under transformation. In IEA statistics, the production item in the commodity balance includes both primary production and secondary fuel output. In contrast, in energy balance, only primary production is recorded as domestic production. The IEA also consists of an "Other Sources" category for energy recovered from fuels that have already been produced but were not previously accounted for or stored. Statistical treatment of primary electricity and primary heat within domestic production requires care, as discussed earlier, under "Primary Energy Commodities" and "Renewables."

4.1.17 External Trade (Imports and Exports)

Imports are energy commodities that are extracted or manufactured abroad and transported into the economy for domestic use. Energy embedded in imported industrial goods is counted as an energy import only when such goods are imported specifically to be reconverted into energy (i.e., used as energy sources). In nuclear power, the primary heat produced domestically is recorded as domestic production; nuclear fuel imports are not recorded as energy imports.

Historically, the legacy balance treated refining as occurring "outside the border," and recorded refined product supply under an "oil production" subitem within oil imports. In the revised framework, refining is handled under transformation as refining and petrochemical processes.

Exports record energy commodities produced or transformed domestically and shipped abroad. Fuel used by transport modes for international movements is recorded under "International Bunkering." To derive the domestic energy supply, exports are deducted, so they appear with a negative sign under "Supply." In principle, pure "import-for-reexport" flows are excluded from the balance. The IEA recommends tracing exports and imports to the actual producing economy (for imports) and the actual consuming economy (for exports). In the ROK, however, trade statistics are compiled on a customs-clearance basis.

4.1.18 International Marine and Aviation Bunkers

Petroleum products consumed as fuel by ships and aircraft engaged in international traffic, regardless of the vessel or aircraft's nationality, are recorded as international bunkering. This also applies to navy vessels on international voyages. Fuel for distant-water fishing fleets is not recorded as bunkering but as final consumption in fishing. The legacy balance used the carrier's nationality rather than the route; the revised balance follows the IEA practice and uses the international route criterion.

4.1.19 Stock Change

Both suppliers and consumers hold inventories to cope with fluctuations in production and consumption. Inventories include government stocks, large consumer stocks, stockholding companies, onboard ship stocks, and bonded-warehouse stocks. The balance should cover all stocks within the national territory. A stock qualifies if it can be drawn upon to meet temporary over or under demand. Stock change is the difference between the opening and closing stock. A decrease in stocks adds to supply (positive sign); an increase subtracts from supply (negative sign). Numerically, stock change = opening stock – closing stock.

4.1.20 Transfers Between Commodities

Transfers mainly arise from reclassification of energy commodities (e.g., downgrading a product to a lower-grade category due to quality criteria). Transfers are distinct from transformations and serve a practical purpose by moving quantities between commodity headings within the same row. The IEA defines sources of supply as domestic production, imports/exports, international bunkers, and stock changes; and domestic supply equals sources of supply plus transfers.

4.1.21 Statistical Difference

The statistical difference is the gap between total supply and total demand, or, equivalently, between total primary energy supply (including transfers) and total primary energy demand. The IEA recommends investigating large discrepancies to identify erroneous or incomplete data; however, it recognizes that not all errors can be corrected. When correction is impractical, the difference should be left unadjusted and explicitly noted. The IEA's tolerance guidelines are: ≤1% of supply for major commodities (e.g., natural gas, electricity) and ≈10% for the less significant ones. A "zero" statistical difference often signals that figures have been forced to balance (e.g., by a single reporter); such cases require critical assessment of the reported data.

4.1.22 Transformation Processes

Energy transformation converts primary or secondary fuels into secondary energy commodities via physical or chemical processes. In the balance, fuel inputs for secondary fuel production and for electricity/heat production are recorded with negative signs; outputs of energy commodities are recorded with positive signs.

Eurostat separates transformation into inputs and outputs within a split matrix; the IEA (and the ROK's balance) uses a single matrix, distinguishing inputs and outputs by sign. Within transformation, each secondary fuel or energy production activity is recorded under its specific process category.

4.1.23 Power and Heat Production (Electricity-only, CHP, Heat-only)

Electricity and heat are classified by plant type: electricity-only, CHP, and heat-only plants. Producers are also classified by purpose: main activity producers (primarily sell electricity/heat) and autoproducers (produce mainly for their own use but may sell a portion). If any unit in a plant operates in CHP mode, the plant is treated as CHP. Heat-only refers to boilers that produce heat for sale; these are classified as main-activity or autoproducer heat.

4.1.24 Main Activity Producer vs. Autoproducer

Main activity producers sell electricity/heat as their principal business; autoproducers generate electricity or heat for their own use, selling only part of their output. Ownership may be private or public. In practice, the classification involves a convention for statistical convenience, driven by corporate registration requirements, differing compilation practices, and complex production/sales arrangements. In the ROK's balance, KEPCO and its generation subsidiaries, private IPPs, and district-heating operators (for district heating) are treated as main activity producers. Community energy providers are subdivided into district heating operators, industrial-complex operators, and combined operators. Only district heating operators are treated as main activity producers, while industrial-complex and combined operators are treated as autoproducers. Renewable generators recorded as "KEPCO and subsidiaries" or "others" in KEPCO statistics are generally classified as main activity producers. Applying these rules, the electricity commodity balance counts KEPCO's main-producer generation, excluding community energy output from industrial complexes and combined operators. Those outputs are captured under KPX IPP (autoproducer) generation. In renewable energy statistics, KEPCO's renewable generation is assigned to main producers, and the remainder is allocated to IPPs. On the consumption side, electricity-use statistics combine KEPCO sales with community energy direct sales and own use, as well as IPP/renewable self-generation consumed by end users.

4.1.25 Chemical Heat for Electricity Production

Chemical heat refers to heat released by chemical reactions without fuel input (e.g., treating zinc ore with hydrochloric acid). Unlike recovered waste heat from fuel processes, chemical heat has no energy input and is therefore treated as a primary energy source. Electricity produced from chemical heat is classified as secondary electricity.

4.1.26 Coal Transformations (Coking Plants, Blast Furnaces, Patent Fuel)

Coal transformations include coking coal processing in coking plants (producing coke); use of coke and other fuels in blast furnaces; and production of patent fuel (solid manufactured fuels). Gases produced (coke oven gas, blast furnace gas, and converter/other gases) are used onsite or sold; small amounts of coal tar are used as petrochemical feedstock.

Coke-making thermally decomposes coking coal to produce metallurgical coke and coke-oven gas. In blast furnaces (and in COREX/FINEX direct processes), coke and/or coal reduce iron ore to pig iron while generating blast furnace gas. In the basic oxygen furnace (converter), oxygen injection removes carbon from pig iron, producing converter gas. These coal gases are treated as transformation outputs recovered from the carbon and hydrogen in coke and coking coal. This differs from integrated gasification combined cycle (IGCC), in which coal is gasified at high temperatures and pressures to produce synthesis gas. Patent fuel production compresses fine coal into briquettes, and in the revised balance, briquettes and coal-based manufactured solid fuels (e.g., coal briquettes) are included.

4.1.27 Oil Transformations

Oil transformations encompass refining (the processing of crude oil and refinery feedstocks to produce oil products such as gasoline and diesel) and petrochemicals (the manufacturing of oil products from intermediate petrochemicals). Refining includes both refinery outputs and refinery fuel used by petrochemical producers as byproducts. Petrochemical transformation differs from the final consumption of fuels and from nonenergy use (petrochemical feedstocks) in the chemicals sector.

4.1.28 Gas Transformations

Gas transformation refers to the manufacturing of city gas by vaporizing LNG and adjusting its calorific value (with LPG) for delivery through pipelines to general consumers. For small LPG distribution schemes (simple gas businesses), LPG retailing is not treated as gas transformation. The IEA identifies energy consumption by industries engaged in liquefaction/regasification for transport and trade. Still, it does not treat city gas as a separate commodity because natural gas changes physical state (gas ↔ liquid) without altering its energy content.

4.1.29 Coal Synthesis Gas and Other Transformations

These categories cover transformation processes not otherwise classified. The revised balance includes items not separately treated by the IEA but relevant domestically, such as coal synthesis gas for IGCC and hydrogen for fuel cells. If these gases are used solely for electricity generation, they are effectively part of coal-to-electricity or gas-to-electricity transformations and need not be separate categories. However, if they are used elsewhere (e.g., hydrogen in fuel-cell vehicles), they must be distinguished from the use of coal and natural gas. Given domestic renewables regulation and potential future uses, they are retained as separate transformation items.

4.1.30 Energy Industry Own Use

The energy industry's own use covers energy commodities consumed to sustain operations in extraction and transformation industries and in energy production plants. Unlike transformation (which yields secondary commodities), own use is not recorded in energy accounts. It must also be distinguished from final industrial consumption. Own use includes fuels consumed by transformation industries and also by extraction/processing industries (e.g., coal mining, oil and gas extraction, gas liquefaction, and nuclear fuel processing). A special case is pumped storage. If pumped storage were treated as hydropower (and its output were included in the primary electricity supply), double-counting in the primary supply would occur. Therefore, pumped-storage generation is excluded from hydropower output. In its own use, only the difference between the electricity input to the pumps and the electricity output of the pumps is recorded.

4.1.31 Losses

Losses are distinct from energy industry activities and refer to losses incurred from production to consumption—e.g., transmission/distribution losses for electricity and gas. Losses can also occur during the distribution of blast furnace gas or coke oven gas, or during the transport of oil products via pipelines. In the ROK, blast furnace and coke oven gases are typically consumed within integrated steel works, and losses in pipeline or road transport of oil products are not reported. Thus, such losses are presumed to be embedded in the statistical difference.

4.1.32 Final Consumption

Final consumption records energy commodities used in the production of non-energy goods and services, or for household/other activities, whether for energy or non-energy purposes. Energy commodities are assumed to be removed from the accounts at this stage because they are not further transformed into other commodities (even though they physically convert to other forms).

Fuels used for power generation and for heat sold are excluded from final consumption and recorded under Transformation; the resulting electricity and sold heat are recorded as final consumption. For electricity, all fuel inputs to generation are recorded under transformation inputs, and all generated electricity is recorded under final consumption. For heat, fuels used to produce sold heat are transformation inputs, and sold heat is recorded in final consumption. Self-used heat is recorded by entering the entire fuel input under final consumption. This follows from the commodity nature of the balance.

Final consumption is broken into four major groups: industry, transport, other, and non-energy use. Subclassifications differ among international organizations and economies. The IEA places agriculture, fishing, commerce & public services, households, and other under "other." The revised Korean balance of payments classifies households, commerce, and public under "other," whereas agriculture and fishing are classified under industry. Final energy use in industry, transport, and other is called final energy consumption, whereas use for non-energy purposes is non-energy use.

In the revised balance, the iron and steel chain (coking plants, blast furnaces, converters) is treated under transformation for the input of coking coal and for the byproduct gases produced; therefore, the iron & steel entry in final consumption excludes those transformation inputs and records only fuel use in other steps. This differs from petrochemicals, where naphtha used as a feedstock is included in final consumption as a nonenergy use.

4.1.33 Industry

The industry sector records fuel use for enterprises' production activities, including both process energy and support facilities (e.g., lighting, HVAC). Fuels used for power generation and for the sale of heat are recorded under transformation. Subclassifications follow the Korean Standard Industrial Classification (KSIC). The revised balance uses 15 industry subsectors: agriculture and forestry; fishing; mining (excluding coal); food and tobacco; textiles and leather; wood and wood products; pulp, paper, and printing; chemicals and petrochemicals; nonmetallic minerals; iron and steel; nonferrous metals; machinery; transport equipment; other manufacturing; and construction.

A key difference from IEA practice is that agriculture, forestry, and fishing are included in industry (not "other"). Notably, fishing fuel covers all fleets, including distant-water (fuel for distant-water fishing is not treated as international marine bunkers). Conversely, where distinguishable, fuels used by construction and industrial mobile equipment on public roads should be assigned to the transport category.

4.1.34 Transport

The transport sector covers fuel used by transport modes. A common source of confusion is distinguishing fuel used by transport companies (non-transport uses belong to services) and fuel used by construction/industrial mobile equipment, where onsite movement is industry and offsite movement is transport. Transport is divided into four modes: road, rail, domestic aviation, and domestic navigation. The IEA includes pipelines in transport, whereas Eurostat records pipeline energy under the energy industry's own use. The revised balance also includes pipeline energy under the energy industry's own use category. As noted, the revised balance aligns international bunkering methods with international standards: international aviation fuel is recorded as international aviation bunkers, so the transport sector includes only domestic aviation. Likewise, marine fuel on global routes is recorded as international marine bunkers, and only domestic routes appear under domestic navigation, regardless of vessels' nationality.

4.1.35 Other

The Other sector comprises households, commerce, and the public sector. International practices vary; the IEA's typical "other" grouping includes agriculture, forestry, and fishing, which in the ROK are included under industry.

4.1.36 Nonenergy Use

Nonenergy use refers to the use of energy commodities for nonfuel purposes, such as naphtha as a petrochemical feedstock or asphalt for construction. In the IEA energy balance, nonenergy quantities, apart from petrochemical feedstocks, are disaggregated by consuming sectors (industry, transport, other, including transformation and energy industry, where applicable). Petrochemical nonenergy use is presented as a memorandum item. The revised balance similarly breaks out nonenergy use by industry, transport, households, commerce, and public, and separately identifies feedstock use in petrochemicals.

4.1.37 Electricity and Heat Production

This auxiliary section reports output by fuel for electricity and heat produced in transformation (generation and heat production). These data support the estimation of fuel-specific production efficiencies.

4.2 Japan's Case

In Japan, the Energy Balance Table (EBT) serves multiple objectives (Figure 4.4). It is used to monitor energy markets, evaluate energy security, plan for sustainable development, mitigate environmental impacts, and analyze economic opportunities derived from technological innovation, particularly energy efficiency. It also supports energy planning and policy formulation; facilitates the reporting of Japan's energy supply, demand, and CO_2 emissions to international bodies such as the IEA and the UN; and contributes to the transparency framework of the Paris Agreement.

Users of Japan's EBT include policymakers, businesses, statisticians, international organizations, and the general public. Policymakers rely on it to formulate and monitor the effectiveness of energy and environmental policies. Enterprises use it to evaluate investment and operational strategies, while international organizations use it to monitor global energy trends, climate change, and greenhouse gas emissions. For the public, timely access to energy statistics supports better-informed decision-making regarding energy prices, costs, and sustainability issues.

The compilation of Japan's EBT requires careful data collection and processing. It begins with energy statistics on supply and demand for oil, gas, electricity, heat, and renewables. Conversion factor tables are then applied to standardize all energy forms into comparable units. The EBT is constructed by combining statistical tables and conversion factors, and then undergoes review processes. These reviews ensure consistency between supply and demand, validate transformation efficiencies, check year-on-year changes, and reconcile discrepancies with international reporting standards. Adjustments are made, as needed, to account for domestic or global changes and newly available primary data.

Sources of data for the EBT are extensive. On the supply side, trade statistics, petroleum product surveys, gas company reports, and power generation data are used. On the demand side, energy consumption data are drawn from agricultural, manufacturing, residential, commercial, and transportation sectors. Each of these relies on a wide range of official surveys, company reports, and sectoral statistics.

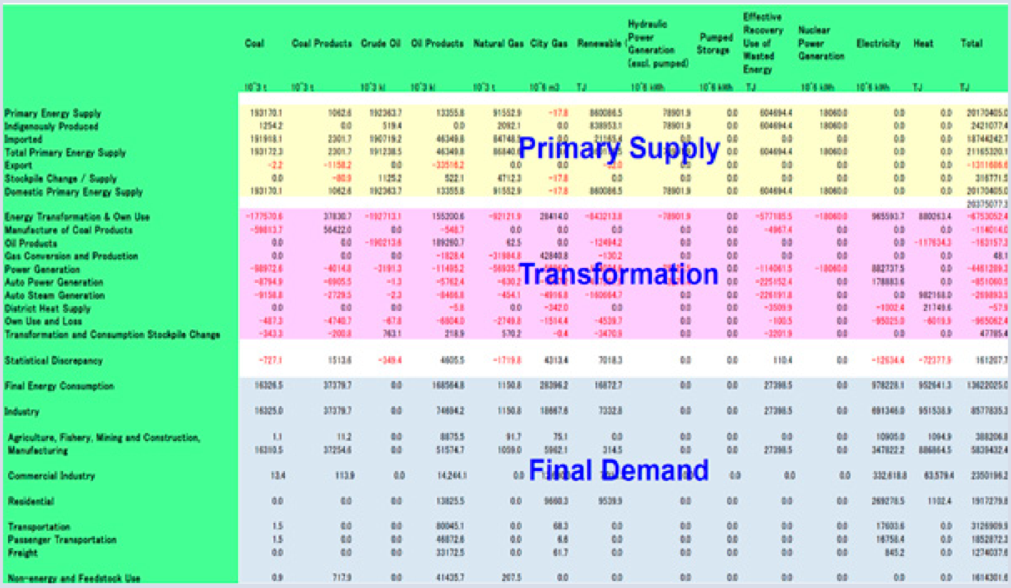
Uniform measurement is critical for the credibility of the EBT. Japan expresses all energy in joules, supported by periodic reviews of conversion and emission factors. This not only enables aggregation across heterogeneous energy sources but also allows for the calculation of CO_2 emissions using standard emission coefficients.

For developing economies, where detailed consumption statistics are often unavailable, the presentation highlighted the use of sales data as a proxy for final consumption. However, it emphasized the need to process such sales figures carefully to avoid misclassification. For example, diesel fuel sales may serve different purposes, such as industrial boilers, transportation, or electricity generation, each of which must be allocated correctly in the balance. Similarly, discrepancies between reported fuel sales and actual electricity generation must be checked against plant efficiency to ensure accurate accounting.

In conclusion, the EBT is both a statistical tool and a policy instrument. It integrates data from diverse sources into a consistent framework, providing critical insights for energy management, security, and sustainability. For Japan, the EBT not only supports national energy planning but also enhances its role in international energy governance by ensuring transparency and comparability.

FIGURE 4.4

STRUCTURE OF ENERGY BALANCE TABLE (SAMPLE).



Source: IEEJ (2019).

TABLE 4.2

DATA SOURCE FOR EBT.

Parts	Data Sources
Primary supply	
Import, export	Trade Statistics
Import, export of oil products	Current Survey of Petroleum Products Supply and Demand
Transformation	
Oil products	Current Survey of Petroleum Products Supply and Demand
Gas conversion and production	Report of Gas Company
Power generation	Electric Power Statistics
Auto power generation, Auto steam generation	Current Survey of Energy Consumption Energy Consumption Statistics
District heat supply	Report of District Heating Company

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Parts	Data Sources
Final consumption	
Agriculture, forestry, fishery	Statistics from the Ministry of Agriculture, Forestry and Fisheries (MAFF)
Major nine sectors in manufacturing	Current Survey of Energy Consumption
Other manufacturing, Non-manufacturing	Energy Consumption Statistics
Commercial	Energy Consumption Statistics Report of District Heating Company
Residential	Report on the Family Income and Expenditure Survey Report of Gas Company Report of District Heating Company
Transportation	Monthly Statistical Report on Fuel Consumption by Motor Vehicle Transport Monthly Report on Air Transport Monthly Report on Coastwise Vessel Transport Monthly Report on Railway Transport

Source: IEEJ (2019).

In the 2019 edition of IEEJ Energy Balances (Table 4.2), data for Japan were revised back to 1990 based on a new methodology. Additional details are given under each fuel. From 1990, data are reported on a fiscal year basis (e.g., April 2015 to March 2016 for 2015). Consumption data for commercial/public services may include consumption in small- and medium-sized industries. The Japanese administration expects this shortcoming to be corrected in the near future.

4.2.1 Coal

The IEA Secretariat has recalculated the net calorific values for coal and coal products based on gross values provided by Japan. In the 2023 edition, the Japanese administration revised several flows for anthracite, other bituminous coal, and coke-oven coke for 2020 based on newly available information. Data on hard coal before 1978 may include subbituminous coal.

Supply: In the 2022 edition, the Japanese administration revised the import-by-origin and export-by-destination data, extending the coverage back to 1990. In 2020, the Japanese administration revised the import figures for other bituminous coal for 1991, 2015, and 2017. Statistical differences in hard coal include changes in stock since 2001. Large positive differences over several years since 2004 are partly attributable to stockpiling by final consumers.

Transformation: The IEA has estimated preliminary coke-oven coke use in the transformation sector for 2023. The IEA Secretariat has estimated the inputs of coke-oven coke to blast furnaces and its final use in the iron and steel industry since 1990. Since 1998, inputs of coke-oven gas, blast furnace gas, and other recovered gases into autoproducer electricity plants have included the amount used to produce electricity with top-pressure recovery turbines

(TRTs), which was previously included in industry. Inputs of manufactured gases (coke-oven gas, blast furnace gas, and other recovered gases) to main-activity electricity and heat plants are calculated based on outputs and using efficiencies of main-activity producers from different fuels. For autoproducers, the specific inputs are known; however, the electricity production of each gas is estimated as a pro rata share of the total electricity generation across all gas types. Coal injected into blast furnaces (PCI) is classified as coking coal to align with Japanese trade statistics. In 2016, the liberalization of the electricity market made electricity autoproducers the primary producers.

Consumption: Nonenergy use in the chemical and petrochemical sector for coke-oven coke was revised from 1994 to 1998, based on newly available information. In the 2020 edition, the figure for anthracite consumption in agriculture/forestry has been revised. In the 2020 edition, following an investigation by the Japanese administration, the coal tar previously reported under total final consumption in the chemical sector has been reallocated to the nonenergy use category. Since 1990, the IEA has estimated coal tar consumption in the chemical and petrochemical industry.

4.2.2 Oil

In the 2022 and 2023 editions, the Japanese administration revised Japan's data back to 1990 due to changes in Japan's EBT. In the 2021 edition, the Japanese administration revised several NCVs for both primary and secondary oil products, dating back to 1990, due to improved calculation methods. The Japanese administration reviews calorific values every few years, with recent revisions occurring in 2005, 2013, and 2016.

Supply: In 2018, refinery runs were impacted by a heavier-than-usual maintenance season. The large statistical difference in crude oil for 2013 and 2014 was explained by a large stockpile of crude oil held on board incoming vessels in port or at mooring in March 2014 (at the end of Japan's 2013 financial year). These amounts are included in the stock change but not in the imports in the 2013 annual data. Orimulsion was imported for electricity generation between 1991 and 2006.

Transformation: Other hydrocarbons in non-specified transformation represent orimulsion burnt for power generation. Historical revisions are pending. In 2016, the liberalization of the power market led to electricity autoproducers becoming the main producers.

Consumption: Because data are reported on a fiscal-year basis, the impact of COVID-19 is evident in 2019, as oil consumption in some sectors declined between January and March 2020. Oil consumption continued to fall in 2018 as more nuclear capacity returned to service. Demand for heating oil and other kerosene fell amid a warmer-than-usual winter in 2018. Road consumption is based on the "Automobile fuel consumption survey" from the Ministry of Land, Infrastructure, Transport and Tourism (MLIT). Lubricant consumption has been estimated by the Japanese administration since 2000.

4.2.3 Natural Gas

The 2022 edition contains minor revisions to the time series, which go back to 1990 for imports and stock levels. These reflect revisions to the EBT from the Ministry of Economy, Trade and Industry. The 2019 edition contains major revisions to the time series, which go back to 1990. These also reflect revisions to the EBT from the Ministry of Economy, Trade and Industry. Since 1990, most of the gas works' gas production and consumption have been accounted for by natural gas.

Supply: Indigenous production, receipts from other sources, import data, stock changes, and stock levels were revised back to 1990.

Transformation: Main activity and autoproducer electricity plants were revised back to 1990. Similarly, energy-sector flows were revised back to 1990.

Consumption: Own consumption of electricity, CHP, and heat plants has been subject to major revisions since 1990. In the 2019 edition, all flows for transport, industry, and other sectors were revised to 1990.

4.2.4 Biofuels waste

In the 2024 edition, the Japanese administration revised several supply-and-demand flows for industrial waste, municipal waste, and primary solid biofuels, dating back to 1990, based on newly available information. For the 2024 edition, the Japanese administration confirmed that no biogasoline was produced in 2021 and 2022. In the 2019 edition, data for Japan were revised to 1990 using a new methodology. There was a large revision in municipal waste data in the 2016 edition of this publication. This revision has removed municipal waste data for the entire time series up to 2010. For municipal waste data, the breakdown between renewable and nonrenewable municipal waste is estimated by the IEA Secretariat, assuming a 50% split in transformation and supply.

Transformation: Input data of solid biofuels for charcoal production are estimated by the IEA Secretariat, assuming an efficiency of 40%. In the 2024 edition, the IEA Secretariat estimated the amount of biogasoline blended with fossil fuels in 2023 to ensure consistency with the data reported in the Oil questionnaire. Furthermore, in 2023, for the first time, the Japanese administration reported bioethanol data. In the 2024 edition, the amount of biogas blended with natural gas in the gas grid in 2022 was estimated by the Japanese administration to be equal to that in 2021, because the actual quantity was unknown at the time of publication. This is likely to be revised in the next publications. Industrial waste consumption in the non-specified transformation sector surged in 2013 due to increased use of waste plastics for coke production.

Consumption: In the 2024 edition, the IEA Secretariat estimated that the 2023 final consumption of geothermal energy was equal to that of 2022. In the 2020 edition, revisions were made to solar thermal consumption data for the commercial, public services, and residential sectors for the period 1990 to 2004.

4.2.5 Electricity and Heat

Supply: In the 2019 edition, electricity data were revised back to 1990 to include additional autoproducer production that had previously been excluded. Following the liberalization of the electricity market in April 2016, some generation previously reported under autoproducer plants is now reported as the main activity producer, 2016 onward. As a result, breaks in the series occur between 2015 and 2016, particularly for solar PV and wind. In the 2019 edition, the methodology for estimating heat production from other sources was revised.

Electricity and heat generation from combustible fuels are calculated by subtracting those from other sources, such as wind, solar, and nuclear, leaving a residual. Splits between combustible fuel types and consumption flows are also calculated. Due to the events related to the March 2011 tsunami, the Japanese administration decided to scale back the level of its nuclear program. As a consequence, there was no nuclear electricity generation in 2014. Nuclear electricity generation resumed at a greatly reduced scale in 2015, followed by significant increases in 2017 and 2018, with generation resuming at several facilities (Takahama 3 and 4, Ooi 3, and Genkai 3 in 2017; and Genkai 4, Ikata 3, and Ooi 4 in 2018). In 2020, output decreased due to inspections at some plants. Other electricity sources are generated using purchased steam. Other sources of heat are waste heat. Net and gross electricity generation from autoproducers are equal, as no information is collected concerning autoproducers' own use. Own use at main electricity plants has been constant since 2015, as data are no longer available following liberalization. Data for electric boilers includes heat pumps. For this reason, calculated efficiencies exceed 100% for some years. Autoproducer solar photovoltaic capacity is derived using data from the Japanese administration as well as the IEA Photovoltaic Power Systems Programme (IEA-PVPS) report, "Trends in Photovoltaic Applications," published in 2019.

Data on wind electricity production began in 1992. Heat produced for sale in main-activity producer heat plants from waste heat and electric boilers is available from 1977 and 1983, respectively.

Transformation: The Japanese Administration attributes heat outputs (except for heat from electric boilers) to individual fuels based on their share of inputs, assuming efficiencies of 100% or less. As a result, fuel-specific transformation efficiencies may not reflect actual efficiencies. Data on the heat produced for sale by autoproducer heat plants are unavailable.

Fuels used and the corresponding electricity and heat produced in CHP plants are not included in the CHP data time series; instead, they are reported as separate electricity and heat components, resulting in some plant efficiency figures being calculated inaccurately. Data on biofuel and waste inputs for electricity production, and related outputs, are available from 1982. Net electricity production by autoproducers before 1982 includes only production from combustible fuel sources. Between 1972 and 1976, the use of combustible fuels in main-activity producer heat plants was classified in the non-specified category.

Consumption: In the 2020 edition, there are revisions to solar thermal consumption in the commercial, public services, and residential sectors from 1990 to 2004. Electricity consumption in the non-specified industry includes wood and wood products, and construction before 1982.

4.3 Comparison of Energy Balance Compilation: The ROK vs. Japan

The IEA Energy Balance framework ensures cross-economy comparability through standardized definitions that cover energy products (coal, oil, gas, electricity, and renewables); flow categories (supply, transformation, losses, and final consumption); and unified energy units such as tons of oil equivalent (toe) and terajoules (TJ). It operates under the accounting principle that total supply equals total demand, with any residual treated as a statistical difference. The ROK and Japan both follow this structure, but differences arise due to their respective energy markets, industrial structures, and data-collection methods.

In the ROK, the Korea Energy Economics Institute (KESIS) under the Ministry of Trade, Industry and Energy (MOTIE) is responsible for compiling the official energy balance. The process is legally mandated by Article 19 of the Energy Act. The ROK's approach is characterized by a dual system: a monthly Simple Balance for real-time monitoring and an annual Extended Balance for comprehensive analysis of energy flows. The Extended Balance incorporates detailed transformation flows, including power generation, heat production, refining, coking, and steel manufacturing.

The Korean system emphasizes reconciliation across multiple data sources, including KEPCO (electricity), KOGAS (natural gas), KNOC (petroleum), KDHC (district heating), and KEA (renewables). Feedstock energy used for non-fuel purposes is separated from fuel-based use, reflecting the dominance of the petrochemical and steel industries. Conversion factors are applied in accordance with the official calorific tables provided by the Korea Energy Agency, and the partial substitution method is used for renewable energy sources, including solar, waste, and geothermal. In the ROK, CHP plants use the Ecabert method to allocate fuel inputs between electricity and heat outputs.

Overall, the ROK's compilation method prioritizes systematic consistency and integration of diverse energy statistics, allowing for precise tracking of transformation efficiency and end-use consumption across sectors.

In Japan, the energy balance is managed by the Agency for Natural Resources and Energy (ANRE) under the Ministry of Economy, Trade and Industry (METI), with technical support from the Institute of Energy Economics, Japan (IEEJ). Japan's compilation process is closely linked to the Energy Consumption Survey, which provides detailed energy-use data at the industrial level. This structure ensures high reliability and precision in tracking energy demand by sector.

Japan consistently adopts the physical energy content method, in line with IEA recommendations, for all renewables and nuclear energy. This method directly measures the physical energy produced, such as electricity output, rather than assigning substitution values. Industrial sectors, such as iron and steel, chemicals, and machinery, are captured through comprehensive survey data. The transformation sector is represented in a simplified manner to avoid redundancy, while renewable electricity is counted directly as primary energy. This ensures that Japan's balance remains highly compatible with the IEA's international reporting standards.

Overall, Japan's methodology emphasizes micro-level accuracy and consistency through centralized data collection. This approach minimizes statistical adjustments and improves the comparability of national and industrial energy use over time.

TABLE 4.3

COMPARISON BETWEEN THE ROK AND JAPAN.

Category	The ROK	Japan
Compilation authority	KESIS (under MOTIE)	ANRE/METI (with IEEJ support)
Legal basis	Energy Act (2006, Article 19)	Energy Conservation Act
Data collection	Multiagency (KEPCO, KOGAS, KNOC, KDHC, KEA)	Centralized via METI surveys
Renewable accounting	Partial substitution (thermal equivalent)	Different methods for different energy sources, including physical energy content (direct output)
Transformation detail	Highly disaggregated (CHP, refinery, steel, etc.)	Moderate aggregation
Industrial data integration	Based on KEPCO/KEA data	Based on the METI industrial survey

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Category	The ROK	Japan
Update frequency	Monthly (simple), Annual (extended)	Annual only
Statistical adjustment	Reconciliation via statistical difference	Direct consistency with survey totals

Source: Author (2025).

5. Policy Implications for ASEAN members

The development of robust, comparable EEIs requires a coherent statistical foundation based on reliable energy-balance data. The ROK and Japan, whose national energy statistics follow the IEA's methodological standards, offer mature examples of how commodity balance and energy balance tables can be constructed with precision using legally mandated reporting systems, standardized calorific values, and detailed transformation-flow data. When extending this EEI development framework to ASEAN economies, several practical considerations emerge due to the distinct characteristics of ASEAN's energy systems, statistical capacity, and data availability. The following implications summarize how the APO EEI framework can be adapted and strengthened within the ASEAN context.

(1) Strengthening Primary Data Availability for Commodity Balances

Many ASEAN economies face persistent limitations in foundational commodity balance data. These include incomplete reporting of domestic production, inconsistent documentation of imports and exports, and substantial gaps in sector-level final consumption, especially in industry, transport, and noncommercial household sectors. For the APO's EEI methodology, which requires disaggregated information on energy flows by product and sector, improving the quality of the commodity balance is a prerequisite. ASEAN economies may therefore need to develop clearer reporting obligations, similar to the ROK's legally mandated statistical system, or adopt standardized templates, such as those used in the APEC–ASEAN joint questionnaire. Enhancing data completeness at this foundational stage would significantly increase the quality and comparability of energy intensity measures across member economies.

(2) Addressing Transformation-process Data Gaps

A key strength of the Korean and Japanese systems is their highly detailed accounting of energy transformation processes, including power generation, refinery operations, coke production, district heating, and CHP. These transformation inputs and outputs are essential for deriving accurate primary and final energy values. ASEAN economies, however, often lack such detail. Many national energy balances provide only aggregated figures for electricity generation or omit CHP heat–electricity splits. Inconsistent or missing transformation data limit the ability to convert commodity balances into full energy balances, which, in turn, hampers the construction of thermodynamically consistent EEIs. Adopting simplified yet standardized transformation accounting rules, modeled on the Korean/Japanese frameworks, would significantly enhance the feasibility of EEI estimation in ASEAN economies.

(3) Improving Calorific Value Standardization

It has been highlighted that ASEAN member economies frequently use inconsistent or estimated calorific values, particularly for biomass, waste fuels, and locally sourced solid fuels. For APO EEI calculations, where energy intensity must be measured in standardized units (e.g., toe, TJ), inconsistent calorific conversion factors can introduce significant distortions. Establishing regionally harmonized NCV-based conversion tables, aligned with IEA practices, would reduce cross-economy comparability issues and prevent systemic bias in measured energy performance.

(4) Managing High Shares of Noncommercial Energy

Several ASEAN economies rely heavily on traditional biomass and other noncommercial fuels. These fuels may account for 30–60% of the final energy consumption in some rural or developing regions. The measurement of such fuels is often highly uncertain, relying on surveys or imprecise estimates. This presents a structural challenge for EEI construction, as energy-intensity metrics can be biased when large fractions of supply and consumption are unmeasured or estimated. The APO's EEI framework may therefore require separate treatment of commercial and noncommercial energy, methodological guidance for consistent biomass estimation, and capacity-building for household energy-use surveys.

(5) Enhancing Sectoral Disaggregation for Industrial Energy Intensity

A core component of the APO EEI framework is the calculation of industry-level energy intensity. The ROK and Japan can do this reliably because both maintain detailed sectoral statistics based on standardized industry classifications (KSIC/JSIC). In contrast, many ASEAN economies provide only aggregated consumption figures, often limited to electricity use in manufacturing. To apply the EEI framework effectively, ASEAN economies will need to improve the granularity of their sectoral energy reporting. This may involve adopting industry-level surveys, integrating utility billing data with industrial classifications, and using Indonesia- or Thailand-style energy audits as supplemental data sources. Sectoral detail is essential for constructing both bottom-up (process-level) and top-down (aggregate intensity) indicators that the APO requires.

(6) Reducing Statistical Discrepancies for Reliable EEI Calculation

Energy balances from several ASEAN economies exhibit large statistical differences between total supply and total demand. These discrepancies undermine the credibility of derived EEIs by introducing uncertainty into final energy consumption levels and sectoral allocations. The ROK and Japan exhibit extremely small statistical differences due to strong institutional coordination and mandatory reporting structures. ASEAN economies may benefit from developing national "energy statistics centers," improving integration among ministries, utilities, customs authorities, and survey units, and adopting automated validation routines used in IEA reporting systems. Reducing error margins is essential for credible EEI benchmarking.

(7) Building Institutional Capacity for Continuous EEI Updates

The APO EEI framework assumes that EEI indicators can be updated annually or biannually. ASEAN economies often experience delays in data submission to ASEAN Centre for Energy (ACE) or rely on intermittent survey-based estimates. Institutional capacity building through training, digital data management systems, and harmonized reporting calendars will be crucial in ensuring that EEI indicators are consistently maintained and that time-series analyses remain meaningful.

6. Summary and Discussion

This chapter discusses the development of refined EEIs within the APO's Green Productivity (GP) framework, emphasizing their role in promoting sustainable economic growth and environmental responsibility. Traditional energy intensity, i.e., energy use per unit of GDP, provides a simple measure but fails to capture true technological improvements in efficiency.

The report highlights the conceptual distinction between engineering-based energy efficiency and economic energy intensity, noting that the latter is affected by structural and price changes rather than genuine efficiency gains. A refined EEI framework should integrate thermodynamic principles with economic data to enable more accurate national and sectoral assessments of efficiency.

Choi et al. (2017) introduce the concept of Relative EEI, benchmarking industry-level EEI across economies against USA standards to ensure cross-economy comparability. Parker and Liddle (2016) use a decomposition approach based on the Logarithmic Mean Divisia Index (LMDI) to separate efficiency and structural effects, showing that both respond differently to energy prices.

The key data required to construct EEI statistics are detailed energy supply and consumption data disaggregated by demand and supply categories, which are provided in the Energy Balance. The case studies for the ROK and Japan provide advanced examples of national EEI systems, While the ROK has developed over 70 EEIs, disaggregated by fuel type, transport mode, and usage category, Japan integrates EEIs into household surveys and modeling tools to support evidence-based planning. The ROK case study demonstrates how a revised national energy framework, supported by legal mandates and aligned with IEA standards, provides a strong institutional foundation for detailed implementation of EEI. Japan's EBT serves as a comprehensive statistical and policy tool, integrating diverse energy data to ensure transparency, comparability, and alignment with the Paris Agreement framework. Both the ROK and Japan underline the importance of interministerial cooperation, standardized calorific conversion factors, and consistent sectoral data to ensure the reliability of EEIs.

Now, we discuss EEI and the gap between energy efficiency as an engineering concept and energy efficiency as it is represented in macroeconomic statistics and policymaking. We then highlight a major limitation: the implicit merging of energy efficiency and energy consumption data across different analytical levels—a phenomenon whose validity has not yet been tested. Addressing this issue would strengthen the methodological consistency of energy efficiency statistics. Proskuryakova and Kovalev (2015) have discussed that it is important to distinguish between energy efficiency and energy consumption (intensity) indicators and to establish a conceptual link between them, grounded in engineering thermodynamics and informed by the economic tradeoffs associated with energy efficiency at both the corporate (micro) and national (macro) levels.

EEI may offer an indirect indication of the overall state of an industry or economy, but it does not provide a foundation for specific recommendations on energy efficiency development. Nor does it estimate the potential for efficiency improvements within a given technology or device. While a reduction in energy intensity implies a decoupling of economic growth from energy consumption, it is more accurate to view energy intensity as a measure of consumption rather than efficiency itself, since such decoupling does not necessarily equate to achieving ultimate energy efficiency. EEI is most commonly applied at the macro level (e.g., the national level) to approximate energy efficiency, whereas actual efficiency decisions are made at the micro level (so, intensity data only reflect such changes indirectly). The limitations of energy intensity as an indicator can be addressed by introducing supplementary thermodynamic indicators that describe energy efficiency at physical, technological, enterprise, sectoral, subsectoral, and national levels, without reliance on economic or financial parameters (Proskuryakova and Kovalev, 2015).

Energy efficiency consultants and engineers typically determine which energy-saving technologies to include in the list of options for further feasibility studies in enterprise (facility) renovation plans. However, even highly innovative and efficient technologies may take years to reach mass production and widespread adoption, partly because consultants and engineers are often unaware of the engineering–economic opportunities enabled by truly novel technologies. For instance, it is often difficult to assess whether the financial breakeven point of a brand-new energy technology has already been achieved. Addressing such questions requires establishing publicly available, well-defined thermodynamic indicators of energy efficiency that clearly demonstrate the technological advancement of machinery. Such a system of indicators would help accelerate the diffusion of energy-efficient solutions and promote best practices in technology adoption among corporate decision-makers and engineering managers who shape a company's technology strategy.

To overcome these limitations, Proskuryakova and Kovalev (2015) proposed introducing aggregated (macro-level) engineering thermodynamic indicators that more accurately capture energy efficiency than the traditionally employed energy intensity metrics. They also suggested establishing a multilayered system of energy-efficiency indicators grounded in thermodynamic efficiency, while recommending that energy-efficiency and energy-consumption data be aggregated separately. Of course, these two dimensions may still be used jointly to provide a broader perspective for analyzing energy issues.

Finally, applying the APO EEI framework to ASEAN economies offers significant potential to improve regional understanding of energy performance, support SDG 7.3 goals, and guide national energy-efficiency strategies. However, the successful implementation of EEI metrics requires strengthening foundational statistical systems, including commodity balances, energy balances, transformation flow accounting, calorific value consistency, and sectoral energy-use data. The experiences of the ROK and Japan demonstrate that high-quality EEIs depend on robust statistical institutions, well-defined reporting obligations, and detailed engineering-based accounting of energy flows. By progressively adopting these practices and leveraging regional coordination through ACE, ASEAN member economies can significantly enhance the quality and policy relevance of their energy-efficiency indicators.

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CONCLUSION

The objectives of the APO Productivity Outlook 2026 are threefold. First, the report aims to establish a coherent analytical framework for understanding how improvements in energy efficiency influence productivity in APO member economies. Second, it explores how these effects differ across key economic sectors—particularly agriculture and manufacturing—where energy intensity, technological capability, and structural characteristics vary widely. Finally, the report presents evidence-based policy recommendations to enhance productivity through energy-efficiency improvements while supporting members' long-term sustainability and economic transformation goals. Together, these objectives highlight the central role of energy efficiency in driving sustainable productivity growth in the Asia–Pacific region.

The first component of the report analyzes macro-level productivity trends and their relationship with energy efficiency. Using a set of proxy indicators—including economywide energy intensity, electricity consumption per output, and sector-specific energy consumption ratios—the analysis finds a consistently positive relationship between improvements in energy efficiency and both labor productivity (LP) and total factor productivity (TFP). These gains arise through two channels: (1) short-term improvements from reduced energy costs and process optimization; and (2) long-term gains from capital upgrading, technological adoption, and structural transformation. Importantly, the productivity benefits differ across income groups. Lower-income economies demonstrate greater marginal gains from improvements in energy efficiency because they are farther from the efficiency frontier. In contrast, higher-income economies face diminishing returns as they approach technological and structural limits. This pattern underscores the importance of designing income-differentiated and sector-specific policy interventions.

The analysis of agriculture reveals that energy efficiency plays a central role in enhancing productivity in a sector that remains highly vulnerable to climate variability, input cost fluctuations, and structural limitations. Improvements in irrigation efficiency, mechanization, and cold-chain logistics significantly improve output stability and lower production costs. Economies with a high share of agricultural GDP experience larger productivity gains from energy-efficiency improvements, whereas low-efficiency agricultural economies realize the highest marginal benefits. These findings emphasize the need for targeted investments in modern irrigation systems, integration of renewable energy into farm operations, and adoption of precision farming technologies. Strengthening energy efficiency in agriculture enhances not only productivity but also climate resilience, especially for low- and middle-income economies.

Manufacturing, characterized by higher baseline energy intensity and standardized production processes, exhibits the greatest productivity gains from energy-efficiency improvements. The analysis highlights how modern equipment upgrades, industrial automation, and advanced energy management systems substantially enhance productivity. However, these gains remain uneven across APO members. High-income members benefit from supportive infrastructure, strong capital stock, and advanced technological capabilities, while lower-income members face constraints related to capital shortages, skill gaps, and limited adaptation capacity. The findings suggest that promoting industrial energy audits, technology diffusion programs, and targeted financial incentives can help close this gap and accelerate productivity growth in the manufacturing sector.

Drawing on the empirical findings presented across chapters, the report identifies a set of policy implications centered on enhancing energy efficiency as a core tool for improving productivity. These implications reflect both the structural differences across sectors and the data limitations that APO member economies continue to face. Table 5.1 summarizes the main recommendations.

TABLE 5.1

SUMMARY OF SECTORAL AND DATA-RELATED POLICY IMPLICATIONS.

Category	Policy Direction	Detailed and Concrete Implications
Crosscutting (all sectors)	Standardizing energy efficiency indicators	• Develop a composite APO Energy Efficiency Index using harmonized energy intensity, electricity consumption ratios, and sector disaggregation. • Require member economies to adopt consistent conversion factors (NCV-based) aligned with IEA statistical conventions. • Promote uniform reporting templates for annual energy data submissions (similar to APEC–ASEAN joint questionnaire).
	Expanding energy-efficient technologies and systems	• Support diffusion of smart energy management systems (EMS) for industries and farms. • Promote adoption of high-efficiency motors, lighting, HVAC, and industrial automation across sectors. • Encourage cross-economy technology sharing platforms under APO Green Productivity.
	Reducing energy costs for productivity gains	• Implement energy-saving audits for SMEs, with APO-led training packages. • Support bulk procurement or subsidies for high-efficiency machinery in developing members. • Develop sectoral energy benchmarking databases for cross-economy productivity comparison.

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Category	Policy Direction	Detailed and Concrete Implications
Agriculture	Improving irrigation and water-energy efficiency	• Upgrade outdated irrigation canals to energy-efficient pump and sensor-based systems. • Promote solar-powered irrigation in rural and off-grid agricultural regions. • Introduce water-saving technologies (drip irrigation, precision nozzles).
	Enhancing farm mechanization and input efficiency	• Support transition from diesel machinery to electric or hybrid farm equipment. • Promote GPS-based precision agriculture to reduce fertilizer and water use. • Expand cold-chain infrastructure with strict energy-efficiency performance standards.
	Tailored support for low-income members	• Prioritize investment in regions with low agricultural Agriculture Energy Efficiency (AEE). • Expand irrigation, flood-control, and drought-management systems in low-income economies. • Implement rural energy training programs to improve farmers' capacity to use EE technologies.
Manufacturing	Process-level efficiency enhancement	• Promote adoption of heat-recovery systems, waste-heat boilers, and cogeneration (CHP). • Introduce industrial automation and digital control systems to reduce energy losses. • Deploy efficient electric furnaces, compressors, and machine tools.
	Strengthening energy management capacities	• Require large factories to introduce ISO 50001-based energy management systems. • Provide APO-based training modules on energy accounting, monitoring, and benchmarking. • Encourage third-party verified energy audits for high-energy-consuming industries.
	Income-level-differentiated strategies	• For high-income members: promote next-generation EE technologies (AI-based process control, robotics). • For middle-income members: expand financing schemes for high-efficiency machinery. • For low-income members: provide ODA-supported industrial upgrading, grid stability reinforcement, and training.
	Supporting renewable integration	• Facilitate integration of solar PV into industrial facilities (rooftop installations). • Support battery systems and demand-response mechanisms for factory load balancing. • Establish renewable-linked tariff reforms for industrial users.

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Category	Policy Direction	Detailed and Concrete Implications
Energy statistics and data systems	Strengthening commodity balances	• Address gaps in domestic production, import/export reporting, and final consumption data. • Introduce mandatory reporting rules similar to the Korean legal system for energy statistics. • Reduce statistical differences to within IEA tolerance ranges (1% for major fuels, 10% for others).
	Improving transformation-process data	• Require detailed reporting for refinery operations, coking, power generation, district heating, and CHP. • Adopt standardized transformation input-output ratios for ASEAN economies lacking detailed systems. • Provide training on thermodynamically consistent EEI construction.
	Standardizing calorific values (NCV)	• Establish regional NCV conversion tables for biomass, waste fuels, and solid fuels. • Reduce distortions from inconsistent calorific values across member economies. • Align national conversion factors with IEA methodology.
	Addressing noncommercial energy issues	• Develop statistical guidelines for traditional biomass measurement. • Conduct household energy-use surveys to improve estimation accuracy. • Introduce separate reporting for commercial vs. noncommercial energy categories.
	Enhancing sectoral disaggregation	• Encourage ASEAN economies to expand industry-level energy reporting beyond electricity use. • Integrate utility billing data with industrial classifications (KSIC/ JSIC). • Adopt Indonesia/Thailand-style energy audit datasets to fill sub-sector data gaps.
	Integrating energy data with economic accounts	• Upgrade national energy balances to link with real-value-added statistics at the industry level. • Ensure alignment of industrial classifications to enable energy intensity calculation. • Promote integrated datasets for cross-economy productivity modeling.

Source: Author (2025).

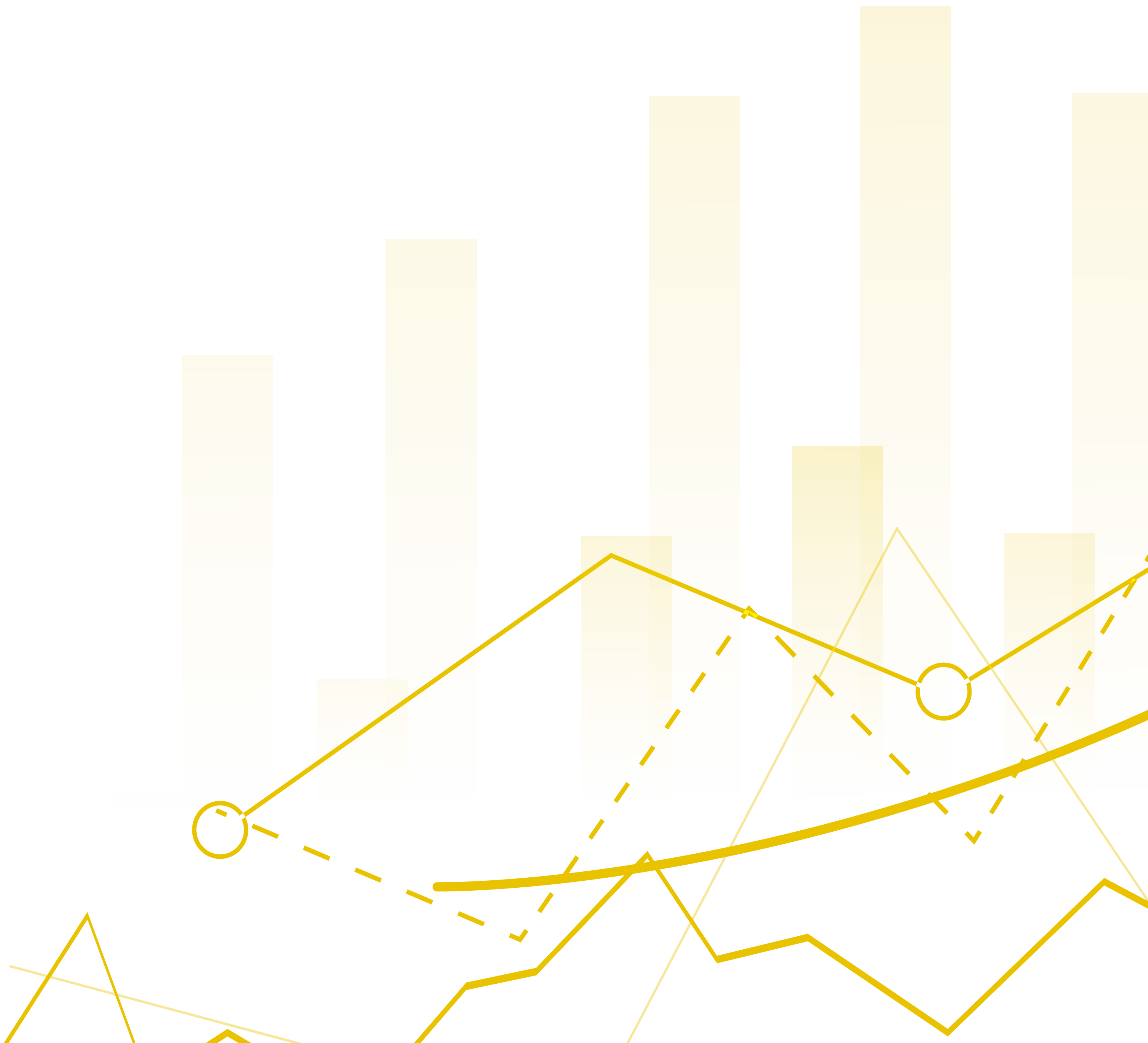
The APO Productivity Outlook 2026 highlights the need for a comprehensive, multilayered policy approach to strengthen productivity by improving energy efficiency. First, all APO member economies should prioritize the standardization of energy-efficiency indicators and statistical systems. Establishing harmonized measures, such as composite energy-efficiency indices, standardized energy-intensity metrics, and unified calorific conversion factors, will substantially improve data comparability and enable more accurate cross-economy productivity assessments. Enhancing energy and commodity balance systems, particularly in economies with incomplete reporting structures, is essential to establishing a reliable foundation for policy evaluation. Improved transformation-process reporting, standardization of NCV-based conversion tables, and sectoral disaggregation of energy consumption—particularly in ASEAN economies—are critical steps toward developing robust, thermodynamically consistent EEI frameworks.

In agriculture, policies should focus on expanding the use of energy-efficient irrigation systems, improving water-energy management, and promoting the use of renewable energy in farm operations. The integration of solar-powered irrigation pumps, sensor-based irrigation scheduling, and modernized water delivery systems can significantly reduce energy wastage while stabilizing yields. Mechanization strategies should prioritize transitioning to electric or hybrid farm machinery and adopting precision agriculture technologies, thereby reducing input costs and enhancing productivity. Cold-chain and storage infrastructure must also incorporate strict efficiency standards to minimize losses and mitigate the impacts of rising energy costs. APO member economies with low agricultural energy efficiency or a high dependence on the farming sector should be prioritized for strategic investment and capacity-building initiatives.

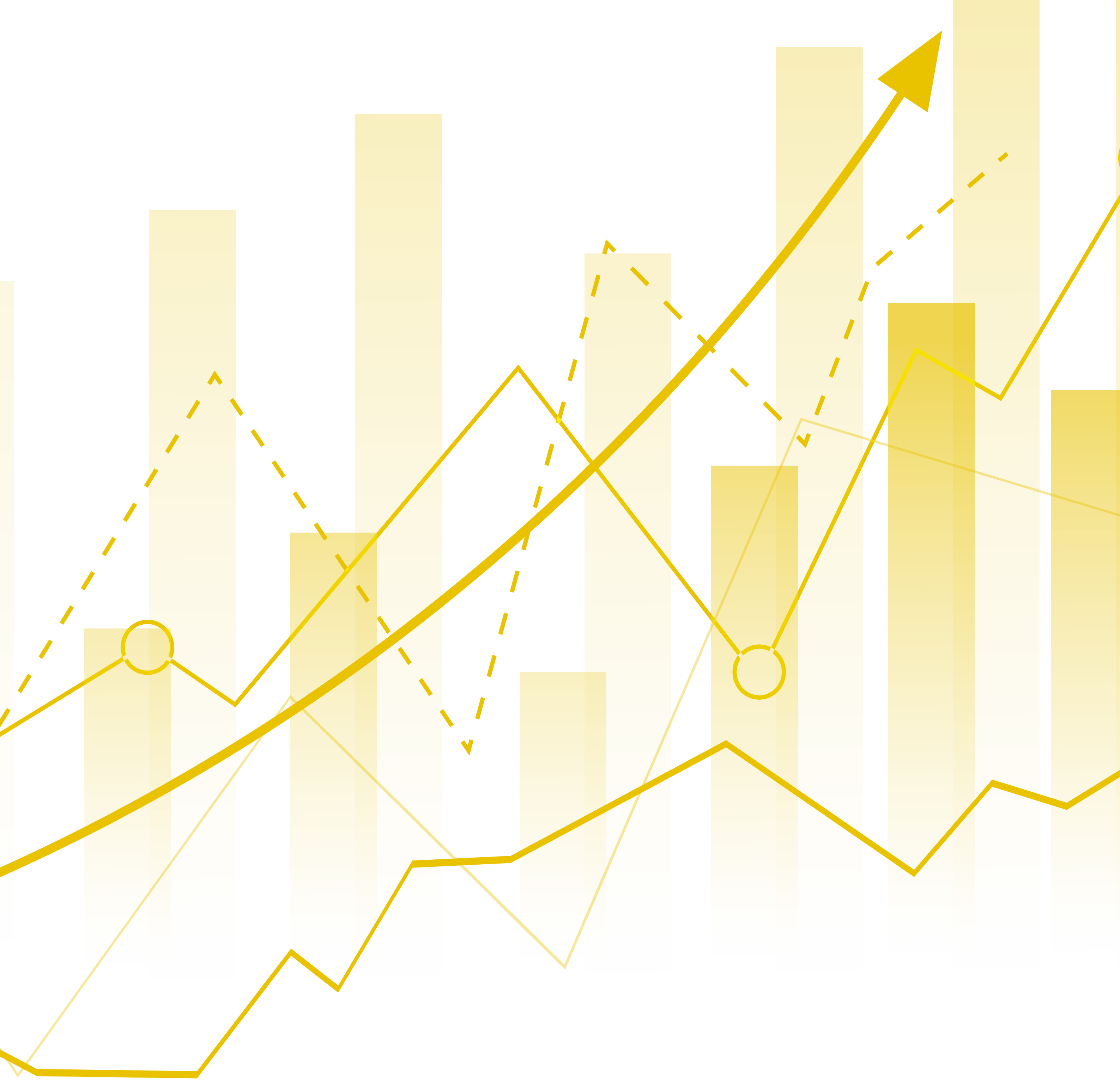
In the manufacturing sector, where productivity gains from energy efficiency are most pronounced, APO members should implement measures to support process optimization and technological upgrading. These include promoting heat-recovery systems, cogeneration technologies, and high-efficiency industrial equipment, as well as expanding the use of automation and digital process control systems that reduce energy losses. Strengthening firms' capacity to manage energy use through ISO 50001-based energy management systems, third-party audits, and national benchmarking systems will improve energy performance across industries. Policy strategies must be differentiated by income level: high-income members should focus on advanced technologies such as AI-based process optimization, middle-income members require financing frameworks to facilitate the adoption of efficient machinery, and lower-income members need ODA-supported infrastructure development and workforce training.

Cross-cutting strategies also include expanding the adoption of renewable energy within industrial facilities, strengthening demand-response systems, and deploying battery storage solutions that support factory-level load balancing. Regulatory reforms, such as renewable-linked tariff adjustments and financial incentives for high-efficiency equipment, can accelerate the transition to cleaner and more efficient manufacturing environments.

Finally, strengthening the statistical and data infrastructure is essential for enabling evidence-based policymaking. APO member economies should reduce statistical discrepancies in commodity balances to within internationally recommended tolerance levels and improve the measurement of noncommercial energy sources such as traditional biomass. Integrating energy statistics with national accounts, harmonizing industrial classifications, and improving sectoral reporting will support more accurate estimates of energy intensity and productivity relationships. Collectively, these policy directions will help APO member economies leverage energy efficiency as a catalyst for productivity growth, environmental sustainability, and economic competitiveness.



ECONOMY PROFILES



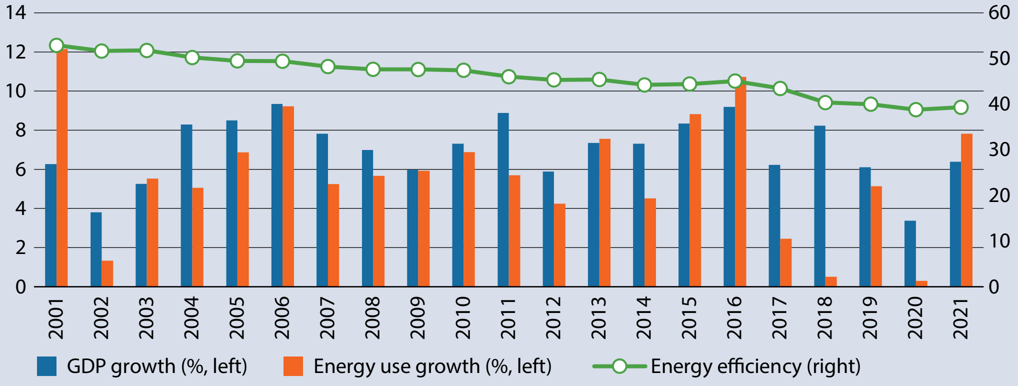
BANGLADESH

All Sectors

GDP growth has generally outpaced energy-use growth, leading to a decline in EE Index and a steady improvement in the overall energy efficiency (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

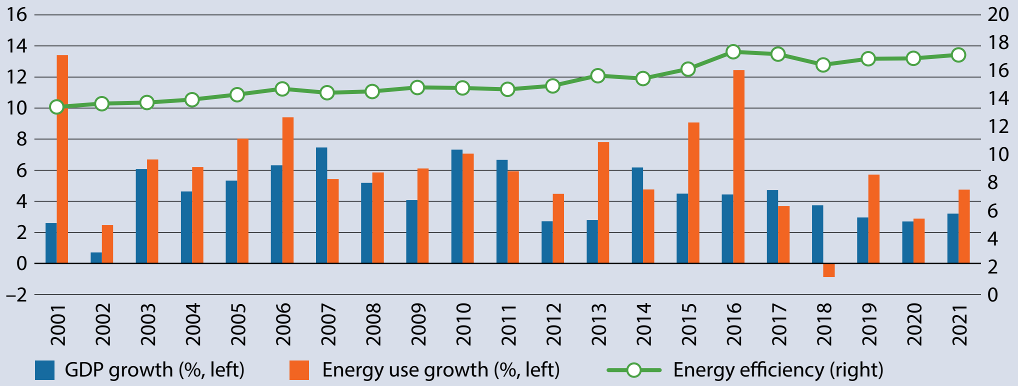


Agriculture Sector

Energy use has showed strong volatility—surging in 2001 and 2016 and falling in 2018—resulting in a long-term increase in energy efficiency (EE) Index and, in turn, a deterioration in agricultural energy efficiency (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

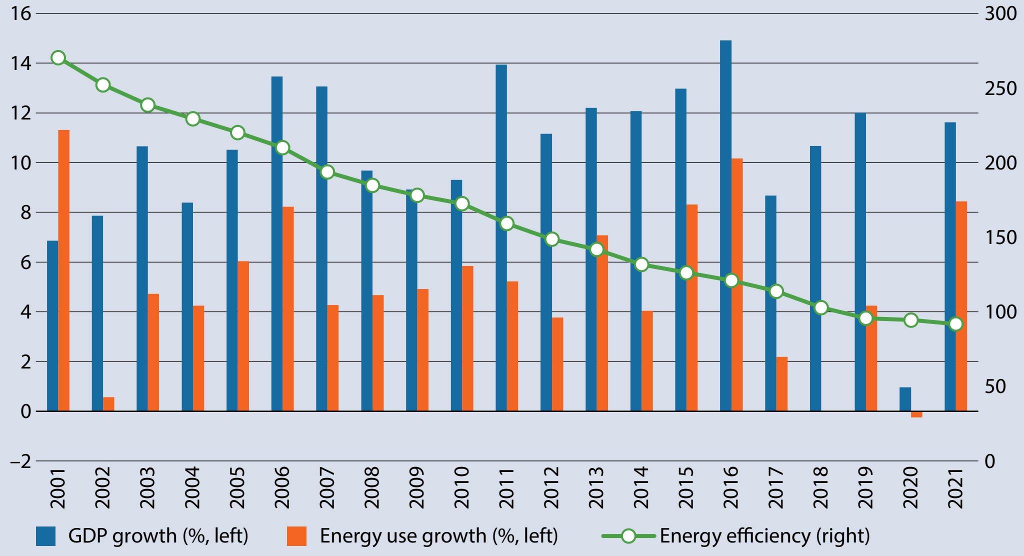


Manufacturing Sector

Although GDP growth was often higher, energy-use growth remained high for several years, leading to higher EE Index and a worsening overall manufacturing energy efficiency (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

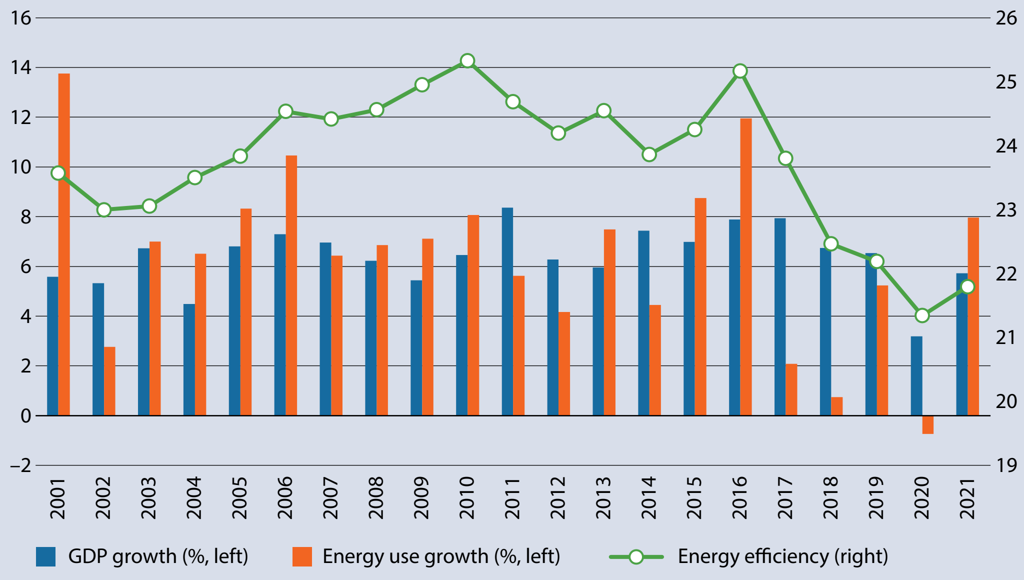


Services Sector

GDP grew steadily while energy use fluctuated, causing EE to alternate between improvement and deterioration, but ultimately showing a mild long-term efficiency improvement (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

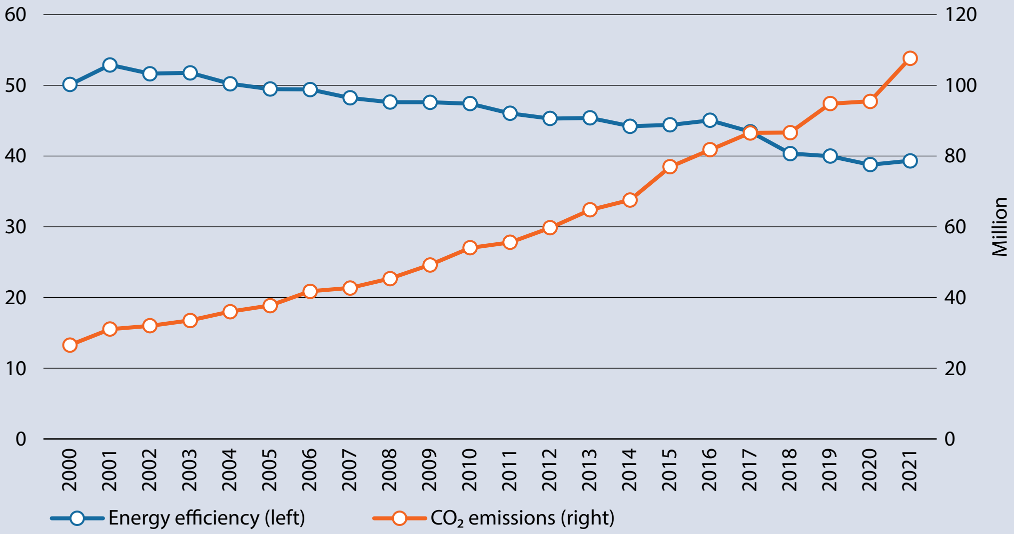


Energy Efficiency and CO_2 Emissions

Despite an increase in CO_2 from 5.4×107 to 3.6×108, efficiency has improved, with EE decreasing from 85.6 to 83.6 (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

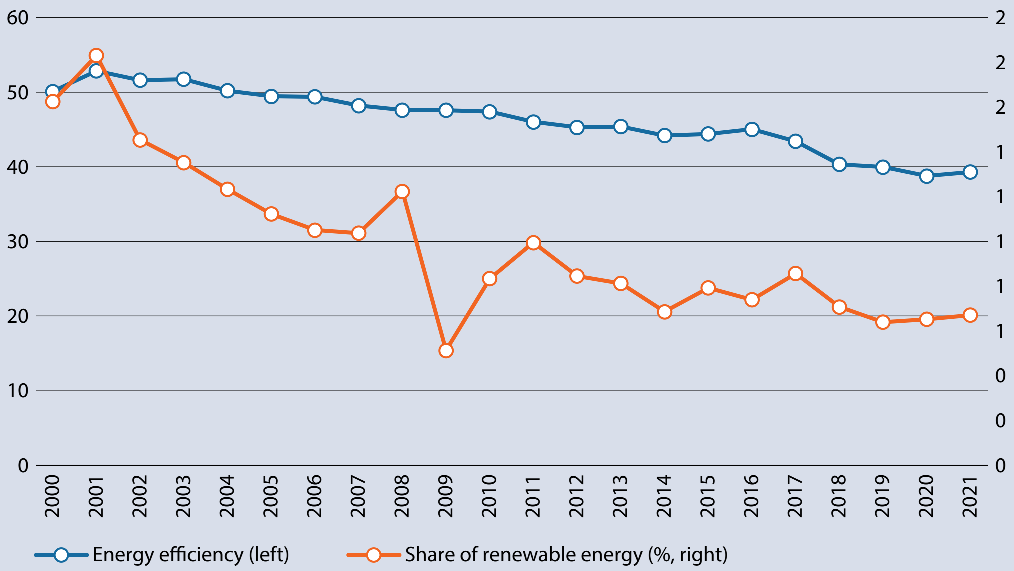


Energy Efficiency and the Share of Renewable Energy

While the share of renewable energy increased from 13.9 to 22.2, EE decreased from 92 to 79, indicating that efficiency improved as renewable energy capacity expanded (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND THE SHARE OF RENEWABLE ENERGY.

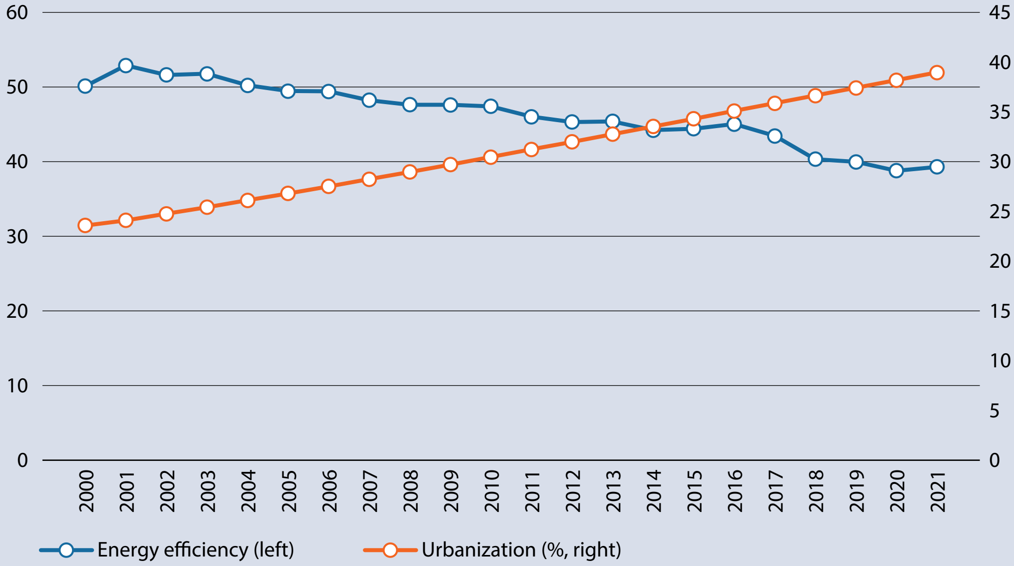


Energy Efficiency and Urbanization

While the urbanization rate increased from 24% to 38%, EE declined from 92% to 79%, indicating that efficiency improved alongside urban expansion (Figure 7).

FIGURE 7

ENERGY EFFICIENCY AND URBANIZATION.

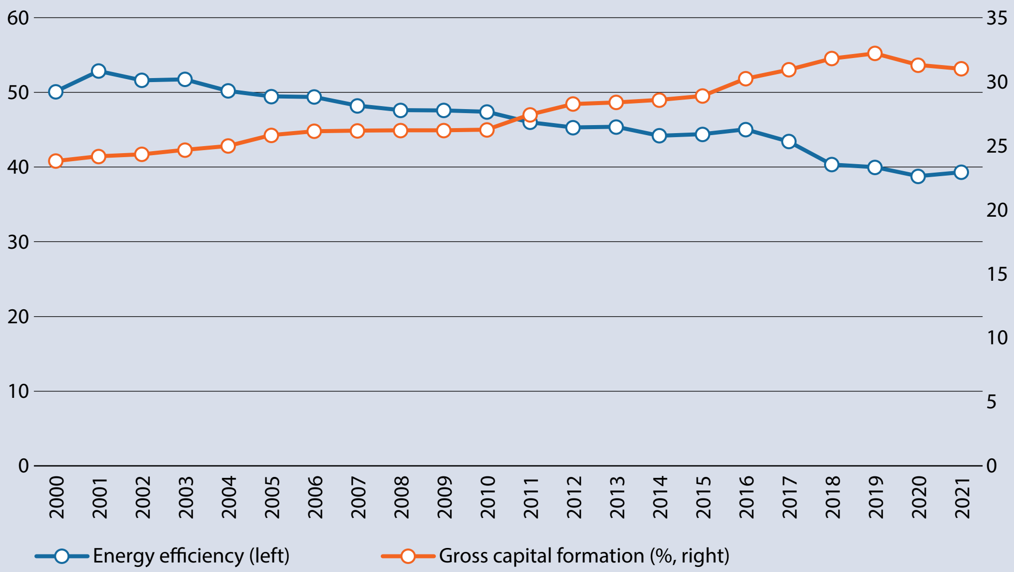


Energy Efficiency and Gross Capital Formation

While GF stabilized at 30–33%, EE decreased from 92 to 79, indicating improved efficiency while maintaining the investment level (Figure 8).

FIGURE 8

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



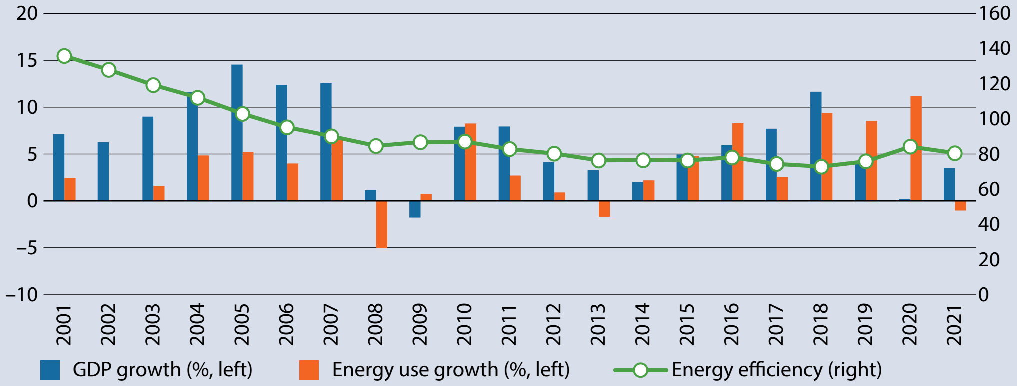
CAMBODIA

All Sectors

GDP growth generally outpaced energy-use growth, with notable drops in energy use in 2008 and 2012. As a result, energy efficiency (EE) Index consistently declined, indicating a steady improvement in overall energy efficiency (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

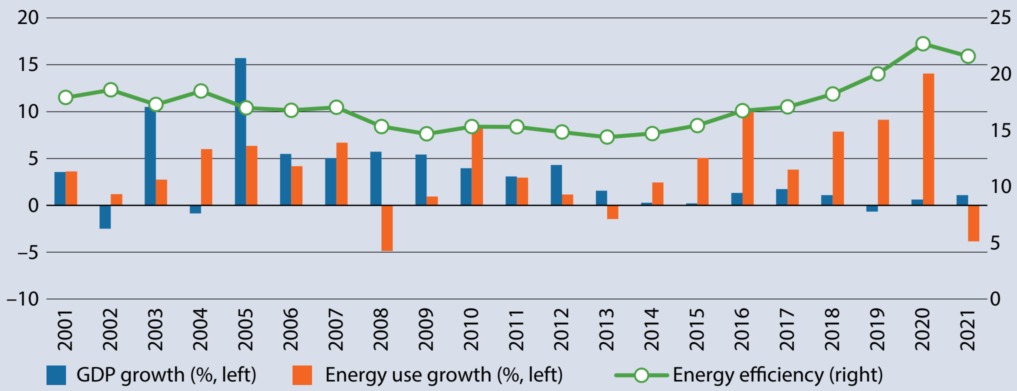


Agriculture Sector

Agricultural energy use surged in 2001 and 2016 and fell in 2021, while agricultural GDP grew more steadily. Consequently, EE Index increased over the long term, indicating deteriorating energy efficiency in the agricultural sector (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

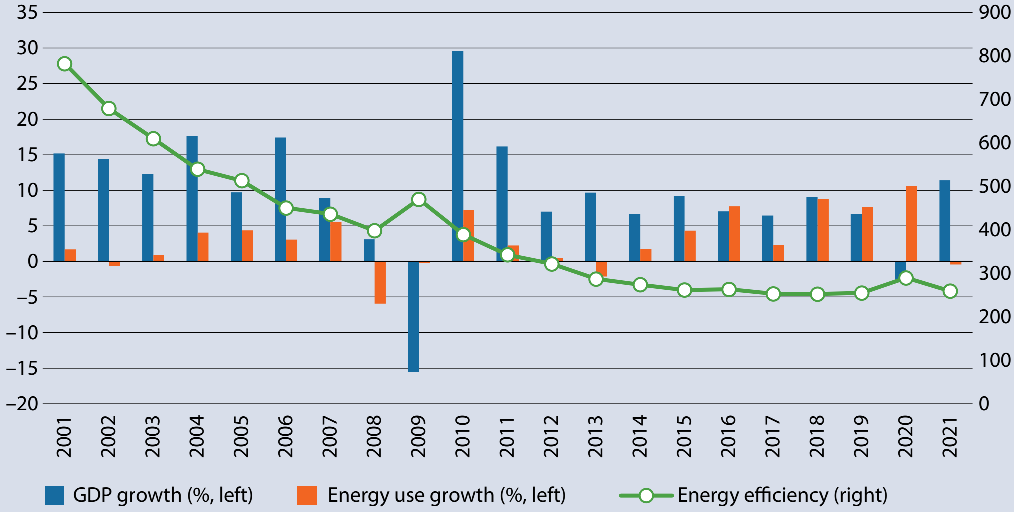


Manufacturing Sector

Manufacturing GDP fluctuated sharply—surging in 2010 and plunging in 2009—while energy use also spiked in several years. Because energy use grew relatively faster than GDP, EE Index increased noticeably, reflecting worsening energy efficiency in manufacturing (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

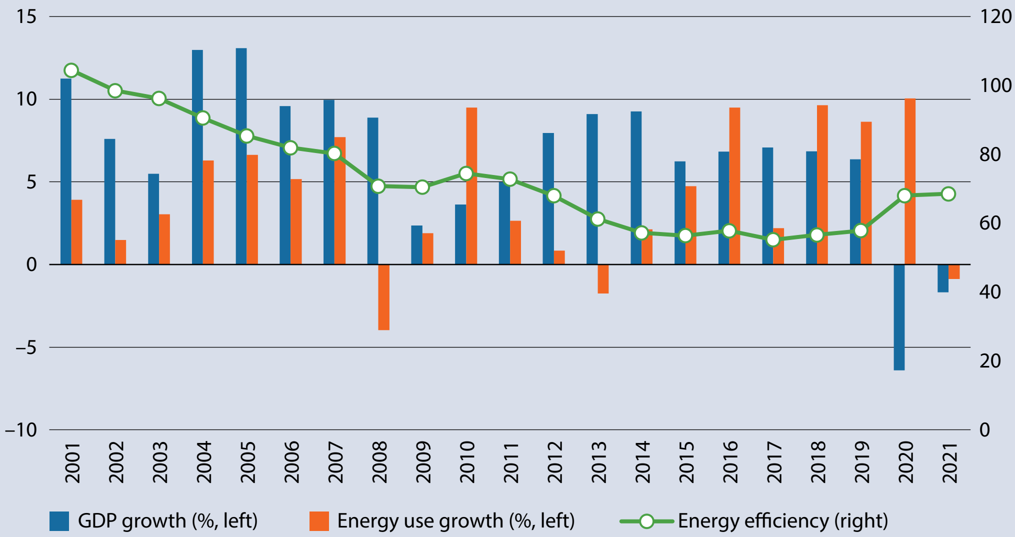


Services Sector

The services sector's GDP rose steadily, while energy use fluctuated year-on-year with a significant drop in 2020. Amid these variations, EE Index gradually decreased overall, indicating a mild improvement in service-sector EE (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

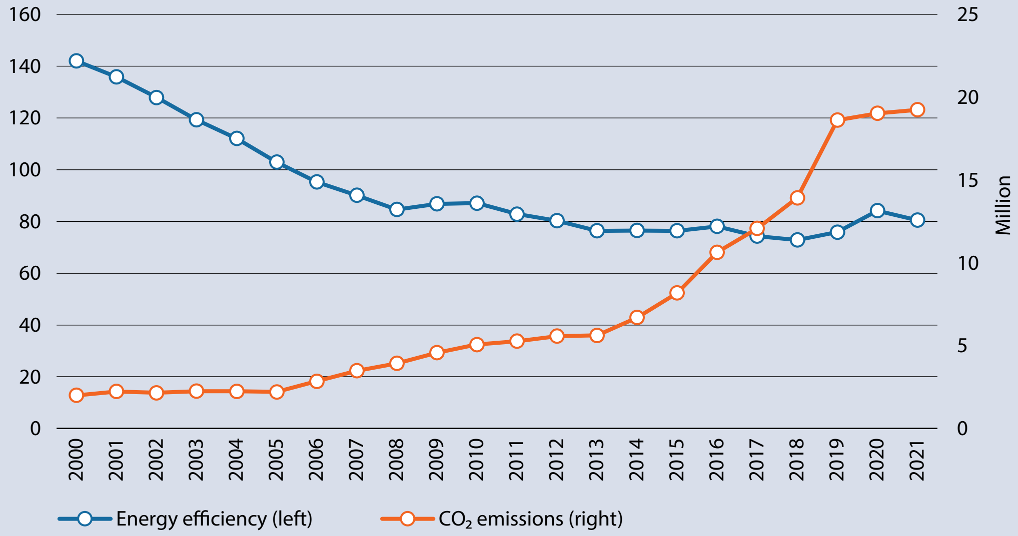


Energy Efficiency and CO_2 Emissions

Despite a rapid rise in CO_2 emissions from 2 million to 19.24 million, EE decreased from 142 to 80, indicating that efficiency has been improving despite the surge in emissions (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

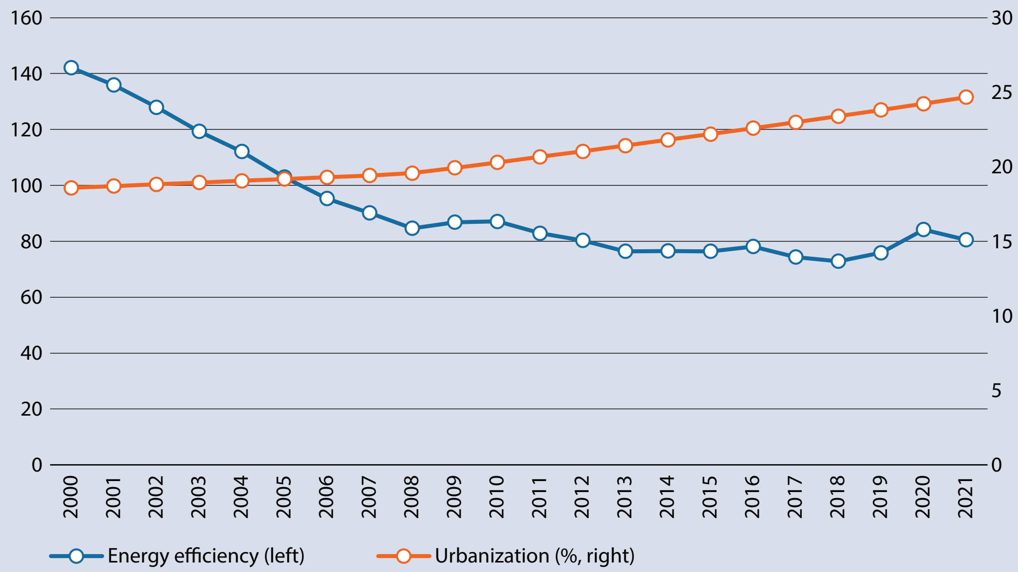


Energy Efficiency and Urbanization

While the urbanization rate steadily increased from 18.6% to 24.7%, EE decreased significantly from 142 to 80, clearly demonstrating an improvement in efficiency as urbanization expanded (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND URBANIZATION.

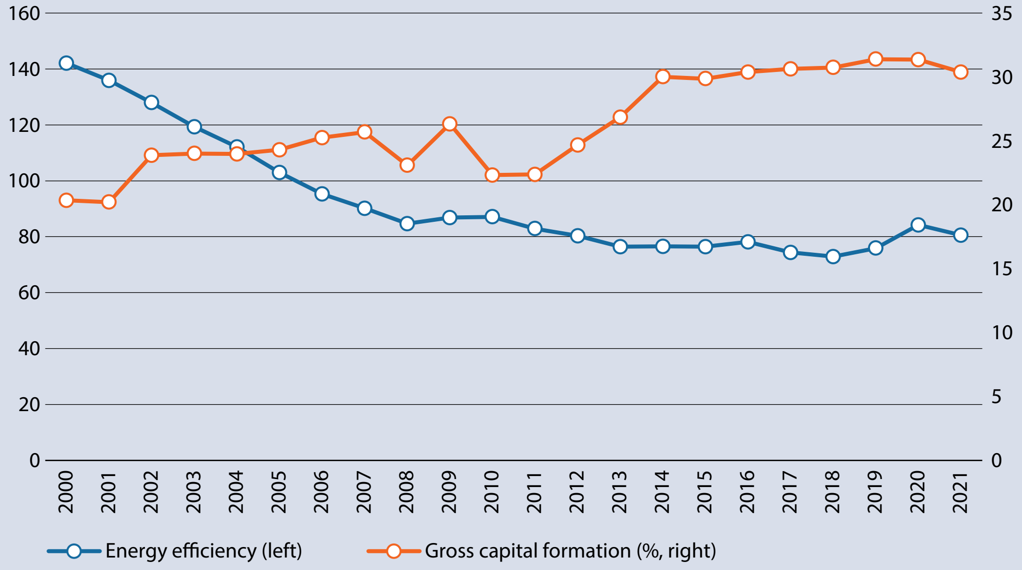


Energy Efficiency and Gross Capital Formation

As gross capital formation increased from 20% to 30%, EE decreased from 142% to 80%, resulting in continuous improvement in efficiency alongside increased investment (Figure 7).

FIGURE 7

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



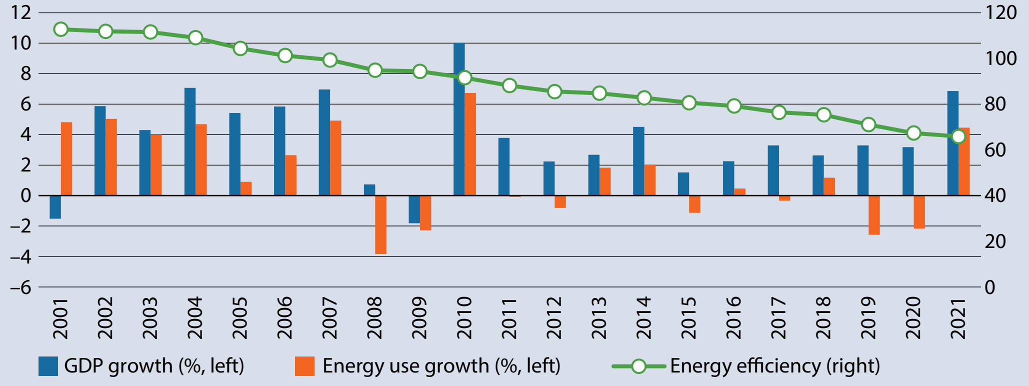
THE REPUBLIC OF CHINA

All Sectors

GDP growth generally exceeded energy-use growth, whereas energy use declined notably in 2008 and 2011. As a result, energy efficiency (EE) Index steadily declined over the period, indicating continuous improvement in overall energy efficiency (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

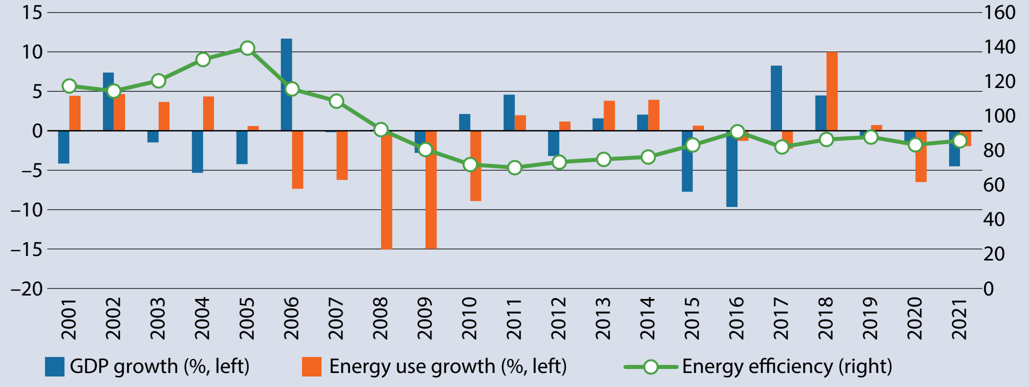


Agriculture Sector

Agricultural energy use decreased sharply in 2007–09 and again in 2018–21, while GDP growth remained modest. Consequently, EE Index fell over time, reflecting improved energy efficiency in the agricultural sector (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

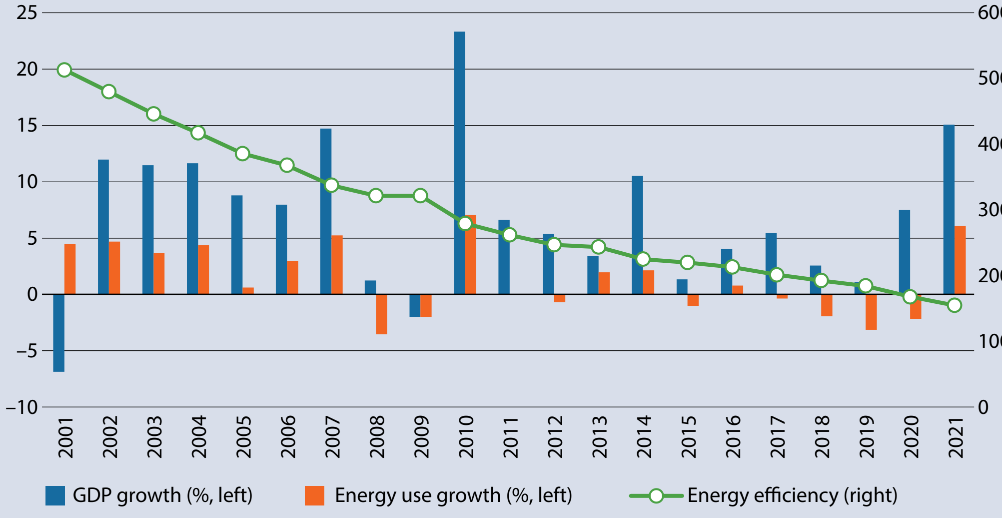


Manufacturing Sector

Manufacturing GDP fluctuated widely—plunging in 2009 and surging in 2010—while energy-use growth also varied but generally stayed lower than GDP growth. This led to a consistent decline in EE Index, indicating improved energy efficiency in manufacturing (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

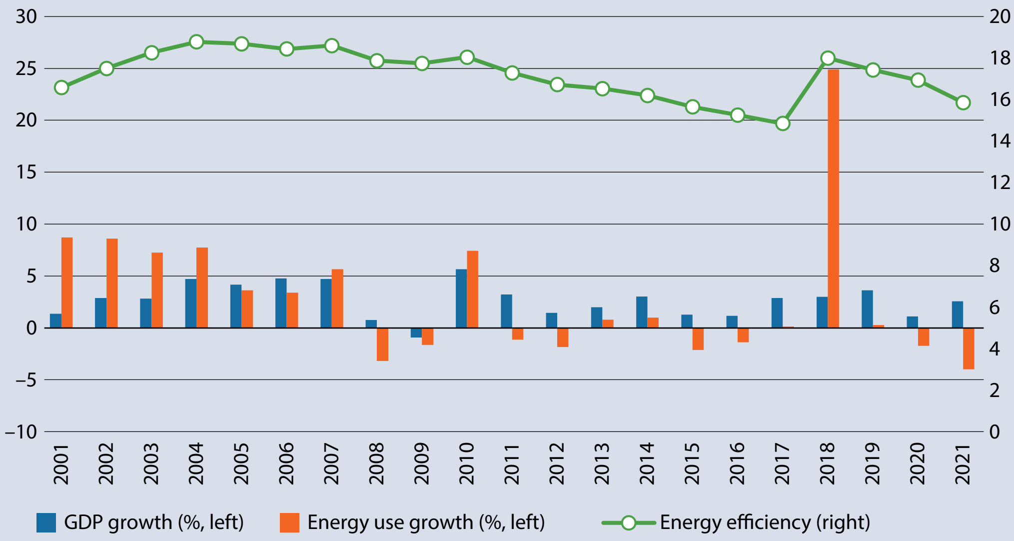


Services Sector

Services sector's GDP grew steadily, whereas energy-use growth fluctuated, with a sharp spike in 2018. Despite these fluctuations, EE Index decreased gradually over time, showing an overall improvement in the services sector's energy efficiency (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

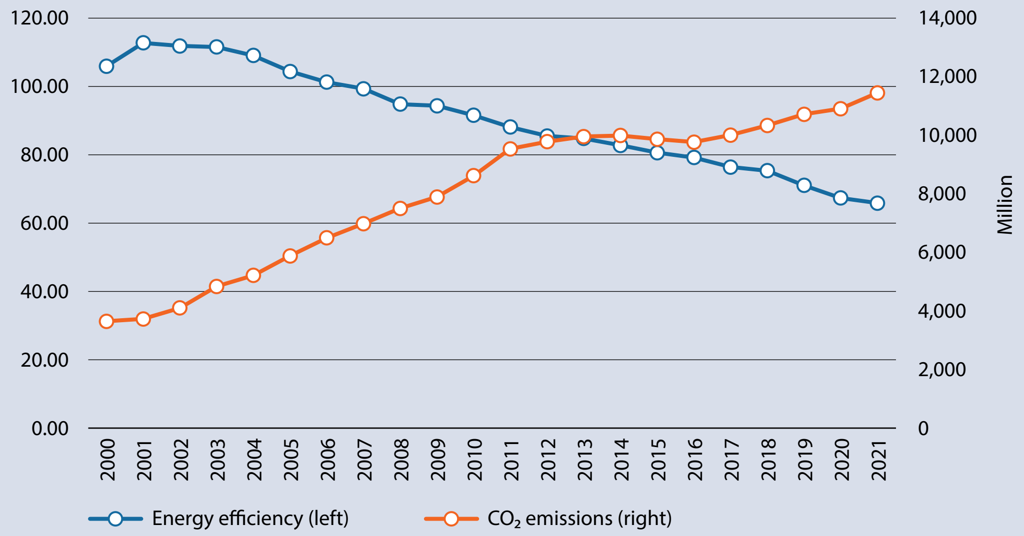


Energy Efficiency and CO_2 Emissions

While CO2 emissions increased steadily from 3.6 billion to 11.4 billion tons, EE decreased from 105.9 to 65.9, indicating a discernible enhancement in efficiency despite the rise in emissions (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

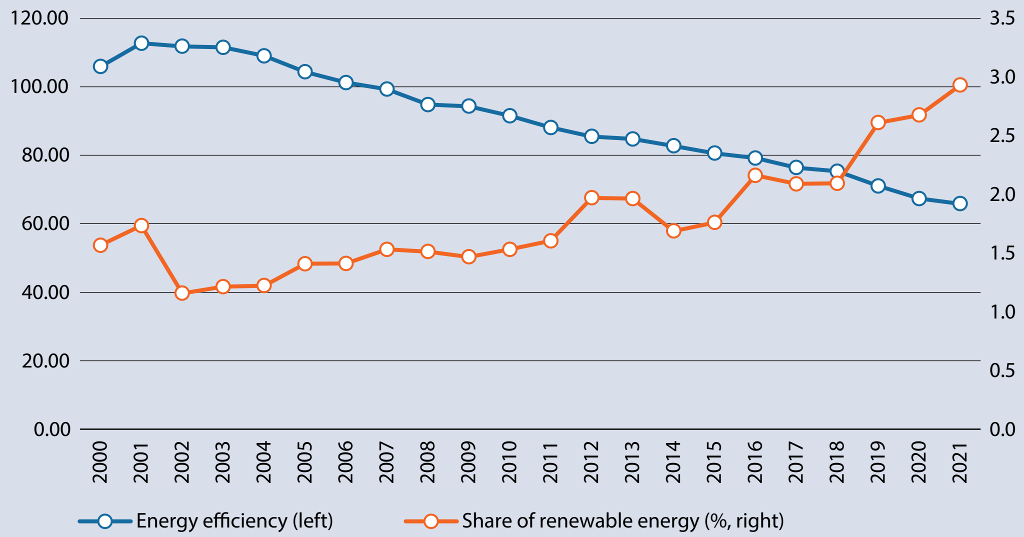


Energy Efficiency and the Share of Renewable Energy

During the period when the share of renewable energy increased from 1.56 to 2.93, EE decreased from 105.9 to 65.9, indicating that the trend of efficiency improvement continued along with the expansion of renewable energy (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND THE SHARE OF RENEWABLE ENERGY.



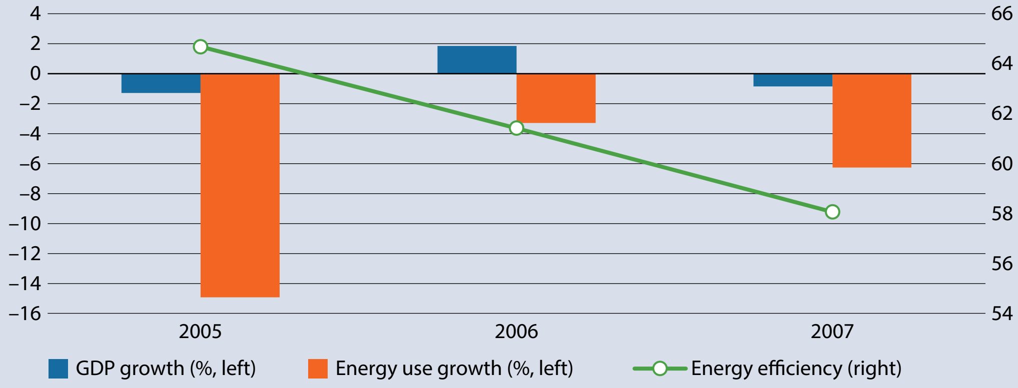
FIJI

All Sectors

Energy-use growth fell sharply in 2005–07, while GDP growth fluctuated at modest levels. As energy use declined faster than GDP, EE Index decreased steadily, indicating improved overall energy efficiency (Figure 1).

FIGURE 1

GDP AND ENERGY USE GROWTH IN ALL SECTORS.

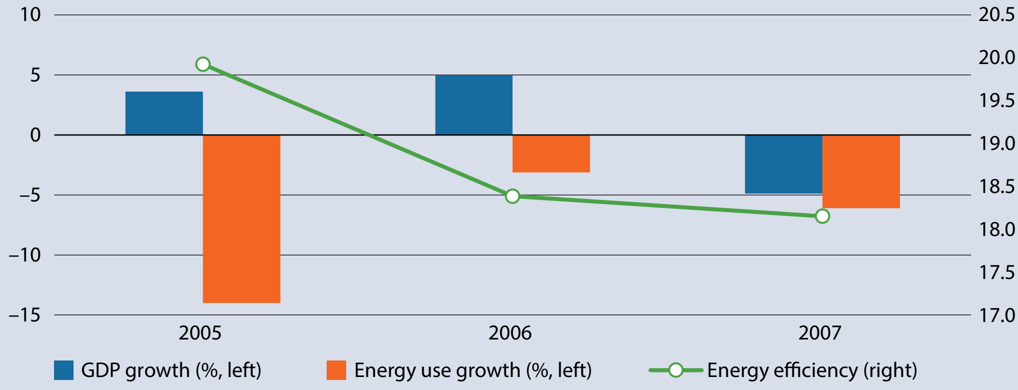


Agriculture Sector

Agricultural energy use dropped sharply in 2005–07, whereas GDP growth remained relatively stable. This led to a continuous decline in EE Index, reflecting improved energy efficiency in agriculture (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

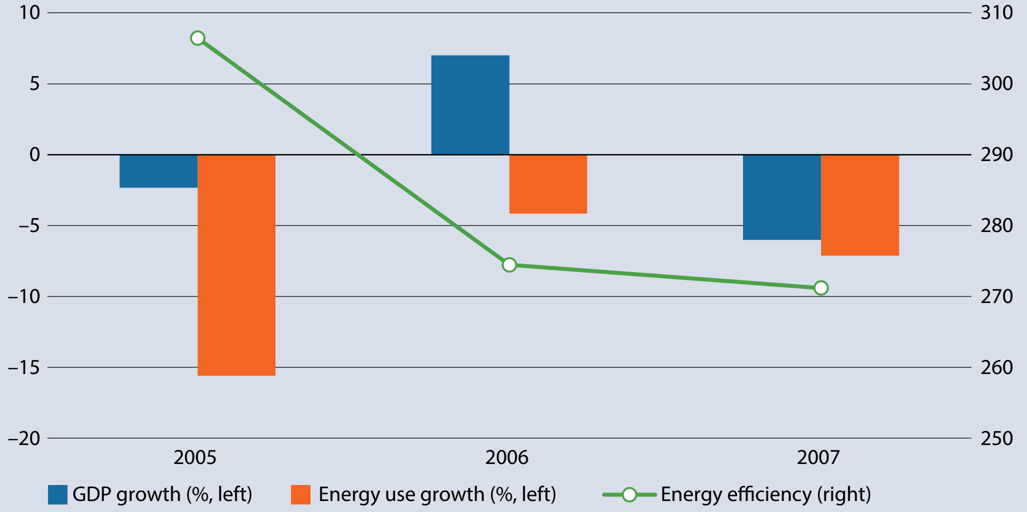


Manufacturing Sector

Manufacturing GDP rose in 2006 but fell in 2005 and 2007, while energy use declined strongly in all three years. Since energy use contracted more than GDP, EE Index decreased consistently, showing improved manufacturing energy efficiency (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

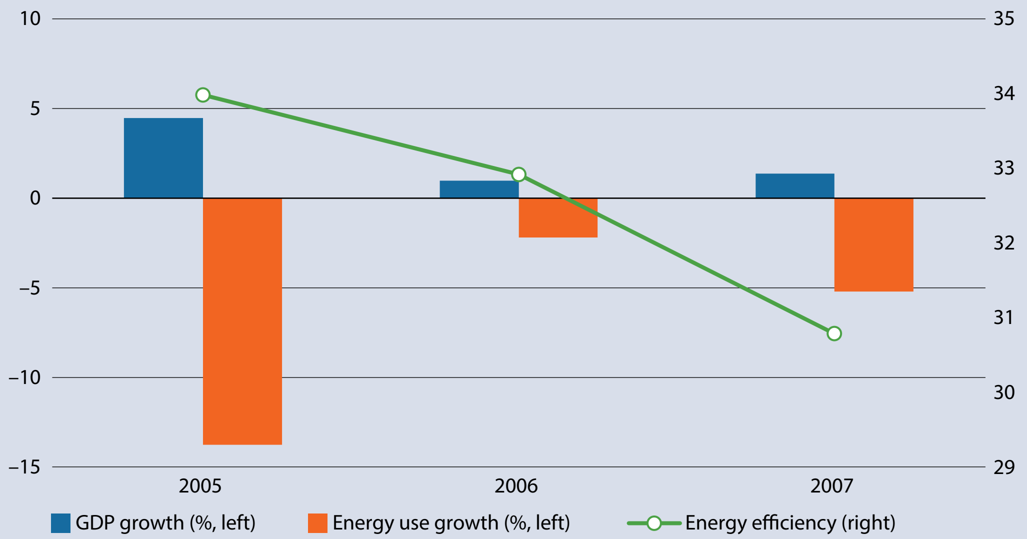


Services Sector

The services sector's energy use dropped sharply during 2005–07, while GDP growth stayed low but positive. As a result, energy efficiency (EE) Index steadily declined, indicating improved energy efficiency in the services sector (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.



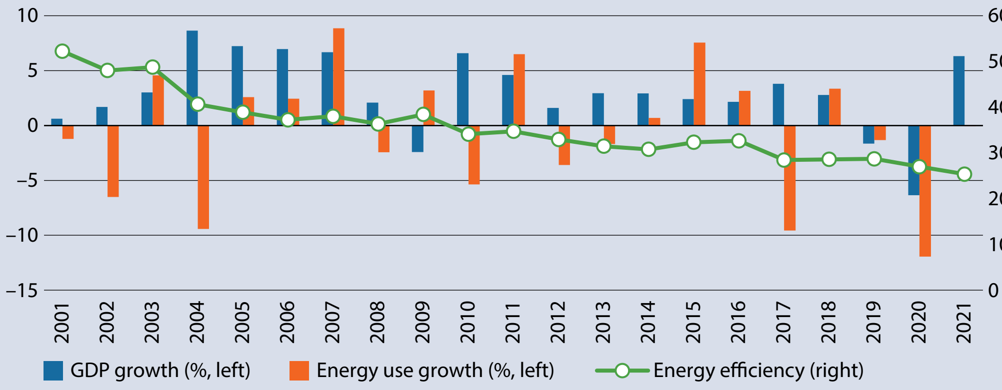
HONG KONG

All Sectors

GDP growth was generally higher than energy-use growth, whereas energy use exhibited pronounced negative spikes in 2004, 2010, and 2020. As energy use declined more sharply than GDP, EE Index gradually decreased, indicating improvements in overall energy efficiency (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

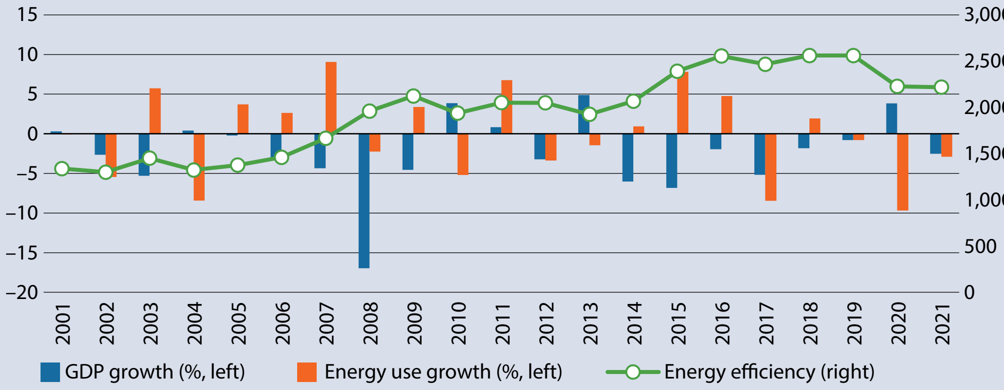


Agriculture Sector

Agricultural energy use fell sharply in several years—especially 2005, 2008–10, and 2018—while GDP growth fluctuated but remained mostly modest. As energy use contracted faster, EE Index declined steadily, reflecting improved agricultural energy efficiency (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

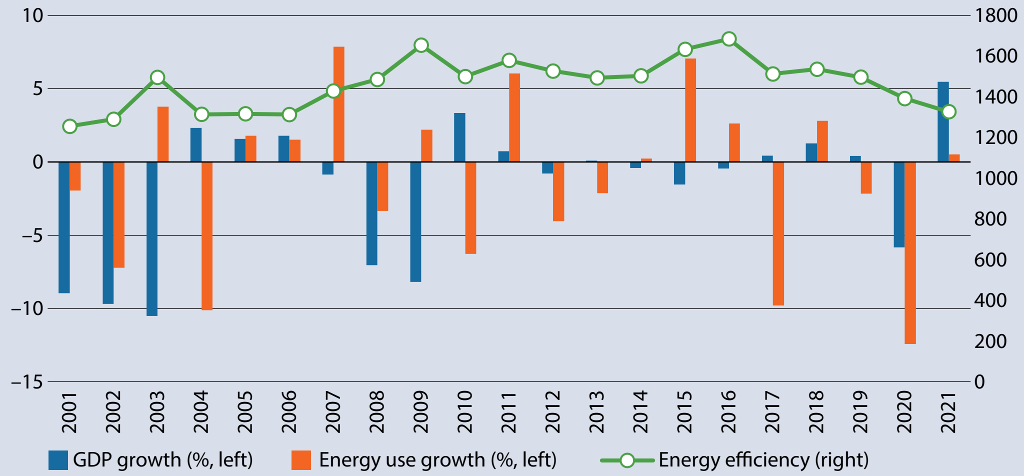


Manufacturing Sector

Manufacturing GDP exhibited repeated negative growth, particularly in 2001–2003, 2009, and 2020, while energy use also fell sharply in several years. Because energy use contracted more strongly than GDP in many periods, EE Index declined overall, showing improved manufacturing energy efficiency (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

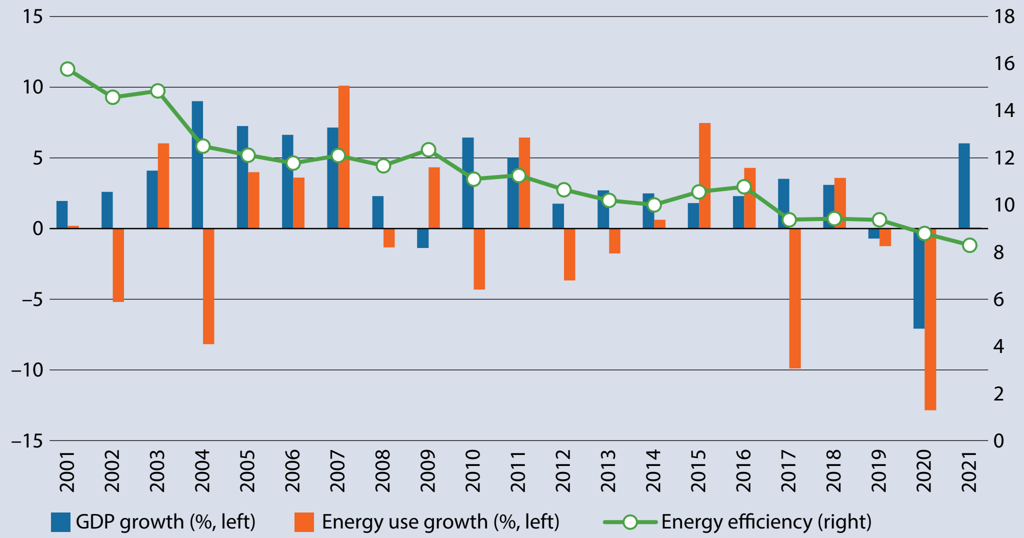


Services Sector

The services sector's GDP grew moderately, whereas energy use declined substantially in 2002, 2004, 2010, and 2020. This pattern led to a gradual decrease in EE Index, indicating a steady improvement in the services sector's energy efficiency (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

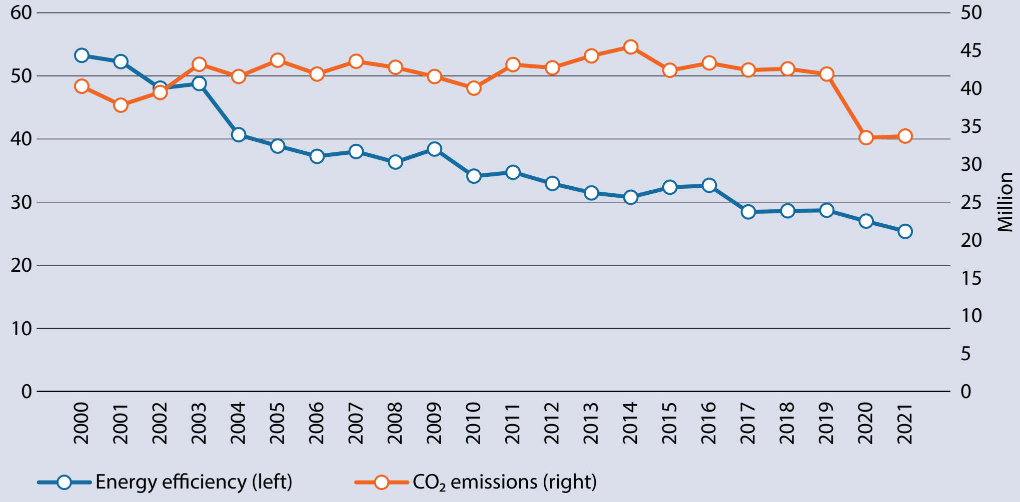


Energy Efficiency and CO_2 Emissions

During the period when CO2 emissions decreased from approximately 40 million tons to 33 million tons, EE also reduced from 53.2 to 25.4, indicating that EE improved in parallel with the emission reduction (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

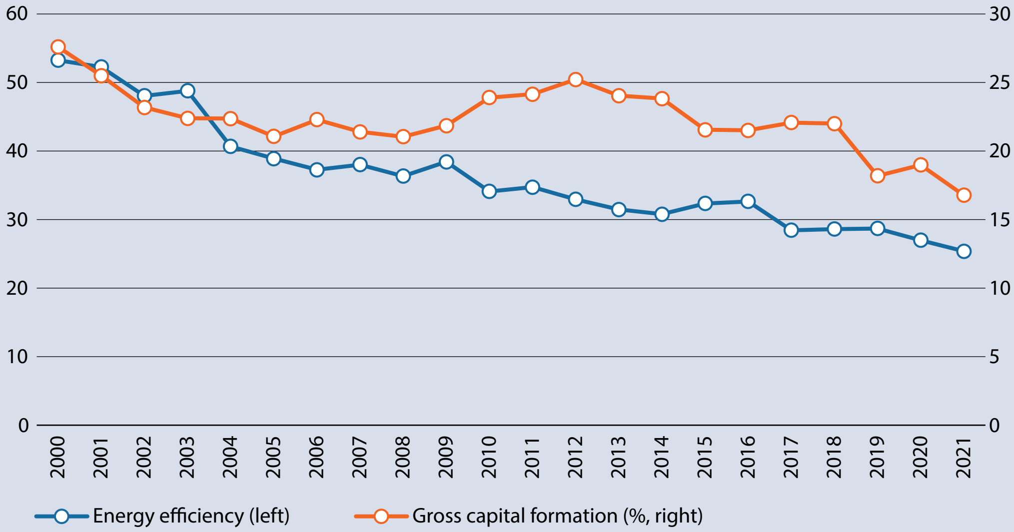


Energy Efficiency and Gross Capital Formation

While GF decreased from 27.6% to 16.8%, EE also declined significantly from 53.2% to 25.4%, indicating a consistent improvement in efficiency despite the trend toward reduced investment (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



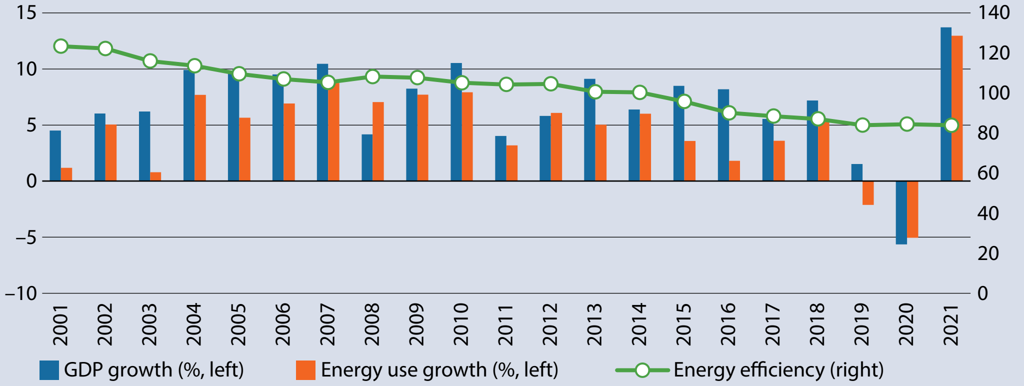
INDIA

All Sectors

GDP growth generally exceeded energy-use growth in most years, while energy use declined sharply in 2019 and 2020. As energy use grew more slowly than GDP, energy efficiency (EE) Index steadily decreased, indicating long-term improvements in total-sector energy efficiency (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

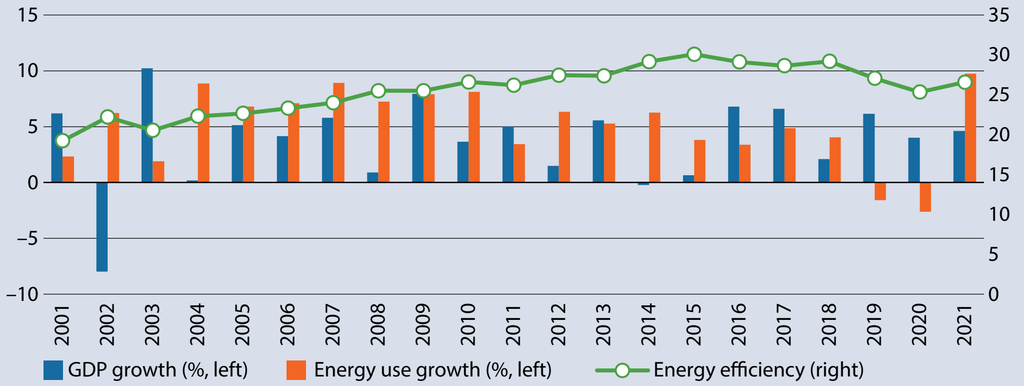


Agriculture Sector

Agricultural energy use exhibited pronounced volatility—with notable spikes in 2004, 2007, 2010, and 2021—while GDP growth fluctuated but remained positive in most years. As energy use often rose faster than GDP, EE Index increased over time, reflecting a deterioration in agricultural energy efficiency (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

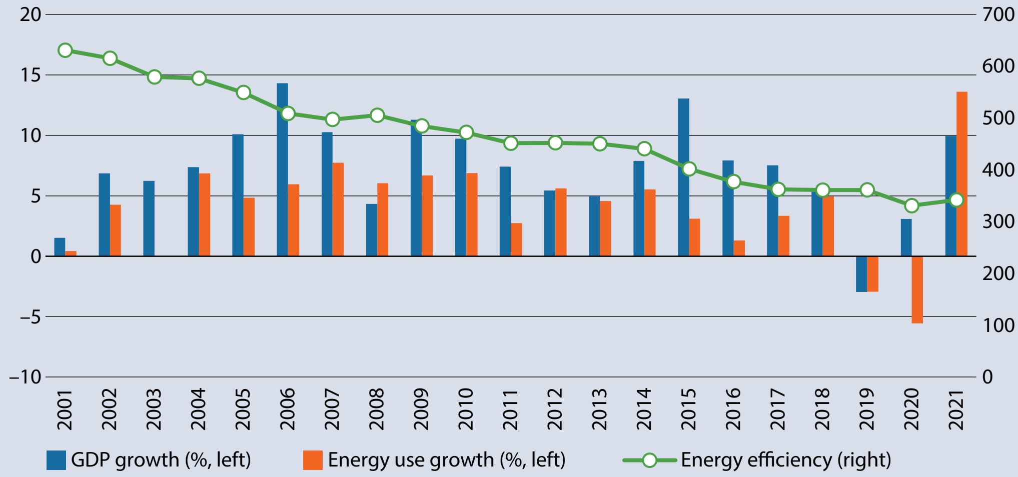


Manufacturing Sector

Manufacturing GDP exhibited pronounced fluctuations, particularly in 2009 and 2020, when sharp contractions occurred, while energy use also declined substantially in multiple years. Because energy use tended to decrease more rapidly than GDP in several periods, EE Index declined gradually, indicating improved energy efficiency in manufacturing (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

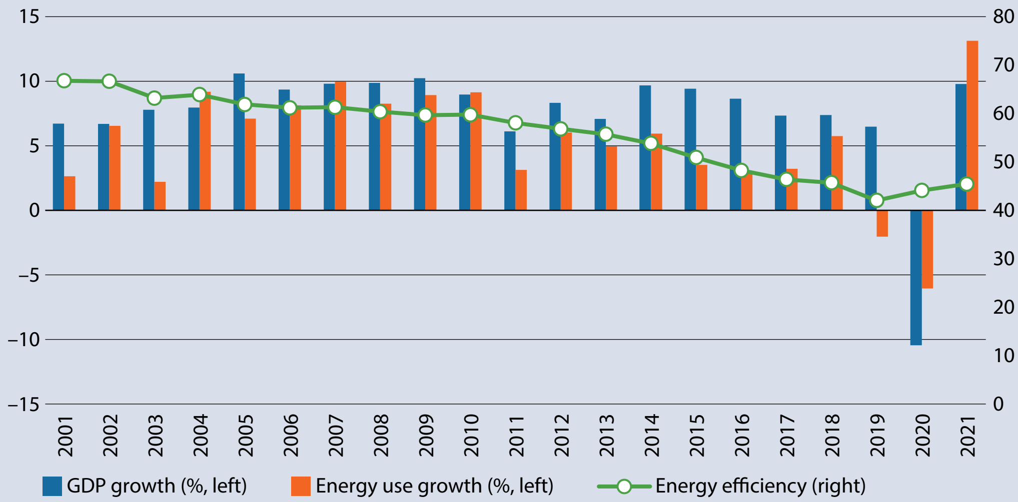


Services Sector

The services sector's GDP grew steadily in most years, whereas energy use exhibited pronounced fluctuations and negative growth in 2019 and 2020. Since energy use generally expanded more slowly than GDP, EE Index declined over time, suggesting a long-term improvement in the services sector's energy efficiency (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

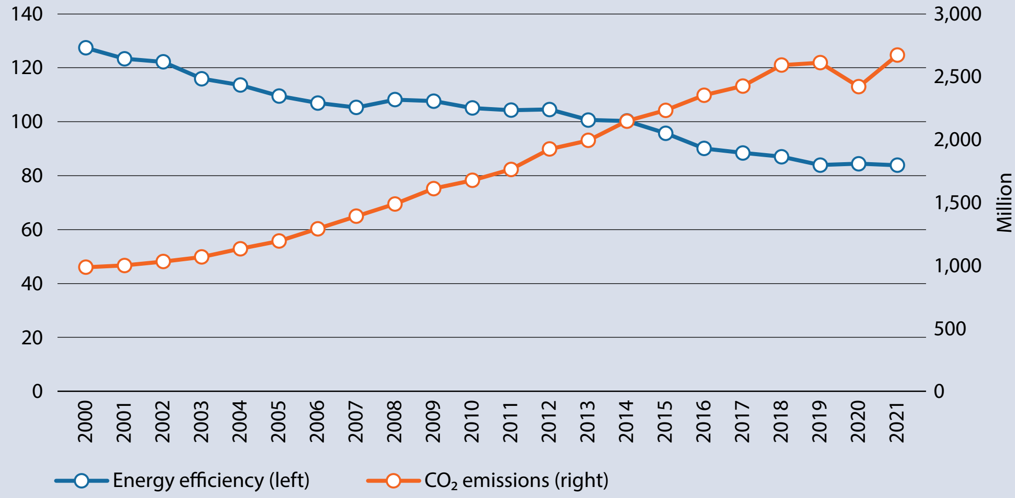


Energy Efficiency and CO_2 Emissions

Although CO2 emissions increased from approximately 990 million tons to 2.67 billion tons, efficiency declined from 127 to 83, indicating that EE has improved over the long term despite rising emissions (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

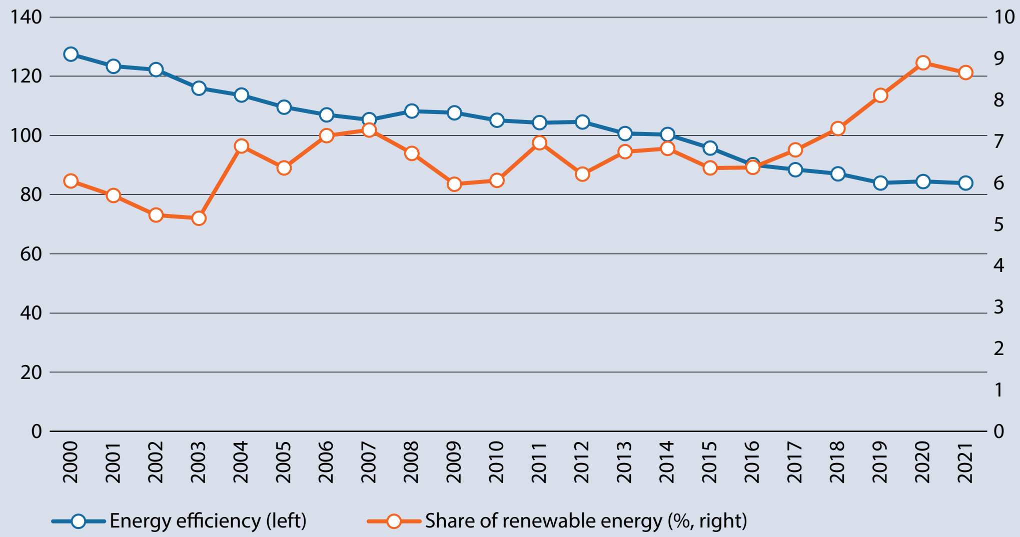


Energy Efficiency and the Share of Renewable Energy

While the share of renewable energy increased from 6.04 to 8.66, EE decreased from 127 to 84, indicating a simultaneous increase in the share of renewable energy and an improvement in efficiency (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND SHARE OF RENEWABLE ENERGY.

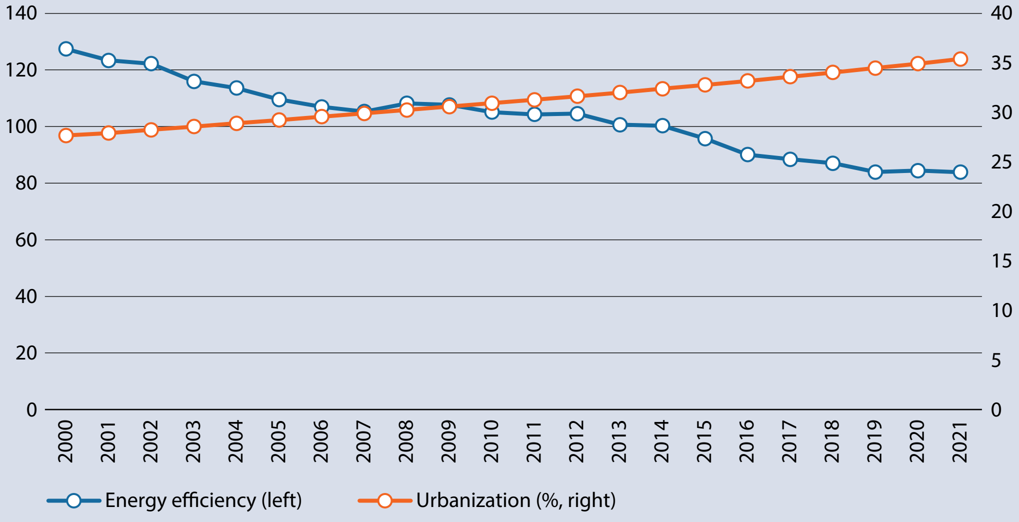


Energy Efficiency and Urbanization

While the urbanization rate rose steadily from 27.7% to 35.4%, efficiency declined significantly from 127.4 to 83.9, suggesting that efficiency improvements were concomitant with urban expansion (Figure 7).

FIGURE 7

ENERGY EFFICIENCY AND URBANIZATION.

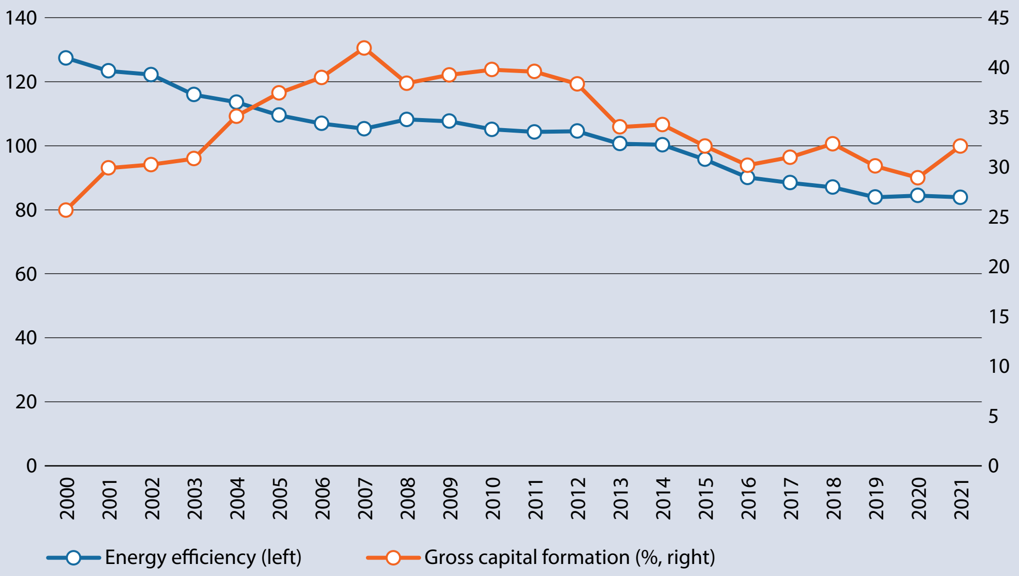


Energy Efficiency and Gross Capital Formation

Although GF showed structural changes, fluctuating between 25.7% and 32.1%, EE decreased overall from 127 to 84, indicating a steady improvement in efficiency regardless of changes (Figure 8).

FIGURE 8

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



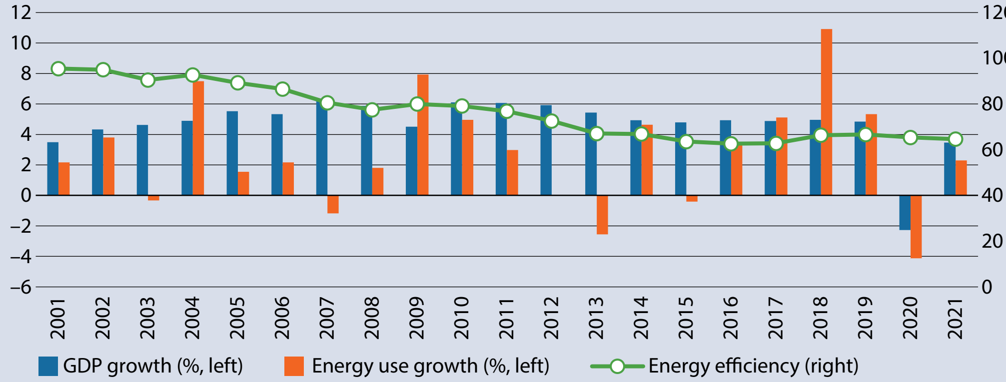
INDONESIA

All Sectors

GDP growth consistently outpaced energy-use growth in most years, whereas energy use declined sharply in 2014, 2017, and 2020. As energy use increased more slowly than GDP, energy efficiency (EE) Index steadily declined, indicating long-term improvements in total-sector energy efficiency (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

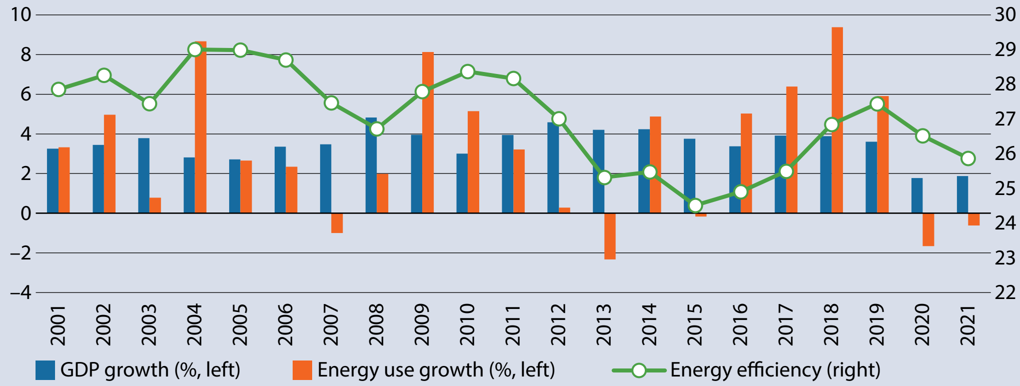


Agriculture Sector

Agricultural energy use fluctuated widely—with sharp increases in 2004, 2007, 2010, and 2018—while GDP growth remained relatively moderate. Because energy use often rose faster than GDP, EE Index increased over time, reflecting a deterioration in agricultural energy efficiency (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

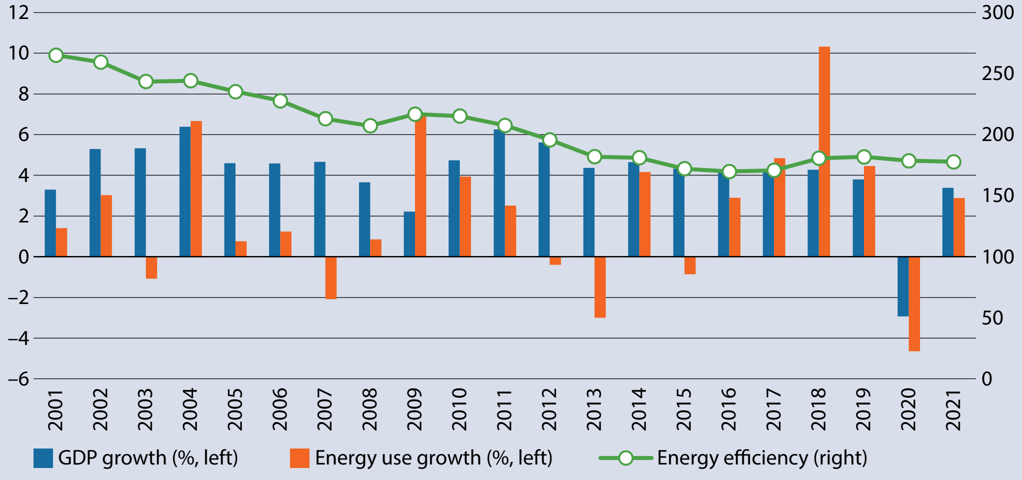


Manufacturing Sector

Manufacturing GDP grew strongly for several years but fell sharply in 2020, while energy-use growth also showed distinct spikes, especially in 2018. In multiple periods, energy use rose faster than GDP, and EE Index increased gradually, indicating worsening manufacturing energy efficiency (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

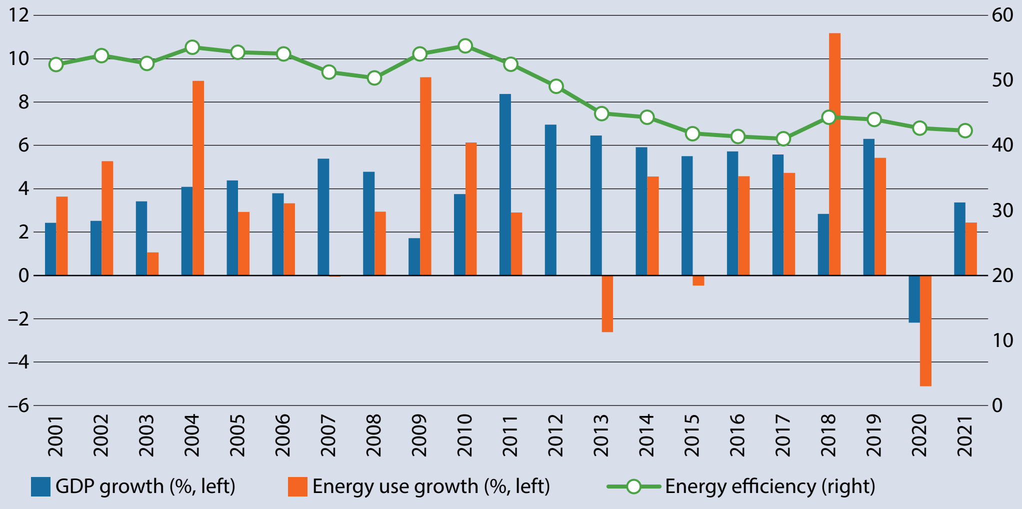


Services Sector

The services sector's GDP grew steadily, whereas energy use showed noticeable volatility, including a large spike in 2018 and a sharp decline in 2020. As energy use generally expanded faster than GDP, EE Index increased slightly over time, suggesting mild deterioration in service-sector energy efficiency (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

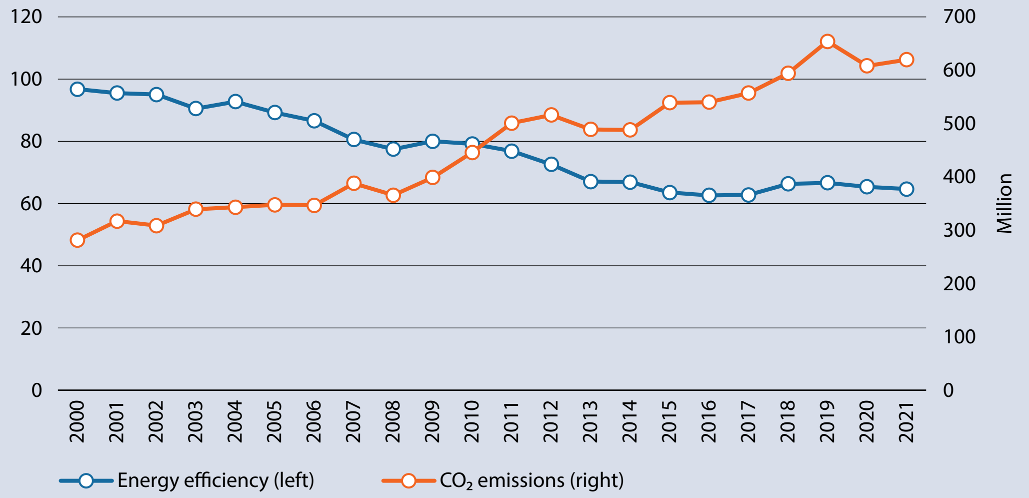


Energy Efficiency and CO_2 Emissions

Despite a notable rise in CO2 emissions, from approximately 280 million tons to 620 million tons, the EE decreased from 96.7 to 64.6, indicating that the trend of improving efficiency was maintained regardless of the increase in emissions (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

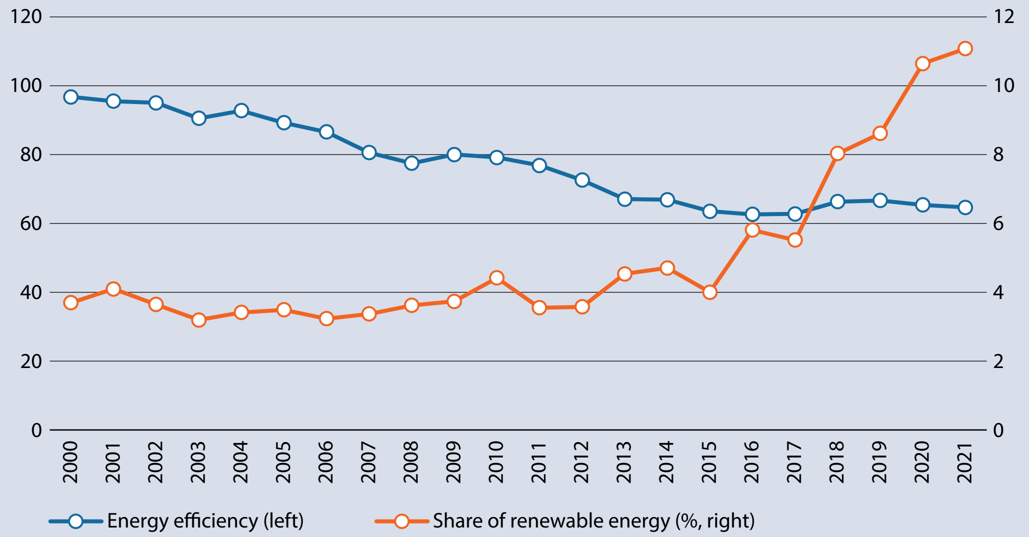


Energy Efficiency and the Share of Renewable Energy

While RE steadily increased from 3.70 to 11.08, EE decreased from 96.7 to 64.6, indicating that the expansion of renewable energy and efficiency improvements are occurring simultaneously (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND SHARE OF RENEWABLE ENERGY.

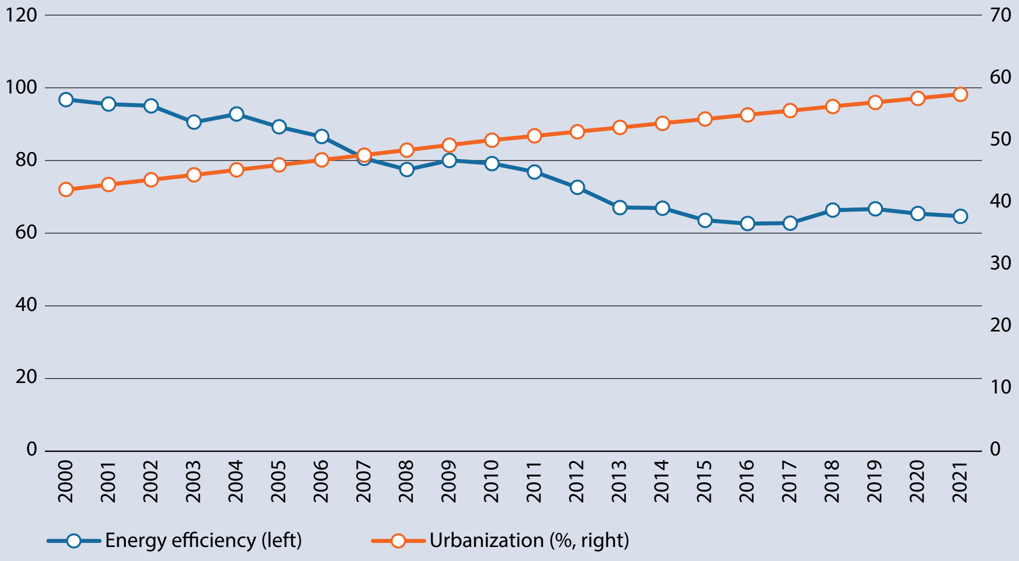


Energy Efficiency and Urbanization

While the urbanization rate increased significantly from 42.0% to 57.3%, EE decreased from 96.7% to 64.6%, indicating that efficiency improved steadily as urbanization expanded (Figure 7).

FIGURE 7

ENERGY EFFICIENCY AND URBANIZATION.

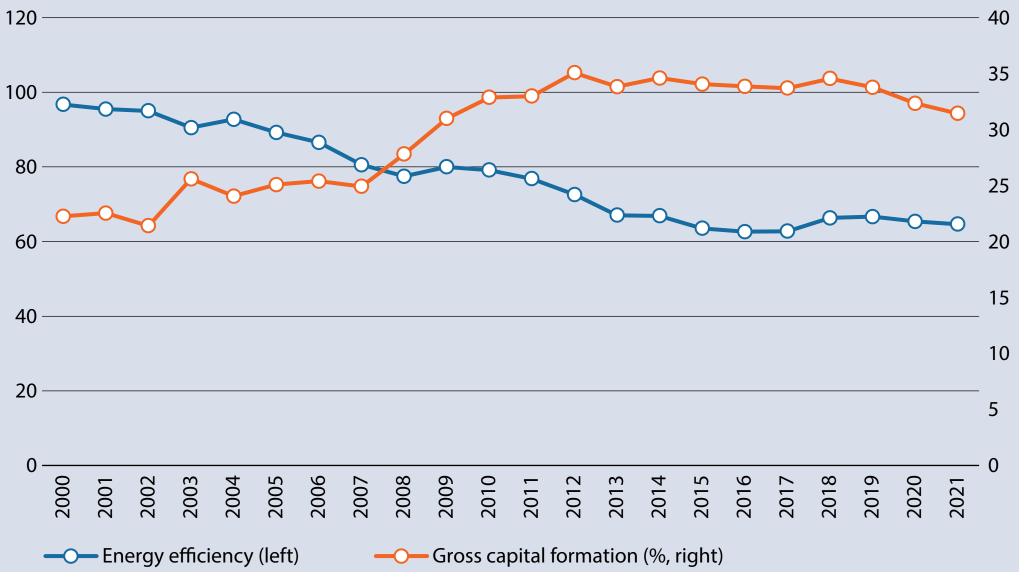


Energy Efficiency and Gross Capital Formation

While GF increased from 22.2% to 31.4%, EE declined from 96.7% to 64.6%, indicating a consistent improvement in efficiency despite increased investment (Figure 8).

FIGURE 8

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



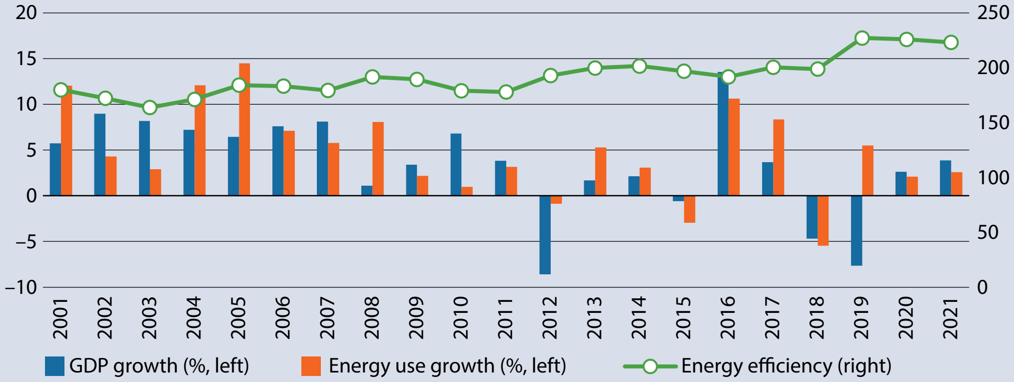
IR IRAN

All Sectors

GDP growth fluctuated moderately across the years, while energy-use growth showed sharp negative values in 2012, 2018, and 2020. Since energy use often declined more than GDP, EE Index decreased steadily overall, indicating long-term improvement in total-sector energy efficiency (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

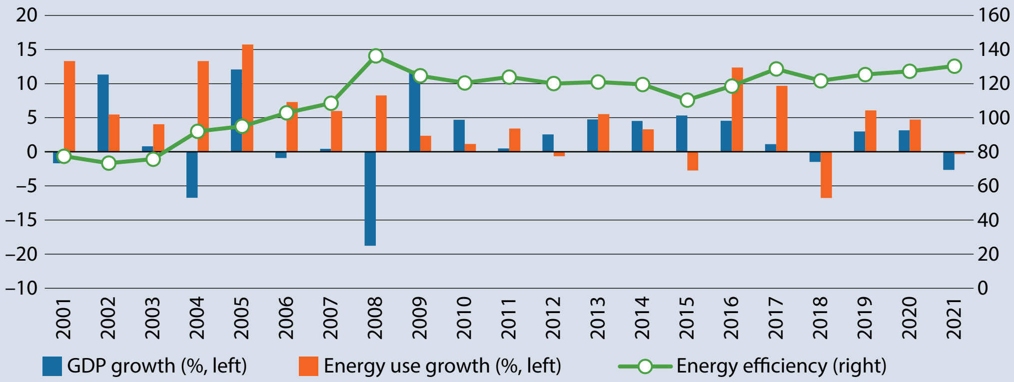


Agriculture Sector

Agricultural energy use displayed significant volatility—with large increases in 2004, 2005, and 2016 and decreases in 2008 and 2019—while GDP growth remained stable. As energy use rose faster than GDP in many years, EE Index increased overall, reflecting deteriorating agricultural energy efficiency (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

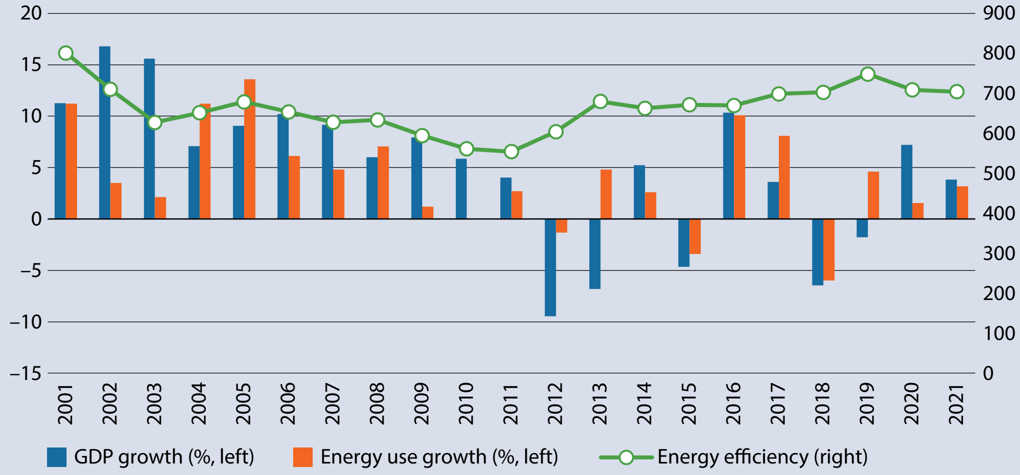


Manufacturing Sector

Manufacturing GDP experienced large swings, with severe contractions in 2009 and 2020, while energy use also declined sharply in several years. Because energy use tended to fall more sharply than GDP in many periods, EE Index decreased gradually, indicating improved energy efficiency in the manufacturing sector (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

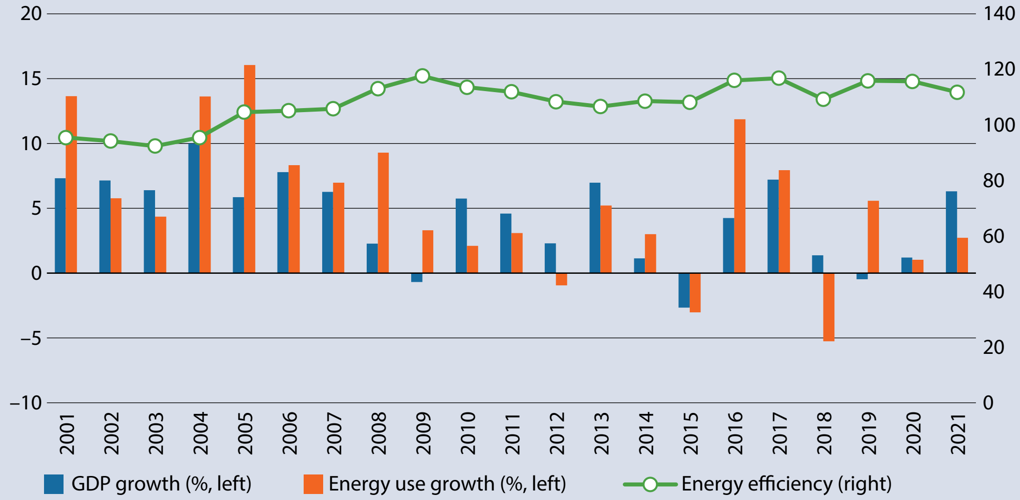


Services Sector

The services sector's GDP grew moderately, whereas energy use fluctuated with notable spikes in 2005, 2016, and 2021 and a major drop in 2018. As energy use frequently rose faster than GDP, EE Index increased slightly over time, indicating mild deterioration in service-sector energy efficiency (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

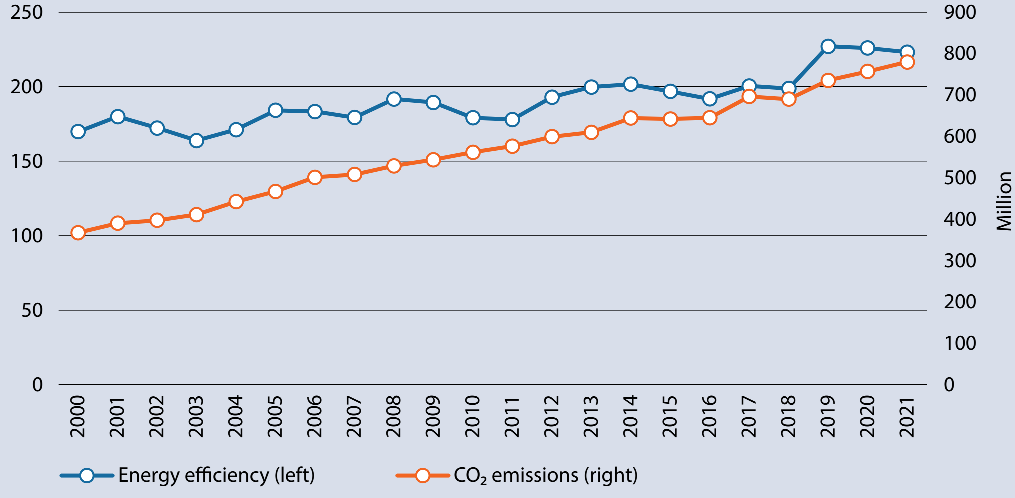


Energy Efficiency and CO_2 Emissions

While CO2 emissions increased significantly from approximately 370 million tons to 780 million tons, EE also rose from 169 to 223, showing no trend toward improved efficiency despite the increase in emissions (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

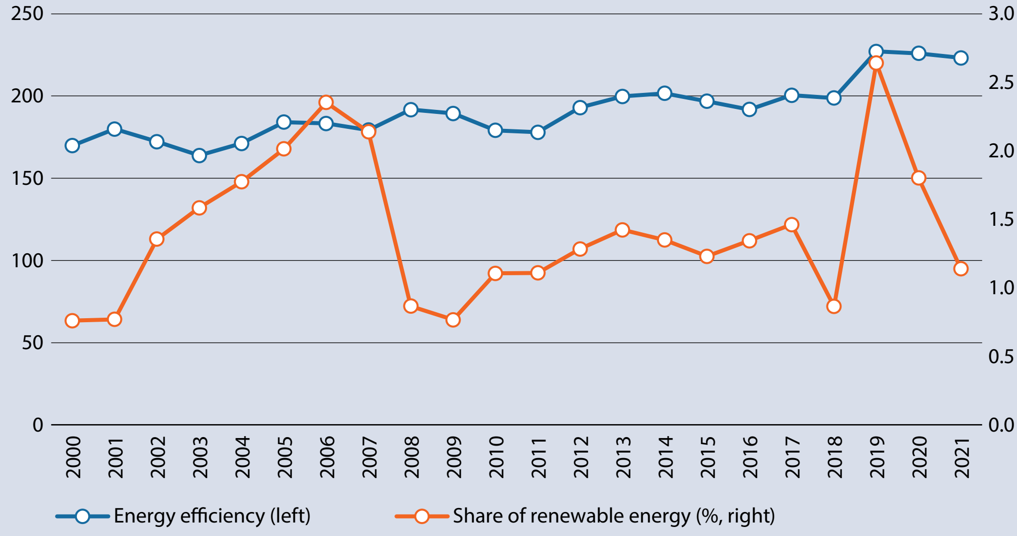


Energy Efficiency and the Share of Renewable Energy

Although RE showed year-on-year fluctuations, such as from 0.76 to 1.14, EE remained at 170-220 overall, indicating that changes in the proportion of renewable energy did not affect efficiency (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND SHARE OF RENEWABLE ENERGY.

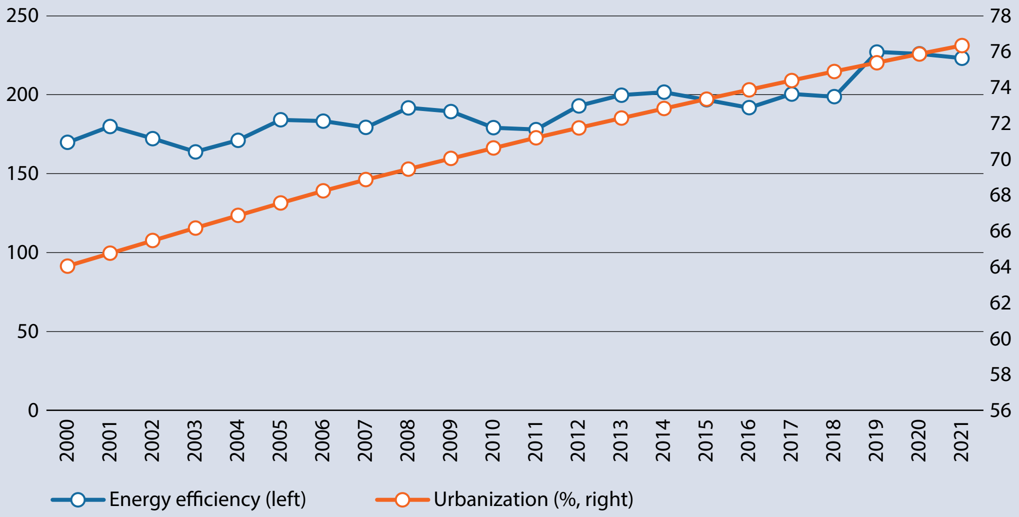


Energy Efficiency and Urbanization

While the urbanization rate rose steadily from 64.0% to 76.3%, the EE fluctuated between 169.8 and 223.1, remaining consistently high. This suggests that there is no clear correlation between urbanization expansion and changes in efficiency (Figure 7).

FIGURE 7

ENERGY EFFICIENCY AND URBANIZATION.

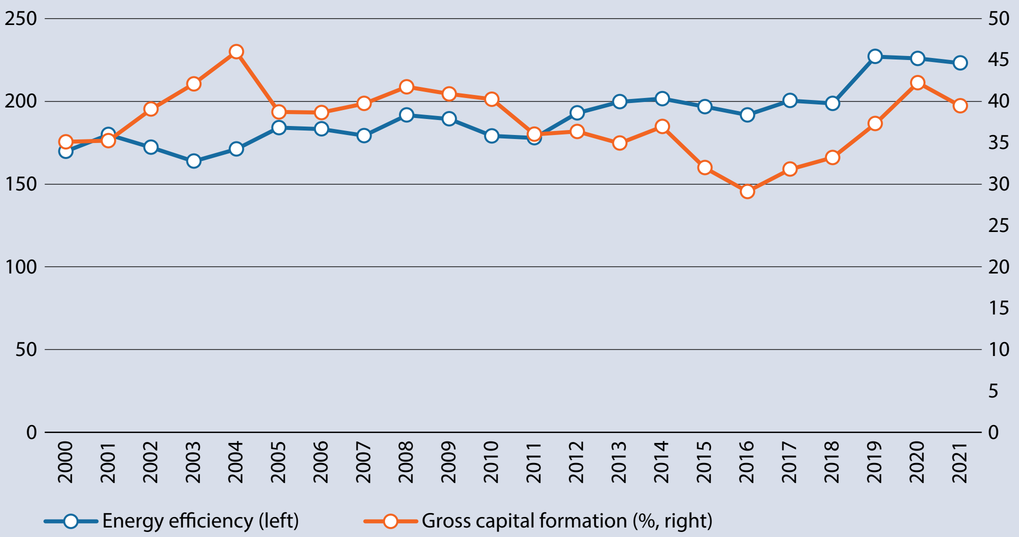


Energy Efficiency and Gross Capital Formation

While GF remained stable, fluctuating between 35.1% and 39.4%, EE fluctuated between 169 and 223, suggesting no significant direct link between investment fluctuations and efficiency improvement trends (Figure 8).

FIGURE 8

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



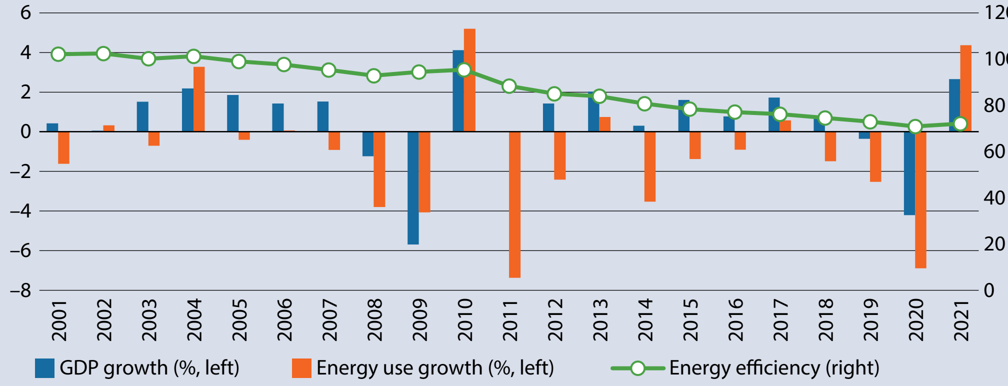
JAPAN

All Sectors

GDP growth stayed modest, while energy use declined sharply in several years (2008, 2011, 2020). As energy use fell faster than GDP, EE Index declined steadily, indicating improved total-sector energy efficiency (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

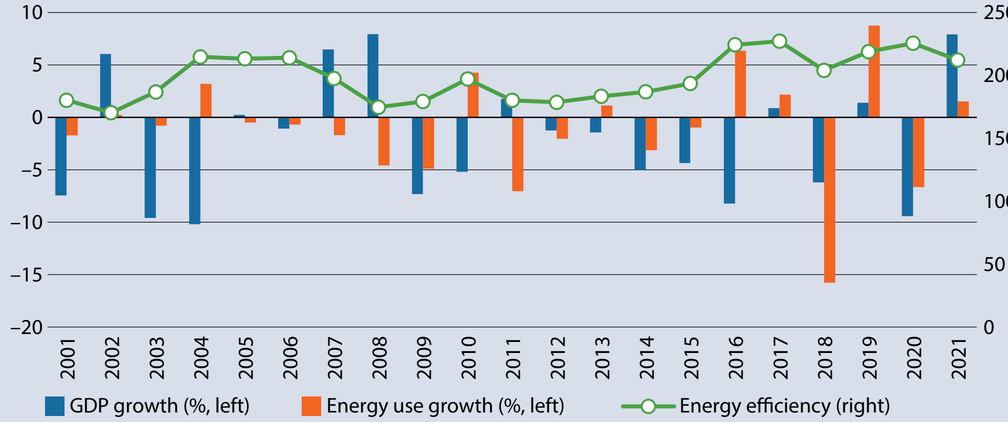


Agriculture Sector

Agricultural energy use declined repeatedly—especially around 2008–11—while GDP growth remained low. EE Index decreased overall, reflecting improved agricultural energy efficiency (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

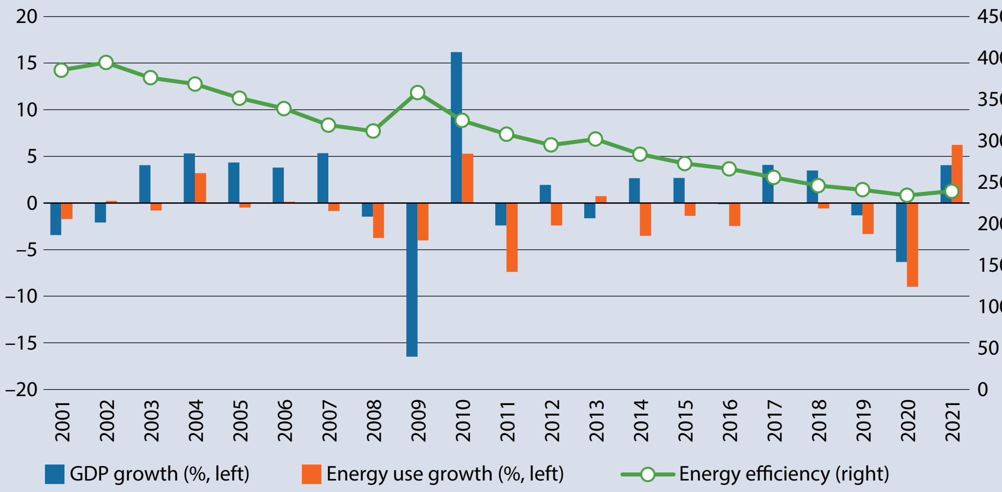


Manufacturing Sector

Manufacturing GDP fluctuated widely with deep drops in 2008–09, while energy use also contracted in many years. Since energy use generally fell more than GDP, EE Index declined, indicating efficiency improvements in manufacturing (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

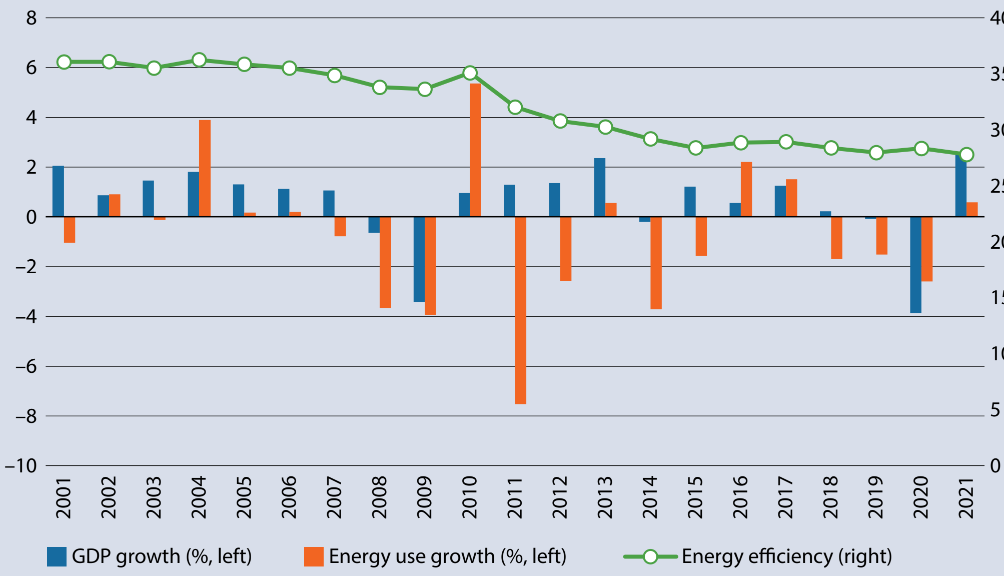


Services Sector

The services sector's GDP remained stable, whereas energy use declined in many years. EE Index declined gradually, indicating steady efficiency gains in the services sector (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

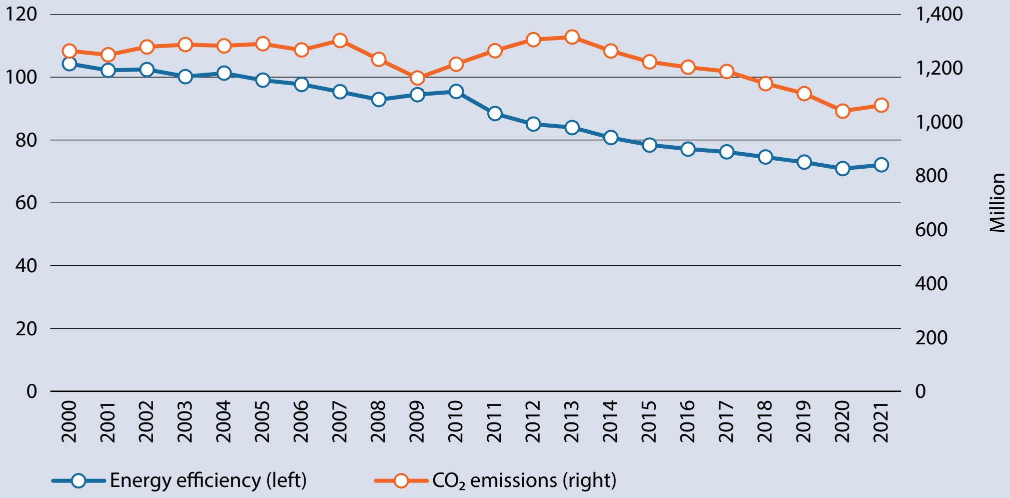


Energy Efficiency and CO_2 Emissions

While CO2 emissions decreased from approximately 1.26 billion tons to 1.06 billion tons, the EF also reduced from 104 to 72, indicating that emissions reductions and efficiency improvements occurred simultaneously (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

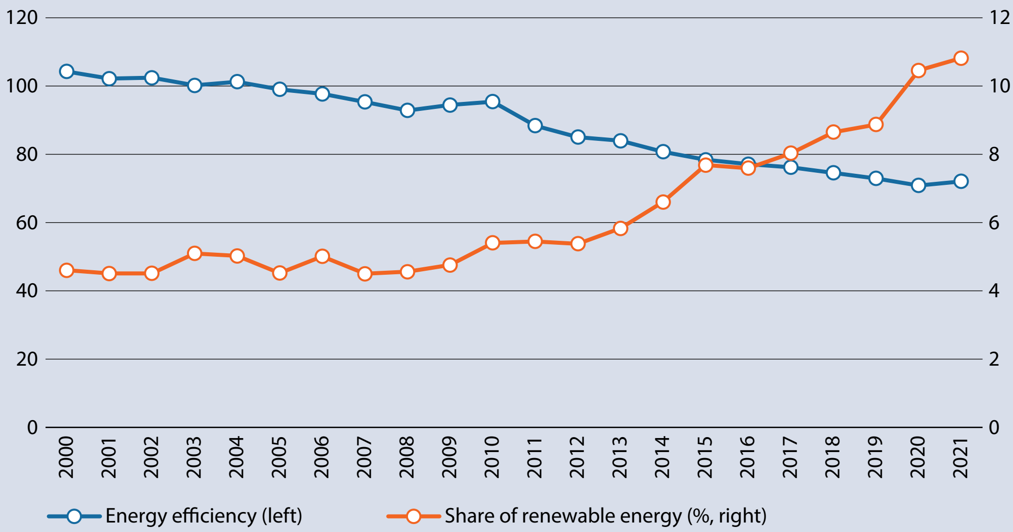


Energy Efficiency and the Share of Renewable Energy

During the period when the share of renewable energy increased significantly from 4.60 to 10.81, EE decreased from 104 to 72, indicating that renewable energy expansion and efficiency improvement occurred simultaneously (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND SHARE OF RENEWABLE ENERGY.

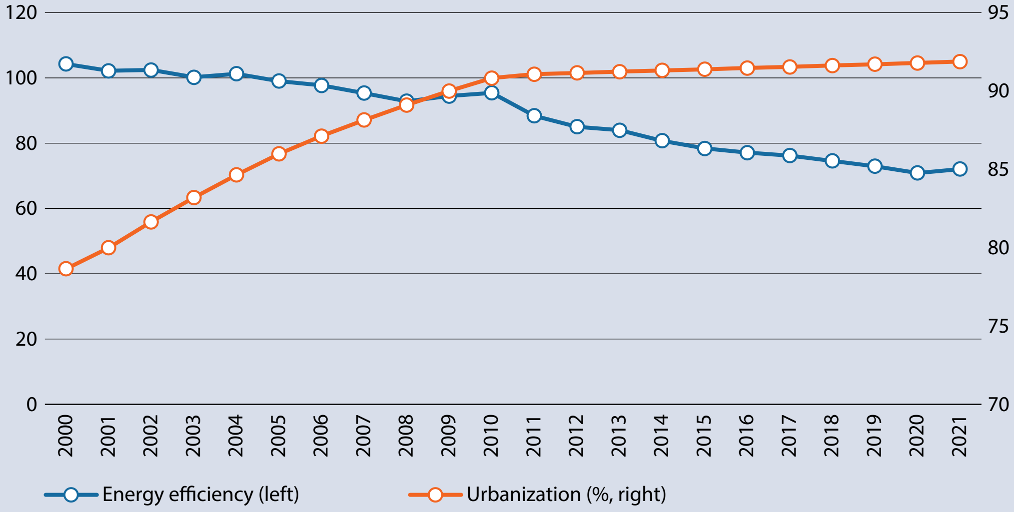


Energy Efficiency and Urbanization

While the urbanization rate increased steadily from 78.6% to 91.9%, efficiency declined significantly from 104.3% to 72.1%, indicating that efficiency continued to improve as urbanization expanded (Figure 7).

FIGURE 7

ENERGY EFFICIENCY AND URBANIZATION.

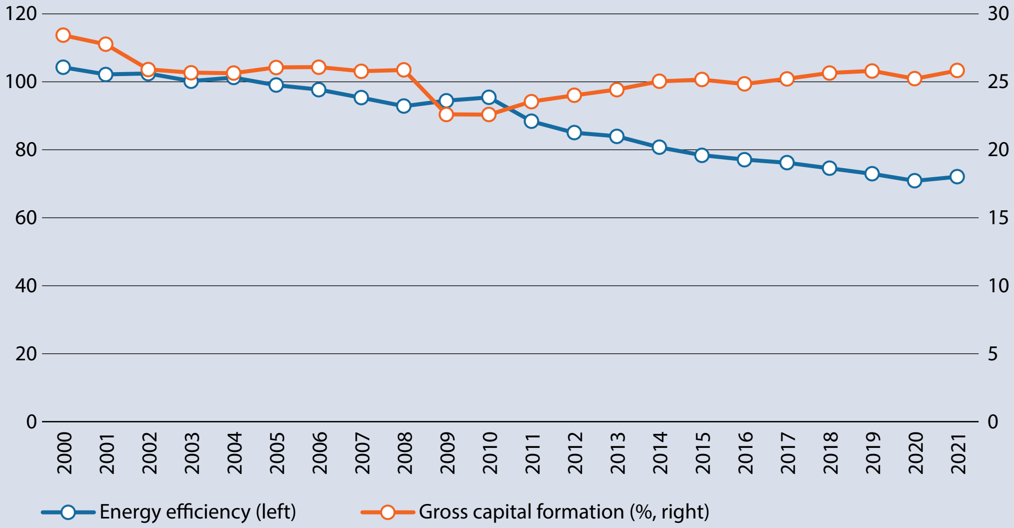


Energy Efficiency and Gross Capital Formation

While GF decreased slightly from 28.4% to 25.8%, EE declined significantly from 104 to 72, indicating a steady improvement in efficiency despite changes in the investment ratio (Figure 8).

FIGURE 8

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



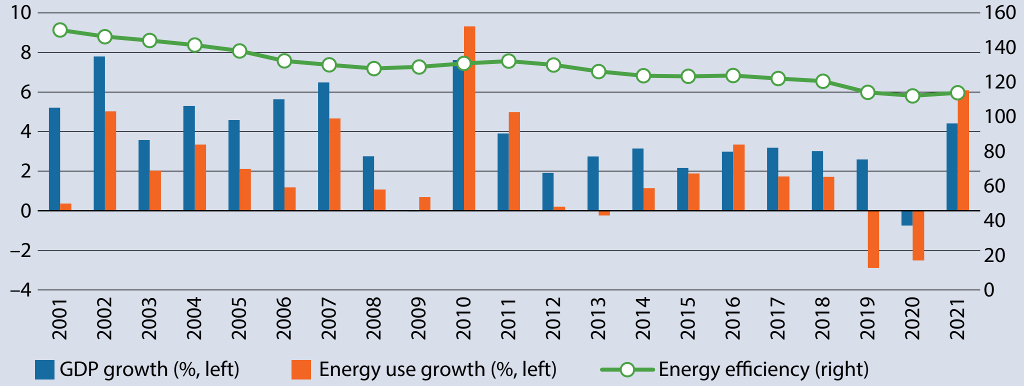
THE REPUBLIC OF KOREA

All Sectors

GDP growth was relatively stable, whereas energy use declined sharply in 2020. Since energy use grew more slowly than GDP over most years, EE Index declined steadily, indicating long-term improvement in total energy efficiency (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

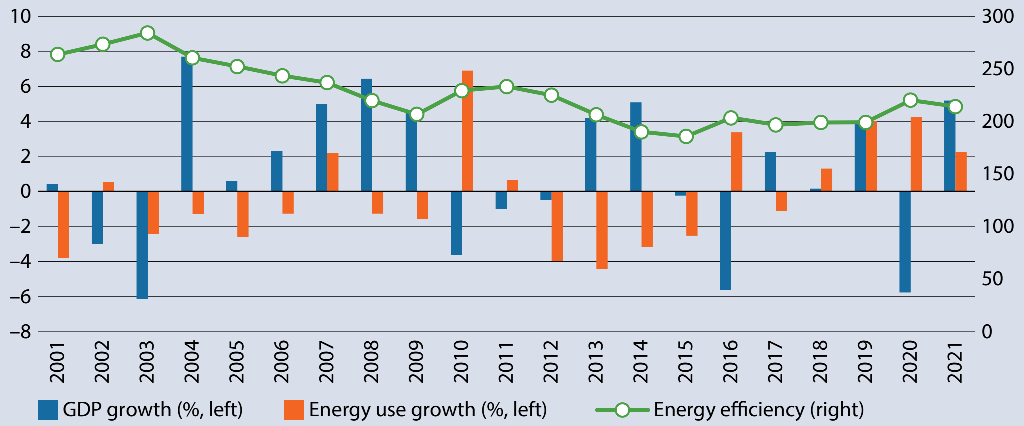


Agriculture Sector

Agricultural energy use fluctuated with sharp drops in 2003–04 and strong increases in 2010 and 2021, while GDP growth remained modest. As energy use often rose faster than GDP, EE Index increased overall, reflecting a deterioration in agricultural energy efficiency (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

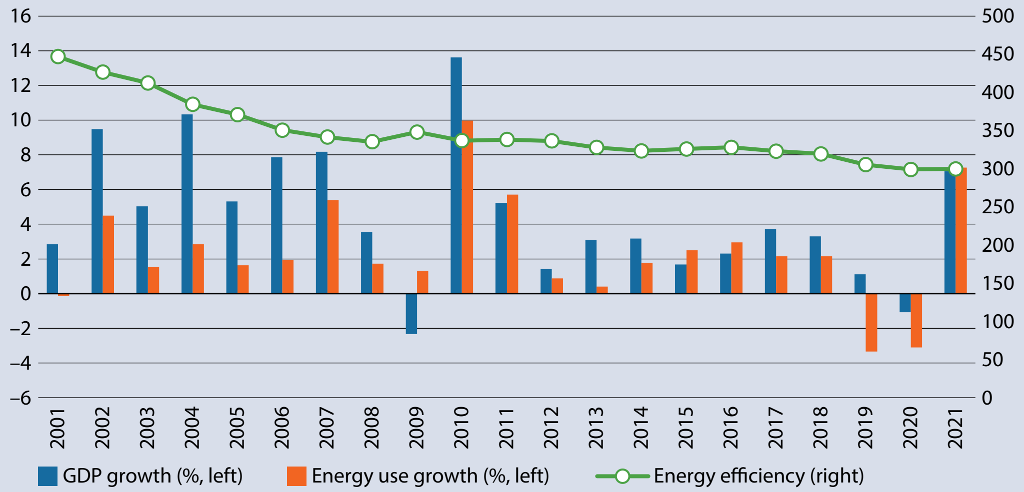


Manufacturing Sector

Manufacturing GDP experienced strong early growth but large contractions in 2009 and 2020, while energy use frequently declined. Because energy use typically fell more than GDP, EE Index decreased over time, indicating improved manufacturing energy efficiency (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

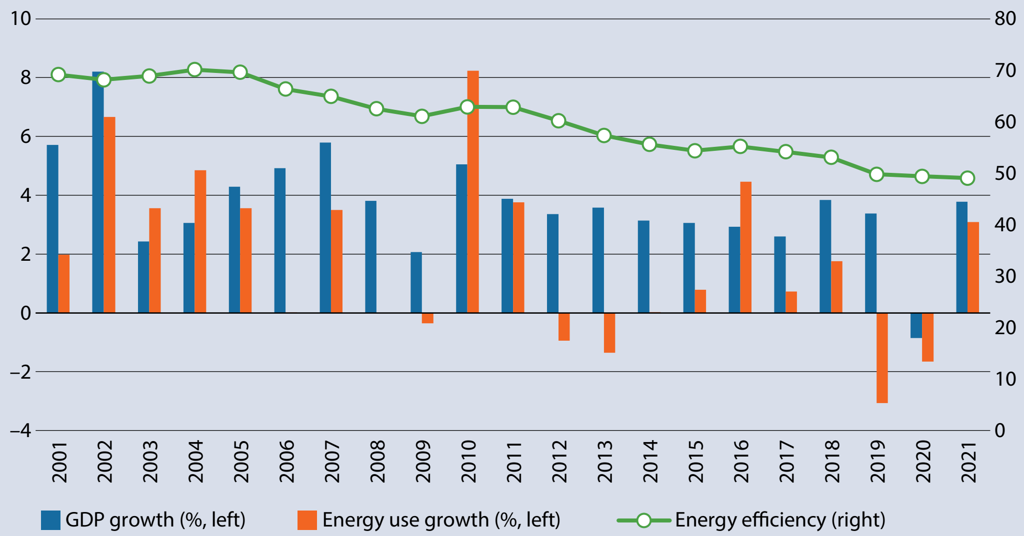


Services Sector

The services sector's GDP grew steadily, whereas energy use fluctuated, with notable declines in 2010 and 2020. With energy use generally rising more slowly than GDP, EE Index declined gradually, suggesting improved energy efficiency in the services sector (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

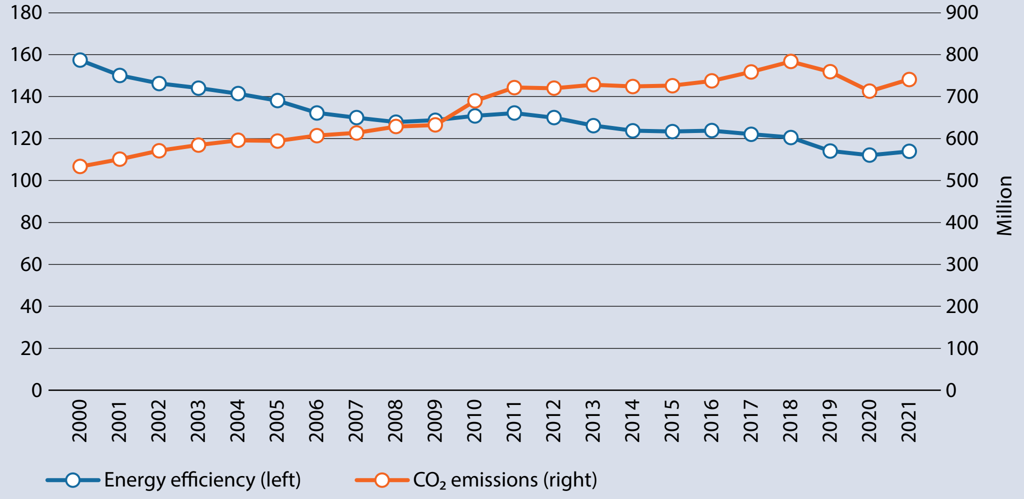


Energy Efficiency and CO_2 Emissions

EE decreased from approximately 160 in 2000 to approximately 110 in 2021, indicating improved energy use relative to GDP, whereas CO_2 Emissions increased from roughly 105 million tons to about 150 million tons over the same period, indicating that emissions continued to rise alongside efficiency gains (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

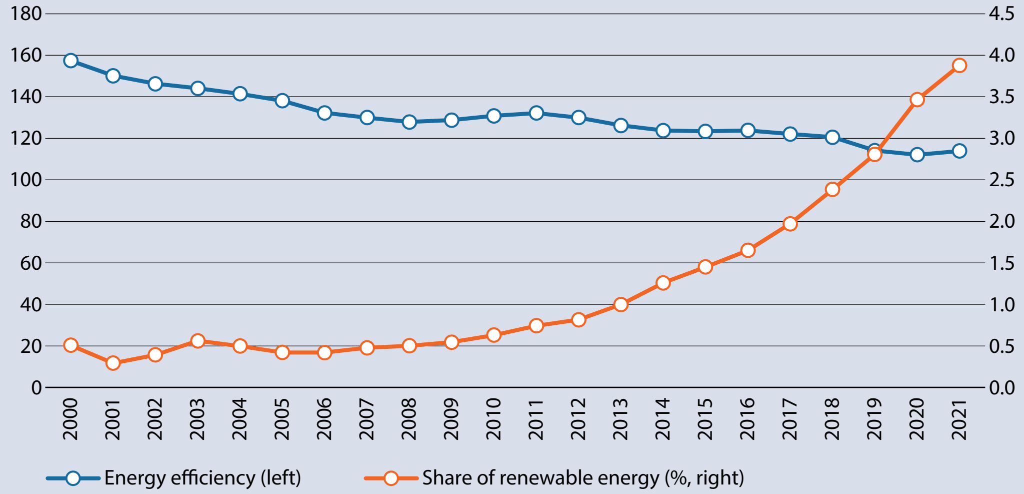


Energy Efficiency and the Share of Renewable Energy

While the share of renewable energy increased significantly from 0.51 to 3.88, EE decreased from 157 to 114, demonstrating that renewable energy expansion and efficiency improvement occurred simultaneously (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND SHARE OF RENEWABLE ENERGY.

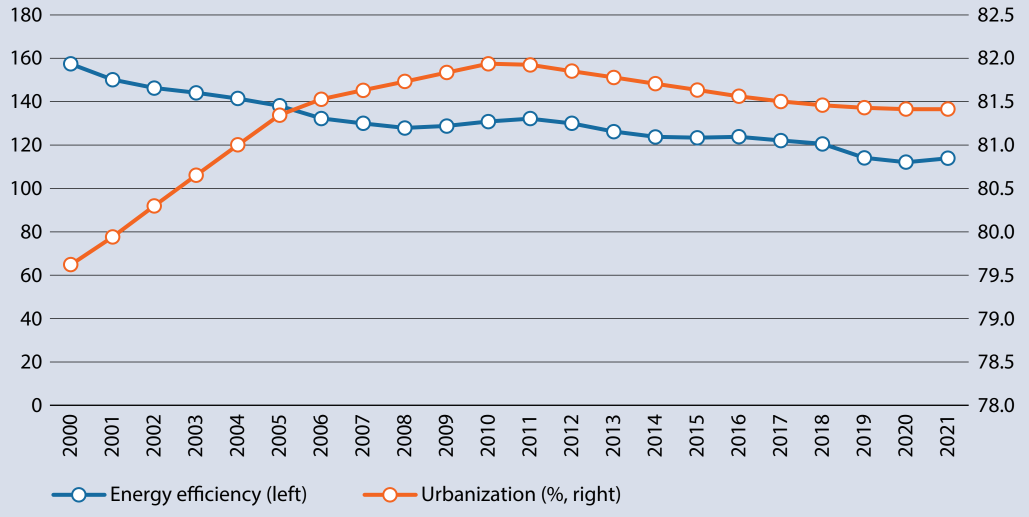


Energy Efficiency and Urbanization

While the urbanization rate increased steadily from 79.6% to 81.4%, efficiency declined significantly from 157.4 to 113.9, indicating that efficiency continued to improve with urbanization (Figure 7).

FIGURE 7

ENERGY EFFICIENCY AND URBANIZATION.

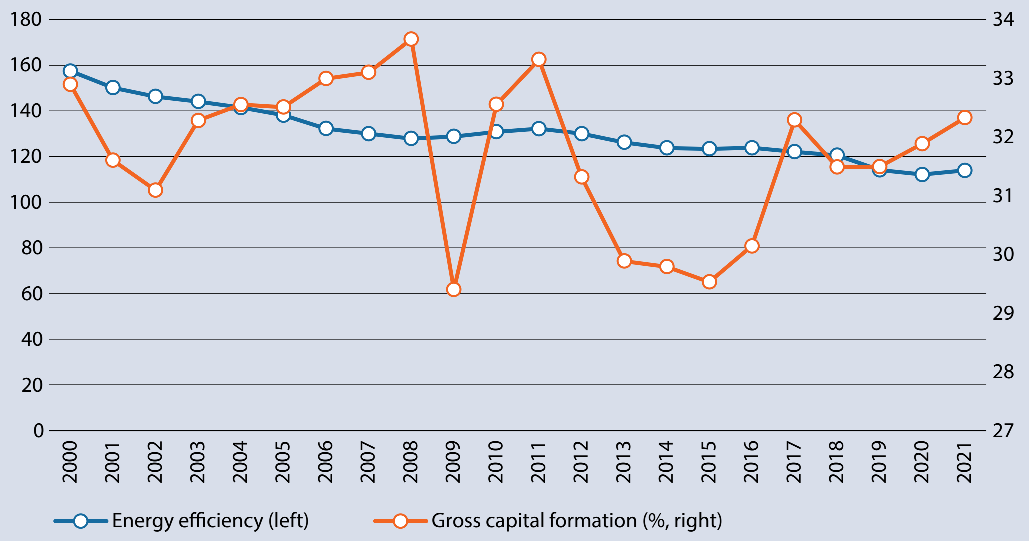


Energy Efficiency and Gross Capital Formation

There was no significant change in GF, which remained within the range of 32.9%-32.3%. However, EE declined from 157 to 114, indicating an improvement in efficiency despite fluctuations in the investment ratio (Figure 8).

FIGURE 8

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



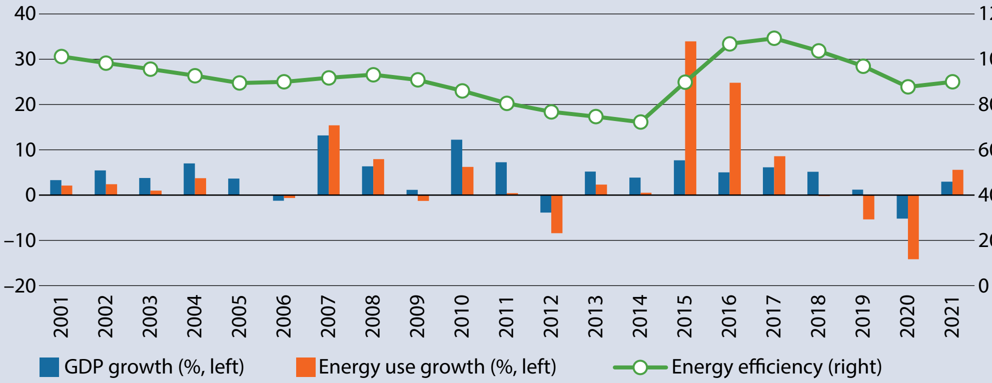
LAO PDR

All Sectors

GDP growth was relatively stable, whereas energy use exhibited sharp fluctuations—particularly large increases in 2015–16 and a sharp decline in 2020. Since energy use often rose faster than GDP, EE Index increased, indicating a deterioration in overall energy efficiency (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

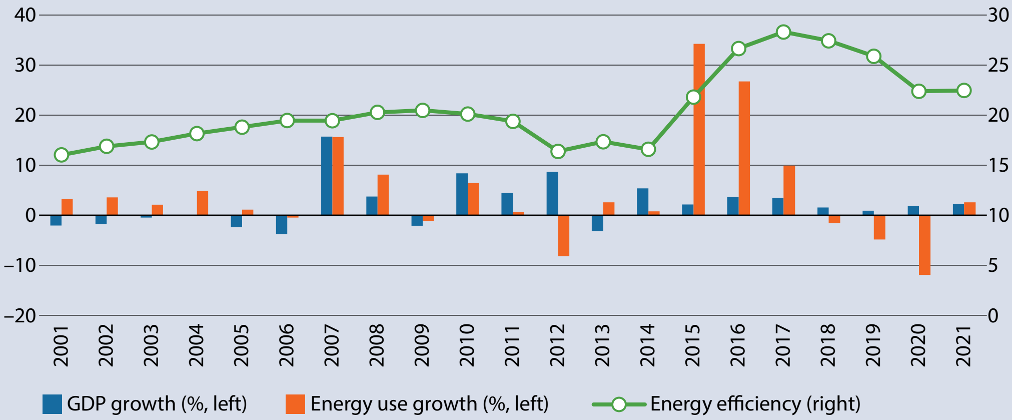


Agriculture Sector

Agricultural energy use rose sharply in 2007, 2015, and 2016, while GDP growth stayed modest. As energy use repeatedly exceeded GDP growth, EE Index increased over time, signaling worsening agricultural energy efficiency (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

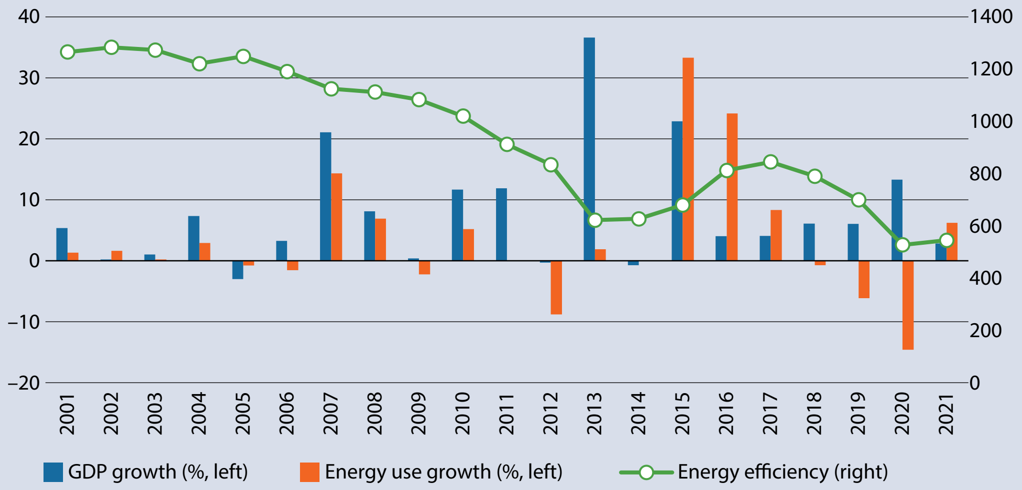


Manufacturing Sector

Manufacturing GDP fluctuated widely—with big surges in 2007, 2013, and 2016—while energy use also showed major spikes in 2015 and 2016. Because energy use tended to grow faster than GDP, EE Index increased overall, indicating deteriorating manufacturing energy efficiency (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

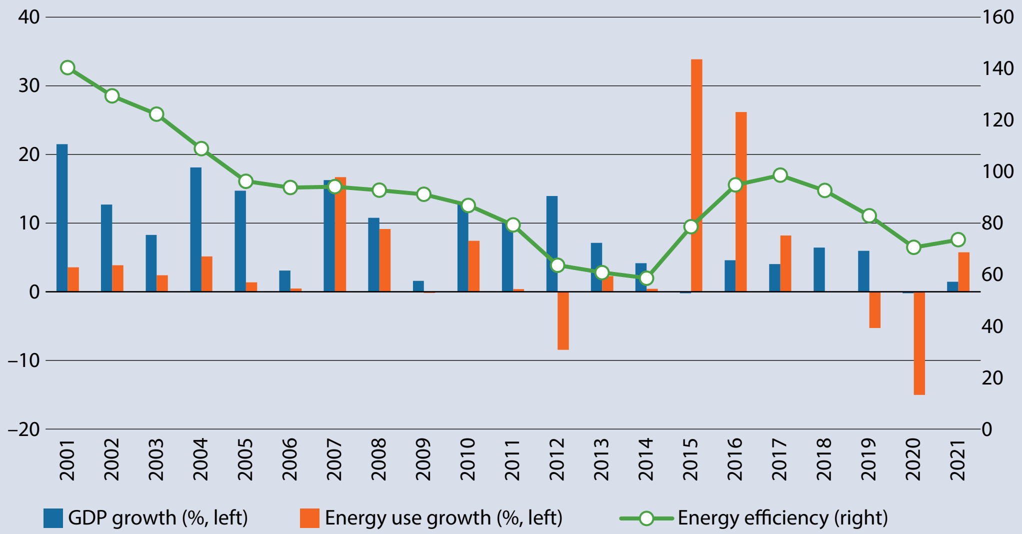


Services Sector

The services sector's GDP grew steadily, but energy use repeatedly spiked, especially in 2015–16. As energy use generally expanded faster than GDP, EE Index rose, implying worsening energy efficiency in the services sector (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

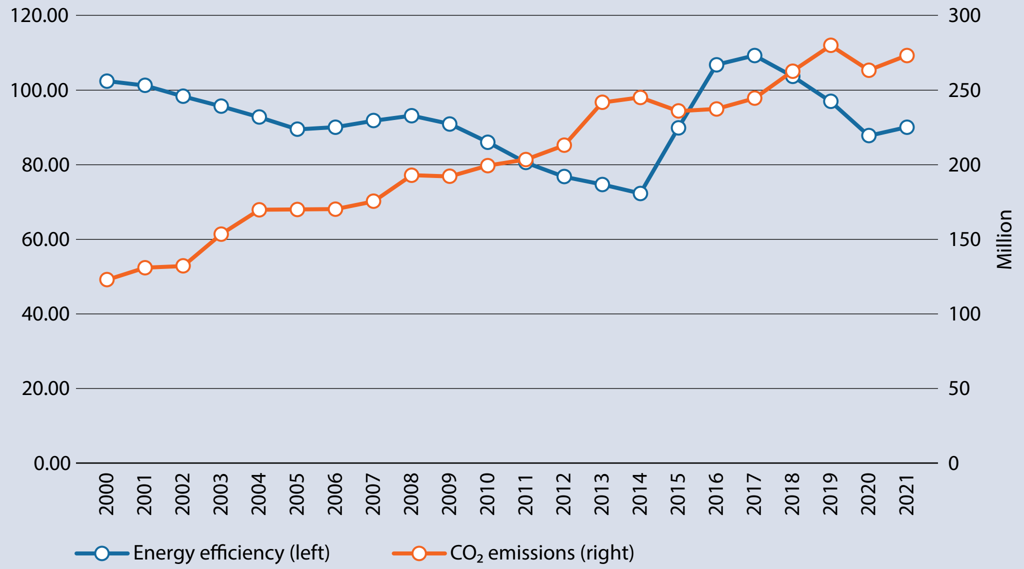


Energy Efficiency and CO_2 Emissions

While CO2 emissions rose from approximately 123 million tons to 273 million tons, EE declined from 102.4 to 90.0, indicating a long-term trend of improving efficiency despite increasing emissions (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.



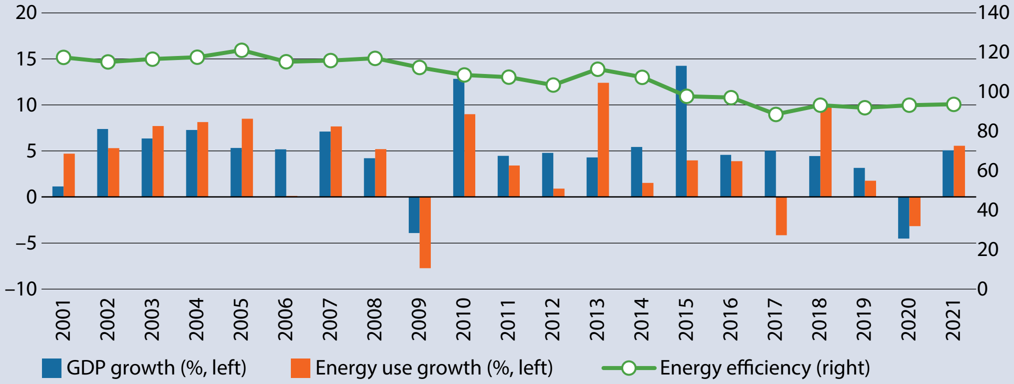
MALAYSIA

All Sectors

GDP growth was relatively stable, whereas energy use exhibited pronounced spikes around 2010 and 2018 and a major decline in 2020. Because energy use often rose faster than GDP, EE Index increased slightly over time, indicating a mild decrease in total energy efficiency (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

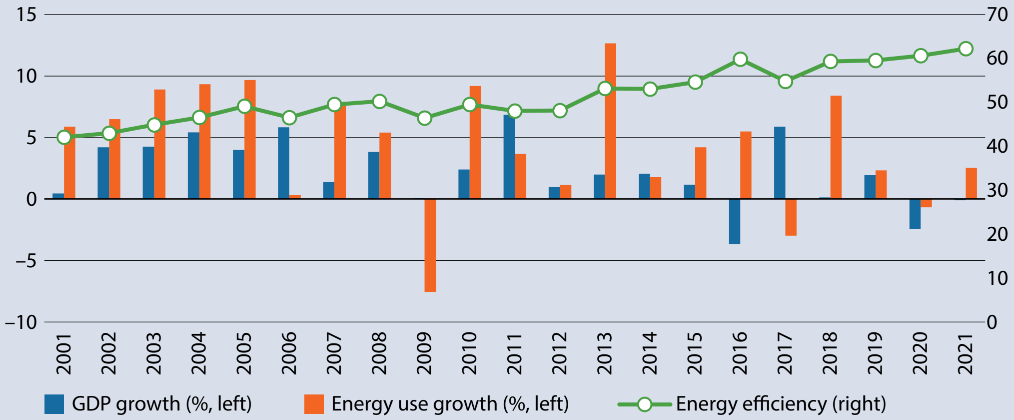


Agriculture Sector

Agricultural energy use fluctuated sharply—with strong increases in 2003–05, 2010, and 2018—while GDP growth remained modest. As energy use frequently outpaced GDP growth, EE Index increased steadily, reflecting worsening agricultural energy efficiency (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

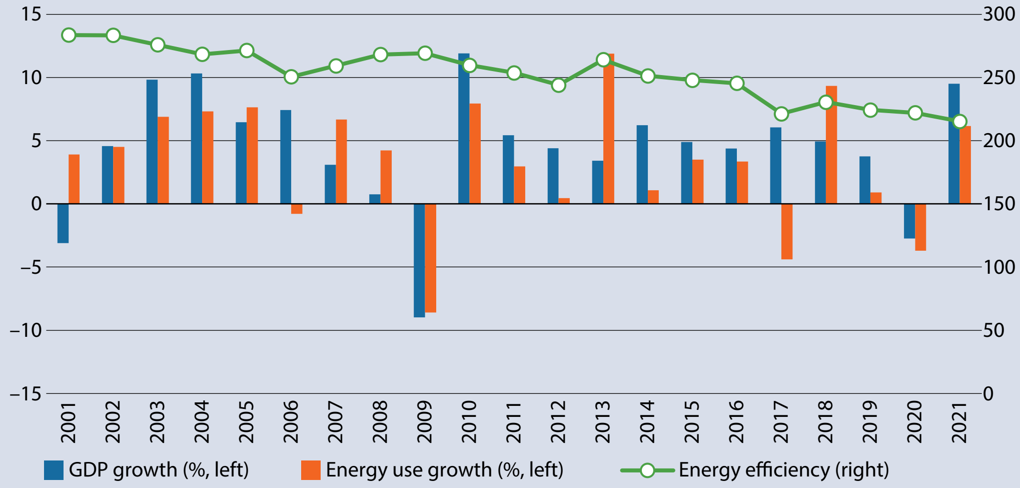


Manufacturing Sector

Manufacturing GDP experienced periods of strong growth, particularly in 2002–04 and 2010, while energy use also increased in several years. Since energy use often expanded faster than GDP, EE Index increased, indicating a gradual deterioration in manufacturing energy efficiency (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

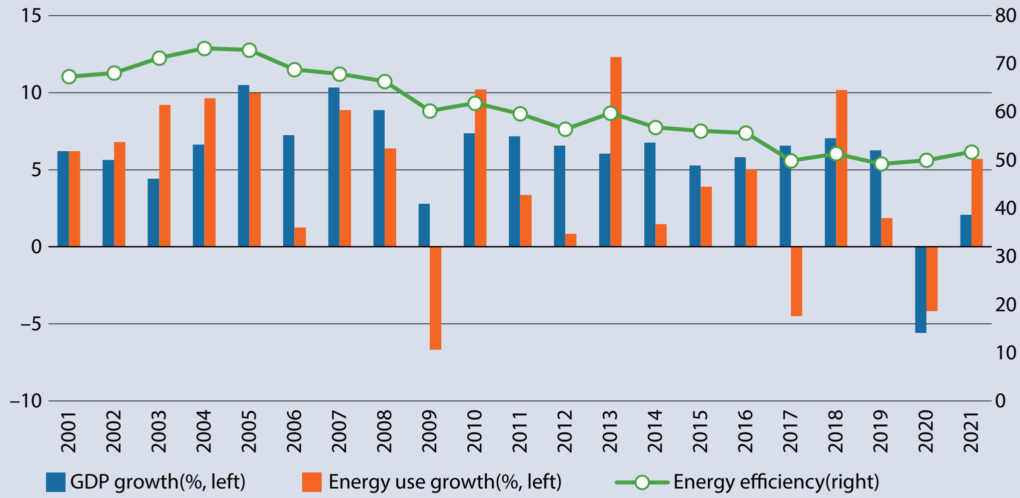


Services Sector

The services sector's GDP was stable and positive in most years, whereas energy use showed significant volatility, with a sharp drop in 2009 and a sharp increase in 2010. Because energy use generally rose faster than GDP, EE Index increased over time, suggesting declining efficiency in the services sector (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

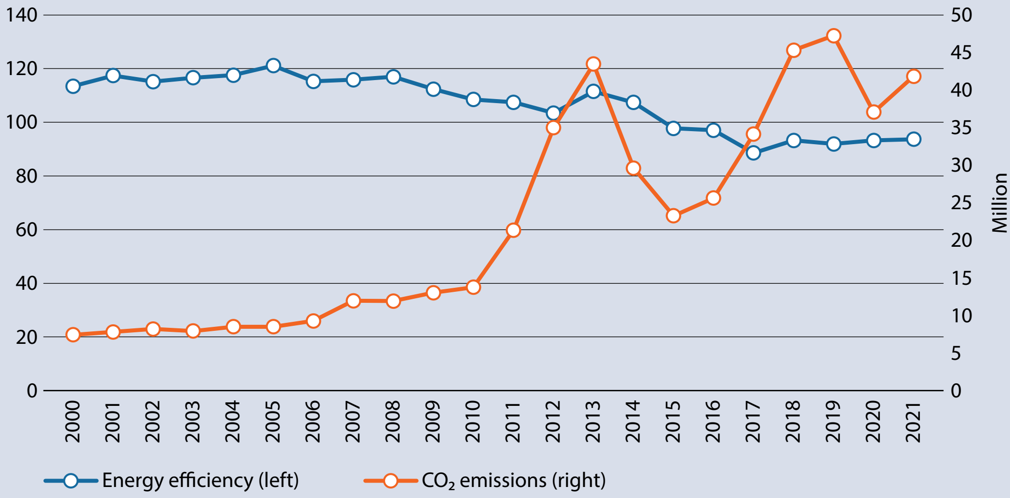


Energy Efficiency and CO_2 Emissions

Despite a considerable increase in CO2 emissions over a significant period, from approximately 7.43 million tons to 41.9 million tons, the EE decreased from 113 to 94. This indicates that the trend of efficiency improvement continued even amid rising emissions (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

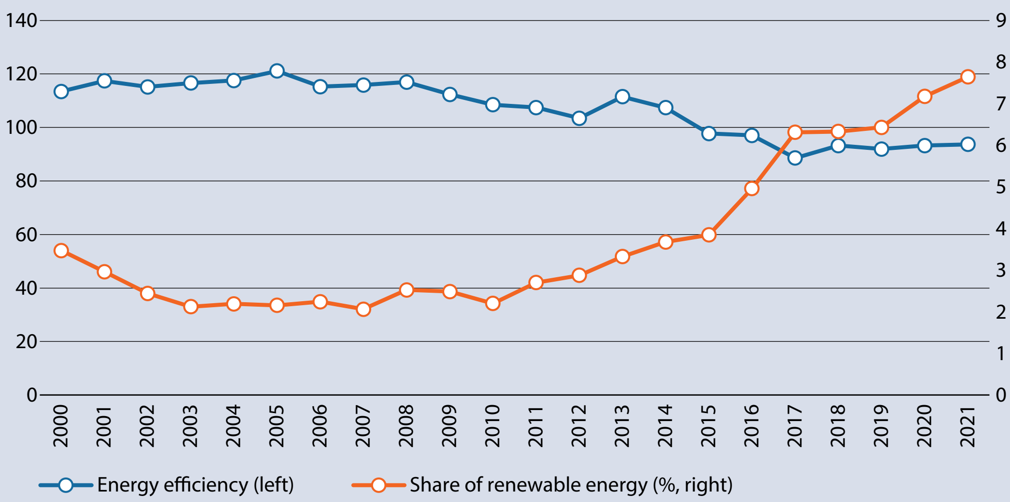


Energy Efficiency and the Share of Renewable Energy

As the share of renewable energy increased significantly from 3.47 to 7.65, EE decreased from 113 to 94, indicating a trend toward greater renewable energy deployment and improved efficiency (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND SHARE OF RENEWABLE ENERGY.

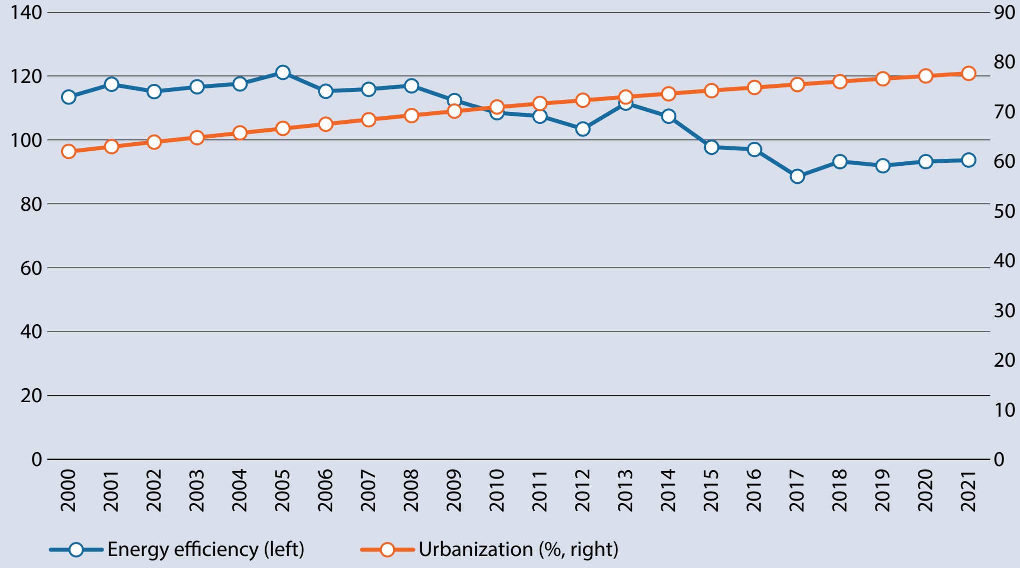


Energy Efficiency and Urbanization

While the urbanization rate increased from 62.0% to 77.7%, efficiency declined from 113.4% to 93.7%, indicating that overall efficiency declined as urbanization expanded (Figure 7).

FIGURE 7

ENERGY EFFICIENCY AND URBANIZATION.

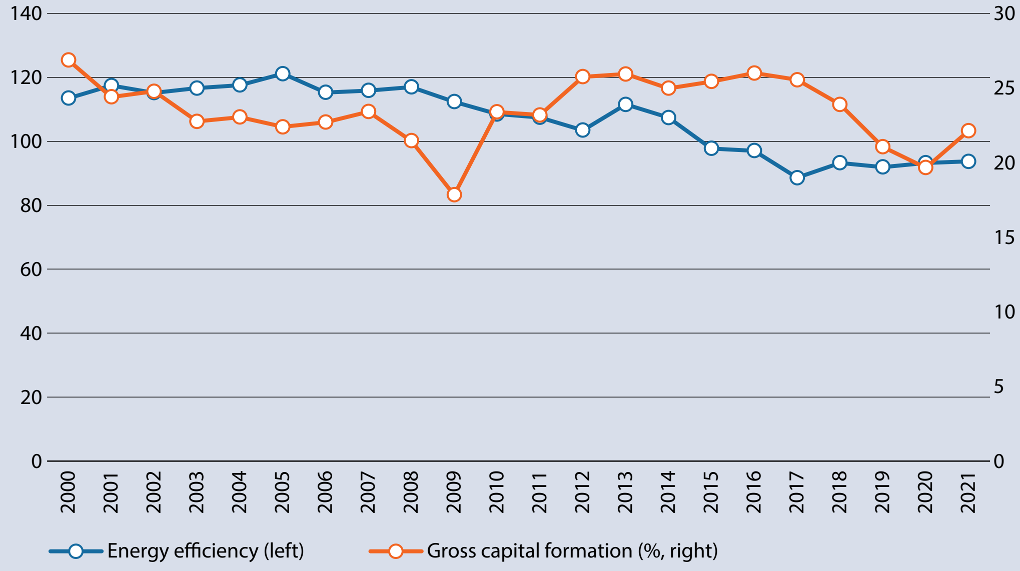


Energy Efficiency and Gross Capital Formation

While GF declined steadily from 26.9% to 22.1%, EE also decreased from 113 to 94, indicating a simultaneous improvement in efficiency and a reduction in the investment ratio (Figure 8).

FIGURE 8

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



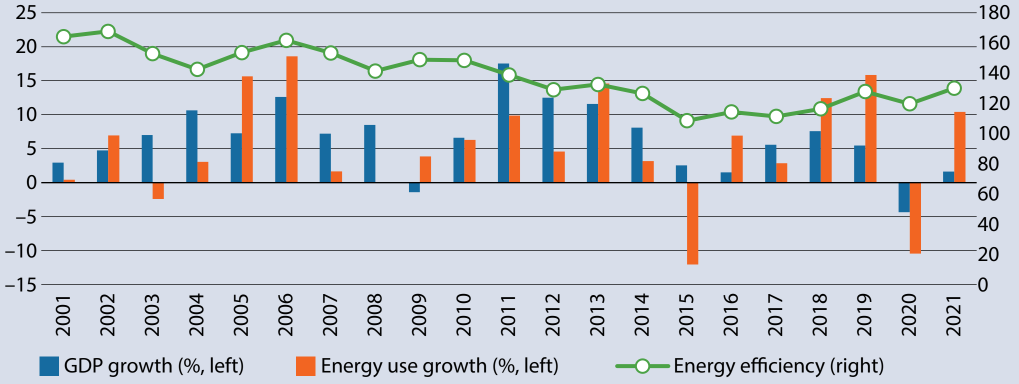
MONGOLIA

All Sectors

GDP growth fluctuated significantly, whereas energy use exhibited sharp declines in 2009, 2016, and 2020. Because energy use often fell faster than GDP, EE Index declined steadily, indicating improved total-sector energy efficiency (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

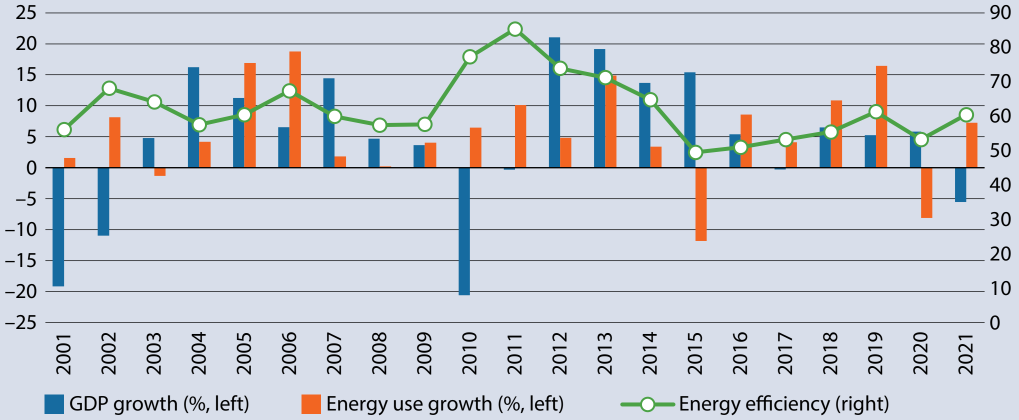


Agriculture Sector

Agricultural energy use was highly volatile—falling sharply in 2009 and 2016 and rising sharply in several years—while GDP growth remained volatile. Since energy use often deviated more than GDP, EE Index showed mixed movement, increasing slightly overall, suggesting mild deterioration in agricultural efficiency (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

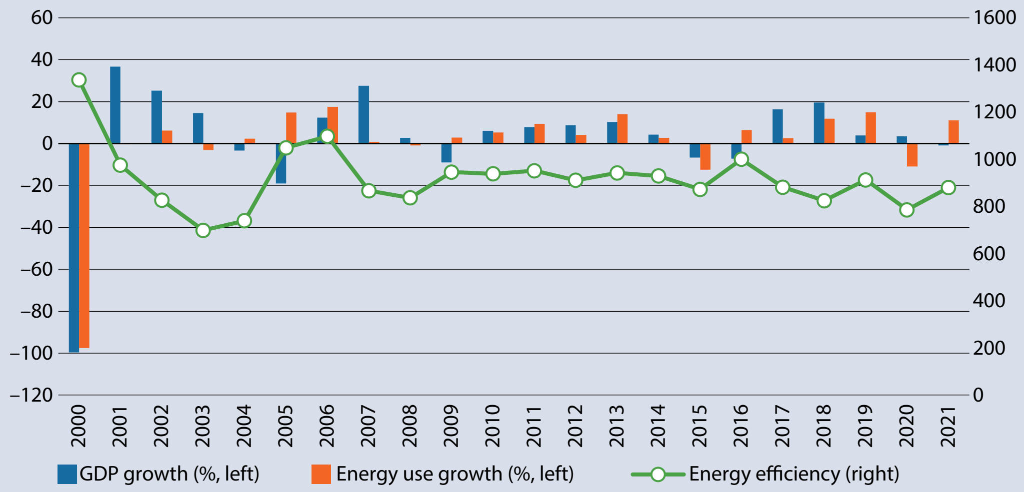


Manufacturing Sector

Manufacturing GDP and energy use were both highly volatile, particularly in the early 2000s and 2009–10. Energy use declined sharply in many years, often by more than GDP, indicating improved energy efficiency in manufacturing (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

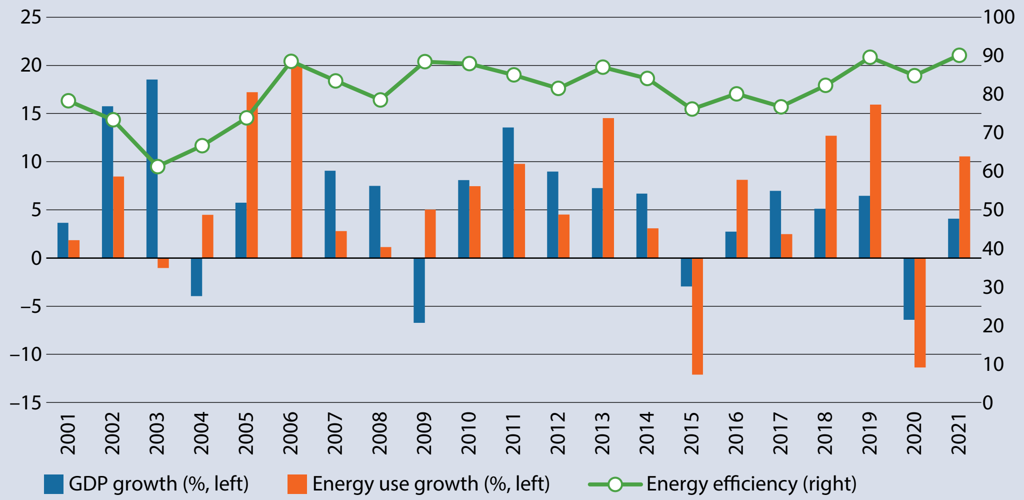


Services Sector

The services sector's GDP grew steadily, whereas energy use fluctuated, with strong increases in 2010 and 2019 and sharp declines in 2016 and 2020. Because energy use often rose faster than GDP, EE Index increased slightly, suggesting a gradual decline in energy efficiency in the services sector (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

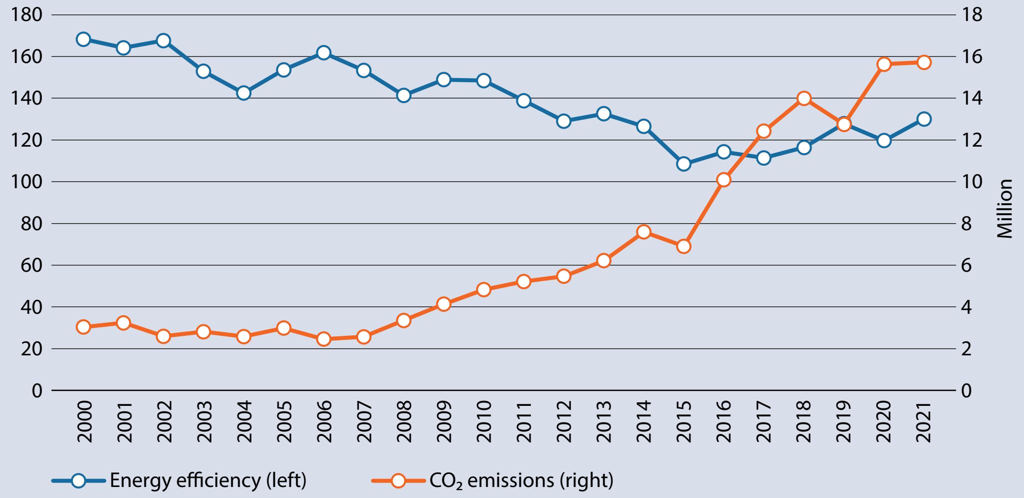


Energy Efficiency and CO_2 Emissions

Despite a considerable increase in CO2 emissions, from approximately 3 million tons to 15.7 million tons, the EE decreased from 168 to 130, demonstrating that efficiency improvements were sustained even in the face of rising emissions (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

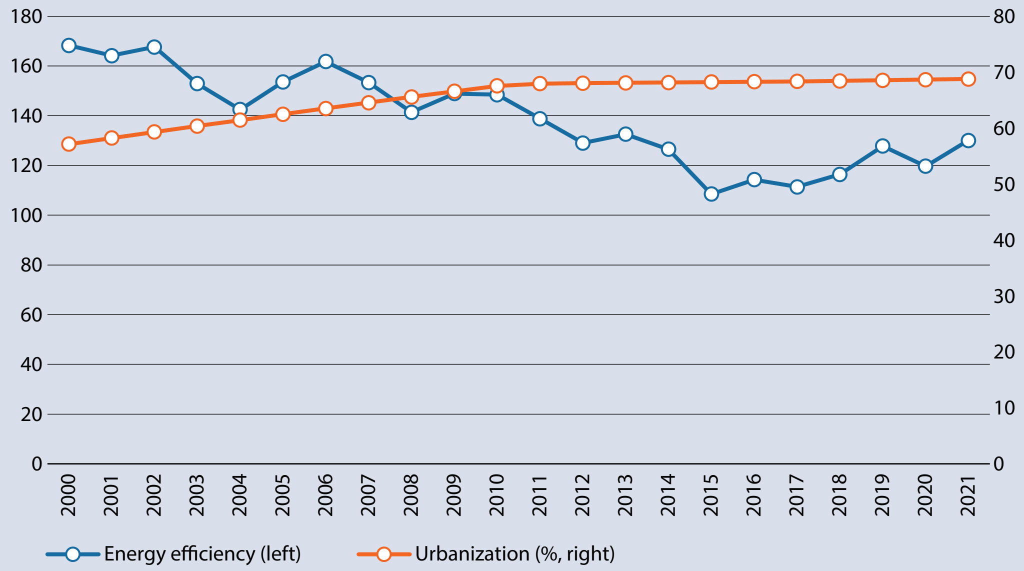


Energy Efficiency and Urbanization

While the urbanization rate increased steadily from 57.1% to 68.8%, efficiency declined from 168.3 to 130.0, indicating that efficiency improved overall as urbanization expanded (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND URBANIZATION.

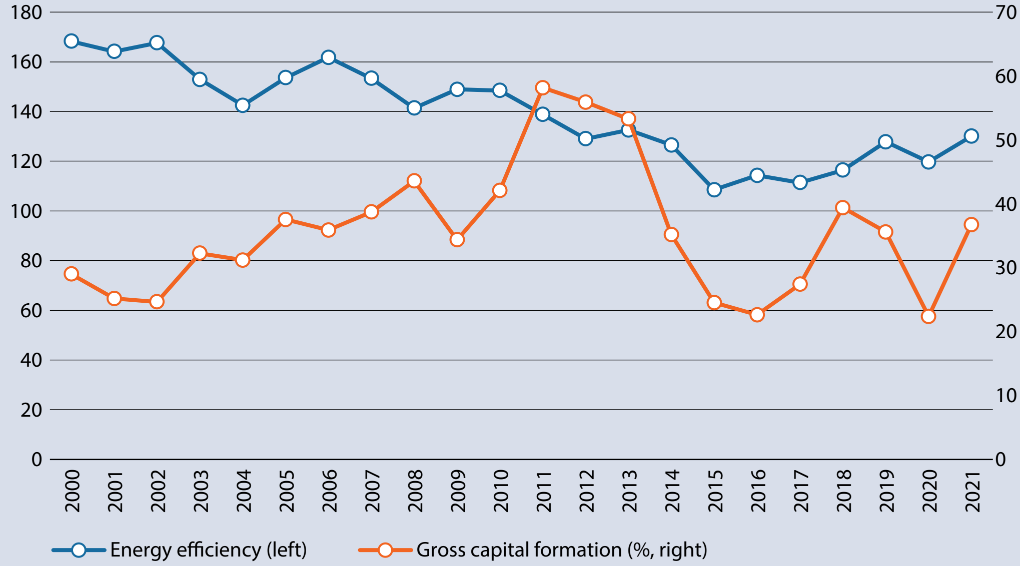


Energy Efficiency and Gross Capital Formation

While GF increased over the long term from 29.0% to 36.7%, EE decreased from 168 to 130, indicating an improvement in efficiency alongside investment expansion (Figure 7).

FIGURE 7

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



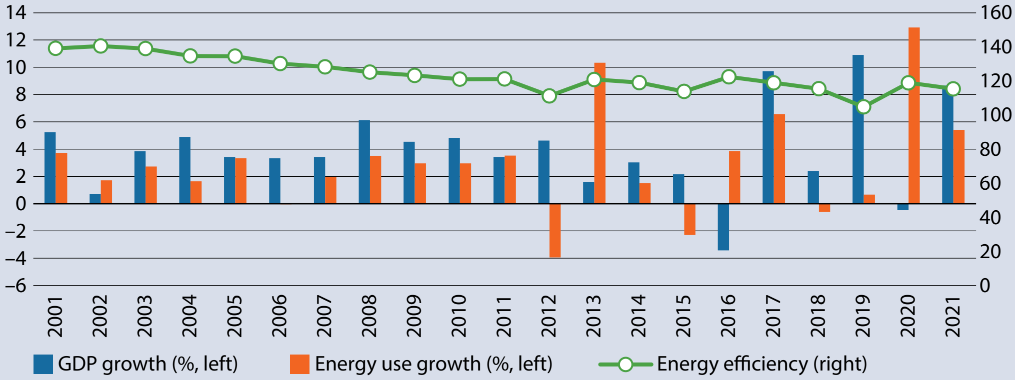
NEPAL

All Sectors

GDP growth remained relatively stable, with modest fluctuations, whereas energy use exhibited greater volatility, including sharp declines in 2012 and 2020. As a result, energy efficiency (EE) Index gradually declined across the period, indicating improved energy productivity (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

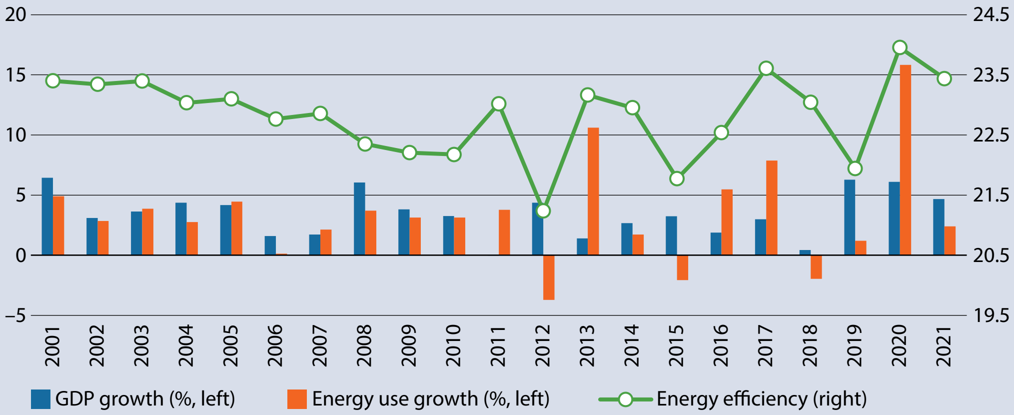


Agriculture Sector

Agricultural GDP increased steadily, whereas energy use varied moderately over the years. Despite fluctuations, EE Index exhibited a mild upward trend over the long term, reflecting gradual gains in efficiency in agricultural operations (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

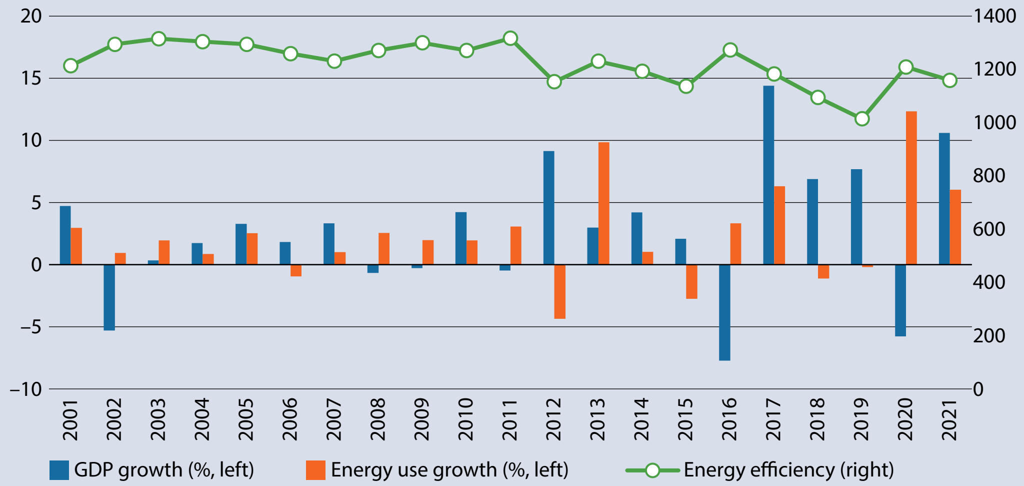


Manufacturing Sector

Manufacturing GDP grew with noticeable year-to-year variability, and energy use exhibited even larger swings, including major drops in 2012 and 2020. Energy efficiency increased overall, suggesting improved productivity per unit of energy used (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

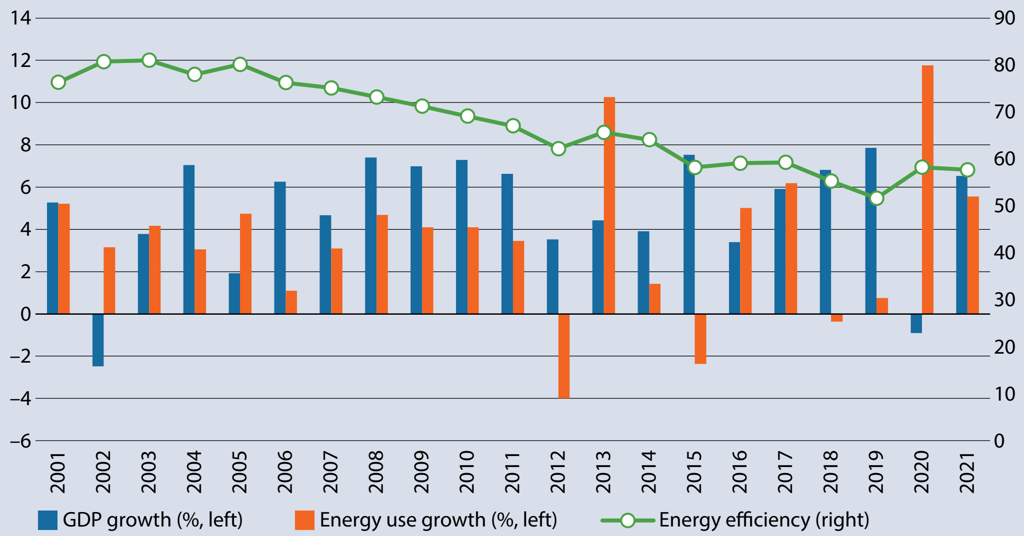


Services Sector

The services sector's GDP remained relatively stable, with moderate growth, whereas energy use fluctuated more strongly and declined in several years. Energy efficiency improved slightly over time, implying better energy use relative to output (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

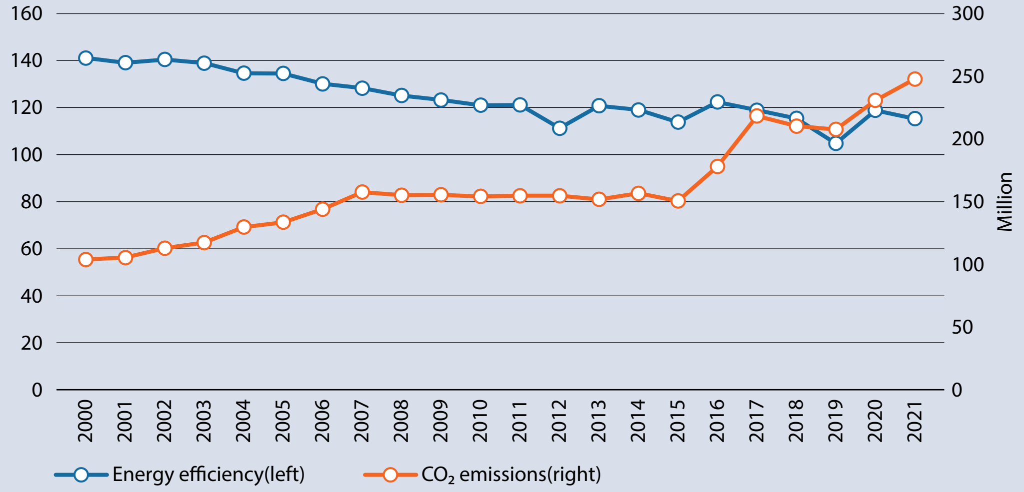


Energy Efficiency and CO_2 Emissions

While CO2 emissions increased significantly from approximately 104 million tons to 248 million tons, EE decreased from 141 to 115, showing an overall improvement in efficiency despite the rising emissions trend (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

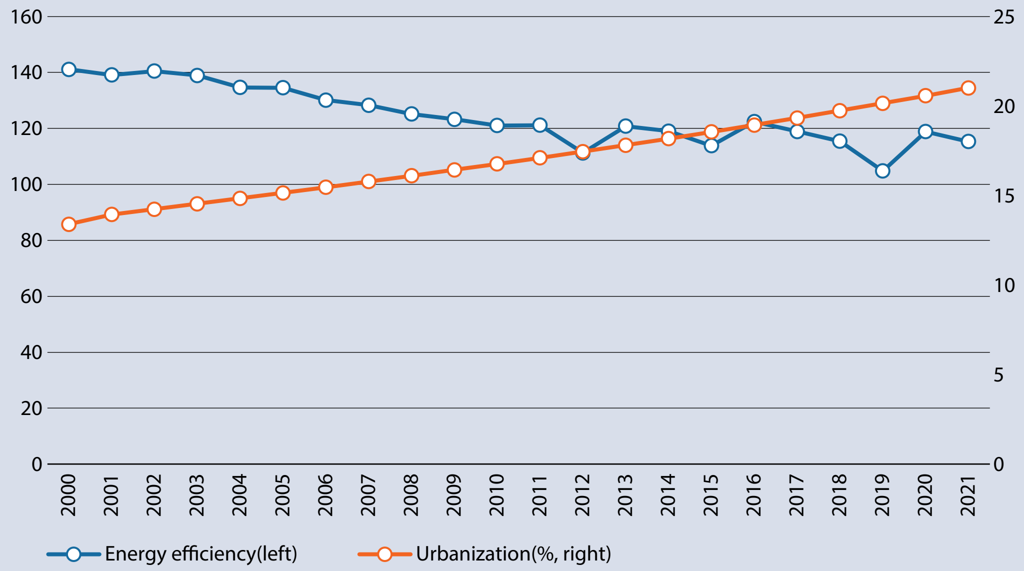


Energy Efficiency and Urbanization

While the urbanization rate increased steadily from 13.4% to 21.0%, EE declined from 141.1 to 115.3, indicating that efficiency improved overall as urbanization expanded (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND URBANIZATION.

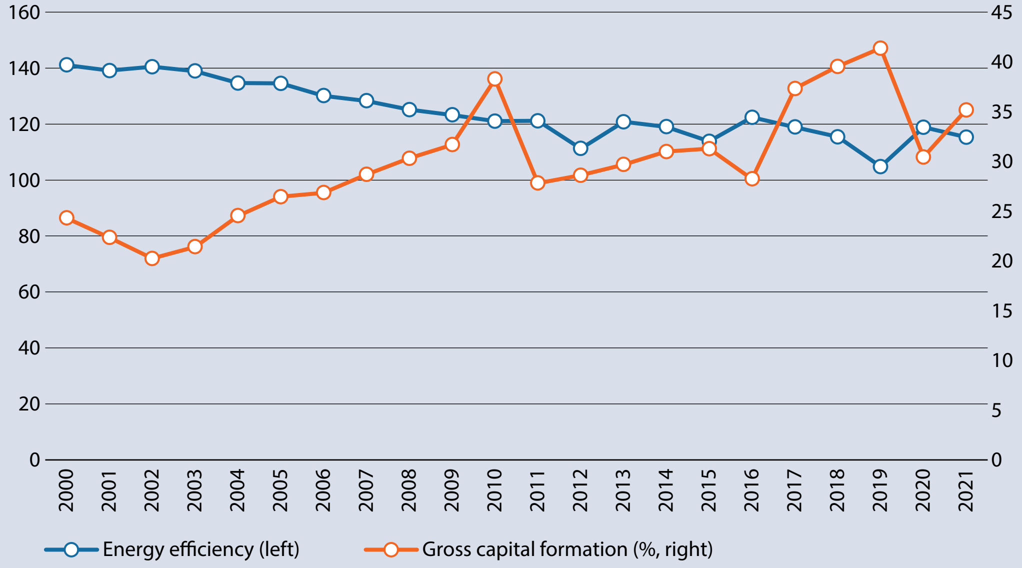


Energy Efficiency and Gross Capital Formation

While GF increased over the long term from 24.3% to 35.2%, EE decreased from 141 to 115, indicating that investment expansion and efficiency improvement occurred simultaneously (Figure 7).

FIGURE 7

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



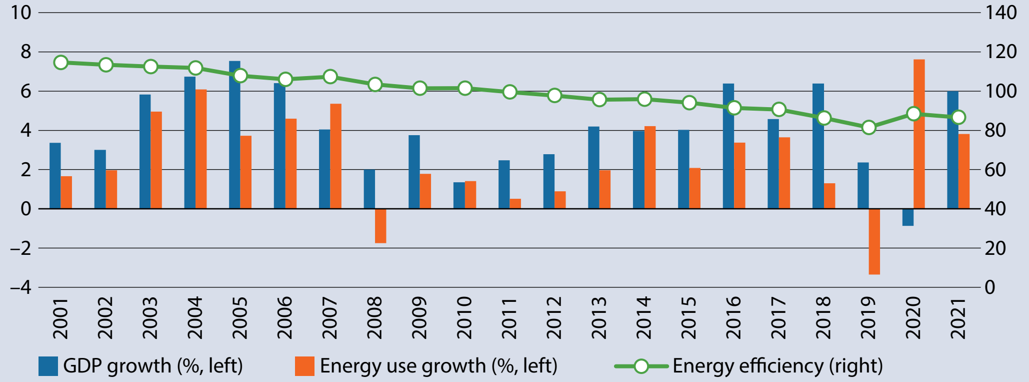
PAKISTAN

All Sectors

GDP growth shows steady positive expansion in most years, whereas energy-use growth is more volatile, with sharp declines in 2008, 2012, and 2019. Because GDP grows more stable than energy use, energy efficiency Index (energy use per unit GDP) gradually declines, indicating improved efficiency over time (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

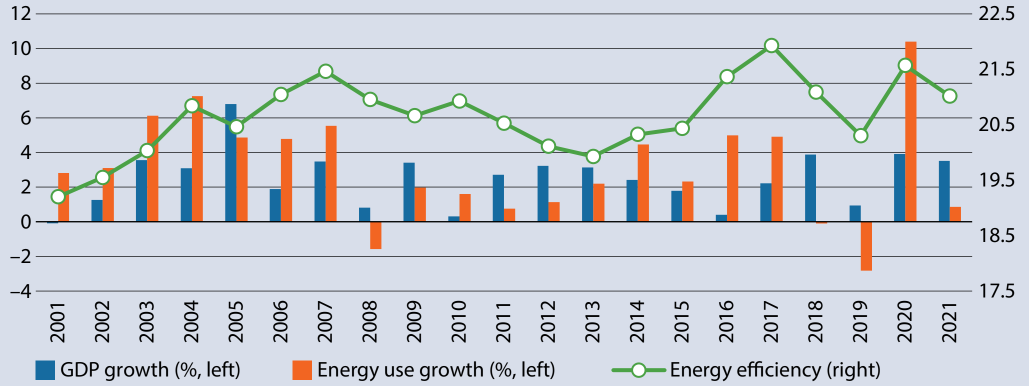


Agriculture Sector

Agricultural GDP trends upward but with modest fluctuations. Energy-use growth is highly volatile, with strong surges in 2005 and 2018 and a major decline in 2019. As agricultural output grows more steadily than energy consumption, overall efficiency improves despite short-term fluctuations (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

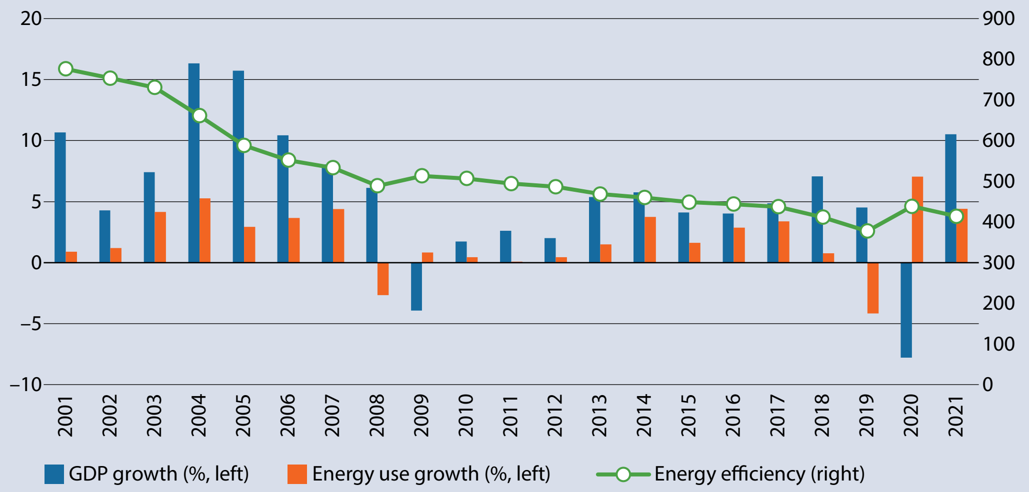


Manufacturing Sector

Manufacturing GDP generally increases, but energy-use growth fluctuates heavily, with severe contractions in 2008 and 2019. Because energy use declines faster than manufacturing output in several periods, energy efficiency steadily rises, particularly after 2015 (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

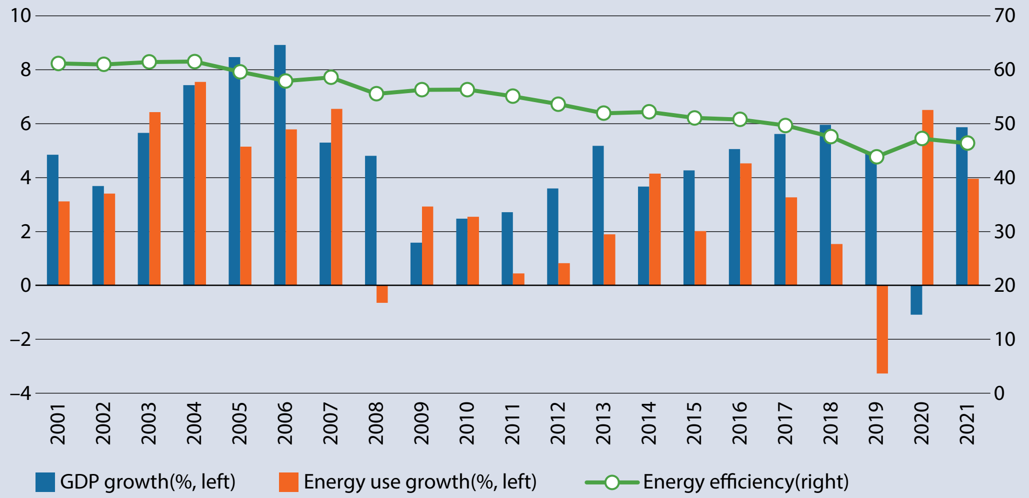


Services Sector

The services sector's GDP continues to grow at a consistent rate, whereas energy-use growth exhibits irregular spikes, such as in 2005 and 2020. Because GDP grows at a more stable rate than energy input, service-sector energy efficiency has improved gradually, particularly since 2018 (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

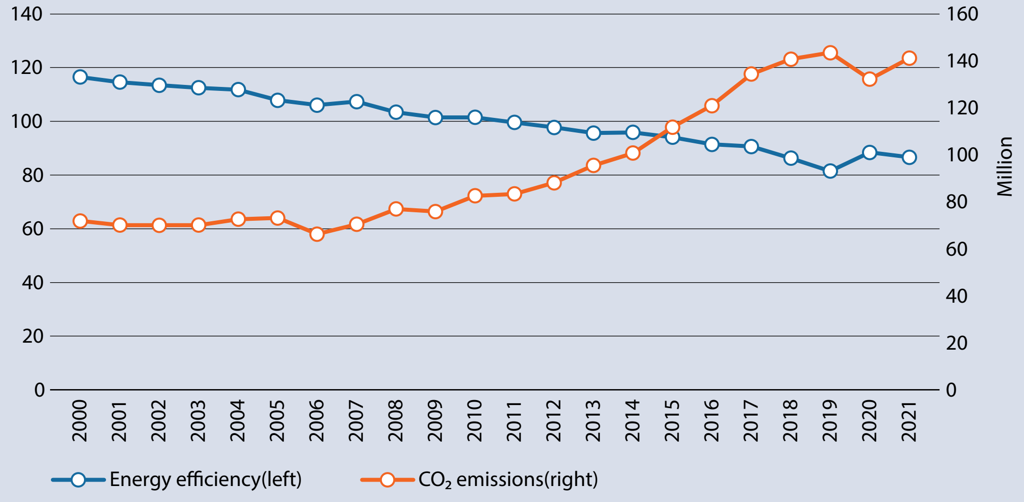


Energy Efficiency and CO_2 Emissions

Despite a rise in CO2 emissions from approximately 72 million tons to 141 million tons, the EE decreased from 116 to 86, indicating a steady improvement in efficiency despite the increase in emissions (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

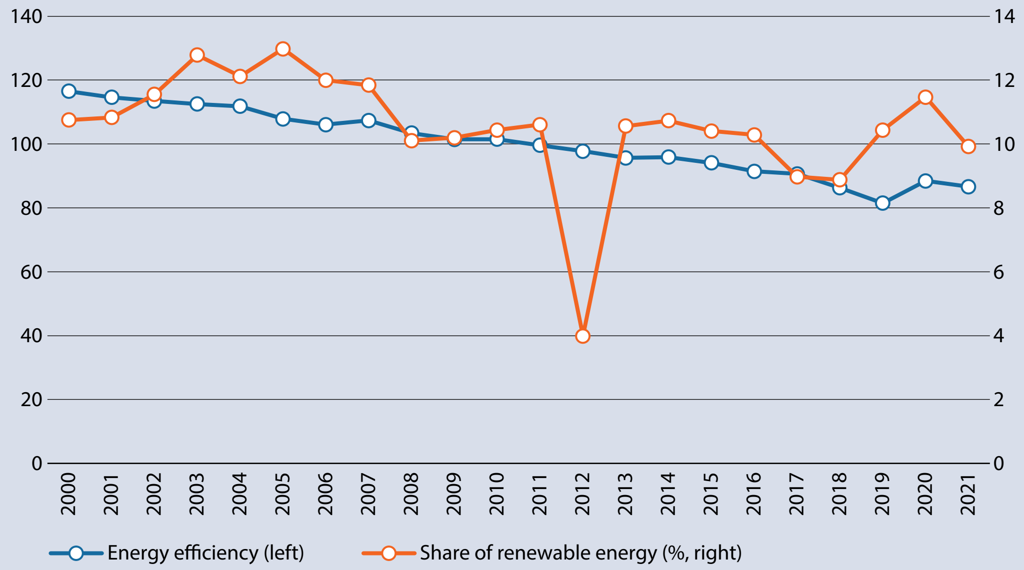


Energy Efficiency and the Share of Renewable Energy

While RE fluctuated between 10.8 and 9.9, EF decreased from 116 to 87, indicating that efficiency continued to improve despite fluctuations in renewable energy (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND SHARE OF RENEWABLE ENERGY.

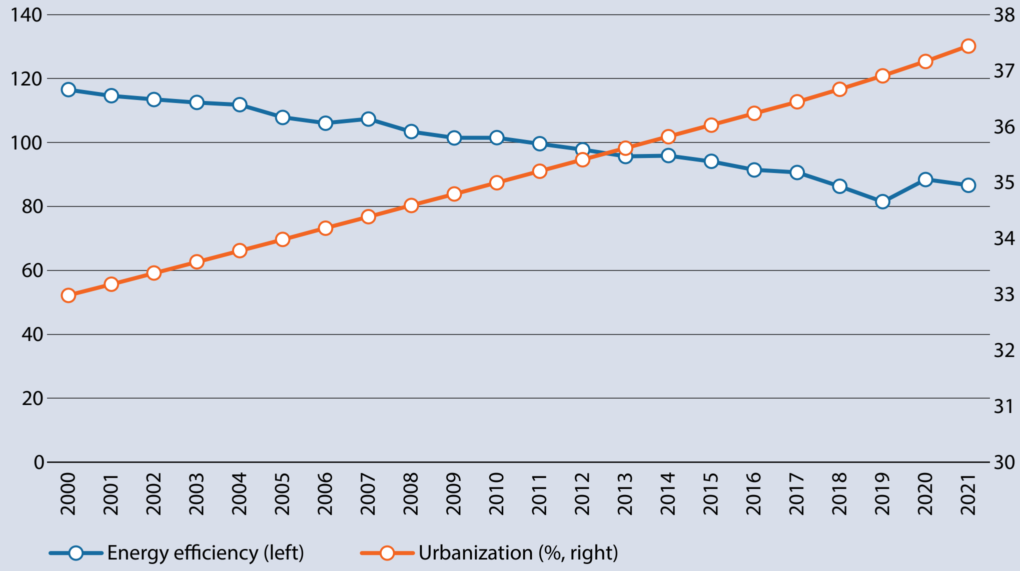


Energy Efficiency and Urbanization

While the urbanization rate increased steadily from 33.0% to 37.4%, EE declined from 116.5 to 86.6, indicating that efficiency improved overall as urbanization expanded (Figure 7).

FIGURE 7

ENERGY EFFICIENCY AND URBANIZATION.

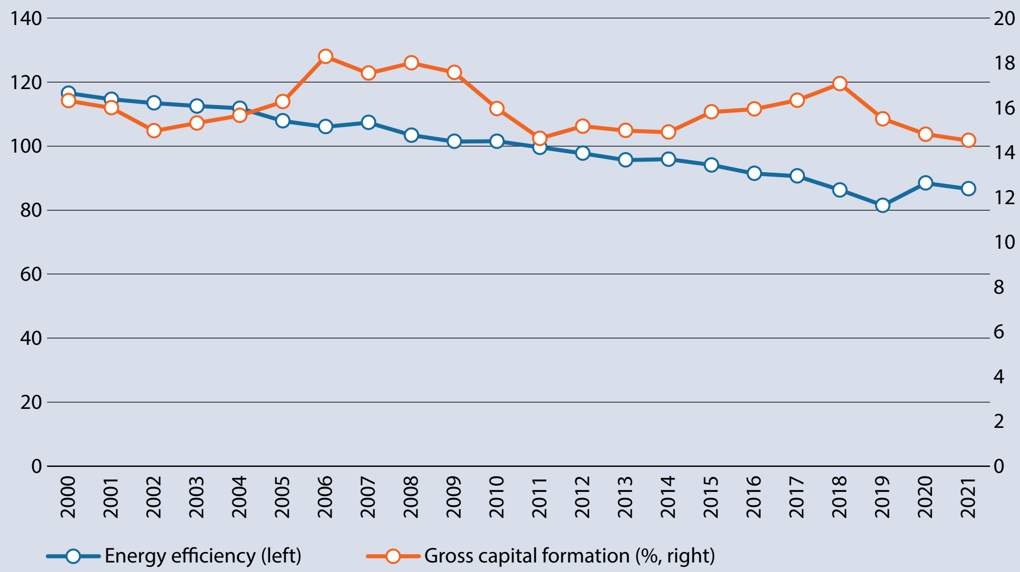


Energy Efficiency and Gross Capital Formation

As GF decreased slightly from 16.3% to 14.5%, EE also declined from 116 to 87, indicating that efficiency improvements persisted despite changes in the investment ratio (Figure 8).

FIGURE 8

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



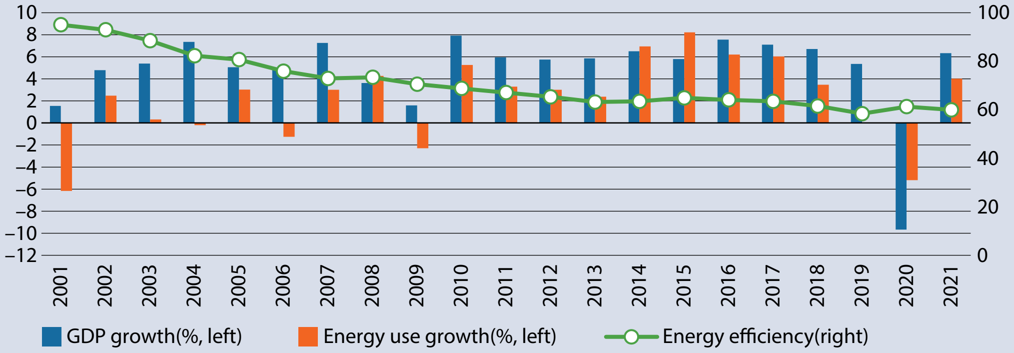
THE PHILIPPINES

All Sectors

The Philippines' GDP growth trend shows a generally positive trajectory through the 2000s and 2010s, with notable downturns in 2009 and a severe contraction in 2020. Energy use growth fluctuates more widely, including sharp declines during global crisis periods. Energy efficiency (EE) Index declined steadily from the early 2000s through 2020, with only a modest recovery in 2021 (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

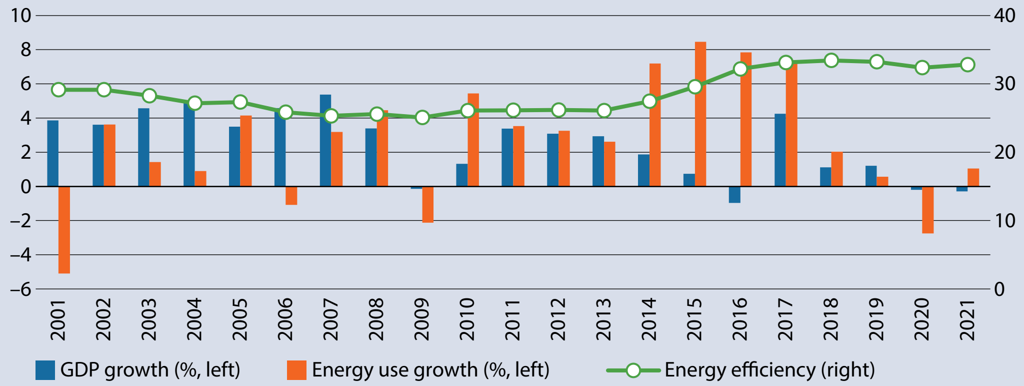


Agriculture Sector

Agricultural GDP growth remains modest, with frequent small positive rates and occasional contractions, notably in 2009 and 2016. Growth in energy use is volatile but remains largely positive. Energy efficiency gradually improves over time, rising especially after 2015 and stabilizing at higher levels by 2021 (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

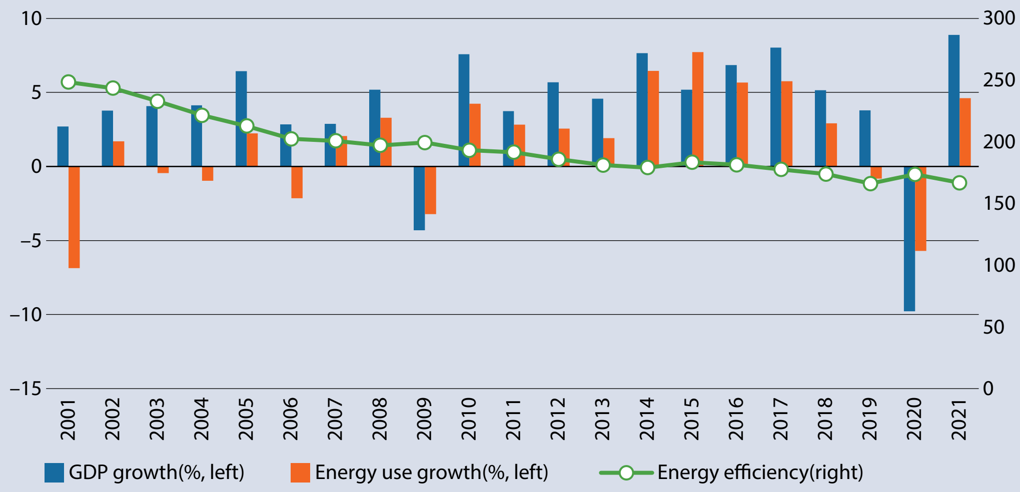


Manufacturing Sector

Manufacturing GDP growth fluctuates significantly, showing strong expansions in the early 2000s and mid-2010s but sharp declines during 2009 and 2020. Energy use growth also varies sharply, including pronounced declines during crisis years. Energy efficiency exhibits a slow but persistent decline, declining throughout the period, with only limited recovery in 2021 (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

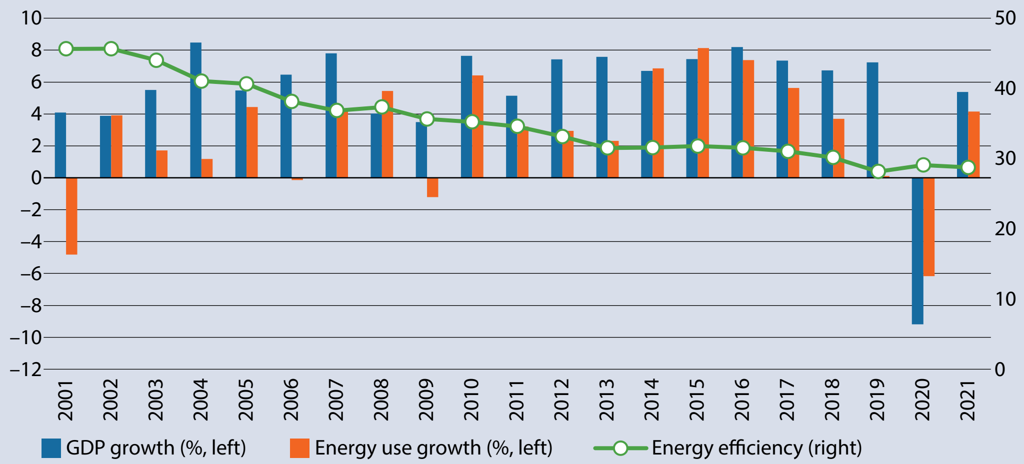


Services Sector

The services sector's GDP growth is relatively stable and consistently positive except for pronounced drops in 2009 and 2020. Energy use growth is positive in most years but dips in major shock periods. Energy efficiency gradually declines over the 2000–21 period, though it appears to stabilize after 2018 (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

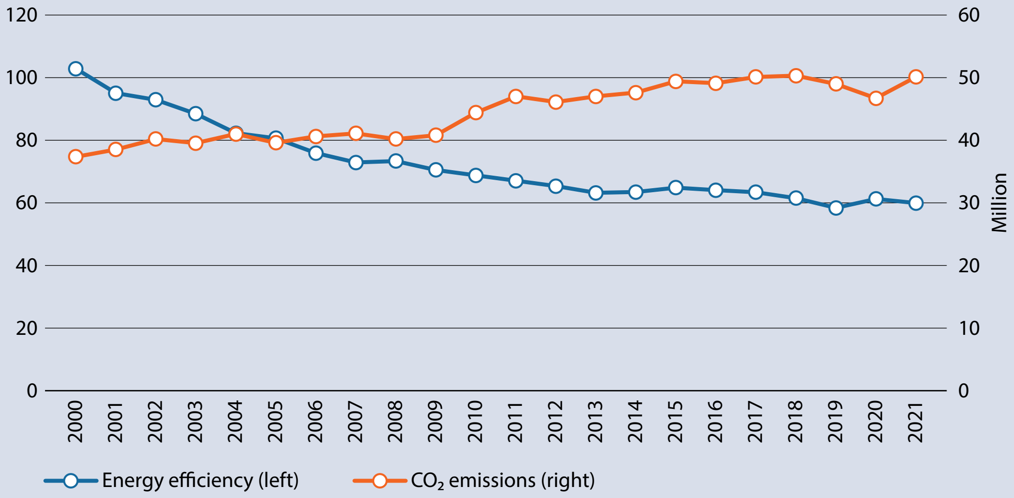


Energy Efficiency and CO_2 Emissions

Despite a notable rise in CO2 emissions, from approximately 37 million tons to 50 million tons, the EE demonstrated a substantial decrease, from 103 to 60. This indicates that efficiency levels were consistently improved, despite rising emissions (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

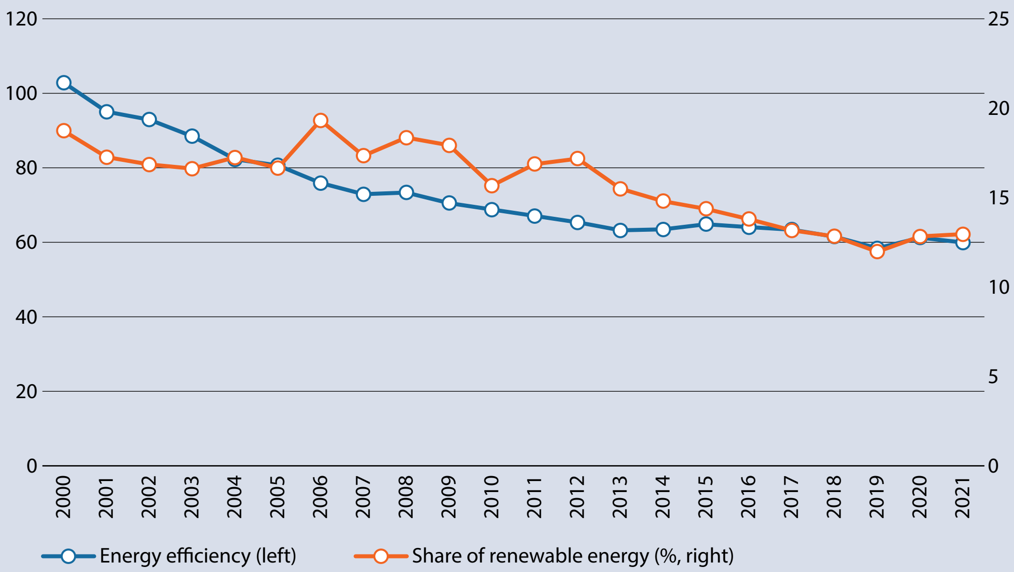


Energy Efficiency and the Share of Renewable Energy

While RE decreased from 18.7 to 12.9, EE decreased from 103 to 60, indicating that efficiency improvements persisted despite changes in the proportion of renewable energy (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND SHARE OF RENEWABLE ENERGY.

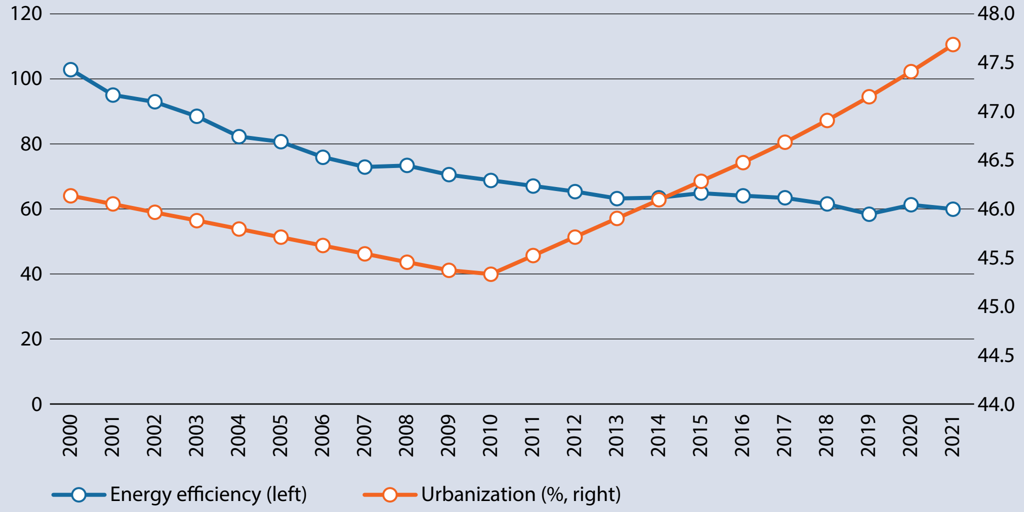


Energy Efficiency and Urbanization

Although the urbanization rate increased gradually from 46.1% to 47.7%, efficiency declined significantly from 102.8% to 59.9%, indicating a clear improvement in efficiency alongside urbanization (Figure 7).

FIGURE 7

ENERGY EFFICIENCY AND URBANIZATION.

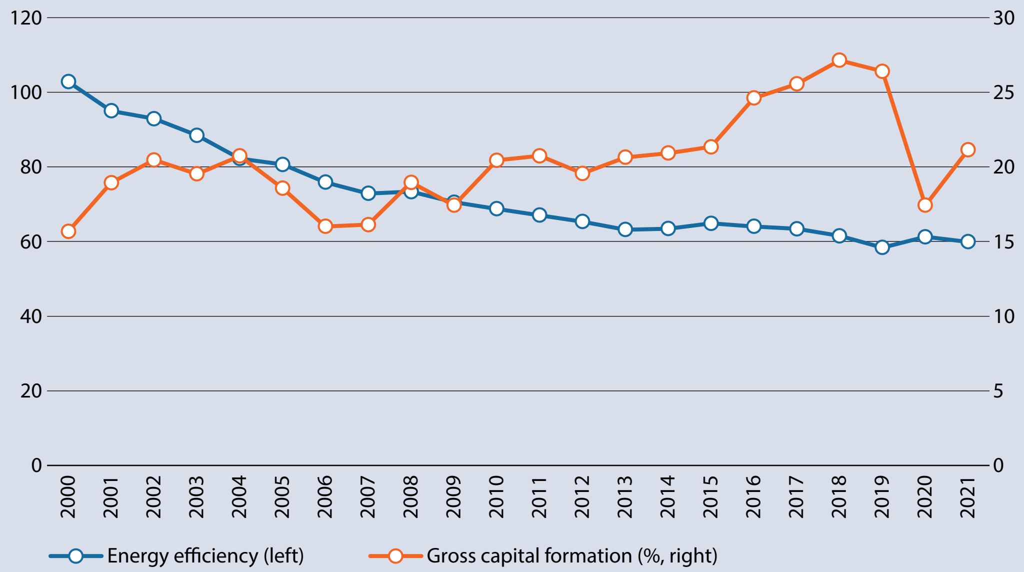


Energy Efficiency and Gross Capital Formation

While GF increased overall from 15.7% to 21.1%, EE decreased from 103 to 60, indicating a simultaneous increase in investment and improvement in efficiency (Figure 8).

FIGURE 8

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



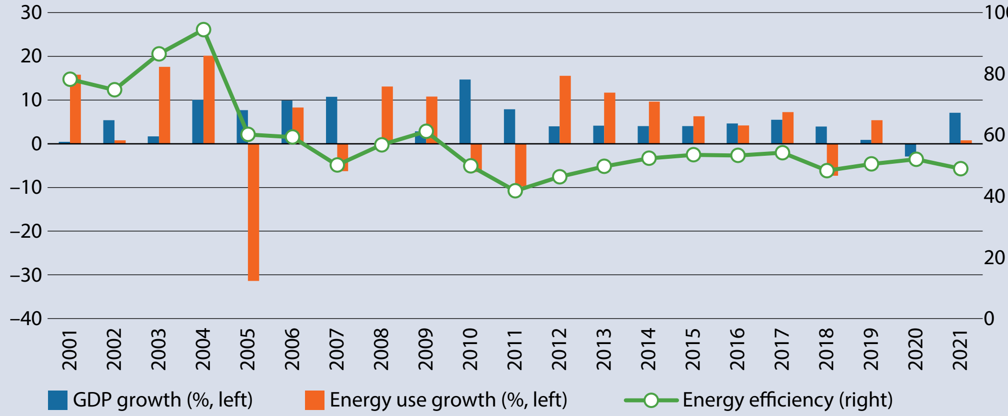
SINGAPORE

All Sectors

GDP growth remains relatively steady, while energy-use growth fluctuates more sharply (notably in 2005, 2011, 2020). Energy efficiency (EE) Index has declined gradually over the long term, indicating that energy use has risen faster than GDP (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

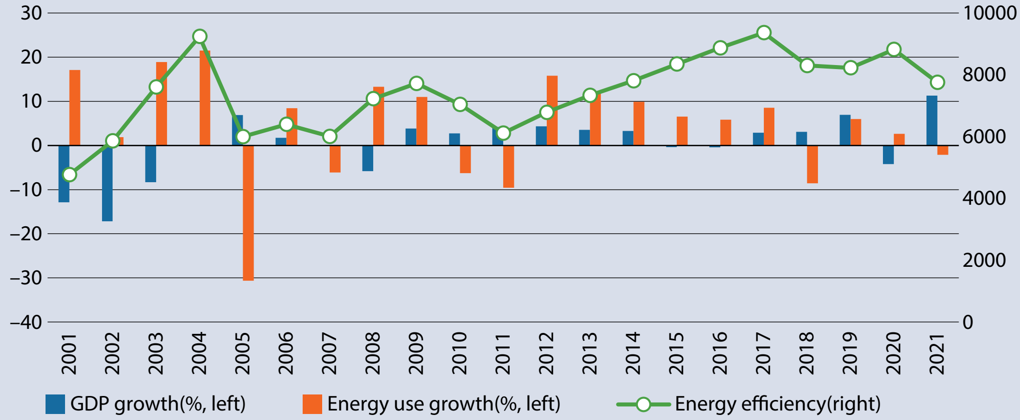


Agriculture Sector

Agriculture is extremely small in Singapore, so both GDP and energy-use growth fluctuate irregularly. Energy efficiency remains mostly stable with only minor year-to-year variation (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

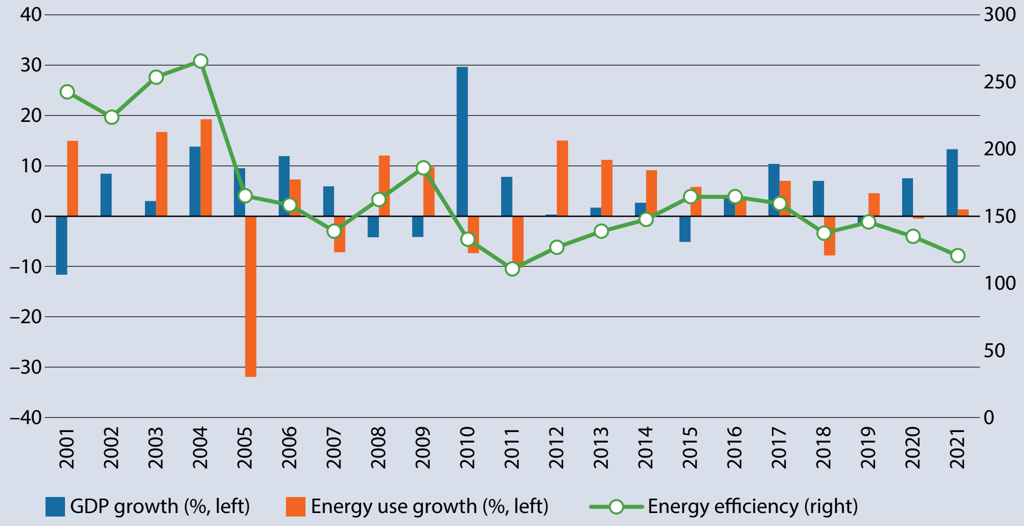


Manufacturing Sector

Manufacturing exhibits pronounced fluctuations in GDP and energy-use growth, particularly during global downturns (2009 and 2020). Energy efficiency trends downward over the long term, indicating higher energy input relative to output (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

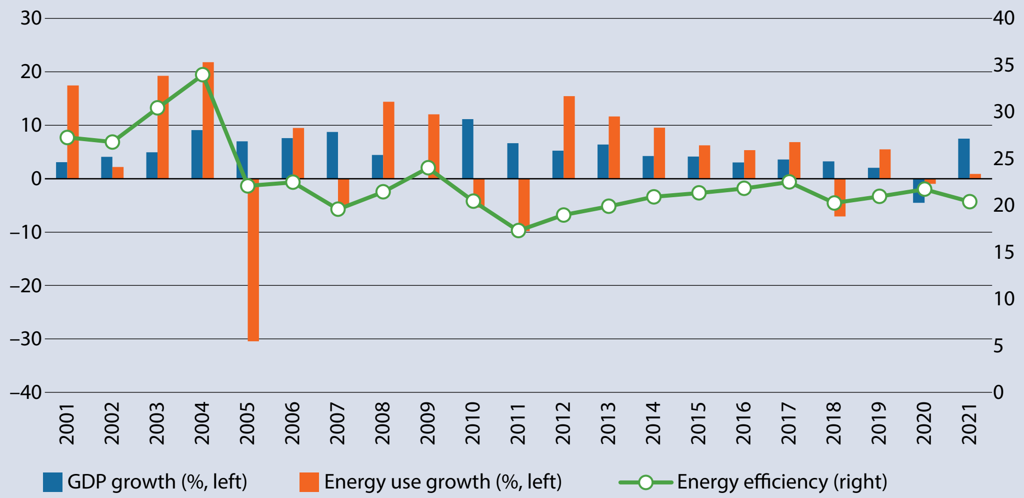


Services Sector

GDP growth is stable with moderate fluctuations, while energy-use growth varies more widely. Energy efficiency shows a mild declining pattern, consistent with increasing energy use relative to service-sector output (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

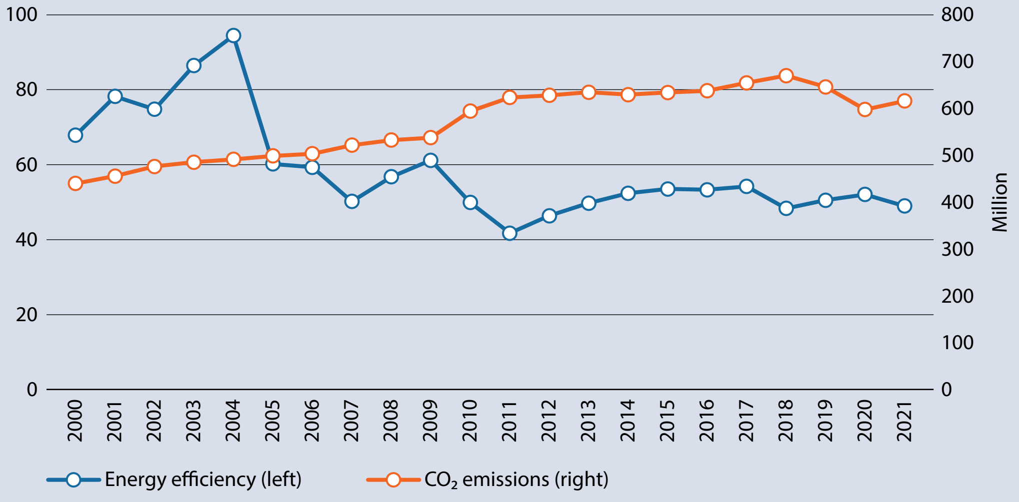


Energy Efficiency and CO_2 Emissions

Despite a rise in CO2 emissions from approximately 440 million tons to 616 million tons, the EE fell from 67.8 to 49.0, indicating a long-term trend of enhanced efficiency despite the rising emissions (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

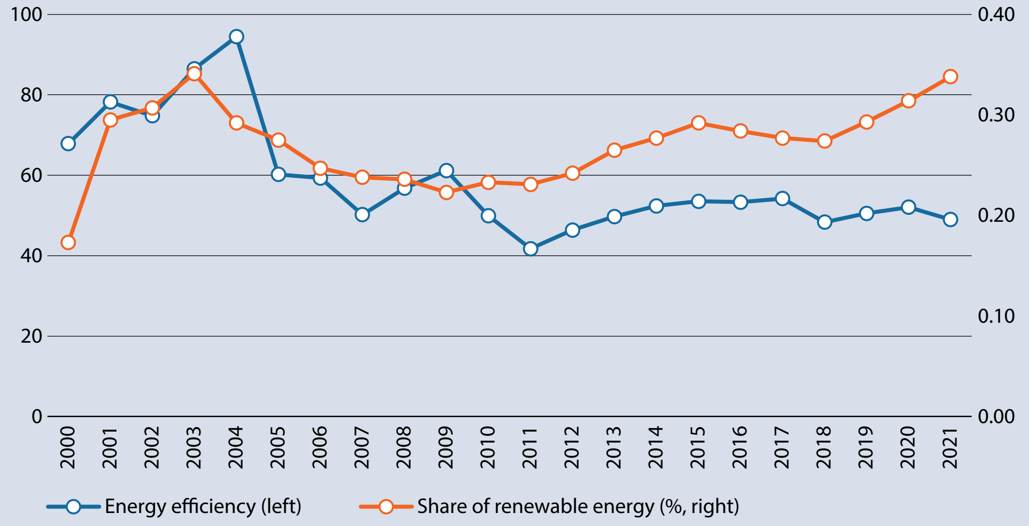


Energy Efficiency and the Share of Renewable Energy

While the share of renewable energy increased marginally from 0.17 to 0.34, EE decreased from 67.8 to 49.0, indicating a trend toward greater renewable energy deployment and improved efficiency (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND SHARE OF RENEWABLE ENERGY.

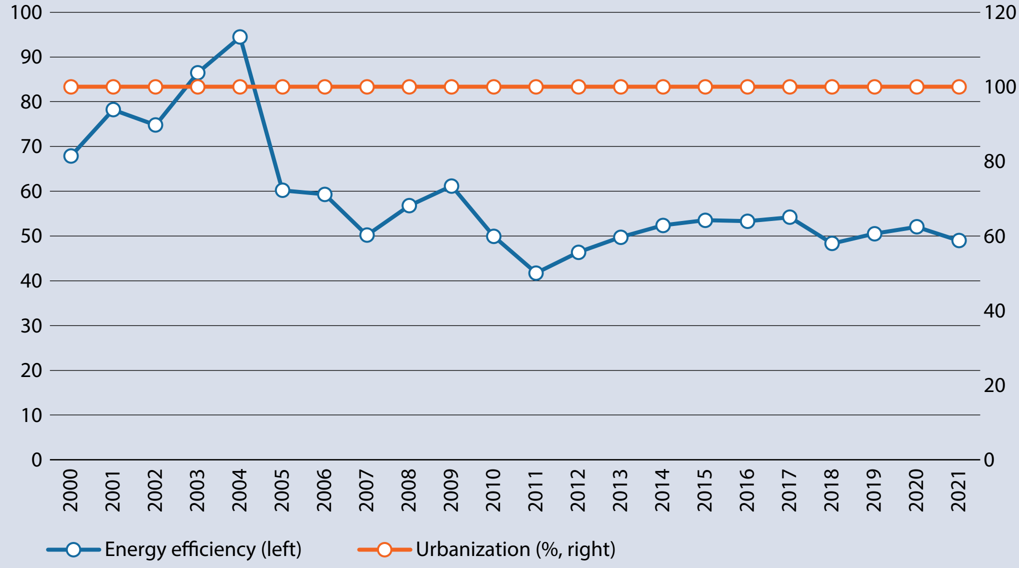


Energy Efficiency and Urbanization

While the urbanization rate remained at 100%, the EE declined from 67.8 to 49.0, indicating a steady improvement in efficiency despite no changes in urban structure (Figure 7).

FIGURE 7

ENERGY EFFICIENCY AND URBANIZATION.

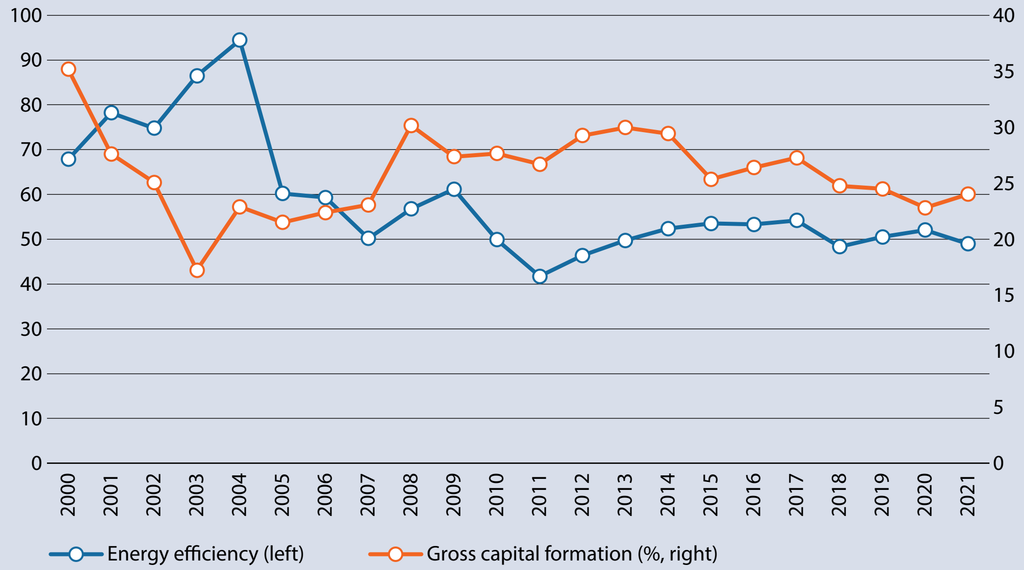


Energy Efficiency and Gross Capital Formation

While GF decreased from 35.2% to 24.0%, EE also fell from 67.8% to 49.0%, resulting in a lower investment proportion and improved efficiency (Figure 8).

FIGURE 8

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



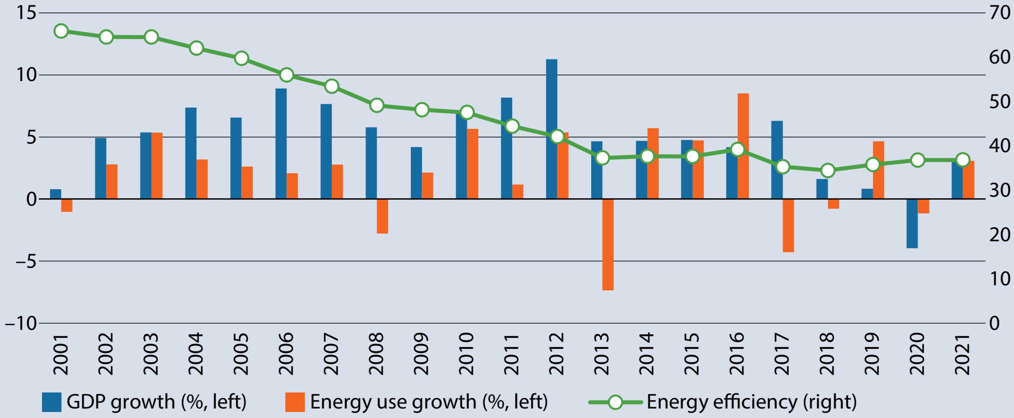
SRI LANKA

All Sectors

GDP grows modestly, while energy-use growth is highly volatile with several negative dips. Because energy use often lags GDP, EE Index shows a clear downward trend from the early 2000s to the mid-2010s, then stabilizes slightly in recent years (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

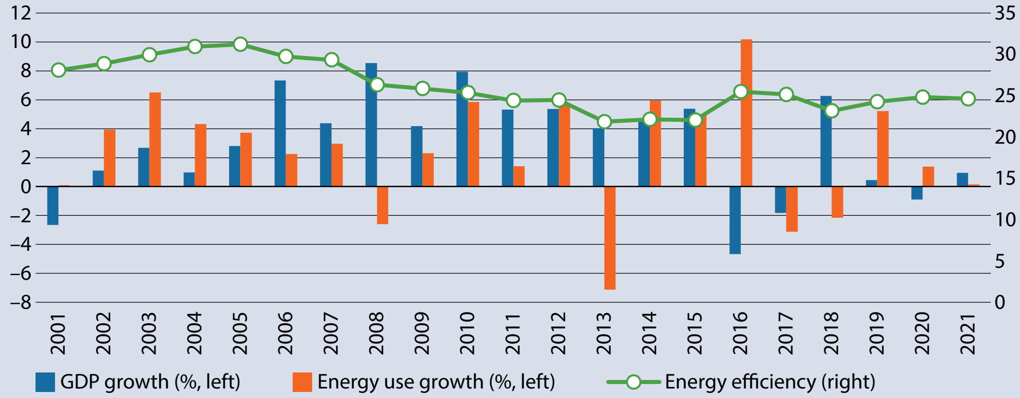


Agriculture Sector

Agricultural GDP rises modestly; energy use fluctuates, with several years of decline. EE gradually declines overall, indicating slower productivity relative to energy use, with small improvements after 2016 (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

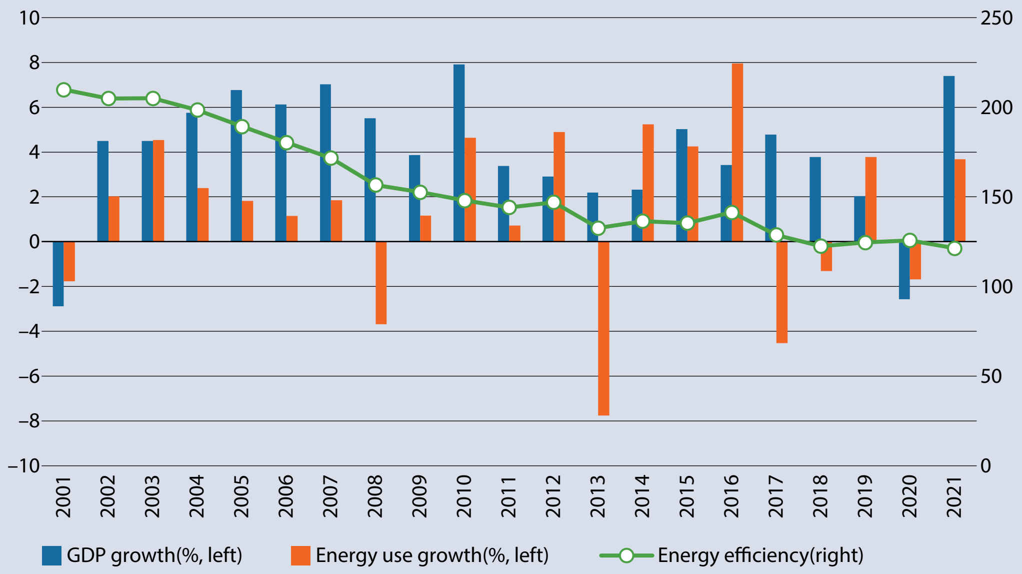


Manufacturing Sector

Manufacturing GDP is positive, but energy-use growth swings sharply, including deep drops. EE has steadily declined since the mid-2000s, recovering only slightly after 2017 (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

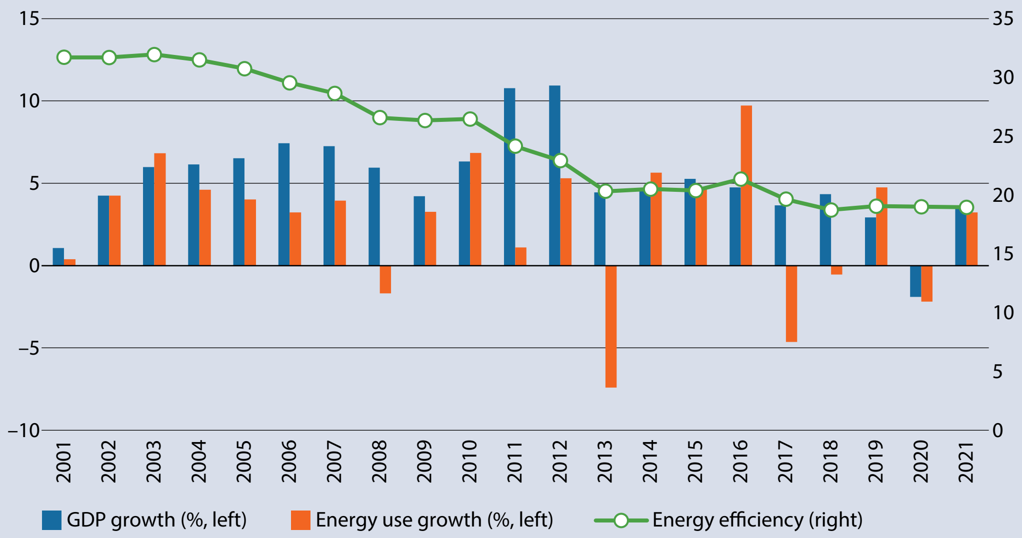


Services Sector

Service GDP stays positive; energy-use growth varies sharply. EE declines continuously until the mid-2010s, after which it levels off, implying rising energy intensity (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

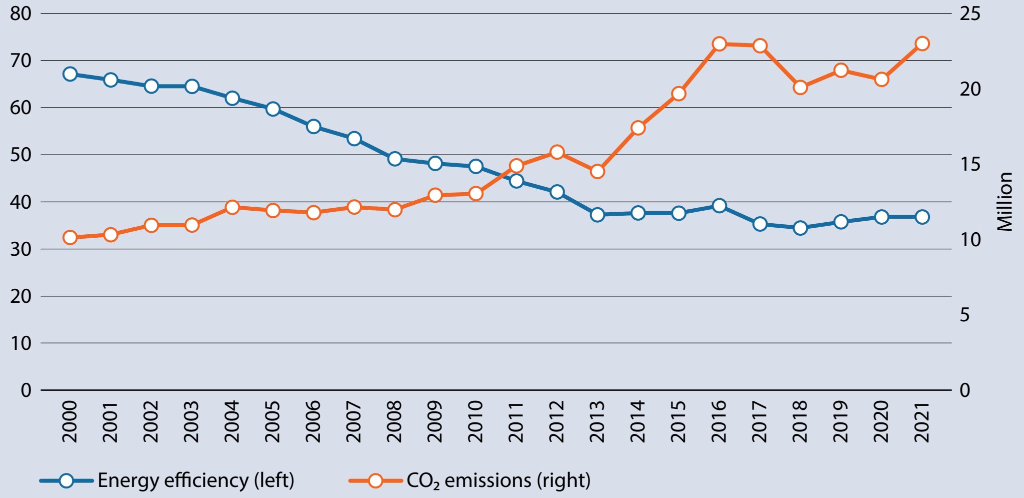


Energy Efficiency and CO_2 Emissions

While CO2 emissions increased from approximately 10.1 million tons to 23 million tons, EF decreased from 67 to 37, showing that efficiency has steadily improved even amid rising emissions (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

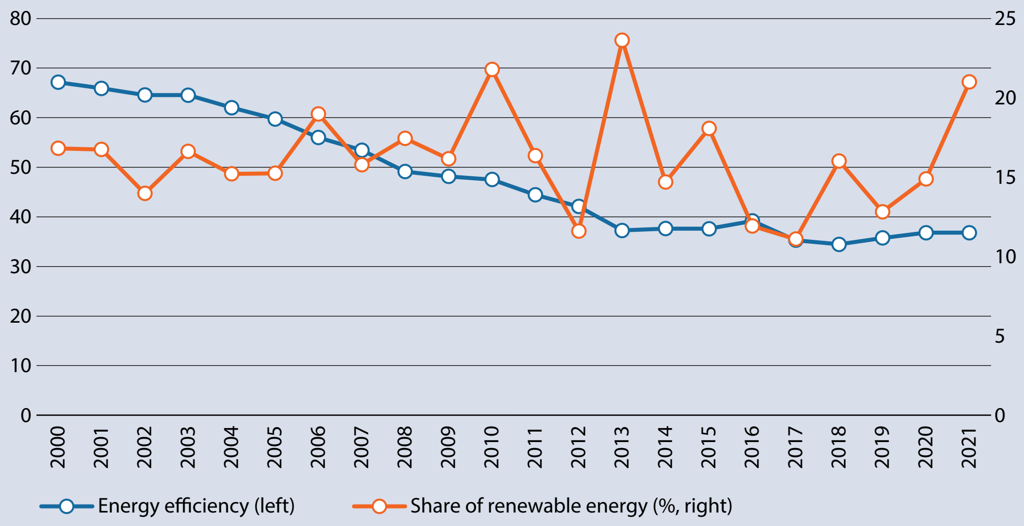


Energy Efficiency and the Share of Renewable Energy

As the share of renewable energy increased from 16.8 to 21.0, EE also decreased from 67 to 37, showing a pattern in which renewable energy expansion and efficiency improvement occurred simultaneously (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND SHARE OF RENEWABLE ENERGY.

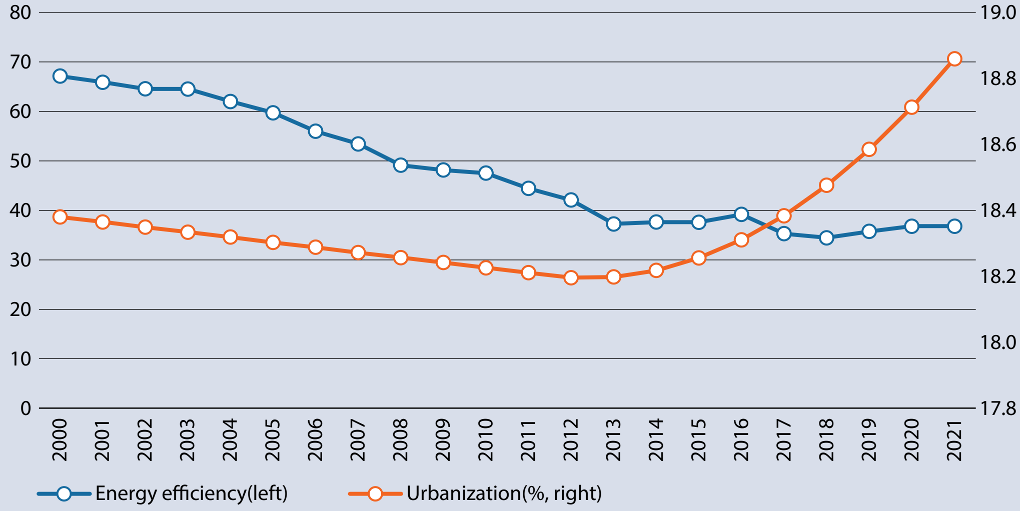


Energy Efficiency and Urbanization

While the urbanization rate remained almost constant from 18.38% to 18.86%, the EE decreased significantly from 67.1 to 36.8, indicating that although the urban structure changed, efficiency continued to improve (Figure 7).

FIGURE 7

ENERGY EFFICIENCY AND URBANIZATION.

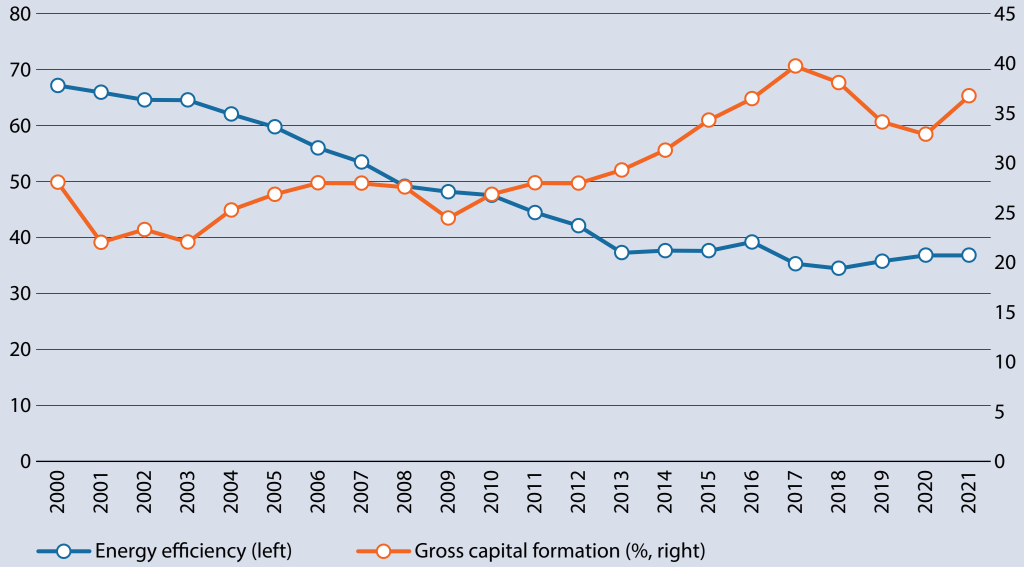


Energy Efficiency and Gross Capital Formation

While GF increased from 28.0% to 36.7%, EE decreased from 67 to 37, showing a trend of increased investment and improved efficiency (Figure 8).

FIGURE 8

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



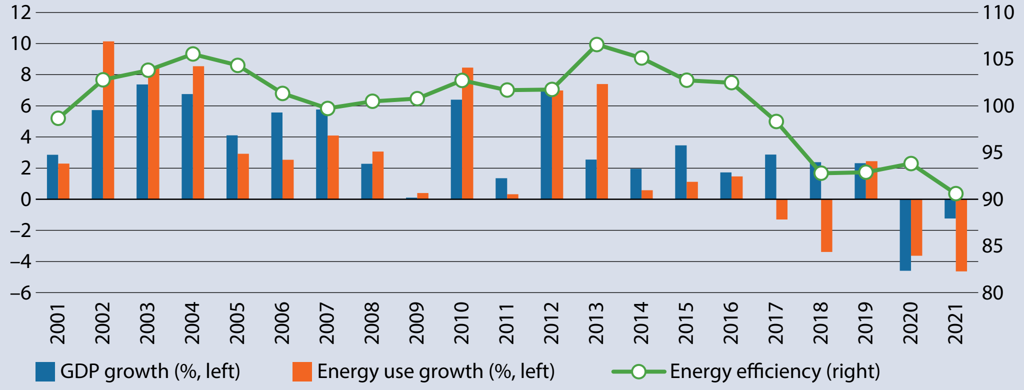
THAILAND

All Sectors

GDP grew steadily, while energy-use growth fluctuated sharply, showing large drops in 2005, 2011, and 2018. As a result, EE Index declined gradually from about 95 in 2001 to around 88 in 2021, indicating a slow increase in energy intensity over time (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

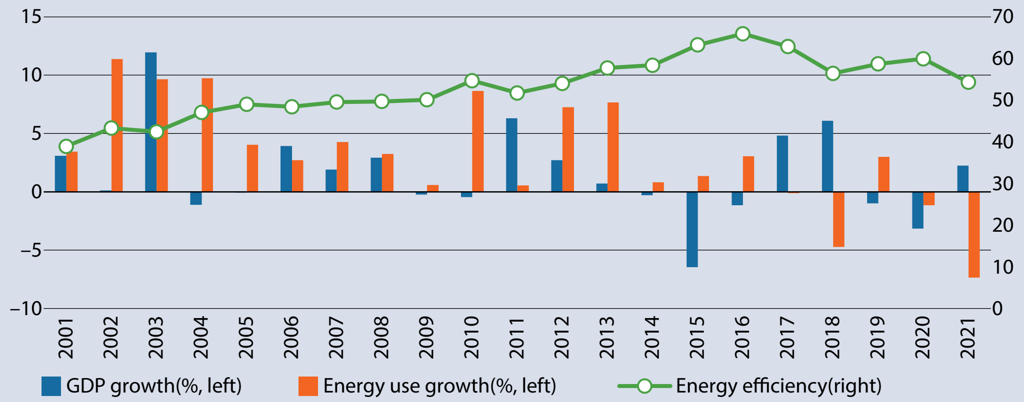


Agriculture Sector

Agricultural GDP maintained a stable positive trend, but energy-use growth showed strong volatility—surging in 2002–05 and falling sharply in 2019 and 2021. EE Index rose slightly in the early 2000s but declined again from the mid-2010s, suggesting a gradual deterioration in agricultural energy efficiency (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

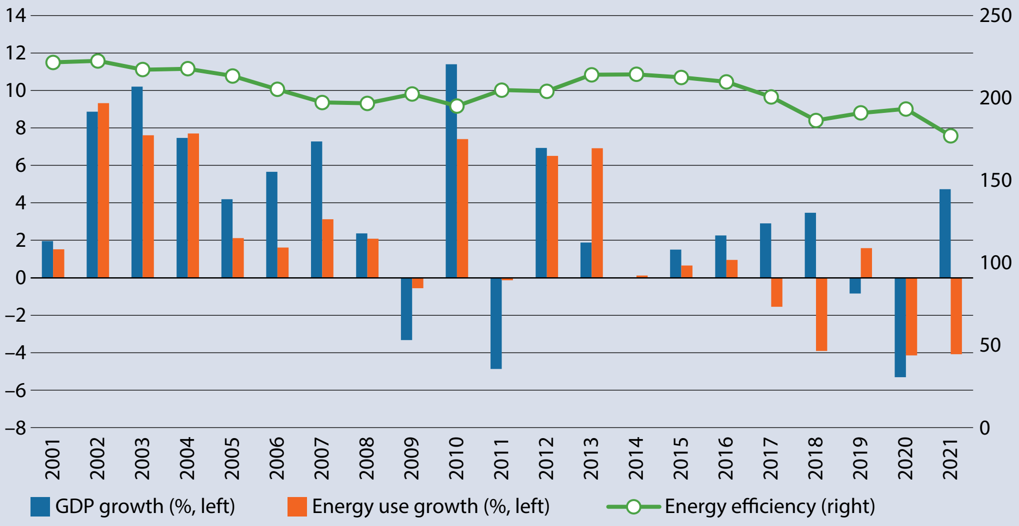


Manufacturing Sector

Manufacturing shows strong early-2000s GDP growth, then moderate levels after 2010. Energy use growth is highly volatile, including several negative years. Energy efficiency steadily declines from above 110 to around 80 (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

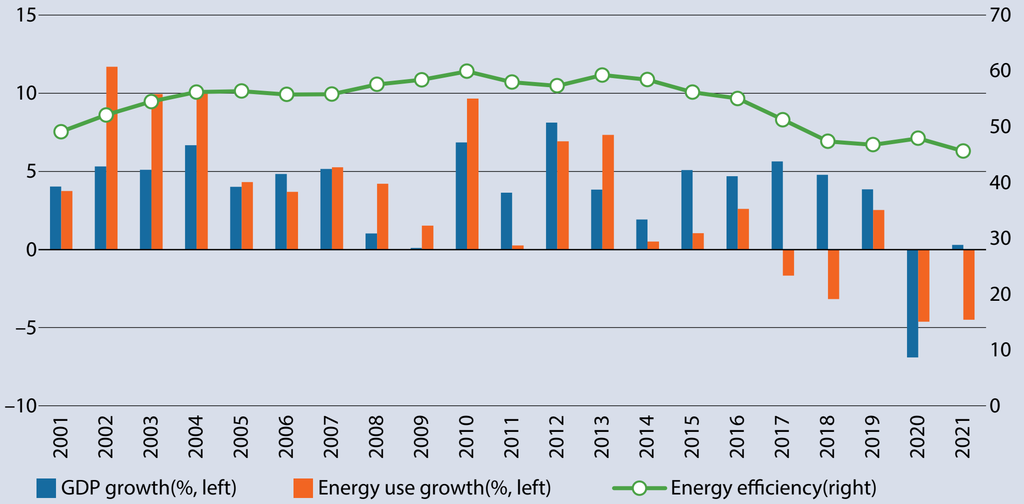


Services Sector

Services maintain steady GDP growth, except during major shocks. Energy use growth fluctuates, with multiple negative years. Energy efficiency rises slightly until early 2010s, then trends downward (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

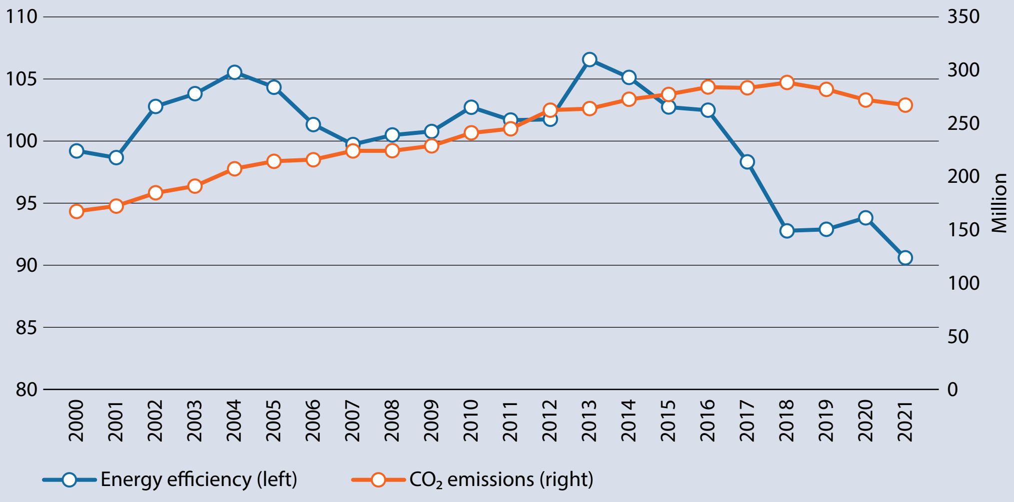


Energy Efficiency and CO_2 Emissions

Despite a rise in CO2 emissions from approximately 167 million tons to 267 million tons, the EE has decreased from 99 to 91, indicating that efficiency is improving steadily despite the rising emissions trend (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

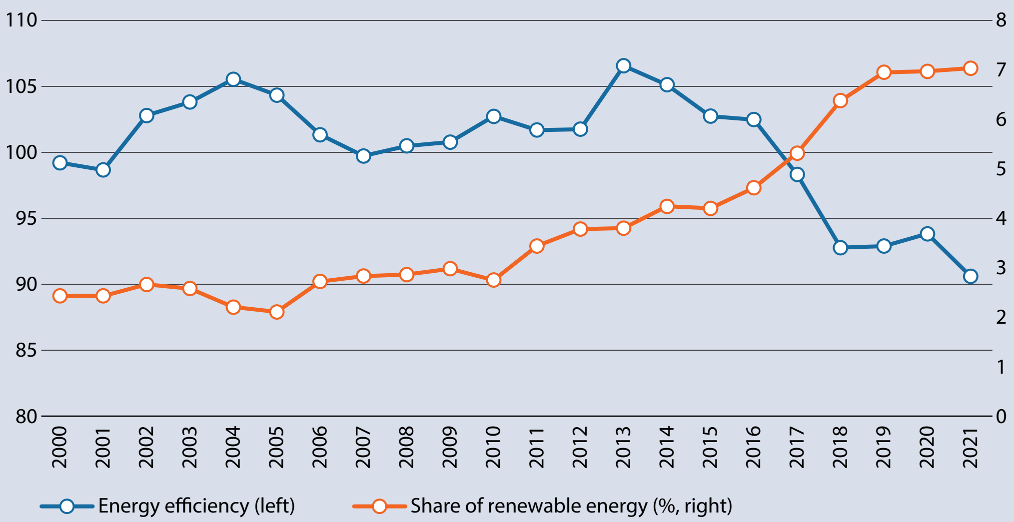


Energy Efficiency and the Share of Renewable Energy

While the share of renewable energy increased significantly from 2.43 to 7.03, EE decreased from 99 to 91, indicating an increase in the proportion of renewable energy and an improvement in efficiency (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND SHARE OF RENEWABLE ENERGY.

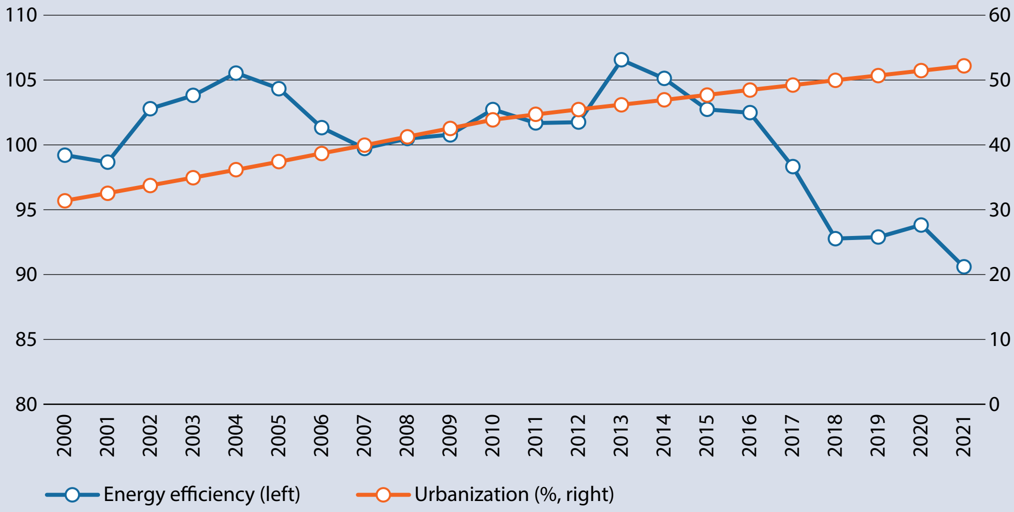


Energy Efficiency and Urbanization

While the urbanization rate steadily increased from 31.4% to 52.2%, the EE decreased overall from 99.2% to 90.6%, indicating that efficiency gradually improved along with the progress of urbanization (Figure 7).

FIGURE 7

ENERGY EFFICIENCY AND URBANIZATION.

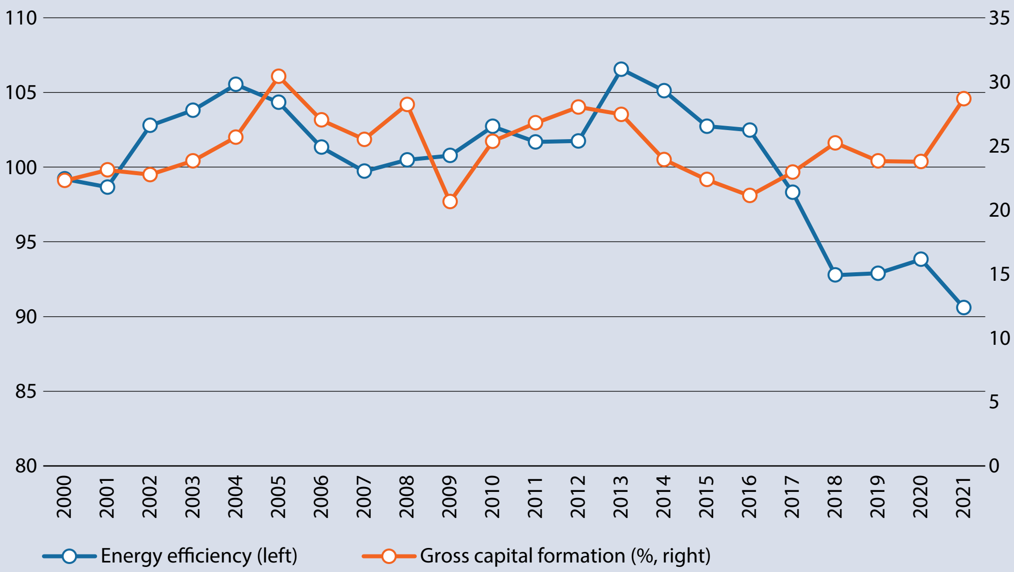


Energy Efficiency and Gross Capital Formation

While GF increased from 22.3% to 28.7%, EE decreased from 99 to 91, indicating a simultaneous pattern of investment expansion and efficiency improvement (Figure 8).

FIGURE 8

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



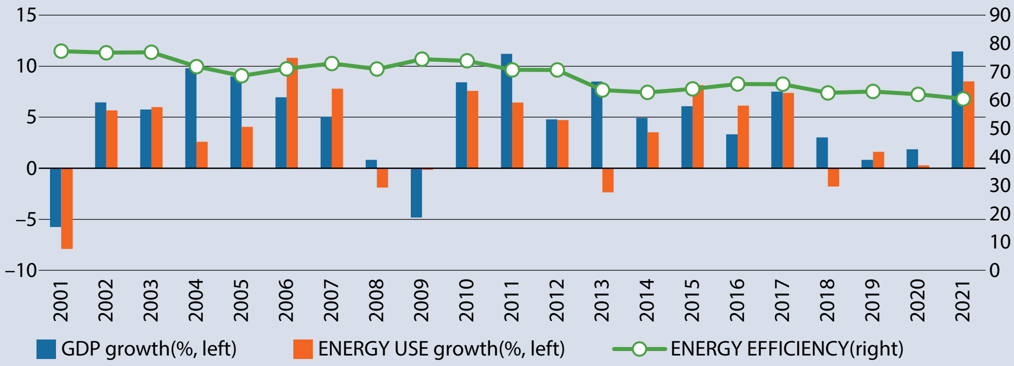
TURKIYE

All Sectors

Turkiye's GDP growth is highly volatile, with sharp drops in 2001, 2009, 2018, and 2020. Energy-use growth also swings widely, especially in crisis years. Energy efficiency (EE) Index has declined gradually since the early 2000s, stabilizing around the mid-2010s and then slightly weakening again after 2018. Overall, the pattern is one of high macro volatility with a slow, long-term erosion in efficiency (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

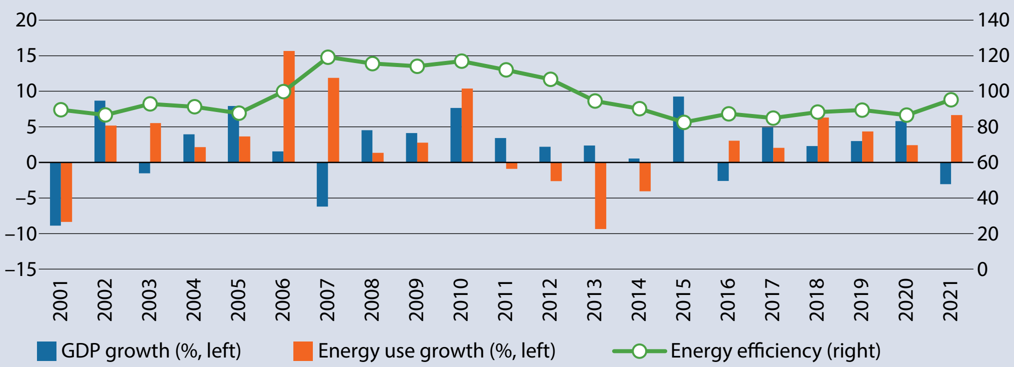


Agriculture Sector

Agricultural GDP growth fluctuates but is generally more stable than total GDP. Energy-use growth shows several large negative spikes (2001, 2008, 2014), indicating strong sensitivity to weather and production cycles. Energy efficiency trends have declined gently since the mid-2000s and stabilized around 2016–21. The sector shows moderate output growth but weakening efficiency over time (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

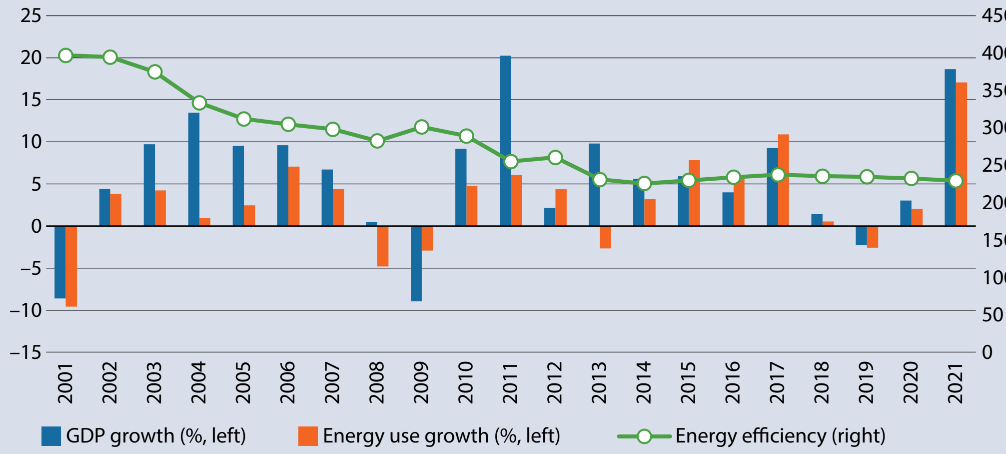


Manufacturing Sector

Manufacturing GDP and energy-use growth exhibit sharp cyclical swings, with pronounced rebounds in 2011 and 2021. Energy efficiency declines steadily from 2001 to around 2013, then remains relatively flat. Overall, manufacturing shows high volatility and a long-term decline in efficiency despite periodic output surges (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

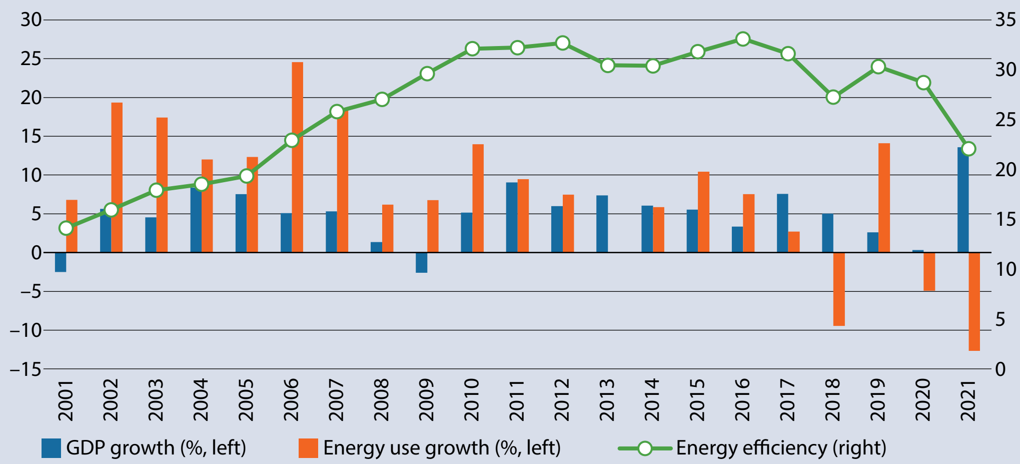


Services Sector

Services GDP growth is more stable than other sectors, with downturns in 2001, 2009, 2016, and 2020. Energy-use growth varies strongly, especially during economic shocks. Energy efficiency improves steadily from 2001 to around 2012, then remains high until 2017, after which it begins to decline. Services is the only sector that shows a clear early efficiency improvement before the recent downturn (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

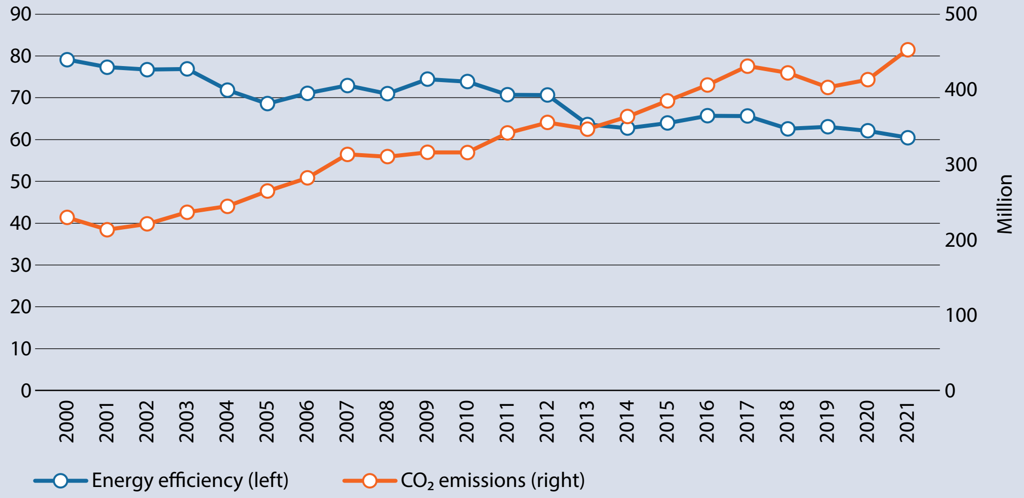


Energy Efficiency and CO_2 Emissions

Despite a notable rise in CO2 emissions, from approximately 230 million tons to 453 million tons, there has been a decrease in the EE from 79 to 60. This suggests that the trend of efficiency improvement has persisted, despite the increase in emissions (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

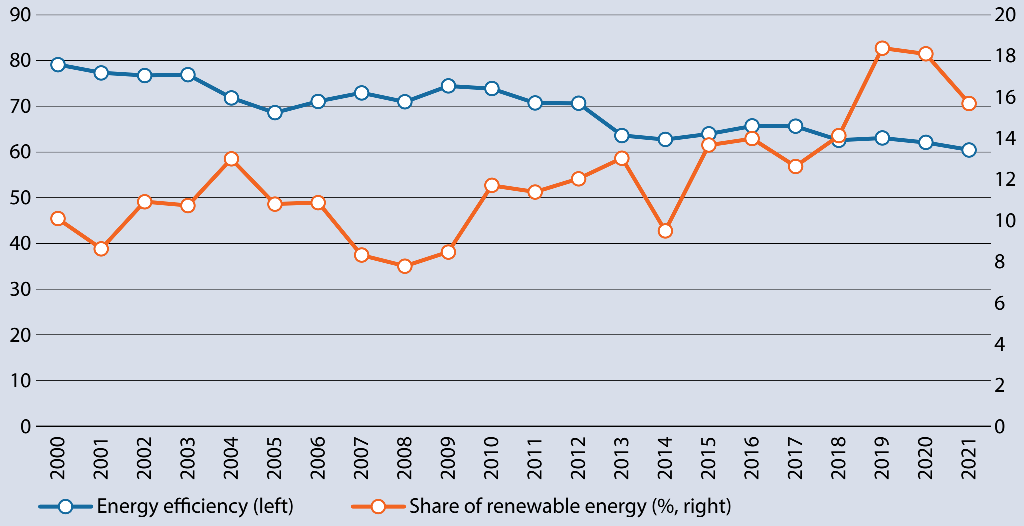


Energy Efficiency and Share of Renewable Energy

During the period when the share of renewable energy increased from 10.1 to 15.7, EE decreased from 79 to 60, indicating that renewable energy expansion and efficiency improvement occurred simultaneously (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND SHARE OF RENEWABLE ENERGY.

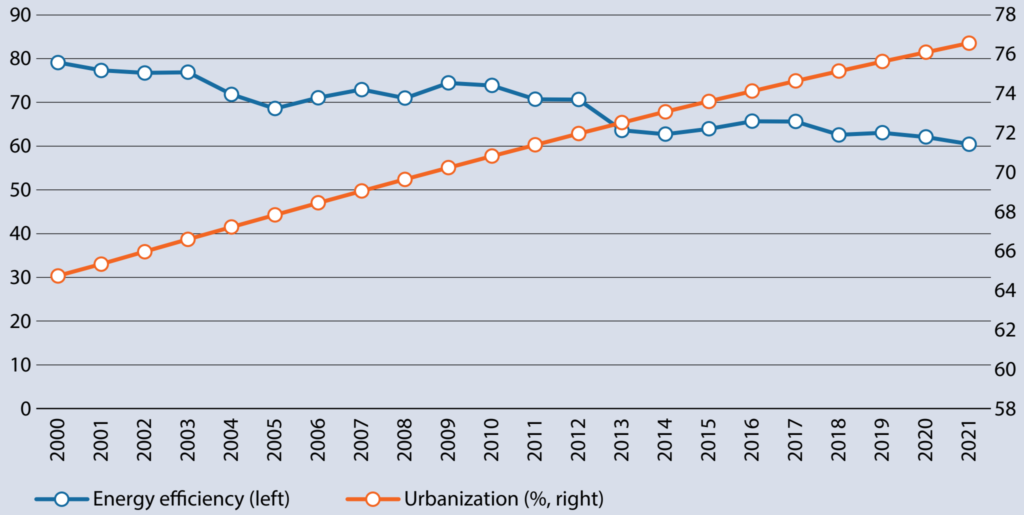


Energy Efficiency and Urbanization

While the urbanization rate increased steadily from 64.7% to 76.6%, efficiency declined from 79.1% to 60.5%, indicating a consistent decline in efficiency alongside urbanization (Figure 7).

FIGURE 7

ENERGY EFFICIENCY AND URBANIZATION.

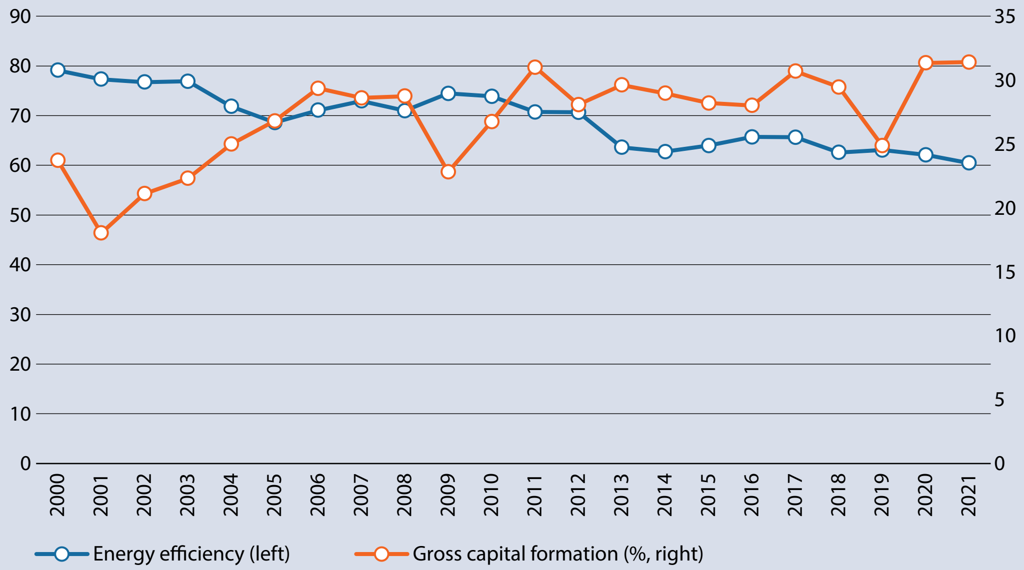


Energy Efficiency and Gross Capital Formation

While GF increased from 23.7% to 31.4%, EE decreased from 79% to 60%, indicating a trend toward increased investment and improved efficiency (Figure 8).

FIGURE 8

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



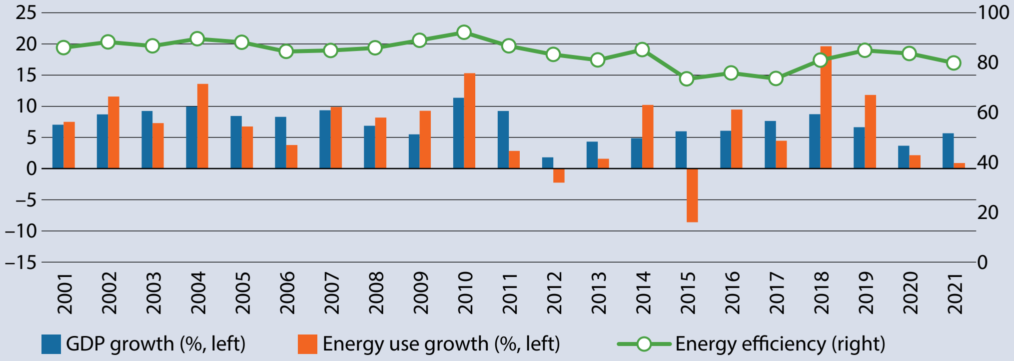
VIETNAM

All Sectors

Vietnam shows consistently strong GDP growth, generally between 5% and 10%, with only brief dips (2009, 2011, 2020). Energy use growth is volatile, oscillating between negative values (2009, 2012, 2016) and large spikes (2010, 2018, 2021). Energy efficiency (EE) Index trends downward over time, indicating rising energy consumption relative to output despite solid economic performance (Figure 1).

FIGURE 1

GDP AND ENERGY-USE GROWTH IN ALL SECTORS.

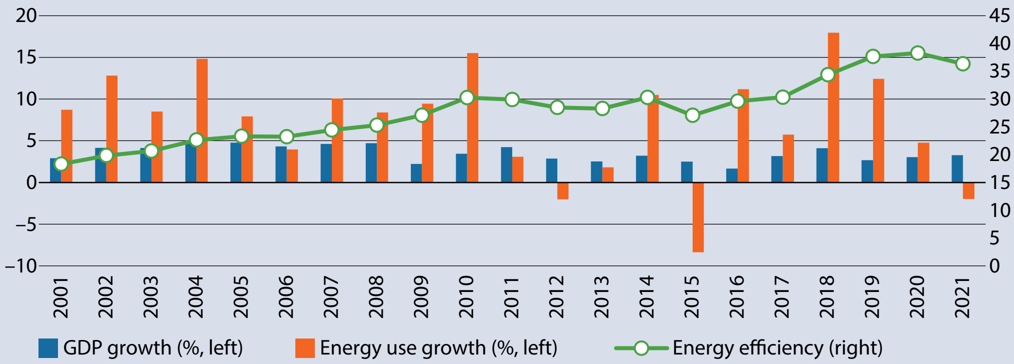


Agriculture Sector

Agricultural GDP grows steadily at 2–6%, while energy use growth is highly unstable, with several deep declines (2008, 2013, 2016, 2020). Energy efficiency improves moderately from the mid-2000s to the late-2010s, though it softens again after 2018. Overall, agriculture shows stable output but inefficient, volatile energy use (Figure 2).

FIGURE 2

GDP AND ENERGY-USE GROWTH IN THE AGRICULTURE SECTOR.

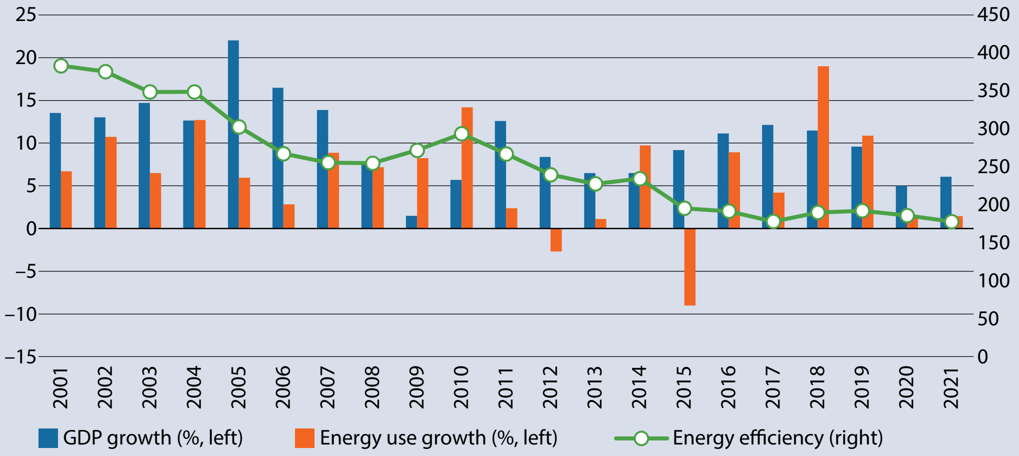


Manufacturing Sector

Manufacturing GDP expands strongly (often by 7–15%), but energy-use growth fluctuates sharply, including major negative years (2009, 2013, 2016). Energy efficiency declines notably over the period—from about 400 to about 200—indicating a long-term deterioration in energy productivity despite robust industrial expansion (Figure 3).

FIGURE 3

GDP AND ENERGY-USE GROWTH IN THE MANUFACTURING SECTOR.

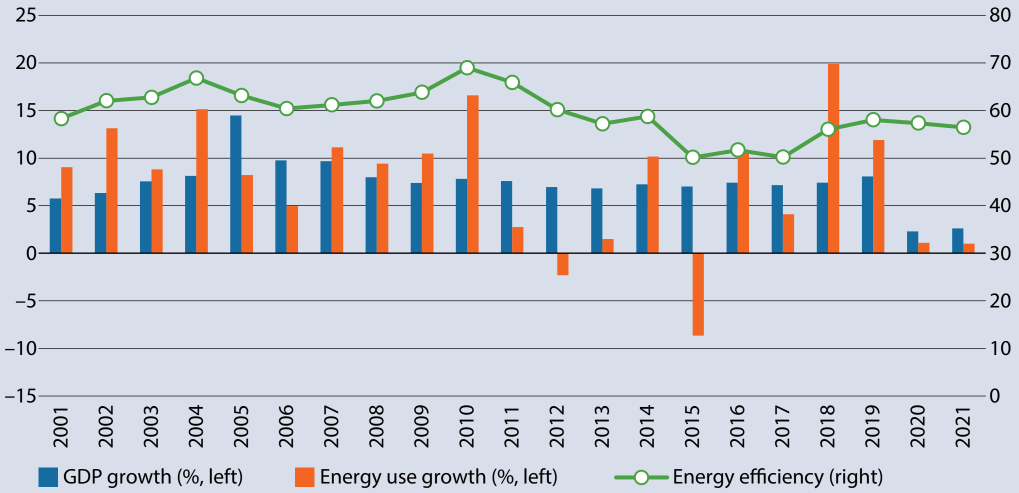


Services Sector

The services sector's GDP maintains solid, positive growth, usually 6–10%. Energy use trends are uneven, with spikes (2010, 2018) and drops (2016, 2020). Energy efficiency is fairly stable around 25–30, with only a mild decline after 2015, suggesting more consistent energy productivity relative to other sectors (Figure 4).

FIGURE 4

GDP AND ENERGY-USE GROWTH IN THE SERVICES SECTOR.

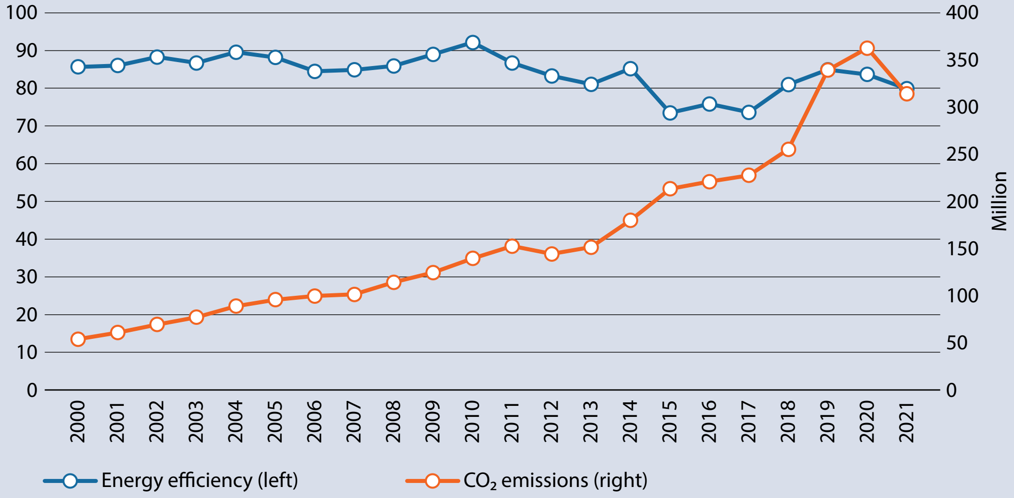


Energy Efficiency and CO_2 Emissions

Despite a substantial increase in CO2 emissions, from approximately 54 million tons to 314 million tons, there has been a notable decline in EE, from 86 to 80. This indicates a general improvement in efficiency, despite the increase in emissions (Figure 5).

FIGURE 5

ENERGY EFFICIENCY AND CO2 EMISSIONS.

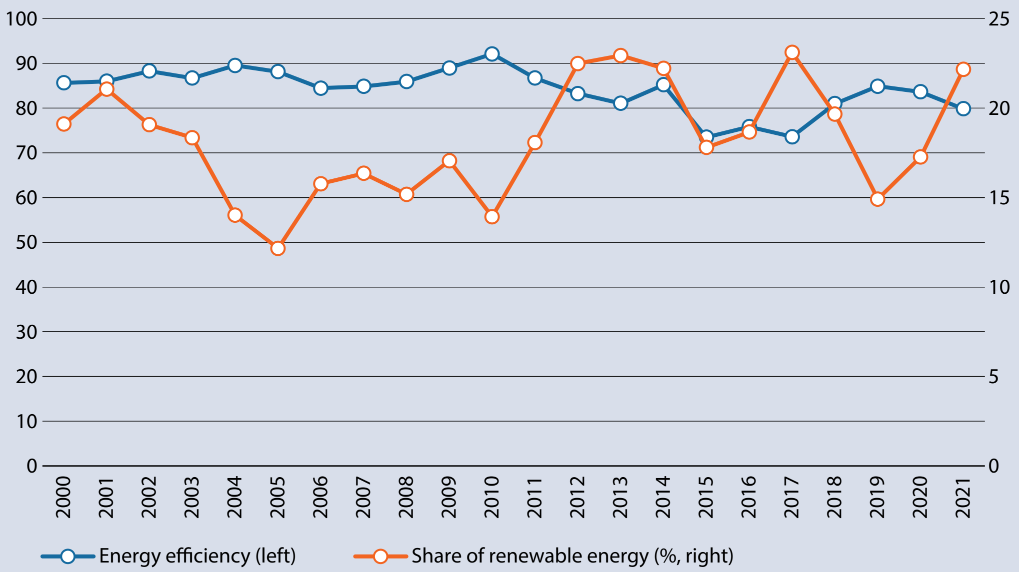


Energy Efficiency and Share of Renewable Energy

As the share of renewable energy increased from 19.1 to 22.2, EE decreased from 86 to 80, indicating an improvement in efficiency associated with the expansion of renewable energy (Figure 6).

FIGURE 6

ENERGY EFFICIENCY AND SHARE OF RENEWABLE ENERGY.

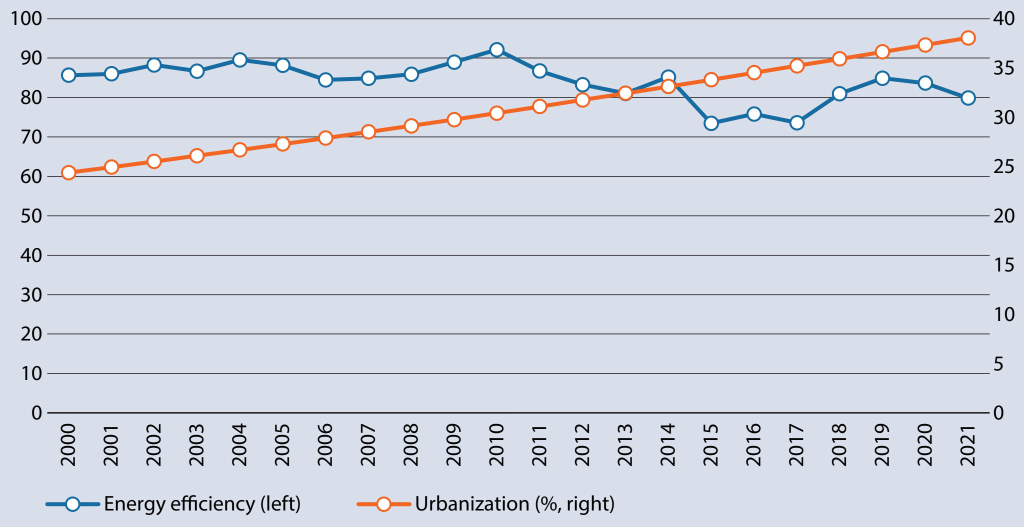


Energy Efficiency and Urbanization

While the urbanization rate increased steadily from 24.4% to 38.1%, EE declined from 85.6% to 79.9%, indicating that efficiency improvements were accompanied by urbanization (Figure 7).

FIGURE 7

ENERGY EFFICIENCY AND URBANIZATION.

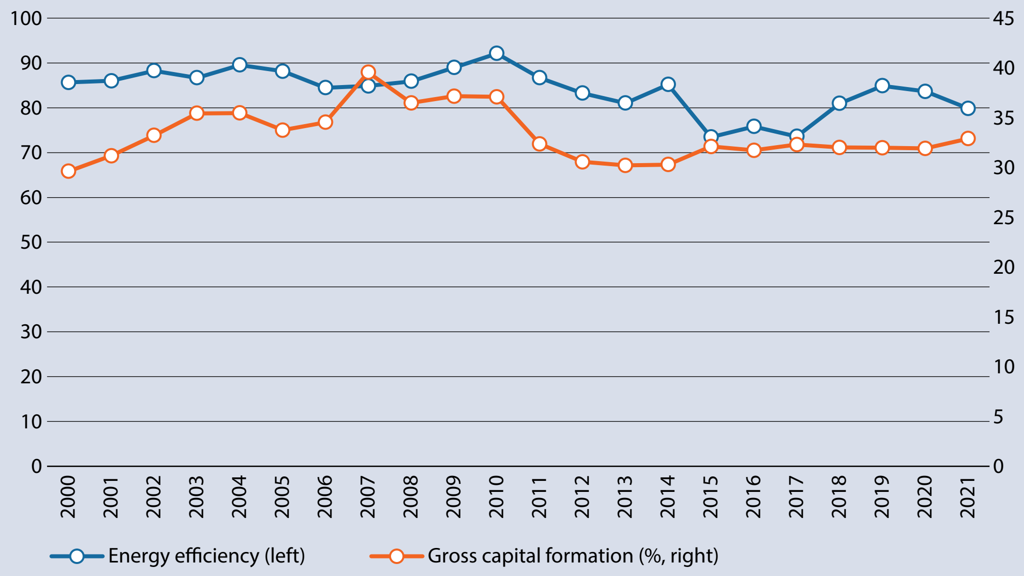


Energy Efficiency and Gross Capital Formation

While GF increased from 29.6% to 32.9%, EE decreased from 86% to 80%, indicating that investment expansion and efficiency improvement occurred simultaneously.

FIGURE 8

ENERGY EFFICIENCY AND GROSS CAPITAL FORMATION.



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APO PRODUCTIVITY OUTLOOK 2026

Energy Efficiency, Productivity Impacts, and Composite Indicator Development