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Global energy efficiency transition tendencies: Development phenomenon or not?

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ABSTRACT

I assessed energy efficiency performance and investigated transition tendencies for economies at different development levels. I found that energy efficiency performance is tied to the level of economic development, with developed economies exhibiting higher performance than developing economies. Furthermore, developed economies are more likely than developing countries to transition out of a low energy-efficient (LEE) state. Consequently, achieving higher energy efficiency (HEE) status is expected to be highly sustainable in the short-, medium-, and long-term for developed countries. However, for similar achievements, I found moderate sustainability in the medium-to long-term for upper-middle-income countries and higher unsustainability in the medium-to long-term for lower-middle-income countries. Addressing the gap in the global energy efficiency system requires a 'big push' investment in energy efficiency, particularly in developing countries, in addition to implementing a broad policy overhaul aimed at eliminating or reducing market barriers and inefficiencies in energy efficiency.

1. Introduction

In an era of continuous threat from climate change events, governments and researchers agree on the need to design and implement climate mitigation and adaptation measures. As current energy use patterns reflect a higher share of fossil fuels, transitioning to low-carbon energy sources has emerged as a critical strategy to address today's climate change challenges. Not surprisingly, the United Nations Sustainable Development Goals identify universal access to clean energy sources and improvements in energy efficiency as developmental milestones for global economies. Energy efficiency enhancement – defined as increased energy service with less energy input - is one of the transitional paths that can guarantee the least cost reduction in carbon dioxide emissions [1]. Estimates reveal that energy efficiency improvements alone constitute 40 % of the global greenhouse gas emissions reduction potential that can be realized at 60 euros per metric ton of carbon dioxide equivalent [2]. A recent projection by the International Energy Agency [IEA] [3,4] also highlights that improvements in energy efficiency would be responsible for up to 40 % reduction in global greenhouse emissions in the next 20 years.

The low carbon associated with energy efficiency improvements stems from the fact that efficient use of energy leads to significant energy savings. The IEA [5] documents that between 2000 and 2015, improvements in energy efficiency saved 450 million tons of oil equivalent in IEA countries. Bogmans et al. [6], based on global data, found that energy efficiency improvements reduce energy demand by 1.2 % per year. The reduction in energy demand can ease demand congestion [7], expand infrastructure lifespan, and help expand access to energy services [8]. Aside from reducing physical capacity constraints, energy efficiency improvement reduces budget constraints. For energy users, energy saved through energy efficiency helps minimize energy expenditure [9,5]. It also reduces investment requirements in the energy sector [10,11]. These monetary gains from energy efficiency improvements connect to broader macroeconomic and social outcomes such as economic growth ([12,13]; [14], *inter alia*), employment [3,15,16], education, and health [9,17]. The multiple benefits inherently make it possible for energy efficiency to reduce the tension between economic growth goals and sustainable development commitments [8].

The links between energy efficiency and socioeconomic indicators can be guaranteed and strengthened if sustainable progress toward energy efficiency can be achieved in the medium to long term [18,19]. As noted by Adom, Amuakwa-Mensah, and Akorli [20], failure to realize a sustainable energy efficiency transition is a threat to Sustainable Development Goals (SDGs). However, achieving such fate is not a smooth process [21] as it can prove challenging and difficult [18]; reasons such as regulatory inefficiencies, poor infrastructure,

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inefficiency pricing, and undeveloped markets have been cited in the literature [18,19,21–25]. Previous and recent global crises have elucidated this fact. While global energy intensity improved (i.e., increase in energy efficiency) by 2.3 % in 2011/2016, it decreased to 1.8 % and 1.1 % in 2017 and 2018, respectively [3]. Though it bumped back in 2019 with a 2 % improvement, it fell to less than a 1 % improvement in 2020 and 2021 [3]. In 2022, there was an improvement of 2 % only for it to decline to 1.8 % in 2023 [26]. The financial and economic crises, COVID-19, and the Russia-Ukraine war have something in common: they increased investment uncertainty, delaying investment in energy-efficient technology, and thereby increasing the risk of 'lock-in' to low energy efficient technology paradigm. As noted by Adom [27], business cycle effects impact energy efficiency improvements. These facts indicate much deeper problems in attaining energy efficiency goals.

Investigating the energy efficiency transitional paths of economies in the short, medium, and long term could provide deeper insights into understanding the nature of the energy efficiency problem, which is critical for global strategies to achieve sustainable progress in energy efficiency. The current literature documents considerable evidence on the measurement of energy efficiency ([28–33], *inter alia*), techno-socio-economic-financial drivers of energy efficiency ([20,34,35], *inter alia*), and the welfare effects of energy efficiency ([9,12–15,36]; [3]; [16], *inter alia*). Few studies exist on energy efficiency transition tendencies, with a focus on either a particular country [19,21,22] or a region [18]. Global evidence is currently lacking. For example, both Adom [21] and Adom and Adams [22] considered the case of Cameroon and Nigeria, respectively, highlighting a situation of 'lock-in' low energy efficient state. Zhang and Adom [19] used provincial-level data to reveal the unsustainable nature of energy efficiency progress, highlighting provincial heterogeneities. Akorli and Adom [18] focused on African countries by considering transitional paths for total primary energy, electricity, and gasoline consumption. The authors indicate that African countries are 'lock-in' low energy-efficient states. Their results further reveal that improving regulatory efficiency and reducing corruption incidence can leapfrog African countries from the low-energy-efficient trap.

The current study builds on previous panel-level studies by Zhang and Adom [19] and Akorli and Adom [18] by extending the evidence of energy efficiency transition tendencies to include global-level data. The use of global-level data makes it possible to address differences in economic development, which may have implications for countries' transitional processes. The difference in the wealth gap between developed and developing economies strategically places advanced economies in a better position to make large investments in energy infrastructure, such as alternative energy sources and energy-efficient technologies. Furthermore, the wealth gap provides a collateral advantage to advanced economies, making it possible for such economies to secure favorable financial assistance that aids the financing of such transformative initiatives. There are studies connecting the level of development to technology adoption [37], energy demand [6,38], and levels of energy efficiency [34].

Wealth gap differences also manifest in areas such as regulatory and policy requirements, investment commitment, and institutional readiness. Understanding the wealth gap differences and their implications for the transitional tendencies of countries is key to unraveling the energy efficiency deficiency problem, which could aid in the design of a global adaptable energy efficiency program. Moreover, little to no 'low-hanging fruit' might exist in advanced economies as related to energy efficiency improvement, but the opposite is likely to be the case in developing economies [34]. In addition, the use of global data enhances the external validity of the results, which is not a guarantee in country- [21,22] and region-specific studies [18,19].

While I acknowledge the existence of similar global-level analyses of energy efficiency in the literature (see: [28,34,35]; *inter alia*), the current study is unique in the following ways. Beyond analyzing the global level measurement of energy efficiency, I estimate the energy efficiency transition tendencies for economies at different development pedestals for the short, medium, and long term.

Finally, I separate unobserved heterogeneity from transient and persistent energy efficiency, as recommended by Colombi et al. [39] and Kumbhakar et al. [40]. Delineating transient and persistent efficiency is particularly useful for directing policymakers into areas of energy efficiency that should receive policy attraction. Transient efficiency focuses on policies that change short-term behaviors, whereas persistent efficiency focuses on policies that change long-term behaviors. In this regard, the current study is comparable to the study by Liddle and Sadorsky [28], which estimated both transient and persistent energy consumption efficiency for OECD and non-OECD countries. Section 2 discusses the method and data. Section 3 presents the results of the study. Section 4 concludes the study with some policy implications.

2. Data and methods

2.1. Data

This study used unbalanced panel data consisting of 78 countries from 1960 to 2016. Specifically, the data variables include total final energy consumption in tonnes of oil equivalent, the average aggregate real economy-wide price index, and real GDP per capita (in 2010 US$ using PPPs). Data on total final energy consumption come from the IEA World Statistics. The economy-wide real price index is measured as the weighted average of end-use prices from residential, industry, and transport sectors, and this unique data is adopted from Liddle and Huntington [41]. Data on real GDP per capita come from the IEA World Statistics.

Based on the World Bank classification, the data are categorized into OECD-high income (37 countries) and non-OECD countries (41 countries). Further, the non-OECD country group is subdivided into Upper-Middle-Income (UMI) [23] and Lower-Middle-Income (LMI) [16] countries, following a similar World Bank classification. A significant share of the data observations from 1960 to the 1980s originate from OECD/high-income countries, but they become almost evenly split between high-income, UMI, and LMI countries from 1990 to 2016.

2.2. Estimation of energy efficiency

The empirical model for estimating energy consumption efficiency is derived from the theoretical descriptions of Kopp's [42] non-radial input technical efficiency and Filippini and Hunt's [43] stochastic input demand function.[1] I estimate a stochastic energy demand frontier in a manner that mimics the theoretical description of Filippini and Hunt, which is based on a non-radial input efficiency measure. Equation (1) shows the stochastic energy demand frontier, where e_{it}^{d} denotes the total final energy consumption of country 'i' at time 't', $f(X_{it}:\beta)e^{\epsilon_{it}}$ denotes the benchmark/optimal energy input use required to produce energy services, $e^{-s\mu_{it}}$ denotes the margin of deviation from the benchmark or normative energy use level, f denotes the frontier function, X_{it} is a vector of independent variables influencing energy consumption, β is a vector of frontier parameters, ϵ_{it} denotes the two-sided noise term assumed to be normally distributed, and μ_{it} denotes the one-sided inefficiency term assumed to be half-normal in this study.

$$e_{it}^{d} = f(X_{it}:\beta)e^{\epsilon_{it}} * e^{-s\mu_{it}} \tag{1}$$

$$s = \begin{cases} 1 & production \\ -1 & cost \end{cases} \tag{2}$$

[1] In non-radial measure, each of the input/output can change independently, making it a suitable general framework that accounts for non-radial slacks, which if ignored can bias the estimate of technical efficiency.

In this study, I used the skewness test by Coelli [44], which is superior to the Schmidt and Lin [45] test, to determine whether a cost or production frontier should be estimated. The least squares residuals are negatively skewed (i.e., −0.5279) and the Coelli negative skewness test produces a statistic of −5.882, which indicates rejection of the null of no negative skewness. Consequently, I estimate the production function.

The inefficiency term could result from either short- or long-term moral hazards. Therefore, Colombi et al. [46], Kumbhakar et al. [40], and Filippini and Hunt [47] recommend separating short-run technical energy consumption efficiency (transient efficiency) from long-run technical energy consumption efficiency (persistent efficiency). This separation has practical utility. First, it reveals the main sources of inefficiency, which in the second case helps direct policymakers to make informed energy efficiency policy decisions. Based on the revelation, the government may be advised to design an energy efficiency policy to target either influencing short-run behaviors (i.e., real-time pricing, changing appliance use behaviors, and social norms) or long-run behaviors (i.e., improving the regulatory setting, incentivizing the purchase of energy-efficient technologies, and changing appliance use habits). Equation (3) is the resultant equation when I perform a log transformation of (1) and consider the concerns of transient (τ_{it}) and persistent energy consumption efficiency (ρ_i).

$$ln\ e_{it}^{d} = lnf(X_{it} : \beta) + \epsilon_{it} - (\tau_{it} + \rho_i) \tag{3}$$

The time-invariant component of inefficiency (i.e., persistent) can detect unobserved heterogeneity and treat it as an inefficiency term. This introduces bias in the estimation of the persistent component of inefficiency [40,46,48]. Therefore, it is recommended to separate such unobserved heterogeneity from persistent inefficiency. In this study, I follow the multistage procedure of Kumbhakar et al. [40], which decomposes the error component into four components (i.e., country latent heterogeneity [δ_i], persistent inefficiency [ρ_i], transient inefficiency [τ_{it}], and the two-sided noise term [ϵ_{it}]) and estimates them using a maximum likelihood estimator with distributional assumptions defined for all components. I then follow Jondrow et al. [49] approach to derive energy consumption efficiency (see Equation (5)), where e_{it}^{f} is the benchmark energy consumption, e_{it}^{a} is the actual energy consumption, EE_{it}^{t} is the transient efficiency, and EE_{i}^{p} is persistent efficiency.

$$ln\ e_{it}^{d} = lnf(X_{it} : \beta) + \epsilon_{it} - (\tau_{it} + \rho_i + \delta_i) \tag{4}$$

$$OEE_{it} = \frac{e_{it}^{f}}{e_{it}^{a}} = exp - (\tau_{it} + \rho_i) = EE_{it}^{t} * EE_{i}^{p} \tag{5}$$

There are some practical things to consider before estimating equation (4). First, are the components of the X vector. There is significant variability across empirical studies, which could be informed by the fact that energy consumption has multiple connections with various aspects of the social economy (see Ref. [30,31,33]; [20,38,50], *inter alia*). Reasons such as data availability, context relevance, and research questions account for this variability. Consistent across these studies, whether with a micro- or macro-level focus, is the influence of price and income, which derive their basis from the neoclassical demand theory. In this study, for reasons of simplicity and comparability, and to retain the data information level, I include the aggregate real price of energy, real income per capita, and a trend term in the X vector in the baseline model. The trend term captures the underlying energy demand trend and social and economic innovation (see Ref. [31]; [29], [6], *inter alia*).

The second consideration is the identification of the nature of the energy demand frontier. This is crucial because the wrong identification of the functional form of the energy demand frontier would introduce bias in the frontier and hence the identification of the (in) efficiency term. Following previous studies [20,28,51], I conducted a likelihood ratio test for a Cobb-Douglas production function versus a translog production function. The likelihood ratio statistic is 392.24 with a p-value of 0.000, supporting the claim that the Cobb-Douglas function is nested within the translog function and, hence, the superiority of the translog function over the Cobb-Douglas function. The Akaike and Bayesian Information Criteria also recommend the translog function as the appropriate model. Therefore, I estimate the translog form of Equation (4), which is Equation (6), with the Cobb-Douglas function providing the base regression. Beyond the statistical justification, the translog function is preferred in most cases because of its flexibility and the lack of a priori imposition of technological constraints [52]. Moreover, the flexible nature of the translog function makes it more robust to omitted variable bias than the Cobb-Douglas function.

$$\begin{aligned} ln\ e_{it}^{d} = {} & \alpha + \beta_1\ ln\ y_{it} + \beta_2\ ln\ pe_{it} + \beta_3\ ln\ t_{it} + 0.5 * \beta_4\ ln\ y_{it} * ln\ pe_{it} + 0.5 \\ & * \beta_5\ ln\ y_{it} * ln\ t_{it} + 0.5 * \beta_6\ ln\ pe_{it} * ln\ t_{it} + 0.5 * \beta_7\ ln\ y_{it}^2 + 0.5 \\ & * \beta_8\ ln\ pe_{it}^2 + 0.5 * \beta_9\ ln\ t_{it}^2 + \epsilon_{it} - (\tau_{it} + \rho_i + \delta_i) \end{aligned} \tag{6}$$

However, there are some practical challenges with estimating a translog function. One major challenge with the translog function is the problem of deriving a meaningful interpretation of the coefficients, which is aggravated by the inclusion of more arguments. The trick is to keep it simple and realistic, which guided the choice of independent variables in this study. In this context, the argument about whether energy consumption reflects development patterns [53–57] - popularly referred to as the Energy-Kuznet curve—is a testable claim in empirical literature (see: [6,38,58]). The level and square terms of income in the translog function in Eq. (6) mimic the Energy-Kuznet curve. There is a case for the nonlinear or changing slope nature of energy prices on energy consumption [59,55,60,61]. This is captured by the level and square terms of price in the translog function. There is also evidence of income-price interaction [20]. Raising the price of energy can reduce the positive effect of income on energy consumption, particularly in low-income countries, where energy poverty is high and expenditure on energy could be 10 % or higher of their income. Finally, the interaction between the trend term, price, and income signifies the parallel movement of technology amidst income growth and energy price inflation. Due to the efficiency requirements of technological advancement, technology is expected to either reduce or increase the price and income effects. Thus, by estimating the translog form, model identification improves, as omitted variable bias mimicking nonlinearity in income and price effects and interactive effects can now be addressed.

Second, the independent variables may suffer from perfect collinearity, which can bias coefficient estimates. While some multicollinearity is inevitable with observational data, it becomes problematic when severe. I tested for multicollinearity using the variance inflation factors (VIF) in the translog energy demand frontier estimation. The mean VIF is 5.3, below the threshold of 10, and no individual VIF meets or exceeds 10, ruling out significant multicollinearity.

Finally, I address another source of heterogeneity bias due to the level of economic development. In this study, I use income or level of development as the differentiating factor to group countries into high OECD, Upper Middle-Income, and Low Middle-Income countries. To some extent, this could also help address possible heterogeneity bias in production technology (see: [62,63]). Later, I conducted some robustness checks on the results.

2.3. Estimation of energy efficiency transition (EET) tendencies

Next, I conceptualize energy efficiency as a state that economies can achieve, following the studies of Adom [21], Adom and Adams [22], Zhang and Adom [19], and Akorli and Adom [18]. I model the probabilistic behavior of transitioning between high and low energy-efficient states, as described in the aforementioned studies, for different future periods. High energy-efficient (HEE) states represent scenarios close to or at the benchmark situation, while low energy-efficient (LEE) states represent the opposite.

Given the known energy-efficient state at time t, I predict the future state of energy efficiency in the first, fifth, tenth, fifteenth, and twentieth years, conditioned on covariate effects such as real GDP per capita, the real price of energy, and time/year-specific effects. Understanding the persistent nature of these states is critical, as it has implications for the robustness of energy efficiency systems governed by policies and programs.

Previous studies have identified several factors that can trap economies in low energy-efficient states, including poor or lack of maintenance culture, behavioral dynamics, inefficient pricing, regulatory inefficiencies, corruption, suboptimal investment, changing conventions and standards, asset depreciation, and poorly developed markets [18,19,21,22].

Fig. 1, adapted from Zhang and Adom [19], depicts the modeled behavior trend, where the vertical axis denotes the level of energy efficiency and the horizontal axis reflects the time dynamics. For any defined time t, there is observed information about the ith country's energy efficiency performance, which can be on the frontier (like point A in the figure) or further away from the frontier (like point B in the figure). The arrows in the figure show the possible transition paths given the defined states at time t. The future evolution of states for each country and the timing of changes are uncertain and governed by a set of transition intensities, which depend on time or, more generally, individual-specific and time-varying explanatory variables [64].

The objective is to estimate the transition intensity matrix, assuming a Markov chain distribution, which posits that the future evolution of behaviors depends only on the current state [65,66]. Suppose there are n states of energy efficiency. Equation (7) describes the conditional probability, where S_n^{ob} is the energy-efficient state observed at time t_n and S_{n-1}^{ob} denotes the observed energy-efficient state at time t_{n-1}. The corresponding likelihood function for a time-homogeneous case is derived as the product of the conditional probabilities in Equation (8), where $D_{ij,n}$ denotes the total number of countries in the sample observed in state S_i at time t_{n-1} and in state S_j at time t_n.

$$P_{S_{n-1},S_n} = P_r\left(Z_{t,n} = S_n^{ob} \middle| Z_{t,n-1} = S_{n-1}^{ob}\right) \tag{7}$$

$$L(\theta) = \prod_{n=1}^{M} \left\{ \prod_{i,j=1}^{K} P_{ij}(t_{n-1}, t_n)^{D_{ij,n}} \right\} \tag{8}$$

Next, I allow the transition probabilities to be time-dependent (T_n) and control for the effects of income, price, and year-fixed effects (X_n). I then adopt Kalbfleisch and Lawless's [65] quasi-Newton method and the maximum likelihood estimator to estimate the log-likelihood function (i.e., equation (9)).

$$Log\ L(\varnothing) = \sum_{n=1}^{N} \sum_{i=1}^{M} \sum_{j=1}^{K} D_{ij,n}\ Log\ P_{ij}(T_n, X_n) \tag{9}$$

In estimating Equation (9), there are some practical empirical issues to consider. First is the choice of the number of states, which, if not correctly chosen, results in model misspecification and biased estimates of model parameters. For ease of interpretation, I restrict the experiments to two and three states: the former consists of high and low energy-efficient states, and the latter denotes high, medium/moderate, and low energy-efficient states.

The next empirical consideration is the choice between time-homogeneous and time-inhomogeneous Markov panel models. The time-homogeneous model imposes a constant transition matrix, while the time-inhomogeneous model relaxes this assumption. Finally, it is important to test the Markov model with covariates against the model without covariates. To do this, I employ model selection criteria, such as the Akaike Information Criterion (AIC), and the likelihood ratio test to choose the model that best fits the data.

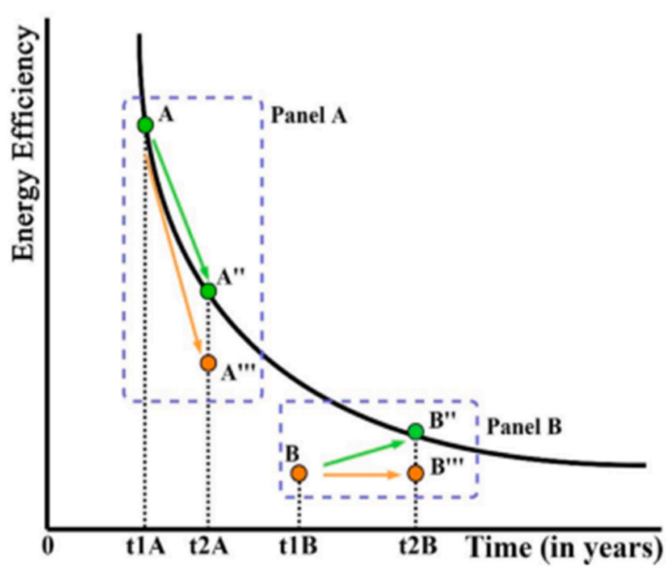


Fig. 1. Energy efficiency transition dynamics.
(Adapted from Ref. [19])

3. Results and discussion

3.1. Frontier determinants

Table 1 presents the frontier determinants for both the global and income-based samples across various functional forms, namely, translog (TRLG) and Cobb-Douglas (CBD). Because the likelihood ratio test favored a TRLG over CBD function, the discussion is limited to the translog function, with the CBD providing the base results. The level income effect is positive, less than unity, and statistically significant across the different samples and functional forms, which is consistent with previous global and regional-specific studies such as Liddle and Huntington [41] and Liddle et al. [67]. According to the estimates, increasing the level of real income by 10 % is associated with 6.1 %, 4.58 %, 7.86 %, and 6.61 % increases in energy consumption for the global, OECD, UMI, and LMI samples, other things being equal. In the study by Liddle and Huntington [41], the authors found that the income effect for UMI and LMI is around 0.7, which is confirmed by Liddle et al. [67]. The square term of income is negative in the global and OECD cases, but statistically significant only in the latter case. In the case of UMI and LMI, the square term is positive and statistically significant, indicating a monotonic effect of income in these economies. This finding corroborates those of Bogmans et al. [6], who found that income has an inverted U-shaped effect in developed economies, but the effect is monotonic in less developed economies.

The level price effect is negative, less than unity, and statistically significant for the global, OECD, UMI, and LMI samples across all functional forms. According to the estimates, an increase in the real price of energy by 10 % is associated with a 1.3 %, 2.14 %, 0.65 %, and 2.25 % reduction in energy consumption for the global, OECD, UMI, and LMI samples. While Liddle and Hungtinton [41] confirm the negative effects of price on energy consumption in different modeling scenarios, Liddle et al. [67] find the negative price elasticity to be insignificant in the case of Middle-Income countries. The square term of price is positive and statistically significant for the OECD case and negative and statistically significant for the LMI case, implying a U-shaped effect and monotonic effect of price for the OECD and LMI samples, respectively. The evidence of the U-shaped effect of price and the inverted U-shaped effect of income found for the OECD is confirmed in Fouquet [55]. In a long-term view of the evolution of income and price elasticities, Fouquet [55] revealed that as economies develop and the price of energy services falls, income elasticities generally follow an inverse U-shaped curve, and price elasticities generally follow a U-shaped curve.

Table 1
Estimation of Frontier determinants and efficiency scores based on KLH approach.

Variables	Global		OECD_high		UMI		LMI	
	TRL	CBD	TRLG	CBD	TRLG	CBD	TRLG	CBD
$ln\ y_{it}$	0.610***	0.578***	0.458***	0.581***	0.786***	0.537**	0.661***	0.517***
	(0.0202)	(0.0156)	(0.0298)	(0.0207)	(0.0472)	(0.033)	(0.0429)	(0.0296)
$ln\ pe_{it}$	−0.137***	−0.211***	−0.214***	−0.441***	−0.065***	−0.051***	−0.225***	−0.187**
	(0.0134)	(0.0117)	(0.0214)	(0.0197)	(0.0203)	(0.0170)	(0.0256)	(0.0181)
$ln\ t_{it}$	−0.019	0.065***	0.015	0.086***	0.244***	0.282***	−0.124***	0.065**
	(0.0159)	(0.0090)	(0.0206)	(0.0107)	(0.0449)	(0.0368)	(0.0390)	(0.0272)
$0.5 * ln\ y_{it} * ln\ pe_{it}$	0.166***		0.374***		−0.153		−0.003	
	(0.0286)		(0.0672)		(0.1030)		(0.0886)	
$0.5 * ln\ y_{it} * ln\ t_{it}$	−0.287***		−0.297***		−1.057***		−0.879***	
	(0.0267)		(0.0391)		(0.1840)		(0.1610)	
$0.5 * ln\ pe_{it} * ln\ t_{it}$	0.131***		−0.095**		0.005		−0.137	
	(0.0342)		(0.0456)		(0.1080)		(0.1210)	
$0.5 * ln\ y_{it}^2$	−0.023		−0.283***		0.530***		0.469***	
	(0.0189)		(0.0386)		(0.0825)		(0.0818)	
$0.5 * ln\ pe_{it}^2$	−0.034		0.153*		0.036		−0.109**	
	(0.0239)		(0.0819)		(0.0293)		(0.0439)	
$0.5 * ln\ t_{it}^2$	−0.064***		0.003		−0.204		0.601***	
	(0.0099)		(0.0133)		(0.1740)		(0.1620)	
Constant	0.435***	0.395***	0.951***	0.894***	−0.261***	−0.272***	−1.042***	−1.028***
	(0.0080)	(0.0043)	(0.0053)	(0.0040)	(0.0152)	(0.0125)	(0.0158)	(0.0110)
sigma_u	0.5123	0.5127	0.4108	0.3844	0.2701	0.2876	0.2877	0.2615
sigma_e	0.1485	0.1596	0.1335	0.1564	0.1367	0.1466	0.1006	0.1072
R-square	0.689	0.640	0.783	0.701	0.728	0.684	0.711	0.667
Obs	2,749	2,749	1,600	1,600	630	630	470	470
Id	78	78	37	37	23	23	16	16
Mean Efficiency scores								
OE	0.8877	0.8670	0.9087	0.7066	0.8882	0.9100	0.7209	0.7223
TE	0.8980	0.8772	0.9115	0.8814	0.9135	0.9981	0.9392	0.9262
PE	0.9885	0.9883	0.9969	0.8016	0.9536	0.9118	0.7675	0.7796

Note: Standard errors are in parentheses. ***, **, and * denote significance levels at the 1 %, 5 %, and 10 % levels, respectively. OE, TE, and PE denote overall efficiency, technical efficiency, and persistent efficiency. TRLG and CBD denote translog and Cobb Douglass functions.

The interaction between income and price is positive and statistically significant in the global and OECD sample, but negative and statistically insignificant in the UMI and LMI. In advanced economies, the increase in price relative to the change in income is expected to be very small. Consequently, raising the price in such an economy is less likely to reduce the positive income effect on energy consumption. However, in less developed economies, where energy poverty is high, raising the price of energy is expected to reduce the positive income effect on energy consumption.

The interaction between income and the trend term is negative and statistically significant, implying that irrespective of the economy, the parallel movement of economic growth and technological advancement is not energy consuming. However, the interaction between price and trend term is not straightforward. While the evidence suggests that technology reduces the negative price effect for the global sample, it reinforces this negative price effect for the OECD-high sample, other things being equal.

3.2. Estimation of energy efficiency

The bottom part of Table 1 shows the estimated average overall energy consumption efficiency and the transient and persistent components for the different sample groups. For the global sample, the average efficiency score is approximately 90 %, ranging from a minimum value of 43 % to a maximum value of 96 % (see top left figure in Fig. 2 for the kernel density plot for the global sample). Liu et al. [34] in a similar global-level analysis revealed a mean efficiency score of 77 %, ranging from 18 % to 95 % while Liddle and Sadorsky [28] showed a mean score of 62 %, ranging from 18 % to 98 %. The decomposition shows transient and persistent efficiency scores of 89.8 % and 98.9 %, respectively. The relatively lower transient component indicates that inefficiency is more short-term oriented. In contrast, Liddle and Sadorsky [28] present evidence indicating that global energy consumption inefficiency problem is persistent in nature, with transient and persistent efficiency scores of 96.8 % and 63.8 %, respectively. The variance in model structure and estimation technique may account for this disparity. Notably, Liddle and Sadorsky [28] do not simultaneously estimate transient and persistent efficiency.

The level of overall efficiency mimics the level of economic development, which is not the case in Liddle and Sadorsky [28]. The overall efficiency score is approximately 91 % for high-income OECD countries, approximately 89 % for UMI countries, and 72 % for LMI countries, respectively (see Fig. 2 for the kernel density plot). The varying efficiency performance may reflect the differential institutional and regulatory environment, policy framework, and pricing regime that characterize these economies. Popkova and Sergi [38] assert that energy intensity (a measure of energy efficiency) rises during the early and middle stages of economic development when there is strong industrialization and motorization of the economy, saturates, and then begins to decline at the latter/advanced stages of development when the share of the less energy-intensive sectors dominates in overall production. Reilly [68] attributes the long-standing performance in energy efficiency in developed economies to technological change, which is more advanced in developed economies than in less developing economies.

The decomposition shows that for OECD and UMI countries, transient inefficiency is the major source of efficiency problems, but in LMI countries, inefficiency largely originates as persistent in nature. In a similar study decomposing energy consumption efficiency into transient and persistent components for Africa, Akorli and Adom [18] found that inefficiency in Africa is more structural or persistent in nature. This implies that improving global energy efficiency would require different policy orientations. In developing economies, policymakers need to focus on policies aimed at altering long-term behaviors, such as enhancing the regulatory and policy environment, incentivizing the

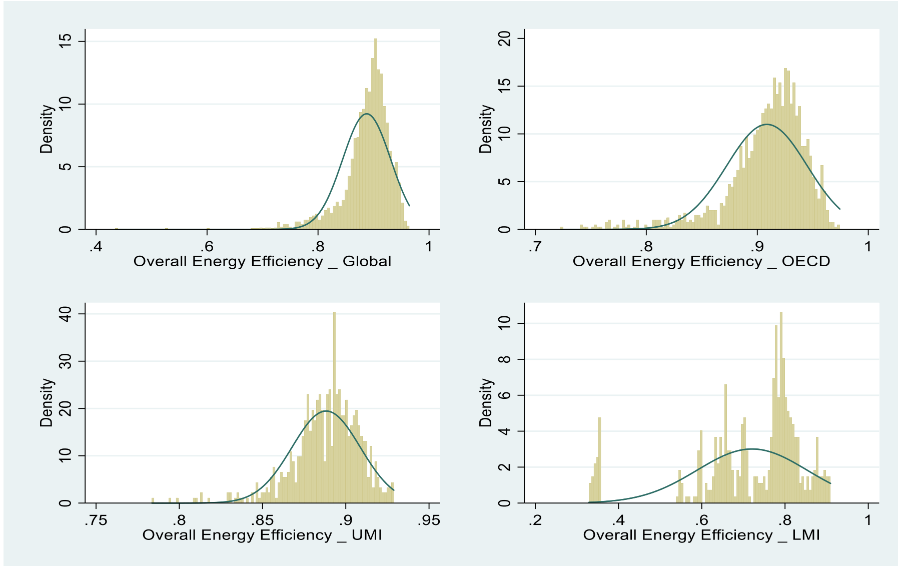


Fig. 2. Kernel density plot of the overall energy efficiency by region.

adoption of energy-efficient technologies, changing appliance use habits, and fostering managerial competencies. In the case of developed economies, policymakers need to focus attention on energy efficiency policies aimed at changing short-term behavior, such as implementing real-time pricing, changing appliance use habits, and promoting energy conservation as a social value. This does not discount the relevance of short-term policies in developing countries or long-term policies in developed countries.

3.3. Robustness checks

I subjected the above results to important concerns that could influence the outcome. First is the concern of cross-sectional dependence. The initial strategy involved clustering the standard errors to permit correlation among panels in the sample. The first part of Table 2 shows the results when correlation among the panels is allowed. Additionally, because the fixed effect captures concerns of unobserved heterogeneity across individuals and allows the estimation of within-individual variation, it helps minimize potential bias originating from cross-sectional dependence. Nonetheless, cross-sectional dependence may arise because individuals in the sample are exposed to common aggregate time-varying shocks. I address this omitted variable concern by controlling for time-varying fixed effects in the regression. This helps neutralize common aggregate trends, absorb residual variation, and minimize cross-sectional dependence. This is shown in the second part of the table.

Second, efficiency values may mimic business cycle effects. As noted by Adom [27], business cycles influence energy efficiency behavior. Moreover, switching between technologies may prove difficult. Consequently, inefficiency is less likely to exhibit very rapid changes, at least in the short run [20]. Moreover, nonstationary series can result in nonsensical results. However, the treatment of nonstationarity series within the stochastic frontier framework is not well developed. Estimating a 5-year average regression limits the relevance of the above concern in addition to addressing measurement errors in the covariates.[2] The last part of Table 2 contains the results for the 5-year average regression. Table 2 shows that both the frontier parameters and efficiency scores remain robust, discounting the fact that the results might have been influenced by business cycle effects, cross-sectional dependence, and nonstationary series.

3.4. Estimating the energy efficiency transition tendency (EETT)

3.4.1. Pre-diagnostics

In this section, I analyze the tendencies of energy efficiency transitions both between and within states. Using data on energy efficiency states at time t, I forecast the probability of remaining in the same energy-efficient state or transitioning to a different one after one, five, ten, fifteen, and twenty years. Prior to estimating equation (9), I conducted pre-diagnostic tests to determine the most suitable model for the data-generating process. I identified the optimal number of states for the Markov switching model, limiting it to a maximum of three states for practical interpretability.

First, I estimated a two-state energy efficiency model, distinguishing between high (HEE) and low (LEE) energy-efficient states. High energy-efficient states represent performance scores above the 50th percentile value (0.8963), while low energy-efficient states represent scores equal to or below this threshold.

Second, I extended the model to three states: high, medium/moderate, and low energy efficiency states. High efficiency denotes scores above the 75th percentile (0.91448), medium/moderate includes scores between the 25th and 75th percentiles (0.87136–0.91448), and low efficiency comprises scores below the 25th percentile (0.87136).

I employed model selection criteria, such as the Akaike Information Criteria, and likelihood ratio statistics tests to determine the most suitable model. The AIC value for the two-state energy-efficient model (1822.299) is lower than that for the three-state model (2760), indicating better fit. This preference for the two-state model is supported by the likelihood ratio test (statistics value of −930.338, p-value of 1.000).

I present summary statistics for both high- and low-energy-efficient states, then conduct a mean difference test to assess their statistical distinction (see Table 3). The mean efficiency score is 85.79 % for the low state and 91.75 % for the high state, confirming their significant difference in energy efficiency performance.

Next, I estimated a two-state energy-efficient model assuming time homogeneity and time heterogeneity in the transition intensity matrix. The AIC value is smaller for the time-heterogeneous model (i.e., 1815.261) than for the time-homogeneous model (i.e., 1822.299). The likelihood ratio test confirms the choice of the time-heterogeneous model, producing LR statistics of 11.0385 with a p-value of 0.004. Finally, I tested the time-heterogeneous models with and without

[2] This could not be done for LMI because of significant data loss.

Table 2
Test for robustness.

VARIABLES	Allowing for correlation among panels				Allowing for Year Fixed effects				5-year average regression		
	global	OECD_hi	UMI	LMI	Global	OECD_hi	UMI	LMI	Global	OECD_hi	UMI
$ln\ y_{it}$	0.610***	0.458***	0.786***	0.661***	0.616***	0.498***	0.938***	0.651***	0.566***	0.510***	0.653***
	(0.113)	(0.105)	(0.168)	(0.166)	(0.0201)	(0.0305)	(0.0524)	(0.0906)	(0.0450)	(0.0674)	(0.0953)
$ln\ pe_{it}$	−0.137***	−0.214***	−0.065	−0.225**	−0.131***	−0.182***	−0.0573***	−0.278***	−0.111***	−0.196***	−0.0682
	(0.0494)	(0.0670)	(0.0439)	(0.0813)	(0.0144)	(0.0333)	(0.0206)	(0.0591)	(0.0309)	(0.0522)	(0.0440)
$ln\ t_{it}$	−0.0185	0.0151	0.244	−0.124	−0.252	0.393	101.4	−0.0725	−0.0171	−0.0606	0.348***
	(0.0877)	(0.101)	(0.205)	(0.143)	(18,743)	(15,754)	(152.2)	(0.0808)	(0.0350)	(0.0484)	(0.0807)
$0.5 * ln\ y_{it} * ln\ pe_{it}$	0.166	0.374	−0.153	−0.003	0.173***	0.440***	−0.244**	−0.0998	0.243***	0.551***	0.0727
	(0.109)	(0.247)	(0.279)	(0.283)	(0.0287)	(0.0687)	(0.105)	(0.210)	(0.0665)	(0.153)	(0.220)
$0.5 * ln\ y_{it} * ln\ t_{it}$	−0.287**	−0.297	−1.057	−0.879**	−0.227***	−0.163***	−1.452***	−0.687**	−0.236***	−0.430***	−0.336
	(0.119)	(0.179)	(0.709)	(0.356)	(0.0271)	(0.0398)	(0.199)	(0.323)	(0.0678)	(0.122)	(0.328)
$0.5 * ln\ pe_{it} * ln\ t_{it}$	0.131	−0.095	0.005	−0.137	0.286***	0.147***	−0.00256	−0.147	0.291***	0.134	0.0284
	(0.103)	(0.181)	(0.211)	(0.334)	(0.0381)	(0.0496)	(0.108)	(0.269)	(0.0969)	(0.140)	(0.259)
$0.5 * ln\ y_{it}^2$	−0.0228	−0.283**	0.530*	0.469**	−0.0681***	−0.278***	0.657***	0.426**	−0.0864*	−0.151	0.271
	(0.115)	(0.118)	(0.277)	(0.212)	(0.0190)	(0.0383)	(0.0854)	(0.176)	(0.0441)	(0.0921)	(0.168)
$0.5 * ln\ pe_{it}^2$	−0.0335	0.158	0.036	−0.109	−0.0630***	0.175*	0.0735**	−0.119	−0.0987**	−0.0739	0.0124
	(0.0855)	(0.260)	(0.0431)	(0.102)	(0.0240)	(0.0891)	(0.0300)	(0.106)	(0.0484)	(0.216)	(0.0586)
$0.5 * ln\ t_{it}^2$	−0.0638	0.003	−0.204	0.601*	−0.273	0.217	−154.3	0.488	−0.187***	−0.120**	−0.716**
	(0.0389)	(0.0642)	(0.595)	(0.316)	(28,105)	(23,623)	(231.5)	(0.344)	(0.0381)	(0.0543)	(0.324)
Constant	0.435***	0.951***	−0.261***	−1.042***	0.595	0.533	−33.52	−1.050***	0.443***	0.970***	−0.250***
	(0.0373)	(0.0136)	(0.0662)	(0.0536)	(6,249)	(5,252)	(50.01)	(0.0340)	(0.0203)	(0.0127)	(0.0327)
Year Effects	NO	NO	NO	NO	YES	Yes	YES	YES	–	–	–
Sigma_u	0.5123	0.4108	0.2701	0.2877	0.4958	0.4032	0.2658	0.2837	0.5189	0.4019	0.2732
Sigma_e	0.1485	0.1334	0.1367	0.1006	0.1459	0.1279	0.1339	0.10057	0.1528	0.1273	0.1497
Observations	2,749	1,600	630	470	2,749	1600	630	108	583	319	143
Number of ID	78	37	23	16	78	37	23	16	78	37	23
R-squared	0.689	0.783	0.728	0.711	0.706	0.808	0.757	0.751	0.66	0.788	0.716
Efficiency Estimates											
Overall	0.8877	0.9087	0.8882	0.7209	0.9080	0.8338	0.996	0.722	0.9021	0.9214	0.8731
Transient	0.8980	0.9115	0.9315	0.9392	0.9114	0.9367	0.9987	0.9421	0.9093	0.9263	0.9427
Persistent	0.9885	0.9969	0.9536	0.7675	0.9963	0.8901	0.9973	0.7663	0.9921	0.9948	0.9261

Standard errors in parentheses.
$p < 0.01$, $p < 0.05$, $p < 0.1$.

Table 3
Summary statistics of the states and mean difference test.

State	Frequency	Percentage	Mean	Std dev	Min	Max
LEE	1,376	50.05	0.8579	0.0416	0.4347	0.8963
HEE	1,373	49.95	0.9175	0.0151	0.8964	0.9647
Null	LEE	HEE	Diff	P-value		
Diff ! = 0	0.85785	0.91755	−0.05969	0.000		

control variables. The AIC value is smaller for the time-heterogeneous model with controls (i.e., 1810.07) than for the corresponding model without controls (i.e., 1815.261). On the basis of the above pre-diagnostics, I estimated a two-state time-heterogeneous panel Markov model controlling for the effects of income, the price of energy, and year-fixed effects.

3.4.2. *Energy efficiency transition trends: global sample*

Table 4 shows the probability of transition between high- and low-energy-efficient states. The post-diagnostics for the model indicate the fitness of the model. The prevalence graph (see Appendix A) shows that for some years, the predicted states mimicked the actual observed states well. This is confirmed by the Pearson test of goodness of fit [69], which is a more robust test for goodness of fit, with an upper p-value of >10 % (i.e. −1138).

First, I begin with the scenario in which the global sample is considered to be in a HEE state. In the first year, it is predicted that there is approximately a 90 % chance of remaining in the HEE state. The same situation is observed for the LEE state, where there is approximately a 90 % chance of remaining in the LEE state the next year, given that in the previous year, the global sample was already in the LEE state. The high persistence nature of both the HEE and LEE states is expected. As explained by Akorli and Adom [18] and Zhang and Adom [19], technology takes time to depreciate, and learning and technology adoption takes time to materialize. Therefore, countries that are identified as being in any of these states are less likely to escape after the first year. However, the dynamics change with time. Both states become less sustainable in the medium to long term. As shown in the table, given that the global sample is declared to be in the HEE state, five years from now, there is approximately a 66 % chance of remaining in the same state. Thus, the transition tendency out of the HEE state increases with approximately a 34 % chance. After 10 years, there is a 55 % chance of remaining in the HEE state, implying a 45 % chance of transitioning out of the HEE state to the LEE state. In the fifteenth and twentieth years from now, the transition probability will become steady, indicating a 52 % and 51 % chance of remaining in the HEE state, respectively. This implies that for the global sample, given that we have achieved the fate of the HEE state now, it is highly sustainable only in the short term (1–5 years) and becomes moderately sustainable in the medium to long term (10–20 years).

In the case of the LEE state, there is a 65 % chance of remaining in the LEE state five years from now, indicating a 35 % chance of transition tendency out of the LEE state to the HEE state. By the tenth year, there is a 55 % chance of remaining in the LEE state, indicating a 45 % chance of transitioning out of the LEE state to the HEE state. The probability of transition to remain in the LEE state in the fifteenth and twentieth years reduced to 51 % and 50 %, respectively, implying a 49 % and 50 % chance of transition from the LEE state to the HEE state. Thus, upon attaining the LEE state, the global sample will find it highly difficult to escape this trap in the short term but in the medium to long term experience a moderate chance of 50 % to escape to the HEE state. These results reflect the idea that the global energy efficiency system looks moderately fragile in the medium to long term but shows moderate prospects of escaping scenarios with low energy efficiency performances. I estimated the total number of years it would take to fully escape each state. As shown in the bottom part of the table, it would take approximately eight and a half years to escape the LEE state and four and a half years to escape the HEE. This indicates that, comparatively, the LEE state is more persistent than the HEE state, implying that the global economy is trapped in a low energy-efficient performance state. Several factors may be responsible for this, such as a general lack of a global long-term view of policies and regulatory frameworks, insufficient investments in energy-efficient technologies, varying levels of regulatory environment performance, and large market failures in some regions of the world. Similar to any global analysis, there is likely to be hidden heterogeneity bias. In particular, in this case, the level of development may significantly influence the transition paths and sustainability of each state. To address this concern, I examined the transition paths and sustainability of each state by considering the level of economic development in the next section.

3.4.3. *Energy efficiency transition tendencies by level of development*

Table 5 shows the transition tendencies for the high-income OECD sample. The post-diagnostics indicate that the model is a correct fit. As shown in the prevalence plot in panel B of the appendix, the predicted states generally mimicked the actual observed states. The Pearson test

Table 4
Energy efficiency transition trends: Global.

		Future Outlook Scenarios				
		1 year	5 years	10 years	15 years	20 years
Global	*HEE ➡ HEE*	*0.8982 (0.8776, 0.9158)*	*0.6617 (0.6082, 0.7119)*	*0.5548 (0.4854, 0.6194)*	*0.5210 (0.4553,0.5870)*	*0.5103 (0.4507, 0.5824)*
	HEE ➡ LEE	*0.1018 (0.0842, 0.1224)*	*0.3383 (0.2881, 0.3918)*	*0.4452 (0.3806, 0.5146)*	*0.4790 (0.4130,0.5447)*	*0.4897 (0.4176, 0.5493)*
	LEE ➡ HEE	*0.104 (0.0840, 0.1267)*	*0.3456 (0.2943, 0.4019)*	*0.4549 (0.3885, 0.5274)*	*0.4894 (0.4239,0.5542)*	*0.5003 (0.4397, 0.5737)*
	LEE ➡ LEE	*0.896 (0.8733, 0.9160)*	*0.6544 (0.5981, 0.3918)*	*0.5451 (0.4726, 0.5146)*	*0.5106 (0.4458, 0.5761)*	*0.4997 (0.4263, 0.5603)*

Total Duration of States in Years	LEE-state	HEE-state
Res	*8.515*	*4.485*
2.5 %	*7.848*	*3.809*
97.5 %	*9.191*	*5.152*

Note: Figures in parentheses are the lower and upper confidence values at the 95 % level. The model allows for time inhomogeneity in the transition matrix and controls for the effects of income, energy prices, and year-fixed effects. LEE denotes low energy-efficient and HEE denotes high energy-efficient states.
Source: Author's construction

Table 5
Energy efficiency transition trends for the OECD sample.

		Future Outlook Scenarios				
		1 year	5 years	10 years	15 years	20 years
OECD	*HEE* ➡ *HEE*	*0.95316 (0.9361, 0.9663)*	*0.8491 (0.7959, 0.8894)*	*0.8060 (0.7384, 0.8603)*	*0.7937 (0.7127, 0.8551)*	*0.7902 (0.7902, 0.8527)*
	HEE ➡ *LEE*	*0.0468 (0.0338, 0.0639)*	*0.1509 (0.1106, 0.2041)*	*0.1940 (0.1397, 0.2616)*	*0.2063 (0.1449, 0.2873)*	*0.2098 (0.1473, 0.2903)*
	LEE ➡ *HEE*	*0.1749 (0.12914, 0.2379)*	*0.5636 (0.4524, 0.6877)*	*0.7245 (0.6122, 0.8124)*	*0.7704 (0.6743, 0.8431)*	*0.7836 (0.6980, 0.8490)*
	LEE ➡ *LEE*	*0.82508 (0.7621, 0.8709)*	*0.4364 (0.3123, 0.5476)*	*0.2755 (0.1876, 0.3878)*	*0.2296 (0.1569, 0.3257)*	*0.2164 (0.1510, 0.3020)*

Total duration of states in years		
	LEE-state	HEE-state
Res	*5.771*	*7.229*
2.5 %	*4.605*	*5.986*
97.5 %	*7.014*	*8.395*

Note: Figures in parentheses are the lower and upper confidence values at the 95 % level. The model allows for time inhomogeneity in the transition matrix and controls for the effects of income, energy prices, and year-fixed effects. LEE denotes low energy-efficient and HEE denotes high energy-efficient states.
Source: Author's construction

confirms this with an upper p-value of >10 % (0.2635). For the OECD sample, given that they find themselves in the HEE state, there is a 95 % chance that they will remain in the HEE state the following year. In five years, there is an 85 % chance of remaining in the HEE state. The chance of remaining in the same state reduces to 81 % in 10 years and to 79 % ten in 15 and 20 years. These estimated values indicate the persistent nature of the HEE state for the OECD sample. As noted in the transition out of the HEE state, even by the twentieth year from now, there is a 21 % chance of transitioning from the HEE state to the LEE state. Thus, for the OECD sample, achieving the HEE state is highly sustainable in the short, medium, and long term. The transition path from and within the LEE state reveals a similar trend. Given that the OECD sample finds itself in the LEE state, there is an 83 % chance of remaining in the same state. As indicated above, transitioning out of either HEE or LEE states is very unlikely after the first year because technology takes time to depreciate as well as learning opportunities and technology adoption. However, after the fifth, tenth, fifteenth, and twentieth years, the LEE state becomes highly unsustainable, indicating greater prospects for the OECD sample to transition from the LEE state to the HEE state. As shown in the table, there is a 17.5 %, 56 %, 72 %, and 78 % chance of transitioning from the LEE state to the HEE state, one year, five years, ten years, fifteen years, and twenty years from now. The high persistent nature of the HEE state and the low persistent nature of the LEE state are confirmed by the number of years it would take to escape both states. As shown in the bottom part of the table, the OECD sample takes approximately 5.8 years to escape the LEE state and 7.2 years to escape the HEE state. These figures indicate a medium to high chance for OECD countries to escape the trap of a low energy-efficient state.

The dynamics change drastically as I consider the transition tendencies for UMI and LMI economies. Table 6 shows the transition tendencies for the UMI countries. Like other contexts, it is relatively difficult to escape either the HEE or LEE state after one year. However, five, ten, fifteen, and twenty years from now, the likelihood for UMI countries to remain highly energy-efficient reduces to 67 %, 57 %, 54 %, and 53 %, respectively, indicating moderate sustainability of high energy-efficient status. Thus, compared with the OECD high-income region, attaining a high energy-efficient status is less sustainable in UMI countries. Notwithstanding, UMI countries have the potential to escape a low energy-efficient status. As indicated in the table, the likelihood of sustaining a low energy-efficient status diminishes significantly from 89 % in the first year to 61 % in the fifth year, 53 % in the tenth year, 49 % in the fifteenth year, and 48 % in the twentieth year.

Table 6
Energy efficiency transition trends for upper middle-income countries.

		Future Outlook Scenarios				
		1 year	5 years	10 years	15 years	20 years
UMI	*HEE* ➡ *HEE*	*0.9029 (0.8526, 0.9377)*	*0.6761 (0.5585, 0.7797)*	*0.5728 (0.4271, 0.7209)*	*0.5399 (0.3755, 0.6960)*	*0.5294 (0.3749, 0.6763)*
	HEE ➡ *LEE*	*0.0972 (0.0623, 0.1475)*	*0.3239 (0.2203, 0.4415)*	*0.4272 (0.2791, 0.5729)*	*0.4601 (0.3040, 0.6245)*	*0.4706 (0.3237, 0.6251)*
	LEE ➡ *HEE*	*0.1071 (0.0653, 0.1699)*	*0.3571 (0.2361, 0.5162)*	*0.4711 (0.3036, 0.6598)*	*0.5074 (0.3376, 0.6789)*	*0.5190 (0.3629, 0.6655)*
	LEE ➡ *LEE*	*0.8929 (0.8301, 0.9347)*	*0.6429 (0.4838, 0.7639)*	*0.5289 (0.3402, 0.6964)*	*0.4926 (0.3211, 0.6624)*	*0.4810 (0.3345, 0.6371)*

Total Duration of States in Years		
	LEE-state	HEE-state
Res	*8.360*	*4.640*
2.5 %	*6.685*	*3.0999*
97.5 %	*9.900*	*6.315*

Note: Figures in parentheses are the lower and upper confidence values at the 95 % level. The model allows for time inhomogeneity in the transition matrix and controls for the effects of income, energy prices, and year-fixed effects. LEE denotes low energy-efficient and HEE denotes high energy-efficient states.
Source: Author's construction

This translates to a probability of escape of 11 % in the first year, 36 % in the fifth year, 47 % in the tenth year, 51 % in the fifteenth year, and 52 % in the twentieth year. Compared with the OECD region, UMI countries exhibit relatively lower prospects of escaping a low energy-efficient state. As indicated by the duration of states, it takes UMI countries approximately 8.4 years to escape the LEE state and 4.6 years to escape the HEE state. These dynamics imply that OECD high-income countries have a more robust energy efficiency system than UMI countries.

Transition dynamics change drastically for economies in the lower stages of development. Table 7 shows the transition dynamics for the LMI countries. Similar to the OECD and UMI samples, the LMI countries exhibit high persistence of HEE and LEE states one year later. However, the sustainability dynamics for HEE and LEE states change drastically in the short, medium, and long term. Given that LMI countries find themselves in an HEE state now, there is a 34 %, 16 %, 11 %, and 9 % chance of remaining in the same state, five, ten, fifteen, and twenty years from now. Compared with the OECD and UMI sample, this shows high unsustainability of HEE status in LMI in the short-, medium-, and long-term. Meanwhile, LMI countries exhibit strong persistence once they find themselves in a low energy-efficient state, with a 94 % chance of remaining in the LEE state five years from now and a 92 % chance of remaining in the LEE state ten, fifteen, and twenty years from now. The total duration for LEE and HEE states in LMI countries is 12.2 and 7.8 years, respectively. Compared with the OECD and UMI countries, LMI countries are in a relatively difficult situation to escape a low energy-efficient state as their economies exhibit very fragile energy efficiency systems. This conclusion corroborates the findings of Akorli and Adom [18], who found that in Africa, escaping the LEE state is relatively more difficult than escaping the HEE state. The results indicate that the tendency to transition to a high energy-efficient status and its subsequent sustainability is a development phenomenon.

Several reasons may account for the discrepancy in energy efficiency transition tendency across economies of different economic development levels. Less developing economies exhibit significant market failures and barriers compared with developed economies. Developing economies lag behind developed economies in terms of energy efficiency investment commitment. Fig. 3 plots investment in energy efficiency. Generally, investment in energy efficiency depicts a rising trend for the world, with investment suffering mostly during the crises periods of 2017/2018 (financial crisis), 2020 (COVID-19), and 2023 (Russia-Ukraine War). For advanced economies, investment in energy efficiency experienced a significant drop at the peak of the 2018 financial crisis but remained robust throughout the COVID-19 period, only to be marginally hit by the Russia-Ukraine War in 2023. In the case of Emerging Markets and Developing Economies (EMDE), investment in energy efficiency has been fragile, particularly during crisis periods. The decline was immediately felt at the onset of the financial crisis in 2017, recovering in 2018 and 2019 only to be hard hit by COVID-19, which has plunged EMDE into a low energy-efficient investment trap. The regional dynamics appear similar (see Fig. 4). Europe and the Asia Pacific recorded the highest energy efficiency investment from 2015 to 2023. Prior to the peak of the financial crisis in 2018, the Asia Pacific region invested more than Europe, but the onset of the financial crisis changed the dynamics greatly, with investment in the Asia Pacific region being hardest hit the most. Even though this persisted into 2019, Europe showed a strong recovery. Both regions experienced a recovery in energy efficiency investment during 2020 and 2022, but the recovery was stronger in Europe than in the Asia Pacific. Again, both showed glimpses of crisis shock in 2023, but it was more felt in the Asia–Pacific region than in Europe. Despite these shocks, Europe and the Asia-Pacific region have exhibited robust positive trends in energy efficiency investment. North America also had its fair share of investment plummeting during the crisis period, but this was more visible during the financial crisis of 2017/2018. Central and South America's investment in energy efficiency was more fragile during crisis periods, plunging the region into a low investment trap post-crisis. In Africa, the Middle East, and Eurasia, investment in energy efficiency has been low compared to other regions, showing some vulnerability mainly during the COVID-19 period. These dynamics underscore the fragile nature of energy efficiency investment in less developing economies compared with that in developed economies.

Next, while in developed economies, constraints such as inefficient energy pricing, high non-technical losses, capital market failures, and poor power quality have eased significantly if not eliminated, they persist to a higher degree in less developing economies [8,24,25]. As noted by Bates and Moore [70] and Komives et al. [71], persistent inefficiency in energy pricing is discouraging private investment in lower-middle-income countries below the socially optimal level. Inefficiency in energy prices can have a perverse effect on power quality and reliability investment [72]. Subsidizing energy prices, which is a common practice in developing economies, can trap energy users into a low energy-efficient state as it reduces their willingness to pay for energy-efficient appliances and technologies.

Billing inefficiencies, metering inefficiencies, and electricity theft are common practices in developing economies that are increasing the level of non-technical losses in these economies [8]. These inefficiencies in

Table 7
Energy efficiency transition trends for low-income countries.

		Future Outlook Scenarios				
		1 year	5 years	10 years	15 years	20 years
LMI	*HEE → HEE*	*0.79587 (0.4115, 0.9486)*	*0.34402 (0.0295, 0.7784)*	*0.15838 (0.0199, 0.6523)*	*0.1058 (0.0150, 0.5335)*	*0.0910 (0.0139, 0.3347)*
	HEE → LEE	*0.20413 (0.05514, 0.5885)*	*0.65598 (0.2216, 0.9705)*	*0.84162 (0.3477, 0.9801)*	*0.8942 (0.4665, 0.9850)*	*0.9090 (0.5162, 0.9846)*
	LEE → HEE	*0.01899 (0.0038,0.0801)*	*0.0610 (0.0104, 0.2385)*	*0.0783 (0.0138, 0.3268)*	*0.0832 (0.0133, 0.3135)*	*0.0846 (0.0139, 0.3347)*
	LEE → LEE	*0.98101 (0.9219, 0.9896)*	*0.9390 (0.7615, 0.9896)*	*0.9217 (0.6732, 0.9862)*	*0.9168 (0.6865, 0.9867)*	*0.9154 (0.6653, 0.9861)*

Total Duration of States in Years		
	LEE-state	HEE-state
Res	*12.218*	*0.782*
2.5 %	*10.0168*	*0.1369*
97.5 %	*12.8631*	*2.9832*

Note: Figures in parentheses are the lower and upper confidence values at the 95 % level. The model allows for time inhomogeneity in the transition matrix and controls for the effects of income, energy prices, and year-fixed effects. LEE denotes low energy-efficient and HEE denotes high energy-efficient states.
Source: Author's construction

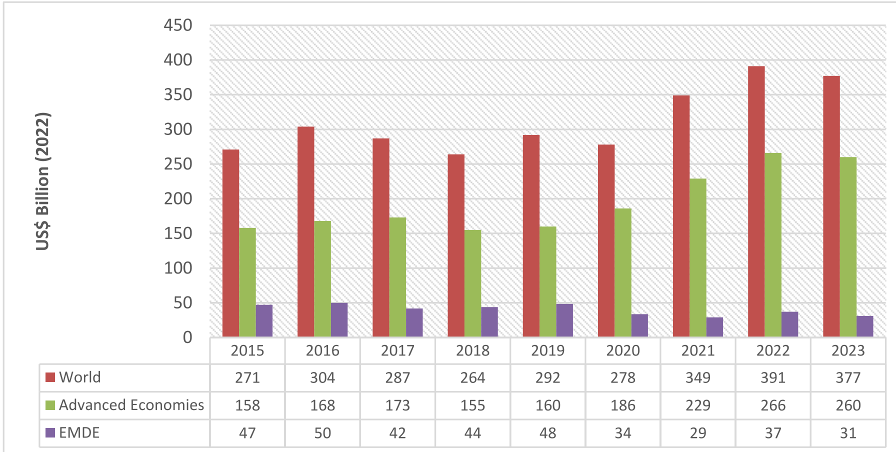


Fig. 3. Energy investment trends by level of development (US$ billion).
Source: Auhtor's Construction using data from the IEA (2024)

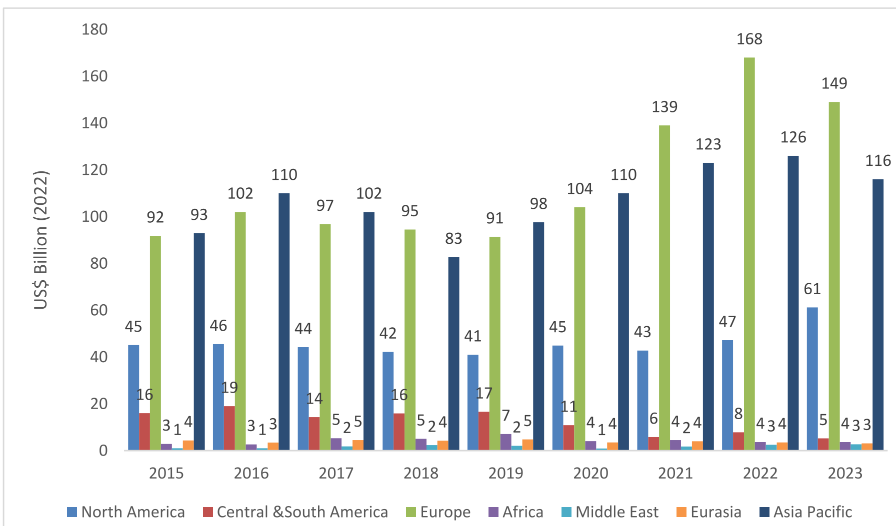


Fig. 4. Plot of energy efficiency investment by region.
Source: Auhtor's Construction using data from the IEA [26].

revenue collection provide implicit subsidies to energy users, discouraging them from being willing to pay for energy-efficient technologies. Also, less developed economies lack adequate energy storage solutions, leading to unreliable energy supply challenges. This situation reduces the utilization rate of appliances in these economies, thereby reducing the willingness to pay for energy-efficient appliances. According to McRae [73], poor power supply conditions influence households' choice of appliances, mostly locking them into inefficient appliance stock.

Capital market failures are more persistent in developing economies. Limited or lack of access to affordable capital limits technology adoption, including low-carbon content technologies such as energy-efficient technologies. Less developing countries suffer from the twin problem of low access and high borrowing costs, constraining efforts to boost energy efficiency investment [74]. As noted by Golove and Eto [75], lower interest rates are a prerequisite for faster investment in energy efficiency technologies.

Moreover, in developing economies, there is still heavy reliance on the state to fund investment in energy-efficient technologies, in contrast to the case of developed economies, where a complex mixture of incentives is adopted to support the funding of energy-efficient investments. There is a push for a more market-oriented approach to funding energy-efficient technologies in developed countries. For example, regulatory requirements have been strengthened for the private sector to help them develop low-carbon technologies. Technology-neutral tax incentives have been implemented to support the development of low-carbon technologies, and marketable permits and related systems have been developed to support investment in low-carbon technologies [8]. As noted by Reilly [68], technological change is the reason for the long-standing performance of developed economies in energy efficiency.

Finally, the regulatory and institutional environment to support energy efficiency investment is more developed in advanced economies than in developing economies, where there are serious regulatory lapses and institutional bottlenecks. Adom [21] for Cameroon, Adom and Adams [22] for Nigeria, and Akorli and Adom [18] for Africa attributed the low energy-efficient traps of these economies to regulatory inefficiencies. Akorli and Adom [18] found that simply improving regulatory quality and controlling corruption in Africa can increase the region's tendency to transition out of a low energy-efficient state.

4. Conclusion and policy implications

This study assessed the energy efficiency performance of economies and investigated the transition tendencies between/within high- and low-energy-efficient states. In assessing the energy efficiency performance, I employed a panel stochastic frontier approach that can separate transient and persistent inefficiency from unobserved heterogeneity. Panel Markov switching regression was then used to model the transition within and between different energy-efficient states. I employed global panel data that consisted of 78 countries with data spanning from 1960 to 2016. The following results emerged from this study.

First, the level income effect on energy consumption is positive and less than unity, whereas the level effect of real economic-wide energy prices is negative and less than unity regardless of the level of economic development. However, the claim of an inverted U-shaped effect of income and a U-shaped effect of energy price on energy consumption is only strong for the OECD sample. These results imply the following: (1) economic growth is probably more energy-consuming in developing countries and less so for developed economies, and (2) raising the price of energy through taxation or its analog can limit energy consumption in developing countries, but in developed economies, there is a limit on how such similar initiatives can continually promote energy conservation.

Furthermore, the frontier parameters showed that for all economies regardless of their level of economic development, parallel movements of economic growth and technological advancement are not energy-consuming, unlike the case with price. This implies that the simultaneous attainment of economic growth and technological advancement could improve energy resource use and mitigate the possible environmental implications associated with energy consumption. Finally, the frontier regression showed that the interaction between income and price is negative only for developing economies.

Globally, the average energy efficiency score indicates good progress in energy efficiency, driven mainly by persistent energy consumption efficiency. This suggests that addressing global inefficiency in energy consumption effectively requires a focus on policies aimed at changing short-term behaviors. These dynamics change once the level of economic development is considered. Overall energy efficiency is higher in OECD-high income countries compared to UMI and LMI countries. This pattern generally supports the claim that energy efficiency performance is a development phenomenon.

Both developed and developing countries exhibit transient and persistent technical inefficiency, but the relative importance of these inefficiencies differs. Inefficiency tends to be more transitory in developed countries and more persistent in developing countries. While it is crucial to implement policies aimed at changing both short- and long-term behaviors in both types of economies, the policy focus should differ accordingly. In developing economies, policymakers should prioritize policies that alter long-term behaviors. This includes enhancing the regulatory and policy environment, incentivizing the adoption of energy-efficient technologies, changing appliance use habits, and fostering managerial competencies. However, they should not neglect the complementary role of short-term policies. In developed economies, policymakers should focus more on energy efficiency policies that influence short-term behavior, such as implementing real-time pricing, changing appliance use habits, and promoting energy conservation as a social value. Nevertheless, the importance of long-term policies should not be overlooked.

Finally, regarding the sustainability of the energy efficiency system, the results showed that OECD high-income countries exhibit a higher tendency to transition out of low energy-efficient states than Upper Middle Income and Lower Middle-Income countries. Consequently, the attainment of HEE state is expected to be more robust and sustainable in the short-, medium-, and long-term in developed economies. However, similar achievements are expected to be moderately sustainable in the medium-to long-term for upper-middle-income countries and highly unsustainable for lower-middle-income countries. These results reflect the fact that developed economies show a more potent and robust energy efficiency system than less developed economies. Addressing this gap in the global energy efficiency system would require a 'big push' in energy efficiency investment in developing countries, in addition to implementing a broad policy overhaul that eliminates market barriers and inefficiency in energy efficiency, specifically in the areas of energy pricing, energy infrastructure, energy regulation, energy policy, and economic institutions.

Ethical statement

I declare that this study did not involve humans or animals. The outcome of this article is an original investigation conducted by the authors. This article has solely been submitted to this journal and no part of this document has been submitted to or published in another journal. The author has also cited relevant literature related to this study.

Funding statement

The author did not receive funding for conducting this study.

Data statement

This study used data compiled by Liddle and Huntington [41], which is publicly available at the following website data.mendeley.com/datasets/3nmbz2jyd2/1. Upon request, the author would provide the codes used to generate the results of this study.

CRediT authorship contribution statement

Philip Kofi Adom: Conceptualization, Methodology, Software, Data curation, Formal analysis, Writing – original draft, Visualization, Investigation, Supervision, Writing – review & editing.

Declaration of competing interest

The author has no conflict of interests (financial or non-financial) that are relevant to the content of this article.

Data availability

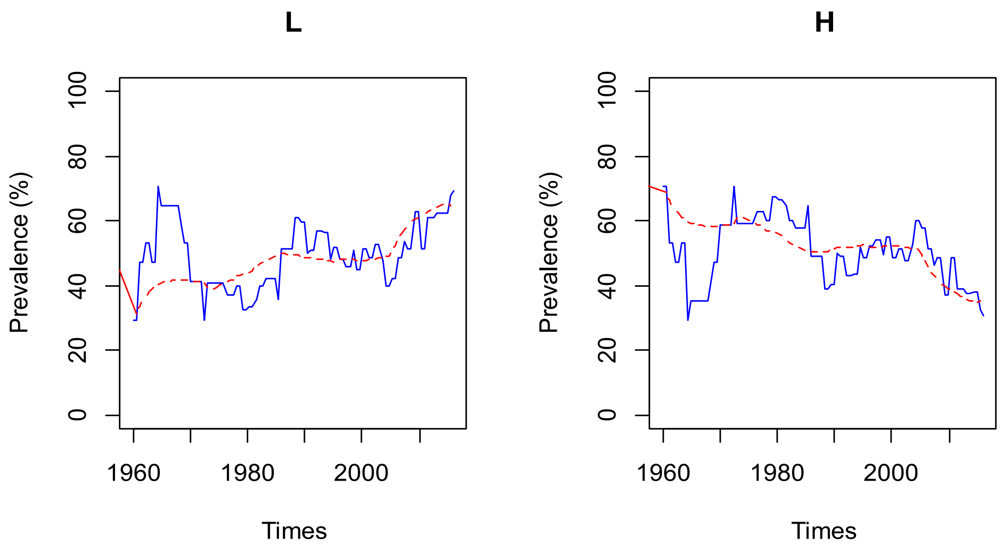
Data will be made available on request.

Acknowledgment

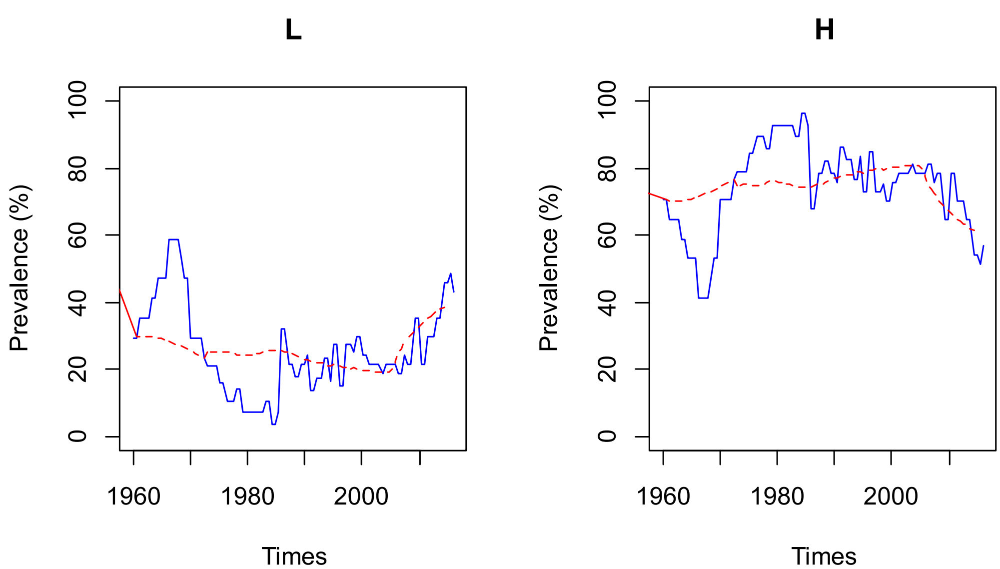
This manuscript benefited from comments from three anonymous reviewers. The usual disclaimer applies.

Appendix

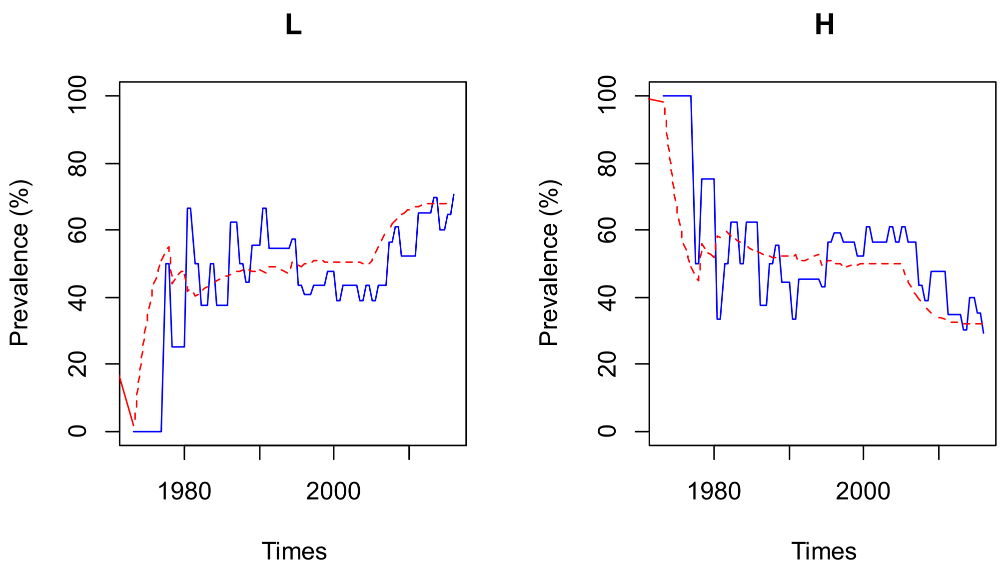
Panel A.



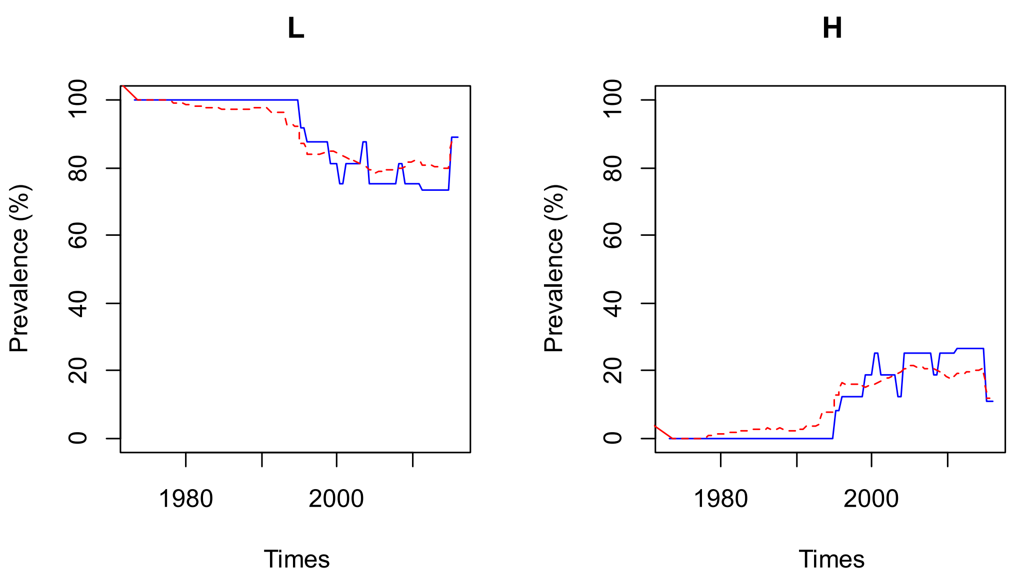
Panel B.



Panel C.



Panel D.



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