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Effects of Green Quality of Energy Mix and Financial Development on Load Capacity Factor in China: A Novel Rolling Window Kernel-based Regularized Least Square Approach

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Abstract

Amidst ongoing global worries over climate change and its ecological ramifications amidst rapid economic growth, the United Nations has set forth a comprehensive agenda known as the Sustainable Development Goals (SDGs), aiming to achieve them by 2030. These goals are tailored to foster sustainable socio-economic progress while enhancing the quality of the global environment. Therefore, this study explores the connections between load capacity factor, green quality of energy mix, financial development, economic growth and

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natural resources in alignment with SDGs 7, 11, 13 and 12, focusing on China from 1981 to 2021. The study introduces the rolling window kernel-based regularized least squares (RWKRLS) method to assess the interrelationship. The RWKRLS analysis exposes that a green quality of energy mix and financial development positively influence ecological quality. Furthermore, natural resource consumption and economic growth affect ecological quality negatively. Drawing on these critical time-varying interrelationships, a set of interactive policies aligned with the SDGs is proposed, specifically tailored to address China's unique context.

Keywords: Green quality of energy mix, load capacity factor, financial development, natural resources, economic growth, rolling window KRLS

JEL Classification: Q40, Q43, Q56, C22

1. Introduction

Climate change poses significant challenges for China, affecting ecosystems, air quality and economic stability. As the largest emitter of carbon dioxide globally, China is taking ambitious steps to combat climate change with a strong commitment to carbon neutrality by 2060. The country ratified the Paris Agreement in September 2016, aligning itself with global objectives to limit global temperature rise to below 2 °C compared to pre-industrial levels (UNFCCC, 2015). To achieve its goals, China aims to peak carbon emissions before 2030 and has accelerated its transition towards renewable energy, currently contributing more than 30% of the world's total installed renewable power capacity (IEA, 2023). Additionally, China plans to reduce its carbon intensity by over 65% from 2005 levels by 2030 (NDRC, 2022). The commitment to carbon neutrality and substantial investment in renewable energy demonstrate China's active role in addressing the climate crisis and meeting its obligations under the COP21 agreement.

The green quality of energy mix (*GQEM*) affects ecological quality by reducing greenhouse gas emissions through renewable energy use while also potentially causing short-term ecological disruptions due to land use and habitat alteration. On the positive side, the *GQEM* enhances ecological quality by promoting the adoption of renewable energy sources, which significantly reduce greenhouse gas emissions and environmental degradation (Lau *et al.*, 2023). By decreasing reliance on fossil fuels and transitioning towards cleaner energy sources such as wind, solar and hydropower, the *GQEM* contributes to a reduction in carbon footprints and the conservation of biodiversity (Eweade *et al.*, 2023; Lau *et al.*, 2023). However, the transition towards a greener energy mix may also have adverse effects, particularly in the short term, such as increased land use for renewable energy installations and the potential disruption of natural habitats (Amin *et al.*, 2023). These trade-offs between the benefits of reduced emissions and the ecological costs of expanding renewable infrastructure present a complex challenge in balancing the overall impact of the *GQEM* on ecological quality.

Financial development plays a critical role in influencing ecological quality, as it can either promote sustainable practices through green investments or contribute to environmental degradation depending on the structure and focus of financial policies (Zhang *et al.*, 2024). Several studies have argued that financial development positively contributes to ecological quality by facilitating investments in green technologies, renewable energy and environmentally-friendly projects, which collectively help in reducing pollution and improving environmental sustainability (Abbasi and Riaz, 2016; Al-Mulali *et al.*, 2015). Well-developed financial systems can mobilize resources efficiently, support green innovation and incentivize sustainable practices, thereby contributing to ecological conservation (Abbasi and Riaz, 2016; Achuo *et al.*, 2024; Ozkan, Usman, *et al.*, 2024). Conversely, other studies suggest that financial development can negatively affect ecological quality due to its potential to drive industrial expansion, increase energy consumption and support activities that exploit natural resources unsustainably, leading to increased environmental degradation (Adams and Kaffo Fotio, 2024; Bashir *et al.*, 2022). This negative impact is often observed in cases where financial institutions prioritize profit over environmental considerations, resulting in unchecked industrial growth and associated ecological harm (Al-Mulali *et al.*, 2015). These contrasting findings highlight the importance of the policy environment in determining the overall effect of financial development on ecological quality.

The effect of natural resources on ecological quality has been a subject of considerable debate, with studies showing both positive and negative impacts. On the one hand, natural resources can contribute to ecological quality through the provision of ecosystem services, such as carbon sequestration, soil preservation and biodiversity conservation, which help maintain environmental balance (Badeeb *et al.*, 2020; Ozkan, Eweade, *et al.*, 2024). The sustainable use of natural resources, including renewable energy sources, has been associated with improved ecological outcomes, fostering sustainable economic growth while preserving environmental quality (Caglar *et al.*, 2022; Danish *et al.*, 2019). On the other hand, excessive exploitation of natural resources, such as deforestation, overfishing and fossil fuel extraction, can lead to significant environmental degradation, including loss of biodiversity, soil erosion and increased greenhouse gas emissions (Gerelmaa and Kotani, 2016; Usman *et al.*, 2024). This overuse not only reduces ecological quality but also accelerates climate change and disrupts the natural cycles vital for maintaining ecological balance (Aladejare, 2022; Danish *et al.*, 2019).

Based on the above information, this study explores the drivers of ecological quality in China by addressing the following questions:

a) Does green quality of energy mix influence China's load capacity factor over time?

b) What is the effect of financial development on load capacity factor in China?

c) Do natural resources affect the load capacity factor?

This research contributes to the existing literature in several ways. Firstly, it pioneers the investigation of the impact of the green quality of energy mix (*GQEM*) on ecological quality, using the load capacity factor (*LF*) as a proxy. Notably, the *LF* serves as a more comprehensive measure of ecological quality as it captures both the supply and demand sides of environmental factors, unlike other ecological proxies such as CO_2 emissions, greenhouse gas emissions or ecological footprint. Secondly, the study examines the time-varying impact of the independent variables on the dependent variable by introducing the rolling window kernel-based regularized least squares (RWKRLS) method. The RWKRLS approach effectively analyses the influence of independent variables on ecological quality, capturing dynamic relationships over time and allowing the identification of temporal variations in these effects.

The rest of the paper is organized as follows: Section 2 reviews prior studies. Section 3 details data and econometric methods. Section 4 presents empirical results. Lastly, Section 5 offers policy insights and suggests future research directions.

2. Literature Review

Achieving climate change reduction goals is of paramount importance for every country. However, this objective has become increasingly challenging. The pro-growth agendas of many countries are creating obstacles to achieving these goals. While numerous scholars (Eweade *et al.*, 2022; Ozkan, Eweade, *et al.*, 2024; Pata *et al.*, 2023) have explored the drivers of ecological quality, the resulting mixed findings make it difficult to establish unified policy directions. For instance, Khan *et al.* (2020) utilized a simultaneous modelling technique to scrutinize the relationship between natural resources (NAR) and CO_2 emissions in the case of BRI countries. The study results showed that NAR contribute to the surge in CO_2 emissions. Similarly, Danish *et al.* (2019) investigated drivers of CO_2 emissions within the framework of BRICS countries. The study used data covering the period from 1990 to 2015. The study employed the AMG and the results showed that NAR affects CO_2 positively. Furthermore, Danish *et al.* (2023) examined the nexus between natural resources and CO_2 emissions. The research utilized both dynamic ARDL and KRLS algorithm methods. The results revealed that a surge in NAR fosters an increase in CO_2.

Significant studies have documented the nexus between economic growth and ecological quality. For instance, Akadiri *et al.* (2022) found a short-term positive correlation between economic growth and the load capacity factor in India. Khan *et al.* (2022) scrutinized the dynamics within G7 and E7 countries regarding *LF* drivers. They observed a reduction in the *LF* as economic growth increased. In a comparable study, Awosusi *et al.* (2022) used the South African scenario to assess how growth affected ecological quality from 1980 to 2017. The study results showed a negative relationship between the *LF* and economic growth.

Few studies have been conducted regarding the green quality of energy mix (*GQEM*) and its effect on ecological quality. For instance, Lau *et al.* (2023) explored how the *GQEM* affects CO_2. The authors utilized a panel dataset spanning 36 OECD countries between 1970 and 2021. The study outcome showed that the *GQEM* affects CO_2 negatively. Similarly, employing a dataset between 1970 and 2021, Lau *et al.* (2023b) explored the effect of the *GQEM* on CO_2 emissions in the United States. The authors used the ARDL approach in examining this connection, with the results showing a significant connection between the *GQEM* and ecological deterioration. Another area of debate is how financial development (*FD*) affects CO_2 emissions. For instance, Wang, Hu and Li (2024) used data from 92 countries to explore the impact of *FD* on CO_2. The authors used 92 countries and the findings showed a positive/negative impact on CO_2. In another investigation by Farooq *et al.* (2024), using the GCC economies for the years 2000–2019, the authors found that the surge in CO_2 is attributed to the rise in *FD*.

After a careful evaluation of the above studies, it is evident that there is a significant body of research exploring the drivers of ecological quality and degradation, primarily focusing on either individual countries or groups of countries. Most of these studies rely on time-domain, frequency-based and quantile-based approaches. Furthermore, there is limited research on the impact of the green quality of energy mix on ecological quality, indicating a notable gap that warrants further investigation. Additionally, no study has been found examining the time-varying association in this context. Therefore, based on this gap, we introduced rolling window kernel-based regularized least squares (RWKRLS). The RWKRLS method is effective in examining the effect of financial development, natural resources, economic growth and the *GQEM* on ecological quality as it captures the dynamic relationships over time, allowing identification of temporal variations in these effects.

3. Data and Method

3.1 Data

This research study aims to unlock the time-varying environmental effects of the green quality of energy mix (*GQEM*), financial development (*FD*), natural resources (*NR*) and economic growth (*EG*) in China utilizing an annual time-series dataset spanning from 1977 to 2021[1]. In this study, we measure the level of environmental quality by employing the load capacity factor (*LF*), which is a ratio of biocapacity (BioC) to the ecological footprint (EcoFP). Furthermore, the *GQEM* is an index propounded by Lau *et al.* (2023a) as a new measure of energy transition. By following Lau *et al.* (2023a), we calculate the annual *GQEM* data of China for the sample period by utilizing the formula written as follows:

$$GQEM_i = \frac{1}{1.0121 \times \frac{CEU_i}{TPEU_i} + 0.9513 \times \frac{PEU_i}{TPEC_i} + 0.4107 \times \frac{NGEU_i}{TPEC_i}} \tag{1}$$

where *GQEM* represents the index value of green quality of energy mix, *CEU* denotes coal energy use, *PEU* symbolizes petroleum energy use, *NGEU* indicates natural gas energy use and *TPEU* stands for total primary energy use for the *i*-th time (Lau *et al.*, 2023a).

It is crucial to emphasize that the annual Chinese *CEU*, *PEU*, *NGEU* and *TPEU* data for the period from 1977 to 2021 are downloaded from OWD (2023). Figure 1 presents the time paths of the studied dataset and table 1 provides the details.

Table 1: Dataset details

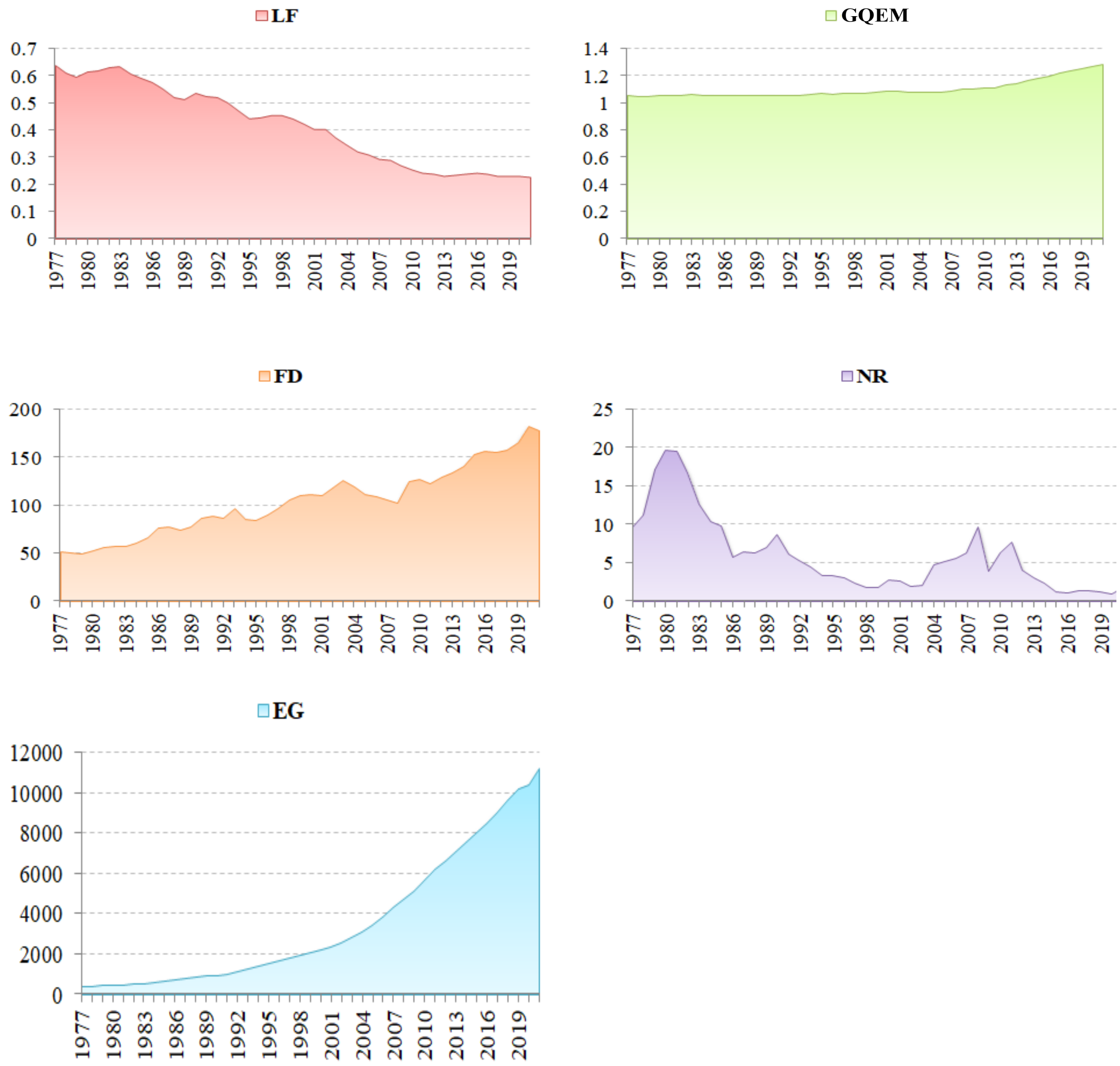
Variable	Symbol	Description	Source
Load capacity factor	*LF*	BioC/EcoFP (gha per capita)	GFN (2023)
Green quality of energy mix	*GQEM*	Index	Authors' own calculations
Financial development	*FD*	Domestic credit to private sector (% of GDP)	WB (2023)
Natural resources	*NR*	Total rents (% of GDP)	WB (2023)
Economic growth	*EG*	Per capita GDP (constant 2015 US$)	WB (2023)

Source: Authors' own elaboration

1 1977 and 2021 are dictated by the available financial development and natural resources data, respectively.

To avoid being affected by the possible effects of small sample bias, non-stationarity and heteroscedasticity, the annual dataset was first transformed into a quarter frequency by implementing the quadratic-sum method and then log-differenced (Alola *et al.*, 2023b; Balcilar *et al.*, 2023; Olanipekun *et al.*, 2023; Ozkan *et al.*, 2023b).

Figure 1: Time paths of variables



Source: Authors' own elaboration

3.2 Econometric technique

The following econometric model is designed in line with the purpose of delving into the influence of the *GQEM*, *FD*, *NR* and *EG* on the *LF* in China:

$$LF = f(GQEM, FD, NR, EG) \tag{2}$$

where *f* represents the function, *LF* stands for the load capacity factor, *GQEM* is the green quality of the energy mix, *NR* represents natural resources and *EG* denotes economic growth. In order to test this model in a time-varying manner, we introduce the rolling window kernel-based regularized least squares (RWKRLS) approach, which is a hybrid technique that combines Hainmueller and Hazlett's (2014) KRLS and the rolling window methods.

KRLS is a machine learning regression algorithm designed to address both regression and classification tasks without requiring manual specification or rigid assumptions about the functional form. Unlike traditional models, KRLS derives the functional form directly from the data, reducing the risk of misspecification bias, which is particularly beneficial in fields such as social science, where relationships between variables may not follow strict parametric patterns. It operates on the principle that similar covariate values will yield similar outcomes, allowing it to capture more nuanced patterns in the data. Additionally, KRLS incorporates a regularization feature that favours smoother functions, which helps prevent overfitting, reduce variance and mitigate the influence of outliers. This makes KRLS versatile and effective for a range of tasks, including exploratory analysis, causal inference, prediction and various regressions and classification challenges (Ferwerda *et al.*, 2017; Hainmueller and Hazlett, 2014). KRLS was selected for this study due to its flexibility in handling complex, non-linear relationships without predefined assumptions about the functional form. This capability makes it particularly suitable for analysing unpredictable and non-linear interactions, as often seen in social science and environmental studies. By allowing the model to adapt to the data, KRLS enhances the accuracy and robustness of the results. In this study, the pointwise marginal effects of the *i*-th independent variable (V^i), where V represents *GQEM*, *FN*, *NR* and *EG*, on the *LF* can be estimated by the KRLS as follows:

$$\frac{\tau\widehat{LF}}{\tau V_t^i} = \frac{-2}{\propto^2}\sum_j c_j e^{\frac{\left\|V_j - V_t\right\|^2}{\propto^2}}\left(V_j^i - V_t^i\right) \tag{3}$$

Here, t and j represent the t- and j-th observation, $e^{\frac{\left\|V_j - V_t\right\|^2}{\propto^2}}$ is the Gaussian kernel, where $||V_j - V_t||^2$ denotes the Euclidean distance among the independent variable vectors $V_j - V_t$ and α^2 symbolizes the bandwidth of the kernel function. Furthermore, the average marginal effects of the i-th independent variable V^i on the *LF* can be estimated by the KRLS as follows:

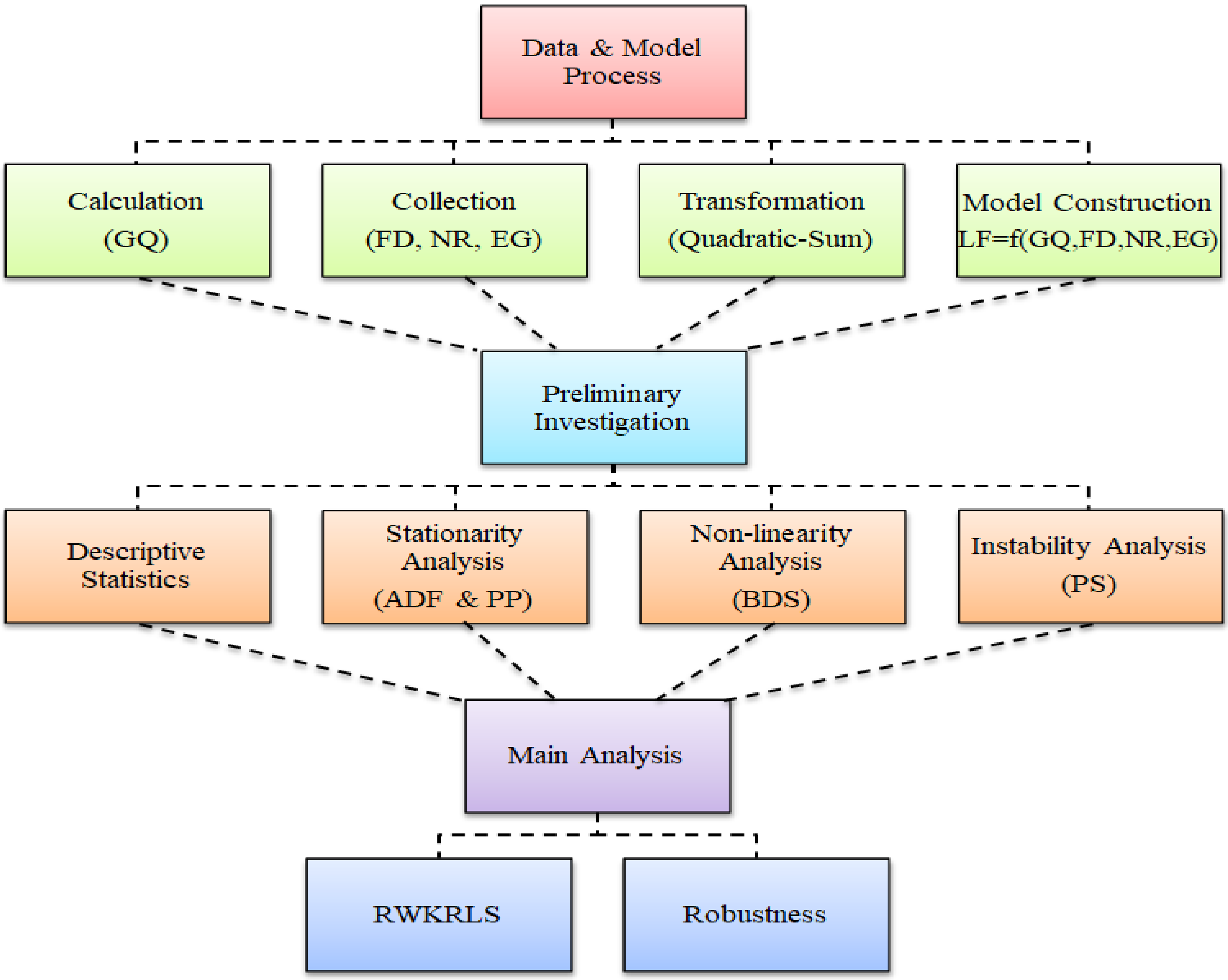
$$\frac{1}{N}\sum_{t=1}^{N}\left[\frac{\tau\widehat{LF}}{\tau V_t^i}\right] = \frac{-2}{\propto^2 N}\sum_{t}\sum_{j} c_j e^{\frac{\left\|v_j - v_t\right\|^2}{\propto^2}}\left(V_j^i - V_t^i\right) \tag{4}$$

In the application, the KRLS provides both the pointwise marginal effects plots and the average marginal effects table. In particular, in the sample period, while pointwise marginal effects plots allow practitioners to detect whether the effect of the *i*-th independent variable on the dependent variable is heterogeneous (non-linear), the average marginal effects table shows the average marginal effect of the *i*-th independent variable on the dependent variable and also demonstrates whether this effect is statistically significant.

Although pointwise marginal effects plots reveal the marginal effects of independent variables on each observation of the dependent variable, a single value indicates statistical significance, the average marginal effect. Therefore, the KRLS is insufficient to show the change in the effects of the independent variables over time and the statistical significance of these effects over periods. By examining pointwise marginal effects, the KRLS inherently focuses on the overall distribution of variables, not on their means, as in traditional linear methods. In this context, analysing the change in the relationship between variables over time with the KRLS method will take into account the non-normal distribution, non-linearity and structural changes of the variables, and thus provide robust results.

To achieve this, we develop the RWKRLS by combining the KRLS and the rolling window techniques. The RWKRLS method divides a sample period into different subsamples through windows and calculates the average marginal effects by applying KRLS to each sub-sample. With this process, the RWKRLS reveals the change in the effects of each independent variable on the dependent variable over time with statistical significance. We set the window length to 75 in order to reach a sufficient number of sub-samples within the sample period and also to ensure that the windows have a sufficient number of observations against the small sample bias. We also use window lengths of 60 and 90 in order to check the results of the window length of 75. In addition, Rahman *et al.* (2019) stated that the 10% significance level would be appropriate for the statistical inference in the sub-sample analysis as it contains a relatively small sample compared to the whole sample analysis. Thus, we determine the significance level to be 10%. Our empirical analysis framework is presented in figure 2.

Figure 2: Empirical analysis diagram



Source: Authors' own elaboration

4. Empirical Outcomes and Discussion

In this section, we elucidate the empirical findings derived from our preliminary analyses, including descriptive statistics, stationarity, non-linearity and instability analyses, as well as RWKRLS and robustness analyses, in assessing the dynamic impacts of the *GQEM*, *FD*, *NR* and *EG* on the *LF* over time in China.

4.1 Descriptive statistics

It is crucial to acquire foundational insights into the statistical properties of the dataset under consideration before proceeding with the main analysis. Some important descriptive statistics of the log-differenced quarter data series are provided in table 2. The mean results conclude that, in the studied period, the *GQEM*, *FD* and *EG* had a positive average, while the *LF* and *NR* had a negative one. The standard deviation results show that *NR* exhibited the highest volatility over the sample period, whereas the *GQEM* had the lowest one. Moreover, the skewness results indicate that the distribution of *LF*, *GQEM* and *FD* is skewed to the right and that of *NR* and *EG* is skewed to the left. Moreover, the kurtosis analysis reveals that all the variables in the dataset display heavy-tailed distributions, signified by their positive excess kurtosis values (*e.g.*, kurtosis higher than 3). The Jarque and Bera (1980) normality test results confirm the skewness and kurtosis findings, that is, the data of all the variables have a non-normal distribution in the sample period.

Table 2: Descriptive statistics

	LF	***GQEM***	***FD***	***NR***	***EG***
Mean	−0.0015	0.0003	0.0017	−0.0017	0.0049
Median	−0.0017	0.0002	0.0016	−0.0027	0.0048
Max	0.0082	0.0027	0.0287	0.1154	0.0102
Min	−0.0090	−0.0016	−0.0207	−0.1617	−0.0025
SD	0.0024	0.0006	0.0050	0.0295	0.0018
Skewness	0.3034	0.5602	0.6240	−0.2106	−0.2958
Kurtosis	4.4618	5.8717	10.5329	9.9570	4.9204
Jarque–Bera	18.6850*** (0.0001)	70.8669*** (0.0000)	434.8316*** (0.0000)	362.3033*** (0.0000)	30.1155*** (0.0000)

Note: *** denotes statistical significance at the 1% level, respectively.
Source: Authors' own calculations

4.2 Stationarity analysis

Verifying the stationarity status of the utilized data series is crucial to ensure the reliability of findings and avoid spurious outcomes. To accomplish this, two unit root tests, specifically the augmented Dickey–Fuller (ADF) test (Dickey and Fuller, 1979) and the Phillips Perron (PP) test (Phillips and Perron, 1988), are utilized in this context in order to get robust results (see Olasehinde-Williams and Özkan, 2023). Based on the ADF and PP unit root results provided in table 3, the conclusion is that the log-differenced quarter data series of the variables show stationarity, ensuring reliable findings and avoiding spurious outcomes.

Table 3: ADF & PP unit root results

	ADF		PP	
	C	*C + T*	C	*C + T*
LF	−5.493*** (0.000)	−5.486*** (0.000)	−5.547*** (0.000)	−5.527*** (0.000)
GQEM	−6.226*** (0.000)	−7.560*** (0.000)	−8.182*** (0.000)	−8.009*** (0.000)
FD	−6.919*** (0.000)	−6.902*** (0.000)	−6.120*** (0.000)	−6.089*** (0.000)
NR	−6.230*** (0.000)	−6.215*** (0.000)	−5.575*** (0.000)	−5.556*** (0.000)
EG	−4.818*** (0.000)	−4.899*** (0.000)	−4.915*** (0.000)	−4.947*** (0.000)

Note: *** denotes statistical significance at the 1% level, respectively.
Source: Authors' own calculations

4.3 Non-linearity analysis

The BDS test results (table 4) confirm non-linearity across all the variables. Non-linearities can significantly affect relationships between variables, justifying the use of the novel rolling window kernel-based regularized least squares (RWKRLS) method. This approach captures time-varying, non-linear effects, allowing a deeper understanding of how green quality of energy mix, financial development and natural resources influence the load capacity factor. By addressing these non-linear dynamics, the model ensures more accurate and robust results. The findings of the descriptive statistics show that all the data series under consideration have an asymmetric distribution, indicating non-linearity. In order to further validate the non-linearity of the data series, we employ the Broock, Dechert and Scheinkman test (BDS) (Broock *et al.*, 1996), which is the most widely used method for analysing (non) linearity (Alola *et al.*, 2023a). These outcomes also support that the data series of all the variables present non-linearity over the sample period.

Table 4: BDS results

	LF	*GQEM*	*FD*	*NR*	*EG*
2	14.398*** (0.000)	13.040*** (0.000)	11.570*** (0.000)	12.175*** (0.000)	12.231*** (0.000)
3	12.438*** (0.000)	11.363*** (0.000)	10.484*** (0.000)	11.948*** (0.000)	13.434*** (0.000)
4	8.128*** (0.000)	6.735*** (0.000)	5.762*** (0.000)	5.892*** (0.000)	6.280*** (0.000)
5	6.870*** (0.000)	5.034*** (0.000)	3.813*** (0.000)	3.829*** (0.000)	3.746*** (0.000)
6	15.702*** (0.000)	15.273*** (0.000)	14.824*** (0.000)	15.677*** (0.000)	17.021*** (0.000)

Note: *** denotes statistical significance at the 1% level, respectively.
Source: Authors' own calculations

4.4 Instability analysis

The PS test results (table 5) indicate structural breaks in the *LF*, *GQEM* and *EG* data series, suggesting time-varying relationships. If not addressed, these breaks could lead to misleading inferences in the econometric model. To mitigate this, we employ the rolling window kernel-based regularized least squares (RWKRLS) method, which captures time-varying effects by analysing smaller, rolling sub-samples. By incorporating structural breaks, RWKRLS enhances the robustness and reliability of the results, providing a more accurate representation of the dynamic relationships among the variables. Overall, the PS test results confirm the need for a time-varying method, as the *FD* and *NR* series do not exhibit structural breaks (Andrews, 1993; Andrews and Ploberger, 1994; Hansen, 1997; Lee *et al.*, 2023).

Table 5: PS results

	LF	*GQEM*	*FD*	*NR*	*EG*
Ave	4.172** (0.016)	42.362*** (0.000)	0.631 (0.545)	0.518 (0.631)	6.103*** (0.002)
Max	14.098*** (0.004)	102.395*** (0.000)	2.731 (0.612)	2.441 (0.678)	25.801*** (0.000)
Exp	4.309*** (0.002)	47.123*** (0.000)	0.372 (0.558)	0.307 (0.634)	10.177*** (0.000)

Note: ***, ** denote statistical significance at the 1%, and 5% levels, respectively.
Source: Authors' own calculations

The characteristics of the variable data series, as revealed by descriptive statistics and stationarity, BDS and PS analyses, confirm the suitability of the RWKRLS method for this study.

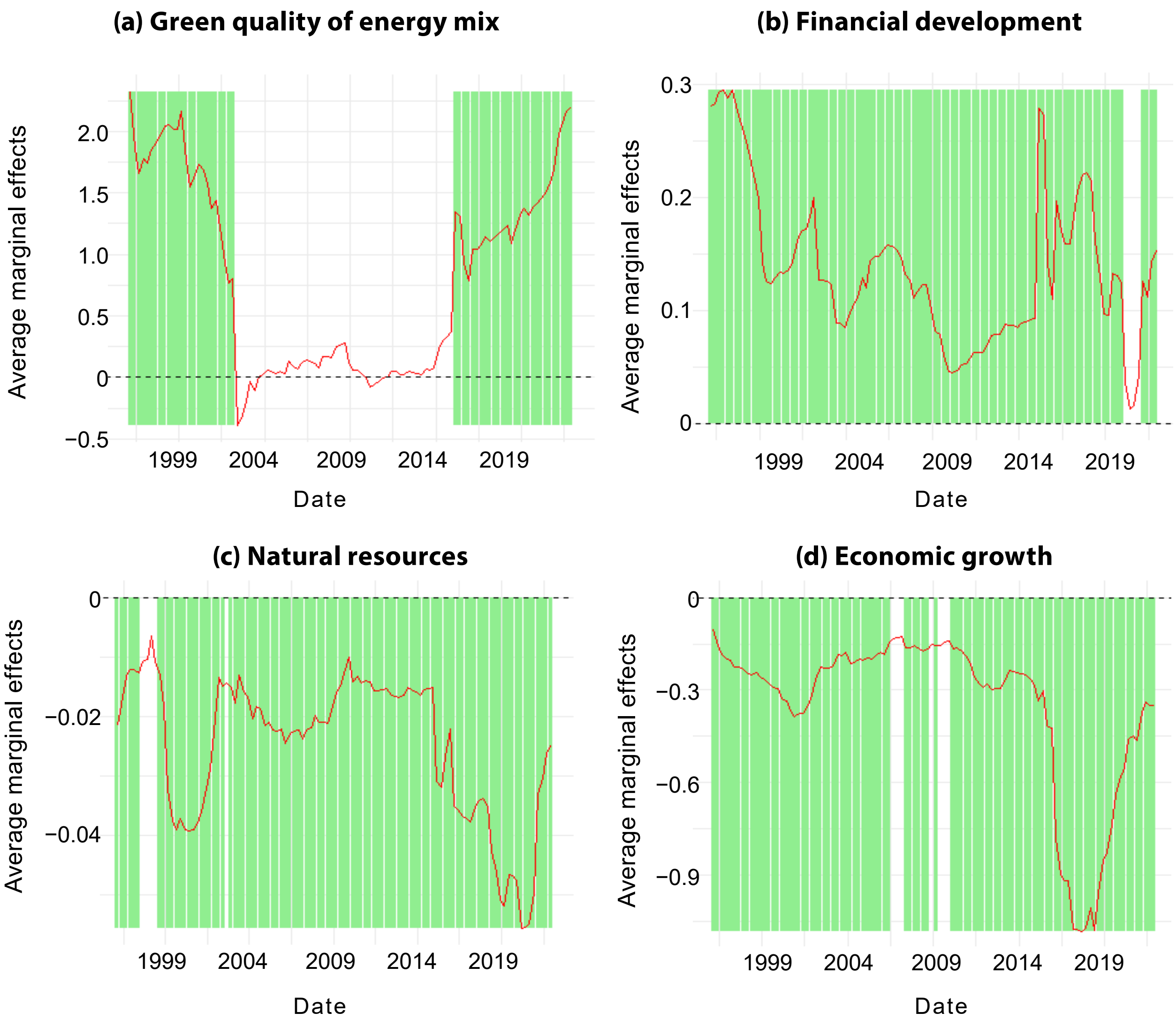
4.5 Rolling window KRLS results

Figure 3 exhibits the estimates of the RWKRLS approach based on the model *LF = f*(*GQEM, FD, NR, EG*). More specifically, Figures 3a, 3b, 3c and 3d show the average marginal effects of the *GQEM*, *FD*, *NR* and *EG* on the *LF* over the sample period, respectively, by controlling for the effects of the other remaining variables.

Figure 3a shows the impact of the green quality of energy mix (*GQEM*) on ecological quality (proxied by the load capacity factor) in China, over the period from 1995 to 2023. The red line denotes the average marginal effect of the *GQEM* on ecological quality, while the green regions highlight statistically significant periods of influence. The initial significant effect from the late 1990s to the early 2000s was characterized by a strong positive impact, implying that an improved green energy mix significantly contributed to ecological quality in these years. This was followed by a period of insignificance from around 2004 to 2013, where the effect was relatively neutral or even slightly negative, suggesting that changes in the energy mix did not have a measurable impact on ecological quality. From 2014 onwards, the impact turned significantly positive again, with a noticeable upward trend, which implies that increased adoption of renewable energy sources was effective in enhancing ecological quality. This positive impact aligns with findings of Kılıç Depren *et al.* (2022), who demonstrated that an increase in renewable energy use significantly improves environmental quality by reducing emissions. However, this trend is not universally agreed upon. Some studies, such as that by Alola *et al.* (2022), argue that an increase in renewable energy sources does not always lead to immediate improvements in ecological quality due to the intermittent nature of renewables and the challenges in integrating them into the existing energy infrastructure. The significant positive impacts in the green regions suggest that policies and investments aimed at improving the green energy mix were effective, particularly in the later years of the study. However, the period of insignificance also indicates that structural and policy-level adjustments are needed to ensure the consistent effectiveness of green energy on ecological quality, which reflects similar challenges highlighted by Caglar *et al.* (2021), who noted the importance of systemic changes for renewable energy adoption to truly yield ecological benefits.

Figure 3b shows the impact of the impact of financial development on ecological quality in China, proxied by the load capacity factor, from 1995 to 2023. Throughout the observed timeframe, the impact of financial development on ecological quality shows a positive, albeit moderate, influence, as evidenced by the values of the average marginal effect hovering around 0.1 to 0.3. The significant green regions indicate that from 1995 to 2023, financial development consistently contributed to ecological quality, particularly during the early years of the observation period and again from 2014 onwards. This suggests that increased access to financial resources has supported ecological improvements, likely by fostering investments in green technologies and infrastructure. These findings align with the arguments of Abbasi and Riaz (2016), who suggested that financial development can have a positive effect on environmental quality by providing the necessary funds to invest in cleaner technologies and green energy projects. However, the fluctuating nature of the average marginal effect, with occasional dips even during significant periods, implies that the relationship between financial development and ecological quality is not straightforward. At certain times, the effect of financial development appears to diminish, indicating potential trade-offs between economic growth facilitated by financial expansion and its environmental impact. This complexity has been highlighted by Khan and Ozturk (2021), Zhang *et al.* (2024) and Li *et al.* (2024), who have found that while financial development can lead to improved environmental outcomes through investment, it may also encourage higher levels of consumption and industrial activity, which can adversely affect ecological quality. The small but persistent positive impact observed throughout the period suggests that the benefits of financial development for ecological quality are present but need to be reinforced through targeted policy measures that prioritize green investments.

Figure 3: RWKRLS estimates for window length of 75



Notes: Estimated model: *LF* = *f*(*GQEM*, *FD*, *NR*, *EG*); (a): average marginal effects of *GQEM* on *LF*; (b): average marginal effects of *FD* on *LF*; (c): average marginal effects of *NR* on *LF*; (d): average marginal effects of *EG* on *LF*. Green areas indicate *p*-value < 0.1.

Source: Authors' own elaboration

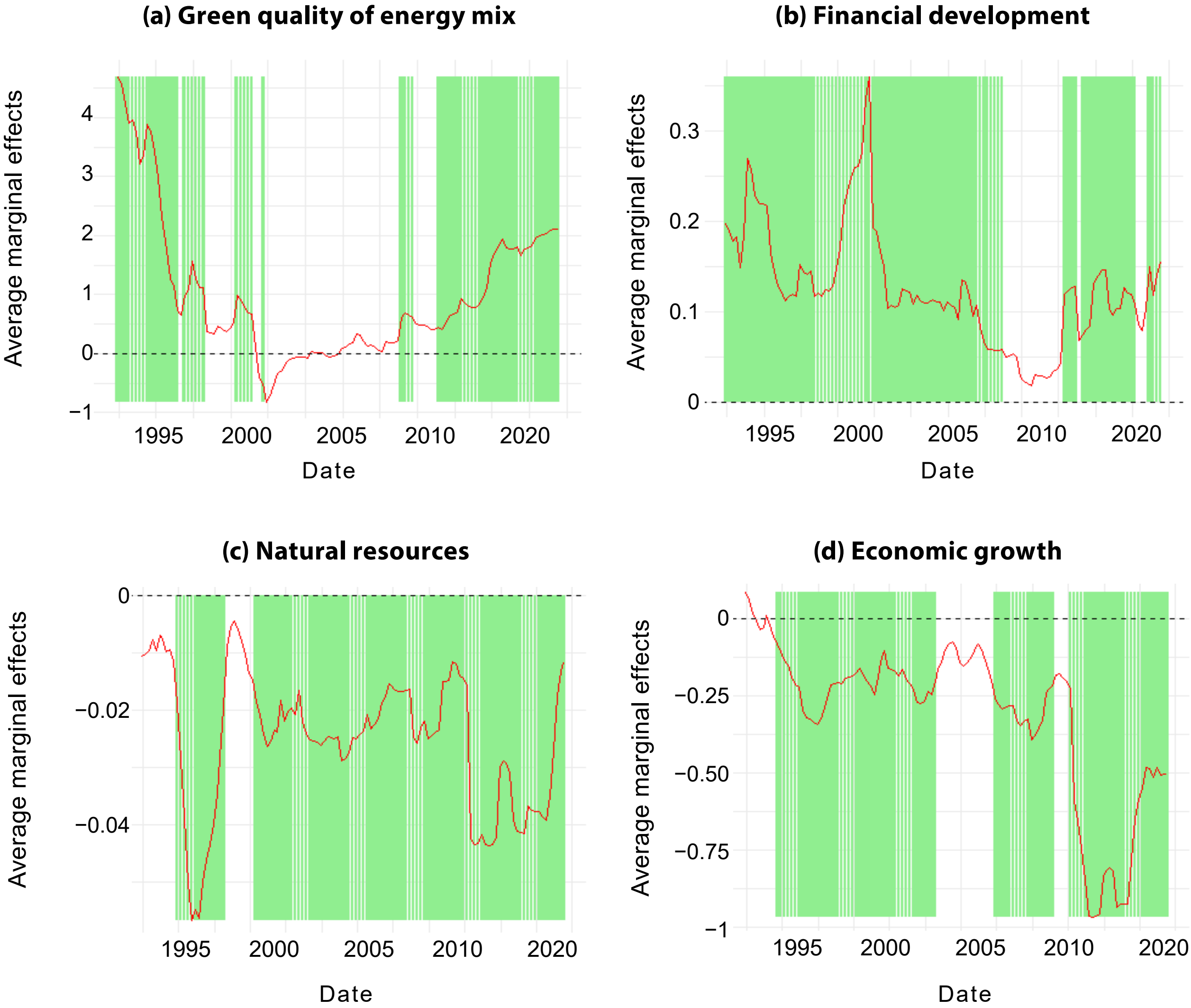
Figure 3c shows the impact of natural resources on ecological quality in China, proxied by the load capacity factor, from 1995 to 2023. Throughout the timeframe, the impact of natural resources on ecological quality appears to be consistently negative, with average marginal effect values ranging between −0.01 and −0.05. This suggests that increased natural resource utilization has led to a decline in ecological quality, likely due to the over-extraction of resources and unsustainable practices. The continuous green regions indicate that these negative effects were significant for most of the observed period. These findings align with those of Danish *et al.* (2019), who argued that resource-abundant economies often face challenges in maintaining ecological quality due to reliance on extractive activities. On the other hand, some scholars, such as Balsalobre-Lorente *et al.* (2018), have suggested that natural resource wealth, if properly managed, can contribute to sustainable development and enhance ecological quality, but such positive effects are not evident in this analysis, indicating that unsustainable resource management practices might be prevalent.

Figure 3d shows impact of economic growth on ecological quality in China, proxied by the load capacity factor, from 1995 to 2023. The average marginal effect fluctuates between −0.3 and −0.9, suggesting that as economic activities expand, they tend to degrade ecological quality, potentially due to increased industrial output, energy consumption and pollution. The significant green regions across almost the entire period reveal the persistent adverse effects of economic growth on ecological quality, except a few short insignificant periods. These findings align with the Environmental Kuznets Curve (EKC) hypothesis, as noted by Grossman and Krueger (1995), which suggests that economic growth initially worsens environmental quality before improvements can be seen at higher income levels. However, the significant and sustained negative impact observed here implies that such improvements have not yet materialized. In contrast, studies such as that of Al-Mulali *et al.* (2016) have argued that economic growth can eventually contribute to better ecological outcomes when combined with effective environmental policies, highlighting the importance of sustainable growth strategies.

4.6 Robustness check results

Additionally, as part of our robustness analysis, we adjusted the window lengths to 60. The outcomes of this robustness check are shown in figure 4. In figure 4a, we spot the impact of the *GQEM* on ecological quality (proxied by the *LF*), indicating a positive effect between 1992 and 2000, with no discernible connection between 2002 and 2009. However, from 2012 to 2021, the *GQEM* had a notable positive impact on ecological quality (proxied by the *LF*), suggesting that the *GQEM* contributes to enhancing ecological excellence. These results align with the observations made in figure 3a. Moving on to figure 4b, which illustrates the impact of *FD* on ecological quality (proxied by the *LF*), we notice a consistently positive effect in most sub-timeframes, except the period between 2011 and 2015. This positive effect corresponds well with the results seen in figure 3b. Figure 4c mirrors the findings documented in figure 3c, confirming the adverse effect of *NR* on ecological quality (proxied by the *LF*). Lastly, figure 4d highlights the dominant negative effect of *EG* on ecological quality (proxied by the *LF*), with insignificance observed from 2006 to 2010 (as depicted in figure 4d). The obtained results correspond with the patterns observed in figure 3d, reaffirming the association between economic growth and its adverse effects on ecological quality.

Figure 4: RWKRLS estimates for window length of 60

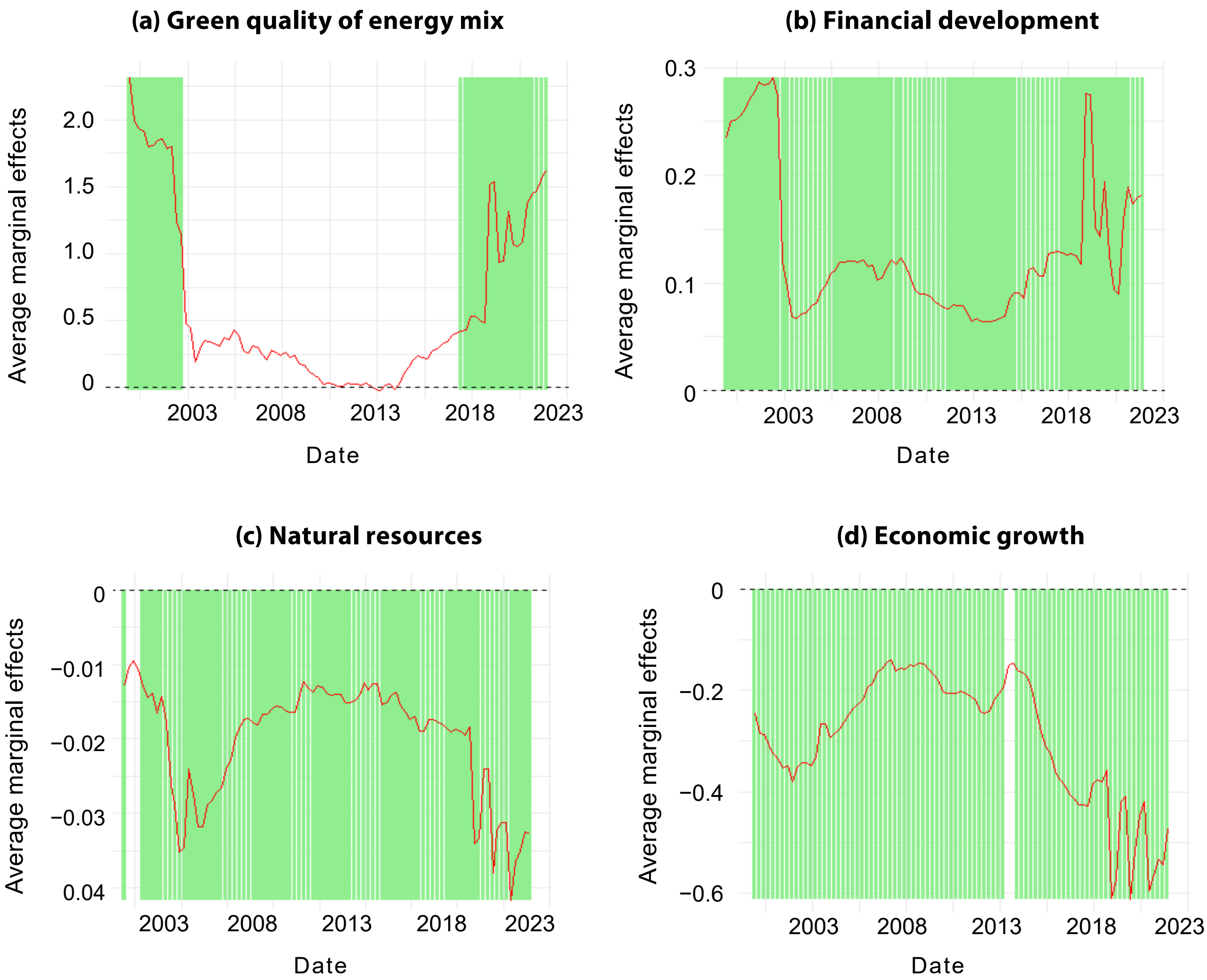


Notes: Estimated model: *LF* = *f*(*GQEM*, *FD*, *NR*, *EG*); (a): average marginal effects of *GQEM* on *LF*; (b): average marginal effects of *FD* on *LF*; (c): average marginal effects of *NR* on *LF*; (d): average marginal effects of *EG* on *LF*. Green areas indicate *p*-value < 0.1.

Source: Authors' own elaboration

Furthermore, we adjusted the window lengths once more, extending them to 90. Figure 5 displays the outcomes of this robustness check. In figure 5a, the influence of the *GQEM* on ecological quality (proxied by the *LF*) shows a positive effect between 2000 and 2003, but there is no evident connection between 2017 and 2021. However, a notably significant positive effect of the *GQEM* on ecological quality (proxied by the *LF*) emerges from 2018 to 2021. These findings align with our observations from figure 3a. Transitioning to figure 5b, depicting the impact of *FD* on ecological quality (proxied by the *LF*), we discern a consistently positive effect across all the timeframes. This positive trend corresponds well with the patterns observed in figure 3b. Furthermore, figure 5c mirrors the conclusions drawn in figure 3c, confirming the detrimental effect of *NR* on ecological quality (proxied by the *LF*). Lastly, figure 5d emphasizes the prevailing negative effect of *EG* on ecological quality (proxied by the *LF*) throughout all the studied timeframes. The findings align with the trends depicted in figure 3d.

Figure 5: RWKRLS estimates for window length of 90



Notes: Estimated model: *LF* = *f*(*GQEM*, *FD*, *NR*, *EG*).; (a): average marginal effects of *GQEM* on *LF*; (b): average marginal effects of *FD* on *LF*; (c): average marginal effects of *NR* on *LF*; (d): average marginal effects of *EG* on *LF*. Green areas indicate *p*-value < 0.1.

Source: Authors' own elaboration

5. Conclusion and Policy Implications

5.1 Conclusion

The United Nations has initiated the implementation of its 2,030 Sustainable Development Goals (SDGs) in response to growing concerns over the simultaneous decline in environmental conditions and rapid global economic advancement, aiming to achieve a harmonious integration of economic progress and environmental preservation. While the specified targets across the 17 SDGs are comprehensive individually, it becomes imperative to consider the interconnections among multiple SDGs when devising interactive strategies to foster sustainable development. Therefore, this study took a distinctive approach to assess the causal links between economic growth, environmental degradation, financial development and the utilization of renewable energy in the context of China, specifically addressing SDGs 7, 11, 12 and 13. Given China's significance as a leading country and a signatory to the 2,030 SDG commitment, this analysis is of paramount importance to the country. While prior studies have primarily concentrated on examining the determinants of ecological quality, there has been limited effort in mapping the interrelationships among these variables, especially considering the time-varying effects under the purview of the load capacity factor. Thus, we examined, for the first time, the time-varying impact of the green quality of energy mix and natural resources on the load capacity factor using data from 1981 to 2021. Additionally, we introduced the rolling window kernel-based regularized least squares (RWKRLS) method to analyse these connections. The RWKRLS analysis revealed that a green energy mix and financial development positively affect ecological well-being. Conversely, the consumption of natural resources and economic growth negatively affect ecological quality.

5.2 Policy implications

Based on the above findings, the following policy initiatives are recommended:

Firstly, increasing the green quality of energy mix (*GQEM*) should remain a priority. Policymakers in China should focus on expanding renewable energy adoption by providing financial incentives, improving energy infrastructure and enhancing technological innovation in renewable energy. Investments in energy storage solutions and grid modernization are essential to overcome the intermittent nature of renewable energy sources. Policymakers should also ensure the stability of renewable energy supply and promote technological transfer to support countries or regions facing challenges in green energy adoption.

Secondly, financial development should be used as a tool to enhance ecological quality by channelling resources into environmentally friendly projects. Policymakers must promote the issuance of green bonds, establish incentives for banks to finance clean energy initiatives and create regulatory frameworks that encourage financial institutions to include environmental considerations in their lending practices. Additionally, mechanisms should be put in place to mitigate the potential negative effects of financial development, such as overconsumption and increased industrial activity, by prioritizing investments in projects that minimize environmental impacts.

Lastly, natural resource management and sustainable economic growth must be key focus areas for policymakers. To mitigate the negative impact of natural resource utilization, sustainable extraction practices should be enforced and the use of resource-efficient technologies should be encouraged. Implementing green taxation and ensuring adherence to environmental regulations are important measures to balance resource extraction with ecological preservation. Economic growth should be accompanied by environmental safeguards, such as investing in cleaner technologies, adopting a circular economy approach and integrating sustainability into development strategies. Policymakers should focus on balancing economic and environmental objectives to ensure long-term ecological quality improvement.

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References

Abbasi, F., Riaz, K. (2016). CO_2 emissions and financial development in an emerging economy: An augmented VAR approach. *Energy Policy*, 90, 102–114. https://doi.org/10.1016/j.enpol.2015.12.017

Achuo, E., Kakeu, P., Asongu, S. (2024). Financial development, human capital and energy transition: A global comparative analysis. *International Journal of Energy Sector Management*, 19(1), 59–80. https://doi.org/10.1108/IJESM-11-2023-0004

Adams, S., Kaffo Fotio, H. (2024). Economic integration and environmental quality: Accounting for the roles of financial development, industrialization, urbanization and renewable energy. *Journal of Environmental Planning and Management*, 67(3), 688–713. https://doi.org/10.1080/09640568.2022.2131510

Akadiri, S. S., Adebayo, T. S., Riti, J. S., et al. (2022). The effect of financial globalization and natural resource rent on load capacity factor in India: An analysis using the dual adjustment approach. *Environmental Science and Pollution Research*, 29(59), 89045–89062. https://doi.org/10.1007/s11356-022-22012-0

Aladejare, S. A. (2022). Natural resource rents, globalisation and environmental degradation: New insight from 5 richest African economies. *Resources Policy*, 78, 102909. https://doi.org/10.1016/j.resourpol.2022.102909

Al-Mulali, U., Solarin, S. A., Ozturk, I. (2016). Investigating the presence of the environmental Kuznets curve (EKC) hypothesis in Kenya: An autoregressive distributed lag (ARDL) approach. *Natural Hazards*, 80(3), 1729–1747. https://doi.org/10.1007/s11069-015-2050-x

Al-Mulali, U., Tang, C. F., Ozturk, I. (2015). Does financial development reduce environmental degradation? Evidence from a panel study of 129 countries. *Environmental Science and Pollution Research*, 22(19), 14891–14900. https://doi.org/10.1007/s11356-015-4726-x

Alola, A. A., Adebayo, T. S., Onifade, S. T. (2022). Examining the dynamics of ecological footprint in China with spectral Granger causality and quantile-on-quantile approaches. *International Journal of Sustainable Development & World Ecology*, 29(3), 263–276. https://doi.org/10.1080/13504509.2021.1990158

Alola, A. A., Özkan, O., Obekpa, H. O. (2023a). Examining the patterns of disaggregate energy security risk and crude oil price: The USA scenario over 1970–2040. *Resources Policy*, 82, 103514. https://doi.org/10.1016/j.resourpol.2023.103514

Alola, A. A., Özkan, O., Usman, O. (2023b). Examining crude oil price outlook amidst substitute energy price and household energy expenditure in the USA: A novel nonparametric multivariate QQR approach. *Energy Economics*, 120, 106613. https://doi.org/10.1016/j.eneco.2023.106613

Amin, N., Shabbir, M. S., Song, H., et al. (2023). A step towards environmental mitigation: Do green technological innovation and institutional quality make a difference? *Technological Forecasting and Social Change*, 190, 122413. https://doi.org/10.1016/j.techfore.2023.122413

Awosusi, A. A., Kutlay, K., Altuntaş, M., et al. (2022). A Roadmap toward Achieving Sustainable Environment: Evaluating the Impact of Technological Innovation and Globalization on Load Capacity Factor. *International Journal of Environmental Research and Public Health*, 19(6), 3288. https://doi.org/10.3390/ijerph19063288

Badeeb, R. A., Lean, H. H., Shahbaz, M. (2020). Are too many natural resources to blame for the shape of the Environmental Kuznets Curve in resource-based economies? *Resources Policy*, 68, 101694. https://doi.org/10.1016/j.resourpol.2020.101694

Balcilar, M., Usman, O., Özkan, O. (2023). Tourism development and U.S energy security risks: A KRLS machine learning approach. *Current Issues in Tourism*, 27(1), 37–44. https://doi.org/10.1080/13683500.2023.2245109

Balsalobre-Lorente, D., Shahbaz, M., Roubaud, D., et al. (2018). How economic growth, renewable electricity and natural resources contribute to CO_2 emissions? *Energy Policy*, 113, 356–367. https://doi.org/10.1016/j.enpol.2017.10.050

Bashir, M. F., Ma, B., Hussain, H. I., et al. (2022). Evaluating environmental commitments to COP21 and the role of economic complexity, renewable energy, financial development, urbanization, and energy innovation: Empirical evidence from the RCEP countries. *Renewable Energy*, 184, 541–550. https://doi.org/10.1016/j.renene.2021.11.102

Broock, W. A., Scheinkman, J. A., Dechert, W. D., et al. (1996). A test for independence based on the correlation dimension. *Econometric Reviews*, 15(3), 197–235. https://doi.org/10.1080/07474939608800353

Caglar, A. E., Guloglu, B., Gedikli, A. (2022). Moving towards sustainable environmental development for BRICS: Investigating the asymmetric effect of natural resources on CO_2. *Sustainable Development*, 30(5), 1313–1325. https://doi.org/10.1002/sd.2318

Caglar, A. E., Mert, M., Boluk, G. (2021). Testing the role of information and communication technologies and renewable energy consumption in ecological footprint quality: Evidence from world top 10 pollutant footprint countries. *Journal of Cleaner Production*, 298, 126784. https://doi.org/10.1016/j.jclepro.2021.126784

Danish, Baloch, M. A., Mahmood, N., et al. (2019). Effect of natural resources, renewable energy and economic development on CO_2 emissions in BRICS countries. *Science of The Total Environment*, 678, 632–638. https://doi.org/10.1016/j.scitotenv.2019.05.028

Danish, Ulucak, R., Baloch, M. A. (2023). An empirical approach to the nexus between natural resources and environmental pollution: Do economic policy and environmental-related technologies make any difference? *Resources Policy*, 81, 103361. https://doi.org/10.1016/j.resourpol.2023.103361

Eweade, B. S., Karlilar, S., Pata, U. K., et al. (2023). Examining the asymmetric effects of fossil fuel consumption, foreign direct investment, and globalization on ecological footprint in Mexico. *Sustainable Development*, 32(4), 2899–2909. https://doi.org/10.1002/sd.2825

Eweade, B. S., Uzuner, G., Akadiri, A. C., et al. (2022). Japan energy mix and economic growth nexus: Focus on natural gas consumption. *Energy & Environment*, 35(2), 0958305X221130460. https://doi.org/10.1177/0958305X221130460

Gerelmaa, L., Kotani, K. (2016). Further investigation of natural resources and economic growth: Do natural resources depress economic growth? *Resources Policy*, 50, 312–321. https://doi.org/10.1016/j.resourpol.2016.10.004

Global Footprint Network (2023). *Global Footprint Network*. [Retrieved 2024-04-22]. Available at: https://www.footprintnetwork.org/

Grossman, G. M., Krueger, A. B. (1995). Economic Growth and the Environment. *The Quarterly Journal of Economics*, 110(2), 353–377. https://doi.org/10.2307/2118443

Hainmueller, J., Hazlett, C. (2014). Kernel Regularized Least Squares: Reducing Misspecification Bias with a Flexible and Interpretable Machine Learning Approach. *Political Analysis*, 22(2), 143–168. https://doi.org/10.1093/pan/mpt019

IEA (2023). *China*. [Retrieved 2024-04-22.] Available at: https://www.iea.org/countries/china

Jarque, C. M., Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters*, 6(3), 255–259. https://doi.org/10.1016/0165-1765(80)90024-5

Khan, A., Chenggang, Y., Hussain, J., et al. (2020). Natural resources, tourism development, and energy-growth-CO_2 emission nexus: A simultaneity modeling analysis of BRI countries. *Resources Policy*, 68, 101751. https://doi.org/10.1016/j.resourpol.2020.101751

Khan, M., Ozturk, I. (2021). Examining the direct and indirect effects of financial development on CO_2 emissions for 88 developing countries. *Journal of Environmental Management*, 293, 112812. https://doi.org/10.1016/j.jenvman.2021.112812

Khan, U., Khan, A. M., Khan, M. S., et al. (2022). Are the impacts of renewable energy use on load capacity factors homogeneous for developed and developing nations? Evidence from the G7 and E7 nations. *Environmental Science and Pollution Research*, 30(9), 24629–24640. https://doi.org/10.1007/s11356-022-24002-8

Kılıç Depren, S., Kartal, M. T., Çoban Çelikdemir, N., et al. (2022). Energy consumption and environmental degradation nexus: A systematic review and meta-analysis of fossil fuel and renewable energy consumption. *Ecological Informatics*, 70, 101747. https://doi.org/10.1016/j.ecoinf.2022.101747

Lau, C. K., Gozgor, G., Mahalik, M. K., et al. (2023). Introducing a new measure of energy transition: Green quality of energy mix and its impact on CO_2 emissions. *Energy Economics*, 122, 106702. https://doi.org/10.1016/j.eneco.2023.106702

Li, X. I. N. G., Aghazadeh, S., Liaquat, M., et al. (2024). Transforming Costa Rica's Environmental Quality: The Role of Renewable Energy, Rule of Law, Corruption Control, and Foreign Direct Investment in Building a Sustainable Future. *Renewable Energy*, 239, 121993. https://doi.org/10.1016/j.renene.2024.121993

NDRC (2022). *China opens up wider in 2021*. [Retrieved 2024-04-22] Available at: https://en.ndrc.gov.cn/netcoo/achievements/202201/t20220129_1315528.html

Olanipekun, I. O., Ozkan, O., Olasehinde-Williams, G. (2023). Is renewable energy use lowering resource-related uncertainties? *Energy*, 271, 126949. https://doi.org/10.1016/j.energy.2023.126949

Olasehinde-Williams, G., Olanipekun, I., Özkan, O. (2023a). Stock Market Response to Quantitative Easing: Evidence from the Novel Rolling Windows Nonparametric Causality-in-Quantiles Approach. *Computational Economics*, 64, 947–977. https://doi.org/10.1007/s10614-023-10450-y

Olasehinde-Williams, G., Özkan, O. (2023). A consideration of the environmental externality of Turkey's integration into global value chains: Evidence from dynamic ARDL simulation model. *Environmental Science and Pollution Research*, 30(11), 29154–29163. https://doi.org/10.1007/s11356-022-24272-2

Our World in Data (n.d.). *Our World in Data*. [Retrieved 2023-09-23.] Available at: https://ourworldindata.org

Ozkan, O., Eweade, B. S., Usman, O. (2024). Assessing the impact of resource efficiency, renewable energy R&D spending, and green technologies on environmental sustainability in Germany: Evidence from a Wavelet Quantile-on-Quantile Regression. *Journal of Cleaner Production*, 450, 141992. https://doi.org/10.1016/j.jclepro.2024.141992

Ozkan, O., Haruna, R. A., Alola, A. A., et al. (2023b). Investigating the nexus between economic complexity and energy-related environmental risks in the USA: Empirical evidence from a novel multivariate quantile-on-quantile regression. *Structural Change and Economic Dynamics*, 65, 382–392. https://doi.org/10.1016/j.strueco.2023.03.010

Ozkan, O., Sharif, A., Mey, L. S., et al. (2023d). The dynamic role of green technological innovation, financial development and trade openness on urban environmental degradation in China: Fresh insights from carbon efficiency. *Urban Climate*, 52, 101679. https://doi.org/10.1016/j.uclim.2023.101679

Ozkan, O., Usman, O., Eweade, B. S. (2024). Global evidence on the energy–environment dilemma: The role of energy-related uncertainty across diverse environmental indicators. *International Journal of Sustainable Development & World Ecology*, 31(8), 1128–1144. https://doi.org/10.1080/13504509.2024.2389526

Pata, U. K., Karlilar, S., Eweade, B. S. (2023). An environmental assessment of non-renewable, modern renewable, and combustible renewable energy in Cameroon. *Environment, Development and Sustainability*, 27, 7279–7296. https://doi.org/10.1007/s10668-023-04192-y

Pata, U. K., Olasehinde-Williams, G., Ozkan, O. (2023b). Carbon efficiency in China: Should we be concerned about the shadow economy and urbanization? *Geological Journal*, 58(10), 3646–3658. https://doi.org/10.1002/gj.4777

Pata, U. K., Usman, O., Olasehinde-Williams, G., et al. (2023c). Stock Returns, Crude Oil and Gold Prices in Turkey: Evidence from Rolling Window-Based Nonparametric Quantile Causality Test. *Asia-Pacific Financial Markets*, 31, 779–797. https://doi.org/10.1007/s10690-023-09430-x

Qalati, S. A., Kumari, S., Tajeddini, K., et al. (2023). Innocent devils: The varying impacts of trade, renewable energy and financial development on environmental damage: Nonlinearly exploring the disparity between developed and developing nations. *Journal of Cleaner Production*, 386, 135729. https://doi.org/10.1016/j.jclepro.2022.135729

Rahman, M. L., Shamsuddin, A., Lee, D. (2019). Predictive power of dividend yields and interest rates for stock returns in South Asia: Evidence from a bias-corrected estimator. *International Review of Economics & Finance*, 62, 267–286. https://doi.org/10.1016/j.iref.2019.04.010

UNFCCC (2015). *United Nations Framework Convention on Climate Change, 2015*. New York: United Nations Framework Convention on Climate Change. Available at: https://unfccc.int/files/meetings/paris_nov_2015/application/pdf/paris_agreement_english_.pdf

WB (2023). *World Development Indicators*. [Retrieved 2023-11-10] Available at: https://databank.worldbank.org/source/world-development-indicators

Zhang, H., Khan, K. A., Eweade, B. S., et al. (2024). Role of eco-innovation and financial globalization on ecological quality in China: A wavelet analysis. *Energy & Environment*, 36(8), 0958305X241228518. https://doi.org/10.1177/0958305X241228518