Balkan Journal of Social Sciences

BJSS

Derginin ana sayfası: https://dergipark.org.tr/bsbd

Araştırma Makalesi ● Research Article

Gelişmekte Olan Ekonomilerde Doğrudan Yabancı Yatırımlar ve Enerji Tüketimi: Yatay Kesit Bağımlılığı Altında Heterojen Dinamik Panel Veri Analizi

Foreign Direct Investment and Energy Consumption in Developing Economies: An Analysis of Heterogeneous Dynamic Panel Data Models with Cross Sectional Dependency

Muhammed Benli [a,*]

[a] Doç. Dr., Bilecik Şeyh Edebali Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, İktisat Bölümü, 11230, Bilecik/Türkiye.
ORCID: 0000-0001-6486-8739

M A K A L E B İ L G İ S İ

Makale Geçmişi:
Başvuru tarihi: 16 Eylül 2021
Düzeltme tarihi: 21 Eylül 2021
Kabul tarihi: 15 Ekim 2021

Anahtar Kelimeler:
Enerji Tüketimi
FDI
Panel Veri Analizi

ÖZ

Bu çalışma, 1987-2016 dönemi için 40 gelişmekte olan ülkede, doğrudan yabancı yatırımların yenilenebilir ve yenilenemez enerji tüketimi üzerindeki etkisini incelemektedir. Bu amaçla, heterojenlik, içsellik ve/veya yatay kesit bağımlılığı dikkate alınarak, literatürde dinamik panel veri modellerinin tahmini için önerilen çeşitli tahmin edicileri kullanılmıştır. Elde edilen ampirik sonuçlar, ekonomik büyümenin enerji tüketiminin temel itici güçlerinden biri olduğunu göstermekle birlikte, seçili ülkelerde analiz dönemi için doğrudan yabancı yatırımların hem yenilenebilir hem de yenilenemez enerji tüketimi üzerindeki etkisi hakkında herhangi bir ampirik bulgu elde edilememiştir. Dolayısıyla bu bulgular, ev sahibi ülkelerin messetme kabiliyetlerinin, enerji yoğunluklarının ve çevre düzenlemelerinin önemini gösteren önemli politika sonuçları olabilir.

A R T I C L E I N F O

Article history:
Received September 16, 2021
Received in revised form September 21, 2021
Accepted October 15, 2021

Keywords:
Energy Consumption
FDI
Panel Data Analysis

A B S T R A C T

This study reexamines the effect of foreign direct investment on both renewable and nonrenewable energy consumption in 40 developing countries over the period 1987-2016. Taking into account heterogeneity, endogeneity, and/or cross sectional dependency, we employ various estimators proposed for the estimation of dynamic panel data models in the literature. The empirical results suggest that economic growth is one of main drivers of energy consumption, while providing no evidence on the effect of foreign direct investment on both renewable and nonrenewable energy consumption in selected countries for the time period of the analysis. Therefore, these findings may have important policy ramifications, indicating the importance of absorptive capabilities, energy intensity and environmental regulations of host countries.

1. Introduction

Sustainable development is one of the most crucial challenges for both developed and developing economies. Foreign direct investment (FDI), on the other hand, is considered to be an important factor in promoting balanced and sustainable economic growth. This is due to the fact that FDI is view to be one of the most stable components of capital flows. FDI plays a significant role in promoting production and job creation as well as enhancing competitiveness and growth of local firms in host countries through so called spillover effects. FDI also benefits the firms in home country by raising international competition, creating production linkages, enabling greater capacity exploitation and utilization of scale economies and which in turn stimulating overall expansion in global output. Hence, both developed and developing countries adopted many new industrial policies in recent years, relying on a significant degree in attracting foreign investment (UNCTAD, 2019). Although falling three consecutive years, global FDI inflows of $57 billion in 1982 reached $1.3 trillion in 2018 (down from its peak $1.92 trillion in 2015). The share of developing economies in global FDI inflows escalated in 2018 and accounted for 54 per cent of global FDI inflows

* e-posta: muhammed.benli@bilecik.edu.tr

(47 per cent in 2017 and 36 per cent in 2016), while the share of developed economies is decreased to 43 per cent of the total. Global FDI inward stock reached an estimated \$31.5 trillion in 2017 and developing economies absorbed 33 per cent of the total (up from 20 per cent in the beginning of 2000s) due to their eligible investment environment, raw materials, and cheap labor (UNCTAD, 2018 and 2019).

As with the expansion of global production and rising prosperity through global capital flows, the energy consumption per head has considerably increased in the last couple of decades and this upward trend is also estimated to continue in the future. According to the Global Energy Outlook of Resources for the Future, global energy consumption will grow more than 20% through 2040 and beyond, driven mainly by fossil fuels. Primary energy consumption worldwide increased 2.3% in 2018, a double pace higher than its ten year average annual growth, driven mainly by a robust global economy. As a result of this higher energy use, global energy-related CO2 emissions rose by 1.7% to a new record of 33.1 Gt CO2 (Global Energy & CO2 Status Report 2018, International Energy Agency).

Theoretically, the effect of FDI on energy consumption can be decomposed into a scale, composition and technique effects. The scale effect may arise due to the contribution of FDI to industrial production and hence might escalate the level of energy use. The composition effect, on the other hand, may cause an FDI-driven structural change in the industry composition of an economy. An industrial shift towards less energy related sectors, such as services, might result in energy savings and thus reduce energy consumption. On the contrary, FDI in industrial sectors might increase energy consumption. Finally, the technique effect refers to a change in energy intensity and implies the effect of FDI on energy use through transfers of energy-saving technologies and energy-efficient production techniques. The net effect of FDI on energy consumption would depend on the relative role played by these forces.

Overall, from the theoretical perspective, the association between FDI inflows and energy consumption is complex and can be either negative or positive. This theoretical ambiguity is also in accord with empirical evidence varying across countries, country groups, and methodologies. Some studies argue that FDI may promote energy-saving technologies and thus reduce energy consumption, while some others maintain that FDI may even increase energy consumption. Another important point related to this argument is the role of absorptive capacity of host countries for them to capture international technology diffusions and spillovers successfully through FDI inflows. It is reasonable to think that the technique effect may arise for a set of countries with absorptive capacity, rather than taking place in all countries in general. However, it is not the intent of this paper to maintain the role of absorptive capacity in FDI-energy nexus or determine the weight of each decomposed effects in energy consumption. Instead, we examine the overall short- and long-run effect of FDI inflows on energy consumption in middle income countries employing a dynamic panel data analysis. We believe that understanding the association between foreign investment and energy use has important ramifications for policy implications. This is due to the fact that encouraging FDI for sustainable and balanced economic growth requires facing a dual challenge of ‘more energy and less emission’.

Furthermore, the review of the literature below highlights potential methodological problems that may well prevent determining the true effect of FDI on energy consumption. The previous studies mainly suffer from estimation biases arising from the assumption of slopes homogeneity. Although the system GMM effectively controls for endogeneity and country specific fixed effects, it constraints slope coefficients to be identical across cross sections. As a matter of fact, Pesaran & Smith (1995) argue that, unless the slope coefficients are in fact identical (if latent heterogeneity is present), the traditional procedures for estimation of pooled models, such as instrumental variables (IV), the fixed effects (FE), and (GMM) estimators are likely to produce inconsistent and potentially misleading long-run estimates in dynamic panel data models. Moreover, it is obviously reasonable to think that these parameters differ significantly across sections as Maddala et al. 1997 argue that “the homogeneity of slope coefficients is often an unrealistic assumption” given that market conditions are different across countries. Besides, the traditional panel data estimators do not take into account possible cross sectional dependency of errors. However, there may exist a number of omitted and unobserved global factors that may be correlated with the regressors, which may result in inefficient and even inconsistent estimates.

Therefore, the present study contributes to the existing literature by taking implicitly into account potential parameter heterogeneity as well as cross sectional dependence across countries. Specifically, we analyze the impact of FDI on both renewable and non-renewable energy consumption in 40 developing countries over the period 1987 – 2016. It can be argued that these countries are highly integrated given that they are exposed to economic and financial shocks coming from each other. Hence, the model framework requires considering the economic and financial ties of these countries.

2. Literature Review

Assessing the effect of FDI inflows on energy consumption is of obvious importance due to the fact that this task has significant policy implications especially for middle income countries as they are considered to be developing countries that are still in the industrialization process. Even though that is the case, not many studies have focused on determining the quantitative effect of foreign investment on energy use. Instead, most of the studies examine the causal links between the two in multivariate models or the environmental consequences of foreign investment (see Hoffman et al. 2005; Pao & Tsai, 2011; Kim & Adilov, 2012; Blanco et al. 2013; Chandran & Tang, 2013; Kuo et al. 2014; Jiang, 2015; Amri, 2016; Baek, 2016; Zhu et al. 2016; Lin & Benjamin, 2018).

In general, the empirical evidence on the effect of FDI inflows on energy use is ambiguous. One of the earliest papers examining the association between FDI and energy consumption, Mielnik & Goldemberg (2002), argues that the introduction of modern technologies through FDI tends to reduce energy intensity (energy consumption as % of GDP) in developing countries. However, the simple linear regression model used in this study suffers from endogeneity bias arising from omitted variables and does not account heterogeneity as the analysis covers only 20 countries. Hübler & Keller (2010) replicate the results in this study and argues that the variables used by Mielnik & Goldemberg (2002) are both integrated of order one so that results obtained from the classical OLS regression are likely to be misleading. Besides, they present no evidence of cointegration among the variables. As a solution, Hübler & Keller (2010) use panel data models with time and country specific effects to examine the effect of FDI on energy intensity in 60 developing countries over the period 1975–2004. Their findings imply no empirical evidence of energy saving effect of FDI, while they note that foreign development aids might be the source of gains in energy efficiency. A similar result can be found in Polat (2018) which examines the effect of FDI on energy consumption in 85 developed and developing countries over the period 2002–2014. The dynamic panel data estimation implies no evidence of energy saving effect of FDI in developing countries while FDI seems to reduce energy consumption in developed countries. The study also argues that openness and energy prices are the other determinants of energy use in high income economies. Li & Qi (2016), on the other hand, examine the effect of FDI on industrial energy consumption in provinces of China. The empirical results from 2SLS and GMM frameworks indicate that net effect of FDI on energy consumption is negative as the positive technique effect is suppressed by the negative scale and composition effects. A similar approach is adopted by Ting et al. (2011) decomposing the effect of FDI on energy intensity into scale, structure and technology effects. Using data on the province of Jiangsu for the period 1998 - 2008 and Logarithmic Mean Divisia Index (LMDI), they show that the FDI reduces energy consumption through its scale effect, while there is no evidence of energy-saving impact of FDI through the structure and technology effects. Doytch & Narayan (2016), on the other hand, examine the effect of FDI inflows on renewable and non-renewable industrial energy consumption in 74 countries for the period 1985 – 2012 by decomposing FDI inflows into components. Controlling for endogeneity and omitted variable biases, Blundell–Bond dynamic panel estimation implies that FDI contributes to reduction in non-renewable energy consumption (FDI halo effect) but this depends on the income group of a country and what kind of FDI the country attracts more.

To sum up, it is clear from the literature that whether and to what extent FDI an effect on energy consumption has is still an open question. Furthermore, as mentioned earlier, the assumption of parameter homogeneity and ignoring cross sectional dependence across units in such analyses may lead to misleading empirical results. Therefore, the efforts are worthwhile to identify the true association between the two as this task would have important policy implications especially for developing economies.

3. Data and Methodology

For our purpose in this study, we utilize longitudinal panel data on developing countries over the period 1987 – 2016. The selected countries for the analysis are listed in Table 1. The data availability was the main concern in determining the inclusion of any country into our analysis. The variables subject to the empirical analysis are the renewable and nonrenewable primary energy supply (tonne of oil equivalent), GDP (constant at 2010 US$), FDI inflows (constant at 2010 US$). The annual data on energy (lnrenew and lnnonrenew) supply (also called gross inland energy consumption) and real GDP (lngdp) series are extracted from the OECD database, whereas the data real FDI (lnfdi) is obtained from World Development Indicators (WDI) provided World Bank. The real FDI series are constructed by deflating nomal FDI series with consumer price index (2010=100) provided by the WDI. All the variables are expressed in terms of their natural logarithms in order to ease the interpretation.

Table 1. Countries Selected

Bangladesh	Bolivia	Botswana	Brazil	Cameroon
Chile	China	Colombia	Costa Rica	Côte d'Ivoire
Dominican Rep.	Ecuador	Egypt	El Salvador	Gabon
Ghana	Guatemala	Honduras	India	Israel
Jamaica	Jordan	Kenya	Korea, Rep.	Malaysia

Mexico	Morocco	Nigeria	Pakistan	Panama
Peru	Philippines	Senegal	South Africa	Sri Lanka
Thailand	Togo	Tunisia	Turkey	Uruguay

To begin with, assume an autoregressive distributive lag (ARDL) (p, q) dynamic panel specification without time trends and other fixed regressors as the following form:

$$y_{i,t} = \mu_i + \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta'_{i,j} x_{i,t-j} + \varepsilon_{i,t}, \qquad (1)$$

where i and t represent the cross sections (groups) and time period, respectively. μ_i is the group specific effects; x_{it} is a k x 1 vector of explanatory variables and δ_{it} are $kx1$ vector of coefficients to be estimated. For the model can be fitted for each group separately, T must be large enough.

Then the error correction form is given by:

$$\Delta y_{i,t} = \mu_i + \phi_i(y_{i,t-1} - \theta_i' X_{it}) + \sum_{j=0}^{p-1} \lambda_{ij}^{*} \Delta y_{i,t-1} + \sum_{j=0}^{q-1} \delta_{ij}'^{*} \Delta x_{i,t-j} + \varepsilon_{i,t}, \qquad (2)$$

where $\phi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij})$, $\theta_i = \frac{\sum_{j=0}^{q} \delta_{ij}}{1-\sum_k \lambda_{ik}}$, $\lambda_{ij}^{*} = -\sum_{m=j+1}^{p} \lambda_{im}$ where $j = 1,2, \ldots, p-1$, and $\delta_{ij}^{*} = -\sum_{m=j+1}^{q} \delta_{im}$ for $j = 1,2, \ldots, q-1$.

The parameter ϕ_i represents the error-correcting speed of adjustment to the long run equilibrium and if it is equal to zero, then there would be no evidence for a long-run relationship between the selected variables. Specifically, ϕ_i is expected to be significantly negative and the long-run relationships between the variables are contained in the vector θ_i'.

As discussed earlier, the standard pooled estimators may suffer from heterogeneity bias and produce inconsistent and misleading estimates if the slope coefficients are in fact different across cross sections (Pesaran & Smith, 1995). Fortunately, the recent literature suggests alternative approaches to estimate dynamic heterogeneous panels in which both N and T are large. One of the alternative estimation methods to obtain consistent estimates of the individual heterogeneous parameters in Eq. (2) is the Mean Group (MG) Estimator (Pesaran & Smith, 1995) running separate OLS regressions for each cross section and then calculating the arithmetic averages of the specific coefficients over the groups. This estimator allows the intercepts, slope coefficients, and error variances to differ across groups. The MG estimator produces unbiased coefficients in each cross section, unless the time dimension (T) is small and number of cross sections (N) is large relatively to T. Another alternative approach to the estimation of Eq. (2) is dynamic fixed effects (DFE) estimation in which the time series data for each group are pooled and only the intercepts are allowed to freely differ across groups. However, if the slope coefficients are in fact not identical, the DFE approach yields inconsistent and potentially misleading estimations. Another alternative practice is both pooling and averaging the individual regression coefficients and allowing error variances to differ across groups, but constraining the long run coefficients to be identical, which is referred as the pooled mean group (PMG) estimator (Pesaran et al. 1999). However, when the restrictions are in fact not true, this pooling across countries produces inefficient and inconsistent estimates. Fortunately, one might test for slope heterogeneity using Hausman-type test in which MG is consistent under both null and alternative hypotheses, while PMG is consistent under the null but inconsistent under the alternative hypothesis. The Hausman test can also be used to measure the extent of potential endogeneity between the error term and the lagged dependent variable. Baltagi et al. (2000) note that FE models may suffer from simultaneous equation bias which come from this possible endogeneity. Therefore, one might perform Hausman type test to choose between MG and DFE as well.

The traditional FE, MG, and PMG estimators based on the ARDL approach, however, does not account for potential cross sectional dependency of errors. The assumption of cross sectional independency, on the other hand, may not hold as there are a number of omitted or unobserved global factors that are likely correlated with the regressors, which leads to inefficient or even inconsistent estimates.

To overcome this issue, Chudik & Pesaran (2015) propose dynamic common correlated effects (DCCE) estimation method which is an extension of the CCE estimation approach developed by Pesaran (2006) to dynamic models. The general idea of this model is to augment the original regressions with a linear combination of by cross sectional averages of dependent variable ($\bar{y_t}$), the explanatory variables ($\bar{x_t}$) and a sufficient number of lagged variables. Specifically, Chudik & Pesaran (2015) show that the estimator gains consistency if the floor of $p_T = \sqrt[3]{T}$ lags of the cross-sectional averages are added to the original regression.

Extending Eq. (1) with the cross sectional averages to take out the cross sectional dependence leads to:

$$y_{i,t} = \mu_i + \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta'_{i,j} x_{i,t-j} + \sum_{j=0}^{p_T} \gamma_{ij} \bar{z}_{t-j} + \varepsilon_{i,t} \qquad (3)$$

with $\bar{z}_{t-j} = (\bar{y}_{i,t-j}, \bar{x}_{i,t-j})$.

Then the long run coefficients are calculated as:

$$\hat{\theta}_i = \frac{\sum_{j=0}^{q} \hat{\delta}_{ij}}{1-\sum_{j=1}^{p} \hat{\lambda}_{ij}} \quad (4)$$

4. Empirical Findings and Discussion

This section starts with the preliminary analyses of our panel data set. Specifically, we perform Bias-Adjusted Cross Sectional Dependency test developed by Pesaran et al. (2008), Delta test for testing slope homogeneity proposed by Pesaran & Yamagata (2008), and cross-sectionally augmented Dickey-Fuller (CADF) panel unit root test proposed by Pesaran (2007) and present the results in Tables 2-3.

Table 2. Cross Sectional Dependency and Slope Homogeneity Test Results

Dependent Variable:	Nonrenewable Energy Consumption		Renewable Energy Consumption	
CD Test (Pesaran et al. 2008)	Stat	prob	Stat	prob
Bias-adjusted CD test	42.107	0.000	61.88	0.000
Homogeneity (Pesaran and Yamagata, 2008)				
Delta_tilde	34.389	0.000	2468.733	0.000
Delta_tilde_adj	36.848	0.000	48.038	0.000

Table 3. Unit Root Test Results

CADF test (Pesaran, 2007)	Level	First Difference
lnrenew	-1.937	-3.690
	(0.994)	(0.000)
lnnonrenew	-2.411	-3.995
	(0.246)	(0.000)
lngdp	-2.369	-3.525
	(0.344)	(0.000)
lnfdi	-2.416	-2.760
	(0.236)	(0.001)

Notes: P-values in paranthesis. Constant and trend term included. Pesaran test is sensitive to the choice of the lag order, so that the Akaike information criterion (up to 3 lags) was used to select the appropriate lag order for the CADF regressions.

The findings summarized in Table 2 indicate cross sectional dependency in the error terms and heterogeneity of slope coefficients, while the ones presented in Table 3 confirm the stationarity of all the series after first differencing, implying that they are all I(1). Therefore, we can now proceed to the cointegration test for detecting a possible cointegrating relationship between the variables. The results of the Westerlund (2007) panel error correction cointegration tests presented in Table 4 and suggest a long run cointegrating relationship between the series.

Table 4. Panel Cointegration Test Results

Dependent Var:	Nonrenewable Energy Consumption			Renewable Energy Consumption		
Westerlund, 2007	Value	P-value	Robust P-value	Value	P-value	Robust P-value
Gt	-1.940	0.000	0.018	-6.956	0.000	0.441
Ga	-6.478	0.225	0.041	-1.305	0.096	0.014
Pt	-10.854	0.000	0.092	-1.377	0.084	0.002
Pa	-4.636	0.003	0.144	-0.903	0.183	0.020

Notes: The computed the asymptotic and bootstrapped p-values are based on 1000 replications. Constant and trend included

Having established significant evidence of long run relationship between the series, we now proceed to the heterogeneous panel estimates of the specification we discussed earlier. The DFE (assuming slope homogeneity), MG (allowing for slope coefficients to vary across countries), PMG (assuming long run slope homogeneity and allowing for short run slope coefficients to vary across countries) and DCCEMG (accounting for cross sectional dependence) estimates are summarized in Table 5 and Table 6. In particular, the tables report the average estimates of the long-run effects of real FDI and real income on both renewable and non-renewable energy consumption, short run dynamics and the mean estimate of the coefficients of the error term (λ) as well as the Hausman test findings and the results of the weak cross sectional dependency test of Pesaran (2015).

To begin with, the results suggest a direct relationship between economic growth and both renewable and nonrenewable energy consumption. Specifically, the coefficients are mostly positive and significant at 1% significance level across various estimators and lag orders, with different estimators providing close magnitudes. As an exception, DCCEMG estimator does provide no evidence of significant effect of income on renewable energy consumption at any lag level. The other estimators, however, consistently find positive effect of economic growth on renewable energy consumption and nonrenewable energy consumption with one exception of MG estimation at two lags.

On the other hand, the estimation results suggest a negative but insignificant effect of FDI on energy consumption with one exception of MG estimation at two lags which produces a significant negative coefficient for FDI at %10 significance level. As mentioned earlier, cross sectional dependency may lead to biased estimates. We observe that the statistics of the CD test of Pesaran (2015) reported in the tables vary across estimators and different lags. Highly significant with very large test statistics imply the presence of cross-sectional dependence. It can be argued that the estimates with highly significant test statistics might be misleading. Therefore, one should take into account this issue in interpreting the results.

Overall, taking into account heterogeneity and cross sectional dependency across countries, the empirical evidence suggests a positive effect on economic growth and negative but insignificant effect of FDI on both renewable and nonrenewable energy consumption. These results confirm the findings of Doytch & Narayan (2016) and Polat (2018) for developing countries. The results, together with the findings from the earlier literature (see for example, Doytch & Narayan, 2016; Polat, 2018) which mostly find evidence of rising effect of FDI on renewable energy consumption and decreasing effect of FDI on nonrenewable energy consumption in developed economies, imply the fact that absorptive capacity of countries matter for them to capture the technology effect of FDI as we discussed above. Furthermore, it can be argued that relatively weak environmental regulations in less developed countries might be the reason for not being able to benefit from foreign investments to reduce nonrenewable energy consumption and transit to renewable energy technologies from nonrenewable energy sources

Table 5. Estimations based on panel ECM with heterogeneous slopes and/or cross-sectional dependence – Nonrenewable energy

Variables	DFE			MG			PMG			DCEEMG		
	1 lag	2 lag	3 lag	1 lag	2 lag	3 lag	1 lag	2 lag	3 lag	1 lag	2 lag	3 lag
lnfdi	-0.016	-0.017	-0.021	-0.065	-0.119*	-0.103	-0.021	-0.027	-0.029	0.065	-0.338	-0.075
	(0.015)	(0.015)	(0.021)	(0.052)	(0.061)	(0.074)	(0.027)	(0.046)	(0.061)	(0.063)	(0.483)	(0.063)
lngdp	0.876***	0.844***	0.819***	0.814***	0.496	0.821***	0.875***	0.845***	0.840***	0.963***	1.200	0.696
	(0.047)	(0.045)	(0.050)	(0.064)	(0.329)	(0.096)	(0.120)	(0.272)	(0.169)	(0.348)	(1.092)	(0.498)
λ	-0.180***	-0.173***	-0.168***	-0.948***	-0.433***	-0.500***	-0.195	-0.182	-0.155	-0.907***	-1.236***	-1.506***
	(0.024)	(0.022)	(0.023)	(0.008)	(0.040)	(0.051)	(0.122)	(0.154)	(0.153)	(0.067)	(0.137)	(0.310)
Δlnfdi	0.003	0.004	0.004	0.052***	0.074**	0.062**	0.023*	0.031**	0.011	-0.019	0.016	0.098
	(0.004)	(0.004)	(0.004)	(0.0201)	(0.029)	(0.031)	(0.013)	(0.014)	(0.019)	(0.028)	(0.071)	(0.152)
Δlngdp	0.727***	0.789***	0.880***	0.444***	0.425***	0.471***	0.716***	0.709***	0.807***	-0.144	-0.220	-0.758
	(0.182)	(0.247)	(0.255)	(0.107)	(0.135)	(0.150)	(0.102)	(0.138)	(0.144)	(0.216)	(0.333)	(0.738)
Δlnrenew(t-1)		-0.094***	-0.121***		0.017	0.026		-0.039	-0.060		0.178**	0.299
		(0.026)	(0.031)		(0.038)	(0.045)		(0.036)	(0.037)		(0.090)	(0.223)
Δlnrenew(t-2)			-0.070			-0.007			-0.047			-0.037
			(0.049)			(0.045)			(0.040)			0.186
Δlnfdi(t-1)		0.000	0.001		0.029	0.024		-0.006	-0.029		0.051	(0.140)
		(0.003)	(0.003)		(0.018)	(0.023)		(0.012)	(0.022)		(0.052)	0.106*
Δlnfdi(t-2)			-0.001			-0.002			-0.038			(0.055)
			(0.002)			(0.023)			(0.023)			(0.009)
Δlngdp(t-1)		0.024	0.084		-0.018	-0.021		0.117	0.112		-0.451*	-0.123
		(0.143)	(0.143)		(0.129)	(0.106)		(0.106)	(0.116)		(0.271)	(0.577)
Δlngdp(t-2)			0.001			-0.014			0.106			0.029
			(0.073)			(0.136)			(0.111)			(0.426)
CD Test	1.63	0.90	0.99	2.18	2.52	3.09	-0.97	2.13	1.74	-0.92	0.82	2.42
	(0.103)	(0.369)	(0.324)	(0.029)	(0.012)	(0.002)	(0.330)	(0.033)	(0.083)	(0.357)	(0.413)	(0.016)
No. of groups	40	40	40	40	40	40	40	40	40	40	40	40
No. of obs.	1,160	1,120	1,080	1,160	1,120	1,080	1,160	1,120	1,080	1,080	1,080	1,080
	MG-DFE				MG-PMG							
Hausman Test	0.00	0.00	0.00	0.76	1.40	0.55						
	(0.999)	(0.999)	(0.999)	(0.683)	(0.500)	(0.758)						

Notes: Standard errors for coefficients and p-values for CD tests and Hausman tests in parenthesis.

Table 6. Estimations based on panel ECM with heterogeneous slopes and/or cross-sectional dependence – Renewable energy

Variables	DFE			MG			PMG			DCCEMG		
	1 lag	2 lag	3 lag	1 lag	2 lag	3 lag	1 lag	2 lag	3 lag	1 lag	2 lag	3 lag
lnfdi	-0.023	-0.021	-0.009	0.031	-0.152*	0.187	-0.016	-0.016	0.009	-0.047	-0.219	-0.355
	(-0.020)	(-0.022)	(-0.025)	(0.131)	(-0.090)	(0.195)	(-0.032)	(-0.054)	(-0.074)	(-0.079)	(0.206)	(0.316)
lngdp	0.462***	0.454***	0.435***	0.534***	0.478***	0.524***	0.453***	0.449***	0.437**	0.482	0.423	0.542
	(-0.095)	(-0.080)	(-0.080)	(0.173)	(0.158)	(0.178)	(0.171)	(0.101)	(0.198)	(0.783)	(1.372)	(1.425)
λ	-0.143**	-0.160**	-0.201*	-0.276***	-0.330***	-0.353***	-0.153	-0.124	-0.165	-0.644***	-0.757***	-0.885***
	(-0.057)	(-0.070)	(0.117)	(-0.032)	(-0.038)	(-0.050)	(0.269)	(0.141)	(0.413)	(-0.055)	(-0.086)	(0.127)
Δlnfdi	-0.004	-0.003	-0.004	-0.02	-0.02	-0.024	-0.019	-0.018	-0.012	-0.043*	-0.059	-0.244**
	(-0.005)	(-0.005)	(-0.006)	(-0.015)	(-0.019)	(-0.029)	(-0.012)	(-0.013)	(-0.017)	(-0.023)	(-0.045)	(0.101)
Δlngdp	0.063	0.208*	0.069	0.283*	0.337	-0.064	0.07	0.246*	0.119	0.142	0.375*	1.026
	(0.113)	(0.124)	(0.131)	(0.163)	(0.209)	(0.192)	(0.125)	(0.135)	(0.131)	(0.250)	(0.210)	(0.976)
Δlnrenew(t-1)		-0.043	-0.031		0.121***	0.100***		0.095***	0.094**		0.035	-0.047
		(-0.028)	(-0.020)		(-0.029)	(-0.035)		(-0.036)	(-0.046)		(-0.077)	(0.109)
Δlnrenew(t-2)			-0.022			-0.035			-0.025			-0.061
			(-0.050)			(-0.048)			(-0.052)			(-0.073)
Δlnfdi(t-1)		0.009**	0.008**		0.002	0.009		0.021*	0.032**		-0.021	-0.165**
		(-0.004)	(-0.004)		(-0.014)	(-0.020)		(-0.012)	(-0.015)		(-0.028)	(-0.066)
Δlnfdi(t-2)			0.008*			-0.017			0.012			-0.129***
			(-0.005)			(-0.020)			(-0.016)			(-0.049)
Δlngdp(t-1)		-0.509	-0.541*		-0.355*	-0.081		-0.491**	-0.508**		-0.097	0.471
		(0.323)	(0.297)		(0.192)	(0.145)		(0.244)	(0.251)		(0.227)	(0.659)
Δlngdp(t-2)			0.038			0.073			0.0161			0.274
			(-0.071)			(-0.099)			(0.100)			(0.399)
CD Test	-1.243	-0.307	-0.169	-0.14	-1.22	-0.66	-0.97	-2.03	-1.93	-2.05	-1.01	0.38
	(1.786)	(1.241)	(1.339)	(0.888)	(0.222)	(0.512)	(0.330)	(0.042)	(0.053)	(0.040)	(0.313)	(0.707)
No. of groups	40	40	40	40	40	40	40	40	40	40	40	40
No. of obs.	1,160	1,120	1,080	1,160	1,120	1,080	1,160	1,120	1,080	1,080	1,080	1,080
	MG-DFE			MG-PMG								
Hausman Test	0.00	0.00	0.00	3.30	5.67	18.47						
	(0.999)	(0.999)	(0.999)	(0.192)	(0.059)	(0.000)						

Notes: Standard errors for coefficients and p-values for CD tests and Hausman tests in parenthesis.

5. Conclusion

In this study, we attempt to identify the effect of FDI inflows on both renewable and nonrenewable energy consumption in 40 developing countries for the time period spanning from 1987 to 2016. To do so, we use dynamic panel data models under heterogeneity and cross sectional dependency. Specifically, we employ DFE, MG, PMG, and DCCEMG estimators to take into account slopes heterogeneity and cross sectional dependency of errors arising from omitted and unobserved global factors.

The empirical evidence from the traditional dynamic panel data models based on the ARDL framework reveals positive impact of output growth on both renewable and nonrenewable energy consumption, implying the fact that economic growth does not come without a tradeoff in developing countries. This finding is also partly supported by DCCEMG estimator taking implicitly cross sectional dependency into account. As a matter of fact, these findings are in line with the empirical literature, and rising energy consumption and larger output production figures in this set of countries during the last decades. Regarding the effect of FDI on energy consumption, on the other hand, the analyses indicate no significant effect of foreign investments on energy consumption, as we consistently find negative but insignificant coefficients for this variable across different estimators and lag orders.

Essentially, these findings raise an important question regarding the inadequate levels of energy intensity/efficiency. The findings from our analyses clearly indicate that not only attracting foreign investments but also absorbing positive spillovers arising from them are of obvious importance for these countries to reach a sustainable and balanced growth path. Therefore, it is crucial for developing economies to design appropriate trade and development strategies that resolve not only today's problems but also potential environmental challenges facing future generations. By all means, this also requires the mutual efforts of developed and developing countries in transferring energy saving technologies across countries and in designating common agendas for environmental consequences of rising output levels.

References

Amri, F. (2016). The relationship amongst energy consumption, foreign direct investment and output in developed and developing countries. *Renewable and Sustainable Energy Reviews*, 64, 694-702.

Baek, J. (2016). A new look at the fdi–income–energy–environment nexus: Dynamic panel data analysis of ASEAN. *Energy Policy*, 91, 22-27.

Baltagi, B. H., Griffin, J. M., & Xiong, W. (2000). To pool or not to pool: Homogeneous versus heterogeneous estimators applied to cigarette demand. *Review of Economics and Statistics*, 82(1), 117-126.

Blanco, L., Gonzalez, F., & Ruiz, I. (2013). The impact of FDI on CO2 emissions in Latin America. *Oxford Development Studies*, 41(1), 104-121.

Chandran, V. G. R., & Tang, C. F. (2013). The impacts of transport energy consumption, foreign direct investment and income on CO2 emissions in ASEAN-5 economies. *Renewable and Sustainable Energy Reviews*, 24, 445-453.

Chudik, A., & Pesaran, M. H. (2015). Common Correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics*, 188(2), 393-420.

Doytch, N., & Narayan, S. (2016). Does FDI influence renewable energy consumption? An analysis of sectoral FDI impact on renewable and non-renewable industrial energy consumption. *Energy Economics*, 54, 291-301.

Hoffmann, R., Lee, C. G., Ramasamy, B., & Yeung, M. (2005). FDI and pollution: A granger causality test using panel data. *Journal of International Development: The Journal of the Development Studies Association*, 17(3), 311-317.

Hübler, M., & Keller, A. (2010). Energy savings via FDI? Empirical evidence from developing countries. E*nvironment and Development Economics*, 15(1), 59-80.

Jiang, Y. (2015). Foreign direct investment, pollution, and the environmental quality: A model with empirical evidence from the Chinese regions. *The International Trade Journal*, 29(3), 212-227.

Kim, M. H., & Adilov, N. (2012). The lesser of two evils: An empirical investigation of foreign direct investment-pollution tradeoff. *Applied Economics*, 44(20), 2597-2606.

Kuo, K. C., Lai, S. L. Chancham, K., & Liu, M. (2014). *Energy consumption, GDP, and Foreign direct investment in Germany*. In Applied Mechanics and Materials, Trans Tech Publications, 675, 1797-1809.

Li, K., & Qi, S. (2016). Does FDI increase industrial energy consumption of China? Based on the empirical analysis of Chinese provinces industrial panel data. *Emerging Markets Finance and Trade*, 52(6), 1305-1314.

Lin, B., & Benjamin, I. N. (2018). Causal relationships between energy consumption, foreign direct investment and economic growth for MINT: Evidence from panel dynamic ordinary least square models. *Journal of Cleaner Production*, 197, 708-720.

Mielnik, O., & Goldemberg, J. (2002). Foreign direct investment and decoupling between energy and gross domestic product in developing countries. *Energy Policy*, 30(2), 87-89.

Pao, H. T., & Tsai, C. M. (2011). Multivariate granger causality between co2 emissions, energy consumption, FDI (foreign direct investment) and GDP (gross domestic product): Evidence from a panel of BRIC (Brazil, Russian Federation, India, and China) Countries. *Energy*, 36(1), 685-693.

Pesaran, M. H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68(1), 79-113.

Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association*, 94(446), 621-634.

Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, 74(4), 967-1012.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22(2), 265-312.

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, 142(1), 50-93.

Pesaran, M.H., Ullah, A., & Yamagata, T. (2008). A bias-adjusted LM test of error cross-section independence. *The Econometrics Journal*, 11(1), 105-127.

Polat, B. (2018). The influence of FDI on energy consumption in developing and developed countries: A dynamic panel data approach. *Journal of Yasar University*, 13(49).

Ting, Y. U. E., Yin, L. R., & Ying, Z. Y. (2011). Analysis of the FDI effect on energy consumption intensity in Jiangsu province. *Energy Procedia*, 5, 100-104.

Westerlund, J. (2007). Testing for error correction in panel data. *Oxford Bulletin of Economics and Statistics*, 69(6), 709-748.

Zhu, H,. Duan, L., Guo, Y., & Yu, K. (2016). The effects of FDI, economic growth and energy consumption on carbon emissions in ASEAN-5: Evidence from panel quantile regression. *Economic Modelling*, 58, 237-248.