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Revisiting R&D intensity and CO2 emissions link in the USA using time varying granger causality test: 1870~2020

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ABSTRACT

R&D intensity, per capita GDP, and per capita CO2 emissions links in the USA over the period of 1870–2020 reflects the evolution of the economic development and technology for the environment benefit. Using Time varying Granger causality, the empirical results indicate both causal links between R&D intensity and per capita CO2 emissions and between per capita GDP and per capita CO2 emissions are time varying. In addition, R&D intensity significantly affects per capita CO2 emissions since 1975, and the per capita GDP significantly influences per capita CO2 emissions since 1978. That is, these findings not only in supportive of the EKC theory, but further disentangle the subtly linkages for the R&D intensity and CO2 emissions and the per capita GDP and CO2 emissions. Finally, the policy implication is that launch the new technical innovation and increase in R&D investment to maintain its sustainable economic growth are the best government strategy to reduce CO2 emissions in the USA.

1. Introduction

This study extends Chang et al. [1] to reinvestigate causal links between CO2 emissions and R&D intensity on one hand and GDP on the other for the USA over a long time period of 1870–2020 using the test proposed by Shi et al. [2] of Time varying Granger causality. The critical issues challenging countries around the world today are environmental pollution and climate change. Carbon dioxide emission (CO2e), which is mainly caused by economic activities (consumption and production) [3], seems to be the primary reason that causes the global environmental problem. Among the countries in the world, the United States is one of the developed countries with vast economic activities that also need to deal with CO2 emissions. As shown in Fig. 1, among the seven most advanced economies, the United States possesses the leading share of total CO2e (59.45%) in 2019. According to Speight & Singh [4], the primary causes of CO2 emissions in the USA are (1) residential and commercial units, mainly the use of non-renewable energy sources for

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heating, waste disposal, current activities; (2) production activities based on specific technologies; (3) transportation, mainly the burning of fossil fuels; (4) power plants with non-renewable sources and improper technologies. Thus, how to reduce carbon dioxide emissions in these four fields has come to be one of the most important tasks today in the USA.

Experts and scholars related to environmental science suggest innovation on environment-related technologies as an effective way of CO2 emissions reduction [5]. As a result, governments and companies around the world invested heavily in the R&D of environment-related technologies to create new clean technologies or improve existing ones. As shown in Fig. 2, the USA (56.80%) is the country that spends the most on R&D compared to other G7 countries. It still needs to be confirmed whether a large amount of capital investment has achieved the desired results. Higher capital investment could bring a significant improvement in the efficiency of operation for firms. On the contrary, technological innovation could induces the pollution be generated in the environment. State in another way, to the extent of the share of the eco-friendly capital investment whether sufficiently to address the pollution bring by the traditional operation of the firms plays further dominant role. In addition, the inverted-U shape from the EKC theory whether could be supported by historical long-term data also is important issue which does not be explored in the USA and existing papers also facing up the structure changing in the behavior of the time-series data. To fill the exiting gap, this study focuses on the USA and tries to explore the relationship between CO2e and R&D.

Previous studies frequently explore the factors that influence environmental quality based on the Environmental Kuznets Curve (EKC) hypothesis [6,7]. This hypothesis suggests an inverted U-shaped relationship appears as follows [8]: a country with a low economic development has a moderate degree of environmental pollution, the growth of per capita income generates a high environmental pollution and the environmental degradation increases in accordance with the economic growth; a certain level of economic growth allows further increase of per capita income with a steadily decreases of pollution and the quality of environment gradually improves. However, after the EKC theoretical hypothesis was proposed, empirical studies have continued and the findings are diversified, with some supporting the inverted U-shape and others showing a U-shape, N-shape, monotonically rising and monotonically falling between the two (refer to a review in Shahbaz & Sinha [9]).

Based on the EKC hypothesis, scholars have proposed the technology effect, which suggests that innovation and upgrades in technology will produce a beneficial impact on environmental quality (e.g., Dinda [10], Iwata, Okada, & Samreth [11], Sulaiman et al. [12], Al-Mulali & Ozturk [13], Apostu et al. [14], Mao et al. [15]). They believe that high-income levels are closely associated with better environmental technologies and efficient technologies. If the R&D expenditures rise and drive technological progress exert two effects: first, when other things stay the same, technological progress will improve the efficiency of resource use, reduce the inputs-output rate, and diminish the environment harm; second, the dirty technologies are replaced by clean one, circular economy concept allow waste recycle and contribute to CO2e per unit of output.

Even though technological progress is thought to improve environmental quality in most previous investigations, there are also results, like Bölük and Mert [16], and Farhani and Shahbaz [17], contrary to the studies that support the adverse impact of renewable technology on environmental quality. Specifically, Bölük and Mert [16] found a significant lowers (around ½) of GHG emissions by using renewable instead of fossil energy, but 0 positive effect on CO2e. In addition, Farhani and Shahbaz [17] denoted a significant positive impact on CO2e of long-run or short-run of renewable and non-renewable energy consumption. Thus, they appreciate that non-renewable energy has a higher impact on CO2e mitigation than renewable energy and suggest that R&D investment in renewable energy to be considered in correlation with CO2e control.

In addition, as the statement of EKC hypothesis, there has uncertainty on the influence of technological innovation on carbon emissions. R&D has been confirmed a positive impact on economic growth and trade flows [18–22]. The rise in the rate of economic growth and trade openness may lead to a larger-scale effect, which can have a negative impact on environmental quality; while new technologies developed can increase efficiency, they may still need extra natural resource inputs to increase output, potentially increasing CO2e in the process; over time, the diminishing returns from R&D make it more likely that CO2e will increase [23]. Newell [24] also pointed out, that since the knowledge growth, the R&D and innovation harder produce breakthroughs over time and the challenge become more complex. Simultaneously, economic growth continues requiring more natural resource inputs. Therefore, research and development (R&D) investments do not reduce CO2e and improve environmental quality eventually.

Although the environmental impact of technology effects can be derived based on the EKC hypothesis, rarely researchers explore the relationship between R&D and CO2e by empirical tests. Currently, a part of the literature uses integrated assessment models (IAMs)

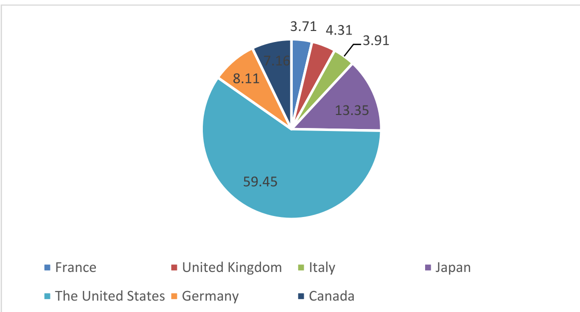

Fig. 1. Share of CO2 emissions among G-7 countries in 2019.

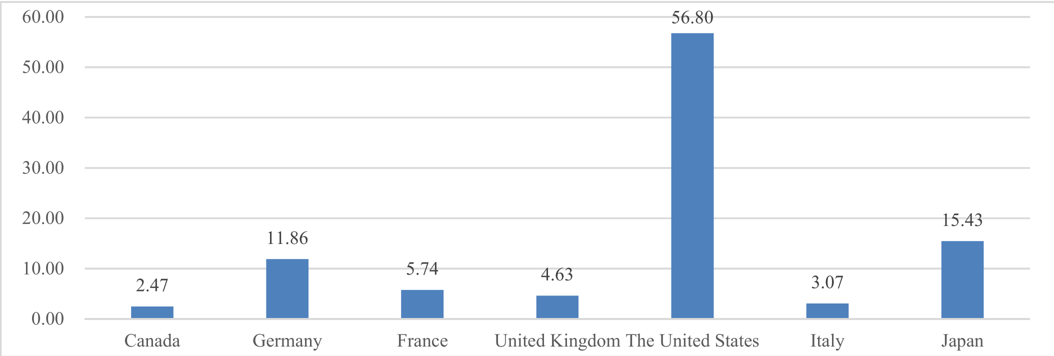

Fig. 2. Share of R&D expenditures among G-7 countries in 2019.

(e.g. Grimaud, Lafforgue, & Magne [25], Marangoni & Tavoni [26], Gu & Wang [27], Noja et al. [28]) to examine the impact of R&D on CO2e. The results of these studies suggest that R&D investments reduce CO2e, but the reduction of CO2e depends on the refinement of the performance of existing technologies. Although IAMs are widely used in policy formulation, there are some shortcomings [29]. For example, IAMs models are extremely sensitive to model assumptions and model performing processes [29,30].

The effect of the R&D is the knowledge transfer in the business environment and the implementation of a sustainable economic growth. The synergy between the knowledge transfer and the innovative jobs in the renewable energy sector was studied by Grigorescu et al. [31] and the result was that the European counties are having different synergy profile.

The study is structured as follows: a description previous literature; research methodology - Time-Varying Granger causality test; data sets used in our study; first presents our empirical findings and then discusses the policy implications; the final concludes.

2. Literature review

There is some literature that addresses the link between national R&D investments and CO2e, but few articles use data from the USA, Fernández Fernández, Fernández López, & Olmedillas Blanco [32] focus on the EU (15), the USA and China for the period 1990 to 2013. The results of their model support the hypothesis that for developed countries such as the USA, R&D expenditures contribute positively to the reduction of CO2e. Shao et al. [33] applied traditional regression models to examine the association between environmental and renewable energy R&D and CO2e and found that this investment can help support carbon neutrality goals and reduce carbon emissions. Jiang et al. [34] investigated the relationship between environment-related R&D investment and CO2e using data for G7 countries from 1990 to 2020, after including imports and exports as well as GDP as control variables. A negative relationship between the two variables in both the long and short term was found. However, because of the limitation of methods that previous studies used, we cannot observe the variation relationship between R&D and CO2 emissions during time.

Notably, Churchill et al. [23] applied a nonparametric panel data model to examine the impact of R&D intensity on CO2e for the G7 countries, including the USA, since the nineteenth century. They denoted that the relationship between R&D and CO2e was time-varying, being positive during 35 years in the second half of the 20th century (1955–1990) and negative at other times. However, because of the panel data they used, we cannot gain an exhaustive look at the variation relationship between R&D and CO2 emissions in the USA.

In short, after a rigorous review of the relevant literature, we infer that the conclusions about the impact of R&D on CO2e are inconclusive. Noticeably, the relationship between R&D and CO2e may be time-varying. Therefore, it is necessary to introduce the advanced empirical method to test this relation. Furthermore, we provide another two contributions to the literature. First, much of the current literature uses short-term data when examining the relationship between R&D and CO2e, but according to Grimaud, Lafforgue, & Magne [25] (p. 938) in presenting their study of climate change mitigation options using IAM modeling, “Addressing climate policy requires a long-term perspective where technological change plays a dominant role.” That is, the relationship between technological progress and CO2e should be examined as a long-term phenomenon. Therefore, the first contribution of this paper is to collect data from the USA for nearly 150 years from 1870 to 2020 to investigate the long-term impact of R&D on CO2e.

Second, existing studies mostly apply traditional econometric methods and do not use the recently developed time-varying Granger causality test. Previous studies have often failed to detect time-varying causality, implicitly assuming that the causal relationship between R&D and CO2e is not time-varying. Given the previous analysis, it may not be time-invariant [23], and the results of the Granger causality test may also vary over time. Therefore, we address this issue employing the method of Shi et al. [2], which is a recursive evolutionary algorithm to capture the time variation of Granger causality between variables. In addition, this approach uses robust econometric methods for integration and cointegration properties. In other words, we do not need to detrend or differential the data. Hence this analysis can locate the time path of the causal relationship between R&D and CO2e. Chang et al. [1] applies similar techniques for the USA over 1870 to 2016 and found that R&D intensity significantly affects per capita CO2e during the 1980 to 2016. On the other hand, that they also find per capita GDP significant affect per capita CO2e during the 1940–1945. Their empirical results indicate that launching the new technical innovation and increase in R&D investment are the best government strategies to reduce CO2 emissions in the USA.

Third, preceding streams of researchers found that innovation not only reduces reliance on fossil fuels but also reduces CO2e. For example, Wang et al. [35] verified that the domestic patents for carbon-free energy technologies reduce CO2 emission in China. Meanwhile, some studies conducted for China (Caglar, [36]; Wang and Zhu, [37]; Yu and Du [38]), displayed that the innovation has a negative effect on CO2. Emission. For other research on markets such as Du and Li [39] for selected 71 countries; Fethi and Rahuma [40] for petroleum companies; Mensah et al. [41] for OECD states; Többelmann and Wendler [42] for EU-27 economies; and Lee and Min [43] for Japan —validated that green innovation and R&D activities play an important role in CO2 mitigating. Comprehensively, these studies consistently show that more technological innovations effectively could reduce CO2 emission around the world. Nevertheless, this study re-examines the connection between the GDP per capita, R&D intensity and CO2 emission by applying the time-varying granger causality tests. Where, one of the novelties is that the Granger Causality test with the time-varying properties is exploited in this study. In addition, the other contribution is that the USA occupies the first place 0f CO2 emission and the of the R&D intensity among the G7 countries. Karsten and van der Bank [44] assert that positive relationship can be confirmed between the carbon tax, CO2 emissions, greenhouse gas, industrial, urbanization and the renewable energy in South Africa. In addition, Jermsittiparsert [44] examines the connection between the energy cost and GDP and find that negative relationship between carbon emissions and GDP growth is obtained and positive association between the share of renewable energy in total energy and the GDP growth is observed in Indonesia, Thailand, and Malaysia. More CO2 emissions could induce the GDP growth decline and stimulate the renewable energy increase. However, the key factor influencing the renewable energy increase depends on the R&D of the firm. Intuitively, the production of the renewable energy is primarily dependent on the technologic of the production of the firm. Aiming to increase renewable energy, higher input of the R&D plays an important role. Therefore, this study explores not only the link between CO2 emission and per capita GDP, but also the R&D intensity and the CO2 emissions. Thus, further long-term data that covers the different backgrounds of the USA economic development is tested in this study by considering the time-varying characteristics, which is another novelty in existing papers.

Comprehensively saying, three aspects of the literature reviews are mentioned in the following. First, reviewing the literature related the CO2 emissions and GDP and the R&D and CO2 emissions in the G7, this study focuses on the USA by comprehensively investigating further long period, which is one contribution in the paper. Second, we focus on the econometric approach of existing papers. Existing papers explore the granger causality between the R&D and CO2 emission or per capita GDP and CO2 emissions mainly applying the fixed window method. However, the structure changing issue has not been addressed. Following Shi et al. we could deal with the structure breaking problem, second contribution of this study. Third, we also incorporate the related study that discusses the issue from a global viewpoint and further include the greenhouse gas and CO2 emissions papers. Where these papers also consider renewable energy plays an important role that reduce CO2 emissions. To produce renewable energy, however, R&D is a key factor. Therefore, this study explores the causal effect between the GDP and CO2 emission by endogenous growth theory. That is, higher R&D intensity could induce higher economic growth, and lower CO2 emissions.

To sum up, this paper investigates the relationship by applying advanced econometric methods, and it includes the impact of economic growth on CO2e by using GDP as a control variable. Based on yearly data for R&D and CO2e during the period 1870–2020 in the USA and using the time-varying causality test, we get two significant outcomes. One is the larger opportunity window of identifying the causal relations and fully confirms the causality relation between R&D and CO2e and their change over time. The results of the empirical study reinforce that CO2e are significantly impacted by the R&D intensity from 1975 until the present. At the same time the economic growth (per capita GDP) also affects CO2e from 1980 till the present when we explore the causal relationship.

3. Research methodology

Aim to explore the causality under Time-Varying characteristics among R&D intensity, per capita CO2e, and per capita GDP, this study exploits the recently novel causality test proposed by Shi et al. [2] with its three time-varying causality algorithms. They are forward-recursive, rolling and recursive evolving causality, respectively. According to Shi et al. (2020) that this study applies lag-augmented VAR (LA-VAR) to form the Time-Varying Granger Causality Test. Because of the time-varying characteristics of the economic development in USA, the causal effects of the variables of interest could face up the structure breaking. Thus, using the granger causality tests consider the dynamic properties of the time series cannot be lacked. According to Shi et al. [2], a novel approach, recursive evolving rolling window, considers the potential dynamical behavior of the time-series data, especially exploring the causal effects. The model of Shi et al. [2] dominants others causal model in terms of overcoming the structure changing issue. Even though the granger causality standing from general testing approach from the parametric perspective, the model used in this study uses the bootstrapping method to carry out the granger causality test, indicating that the subtle information content of the data sufficiently be unveiled. The model and test statistics are briefly discussed in the following.

First, the LA_VAR is shown on equation (1). The dependent variable y_t is a vector with n-dimension.

$$y_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^{k} \beta_i y_{t-i} + \sum_{Gj=k+1}^{k+G} \beta_j y_{t-j} + \varepsilon_t, \tag{1}$$

where $\beta_{k+1} = \cdot\cdot\cdot = \beta_{k+d} = 0$ and G is the largest numbers of the order in stationary vector y_t, containing *R&D intensity*, *per captia CO2 and per capita GDP*. Next, the baseline regression model is shown on the following equation (2):

$$y_t = \Gamma \tau_t + \Phi x_t + \Psi z_t + \varepsilon_t. \tag{2}$$

The $\Gamma = (\alpha_0, \alpha_1)_{n\times(q+1)}$, $\tau_t = (1, t)'_{2\times1}$, $\Phi = (\beta_1, \ldots, \beta_k)_{n\times nk}$, and $\Psi = (\beta_{k+1}, \ldots, \beta_{k+G})_{n\times nk}$, $x_t = (y'_{t-1}, \ldots, y'_{t-k})'_{nk\times1}, z_t = (y'_{t-k-1}, \ldots, y'_{t-k-I})'_{nG\times1}$. Regarding the null hypothesis which is demonstrated on equation (3).

$$H_0 = R\varphi = 0 \tag{3}$$

To examine whether Granger non-causality can be rejected, the corresponding null hypothesis is set by the following restrictions on the matrix $\varphi = vec(\Phi)$ exploiting on row vectorization, and matrix R is a $m \times n^2$ k. The matrix of coefficients Ψ of the final G lagged vectors is neglected as its components are taken to equal to zero. Moreover, equation (1) can be rewritten as equation (4):

$$Y = \tau\Gamma' + X\Phi' + z\Psi' + \varepsilon_t, \tag{4}$$

where $= (y_1, y_2 \ldots, y_T)'_{T\times n}$, $\tau = (\tau_1, \ldots, \tau_T)'_{T\times2}$, $X = (x_1, \ldots, x_T)'_{T\times nk}$, $Z = (z_1, \ldots, z_T)'_{T\times nG}$, and $\varepsilon = (\varepsilon_1, \cdot\cdot\cdot, \varepsilon_T)'_{T\times n}$. Let $Q_\tau = I_T - \tau(\tau'\tau)^{-1}\tau'$ and $Q = Q_\tau - Q_\tau Z(Z'^{Q_\tau}Z)^{-1}Z'Q_\tau$. Thereby the function of the parameter of least square approach is presented in equation (5):

$$\widehat{\Phi} = Y'QX(X'QX)^{-1} \tag{5}$$

To test the null hypothesis $H_{0,}$ the Wald statistic W is proposed in equation (6):

$$W = (R\widehat{\varphi})'\left[R\left\{\widehat{\Sigma}_\varepsilon \otimes (X'QX)^{-1}\right\}R'\right]^{-1}R\widehat{\varphi} \tag{6}$$

where $\widehat{\varphi} = \mathrm{vec}(\widehat{\Phi})$, $\widehat{\Sigma}_\varepsilon = \frac{1}{T}\widehat{\varepsilon}'\widehat{\varepsilon}$, and $\otimes$ is the Kronecker product. According to Toda and Yamamoto [45] and Dolado and Lütkepohl [46], the asymptotic null distribution of the Wald statistics is distributed as the χ^2_m and the number of restrictions is m.

Considering the Granger causality tests, the Wald statistics of recursive perspective are gauged from the subsamples of examined data. Assuming that the f_{r1} and f_{r2} are the (splitting) initialing and terminating points of the estimating observations, respectively, and $f_{rw} = f_{r2} - f_{r1}$. The Wald statistic (based on the lag-augmented VAR) measured from this subsample that notation is set to $\mathrm{W}_{f_{r1}}^{f_{r2}}$. Let $\tau_{r1} = [f_{r1}T]$, $\tau_{r2} = [f_{r2}T]$, $\tau_w = [f_{rw}T]$, where T is the magnitude of sample, and $\tau_{r0} = [f_{r0}T]$ is the at least number of sample required to estimate the VAR. Regarding the forward expanding window algorithm, the starting point τ_{r1} is fixed at the first observation (i.e. $\tau_{r1} = 1$) and the regression window expands from τ_{r0} to T. This process is equivalent to having τ_{r2} move from τ_{r1} to T.

The rolling window size of the rolling regression is fixed. In addition, the window size is supposed to be same here. The initial point τ_{r1} changes from the initial sample to $T - \tau_{r0} + 1$ and the terminal sample $\tau_{r2} = \tau_{r1} + \tau_{r0} - 1$. As a substitute, the τ_{r1} and τ_{r2} of the algorithm can be rewritten as $\tau_{r2} = \{\tau_{r0}, \ldots, T\}$ and $\tau_{r1} = \tau_{r2} - \tau_{r0} + 1$, respectively. The terminal sample of the estimation runs from τ_{r0} to the last observation of the sample T and the initial point follows, maintaining a fixed window size τ_{r0}. For the recursive evolving window algorithm, similar with the rolling one, the terminal sample of the regression $= \{\tau_{r0}, \ldots, T\}$. Nevertheless, the initial sample of the regression τ_{r1}, instead of maintaining a given distance with τ_{r2} as in the rolling algorithm, changing from 1 to $\tau_{r2} - \tau_{r0} + 1$. For each sample of interest f_r, one possesses a sequence of Wald statistics $\{W_{f_{r1}f_{r2}}\}_{fr2=fr}^{f_{r1}\in[0, f_{r2}-f_{r0}]}$. The test statistic is defined to be the supremum of the Wald statistic sequence, as in equation (7):

$$SW_{f_r}(f_{r0}) = \sup_{f_{r2}=f_r, f_{r1}\in[0, f_{r2}-f_{r0}]}\left\{W_{f_{r1}f_{r2}}\right\} \tag{7}$$

Inference on Granger non-causality for observation $[f_rT]$ is relied on the sup Wald statistic $SW_{f_r}(f_{r0})$. Attempt to practical estimating, the optimal lag order of the VAR model is chosen based on the information criteria and the restrictive model is calculated. After that the test statistics is measured. According to simulations from the Shi et al. [2], they found the recursive evolving window algorithm is superior to the other two procedures. The reader of interest, please refer to Shi et al. [2]. Finally, to validate the dominance of the model, some important comparative analysis is as follows: Existing causal effect model considers the dependence of the variables from the static perspective. Time-varying characteristics of the time-series data have not been incorporated. In other words, potential structure changing phenomena of the behaviours of data cannot be subtly captured, implying that spurious results can be obtained. Additionally, introducing the Fourier function in the model to capture the possible trend and changing effect of the data, the estimating cost is high in terms of the non-linear estimation. For the model, proposed by Shi et al. [2] two important superiorities are as follows: First, the model not only all potential information content of the data is captured, but also the structure changing concerns is mitigated by using the recursive evolving the rolling window method. Second, relative to general non-linear model, this model provides the easily estimating nature, resulting in the cost of estimation reductions.

4. Data

The per capita CO2e (PCO2), per capita GDP (PGDP) and R&D intensity (R&D) in the USA from 1870 to 2020 are used and the corresponding descriptive statistics of them are exhibited in each column of Table 1, respectively. Loosely speaking, the dispersion of the PGDP seems higher than that of the PCO2, and R&D over full examined period.[1] The distribution of these three variables is not the

[1] All three data are available upon request. R&D intensity and per capita GDP are from the Carbon Dioxide Information and Analysis Center (CDIAC) database [51] and Madsen and Ang [52], respectively. We extend both data series to 2020. Per capita CO2 emissions are from the following data collection Ritchie, H., Roser, M., Rosado, P [53]. website: https://ourworldindata.org/co2/country/USA.

Table 1
Descriptive statistics.

	PCO2	PGDP	R&D
Mean	14.174	15,219.26	1.524
Median	15.516	9196.54	1.340
Maximum	22.236	65,279.53	3.260
Minimum	2.421	2444.62	0.171
Std. Dev.	5.670	15,603.58	1.071
Skewness	−0.596	1.681	0.104
Kurtosis	2.277	4.933	1.289
Jarque-Bera	12.229***	94.601***	18.685***
Probability	0.002	0.0000	0.0000

Notes: ***, ** and * indicate significance at the 1, 5 and 10% levels, separately.

normal distribution based on the Jarque-Bera statistics. Notably, the maximum of the PGDP is $65,279.53 higher than the mean PGDP of $15,219.26, which seemly shows that the economic gradually progress from 1870 to 2020. However, to inspect whether similar trends of the PCO2 and R&D can be found, we plot these three variables on Fig. 1.

As Fig. 3, stable trend for both R&D intensity and PGDP can be observed before 1940. Afterward, a gradually rising pattern exists for PGDP till the 2000, then sharply jumps to higher economic growth levels. On one hand, the trend of the R&D intensity exhibits the stable status relative the PGDP, where the increasing pattern can be obviously observed during the 1950–1965 and the levels of the R&D intensity persist around the mean, 1.524, to 2020. Notably, the movement of PCO2 is with the more volatile movements than other two series. Specifically, the PCO2 uncovers the increasing from 1870 to 1910, fluctuates around the 15.502 units till 1929, and then plunged below 10 units in 1932. After 1932, the PCO2 continues to increase until 2008 then drops till recent time period. Considering that the increasing trend of the PCO2 caused by the higher pollution growth such as the fossil sectors, however, the sharply downward pattern in 1930 seemly due to the recession of the USA economic during 1930. Thereafter, from 1940 to 1970, the PCO2 gradually increases then maintain the 15 units till 2008 and then declines, which could not only be caused by several crises such as the global financial crisis and European debt crisis. New clean energy production, developed by great deal of the R&D, seemly is an important role.

To precisely evaluate the Granger causality between the R&D intensity and the PGDP with PCO2 emissions are used in this study three statistical approaches proposed by Shi et al. [2], including the forward, rolling window, and recursive algorithms.

5. Empirical study results and policy implication

The findings of the time-varying Granger causality tests is shown and discussed in the following. Intending to avoid the problem of spurious regression, this study exploits three general unit root tests, including the ADF, PP, and KPSS tests, to examine the behavior of PGDP, PCO2, and R&D, and the results are shown on Table 2. The PCO2, PGDP, and R&D are non-stationary before the first-order difference, shown on first three columns of Table 2. After first order differencing for each time-series, however, only the PGDP is stationary and the stationary evidence of other two series, PCO2 and R&D, cannot be obtained. For the PCO2 and R&D, three test statistics present the significant results at 1%, indicating that the structure breaks phenomena is observed. Following Shi et al. [2], therefore, the lag-augmented VAR (LA-VAR) is applied to explore possible existence of causality from the dynamic perspective in this study.

5.1. Time-varying granger causality tests

This subsection shows the results of Wald test statistics based on the recursive approach for the R&D and PCO2 and for the PGDP and PCO2 emissions and the corresponding values from 1870 to 2020 are displayed on Figs. 4 and 5, respectively. Next, the estimated coefficients of the R&D and PGDP from the rolling window regression are drawn on Fig. 6. The Wald statistics and the critical values of PGDP (R&D) granger causes the PCO2 emissions for three different algorithms are revealed on Table 3. All related results are discussed in the following.

Fig. 4 documents the evidence of the causality test from R&D to PCO2 emissions Wald tests statistics based on the recursive algorithm. The higher and lower dash line represents the bootstrapped critical values of 95% and 90% significance levels, separately. The higher and lower dash line represents the bootstrapped critical values of 95% and 90% significance levels, separately. The Wald statistic surrounds about 5 before the 1975, and outpaces the 90% significant level from 1975 to the end of 1990s, and then obviously exhibits the upward increasing pattern persists to the 2020, which over the 95% significant level. Overall, insignificant Granger causality evidence can be found before 1975 and significant R&D caused the PCO2 emissions can be obtained after the 1975, while the statistical significance gradually is stronger after the end of 1990s. Specifically, the Wald statistics explicitly over than the 11.768 (See Table 3), represents the 95% significant level, after the 1998, suggesting that PCO2 emissions is Granger caused by the R&D intensity exists after the 1975, while the influencing extent is further apparent after 1998. Our results are not consistent with those found in Chang et al. [1], they found PCO2 Granger caused by the R&D intensity exists after the 1978, while the influencing extent is further apparent after 2001.

Next, the findings of PGDP Granger causes the PCO2 emissions Wald test statistics based on the recursive framework are sketched

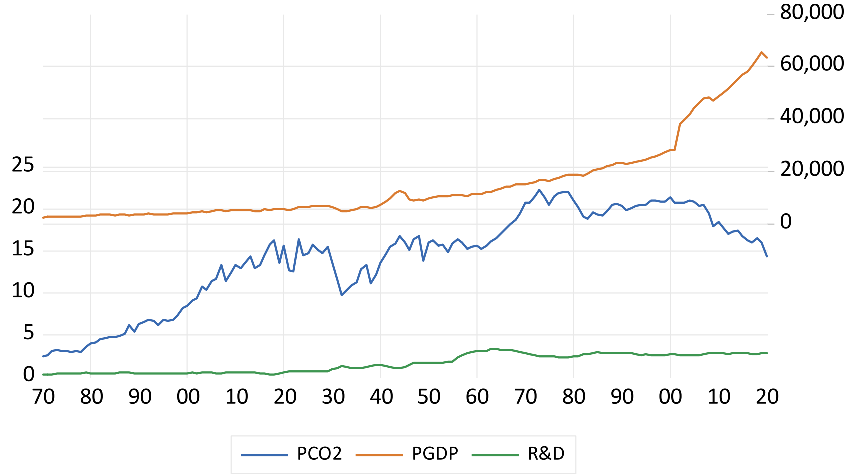

Fig. 3. Plots of R&D intensity, per capita CO2 emissions and per capita GDP

Table 2
Unit root test results.

	ADF	PP	KPSS	ADF	PP	KPSS
		Level		first	difference	
PCO2	−3.89***	−3.987***	1.120***	−15.432***	−12.618***	0.887***
PGDP	0.653	0.897	1.671***	−7.727***	−9.499***	0.166
R&D	−0.958	−1.432	1.537***	−8.833***	−8.526***	−8.076***

Notes: ***, ** and * indicate significance at the 1, 5 and 10% levels, separately.

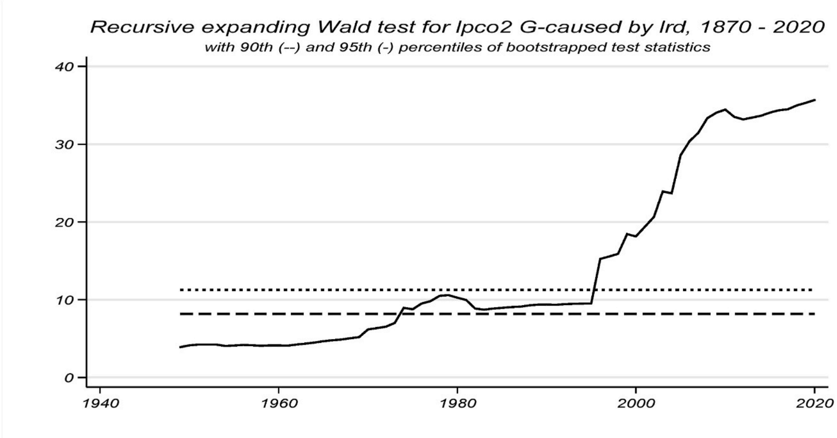

Fig. 4. Recursive Expanding Wald Test for R&D Granger Causes Per capita CO2 Emission.

on Fig. 5. Similarly, the 90% and 95% significant levels are revealed by the higher and lower dash lines, respectively. In comparison of the findings on Fig. 4, the PCO2 emissions is Granger caused by the PGDP shows the different pattern. Specifically, the Wald statistic roughly ranges from 7 to 9 before 1978, and surpasses to the 9.849, critical value of 10% significant level (See Table 3), until to the 2015 although there exists a slightly insignificant result around the 2008. Afterward, the Wald statistic over the 14.264, critical value of 5% significant level (See Table 3), until to the 2020. These findings show that the PGDP Granger causes the PCO2 emissions can be observed after 1978, while the causality relationship is further manifest after 2015. This evidence is not consistent with those found in Chang et al. [1]. They found strongly significant Granger causality relationship running from PGDP to PCO2 emissions during 1950–1945.

Moreover, Shi et al. [2] not only propose the recursive algorithm to estimate the Time-varying Granger causality relationship, but also exploit another two novel algorithms, forward Wald and rolling window, to robust the causality relationship. Consistent with Shi et al. [2], this study does use similar approach between among R&D intensity, PCO2 emissions, and PGDP to do the robustness check.

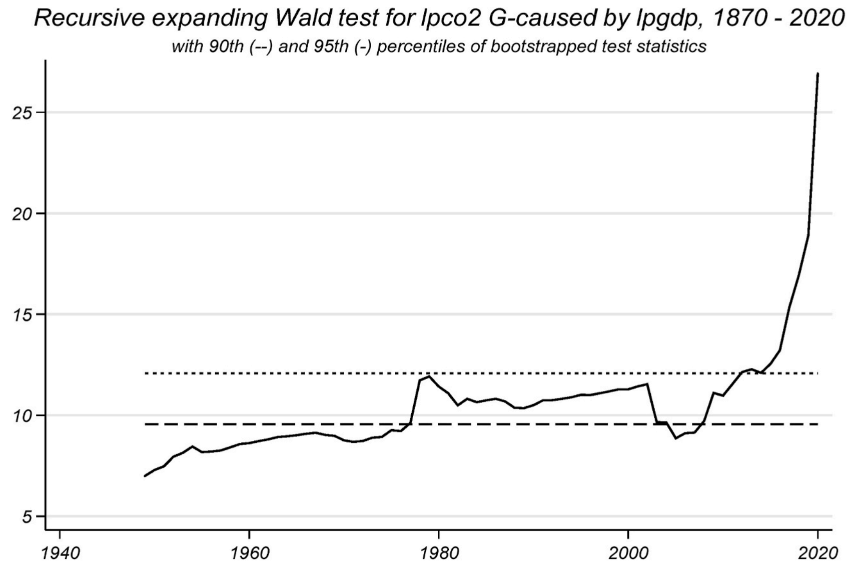

Fig. 5. Recursive Expanding Wald Test for Per capita GDP Granger Causes Per capita CO2 Emission.

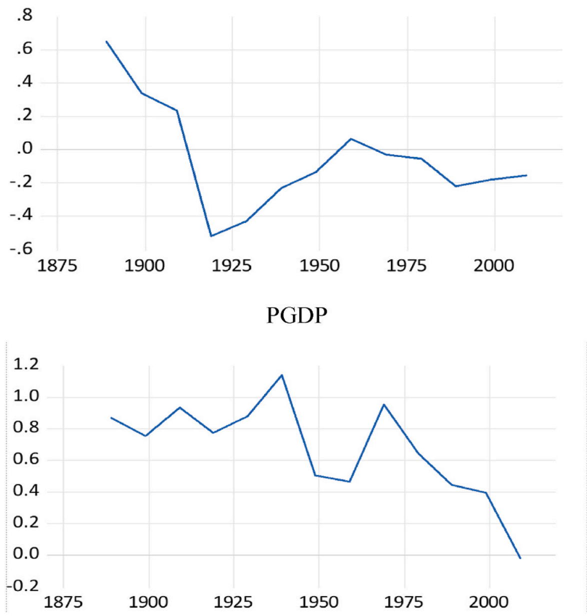

Fig. 6. Estimated coefficients from the rolling window regression for R&D and PGDP

Related findings are reported on Table 3.

For the PGDP causes the PCO2 emissions aspects, first, according to the findings of forward algorithm, the maximum Wald is 15.599 for PGDP and PCO2 emissions and three critical values at 90%, 95%, and 99% are 8.517, 12.782, and 18.286, respectively, indicating that the PCO2 emissions caused by the PGDP can be obtained at 5% significant level. Second, focus on the results of the rolling window algorithm, the maximum Wald is 26.922 and three critical values at 90%, 95%, and 99% are 9.211, 13.8, and 20.638, respectively, showing that the PGDP causes the PCO2 emissions is significant at 1%. Third, considering the results of the recursive evolving, the maximum Wald statistics is 26.992 and three critical values at 90%, 95%, and 99% are 9.849.14.264, and 21.526, respectively, suggesting that the Granger causality from PGDP to PCO2 emissions is significant at 1%. Comprehensively saying, the PCO2 emissions Granger caused by the PGDP is consistently captured by using the forward, rolling window and recursive evolving schemes, which robustly support to our findings.

For the R&D causes the PCO2 emissions viewpoint, first, based on the evidence of forward algorithm, the maximum Wald is 11.824 for R&D and PCO2 emissions and three critical values at 90%, 95%, and 99% are 7.202, 9.923, and 16.894, respectively, indicating

Table 3
The granger causality tests under forward, rolling window and recursive evolving algorithms.

		PGDP Granger Causes CO2 Emissions		
		Max_Wald_forward GC	Max_Wald_rolling window GC	Max_Wald_recursive Evolving GC
Wald statistics		15.599**	26.922***	26.922***
Bootstrap critical values	90%	8.517	9.211	9.849
	95%	12.782	13.8	14.264
	99%	18.286	20.638	21.526
		R&D Granger Cause CO2 Emissions		
		Max_Wald_forward GC	**Max_Wald_rolling window GC**	**Max_Wald_recursive Evolving GC**
Wald statistics		11.824**	28.595***	35.681***
Bootstrap critical values	90%	7.202	8.387	8.451
	95%	9.923	11.017	11.768
	99%	16.894	21.215	22.245

Notes: ***, ** and * indicate significance at the 1, 5 and 10% levels, separately.

that the R&D caused by the PGDP can be obtained at 5% significant level. Second, according to the findings of the rolling window algorithm, the maximum Wald is 28.595 and three critical values at 90%, 95%, and 99% are 8.387, 11.017, and 21.215, respectively, showing that the R&D causes the PCO2 emissions is significant at 1%. Third, considering the results of the recursive evolving, the maximum Wald statistics is 35.681 and three critical values at 90%, 95%, and 99% are 8.451.11.768, and 22.245, respectively, suggesting that the Granger causality from R&D to PCO2 is significant at 1%. In sum, the PCO2 Granger caused by the R&D is consistently observed by using the forward, rolling window and recursive evolving schemes, which robustly support to our evidence.

This study still not aware of whether R&D intensity (and/or PGDP) reduces or increases PCO2 albeit the R&D intensity (and/or PGDP) Granger causes PCO2 is obtained. To measure whether R&D intensity (and/or PGDP) reduces or increases PCO2 in our case that applying the rolling window approach to capture the coefficients for our R&D and PGDP. By looking the coefficients estimated from the rolling window regression model (see Fig. 6) that we find R&D intensity strongly reduces PCO2 emissions. On the other hand, we find PGDP significant increases PCO2 for all the time and the impact from PGDP to PCO2 gradually slow down, especially after 1990s. In short, this study finds R&D intensity Granger causes PCO2 emissions during the 1975 to the end of 2020 and PGDP also Granger causes PCO2 emissions after 1978 till the end of 2020.

5.2. Discussions and policy implications

We find both PGDP and R&D intensity Grange cause CO2e by investigating the data from 1870 to 2020. By examining the long-term period behavior of time-series data, this study uncovers robust results relative to above papers which only consider the short-term period results. Our findings seem to be supported by Akadiri and Adebayo [47] which asserts that positive relationship is found between the carbon emissions and non-renewable energy and similar association also can be obtained between the financial development and the carbon emissions by using the NARDL method. Based on Fig. 6, however, we show that the GDP growth indeed induces the CO2e increasing but the decreasing patterns after 1925. And the growth in R&D firstly increases the CO2e and reduces the CO2e around 1920. Why can the GDP growth induce the CO2e rise, and the inverse relationship can be found between the R&D and CO2e? The examined data period from 1870 to 2020 is examined in this study. Accompanying industrial development and technologic development, the USA generates higher economic growth by scarifying the environment, resulting tremendous CO2e. From the theoretical perspective, a famous hypothesis, Environmental Kuznets Curve (EKC), indicates that the carbon emissions will increase in the beginning when the countries develop, then slump after a turning point is arrived [6,7]. This effect can be attributed to three main channels, including the scale, composition, and technique effects, especially the technique effects are the most related with our studies [7,48]). Some preceding studies also show the negative relationship between the R&D investments CO2e (e.g., Gu and Wang [27], Bosetti and Tavoni [49]). In terms of the endogenous growth theory, a country with higher technology innovation can increase the economic growth of the country. State in another way, combining the EKC, endogenous growth theory, and preceding studies, we provide further long run and robust causality relationship between the CO2e and per capita GDP and between CO2e and R&D intensity.

As mentioned above, an increase in R&D intensity not only induces the CO2 emissions fall but also increases the GDP growth, though the GDP growth triggers the CO2 emissions but the extent gradually decreasing recently. Standing for the policy makers, although the growth in GDP increases the CO2e to rise, however, the extent declines recently. Increasing the R&D investment provides an effect that the reduction in the CO2 emissions. Additionally, global warming risk can be significantly reduced by the clean energy R&D funded by the government [50]. Eco-friendly oriented economic growth plays a further important role. By introducing R&D investment effectively reduces the CO2 emissions in USA recently. Hence, for government or policy makers, they should arise the GDP growth by encouraging the firms to increase the R&D investment, resulting in the reduction in the CO2 emissions.

6. Conclusions

The economy in USA develops could benefit the various sectors and pervade to household. Nevertheless, some disadvantages are created when enjoying the profits. Specifically, CO2 emissions indeed trigger the quality of environment fall and further impair the health of the human. Tacking these problems occupy indispensable roles for government and firms. Hence, this study re-examines the casual relationship between the CO2 emissions and per capita GDP and CO2 emissions and the R&D intensity with a Time-varying effect of the Granger causality, proposed by Shi et al. [2]. Our main findings are shown as follows.

The Granger causality between R&D intensity and PCO2 emissions are time varying. Besides, the R&D intensity significantly affects PCO2 emissions after 1975 until 2020. In addition, we also find the PGDP significantly influences PCO2 emissions after 1978 until 2020. Based on these findings, by increasing the investment of R&D could not only improve the GDP, but also reduce the CO2 emissions, resulting in beneficial the environment and overall economy. From the policy implications, increasing the R&D investment provides an effect that the reduction in the CO2 emissions. Additionally, global warming risk can be significantly reduced by the clean energy R&D funded by the government [50]. Eco-friendly oriented economic growth plays further important role. By introducing R&D investment effectively reduces the CO2 emissions in USA recently. Hence, for government or policy makers, they should raise the GDP growth by encouraging the firms to increase the R&D investment, resulting in the reduction in the CO2 emissions. Therefore, this study proposes that launching the new technical innovation and increase in R&D investment to maintain its economic growth are the best government strategy to reduce CO2 emissions in the USA.

Our findings are not only in support of the EKC theory, but also this phenomenon in the USA primarily is caused by the R&D intensity increasing. With economic development, enormous input in the eco-friendly R&D significantly improves the CO2 emissions. In comparison of existing papers [1,23,and32]], this study use data with longer period (1870–2020) to carry out analysis and evidently robust the results. Overall, this study has provided import interpretation for the USA. However, one of the research limitations is as follows. Due to the R&D intensity and CO2 emissions of the Firm-level data are few. To deeply dig out our findings whether be satisfied is limited. The connection in the firm level provides further important content for the policy makers if the data can be obtained. Therefore, we expect that the research on CO2 emissions and R&D, and CO2 emissions and per capita GDP from firm-level aspect is valuable in the future.

Author contribution statement

Hao-Wen Chang: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper. Tsangyao Chang: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper. Feiyun Xiang: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data. Alexey Mikhaylov: Performed the experiments; Analyzed and interpreted the data. Adriana Grigorescu: Conceived and designed the experiments; Contributed reagents; materials, analysis tools or data; Wrote the paper.

Data availability statement

All three data are available upon request. R&D intensity and per capita GDP are from the Carbon Dioxide Information and Analysis Center (CDIAC) database (Marland et al., 2006) [51] and Madsen and Ang (2016) [52], respectively. We extend both data series to 2020. Per capita CO2 emissions are from the following data collection Ritchie, H., Roser, M., Rosado, P. (2020) [53] website: https://ourworldindata.org/co2/country/USA.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] H.W. Chang, T.Y. Chang, Yifei Cai, Revisit R&D intensity and CO2 emissions in the USA, 1870-2016 using time varying granger causality test, Environ. Sci. Pollut. Control Ser. (2022) (under review).
[2] S. Shi, S. Hurn, P.C.B. Phillips, Causal change detection in possible integrated systems: revisiting the money-income relationship, J. Financ. Econom. 18 (1) (2020) 158–180, https://doi.org/10.1093/jjfinec/nbz004.
[3] Y. Neog, A.K. Yadava, Nexus among CO2 emissions, remittances, and financial development: a NARDL approach for India, Environ. Sci. Pollut. Control Ser. (27) (2020) 44470–44481, https://doi.org/10.1007/s11356-020-10198-0.
[4] J.G. Speight, K. Singh, Environmental Management of Energy from Biofuels and Biofeedstocks, Wiley, 2014. https://books.google.co.kr/books?id=ESfnAgAAQBAJ.
[5] Q. Ding, S.I. Khattak, M. Ahmad, Towards sustainable production and consumption: assessing the impact of energy productivity and eco-innovation on consumption-based carbon dioxide emissions (CCO2) in G-7 nations, Sustain. Prod. Consum. 27 (2021) 254–268, https://doi.org/10.1016/j.spc.2020.11.004.
[6] G.M. Grossman, A.B. Krueger, Environmental impacts of a north American free trade agreement, NBER Working Papers (1991), W3914. https://www.nber.org/system/files/working_papers/w3914/w3914.pdf.
[7] G.M. Grossman, A.B. Krueger, Economic growth and the environment, Q. J. Econ. 110 (2) (1995) 353–377.
[8] J. Frankel, Global Environmental Policy and Global Trade Policy, Harward Kennedy School, John F.Kenedy School of Government, 2008. Discussion Paper 08-14, https://conferences.wcfia.harvard.edu/files/heep/files/dp9_frankel.pdf.
[9] M. Shahbaz, A. Sinha, Environmental Kuznets curve for CO2 emissions: a literature survey, J. Econ. Stud. 46 (1) (2019) 106–168, https://doi.org/10.1108/JES-09-2017-0249.
[10] S. Dinda, Environmental Kuznets curve hypothesis: a survey, Ecol. Econ. 49 (4) (2004) 431–455, https://doi.org/10.1016/j.ecolecon.2004.02.011.
[11] H. Iwata, K. Okada, S. Samreth, A note on the environmental Kuznets curve for CO2: a pooled mean group approach, Appl. Energy 88 (5) (2011) 1986–1996, https://doi.org/10.1016/j.apenergy.2010.11.005.
[12] J. Sulaiman, A. Azman, B. Saboori, The potential of renewable energy: using the environmental Kuznets curve model, Am. J. Environ. Sci. 9 (2) (2013) 103–112. https://www.thescipub.com/pdf/10.3844/ajessp.2013.103.112.

[13] U. Al-Mulali, I. Ozturk, The investigation of environmental Kuznets curve hypothesis in the advanced economies: the role of energy prices, Renew. Sustain. Energy Rev. 54 (2016) 1622–1631, https://doi.org/10.1016/j.rser.2015.10.131.
[14] S.A. Apostu, V. Vasile, M. Panait, V. Sava, Exploring the Ecological Efficiency as the Path to Resilience, Economic Research-Ekonomska Istraživanja, 2022, pp. 1–21.
[15] Y. Mao, Z. Liu, A. Grigorescu, E. Condrea, Reverse relation of the industrial growths and enviromental emissions in China by employment variety, Journal of Environmental Protection and Ecology (JEPE) 20 (2) (2019) 620–630 (2019), ISSN: 1311-5065, http://www.jepe-journal.info/journal-content/vol-20-no2.
[16] G. Bölük, M. Mert, Fossil & renewable energy consumption, GHGs (greenhouse gases) and economic growth, evidence from a panel of EU (European Union) countries. Energy 74 (2014) 439–446, https://doi.org/10.1016/j.energy.2014.07.008.
[17] S. Farhani, M. Shahbaz, What role of renewable and non-renewable electricity consumption and output is needed to initially mitigate CO2 emissions in MENA region? Renew. Sustain. Energy Rev. 40 (2014) 80–90, https://doi.org/10.1016/j.rser.2014.07.170.
[18] D. Castellani, F. Pieri, R&D offshoring and the productivity growth of European regions, Res. Pol. 42 (9) (2013) 1581–1594, https://doi.org/10.1016/j.respol.2013.05.009.
[19] R. Freimane, S. Bāliņa, Research and development expenditures and economic growth in the EU: a panel data analysis, Economics and Business 29 (1) (2016) 5–11, https://doi.org/10.1515/eb-2016-0016.
[20] A. Minniti, F. Venturini, The long-run growth effects of R&D policy, Res. Pol. 46 (1) (2017) 316–326, https://doi.org/10.1016/j.respol.2016.11.006.
[21] M. Panait, R. Ionescu, S.A. Apostu, M. Vasić, Innovation through industry 4.0-driving economic growth and building skills for better jobs, Economic Insights-Trends & Challenges (2) (2022).
[22] J. Zhou, Y. Mao, A. Grigorescu, E. Condrea, Industrial growth and change of energy consumption behavior in eastern European countries, Austria and China, Journal of Environmental Protection and Ecology (JEPE) 21 (3) (2020) 1107–1116. ISSN 1311-5065, http://www.jepe-journal.info.
[23] S.A. Churchill, J. Inekwe, R. Smyth, X. Zhang, R&D intensity and carbon emissions in the G7: 1870–2014, Energy Econ. 80 (MAY) (2019) 30–37, https://doi.org/10.1016/j.eneco.2018.12.020.
[24] R.G. Newell, Literature review of recent trends and future prospects for innovation in climate change mitigation, OECD Environment Working Papers 9 (2009), https://doi.org/10.1787/19970900.
[25] A. Grimaud, G. Lafforgue, B. Magne, Climate change mitigation options and directed technical change: a decentralized equilibrium analysis, Resour. Energy Econ. 33 (4) (2011) 938–962, https://doi.org/10.1016/j.reseneeco.2010.11.003.
[26] G. Marangoni, M. Tavoni, The clean energy R&D strategy for 2 C, Climate Change Economics 5 (1) (2014), 1440003.
[27] G. Gu, Z. Wang, Research on global carbon abatement driven by R&D investment in the context of INDCs, Energy 148 (2018) 662–675, https://doi.org/10.1016/j.energy.2018.01.142.
[28] G.G. Noja, M. Cristea, M. Panait, S.M. Trif, C.Ș. Ponea, The impact of energy innovations and environmental performance on the sustainable development of the EU countries in a globalized digital economy, Front. Environ. Sci. 777 (2022).
[29] J. Weyant, Some contributions of integrated assessment models of global climate change, Rev. Environ. Econ. Pol. 11 (1) (2017) 115–137. https://www.journals.uchicago.edu/doi/epdf/10.1093/reep/rew018.
[30] C. Carraro, E. De Cian, L. Nicita, E. Massetti, E. Verdolini, Environmental policy and technical change: a survey, International Review of Environmental and Resource Economics 4 (2) (2010) 163–219, https://doi.org/10.1561/101.00000033.
[31] A. Grigorescu, A.-E. Ion, C. Lincaru, S. Pirciog, Synergy analysis of knowledge transfer for the energy sector within the framework of sustainable development of the European countries, 2022, Energies 15 (2022) 276, https://doi.org/10.3390/en15010276.
[32] Y. Fernández Fernández, M.A. Fernández López, B. Olmedillas Blanco, Innovation for sustainability: the impact of R&D spending on CO2 emissions, J. Clean. Prod. 172 (2018) 3459–3467, https://doi.org/10.1016/J.JCLEPRO.2017.11.001.
[33] X. Shao, Y. Zhong, Y. Li, M. Altuntaş, Does environmental and renewable energy R&D help to achieve carbon neutrality target? A case of the US economy, J. Environ. Manag. 296 (2021) 1–10, https://doi.org/10.1016/j.jenvman.2021.113229.
[34] S. Jiang, M.Z. Chishti, H. Rjoub, S. Rahim, Environmental R&D and trade-adjusted carbon emissions: evaluating the role of international trade, Environ. Sci. Pollut. Control Ser. (2022) 1–16, https://doi.org/10.1007/s11356-022-20003-9.
[35] Z. Wang, Z. Yang, Y. Zhang, J. Yin, Energy technology patents–CO2 emissions nexus: an empirical analysis from China, Energy Pol. 42 (2012) 248–260.
[36] A.E. Caglar, The importance of renewable energy consumption and FDI inflows in reducing environmental degradation: bootstrap ARDL bound test in selected 9 countries, J. Clean. Prod. 264 (2020), 121663.
[37] Z. Wang, Y. Zhu, Do energy technology innovations contribute to CO2 emissions abatement? A spatial perspective, Sci. Total Environ. 726 (2020), 138574.
[38] Y. Yu, Y. Du, Impact of technological innovation on CO2 emissions and emissions trend prediction on 'New Normal'economy in China, Atmos. Pollut. Res. 10 (1) (2019) 152–161.
[39] K. Du, J. Li, Towards a green world: how do green technology innovations affect total-factor carbon productivity, Energy Pol. 131 (2019) 240–250.
[40] S. Fethi, A. Rahuma, The impact of eco-innovation on CO2 emission reductions: evidence from selected petroleum companies, Struct. Change Econ. Dynam. 53 (2020) 108–115.
[41] C.N. Mensah, X. Long, L. Dauda, K.B. Boamah, M. Salman, Innovation and CO 2 emissions: the complimentary role of eco-patent and trademark in the OECD economies, Environ. Sci. Pollut. Control Ser. 26 (2019) 22878–22891.
[42] D. Többelmann, T. Wendler, The impact of environmental innovation on carbon dioxide emissions, J. Clean. Prod. 244 (2020), 118787.
[43] K.H. Lee, B. Min, Green R&D for eco-innovation and its impact on carbon emissions and firm performance, J. Clean. Prod. 108 (2015) 534–542.
[44] A.A. Karsten, M.M. van der Bank, The role of carbon emissions taxes and carbon greenhouse gas emissions on the renewable energy output: evidence from South Africa, Int. J. Econ. Finance Stud. 14 (2) (2022) 156–174.
[45] H.Y. Toda, T. Yamamoto, Statistical inference in vector autoregressions with possibly integrated processes, J. Econom. 66 (1–2) (1995) 225–250.
[46] J.J. Dolado, H. Lütkepohl, Making Wald tests work for cointegrated VAR systems, Econom. Rev. 15 (4) (1996) 369–386.
[47] S.S. Akadiri, T.S. Adebayo, Asymmetric nexus among financial globalization, non-renewable energy, renewable energy use, economic growth, and carbon emissions: impact on environmental sustainability targets in India, Environ. Sci. Pollut. Control Ser. (2021) 1–13.
[48] W.A. Brock, M.S. Taylor, The green Solow model, J. Econ. Growth 15 (2) (2010) 127–153.
[49] V. Bosetti, M. Tavoni, Uncertain R&D, backstop technology and GHGs stabilization, Energy Econ. 31 (2009) S18–S26.
[50] D. Herzer, The impact on domestic CO2 emissions of domestic government-funded clean energy R&D and of spillovers from foreign government-funded clean energy R&D, Energy Pol. 168 (2022), 113126.
[51] G. Marland, T. Boden, R.J. Andres, Global CO2 Emissions from Fossil-Fuel Burning, Cement Manufacture, and Gas Flaring: 1751-2003. *Carbon Dioxide Information Analysis Center*, Oak Ridge National Laboratory, Oak Ridge, Tennessee, 2006.
[52] J.B. Madsen, J.B. Ang, Finance-led growth in the OECD since the nineteenth century: how does financial development transmit to growth? Rev. Econ. Stat. 98 (3) (2016) 552–572.
[53] H. Ritchie, M. Roser, P. Rosado, CO_2 and greenhouse gas emissions, Published online at OurWorldInData.org (2020). Retrieved from: https://ourworldindata.org/co2-and-other-greenhouse-gas-emissions [Online Resource].