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Mitigating Carbon Emissions: Market-Based vs. Technology Support Policies

Mitigación de las emisiones de carbono: políticas basadas en el mercado frente a políticas de apoyo tecnológico

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Abstract

Various policy instruments are being used to reduce carbon emissions, which are the root cause of climate change. This study aims to empirically test the impact of market-based policies and technological support programs on carbon emissions and to reveal which policy is more effective in mitigation. For this purpose, the dataset of 19 OECD countries for the period 1994-2019 was used. The results of the study confirm that the policy coefficients vary across the values of the dependent variable. Accordingly, market-based policy stringency is effective in reducing emissions, and the effect increases at high carbon values. No significant effects were found for technology support programs.

Keywords: Carbon taxes, quantile regression, regulation.

Resumen

Se están utilizando varios instrumentos políticos para reducir las emisiones de carbono, que son la causa fundamental de cambio climático. Este estudio tiene como objetivo probar empíricamente el impacto de las políticas basadas en el mercado y los programas de apoyo tecnológico en las emisiones de carbono, y revelar qué política es más efectiva en la mitigación. Para ello, se utilizó el conjunto de datos de 19 países de la OCDE para el período 1994-2019. Los resultados del análisis cuantílico del panel confirman que los coeficientes de política varían según los valores de la variable dependiente. En consecuencia, la rigurosidad de las políticas basadas en el mercado es efectiva para reducir las emisiones, y el efecto aumenta con valores altos de carbono. No se encontraron efectos significativos para los programas de apoyo tecnológico.

Palabras clave: Impuestos al carbono, regresión cuantílica, regulación.

JEL Classification/ Clasificación JEL: H23, H50, Q54, Q58.

1. Introduction

Climate change is now perceived as one of the most important global problems. Depending on climate change, many problems such as temperature rise, drought, floods and devastating weather events occur, which not only negatively affect biotic populations, but also harm the economy (Dell et al., 2014; Burke et al., 2015; Batten et al., 2018).

One of the most important steps taken in recent years to combat climate change is the Paris Agreement which aims to limit the global temperature increase to less than 2 degrees Celsius in the long term compared to the pre-industrial era. Adopted in 2015, the treaty marks the first time that all countries worldwide have committed to reducing greenhouse gas emissions. In this context, exploring the impact of different variables on emissions has attracted the attention of researchers, and the current literature addresses this issue in different dimensions.

Preliminary studies addressing the economic determinants of emissions focused mostly on the GDP or economic growth variable, based on the environmental Kuznets curve hypothesis. However, no consensus was reached regarding the validity of the hypothesis. For example, Aslanidis and Iranzo (2009), Saboori and Sulaiman (2013) and Yasin et al. (2021) reached empirical findings supporting the hypothesis, while Cole et al. (1997) found that it was valid only for local pollutants in selected OECD countries. Perman and Stern (2003) argued that quite restrictive assumptions were required for a long-run environmental Kuznets Curve relationship to exist.

Subsequent studies addressing the determinants of emissions focused on different economic and political variables. For example, the impact of foreign direct investments has attracted the attention of many researchers (e.g. Levinson and Taylor, 2004; Blanco et al., 2013; Bae et al., 2017; Mert and Caglar, 2020; Opoku et al., 2021; Akbulut and Yereli, 2023). Trade volume (e.g. Liddle, 2018; Khan et al., 2020; Wang and Zhang, 2021) and financial development (e.g. Abbasi and Riaz, 2016; Jiang and Ma, 2019; Vo and Zaman, 2020; Paramati et al., 2021; Li et al., 2022; He et al., 2022; Akbulut, 2023, 2024) were the other most tested economic variables. In recent years, the effects of different policy instruments such as taxes and standards have been tested frequently (e.g. Hashmi and Alam, 2019; Ahmed, 2020; Wang et al., 2020; Akbulut, 2022). Unfortunately, there is no consensus on whether the policies are successful in mitigating emissions.

The objective of this study is to contribute to the literature by simultaneously testing the impacts of different mitigation tools on carbon emissions, which account for the largest share of total emissions. To this end, we used the Environmental Policy Stringency (EPS) index, a comprehensive index of the OECD, and is widely used in the literature (De Angelis et al., 2019; Wang et al., 2020; Sohag et al., 2021, Akbulut and Yereli, 2023). The index was developed by Botta and Kozluk (2014) and recently modified by Kruse et al. (2022). It measures the stringency of three different types of policy instruments: market-based, nonmarket-based, and technology support policies. Market-based policies include trading schemes and taxes. Nonmarket-based policies include emission limits. Technology support policies include upstream (R&D support) and downstream policies (feed-in tariffs, auctions). Of the policy instruments measured in the EPS, the market-based instruments and technology support programs directly target carbon emissions, so, the impact of these two instruments is used as the baseline in this study.

Some previous studies have used the EPS index in their empirical analyses, but most of these studies have considered the index as a whole and have not disaggregated the effects of different policy instruments. The studies by De Angelis et al. (2019), Wang and Shao (2019), and Akbulut and Yereli (2023) are among the few studies that empirically examine whether the effects of more stringent environmental policies differ by the type of regulatory instrument used. However, these studies made a dual distinction between market-based and nonmarket-based policies, and ignored the effects of technology support programs which can play an important role in reducing carbon emissions by supporting R&D spending on low-carbon production and renewable energy. Thus, to the best of our knowledge, this study is the first to empirically test the impact of the stringency of technology support spending on carbon emissions.

In sum, this study is expected to contribute to the literature in several ways. First, by using panel data, we benefit from a larger number of observations. Second, the use of updated policy index scores obtained with the new methodology allows us to make more reliable policy recommendations. Third, the use of panel quantile regression analysis as a methodology allows for the observation of the effects of independent variables for different values of the dependent variable. Third, the study allows for a comparison of their direct effectiveness in reducing carbon emissions by testing market-based instruments and technology support instruments in the same context. Finally, the empirical results are tested for robustness by including different variables in the analyses.

The remainder of this study is divided into four sections. Section 2 provides a literature review, section 3 discusses data and methodology, section 4 presents the results of the empirical analyses, and section 5 presents the main findings of the study with policy recommendations.

2. Literature review

Numerous studies empirically analyze the determinants of environmental impacts. It is noteworthy that these studies are often based on the IPAT and/or STIRPAT models (Ehrlich and Holdren, 1971; Dietz and Rosa, 1997; Liddle and Lung, 2010; He et al., 2017; Liddle, 2015; Shuai et al., 2018; Hashmi and Alam, 2019, Khan et al., 2021; Akbulut and Yereli, 2023, Zhang et al., 2023; Wang and Taghvaee, 2023; Akbulut, 2024). These models analyze anthropogenic environmental impacts using population, wealth, and technology indicators.

Population impacts on carbon emissions can occur in two different ways. If population growth facilitates energy use, pollution will increase. However, if population growth facilitates intensive energy use and increases efficiency, pollution will decrease (Hao et al., 2018). Satterthwaite (2009) also argues that consumption rather than population growth has an impact on climate change. Empirical studies have also reached different conclusions. Although some studies argue that population has a positive impact on emissions (He et al., 2017; Hashmi and Alam, 2019), there are also studies with opposite results (Begum et al., 2015, Ahmad et al., 2019). While Alam et al. (2016) concluded that there is a significant relationship between population growth and emissions for India and Brazil, they found non-significant results for China and Indonesia. In other words, the results may differ depending on the sample of countries considered.

Generally, per capita income or growth rates have been used as indicators of well-being. The idea that there is an inverted U-shaped relationship between wealth and environmental degradation was first put forward by Grossman and Krueger (1995). This pattern was adopted as EKC in later studies (Panayotou, 1993; Grossman and Krueger, 1995, Stern et al., 1996). Some previous studies confirm the existence of EKC for samples of individual countries: a) China (Yin et al., 2015; Bese et al., 2022), b) Italy (Bento and Moutinho, 2016), c) Malaysia (Lau et al., 2014), d) Russia (Sohag et al., 2021), e) Thailand and Singapore (Saboori and Sulaiman, 2013), f) Turkiye (Gokmenoglu and Taspinar, 2016). Some others confirm EKC for a group of countries: a) less developed countries (Yasin et al., 2021), b) OECD countries (Galeotti et al., 2006), c) some ASEAN countries (Heidari et al., 2015).

Some studies do not confirm the EKC hypothesis. Ozcan (2013) studied the relationship between environmental degradation and per capita income in 12 Middle Eastern countries. However, an inverted U relationship was confirmed for only 3 of the countries. In addition, positive evidence of a U-shaped relationship was found for 5 Middle Eastern countries. In addition, using the STIRPAT model for China, He et al. (2017) showed that carbon emissions increase with income. The results of Hashmi and Alam (2019) showed that GDP is the driving force for the increase in carbon emissions in the context of OECD countries. Similarly, Demiral et al. (2021) found a positive relationship between income and carbon emissions in their study of 15 major emitting countries. Moreover, the direction of the relationship was parallel for different income levels.

Some studies examined whether the environmental Kuznets curve is N-shaped instead of U-shaped. While Allard et al. (2018) supported the existence of an N-shaped EKC in some countries with different income groups, Awan and Azam (2022) confirmed the N-shaped EKC for G-20 economies.

It is useful to emphasize that various variables are used as indicators of technology, but energy consumption is the most commonly used among them. In particular, the increase in fossil fuel-based energy consumption is expected to increase the amount of emissions. Studies in the literature generally confirm this expectation (Alam et al., 2016, Ahmad et al., 2019). In contrast, Allard et al. (2018) used patent applications as a proxy for technological development in their study analyzing the determinants of emissions for 74 countries using a panel quantile regression. They concluded that technology has a positive impact on emissions in low- and middle-income countries and found that the impact was inconclusive in different quantiles of high-income countries. Their explanation for the finding that technology increases emissions was that they used all patents, not just patents related to clean technologies. In a more recent study, Demiral et al. (2021) found that energy productivity reduces emissions in high and middle-income countries, while the mitigating effect is higher in middle-income countries.

In addition to the variables in the IPAT and/or STIRPAT models, policy instruments to reduce emissions must be included in the analysis, consistent with the purpose of this study. The literature has examined the effects of different policy instruments using different samples and methodologies. In the case of China, Hao et al. (2018) used the ratio of the production value of comprehensive recycling of three wastes to GDP as a policy indicator. Using city-level panel data, they concluded that current regulations have not reduced pollution. The results of Hashmi and Alam (2019) suggest a negative effect of environmental tax revenues on emissions in OECD countries. Moreover, they found that a 1% increase in green patents reduces emissions by 0.017%. Therefore, market-based instruments such as carbon pricing and patents have been suggested as effective policy options.

Aydin and Esen (2018) examined the role of various taxes, including environmental, energy, and transport taxes, on emissions in EU countries using a dynamic panel threshold regression model. They concluded that the threshold effect was significant for all tax types except transport taxes. Accordingly, the impact of taxes exceeding certain thresholds changed from insignificantly positive to significantly negative. The study by Neves et al. (2020) is another study that looks at the impact of tax revenues on emissions. According to their results, environmental taxes seem to reduce emissions in the long run in 17 EU countries.

A significant number of subsequent studies have used the OECD's environmental stringency index (De Angelis et al., 2019; Demiral et al., 2021; Ahmed and Ahmed, 2018; Ahmed, 2020; Wang and Shao, 2019; Wang et al., 2020; Sohag et al., 2021; Wolde-Rufael and Weldemeskel, 2020, 2021) because it is an internationally comparable and comprehensive measure. Some of these studies argue that stringent policies are effective tools for mitigation (Ahmed and Ahmed, 2018; De Angelis et al., 2019; Ahmed, 2020; Wang et al., 2020), while other studies argue that stringent policies are ineffective, and in some cases even have emission-increasing effects (Demiral et al., 2021). The study by Sohag et al. (2021), draws attention by dividing the sample into two regimes according to gross regional production in the case of Russia. The results of the dynamic panel regression analysis showed that the EPS had a positive effect on emissions in the lower regime and a negative effect in the upper regime. Thus, the effects of the policy differed by income level. Another notable study comes from De Angelis et al. (2019). In this study, the effects of market-based and non-market-based policies were analyzed separately. Using a fixed-effects model, they found negative coefficients for both policy variables. In another study that differentiates market-based and non-market-based policies, Akbulut and Yereli (2023) revealed that non-market-based policy instruments have threshold effects that can support the pollution halo hypothesis. However, these studies were based on the old methodology of the environmental policy stringency index and ignored technology support programs. Based on the above discussions, it is noteworthy that the effects of the environmental policy stringency index have not been tested with the figures obtained from the current methodology, including the spending instrument.

Finally, some studies have suggested that the EPS has nonlinear effects. For example, Wolde-Rufael and Weldemeskel (2020, 2021) pointed out the existence of an inverted-U relationship in a panel of developing countries. Therefore, it is also important to consider the possible nonlinear effects. In this context, this study is expected to contribute to the literature by considering the expenditure dimension of the current environmental policy stringency index and potential non-linear relationships.

3. Data and methodology

Usual regressions refer to the mean, but as Cade and Noon (2003) suggest, in the case of ecological processes, there may be stronger and useful predictive relationships with other parts of the distribution of the response variable. Because quantile regressions are based on the median or other points in the conditional distribution of the dependent variable, more robust results to outliers can be obtained (Hubler, 2007). Hubler (2007) also draws attention to the marginal and the change in the level of emissions over economic development. This difference justifies the use of quantile regression in estimating emissions.

The technique of quantile regression was first introduced by Koenker and Basset (1978), and given , the conditional quantile of is given as follows:

$$Q_{y_{it}}(\tau|x_{it}) = {x_{it}}^{\tau}\beta_{\tau} \tag{1}$$

where i is the country, t is the year, $Q_{yit}(\tau|x_{it})$ is the τ – th quantile of the dependent variable, x_{it}^{τ} is the vector of explanatory variables for quantile τ, and β_τ symbolizes the slopes of explanatory variables for quantile τ.

This paper tests the relationship between carbon emissions (*crb*) and two important policy instruments: the market-based EPS index (*mp*) and technology support programs index (*ts*). For this purpose, the IPAT model proposed by Ehrlich and Holdren (1971) was used as a basis. The model explains the human impact on the environment, by using the variables of affluence, population and technology. In some later studies (York et al., 2003; Fan et al., 2006; Hashmi et al., 2019), a stochastic structure was added to the model (STIRPAT), and the effects of each variable on the environment were empirically tested. In the model discussed here, based on the aforementioned models, the indicators of affluence (*gdp*), population (*popcit*) and technology (*fs*) were used, and in addition, policy variables (*mp* and *ts*) were included in the model. The variables *crb, gdp, popcit,* and *fs* were used in natural logarithmic form. The explanations and sources of the variables are listed in Table 1. Two models were developed for the analysis as follows:

Model 1:

$$crb_{it} = \propto_0 + \beta_1 popcit_{it} + \beta_2 gdp_{it} + \beta_3 fs_{it} + \beta_4 mp_{it} + e_{it} \tag{2}$$

Model 2:

$$crb_{it} = \propto_0 + \beta_1 popcit_{it} + \beta_2 gdp_{it} + \beta_3 fs_{it} + \beta_4 ts_{it} + e_{it} \tag{3}$$

where the subscripts *i* (*i* = 1, 2, …, N) and *t* (*t* = 1, 2, …, T) denote the cross-section (country) and time period (year), respectively. is the error term such that $e_{it} \sim iid(0,\sigma^2)$.

Table 1. Data description and sources

Variable	Definition	Source
crb	CO_2 emissions (metric tons per capita)	World Bank https://data.worldbank.org/indicator/EN.ATM.CO2E.PC
popcit	Population in the largest city (% of urban population)	World Bank https://data.worldbank.org/indicator/EN.URB.LCTY.UR.ZS
gdp	GDP per capita (constant 2015 USD)	World Bank https://databank.worldbank.org/source/sustainable-development-goals-(sdgs)/Series/NY.GDP.PCAP.KD
fs	Fossil fuels per capita (kWh)	Our World in Data https://ourworldindata.org/grapher/fossil-fuels-per-capita
mp	EPS index (market-based policies)	OECD https://stats.oecd.org/Index.aspx?DataSetCode=EPS

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Variable	Definition	Source
ts	EPS index (technology support policies)	OECD https://stats.oecd.org/Index.aspx?DataSetCode=EPS
tr	Trade volume (% of GDP)	World Bank https://data.worldbank.org/indicator/NE.TRD.GNFS.ZS
fdi	Foreign direct investment inflows (% of GDP)	World Bank https://data.worldbank.org/indicator/BX.KLT.DINV.WD.GD.ZS

Due to data availability, the sample includes 19 OECD countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkiye, United Kingdom, and the United States) with annual data from 1994 to 2019[1].

To examine the impact of environmental policies, we used the EPS index. This index, first constructed by Botta and Kozluk (2014), is based on a dual distinction between market-based and non-market-based policies. While market-based policies consisted of taxes, trading schemes, and feed-in tariffs, non-market-based policies included standards and R&D subsidies. Later, the calculation method of the index was developed by Kruse et al. (2022), so the update of the dataset was based on a threefold distinction: market-based policies, nonmarket-based policies, and technology-support policies. Among these subcomponents, market-based and technology-support programs in particular are closely related to carbon emissions. While market-based instruments have subcomponents such as carbon taxes and carbon trading permits, technology-support programs include low-carbon R&D spending and support for solar and wind energy. The indices take values between zero and six, and the higher their value, the more stringent the environmental policy.

4. Empirical analysis

The empirical analysis starts with the cross-sectional dependency test. With the information obtained from this test result, the appropriate unit root test was determined. Then, the variables were tested for stationarity and became stationary to eliminate the spurious regression problem. Afterward, a cointegration test was performed to test whether there was a long-term relationship between the variables. Upon determining the long-term relationship between the variables, the model was tested first with the linear fixed effects method, and then with the non-linear panel quantile method. In the last part of the analysis, robustness analyses were carried out using additional variables.

When the variables of the countries in the sample exhibit cross-sectional dependence, the first-generation unit root tests lose their reliability. In such a case, it is necessary to apply second-generation unit root tests to check the stationarity of the variables. Therefore, the analysis starts with three different

1 The data set can be shared with interested readers upon request.

tests for cross-sectional dependency: Breusch-Pagan (1980) Lagrange Multiplier (LM) test, the Pesaran, Ullah, and Yamagata (2008) bias-adjusted LM test, and the Pesaran (2004) Cross-Sectional Dependence (CD) test. The results of the tests are shown in Table 2.

TABLE 2. THE RESULTS OF CROSS-SECTIONAL DEPENDENCE TESTS

	LM	LM adj.	LM CD
crb	2642 (0.0000)	361 (0.0000)	38.96 (0.0000)
popcit	2713 (0.0000)	371.4 (0.0000)	-0.8875 (0.3748)
gdp	3354 (0.0000)	465.9 (0.0000)	56.27 (0.0000)
fs	2675 (0.0000)	365.8 (0.0000)	40.71 (0.0000)
mp	1706 (0.0000)	223 (0.0000)	29.87 (0.0000)
ts	1902 (0.0000)	252 (0.0000)	38.95 (0.0000)
tr	2794 (0.0000)	383.4 (0.0000)	49.56 (0.0000)
fdi	425.8 (0.0000)	34.31 (0.0000)	11.83 (0.0000)

Note: Figures in parentheses are p-values.

As can be seen in Table 2, the null hypothesis that there is no covariance between the cross-sectional residuals was rejected in all tests. Therefore, the Cross-Sectionally Augmented Dickey-Fuller (CADF) test developed by Pesaran (2007), one of the second-generation unit root tests, was used to control for stationarity. The test results are summarized in Table 3. Since the variables *crb, fs, mp,* and *ts* are stationary at a 5% significance level, they are used at their levels. For the other variables, their first differences were used.

TABLE 3. PESARAN (2007) CADF SECOND GENERATION UNIT ROOT TEST RESULTS

		Z(t-bar)		p-value	
		Without trend	With trend	Without trend	With trend
crb	level	-0.838	-3.079***	0.201	0.001
	1st diff.	-11.070***	-8.653***	0.000	0.000
popcit	level	2.795	-4.490***	0.997	0.000
	1st diff.	-3.704***	-2.402***	0.000	0.008
gdp	level	-0.968	-0.691	0.166	0.245
	1st diff.	-4.516***	-2.980***	0.000	0.001
fs	level	-1.510*	-3.479***	0.066	0.000
	1st diff.	-11.595***	-9.695***	0.000	0.000
mp	level	-2.051**	-0.107	0.020	0.458
	1st diff.	-9.997***	-8.665***	0.000	0.000
ts	level	-6.641***	-4.139***	0.000	0.000

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		Z(t-bar)		p-value	
		Without trend	With trend	Without trend	With trend
	1st diff.	-9.450***	-7.376***	0.000	0.000
tr	level	0.007*	2.554	0.503	0.995
	1st diff.	-5.803***	-4.392***	0.000	0.000
fdi	level	-0.970	0.577	0.166	0.718
	1st diff.	-11.20***	-8.667***	0.000	0.000

Note: ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

In the next step, the presence of cointegration between variables was confirmed by Pedroni's (1999) panel cointegration test. This test offers significant advantages in that it allows for heterogeneity in both the intercepts and trend coefficients in the structural model across cross-sections, and the coefficient across the cross-sections in equation 4:

$$\hat{e}_{it} = \rho \hat{e}_{it-1} + v_{it} \tag{4}$$

where $\hat{e}_{it}$ refers to the estimated residual of the Model 1 and 2.

The test provides four within-dimension and three between-dimension statistics. In the case of within-dimension, the null and alternative hypotheses are H_0:ρ = 1 for all i and H_1:ρ_1 = ρ < 1, respectively. In the case of between-dimension, the null and alternative hypotheses are H_0:ρ_i = 1 for all i and H_1:ρ_1 < 1 < 1 for at least one i. The test results are shown in Table 4.

Table 4. Pedroni panel cointegration results

	Model 1		Model 2	
	Within-dimension	Between-dimension	Within-dimension	Between-dimension
Modified variance ratio	-2.7966*** (0.0026)	-	-3.2794*** (0.0005)	-
Modified PP t-stat	0.9186 (0.1791)	2.4979*** (0.0062)	1.8921** (0.0292)	2.8311*** (0.0023)
PP t-stat	-3.0529*** (0.001)	-1.8874** (0.0296)	-1.3337* (0.0911)	-0.8517 (0.1972)
ADF t-stat	-3.7250*** (0.0001)	-2.8809*** (0.0020)	-0.3921 (0.3475)	-1.4067* (0.0798)

Note: ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Based on statistical significance at the 5% level, three out of four of the within-dimensions models and all of the between-dimensions models confirm the presence of cointegration among the reference variables of Model 1. Two out of four of the within-dimensions models and one out of three of the between-dimensions models confirm the presence of cointegration among the reference variables of Model 2. Therefore, more detailed regression analyses can be performed.

In the next step, fixed effects regression was performed. The estimator used was the methodology of Driscoll-Kraay (1998), which provides robust results in the case of heteroskedasticity, autocorrelation, and cross-sectional dependence. According to the results, fossil fuel consumption is an important variable affecting emissions in both models. A 1% increase in *fs* increases the *crb* by about 1-1.6%.

While *gdp* is significant at the 10% level in Model 1, it is significant at the 1% level in Model 2. In both models, *gdp* has a positive effect on emissions. This can be interpreted to mean that the countries in the rising part of the EKC dominate among the countries in the sample. The population variable was found to be non-significant in both models.

Table 5. Robust fixed effects regression estimates

	Model 1	Model 2
c	-9.0081*** (0.2823)	-9.4333*** (0.3356)
popcit	0.0477 (0.3449)	0.1501 (0.3736)
gdp	0.1358* (0.0685)	0.1629*** (0.0546)
fs	1.0619*** (0.0273)	1.1003*** (0.0316)
mp	-0.0152** (0.0067)	
ts		0.0015 (0.0035)
R^2	0.9382	0.9368
F-prob.	0.0000	0.0000

Note: Driscoll-Kraay standard errors in parentheses.
***, **, and * denote statistically significance at 1%, 5%, and 10% levels, respectively.

Among the policy variables, it is noteworthy that only the market-based policies are significant at the 5% level. Accordingly, increasing *mp* has a decreasing effect on *crb*. *ts* is not statistically significant at the 5% level, but it may also have an impact on emissions at different quantiles. Therefore, the panel quantile regression analysis (QREG) discussed in the next step focused on both *mp* and *ts*.

Table 6. QREG estimates for model 1

Quantile	0.25		0.5		0.75	
	coefficient	std. error	coefficient	std. error	coefficient	std. error
popcit	0.1620	0.4631	0.0436	0.3483	-0.0791	0.4858
gdp	0.1021	0.0799	0.1370**	0.0601	0.1732**	0.0838
fs	1.0882***	0.0231	1.0610***	0.0175	1.0327***	0.0242
mp	-0.0124*	0.0066	-0.0153***	0.0049	-0.0184***	0.0069

Note: ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Table 6 presents the QREG results of model 1 for the 25th, 50th, and 75th percentiles. The empirical results generally show that the effects of the variables on *crb* are heterogeneous. Accordingly, the coefficient of *gdp* is positive but not significant at the 25th quantile at the 5% significance level. However, at the 50th and 75th quantiles, the coefficients are significant. Moreover, the value of the coefficient increases with the higher quantile. Therefore, the impact of *gdp* on carbon emissions is higher in countries with high emissions. Some countries in the sample (Denmark, Finland, Germany, Ireland, the United Kingdom, and the United States) have both high emission levels and high GDP per capita. These countries may be in the rising part of the EKC, so the increase in *gdp* increases the amount of emissions. This result is consistent with the findings of Allard et al. (2018) and Awan and Azam (2022), which support the N-shaped EKC.

Another important result of the analysis relates to the variable *fs*. Accordingly, the coefficients of *fs* are statistically significant in all three percentiles, but their magnitudes differ. The impact of *fs* on *crb* is lower in high-emission countries. These countries may place more emphasis on mitigation and implement more stringent policies.

As shown in Table 6, the *mp* also has a heterogeneous effect. Although the coefficient of *mp* at the 25th percentile is not statistically significant, the coefficients at the 50th and 75th percentiles are significant. *mp* reduce pollution by increasing the cost of pollution. Policies such as carbon taxes or marketable pollution permits, implemented at high emission levels, impose higher costs. For this reason, producers are more sensitive to rising costs and take initiatives to reduce their emissions. Therefore, policy effectiveness increases at high emission levels. In addition, high-emission countries tend to have more stringent policies as a whole, which increases the impact of market-based policies on mitigation. Therefore, the joint use of different policy instruments also increases the effectiveness of the policy. Figure 1 shows the coefficient shifts during the reference period.

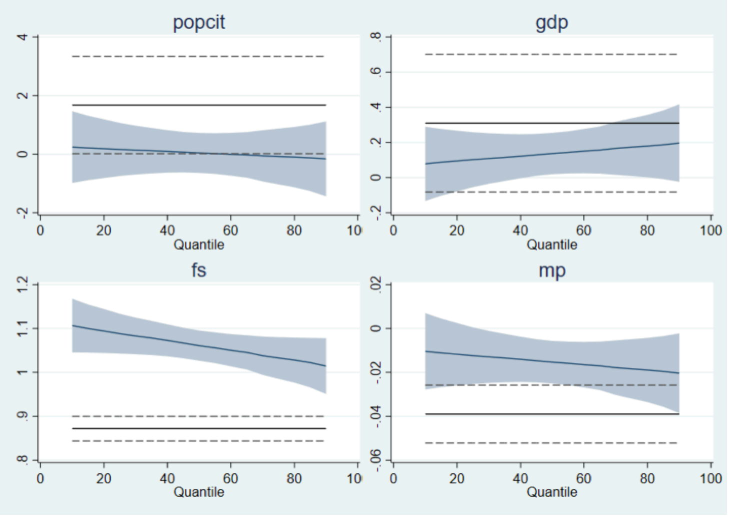
The next step was to test the impact of *ts* with QREG. Table 7 presents the results of Model 2 for the 25th, 50th, and 75th percentiles. The effects of *gdp* and *fs* on *crb* are consistent with Model 1. Accordingly, increases in *gdp* at the 0.5 and 0.75 quantiles have an increasing effect on emissions, and this effect is amplified at high emission levels. An increase in *fs* also leads to an increase in *crb*, but this effect appears to be attenuated at higher emission levels.

Table 7. QREG estimates for model 2

Quantile	0.25		0.5		0.75	
	coefficient	std. error	coefficient	std. error	coefficient	std. error
popcit	0.2574	0.4844	0.1422	0.3689	0.0262	0.5020
gdp	0.1545*	0.0881	0.1635**	0.0671	0.1725*	0.0913
fs	1.1253***	0.0220	1.0984***	0.0170	1.0714***	0.0228
ts	0.0035	0.0028	0.0014	0.0022	-0.0008	0.0029

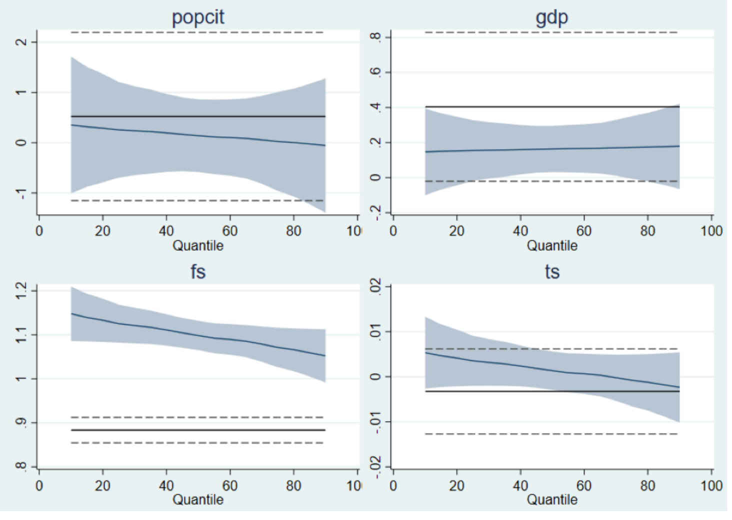
Note: ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Figure 1. QREG graphs for model 1



As shown in Table 7, the effect of *ts* on emissions is not statistically significant, consistent with the fixed effects model. In this case, the *ts* variable does not have a significant effect on *crb* even at different quantiles. Figure 2 shows the coefficient shifts during the reference period.

Figure 2. QREG graphs for model 2



4.1. Robustness analysis

Two robustness check analyses were conducted using alternative models that included additional variables to test the validity of the earlier results. These variables include FDI and trade, which are commonly used in the literature to explain emissions. Two opposing hypotheses come to the fore in explaining the impact of FDI on emissions. According to the Pollution Haven Hypothesis (PHAH), proposed by Walter and Ugelow (1979) and Pethig (1976), FDI, especially from environmentally intensive industries, tends to flow to countries with low environmental regulations, which negatively affects environmental quality in the host country. In contrast, according to the Pollution Halo Hypothesis (PHH), FDI contributes to improving environmental standards by transferring clean technology and environmentally-friendly production standards to the host country. There are numerous studies in the literature that support both hypotheses (Bae et al., 2017; Rafindadi et al., 2018; Balsalobre-Lorente et al., 2019; Hanif et al., 2019; Mert and Caglar, 2020; Neves et al., 2020). Thus, the relationship between FDI and emissions is not clear, yet.

Moreover, the nature of the relationship between trade and emissions remains unclear. Trade can have positive effects by setting the stage for environmental improvements through efficient resource use and economic growth. On the other hand, free trade causes developed countries to shift their dirty industries to developing countries, which may tend to increase pollution in developing countries. There are numerous studies in the literature that empirically estimate the impact of trade on emissions (Hao and Liu, 2015; Shahbaz et al., 2017; Allard et al., 2018; Liobikiene and Butkus, 2019; Essandoh et al., 2020). In this context, the effects of FDI and trade variables were empirically tested in separate models. Model R1 includes FDI flows (% of GDP) (*fdi*) and model R2 includes trade volume of goods and services (% of GDP) (*tr*) as explanatory variables. The coefficient estimates obtained from the QREG analysis are presented in Table 8.

Table 8. QREG estimates for robustness analysis

Quantile	0.25		0.5		0.75	
	R1	R2	R1	R2	R1	R2
popcit	0.1516 (0.4608)	0.2079 (0.4717)	0.0474 (0.3506)	0.0776 (0.3556)	-0.0699 (0.4915)	-0.0609 (0.4956)
gdp	0.1195 (0.0823)	0.1395 (0.0873)	0.1417** (0.0626)	0.1589** (0.0658)	0.1668* (0.0878)	0.1794* (0.0917)
fs	1.0884** (0.0229)	1.0892*** (0.0234)	1.0622*** (0.0176)	1.0616*** (0.0178)	1.0327*** (0.0244)	1.0323*** (0.0245)
mp	-0.0124* (0.0065)	-0.0119* (0.0066)	-0.0152*** (0.0050)	-0.0151*** (0.0050)	-0.0184*** (0.0070)	-0.0185*** (0.0069)
fdi	-0.0003 (0.0003)		-0.0001 (0.0002)		0.0001 (0.0003)	
tr		-0.0006 (0.0005)		-0.0003 (0.0004)		-0.0001 (0.0006)

Note: Standard errors in parentheses.

As can be seen in Table 8, the economic variables included in the analysis are not statistically significant, but the inclusion of these variables did not change our main results. Accordingly, in high-emitting countries, emissions increase at a decreasing rate with an increase in *gdp* and with an increase in *fs*. The effect of the *mp* on emissions is consistent with our earlier results, both in magnitude and sign. Accordingly, *mp* has a negative effect on emissions, and this effect increases at higher emission levels. The coefficient of *mp* is (-0.012) at the 25th percentile, (-0.015) at the 50th percentile, and (-0.018) at the 75th percentile.

5. Conclusions

Different policy tools are used to reduce emissions. Among these instruments, market-based options that increase the price of externalities and technological support programs that encourage the use of renewable energy are important options for reducing emissions. In this study, we compared the impacts of these options by simultaneously testing them empirically. In doing so, we benefited from a large data set and used the panel quantile regression method, which allowed us to better assess the distribution of ecological variables.

The results of the study show that support policy does not have a statistically significant impact on emissions. The results of both the robust fixed-effects model and the panel quantile regression analysis support this finding. As Kruse et al. (2022) suggest, the level of technology-enhancing policies has weakened over the past decade, and this may be the reason why our results regarding these programs are not significant. In addition, the mitigation effects of renewable energy support are likely to occur only in the long term, so it would not be correct to abandon the technology support programs according to our findings. In future studies, thanks to the expansion of the dataset, it will be useful to consider studies that include long-term analyses to show the benefits of technology support.

Market-based policies, on the other hand, were found to be effective in mitigation according to both the robust fixed-effects and the panel quantile regression analyses. As QREG results suggest, this effect is even larger at high emission levels. This result can be explained by the fact that some of the countries with relatively high emissions in the sample (Denmark, Finland, UK) generally have more stringent environmental policies. Accordingly, the joint use of different policy instruments may also be an important factor in increasing policy effectiveness.

The fact that policy instruments have different effects at different emission levels may be due to the fundamental characteristics of the instruments. Market-based instruments impose significant financial burdens on the polluter by increasing the price of the externality, and these burdens automatically increase at high emission levels. Thus, producers' tolerance for increasing financial burdens will decrease. Clearly, under these circumstances, producers are much more willing to reduce their emissions to alleviate their financial burden. On the other hand, technology programs support rather than blame polluters for producing and deploying cleaner technologies. The level of these supports can be increased during periods of high emissions, but unlike market-based instruments, it is not a spontaneous process. Thus, it would be more useful to focus on the long-term effectiveness of support programs than on their impact on reducing the financial burden.

It is worth noting that the study has some limitations. First, policy effects are likely to emerge over longer periods, and as the time dimension of the data set increases in the coming years, the opportunity to conduct a longer-term analysis may arise. The second limitation relates to the policy variable used. The environmental policy stringency index does not cover regulations in all sectors around the world. For this reason, the index may not be a sufficient indicator for countries with high production in the sectors not covered. Additionally, analyzing market-based and technology-support policy instruments by dividing them into sub-components will allow the effects of policy instruments such as solar and wind energy supports to be observed separately.

Finally, the results of the study should be taken as a tribute to market-based instruments rather than a denigration of support programs. In addition, the stringency of market-based policies should be increased, while the long-term effects of support programs should be analyzed in future studies using different methods and a larger data set.

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