South East European Journal
of Economics and Business
ISSN 2233-1999

Volume 22 (1) 2027, 1-20
DOI: 10.2478/jeb-2027-0001

THE WESTERN BALKANS ON THE PATH TO EU ENERGY INTEGRATION: A TOTAL FACTOR ENERGY EFFICIENCY AND CONVERGENCE ANALYSIS

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Abstract

This paper presents a comprehensive assessment of total factor energy efficiency (TFEE) in Western Balkan (WB) countries compared to the European Union (EU) from 2005 to 2019. Using a slacks-based data envelopment analysis model with undesirable outputs and window analysis, we evaluate how efficiently countries transform capital, labour, and energy into economic output while accounting for carbon dioxide (CO_2) emissions. The results reveal substantial heterogeneity in TFEE levels, with persistent inefficiencies in several WB countries and limited convergence towards EU benchmarks. While beta convergence is confirmed, the absence of sustained sigma convergence after 2010 indicates persistent disparities in efficiency levels. Slack analysis highlights significant structural inefficiencies, particularly in labour productivity, energy use, and emissions intensity. These findings underline the need for targeted energy and industrial policies to support productivity growth and sustainable energy transitions in the Western Balkans.

Keywords: total factor energy efficiency, Western Balkans, window analysis, convergence analysis.

JEL: Q40, Q43, Q56, C61, D24, O52.

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1. Introduction

Energy production and consumption have a significant impact on economic growth, environmental quality, and long-term development. As energy demand rises, energy efficiency has become a central policy objective, particularly in the European Union. EU climate and energy policies increasingly aim to reduce energy use and greenhouse gas emissions without hindering economic growth. Improving energy efficiency also supports global efforts to achieve the United Nations Sustainable Development Goals (SDGs) by reducing emissions and enhancing energy security.

Despite this policy focus, progress remains uneven across Europe, especially between EU member states and neighbouring economies outside the Union. Western Balkan countries [1] face specific structural constraints that hinder improvements in energy performance. Their energy systems remain heavily dependent on fossil fuels, ageing infrastructure, and energy-intensive production structures, while productivity levels are relatively low (Damiani & Uvalić, 2018; Energy Community Secretariat, 2021; Uvalić & Bartlett, 2022). Consequently, economic growth in the region is often linked to high energy consumption and elevated CO_2 emissions, reflecting deep structural weaknesses and delayed industrial modernisation (Damiani & Uvalić, 2018; Energy Community Secretariat, 2021). Beyond structural factors, improvements in energy efficiency in the Western Balkans are closely linked to the EU accession process. Candidate and potential candidate countries are required to align with EU objectives for reducing energy consumption, lowering greenhouse gas emissions, and increasing the share of renewable energy sources (European Parliament and Council, 2021). The pace of convergence towards EU standards therefore represents not only an economic challenge but also a key determinant of accession conditions and policy commitments.

Assessing energy efficiency in such heterogeneous economies requires more than traditional single-factor indicators, such as energy intensity, which relate energy use only to economic output. These measures ignore the combined role of capital and labour and provide a limited view of productive performance. To address these limitations, total factor energy efficiency (TFEE) evaluates how effectively countries transform multiple inputs – energy, labour, and capital – into economic output. When environmental pressures are considered, TFEE can be extended to account for undesirable outputs, such as CO_2 emissions, offering a more comprehensive assessment of sustainable energy performance.

While TFEE has been widely applied in studies of developed and large emerging economies, empirical evidence for Western Balkan countries remains limited. In particular, little is known about the dynamic evolution of energy efficiency in the region or its convergence towards EU benchmarks. This methodological and empirical gap motivates the present analysis. This study contributes to the literature by (i) providing a comprehensive TFEE assessment for Western Balkan countries within a unified EU framework, (ii) integrating undesirable outputs and dynamic window analysis to capture efficiency changes over time, and (iii) examining both efficiency levels and convergence patterns with EU member states.

The paper is organised as follows. After introducing the research context and motivation, the literature review summarises key insights on energy efficiency and convergence. The methodology section presents the data and methods used to estimate TFEE and analyse convergence. The results and discussion report TFEE estimates and convergence patterns, followed by concluding remarks and policy implications.

2. Literature review

Energy efficiency has long been recognised as a central challenge for national and supranational energy policies (Ang, 2006; Patterson, 1996). While the concept is widely used, its interpretation varies across disciplines. In macro-level analyses, energy efficiency is often approximated by the energy-to-GDP ratio, an inverse economic–thermodynamic indicator (Patterson, 1996). However, this measure provides an oversimplified view, as it ignores the role of other production inputs and structural differences across economies.

To overcome these limitations, production theory offers a more comprehensive framework for assessing energy efficiency. Filippini and Hunt (2015) argue that energy demand reflects the demand for energy services, such as heating or lighting, and propose an econometric frontier approach in which energy efficiency is measured as the gap between observed and optimal energy use. Nevertheless, approaches based on a single input remain restrictive. A more comprehensive perspective is provided by total factor frameworks that jointly consider energy, labour, and capital as production inputs.

In this context, Hu and Wang (2006) introduced the concept of Total Factor Energy Efficiency (TFEE), which evaluates how efficiently multiple inputs are transformed into economic output. Since then, TFEE has been widely applied in empirical studies at national, regional, and sectoral levels. Most studies adopt Data Envelopment Analysis (DEA), typically incorporating labour, capital, and energy as inputs, GDP as a desirable output, and environmental pollutants, such as CO_2 emissions, as undesirable outputs.

TFEE has been applied across various groups of countries and regions, demonstrating its flexibility in capturing cross-country differences in energy performance. Sueyoshi and Goto (2013) applied a DEA–Malmquist framework to assess environmental performance in the electric power industry of industrial countries, showing that technological innovation in electricity generation and CO_2 reduction is subject to time lags and that nuclear, hydro, and renewable energy sources play an important role in improving environmental performance. Camioto, Moralles, et al. (2016) examined total-factor energy efficiency in in the Group of Seven (G7) and BRICS (Brazil, Russia, India, China, and South Africa) economies using an SBM-DEA model with window analysis and found substantial differences between the two groups: G7 countries generally achieved very high efficiency levels, while BRICS countries displayed wider variation, with technological innovation being particularly relevant for efficiency improvements. Studies focusing on Africa also confirm the usefulness of non-radial DEA approaches with undesirable outputs. Ohene-Asare and Turkson (2019) found significant differences in energy efficiency levels and sources of inefficiency among ECOWAS countries, emphasising the need for country-specific policies, while Amowine et al. (2019) showed that energy efficiency in selected African countries was generally low and that improvements over time were limited. Similarly, Wang et al. (2019) found that developed countries achieved a more balanced relationship between GDP growth and CO_2 emissions, whereas large developing economies such as China and India improved energy intensity but continued to record high energy consumption and emissions.

Within the European context, TFEE analyses have addressed energy efficiency trends (Vlahinić-Dizdarević & Šegota, 2012) and sectoral performance (Borozan, 2018), as well as environmental impacts associated with energy use (Šegota et al., 2017). However, evidence for the Western Balkans remains limited, as existing analyses largely rely on traditional energy consumption-to-GDP indicators.

A growing strand of the literature emphasises that energy efficiency assessment should explicitly account for environmental externalities. Several studies argue that evaluating energy efficiency without considering undesirable outputs, such as CO_2 emissions, may lead to biased and incomplete efficiency estimates (Mandal, 2010; Watanabe & Tanaka, 2007; Wu et al., 2012). To address this issue, extensions of the traditional production framework have been proposed to jointly model desirable and undesirable outputs.

One influential approach is based on the directional distance function, which allows for the simultaneous expansion of desirable outputs and contraction of undesirable outputs (Ball et al., 2004; Chung et al., 1997). Building on this framework, subsequent studies have developed non-radial DEA models that capture inefficiencies more comprehensively by accounting for input excesses and output shortfalls. In particular, slacks-based measure (SBM) models have been widely applied in energy and environmental efficiency studies, as they do not impose proportional input–output adjustments and allow inefficiencies to be decomposed across different inputs and outputs (Alfredsson et al., 2016; Cooper et al., 2007; Halkos & Tzeremes, 2009, 2013; Lee et al., 2017; Lozano et al., 2013; Tone, 2001).

The interpretation of slack values has also received attention in the literature. Rather than representing fixed policy targets, slacks are commonly viewed as indicators of relative inefficiency, highlighting the inputs or outputs that contribute most to inefficiency when countries or regions are compared (Camioto, Rebelatto, & Rocha, 2016; Jorda et al., 2012; Šegota et al., 2017). This perspective supports the use of SBM-based approaches as diagnostic tools for identifying efficiency weaknesses rather than prescribing exact adjustment levels.

Energy efficiency convergence has attracted growing attention in empirical research, particularly in the context of economic integration and environmental policy alignment. A pioneering contribution was provided by Markandya et al. (2006), who analysed energy intensity in 12 Eastern European transition economies in relation to EU15 countries. Their results confirmed convergence towards EU energy intensity levels, while also showing that total energy demand may continue to increase despite reductions in energy intensity. This distinction is important because it suggests that convergence in relative efficiency indicators does not necessarily imply convergence in absolute energy consumption or environmental pressure. For the Western Balkans, the analysis of convergence towards EU benchmarks is especially relevant, as progress in reducing energy consumption, lowering CO_2 emissions, and improving energy efficiency is closely linked to EU accession-related policy commitments.

Empirical studies provide mixed evidence on energy efficiency convergence across countries and regions. Research at the global and OECD levels generally finds signs of convergence in energy efficiency or energy intensity, although results vary depending on the methodology and sample considered (Herrerias, 2012; Meng et al., 2013; Stern, 2012). More recent studies extend the convergence framework to TFEE, often using subnational data and focusing on large economies, such as China, where significant regional heterogeneity and conditional convergence patterns have been identified (Cheng et al., 2020; Zhang et al., 2017).

Evidence on energy efficiency convergence in transition economies, and particularly in the Western Balkans, remains limited. Existing studies on transition economies have mainly examined energy intensity rather than comprehensive total-factor efficiency measures, as in Markandya et al. (2006), while studies related to the Western Balkans have primarily focused on regional energy integration, structural constraints, or broader income convergence rather than energy efficiency convergence (Damiani & Uvalić, 2018; Šiljak, 2018; Uvalić, 2014; Uvalić & Bartlett, 2022). Although TFEE and DEA-based approaches have increasingly been applied to assess energy performance in the region, evidence on the convergence of Western Balkan TFEE towards EU benchmarks remains limited. The present study extends this literature by combining TFEE measurement based on SBM-DEA with undesirable outputs and window analysis, and an explicit assessment of both sigma and beta convergence towards EU efficiency patterns.

3. Methodology and data

This section presents the methodological framework and data used to assess energy efficiency across European Union and Western Balkan countries. The analysis is based on a total factor energy efficiency (TFEE) approach, which allows for a comprehensive evaluation of energy performance by jointly considering multiple production inputs and environmental outcomes. TFEE incorporates energy, labour, and capital as inputs, gross domestic product (GDP) as a desirable output, and carbon dioxide (CO_2) emissions as an undesirable output, thereby capturing both economic efficiency and environmental pressures.

3.1. Variables and data

The analysis relies on macroeconomic panel data for a sample of European Union (EU) and Western Balkan (WB) countries over the period 2005–2019. The WB sample comprises Albania, Bosnia and Herzegovina, North Macedonia, Montenegro,

and Serbia, which, together with Kosovo, form the Western Balkans as defined by the European Parliament (2023); Kosovo is excluded owing to the lack of comparable data. The EU sample comprises the 28 countries that were member states during the study period, including the United Kingdom, which left the EU in 2020. The findings should therefore be interpreted as describing the pre-2020 period and do not capture subsequent developments, including the COVID-19 pandemic, the European energy crisis, and related changes in energy prices, consumption patterns, policy responses, and investment dynamics. Data used in the TFEE and convergence analyses are summarised in Table 1, which reports the definitions and data sources of the variables used in the empirical analysis.

When selecting inputs and outputs for TFEE estimation, the standard DEA rule of thumb was applied, according to which the number of decision-making units should be at least three times the total number of inputs and outputs. With 33 countries and five variables in total, this condition is satisfied ($33 > 3 \times 5$; Cooper et al., 2000).

Table 1. Definition and data sources of variables used in the analysis

Variable	Definition	Data source
Inputs – TFEE model		
Capital	Public and private capital (billions of constant 2017 international dollars)	IMF Investment and Capital Stock Dataset (International Monetary Fund, 2021)
Employment	Number of employed persons (millions), including all individuals engaged in productive economic activities for wages or profits during a short reference period	ILOSTAT (International Labour Organization, n.d.)
Energy	Final energy consumption (petajoules, PJ), representing total energy consumed by end users such as households, industry, and agriculture	International Energy Agency (International Energy Agency, n.d.); UK: Department for Business, Energy & Industrial Strategy (Department for Business, Energy & Industrial Strategy, 2021)
Outputs – TFEE model		
GDP	Gross domestic product (billions of constant 2017 international dollars)	IMF World Economic Outlook Database (International Monetary Fund, n.d.)
CO_2	Carbon dioxide emissions (millions of metric tons)	EDGAR, European Commission Joint Research Centre (Crippa et al., 2020)
Variables – convergence models		
TFEE	Total factor energy efficiency score (0–1), estimated using the SBM-DEA model with undesirable outputs and window analysis	Authors' calculation
GDP per capita	GDP per capita, constant 2017 international dollars	International Monetary Fund (n.d.); population from Penn World Table (Feenstra et al., 2021)
FDI	Foreign direct investment, net inflows (% of GDP)	World Bank World Development Indicators (World Bank, n.d.)
Year effects	Year dummy variables included in the conditional beta-convergence models	Authors' specification

Table 2. Correlation matrix of variables used in the TFEE analysis

	Employment	Capital	Energy	GDP	CO_2 emissions
Employment	1.0000	0.9644	0.9828	0.9856	0.9714
Capital	0.9644	1.0000	0.9831	0.9922	0.9415
Energy	0.9828	0.9831	1.0000	0.9909	0.9774
GDP	0.9856	0.9922	0.9909	1.0000	0.9618
CO_2 emissions	0.9714	0.9415	0.9774	0.9618	1.0000

Source: Authors' calculation.

The correlation matrix presented in Table 2 shows strong positive correlations among all selected inputs and outputs, with all pairwise coefficients exceeding 0.94, supporting the isotonicity assumption underlying the DEA framework. Similar strong positive correlations have been reported in previous TFEE studies (Borozan & Borozan, 2018; Chen & Yang, 2020; Ozkara & Atak, 2015; Vlahinić-Lenz et al., 2018).

3.2. SBM-DEA methodology

Methods for measuring energy efficiency are commonly classified into parametric and non-parametric approaches. While parametric techniques, such as Stochastic Frontier Analysis (SFA), require the specification of a functional form for the production process, non-parametric approaches rely directly on observed input–output relationships. In this study, Data Envelopment Analysis (DEA) is employed due to its flexibility and suitability in situations where the contribution of individual inputs to output production is not explicitly defined. DEA is a non-parametric method based on linear programming and has been widely applied in energy and environmental efficiency studies, particularly in cross-country settings.

Countries are treated as decision-making units (DMUs) with comparable production structures, using capital, labour, and energy as common inputs. To account for environmental performance, CO_2 emissions are explicitly modelled as an undesirable output. Previous research has shown that ignoring undesirable outputs may lead to biased efficiency estimates, especially in energy-intensive economies. Consequently, this study adopts a slacks-based measure (SBM) DEA model, which captures input excesses and output shortfalls directly, without imposing proportional input or output adjustments. Unlike radial models, the SBM framework allows inefficiencies to be identified through slack values, indicating the extent to which specific inputs or outputs contribute to inefficiency. These slack values should be interpreted as indicators of relative inefficiency rather than fixed policy targets.

Following Tone (2001, 2003), suppose that there are n decision-making units (DMUs), representing the EU and Western Balkan countries, each characterised by m inputs, s_1 desirable outputs, and s_2 undesirable outputs. These are represented by $x \in R^m$, $y^g \in R^{s1}$, and $y^b \in R^{s2}$, respectively. The corresponding data matrices are defined as:

$$X = [x_1, \dots, x_n] \in R^{m \times n},\ Y^g = \left[y_1^g, \dots, y_n^g\right] \in R^{s_1 \times n},$$

$$Y^b = [y_1^b, \dots, y_n^b] \in R^{s_2 \times n},$$

with $X > 0$, $Y^g > 0$, and $Y^b > 0$. Under constant returns to scale (CRS), the production possibility set is defined as:

$$P = \{(x, y^g, y^b), |, x, \geq X\lambda\ y^g \leq Y^g\lambda\ y^b \geq Y^b\lambda\ \lambda \geq 0\},$$

where λ denotes the intensity vector.
For, $DMU_0 = \left(x_0, y_0^g, y_0^b\right)$ the SBM model with undesirable outputs is specified as follows (Tone, 2003):

$$\rho^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{r0}^b}\right)}$$

subject to

$$x_0 = X\lambda + s^-$$
$$y_0^g = Y^g\lambda - s^g$$
$$y_0^b = Y^b\lambda + s^b$$
$$s^- \geq 0,\ s^g \geq 0,\ s^b \geq 0,\ \lambda \geq 0.$$

The vectors s^-, s^g, and s^b denote input excesses, desirable-output shortfalls, and undesirable-output excesses, respectively. The efficiency score satisfies $0 < p^* \leq 1$, with $p^* = 1$ indicating SBM efficiency.

The model above is expressed under CRS. Since the empirical analysis is conducted under variable returns to scale (VRS), the additional convexity constraint

$$1^T\lambda = 1$$

is imposed (Banker et al., 1984). The VRS specification allows efficiency to be evaluated while accounting for differences in the scale of operation across countries.

The choice of the returns-to-scale assumption is particularly relevant in the present cross-country setting. Given substantial differences in country size, economic structure, production capacity, and level of development across the EU and Western Balkan countries, VRS is considered more appropriate than CRS. In DEA, efficiency scores obtained under CRS are generally less than or equal to the corresponding VRS scores, since the CRS specification incorporates both pure technical and scale inefficiency, whereas VRS allows these effects to be separated (Banker et al., 1984). Accordingly, the reported TFEE scores should be interpreted as relative efficiency estimates conditional on the VRS specification. Alternative returns-to-scale assumptions may therefore affect absolute efficiency scores and country rankings, and comparisons should be interpreted with this modelling sensitivity in mind.

To capture changes in energy efficiency over time, a DEA window analysis is applied. This dynamic approach treats each country observed in different time periods as a distinct DMU, enabling the assessment of efficiency evolution both across countries and over time. Following Asmild et al. (2004), who recommend a window sufficiently narrow to limit potentially inappropriate comparisons over time while remaining sufficiently wide to ensure an adequate number of observations, a four-year window width is adopted for the DEA assessment. Accordingly, the first window covers 2005–2008, after which the window is shifted forward by one year until the final 2016–2019 window, resulting in 12 overlapping windows and 1,584 country-year appearances across all windows (33 countries × 4 years × 12 windows). Since a given country-year may appear in more than one overlapping window, the final annual TFEE score for each country is calculated as the arithmetic mean of its efficiency scores obtained across all windows in which that country-year appears.

3.3. Convergence analysis

The convergence analysis examines whether Western Balkan countries are converging towards EU energy-efficiency levels as measured by TFEE, using both sigma and beta convergence. The analysis assesses whether TFEE disparities have narrowed over time and whether initially less efficient countries experience faster improvement.

3.3.1. Sigma convergence

Sigma convergence refers to a reduction in the cross-country dispersion of TFEE over time (Sala-i-Martin, 1996). In this study, it is assessed using the coefficient of variation (CV_{TFEE}):

$$CV_{TFEE,t} = \frac{\sigma_{TFEE,t}}{\overline{TFEE_t}}$$

where $\sigma_{TFEE,t}$ denotes the cross-country standard deviation of TFEE and $\overline{TFEE_t}$ denotes the corresponding mean TFEE in year t. A decline in $CV_{TFEE,t}$ indicates narrowing TFEE disparities and hence sigma convergence, while an increase indicates divergence.

3.3.2. Beta convergence

Beta convergence refers to a catch-up process in which countries with lower initial TFEE levels experience faster subsequent TFEE growth (Barro & Sala-i-Martin, 1992; Borić, 2018; Sala-i-Martin, 1996). Following Han et al. (2018), the standard beta-convergence model can be written as:

$$\ln\left(\frac{TFEE_{it}}{TFEE_{i,t-1}}\right) = C + \beta\ln\left(TFEE_{i,t-1}\right) + \varepsilon_{it}$$

where $TFEE_{it}$ denotes total factor energy efficiency in country i in period t, C is a constant, and ε_{it} is the error term. The dependent variable represents TFEE growth, while the lagged TFEE term captures the initial efficiency level. A negative and statistically significant β indicates absolute beta convergence, meaning that countries with lower initial TFEE levels tend to experience faster subsequent TFEE growth.

Conditional beta convergence allows for differences in structural and macroeconomic conditions by extending the model with additional control variables:

$$\ln\left(\frac{TFEE_{it}}{TFEE_{i,t-1}}\right) = C + \beta\ln\left(TFEE_{i,t-1}\right) + \delta X_{it} + \gamma_t + \varepsilon_{it}$$

where X_{it} denotes the vector of control variables and δ the corresponding vector of coefficients, Y_t captures time effects, and ε_{it} is the error term. The conditional specification includes GDP per capita, FDI, and time effects. The dependent variable represents the growth rate of TFEE between periods $t-1$ and t, while the lagged TFEE term captures the initial efficiency level. A negative and statistically significant β indicates that the catch-up relationship remains present after accounting for these factors.

3.3.3. Speed of convergence and half-life

To complement the beta-convergence analysis, the implied speed of convergence is calculated using the standard transformation (Barro & Sala-i-Martin, 1992) from the estimated beta coefficient as:

$$\lambda = -ln(1+\beta)$$

where λ denotes the implied annual speed of convergence and β the estimated coefficient on $ln(TFEE_{i,t-1})$. Following the standard approach in the convergence literature, the corresponding half-life (HL) is calculated as:

$$HL = ln(2)/\lambda$$

where HL denotes the model-implied time required for half of the initial gap to be eliminated.

These measures are calculated for both the absolute and conditional beta-convergence specifications.

4. Total factor energy efficiency

This section presents the results of the TFEE analysis, focusing on efficiency trends across countries, slack-based diagnostics, and a comparison with traditional energy efficiency indicators.

4.1. TFEE trends

Table 3 reports TFEE scores obtained using DEA window analysis for selected years and the 2005–2019 average. Overall, the results reveal pronounced cross-country heterogeneity and distinct regional patterns. Western and Northern EU countries generally exhibit higher TFEE levels, while Western Balkan countries display highly uneven performance: Montenegro, Serbia, and Albania record average TFEE scores above the EU average (0.73), whereas Bosnia and Herzegovina and North Macedonia remain well below it.

Temporal dynamics suggest that many countries experienced moderate improvements in TFEE prior to the global financial crisis, followed by stagnation or declines in the subsequent years. Some smaller and transition economies, such as Latvia, Estonia, and Lithuania, display considerable volatility, reflecting structural adjustments and sensitivity to external shocks.

TFEE declined between 2005 and 2019 in 18 of the 33 countries, and pronounced heterogeneity remains across the sample, shaping divergent paths of economic performance and sustainability potential. Average TFEE scores place Malta, Montenegro, Italy, France, the United Kingdom, Luxembourg, Germany, Ireland, Poland, and Spain among the most efficient economies, while Portugal, Croatia, Slovenia, Hungary, Bulgaria, Bosnia and Herzegovina, Finland, Cyprus, Slovakia, and the Czech Republic rank at the lower end of the efficiency distribution. These rankings are relatively stable for the best-performing economies, whereas several countries, such as Greece, Bulgaria, Austria, and Latvia, move markedly down the distribution over the period.

Table 3. TFEE by country, selected years and 2005–2019 average

DMUs	2005	2007	2010	2013	2017	2019	Average
WB countries							
Albania	0.54	0.93	0.86	0.86	0.52	1.00	0.79
Bosnia and Herzegovina	0.66	0.65	0.53	0.48	0.41	0.40	0.51
North Macedonia	0.56	0.61	0.77	0.64	0.57	0.61	0.63
Montenegro	1.00	1.00	0.94	1.00	1.00	0.84	0.99
Serbia	0.55	1.00	0.77	0.87	0.70	1.00	0.80
EU countries							
Austria	0.75	0.85	0.80	0.71	0.55	0.53	0.71
Belgium	0.67	0.72	0.71	0.72	0.56	0.54	0.68
Bulgaria	0.83	0.65	0.57	0.45	0.39	0.40	0.52
Cyprus	0.51	0.52	0.49	0.48	0.43	0.45	0.48
Czech Republic	0.46	0.53	0.53	0.44	0.39	0.39	0.46
Germany	0.88	1.00	0.92	0.94	0.97	1.00	0.96
Denmark	0.80	0.82	0.79	0.71	0.62	0.63	0.72
Spain	0.85	0.89	0.91	0.89	0.91	1.00	0.91
Estonia	0.87	1.00	0.70	0.64	0.59	1.00	0.75
Finland	0.57	0.60	0.55	0.47	0.42	0.41	0.50
France	0.93	1.00	0.96	0.94	0.96	1.00	0.97
Greece	0.78	1.00	0.74	0.54	0.44	0.45	0.64
Croatia	0.62	0.67	0.59	0.52	0.45	0.45	0.54
Hungary	0.57	0.60	0.57	0.51	0.43	0.45	0.52
Ireland	1.00	1.00	0.98	0.82	0.97	1.00	0.95
Italy	0.95	1.00	0.97	0.98	0.97	1.00	0.98
Lithuania	0.91	1.00	0.76	0.78	0.66	1.00	0.81
Luxembourg	0.85	1.00	0.98	0.92	0.99	1.00	0.97
Latvia	0.77	1.00	0.55	0.58	0.53	0.52	0.65
Malta	1.00	1.00	0.91	1.00	0.98	1.00	0.99
Netherlands	0.69	0.75	0.72	0.68	0.65	0.66	0.70
Poland	0.80	1.00	0.95	0.91	0.89	1.00	0.94
Portugal	0.64	0.71	0.75	0.58	0.47	0.48	0.60
Romania	0.63	0.88	0.68	0.62	0.57	0.61	0.67
Slovakia	0.40	0.49	0.53	0.48	0.43	0.44	0.47
Slovenia	0.52	0.59	0.57	0.51	0.47	0.50	0.53
Sweden	0.88	1.00	0.90	0.83	0.75	0.64	0.86
United Kingdom	0.92	1.00	0.93	0.92	1.00	1.00	0.97

Note. Selected years cover the start of the period, the pre-crisis peak (2007), the post-crisis turning point (2010), 2013, 2017 and the end of the period; the average refers to all years 2005–2019. Annual scores for all years are available from the authors on request.

Source: Authors' calculation.

A closer examination of Western Balkan countries reveals marked differences in the dynamics of total factor energy efficiency over time. Montenegro records consistently high TFEE levels for most of the observed period; however, these results should be interpreted with caution, given the country's limited industrial base and economic structure dominated by low energy-intensive activities. Serbia follows an upward but uneven path. Its TFEE rises from 0.55 in 2005 to the efficiency frontier in 2007, falls back after the 2008 crisis (0.77 in 2010), recovers to 0.87 by 2013, declines again to 0.70 in 2017, and returns to the frontier in 2019. This pattern points to sensitivity to cyclical and structural shocks. Because TFEE is measured relative to a moving window frontier, frontier years for Serbia should be read as best relative performance within the sample rather than as absolute efficiency. Albania displays pronounced volatility, alternating between years of high efficiency and substantial inefficiency, reflecting unstable patterns of input utilisation. North Macedonia improves from a low initial TFEE level in the mid-2000s but fails to sustain this progress in subsequent years. In contrast, Bosnia and Herzegovina experiences a persistent decline in TFEE throughout the period, indicating deep-rooted and unresolved structural inefficiencies.

The spatial distribution of average TFEE across Europe is depicted in Figure 1. A clear regional pattern emerges, with Western and Northern EU countries exhibiting higher efficiency levels, while many Southern and Eastern EU countries, together with Bosnia and Herzegovina and North Macedonia, record lower TFEE values. This spatial clustering highlights persistent structural differences in production efficiency and energy use, reinforcing the relevance of a convergence analysis between the Western Balkans and EU member states.

Figure 1. Average TFEE by country



Country shading represents average TFEE, with the supplied legend ranging from 0.46 to 0.99. Western and Northern EU countries generally have higher TFEE, while many Southern and Eastern EU countries, Bosnia and Herzegovina, and North Macedonia have lower values. Table 3 provides the country averages. The map uses a continuous colour gradient and does not identify countries with text labels.

Source: Authors' creation.

4.2. Slack analysis

The slacks-based measure (SBM) allows efficiency to be decomposed into input excesses and output shortfalls, offering diagnostic insights into the sources of inefficiency. Following the same window-based procedure used to estimate TFEE, absolute slack values were obtained for each Western Balkan country and year and averaged over the 2005–2019 period. The average slack values were then expressed relative to the corresponding average observed input or undesirable output, with the resulting percentages reported in the final column of Table 4 as indicators of country-specific relative inefficiency rather than fixed adjustment targets.

Table 4. Average slack values for Western Balkan countries, 2005–2019

DMUs	Slack	Average slack	Relative slack (%)
Albania	Number of employed persons (millions)	0.40	36%
	Capital (billions of dollars)	9.09	12%
	Energy (PJ)	**11.46**	**14%**
	CO2 (millions of metric tons)	0.14	4%
Bosnia and Herzegovina	Number of employed persons (millions)	0.71	68%
	Capital (billions of dollars)	3.99	6%
	Energy (PJ)	**49.27**	**36%**
	CO2 (millions of metric tons)	9.27	60%
North Macedonia	Number of employed persons (millions)	0.40	60%
	Capital (billions of dollars)	1.28	3%
	Energy (PJ)	**15.47**	**20%**
	CO2 (millions of metric tons)	3.37	46%
Montenegro	Number of employed persons (millions)	0.01	5%
	Capital (billions of dollars)	0.08	0%
	Energy (PJ)	**0.11**	**0%**
	CO2 (millions of metric tons)	0.03	1%
Serbia	Number of employed persons (millions)	0.63	23%
	Capital (billions of dollars)	-	0%
	Energy (PJ)	**54.98**	**14%**
	CO2 (millions of metric tons)	12.20	26%

Note. Relative slack is the average slack expressed as a percentage of the country's average observed input or undesirable output. Annual slack values are available from the authors on request. Capital is measured in billions of constant 2017 international dollars.

Source: Authors' calculation.

The slack-based analysis reveals substantial heterogeneity in the sources of relative inefficiency across Western Balkan countries over the 2005–2019 period (Table 4). Labour slacks are particularly pronounced in Bosnia and Herzegovina, North Macedonia, Albania, and Serbia, while capital-related slacks are generally smaller, with Albania and Bosnia and Herzegovina showing the largest values. Energy inefficiency is most pronounced in Bosnia and Herzegovina (36%) and North Macedonia (20%), whereas Montenegro records negligible energy slack.

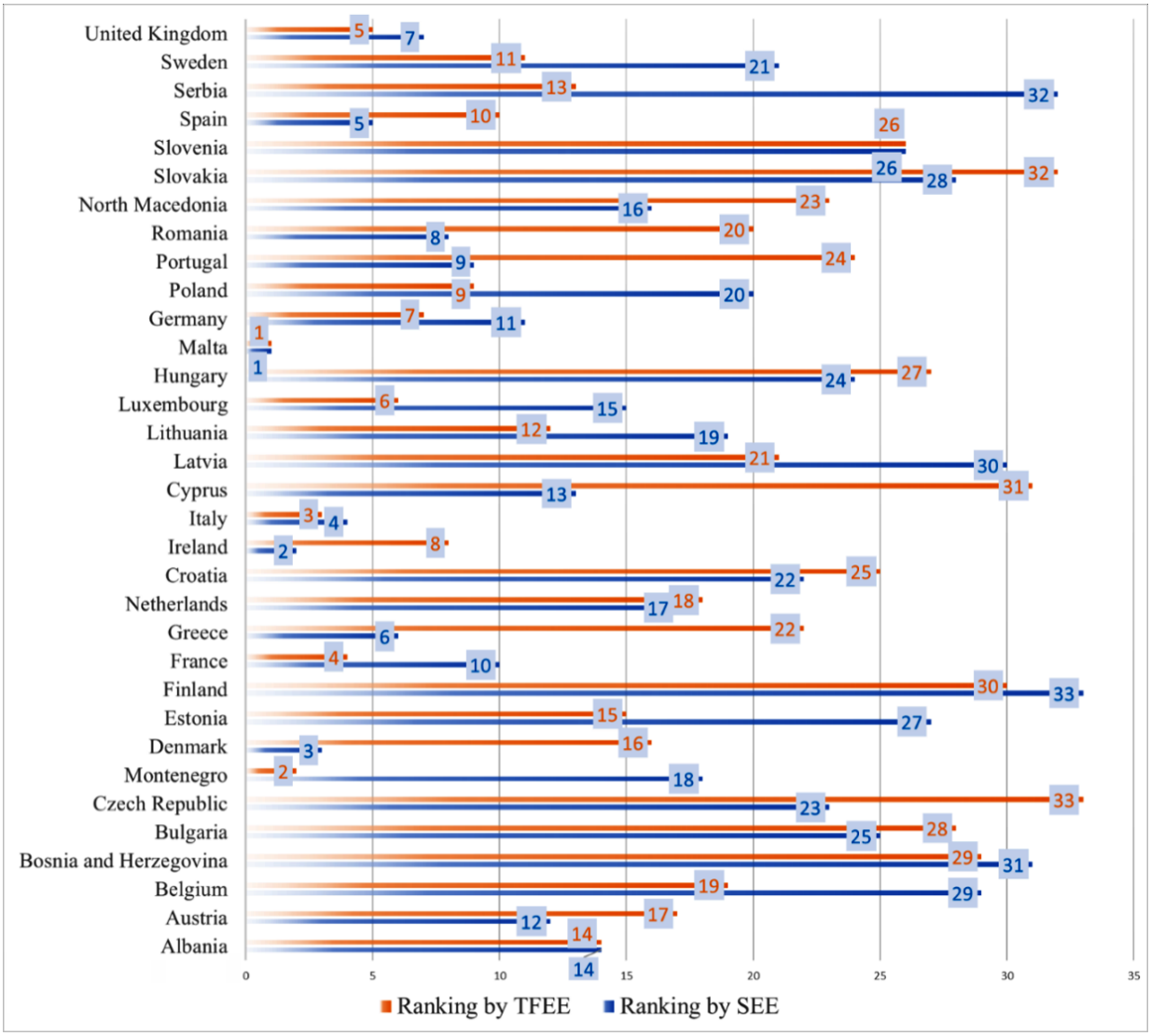
A similar cross-country pattern is observed for the undesirable output. CO_2 slacks are highest in Bosnia and Herzegovina (60%) and North Macedonia (46%), followed by Serbia (26%), while

substantially lower values are observed for Albania and Montenegro. Overall, the results indicate that the magnitude and sources of relative inefficiency differ considerably across countries, with labour utilisation, energy use, and CO_2 emissions representing the main areas of potential improvement. These patterns are consistent with broader structural challenges identified in previous research on Western Balkan economies (Silajdžić & Mehić, 2016; Uvalić, 2014; Uvalić & Bartlett, 2022).

4.3. Comparison with traditional metrics

Modern approaches assess energy efficiency using total-factor measures, while traditional approaches rely on energy intensity and its reciprocal, simple energy efficiency (SEE). For comparison, average SEE and energy intensity values are calculated for 2005–2019. Among Western Balkan countries, energy intensity ranges from 2.74 PJ per billion dollars of GDP in Albania (SEE: 0.368) to 3.70 PJ in Serbia (SEE: 0.273).

Figure 2. Country rankings according to TFEE and SEE



Each country has two labelled rank values: the upper orange bar represents TFEE and the lower blue bar represents SEE. Smaller rank numbers indicate a higher ranking. Malta ranks first on both measures. Montenegro ranks 2nd by TFEE and 18th by SEE; Serbia ranks 13th and 32nd, respectively. Denmark ranks 16th by TFEE and 3rd by SEE. The paired rankings illustrate how total-factor and single-factor measures differ across countries.

Source: Authors' calculation.

A comparison of TFEE and SEE rankings reveals considerable differences across countries (Figure 2). While relatively similar rankings are observed for a limited number of countries, including Malta, Italy, the United Kingdom, Albania, Slovenia, the Netherlands, and Bosnia and Herzegovina, substantial rank differences occur elsewhere. Countries such as Denmark, Greece, Romania, Portugal, Cyprus, and the Czech Republic rank more favourably according to SEE than TFEE, whereas Luxembourg, Montenegro, and Serbia rank more favourably according to TFEE. These differences illustrate how single-factor and total-factor measures can provide different assessments of energy-efficiency performance, supporting the complementary use of TFEE, which accounts for multiple production inputs and environmental pressures.

5. CONVERGENCE ANALYSIS RESULTS

5.1. Sigma convergence results

Table 5 presents the sigma-convergence results, measured by the coefficient of variation of TFEE, for the EU, Western Balkan countries, and selected EU–Western Balkan country groupings over the period 2005–2019.

The results indicate a general pattern of initial convergence followed by divergence after 2010. Across most country groupings, the coefficient of variation remains broadly stable or declines until 2010 but increases thereafter. This pattern is consistent with Han et al. (2018), who report a similar reversal in energy-efficiency convergence across Belt and Road countries after the global financial crisis.

Table 5. Sigma convergence of Western Balkan states towards all or groups of EU countries

CV_{TFEE}	EU	EU_{15}	EU_{2004}-EU_{2007}-EU_{2013}	EU & WB	EU_{15} & WB	EU_{2004}-EU_{2007}-EU_{2013} & WB	EU_{2007}-EU_{2013} & WB	WB
2005	0.22	0.15	0.28	0.23	0.20	0.27	0.24	0.29
2006	0.22	0.16	0.28	0.23	0.20	0.27	0.21	0.27
2007	0.22	0.16	0.28	0.22	0.17	0.26	0.21	0.23
2008	0.22	0.14	0.28	0.22	0.17	0.27	0.24	0.25
2009	0.23	0.15	0.26	0.23	0.17	0.26	0.23	0.24
2010	0.22	0.15	0.23	0.22	0.16	0.23	0.20	0.20
2011	0.24	0.16	0.27	0.23	0.18	0.26	0.25	0.24
2012	0.25	0.18	0.28	0.26	0.20	0.29	0.31	0.29
2013	0.27	0.21	0.30	0.27	0.22	0.30	0.30	0.27
2014	0.31	0.25	0.33	0.30	0.25	0.32	0.31	0.29
2015	0.35	0.29	0.36	0.34	0.29	0.36	0.36	0.32
2016	0.34	0.30	0.34	0.33	0.29	0.33	0.33	0.31
2017	0.35	0.30	0.34	0.34	0.31	0.34	0.35	0.35
2018	0.35	0.31	0.36	0.34	0.31	0.35	0.36	0.33
2019	0.37	0.32	0.41	0.36	0.32	0.39	0.38	0.34

Note. EU_{15} = Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden and the United Kingdom; EU_{2004} = Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia and Slovenia; EU_{2007} = Bulgaria and Romania; EU_{2013} = Croatia; WB = Western Balkans.

Source: Authors' calculation.

The post-2010 divergence is particularly pronounced in the Western Balkans, where CVTFEE increased from 0.20 in 2010 to 0.34 in 2019, indicating growing heterogeneity in TFEE performance.

5.2. Beta convergence results

Table 6 presents the absolute beta-convergence results for the four country groupings considered in the study.

The F-test results confirm the overall statistical significance of all absolute beta-convergence models, with reported probabilities below 0.001 in all specifications. This indicates that the models are jointly statistically significant. Together with the negative and statistically significant β coefficients, these results support the presence of absolute beta convergence across all analysed country groupings. The effect is strongest for the Western Balkans (β = −0.56), indicating faster relative catch-up from a lower initial TFEE base than in the broader EU–WB sample.

This finding is consistent with previous evidence of energy-efficiency convergence (Han et al., 2018; Stern, 2012) and with Markandya et al. (2006), who identified convergence of energy intensity in Eastern European transition economies towards EU15 levels. However, the present analysis considers total-factor energy efficiency, including multiple inputs and CO_2 emissions. The stronger β coefficient for the Western Balkans should therefore be interpreted as faster relative catch-up rather than evidence that the region has closed the absolute efficiency gap.

Table 6. Absolute beta convergence

Independent Variable	EU & WB F(1, 428) = 52.09 Prob > F = 0.000			WB F(1, 64) = 28.13 Prob > F = 0.000		
	Coefficient	Standard Error	t-Statistic	Coefficient	Standard Error	t-Statistic
$lnTFEE_{(t\text{-}1)}$	-0.2203***	0.0305	-7.22	-0.5622***	0.1060	-5.30
Constant	-0.0825***	0.0115	-7.20	-0.1815***	0.0394	-4.61
σ_u σ_e ρ	0.0692 0.0893 0.3754			0.1579 0.1354 0.5762		
	EU15 & WB F(1, 259) = 32.10 Prob > F = 0.000			EU2004 -EU2013 & WB F(1, 233) = 46.42 Prob > F = 0.000		
	Coefficient	Standard Error	t-Statistic	Coefficient	Standard Error	t-Statistic
$lnTFEE_{(t\text{-}1)}$	-0.2358***	0.0416	-5.67	-0.3086***	0.0453	-6.81
Constant	-0.0652***	0.0121	-5.38	-0.1409***	0.0213	-6.63
σ_u σ_e ρ	0.0659 0.0902 0.3479			0.0939 0.1061 0.4388		

*** Significance at the level of 1%.

Source: Authors' calculation.

Table 7. Conditional beta convergence

Independent Variable	EU & WB F(16, 371) = 11.08 Prob > F = 0.0000		WB F(16, 47) = 3.07 Prob > F = 0.0014		EU15 & WB F(16, 214) = 6.21 Prob > F = 0.0000		EU2004 - EU2013& WB F(16, 204) = 8.49 Prob > F = 0.0000	
	Coefficient	t-stat.	Coefficient	t-stat.	Coefficient	t-stat.	Coefficient	t-stat.
lnTFEE(t-1)	-0.3273***	-8.57	-0.6623***	-4.98	-0.3882***	-7.02	-0.4596***	-8.17
lnGDPPC	0.1808***	2.87	0.1388	0.21	0.2634***	2.73	0.2372**	2.01
lnFDI	0.0073	1.45	0.0186	0.46	0.0509	0.71	0.0090	1.06
Year								
2007	0.0347*	1.73	0.1433	1.26	0.0484*	1.72	0.0475	1.47
2008	-0.0387*	-1.90	-0.0046	-0.03	-0.0304	-1.06	-0.0462	-1.38
2009	-0.0551***	-2.63	0.0583	0.43	-0.0251	-0.87	-0.0616*	-1.79
2010	-0.0555***	-2.71	0.0101	0.07	-0.0344	-1.19	-0.0792**	-2.41
2011	-0.0208	-1.04	0.0190	0.12	-0.0121	-0.43	-0.0401	-1.21
2012	-0.0817***	-3.97	0.0282	0.17	-0.0556**	-1.90	-0.0970***	-2.89
2013	-0.097***	-4.65	-0.0047	-0.03	-0.078***	-2.72	-0.1192***	-3.37
2014	-0.1106***	-5.24	-0.0839	-0.44	-0.095***	-3.29	-0.1581***	-4.33
2015	-0.1140***	-5.19	-0.0545	-0.27	-0.0825***	-2.80	-0.1737***	-4.34
2016	-0.1267***	-5.67	-0.1024	-0.45	-0.1182***	-3.99	-0.1827***	-4.31
2017	-0.1273***	-5.31	-0.1688	-0.69	-0.1231***	-3.90	-0.2037***	-4.38
2018	-0.0934***	-3.48	-0.0452	-0.17	-0.0760**	-2.11	-0.1541***	-2.98
2019	-0.0802***	-3.11	-0.0165	-0.06	-0.0885***	-2.63	-0.1207**	-2.28
Constant	-1.8926***	-2.93	-1.4653	-0.24	-2.7723***	-2.76	-2.4512**	-2.11
σu	0.1152		0.1563		0.1685		0.1736	
σe	0.0786		0.1325		0.0848		0.0912	
ρ	0.6820		0.5816		0.7977		0.7838	

*** Significance at the level of 1%; ** Significance at the level of 5%; * Significance at the level of 10%.

Source: Authors' calculation.

The conditional beta-convergence results show that the catch-up relationship remains present after the inclusion of GDP per capita, FDI, and time effects. The β coefficients remain negative and statistically significant across all model specifications, indicating that countries with lower initial TFEE levels continue to exhibit faster TFEE growth after these factors are taken into account. GDP per capita is positively and statistically significantly associated with TFEE growth in the three broader specifications, whereas its coefficient is not statistically significant in the WB-only model. In contrast, FDI is not statistically significant across the analysed specifications.

The F-test results confirm the overall statistical significance of all conditional beta-convergence models, with reported probabilities below 0.01 in all specifications. This indicates that the explanatory variables are jointly statistically significant in each model.

The year dummy variables capture common time-specific effects not accounted for by the other explanatory variables. Their coefficients are mostly negative and statistically significant in the broader EU–WB specifications, particularly after 2012, relative to the omitted reference year (2006). In the WB-only model, the year effects are not statistically significant.

The implied convergence speeds and half-life estimates are reported in Table 8. The estimated convergence speeds range from 24.9% to 82.6% in the absolute models and from 39.6% to 108.6% in the conditional models, with the highest values obtained for the Western Balkan sample. The half-life estimates show the same pattern, with shorter adjustment periods in the conditional models. For the Western Balkans, the estimated half-life decreases from 0.84 years in the absolute model to 0.64 years in the conditional model. Given the particularly high implied adjustment rates, especially the conditional WB estimate above 100%, these measures should be interpreted as model-implied indicators of relative convergence dynamics rather than as literal annual reductions in the observed TFEE gap or forecasts of how quickly observed TFEE differences will be halved.

Table 8. Speed of convergence and half-life indicators

Country grouping	Absolute β	Speed, absolute	HL, absolute (years)	Conditional β	Speed, conditional	HL, conditional (years)
EU & WB	-0.2203	24.9%	2.79	-0.3273	39.6%	1.75
WB	-0.5622	82.6%	0.84	-0.6623	108.6%	0.64
EU15 & WB	-0.2358	26.9%	2.58	-0.3882	49.1%	1.41
EU2004–EU2013 & WB	-0.3086	36.9%	1.88	-0.4596	61.5%	1.13

Source: Authors' calculation

6. Conclusions and policy implications

6.1. Conclusion

This study examined total factor energy efficiency (TFEE) in the Western Balkan (WB) countries relative to EU member states over 2005–2019, using an SBM-DEA window model with CO_2 emissions as an undesirable output, and assessed sigma and beta convergence in TFEE.

The results reveal substantial heterogeneity in TFEE across the Western Balkans. Montenegro, Serbia, and Albania record average scores above the EU average, whereas Bosnia and Herzegovina and North Macedonia are among the least efficient economies in the sample. Serbia shows a strong but uneven improvement, while Bosnia and Herzegovina deteriorates throughout the period. The slack analysis identifies labour utilisation, energy use, and CO_2 emissions as the main sources of relative inefficiency, particularly in Bosnia and Herzegovina and North Macedonia. TFEE-based rankings also differ considerably from those based on single-factor indicators, which supports the complementary use of total-factor measures.

The convergence analysis provides mixed evidence. TFEE disparities generally declined or remained stable until 2010 but increased thereafter, indicating the absence of sustained sigma convergence. In contrast, negative and statistically significant beta coefficients across all analysed country groupings indicate relative catch-up among countries with lower initial TFEE levels. For the Western Balkans, stronger beta convergence therefore reflects faster relative adjustment rather than evidence that the efficiency gap with the EU has been eliminated. This distinction explains why beta convergence can coexist with persistent sigma divergence.

The speed-of-convergence and half-life estimates reinforce this pattern but should be interpreted cautiously. The conditional models imply stronger adjustment and shorter half-lives than the absolute models, with the Western Balkan sample showing the highest model-implied convergence speeds and shortest half-lives. Given the unusually high estimates, particularly the conditional WB convergence speed above 100%, these measures should be interpreted as comparative indicators of adjustment rather than literal forecasts of how rapidly observed TFEE gaps will close.

Several limitations should be acknowledged. TFEE is a relative measure sensitive to sample composition, the VRS assumption, and the selected four-year window width. The analysis also does not explicitly account for exogenous factors such as energy-price volatility, technological shocks, geopolitical developments, or climate conditions. Moreover, the dataset ends in 2019 and therefore does not capture the COVID-19 pandemic, the European energy crisis, or related post-2020 changes in energy consumption, emissions, prices, and policy priorities.

Overall, the findings indicate that relative catch-up alone should not be interpreted as evidence that TFEE disparities between the Western Balkans and the EU are being eliminated. Continued monitoring should therefore consider both rates of improvement and changes in absolute TFEE disparities.

6.2. Policy Implications

The results point to four policy priorities. First, because relative inefficiency in the Western Balkans stems from labour utilisation as well as energy use, improving TFEE requires structural measures beyond energy policy, including industrial, skills, and productivity policies. Since DEA slacks are diagnostic rather than causal estimates, the appropriate policy mix should be based on country-specific evidence.

Second, energy use and CO_2 emissions also represent important areas of potential improvement. Heavy reliance on fossil fuels, particularly coal, remains a broader challenge for the region. Gradual reductions in fossil-fuel dependence, together with investment in renewable energy and cleaner technologies, are therefore relevant to improving both energy and environmental performance, while the EU accession process and Energy Community framework provide an institutional context for aligning national policies with EU energy and climate objectives.

Third, the marked heterogeneity among Western Balkan countries, combined with their shared dependence on fossil fuels and interconnected energy systems, supports deeper regional cooperation. Integrating regional electricity markets, coordinating infrastructure investment, and aligning regulation within the Energy Community could facilitate the transfer of good practices and support catch-up by the less efficient countries (Uvalić, 2014). Because the present results do not measure the effects of specific cooperation instruments, their design should rest on complementary sector-specific analysis.

Finally, the coexistence of beta convergence and the absence of sustained sigma convergence indicates that faster improvement among initially less efficient countries does not necessarily reduce overall TFEE disparities. Policy monitoring should therefore consider both relative rates of improvement and absolute efficiency gaps. Regional coordination may support this process, particularly where energy markets, infrastructure, and regulatory frameworks involve cross-border interdependencies, although the effects of specific cooperation measures require complementary sector-specific analysis.

NOTES

[1] In this paper, Western Balkan countries refer to Albania, Bosnia and Herzegovina, Montenegro, North Macedonia, and Serbia. Kosovo is not included in the analysis due to the lack of comparable data for the observed period.

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