Energy Economics 125 (2023) 106879

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

Is there a macroeconomic carbon rebound effect in EU ETS?

C. Kaan Bolat [a], Ugur Soytas [b,*], Bulent Akinoglu [c], Saban Nazlioglu [d,e]

[a] Earth System Science Graduate Program, Middle East Technical University, Ankara, Turkey
[b] Department of Technology, Management, and Economics, Climate Economics and Risk Management Section, Technical University of Denmark, Kongens Lyngby, Denmark
[c] Department of Physics, Earth System Science Graduate Program, Middle East Technical University, Ankara, Turkey
[d] Department of International Trade and Finance, Pamukkale University, Denizli, Turkey
[e] Department of Economics and Finance, Nisantasi University, Istanbul, Turkey

ARTICLE INFO

Keywords:
ETS
Carbon rebound effect
EU, panel data

ABSTRACT

This study examines the macroeconomic carbon rebound effect for the European Union (EU) Emissions Trading System (ETS) by using data for the 2005–2019 period for 26 European countries. We estimate the panel data models which link emissions to allowances by controlling for economic growth, investment, employment, and energy intensity. The results from both the recent panel estimation approaches and Granger causality analysis indicate a macroeconomic carbon rebound effect of the EU ETS. The bidirectional Granger causality between emissions and allowances highlights a self-enforcing macroeconomic rebound. Energy intensity significantly impacts emissions directly and indirectly via the macroeconomic rebound effect. Our results show that positive economic spillovers of ETSs may hamper the efforts to meet climate targets.

1. Introduction

The Emissions Trading System (ETS) is the primary weapon of climate change mitigation. Many countries rely on the efficacy of ETS to meet ambitious net-zero targets. Internalizing the cost of producing emissions-intensive goods leads to either abatement or investment in green technologies; as a result, emissions decline. In theory, it is only a matter of having the right price for carbon to mitigate climate change efficiently. There are some problems in the implementation. Leakage, for example, can undermine the efficacy of a carbon market, whereby firms move their activities to unregulated areas. Of course, global carbon pricing would eliminate it, but tariffs on countries outside the ETS club may curb the problem (Baranzini et al., 2017).[1] Too much volatility in the carbon market increases uncertainty, which is also a problem. The excess volatility problem can be resolved by constantly monitoring bubbles (Cretí and Joëts, 2017). Another threat to ETS's efficacy is not easy to address directly, probably because it is difficult to assess the waterbed and rebound effects (Flachsland et al., 2020). Carbon policies improve energy efficiency, which involves an energy rebound effect. The energy rebound effect, in return, transfers into a carbon rebound effect. If the size of the rebound effect offsets a large amount of the initial gains from ETS, then we run the risk of not meeting the emission reduction targets. In the literature, this link is examined at the firm, sectoral, and regional levels. However, the macroeconomic rebound effect, a combination of economy-wide and indirect rebounds, deserves more attention since it is critical for updating mitigation strategies. For instance, a sizeable macroeconomic carbon rebound effect would call for a faster energy transition to meet net-zero targets.

Although the theory behind ETS is clear, it is not as straightforward to prove its effectiveness in empirical work. Nevertheless, some scholars took up the challenge and provided evidence that ETS works. For example, Klemetsen et al. (2020) provide weak evidence of carbon reduction in the Norwegian manufacturing industry. Focusing on the French manufacturing industry, Colmer et al. (2020) find that regulated firms reduce emissions more than unregulated ones. They account for leakage, but do not find evidence of it.[2] Both of these studies report the positive impact of the ETS scheme on productivity and economic performance. The positive economic impact finding aligns with Löschel et al.'s (2019) results for German manufacturing firms. Marin et al. (2018) also point out the positive impact of ETS on multiple firm-level indicators for a large sample of European firms. Recent studies consider the environmental and economic impacts of ETS in other

* Corresponding author.
E-mail addresses: kaan.bolat@metu.edu.tr (C.K. Bolat), uguso@dtu.dk (U. Soytas), bulo@metu.edu.tr (B. Akinoglu), snazlioglu@pau.edu.tr (S. Nazlioglu).

[1] The EU is recently considering Carbon Border Adjustment Mechanisms as an alternative to free allowances in ETS to prevent carbon leakage.
[2] Contrarily, Koch and Mama (2019) report limited leakage in Germany.

https://doi.org/10.1016/j.eneco.2023.106879
Received 6 December 2022; Received in revised form 16 June 2023; Accepted 12 July 2023
Available online 19 July 2023

countries. Their results do not differ a lot from European studies. To cite a few, Yang et al. (2020) find that the Chinese ETS scheme helped curb emissions and improved employment. Kim and Bae (2022) unveil that ETS encouraged Korean manufacturing firms to improve energy efficiency and electricity generation firms to substitute clean energy sources for fossil fuels.

On the other hand, some studies fail to support that ETS reduces carbon emissions. Calel (2020) showed that the EU ETS did not lead to emissions reductions in UK firms but improved economic performance. However, he argues that the positive impact on low-carbon patenting and R&D expenditures is promising. Chen et al. (2021) found that ETS did not work as expected when regional rebound effects were considered for China. Indeed, significant carbon rebound effects at the macro level may undermine the initial progress at the firm or sectoral level of emissions reductions due to ETS. The empirical studies usually focus on sectors and not the macro economy. ETS encourages energy efficiency. However, the positive impact of ETS on economic performance at the firm and industry levels suggests a macroeconomic energy rebound effect, which turns into a carbon rebound effect. The scale of the rebound effect, if it exists, is crucial to assess the capabilities of countries to meet their net-zero targets. The energy and carbon rebound effects depend on energy intensity and mix.

This paper examines the macroeconomic carbon rebound effect for the EU ETS. We use recent panel econometric techniques to find evidence of a positive dynamic link between allowances and emissions, controlling for economic growth, investment, employment, and energy intensity. The significant positive impact of past emissions allowances on current emissions indicates a carbon rebound effect of ETS at the macroeconomic level. The dynamic link works through a channel that involves economic output and energy intensity. Our results imply that the emissions, economic performance, energy intensity, and carbon trade links are rich and warrant further research. Economic growth seems to exhibit its impact on emissions directly and indirectly via allowances and energy intensity. The causality results indicate a macroeconomic carbon rebound effect due to the EU ETS. We also find that energy intensity leads to economic growth; hence, the EU economic output is not entirely decoupled from energy used, and pursuing economic growth may hamper mitigation efforts.

This is the first study that directly considers the EU ETS's macroeconomic carbon rebound effect to the extent of our knowledge. There is abundant evidence that ETS improves economic and emission performances in several industries, cities, and regions. However, the sectoral and regional studies on the efficacy of ETS do not provide an overall picture. In that respect, this study helps fill an important knowledge gap. Furthermore, we employ a methodology that accounts for cross-sectional dependence and endogeneity issues.

The paper is organized as follows. The literature review in section 2 is a combined discussion of ETS efficacy and rebound effect studies and provides a perspective on how this study fits the picture. Section 4 illustrates the methodology and introduces variable definitions and data sources. Section 5 discusses empirical results. Section 6 concludes with implications for policymakers and future research.

2. ETS Efficacy and rebound effect

The EU ETS has officially been a part of our lives since 2005. Several studies have investigated its role in mitigation, from the earliest stages of the mechanism to its mature stages. The EU ETS has gone through 4 phases. Phase 1 (2005–2007) is the pilot phase, in which almost all allowances were allocated gratis. In Phase 2 (2008–2012), a tighter cap was introduced, and two new countries joined, Norway and Lichtenstein. An increased non-compliance penalty also marks this phase. Auctions became the allowance allocation mechanism in Phase 3 (2013−2020). Phase 4 (2021–2028) started in January 2021, and yearly allowances were reduced to 2.2%, compared to 1.7% in previous phases. While the oldest and, therefore, more mature ETS is operating in the EU, there are many studies conducted on ETS in China, ETS in Australia, and New Zealand.

Moreover, these studies tackle the matter from numerous angles. We try to cover all relevant studies regardless of ETS they focus on in what follows. We first discuss the studies that examine the efficacy of ETSs. Then we briefly discuss the methods and approaches used to test for and measure the rebound effect.

2.1. ETS efficacy

The literature points out three main problems with ETS applications; leakage (Baranzini et al., 2017; Colmer et al., 2020), bubbles (Cretí and Joëts, 2017; Zhang et al., 2019; Zhang et al., 2020a; Zhang et al., 2020b) and backlash (Berritella and Cimino, 2017; Ciarreta et al., 2017; Meyer et al., 2018; Flachsland et al., 2020; Tang et al., 2020; Colmer et al., 2020; Pahle et al., 2022). Leakage is when companies move their carbon-intensive activities outside the ETS region due to extra carbon prices they are asked to pay. Bubbles refer to high volatility in carbon prices, which results in uncertainty and an increase in the risk premium of low-carbon technology investments. Backlash, however, can be defined as razing or softening a policy application due to inefficiency or negative feedback.

The literature on ETS performance is abundant with sectoral studies. These studies focus on specific industries governed by different ETSs and examine how ETS policies affect economic and energy performances (Barbot et al., 2014; Barragan-Beaud et al., 2018; Cao et al., 2019). For example, Barbot et al. (2014) focus on the airline industry in the EU. The ETS policies make it harder for a new competitor to enter the market in equilibrium in their game theoretical model. Barragan-Beaud et al. (2018), on the other hand, study the electricity sector in Mexico to compare ETS to carbon tax using a bottom-up cost optimization model. They show that ETS is preferable to a tax. They provide support for their findings via political feasibility analyses. Cao et al. (2019) analyze a proposed hybrid system for China where the electricity and cement sectors are governed by an ETS, while a carbon tax is applied to the rest of the industry. They employ a dynamic recursive economic energy model and show that a hybrid model achieves the same reductions in emissions with lower permit prices. The partial equilibrium analysis focusing on specific industries may miss the larger picture. What matters for effective climate change mitigation is the overall performance of the ETS.

Berritella and Cimino (2017) underline the VAT fraud in EU ETS and show how it affects ETS operations and the economy using a computational general equilibrium model. Cretí and Joëts (2017), on the other hand, develop recursive right-sided unit root approaches to show the volatile behaviors in the EU ETS market and try to define the core reasons behind bubbles. These studies do not limit themselves to specific industries. They point out particular problems associated with ETSs, and just like sectoral studies, they do not aim to examine the overall efficacy of the ETS in reducing GHG emissions.

Zhang et al. (2019), Zhang et al. (2020a), and Zhang et al. (2020b) examine the Chinese ETS but with different coverage or methodologies. Zhang et al. (2019) use difference-in-differences methods to analyze the economic efficiency of the ETS in China and measure the emission reduction effects and development mechanisms. The authors underline that the ETS achieves a meaningful reduction in GHG emissions while also being economically efficient. Employing the same methodology but utilizing regional data from 30 provinces, Zhang et al. (2020a) test the system's efficacy on the economy and the environment. The conclusion is that the mechanism achieves significant emissions reduction and economic efficiency. Zhang et al. (2020b) divides the ETS mechanism in China into three different periods to investigate the efficacy of eight different carbon markets using robust variance ratio tests. Results indicate that the ETS starts with high market volatility, and the volatility becomes moderate over time. All three studies on the efficacy of Chinese ETS suggest policies to improve the carbon reduction potential of the

ETS mechanism. This suggests that there is room for improving the efficacy of the ETSs. These studies do not explicitly check the role of the energy and carbon rebound effects.

Studies combining ETS efficacy and rebound effects make up a rapidly growing line in the literature (Ciarreta et al., 2017; Meyer et al., 2018; Flachsland et al., 2020; Tang et al., 2020; Colmer et al., 2020). Ciarreta et al. (2017) employ a game-theoretical model to compare the feed-in tariff mechanism to green certificates using panel data. They conclude that green certificates would rebound less than the feed-in tariff mechanism. Meyer et al. (2018) developed an input-output model (IO) to define and express the rebound effects of efficiency improvements on regional and worldwide energy consumption. They suggest various policy implications, such as ETS, to tackle the rebound effects. Flachsland et al. (2020) focus on the rebound effects caused by the interactions of the EU ETS with other regional policies. They suggest a price floor to avoid possible rebound effects, drawing attention to the efficacy of the Market Stability Reserve. Tang et al. (2020) consider the 273 cities in China for the pilot ETS application using panel data and difference in differences method. They suggest a transition from regional to national ETS as the mechanism seems to be successful, underlining that this transition might also help reduce the rebound effects arising from technological progress and energy improvements. Colmer et al. (2020) discuss the possibility of carbon leakage by manufacturing companies in France using the difference-in-differences method. Their results show that EU ETS helped mitigate climate change. They argue that EU ETS did not cause any leakage, but these results do not guarantee the overall efficacy of ETS as the study focuses only on the manufacturing industry.

The macroeconomic carbon rebound effect is not explicitly modeled or estimated in empirical work. We next review the applied studies to choose or develop an appropriate approach for this purpose.

2.2. Rebound effect

The rebound effect refers to reduced gains from new technologies in energy efficiency, compared to the expectations in the first place, caused by systematic or behavioral responses (Brookes, 1979; Khazzoom, 1980; Grubb, 1990). While there are various classifications of rebound effect in the literature, we consider the approach of Greening et al. (2000), who divides the rebound effect into four main categories; direct rebound, indirect rebound, economy-wide rebound, and macroeconomic rebound. Chitnis et al. (2013) define direct rebound as a phenomenon where the energy consumption of the energy service increases due to improved energy efficiency, causing a decrease in the unit price of energy, and increased energy efficiency leads to an increase in energy usage per capita. Indirect rebound is the effect on other goods and services with energy efficiency improvements. The indirect rebound effect occurs when consumers spend their savings from energy efficiency improvements on other goods and services (Ghosh and Blackhurst, 2014). Freire-Gonzalez (2017), and Herring and Roy (2007), define an economy-wide rebound as the rebound effect where energy improvements result in the alteration of prices, demand quantities, and production in the selected unit. Economy-wide rebound includes direct and indirect effects (Peters et al., 2012). The macroeconomic rebound effect combines economy-wide and indirect rebounds (Barker et al., 2009). Energy efficiency improvements bring macroeconomic growth, which increases energy consumption. Therefore, a mix of economy-wide and indirect energy rebound effects exists; this mixed effect is named the macroeconomic rebound (Zhang and Lawell, 2017).

The literature shows various methodologies and approaches when measuring the different rebound effects. They can be categorized into simple statistical approaches, input-output type models, and econometric methods. Naturally, some studies involve a combination of approaches. However, studies rely solely on simple statistical approaches (Pakusch et al., 2018; Bieser and Hilty, 2018; Carratu et al., 2020). Pakusch et al. (2018) use discriminant analysis to investigate the rebound effect of autonomous driving, revealing that the technology might drive people away from public transportation and increase GHG emissions. Bieser and Hilty (2018), on the other hand, take virtual goods under their scope and use descriptive statistics as well as simple regression to show that each virtual good comes with its rebound effect. Carratu et al. (2020) consider extra costs to firms in Phase 3. These studies have limited scope since they focus on a specific good or service.

Several studies measure the rebound effect using IO (Pfaff and Sartorius, 2015; Li and Jiang, 2016; Wu et al., 2018; Font Vivanco et al., 2016) as well as other studies using computable general equilibrium (CGE) models (Lu et al., 2017; Zhou et al., 2018; Somuncu and Hannum, 2019; Barkhordar, 2019; Peng et al., 2019). Pfaff and Sartorius (2015) studied non-energy raw materials in the production sector in Germany, and Li and Jiang (2016) analyzed the subsidies in China, both for economy-wide rebound effects using the IO method. Wu et al. (2018) evaluate the direct rebound of water-saving technologies in agricultural water use in China, while Font Vivanco et al. (2016) focus on the worldwide rebound effect of smartphone usage. Both utilize the IO method and provide evidence of significant rebound effects. Lu et al. (2017) examine 135 production sectors and five energy sources in China, using a static CGE model to investigate the economy-wide rebound effects of energy efficiency in these sectors. In a similar study, Zhou et al. (2018) considered the same sectors using a two-stage decomposition method and their CGE model. They identify significant rebound effects and propose policies to overcome them. Somuncu and Hannum (2019) develop two different energy-economy CGE models for the Turkish economy. They consider rebound effects arising from energy efficiency improvements in Turkey and the role of energy theft. Barkhordar (2019) and Peng et al. (2019) address the rebound effects caused by government policies. The former focuses on the economy-wide rebound introduced by household lighting in Iran, where the government provides free-of-charge LED lighting for energy efficiency. The latter examines the direct rebound effect of an energy excise tax in Jiangsu Province in China. IO models are often criticized for their exclusive focus on production and overly simplified and static structures. The CGE models overcome some of these shortcomings in expense for detailed information on sectors. They are also subject to the black box critique; hence, it may be difficult to identify what drives the results (e.g., carbon rebound).

A wide range of studies combines panel data or time-series econometrics with several other approaches in the rebound effect literature. Fukui and Miyoshi (2017), Chen et al. (2018), Belaid et al. (2018), Schusser and Jaraite (2018), Su (2019), and Borozan (2019) contribute significantly to this line of literature by handling different cases. Fukui and Miyoshi (2017) examine the consequences of introducing emission taxes on aviation fuels in the United States Airline Industry. They show that there are significant short-term and long-term rebound effects. Chen et al. (2018) studied the manufacturing industry in China using a dynamic ordinary least squares approach with seemingly unrelated regression. They calculate the direct rebound caused by energy efficiency improvements and suggest some carbon taxing or ETS to control energy consumption.

On the other hand, Belaid et al. (2018) focus on the government energy efficiency policies and the rebound effect in the residential gas demand in France. They use time-series data and develop models using ordinary least squares and the autoregressive distributed lag (ARDL) approach to find out that there are short-term and long-term energy rebound effects. The rebound effect comparison of the EU ETS and Swedish Tradable Green Certificate System is conducted by Schusser and Jaraite (2018). They adopt a panel vector autoregression (VAR) approach and show a positive correlation in the short run between the two. They argue that combining these two systems might affect each other negatively in the long run. Su (2019) investigates the rebound effect of energy efficiency improvements on household electricity demand in Taiwan by employing primary data on electricity consumption and 30 variables collected via a survey. Their results point out a significant rebound effect of energy-efficient appliances. Borozan (2019) considers the final household energy demand in the European Union region. Their panel data model detects rebound effects arising from energy taxes. The author suggested a variety of policy implications among energy taxes, such as revenue recycling and tailormade policies for different sectors, to tackle the rebound effects. The cases presented here concern rebound effects due to household behavior in different energy efficiency cases. They do not attempt to identify a macroeconomic rebound effect of the ETS.

There are several recent studies on carbon emissions, carbon prices, and clean energy assets employing similar methodologies to this study. For example, Kayani et al. (2022) explore the relationship between CO2 emissions, foreign direct investments, and clean energy contribution in the United Arab Emirates using panel data from 1971 to 2009. Using the fixed-effect regression model, the authors demonstrate a clear impact of foreign investments on the country's emissions, and they advise policymakers to implement more energy initiatives, such as the Energy Strategy 2050, to improve energy efficiency and renewable energy access. Farid et al. (2023), on the other hand, investigate the interconnections between dirty and clean energies through a co-movement analysis of clean energy stocks and dirty energies before the Covid-19 pandemic. The authors compare crude oil, heating oil, gas oil, natural gas, and gasoline with the S&P Global Clean Energy Index and the Wilder Hill Clean Energy Index. They discover weak linkages in the short run and that clean energy markets are isolated from dirty energies. Finally, the authors emphasize that the study contains important policy implications because green programs can decouple clean energy investments from dirty energies and that they should be encouraged more. Using a network approach to investigate the interdependence of clean energy, green markets, and cryptocurrencies Arfaoui et al. (2023) analyze data between 2018 and 2021 collected from the S&P Dow Jones Green Bonds Index, the Dow Jones Sustainability Index, the S&P Global Clean Energy Index, and the MSCI World ESG Leaders Index. Then, they compare it to the data for major cryptocurrencies Bitcoin, Ethereum, Ripple, and Cardano; using rolling windows estimation. They see an increased dependency among these markets during the Covid-19 pandemic. The authors recommend that policymakers rethink their policies to encourage sustainable and environmentally favorable investments. Naeem et al. (2022) investigate the links between green finance assets and sectoral and commodities stock markets. The authors analyze the positive and negative effects of volatility in some large pond markets by collecting data from the US stock markets between 2010 and 2021. They advocate for a clear separation between short-run and long-run volatility spillovers in terms of return and volatility connections so that policymakers can discover the risk-adjusted potential of green markets in mitigating the hazards of the stock and commodity markets. Utilizing panel data from 2000 to 2019 for the 10 most polluted countries, Kayani et al. (2023) investigate the relationship between foreign direct investments, tourism, urbanization, economic growth, and CO2 emissions. Using the unit root tests, they ensure that the data is stationary and examine the long-run connections of all the dependent variables with the emissions. They find a positive and significant relationship between carbon emissions and foreign direct investments, as well as economic growth, urbanization, and tourism while observing a negative and insignificant relationship between renewable energy and carbon emissions. Finally, the authors underline the need of attracting clean foreign direct investments through enhancing environmental legislation, as well as promoting the adoption of green technologies and upgrading urban architecture. The studies employing panel data analysis fill important knowledge gaps regarding emissions and emission prices; however, they do not consider the rebound effect of carbon trading.

This study attempts to add a broader perspective by testing and estimating the macroeconomic carbon rebound effect of the EU ETS. The literature is rich in examining market-based instruments, evaluating the efficacy of ETS from different perspectives, and considering energy rebound effects in different sectors, regions, technologies, and behaviors. However, what matters for meeting ambitious net-zero targets is the overall emissions. The macroeconomic carbon rebound effect can be detrimental to our efforts to reach these targets. ETS is the primary climate change mitigation tool that countries rely on. Yet, to the extent of our knowledge, the overall carbon rebound effect of ETSs has not been questioned. Our study fills this critical gap and may lead the way to a new line of literature that would provide a much-needed overall guideline for our mitigation efforts.

3. Methodology and data

To examine the macroeconomic carbon rebound effect of the EU ETS, we conduct an econometric analysis within panel data framework. Specifically, our panel regression is based on a growth specification of CO2 emissions, defined as

$$\begin{aligned}\Delta lnEMI_{it} =& \alpha_i + \beta_1 \Delta lnGDP_{it} + \beta_2 \Delta lnLAB_{it} + \beta_3 \Delta lnFCF_{it} + \beta_4 \Delta lnALL_{it} \\ & + \beta_5 \Delta lnINT_{it} + \varepsilon_{it}\end{aligned} \tag{1}$$

where EMI is CO2 emissions, GDP is gross domestic product, LAB is labor, FCF is fixed capital formation, ALL is emissions allowances, and INT is energy intensity, $i = 1, \ldots,$ N denotes the cross-sectional dimension, $t = 1, \ldots,$ T denotes the time dimension, α_i are individual fixed effects, and ε_{it} is the error term. As it is clear from using the log-differenced form (Δln where Δ and ln denote the first difference and natural logarithm operators, respectively), we employ all variables in growth rates.

Baltagi (2013) outlines that most panel data applications utilize the error component model for the disturbances to eliminate unobservable individual fixed effects. Since pooled OLS ignores unobservable fixed effects in estimations, it is straightforward to estimate model (1) using the fixed-effects model when panel data consists of a specific set of N individuals (such as in European countries). The panel data model in eq. (1) may suffer from inconsistency and invalid statistical inference because the fixed effects estimation is inconsistent as N increases for a fixed T (Nickell, 1981) - known as the Nickell bias- arising from a possible endogeneity problem that is the correlation between regressors and regression errors. The solution for Nickell bias is to employ the generalized method of moments (GMM) estimator, and the system GMM approach proposed by Blundell and Bond (1998) is widely used in the empirical literature.

The inconsistency and invalid statistical inference problems may also stem from cross-sectional dependence, implying that some common factors affect cross-sectional units in the panel. Hence, current efforts have focused on estimating the panel data models under cross-sectional dependence. The common factor representation of the regression error can be defined as $\varepsilon_{it} = \lambda_i^{'} F_t + u_{it}$ where F_t is a vector of unobserved common factors and λ_i is a vector of factor loadings. The factor representation of eq. (1) can be written as

$$\begin{aligned}\Delta lnEMI_{it} =& \alpha_i + \beta_1 \Delta lnGDP_{it} + \beta_2 \Delta lnLAB_{it} + \beta_3 \Delta lnFCF_{it} + \beta_4 \Delta lnALL_{it} \\ & + \beta_5 \Delta lnINT_{it} + \lambda_i^{'} F_t + u_{it}\end{aligned} \tag{2}$$

which is called as the common correlated effects (CCE) model (Pesaran, 2006) or the interactive fixed effects (IFE) model (Bai, 2009). The different estimators are proposed to estimate the model (2) based on how unobservable common factor F_t is estimated. Pesaran (2006) employs the cross-sectional averages of dependent and explanatory variables as common factors. Bai (2009) estimates F_t by the method of principal components applied to the estimated residuals $\widehat{\varepsilon}_{it}$.He uses the fixed-effects estimates as initial values and runs an iteration procedure to consistently estimate the common factor and factor loadings.

After establishing the long-run relationship between CO2 emissions growth and its macroeconomic determinants, we further investigate dynamic causality among CO2 emissions, GDP, emissions allowances, and energy intensity. Our causality analysis is based on the panel vector autoregression (VAR) specification of model (1) to identify the existence and direction of causality using the Granger (1969) procedure. The panel VAR model can be written as

$$\begin{aligned}\Delta lnEMI_{it} = & a_{1i} + \sum_{j=1}^{p} \phi_{11j} \Delta lnEMI_{it-j} + \sum_{j=1}^{p} \phi_{12j} \Delta lnGDP_{it-j} \\ & + \sum_{j=1}^{p} \phi_{13j} \Delta lnLAB_{it-j} + \sum_{j=1}^{p} \phi_{14j} \Delta lnFCF_{it-j} \\ & + \sum_{j=1}^{p} \phi_{15j} \Delta lnALL_{it-j} + \sum_{j=1}^{p} \phi_{16j} \Delta lnINT_{it-j} + v_{1it}\end{aligned} \quad (3.1)$$

$$\begin{aligned}\Delta lnGDP_{it} = & a_{2i} + \sum_{j=1}^{p} \phi_{21j} \Delta lnEMI_{it-j} + \sum_{j=1}^{p} \phi_{22j} \Delta lnGDP_{it-j} \\ & + \sum_{j=1}^{p} \phi_{23j} \Delta lnLAB_{it-j} + \sum_{j=1}^{p} \phi_{24j} \Delta lnFCF_{it-j} \\ & + \sum_{j=1}^{p} \phi_{25j} \Delta lnALL_{it-j} + \sum_{j=1}^{p} \phi_{26j} \Delta lnINT_{it-j} + v_{2it}\end{aligned} \quad (3.2)$$

$$\begin{aligned}\Delta lnALL_{it} = & a_{3i} + \sum_{j=1}^{p} \phi_{31j} \Delta lnEMI_{it-j} + \sum_{j=1}^{p} \phi_{32j} \Delta lnGDP_{it-j} \\ & + \sum_{j=1}^{p} \phi_{33j} \Delta lnLAB_{it-j} + \sum_{j=1}^{p} \phi_{34j} \Delta lnFCF_{it-j} \\ & + \sum_{j=1}^{p} \phi_{35j} \Delta lnALL_{it-j} + \sum_{j=1}^{p} \phi_{36j} \Delta lnINT_{it-j} + v_{3it}\end{aligned} \quad (3.3)$$

$$\begin{aligned}\Delta lnINT_{it} = & a_{4i} + \sum_{j=1}^{p} \phi_{41j} \Delta lnEMI_{it-j} + \sum_{j=1}^{p} \phi_{42j} \Delta lnGDP_{it-j} \\ & + \sum_{j=1}^{p} \phi_{43j} \Delta lnLAB_{it-j} + \sum_{j=1}^{p} \phi_{44j} \Delta lnFCF_{it-j} \\ & + \sum_{j=1}^{p} \phi_{45j} \Delta lnALL_{it-j} + \sum_{j=1}^{p} \phi_{46j} \Delta lnINT_{it-j} + v_{4it}.\end{aligned} \quad (3.4)$$

The direction of causation can be examined by testing for the significance of the coefficients of the independent variables in eqs. (3.1)–(3.4). For instance, the null hypothesis of no-Granger causality from GDP growth ($\Delta lnGDP$) to CO2 emissions growth ($\Delta lnEMI$) is defined as $H_0 : \phi_{12j} = 0$ for all j in eq. (3.1) and is tested based on the Wald principle.

We use annual data covering the 2005–2019 period for 26 European countries amounting to 390 observations. CO2 emissions (EMI) and emissions allowances (ALL) are measured by millions of tons of CO2 equivalent (MtCO2eq) and obtained from European Environment Agency. Gross Domestic Product (GDP) is measured as millions of chained 2010 Euros, labor (LAB) is measured by the number of people, and fixed capital formation (FCF) is measured as a percentage share of GDP, which is obtained from the FRED Database. Finally, electricity consumption to construct energy intensity (INT) is measured by terawatt-hours (TWh) and sourced from the International Energy Agency.

Table 1 reports some descriptive statistics of the series. Since we use the growth rates, it is not surprising that the mean of all the variables is around zero. Concerning the volatility structure, while emissions allowances have the largest standard deviation, fixed capital formation exhibits the largest coefficient of variation. The negative skewness implies a left-tail distribution in CO_2 emissions, GDP, labor, and emissions allowances; the positive skewness supports the prevalence of right-tailed distribution in fixed capital formation and energy intensity; and the positive excess kurtosis (Kurtosis >3) reveals a leptokurtic distribution in each of the variables. The Jarque and Bera (1987) test provides evidence for non-normal distributions in the data since the null hypothesis of normality is rejected for all series.

4. Empirical results

We must first confirm the stationarity of the variables before proceeding with the inferences regarding parameter estimations and causality analysis. One key consideration when testing for unit roots in panel data is cross-sectional dependence. As a first step, we test for cross-sectional dependence using the LM (Lagrange Multiplier) test proposed by Breusch and Pagan (1980), as well as the CD_{LM} and CD tests published by Pesaran (2021).[3] The test statistics at the bottom of Table 2 show that the null hypothesis of cross-sectional independence is strongly rejected for all variables, corroborating the evidence of cross-sectional dependence. We use the PANIC approach of Bai and Ng (2004, 2010) and the PANICCA approach of Reese and Westerlund (2016) to study the unit root features of the variables, which both account for cross-section dependence in a common factor framework. It should be noted that the PANIC approach uses the method of principal components to estimate common factors, whereas the PANICCA approach uses cross-sectional averages.[4] The panel unit root statistics presented in Table 2, namely Pa, Pb, and PMSB,[5] suggest that the null hypothesis of unit root is rejected for all variables. We can now perform parameter estimations and panel causality analysis because we have ensured that the variables in growth rates are stationary.

Table 3 represents the results from different panel estimation methods for the sake of the robustness of estimations. Following Chen et al. (2018), let start with the conventional OLS estimator. The point estimates from pooled OLS indicate that GDP, emissions allowances, and energy intensity have significant and positive effects; fixed capital formation has a significant and negative effect; and labor does not significantly impact CO2 emissions.. We should note that these results may be biased since pooled OLS does not account for unobserved individual effects of the EU countries that may play a crucial role in the growth of CO2 emissions. In that respect, we proceed with the fixed effects (FE) model and find out that the sign and significance of the explanatory variables are in line with those from pooled OLS with a slight difference in the magnitudes of the coefficients.

The results from the fixed-effects model may still suffer from inconsistency and invalid statistical inference that arise from a possible endogeneity between regressors and regression errors, known as the Nickel bias. In that respect, we employ the two-step system GMM estimator of Blundell and Bond (1998) by using two lagged values of the dependent variable and levels of the explanatory variables as the instrumental variables. Note that the system GMM estimation requires the validity of instrumental variables and the absence of second-order autocorrelation in the regression residuals. The Hansen statistic is 20.08 (p-value = 1.000), which supports the validity of the instrumental variables. The AR(2) statistic is −1.64 (p-value = 0.101), indicating that the second-order autocorrelation problem is insignificant. Compared to pooled OLS and FE models, the estimations from system GMM indicate that GDP, emissions allowances, and energy intensity keep their significant and positive effects with similar magnitudes. In contrast, the significant negative impact of fixed capital formation is insignificant.

Caution with the results from the pooled OLS, fixed-effects model, and system GMM estimations is that these approaches do not consider cross-correlations across individuals. Ignoring potential cross-correlations may lead to inconsistency and invalid statistical inference.

[3] We omit the details of the cross-sectional dependence tests to save space and refer an interest reader to Breusch and Pagan (1980) and Pesaran (2021).

[4] Since the PANIC procedure requires determining the number of common factors, we determine it by using the IC_2 information criterion proposed by Bai and Ng (2002).

[5] We omit the details of the unit root statistics to save space and refer an interest reader to Bai and Ng (2004, 2010) and Reese and Westerlund (2016).

Table 1
Descriptive statistics.

	ΔlnEMI	ΔlnGDP	ΔlnLAB	ΔlnFCF	ΔlnALL	ΔlnINT
Mean	−0.0252	0.0198	0.0051	−0.0060	−0.0371	−0.0151
SD	0.0978	0.0375	0.0169	0.0941	0.1452	0.0354
CV	−3.8858	1.8963	3.3238	−15.7500	−3.9151	−2.3516
Minimum	−0.6227	−0.1588	−0.0831	−0.3767	−0.7202	−0.1952
Maximum	0.3354	0.2246	0.0886	0.6406	0.5274	0.1317
Skewness	−0.6202	−0.7299	−0.0462	0.7935	−0.9519	0.3305
Kurtosis	9.3561	9.0047	8.0788	11.9242	5.5189	6.7029
JB	629.1	579.2	391.3	1246.1	149.5	214.6
p-val.	0.000	0.000	0.000	0.000	0.000	0.000

ΔlnEMI is the CO_2 emissions annual growth rate, ΔlnGDP is the GDP annual growth rate, ΔlnLAB is the labor annual growth rate, ΔlnFCF is the fixed capital formation annual growth rate, ΔlnALL is the emissions allowances annual growth rate, and ΔlnINT is the emissions intensity annual growth rate. SD is standard deviation, CV (SD/mean) is coefficient of variation, JB is Jarque and Bera (1987) normality statistic, p-val. is *p*-value corresponding to JB based on the chi-square distribution with two degrees of freedom. p-val. < 0.01, 0.05, and 0.1 indicate significance at 1%, 5%, and 10%, respectively.

Table 2
Results from panel unit root tests.

Tests	ΔlnEMI		ΔlnGDP		ΔlnLAB		ΔlnFCF		ΔlnALL		ΔlnINT	
PANIC												
Pa	−8.561	***	−6.742	***	−6.663	***	−8.596	***	−20.417	***	−16.064	***
	[0.000]		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]	
Pb	−80.005	***	−378.159	***	−568.981	***	−106.937	***	−108.786	***	−385.231	***
	[0.000]		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]	
PMSB	−2.479	***	−1.812	***	−1.942	***	−2.498	***	−3.472	***	−3.167	***
	[0.000]		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]	
PANICCA												
Pa	−21.845	***	−11.245	***	−14.594	***	−22.443	***	−26.949	***	−23.269	***
	[0.000]		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]	
Pb	−61.149	***	−302.971	***	−624.792	***	−101.320	***	−29.425	***	−336.106	***
	[0.000]		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]	
PMSB	−3.358	***	−2.787	***	−3.094	***	−3.525	***	−3.541	***	−3.435	***
	[0.000]		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]	
CD tests												
LM	622.156	***	2165.147	***	551.923	***	905.041	***	1743.704	***	742.974	***
	[0.000]		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]	
CD_{LM}	11.655	***	72.176	***	8.901	***	22.751	***	55.646	***	16.394	***
	[0.000]		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]	
CD	53.411	***	166.885	***	34.956	***	92.438	***	133.252	***	72.867	***
	[0.000]		[0.000]		[0.000]		[0.000]		[0.000]		[0.000]	

ΔlnEMI is the CO_2 emissions annual growth rate, ΔlnGDP is the GDP annual growth rate, ΔlnLAB is the labor annual growth rate, ΔlnFCF is the fixed capital formation annual growth rate, ΔlnALL is the emissions allowances annual growth rate, and ΔlnINT is the emissions intensity annual growth rate.
PANIC: Panel Analysis of Nonstationarity in Idiosyncratic and Common components, developed by Bai and Ng (2004 and 2010). The PANIC is based on the principal component analysis. The optimal number of factors are selected by the IC_2 panel information criterion of Bai and Ng (2002) by setting maximum numbers to 3. Pa, Pb, and PMSB statistics test for the null of unit root against the alternative of stationarity; and have standard normal distribution.
PANICCA: PANIC on cross-section averages, proposed by Reese and Westerlund (2016). The cross-sectional averages of the variable were used as the estimated common factors. Pa, Pb, and PMSB statistics test for the null of unit root against the alternative of stationarity; and have standard normal distribution.
CD (cross-section dependency) tests: *LM* test of Breusch and Pagan (1980) has chi-square distribution with N(N-1)/2 degrees of freedom, CD_{LM} and *CD* tests of Pesaran (2021) have standard normal distribution. These statistics test for the null of no cross-sectional dependence against the alternative of cross-sectional dependence. The tests were based on the OLS residuals from the regression of the variable in question on constant term.
The numbers in brackets are the *p*-values. ***, **, and * indicate statistical significance at 1, 5, and 10% level of significance, respectively.
The PANIC, PANICCA, and CD tests were conducted with GAUSS Time Series and Panel Data (TSPD) library of Nazlioglu (2021) and publicly available at: https://github.com/aptech/tspdlib.

Before benefiting from the estimation methods with cross-sectional dependence, we test for the significance of cross-correlations with a battery of tests by using the LM (Lagrange Multiplier) test of Breusch and Pagan (1980), and CD_{LM} and *CD* tests of Pesaran (2021). The cross-section dependency tests, reported at the bottom of Table 3, reject the null hypothesis of no cross-sectional dependence at 1%, indicating significant cross-correlations across the EU countries for CO2 emissions growth.

Given the existence of cross-section dependence in the CO2 emissions growth model, we proceed with the common correlated effects (CCE) model of Pesaran (2006) and the interactive fixed effects (IFE) model of Bai (2009). As we outlined before, the CCE approach uses cross-sectional averages; and the IFE method estimates unobserved common factors by the method of principal components. The results from the CCE show that GDP and energy intensity have significant and positive effects; fixed capital formation has a significant and negative effect; labor and emissions allowances do not significantly affect CO2 emissions. The IFE approach reveals similar results to the CCE method by unveiling the significant impact of emission allowances.

Different estimators yield similar results regarding the signs and magnitudes of the coefficients. Economic growth, allowances, and energy intensity positively drive emissions, whereas fixed capital formation has a negative impact. Although its magnitude is small, we interpret the positive coefficient of allowances as the first indicator of a carbon rebound effect. Economic growth and energy intensity have much larger coefficient estimates. Economic growth does not seem to have

Table 3
Results from panel estimations.

	Pooled OLS		FE		System GMM		CCE		IFE	
ΔlnGDP	1.270	***	1.342	***	1.313	***	1.387	***	1.386	***
	(7.98)		(4.78)		(5.27)		(3.56)		(9.08)	
ΔlnLAB	−0.447		−0.277		−0.322		0.384		−0.311	
	(−1.52)		(−0.69)		(−0.96)		(0.60)		(−1.07)	
ΔlnFCF	−0.041	*	−0.085	**	−0.037		−0.149	**	−0.052	**
	(−1.73)		(−2.38)		(−1.36)		(−2.05)		(−2.18)	
ΔlnALL	0.080	**	0.067	*	0.076	**	0.064		0.083	***
	(2.52)		(2.03)		(2.31)		(0.85)		(2.72)	
ΔlnINT	1.240	***	1.289	***	1.269	***	1.999	***	1.350	***
	(7.93)		(4.24)		(4.30)		(7.09)		(8.84)	
CD tests										
LM	392.691	***								
	[0.000]									
CD_{LM}	2.655	***								
	[0.008]									
CD	17.043	***								
	[0.000]									

ΔlnEMI is the CO_2 emissions annual growth rate, ΔlnGDP is the GDP annual growth rate, ΔlnLAB is the labor annual growth rate, ΔlnFCF is the fixed capital formation annual growth rate, ΔlnALL is the emissions allowances annual growth rate, and ΔlnINT is the emissions intensity annual growth rate.
Pooled OLS: Pooled ordinary least squares estimator.
FE: Panel fixed effects model.
System GMM: Two-step system GMM estimator of Blundell and Bond (1998). The two lagged values of dependent variable and levels of the explanatory variables are used as the instrumental variables. Hansen statistic is 20.08 with p-value $= 1.000$ for validity of the over-identifying restrictions. AR(2) statistic is -1.64 with p-value $= 0.101$ for second order autocorrelation.
CCE: Common correlated effects model of Pesaran (2006). The cross-sectional averages of the dependent and explanatory variables were used as the estimated common factors.
IFE: Interactive fixed effects model of Bai (2009). The common factors were estimated by the method of principal components applied to the estimated residuals $\hat{\varepsilon}_{it}$.
CD (cross-section dependency) tests: *LM* test of Breusch and Pagan (1980) has chi-square distribution with N(N-1)/2 degrees of freedom, CD_{LM} and *CD* tests of Pesaran (2021) have standard normal distribution. These statistics test for the null of no cross-sectional dependence against the alternative of cross-sectional dependence. The tests were based on the OLS residuals from the eq. (1).
The t-statistics in parentheses were estimated with the corrected standard errors of Windmeijer (2005) for system GMM, and with the HAC standard errors of Newey and West (1987) for pooled OLS, FE, CCE, and IFE. The numbers in brackets are the p-values. ***, **, and * indicate statistical significance at 1, 5, and 10% level of significance, respectively.

Table 4
Results from panel causality test.

	Independent variables							
	ΔlnEMI		*ΔlnGDP*		*ΔlnALL*		*ΔlnINT*	
ΔlnEMI			10.17***	[0.017]	13.18***	[0.004]	10.42**	[0.015]
ΔlnGDP	4.73	[0.192]			6.39*	[0.094]	9.27**	[0.025]
ΔlnALL	22.16***	[0.000]	14.61***	[0.002]			11.78***	[0.008]
ΔlnINT	13.53***	[0.003]	11.33**	[0.010]	1.71	[0.635]		

ΔlnEMI is the CO_2 emissions annual growth rate, ΔlnGDP is the GDP annual growth rate, ΔlnLAB is the labor annual growth rate, ΔlnFCF is the fixed capital formation annual growth rate, ΔlnALL is the emissions allowances annual growth rate, and ΔlnINT is the emissions intensity annual growth rate.
Read the table in rows. For instance, statistic 10.17 tests for the null hypothesis of no Granger causality from GDP growth to EMI growth. Wald statistics are reported with respect to zero restrictions and the figures in brackets are the p-values corresponding to Wald statistics. Panel VAR model is estimated with the GMM estimation procedure as outlined in Arellano and Bond (1991). The number of lags in panel VAR model is determined to ensure the serially uncorrelated error terms, and 3 lags are used accordingly. ***, **, and * indicate statistical significance at 1, 5, and 10% level of significance, respectively.

decoupled from carbon emissions. Furthermore, the sizeable positive coefficient estimate for energy intensity indicates the need for a rapid EU green transition.

The results from the panel causality analysis are presented in Table 4. Following Costantini and Martini (2010), we use an instrumental variable estimator to eliminate the correlation between the error term and the lagged dependent variables in the dynamic panel model and estimate the panel VAR model by the GMM procedure outlined in Arellano and Bond (1991). The number of lags in the panel VAR model is determined to ensure the validity of over-identifying restrictions and serially uncorrelated error terms; hence, three lags are used. On the one hand, there is unidirectional causality from GDP growth to CO2 emissions, energy intensity, and emissions allowances. On the other hand, the results indicate bi-directional causal flows for CO2 emissions-allowances, CO2 emissions-energy intensity, economic growth-allowances, and economic growth-energy intensity. The bi-directional causal relations imply that the intertemporal dynamics between the variables are rich. Moreover, the results hold on all phases of ETS considered in this study. The dummy variables and their interactions with allowances do not significantly enter the model. Hence, the phases do not have a meaningful effect. Therefore, we stick to the model without the dummies. The results with dummy variables and interaction terms are available upon request.

The bi-directional emissions-allowances causality can be viewed as another piece of evidence of a macroeconomic carbon rebound effect. The bi-directional economic growth-allowances causality combined with the unidirectional causality running from economic growth to emissions also supports the macroeconomic carbon rebound effect of the

ETS story. ETS reduces emissions in the industries that it covers. However, it also has positive economic spillovers across the economy. Since economies are not decoupled from emissions, economic growth leads to more emissions.

5. Discussion and conclusions

The efficacy of ETSs is vital to meeting climate targets. Several studies at the sectoral level have provided evidence that they help reduce emissions. They also imply the positive impacts of ETS on economic performance at the firm and sectoral levels. However, the macroeconomic rebound effect is not considered, even though it ultimately matters the most for climate change. This paper attempts to help fill that gap.

We find that a 1% change in allowances results in a 7–8% increase in emissions. We also find that information on past allowances helps improve the predictions of current emissions and vice versa. The panel estimation and Granger causality results support the claim of a carbon rebound effect of the EU ETS at the macroeconomic level. The Granger causality is bidirectional, suggesting a self-enforcing carbon rebound effect in the longer run.

Our findings suggest that the macroeconomic carbon rebound effect of ETSs must be considered in assessing the capability to meet climate targets. The carbon rebound effect may intensify globally since economic growth in the EU ETS will result in positive spillovers in other economies. Since there are positive economic impacts of other ETSs at the firm, sectoral, and regional scales, similar concerns arise for all ETSs. Reaching a globally integrated and all-inclusive ETS does not seem likely in the foreseeable future. Hence, countries must use a portfolio of tools rather than relying solely on carbon markets to meet global climate targets.

Energy intensity and allowances lead to economic growth. This shows that the EU economic growth is driven by energy consumption. We also find that energy intensity plays a significant role in emissions directly and indirectly via the macroeconomic rebound effect. Hence, a faster green energy transition may be necessary to decouple economic activities from emissions. It is essential to recognize that the marginal impact of economic growth on societal well-being, especially in developed countries, may be insignificant. Hence, adopting societal well-being as an overall goal instead of economic growth may help set priorities straight.

The EU is trying to increase the functionality of ETS by implementing new policies and reforms, such as the Market Stability Reserve, to provide price stability. Moreover, as mentioned earlier, there are various regional ETS applications and carbon clubs worldwide. It can also be seen that economic development requires energy which will result in more emissions. As a policy, a single global ETS that covers all sectors would eliminate the macroeconomic rebound effect. With a similar approach such as Paris Agreement; World ETS, the single cap and trade system valid for all countries and regulated by an authority including representatives from all joined countries such as the UN, can determine the emissions limits and allowances. A global carbon market can work in theory but is impossible to achieve with the current state of international cooperation. It is also challenging to monitor emissions and assess the number of allowances required to meet global climate targets. Carbon taxes may seem more promising, but they are less popular and may be subject to resistance from society. Alternatives to carbon pricing must be considered. Furthermore, climate change is not the only challenge, and it has close links to SDGs. To align climate and sustainability strategies, we need a holistic perspective. The carbon border adjustment mechanisms (CBAM) might be a good starting point in the direction of a global view. It is a tool designed to deal with the leakage problem. Yet, it would need correct regulations to prevent bubbles. Those regulations would need to be well-designed to prevent political backlash, especially in the Global South, as Eicke et al. (2021) state.

The results shown here shed light on countries that consider implementing a market-based carbon pricing mechanism into their toolbox to reach their emission reduction targets. The Republic of Türkiye, for example, is among the countries that plan to introduce an ETS to reach their 2053 emission targets. The comparison that Barragan-Beaud et al. (2018) did with political feasibility analyses, as mentioned earlier, indicates the idea of choosing an ETS over a carbon tax. Our study suggests that the ETS that is going to be in action in Türkiye should at least be compatible with the EU ETS. Of course, the study conducted by Zhang et al. (2020b), should be considered when managing the market volatility that will most likely take place at the early stages of the ETS. Keeping in mind the Market Stability Reserve that is introduced by the EU, a price floor approach that is in line with the EU ETS can be useful when designing a new ETS, as suggested by Flachsland et al. (2020). As mentioned above, the results of this study indicate that there is a need for a holistic perspective to prevent the possible rebound effects of an ETS, instead of a fragmented approach. Slowly adding neighboring countries, the EU ETS can increase the region borders and, in the end, come up with an increased efficacy; the examples from China also suggest that an ETS covering larger regions as Tang et al. (2020) suggest might be more effective. Of course, ETS 2, the next step of the EU ETS can benefit from these results to prevent carbon leakage in new sectors, deal with the political backlash, and while allocating the allowances. In addition, these results can guide policymakers when introducing new approaches to clean technology development. The foundation of the Hydrogen Bank by the EU can be a good example of this; one of the main outcomes of the Russian – Ukrainian war that took place in 2022 has been the raised concerns about energy security in the EU. While Russia's actions to stop providing natural gas to the EU started an energy crisis within the continent, the region realized that hydrogen can be an alternative fuel that can secure the energy supply and is still compatible with the emission reduction ambitions. With these in mind, the EU decided to form a Hydrogen Bank, to support investments in clean hydrogen technologies and provide financing for these activities. In this regard, preventing carbon leakage while subsidizing new hydrogen technologies seems like it might be one of the main challenges of the Hydrogen Bank, and our results may provide guidance for the design of these policies as allowance allocation and carbon leakage can be critical issues of the bank. Combining the study of Mirza et al. (2023) that unveils the interlinkages between sustainability investments and major economic events such as market crashes and COVID–19, with our study that shows policy implications that aim to increase sustainable investments might result in macroeconomic carbon rebound effect, policymakers can design more efficient mechanisms for new applications such as the Hydrogen Bank and CBAM.

Our results highlight the need for follow-up studies, including a forecast analysis on Phase 4 of EU ETS to see whether the expectations comply with our results. In addition, similar analyses on other ETS applications, such as those in China, Australia, and New Zealand, and regional applications in the US can be conducted using our approach to see whether there is a macroeconomic rebound coming from the ETS itself. The addition of a possible macroeconomic rebound study on the upcoming European Union CBAM application would also provide a helpful framework.

Author statement

Kaan Bolat: literature review, data curation, analysis, writing, revision.

Ugur Soytas: supervision, theory, literature review, writing, editing, revision.

Saban Nazlioglu: supervision, analysis, unit root tests, editing, writing, revision.

Bulent Akinoglu: supervision, editing, revision.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.106879.

References

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev. Econ. Stud. 58, 277–297.

Arfaoui, N., Naeem, M.A., Boubaker, S., Mirza, N., Karim, S., 2023. Interdependence of clean energy and green markets with cryptocurrencies. Energy Econ. 120, 106584.

Bai, J., 2009. Panel data models with interactive fixed effects. Econometrica 77, 1229–1279.

Bai, J., Ng, S., 2002. Determining the number of factors in approximate factor models. Econometrica 70 (1), 191–221.

Bai, J., Ng, S., 2004. A PANIC attack on unit roots and cointegration. Econometrica 72 (4), 1127–1177.

Bai, J., Ng, S., 2010. Panel unit root tests with cross-section dependence: a further investigation. Econ. Theory 26 (4), 1088–1114.

Baltagi, B.H., 2013. Econometric Analysis of Panel Data, Fifth edition. John Wiley & Sons, UK, Chichester.

Baranzini, A., van den Bergh, J.C.G.M., Carattini, S., Howarth, R.B., Padilla, E., Roca, J., 2017. Carbon pricing in climate policy: seven reasons, complementary instruments, and political economy considerations. WIREs Clim Change 8, e462. https://doi.org/10.1002/wcc.462.

Barbot, C., Betancor, O., Socorro, M.P., Viecens, M.F., 2014. Trade-offs between environmental regulation and market competition: airlines, emission trading systems and entry deterrence. Transp. Policy 33, 65–72.

Barker, T., Dagoumas, A., Rubin, J., 2009. The macroeconomic rebound effect and the world economy. Energy Efficiency 2, 411–427.

Barkhordar, Z.A., 2019. Evaluating the economy-wide effects of energy efficient lighting in the household sector of Iran. Energy Policy 127, 125–133.

Barragan-Beaud, C., Pizarro-Alonso, A., Xylia, M., Syri, S., Silveira, S., 2018. Carbon tax or emissions trading? An analysis of economic and political feasibility of policy mechanisms for greenhouse gas emissions reduction in the Mexican power sector. Energy Policy 122, 287–299.

Belaid, F., Bakaloglou, S., Roubaud, D., 2018. Direct rebound effect of residential gas demand: empirical evidence from France. Energy Policy 115, 23–31.

Berritella, M., Cimino, F.A., 2017. An assessment of carousel value-added tax fraud in the European carbon market. Rev. Law Econ. 13 (2), 20140023.

Bieser, J.C.T., Hilty, L.M., 2018. Assessing indirect environmental effects of information and communication technology: a systematic literature review. MDPI Sustain. 10, 2662.

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. J. Econ. 87 (1), 115–143.

Borozan, D., 2019. Unveiling the heterogenous effect of energy taxes and income on residential energy consumption. Energy Policy 129, 13–22.

Breusch, T.S., Pagan, A.R., 1980. The Lagrange multiplier test and its applications to model specification in econometrics. Rev. Econ. Stud. 47 (1), 239–253.

Brookes, L., 1979. A low energy state for the UK. Atom 269, 3–8.

Calel, R., 2020. Adopt or innovate: understanding technological responses to cap-and-trade. Am. Econ. J. Econ. Pol. 12 (3), 170–201. https://doi.org/10.1257/pol.20180135.

Cao, J., Ho, M.S., Jorgenson, D.W., Nielsen, C.P., 2019. China's emissions trading system and an ETS-carbon tax hybrid. Energy Econ. 81, 741–753.

Carratu, M., Chiarini, B., Piselli, P., 2020. Effects of European emission unit allowance auctions on corporate profitability. Energy Policy 144, 111584.

Chen, G., Lin, B., Ye, B., 2018. Is China's manufacturing industry efficient? Evidence from an energy-rebound effect perspective. Emerg. Mark. Financ. Trade 54 (10), 2245–2257.

Chen, Z., Song, P., Wang, B., 2021. Carbon emissions trading scheme, energy efficiency and rebound effect – evidence from China's provincial data. Energy Policy 157, 112507. https://doi.org/10.1016/j.enpol.2021.112507.

Chitnis, M., Sorrell, S., Druckman, A., Firth, S.K., Jackson, T., 2013. Turning lights into flights: estimating direct and indirect rebound effects for UK households. Energy Policy 55, 234–250.

Ciarreta, A., Espinoza, M.P., Pizarro-Irizar, C., 2017. Optimal regulation of renewable energy: a comparison of feed-in tariffs and tradable green certificates in the Spanish electricity system. Energy Econ. 67, 387–399.

Colmer, J., Martin, R., Muûls, M., Wagner, U.J., 2020. Does pricing carbon mitigate climate change? Firm-level evidence from the European Union emissions trading scheme. Collaborative research center Transregio 224, discussion paper no. 232, project B 07.

Costantini, V., Martini, C., 2010. The causality between energy consumption and economic growth: a multi-sectoral analysis using non-stationary cointegrated panel data. Energy Econ. 32 (3), 591–603.

Cretí, A., Joëts, M., 2017. Multiple bubbles in the European Union emission trading scheme. Energy Policy 107, 119–130. https://doi.org/10.1016/j.enpol.2017.04.018.

Eicke, L., Weko, S., Apergi, M., Marian, A., 2021. Pulling up the carbon ladder? Decarbonization, dependence and third country risks from the European carbon border adjustment mechanism. Energy Res. Soc. Sci. 80, 102240.

Farid, S., Karim, S., Naeem, M.A., Nepal, R., Jamasb, T., 2023. Co-movement between dirty and clean energy: a time-frequency perspective. Energy Econ. 119, 106565.

Flachsland, C., Pahle, M., Burtraw, D., Edenhofer, O., Elkerbout, M., Fischer, C., Tietjen, O., Zetterberg, Z., 2020. How to avoid history repeating itself: the case for an EU emissions trading system (EU ETS) price floor revisited. Clim. Pol. 20 (1), 133–142. https://doi.org/10.1080/14693062.2019.1682494.

Font Vivanco, D., Kemp, R., Van der Voet, E., 2016. How to deal with the rebound effect? A policy-oriented approach. Energy Policy 94, 114–125.

Freire-Gonzalez, J., 2017. A new way to estimate the direct and indirect rebound effect and other rebound indicators. Energy 128, 394–402.

Fukui, H., Miyoshi, C., 2017. The impact of aviation fuel tax on fuel consumption and carbon emissions: the case of US airline industry. Transp. Res. D 50, 234–253.

Ghosh, N.K., Blackhurst, M.F., 2014. Energy savings and the rebound effect with multiple energy services and efficiency correlation. Ecol. Econ. 105, 55–66.

Granger, C.W., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econ. J. Econom. Soc. 424–438.

Greening, L.A., Greene, D.L., Difiglio, C., 2000. Energy efficiency and consumption – the rebound effect – a survey. Energy Policy 28, 389–401.

Grubb, M.J., 1990. Energy efficiency and economic fallacies. Energy Policy 18 (8), 783–785.

Herring, Horace, Roy, Robin, 2007. Technological innovation, energy efficient design and the rebound effect. Technovation. 27, 194–203. https://doi.org/10.1016/j.technovation".2006.11.004.

Jarque, C.M., Bera, A.K., 1987. A test for normality of observations and regression residuals. Int. Stat. Rev./Rev. Int. Stat. 163–172.

Kayani, U.N., Aysan, A.F., Iqbal, U., Arif, M., Rehman, I.U., 2022. Foreign direct investment settlement, novel energy methods and CO_2 emissions: evidence from United Arab Emirates. Int. J. Energy Econ. Policy 12 (6), 364–369.

Kayani, U.N., Sadiq, M., Aysan, A.F., Haider, S.A., Nasim, I., 2023. The impact of investment, economic growth, renewable energy, urbanisation, and tourism on carbon emissions: global evidence. Int. J. Energy Econ. Policy 13 (1), 403–412.

Khazzoom, J.D., 1980. Economic implications of mandated efficiency in standards for household appliances. Energy J. 1 (4), 21–40.

Kim, P., Bae, H., 2022. Do firms respond differently to the carbon pricing by industrial sector? How and why? A comparison between manufacturing and electricity generation sectors using firm-level panel data in Korea. Energy Policy 162, 112773. https://doi.org/10.1016/j.enpol.2021.112773.

Klemetsen, M.E., Rosendahl, K.E., Jakobsen, A.L., 2020. The impacts of the EU ETS on Norwegian plants' environmental and economic performance. Climate Change Econ. 11 (1), 2050006. https://doi.org/10.1142/S2010007820500062.

Koch, N., Mama, H.B., 2019. Does the EU Emissions Trading System induce investment leakage? Evidence from German multinational firms. Energy Econ. 81, 479–492.

Li, K., Jiang, Z., 2016. The impacts of removing energy subsidies on economy-wide rebound effects in China: An input-output analysis. Energy Pol. 98, 62–72.

Löschel, A., Lutz, B.J., Managi, S., 2019. The impacts of the EU ETS on efficiency and economic performance – an empirical analyses for German manufacturing firms. Resour. Energy Econ. 56, 71–95. https://doi.org/10.1016/j.reseneeco.2018.03.001.

Lu, Y., Liu, Y., Zhou, M., 2017. Rebound effect for improved energy efficiency for different energy types: A general equilibrium analysis for China. Energy Econ. 62, 248–256.

Marin, G., Marino, M., Pellegrin, C., 2018. The impact of the European emission trading scheme on multiple measures of economic performance. Environ. Resour. Econ. 71, 551–582. https://doi.org/10.1007/s10640-017-0173-0.

Meyer, M., Hirschnitz-Garbers, M., Distelkamp, M., 2018. Contemporary resource policy and decoupling trends – lessons learnt from integrated model-based assessments. MDPI Sustain. 10, 1858.

Mirza, N., Naeem, A.B., Nguyen, T.T.H., Arfaoui, N., Oliyide, J.A., 2023. Are sustainable investments interdependent? The international evidence. Econ. Model. 119, 106–120.

Naeem, M.A., Karim, S., Uddin, G.S., Junttila, J., 2022. Small fish in big ponds: connections of green finance assets to commodity and sectoral stock markets. Int. Rev. Financ. Anal. 83, 102283.

Nazlioglu, S., 2021. TSPDLIB: GAUSS time series and panel data methods (version 2.0). Source code. https://github.com/aptech/tspdlib.

Newey, W.K., West, K.D., 1987. A simple, positive-definite, Heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Nickell, S., 1981. Biases in dynamic models with fixed effects. Econom. J. Econom. Soc. 1417–1426.

Pahle, M., Tietjen, O., Osorio, S., Egli, F., Steffen, B., Schmidt, T.S., Edenhofer, O., 2022. Safeguarding the energy transition against political backlash to carbon markets. Nat. Energy 7, 290–296.

Pakusch, C., Stevens, G., Boden, A., Bossauer, P., 2018. Unintended effects of autonomous driving: A study on mobility preferences in the future. MDPI Sustain. 10, 2404.

Peng, J.T., Wang, Y., Zhang, X., He, Y., Taketani, M., Shi, R., Zhu, X.D., 2019. Economic and welfare influences of an energy excise tax in Jiangsu province of China: a computable general equilibrium approach. J. Clean. Prod. 211, 1403–1411.

Pesaran, H., 2006. Estimation and inference in large heterogeneous panels with a multi-factor error structure. Econometrica 74, 967–1012.

Pesaran, M.H., 2021. (2021) General diagnostic tests for cross section dependence in panels. Empir. Econ. 60, 13–50.

Peters, A., Sonnberger, M., Dütschke, E., Deuschle, J., 2012. "Theoretical perspective on rebound effects from a social science point of view – working paper to prepare empirical psychological and sociological studies in the REBOUND project". Econstor, no. S2/2012.

Pfaff, M., Sartorius, C., 2015. Economy-wide rebound effects for non-energetic raw materials. Ecol. Econ. 118, 132–139.

Reese, S., Westerlund, J., 2016. Panicca: Panic on cross-section averages. J. Appl. Econ. 31 (6), 961–981.
Schusser, S., Jaraite, J., 2018. Explaining the interplay of three markets: green certificates, carbon emissions and electricity. Energy Econ. 71, 1–13.
Somuncu, T., Hannum, C., 2019. The rebound effect of energy efficiency policy in the presence of energy theft. Energies 11, 3379.
Su, Y.W., 2019. Residential electricity demand in Taiwan: consumption behavior and rebound effect. Energy Policy 124, 36–45.
Tang, K., Liu, Y., Zhou, D., Qiu, Y., 2020. Urban carbon emission intensity under emission trading system in a developing economy: evidence from 273 Chinese cities. Springer Environ. Sci. Pollut. Res. https://doi.org/10.1007/s11356-020-10785-1.
Windmeijer, F., 2005. A finite sample correction for the variance of linear efficient two-step GMM estimators. J. Econ. 126 (1), 25–51.
Wu, L., Chen, Y., Feylizadeh, M.R., Liu, W., 2018. Estimation of China's macro-carbon rebound effect: Method of integrating Data Envelopment Analysis production model and sequential Malmquist-Luenberger index. J. Clean. Prod. 198, 1431–1442.
Yang, X., Jiang, P., Pan, Y., 2020. Does China's carbon emission trading policy have an employment double dividend and a porter effect? Energy Policy 142, 111492. https://doi.org/10.1016/j.enpol.2020.111492.
Zhang, J., Lawell, L., 2017. The macroeconomic rebound effect in China. Energy Econ. 67, 202–212.
Zhang, H., Zhang, R., Li, G., Li, W., Choi, Y., 2019. Sustainable feasibility of carbon trading policy on heterogenetic economic and industrial development. MDPI Sustain. 11, 6869.
Zhang, W., Li, J., Li, G., Guo, S., 2020a. Emission reduction effect and carbon market efficiency of carbon emissions trading policy in China. Energy 196, 117117.
Zhang, S., Jiang, K., Wang, L., Bongers, G., Hu, G., Li, J., 2020b. Do the performance and efficiency of China's carbon emission trading market change over time? Environ. Sci. Pollut. Res. 27, 33140–33160.
Zhou, M., Liu, Y., Feng, S., Liu, Y., Lu, Y., 2018. Decomposition of rebound effect: an energy-specific, general equilibrium analysis in the context of China. Appl. Energy 221, 280–298.