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From Energy to Information: Green Knowledge Production Function in Fragile Five Economies

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ABSTRACT

Climate change and sustainable development goals make green energy (the development of environmentally related technologies) the main determinant of economic growth in the Fragile Five economies. In this study, the determinants of green innovation in the Fragile Five economies (Brazil, India, Indonesia, South Africa, and Turkey) during the period 2002-2020 are examined through panel data analysis. The empirical findings show that in the short run, increases in output encourage demand-driven innovation. In the long run, however, fixed capital investments, the stringency of environmental policies, and the level of human capital are indicated to be effective on green innovation. While in India, income growth and fixed capital investments feed innovation, in the Turkish economy, energy efficiency and renewable energy investments provide support. In Indonesia and South Africa, human capital strengthens the capacity for knowledge absorption and supports innovation. In Brazil, on the other hand, due to income growth being directed towards traditional energy-intensive sectors, the green innovation process slows down. According to the empirical findings, the stringency of environmental policies may suppress green innovation in the short term by increasing compliance costs, but in the long term, in line with the Porter hypothesis, it may stimulate green innovation. For these reasons, in the Fragile Five economies, it is necessary to direct physical capital toward green technologies through green financing instruments and to reduce firms' compliance costs with predictable environmental policies.

Keywords: Green Energy, Human Development, Fixed Capital Investment, Environmental Policy Stringency
JEL Classifications: O13, O33, P48

1. INTRODUCTION

The spread of technologies that take environmental quality into account plays a leading role in the process of achieving the sustainable development goals of the 21st century. In recent years, policies aimed at reducing the carbon footprint have demonstrated the importance given to environmental quality. For this reason, technological innovations that prioritize environmental quality are advancing into the depths of the macroeconomy in many respects. In this study, the determinants of the development of technologies that give importance to environmental quality in the fragile five (hereafter FF) economies during the period 2010-2020 are examined. Despite their high growth potential, FF economies have been placed into a specific classification due to structural problems such as internal political instability, fragility in external economic relations, and high debt ratios. Therefore, identifying the determinants of technological developments that direct environmental quality in FF economies aims to fill an important gap both for low-income economies and for global environmental sustainability. On this basis, it has been determined that there is a significant gap in the literature. While studies examining the determinants of environmental quality are widespread in the EU or OECD economies, they are quite limited in the FF economies. However, FF economies are situated at the very center of environmental policies and technological transformation due to both their high carbon emissions and their high growth rates (Shahbaz et al., 2013). Another reason for examining FF economies is that, due to their high openness ratios, they are directly affected by global commodity and energy shocks. This phenomenon makes capital movements and policy adjustments more prominent in the process of environmental technology development.

Classical economics limits the factors of production to labor, capital, and natural resources, while Neo-Classical economics asserts that with technological progress, capital per worker and output will decline. With endogenous growth models, it has been argued that knowledge, innovation, and R&D investments are the fundamental motivations of the economic growth process. Thus, alongside theoretical and empirical developments in economic theory, ideas regarding the integration of environmentally friendly technologies into the growth process have come to the forefront. Empirical studies on energy economics attempt to explain the development of environmental technologies through the Environmental Kuznets Curve, while more recent research suggests that with the advancement of environmental technologies, environmental degradation can be controlled even at low income levels (Popp, 2002; Johnstone et al., 2010). The variables used in the empirical model have strong economic underpinnings. Gross fixed capital investments are considered the main source of growth in both Classical and Neo-Classical economics. Through endogenous growth models (Lucas, 1988; Romer, 1990), the cumulative effect of human capital and the technological adaptation capacity of the labor force are emphasized. According to Porter and Van der Linde (1995), the environmental policy stringency index creates a strong positive effect on technological innovations by measuring the rigidity of institutional regulations aimed at improving environmental quality. Finally, GDP per capita is included in the model as a proxy variable for market demand, and income growth positively affects the demand for environmentally friendly products, leading firms to adopt more innovative technologies. Ultimately, this study aims to make a unique contribution to the empirical literature by testing the Porter hypothesis in the context of FF economies, examining whether environmental policies influence technological innovations. Although there are many empirical studies on this hypothesis in the literature, this study draws a more comprehensive framework by incorporating not only environmental policy stringency but also human capital and fixed capital investments into the model. Panel data methods are preferred in the empirical analyses. In this way, more robust estimates with higher degrees of freedom are achieved by utilizing both time series and cross-sections. Therefore, cross-sectional dependence (hereafter CSD), panel unit root (hereafter PUR), panel cointegration, causality, and parameter estimations will first be carried out. Among these methods, heterogeneity and CSD in FF economies will be taken into account to model different macroeconomic dynamics. In summary, the contribution of this study to the energy economics literature is: (i) To examine the development of environmental technologies in FF economies, (ii) to consider heterogeneity with panel data methods, (iii) to reveal the effects of fixed capital investments and human capital within the framework of the knowledge production function, and (iv) to determine the impact of environmental policy stringency on environmental technology production.

2. THEORETICAL BACKGROUND AND LITERATURE REVIEW

In its simplest form, the model in this study is expressed as:

$$GI_t = \beta_0 + \beta_1 GFCI + \beta_2 GDPPC + \beta_3 EPS + \beta_4 HDI + \varepsilon_t \tag{1}$$

Since it takes environmentally related technological output (hereafter GI) as the dependent variable, it can also be considered a knowledge production function (hereafter KPF). This is because cumulative knowledge accumulation and innovative production emerge as guiding forces. According to the classical KPF, economic actors are assumed to generate new knowledge stocks through R&D, human capital (hereafter HDI), and gross fixed capital investments (hereafter GFCI). In this context, GI assumes the role of green knowledge output. The main argument of the KPF is that knowledge production is shaped both by supply-push factors (R&D, HDI, GFCI) and demand-pull factors (GDP, market size). In equation (1), GFCI is the complementary capital input of knowledge production. GFCI encompasses a large set ranging from physical infrastructure, production scale, digital equipment, to logistical infrastructure. HDI, on the other hand, represents the cumulative knowledge stock of the KPF and its absorptive capacity. EPS directs the composition of knowledge production toward the green domain through induced technical change. GDP reflects the demand-pull pressure on innovation by influencing the expected returns of R&D activities through market demand. The log-linear structure of regression (1) allows us to obtain scale elasticities and, consequently, semi-elasticities in knowledge production. The sign of the coefficient β_1 for GFCI may vary across cross-sections and therefore can be either positive or negative. If capital accumulation supports green innovation, then $\beta_1 > 0$. If, however, due to misallocation of resources and scale-substitution effects, resources flow into polluting capital, then $\beta_1 < 0$. In economies with higher GDP levels, larger market size and demand conditions suggest that $\beta_2 < 0$. Since EPS increases the cost of polluting technologies through price signals and standards, thereby channeling resources into green technologies, β_3 is expected to be positive $\beta_3 > 0$ (Ambec et al., 2013). Finally, because HDI enhances productivity both in generating new ideas and adapting existing knowledge, β_4 is also expected to be positive $\beta_4 > 0$.

One of the most debated issues in economic theory is the marginal productivity of the returns to the factors of production. While Neo-Classical economics refers to diminishing returns, with the inclusion of innovation, knowledge, environmental and institutional quality into the production process through endogenous growth models, the concept of "at least constant returns" has emerged. The marginal productivity of GFCI varies according to the sectoral capital/output ratio. Tone and Sahoo (2003) state that because GFCI is indivisible, marginal productivity is low in small-scale firms but high in large-scale firms. Assuming that small-scale firms in FF economies have low sectoral densities, it can be said that their marginal productivity is low. Therefore, the contribution of GFCI in FF economies remains more limited. On the other hand, the marginal productivities of knowledge, innovation, and R&D have a structure different from other production factors. According to Lööf and Heshmati (2002), firms exhibit heterogeneous responses in the process of incorporating knowledge into production. Cohen and Klepper (1996) argue that large-scale firms achieve higher returns from innovation outputs due to their larger volume of production. Acs and Audretsch (1987), however, argue that small-scale firms are able to engage in more innovative and creative innovations. Considering these studies, it is observed that GI differs according to firm size. GDP, which is used as a proxy variable for market demand volume, plays a critical role in determining marginal productivity. According to Scherer (1965) and Schmookler (1966), the innovation process is driven by market size and, therefore, demand. For this reason, in economies with high GDPPC, the demand-pull channel is valid. In economies with high HDI capacity, the labor force adapts to work more quickly and the average stock of knowledge in society increases more rapidly. According to Cohen and Levinthal (1990), the effect of HDI on GI occurs through both productivity and knowledge spillovers. EPS has both direct and indirect effects on marginal productivity. Porter and van der Linde (1995) and Ambec et al. (2013) argue that EPS creates a positive long-term impact on firms' level of competitiveness. Johnstone et al. (2010) state that green energy policies have a positive effect on green patent production, while Ghisetti and Pontoni (2015) argue that these policies create nonlinear heterogeneous effects on innovation outputs. Costantini et al. (2017) claim that these policies are both demand-pull and technology-push. Finally, the energy economics literature suggests that the effect of EPS on GI creates different and nonlinear impacts for each cross-section. Özbay (2024) and Murtas (2025) claim that R&D expenditures and HDI have a positive effect on GI and that this effect is heterogeneous. The claim of heterogeneity is also voiced by Acs et al. (1994) and Jaffe et al. (1993), noting that spatial differences affect knowledge spillovers. To summarize, the impact of GFCI, GDP, HDI, and EPS on GI varies both according to economies of scale and to the production structure of the country. While GFCI and GDP create stronger effects in developed economies, HDI and GFCI come to the fore in developing economies. The effect of EPS on GI, within the framework of the Porter hypothesis, positively influences innovation in the long term, while in the short term it creates heterogeneous effects across cross-sections.

3. DATA AND METHODOLOGY

This study investigates the factors influencing GI production in FF economies over the period 2002-2020. The definitions of the variables are provided in Table 1.

Table 1: Definitions

Data	Symbol	Source
Development of environment-related Technologies index	lnGI	OECD
Gross fixed capital formation (% of GDP)	GFCI	WB
Per capita gross domestic product (GDP) at current prices in US dollars, representing market demand	lnGDPPC	WB
Human Capital Index	lnHDI	UNDP
Environmental Policy Stringency Index, representing the strictness of environmental policies	lnEPS	OECD

Cross-sectional dependence (CSD) tests developed by Breusch and Pagan (1980), Pesaran (2004) and Pesaran et al. (2008) are employed to assess the presence of such dependence. In the Lagrange Multiplier (hereafter LM) test, $LM = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^2$ and $LM_{adj} = \sqrt{\frac{2}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^2\frac{(T-k)\hat{\rho}_{ij}^2-\mu_{Tij}}{\sqrt{\vartheta_{Tij}^2}}$ (Breusch and Pagan, 1980; Pesaran et al., 2008). In CD tests, test statistics are calculated as $CD_{LM} = \sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left(T\hat{\rho}_{ij}^2-1\right)}$ and $CD = \sqrt{\frac{2T}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^2}$ (Pesaran, 2004).

According to Table 2, there is clearly CSD in all variables. In the production of lnGI, economies are directly influenced by each other. The lnGI patent mechanisms developed in one economy spread to other economies through international trade flows and foreign investments (Jaffe et al., 1993). Therefore, a GI produced within the FF can be absorbed by the others. In the context of lnGI, the CSD observed in the FF is consistent with the knowledge spillovers proposed by Griliches (1992). GFCI is affected by global economic cycles, since FF economies are dependent on capital flows and therefore influenced by changes in the interest rates of reserve currencies. GDPPC is affected by international trade, income distribution, energy and raw material prices, and supply/demand shocks, because the process of integration into international markets has synchronized the FF economies. lnEPS is influenced by global environmental policies. With the policy convergence hypothesis, Holzinger and Knill (2005) indicate that steps regarding lnGI regulations are taken jointly within the FF. lnHDI is related to global knowledge flows and labor movements. According to Lucas (1988), HDI is mobile both within a country and across economies, and this enhances productivity. At the country level, Brazil is exposed to CSD due to fluctuations in commodity prices, while Indonesia's dependence on energy prices leads to CSD. In South Africa and Turkey, in addition to these two situations, financial fragility stemming from openness has always existed. In India, knowledge flows are integrated with other economies due to R&D and service exports in the software sector. In summary, the main reason for the emergence of CSD in the variables is the synchronized impact of global supply/demand shocks, knowledge and technology spillovers, and convergence in environmental policies.

In the panel unit root (hereafter PUR) test proposed by Smith et al. (2004), the test's critical values are obtained using the bootstrap method. This test yields more reliable results in the presence of CSD within the panel. The test statistics (LM) are $\overline{LM} = N^{-1}\sum_{i=1}^{N}LM_i$

Table 2: CSD results

Tests	lnGI	GFCI	lnGDPPC	lnEPS	lnHDI
LM	43.524 (0.00)[a]	17.457 (0.06)[c]	24.026 (0.00)[a]	30.268 (0.00)[a]	21.989 (0.00)[a]
CD_{LM}	−7.496 (0.00)[a]	1.668 (0.04)[b]	3.136 (0.00) [a]	4.532 (0.00)[a]	2.681 (0.00)[a]
CD	−3.502 (0.00)[a]	−3.185 (0.00)[a]	−3.172 (0.00)[a]	−3.181 (0.00)[a]	−2.678 (0.00)[a]
LM_{adj}	−0.816 (0.79)	3.934 (0.00)[a]	7.708 (0.00)[a]	9.170 (0.00)[a]	3.156 (0.00)[a]

[a]P<0.01, [b]P<0.05, [c]P<0.1, LM BP (1980), CD_{LM} and CD Peseran (2004), LM_{adj}. Calculated by the authors

and LM is the arithmetic mean of the test statistics. The PANICCA PUR panel developed by Reese and Westerlund (2016) tests for unit roots in two different planes: Common components and idiosyncratic components. In the model $y_{it} = \lambda_i f_t + e_{it}$ unit root tests are applied tofactor loadings and common factors. $Z^c_{\hat{e}}$ tests the stationarity of the common components, while $P^c_{\hat{e}}$ tests the stationarity of the idiosyncratic components. $\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$ tests test the assumption that all cross sections in the panel have the same coefficient. In the homogeneity test proposed by Pesaran and Yamagata (2008), $\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S}-k}{\sqrt{2k}}\right)$ and $\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S}-E(\tilde{Z}_{iT})}{\sqrt{var(\tilde{Z}_{iT})}}\right)$ are obtained. The cointegration test examines whether the independent variables have an impact on lnGI in the long run. Westerlund (2007; 2008) developed a cointegration model to test whether the error correction term is zero. $\alpha_i(L)\Delta y_{it} = \delta_{1i} + \delta_{2i}t + \alpha_i\left(y_{it-1} - \beta_i x_{it-1}\right) + \gamma_i(L)\vartheta_{it} + \varepsilon_{it}$, there is no cointegration in the model. In the Durbin-Hausman panel cointegration test proposed by Westerlund (2008), the DH_g test statistic assumes that the autoregressive parameters are heterogeneous, while the DH_p test statistic assumes that the autoregressive parameters are homogeneous. Accordingly, the test statistics are $DH_g = \sum_{i=1}^{n}\tilde{S}_i\left(\tilde{\phi}_i - \hat{\phi}_i\right)^2\sum_{t=2}^{T}\hat{e}^2_{it-1}$ and $DH_p = \tilde{S}_n\left(\tilde{\phi} - \hat{\phi}\right)^2\sum_{j=1}^{n}\sum_{t=2}^{T}\hat{e}^2_{it-1}$.

Table 3 presents the PUR, CSD, and panel cointegration results The lnGI variable is stationary at level in the Smith et al. (2004) PUR test, while in the PANICCA PUR test it becomes stationary when the first difference is taken. GFCI, on the other hand, is stationary in the constant model of the Smith et al. (2004) PUR test, but carries a unit root in the trend model. The other variables are difference-stationary in the PUR test presented in Panel A. Different results are obtained in the PANICCA test. These differences are due to GFCI having a unit root in the first difference with the trend model and HDI being I(2). As a result, considering the economic shocks experienced by the fragile five economies and the different powers of the tests, it is assumed that the variables included in the model have long memory and that all variables are I(1). In the CSD and delta tests, the alternative hypotheses are accepted, and it is observed that the slope parameters differ among the fragile five economies. In the LM bootstrap and Durbin-Hausmann panel cointegration tests, it is found that the variables move together in the long run and exert an effect on one another. These findings are consistent with the long-term knowledge equilibrium of the KPF. The cointegrated relationship shows that the model follows a common knowledge growth path in the long run.

In the panel vector autoregression (PVAR) model, the panel error correction model (PVECM) is established by including the error correction parameters $\phi_1\hat{\varepsilon}_{it-1}$, $\phi_2\hat{\varepsilon}_{it-1}$, $\phi_3\hat{\varepsilon}_{it-1}$, $\phi_4\hat{\varepsilon}_{it-1}$ and $\phi_5\hat{\varepsilon}_{it-1}$:

$$\Delta lnGI = \delta_{1i} + \sum_{p=1}^{k}\delta_{11ip}\Delta lnGI_{it-p} + \sum_{p=1}^{k}\delta_{12ip}\Delta GFCI_{it-p} + \sum_{p=1}^{k}\delta_{13ip}\Delta lnGDPPC_{it-p} + \sum_{p=1}^{k}\delta_{14ip}\Delta lnEPS_{it-p} + \sum_{p=1}^{k}\delta_{15ip}\Delta lnHDI_{it-p} + \phi_1\hat{\varepsilon}_{it-1} + v_{1t} \quad (2)$$

$$\Delta lnGFCI = \delta_{2i} + \sum_{p=1}^{k}\delta_{21ip}\Delta lnGFCI_{it-p} + \sum_{p=1}^{k}\delta_{22ip}\Delta GI_{it-p} + \sum_{p=1}^{k}\delta_{23ip}\Delta lnGDPPC_{it-p} + \sum_{p=1}^{k}\delta_{24ip}\Delta lnEPS_{it-p}\sum + \sum_{p=1}^{k}\delta_{25ip}\Delta lnHDI_{it-p} + \phi_2\hat{\varepsilon}_{it-1} + v_{2t} \quad (3)$$

$$\Delta lnGDPPC = \delta_{3i} + \sum_{p=1}^{k}\delta_{31ip}\Delta lnGDPPC_{it-p} + \sum_{p=1}^{k}\delta_{32ip}\Delta GI_{it-p} + \sum_{p=1}^{k}\delta_{33ip}\Delta lnGFCI_{it-p} + \sum_{p=1}^{k}\delta_{34ip}\Delta lnEPS_{it-p} + \sum_{p=1}^{k}\delta_{35ip}\Delta lnHDI_{it-p} + \phi_3\hat{\varepsilon}_{it-1} + v_{3t} \quad (4)$$

$$\Delta lnEPS = \delta_{4i} + \sum_{p=1}^{k}\delta_{41ip}\Delta lnEPS_{it-p} + \sum_{p=1}^{k}\delta_{42ip}\Delta GI_{it-p} + \sum_{p=1}^{k}\delta_{43ip}\Delta lnGFCI_{it-p} + \sum_{p=1}^{k}\delta_{44ip}\Delta lnGDPC_{it-p} + \sum_{p=1}^{k}\delta_{45ip}\Delta lnHDI_{it-p} + \phi_4\hat{\varepsilon}_{it-1} + v_{4t} \quad (5)$$

$$\Delta lnHDI = \delta_{5i} + \sum_{p=1}^{k}\delta_{51ip}\Delta lnHDI_{it-p} + \sum_{p=1}^{k}\delta_{52ip}\Delta GI_{it-p} + \sum_{p=1}^{k}\delta_{53ip}\Delta lnGFCI_{it-p} + \sum_{p=1}^{k}\delta_{54ip}\Delta lnGDPPC_{it-p} + \sum_{p=1}^{k}\delta_{55ip}\Delta lnEPS_{it-p} + \phi_5\hat{\varepsilon}_{it-1} + v_{5t} \quad (6)$$

In this (7) model, the null hypotheses for short-term causality are $\sum_{p=1}^{k}\delta_{12ip}\Delta GFCI_{it-p} = 0$ from GFCI to lnGI, $\sum_{p=1}^{k}\delta_{13ip}\Delta lnGDPPC_{it-p} = 0$ from lnGDPPC to lnGI, $\sum_{p=1}^{k}\delta_{14ip}\Delta lnEPS_{it-p} = 0$ from lnEPS to lnGI, $\sum_{p=1}^{k}\delta_{15ip}\Delta lnHDI_{it-p} = 0$ from lnHDI to lnGI, this indicates no causality. The alternative hypotheses are $\sum_{p=1}^{k}\delta_{12ip}\Delta GFCI_{it-p} \neq 0$ from GFCI to lnGI, $\sum_{p=1}^{k}\delta_{13ip}\Delta lnGDPPC_{it-p} \neq 0$ from lnGDPPC to lnGI, $\sum_{p=1}^{k}\delta_{14ip}\Delta lnEPS_{it-p} \neq 0$ from lnEPS to lnGI, $\sum_{p=1}^{k}\delta_{15ip}\Delta lnHDI_{it-p} \neq 0$ from lnHDI to lnGI, this indicates causality. In the long run $\phi_1\hat{\varepsilon}_{it-1} = 0$ indicates no causality from GFCI, lnGDPPC, lnEPS and lnHDI to lnGI as a whole.

Table 4 presents the short and long run panel causality results. In the short run, causality is found only from lnGDPPC to lnGI,

Table 3: PUR, CSD, Delta tests, cointegration

Panel A. Smith et al. (2004) "bootstrap" PUR					
Variable		**Constant**		**Constant and Trend**	
Levels		**Statistic**	**Bootstrap (P-value)**	**Statistic**	**Bootstrap (P-value)**
lnGI		−2.919	0.00[a]	−3.879	0.00[a]
GFCI		−2.061	0.08[c]	−1.986	0.62
lnGDPPC		−1.276	0.68	−1.582	0.89
lnEPS		−0.985	0.81	−1.572	0.90
lnHDI		−1.721	0.24	−0.465	0.99
First difference					
lnGI		−4.890	0.00[a]	−4.897	0.00[a]
GFCI		−3.823	0.00[a]	−3.937	0.00[a]
lnGDPPC		−4.213	0.00[a]	−4.197	0.00[a]
lnEPS		−6.610	0.00[a]	−6.599	0.00[a]
lnHDI		−2.603	0.00[a]	−2.684	0.02[b]
Panel B. PANICCA PUR					
Variable		**Constant**		**Constant and Trend**	
Levels		**Statistic**	**Asymptotic (P-value)**	**Statistic**	**Asymptotic (P-value)**
lnGI	$Z_{\hat{e}}^{c}$	1.043	0.14	1.716	0.04[b]
	$P_{\hat{e}}^{c}$	14.665	0.14	17.686	0.06
GFCI	$Z_{\hat{e}}^{c}$	−1.557	0.94	−1.238	0.89
	$P_{\hat{e}}^{c}$	2.033	0.98	4.461	0.92
lnGDPPC	$Z_{\hat{e}}^{c}$	−1.319	0.90	0.160	0.43
	$P_{\hat{e}}^{c}$	4.101	0.94	10.718	0.37
lnEPS	$Z_{\hat{e}}^{c}$	−2.082	0.98	0.723	0.23
	$P_{\hat{e}}^{c}$	0.684	0.99	13.233	0.21
lnHDI	$Z_{\hat{e}}^{c}$	−1.567	0.94	−1.781	0.96
	$P_{\hat{e}}^{c}$	2.99	0.98	2.031	0.99
First difference					
lnGI	$Z_{\hat{e}}^{c}$	4.050	0.00[a]	3.087	0.00[a]
	$P_{\hat{e}}^{c}$	28.116	0.00[a]	23.806	0.00[a]
GFCI	$Z_{\hat{e}}^{c}$	1.652	0.04[b]	0.544	0.29
	$P_{\hat{e}}^{c}$	17.389	0.06[c]	12.433	0.25
lnGDPPC	$Z_{\hat{e}}^{c}$	6.708	0.00[a]	3.419	0.00[a]
	$P_{\hat{e}}^{c}$	40.010	0.00[a]	25.612	0.00[a]
lnEPS	$Z_{\hat{e}}^{c}$	2.123	0.00[a]	3.930	0.00[a]
	$P_{\hat{e}}^{c}$	19.498	0.00[a]	27.578	0.00[a]
lnHDI	$Z_{\hat{e}}^{c}$	−0.042	0.51	−1.485	0.91
	$P_{\hat{e}}^{c}$	9.811	0.45	3.356	0.97
Panel C. CSD and Delta Tests					
CSD Tests		**Statistic**	**Asymptotic (P-value)**	**Bootstrap (P-value)**	
LM		416.841	0.00[a]	-	
CD_{LM}		7.618	0.00[a]	-	
CD		13.945	0.00[a]	-	

(Contd...)

Table 3: *(Continued)*

Panel C. CSD and Delta Tests				
Models		**Statistic**	**Asymptotic (P-value)**	**Bootstrap (P-value)**
LM_{adj}		6.617	0.00[a]	-
$\tilde{\Delta}$		0.914	0.08[a]	-
$\tilde{\Delta}_{adj}$		1.465	0.04[b]	-
Panel D. LM bootstrap (LM_N^+) Panel Cointegration				
Constant		3.159	0.80	0.00[a]
Constant and trend		8.007	0.80	0.00[a]
Panel E. Durbin Hausmann Cointegration				
Constant	DH_g	6.598	0.99	
	DH_p	10.323	0.99	
Constant and trend	DH_g	16.085	0.99	
	DH_p	26.597	0.99	

H_0: Cointegration in LM bootsrap, H_0: no cointegration Durbin and Hausmann panel cointegration tests. The maximum lag length 4, 5000 bootstrap distributions. [a]P<0.01, [b]P<0.05, [c]P<0.1. Calculated by the authors.

Table 4: Short and long run causality

Variables	**Short run (PVAR)**					**Long run (PVECM)**
	Δ(lnGI)	**Δ(GFCI)**	**Δ(lnGDPPC)**	**Δ(lnEPS)**	**Δ(lnHDI)**	**ECT(−1)**
Δ(lnGI)	-	5.291 (0.15)	17.055 (0.00)[a]	0.353 (0.94)	2.761 (0.42)	$\phi_1\hat{\varepsilon}_{it-1}$ −1.402 [−6.832][a]
Δ(GFCI)	2.715 (0.43)	-	1.500 (0.68)	10.655 (0.01)[b]	3.316 (0.34)	$\phi_2\hat{\varepsilon}_{it-1}$ −4.118 [−1.624][c]
Δ(lnGDPPC)	16.351 (0.00)[a]	11.698 (0.00)[a]	-	4.976 (0.17)	5.226 (0.15)	$\phi_3\hat{\varepsilon}_{it-1}$ −0.073 [0.679]
Δ(lnEPS)	0.436 (0.93)	10.216 (0.01)[b]	2.091 (0.55)	-	0.493 (0.92)	$\phi_4\hat{\varepsilon}_{it-1}$ −0.205 [−1.235][c]
Δ(lnHDI)	4.499 (0.21)	0.662 (0.88)	1.239 (0.74)	6.010 (0.11)	-	$\phi_5\hat{\varepsilon}_{it-1}$ −0.007 [−1.326][c]

[a]P<0.01, [b]P<0.05, [c]P<0.1, () probability and [] t statistics. Calculated by the authors.

whereas in the long run, causality is found from GFCI, lnGDPPC, lnEPS, and lnHDI as a whole toward lnGI. In this model, where lnGI is the dependent variable, short-run disequilibria are corrected within 0.71 years. The causality from lnGDPPC demonstrates the validity of the demand-pull model. Economies with high income levels increase the demand for products generated with green energy. Thus, by benefiting from economies of scale and optimal risk management, they enhance the expected returns of R&D expenditures. The short-run causality from lnGDPPC (demand shock) to lnGI (innovation output) reflects the short/long-run components of the Porter hypothesis (from lnEPS to lnGI), as well as the delayed impact of lnHDI on production process innovations (Love and Zicchino, 2006). The differences between short- and long-run causality indicate that within the KPF, different channels operate under adaptive expectations and discrete-time assumptions. Consequently, short-run causality aligns with the demand-pull innovation hypothesis. According to Schmookler (1966) and Scherer (1965), a high level of output has a positive effect on innovation outputs. In economies with high output levels, demand for green products is strong, leading firms to turn toward lnGI. Long-run causality, on the other hand, reveals the multi-component structure of the KPF. This finding is consistent with Özbay (2024) and Murtas (2025). In the short run, causality is found from lnGDPPC and lnEPS to GFCI, while in the long run, causality exists as a whole from lnGI, lnGDPPC, lnEPS, and lnHDI toward GFCI. In this model, where GFCI is the dependent variable, short-run disequilibria are corrected within 0.24 years.

The long-run causality toward GFCI indicates the effectiveness of the "feedback mechanism." According to Love and Zicchino (2006), with financial development, the investment behavior of economic agents becomes more dynamic and shifts toward alternative financial instruments. Therefore, instruments aimed at financing green energy are prioritized by households. Although there is short-run causality from lnGI to lnGDPPC, no causality relationship is detected in the long run. The absence of long-run causality, despite its presence in the short run, suggests that the positive effects arising in the innovation–growth relationship diminish over time. Although the economic literature identifies innovation as the fundamental determinant of growth in the long run, in the case of the FF economies, it reveals that some challenges exist in the adaptation of the labor force to technology. In the short run, causality is found from GFCI to lnEPS, while in the long run, causality exists from lnGI, GFCI, lnGDPPC, and lnHDI toward lnEPS. In this model, where lnEPS is the dependent variable, short-run disequilibria are corrected within 4.87 years. High lnEPS ratios can redirect the foundations of the KPF toward clean technologies. Legal standards and public policies such as taxes/subsidies aimed at developing institutional infrastructure encourage firms' R&D investments. The long-run causality that emerges indicates that institutional regulations respond to technological developments. Ambec et al. (2013) and Fabrizi et al. (2018) argue in their studies that there is a strong link between EPS and the innovation process. Finally, while no causality is found toward lnHDI from the variables in the model, in the long run causality exists from lnGI, GFCI, lnGDPPC, and lnEPS toward lnHDI. In this model, where lnHDI is the dependent variable, short-run disequilibria are corrected within 142.8 years. In the KPF, HDI is both a productive input and the main mechanism of knowledge absorption and capture (Cohen and Levinthal, 1990). Economies within the FF that have lower initial levels can experience a faster convergence process if they possess sufficient levels of HDI (Benhabib and Spiegel, 2005). In the FF economies, it is considered that in terms of the KPF, regulatory convergence and the spillover effects of green knowledge production are significant.

The results presented in Table 5 reveal that the FF economies exhibit a highly heterogeneous structure. No causality is found from lnGI to GFCI in any of the countries. In economies with low per capita income, the fact that innovation outputs do not transform into capital accumulation indicates that financial markets lack sufficient depth and the marginal propensity to save is low (Dosi et al., 2017). Causality from GFCI to lnGI is found only in India. This finding is consistent with the Schumpeterian approach, which emphasizes that GFCI is a technological prerequisite. Similarly, no causality is found from lnGI to lnGDPPC in any country, while only in India causality is found from lnGDPPC to lnGI. This outcome, observed exclusively in the Indian economy, supports the demand-pull innovation model. In India, the increase in lnGDPPC enhances the savings tendency of both the public and households, thereby raising the demand for environmentally friendly products. The absence of this phenomenon in other FF economies may be due either to insufficient demand pressure or to the fact that the innovation process depends on inflows of external resources. In India and Turkey, there is causality from lnGI to lnEPS. This finding indicates the validity of the opposite of the Porter hypothesis, suggesting that the innovation process may influence policy stringency. After 2010 in India and after 2016 in Turkey, energy efficiency and renewable energy investments have been accelerating (Bhattacharya et al., 2016; Çetin and Ecevit, 2019). No causality is found from lnEPS to lnGI in any FF economy. As Ambec et al. (2013) suggest, environmental policies affect innovation not in the short but in the long run. Finally, causality from lnGI to lnHDI is found only in India, while in Indonesia and South Africa causality runs from lnHDI to lnGI. These findings indicate that the relationship between lnHDI and lnGI has a heterogeneous structure across countries. In Indonesia and South Africa, lnHDI fosters innovation (Aghion et al., 2009), whereas in Turkey and Brazil weak institutional infrastructure prevents this relationship (Cirera and Maloney, 2017).

Due to the detection of heterogeneity in slope coefficients and differences in the levels of stationarity of the variables, the Augmented Mean Group (AMG) and Common Correlated Effects (CCE) methods were applied for parameter estimation. The AMG estimation is conducted in two stages. The first stage estimates $\delta Y_{it} = \varphi_i + \delta_i \delta X_{it} + \theta_i f_t + \sum_{t=2}^{T} \pi_i \delta D_t$ and the second stage estimates $\hat{\delta}_{AMG} = N^{-1} \sum_{i=1}^{N} \hat{\delta}_i$. Where φ_i is the constant term, Y_{it} and X_{it} are the dependent and independent variables, f_t the heterogeneous components, and $\delta\hat{\delta}_{AMG}$ AMG are the estimators (Westerlund and Edgerton, 2008; Eberhardt and Bond, 2009). The CCE panel regression method, which accounts for the effects of common factors using cross-sectional averages, also prevents biased estimates associated with unobservable economic shocks that affect all cross-sections (Eberhardt and Bond, 2009). In the model $y_{it} = \alpha_i + \beta_i x_{it} + \gamma_i \bar{x}_t + \varepsilon_{it}$ where $M_{\bar{Z}}$ is the projection matrix obtained from the cross-sectional mean matrix, the test statistic $\hat{\beta}_{CCE} = \left(\sum_{i=1}^{N} X_i M_{\bar{Z}} X_i \right)^{-1} \left(\sum_{i=1}^{N} X_i M_{\bar{Z}} y_i \right)$ (Pesaran, 2006).

The KPF bases knowledge production on externalities and spillover effects (Jaffe et al., 1993; Coe and Helpman, 1995). In the case of FF economies, factors such as common economic policy shocks and the integration of production processes indicate the existence of a common-factor knowledge environment. Therefore, heterogeneous panel estimators such as CCE and AMG, which take into account multiple factors, estimate parameters unbiasedly by controlling for unobservable factors (Eberhardt and Bond, 2009; Westerlund and Edgerton, 2008). According to Table 6, in the AMG and CCE tests, when GFCI increases by 1% across the entire panel, lnGI decreases by 0.008% and 0.02%, respectively, and in the CCE test,

Table 5: Emirmahmutoğlu and Köse (2011) panel causality test results

Countries	Lags	lnGI⇏lnGFCI	GFCI⇏lnGI	Lags	lnGI⇏lnGDPPC	lnGDPPC⇏lnGI
Brazil	3	1.987 (0.57)	1.812 (0.61)	3	5.104 (0.16)	2.387 (0.49)
India	3	3.693 (0.29)	8.076 (0.04)[b]	3	5.120 (0.16)	8.934 (0.03)[b]
Indonesia	3	5.787 (0.12)	3.772 (0.28)	1	0.596 (0.43)	1.631 (0.20)
South Africa	1	0.482 (0.48)	0.172 (0.99)	2	3.030 (0.21)	1.014 (0.60)
Turkiye	1	1.089 (0.29)	0.193 (0.66)	3	1.91 (0.61)	5.192 (0.15)
Fisher Stat.		11.608 (0.31)	10.540 (0.39)		12.876 (0.23)	16.309 (0.09)[c]
Countries	**Lags**	**lnGI⇏lnEPS**	**lnEPS⇏lnGI**	**Lags**	**lnGI⇏lnHDI**	**lnHDI⇏lnGI**
Brazil	3	0.436 (0.93)	4.226 (0.23)	3	1.710 (0.63)	5.511 (0.13)
India	3	6.670 (0.08)[c]	2.220 (0.52)	3	7.512 (0.05)[c]	5.553 (0.13
Indonesia	1	0.002 (0.95)	0.205 (0.65)	2	2.266 (0.32)	6.205 (0.04)[b]
South Africa	1	0.124 (0.72)	0.232 (0.62)	2	3.844 (0.14)	10.314 (0.00)[a]
Turkiye	3	8.209 (0.04)[b]	3.340 (0.34)	1	2.304 (0.12)	0.519 (0.47)
Fisher Stat.		12.189 (0.27)	8.078 (0.62)		16.837 (0.07)[c]	25.984 (0.00)[a]

[a]P<0.01, [b]P<0.05, [c]P<0.1. Calculated by the authors.

Table 6: CCE and AMG parameters estimators

Countries	Constant	GFCI	lnGDPPC	lnEPS	lnHDI
Panel A. AMG estimation					
Brazil	3.449 (0.03)[b]	−0.020 (0.35)	−0.618 (0.06)[c]	−0.343 (0.07)[c]	1.536 (0.06)[c]
India	−1.140 (0.55)	−0.008 (0.10)	0.413 (0.33)	−0.488 (0.28)	−0.693 (0.81)
Indonesia	1.408 (0.39)	0.0003 (0.98)	−0.571 (0.18)	0.233 (0.46)	−2.410 (0.50)
South Africa	0.389 (0.67)	−0.003 (0.83)	−0.163 (0.54)	−0.047 (0.75)	−1.626 (0.18)
Turkey	0.928 ((0.44)	−0.009 (0.55)	−0.111 (0.74)	−0.562 (0.19)	2.275 (0.31)
Panel	1.007 (0.17)	−0.008 (0.02)[b]	−0.210 (0.26)	−0.241 (0.10)	0.816 (0.61)
Panel B. CCE estimation					
Brazil	−1.235 (0.78)	−0.022 (0.37)	−0.788 (0.07)[c]	−0.229 (0.34)	4.442 (0.64)
India	−0.435 (0.87)	−0.021 (0.18)	−0.418 (0.62)	−0.211 (0.74)	3.792 (0.66)
Indonesia	−6.625 (0.12)	0.018 (0.43)	−0.754 (0.16)	−0.614 (0.26)	−14.001 (0.14)
South Africa	3.432 (0.21)	−0.060 (0.02)[b]	−1.085 (0.09)[c]	0.711 (0.70)	−1.657 (0.00)[a]
Turkey	−1.679 (0.75)	−0.017 (0.39)	−0.594 (0.38)	−0.724 (0.29)	1.864 (0.31)
Panel	−1.308 (0.41)	−0.02 (0.09)[c]	−0.728 (0.00)[a]	−0.341 (0.01)[b]	1.445 (0.79)

[a]P<0.01, [b]P<0.05, [c]P<0.1. Calculated by the authors.

it decreases by 0.06% in South Africa. GFCI affects the KPF in three ways. First, it provides complementary infrastructure for the R&D process. Second, it increases the average stock of knowledge in society through diffusion. Finally, it facilitates access to economies of scale for green technologies (Hall and Lerner, 2010). However, being locked into polluting capital can make the transition to green knowledge difficult in the short run. The parameter determines which of these effects is valid. As mentioned earlier in the literature review, in the KPF, knowledge production is influenced both by internal R&D activities and by positive externalities and technology shocks. This empirical finding shows that GFCI, rather than directly contributing to innovation, in the short run concentrates on polluting sectors. In particular, the negative effect observed in South Africa shows that GFCI is persistently dependent on traditional energy. According to Hall and Lerner (2010), GFCI affects the KPF through three channels: providing infrastructure, increasing knowledge spillovers, and achieving economies of scale. However, in the case of polluting capital lock-in, these effects work in the opposite direction. According to the AMG test, when lnGDPPC increases by 1% in Brazil, lnGI decreases by 0.618%. According to the CCE test, when lnGDPPC increases by 1%, lnGI decreases by 0.788% in Brazil and 1.085% in South Africa. This is due to the fact that in the Brazilian and South African economies, increasing firm revenues are directed toward consumption-oriented traditional sectors rather than production with green innovation. According to the AMG test, when lnEPS increases by 1% in Brazil, lnGI decreases by 0.343%. In the CCE test, across the entire panel, when lnEPS increases by 1%, lnGI decreases by 0.341%. This finding shows that in the short run, regulations aimed at improving environmental quality suppress innovation due to increased compliance costs (Ambec et al., 2013). However, the long-term predictions of the Porter hypothesis suggest that this situation may be reversed. Finally, according to the AMG test, when lnHDI increases by 1% in Brazil, lnGI increases by 1.536%, while in the CCE test, when lnHDI increases by 1% in South Africa, lnGI decreases by 1.657%. This empirical finding is consistent with Cohen and Levinthal's (1990) "absorptive capacity" approach, since the marginal productivity of the labor force supported by technological development increases. On the other hand, in South Africa, the negative effect of lnHDI may be due to its adaptation to different service sectors rather than innovation.

4. CONCLUSION

In this study, the effects of demand, physical capital, human capital, and policy changes on green innovation in the FF economies during the period 2002-2020 are examined using panel data analysis. The most significant contribution of the study to the literature is the integration of demand-pull, supply-push, and policy effects within the same model. Thus, green innovation is addressed within the framework of the knowledge production function, which considers multiple factors. In this context, PVAR and PVECM are used to capture short- and long-term relationships, while AMG and CCE methods are employed to account for CSD and heterogeneity. The reason for detecting CSD is knowledge spillovers. According to Jaffe et al. (1993) and Griliches (1992), knowledge flows occur through patents, capital movements, and core–periphery country relations. Since GFCI is influenced by financial cycles, lnGDPPC by global trade and commodity prices, lnEPS by global environmental policies, and lnHDI by labor mobility, it is considered that CSD emerges. PUR tests show that the variables included in the model exhibit long memory. According to this finding, the FF economies are frequently exposed to shocks during the empirical analysis period. Panel cointegration tests indicate that the green KPF operates within a long-term equilibrium mechanism. The fact that in the short run causality exists only from lnGDPPC to lnGI confirms the demand-pull innovation hypothesis proposed by Schmookler (1966) and Scherer (1965). In the long run, causality as a whole toward lnGI demonstrates the multi-component structure of the KPF. Different adjustment speeds obtained from the PVECM method indicate that the institutional adaptation process in the FF economies occurs over different time horizons. PVAR findings show that in the short run, lnGDPPC and lnEPS influence GFCI. In the long run, however, the relationship between lnGDPPC and lnGI is observed to weaken. This weakening relationship is consistent with Cohen and Levinthal's (1990) absorptive capacity approach. The impact of lnEPS on lnGI in the short run parallels Ambec et al. (2013), who found that environmental policies affect innovation in the long run. The impact of lnHDI on lnGI shows that it is heterogeneous at the country level. While it creates an increase in absorptive capacity in the Brazilian economy, it generates a negative effect in South Africa. Country-level causality tests indicate that in the

Indian economy, GFCI and lnGDPPC affect lnGI. This finding is consistent with Bhattacharya et al. (2016), who argue that green energy investments support growth. In Turkey and India, lnGI affects lnEPS, whereas in Indonesia and South Africa, lnHDI affects lnEPS. The reason for this heterogeneous structure is that the countries have different institutional frameworks. Parameter estimates reveal that in the short run, GFCI has a negative effect on lnGI, thereby confirming the carbon lock-in hypothesis. The negative impact of lnGDPPC on lnGI in the Brazilian and South African economies shows that economic growth in these economies originates from traditional energy-intensive sectors. The negative effect of lnEPS on lnGI reflects the influence of compliance costs. The positive and negative effects of lnHDI on lnGI indicate that the FF countries have different levels of absorptive capacity. In conclusion, the FF economies share the combined effects of global economic shocks, knowledge spillovers, and environmental policy reflections. Thus, although the short- and long-term adjustment speeds differ in the FF economies, the reasons for this difference stem from the institutional structures of the countries.

Some policy implications can be derived from the empirical results. First, as discussed by Hall and Lerner (2010), in order to channel GFCI toward green-producing sectors, financial taxonomy and diversity of green financial instruments should be ensured. Second, as suggested by Johnstone et al. (2010), in order to strengthen the demand-pull channel, the public sector should support green production and consumption. Third, in line with Cohen and Levinthal (1990), to increase absorptive capacity, policy packages should be designed to support the labor force with technology and to accelerate the adaptation process of labor to technology. Finally, as proposed by Costantini et al. (2017), national economies should focus on regulations that are aligned with global environmental policies, aim to reduce uncertainty, and enhance environmental quality. In future studies, product and process innovations can be distinguished using sectoral and firm-level microdata, and financial constraints can be measured at the firm and sectoral level. In addition, the complementary effects of energy infrastructures and data on improving institutional quality should be incorporated into the analyses. Finally, the threshold value of the carbon pricing mechanism should be determined through nonlinear models.

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