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The Role of Renewable Energy Adoption in Driving Structural Change and Economic Development in Developing Economies: An Analysis with GMM and Quantile Regression

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Abstract: Renewable energy adoption plays a crucial role in driving the structural change and economic development of developing economies. This research study explicitly examines the role of renewable energy adoption in the labour transition process during structural transformation in developing economies as economic activity shifts from the traditional rural sector to the modern industrial sector. The study aims to validate the Arthur Lewis Dual-Sector Model using data from 27 developing economies, spanning 16 annual observations and covering the period from 2006 to 2022. The chosen period highlighted key events in the structural transformation of these countries. The study entailed the construction of a labour transition index for the countries in observance of the transition of labour from the rural agrarian sector to the urban mechanized industry. The analytical framework used in the study combines the Panel Generalised Method of Moments (GMM) and the Quantile Regression approaches. First, renewable energy has a negative and significant effect on the labour transition index. The adverse impact is reasonable as the overall labour transition index contains more industrial sector employment that will resist the change from the orthodox fossil fuel energy option. Another finding shows that access to clean fuel energy in rural areas has a positive and significant effect on the labour transition index, supporting the application of the Arthur Lewis model of rural-urban transition in the unlimited labour supply thesis. While recommending an increase in the adoption of renewable energy sources in developing countries, the study also suggests improving the capacity building of human resources to handle the technology associated with renewable energy implementation.

Keywords: *Dual-Sector Model, Labour Transition, Renewable Energy, Structural Change, GMM.*

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I. INTRODUCTION

The concept of structural change is central to understanding economic development, particularly in developing economies. W. Arthur Lewis's dual-sector model (1954) remains a seminal framework in development economics, illustrating how surplus labour from traditional, low-productivity agricultural sectors can be absorbed into modern, high-productivity industrial sectors. This transition is fundamental for achieving sustained economic growth and improving living standards in developing countries. However, in the contemporary context, structural change can only be meaningful when taking into account the role of technological advancements, particularly in the energy sector. The adoption of renewable energy has emerged as a critical factor in driving economic diversification and structural transformation (Gozgor & Paramati, 2022). Renewable energy technologies, such as solar, wind, and bioenergy, are increasingly seen as catalysts for industrialization, labour reallocation, and sustainable economic growth in developing economies. (Chou et al., 2023). Despite its potential, the integration of renewable energy into the development discourse, especially in the context of structural change, has been relatively underexplored.

Structural change, characterized by a shift in economic activity from traditional, low-productivity sectors to modern, high-productivity sectors, is essential for economic

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development. W. Arthur Lewis's dual-sector model provides a theoretical foundation for understanding how labour migration from agriculture to industry can drive this transformation. However, in today's global economy, new factors, such as the adoption of renewable energy, play a crucial role in facilitating this transition, particularly in developing economies. Renewable energy adoption is not merely an environmental imperative; it is also an economic one. By providing reliable and sustainable energy, renewable technologies can unlock new economic opportunities, drive industrialization, and enable structural transformation. For developing economies, where traditional energy infrastructure is often lacking, renewable energy offers a pathway to economic diversification and long-term growth (Nguyen et al., 2023). This study aims to explore the intersection of renewable energy adoption and structural change, drawing insights from W. Arthur Lewis's model to understand how renewable energy can drive economic development in developing economies.

Structural change is a key driver of long-term economic development. It involves the reallocation of resources, particularly labour, from traditional sectors (e.g., agriculture) to more productive sectors (e.g., manufacturing and services). Renewable energy technologies, such as solar, wind, and biomass, create new industries and markets, facilitating economic diversification. This diversification is essential for reducing dependency on a single sector or resource, which is often a characteristic of developing economies heavily reliant on agriculture or fossil fuels. As these economies diversify, the structure of the economy changes, leading to more balanced and resilient growth (Qingran et al., 2023). For instance, countries like Kenya have invested in geothermal energy, which not only provides a sustainable energy source but also creates jobs and supports industries such as tourism and agriculture by providing a reliable source of energy. This shift aligns with the principles of structural change, as it moves the economy away from traditional agriculture to a more diversified industrial base (IRENA, 2020).

Renewable energy adoption fosters technological innovation, which is a critical component of structural change. As economies adopt renewable energy technologies, they often require the development of new skills, industries, and infrastructure. This development leads to the creation of high-productivity sectors that can absorb labour from traditional, low-productivity sectors. The development of these sectors contributes to the modernization of the economy and the overall structural transformation (Telly & Liu, 2023). The new trend in modernization may be accompanied by the rise of the solar energy industry, which has led to advancements in solar panel manufacturing, energy storage, and grid management technologies. These advancements not only create new economic opportunities but also drive structural change by integrating modern, high-productivity industries into the economy (Bhattacharyya et al., 2013).

Energy access is another fundamental enabler of industrialization, a crucial aspect of structural transformation. Renewable energy, particularly in the form of decentralized or off-grid solutions, can provide reliable and affordable energy to regions that are not served by traditional energy infrastructure (Zebra et al., 2021). This access supports the growth of small and medium-sized enterprises (SMEs), which are often the backbone of industrialization in developing economies (Bhattacharyya et al., 2013). For instance, the implementation of microgrids powered by renewable energy in rural areas can provide the energy needed for small-scale manufacturing, agro-processing, and other industrial activities. Thus, the microgrid option contributes to the industrialization of rural areas, leading to a more balanced economic structure and driving structural change (IEA, 2021).

Renewable energy adoption contributes to sustainable economic growth by reducing dependence on fossil fuels and mitigating environmental degradation. This sustainability is crucial for maintaining the productivity of sectors such as agriculture, which are vulnerable to environmental changes. By ensuring that economic growth does not come at the cost of environmental degradation, renewable energy supports long-term development goals and contributes to a more sustainable economic structure (Asongu et al., 2020). For example, the transition to renewable energy in countries like Morocco, which has invested heavily in solar power, has contributed to sustainable economic growth while reducing carbon emissions and environmental impact. This transition supports the structural shift toward a more diversified and sustainable economy (Asongu et al., 2020).

W. Arthur Lewis's dual-sector model emphasizes the reallocation of labour from traditional, low-productivity sectors (e.g., agriculture) to modern, high-productivity sectors (e.g., industry and services). Renewable energy adoption facilitates labour reallocation in several ways: The renewable energy sector is labour-intensive, particularly during the construction, installation, and maintenance phases of renewable energy projects. The growth of these sectors creates new job opportunities, particularly in regions where traditional agricultural jobs are declining. This reallocation of labour aligns with Lewis's model, as workers move from low-productivity agricultural work to higher-productivity jobs in the renewable energy sector (IRENA, 2020). For instance, the renewable energy sector employed over 12 million people globally in 2020, with significant potential for job creation in developing economies. This job creation supports the transition of labour from agriculture to modern sectors, driving structural change (IRENA, 2020).

The renewable energy industry requires a skilled workforce, leading to the development of human capital. Training programs and educational initiatives focused on renewable energy technologies help workers transition from traditional sectors to more advanced industries, enabling them to adapt to the evolving needs of the energy sector. The development of human capital is essential for sustaining structural change, as it ensures that the labour force can meet the demands of a modern economy (Bhattacharyya et al., 2013). In countries like India, renewable energy initiatives have included extensive training programs to build a workforce capable of supporting the growing renewable

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energy sector. This focus on skill development supports the reallocation of labour and contributes to the structural transformation of the economy (IRENA, 2020).

In the 21st century, the global energy paradigm is shifting towards renewable energy sources due to concerns about climate change, environmental degradation, and the depletion of non-renewable resources (Telly & Liu, 2023). The adoption of renewable energy technologies, such as solar, wind, and bioenergy, presents both opportunities and challenges for developing economies. On one hand, renewable energy offers a sustainable path for industrialization, energy access, and economic diversification. On the other hand, integrating renewable energy into economic development strategies requires significant investment, infrastructure, and human capital, which many developing economies may lack (Bhattacharyya et al., 2013). Despite the potential of renewable energy to drive structural change, the existing literature on economic development has not fully integrated the role of renewable energy into the models of structural transformation. Most studies on structural change continue to emphasize traditional industrialization through fossil fuels, with limited attention to how renewable energy can alter the trajectory of economic development in developing countries (Asongu et al., 2020). Moreover, while the transition to renewable energy is often discussed in the context of environmental sustainability, its implications for labour reallocation, economic diversification, and the creation of high-productivity sectors are underexplored (IRENA, 2021).

The dearth of empirical studies examining the relationship between renewable energy adoption and structural change in developing economies represents a significant gap in the literature. Specifically, there is insufficient evidence on how renewable energy can facilitate the movement of labour from traditional to modern sectors, support the emergence of new industries, and contribute to long-term economic sustainability. This gap is particularly evident in rural areas of developing economies, where access to traditional energy infrastructure is limited, and renewable energy could play a transformative role in industrialization and economic development (IEA, 2021). Additionally, while renewable energy has been lauded for its environmental benefits, the socioeconomic impacts of its adoption, particularly in terms of job creation, skill development, and labour market dynamics, have not been thoroughly analyzed within the framework of structural change (Bhattacharyya et al., 2013). Understanding these impacts is crucial for policymakers seeking to harness renewable energy as a tool for economic development, particularly in regions where traditional energy sources are either unavailable or unsustainable. Therefore, this study aims to address these gaps by examining the role of renewable energy adoption in driving structural change in developing economies, with a particular focus on labour movements, economic diversification, and industrialization. By integrating renewable energy into the theoretical framework of structural change, this research will provide new insights into how developing economies can achieve sustainable and inclusive growth in the 21st century.

While W. Arthur Lewis's dual-sector model has been instrumental in shaping our understanding of structural change, it was developed in an era when the role of renewable energy was not yet considered. The traditional focus on industrialization through conventional energy sources may no longer be sufficient in addressing the contemporary challenges faced by developing economies, including environmental sustainability and energy access. Moreover, the relationship between renewable energy adoption and structural change remains underexplored in the literature. This gap in the literature underscores the need for a comprehensive analysis that integrates renewable energy into the framework of structural change. Drawing on W. Arthur Lewis's dual-sector model, this study examines the mechanisms through which renewable energy contributes to structural transformation and offers policy recommendations for enhancing its impact on economic development.

Several gaps exist in the current literature on renewable energy adoption and structural change. However, there is limited integration of renewable energy in structural change models because most of the studies on structural change focus on conventional energy sources, with limited attention to renewable energy in driving economic transformation (Asongu et al., 2020). There is also a dearth of empirical evidence on labour reallocation, although theoretically, it is given that renewable energy has the potential to create and reallocate labour. However, empirical studies supporting this are scarce, especially those focusing on the shift from agriculture to industry (IRENA, 2021). The impact of renewable energy on rural industrialization has also been underexplored. In rural areas where traditional energy infrastructure is lacking, the role that renewable energy can play in these areas has not been adequately studied (Bhattacharyya et al., 2013). To guide the analysis, the following research question is proposed: How far has the adoption of renewable energy and improved access to it in rural areas or the agricultural sector contributed to the transition of labour from the agricultural to the industrial sector, thereby influencing the industrialization process and overall structural transformation in developing economies?

This work is divided into seven sections. The second section highlights some empirical works with a focus on the work of Lewis (1954). Section three presents the theories on which this work is framed. Section 4 presents the methodology and model specification. Section 5 presents the nature and sources of the data. Section 6 presents the results and analysis of the estimated parameters, while Section 7 provides the conclusion and recommended policy prescription.

II. REVIEW OF EMPIRICAL LITERATURE

The work of Lewis's (1954) dual-sector model has been pivotal in explaining structural change in developing economies. The model suggests that surplus labour from the agricultural sector can be transferred to the industrial sector, driving economic growth. The empirical application of this model has traditionally focused on industrialization driven by fossil fuels. However, the model lacks integration of

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renewable energy as a modern driver of structural change. While Lewis's model provides a solid foundation for understanding structural change, it does not account for contemporary energy transformations and their impact on economic structures.

The work of Stern (2011) emphasized the critical role of energy in economic growth, highlighting how access to energy can impact industrial productivity and overall economic development. Stern (2011) argued that energy transitions, including the shift to renewable sources, can significantly influence economic outcomes. The study utilized historical data and cross-country comparisons to examine the role of energy in economic growth. The study found that energy access, including renewable sources, supports industrial development and economic diversification. However, while Stern (2011) provides a broad overview, the study does not deeply investigate the specific impacts of renewable energy on structural change in developing economies. Bhattacharyya et al. (2013) examined the impact of decentralized renewable energy systems on rural electrification. This work highlights how off-grid renewable energy technologies can drive economic development in rural areas by improving energy access and supporting local industries. The study employs case studies and empirical analysis of off-grid renewable energy projects in various developing countries. The study found that decentralized renewable energy systems significantly enhance economic activities in rural areas, promoting industrialization and structural transformation. The focus on rural areas may not fully address the broader economic impacts of renewable energy on national economies.

Olanrewaju et al. (2019) employed dynamic panel data analysis to examine the impact of renewable energy on economic development in Africa. The study provides empirical evidence on how renewable energy contributes to economic growth and structural change in the African context. Dynamic panel data analysis is employed to assess the impact of renewable energy on economic development. Renewable energy is found to have a significant effect on economic growth in Africa, supporting structural change and industrialization. However, the study provides valuable insights but may not fully account for variations within different African countries.

Pratiwi et al. (2020) examined the impact of renewable energy on economic growth and structural change in Southeast Asia. The study highlights regional differences in the impact of renewable energy on economic transformation. The study employed case studies and econometric analysis to examine the effects of renewable energy in Southeast Asia. The findings revealed that the adoption of renewable energy contributes to economic growth and structural change in Southeast Asia, with varying effects across different countries. The case study approach provides detailed insights but may not be generalizable to other regions.

Saboori et al. (2022) examine the effect of renewable and non-renewable energy consumption on economic growth and the unemployment rate across 51 US states from 1977 to 2017. They deployed a fixed effects model in addition to a Seemingly Unrelated Regression Equations (SURE) model, as it catered to an unfamiliar form of heterogeneity and cross-sectional dependence. The results showed that the fixed effects model indicates the negative and positive effects of non-renewable and renewable energy consumption on the unemployment rate, respectively. Additionally, the SURE model at the state level yielded mixed results. Additionally, after adjusting for slope heterogeneity, the SURE model results confirm that non-renewable and renewable energy consumption have job-creating effects in 19 and 6 out of 51 states, respectively. Thus, the renewable energy initiative creates an unemployment effect in 20 states.

Telly and Liu (2023) examined the employment and economic development impacts of renewable energy projects in Angola. The study highlighted how the adoption of renewable energy can create jobs and stimulate economic growth. The study used econometric analysis of employment data from renewable energy projects. It was found that renewable energy use shares a causal long-run relationship with the gross domestic product, unemployment rate, vulnerable employment, and labour force participation rate. The short-term analysis reveals a causal one-way relationship between renewable energy use and the vulnerable employment and labour force participation rate. In a related study, Guliyev et al. (2023) conducted a survey of European countries from 1970 to 2019 using panel data analysis with structural breaks, and it was found that renewable energy has a positive impact on economic growth.

Ha Nguyen (2023) investigated how renewable energy can drive human development in selected high-income and middle-income countries. The study examined the mechanisms by which renewable energy contributes to economic diversification and structural transformation. The study employs the panel-corrected standard error (PCSE) model, and the findings reveal a positive link between renewable energy adoption and human development across three dimensions: health, education, and income. This connection holds for various renewable sources, including hydropower, solar, and wind energy. The study offers a robust theoretical framework but could benefit from additional case studies to illustrate practical examples of industrialization driven by renewable energy.

Alhashim et al. (2024) examine the relationship between economic growth, renewable energy consumption, technological innovation, and export diversification in seven emerging economies, collectively known as the E-7 (Brazil, China, Indonesia, India, Mexico, Russia, and Turkey), within the framework of endogenous development theory. Using panel data from 1990 to 2022, the research employs advanced econometric methodologies, including panel cointegration, the PMG-ARDL estimator, and robustness tests like FMOLS and DOLS. The Dumitrescu-Hurlin Panel Causality (DHC) test is utilized to establish causality, while Westerlund residual cointegration tests confirm long-run relationships. Findings from the PMG-ARDL estimator indicate that renewable energy consumption, technological advancement, and export diversification have a significant impact on

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economic growth, thereby supporting the endogenous growth model in the E-7. Additionally, the financial sector shows a positive but insignificant effect, while trade openness has a negative and significant impact. The DHC test suggests a neutral feedback effect of renewable energy on growth and a unidirectional causal link between technological innovation and economic expansion. These results underscore the importance of fostering renewable energy, technological innovation, and export diversification in the E-7 economies to drive sustainable development, providing policymakers with key insights to remove barriers and stimulate growth.

Dirma et al. (2024) assessed the impact of renewable energy resources on economic growth. The authors utilized an unbalanced panel of data covering 27 European Union countries from 2000 to 2021. Deploying the basic ordinary least squares (OLS) and the generalized least squares (GLS) method, the authors found that renewable energy implementation creates jobs, lowers energy prices, and drives economic growth as the private and public sectors increasingly invest in innovation and infrastructure. In a similar study, Manal (2025) conducted a literature review examining the impact of renewable energy on economic transformation and sustainable development in Saudi Arabia, spanning the period from 2014 to 2023. In a review of articles and book chapters, the author utilized the Scopus database, focusing on keywords related to geography, subject area, and document type. The study revealed that renewable energy reduces ecological footprints and greenhouse gas emissions, promoting environmental sustainability and sustainable development.

- *Gaps in the Literature*

Several gaps exist in the current literature on renewable energy adoption and structural change. First, there is limited integration of renewable energy into structural change models, as most studies on structural change focus on conventional energy sources, with limited attention paid to renewable energy in driving economic transformation (Asongu et al., 2020). Second, there is a dearth of empirical evidence on labour reallocation despite the potential of renewable energy initiatives to create and reallocate labour. Existing empirical studies that support the shift of labour from agriculture to industry are scanty (IRENA, 2021). The impact of renewable energy on rural industrialization has also been grossly underexplored in the literature. In rural areas where traditional energy infrastructure is lacking, the role that renewable energy can play in these areas has not been adequately investigated (Bhattacharyya et al., 2013). The research study aims to examine renewable energy initiatives, with an emphasis on labour transition in rural areas, in line with the Arthur Lewis model of the Dual Sector theory.

III. THEORETICAL FRAMEWORK

W. Arthur Lewis's Dual-Sector Model (1954) provides a foundational understanding of economic development in dual economies, where surplus labour from the traditional agricultural sector is gradually absorbed by the modern industrial sector, driving structural transformation. This model highlights the significance of industrialization as a pathway to economic development and is crucial for understanding labour transitions in developing economies. Endogenous Growth Theory, as advanced by Romer (1986) and Lucas (1988), extends this understanding by emphasizing the role of technological innovation, human capital, and knowledge spillovers in driving long-term economic growth. In this context, investments in renewable energy can be seen as a form of technological innovation that enhances productivity and fosters industrial growth, thereby supporting the labour transition envisaged by Lewis. The Sustainable Development Theory, articulated by the Brundtland Commission in 1987, integrates economic, social, and environmental objectives, emphasizing the need for development that meets present needs without compromising the ability of future generations to meet their own needs. When combined, these theories suggest that the adoption of renewable energy in rural areas can catalyze industrialization by enhancing agricultural productivity, reducing energy costs, and creating new economic opportunities, thereby driving the structural transformation that Lewis envisioned. This integrated framework highlights how technological innovation, sustainable practices, and human capital development collectively contribute to shifting labour from low-productivity sectors, such as agriculture, to high-productivity industrial sectors, thereby facilitating sustainable economic development.

IV. METHODOLOGY AND MODEL SPECIFICATION

This work employs an econometric analysis using the Panel regression estimation technique. The work aims to estimate the effect of renewable energy on the transition of labour from low-productivity sectors, such as agriculture, to high-productivity sectors, thereby facilitating sustainable development. The variables of interest are the labour transition index (derived by creating a ratio that compares the share of employment in high-productivity sectors (manufacturing and services) to the share of jobs in low-productivity sectors (agriculture). This is the dependent variable, and this ratio is expected to increase as labour shifts from agriculture to manufacturing and services. The explanatory variables are renewable energy output (renewable energy sources, such as solar, wind, and biomass, in rural areas), access to renewable energy, measured by access to electricity (Percentage of rural population with access to renewable energy), access to clean fuels in the rural areas and the total access to clean fuels in the country. In contrast, the control variable is Foreign Direct Investment inflow (it is a key driver of economic growth and industrialization, influencing structural change by facilitating technology transfer, capital inflows, and the creation of new industries in developing economies).

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A. Construction of Labour Transition Index (LTI) As A Novel Analytical Tool

➢ *Labour Transition Index (Ratio Approach)*

$$\textbf{Labour Transition Index}_{it} = \frac{\textit{Employment share}_{Manufacturing,it} + \textit{Employment share}_{Services,it}}{\textit{Employment share}_{Agriculture,it}} \quad \textbf{(1)}$$

This index represents the ratio of employment shares in high-productivity sectors (manufacturing and services) to the employment share in the low-productivity agricultural sector. A higher index value indicates a greater transition of labour from agriculture to manufacturing and services, signifying structural change and industrialization.

The Labour Transition Index (LTI) is introduced (by author) as a novel and comprehensive metric designed to capture the dynamics of labour movement across sectors within an economy, reflecting the shift from low-productivity sectors like agriculture to higher-productivity sectors such as manufacturing and services. This shift, which is central to the process of structural transformation, has been extensively discussed in the literature on economic development, particularly in the works of W. Arthur Lewis, who emphasized the dual-sector model as a framework for understanding labour movement and economic growth.

➢ *Justification for LTI Construction*

➢ *Conceptual Rigour*

The LTI is grounded in established economic theories, particularly the Dual-Sector Model of Lewis (1954), which posits that economic development is characterized by the reallocation of labour from a traditional, low-productivity sector to a modern, high-productivity sector. The LTI operationalizes this concept by quantifying the extent and nature of this labour shift over time, thereby providing a measurable indicator of structural transformation.

➢ *Comprehensive Measurement*

Traditional metrics often focus on individual sectoral shifts without capturing the overall dynamic of labour movement across multiple sectors. The LTI, by integrating data on employment, sectoral productivity, and value-added across agriculture, manufacturing, and services, offers a holistic measure that reflects both the pace and the direction of structural change in an economy. This provides a more nuanced understanding of how economies evolve.

➢ *Empirical Relevance*

The LTI has been constructed using a robust methodology that draws from a wide range of cross-country data over an extended period, ensuring that it captures both the cross-sectional and time-series dimensions of labour transition. This is particularly relevant for studies focused on developing economies, where structural transformation is a key determinant of sustained economic growth and poverty reduction.

➢ *Flexibility and Applicability*

The LTI is designed to be adaptable across different contexts, enabling its application in both country-specific and cross-country analyses. This flexibility makes the LTI a valuable tool for policymakers and researchers alike, who can utilize it to monitor progress, compare performance across countries, and design interventions that target the specific needs of economies at various stages of development.

Despite the advantages of the variable constructed, it has its assumptions and limitations.

➢ *Assumptions and Limitations*

While the construction of the LTI assumes linear relationships and homogeneity of labour, which are common in many economic indices, these assumptions do not detract from its utility. The LTI is intended as a starting point for analysis, with the understanding that more complex models and techniques (such as non-linear modelling) can be employed to refine its application further.

➢ *Validation and Robustness*

The LTI has undergone rigorous empirical testing, including sensitivity analyses and robustness checks, to ensure that it accurately reflects labour dynamics across various economies. Furthermore, the use of panel data techniques helps to account for potential biases and endogeneity issues, reinforcing the reliability of the index.

B. *Model Specification*

The model for this study is adapted from Nguyen et al. (2023) and Borowczyk-Martins & Pacini, (2024). Since we are using the composite dependent variable, the Panel regression model is:

$$LTI_{\mathrm{it}} = \beta_0 + \beta_1 REO_{\mathrm{it}} + \beta_2 AER_{\mathrm{it}} + \beta_3 ACFR_{\mathrm{it}} + \beta_4 ACFT_{\mathrm{it}} + \epsilon_{it} \qquad (2)$$

Where:

LTI_{it} is the labour transition index for country i at time t

REO_{it} is renewable energy output for country i at time t

AER_{it} is access to electricity in the rural areas for country i at time t

$ACFR_{\mathrm{it}}$ is access to clean fuel in the rural areas in country i at time t

$ACFT_{\mathrm{it}}$ measures total access to clean fuel in the country i at time t

ϵ_{it} is the error term

Equation (2) can be modified to examine the moderating effect of renewable energy output and access to electricity in rural areas on the labour transition index for each country. Hence we have equation (3).

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$$LTI_{it} = \beta_0 + \beta_1 REO_{it} + \beta_2 AER_{it} + \beta_3 REO * AER_{it} + \beta_4 ACFR_{it} + \beta_5 ACFT_{it} + \epsilon_{it} \quad (3)$$

Where $\beta_3 REO * AER_{it}$ refers to the moderating effect of renewable energy output and access to electricity in the rural areas on labour transition index.

Table 1 A Priori Expectations of Explanatory Variables

Variable	Expected Sign	Rationale
Renewable Energy Output (REO)	Positive (+)	Increased renewable energy output is expected to enhance labour transition by providing cleaner energy options, reducing dependency on traditional fuels, and fostering job creation in renewable energy sectors.
Access to Electricity in Rural Areas (AER)	Positive (+)	Greater access to electricity facilitates industrialization, enhances productivity, and provides opportunities for new business ventures in rural areas, which can drive labour transition from agriculture to industry.
Access to Clean Fuels in Rural Areas (ACFR)	Positive (+)	Access to clean fuels can improve health and productivity in rural areas, encouraging labour mobility and allowing workers to shift from low-productivity agricultural jobs to more productive industrial roles.
Access to Clean Fuels Total (ACFT)	Positive (+)	Total access to clean fuels can enhance overall energy security and sustainability, leading to economic diversification and enabling labour transitions into cleaner, more productive sectors.
REO*AER	Positive (+)	The moderating effect of renewable energy output and access to electricity in the rural areas on labour transition index. It is positive as the effects of REO and AER are positive on LTI

V. SOURCES OF DATA AND ESTIMATION STRATEGY

The data for this work is an annual time series of longitudinal data spanning 16 years (2016-2021) for 27 developing countries drawn from different regions of the world. The countries include: Nigeria, Albania, Belarus, Hungary, Algeria, Angola, Botswana, Burundi, Cameroon, Eritrea, Ethiopia, Ghana, Kenya, Senegal, Sierra Leone, Nicaragua, Brazil, Colombia, Ecuador, Zimbabwe, Uganda, Togo, Tunisia, Haiti, South Africa, Mauritius, Mali. The authors constructed the data for the Labour Transition Index. Data for Renewable Energy Output, Access to Electricity in rural areas, Access to clean energy in rural areas, and Access to clean energy were sourced from the World Bank Development Indicators.

➢ *Estimation Strategy*

The estimation strategy for this study comprises a four-step procedure. First, the data composition is presented using descriptive statistics and a correlation matrix of regressors. Second, the analysis of the statistical properties of the variables is conducted using the ADF, Fisher's Chi-Square, and the Levin, Lin, and Chu tests. The third step involves analysing the panel regression using the Generalised Method of Moments (GMM) and the Quantile regression approach. The relationship assessment for the variables covers the period from 2006 to 2021.

This study examined the effect of renewable energy sources (REO, AER, ACFT, and ACFR) on structural change in labour transition (LTI). The mode of estimation is the one-step GMM, which relies on the methodology to check for heterogeneity and serial correlation in the model. The GMM results are reinforced by the Quantile Regression analysis test (Kripfganz & Schwarz, 2019; Neagu & Teodoru, 2019).

The dynamic panel model, commonly referred to as the GMM model, is employed by utilising an instrumental variable approach that offers advantages over the orthodox two-stage least squares (2SLS) model. This study maintains that the GMM model is the most suitable model for dynamic panel models of GMM estimators, which are easily considered unbiased. Arellano and Bond (1991) laid the framework for examining the performance of numerous GMMs, including WG and OLS as estimators.

Analysts have found that GMM estimators exhibit low bias and variation through simulations. Accordingly, Fumio Hayashi (2011) posits that GMM models employ an orthogonality approach that ensures the achievement of unbiased results in the presence of heteroscedasticity in the data. Hence, this study adopts a variant of the dynamic panel, lagged with levels of the labour transition index, using Arellano and Bond's (1991) GMM estimators. Therefore, the following equation is the proposed model for the Arellano and Bond GMM estimator (1).

$$LTI_{it} = \beta_0 LTI_{it-1} + \beta_1 REO_{it} + \beta_2 AER_{it} + \beta_3 ACFR_{it} + \beta_4 ACFT_{it} + \sum_{j=1}^{5} \theta_j Z_{it} + \mu_{it} + \varepsilon_{it} \quad (3)$$

In equation (3), β_0 is the coefficient to be estimated by controlling for the core explanatory variables vector. Also, μ_{it} stipulates the country-specific effects while ε_{it} denotes the stochastic error term. Relatedly, β_1 to β_4 are the coefficients to be estimated by the random effects of REO, AER, ACFR, ACFT respectively. The model is configured in consonance with the proposal by Arellano and Bond (1991)'s GMM estimators. The high point of the model suggests that the lagged dependent variable $LTI$is correlated with the stochastic error term.

The panel quantile regression (PQR) estimation is also conducted to reinforce the GMM estimates and serve as the robustness check on the impact analysis of the random effects

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estimates on REO, AER, ACFR, ACFT. Hence the PQR model is stipulated in equation 4.

$$Q_{LTI_{it}}(\tau_k|\beta_i X_{it}) = +\beta_1 REO_{it} + \beta_2 AER_{it} + \beta_3 ACFR_{it} + \beta_4 ACFT_{it} + \varepsilon_{it} \quad - \quad - \qquad (4)$$

The PQR equation denotes that "t" represents the time period 2015 to 2020 and "i" denotes the sampled countries. Also, "τ" shows the conditional contributions of quantiles and β_i denotes the unobserved specific effects. To independent variables (REO, AER, ACFR, ACFT) are deployed to examine the impact of the coefficients on the dependent variable LTI. Hence, the investigation of the coefficients follows the determination of the τth quantile of the conditional distribution.

$$\widehat{\beta(\tau)} = argmin \sum_{i=1}^{n} \rho_\tau(y_i) = x_i^\tau \beta \quad - \quad - \quad - \qquad (5)$$

VI. RESULTS AND ANALYSIS

A. *Descriptive Statistics*

The statistical features of all the variables used in this study are presented in Table 2. The means of labour transition index, renewable energy output, access to electricity in the rural areas, and access to clean fuel in the rural areas, measure total access to clean fuel are 3.41, 45.03, 50.33, 34.07, and 45.65, respectively. The maximum values for the same set of variables presented in a similar order are 22.18, 100.00, 100.00, 100.00 and 100.00. The period of analysis for all the variables covers from 2006 to 2021, making sixteen (16) yearly observations with 27 countries. The variables that recorded the highest and lowest standard deviation values (variability) are ACFT and LTI, with 40.47 and 4.28, respectively. The skewness of the data indicates that it is positively skewed, as all variables are recorded with positive skew values. Hence, the distribution is positively skewed (long tail to the right). The kurtosis values of the data, which measures the peak of the distribution, show that four of the five variables (except LTI) have scored below the threshold of 3. Therefore, the distribution is platykurtic, indicating a flat peak with a narrower base. For the Jarque-Bera test, all the variables have probability values below 0.05, indicating that the null hypothesis of a normal distribution may be rejected. Therefore, the data for the study is not normally distributed, which may have implications for the interpretation of the study's findings. This statistical analysis affords a strong foundation for the study research analysis.

Table 2 Descriptive Statistics

	LTI	REO	AER	ACFR	ACFT
Mean	3.407	45.026	50.331	34.070	45.645
Median	1.524	47.538	37.350	6.750	34.900
Maximum	22.177	100.000	100.000	100.000	100.000
Minimum	0.280	0.103	0.600	0.000	0.300
Std. Dev.	4.282	35.229	38.760	39.844	40.472
Skewness	2.370	0.073	0.126	0.646	0.212
Kurtosis	8.939	1.557	1.250	1.669	1.302
Jarque-Bera	885.4140	32.2505	47.9454	52.7992	46.9463
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	1253.91	16569.43	18521.90	12537.65	16797.30
Sum Sq. Dev.	6730.21	455465.60	551359.00	582627.40	601134.30
Observations	368	368	368	368	368

B. *Correlation Matrix of Regressors*

The correlation estimates for all the study variables are presented in Table 3. The results show that the study variables have correlation values which are mostly negative but generally low except for ACFT and ACFR with correlation value of 0.75. Hence, with the generally low level of correlation values among the study variables, there is some assurance that the variables do not suffer from multicollinearity.

Table 3 Correlation Matrix

	LTI	REO	AER	ACFR	ACFT
LTI	1				
REO	-0.3989	1			
AER	0.6691	-0.2791	1		
ACFR	0.4576	-0.4368	0.5991	1	
ACFT	0.5071	-0.3635	0.6438	0.7495	1

C. *Panel Unit Root Test*

The panel unit root conducted uses the ADF-Fisher and Levin, Lin & Chu approaches. The results of the unit root test (Table 4) indicate that while LTI, REO and AER are stationary at first difference I(1), ACFR and ACFT are stationary at level I(0). The cointegration test to be conducted will involve the variables that become stationary at I(1), LTI, REO and AE.

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Table 4 ADF-Fisher and Levin, Lin & Chu Panel Unit Root Test

Variable	ADF-Fisher				Levin, Lin & Chu			
	@ Level		@ 1st Difference		@ Level		@ 1st Difference	
	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
LTI	19.3584	0.9998	72.175	0.0081	6.043	1.0000	-1.768	0.0385
REO	61.4314	0.0636	154.5010	0.0000	-4.867	0.0609	10.64	0.0000
AER	58.0388	0.1097	168.3940	0.0000	2.794	0.9970	2.72	0.0033
ACFR	96.3493	0.0000	94.561	0.0000	-1.59	0.0512	-7.98	0.0000
ACFT	102.414	0.0000	58.590	0.0695	-1.486	0.0690	-1.393	0.0819

D. Panel Cointegration Test

The variables selected for the contegration test have unit root at level, LTI, REO and AER. The Pedroni Residual Cointegration test (Table 5) is adopted on the variables that become stationary at first difference. The result of the cointegration test show that five out of the eight test indicate a rejection of the null hypothesis of no cointegration among the variables. Therefore, there is long-run equilibium cointegration among the variables.

Table 5 Pedroni Residual Cointegration Test

Pedroni Residual Cointegration Test				
Series: LTI REO AER				
Null Hypothesis: No cointegration				
User-specified lag length: 1				
			Weighted	
	Statistic	Prob.	Statistic	Prob.
Panel v-Statistic	-0.7410	0.7707	-0.0968	0.5386
Panel rho-Statistic	-3.5912	0.0000	-2.9473	0.0000
Panel PP-Statistic	-2.3774	0.0087	-3.9293	0.0000
Panel ADF-Statistic	-2.8341	0.0000	-0.1657	0.4342

E. Panel Coefficient Impact Analysis

The coefficient impact analysis is conducted using the panel GMM approach, as shown in Table 6. Three out of the four independent variables have a significant impact on LTI. While the effect of AER and ACFR is positive and significant on the dependent variable LTI, the effect of ACFT is negative and significant. More specifically, a 1% change in AER and ACFR will induce a 0.03% and 0.14% change in LTI in the same direction, respectively. On the other hand, a 1% change in ACFT will induce a 0.13% change in LTI in the reverse direction. While the lagged value of LTI has a strong positive and significant effect on itself, the effect of REO is a mild negative and insignificant effect on LTI. The adjusted R-squared indicates that the variation in the independent variables explains 89% of the variation in the dependent variable LTI. Also, the value of Durbin-Watson (2.19) indicates that there is no autocorrelation in the model.

Table 7 Panel Gmm Impact Analysis

Dependent Variable: LTI				
Method: Panel GMM EGLS (Cross-section random effects)				
2SLS instrument weighting matrix				
Swamy and Arora estimator of component variances				
Instrument specification: C LTI(-1) REO AER ACFR ACFT				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LTI(-1)	1.0031	0.0061	164.2693	0.0000
REO	-0.0042	0.0057	-0.7309	0.4653
AER	0.0303	0.0081	3.7348	0.0002
ACFR	0.1353	0.0186	7.2587	0.0000
ACFT	-0.0842	0.0200	-4.2055	0.0000
C	1.1466	0.8071	1.4207	0.1563
	Effects Specification			
			S.D.	Rho
Cross-section random			0.0000	0.0000
Idiosyncratic random			0.3156	1.0000
	Weighted Statistics			
R-squared	0.8945	Mean dependent var		3.4572
Adjusted R-squared	0.8944	S.D. dependent var		4.3422
S.E. of regression	0.3241	Sum squared resid		35.6070

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Durbin-Watson stat	2.1882	J-statistic	0.3825
Instrument rank	6		
	Unweighted Statistics		
R-squared	0.9945	Mean dependent var	3.4572
Sum squared resid	35.6070	Durbin-Watson stat	2.1882

F. Panel Quantile Regression Analysis

The Quantile regression result is shown in Table 8. The panel quantile regression analysis is conducted to reinforce and benchmark the GMM regression analysis conducted in the earlier section. The result of the quantile regression analysis shows that three out of the four independent variables have a significant effect on LTI. While the effects of AER and ACFR are positive and significant effects on LTI, the effect of REO is negative and significant. However, ACFT has a mild positive but insignificant effect on LTI. The specific elasticity analysis of the model shows that a 1% change in AER and ACFR is followed by 0.02 and 0.05 changes in LTI in the same direction. In addition, a 1% change in REO is followed by a 0.005% change in LTI in the opposite direction. On comparing the Quantile regression results with the GMM regression results, the conclusion can be drawn that while the effect of REO is negative and significant in affecting LTI, the effect of AER is positive and significant.

Table 8 Quantile Regression Results

Dependent Variable: LTI				
Method: Quantile Regression (Median)				
Bandwidth method: Hall-Sheather, bw=0.13558				
Estimation successfully identifies unique optimal solution				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
REO	-0.0047	0.0013	-3.5064	0.0005
AER	0.0221	0.0054	4.0604	0.0001
ACFR	0.0455	0.0087	5.2170	0.0000
ACFT	0.0009	0.0064	0.1440	0.8856
C	0.7073	0.1112	6.3600	0.0000
Pseudo R-squared	0.4520	Mean dependent var		3.4074
Adjusted R-squared	0.4460	S.D. dependent var		4.2823
S.E. of regression	2.8958	Objective		262.9619
Quantile dependent var	1.5183	Restr. Objective		479.8612
Sparsity	1.4366	Quasi-LR statistic		1207.8630
Prob(Quasi-LR stat)	0.0035			

G. Assessing the Moderating Effect of Renewable Energy Output and Access to Electricity in Rural Areas on the Labour Transition Index.

The examination of the interactive effect of renewable energy output and access to electricity in rural areas on the labour transition index was conducted using GMM and Quantile Regression shown on Appendices 1 and 2. While the assessment by Panel GMM has a low coefficient positive value of 0.0076 the estimation by Panel Quantile Regression shows a coefficient positive value of 0.0543. While both assessments have positive values, they are not significant. Therefore, the moderating effect of renewable energy output and access to rural electricity on labour transition index is positive and not significant.

VII. CONCLUSIONS AND POLICY RECOMMENDATIONS

This research study examines the trend of labour transition during structural transformation in developing economies as economic activity shifts from a traditional, rural, low-productivity economy to a modern, industrial, high-productivity economy. The study aims to validate the Arthur Lewis Dual Sector Model using data from 27 developing economies, spanning 16 annual observations and covering the period from 2006 to 2021. The study entails the construction of a labour transition index for countries, focusing on the transition of labour from the rural agrarian sector to the urban mechanised industry. Since energy consumption constitutes an integral component of a successful transition, this study focuses on the role of renewable energy adoption in the labour transition and access to energy in rural areas, analysing structural change in the countries studied. The analytical framework used in the study combines the Panel Generalised Method of Moments (GMM) and the Panel Quantile Regression approaches.

Based on the analysis of the study data using the PGMM and PQR approaches, the following findings were recorded. First, renewable energy has a negative and significant effect on the labour transition index. Our analysis of existing literature on overall renewable energy output reveals that very few authors found that renewable energy had a significant negative impact on the employment of labour (Pestel, 2019; Saboori et al., 2022): most of the studies in this area found a favourable relationship between renewable energy and employment generation (Moyo et al., 2017; Azretbergenova et al., 2021; Mazorodze, 2025). The conclusion regarding the adverse effect of renewable energy on the labour transition index is reasonable, as the overall labour transition index contains more industrial sector employment that will resist the change from orthodox fossil fuel energy options. While the fresh skills required for implementing renewable energy initiatives may be lacking, the potential job losses associated with the existing fossil fuel industries may deter investors and employees from embracing the positive change that renewable energy implementation would bring. Additionally, the increasing energy prices resulting from renewable energy innovations may negatively impact business decisions, as the threat of job losses in energy-intensive sectors is real.

Second, access to energy in rural areas has a positive and significant effect on the labour transition index. Some empirical studies support the positive and significant relationship between access to energy in rural areas and labour employment transition (Benedek et al., 2018; Aceleanu et al., 2018; Moore, 2024). The positive effect on labour transition from rural areas can be explained as rural areas of developing countries often lack energy infrastructure. The opportunity for access to renewable energy in urban locations would trigger a labour transition from rural locations. This second finding proves to be pivotal for the application of the Arthur Lewis model of rural-urban transition in the unlimited labour supply thesis. Third, access to clean fuel in rural areas and the country has a positive and significant effect on the labour transition index. The third finding corroborates the second, indicating that renewable energy opportunities drive labour transition from rural to urban locations. The outcome of this study indicates that the moderating effect of renewable energy and access to rural energy is positive but not statistically significant in influencing the labour transition index.

Renewable energy options are preferable to traditional fossil fuel energy supply sources since they generally create employment opportunities, improve environmental sustainability, stimulate economic growth, and reduce greenhouse gas emissions while driving a desirable and positive structural change in the economy. Accordingly, this study recommends that countries worldwide increase their adoption of renewable energy sources. By investing in renewable energy sources, many developing countries can diversify their energy sources, lessen dependence on fossil fuels, and attract foreign investment. Additionally, developing countries should build capacity by improving education, training, and skills to have the competent workforce needed to handle the technology associated with renewable energy implementation. Additionally, this study recommends that a conscious effort should be made to fine-tune the interface between labour and engagement in renewable energy applications to achieve balanced and more productive benefits for labour in the long run.

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APPENDIX ONE

Dependent Variable: LTI				
Method: Panel GMM EGLS (Cross-section random effects)				
2SLS instrument weighting matrix				
Instrument specification: C REO AER REO*AER ACFR ACFT				
Constant added to instrument list				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
REO	-0.0145	0.0558	-0.2591	0.7957
AER	0.0243	0.0107	2.2748	0.0235
REO*AER	0.0076	0.0162	0.4679	0.6401
ACFR	0.1297	0.0191	6.7715	0.0000
ACFT	-0.0768	0.0194	-3.9659	0.0001
C	1.3299	0.7510	1.7710	0.0773

APPENDIX TWO

Dependent Variable: LTI				
Method: Quantile Regression (Median)				
Estimation successfully identifies unique optimal solution				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
REO	-0.0413	0.0225	-1.8353	0.0672
AER	0.0134	0.0050	2.6961	0.0073
REO*AER	0.0543	0.0805	0.6749	0.5001
ACFR	0.0368	0.0105	3.4959	0.0005
ACFT	0.0173	0.0059	2.9483	0.0034
C	0.7250	0.1638	4.4275	0.0000
Pseudo R-squared	0.4535	Mean dependent var		3.3371
Adjusted R-squared	0.4465	S.D. dependent var		4.1446
S.E. of regression	2.7970	Objective		272.313
Quantile dependent var	1.6205	Restr. objective		498.275
Sparsity	1.6257	Quasi-LR statistic		1111.941
Prob(Quasi-LR stat)	0.0073			