Asian Journal of Social Science and Management Technology
ISSN: 2313-7410
Volume 7, Issue 2, March-April, 2025
Available at www.ajssmt.com

The Green Revolution: The Impact of Female Labor Force Participation on Carbon Dioxide Emissions Across the Global Demographic Dividend Stages

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Abstract: The female labor force participation rate (FLFPR) remains low globally, despite an equal gender distribution. Its improvement is essential for achieving social and economic development by empowering women and enhancing demographic dividends (DDs). However, climate change results from human CO2 emissions. Understanding the impact of FLFPR on CO2 emissions across different DD stages is vital for augmenting DDs while minimizing CO2 emissions. This panel study innovatively investigates how FLFPR affects CO2 emissions globally and in Pre, Early, Late, and Post DD countries using the extended STIRPAT model from 1990 to 2019. The study employed Driscoll-Kraay robust standard error regression and the Dumitrescu–Hurlin causality test. The empirical results highlight that FLFPR lowers CO2 emissions globally and in all DD panels. Additionally, FLFPR exhibits a U-shaped relationship with CO2 emissions during the pre-and late-DD stages but an inverse U-shaped relationship during the early- and post-DD stages globally. Furthermore, FLFPR demonstrates bidirectional causality with CO2 emissions globally and at all dividend levels. This new evidence may assist policymakers in optimizing FLFPR, maximizing the first demographic dividends, and reducing CO2 emissions simultaneously.

Key Words: CO2 emissions, Female labor force participation rate, Demographic dividends, extended STIRPAT model, Panel data analysis, Women empowerment.

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1. Introduction

Climate change is one of the world's most significant challenges, with human-generated carbon dioxide (CO2) emissions and other greenhouse gases being crucial contributors. Reducing CO2 emissions is vital to combating climate change and environmental issues, as it is the primary greenhouse gas produced by the burning of fossil fuels, industry, and land use, accounting for 75% of emissions in 2016 (Ritchie, Hannah, Max Roser, 2020). Research has shown that technology, wealth, energy composition, economic framework, and demographic diversity influence CO2 emissions (Fan et al., 2006). Studies by Dietz & Rosa (1997); Shi (2003); Cole & Neumayer (2004); Martínez-Zarzoso et al. (2007); Brant Liddle & Lung (2010); Liddle (2014) Indicates that population exerts a more substantial influence on CO2 emissions than affluence.

By 2100, the world's population is expected to have tripled since the mid-1900s, putting a strain on natural resources and contributing to climate change (John Wilmoth, 2022). Lee (2003) and R. D. Lee & Mason (2006) This highlights that the "demographic transition" refers to the shift from high fertility and death rates in agricultural societies to lower rates in urban and industrial communities, alongside increases in economic development and family welfare resources, resulting in a "first dividend." The first dividend comprises four stages: pre, early, late, and post. The pre-stage is characterized by high birth and mortality rates, leading to a large youth population. The early stage is marked by a decline in mortality rates, resulting in a larger working-age population. The late stage sees a decline in birth rates, resulting in a smaller youth population. Finally, the post-stage occurs when the working-age population begins to age and retire, decreasing the ratio of workers to dependents. The "second dividend" refers to the accumulation of assets by the elderly population, which could enhance national income if managed effectively. The global gender composition of the working-age population is roughly equal, yet female labor force participation (FLFP) remains consistently low worldwide. Maximizing the dividends and economic growth necessitates policies that support various groups, particularly women, in entering the workforce. (Lee & Mason, 2019).

The FLFPR refers to the percentage of women working or actively seeking employment in a given country or region (Psacharopoulos & Tzannatos, 1989). It measures the extent to which women are engaged in the labor force and is usually expressed as a percentage of the total female population. This rate is an essential indicator of gender equality and economic development. It is calculated by dividing the number of women in the labor force by the total number of women in the working-age population. FLFP has gained significant attention in recent years as women continue to strive for equality in the workplace. Historically, women have met tremendous barriers to entering and advancing in the workforce, including discrimination, lack of education and training, and societal expectations around gender roles. Increased female labor force participation (FLFP) is a crucial driver of economic growth, as it can help increase productivity, reduce poverty, and promote gender equality (Tasseven, 2017).

Also, FLFP has the potential to contribute directly and indirectly to achieving the United Nations Sustainable Development Goals (SDGs)(Foster, 2016; Balakrishnan & Dharmaraj, 2018; Denney, 2015; Taheri et al., 2021). The SDGs include eradicating poverty and hunger, promoting healthy lifestyles, achieving quality education and gender equality, minimizing inequality, ensuring sustainable consumption and production, combating climate change, and promoting peace and an inclusive society. FLFP can generate numerous benefits for sustainable development's economic, social, and environmental pillars(Choudhry & Elhorst, 2018; Ustabaş & Gülsoy, 2017; Appiah, 2018).

Policymakers frequently ignore the effect of the demographic transition on FLFP. Based on a nation's age distribution, the DD stage significantly impacts individual and family life cycles and can change a nation's income level. Confirming the nexus between economic progress and DDs, Ahmed et al. (2016) pointed out that most countries at the pre-, early-, late-, and post-DD stages are low, low-middle, upper-middle, and upper-income, respectively. This study attempts to determine how FLFP affects CO_2 emissions at different DD stages and globally. This new knowledge is helpful for policymakers to develop effective long-term policies for the country, region, and global to optimize global FLFPR, maximize the DDs, and minimize CO_2 emissions.

This study is significant in several ways. First, this study analyzes the effect of FLFPR and Male Labor Force Participation Rate (MLFPR) on carbon emissions using the expanded Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model designed to evaluate human intervention's global impact on the environment. Second, this study constructs country panels based on the stages of the first DDs. This method enables legitimate long-term policies. Thirdly, this study investigates how gender differences in labor force participation rates affect carbon emissions at various stages of the DD. Also, it explores the causal relationship among CO_2 emissions, population, affluence, energy, and gender-wise labor force participation rates for the first time. This study fourthly analyses the effects of gender-wise labor force participation on CO_2 emission at each DD stage to assist in developing effective strategies. Fifth, the first DD era may span 50 years or more; every country passes through the Pre, Early, Late, and Post demographical dividend stages accordingly. Identifying the dynamics of the impact of gender-wise labor force participation on CO_2 emissions at each DD stage helps create effective national, regional, or global policies. Experience in late and post-diverse aerial dividend countries may help make effective policies in pre- and early-diverse aerial dividend countries. Furthermore, the study employs econometric techniques such as slope homogeneity tests, second-generation unit root tests, and Westerlund cointegration tests; the panel estimates Driscoll-Kraay standard errors, Newey-

West Standard Errors, and Dumitrescu-Hurlin Granger non-causality test to overcome the problem of heterogeneity and cross-sectional dependence.

The study is organized into five sections: Section 2, Model Specification and Data Sources, contains the theoretical framework, modelling, and data collection. Section 3, Estimation strategy, presents the study's panel pretests and estimation techniques. Section 4, Empirical results and discussion, presents findings with a discussion. Section 5, Conclusions, provides the ultimate remarks on practical implications and suggestions for future research.

2. Model Specification and Data Sources

2.1 Theoretical framework

Various models are used to understand the impact of human activities on the environment, including IPAT, STIRPAT, ImPACT, ICE-STIRPAT, ImPACTS, IPBAT, and the extended STIRPAT model. The IPAT model, first proposed by Paul R. Ehrlich and John P. Holdren in 1971, the quality of the environment was evaluated based on Population, Affluence, and Technology. However, the original IPAT model was limited in its use as it relied on several assumptions (Shi, 2003). Later, Dietz & Rosa (1997) proposed the stochastic version of IPAT as STIRPAT, a model with practical applications refined by York et al. (2003). The STIRPAT model is commonly used for empirical research and policy suggestions to reduce environmental degradation by investigating the influence of diverse actors on environmental deterioration (Shi (2003); K. Li & Lin (2015); Xu & Lin (2015)). According to York et al. (2003), a large group of researchers expanded the STIRPAT model by adding and eliminating specific variables to investigate the influence of diverse actors on environmental deterioration. The extended STIRPAT model is used in a study to generate empirical evidence of the relationship between FLFP and CO2 emissions. The climate is found to have a multiplier or diminutive effect on factor influences:

$$I = P*A*T \qquad (1)$$

Here, **I** stand for environmental effect, **P** for population, **A** for affluence, and T for the influence of technology. Taking into account a stochastic form such as the STIRPAT model expands the applicability of the IPAT model.

$$I_i = \alpha_i P_i^b A_i^c T_i^d \varepsilon_i \qquad (2)$$

The subscript **i** denotes the cross-sectional unit (i.e., nation or separate). The constant is **α**, the parameters that need to be valued are **b**, **c**, and **d**, and the error term is $\boldsymbol{\varepsilon}_i$. When the equation above is rewritten in log-linear form, the valued parameters can be considered appropriate elasticities.

Also, Bekhet & Othman (2017) Converting all the data into logarithms is necessary to reduce the possible existence of autocorrelation and heteroscedasticity. Moreover, the log-linear model offers more reliable results than the simple model by reducing the sharpness of the data (Shahbaz, 2013).The calculated parameters can be considered the corresponding elasticities for the equation above in log-linear form (Liu et al., 2022).

$$L\,I_i = La_i + bLP_i + cLA_i + dLT_i + L\varepsilon_i \qquad (3)$$

In practical terms, **I** have typically considered CO2 or GHG emissions. However, researchers are still isolating other control factors from ε_i.

STIRPAT is a research program that studies the connections between human systems and the ecosystems they rely on. The STIRPAT model allows for the inclusion of new factors and identifies the most responsive reasons for the policy. It is widely used to study CO2 emissions (Wu et al., 2021). It also has a log-linear form that is adaptable to different studies. This study extends the STIRPAT model to meet specific research requirements.

Table 1: Summary of panel studies used Extended STIRPAT models with CO_2 as a dependent variable.

Study	Panel	Period	Variables and Results				
			Population (P)	Affluence (A)	Technology (T)	Extended Variables	Estimation Tools
Aguir Bargaoui et al. (2014)	Global and seven regionals	1980 to 2010	total population (+)	GDP per capita (+)	energy efficiency (+)	Urbanization (+), Kyoto Protocol (-)	fixed-effects
Wu et al., (2021)	18 economies	2005 to 2016	+	+	Energy intensity (+)	Renewable energy share (-), Industrial structure (+) Fossil CO2 intensity (+)	fixed-effects, Granger causality
Liddle (2015)	Global, OECD and Non-OECD	1971 to 2011	+	+	Industry energy intensity (+)	share of non-fossil fuels in primary energy (-)	CMG, AMG
Lin et al. (2017)	All non-high-income, Upper middle-income, Lower middle-income	1991 to 2013	+	+	energy efficiency (+)	Labor Productivity (-) Urbanization level (+) Urban employment level (+/-) Industrialization level (+/-) intensity of real added (+/-) economy CO2 emission intensity (+)	fixed-effects, Random Effect
Fan et al. (2006)	High, Upper-middle, Lower-middle and Low Income+ World +China	1975 to 2000	+	+	Energy use per constant 1995 PPP$ GDP (+)	Urbanization (+), the population aged 15–64 Emissions (+/-)	PLS
Koçak & Ulucak, (2019)	19 high-income OECD countries	2003 to 2015	Ln Urban (+)	+	Ln Indust (+)	Energy efficiency R&D (+) Fossil fuel R&D (+) Renewable energy R&D Nuclear energy R&D Other power and storage R&D (+)	GMM
Lohwasser et al., (2020)	84 countries	1980 to 2014	+	+	(-)	Urban (+), Working (+)	fixed-effects
Liu & Xiao (2018)	30 provinces in China	2000 to 2012	+	+	+	energy structure (-) industrial structure (+/-) total fixed investment (+/-)	SUR
Ghazali & Ali, (2019)	10 NIC	1991 to 2013	+	+	+	CO2 emission intensity (+) Trade Openness (+) UEL (-) Productivity of labor (-)	DCCE

Khan et al. (2021)	South Asian countries	1985 to 2016	Urban population (+)	Trade % of GDP (+)		population ages 15–64 (+) Industry value added (-)	D&K, FMOLS
Sadorsky (2014)	16 emerging countries	1971 to 2009	+	+	+	Urban (+/-)	MG, CCEMG, AMG, PCSE
Martínez-Zarzoso & Maruotti, (2011)	88 developing countries	1975 to 2003	+	+	(-)	industrial activity (+) population age 65 + (+) population (14 and 64) (+) population density (+)	FE, CLSDV, GMM
Li et al., (2018)	30 provinces of China	1999 to 2014	+	+	+	population aging (+) Urban (+) per capita consumption (+) the industrial structure in China (+)	FGLS
Zhang & Zhao (2019)	30 provinces in China	1996 to 2015	+	+	RD (-)	URB (+) ES (+) ECL (+/-) SL (-)	SYS-GMM FE, RE Pooled OLS
Y. Liu et al., (2022)	30 provinces in China	2000 to 2018	Urbanization level (-)	Per capita Disposable income (+)	Scientific and technological innovation level Computing (-)	Industrial structure (+) Average family size (-)	panel quantile

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Table 1 summarizes the previous panel studies on CO2 emissions using the extended STIRPAT model. The findings of those studies highlighted the impact of explanatory variables. Although few studies have examined the impact of labor force participation on CO2 emissions, they are limited to a few countries.

2.2 Specifications of the Empirical Model

We developed an empirical model based on the expanded STIRPAT model with gender-specific labor force participation rates to analyze the influence of FLFP on carbon emissions at various DD stages.

$$CO2 = f(POP, GDP, ENG, FLPFR, MLFPR) \tag{4}$$

$$Co2 = \beta_0 POP^{\beta_1} GDP^{\beta_2} ENG^{\beta_3} FLFPR^{\beta_4} MLFPR^{\beta_5} \varepsilon \tag{5}$$

After applying logarithms, the empirical models of this study are specified as follows:

$$\mathrm{LCO2_{it}} = \mathrm{L}\beta_0 + \beta_1 \mathrm{LPOP_{it}} + \beta_2 \mathrm{LGDP_{it}} + \beta_3 \mathrm{LENG_{it}} + \beta_4 \mathrm{LFLFPR_{it}} + \beta_5 \mathrm{LMLFPR_{it}} + \mathrm{L}\varepsilon_{\mathrm{it}} \tag{6}$$

$$\mathrm{LCO2_{it}} = \mathrm{L}\beta_0 + \beta_1 \mathrm{LPOP_{it}} + \beta_2 \mathrm{LGDP_{it}} + \beta_3 \mathrm{LENG_{it}} + \beta_4 \mathrm{LFLFPR_{it}} + \beta_5 \mathrm{LMLFPR_{it}} + \beta_6 \mathrm{LFLFPR^2_{it}} + \mathrm{Ln}\varepsilon_{\mathrm{it}} \tag{7}$$

In models (6) and (7), β_1, β_2, β_3, $\beta_{4,}$, β_5 and β_6d reflect the elasticity relations between the independent variable and dependent variables. Every 1% change in LPOP, LGDP, LENG, LFLFPR, LMLFPR, and $LFLFPR^2$ leads to a β_1, β_2, β_3, $\beta_{4,}$, β_5 or β_6 Change in environmental impact.

2.3 Data sources

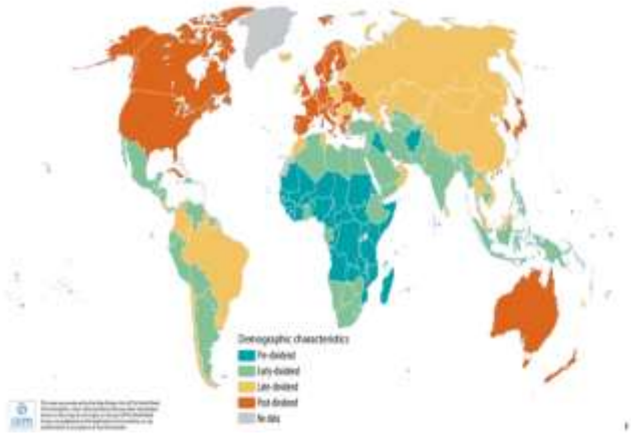
For our investigation, we collected secondary data from reliable databases. To represent the environmental impact in the STIRPAT model, we used per capita CO2 emissions (CO2) data in kilograms from the World Bank's World Development Indicators database. We utilized per capita GDP (in constant 2015 U.S. dollars) (GDP) and mid-year total population (POP) data from the same source to represent affluence and population within the model. For the technology variable, we employed data on energy use (per capita 2020) (ENG) in kilowatt-hours from the BP & Shift Data Portal (2022). Additionally, we included the Female Labor Force Participation Rate

(FLFPR) and Male Labour Force Participation Rate (MLFPR) variables from the World Development Indicators database as extended variables in the STIRPAT model. Table 1 of the supplementary materials describes each variable and its data source.

2.4 Classification of the study panels.

Ahmed et al. (2016) developed a global classification of countries based on demographic features, using R. D. Lee & Mason's (2006) The concept of the first DD as a starting point. Countries are classified as pre-, early, late, and post-DD. Based on this, 191 global countries were classified into four stages of DDs in the World Bank's open database. Figure 1 depicts a visual representation of the classification described above of countries.

Figure 1: The world through the lens of the demographic typology



Source: Global Monitoring Report 2015/2015, www.worldbank.org/gmr

According to the above classification, 37 countries are in the pre-DD stage, while 62, 54, and 38 are in the Early, Late, and post-DD stages. Considering data availability, the study focuses on 118 countries for the Global Panel and 20-41-29-28 countries for the Pre, Early, Late, and Post DD country panels from 1990 to 2019. A list of selected countries for each DD panel is presented in Table 2 of the supplementary materials,

2.5 Descriptive Statistics of Study Variables

The descriptive statistics in logarithms indicate (see Table 2) an upward trend in CO2, GDP, and ENG across the DD stages. The average FLFPR remains low and varies throughout all dividend stages, whereas the MLFPR remains stable. The correlation (refer to Table 3 in the supplementary materials) between population size and carbon emissions fluctuates across the different dividend stages. The standard deviation of CO2 emissions is high in all stages, while the standard deviation of MLFPR is low. Additionally, the standard deviation of GDP and ENG is lower in the later stages.

Table 2: Descriptive statistics

Pre-Dividend Panel					
Variable	Obs	Mean	Std. Dev.	Min	Max
LCO2	600	2.322	0.499	1.309	3.744
LPOP	600	7.034	0.398	5.98	7.763
LGDP	600	2.926	0.299	2.31	3.715
LENG	600	3.08	0.422	2.166	4.32
LFLFPR	600	1.74	0.212	.929	1.963
LMLFPR	600	1.883	0.047	1.766	1.965
Early-Dividend Panel					
LCO2	1230	3.062	0.532	1.398	4.402
LPOP	1230	7.041	0.847	4.978	9.136
LGDP	1230	3.455	0.405	2.264	4.366
LENG	1230	3.775	0.525	2.463	5.227

LFLFPR	1230	1.636	0.214	.797	1.952
LMLFPR	1230	1.894	0.054	1.689	1.98
Late-Dividend Panel					
LCO2	870	3.517	0.426	2.346	4.502
LPOP	870	6.96	0.819	5.413	9.149
LGDP	870	3.771	0.437	2.769	4.876
LENG	870	4.239	0.418	3.045	5.337
LFLFPR	870	1.721	0.121	1.364	1.902
LMLFPR	870	1.903	0.028	1.817	1.979
Post-Dividend Panel					
LCO2	840	3.899	0.2	3.271	4.482
LPOP	840	7.079	0.709	5.417	8.516
LGDP	840	4.431	0.368	3.12	5.051
LENG	840	4.672	0.224	3.944	5.242
LFLFPR	840	1.796	0.078	1.512	1.913
LMLFPR	840	1.9	0.025	1.822	1.959
Global Panel					
LCO2	3540	3.247	0.686	1.309	4.502
LPOP	3540	7.029	0.75	4.978	9.149
LGDP	3540	3.674	0.633	2.264	5.051
LENG	3540	3.984	0.68	2.166	5.337
LFLFPR	3540	1.713	0.18	.797	1.963
LMLFPR	3540	1.896	0.042	1.689	1.98

Authors calculations

3. Estimation strategy

This study follows a panel data analysis procedure to account for heterogeneity, cross-sectional dependence, and autocorrelation issues to ensure more reliable results. This panel study applies pretests such as slope homogeneity tests, cross-sectional dependence (CD) tests, CADF and CIPS unit root tests, and error-correction-based panel cointegration tests. The panel estimation methods include Driscoll and Kraay standard errors for coefficients appraised by pooled OLS and Newey-West standard errors for OLS regression for linear cross-sectional time series models—the Dumitrescu-Hurlin Panel individual causality estimation test to identify causal relationships.

3.1 Slope Homogeneity Tests

Swamy (1970) Developed the framework to find if the slope coefficients of the cointegration equation are homogeneous. Hashem Pesaran & Yamagata (2008) improved Swamy's slope homogeneity test and formed two "**delta**" test statistics; $\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$.

$$\tilde{\Delta}= \sqrt{N}\left(\frac{N^{-1}\,\bar{S}-k}{\sqrt{2k}}\right)\sim X_k^2 \quad (8)$$

$$\tilde{\Delta}_{adj}= \sqrt{N}\left(\frac{N^{-1}\,\bar{S}-k}{v\,\sqrt{Tk}}\right)\sim N(0,1) \quad (9)$$

N represents the number of cross-section units, S represents the Swamy test statistic, and k represents independent variables. The standard delta test requires errors not to be autocorrelated. However, a Heteroscedasticity and Autocorrelation Consistent (HAC) robust version of the slope homogeneity test has been developed to relax the assumptions of homoscedasticity and serial independence. If the p-value of the test is less than 5%, the cointegrating coefficients are considered non-homogenous. Increment$\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$ are fit for large and small samples, respectively, where $\tilde{\Delta}_{adj}$ is the "mean-variance bias adjusted" version of $\Delta\tilde{}$. Therefore, the delta test ($\tilde{\Delta}$) does not want the error autocorrelated. Hashem Pesaran & Yamagata (2008) and Blomquist

& Westerlund (2013) developed a Heteroscedasticity and Autocorrelation Consistent (HAC) robust version of the slope homogeneity test By soothing the assumptions of homoscedasticity and serial independence ; Δ_{HAC} and $(\Delta_{HAC})_{adj}$:

$$\Delta_{HAC} = \sqrt{N}\left(\frac{N^{-1}\bar{S}_{HAC}-k}{\sqrt{2k}}\right) \sim X_k^2 \quad (10)$$

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\bar{S}_{HAC}-k}{v\sqrt{Tk}}\right) \sim N(0,1) \quad (11)$$

3.2 Cross-sectional dependence tests

Cross-sectional dependence commonly exists in panel data because the countries are interlinked at the regional and global levels. If studies do not control for the cross-sectional dependence, the estimators will be inconsistent and biased (Peter C. Phillips and Donggyu Sul, 2003). Therefore, examining the cross-sectional dependence in the panel data is essential.

In doing so, this study uses three different tests to detect cross-sectional dependency among the selected variables. N. Bailey, G. Kapetanios (2015) along with Bailey et al. (2019), Chudik & Pesaran (2015), and Pesaran (2004) CD tests are estimated to examine the presence of cross-sectional dependence in residuals of the estimable model.

The following equation of the Bailey, Kapetanios, and Pesaran Cross-Sectional Dependence test is used to examine the study variables:

$$CD_{BKP} = \sqrt{\frac{TN(N-1)}{2}\,\hat{\bar{\rho}}N} \quad (12)$$

Also, the following equation of the CD test is used for examining the cross-sectional dependence suggested by Pesaran (2004):

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\rho_{ij}\right) \quad (13)$$

Where N represents the sample size, T indicates the period, and ρ_{ij} It shows the estimate of the cross-sectional correlation of errors in countries *i* and *j*.

3.3 Panel unit root tests

The first-generation unit root results are ineffective in cross-sectional dependence (Dogan & Seker, 2016)Therefore, this study employs the augmented cross-sectional IPS (CIPS) and augmented cross-sectional ADF (CADF) approaches to investigate the variables' stationarity properties. Moreover, the reliability of the results increases when suitable unit root tests are used, with cross-sectional dependence within panel data. Pesaran (2007) suggested the following equation of the IPS cross-section augmented version to test the unit root:

$$\Delta x_{it} = \alpha_{it} + \beta x_{it-1} + \rho_i T + \sum_{j=1}^{n}\theta_{ij}\,\Delta x_{i,t-j} + \varepsilon_{it} \quad (14)$$

Where Δ represents the difference operator, x_{it} Shows the analyzed variable, α is an individual intercept, T denotes the time trend in the data, and ε_{it} is the error term. The Schwarz information criterion (SIC) method determines the lag length. For both tests, the null hypothesis is that all individuals are not stationary within time series panel data, and the alternative hypothesis is that at least one individual is stationary within time series panel data.

3.4 Panel Cointegration Test

This study uses the Westerlund cointegration test to observe long-run equilibrium among model variables. Westerlund (2007) Suggests four basic panel cointegration tests to explore the alternative hypothesis of cointegration for the entire panel or at least one cross-sectional unit. The null hypothesis of this technique is "there is no error correction," and if rejected, there is proof of cointegration. The significance of the error correction term is examined using a restricted panel error correction model, and the p-values generated by the bootstrapping are robust against cross-sectional dependence.

Westerlund considers the following error correction model:

$$\Delta Y_{it} = \delta_i' d_t + \alpha_i Y_{i,t-1} + \lambda_i' X_{i,t-1} + \sum_{j=1}^{pi} \alpha_{ij} \Delta Y_{i,t-1} + \sum_{j=-qi}^{pi} \gamma_{i,j} \Delta X_{i,t-1} + \varepsilon_{it} \quad (15)$$

Where *i* represents the cross-sections, t represents observations, d_t refers to the deterministic components and computes the convergence speed to the equilibrium state after an unexpected shock.

3.5 Panel long-run estimation method

Efficient and robust estimation with due care of autocorrelation, heteroscedasticity, and cross-sectional dependence is necessary because, with their presence, the standard fixed effect model may not generate unbiased and efficient outcomes. Wang et al. (2021) emphasized that the existence of cross-sectional dependence makes the estimated results from conventional methods such as FMOLS and DOLS no longer accurate or unreliable. Therefore, we use Driscoll & Kraay's (1998) standard error technique following the methodology of Wang et al. (2021) to estimate long-run coefficients in this study as the studies of Kongbuamai et al. (2020), Baloch et al. (2019); Hashemizadeh et al. (2021) and Rahman & Alam, (2022). This sophisticated method addresses all the problems of autocorrelation, heteroscedasticity, and cross-sectional dependence in the estimated model. Compared to many other methods, Driscoll & Kraay's (1998) standard error technique provides various additional benefits: firstly, this can be adopted in the case of unbalanced panel data; secondly, this approach can be used in the case of missing values of the dataset; thirdly, it is a non-parametric procedure having flexible features and greater time dimension; finally, and most importantly, this approach can accurately cure about heteroscedasticity, autocorrelation, and cross-sectional dependence issues (Hoechle (2007); Rahman & Alam (2022); Wang et al. (2021); Kongbuamai et al. (2020); Baloch et al. (2019)).

After the estimation of Driscoll and Kraay's (1998) standard error technique, the robustness of the findings is to be checked through another well-known panel standard error estimating technique. The Newey-West standard errors regression (Newey & West, 2010) performs according to the methodology of Wang et al. (2021), and the model also addresses the issues of autocorrelation, heteroscedasticity, and cross-sectional dependence in the models efficiently and effectively.

3.6 Dumitrescu and Hurlin panel causality test

Dumitrescu & Hurlin (2012) proposed a modified version of the Granger causality test known as the heterogeneous panel Granger non-causality test, which accounts for heterogeneity. This test is adaptable for both T > N and T < N, and it takes unobserved heterogeneity in data into account, utilizing the Vector Autoregressive (VAR) framework on stationary data. Furthermore, it conducts separate regressions for each cross-section to ascertain causal relationships among variables.

4. Empirical results and discussion

In the Pesaran and Yamagata slope homogeneity test, the null hypothesis posited that slope coefficients are homogeneous. Delta estimates (Table 4, Supplementary Materials) were significant across all panels at the 1% level. Heterogeneity was identified among sample countries, prompting this study to utilise appropriate panel techniques to address the issue of heterogeneity.

Three tests were performed to ascertain cross-sectional dependence among the studied variables. The results (Table 5, Supplementary Materials) presented substantial evidence of cross-sectional dependence for most panels. The variables LCO2, LPOP, LGDP, LENG, LFLFPR, and LMLFPR exhibited interdependence globally across all demographic dividend stages. Consequently, a cross-sectional dependency problem arises within the study panels.

The second-generation CADF and CIPS panel unit root tests suit data exhibiting heterogeneity and cross-sectional dependency issues. As the results in Table 6 of the supplementary materials indicate, the variables LCO2, LPOP, LGDP, LENG, LFLFPR, and LMLFPR are non-stationary at their levels but stationary at the first difference. In other words, all variables in this study are integrated at level 1 across all study panels.

Table 3 presents the findings of the Westerlund cointegration test for two models: the linear model featuring only the main effects and the nonlinear model incorporating LFMLFPR2. The results suggest that the Gt and Pt statistics null hypothesis in both the linear and nonlinear models is rejected at the 1% significance level (based on a robust p-value). Therefore, we have evidence to conclude that cointegration exists for at least one of the cross-section units in both models.

Table 3: Results of the Westerlund (2007) cointegration test.

Ho: No cointegration

Pre-Dividend Panel				
Statistic		Linear Model		Nonlinear Model
	Value	Z-Value	Value	Z-Value
Gt	-4.097^{a}	-8.345	-4.401^{a}	-8.655
Ga	-3.276	4.920	-2.087	6.310
Pt	-12.786^{a}	-3.577	-13.156^{a}	-3.058
Pa	-3.809	2.375	-2.017	4.081
				Early-Dividend Panel
Gt	-3.235^{a}	-6.522	-3.507^{a}	-6.781
Ga	-5.519	5.174	-4.088	7.499
Pt	-16.275^{a}	-3.460	-18.558^{a}	-4.145
Pa	-4.408	2.918	-3.645	4.652
				Late-Dividend Panel
Gt	-3.097^{a}	-4.756	-3.301^{a}	-4.619
Ga	-6.933	3.360	-7.627	4.022
Pt	-11.390	-1.029	-14.864^{a}	-2.863
Pa	-5.764	1.536	-6.775	1.988
				Post-Dividend Panel
Gt	-2.759^{a}	-2.914	-3.326^{a}	-4.669
Ga	-6.942	3.295	-7.355	4.125
Pt	-11.565^{c}	-1.316	-9.817	1.199
Pa	-4.852	2.115	-4.707	3.203
				Global Panel
Gt	-3.234^{a}	-11.057	-3.565^{a}	-12.124
Ga	-7.135	6.491	-6.772	9.227
Pt	-29.696^{a}	-7.575	-30.646^{a}	-6.331
Pa	-6.717	1.796	-5.972	5.006

"a "p<.01, "b "p<.05, "c "p<.1

Authors calculations

Table 4: Driscoll-Kraay standard errors estimate.

Dependent Variable - LCO2			Linear Model							Nonlinear Model
Panel	Pre	Early	Late	Post	Global	Pre	Early	Late	Post	Global
Independent Variables	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
LPOP	-0.078^{b}	0.059^{a}	0.077^{a}	0.043^{a}	0.051^{a}	-0.118^{a}	0.058^{a}	0.045^{a}	$.028^{a}$	0.053^{a}
LGDP	0.648^{a}	0.292^{a}	0.136^{a}	0.061^{b}	0.108^{a}	0.806^{a}	0.287^{a}	0.159^{a}	0.067^{b}	0.108^{a}
LENG	0.639^{a}	0.731^{a}	0.885^{a}	0.603^{a}	0.888^{a}	0.538^{a}	0.727^{a}	0.881^{a}	0.574^{a}	0.886^{a}
LFLFPR	-0.140^{a}	-0.172^{a}	-0.068^{c}	-0.297^{a}	-0.208^{a}	-3.894^{a}	0.312^{b}	-10.856^{a}	12.818^{a}	0.393^{b}
$LFLFPR^2$						1.244^{a}	-0.163^{a}	3.269^{a}	-3.762^{a}	-0.194^{a}
LMLFPR	-1.200^{a}	-0.650^{a}	-1.495^{a}	-0.606^{b}	-0.985^{a}	-2.009^{a}	-0.627^{a}	-1.677^{a}	-0.133	-0.949^{a}
Cons	1.513^{a}	0.388^{a}	1.680^{a}	2.192^{a}	1.176^{a}	5.873^{a}	0.032	11.015^{a}	-9.884^{a}	0.647^{a}
Num of obs	600	1230	870	840	3540	600	1230	870	840	3540
Num of groups	20	41	29	28	118	20	41	29	28	118

F (5, 29)	11467.39	12415.46	18154.15	929.17	42935.22	13359.56	11469.66	16304.11	3177.40	57044.01
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R-squared	0.9026	0.9201	0.8947	0.5164	0.9443	0.9169	0.9204	0.9108	0.5337	0.9445
Root MSE	0.1565	0.1507	0.1388	0.1394	0.1619	0.1447	0.1505	0.1278	0.1370	0.1617

"a "p<.01, "b "p<.05, "c "p<.1

Authors calculations

The estimates of the Driscoll-Kraay standard error regression are presented in Table 4 under two parts: the linear and nonlinear models. The findings of the linear model can be highlighted as follows:

➢ The findings indicate a significant relationship between total population (LPOP) and CO2 emissions (LCO2) across all study panels. The elasticities are -7.8%, 5.9%, 7.7%, and 4.4% during the pre-, early, late, and post-dividend stages. This finding is consistent with recent studies that have observed a positive relationship between population and CO2 emissions in most countries, while noting a negative relationship in some countries. Also, The findings of Holdren (1971), Dietz & Rosa (1997), Shi (2003), Zhu & Peng (2012), Liddle, (2014), Yang et al. (2015), Yeh & Liao (2017a)), Yeh & Liao, (2017b), Sulaiman & Abdul-Rahim, (2018), Ghazali & Ali, (2019), Lohwasser et al., (2020) highlight that the population increases carbon emissions. Nevertheless, our findings confirm that population reduces carbon emissions per capita in countries at the pre-demographic dividend stage.

➢ The per capita GDP of a country is positively correlated with its per capita CO2 emissions across all study panels. The effect of per capita GDP on CO2 emissions is statistically significant at the 5% level. Furthermore, the research revealed that the elasticities between GDP and CO2 emissions are 64.8%, 29.2%, 13.6%, and 6.1% during the pre-, early, late, and post-DD stages, highlighting the importance of considering a country's demographic stage when evaluating the relationship between GDP and carbon dioxide emissions. The conclusions of Aguir Bargaoui et al. (2014), Yeh & Liao (2017b), Koçak & Ulucak (2019), Lohwasser et al. (2020), Wu et al. (2021) Conform to the findings.

➢ Energy usage has a significant positive impact on CO2 emissions, as supported by the conclusions of Zaman & Moemen (2017), Fan et al. (2006), Rahman & Kashem (2017), and X. P. Zhang & Cheng (2009). Burning non-renewable energy sources like coal, oil, and natural gas releases carbon dioxide (Ahmad et al., 2016) and other greenhouse gases into the air, contributing to climate change. However, renewable energy sources like solar, wind, hydro, and geothermal reduce CO2 emissions. (Anwar et al. (2022); Zafar et al. (2020); Cai et al. (2018)). The study found that the elasticities between ENG and CO2 emissions are 63.9%, 73.1%, 88.5%, and 60.3% at the pre-, early, late, and post-DD stages. These values highlight the increasing pattern of the Impact of ENG use on CO2 emissions at the pre-, early, and late DD stages and go down at the post-DD stage.

➢ According to the linear model estimates, increasing the FLFPR by 1 unit reduces CO2 emissions by 0.14, 0.172, 0.07, and 0.30 at the pre-, early, late, and post-DD stages, respectively. The findings of numerous studies on countries and regions confirm our results. Wang (2023) determined that a 1 unit increase in the ratio of FLFPR is associated with a 0.30 per cent decrease in CO2 emissions per capita based on panel data from 16 European countries in the post-demographic dividend stage, covering the years 2000 to 2016. Also, according to the findings of Quz Zaman et al. (2021), S. Zaman et al. (2022), S. Zaman et al. (2022b), Khan (2023), Mehmood (2022), Bilgili et al. (2022), the increase of FLFPR would significantly reduce carbon emissions in China, Pakistan, South Asian countries, and Asian countries, respectively. Identifying how FLFP reduces CO2 emissions is crucial. Previous studies suggest the following factors are significant:

- In 2016, the Energy (73.2%), Agriculture, Forestry, and Land Use (18.4%), Cement and Chemical Industries (5.2%), and Waste (3.2%) sectors accounted for global GHG emissions, with 78% derived from carbon emissions)(Gosh, 2020). FLFP can manage these sectors and reduce emissions, especially since fossil fuels are the primary carbon emitters. Burke & Dundas (2015) employing national-level longitudinal data for up to 175 countries between 1990 and 2010 demonstrated that female labor force participation (FLFP) is linked to reductions in household biomass energy use and can affect the decision to adopt biogas technology. Also, the study of Yasmin & Grundmann (2020) showed that older, educated, financially empowered women with more excellent agency and resource control strongly influenced the decision to adopt biogas technology.

- Mujeed et al. (2021) shows that technological innovations and renewable energy consumption positively impact women's autonomy within China's sustainable development agenda. As the International Labor Organization states, women's employment in renewable energy can also mitigate climate change by encouraging renewable energy utilization and decreasing fossil fuel dependence. (Policy Brief, 2015).
- The behavior of female workers can influence the reduction of carbon emissions. Women are predominant in several professions known as "pink-collar fields," such as teaching and nursing. In developing nations, women are also engaged in labor-intensive tasks. This approach can decrease carbon emissions and energy consumption.
- Population growth leads to more carbon emissions (Dodson et al. (2020), O'Neill et al. (2012)). When women join the workforce, they tend to have fewer children, which reduces population growth and subsequently reduces carbon emissions.
- Women's empowerment is crucial in today's world. Increasing FLFP is a global strategy to empower women. Research shows that gender equality and women's empowerment positively impact the environment (Bilgili et al., (2022b), including using renewable energy, reducing deforestation, and better water management. Studies also indicate that nations with higher political status for women have lower CO2 emissions per capita (Ergas & York., 2012).
- Moreover, companies with women in senior management are more inclined to adopt environmentally friendly practices and invest in renewable energy (Noland & Kotschwar, 2016). Women also advocate for policies such as investing in clean energy, regulating carbon emissions, and safeguarding natural resources (Warner & Corley, 2017). Enhancing FLFP empowers women in multiple ways and significantly impacts the economy, liberal arts, and environmental footprint. According to Khan (2023), independent women have more education and work experience, which reduces carbon output.

➢ The male labour force participation rate significantly negatively affects carbon emissions across all dividend stages and globally. An increase of 1% in the MLFPR results in reductions of CO2 emissions by -1.2%, -0.65%, -1.5%, and -0.61% at the pre-, early, late, and post-DD stages, respectively. According to the linear model estimates, the MLFPR demonstrates the most substantial negative impact on carbon emissions. Especially at pre and late stages, elasticity is more than one. But, according to Bilgili et al. (2022), the male labor force in the agricultural and industrial sectors can increase CO2 emissions.

In the pre-demographic dividend stage, the linear model accounts for 90% of the variation in CO2 emissions. GDP and ENG contribute to increasing CO2 emissions, whereas POP, FLFPR, and MLFPR lead to a reduction in CO2 emissions. At the early DD stage, the linear model explains 92% of the total variation in CO2 emissions; among the independent variables, POP, GDP, and ENG enhance the impact on CO2 emissions, while FLFPR and MLFPR decrease them. The linear model accounts for 89% of the total variation in CO2 emissions and reveals the same impact patterns at the late demographic stage. However, the linear model accounts for only 52% of CO2 emissions at the post-dividend stage. The linear model describes 94% of global CO2 emissions. The estimates from the nonlinear model employing Driscoll-Kraay standard errors regression are presented in Table 11, highlighting that:

➢ The nonlinear model illustrates the dynamic impact of FLFPR at each DD stage. At the Pre, Early, Late, and Post DD stages, FLFPR exhibits a U-shape, Inverse U-shape, U-shape, and Inverse U-shape impact on CO2 emissions, respectively. Globally, it shows an Inverse U-shape impact on CO2 emissions. According to the estimates, the coefficients of LFLFPR and LFLFPR2 are -3.894 and 1.244, 0.312 and -0.163, -10.856 and 3.269, and 12.818 and -3.762 at the pre, early, late, and post DD stages, respectively. Moreover, the impact of FLFPR is the highest among all study variables.

The results of the Driscoll-Kraay standard errors regression for the global panel estimate in Table 11, along with the estimates from both linear and nonlinear models, yield the following findings:

➢ According to the linear model, the elasticities of POP, GDP, ENG, FLFPR, and MLFPR are 5.1%, 10.8%, 88.8%, -20.8%, and 98.5%, respectively. Furthermore, the linear model's estimated elasticities for POP, GDP, ENG, and MLFPR are nearly identical. The estimates for LFLFPR and LFLFPR^2 are 39.3% and -19.4%, respectively.

MLFPR is the most significant factor influencing global CO_2 emissions, while FLFPR exhibits an inverse-U shape dynamic impact on CO_2 emissions.

Table 7 of the supplementary materials presents the estimates of the linear and nonlinear models using Newey-West standard error regression to verify the robustness of the Driscoll-Kraay standard error regression estimates. The estimated coefficient values are identical to those of the Driscoll-Kraay standard error regression; however, the coefficients' t-statistics are significantly higher than those of the Driscoll-Kraay standard error regression estimates. According to the Newey-West Standard Errors Estimates, all explanatory variables of the linear and nonlinear models are significant at the 1% level.

Table 5 illustrates the analysis of the Dumitrescu-Hurlin panel non-causality test. Our empirical findings demonstrate a bidirectional causality between population and per capita CO_2 emissions across all study panels. Per capita GDP exhibits bidirectional causality with per capita CO_2 emissions, except the post-dividend panel, indicating unidirectional causality from GDP to CO_2 emissions at the post-DD stage. Across all study panels, per capita energy use shows bidirectional causality with carbon emissions. The female labour force participation rate (FLFPR) exhibits bidirectional causality with CO_2 emissions at all demographic stages and globally.

Moreover, there is evidence of bidirectional causality relationships between male labor force participation and carbon emissions. Additionally, at the four demographic dividend stages and globally, the population shows bidirectional Granger causality with GDP, energy use (ENG), FLFPR, and male labor force participation rate (MLFPR) at a 1% significance level. GDP exhibits a bidirectional causal relationship with ENG, FLFPR, and MLFPR. Energy usage shows a bidirectional causal relationship with male and female labor force participation. Highlighting an interdependency between gender-based labor force participation rates, FLFPR demonstrates bidirectional causality with MLFPR. These results corroborate the findings from the Driscoll-Kraay standard error estimates.

Table 5: Dumitrescu Hurlin panel causality test results

Causality	Panel				
	Pre-Dividend	Early-Dividend	Late-Dividend	Post-Dividend	Global
	W-Stat.	W-Stat.	W-Stat.	W-Stat.	W-Stat.
LPOP → LCO2	5.91036[a]	6.46207[a]	7.68674[a]	7.22888[a]	6.85149[a]
LCO2 → LPOP	16.3182[a]	12.7717[a]	19.3645[a]	6.73612[a]	13.5609[a]
LGDP → LCO2	5.04130[a]	5.43070[a]	8.40192[a]	5.37466[a]	6.08162[a]
LCO2 → LGDP	4.06628[a]	3.44782[a]	7.67570[a]	2.05123	4.26031[a]
LENG → LCO2	2.84040[a]	3.74435[a]	4.58303[a]	4.76041[a]	4.03835[a]
LCO2 → LENG	3.28207[a]	3.55188[a]	5.18437[a]	3.99834[a]	4.01330[a]
LFLFPR → LCO2	4.99507[a]	5.02108[a]	5.26136[a]	3.61452[a]	4.74196[a]
LCO2 → LFLFPR	2.30829[a]	3.62920[a]	3.04853[a]	3.95420[a]	3.33973[a]
LMLFPR → LCO2	4.72436[a]	3.17272[a]	3.86854[a]	3.09305[b]	3.58781[a]
LCO2 → LMLFPR	3.48231[a]	3.92440[a]	4.26767[a]	4.90802[a]	4.16723[a]
LGDP → LPOP	14.0715[a]	24.8025[a]	22.1136[a]	11.9727[a]	19.2785[a]
LPOP → LGDP	8.61941[a]	6.69086[a]	8.92700[a]	4.72481[a]	7.10077[a]
LENG → LPOP	9.07943[a]	17.2033[a]	12.6827[a]	7.26536[a]	12.3572[a]
LPOP → LENG	6.40412[a]	6.12195[a]	7.12084[a]	6.38943[a]	6.47873[a]
LFLFPR → LPOP	30.4652[a]	23.6234[a]	7.23363[a]	5.54287[a]	16.4647[a]
LPOP → LFLFPR	7.15568[a]	6.18820[a]	5.46381[a]	6.83721[a]	6.32815[a]
LMLFPR → LPOP	25.0918[a]	17.2919[a]	8.97930[a]	7.60309[a]	14.2720[a]
LPOP → LMLFPR	5.84980[a]	6.85748[a]	6.82739[a]	6.25515[a]	6.53637[a]
LENG → LGDP	3.08842[a]	4.30724[a]	6.69898[a]	2.68196	4.30280[a]
LGDP → LENG	6.18147[a]	4.47700[a]	6.47053[a]	6.68370[a]	5.77945[a]
LFLFPR → LGDP	5.32654[a]	4.93106[a]	5.07400[a]	3.62696[a]	4.72377[a]
LGDP → LFLFPR	6.98918[a]	4.40772[a]	4.24196[a]	6.41768[a]	5.28146[a]
LMLFPR → LGDP	3.37131[a]	4.51786[a]	5.50511[a]	2.72171	4.13995[a]
LGDP → LMLFPR	5.49906[a]	6.79916[a]	8.20976[a]	5.90422[a]	6.71312[a]
LFLFPR → LENG	6.04307[a]	3.21631[a]	4.54856[a]	4.06339[a]	4.22384[a]
LENG → LFLFPR	3.63703[a]	4.15946[a]	3.64879[a]	4.70409[a]	4.07464[a]

LMLFPR → LENG	5.71592[a]	3.01438[a]	3.91250[a]	3.42137[a]	3.78957[a]
LENG → LMLFPR	3.24057[a]	3.26970[a]	4.56685[a]	4.67761[a]	3.91763[a]
LMLFPR → LFLFPR	5.63254[a]	6.23604[a]	7.40343[a]	6.07181[a]	6.38168[a]
LFLFPR → LMLFPR	5.34725[a]	4.55737[a]	4.99423[a]	4.80429[a]	4.85720[a]

"a "p<.01, "b "p<.05, "c "p<.1

Authors calculations

5. Conclusions and Policy Recommendations

Population growth contributes to rising CO2 emissions globally and at all development (DD) stages except pre-DD. GDP and energy generation (ENG) also elevate carbon emissions globally and at every DD stage. Conversely, the female labor force participation rate (FLFPR) diminishes CO2 emissions globally and at all DD stages. The connection between FLFPR and CO2 emissions exhibits a U-shape in pre- and late-DD stages, an inverse U-shape globally, and early- and post-dividend stages. The male labor force participation rate (MLFPR) similarly reduces carbon emissions across all DD stages. The estimations are applicable for policy development, as evidenced by the Westerlund cointegration test. The Dumitrescu-Hurlin panel non-causality test verifies long-run stability and bidirectional causality among the study variables in all panels.

Countries must formulate strategies to manage optimal population size in the long term, considering the DD stage and population transition process. FLFP lowers fertility rates and curtails population growth, decreasing carbon emissions. Policies that promote low-carbon lifestyles and sustainable practices are essential for reducing emissions. Education on lowering carbon emissions, incentives for sustainable behaviors, carbon tax implementation, and sustainable urban planning policies can aid in achieving these goals.

GDP influences CO2 emissions differently across various demographic phases. The EKC hypothesis predicts a long-term balance between environmental protection and economic growth. Research on national carbon emissions and GDP per capita supports this hypothesis. FLFP enhances GDP, while FLFPR may lower carbon emissions by fostering economic growth. Policies to reduce CO2 emissions should focus on sustainable business practices, industrial emission regulations, green transport and urban planning, and sustainable consumption and production patterns.

According to a study, reducing individual energy usage can significantly decrease carbon emissions, so policies should be implemented to lower energy consumption. There are three energy mixes: fossil fuels, renewable/atomic energy, and a combination. Fossil fuels are the primary source of carbon emissions, whereas renewable/nuclear energy is regarded as clean. FLFP can empower women's socioeconomic status and promote the adoption of cleaner energy sources and technologies, ultimately reducing carbon emissions. Increased investment in renewable energy sources such as solar, wind, and hydropower may be achieved through financial incentives and government research. A comprehensive strategy to reduce carbon dioxide emissions must include boosting investment in renewable energy, implementing energy efficiency measures, and establishing financial incentives for businesses and individuals to lower their energy consumption.

Enhancing FLFPR is essential for reaping the benefits of FLFP while minimizing environmental impacts. Policymakers should identify the DD stage to promote FLFP while managing adverse effects such as increased commuting, air pollution, reduced home gardening and child-rearing time. FLFP can decrease CO2 emissions by influencing women's behavior, adopting eco-friendly practices, and bolstering employment. Optimizing FLFPR aids in achieving sustainable economic, societal, and environmental development goals. However, it is necessary to overcome institutional and cultural barriers to attain higher FLFPR.

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Supplementary Materials

Table 1: Study variables and data sources

Label	Variable	Definition	Unit	Source
CO2	Carbon dioxide emission (per capita)	Carbon dioxide emissions are those stemming from the burning of fossil fuels and the manufacture of cement.	Metric tons	WDI (12/22/2022)
POP	Total mid-year population	The total population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship. The values shown are midyear estimates.	count	WDI (12/22/2022)
GDP	Gross Domestic Product (per capita)	Gross domestic product divided by midyear population	Constant 2015 US$	WDI (12/22/2022)
ENG	Energy use (per capita2020)	Energy use refers to primary energy before transformation to other end-use fuels.	kWh	Our World in Data based on B.P. & Shift Data Portal (2022)

FLFPR	Female Labor Force Participation Rate	The female labor force participation rate is % of the female population ages 15-64. (Modeled ILO estimate)	%	WDI ((12/22/2022)
MLFPR	Male Labor Force Participation Rate (% of male population ages 15-64) (modeled ILO estimate)	The male labor force participation rate is % of the male population ages 15-64. (Modeled ILO estimate)	%	WDI ((12/22/2022)

Created by the Autor

Table 2: List of countries selected for the study panels.

Table 2.1: List of 20 selected countries for the pre-demographic dividend panel.

Benin	Cote d'Ivoire	Mauritania	Sudan
Burundi	Gambia, The	Mozambique	Tanzania
Cameroon	Iraq	Niger	Togo
Central African Republic	Kenya	Senegal	Uganda
Congo, Rep.	Malawi	Sierra Leone	Zambia

Source: Created by the author based on the WDI (2022), https://data.worldbank.org/country/V1.

Table 2.2: List of 41 selected countries for the early-demographic dividend panel.

Argentina	Eswatini	Lao PDR	Paraguay
Bahrain	Gabon	Lesotho	Peru
Bangladesh	Ghana	Mexico	Philippines
Belize	Guatemala	Myanmar	Rwanda
Bolivia	Haiti	Namibia	Samoa
Botswana	Honduras	Nepal	Saudi Arabia
Dominican Republic	India	Nicaragua	South Africa
Ecuador	Indonesia	Pakistan	Tonga
Egypt, Arab Rep.	Iran, Islamic Rep.	Panama	Türkiye
El Salvador	Jordan	Papua New Guinea	Yemen, Rep.
			Zimbabwe

Source: Created by the author based on the WDI (2022), https://data.worldbank.org/country/early-demographic-dividend

Table 2.3: List of 29 selected countries for the late-demographic dividend panel.

Albania	Fiji	Morocco	Uruguay
Armenia	Guyana	Poland	Vietnam
Brazil	Ireland	Romania	
Brunei Darussalam	Jamaica	Russian Federation	
Chile	Kazakhstan	Sri Lanka	
China	Kyrgyz Republic	Thailand	
Colombia	Malaysia	Trinidad and Tobago	
Costa Rica	Mauritius	Tunisia	

Source: Created by the author based on the WDI (2022), https://data.worldbank.org/country/late-demographic-dividend

Table 2.4: List of 28 selected countries for the post-demographic dividend panel.

Australia	Denmark	Korea, Rep.	Singapore
Austria	Finland	Luxembourg	Spain

Barbados	France	Malta	Sweden
Belgium	Germany	Netherlands	Switzerland
Bulgaria	Greece	New Zealand	Ukraine
Cuba	Italy	Norway	United Kingdom
Czech Republic	Japan	Portugal	United States

Source: Created by the author based on the WDI (2022), https://data.worldbank.org/country/post-demographic-dividend

Table 3: Pairwise correlation

Correlation Probability	LCO2	LPOP	LGDP	LENG	LFLFPR	LMLFPR
Pre-Dividend Panel						
LCO2	1.000000					

LPOP	0.066639	1.000000				
	0.1029	-----				
LGDP	0.871034	0.204641	1.000000			
	0.0000	0.0000	-----			
LENG	0.904200	0.162207	0.805542	1.000000		
	0.0000	0.0001	0.0000	-----		
LFLFPR	-0.692389	-0.038151	-0.643808	-0.642367	1.000000	
	0.0000	0.3509	0.0000	0.0000	-----	
LMLFPR	-0.337747	0.352996	-0.190232	-0.199692	0.334394	1.000000
	0.0000	0.0000	0.0000	0.0000	0.0000	-----
Early-dividend Panel						
LCO2	1.000000					

LPOP	-0.013562	1.000000				
	0.6347	-----				
LGDP	0.891049	-0.212315	1.000000			
	0.0000	0.0000	-----			
LENG	0.947960	-0.069757	0.909811	1.000000		
	0.0000	0.0144	0.0000	-----		
LFLFPR	-0.412103	-0.208551	-0.254548	-0.351235	1.000000	
	0.0000	0.0000	0.0000	0.0000	-----	
LMLFPR	-0.168758	0.375284	-0.227125	-0.102413	0.203709	1.000000
	0.0000	0.0000	0.0000	0.0003	0.0000	-----
Late-Dividend Panel						
LCO2	1.000000					

LPOP	-0.088424	1.000000				
	0.0091	-----				
LGDP	0.721194	-0.260005	1.000000			
	0.0000	0.0000	-----			
LENG	0.934095	-0.203120	0.745840	1.000000		
	0.0000	0.0000	0.0000	-----		
LFLFPR	0.221149	0.258870	0.071407	0.229395	1.000000	
	0.0000	0.0000	0.0352	0.0000	-----	

LMLFPR	-0.009393[-]	0.186879	0.255588	0.032705[-]	0.067502	1.000000
	0.7820	0.0000	0.0000	0.3353	0.0465	-----
Post-Dividend Panel						
LCO2	1.000000					

LPOP	0.122908	1.000000				
	0.0004	-----				
LGDP	0.466154	-0.049833[-]	1.000000			
	0.0000	0.1490	-----			
LENG	0.689307	-0.033168[-]	0.656869	1.000000		
	0.0000	0.3370	0.0000	-----		
LFLFPR	0.120402	0.073885[-]	0.376794	0.316497	1.000000	
	0.0005	0.0323	0.0000	0.0000	-----	
LMLFPR	0.079265	-0.101699	0.510680	0.236530	0.411386	1.000000
	0.0216	0.0032	0.0000	0.0000	0.0000	-----
Global Panel						
CO2	1.000000					

LPOP	-0.003192[-]	1.000000				
	0.8494	-----				
LGDP	0.885995	-0.086781	1.000000			
	0.0000	0.0000	-----			
LENG	0.966684	-0.043501	0.907622	1.000000		
	0.0000	0.0096	0.0000	-----		
LFLFPR	-0.093030	-0.043242	0.055530	-0.031673[-]	1.000000	
	0.0000	0.0101	0.0009	0.0595	-----	
LMLFPR	0.006458[-]	0.241690	0.086012	0.064798	0.225700	1.000000
	0.7009	0.0000	0.0000	0.0001	0.0000	-----

All estimated correlation coefficients are significant at 5% except the values indicated in the "- "sign

Authors Calculations

Table 4: Results of the slope homogeneity tests.

Test Statistic	**Pre-Dividend Panel**	**Early-Dividend Panel**	**Late-Dividend Panel**	**Post-Dividend Panel**	**Global Panel**
$\bar{\Delta}$	21.195[a]	28.639[a]	23.274[a]	24.284[a]	50.404[a]
$\bar{\Delta}_{adj}$	24.206[a]	32.708[a]	26.581[a]	27.734[a]	57.565[a]
Δ_{HAC}	23.259[a]	21.684[a]	39.803[a]	25.072[a]	57.091[a]
$(\Delta_{HAC})_{adj}$	26.563[a]	24.765[a]	45.458[a]	28.634[a]	65.202[a]

H_0: slope coefficients are homogenous. [a] represents statistical significance at 1%.

$\bar{\Delta}$ and $\bar{\Delta}$adj represent the "simple" and "mean-variance bias adjusted" slope homogeneity tests, respectively (Pesaran, Yamagata. 2008. Journal of Econometrics).

Δ_{HAC} and $(\Delta_{HAC})_{adj}$ represent the "Heteroscedasticity and Autocorrelation Consistent" versions of "simple" and "mean-variance bias adjusted" slope homogeneity tests, respectively (Blomquist, Westerlund. 2013. Economic Letters).

"a "p<.01, "b "p<.05, "c "p<.1

Authors Calculations

Table 5: Cross-sectional dependence test

variable	Pre-Dividend	Early-Dividend	Late-Dividend	Post-Dividend	Global
Exponent estimation test - Estimation of cross-sectional exponent (alpha) 0.5 <= alpha < 1 implies solid cross-sectional dependence.					
LCO2	0.752	1.004	0.884	0.971	0.830
LPOP	1.006	1.005	1.005	1.005	1.004
LGDP	0.989	0.991	0.995	1.005	0.998
LENG	0.723	0.991	0.909	0.963	0.878
LFLFPR	0.428	0.965	0.914	1.005	0.971
LMLFPR	0.854	0.973	0.817	0.885	0.952
Pesaran's (2015) test for weak cross-sectional dependence test - H0: errors are weakly cross-sectional dependent.					
LCO2	21.787^{a}	62.623^{a}	15.741^{a}	42.211^{a}	40.421^{a}
LPOP	74.928^{a}	153.226^{a}	42.862^{a}	63.095^{a}	330.290^{a}
LGDP	24.960^{a}	97.913^{a}	69.977^{a}	90.420^{a}	274.364^{a}
LENG	12.524^{a}	66.021^{a}	22.543^{a}	25.467^{a}	61.156^{a}
LFLFPR	-0.801	15.422^{a}	7.946^{a}	51.404^{a}	49.213^{a}
LMLFPR	25.050^{a}	43.472^{a}	19.826^{a}	4.929^{a}	72.172^{a}
Pesaran's (2004) cross-sectional dependence (CD)test					
LCO2	21.790^{a}	62.620^{a}	15.740^{a}	42.210^{a}	40.420^{a}
LPOP	74.930^{a}	153.230^{a}	42.860^{a}	63.090^{a}	330.290^{a}
LGDP	24.960^{a}	97.910^{a}	69.980^{a}	90.420^{a}	274.360^{a}
LENG	12.520^{a}	66.020^{a}	22.540^{a}	25.470^{a}	61.160^{a}
LFLFPR	-0.800	15.420^{a}	7.950^{a}	51.400^{a}	49.210^{a}
LMLFPR	25.050^{a}	43.470^{a}	19.830^{a}	4.930^{a}	72.170^{a}

"a "p<.01, "b "p<.05, "c "p<.1

Authors Calculations

Table 6: Results of the CADF and CIPS panel unit root tests.

	Pre-Dividend Panel					**Early-Dividend Panel**				
Variable	**CADF**		**CIPS**			**CADF**		**CIPS**		
	Cons	**Trend**	**Cons**	**Trend**		**Cons**	**Trend**	**Cons**	**Trend**	
LCO2	-1.036	-2.509	-2.217^{c}	-2.805^{c}		-1.311	-1.817	-1.776	-2.038	
ΔLCO2	-3.859^{a}	-3.981^{a}	-5.289^{a}	-5.390^{a}	***I (1)***	-3.372^{a}	-3.673^{a}	-4.720^{a}	-4.888^{a}	***I (1)***
LPOP	-2.772^{a}	-1.719	-2.699^{a}	-1.994		-2.565^{a}	-2.447	-1.721	-1.874	
Δ LPOP	-4.197^{a}	-5.613^{a}	-1.976	-3.089^{a}	***I (1)***	-4.657^{a}	-4.904^{a}	-2.520^{a}	-3.264^{a}	***I (1)***
LGDP	-0.887	-1.902	-1.729	-2.142		-0.882	-2.291	-1.736	-2.174	
Δ LGDP	-3.184^{a}	-3.577^{a}	-4.440^{a}	-4.615^{a}	***I (1)***	-3.202^{a}	-3.353^{a}	-4.187^{a}	-4.387^{a}	***I (1)***
LENG	-0.594	-2.509	-1.970	-2.905^{b}		-0.558	-2.426	-1.963	-2.517	
Δ LENG	-4.034^{a}	-4.124^{a}	-5.328^{a}	-5.369^{a}	***I (1)***	-3.520^{a}	-3.549^{a}	-4.675^{a}	-4.821^{a}	***I (1)***
LFFPR	-0.920	-1.974	-1.318	-1.346		-1.383	-3.186	-2.027	-1.952	
Δ LFFPR	-2.128^{b}	-2.041	-2.229^{b}	-2.519	***I (1)***	2.827^{a}	-3.041^{a}	-3.629^{a}	-3.846^{a}	***I (1)***
LMLFPR	-0.300	-1.541	-0.359	-0.817		-1.419	-2.147	-1.246	-1.702	
Δ LMLFPR	-2.037^{c}	-1.263	-2.277^{b}	-2.336	***I (1)***	-2.816^{a}	-3.111^{a}	-3.471^{a}	-3.691^{a}	***I (1)***
	Late-Dividend Panel					**Post-Dividend Panel**				
LCO2	-2.039^{c}	-2405	-2.070	-2.337		-1.504	-2.489	-2.497^{a}	-3.092^{a}	
ΔLCO2	-3.424^{a}	-3.597^{a}	-4.458^{a}	-4.721^{a}	***I (1)***	-4.150^{a}	-4.322^{a}	-5.370^{a}	-5.609a	***I (1)***

LPOP	-1.376	-2.301	-1.778	-2.613[c]		-1.563	-1.555	-1.015	-1.023	
Δ LPOP	-3.348[a]	-4.283[a]	-2.191[b]	-2.975[a]	***I (1)***	-3.289[a]	-3.640[a]	-4.408[a]	-4.873[a]	***I (1)***
LGDP	-0.710	-2.480	-2.283[b]	-2.424		-1.212	-2.011	-2.306[a]	-2.581[c]	
Δ LGDP	-3.185[a]	-3.332[a]	-3.774[a]	-3.836[a]	***I (1)***	-3.192[a]	-3.370[a]	-3.899[a]	-3.995[a]	***I (1)***
LENG	-1.434	-2.086	-2.192[b]	-2.238		-0.659	-2.325	-1.993	-3.099[a]	
Δ LENG	-3.280[a]	-3.460[a]	-4.476[a]	-4.763[a]	***I (1)***	-4.107[a]	-4.199[a]	-5.118[a]	-5.396[a]	***I (1)***
LFFPR	-1.310	-1.892	-1.283	-1.412		-1.367	-1.852	-1.801	-1.756	
Δ LFFPR	-2.690[a]	-3.090[a]	-3.616[a]	-4.049[a]	***I (1)***	-3.102[a]	-3.439[a]	-4.409[a]	-4.735[a]	***I (1)***
LMLFPR	-0.886	-2.418	-1.550	-1.866		-1.318	-2.001	-1.856	-2.178	
Δ LMLFPR	-2.824[a]	-2.946[a]	-3.851[a]	-3.990[a]	***I (1)***	-3.186[a]	-3.421[a]	-4.543[a]	-4.720[a]	***I (1)***
	Global-Dividend Panel									
LCO2	-1.058	-2.242	-2.036[c]	-2.030						
ΔLCO2	-3.485[a]	-3.754[a]	-4.823[a]	-5.119[a]	***I (1)***					
LPOP	-2.160[a]	-2.212	-1.835	-2.079						
Δ LPOP	-3.425[a]	-4.326[a]	-2.183[a]	-2.678[a]	***I (1)***					
LGDP	-1.561	-2.207	-2.093[b]	-2.149						
Δ LGDP	-3.073[a]	-3.273[a]	-3.882[a]	-4.039[a]	***I (1)***					
LENG	-1.387	-2.074	-2.167[a]	2.343						
Δ LENG	-3.449[a]	-3.590[a]	-4.913[a]	-5.010[a]	***I (1)***					
LFFPR	-1..292	-2.025	-1.653	-1.704						
Δ LFFPR	-2.713[a]	-2.967[a]	-3.614[a]	-3.916[a]	***I (1)***					
LMLFPR	-1.910[b]	-2.178	-1.448	-1.783						
Δ LMLFPR	-2.837[a]	-3.030[a]	-3.611[a]	-3.842[a]	***I (1)***					

"a "p<.01, "b "p<.05, "c "p<.1

Authors Calculations

Table 7: Newey-West standard errors estimate.

Dependent Variable - LCO2	Linear Model					Nonlinear Model				
Panel	Pre	Early	Late	Post	Global	Pre	Early	Late	Post	Global
Independent Variables	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
LPOP	-0.078[a]	0.059[a]	0.077[a]	0.043[a]	0.051[a]	-0.118[a]	0.058[a]	0.045[a]	0.028[a]	0.053[a]
LGDP	0.648[a]	0.292[a]	0.136[a]	0.061[a]	0.108[a]	0.806[a]	0.287[a]	0.159[a]	0.067[a]	0.108[a]
LENG	0.639[a]	0.731[a]	0.885[a]	0.603[a]	0.888[a]	0.538[a]	0.727[a]	0.881[a]	0.574[a]	0.886[a]
LFLFPR	-0.140[a]	-0.172[a]	-0.068[b]	-0.297[a]	-0.208[a]	-3.894[a]	0.312[b]	-10.856[a]	12.818[a]	0.393[a]
$LFLFPR^2$						1.244[a]	-0.163[a]	3.269[a]	-3.762[a]	-0.194[a]
LMLFPR	-1.200[a]	-0.650[a]	-1.495[a]	-0.606[b]	-0.985[a]	-2.009[a]	-0.627[a]	-1.677[a]	-0.133	-0.949[a]
Cons	1.513[a]	0.388[b]	1.680[a]	2.192[a]	1.176[a]	5.873[a]	0.032	11.015[a]	-9.884[a]	0.647[a]
Num of obs	600	1230	870	840	3540	600	1230	870	840	3540
F-Stat	1234.092	4596.387	1904.990	155.085	12195.617	1662.221	3891.773	1746.500	126.393	10262.405
Prob > F	0.000	0.000	0.000	0.000	0.0000	0.000	0.000	0.000	0.000	0.0000

"a "p<.01, "b "p<.05, "c "p<.1

Authors Calculations

Table 8. Testing for Multicollinearity.

Panel	**Pre Dividend**		**Early Dividend**		**Late Dividend**		**Post Dividend**		**Global**	
Variable	**VIF**	**1/VIF**	**VIF**	**1/VIF**	**VIF**	**1/VIF**	**VIF**	**1/VIF**	**VIF**	**1/VIF**
LGDP	3.17	0.315	7.23	0.138	2.78	0.360	2.31	0.433	6.00	0.167
LENG	3.08	0.325	7.20	0.139	2.61	0.382	1.84	0.543	5.94	0.168
LMLFPR	1.99	0.502	1.38	0.723	1.26	0.793	1.54	0.649	1.14	0.877

LFLFPR	1.33	0.751	1.38	0.723	1.23	0.810	1.31	0.762	1.10	0.906
LPOP	1.25	0.798	1.38	0.726	1.19	0.839	1.03	0.972	1.09	0.915
Mean VIF	2.17		3.72		1.82		1.61		3.05	

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How to cite/reference this article: Chulan Lasantha Kukule Nawarathna, The Green Revolution: The Impact of Female Labor Force Participation on Carbon Dioxide Emissions Across the Global Demographic Dividend Stages, *Asian. Jour. Social. Scie. Mgmt. Tech*. 2025; 7(2): 105-129.