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When Does Technological Capacity Reduce Carbon Emissions? The Conditioning Role of Trade Openness

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ABSTRACT

Technological capacity is widely regarded as a key driver of sustainable growth and environmental improvement. However, its environmental effects may depend on the degree of countries' integration into the international trade system. In this context, the aim of the study is to investigate whether the effect of technological capacity on carbon emissions varies according to the level of trade openness. Within this scope, using a balanced panel of 20 OECD countries covering the period 2007–2023, a Technological Capacity Index (TCI) was constructed through Principal Component Analysis (PCA). The relationship is estimated using one-step and two-step System Generalized Method of Moments (System GMM) estimators to account for the dynamic nature of carbon emissions and potential endogeneity. The empirical findings show that the interaction coefficient between technological capacity and trade openness is negative and statistically significant across all baseline model specifications. This result indicates that the carbon emission-reducing effect of technological capacity becomes stronger with an increase in trade openness. The marginal effects analysis, on the other hand, reveals that the effect of technological capacity on CO_2 emissions is not statistically significant at low levels of trade openness. In contrast, as the level of trade openness increases, the marginal effect of technological capacity becomes significantly negative. This finding shows that technological capacity alone is not sufficient to ensure environmental sustainability and that international trade integration plays a critical role in the emergence of its environmental benefits. The study contributes to the literature by measuring technological capacity with a multidimensional index. In addition, it is empirically tested whether trade openness is an important condition determining the environmental effect of technological capacity. Overall, the findings suggest that technological capacity alone is insufficient to achieve low-carbon growth. Its environmental benefits depend critically on trade openness, implying that technology and trade policies should be designed as complementary instruments.

1. INTRODUCTION

Climate change and the resulting increase in carbon emissions have become one of the most important global challenges to sustainable economic growth [1, 2]. In this regard, in line with both the Paris Agreement and the 2050 net-zero emission targets, countries are trying to develop policy instruments that can reduce carbon intensity while maintaining economic growth. In this process, technological development and international trade play a critical role in supporting low-carbon development. However, the conditions under which technological progress and trade integration reduce or increase carbon emissions have not yet been fully clarified [3, 4].

Economies with high technological capacity can support the development of environmentally friendly technologies by increasing productivity and energy efficiency in production processes [5, 6]. Similarly, an increase in trade openness facilitates countries' access to advanced technologies, accelerates knowledge diffusion, and can encourage the more rapid adoption of clean production technologies [7, 8]. Nevertheless, empirical studies show that the effects of technological development and trade openness on carbon emissions differ significantly across countries [9, 10]. Therefore, theoretically, both technological capacity and trade openness are expected to contribute to the reduction of carbon emissions. However, this theoretical expectation is not always confirmed in the empirical literature.

Within this framework, trade openness emerges as an important factor shaping the environmental effect of technological capacity. In economies with high trade openness, technological innovations spread more rapidly, access to environmentally friendly production technologies becomes easier, and firms can adopt more efficient production processes [11, 12]. In contrast, in economies with limited trade integration, the same technological capacity may not provide similar environmental gains. Therefore, trade openness accelerates technology diffusion, and the interactions between technological innovation and trade openness may be decisive for carbon emissions. The findings [7, 13] indicate that the effect of technological capacity on carbon emissions may vary

according to the level of trade openness across countries.

A significant part of the existing literature examines separately the relationship between technological capacity and carbon emissions or the relationship between trade openness and carbon emissions [14, 15]. In contrast, the question of whether the environmental effect of technological capacity varies depending on the level of trade openness has largely been neglected. Therefore, examining the interaction mechanism between technological capacity and trade openness contributes to filling an important gap in the literature.

This study aims to fill this gap in the literature. Within this scope, a balanced panel dataset consisting of 20 OECD countries covering the period 2007–2023 is used. It is tested whether the effect of technological capacity on carbon emissions varies according to the level of trade openness. Technological capacity is represented by a composite index Technological Capacity Index (TCI) constructed from indicators of high-technology exports, research and development expenditures, and computer technology patents using Principal Component Analysis (PCA). In the analyses, the System Generalized Method of Moments (System GMM) is used in order to take into account the dynamic structure and potential endogeneity problems [16, 17].

This study contributes to the literature in three respects. First, technological capacity is measured through a multidimensional index rather than a single indicator. Second, the interaction between technological capacity and trade openness is directly included in the model, and the conditional nature of the environmental effect of technological development is analyzed. Third and finally, by using marginal effects analysis, it is revealed how the effect of technological capacity on carbon emissions changes at different levels of trade openness. In addition, the interpretation of this relationship is supported by graphical presentation.

The remainder of the paper is organized as follows. The second section reviews the relevant literature. The third section describes the dataset, variables, and methodology. The fourth section presents the preliminary analysis. The fifth section reports and discusses the empirical findings, including the marginal effects analyses. The final section presents the conclusions and policy recommendations.

2. LITERATURE REVIEW

The relationship between technological development, international trade, and environmental sustainability has become one of the most intensively discussed research areas in recent years. However, the existing literature has mostly examined these three elements through bilateral relationships. One group of studies focuses on the relationship between technological innovation and environmental quality, while other studies examine the environmental consequences of trade openness. In contrast, studies suggesting that the environmental effect of technological capacity may vary depending on the level of trade openness are quite limited.

The classical growth and innovation literature considers technological progress as a fundamental factor that increases productivity and improves the efficiency of resource use. Classical and endogenous growth theories argue that knowledge production and technological innovation are the main catalysts of long-term economic growth [18, 19]. The environmental economics literature, on the other hand, argues that technological innovations can transform production processes by increasing energy efficiency. It also suggests that technological innovations can support the development of new technologies that can reduce environmental damage [5, 20]. Similarly, Porter and Linde [21] argued that environmental regulations can direct firms toward more efficient production processes and innovative technologies. More recent studies emphasize that contemporary "green technological innovations" reduce production costs on the one hand, while shifting industrial transformation toward an environmentally friendly direction on the other hand [22]. Therefore, technological capacity establishes an important link between economic growth and environmental sustainability [23].

However, the environmental effects of technological progress may not always directly result in emission reductions. Technological development may increase productivity and production capacity, thereby expanding the volume of economic activity. In this case, energy demand may increase, and carbon emissions may rise, especially in economies where the energy structure is based on fossil fuels. Therefore, the environmental effect of technological progress depends on the balance between productivity gains and the expansion of the scale of production. This is because technology, on the one hand, makes production more efficient, while, on the other hand, it may increase total energy use by expanding the volume of economic activity. The trade and environment literature addresses this mechanism within the framework of the distinction between scale, composition, and technique effects developed to explain the environmental effects of trade [3, 24]. Recent studies show that the effect of technological innovation on carbon emissions is not homogeneous across countries and that this effect may vary considerably under different economic conditions and emission levels [25]. In addition, this reverse effect, defined in the literature as the "rebound effect," indicates that efficiency gains may increase production and consumption by reducing costs. It is emphasized that the increasing volume of production and consumption may raise total emissions again [26]. In this context, it can be stated that the net environmental effect of technological progress is related to the balance between two different effect mechanisms. This net effect depends on the interaction between the "scale effect," which increases pollution by expanding production, and the "technique effect," which makes the production process cleaner. Therefore, the ability of technological innovations to improve environmental performance depends on the technique effect dominating the scale effect [27].

A similar debate also exists in the trade openness literature. On the one hand, trade openness facilitates countries' access to foreign technology, accelerates knowledge diffusion, and increases productivity. This is also supported by studies showing that open economies are able to benefit more from international R&D spillovers [7, 11]. On the other hand, trade openness also has the potential to improve environmental quality by facilitating the diffusion of more efficient and cleaner production technologies. Indeed, Antweiler et al. [27] showed that the technique effect can improve environmental quality by decomposing the environmental effect of trade into scale, composition, and technique effects. Similarly, Frankel and Rose [4] demonstrated that the environmental effect of trade is not unidirectionally negative and that, under certain conditions, it may also lead to improvements in environmental indicators. On the other hand, the international competitive pressure brought about by participation in international trade

encourages domestic firms to adopt more energy-efficient and environmentally friendly production standards. Therefore, trade openness not only accelerates economic integration but also provides a suitable basis for the widespread adoption of more environmentally friendly production practices on a global scale [21, 28]. However, considering the recent empirical literature, the critical point that should be noted is that these environmental benefits brought about by trade openness do not emerge automatically. The emission-reducing effect of clean technologies transferred through trade depends on the level of technological development of countries and their capacity to apply these technologies effectively [14].

On the other hand, the effect of trade openness on the environment is not always positive. Indeed, trade openness may increase energy consumption by expanding the scale of production and may thereby contribute to higher carbon emissions [3, 29]. However, it is not possible to speak of a consensus in the empirical literature regarding the relationship between trade openness and carbon emissions. Shahbaz et al. [9] examined the trade openness–CO_2 relationship across a large sample of countries by income groups and show that this relationship may vary depending on the level of economic development of countries. Chen et al. [30], on the other hand, showed that the relationship between trade openness and carbon emissions has a heterogeneous structure and that this relationship may vary depending on the economic and energy structures of countries. Similarly, Wang and Zhang [10], in their analysis covering 182 countries, show that the effect of trade openness on carbon emissions differs significantly across income groups and that the environmental effect varies depending on the structural characteristics of countries. These findings indicate that the effect of trade openness on carbon emissions is neither unidirectional nor constant. The economic structure, income level, and emission profile of countries are among the main factors determining the direction and magnitude of this relationship [10, 30].

When the existing literature is evaluated as a whole, it is seen that there is no common consensus regarding the effects of technological capacity and trade openness on carbon emissions. Indeed, Dechezleprêtre and Sato [31], by evaluating the literature examining the effects of environmental regulations on competitiveness, trade, employment, productivity, and innovation, emphasized that these effects may vary according to sectors and policy design. Similarly, Costantini and Mazzanti [32] showed that environmental innovation can support international competitiveness and export performance. These findings indicate that the relationship between environmental innovation and international trade cannot be evaluated independently of the policy and production structure of countries. Nevertheless, the existing literature largely examines the environmental effects of technological capacity and trade openness separately. Empirical studies directly addressing how trade openness conditions the effect of technological capacity on carbon emissions remain quite limited.

The differences in the empirical findings indicate that the environmental effects of both technological development and trade openness may vary depending on the level of economic development and technological capacity of countries. These findings suggest that trade openness may be an important conditioning factor shaping the effect of technological capacity on carbon emissions. Nevertheless, empirical studies directly examining the interaction mechanism between technological capacity and trade openness remain quite limited. Therefore, in this study, the interaction between technological capacity and trade openness is directly included in the model. Thus, the conditioning role of trade openness in the effect of technological capacity on carbon emissions is empirically analyzed.

3. DATA SET AND METHODOLOGY

3.1 Data and variables

In this study, annual data covering the period 2007–2023 are used for 20 OECD countries (Austria, Belgium, Canada, the Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Japan, Latvia, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, the United Kingdom, and the United States) in the baseline analysis. The sample composition is primarily determined by the availability of the WIPO patent data required to construct the technological capacity indicator. Specifically, the patent component of the TCI is calculated as the share of computer technology patents in total patents. Therefore, the sample includes OECD countries for which the WIPO data required to calculate this indicator are consistently available throughout the 2007–2023 period. Other OECD countries were excluded from the sample because the WIPO patent data required to consistently calculate the share of computer technology patents in total patents over the entire 2007–2023 period were not available. The resulting baseline sample is a balanced panel consisting of 20 countries observed over 17 years (N = 20, T = 17), with a total of 340 observations. Additional variables with different data coverage are used in the robustness analyses, as explained in Section 3. The definitions and data sources of the variables used in the study are presented in Table 1.

The sample period covers a period in which technological transformation accelerated, global trade integration increased, and low-carbon development policies gained importance. The data on carbon emissions were obtained from the OECD database, while the indicators constituting technological capacity were compiled from the World Bank (World Development Indicators) and the World Intellectual Property Organization (WIPO) databases.

The dependent variable is defined as the natural logarithm of per capita CO_2 emissions ($\ln CO_2$). The main explanatory variable of the study is the TCI. This index is a composite indicator consisting of high-technology exports, the share of research and development expenditures in GDP, and computer technology patents in total patents. The index was constructed by using PCA in order to combine the common information into a single variable. Before applying PCA, all component variables were standardized, and the first principal component was used as the TCI.

Table 1. Variable definitions and data sources

Variable	Definition	Data Source
$\ln CO_2$	Natural logarithm of per capita CO_2 emissions	OECD
TCI	Technology Capacity	WDI, WIPO

	Index constructed using PCA	
lnopen	Natural logarithm of trade openness	WDI
lnreer	Natural logarithm of the real effective exchange rate	WDI
lnpergdp	Natural logarithm of GDP per capita	WDI
TCI × Trade Openness	Interaction term constructed using mean-centered trade openness	Author's calculation
Urban	Urban population (% of total population)	WDI
Renewable	Renewable energy consumption (% of total final energy consumption)	WDI
EPS	Environmental Policy Stringency Index	OECD

Notes: 1. The TCI variable is constructed via PCA, based on standardized high-technology exports (*htx*), R&D expenditures (*rd*), and computer technology patents (*comp_pat*). 2. Urbanization, renewable energy use, and environmental policy stringency (EPS) are included as additional control variables in the robustness analyses. 3. PCA = principal component analysis, TCI = Technological Capacity Index, EPS = environmental policy stringency.

Table 2. Principal Component Analysis (PCA) results and construction of the Technological Capacity Index (TCI)

Panel A: KMO, Correlation Matrix, and VIF Values Prior to PCA					
Variables	KMO	z_htx	z_rd	z_comp_pat	VIF
z_htx	0.682	1.000	0.264	0.381	1.30
z_rd	0.611	0.264	1.000	0.481	1.30
z_comp_pat	0.580	0.381	0.481	1.000	1.30
Overall KMO	0.613				
Panel B: Eigenvalues and Component Loadings					
Component	Eigenvalue	Proportion of variance		Cumulative Variance	
PC1	1.758	0.586		0.586	
PC2	0.747	0.249		0.835	
PC3	0.500	0.165		1.000	
Variable	PC1	PC2		PC3	
htx	0.518	0.812		0.268	
rd	0.580	-0.564		0.590	
comp_pat	0.629	-0.149		-0.763	

Notes: 1. VIF values are calculated to assess potential multicollinearity among the variables. 2. PCA is conducted using standardized (z-score) variables. 3. PCA = principal component analysis, KMO = Kaiser–Meyer–Olkin.

Trade openness (lnopen) is represented by the natural logarithm of the ratio of total exports and imports to GDP. The real effective exchange rate (lnreer) and real income per capita (lnpergdp) are included in the model as control variables. The real effective exchange rate is considered a control variable because of its potential effects on external competitiveness, trade structure, and production activities. In addition, trade openness is mean-centered around its sample mean before constructing the TCI × Trade Openness interaction term, which is used to test whether the effect of technological capacity on carbon emissions varies according to the level of trade openness.

3.2 Construction of the Technological Capacity Index

Technological capacity is a multidimensional concept that refers to the ability of countries to develop new technologies, use existing technologies, and transform innovation activities into economic production [33]. Therefore, in measuring technological capacity, it is a more appropriate approach to use indicators reflecting innovation production and technological development in different dimensions rather than a single indicator [34].

In this study, a TCI representing the level of technological capacity was constructed. In constructing this index, three main indicators were used to jointly reflect the technological production, innovation activities, and knowledge production capacity of countries. These indicators are the share of high-technology exports (htx), the share of research and development expenditures in GDP (rd), and the share of computer-technology patents in total patents (comp_pat). These indicators represent the technological production capacity, innovation activities, and knowledge production ability of countries, respectively. In constructing the index, first, all variables were standardized using the z-score method in order to eliminate scale differences among the indicators. Then, PCA was applied in order to capture the common variation among the indicators and obtain a single composite index [35].

The preliminary diagnostic tests presented in Table 2 show that the dataset is suitable for PCA. The overall Kaiser–Meyer–Olkin (KMO) coefficient of 0.613 indicates that the dataset is acceptable for PCA according to the criteria of Kaiser [36]. In addition, the Variance Inflation Factor (VIF) values, calculated at approximately *1.30* for all variables, indicate that there is no serious multicollinearity problem among the indicators.

As shown in Table 2, the PCA results reveal the presence of a dominant first principal component. The eigenvalue of 1.758 for the first principal component (PC1) is above the threshold value of 1 suggested by Kaiser [37], and this component alone explains 58.6% of the total variance in the dataset. This finding shows that the common variance among the technological indicators can be adequately represented by a single composite dimension. Therefore, PC1 was used as the composite indicator representing technological capacity, and the TCI variable was constructed based on this component.

In addition, the component loadings of all indicators on the first principal component are positive and above 0.50. This result supports that PC1 successfully reflects the common technological capacity of countries. Accordingly, the TCI was constructed by using the coefficients of the first principal

component of the standardized variables through the following linear combination:

$$TCI = 0.5181z_{htx} + 0.5799z_{rd} + 0.6287z_{com_pat} \quad (1)$$

3.3 Empirical strategy: System Generalized Method of Moments

In this study, the dynamic relationship between carbon emissions and technological capacity is estimated by using the System GMM. This method reduces the biases arising from potential endogeneity and unobserved country-specific effects while taking into account the dynamic nature of carbon emissions. Therefore, a dynamic panel data model including the lagged dependent variable is preferred in the analysis.

The System GMM estimator was developed by Arellano and Bover [16] and Blundell and Bond [17]. This method can provide more efficient and consistent estimates by using the first-difference and level equations together. In addition, it reduces the biases arising from endogeneity, fixed effects, and reverse causality by using the appropriate lags of the explanatory variables as instrumental variables.

For the baseline estimations, both one-step and two-step System GMM estimators were implemented using the lag (2–3) instrument structure. Before constructing the interaction term, trade openness was mean-centered around its sample mean. Accordingly, the baseline models include mean-centered trade openness and the interaction term between TCI and mean-centered trade openness. In the two-step estimations, the Windmeijer [38] correction was used in order to correct for small-sample bias. In order to evaluate the robustness of the findings, additional estimations were performed by using the alternative lag (2–4) instrument structure.

The dynamic panel data model used in the analysis is defined as follows:

$$\begin{aligned} lnCO_{2_{it}} = \alpha lnCO_{2_{i,t-1}} + \beta_1 TCI_{it} + \beta_2 c_lnopen_{it} \\ +\beta_3 (TCI\ c_lnopen)_{it} \\ +\beta_4 lnreer_{it} + \beta_5 lnpergdp_{it} + \eta_i + \epsilon_{it} \end{aligned} \quad (2)$$

Here, *c_lnopen* denotes trade openness mean-centered around its sample mean, and the interaction term is constructed as *TCI* × *c_lnopen*. *i* represents the countries and *t* represents the time dimension. η_i denotes the unobserved country-specific fixed effects, and ϵ_{it} denotes the error term.

The validity of the model was evaluated by using the Arellano–Bond autocorrelation tests *(AR(1) and AR(2))* and the Hansen overidentification test. In addition, in order to prevent the instrument proliferation problem, care was taken to keep the number of instruments lower than the number of cross-sectional units.

4. PRELIMINARY ANALYSIS

In this section, the main characteristics of the dataset are examined before the empirical analysis. First, descriptive statistics for the variables are calculated to evaluate the general structure of the sample. Then, the correlation matrix is reported in order to examine the bivariate relationships among the variables and to make a preliminary assessment of the potential multicollinearity problem.

Table 3. Descriptive statistics

Variables	Obs.	Mean	Std. Dev.	Min	Max
$lnCO_2$	340	1.929	0.405	1.054	3.014
TCI	340	0.000	1.326	-2.797	3.750
lnopen	340	4.409	0.470	3.153	5.253
lnreer	340	4.574	0.094	4.063	4.854
lnpergdp	340	10.507	0.519	9.323	11.602

Note: TCI is constructed using Principal Component Analysis (PCA), TCI = Technological Capacity Index.

Table 4. Correlation matrix and variance inflation factor (VIF) diagnostics

Panel A. Correlation Matrix					
Variables	$lnCO_2$	TCI	lnopen	lnreer	lnpergdp
$lnCO_2$	1.000				
TCI	0.044	1.000			
lnopen	0.279***	-0.417***	1.000		
lnreer	0.008	-0.020	0.075	1.000	
lnpergdp	0.258***	0.667***	-0.290***	0.057	1.000

Panel B. VIF Diagnostics for the Mean-Centered Interaction Specification						
Variable	TCI	lnpergdp	TCI × Trade Openness	c_lnopen (mean-centered)	lnreer	Mean VIF
VIF	2.96	2.37	2.16	1.60	1.07	2.03

Notes: 1. Pearson correlation coefficients are reported in Panel A. VIF statistics in Panel B are calculated for the baseline specification using mean-centered trade openness and the corresponding interaction term (TCI × mean-centered trade openness). 2. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. 3. TCI = Technological Capacity Index.

Table 3 presents the descriptive statistics for the variables used in the model. The mean value of the TCI variable is close to zero, which is an expected outcome of the standardization process. However, the standard deviation of 1.326 and the wide range of values (from −2.797 to 3.750) indicate that the OECD countries included in the sample exhibit considerable differences in terms of technological capacity. These differences provide an appropriate basis for empirically examining the effect of technological capacity on carbon emissions. Similarly, the other variables included in the model also exhibit a sufficient degree of cross-sectional and temporal variation throughout the analysis period. Overall, these findings indicate that the dataset has a suitable structure for dynamic panel data analysis.

Following the descriptive statistics, Pearson correlation analysis was performed in order to examine the linear relationships among the variables used in the model. On the one hand, the correlation matrix reveals the direction and strength of the relationships, and on the other hand, it provides preliminary evidence regarding the potential multicollinearity problem. The results obtained are presented in Table 4.

Table 4 presents the Pearson correlation coefficients among the variables included in the model. The results show that there is a positive but statistically insignificant relationship between

TCI and CO_2 emissions ($r = 0.044$). In contrast, trade openness (lnopen) and income per capita (lnpergdp) have positive and significant correlations with CO_2 emissions. Although there is a relatively high positive relationship between technological capacity and income per capita ($r = 0.667$, $p < 0.01$), none of the correlation coefficients exceeds the commonly used threshold value of 0.80. This finding provides preliminary evidence that serious multicollinearity is unlikely to be present among the variables.

However, since correlation analysis only reveals the bivariate linear relationships among the variables, potential multicollinearity in the interaction specification also needs to be evaluated separately. For this purpose, VIF statistics were calculated for the baseline specification using mean-centered trade openness and the corresponding interaction term. The VIF values range from 1.07 to 2.96, while the mean VIF is 2.03. In particular, the VIF values for TCI and the interaction term are 2.96 and 2.16, respectively. These results indicate that the interaction specification does not exhibit a serious multicollinearity problem. The dynamic effects of the variables are evaluated in the following section using System GMM estimations.

5. EMPIRICAL FINDINGS AND DISCUSSION

Table 5 presents the results of the baseline model and robustness analyses obtained using the one-step and two-step System GMM estimators. In these specifications, trade openness is mean-centered around its sample mean, and the interaction term is constructed using mean-centered trade openness.

Table 5. Baseline and robustness checks: System Generalized Method of Moments (System GMM) estimates

Variables	GMM (1-Step)	GMM (2-Step) (Lag 2–3)	GMM (2-Step) (Lag 2–4)
L.lnCO_2	1.085*** (0.083)	1.110*** (0.105)	1.065*** (0.096)
TCI	−0.058*** (0.019)	−0.048 (0.029)	−0.036 (0.026)
c_lnopen (mean-centered)	0.100* (0.049)	0.110** (0.051)	0.123* (0.060)
TCI × Trade Openness	−0.079*** (0.023)	−0.067** (0.027)	−0.087** (0.033)
lnreer	−0.128 (0.123)	−0.134 (0.151)	−0.090 (0.144)
lnpergdp	0.102** (0.044)	0.074 (0.055)	0.058 (0.060)
Diagnostic Tests (*p*-values)			
AR(1)	0.002	0.002	0.002
AR(2)	0.206	0.181	0.171
Hansen test	0.128	0.128	0.162
Model Information			
Instruments	15	15	19
Groups	20	20	20
Observations	320	320	320

Notes: 1. Parentheses report robust standard errors. 2. In the interaction specifications, trade openness is mean-centered around its sample mean. 3. The interaction term (TCI × Trade Openness) is constructed using mean-centered trade openness. 4. Columns (2) and (3) employ the two-step System GMM estimator with finite-sample corrected standard errors. 5. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. 6. GMM = Generalized Method of Moments, TCI = Technological Capacity Index.

Table 6. Wald tests for the lagged dependent variable coefficient

Specification	L.lnCO_2	Robust SE	95% CI	Wald F: H_0: $\beta = 1$	*p*-Value
GMM (1-step), Lag 2–3	1.085***	0.0833	[0.9110, 1.2597]	1.05	0.3186
GMM (2-step), Lag 2–3	1.110***	0.1054	[0.8891, 1.3301]	1.08	0.3112
GMM (2-step), Lag 2–4	1.065***	0.0957	[0.8649, 1.2655]	0.46	0.5040

Notes: 1. Robust standard errors are reported. 2. The Wald test evaluates the null hypothesis that the coefficient of the lagged dependent variable is equal to one (H_0: $\beta = 1$). 3. *** denotes statistical significance at the 1% level. 4. SE = standard error, CI = confidence interval.

The diagnostic test results indicate that the estimated models satisfy the main validity conditions. The Arellano–Bond AR(2) tests do not reject the null hypothesis of no second-order autocorrelation (*p*-values = 0.171–0.206). Similarly, the insignificant results of the Hansen overidentification tests (*p*-values = 0.128–0.162) provide no evidence against the validity of the instruments used. In addition, keeping the number of instruments lower than the number of cross-sectional units in all model specifications indicates that the risk of instrument proliferation is limited.

The coefficient of the lagged dependent variable is positive and statistically significant at the 1% level in all specifications, and the estimated coefficients range from 1.065 to 1.110. However, coefficients above one may raise concerns regarding potentially unstable dynamics. Therefore, in order to examine the issue in more detail, Wald tests were conducted for the null hypothesis that the coefficient of the lagged dependent variable is equal to one. The results are presented in Table 6.

The findings show that the null hypothesis cannot be rejected either in the one-step specification ($p = 0.319$) or in the two-step specifications with lags 2–3 ($p = 0.311$) and lags 2–4 ($p = 0.504$). In addition, the 95% confidence intervals for the coefficient of the lagged dependent variable include one in all three specifications. Therefore, although the estimated coefficients are above one, there is insufficient evidence to conclude that the coefficients are statistically different from one.

On the other hand, panel unit root tests were also conducted for lnCO_2 in order to examine the time-series properties of CO_2 emissions in more detail. The results are reported in Table 7.

Table 7. Panel unit root test results for $\ln CO_2$

Test	Statistic	*p*-Value / Critical Values	Result
Levin–Lin–Chu (LLC)	Adjusted t* = −4.3960	p = 0.000	Unit root H_0 is rejected
Im–Pesaran–Shin (IPS)	W-t-bar = −1.8208	p = 0.034	Unit root H_0 is rejected at the 5% level
Pesaran CADF/CIPS	t-bar = −2.684	CV10 = −2.630; CV5 = −2.730; CV1 = −2.920	Rejected at the 10% level, but not at the 5% level, based on finite-sample critical values
Pesaran standardized statistic	Z[t-bar]= −1.788	p = 0.037	Additional evidence in favor of stationarity

Notes: 1. The null hypothesis of the LLC, IPS, and Pesaran CADF/CIPS tests is the presence of a unit root. 2. The Pesaran CADF/CIPS test is evaluated using the reported finite-sample critical values. 3. CV10, CV5, and CV1 denote the critical values at the 10%, 5%, and 1% significance levels, respectively. 4. CADF = cross-sectionally augmented Dickey–Fuller; CIPS = cross-sectionally augmented Im–Pesaran–Shin.

According to the results obtained, the Levin–Lin–Chu test rejects the null hypothesis of a unit root ($p < 0.001$), while the Im–Pesaran–Shin test also rejects the unit root hypothesis at the 5% significance level ($p = 0.034$). In addition, the t-bar statistic in the Pesaran CADF/CIPS test is −2.684, and the null hypothesis of a unit root is rejected at the 10% significance level according to the finite-sample critical values. The *p*-value of the standardized Z[t-bar] statistic is 0.037.

When the Wald tests and panel unit root tests are evaluated together, there is no consistent empirical evidence that CO_2 emissions follow an unstable dynamic process. However, since the estimated coefficients for the lagged dependent variable are above one, this finding is not disregarded, and the results regarding dynamic stability are interpreted cautiously.

Trade openness was mean-centered around its sample mean, and the mean-centered variable was used both as the main effect and in constructing the interaction term. Therefore, the zero value of the mean-centered trade openness variable corresponds to the average level of trade openness in the sample. Accordingly, the TCI coefficient shows the conditional effect of technological capacity on carbon emissions at the average level of trade openness. The TCI coefficient is negative and statistically significant at the 1% level in the one-step System GMM estimation ($\beta = -0.058$, $p < 0.01$). In the baseline two-step System GMM model (*lag 2–3*), the coefficient is negative but not statistically significant ($\beta = -0.048$, $p > 0.10$). Similarly, in the two-step model with the alternative lag structure (lag 2–4), the coefficient is negative but statistically insignificant ($\beta = -0.036$, $p > 0.10$). These results show that, at the average level of trade openness, the TCI coefficient is negative in all specifications, but this conditional effect is statistically significant only in the one-step estimation. However, since the model includes an interaction term, the effect of technological capacity on carbon emissions cannot be evaluated solely through the TCI coefficient; this effect varies depending on the level of trade openness [39].

The most important finding of the study is that the interaction coefficient between TCI and mean-centered trade openness is negative and statistically significant in all model specifications. Although the interaction coefficient ranges from −0.067 to −0.087, it remains stable across different estimation methods and alternative lag structures. This result indicates that the effect of technological capacity on carbon emissions may vary depending on the level of trade openness. Although technological capacity may initially increase production activities and energy use, increasing trade integration may strengthen knowledge diffusion, access to clean technologies, and environmental competitive pressure. Thus, as trade openness increases, the effect of technological capacity on carbon emissions becomes more negative, suggesting that technological capacity may contribute more strongly to emission reduction in more open economies. This finding is also consistent with theoretical approaches arguing that the interaction between technological progress and international trade openness shapes environmental outcomes [3, 7, 27].

The interaction coefficient maintaining similar signs and magnitudes across different estimation methods and lag structures supports the robustness of the main findings. However, to assess whether this coefficient is sensitive to the way *TCI* is constructed, the baseline model was re-estimated using two alternative technological capacity measures. First, an equal-weighted index was constructed using the three standardized indicators. Second, considering the relatively strong loading of high-technology exports on PC2, an alternative measure based only on R&D and computer-technology patents, excluding high-technology exports, was used. The interaction coefficient between technological capacity and trade openness remained negative in both alternative specifications and yielded results consistent with the finding in the baseline model ($\beta = -0.110$, $p = 0.059$ and $\beta = -0.160$, $p = 0.001$, respectively). The full estimation results are reported in Appendix Table A1. These findings indicate that the main interaction result is robust to alternative constructions of technological capacity.

When the control variables are examined, it is seen that the direct effect of trade openness on carbon emissions is positive. However, the statistical significance of this effect varies across specifications, reaching the 5% level in the baseline two-step model and the 10% level in the other specifications. The real effective exchange rate and income per capita variables are not statistically significant in the two-step estimations.

Beyond these baseline controls, the literature on the determinants of CO_2 emissions shows that emission dynamics are associated not only with economic and technological factors but also with demographic structure, energy mix, and environmental policy conditions. For example, urbanization is considered an important demographic factor associated with CO_2 emission dynamics through channels such as the expansion of urban areas, population density, and changes in energy use [40, 41]. Renewable energy use is important for emission dynamics because it changes the carbon intensity of the energy mix. Indeed, empirical findings for OECD countries show that renewable energy production is significantly associated with CO_2 emissions [42]. In addition, environmental policy stringency (EPS) is an institutional factor reflecting countries' regulatory frameworks for emission reduction. Recent empirical findings show that the effect of EPS on CO_2 emissions may vary across countries and time-frequency dimensions and that, in some cases, more stringent environmental policies are associated with lower CO_2 emissions [43].

In this context, additional robustness analyses were

conducted to assess the sensitivity of the baseline model to these factors. Urbanization, renewable energy use, and EPS included in the additional robustness analyses are not randomly selected additional controls but are considered potential omitted factors representing the demographic, energy, and institutional/policy dimensions of emission dynamics, respectively. The purpose of these analyses is not to re-examine the direct effects of these variables on CO_2 emissions, but rather to assess whether the main finding regarding the interaction between technological capacity and trade openness is preserved when these alternative factors are controlled for.

The data period used in the additional robustness analyses was determined by taking into account the common data availability of the additional control variables. Although the main analysis covers the 2007–2023 period, the data coverage of the additional controls differs. While urbanization data are available for the entire period of the main analysis, the data coverage of the renewable energy consumption indicator extends through 2022. In contrast, the current series of the OECD EPS index covers the 1990–2020 period [44]. Therefore, the common data period of 2007–2020 was used for the robustness analyses in order to allow the additional control variables to be evaluated jointly and the alternative specifications to be compared using the same sample. Since EPS data are not available for Latvia among the countries included in the study, the common sample was restricted to 19 countries. As a result of using a one-period lag of the dependent variable in the dynamic System GMM model, the effective estimation sample covers the 2008–2020 period and consists of 247 observations. Estimating all alternative specifications using the same country and period sample makes it possible to distinguish changes resulting from the inclusion of additional control variables from changes in sample composition. The results of the additional robustness analyses estimated using this common sample are presented in Table 8.

Table 8. Robustness checks with additional controls: two-step System Generalized Method of Moments (System GMM) estimates

Variables	(1) Same-Sample Baseline	(2) + EPS	(3) + Urban + EPS	(4) + Urban + Renewable + EPS
L.lnCO_2	1.118*** (0.160)	1.138*** (0.145)	1.137*** (0.137)	1.064*** (0.237)
TCI	−0.060 (0.053)	−0.050 (0.035)	−0.040 (0.035)	−0.018 (0.043)
c_lnopen (mean-centered)	0.044 (0.059)	0.051 (0.052)	0.064 (0.050)	0.100 (0.108)
TCI × Trade Openness	−0.076** (0.033)	−0.072** (0.028)	−0.070** (0.029)	−0.072 (0.045)
lnreer	−0.111 (0.194)	−0.123 (0.141)	−0.015 (0.168)	−0.153 (0.134)
lnpergdp	0.079 (0.066)	0.069 (0.057)	0.025 (0.056)	0.046 (0.092)
Urban	—	—	0.003 (0.004)	0.000 (0.004)
Renewable	—	—	—	−0.001 (0.005)
EPS	—	−0.017 (0.043)	−0.020 (0.035)	−0.008 (0.039)
AR(2), p	0.506	0.502	0.451	0.451
Hansen, p	0.293	0.412	0.369	0.382
Instruments	15	16	17	18
Countries	19	19	19	19
N	247	247	247	247

Notes: 1. Column (1) reports the baseline model estimated using the common sample (19 countries; 2008–2020; N = 247). 2. Columns (2)–(4) sequentially add EPS, urbanization, and renewable energy use, respectively. 3. All specifications use the same country-year sample. 4. Trade openness is mean-centered around its sample mean, and the interaction term is constructed using mean-centered trade openness. 5. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. 6. Robust standard errors are reported in parentheses. 7. TCI = Technological Capacity Index.

The results show that the inclusion of additional control variables in the analysis does not substantially change the direction and magnitude of the interaction coefficient between technological capacity and trade openness. In the baseline model estimated using the same sample, the interaction coefficient is found to be −0.076 (p = 0.033). When EPS is controlled for, the coefficient is estimated at −0.072 (p = 0.019), and when urbanization is also included in the model, it is estimated at −0.070 (p = 0.024), with the negative sign and statistical significance being preserved. In the most comprehensive specification, in which renewable energy consumption is also included in the control set, the direction and magnitude of the interaction coefficient are largely preserved (β = −0.072), but statistical significance is lost (p = 0.123). Despite the absence of a notable change in the magnitude of the coefficient, the increase in the standard error of the interaction coefficient from 0.029 to 0.045 indicates that this weakening is more consistent with a reduction in estimation precision than with a substantial change in the estimated relationship. In addition, the null hypothesis of the AR(2) test cannot be rejected in all specifications, and the Hansen test does not reject the joint validity of the instrumental variables.

Finally, the marginal effects analysis presented in Table 9 and visualized in Figure 1 supports the main findings obtained from the interaction coefficient.

Figure 1 shows that the conditional marginal effect of Technological Capacity Index (TCI) on CO_2 emissions varies depending on the level of trade openness. The figure reveals that the marginal effect decreases steadily as trade openness increases and becomes negative and statistically significant at high levels of trade openness. These results are consistent with the marginal effects estimates reported in Table 9 and support that trade openness plays a conditioning role in the relationship between technological capacity and carbon emissions.

Table 9 presents the conditional marginal effect of technological capacity (TCI) on CO_2 emissions at different levels of trade openness. The findings show that the marginal effect of TCI on CO_2 emissions is not constant. They reveal that this effect varies depending on the level of trade openness. At the lowest level of trade openness, the marginal effect of technological capacity on carbon emissions is positive but not statistically significant (β = 0.036, p = 0.499). At the sample mean, although this effect becomes negative, it still does not become statistically significant (β = −0.048, p = 0.105). In contrast, at the highest level of trade openness, the marginal

effect of technological capacity becomes negative and statistically significant ($\beta = -0.104$, $p < 0.001$). These findings indicate that the environmental benefits of technological capacity become more evident, particularly at high levels of international trade integration. In other words, trade openness emerges as an important conditioning factor shaping the effect of technological capacity on carbon emissions. These results provide empirical evidence that the complementary relationship between technological progress and trade integration is important for environmental sustainability.

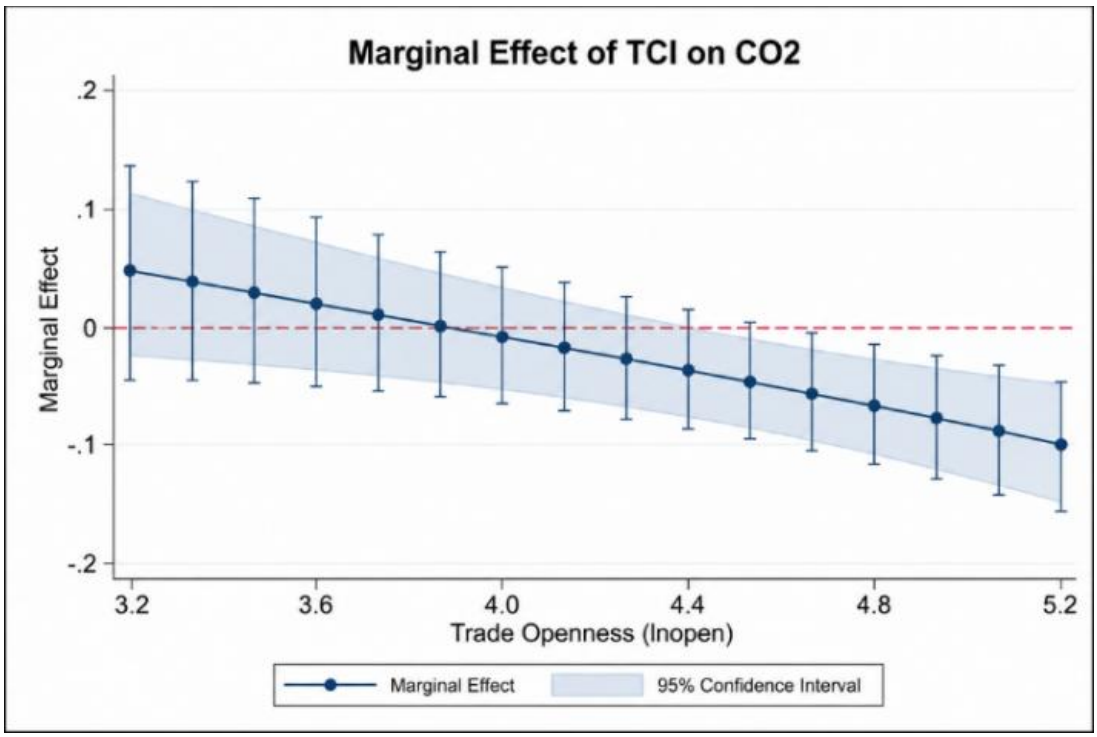


Figure 1. Conditional marginal effect of Technological Capacity Index (TCI) on CO_2 emissions across different levels of trade openness

Note: The figure reports the conditional marginal effect of TCI estimated from the baseline two-step System GMM model. The error bars represent the 95% confidence interval.

Table 9. Conditional marginal effects of Technological Capacity Index (TCI) across different levels of trade openness

Levels of lnopen	Value	Marginal Effect	Delta-Method S.E.	*z*-Statistic	*p*-Value
At Minimum Level	3.153	0.036	0.0533	0.68	0.499
At Mean Level	4.409	-0.048	0.0295	-1.62	0.105
At Maximum Level	5.253	-0.104***	0.0296	-3.51	<0.001

Notes: 1. Conditional marginal effects are calculated from the baseline two-step System GMM model. 2. The interaction model is estimated using mean-centered trade openness (c_lnopen), and the marginal effects are evaluated at the centered values corresponding to the minimum, mean, and maximum levels of lnopen. 3. *** denotes significance at the 1% level.

6. CONCLUSIONS AND POLICY RECOMMENDATIONS

This study investigates whether the effect of technological capacity on carbon emissions varies depending on the level of trade openness. For this purpose, a balanced panel dataset covering 20 OECD countries over the period 2007–2023 was used. Technological capacity was measured by the *TCI*, constructed from high-technology exports, research and development expenditures, and computer technology patents. The System GMM method was applied in order to take into account the dynamic structure and potential endogeneity problems. The robustness of the findings was tested by using alternative lag structures and different estimation methods.

The empirical findings show that carbon emissions exhibit strong dynamic persistence. However, the main finding of the study reveals that the environmental effect of technological capacity is not constant. At the average level of trade openness, the conditional effect of TCI is negative across all specifications, although it is statistically significant only in the one-step estimation. More importantly, the interaction term between technological capacity and trade openness is negative and statistically significant in all baseline model specifications. This finding shows that the effect of technological capacity on carbon emissions varies depending on the level of trade openness.

The marginal effects analysis also supports this finding. In economies with low trade openness, the effect of technological capacity on carbon emissions is not statistically significant. In contrast, as trade openness increases, the marginal effect of technological capacity on emissions decreases and becomes negative and statistically significant at high levels of trade openness. This indicates that the effect of technological capacity on environmental performance is conditioned by the level of countries' integration into international trade.

In this respect, the study makes three main contributions to the literature. First, technological capacity was measured through a composite TCI that jointly reflects technological

production, innovation, and knowledge production capacity rather than a single indicator. In addition, by including the interaction between technological capacity and trade openness in the model, it is shown that the environmental effect of technological capacity varies depending on the level of trade openness. Finally, the marginal effects analysis shows how the effect of technological capacity on carbon emissions changes at different levels of trade openness. These findings support the theoretical approaches suggesting that the interaction between technological progress and trade integration is important for environmental performance.

The findings obtained show that promoting technological innovations alone is not sufficient for technological capacity to reduce carbon emissions. In this process, the economic environment in which technologies are used should also be taken into consideration. Indeed, strengthening trade integration, facilitating access to clean technologies, and supporting the international movement of high-technology products are important for technological investments to be transformed into environmental benefits. Accordingly, R&D incentives, policies supporting high-technology exports, and trade policies promoting environmentally friendly production standards should be addressed together. Such integrated policy approaches play a critical role, particularly in achieving green transition targets in OECD countries. These findings also show that technological capacity and trade openness are complementary policy elements in terms of environmental sustainability.

Nevertheless, the study has some limitations. First, technological capacity was measured through a composite index, and the environmental effects of different types of technology were not examined separately. Second, the sample of the study is limited to OECD countries for which the patent data required to construct the technological capacity indicator are consistently available throughout the study period. Therefore, the findings obtained should be evaluated within the context of the characteristics of the countries included in the analysis. In particular, the possibility that other OECD countries not included in the sample (Australia, Chile, Colombia, Costa Rica, Estonia, Iceland, Ireland, Israel, Italy, South Korea, Lithuania, Luxembourg, Mexico, New Zealand, the Slovak Republic, Slovenia, Switzerland, and Türkiye) and non-OECD countries have different characteristics in terms of technological capacity, trade integration, economic structure, and environmental conditions limits the direct generalization of the findings to these countries. Future studies may examine whether the conditioning role of trade openness varies across broader and different country groups when comparable technological capacity data are available. In addition, the use of alternative technology measures, such as green patents, digital transformation indicators, or renewable energy technologies, may contribute to a more detailed understanding of the relationship between technological capacity and environmental sustainability.

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NOMENCLATURE

c_lnopen	Mean-centered natural logarithm of trade openness
comp_pat	Share of computer technology patents in total patents
htx	Share of high-technology exports
lnCO₂	Natural logarithm of per capita CO_2 emissions
lnpergdp	Natural logarithm of GDP per capita

lnreer	Natural logarithm of the real effective exchange rate
rd	Research and development expenditure as a share of GDP
TCI	Technological Capacity Index
z	Standardized (z-score) value

Greek symbols

α	Coefficient of the lagged dependent variable
β_1–β_5	Estimated coefficients of the explanatory variables
ε	Error term
η	Unobserved country-specific effect

Subscripts

i	Country
t	Time period

APPENDIX

Table A1. Robustness checks using alternative measures of technological capacity

Variables	Baseline PCA-Based TCI	Equal-Weighted TCI	R&D + Patents TCI
L.lnCO_2	1.110*** (0.105)	1.099*** (0.102)	1.106*** (0.073)
TCI/Alternative TCI	−0.048 (0.029)	−0.074 (0.044)	−0.076 (0.054)
c_lnopen (mean-centered)	0.110** (0.051)	0.114** (0.053)	0.124** (0.052)
TCI × Trade Openness	**−0.067**** (0.027)	**−0.110*** (0.055)	**−0.160***** (0.038)
lnreer	−0.134 (0.151)	−0.130 (0.150)	−0.156 (0.140)
lnpergdp	0.074 (0.055)	0.071 (0.052)	0.076 (0.076)
AR(1), p	0.002	0.002	0.002
AR(2), p	0.181	0.181	0.132
Hansen, p	0.128	0.128	0.190
Instruments	15	15	15
Groups	20	20	20
Observations	320	320	320

Notes: 1. Parentheses report finite-sample corrected robust standard errors. 2. All specifications are estimated using the two-step System GMM estimator with lags (2–3). 3. In all specifications, trade openness is mean-centered around its sample mean, and the interaction terms are constructed using mean-centered trade openness. 4. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.