

Carbon intensity and policy uncertainties (EGPU, ESGUI & CPU) in sustainable development for China^{a,*} Serdar Ongan, ^b İlyas Kays İmamoğlu, ^c Buket Aydın^a, Faculty of Economics, University of West Bohemia in Pilsen, Czech Republic, ^b, Vocational School of Social Sciences, Bayburt University, Bayburt, Türkiye, ^c, Department of Economics, Faculty of Economics and Administrative Sciences, Atatürk University, Erzurum, Türkiye**ARTICLE INFO****Keywords:**Sustainability uncertainty (ESGUI)
Environmental governance policy
uncertainty (EGPU)
Climate policy uncertainty (CPU)
Renewable energy
Carbon intensity
China**ABSTRACT**

Reducing carbon emissions is crucial for achieving sustainable development goals (SDGs). However, existing literature primarily examines carbon intensity through technical and economic factors, while the influence of policy and governance uncertainties is often overlooked. This research aims to examine the effects of three different uncertainty indicators—climate policy uncertainty (CPU), newly created sustainability uncertainty (ESGUI), and environmental governance policy uncertainty (EGPU) indices —and renewable energy generation (REN) on carbon intensity in the case of China. Fourier ARDL and Fourier Toda-Yamamoto methods are applied with quarterly data for 2015Q1–2023Q4. The findings reveal that EGPU increases carbon intensity, while CPU, ESGUI, and REN have a decreasing effect. The increasing impact of EGPU indicates that environmental policies may be rendered ineffective due to institutional weaknesses and implementation uncertainties. These results show that carbon intensity is directly related not only to energy policies but also to the quality of governance and the nature of policy uncertainties.

1. Introduction

In recent years, combating climate change, environmental degradation, and carbon emissions have become central to the global policy agenda (İşık, 2026). Especially in rapidly industrializing countries such as China, reducing carbon emissions-intensity has become a critical priority in achieving sustainable development goals (IEA, 2021; Wu et al., 2024; Wu, 2024). In this context, not only energy supply policies but also the stability of these policies and the uncertainties related to governance processes substantially impact environmental indicators.

In this context, our study offers a unique approach by addressing the multidimensional effects of energy supply policies and their continuity and administrative uncertainties on environmental performance.

This research seeks to answer the following fundamental research question:

RQ: How and in what direction do different dimensions of policy uncertainty (climate, sustainability, and governance) affect carbon intensity?

This study presents a holistic approach that evaluates the factors affecting China's carbon intensity not only from the perspective of energy production but also from the perspective of policy uncertainty and sustainability. Although literature has mostly examined the impact of renewable energy production on environmental outputs (Girgibo, 2024), the uncertainties in environmental governance and the direct effects of fluctuations in sustainability on carbon intensity have largely been neglected. In this context, our study fills a critical research gap in both theoretical and methodological terms.

In this context, for the first time, ESGUI, EGPU, and CPU indices are addressed holistically in the same model, and the effects of environmental uncertainties on carbon intensity are analyzed comparatively. In this respect, the study provides an original contribution to the literature not only at the conceptual but also at the empirical level.

The most fundamental contribution of the research is the use of two new indices – the Sustainability Uncertainty Index (ESGUI) developed by Ongan et al. (2025) and the Environmental Governance Policy Uncertainty (EGPU) index developed by Wu et al. (2025) – in evaluating the determinants of carbon intensity. These indices make it possible to further deepen academic and applied evaluations in related fields and allow decision-makers to develop foresight-based environmental policies. In addition, the Climate Policy Uncertainty Index (CPU), which has previously been included in the literature, was integrated into the model, and the simultaneous effects of these three uncertainty indicators were analyzed comparatively. Thus, the effects of not only the content of environmental policies but also the uncertainty levels on environmental performance were revealed.

In addition, the relative impact levels between CPU, ESGUI, and EGPU were determined, the long-term effects of these indices were analyzed with the Fourier ARDL method, and the causality relationships were analyzed with the Fourier Toda-Yamamoto test. Thus, more robust policy inferences were made by considering both nonlinear trends and structural breaks.

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Received: 15 April 2026; Received in revised form 28 July 2026; Accepted 30 July 2026

<https://doi.org/10.58251/ekonomi.1971715>

In this respect, the study provides a new uncertainty-based explanation framework to the existing literature focusing on carbon intensity and significantly contributes to environmental policy designs, especially in developing economies. The study also provides guiding suggestions for policymakers, emphasizing that environmental policies in developing countries like China should be shaped not only in terms of content but also of governance (EGPU) quality and predictability. The remainder of this paper is organized as follows: Section 2 presents a literature review, Section 3 discusses the theoretical background, and Section 4 outlines the data set and research model. Section 5 details the empirical methodology. Sections 6 and 7 include the empirical findings and discussions, respectively. Section 8 provides the conclusions and policy implications, while Section 9 addresses the study's limitations and offers suggestions for future research.

2. Literature Review

Carbon emissions are recognised as an essential determinant of pollution. The efforts of countries to reduce carbon emissions have also been the subject of academic research and have been extensively analysed in recent years. To ensure sustainable development, it becomes important to use cleaner energy combinations in energy consumption and to reduce carbon emission intensity. For this reason, it is necessary to identify the factors affecting carbon intensity when designing policies to reduce it. It is important to recognize the uncertainty of sustainability, environmental governance uncertainty, climate policy uncertainty, and the link between renewable energy and carbon intensity. Given this importance, this section focuses on China by reviewing the literature investigating the effects of sustainability uncertainty, environmental governance uncertainty, climate policy uncertainty, and renewable energy on carbon intensity.

2.1. Sustainability and Carbon Intensity

Sustainability has gained increasing importance recently and is addressed with its economic, social, and environmental dimensions. Studies linking these basic dimensions of sustainability with the environment have brought diversity to the literature. In some studies on the subject, it is concluded that economic growth, green taxation and sustainable energy transition incentives (Jabeen et al., 2025) drive CO₂ emissions (CO₂E), and economic and environmental factors affect energy efficiency and energy transition. The result that economic development reduces carbon intensity (Wang et al., 2022) shows that environmental impact can be created through sustainability policies.

In some studies on the Chinese economy about sustainability, Liu et al. (2021) concluded that changes in sustainable economic development goals led to significant reductions in the carbon emission intensity of Chinese firms. Peng and Deng (2021) found that sustainable development has greatly improved environmental quality. Zhang (2022) determined that a sustainable development policy can reduce environmental degradation. Sun and Huang (2022) pointed out that economic development in Chinese cities promotes reducing CO₂E intensity. Zhang et al. (2023) found that CO₂E reduction targets in China's long-term development plans significantly impact energy saving and CO₂E reduction. Zhang (2024a) conclude that sustainable finance in China accelerates the low-carbon energy transition. Zhang (2024b) found that ESG investments in China have an important role in net-zero CO₂E. Xie (2024) concluded that optimising ESG performance in China reduces carbon intensity.

2.2. Environmental Governance Uncertainty and Carbon Intensity

Countries endeavouring to reduce carbon emissions that negatively impact the environment have become parties to global environmental policies and put these policies into practice. Achieving the targets with these practices depends on the government's environmental governance skills. A significant body of literature has recently emerged on the environmental impacts of environmental governance policies. This means that it is necessary to focus on the impact of environmental governance uncertainties on the environment. Studies on the environmental impacts of environmental governance policies recognise that governance has a regulatory effect on environmental policies (Hunjra, 2024), reduces carbon dioxide emissions (Cui et al., 2024), and government stability is a key dynamic for reducing environmental degradation (Deng, 2023). Moreover, it is argued that environmental governance reduces consumption-based resource footprints (Wang and Razzaq, 2023), contributes to the reduction of CO₂E (Wang et al., 2024a), strengthens environmental resilience (Bakhsh et al., 2024) and significantly supports energy transition (Wu and Hussain, 2025). In addition, environmental policy stringency, environmental taxes, and environmental technological developments are reported to drive the transition to renewable energy (Niu et al., 2022). With this motivation, studies for China have revealed that government-oriented urbanisation (Liu et al., 2024), new urbanisation policy (Li et al., 2023), urban environmental governance (Zeng et al., 2023), environmental management practices (Wu, 2024) and strengthening environmental governance (Xu and Xu, 2022) in China reduce CO₂E intensity. In addition to these results, some studies have found that the intensity of environmental regulation in China (Zhang and Chen, 2022), environmental governance policy synergy (Lu et al., 2023), environmental protection fee taxation policy (Du et al., 2024) and the government's green discourse-behaviour alignment (Mu, 2025) contribute to the reduction of carbon emissions in China. Moreover, Xin (2024) emphasise that China's environmental governance will promote carbon reduction through policies integrated into household energy security.

2.3. Renewable Energy and Carbon Intensity

Today, high carbon emissions and their negative impacts on the environment still occupy the policy agenda (Rahman et al., 2022). For this reason, it is necessary to identify the factors affecting CO₂E intensity and follow the process sensitively to achieve CO₂E reduction targets (Ali, 2022). Renewable energy is recognised as one factor affecting carbon emissions and plays a critical role in the global energy transition (Shahnazi

and Dehghan Shabani, 2021; Lian, 2024).

The importance of renewable energy on CO₂E has aroused researchers' interest and has been the subject of numerous studies in the literature. In these studies, it has been revealed that renewable energy consumption reduces CO₂E in EU countries (Shahnazi and Dehghan Shabani, 2021), MINT countries (Akram vd., 2022), G7 countries (Chen et al., 2025), E7 countries (Behera et al., 2025), and BRICS economies (Amin et al., 2025). In addition to these results, Wang et al. (2024b) found that renewable energy consumption reduces the ecological footprint in G20 countries. In another study, Tauseef Hassan (2024) found that renewable energy and environmental technology facilitate GHG emission reduction in BRICS economies. In some studies focusing on renewable energy investments, Dong et al. (2023) concluded that renewable energy investments in BRICS. In studies conducted to determine the impact of renewable energy on carbon intensity, Rahman et al. (2022) found that renewable energy reduces carbon intensity in 25 developing countries, and Shu et al. (2024) in eighteen countries with high geopolitical risk.

In studies on the Chinese economy, Alam and Hossain (2024) found that using renewable energy in China reduces carbon dioxide emissions, while Ahmad (2024) found that using renewable energy has a strong destructive relationship with CO₂E. Wang (2022) determined that regional renewable energy consumption in China reduces carbon dioxide emissions. However, contrary to these results, Zheng (2021) found that renewable energy generation, Lee (2023) found that renewable energy development, and Lian (2024) found that renewable energy utilisation has a mitigating effect on CO₂E intensity. In another study, Zhang et al. (2025) found that in the Chinese provincial panel, renewable energy technology innovations suppress the synergistic effect of CO₂E, and this effect is due to upgrading the industrial structure, improving energy efficiency, and expanding the scale of production.

2.4. Climate Policy Uncertainty and Carbon Intensity

It is argued that geopolitical risks and uncertainties will increase CO₂E intensity by increasing dependence on fossil fuels (Shu et al., 2024). In studies investigating this inference, the results that economic policy uncertainty affects renewable energy consumption (Athari, 2024) and CO₂E (Hussain et al., 2025), and that energy policy uncertainty drives energy consumption (Dai et al., 2025) come to the fore. In studies focusing on the effects of climate policy uncertainty (CPU), the results that CPU affects renewable energy demand (Shang et al., 2022), renewable energy consumption (Borozan and Pirgaip, 2025), carbon trading price (Su et al., 2024), and CO₂E (Liu, 2023) stand out. In studies conducted for China, Yan and Cheung (2023) found that CPU has time-varying effects on the carbon price in China. Huo et al. (2023) pointed out that the CPU in China has different impacts according to the types of renewable energy consumption. Lin and Cheung (2024) found that the CPU has a negative impact on energy transition in China. In another study, Zhang et al. (2024c) stated that the CPU hurts regional energy transition in China and that this negative impact is manifested through green finance and energy structure channels. On the other hand, Li et al. (2025) argue that the CPU hinders structural transformation and technological innovation in China and reduces the awareness of low-carbon consumption, which will negatively affect the carbon reduction process.

3. Theoretical Background

The theoretical framework of this research is based on the *Managerial Risk Theory*, which explains decision-making behaviors in an environment of uncertainty. This approach, which was first established by Knight (1921) with the distinction between risk and uncertainty, was later associated with the unpredictability of investment decisions by Keynes (1937) and was transformed into formal models by economists such as Caballero and Pindyck (1996) in the contemporary period. According to this theory, decision-makers act more cautiously in periods of economic and political uncertainty; they tend to postpone long-term, innovative, and high-risk investments. This behavior has the potential to directly affect environmental sustainability policies. The indicators of CPU, Sustainability Uncertainty (ESGUI), and Environmental Governance Policy Uncertainty (EGPU) included in the study represent situations where predictability in environmental policies is weakened. Within the framework of *Managerial Risk Theory*, it can be expected that if such uncertainties increase, environmentally friendly energy investments will decrease, policy makers will turn to short-term and fossil-based solutions, and thus carbon intensity (COINT) will increase. In this context, the study can make an empirical contribution to *Managerial Risk Theory* in the field of environmental policy by analyzing the impact of uncertainties in terms of carbon intensity management.

4. Data Set and Research Model

The present study focuses on environmental governance policy uncertainty (EGPU), sustainability uncertainty (ESGU), climate policy uncertainty (CPU), and the impact of renewable electricity generation on carbon intensity for the period 2015Q1-2023Q4 and the sample of China. The decision to focus the study on China is predicated on several factors. Firstly, China is among the countries with the highest carbon intensity. Secondly, China's recently introduced environmental governance policy uncertainty index is calculated. The variables and their explanations in the research model created with this focus are given in Table 1.

COINT, incorporated as a dependent variable within the research model delineated in Eqn. 1, signifies carbon intensity. EGPU, one of the explanatory variables in the equation, is the Environmental Governance Policy Uncertainty Index, which is calculated on a scale ranging from 0 to 100 for the People's Republic of China. The index values, ranging from 0 to 100, indicate the degree to which environmental governance policy uncertainty increases or decreases. ESGU is an acronym for Sustainability Uncertainty, and CPU is an abbreviation for Climate Policy Uncertainty. Both indices are calculated on a scale ranging from 0 to 100. REN denotes electricity generation in TWh from renewable sources.

Furthermore, t is an acronym for 'years', β_0 is an acronym for the constant term, and ε is an acronym for the error term.

Table 1. Research Variables and Explanations

Variables	Variable Definition	Variable Description	Source
Carbon Intensity	COINT	CO ₂ intensity (gCO ₂ /kWh)	https://ember-energy.org/
Sustainability Uncertainty	ESGUI	Sustainability Uncertainty Index (0-100 scale)	Ongan et al. (2025)
Environmental Governance Policy Uncertainty	EGPU	Environmental Governance Policy Uncertainty Index (0-100 scale)	Wu et al. (2025)
Renewable Energy	REN	Electricity from renewable sources (TWh)	https://emberenergy.org/
Climate Policy Uncertainty	CPU	Climate Policy Uncertainty Index (0-100 scale)	Gavrilidis (2021)

The research model, formulated from the variables whose explanations can be found in Table 1, is expressed in Eqn. 1:

$$\text{COINT}_t = \beta_{0t} + \beta_1 \text{EGPU}_t + \beta_2 \text{ESGU}_t + \beta_3 \text{CPU}_t + \beta_4 \text{REN}_t + \varepsilon_{it} \quad (1)$$

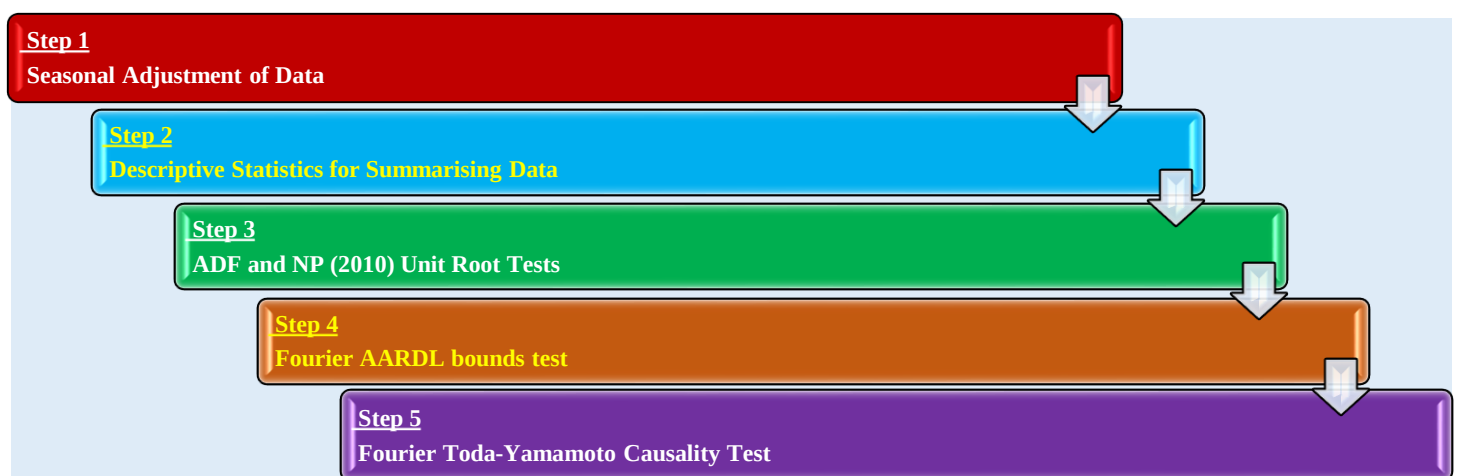


Figure 1 Econometric approach

5. Empirical Methodology

5.1. ADF and NP unit root tests

Traditional unit root tests do not investigate whether the data contain structural breaks. Therefore, data with structural breaks are considered stable, affecting the results' reliability. The literature has developed unit root tests with single and double structural breaks to investigate whether the data contain structural breaks. The first of these tests, [Perron \(1989\)](#), [Zivot and Andrews \(1992\)](#), and [Popp \(2008\)](#) are single-break unit root tests, while [Lumsdaine and Papell \(LP\) \(1997\)](#) and [Lee and Strazicich \(LS\) \(2003\)](#) are double-break unit root tests. In addition, the other test with a double break was developed by [Narayan and Popp \(NP\) \(2010\)](#). The NP (2010) test was obtained by improving the [Popp \(2008\)](#) single-break test. In the NP (2010) test, dummy variables are essential in determining the break dates. In addition, Monte Carlo simulation is used in this test to estimate the break dates in the data more robustly and consistently [\(Narayan and Popp, 2013\)](#).

5.2. Fourier augmented ARDL approach

The ARDL (Autoregressive Distributed Lag) method, developed by [Pesaran et al. \(2001\)](#), is used to analyze the long-run relationship within a model and determine its long-run coefficients. In the ARDL approach, it is assumed that the dependent variable is stationary at the I(1) level, while the independent variables can be stationary at either I(0) or I(1) levels. A notable limitation of this method is that the dependent variable must be stationary at the I(1) level. The ARDL equation can be expressed as follows:

$$\text{COINT}_t = \gamma_0 + \sum_{i=1}^n \gamma_1 \Delta \text{COINT}_{t-1} + \sum_{i=1}^m \gamma_2 \Delta \text{ESGUI}_{t-1} + \sum_{i=1}^o \gamma_3 \Delta \text{EGPU}_{t-1} + \sum_{i=1}^r \gamma_4 \Delta \text{REN}_{t-1} + \sum_{i=1}^p \gamma_5 \Delta \text{CPU}_{t-1} + \delta_1 \text{COINT}_{t-1} + \delta_2 \text{ESGUI}_{t-1} + \delta_3 \text{EGPU}_{t-1} + \delta_4 \text{REN}_{t-1} + \delta_5 \text{CPU}_{t-1} + \mu_t \quad (2)$$

In Eq. 2, γ_0 is constant terms, $\gamma_{(1,...,5)}$ is short-run coefficients, $\delta_{(1,...,5)}$ is long-run coefficients, μ_t is error terms and finally n, m, o, r and p are lag symbols. Pesaran et al. (2001) proposed two different tests, F-test ($H_0: \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$) and t test ($H_0: \delta_1 = 0$), to estimate the ARDL model. In addition, the F test ($H_0: \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$) is proposed as a third test, and the existence of cointegration is investigated with three different tests. Therefore, McNown et al. (2018) and Sam et al. (2019) developed the augmented ARDL (A-ARDL) approach. The most important innovation of the A-ARDL approach is that the condition that the dependent variable is $I(1)$, which is the constraint of the ARDL approach, is relaxed. In other words, the A-ARDL approach allows the dependent variable to be stationary at $I(0)$ and $I(1)$ levels along with the independent variables. There are two different degenerations in the A-ARDL model. The first one is when the F and t tests of the lagged independent variables are statistically significant, although the t value of the lagged dependent variable is not significant. The second is where the F and t tests of the lagged independent variables are statistically significant, although the lagged independent variables are not statistically significant. In the second case, the critical values presented by Pesaran et al. (2001) are used. However, the first case has no similar solution (Solarin, 2019). Despite its innovations, the A-ARDL method's results against structural breaks and nonlinear trends have not received adequate discussion. In particular, the reliability of the results becomes controversial when models with nonlinear trends are estimated using methods that consider only the linear trend (Kruse, 2011). Therefore, using Fourier terms in models with linear trends and structural breaks is important for the reliability of the results. Using Fourier terms gives strong performance against general and smooth transition breaks. Therefore, it does not require prior information about the break points, frequencies, and times (Enders and Lee, 2012; Tu, 2024). In this context, the FA-ARDL model obtained with the Fourier terms added to Eqns. 1 and 2 is presented below.

$$\begin{aligned} \text{COINT}_t = & \gamma_0 + \sum_{i=1}^n \gamma_1 \Delta \text{COINT}_{t-1} + \sum_{i=1}^m \gamma_2 \Delta \text{ESGUI}_{t-1} + \sum_{i=1}^o \gamma_3 \Delta \text{EGPU}_{t-1} + \sum_{i=1}^r \gamma_4 \Delta \text{REN}_{t-1} + \sum_{i=1}^p \gamma_5 \Delta \text{CPU}_{t-1} + \delta_1 \text{COINT}_{t-1} + \delta_2 \text{ESGUI}_{t-1} \\ & + \delta_3 \text{EGPU}_{t-1} + \delta_4 \text{REN}_{t-1} + \delta_5 \text{CPU}_{t-1} + \delta_6 \sin\left(\frac{2\pi kt}{T}\right) + \delta_7 \cos\left(\frac{2\pi kt}{T}\right) + \mu_t \end{aligned} \quad (3)$$

The terms δ_6 and δ_7 in Eqn. 3 represent the coefficients of the Fourier functions. In addition, k represents the Fourier frequency, T represents the sample size, and t represents the trend, while the π term is 3.14.

5.3. Fourier Toda-Yamamoto causality test approach

The Granger causality test proposed by Toda and Yamamoto (TY) (1995) is based on the VAR ($p+d_{\max}$) model, which is constructed using the lag length of p and the highest integration of d . The VAR($p+d_{\max}$) model is presented in Eqn. 4. In this equation, a denotes the constant term, the coefficient matrices, the dependent variable, and the error term. The constraint in the equation is $H_0: \beta_1 = \dots = \beta_p = 0$. The Wald statistic is used to test this hypothesis (Nazlioglu et al. 2016).

$$y_t = a + \beta_1 y_{t-1} + \dots + \beta_{p+d} y_{t-(p+d)} + \varepsilon_t \quad (4)$$

The TY causality test can be used for series with different levels of stationarity. This feature is an important advantage. However, this test does not provide information about the number, timing, and form of structural breaks. Not taking structural breaks into account in the VAR model can result in wrongly rejecting the null hypothesis in the Granger causality test (Nazlioglu et al., 2016). Therefore, findings obtained from Granger causality tests conducted without considering structural breaks may be questionable. Nazlioglu et al. (2016) added Fourier terms to the TY causality test in their studies. Therefore, they use the Fourier TY test as a robust estimator against structural breaks in the series. In the Fourier TY test, if the explanatory variables cause dependent variables, the null hypothesis is rejected, and the alternative hypothesis is accepted. The equation of the Fourier TY causality test is presented below.

$$y_t = a(t) + \beta_1 y_{t-1} + \dots + \beta_{p+d} y_{t-(p+d)} + \varphi_1 \sin\left(\frac{2\pi kt}{T}\right) + \varphi_2 \cos\left(\frac{2\pi kt}{T}\right) + \varepsilon_t \quad (5)$$

6. Empirical Findings

6.1. Historical trends and statistical values of data

In time series analysis, the graphs and statistical values of the series should be analyzed first. This approach enables a more accurate investigation of the series' unit root process. Time series frequently exhibit seasonal and cyclical movements, particularly monthly and quarterly. In seasonal series, consecutive periods have a high degree of similarity. However, conjunctural series are irregular in nature and have a non-periodic structure. Examining the graphs of the series used in this study reveals seasonal effects in COINT and REN (Appendix, Figure 1). Therefore, the seasonal adjustment of the COINT and REN series was performed using the Census X-12 method. The ESGUI and CPU series graphs show a conjunctural structure. Finally, it is observed that the EGPU series shows an increasing trend until 2022 but a decreasing trend in the subsequent periods (Figure 2). After seasonal adjustments were made to the series, descriptive statistics are presented. According to descriptive statistics, the series with the highest averages are COINT, CPU, REN, ESGUI, and EGPU, in that order. On the other hand, when looking at the standard deviations of the series, ESGUI and EGPU have the lowest values. The standard deviations of EGUSI and EGPU are 10.233 and

5.467, respectively. According to the skewness and kurtosis coefficients of the series, COINT, EGPU, and REN series are right-skewed, while ESGUI and CPU series are left-skewed. Kurtosis coefficients indicate that all series exhibit a kurtic distribution relative to the normal distribution. According to the probability value of the Jarque-Bera test, all series are statistically insignificant. Therefore, it is understood that the series has a normal distribution (Table 2).

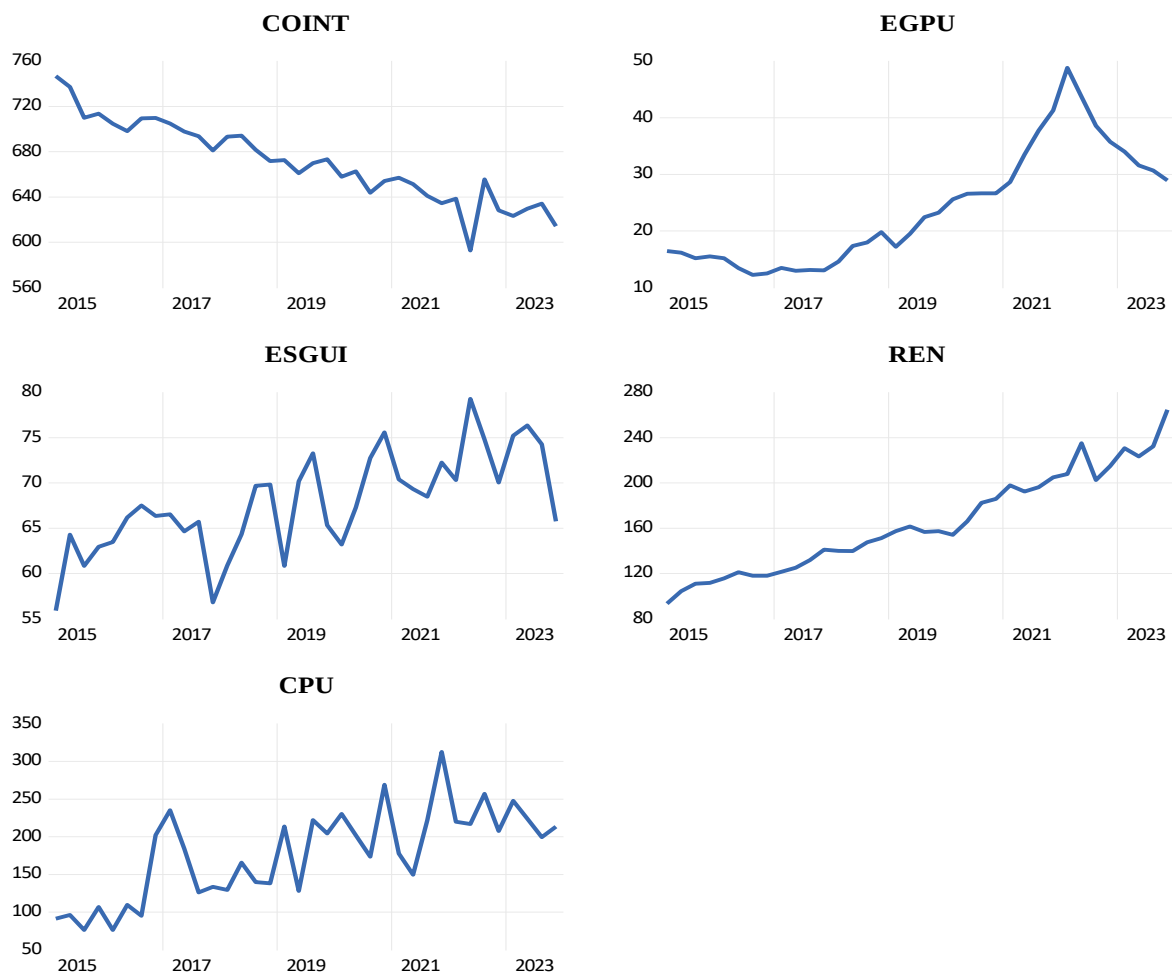


Figure 2 Historical trend of variables

Some of the series that follow a normal distribution have high standard deviations. Logarithmic transformation has been used to adjust the standard deviations. As a result of the logarithmic transformation, the standard deviations of the series are distributed between 0 and 1. Thus, after investigating the seasonality and statistical information of the series, it is understood that they are suitable for econometric analysis. In the next section of the study, we conduct tests to investigate the unit root processes of the series, considering the normality of the data.

Table 2. Descriptive statistics.

	COINT	EGPU	ESGUI	REN	CPU
Mean	670.665	23.884	67.803	164.341	177.665
Median	670.778	21.104	67.401	157.047	191.916
Maximum	746.839	48.829	79.285	264.753	312.433
Minimum	592.840	12.215	55.892	93.284	76.161
Std. Dev.	35.452	10.233	5.467	44.278	59.424
Skewness	0.035	0.687	-0.071	0.378	-0.018
Kurtosis	2.468	2.414	2.606	2.131	2.209
Jarque-Bera	0.431	3.348	0.262	1.992	0.939
Probability	0.805	0.187	0.876	0.369	0.625
Observations	36	36	36	36	36

6.2. Outcomes from unit root test

The study investigated the unit root processes of the series using multiple tests. The suspicion of structural breaks in the series motivates the

use of various tests. This is because the study series covers the period from 2015Q1 to 2023Q4. During the relevant periods, events such as economic tensions between China and the United States, global developments aimed at reducing carbon emissions, and the effects of the COVID-19 pandemic occurred, which could have caused conjunctural fluctuations. For this reason, the unit root processes of the study's series were investigated using the ADF test and the double-break NP test. According to the ADF unit root test results, the COINT, ESGUI, and REN series are stationary at the first difference, while the EGPU and CPU series are stationary at their level values. Based on the NP unit root test results, the series are stationary in the constant model. According to the trend model, only the ESGUI series is stationary in the first difference. The NP unit root test has also identified structural breaks in the series (Table 3). The unit root test highlights three crucial points. First, the COINT series used as the dependent variable is stationary in the first difference in the fixed model. However, it is stationary at the level in the trend model. Second, the explanatory variables are stationary at different levels, such as $I(0)$ and $I(1)$. Third, the series has structural breaks. When the dependent and explanatory variables used in model estimations are stationary at different levels ($I(0)$ and $I(1)$), the AARDL method should be used. Methods incorporating Fourier terms should be employed when the series exhibits structural breaks. Therefore, this study prefers the Fourier AARDL (FA-ARDL) method for estimating the model under investigation. Additionally, the method chosen to investigate the causality relationship between the series should be an estimator resistant to different levels of stationarity and structural breaks. Therefore, the causality relationship between the series is investigated using the Fourier Toda-Yamamoto causality test.

Table 3. ADF and NP unit root tests.

Variable	ADF		NP			
	ADF _c	ADF _{c+t}	NP _c	breaks _c	NP _{c+t}	breaks _{c+t}
COINT	-0.323	-4.074**	-5.555***	2017Q3-2020Q3	-7.377***	2019Q1-2020Q1
ΔCOINT	-3.008**	-	-	-	-	-
ESGUI	-0.626	-1.347	-4.408*	2018Q4-2020Q3	-4.127	-
ΔESGUI	-3.812***	-3.744**	-	-	-5.114*	2017Q4-2018Q4
EGPU	-3.601**	-4.427***	-5.249**	2018Q1-2020Q2	-5.112*	2018Q3-2020Q1
REN	-0.707	-4.971***	-4.686**	2019Q3-202Q1	-21.383***	2019Q3-2020Q3
ΔREN	-7.235***	-	-	-	-	-
CPU	-2.815*	-4.406***	-6.419***	2019Q1-2019Q3	-5.770**	2018Q4-2019Q3

Note: NP (2010) unit root test represents the two-break unit root test developed by Narayan and Pop (2010). ADF_c and ADF_{c+t} denote fixed and fixed-trend models, respectively. NP_c and NP_{c+t} denote fixed and fixed-trend models, respectively. breaks_c and breaks_{c+t} represent the double break dates in the fixed and fixed-trend model, respectively. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively. Δ, symbol represents the first difference of the variables.

6.3. Estimates from FA-ARDL approach

The variables used in the study were found to be stationary at different levels, such as $I(0)$ and $I(1)$, and were determined to have structural breaks. Therefore, the study investigates whether there is a cointegration relationship in the models under examination and subsequently estimates the long-term relationship using the FA-ARDL approach. In this context, the cointegration test results obtained from the FA-ARDL model are first examined. All three tests indicating cointegration must be statistically significant for the cointegration test to be comprehensive. According to the findings obtained from Table 4, the probability values of all three cointegration tests are statistically significant. (Table 4). Therefore, it is understood that there is a long-term relationship between the variables. For this reason, the analysis further investigates the direction of long-term effects between the dependent and explanatory variables.

After determining the existence of cointegration, the relationship's direction between the series is investigated. Table 5 displays the long-term outcomes of the FA-ARDL method. Table 5 consists of three different sections. The first section presents the long-term results. The second section contains error correction and Fourier terms results. The third section reports the diagnostic test results. According to the first section, which includes the long-term findings, all series statistically explain the dependent variable. In this context, the ESGUI, REN, and CPU series coefficients are negative, and a 1% increase in the series decreases the dependent variable by 0.018%, 0.147%, and 0.015%, respectively. On the other hand, the coefficient of the EGPU series is positive. Accordingly, a 1% increase in the EGPU series increases the COINT series by 0.035%. According to the findings obtained from Panel B, the Fourier terms are statistically significant. In addition, the error term is statistically

Table 4. Cointegration tests.

Test	Test Statistics	Critical Values		
		%1	%5	%10
F _{overall}	13.751***	6.25	4.54	3.83
tpv	-7.454***	5.06	4.01	3.52
F _{idv}	16.528***	6.39	4.54	3.76

Note: *** denotes statistical significance at 1%. Table critical values are obtained from Narayan (2005), Pesaran et al. (2001) and Sam et al (2019).

significant, as expected, and has a negative coefficient. According to the findings obtained from Panel C, no autocorrelation and heteroskedasticity problems exist in the FA-ARDL model. Furthermore, there are no model specification errors, and the residuals of the error terms follow normal distribution. Finally, the results of the CUSUM tests are presented, even though Fourier terms are present in the model. According to the CUSUM tests, there is no structural break in the model, and the model is stable (Appendix, Figure 1).

Table 5. Fourier augmented ARDL (3, 1, 1, 2, 3) estimates.

Dependent Variable: COINT		
Variable	Coefficient	P-value
Section A: Findings in the Long-run		
ESGUI	-0.018	0.000***
EGPU	0.035	0.015**
REN	-0.147	0.000***
CPU	-0.015	0.000***
Section B: Fourier and error correction terms		
$\cos(\delta_8)$	0.011	0.000***
$\sin(\delta_7)$	0.010	0.000***
ect	-1.993	0.000***
Section C: Diagnostics test results		
Ramsey Reset Test	0.241	0.812
BG LM Test	1.844	0.188
BPG Test	0.882	0.596
Jarque-Bera	2.140	0.343
Cusum Test	Stabil	
Cusum of Squares Test	Stabil	

Note: ***, ** denote significance at the 1% and 5% levels, respectively. ect term represents the error correction term. The lags of the FA-ARDL model are 3, 1, 1, 2, 3 respectively. The frequency value $k=3$ is calculated by considering the smallest Akaike information criterion (Akaike value is -6.614 for $k=1$, -6.703 for $k=2$, -7.033 for $k=3$, -5.668 for $k=4$, and -5.585 for $k=5$).

6.4. Estimates from Fourier Toda-Yamamoto causality test approach

The study found the series to be stationary at different levels ($I(0)$ and $I(1)$). Furthermore, the study identified structural breaks in the series. Therefore, the causality analysis between the series is performed using the FYT causality test, which is a method suitable for different levels of stationarity and structural breaks. The FYT test is a test based on the VAR model. Therefore, the first step involves determining the VAR model. For this purpose, the most appropriate lag length (p) is selected. Next, the degree of integration ($d_{\max}$) of the series is determined. Thus, the most appropriate lag length ($p+d_{\max}$) for the FYT test based on the VAR model is calculated.

A VAR model with 1 lag has been determined for the FYT model. However, due to the autocorrelation problem (p -value=0.038) in this model, we extended the lag to 2. When the lag value is 2, there are no autocorrelation (p -value = 0.776) and heteroskedasticity (p -value = 0.319) issues in the VAR model. Since the lag length is 2 and the integration level of the series is 1, the optimal lag length ($p+d_{\max}$) for the FYT test has been determined as 3. The findings obtained from the FYT method are presented in Table 6. The findings concluded that the ESGUI, EGPU, REN, and CPU series are Granger causes of the COINT series. Thus, the null hypothesis stating that there is no relationship between the series was rejected, and the alternative hypothesis was accepted (See the results on Figure 3 and Figure 4).

Table 6. Fourier Toda-Yamamoto causality test estimates.

Direction of causality		Null hypothesis	Wald Stat.	df	p-value
ESGUI	COINT	ESGUI does not Granger-cause COINT	23.079	3	0.000***
EGPU	COINT	EGPU does not Granger-cause COINT	9.131	3	0.027**
REN	COINT	REN does not Granger-cause COINT	26.741	3	0.000***
CPU	COINT	CPU does not Granger-cause COINT	13.724	3	0.003***

Note: ***, ** indicate significance at the 1% and 5% levels, respectively. The frequency value $k=3$ is calculated by considering the smallest Akaike information criterion (Akaike value is -14.262 for $k=1$, -13.982 for $k=2$, -14.543 for $k=3$, -14.213 for $k=4$, and -13.702 for $k=5$).

7. Discussion

This study analyzes the main determinants affecting carbon intensity in the Chinese economy—sustainability uncertainty (ESGUI), environmental governance uncertainty (EGPU), renewable energy use (REN), and climate policy uncertainty (CPU)—through Fourier incremental ARDL and Fourier Toda-Yamamoto causality test. The empirical results show that these variables have significant long-term effects

on carbon intensity (COINT), which is consistent with many studies in the literature. First, the link between sustainability uncertainty (ESGUI) and carbon intensity is negative. This finding indirectly supports the results of studies such as Liu et al. (2021), Zhang (2022, 2023, 2024b), Peng and Deng (2021), and Xie (2024). This is indirect because the ESGUI variable is a newly developed index in the literature. The ESGUI variable represents the level of uncertainty felt by market and policy actors regarding sustainability policies. The findings reveal that as this uncertainty decreases, carbon intensity also decreases. Formulating sustainable development goals clearly, reliably, and widely applicable facilitates firms' orientation toward long-term low-carbon strategies.

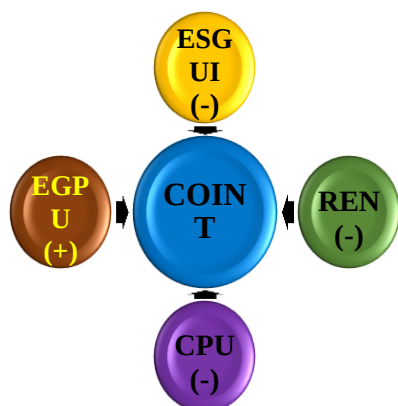


Figure 3 Results of the FA-ARDL Model

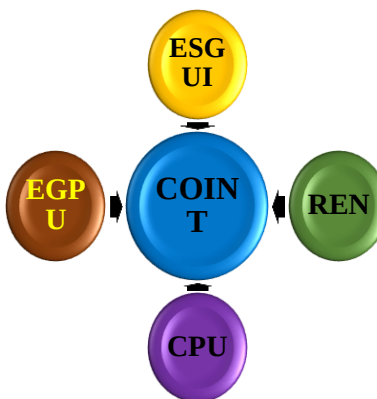


Figure 4 Results of the Fourier Toda-Yamamoto Causality Test

Secondly, a positive relationship was found between the newly developed environmental governance uncertainty (EGPU) index variable and carbon intensity. This result shows that instability and administrative uncertainty in environmental policy implementations negatively affect environmental performance. This finding indirectly confirms that governance capacity and the effectiveness of environmental policies play a critical role in reducing carbon emissions, as indicated by studies such as Cui et al. (2024), Deng et al. (2023), Wu (2024), and Lu et al. (2023). When EG uncertainty increases, firms' tendency to postpone or cancel environmentally friendly investments increases.

Thirdly, it has been observed that there is a strong and negative relationship between renewable energy use (REN) and carbon intensity. This finding is in line with studies such as Shahnazi and Dehghan Shabani (2021), Ahmad et al. (2024), Behera et al. (2025) and Zhang et al. (2025). Renewable energy use reduces emissions and carbon intensity by lowering energy efficiency and the carbon footprint of production. In the case of China, it is understood that renewable energy investments and technology development processes support low-carbon growth by transforming the industrial structure.

Finally, the negative effect of the climate policy uncertainty (CPU) variable on carbon intensity is in line with researches such as Shang et al. (2022), Zhang et al. (2024c) and Lin and Cheung (2024). CPU reflects uncertainties about the future of climate policies. The findings show that reducing such uncertainties also reduces carbon intensity. This situation reveals that the predictability and continuity of climate policies are determinants in energy transition processes and mobilization of green finance. According to the Fourier Toda-Yamamoto causality test, ESGUI, EGPU, REN, and CPU series all explain carbon intensity with Granger causality. These results show that not only technical and technological elements but also policy uncertainties and governance quality should be considered when developing strategies to reduce carbon intensity.

8. Conclusions and Policy Implications

This research purposes to analyze the determinants of carbon intensity in the context of environmental sustainability, which is becoming increasingly critical globally. Especially in large economies such as China, which are in the process of industrialization, not only the content of environmental policies but also the continuity and uncertainty level of these policies play a decisive role in environmental performance. In this context, the study evaluates three different policy uncertainty indicators, the effects of which have not yet been sufficiently examined in literature, in the context of a holistic model for the first time. In this respect, the study significantly contributes to environmental economics and policy literature at both conceptual and applied levels.

In the study, Chinese data for the period 2015Q1–2023Q4 were used; considering the structural breaks and nonlinear trends in the time series, long-term relationships were analyzed with the Fourier ARDL (FA-ARDL) method, and the causality direction was analyzed with the Fourier Toda-Yamamoto (FTY) test. As a result of the empirical analyses, significant effects of the variables on carbon intensity were determined. According to the FA-ARDL findings, it was observed that renewable energy production (REN), sustainability uncertainty (ESGUI), and climate policy uncertainty (CPU) had a decreasing effect on carbon intensity, while environmental governance policy uncertainty (EGPU) had an increasing impact. In addition, the Granger causality of all independent variables on the COINT variable was found to be statistically significant.

The increasing effect of the EGPU index on carbon intensity can be interpreted as an indication of institutional and administrative challenges in implementing consistent environmental regulations. In particular, this finding may reflect the role of weaker governance capacity in limiting the effectiveness of environmental policies. According to the Worldwide Governance Indicators (WGI), China consistently scores lower in

“government effectiveness” percentiles with 73 in 2023 (World Bank, 2025) than developed economies, implying a relative deficiency in policy implementation, regulatory quality, and bureaucratic efficiency. As a result, elevated levels of environmental governance uncertainty may discourage long-term green investments, reduce regulatory compliance, and ultimately increase carbon intensity.

In line with these findings, variable-based policy implications are as follows:

EGPU (Environmental Governance Policy Uncertainty): The stability of environmental policies and the transparency of governance processes are critical to reducing carbon intensity. Therefore, policymakers need to make environmental regulations more predictable, accountable, and institutionally based.

ESGUI (Sustainability Uncertainty): Reducing uncertainty in sustainability policies reduces carbon intensity. This situation reveals the necessity of constructing sustainability policies in a clear, consistent, and long-term manner to create a trust environment in the markets and encourage environmental investments.

CPU (Climate Policy Uncertainty): Interestingly, the carbon intensity-reducing effect of climate policy uncertainty has been observed. This situation shows that policymakers may have turned to more protective and environmental practices during periods of uncertainty. However, this finding must be tested comparatively with different periods and country practices.

REN (Renewable Energy): The negative impact of renewable energy production on COINT demonstrates the capacity of these sources to reduce carbon emissions. Therefore, it is necessary to increase incentives for renewable energy in developing countries such as China, support infrastructure investments, and accelerate technological developments in this area.

As a result, this study sheds light on the multidimensional structure of environmental performance by considering carbon intensity not only with technical energy variables but also with policy and governance uncertainties. In this respect, it reveals how critical policy designs to manage uncertainties are for countries that want to achieve sustainable development goals.

9. Study Limitations and Future Research Suggestions

This research developed a model that includes three China-specific policy uncertainty indices (CPU, ESGUI, EGPU) and renewable energy production to analyze the determinants of carbon intensity. However, some limitations should be noted. First, the study focuses on only one country (China), and the findings cannot be generalized to other developing or developed countries. In addition, uncertainty indices such as EGPU, ESGUI, and CPU are synthetic indicators compiled under certain assumptions, and measurement error or indicator coverage limits may affect the study results.

There are several important areas for further research. First, extending the study to multi-country panel data analyses would enable us to see how the impact of uncertainties varies across countries with different governance structures. Second, adding macroeconomic control variables (e.g., industrial production, exchange rates, energy prices) to the model would enable more holistic analyses. Furthermore, institutional and societal factors such as governance quality, regulatory intensity, or environmental awareness could be integrated into the model to deepen uncertainty-index-based analyses.

Declaration: No conflict of interest exists in the submission of this manuscript

Availability of data and material: Data will be made available on reasonable request

Competing interests: The author declare that they have no competing interests

Funding: Not applicable

Acknowledgements: Not applicable

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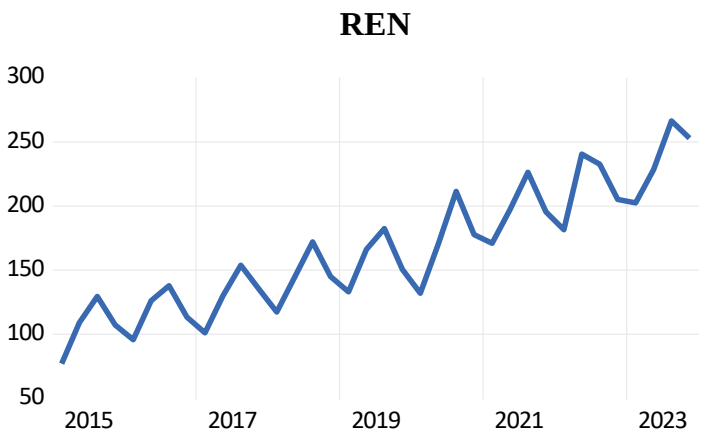
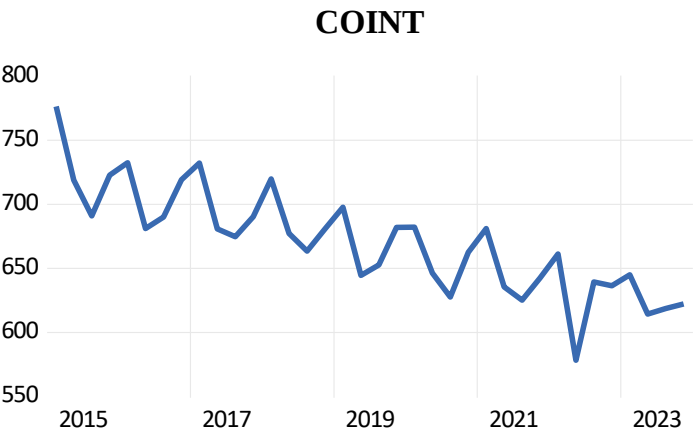
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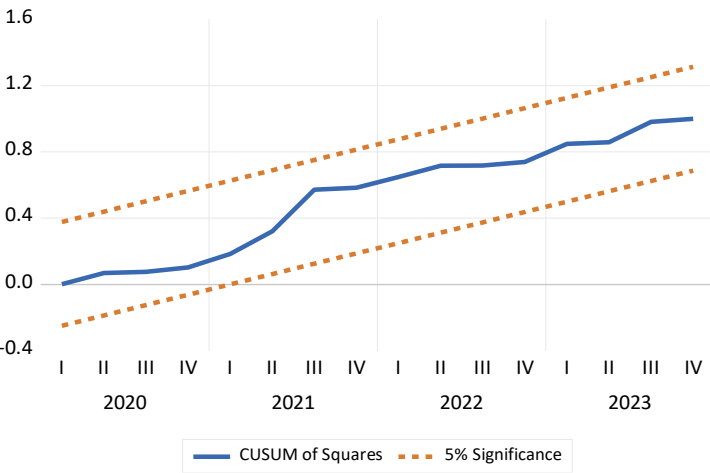
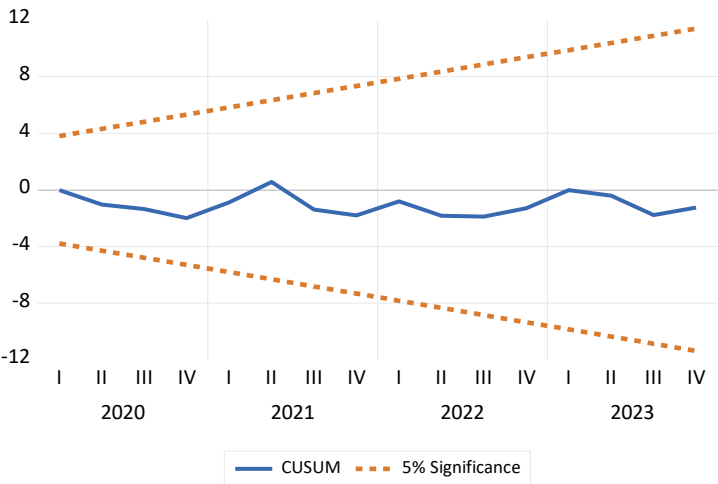
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Appendix Graph 1



Appendix Figure 1