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International Trade and Carbon Emissions: Evaluating the Role of Trade Rule Uncertainty

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Abstract: Based on textual data mining methods and global English articles, we develop an index for measuring the uncertainty of international trade rules and evaluating the role of trade rule uncertainty in the relationship between international trade and carbon emissions, via a mediating effect model. The empirical results show that: (1) Increasing trade volume in developing countries contributes to a rise in trade rule uncertainty, which in turn triggers trade conflicts and even trade wars between countries. (2) There are significant correlations between international trade and carbon emissions, and international trade impacts carbon emissions in both direct and indirect ways. (3) Trade rule uncertainty plays a mediating role in the relationship between international trade and carbon emissions. (4) Trade rule uncertainty significantly impacts carbon emissions in most developed and developing countries, but the impact is not significant in the USA. Our work not only contributes to extending measurements of uncertainty but also helps to quantify the impacts of trade rule uncertainty on carbon emissions.

Keywords: carbon emission; trade rule uncertainty; international trade; mediating effect model

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1. Introduction

Trade-related carbon emissions are an important component of global emissions, and they are essential for the sustainable development of the global economy. Analyzing the effects of international trade on carbon emissions is of direct relevance to greenhouse gas (GHG) emission reductions, especially for major international trade participants [1]. The concepts of international trade and carbon emissions are intertwined [2]; increasing trade volume can drive up total emissions [1]. However, the environmental Kuznets curve (EKC) theory and carbon leakage hypothesis reveal that, while affluent countries buy goods and services from emerging countries, the corresponding carbon emissions are assigned to developing countries [3]. Meanwhile, environmental technologies spread from developed countries to developing countries and reduce GHG emissions at later stages [4]. There is no consensus on the path and mechanism of the impacts of international trade on carbon emissions [5], particularly in an uncertain scenario. The challenges and uncertainties facing the global energy system are at their greatest for almost 50 years (BP Statistical Review of World Energy of 2022), which highlights the essential role of studying how international trade affects carbon emissions under uncertainty.

Carbon emissions are connected with international trade by logistics transportation and shipping emissions [6], which are heavily affected by the international trade environment. International trade can enhance production efficiency, increase revenues, and promote economic growth for resource-rich countries, but the environmental consequences of exploiting natural resources arise spontaneously [7]. The different impacts of exports and imports on carbon emissions have been disclosed recently, and most studies suggest that positive (negative) shocks in exports (imports) decrease CO_2 emissions and vice versa [8]. International trade is an essential pillar for the global economy, and growing international trade helps to promote the global economy on a sustainable development track. Nevertheless, more GHG emissions shifting from developed countries to developing countries makes environmental problems more serious than before [9]. Emerging countries are famous for less pliable environmental regulations, by which they can absorb more FDI and expand international trade scales, which is described as the pollution haven hypothesis (PHH) [2]. The PHH links the environmental policies and trade liberalization together and causes the pollution-intensive industries in developing countries to produce more carbon emissions.

The number of studies on international trade and carbon emissions has increased rapidly in recent years [1], most of which hold that international trade has a substantial influence on consumption-based CO_2 emissions, but only a few studies focus on territorial effects [8]. For territory-based emissions, researchers find that imports can suppress carbon emissions [10]. There are also scholars who believe that exports (imports) reduce (increase) carbon emissions [11–14]. Hasanov et al. find that both imports and exports reduce carbon emissions in oil-exporting countries [15], however, Al-Mulali and Sheau-Ting illustrate that exports and imports increase CO_2 emissions, and there exists a feedback effect in trade, energy consumption, and carbon emissions [16].

According to the findings of Khan Z. et. al. (2020) [17], there is a stable long-term relationship between international trade, CO_2 emissions, renewables consumption, and environmental innovation; any shocks from policy to exports, imports, income, and environmental technologies will significantly impact CO_2 emissions [5]. Multinational enterprises locate operations in developing countries because they can save on environmentally related costs, and low-income countries cannot afford the high costs of rigorous environmental regulations [18]. The "new trade theory" developed recently is trying to exploit the impacts of firm heterogeneity in international trade on carbon emissions, and the results show that larger firms have higher environmental efficiency and can afford more investment in environmental innovations [19].

Although trade volume is the main driver of the increase in carbon emissions [20], there is evidence supporting the hypothesis that growing international trade is beneficial for carbon emission reduction. The CO_2 emissions embodied in international trade are believed to be a more accurate estimator for analyzing the impacts of international trade on carbon emissions [21]. Green technology spillovers in relation to carbon emission efficiency are helpful for emission reduction in developing countries [4], and empirical results show that China's carbon dioxide embodied in exports to developed countries has increased rapidly since the 21st century, which reflects the importance of trade liberalization [21]. Many researchers believe that the opening of trade increases national revenue and enlarges the investment scale in green technologies for public environmental protection, and that internationalization promotes the spread of frontier ecological technologies from developed countries to developing countries, eventually helping them to reduce carbon emissions [19,20].

The existing studies on international trade and carbon emissions are mostly focused on calculating carbon emissions based on estimation techniques, the common methods including index decomposition analysis (IDA) and structural decomposition analysis (SDA) [1], the PMG/ARDL estimation [7], nonlinear ARDL, augmented mean group (AMG), common correlated effect mean group (CCEMG), cross sectional autoregressive distributed lag (CS-ARDL) methods [8], dynamic multivariate Toda–Yamamoto (TY) approach [18], input-output (I-O) model [1,5,10], and Levinson's structural decomposition method [5]. These carbon emission calculation methods are based on certain accounting principles and try to answer the questions of "where the carbon emissions come from" and "who is responsible for carbon emissions" [5], but they ignore the difference between knowledge- and service-based industries and agriculture-based economies [8]. Furthermore, political and economic risks from the international environment are neglected in these studies.

There is empirical evidence supporting the hypothesis that trade policy uncertainty (TPU) and monetary policy uncertainty (MPU) positively affect the carbon emissions trading price (CETP) [22]. High uncertainty can lead to a macroeconomic environment and carbon emission trading (CET) turbulence, which would impact supply and demand for carbon emission rights and trigger fluctuations in the CETP [23]. Increasing challenges from geopolitical risk [24], trade conflicts [25], and international emergencies, e.g., the COVID-19 pandemic and Russia–Ukraine War [26], have led to great economic uncertainty worldwide [27]. Thus, the importance of uncertainties has become increasingly visible in financial and CET markets [22].

A scientific carbon emission trading scheme (ETS) is helpful in mitigating anthropogenic emissions of greenhouse gases and encouraging enterprises to increase investment in green technology [28]. Enterprises that release less carbon dioxide than the carbon quota have the right to sell excess carbon quota for profit gains [29], which is dependent on reasonable CET policies that can guarantee efficient carbon trading. The ETS operates under certain allocation rules and drives enterprises to fulfil their compliance requirements [30]. Nevertheless, uncertainties about trading rules have arisen and threatened the global economy in recent years (Fed's Bostic, 2022), which has caused a debate about CET rules [30–33]. Political risk and government stability are believed to be major causes of high uncertainty and can impact carbon dioxide emissions [34].

In an era of trade protectionism becoming mainstream in the global economy, if one importing country increases tariff rates, other markets will react violently all over the world [35], which is likely to trigger trade conflicts. Recently, as a result of inconsistent awareness and compliance with WTO principles, more economic and political emergencies appeared, along with the reduction of the binding force of trade rules on superpower countries over the last five years. Global emergencies (e.g., international energy price fluctuation, food insecurity, COVID-19 pandemic) highlight the importance of trade rules. Challenges to international trade rules are first manifested in policy adjustment, e.g., increased tariff rates, and the risk is gradually exposed to financial and carbon emission markets.

Trade rules are the general agreement on international trade. Uncertainty regarding trade rules has risen rapidly since 2018, e.g., the China-USA trade war decoupled the largest two economies and has led to a decline in trade volume between China and the USA in recent years. Nevertheless, measuring trade rule uncertainty is challenging, since there is no quantitative indicator that can reasonably measure this uncertainty. The existing studies show that international trade impacts carbon emissions significantly, but they neglect the shocks from the international trade market, especially the uncertainty about the consensus on international trade rules. As shown in Figure 1, the mechanism of the impacts of international trade on carbon emissions is complex, and there are multidimensional paths connecting international trade and carbon emissions, especially in relation to the role of renewables, enterprises, and environmental policies aiming for carbon emission reduction. All these variables and paths in the connection of international trade and carbon emissions are affected by macro uncertainty variables, which can be understood as shocks to the international trade environment. There is a gap in the literature in measuring this uncertainty and its impacts quantitatively.

To the best of our knowledge, there are no theoretical or empirical studies focusing on the relationships between international trade, trade rule uncertainty, and carbon emissions. This paper makes several important contributions to the literature: first, we develop a measurement of trade rule uncertainty based on textual data mining with English articles globally. We collected more than twenty thousand English articles that satisfied our criterion of three keyword sets, including the "trade rules" set, "economy/politics" set, and "uncertainty" set. Considering the above text information as well as trade remedy cases, we build an index of trade rule uncertainty (TRU), which is the first measurement for estimating the uncertainty of international trade rules; second, we evaluate the role of TRU in the relationship between international trade and carbon emissions. The fact that international trade impacts carbon emissions is illustrated by various studies, but there is a lack of studies on the impacts of uncertainty shocks on international trade and carbon emissions. We build mediating effect models and evaluate the role of TRU between international trade and carbon emissions, filling the gap in the literature on impacts of uncertainty on the carbon emission market; third, we provide a new perspective for studying the impact mechanism of international trade on carbon emissions. Most of the literature focuses on calculating trade-embodied carbon emissions, and uncertainty is neglected due to a lack of quantitative measurement. We provide data availability on a new perspective for studying carbon emission reduction.

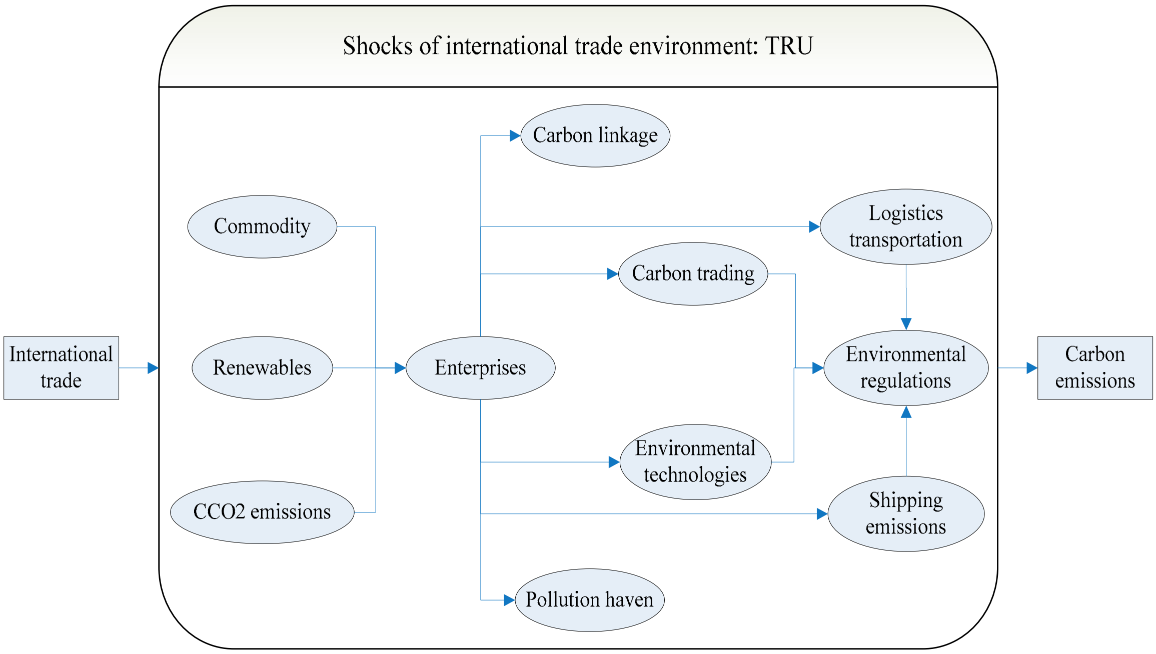

Figure 1. Logical relationship diagram between variables.

The remainder of this paper is structured as follows. In Section 2, a literature review is given. We develop a measurement of trade rule uncertainty in Section 3, and the methodology and data used in this paper are described in this section. Section 4 presents the empirical findings. In Section 5, the discussion and conclusions are provided.

2. Literature Review

2.1. Uncertainty Measuring Theory Based on Textual Data Mining

In the traditional risk management mechanism in finance, uncertainty is risk and can be measured by probability in mathematics [36]. More scholars believe that variance or semivariance are reliable measurements for risk and uncertainty [37], but mathematical probability and variance are not always effective for all problems [38]. Policy uncertainty and rule uncertainty are the main exceptions. Among all uncertainty measurements developed by textual data mining, Baker et al. (2016) [39] pioneered uncertainty index construction with text data, and their EPU index has been the most influential of all uncertainty indices. Moreover, Baker et al. (2016) not only developed the most famous EPU index but also provided the TPU, EMV (USA equity market volatility index), all country-level EPU, and categorical EPU data. Thereafter, uncertainty measured blowouts in the text search methodology, e.g., Huang and Luk (2020) [40] developed the China economic policy uncertainty index based on 10 mainland Chinese newspapers, and Shoag and Veuger (2016) [41] studied policy uncertainty based on newspaper information. In addition to kinds of EPU indices, there are several representative indices worth mentioning, e.g., the WUI (the world uncertainty index) [42], GPR (the geopolitical risk index) [43], TRU (trade rule uncertainty index) [44], and TPU (trade policy uncertainty index) [39,45] indices. In terms of the indices mentioned above, there are only quarterly data in the WUI index, but daily, monthly, quarterly, and annual data are provided in the TRU index;

the other indices are all monthly data. According to the literature, these indices have significant effects on the world macroeconomy [46], foreign direct investment [47], capital structure [48], corporate investment [49], unemployment [50], credit risks and banks' lending decisions [51], export and import [52,53], oil price and return [54,55], stock market volatility [39], housing market [56], welfare [57], supply chain [58], commodities [44], and carbon emissions [22,24,59,60].

2.2. Carbon Emission Trading Mechanism

The ETS is the abbreviation of carbon emission trading system [32] or emissions trading scheme [61], which guarantees ordered carbon emission trading based on national laws or international trading rules. There are three allocation rules for carbon emission trading: auctioning, grandfathering, and benchmarking [62]. Auctioning is usually applied in a mature market (e.g., European Union ETS) where free allocation is adopted to attract enterprises to trade carbon quotas and induce carbon emission reduction overall. Grandfathering is characterized by using historical carbon emission data to reallocate carbon quotas freely; it is a simple and feasible rule and widely used in emerging carbon markets (e.g., the European Union ETS and China pilot ETSs) [63–66]. Benchmarking is a newly built rule for trading carbon quotas and gradually replacing grandfathering in newly built markets (e.g., the newly built China national ETS) [63,67]. Regulators prefer its advantage in trading costs and promoting benchmarking, which is more acceptable in most emerging carbon markets [68].

Scientific allocation rules in ETSs can encourage enterprises to accept and comply with carbon trading mechanisms and help to reduce trading costs and carbon emissions [30]. The European Union carbon emission trading market has been established for more than ten years, and it has relatively mature trading rules. China is an emerging carbon emission trading market, and several carbon trading pilot areas have been established recently, but there is still space for mechanism updating on carbon emission reduction policy. According to the existing empirical results, carbon trading schemes help carbon emission reduction [29], and many countries show a tendency to apply carbon emission schemes in the shipping sector [69]. Carbon dioxide emissions have been effectively reduced under the pilot emissions trading scheme, and policy plays an important part in carbon mitigation, with a long-lasting character [70]. In fact, emission trading schemes are cost-effective policies [71] and market-incentive instruments [72] for environmental regulation. Most environmental permits and regulations are designed based on the principles of material balance [73], and policies related to emission trading schemes are effective tools for saving energy and reducing carbon dioxide emissions [74]. New technologies (e.g., blockchain-enabled trading systems) [75] and methodologies are being used in ETS design [76,77].

2.3. International Trade and Carbon Emissions

Many studies focus on international trade and carbon emissions, most of which believe that international trade can increase carbon emissions [78], and growing imports and exports lead to increasing consumption-based carbon emissions [8] and logistics and transportation carbon emissions [4]. Some researchers suggest that there exists a positive relationship between imports and carbon emissions but a negative relationship between exports and carbon emissions [79]. More specific results were found by Muhammad S. et al. [80], who compared different effects of exports and imports on carbon dioxide emissions across different income groups and found that exports negatively impact carbon dioxide emissions in low- and high-income groups, but positively impact CO_2 emissions in lower-middle groups, and imports positively impact CO_2 emissions in low-income countries and negatively impact CO_2 emissions in middle- and high-income groups. Meanwhile, the impacts of import and export technology spillovers on carbon emission efficiency were analyzed by Shen Y, Liu J, and Tian W [4], and the results reveal that embodied carbon is increasing heavily in sewing, textile, machinery, and equipment manufacturing, leather product manufacturing, metal product manufacturing, and the chemical industry in China, recently. From a long-term perspective, imports promote an increase in consumption-based carbon emissions, but exports significantly suppress consumption-based CO_2 emissions, and this is sensitive to policy changes [14]. Consumption-based carbon emissions, which are adjusted by international trade, are more suitable for measuring environmental pollution, and the rise in exports can decrease the ratio of consumption-based carbon emissions [9]. Researchers argue that EU imports have not reduced CO_2 emissions but outsourced them instead, and a consumption-based carbon emission accounting framework can be an efficient path to CO_2 emission reduction [81]. Foreign trade is an important factor for carbon emissions and impacts in different regions are significantly different [82]. Renewable energy utilization with international trade negatively impacts carbon emissions significantly in developed countries, which implies that international trade and trade liberalization are key factors for carbon emission reduction [21,83].

In summary, international trade impacts carbon emissions significantly, but most of the literature focuses on logistics transportation and shipping emissions. Uncertainties of the global trade environment are neglected because of difficulties in measuring trade rule uncertainty quantitatively. Big data technologies provide us with textual data mining by which we can construct an index of TRU and analyze the relationships between international trade, TRU, and carbon emissions. Our work contributes to estimating the effects of trade conflicts and provides a new perspective for reducing carbon emissions in turbulent international environments.

3. Methodology and Data

3.1. Mediating Effect Model

Mediating effect analysis is widely used in socioeconomics research and can help to explore the impact path and mechanism of independent variables on dependent variables.

Based on mediating effect theory in the literature [84–87], direct and indirect effects could be examined by the mediating effect model. Suppose X is the independent variable and Y is the dependent variable. If there is another variable M through which variable Y could be affected by X, then we name M a mediating variable [87].

Based on the existing mediating effect theory [86,87], we build the following mediating effect models:

$$lnCO_{2it} = a_0 + a_1 lnTrade_{it} + a_2 Controls + \varepsilon_{1it}, \tag{1}$$

$$lnTRU_t = b_0 + b_1 lnTrade_{it} + b_2 lnControls + \varepsilon_{2it}, \tag{2}$$

$$lnCO_{2it} = c_0 + c_1 lnTrade_{it} + c_2 lnTRU_t + c_3 lnControls + \varepsilon_{3it}, \tag{3}$$

where i represents the country, t is the time period, CO_{2it} denotes the carbon dioxide emissions of country i at time t, and TRU_t is the index of trade rule uncertainty at time t. We choose primary energy consumption, renewable consumption, and gross domestic product as control variables; ε_{1it}, ε_{2it}, ε_{3it} are model residuals.

As shown in models (1)–(3), the mediating effect can be estimated by the models with coefficients a, b, and c. The coefficient a_1 in model (1) measures the total impact of independent variable on dependent variable; the coefficient b_1 in model (2) estimates the effect of the independent variable on the mediating variable; the direct effect of the independent variable on the dependent variable can be measured by the coefficient c_1 in model (3); the effect of the mediating variable on the dependent variable can be estimated by the coefficient c_2; and ε_{1it}, ε_{2it}, ε_{3it} are model residuals and follow normal distribution.

According to the existing literature, trade and investment play an important role in CO_2 emissions, but the effects of international trade on carbon emissions are ambiguous [47,88,89] and most of the existing results are based on quasi-natural experiments [90]. We test the mediating effect of trade rule uncertainty on carbon dioxide emissions using models (1)–(3). If these coefficients in models (1)–(3) are all significant, then we can conclude that there is a significant mediating effect in the relationship between the independent variable and dependent variable. A significant coefficient variable c_2 reveals that *TRU* is a partial mediating variable and *TRU* is a complete mediating variable if c_1 is not significant [85].

Since carbon emissions and the trade rule uncertainty index of the current period may be affected by the historical data, the lagged terms of dependent variables are adopted in the models. This can help to eliminate the individual effects of variables and resolve the autocorrelation problem.

3.2. Variables and Data

We choose carbon dioxide emissions from energy (CO_2) as the dependent variable, international trade (Trade) as the independent variable, which represents the amount of imports plus exports, and the trade rule uncertainty index (TRU) as the mediating variable. The control variables are primary energy consumption (EC), renewables consumption (RC), and gross domestic product (GDP). Since CO_2 stays longer than any other gas emissions in the atmosphere, carbon dioxide emissions are the best proxy variable for carbon emissions [91]. China and the USA are the largest carbon emission countries, and the UK and Japan are the most representative developed countries on green technology. Brazil and China are good samples for studying carbon emission policies in developing countries. Trade conflicts between the USA and Australia against China provide us with data evidence for analyzing TRU and its impacts. These countries account for a large proportion of international trade and carbon emissions. Considering the data availability, we use annual data for empirical study from 1996 to 2021 in this paper, including 156 groups of data from China, the USA, the UK, Japan, Brazil, and Australia. The data of the dependent variable (CO_2) and control variables (EC, RC) are from "BP Statistical Review of World Energy 2022 [http://www.bp.com/statisticalreview, (accessed on 19 August 2022)]", and the GDP data are obtained from the CEIC database. We develop an index of trade rule uncertainty and obtain data on the mediating variable (TRU) based on the textual data mining method [44].

We collected more than twenty thousand articles in English related to trade rule uncertainty from the Factiva database, from 1 January 1996 to 31 December 2021, and count the number of keywords as well as article quantity. The Factiva database collected nearly 36,000 kinds of information resources published in 28 languages in nearly 200 countries and regions all over the world. We collected English-language newspapers, reports, magazines, journals, and other electronic publications that met our criteria on three keyword categories. The three categories of keywords of the trade rule uncertainty index are the trade rule category, economy category, and uncertainty category. The first category contains "trade rules", "trading rules", "WTO rules", "WTO principles", and "economy principles"; the second category contains "economic", "economy", "political", "politics", "legislation", and "law"; and the third category contains "uncertainty", "uncertain", "conflict", "violate", and "challenge" keywords (see Table 1).

Table 1. Keywords of TRU.

Category	Keywords
Trade Rule	trade rules; trading rules; WTO rules; WTO principles; economy principles
Economy	economic; economy; political; politics; legislation; law
Uncertainty	uncertainty; uncertain; conflict; violate; challenge

In addition to the quantity of keywords and English articles, global trade remedy case information was included in developing the TRU index, and the quantity of global trade remedy cases was collected from the *China Trade Remedies Information website* [http://cacs.mofcom.gov.cn/cacscms/view/statistics/ckajtj, (accessed on 12 April 2022)]. The TRU index was constructed by following these steps:

Step 1: Count the number of every keyword that appears in a single article, generate crude data on the number of keywords, articles, and remedy cases in one day, and let X_{it}

denote the daily count for statistical item i on day t, where $i = 1, 2, \ldots, 18$ represents the 16 keywords, article number, and remedy case numbers, respectively.

Step 2: Compute the times-series variance σ_i^2 for each statistical item i.

Step 3: Standardize X_{it} by dividing σ_i for all time t, let $Y_{it} = X_{it}/\sigma_i$.

Step 4: Let $Z_t = \overline{Y}_{it}$ be the mean value of Y_{it} for $i = 1, 2, \ldots, 18$, and m be the mean value of Z_t, then the daily index TRU is obtained by TRU = $Z_t \times 100/m$.

Step 5: Transform daily TRU to annual data by taking the annual average.

Table 2 shows the statistical results for the dependent variable CO_2, independent variable trade, mediating variable TRU and control variables RC, EC, and GDP. Considering the data availability, we selected China, the USA, Japan, Brazil, the UK, and Australia as our empirical study samples. These six countries cover the most representative developed and developing countries worldwide and can support our research better with available data. There are only annual data for the variables CO_2, EC, and RC. For the consistency of data frequency, we used annual data in the following empirical study.

Table 2. Summary statistics results.

Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque–Bera
CO_2	2712.3428	830.9762	12,039.7811	296.1190	3235.6667	1.3095	0.5684	45.43 ***
Trade	1.3729×10^6	8.9870×10^5	6.0501×10^6	98,205.4497	1.3266×10^6	1.3185	0.7707	47.59 ***
TRU	93.4084	82.4744	311.4153	41.5876	50.0713	3.1175	11.4159	1036.49 ***
RC	1.1888	0.4046	11.3163	0.0112	1.8586	2.7351	8.3199	608.57 ***
EC	70.3126	14.9308	338.8127	4.2773	109.7597	1.6685	1.0540	77.27 ***
GDP	5.7316×10^6	3.1371×10^6	2.0137×10^7	8.1646×10^5	5.4578×10^6	1.3008	0.2645	43.46 ***

Note: *** denote significance at the 1% level.

We collected English articles and trade remedy case information from 1 January 1996 to 31 December 2021, and generated the daily TRU index. The annual data were obtained by taking the average of the daily data. Thus, the mean value of TRU in Table 2 is 93.41 instead of 100. The maximum and minimum annual TRU are 311.42 and 41.59, respectively, and the standard deviation is 50.23. According to the skewness, kurtosis, and Jarque–Bera values, we can conclude that the annual TRU is not normally distributed. There is a large difference between the mean and median values of CO_2, Trade, and EC. CO_2 emissions account for the largest proportion of energy consumption (EC) and there is a similarity in data characteristics. China and the USA are the largest international trade and carbon emission countries, accounting for 31.1% and 13.9% of global CO_2 emissions, respectively (BP Statistical Review of World Energy of 2022). The quantities of CO_2, Trade, and EC in China and the USA are far greater than the other countries'. However, we have many groups of data most of which are much smaller than those of the USA and China. The mean value is sensitive to extreme values. Nevertheless, the median value measures the number in the middle of the data group; it reflects the data probability distribution in this group, and is not sensitive to the extreme values. Therefore, the difference between the mean and median values of CO_2, Trade, and EC is surprising but reasonable.

From country-level data, we know that China, the USA, and Japan have the three highest proportions of CO_2 emissions and energy consumption; here, China dominates the other countries on these two indices. Meanwhile, the USA and China perform better on renewable consumption, with an average 2.99 and 2.12 exajoules (input-equivalent) every year, respectively. These reflect the carbon dioxide emissions problem faced by China and the USA and demonstrate their great efforts in technological innovation. According to the Jarque–Bera value, all variables are not normally distributed.

4. Empirical Findings

4.1. The Relationship between CO_2 Emissions, International Trade, and TRU

Table 3 shows the empirical results of the direct effect of international trade on CO_2 emissions and the mediating effect of TRU on the relationship between international trade and CO_2 emissions. The data used in this empirical study are from six countries, including

China, the USA, the UK, Japan, Brazil, and Australia, from 1996–2021. The OLS regression results for the independent variables, mediating variables, and dependent variables are shown in Table 3.

Table 3. Main results for the relationship between CO_2 emission, international trade, and TRU.

Model	Intercept	Trade	TRU	EC	RC	GDP	Y(−1)	Y(−2)	R^2
Model (1)	-1.205×10^4 *** (0.0000)	0.0022 *** (0.0000)	-	21.4790 *** (0.0000)	−448.1041 *** (0.0021)	−0.0009 *** (0.0000)	1866.0114 *** (0.0000)	218.1066 (0.2252)	0.932
Model (2)	57.3836 (0.1400)	1.1023×10^{-5} * (0.0991)	-	0.1241 (0.3890)	17.5382 *** (0.0000)	-7.9740×10^{-6} * (0.0941)	9.6148 (0.1293)	−1.0533 (0.8272)	0.275
Model (3)	-1.113×10^4 *** (0.0000)	0.0024 *** (0.0000)	5.4377 *** (0.0000)	22.4221 *** (0.0000)	−531.7134 *** (0.0000)	−0.0010 *** (0.0000)	1823.7349 *** (0.0000)	194.6867 (0.1333)	0.936

Notes: The dependent and independent variables are CO_2 and Trade, respectively, in Model (1): TRU is the dependent variable, and the independent variable is Trade; in Model (2): CO_2, Trade, and TRU are the dependent variable, independent variable, and mediating variable, respectively; in Model (3): Y(−1) and Y(−2) represent the first- and second-order lags of dependent variables. EC, RC, and GDP represent energy consumption, renewables consumption, and gross domestic product, respectively, and they are set to be control variables in Models (1)–(3). The main body of Table 3 is the coefficient estimates, *p* values (in brackets) and R^2. ***, and * denote significance at the 1% and 10% levels, respectively.

As shown in Table 3, Model (1) measures the direct impacts of international trade on CO_2 emissions. According to the results in the table, the coefficient of the independent variable (Trade) equals 0.0022 with a significance at the 1% level, which reveals that international trade can significantly impact CO_2 emissions. Meanwhile, we chose energy consumption (EC), renewables consumption (RC), and GDP as control variables, and Y(−1) and Y(−2) are the first- and second-order lags of the dependent variable, which represents $CO_2(-1)$ and $CO_2(-2)$ in Model (1) here. The results of the coefficients of the control variables reveal that EC, RC, and GDP are factors influencing CO_2 emissions, and the Cointeg value equals −5.6185 with significance at the 1% level, which proves the validity of Model (1).

The relationship between international trade (Trade) and trade rule uncertainty (TRU) is shown in Model (2). The dependent variable is TRU, the independent variable is Trade, EC, RC, and GDP are control variables, and Y(−1) and Y(−2) are lagged terms of the independent variable TRU. According to the results in Table 3, we can conclude that international trade impacts TRU significantly at the 10% level, with a coefficient of 1.1023×10^{-5}, which reveals that the uncertainty of trade rules will rise with increasing imports and exports, which may explain the USA–China trade war with the rising flow of goods and products from China to the United States. Here, the R^2 value in Model (2) is relatively small, which may be due to the fact that variables Trade, EC, RC, and GDP are not the major factors for TRU. TRU is a new variable and developed based on the textual data mining method; it is quite different from traditional macroeconomic variables, but we do not care about the major impact factors for TRU. The results in Table 3 are good enough to demonstrate that TRU is a mediating variable.

The mediating effect of TRU in the relationship between trade and CO_2 emissions is modeled by Equation (3), and the results are shown at the bottom of Table 3. The coefficient of the independent variable is 0.0024, and the mediating effect variable coefficient equals 5.4377. Both are significant at the 1% level, which reveals that there exists a partial mediating effect of TRU in the relationship between international trade and CO_2 emissions. Furthermore, control variables EC, RC, GDP, and the lagged terms of the independent variable perform well in the model, and most of the coefficients, as well as the Cointeg value that measures the validity of the model, are significant at the 1% level.

Based on the results in Table 3, we can conclude that international trade impacts CO_2 emissions and TRU positively and significantly, and there exists a mediating effect of TRU in the relationship between international trade and CO_2 emissions. The empirical results imply that the partial mediating effect is positive and significant at the 1% level. TRU measures the uncertainty about international trade rules and can reflect the carbon trading environment globally. A high TRU index implies high trading costs and risks in the carbon trading market, and ultimately increases carbon dioxide emissions.

4.2. Robustness

The mediating effect of TRU on the relationship between international trade and carbon dioxide emissions has been proven by the empirical results in Table 3, and we performed a robustness test at the national level in this section.

As shown in Table 4, there is a positive relationship between Trade and CO_2 emissions in China, the UK, and Brazil, and the coefficients are significant, with values of 9.9241 $\times$ 10^{-5}, 6.6173 $\times$ 10^{-5}, and 0.0003, respectively. The results for the USA and Australia are quite different, since Trade and CO_2 are not significantly correlated in the USA and are negatively correlated in Australia, with significance at the 1% level. Regardless of the relationship between international trade and CO_2 emissions at the national level, the mediating effect will be suggested if the coefficients are significant in the corresponding Model (3) with the same control variables as Model (1).

Table 4. Direct effect of international trade on CO_2 emission.

Model (1)	China	USA	UK	Japan	Brazil	Australia
Intercept	9836.7403 ***	1.482×10^4 **	−293.0280 *	798.4860	−1250.1459 ***	−519.9385 ***
	(0.0042)	(0.0214)	(0.0843)	(0.6141)	(0.0000)	(0.0000)
Trade	9.9241×10^{-5} ***	5.6223×10^{-5}	6.6173×10^{-5} ***	-1.1942×10^{-5}	0.0003 **	-2.9754×10^{-5} ***
	(0.0062)	(0.1511)	(0.0000)	(0.6763)	(0.0482)	(0.0031)
EC	178.7013 ***	10.2971 ***	63.1542 ***	13.7738 *	57.6451 ***	87.1500 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0821)	(0.0023)	(0.0000)
RC	−58.5138 ***	−317.4149 ***	−70.2701 ***	−242.0630 ***	−44.9568 ***	−59.4263 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GDP	−0.0003 ***	0.0002 ***	-2.869×10^{-5}	0.0003 ***	−0.0002 ***	-2.845×10^{-5} *
	(0.0000)	(0.0000)	(0.1031)	(0.0000)	(0.0000)	(0.0724)
$CO_2(-1)$	−2424.8635 ***	−839.9616 **	−12.5599	131.5996	128.4349 **	22.7077
	(0.0063)	(0.0132)	(0.5154)	(0.3792)	(0.0460)	(0.5520)
$CO_2(-2)$	1054.6469 **	−894.9831	60.8292	−287.2807	129.1869	67.2835 *
	(0.0181)	(0.1072)	(0.0784)	(0.1141)	(0.2332)	(0.0544)
R^2	0.999	0.984	0.997	0.873	0.980	0.994
DW	1.456	1.671	1.167	1.660	1.532	1.878
Cointeg	−3.9524 ***	−2.5888 *	−2.6702 *	−3.8657	−3.3096 **	−4.3928 ***
	(0.0020)	(0.0951)	(0.0792)	(0.0023)	(0.0154)	(0.0000)

Notes: The dependent variable is CO_2, Trade is the independent variable, $CO_2(-1)$ represents the first-order lag of dependent variable, control variables are energy consumption (EC), renewables consumption (RC), and gross domestic product (GDP). In the main body of Table 4 are the coefficient estimates, *p* values (in brackets), R^2, DW, and Cointeg values (the results of cointegration test made by the ADF test on model residuals). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

According to the results in Table 4, we know that energy consumption (EC), renewable consumption (RC) and GDP are efficient control variables because they impact CO_2 emissions significantly. EC and CO_2 emissions are positively correlated with significance at the 1% level in China, the USA, the UK, Brazil, and Australia, and RC impacts CO_2 emissions negatively with significance at the 1% level in all six countries. The relationship between GDP and CO_2 emissions is not clear, and the results mainly depend on national policy and industry conditions. The R^2 value in Table 4 implies the validity of Model (1) describing the relationships between CO_2 emissions, international trade, energy consumption, renewable consumption, and GDP, which is the basis for analyzing how TRU impacts CO_2 emissions in the following sections.

Table 5 shows the impact of international trade on the TRU index. Since TRU is developed based on textual data mining with English articles and trade remedy case information globally, and measures the uncertainty of WTO trade rules as well as the international trade environment, it is a trade war (especially China-USA trade war) indicator and important for CO_2 trading between countries. Trade conflicts would worsen with increasing trade deficit and trade volume and may cause tariff rates to increase, thus, the TRU index would rise as a result. According to the results in Table 5, the trade of China, Japan, Brazil, and Australia contributes to the rise of TRU, with coefficient values of 5.6394 $\times$ 10^{-5}, 0.0001, 0.0005, and 0.0002, respectively, which reveals that imports and exports in these four countries are positively correlated with the uncertainty of trade rules. This result supports the hypothesis that trade volume positively impacts the TRU index. On the other hand, the impacts of trade from the USA and the UK on TRU are not significant, but renewables consumption can impact TRU positively in most countries, which may be caused by trade conflicts in renewable technology innovation and differences in carbon emission policies. Overall, international trade impacts TRU significantly, and there is evidence supporting this positive relationship in most countries.

Table 5. Impact of Trade on TRU.

Model (2)	China	USA	UK	Japan	Brazil	Australia
Intercept	119.2707 (0.4211)	−502.8036 (0.1192)	313.4229 (0.2700)	265.1303 (0.1154)	294.5387 (0.1371)	359.7366 (0.1382)
Trade	5.6394×10^{-5} ** (0.0482)	1.6451×10^{-5} (0.5000)	-8.8080×10^{-5} (0.2163)	0.0001 ** (0.0151)	0.0005 ** (0.0252)	0.0002 * (0.0900)
EC	−0.7700 (0.6261)	1.6188 (0.1400)	−50.4040 (0.1883)	22.0280 ** (0.0300)	−32.9523 ** (0.0113)	−92.1568 (0.1212)
RC	23.8231 *** (0.0000)	28.3844 ** (0.0492)	−67.5254 (0.4011)	228.7142 *** (0.0000)	76.4054 *** (0.0000)	203.4501 * (0.0573)
GDP	-2.553×10^{-5} (0.0013)	-6.766×10^{-6} (0.5114)	0.0001 (0.3161)	−0.0002 *** (0.0000)	−0.0001 (0.1912)	3.975×10^{-5} (0.7403)
TRU(−1)	6.2200 (0.8411)	16.4649 (0.5243)	12.1584 (0.6482)	15.0552 (0.6041)	31.5410 (0.3344)	19.5514 (0.4581)
R^2	0.751	0.532	0.441	0.694	0.649	0.671
DW	1.718	1.332	1.380	2.011	1.798	1.636
Cointeg	−4.4249 *** (0.0000)	−2.8248 * (0.0551)	−1.1188 (0.7072)	−3.5514 *** (0.0071)	−3.7784 (0.0033)	−4.2113 *** (0.0000)

Notes: The dependent variable is TRU, Trade is the independent variable, TRU(−1) represents the first-order lag of dependent variable, control variables are energy consumption (EC), renewables consumption (RC), and gross domestic product (GDP). In the main body of Table 5 are the coefficient estimates, *p*-values (in brackets), R^2, DW, and Cointeg values (the results of cointegration test made by the ADF test on model residuals). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The results in Table 4 imply that international trade can significantly impact CO_2 emissions, and Table 5 shows that TRU is impacted by international trade at the country level. If the coefficients in Model (3) are significant, the mediating effect of TRU in the relationship between international trade and CO_2 emissions is suggested. There is a partial mediating effect of TRU on trade and CO_2 emissions if the coefficients of c_1 and c_2 in Model (3) are both significant. The mediating effect is complete if c_2 is significant and c_1 is not significant.

As shown in Table 6, the impacts of trade and TRU on CO_2 emissions can be verified by the coefficients of c_1 and c_2 in Model (3). The coefficients of Trade are 3.2802×10^{-5}, 6.8692×10^{-5}, 6.4491×10^{-5}, -4.2012×10^{-5}, 8.2551×10^{-5}, and -3.2222×10^{-5} in China, the USA, the UK, Japan, Brazil, and Australia, respectively. Only those in China and Brazil are not significant, but the coefficients of TRU in Table 6 are 1.0182, 0.1098, 0.2932, 0.1825, and 0.0404 in China, the UK, Japan, Brazil, and Australia, respectively. All these coefficients are significant, which reveals that there is a complete mediating effect of TRU in the relationship between Trade and CO_2 emissions in China and Brazil, and a partial mediating effect of TRU in the UK, Japan, and Australia, but the USA is an exception since TRU cannot impact CO_2 emissions significantly in the USA, which is consistent with the results in another study [44].

According to the results in Table 6, we know that TRU positively impacts CO_2 emissions significantly, which implies that carbon dioxide emissions will rise with increasing trade rule uncertainty because TRU measures the uncertainty of the international trade environment and can forecast the severity of trade conflicts. Increasing TRU means more trade barriers. As a result, carbon emission trading costs rise, which ultimately promotes an increase in carbon emissions.

Compared with the results in Table 4, we find that there exists a direct impact of international trade on CO_2 emissions in China, the UK, Brazil, and Australia, and the coefficients are 9.9241×10^{-5}, 6.6173×10^{-5}, 0.0003, and -2.9754×10^{-5}, respectively.

When TRU appears in Model (3) in Table 6, the coefficients of trade in China and Brazil are not significant, which implies that international trade volume contributes to the uncertainty of trade rules and completely impacts CO_2 emissions through TRU. According to the coefficients of trade in the UK and Australia in Table 4, the values decrease in Table 6 since TRU is added into Model (3) and becomes a mediating variable between international trade and CO_2 emissions.

Table 6. Results of the mediating effect.

Model (3)	China	USA	UK	Japan	Brazil	Australia
Intercept	1.0191×10^4 ***	1.4631×10^4 **	−869.2764 ***	469.0504	−1099.0245 ***	−493.5666 ***
	(0.0041)	(0.0213)	(0.0000)	(0.7768)	(0.0000)	(0.0000)
Trade	3.2802×10^{-5}	6.8692×10^{-5} *	6.4491×10^{-5} ***	-4.2012×10^{-5} *	8.2551×10^{-5}	-3.2222×10^{-5} ***
	(0.2800)	(0.0631)	(0.0000)	(0.0722)	(0.5893)	(0.0031)
TRU	1.0182 ***	−0.5069	0.1098 ***	0.2932 *	0.1825 **	0.0404 **
	(0.0000)	(0.1121)	(0.0000)	(0.0954)	(0.0133)	(0.0251)
EC	183.5197 ***	11.2394 ***	65.1813 ***	7.8202	73.3256 ***	90.5247 ***
	(0.0000)	(0.0000)	(0.0000)	(0.4600)	(0.0000)	(0.0000)
RC	−77.0547 ***	−303.8319 ***	−36.9938 **	−302.7455 ***	−58.8179 ***	−68.7108 ***
	(0.0000)	(0.0000)	(0.0241)	(0.0000)	(0.0000)	(0.0000)
GDP	−0.0002 ***	0.0002 ***	-3.666×10^{-5} ***	0.0003 ***	−0.0002 ***	-2.727×10^{-5} **
	(0.0000)	(0.0000)	(0.0031)	(0.0000)	(0.0000)	(0.0372)
$CO_2(-1)$	−2716.3357 ***	−1127.7907 ***	43.8085 **	140.8406	144.3421 **	54.8928 **
	(0.0000)	(0.0043)	(0.0211)	(0.3092)	(0.0281)	(0.0200)
$CO_2(-2)$	1274.9741 ***	−613.3103	93.4623 ***	−260.8631	58.8840	27.1825
	(0.0000)	(0.2721)	(0.0021)	(0.1543)	(0.5891)	(0.3462)
R2	0.999	0.985	0.998	0.882	0.984	0.995
DW	1.549	1.706	1.599	1.863	1.929	1.906
Cointeg	−3.7689 ***	−3.0358 **	−3.3935 **	−4.2841 ***	−3.9790 ***	−4.7055 ***
	(0.0031)	(0.0321)	(0.0111)	(0.0011)	(0.0023)	(8.2164×10^{-5})

Notes: The dependent variable is CO_2, TRU is the independent variable, $CO_2(-1)$ represents the first-order lag of dependent variable, control variables are energy consumption (EC), renewables consumption (RC), and gross domestic product (GDP). In the main body of Table 3 are the coefficient estimates, *p*-values (in brackets), R^2, DW, and Cointeg values (the results of cointegration test made by the ADF test on model residuals). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

In Model (3), we set the control variables as EC, RC, and GDP, and the results in Table 6 show that all three control variables significantly impact CO_2 emissions. There is a significant positive relationship between energy consumption (EC) and carbon dioxide emissions (CO_2) and a significant negative relationship between renewables consumption (RC) and carbon dioxide emissions (CO_2). This result reveals that energy consumption and renewable consumption can significantly impact carbon dioxide emissions, and increasing EC will result in an increase in CO_2 emissions. In contrast, RC depresses CO_2 emissions significantly, which is consistent with the existing results in the carbon emission area.

The R^2 values in Table 6 are close to one, which implies that Model (3) fits well. The Cointeg values are all significant in all six countries, and these indicator values guarantee that the above results are all theoretically trustworthy. Based on the analysis above, we believe that international trade and TRU can impact CO_2 emissions significantly, and TRU is a mediating variable between international trade and carbon dioxide emissions.

The R^2 corresponding to the model is large and there may exist a problem of multicollinearity. The Pearson correlation coefficient and the variance inflation factor (VIF) are the indicators for testing whether there is a multicollinearity problem. Table 7 shows the results of Pearson correlation coefficients between variables.

According to the results in Table 7, the Pearson correlation coefficients between GDP and the other variables are relatively large, the coefficient between CO_2 and GDP is 0.7468, Trade and GDP are correlated with the coefficient of 0.8924, and both RC and EC are linked with GDP with coefficients of 0.7594 and 0.9072, respectively. The coefficient between TRU and GDP is small. The results in Table 7 imply that GDP is highly correlated with the other variables.

Table 7. Pearson correlation coefficients between variables.

Pearson Correlation Coefficients	CO_2	Trade	TRU	RC	EC	GDP
CO_2	1.0000	0.8484	0.0796	0.6082	0.6040	0.7468
Trade	0.8484	1.0000	0.2894	0.8197	0.6574	0.8924
TRU	0.0796	0.2894	1.0000	0.4264	0.0058	0.1629
RC	0.6082	0.8197	0.4264	1.0000	0.4997	0.7594
EC	0.6040	0.6574	0.0058	0.4997	1.0000	0.9072
GDP	0.7468	0.8924	0.1629	0.7594	0.9072	1.0000

The variance inflation factor (VIF) is the ratio (quotient) of the variance of estimating some parameters in a model that includes multiple other terms (parameters) by the variance of a model constructed using only one term. It quantifies the severity of multicollinearity in an ordinary least squares regression analysis. Multicollinearity is high if the VIF value is greater than 10. Table 8 shows the results for the VIF values of Models (1)–(3) and modified Models (1)–(3). We drop GDP from control variable sets in modified Models (1)–(3) to solve the multicollinearity problem. The dependent variable in Table 8 is CO_2, and the only difference between Models (1)–(3) and modified Models (1)–(3) is whether there is a control variable of GDP.

Table 8. Variance inflation factor test results.

	Trade	TRU	EC	RC	GDP	Y(−1)	R^2
Model (1)	11.82	-	26.88	2.73	48.75	7.11	0.9695
Model (2)	10.20	-	17.15	2.88	46.49	1.19	0.4444
Model (3)	13.93	1.81	27.00	3.65	52.37	7.16	0.9699
Modified Model (1)	3.52	-	6.94	2.11	-	6.68	0.9681
Modified Model (2)	3.08	-	2.81	1.99	-	1.17	0.4075
Modified Model (3)	3.94	1.69	7.65	2.63	-	6.68	0.9690

According to the results in Table 8, the VIF values of GDP, EC, and Trade are greater than 10 in Models (1)–(3), which reveals that there is a multicollinearity problem. Since the VIF values of GDP in Models (1)–(3) are the largest among all variables, we drop the control variable GDP and rebuild Models (1)–(3) as modified Models (1)–(3). By dropping the high VIF value variable GDP, we find that the modified models perform better than Models (1)–(3) on the VIF indicator, and all VIF values for the variables in modified Models (1)–(3) are smaller than 10, which indicates that the multicollinearity problem is solved by dropping the variable GDP.

Since the empirical models are modified, we need to test the robustness by applying modified Models (1)–(3). Table 9 shows the results of the modified mediating effect models (1)–(3).

According to the results of modified Model (1) in Table 9, we find that Trade is positively correlated with CO_2, which means that growing international trade can lead to an increase in CO_2 emissions, which is consistent with Tables 3 and 4. EC and RC are positively and negatively linked with CO_2 emissions, which implies that more energy consumption leads to more CO_2 emissions, and renewables consumption can depress CO_2 emissions, which is consistent with the results in the existing literature. The results of the modified Model (2) in Table 9 reveal that Trade is positively correlated with TRU, the coefficient between Trade and TRU is 0.1803, and it is significant at the 1% level, which implies that increasing international trade leads to a rise in TRU. EC and RC are negatively and positively correlated with TRU with coefficients of −0.1880 and 0.1380, respectively, which reveals that energy consumption can depress TRU and renewables consumption can promote a rise in TRU. This is because traditional fossil fuel is the basis for the global economy at present, but with the rise of the renewable industry, more new energy enterprises appear and participate in the competition of energy consumption.

Table 9. Main results based on modified models.

Model	Intercept	Trade	TRU	EC	RC	Y(−1)	R^2
Modified Model (1)	−1.0097 *** (0.006)	0.1681 *** (0.000)	-	0.1659 *** (0.000)	−0.0771 *** (0.000)	0.7370 *** (0.000)	0.9681
Modified Model (2)	2.5951 *** (0.000)	0.1803 *** (0.000)	-	−0.1880) *** (0.000)	0.1380 *** (0.000)	0.0250 (0.720)	0.4075
Modified Model (3)	−1.3306 *** (0.001)	0.1460 *** (0.000)	0.1194 ** (0.039)	0.1879 *** (0.000)	−0.0936 *** (0.000)	0.7381 *** (0.000)	0.9690

Notes: The dependent and independent variables are CO_2 and Trade, respectively, in Model (1); TRU is the dependent variable, and the independent variable is Trade in Model (2); CO_2, Trade, and TRU are the dependent variable, independent variable, and mediating variable, respectively, in Model (3). Y(−1) represents the first-order lag of dependent variables. EC and RC represent energy consumption and renewables consumption, respectively, and they are set to be control variables in Models (1)–(3). In the main body of Table 3 are the coefficient estimates, *p* values (in brackets), and R^2. *** and ** denote significance at the 1% and 5% levels, respectively.

The results of the modified Model (3) show the relationships between the independent variable CO_2 and the dependent variables Trade and TRU. Here, TRU is a mediating variable between CO_2 and Trade. According to the results in Table 9, the coefficient between CO_2 and Trade is 0.0146 and significant at the 1% level, which is consistent with the results in Tables 3 and 6. The coefficient between CO_2 and TRU is 0.1194 and significant at the 5% level, which proves that there exists a partial mediating effect of TRU on the relationship between CO_2 emissions and international trade. This result reveals that there are direct and indirect impacts of international trade on CO_2 emissions; TRU is the mediating variable in this indirect impact.

In summary, the results in Table 9 are consistent with Tables 3–6, the modified Models (1)–(3) perform well on the mediating effect of TRU on international trade and CO_2 emissions. Tables 4–9 show the results of the robustness of our mediating effect models. The empirical findings imply that TRU is an important variable between CO_2 emissions and international trade, and the mediating effect of TRU on CO_2 and Trade is significant, which highlights the importance of our work in developing the TRU index.

5. Discussion and Conclusions

5.1. Conclusions

This paper develops an index for measuring trade rule uncertainty (TRU) and analyzes the mediating effect of TRU on the relationship between international trade and carbon emissions. Several interesting findings are obtained in this paper:

(1) Increasing trade volume in developing countries contributes to the rise of trade rule uncertainty, which in turn triggers trade conflicts and even trade wars between countries. The empirical results show that growing imports and exports can lead to an increase in trade rule uncertainty and carbon dioxide emissions. Energy consumption and renewable consumption are positively and negatively correlated with CO_2 emissions, respectively.

(2) There are significant correlations between international trade and carbon emissions; international trade impacts carbon emissions in both direct and indirect ways. Empirical results about the relationship between TRU and international trade imply that they are positively correlated in China, Japan, Brazil, and Australia, which reveals that the largest international trade developing countries contribute to the greatest increase in trade rule uncertainty.

(3) Trade rule uncertainty plays a mediating role in the relationship between international trade and carbon emissions. According to the mediating effect test results, we find that TRU plays an essential role between international trade and carbon emissions. The mediating effect of TRU on international trade and carbon emissions is significant at the national level.

(4) TRU significantly impacts carbon emissions in most developed and developing countries, but the impact is not significant in the USA. The empirical results show that TRU

impacts CO_2 emissions positively and significantly in China, the UK, Japan, Brazil, and Australia, but cannot significantly impact USA carbon emissions.

Our work not only contributes to extending measurements about uncertainty but can also help to quantify the impacts of trade rule uncertainty on carbon emissions.

5.2. Discussions and Policy Implications

International trade can affect carbon emissions, which is a common conclusion and is recognized by most researchers [4,8,79–81]. The existing results reveal that imports and exports are positively correlated with consumption-based carbon emissions [8,78], since growing international trade can lead to increasing logistics and transportation producing carbon emissions [4]. However, there are also researchers who believe that exports negatively affect carbon emissions [79,80]. To date, we found that carbon emissions are affected by international trade, but regarding why and how international trade impacts carbon emissions we had not reached an agreement. Consequently, we developed an index that measures trade rule uncertainty based on a textual data mining method, and studied the relationship between international trade, trade rule uncertainty, and carbon emissions based on mediating effect models.

Global emergencies have been occurring and have led to recent rises in uncertainty regarding the international environment (e.g., Russo-Ukrainian war, China-USA trade war, bankruptcy of Silicon Valley Bank and Signature Bank, and COVID-19 pandemic). Such emergencies bring uncertainties to the global market and will inevitably impact carbon emissions. Meanwhile, the continuously growing trade deficit of the USA has led to China-USA trade conflicts becoming increasingly fierce. We find that international trade in China, Brazil, Japan, and Australia leads to an increase in trade rule uncertainty, but this effect is not significant in the USA and UK.

International trade effects on carbon emissions have been discussed in various studies, and we provide a new perspective for analyzing international trade and carbon emissions reduction by introducing TRU into mediating effect models. Empirical results show that growing international trade in developing countries contributes to the rise of TRU, which transmits uncertainty in international trade to the carbon emission market. Our work not only depicts the impact path and mechanism of international trade on carbon emissions, but also provides data availability for studying international trade frictions and their impacts.

Based on the conclusions in this paper, we put forward the following policy suggestions:

First, uncertainties in international trade should be given more attention. Existing results about carbon emissions reduction are mainly focused on environmental regulations for polluting industries and enterprises, and only a few studies investigate how economic policy or trade policy uncertainty affect carbon emissions. By developing the TRU index with big data technology, we analyse uncertainty in international trade rules and its impacts on carbon emissions. As an indicator of risks in international trade, TRU positively impacts carbon emissions, which reveals that an increase in TRU can lead to an increase in carbon emissions. Therefore, risks in international trade should be controlled at a low level.

Second, governments should strive for multilateral cooperation and rebuild a new international trade rule mechanism. Uncertainties have been rising rapidly in recent years, and the binding force of international trade rules on superpowers is becoming weaker. Historical experience indicates that trade confrontations and emergencies have a significant impact on global economies. We find that TRU has significant impacts on carbon emissions, which would affect the realization of carbon peak and carbon neutrality goals. Therefore, policymakers should pay more attention to trade rules and make efforts toward multilateral cooperation, rebuilding a new international trade rule mechanism that is accepted by all participants.

Third, government policies about carbon emissions should be associated with uncertainties in international trade rules. Compliance with international trade rules from all countries is the basis for sustainable development of the global economy. Considering the uncertainties in international trade rules, policymakers should develop environmental policies based on the international trade environment, and enhance the policy efficiency of carbon emission reduction.

There are limitations in our work. The first limitation of this study is that industry composition is neglected. Some studies depict international trade and carbon emissions based on industry composition, which is helpful for explaining which industry should be managed with stricter regulations. We developed the TRU index for the first time and did not analyze the impacts on various of industries. The second limitation of our work is that we do not calculate the amount of extra carbon emissions released by TRU. We are trying to choose multidimensional variables and collect the corresponding data for further study, which will be declared in our future work. The third limitation in our study is the scientific method in developing TRU index. We construct TRU with three keyword sets, as well as trade remedy case information, and obtain the TRU index only by averaging each item count in statistics. We have not considered constructing the index via the entropy weight method. However, all data for the item counts are processed by standardization; we will evaluate the impacts of construction methods on the TRU index in the future.

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