# Green credits, Green securities, and Environmental Quality: A comparative Analysis of Sustainable development across Chinese Provinces.

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# Green credits, Green securities, and Environmental quality: A comparative Analysis of Sustainable development across Chinese Provinces

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**Abstract:**

This paper analyzes the effects of green credits and green securities on environmental quality in a multivariate EKC framework across Chinese provinces during the 1992Q1-2020Q4 period. In this comparative analysis, we employ the DOLS and FMOLS estimators along with the method of moments-quantile regression (MM-QR) with the fixed-effects model. First, the FMOLS and DOLS methods show that short-term green credits (*STLs*) and green securities (*CAPs*) reduce carbon emissions (*CE*) in Chinese provinces. Unlike the Western region, long-term green credits (*LTLs*) improve environmental quality in the Eastern and Central regions. Second, large *STLs* and *CAPs* affect *CE* more than their low levels, unlike large *LTLs*. Third, *STLs* and *CAPs* increase *CE* only in the most polluting provinces of the central and western regions, but *LTLs* improve environmental quality only at the 70$^{th}$, 80$^{th}$, and 90$^{th}$ quantiles of *CE* in all provinces. Fourth, although renewable energy consumption inhibits carbon emissions in all provinces, oil prices, urbanization, trade openness, and foreign direct investments have heterogeneous effects on carbon emissions across the quantiles. Finally, our findings validate the EKC hypothesis only in the Eastern and Central regions. Accordingly, we propose policy implications for sustainable development in China.

*JEL classification:* C40; G10; G20; Q20; Q54
*Keywords:* Green credits; Green securities; Sustainable development; Carbon emissions; Chinese provinces; Moments-quantile regression.

*Abbreviations:* EKC: Environmental Kuznets Curve; DOLS: Dynamic Ordinary Least Squares; FMOLS: Fully Modified Ordinary Least Squares

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## 1. Introduction

In 2008, the Chinese central government implemented an RMB 4 trillion (USD 585 billion) stimulus package, or about 13% of GDP, to counter the effects of the 2008 global financial crisis and support Chinese economic growth. According to the report of the World Wide Fund for Nature (WWF 2010), this plan increased the country's economic growth from 9.7% in 2008 to 10.6% in 2010 (Jianlong et al. 2010). The report showed that about 38% (or RMB 1.5 trillion) of this stimulus package was invested in the development of government-run infrastructure (rail and road), and only 5% (about RMB 210 billion) of this package went to pollutant emissions reduction, energy conservancy, renewable energy, and environmental projects. However, it has fostered the expansion of energy-intensive industries (steel and iron, among others) and increased energy demand resulting in additional energy consumption of 113 million tons of coal, equivalent to 260 million tons of carbon dioxide emissions in the next two years[1]. China's economic development mainly promoted energy consumption based on fossil fuels, especially coal and crude oil, during the 10$^{th}$, 11$^{th}$, and 12$^{th}$ Five-Year plans from 2000 to 2015. These industries benefited from financial support and favorable dispatch rules by SOEs and local governments, allowing an increase in energy consumption from coal and oil without regard for the environment. Thus, renewable energy consumption represented around 12.8% of China's total final energy consumption in 2017[2]. According to the March 2019 Global Energy & CO2 Status Report from the International Energy Agency (IEA), China's carbon dioxide (CO2) emissions increased by 2.5%, around 9.5 Gt, mainly due to electricity generation from coal-fired power plants during the period 2017- 2018. China, India, and the United States accounted for 85% of the net increase in global energy-related CO2 emissions, reaching 33.1 Gt of CO2 in 2018[3].

The concept of green credit spread to China on July 30, 2007, when the China Banking Regulatory Commission (CBRC), the People's Bank of China (PBOC), and the National Environmental Protection Bureau of China jointly issued environmental protection policies and regulations to reduce credit risk to slow the growing expansion of industries with high levels of pollution and energy consumption (He et al. 2019b). The Industrial Bank Co., Ltd was the first Chinese bank to adopt the Equator Principles on October 31, 2008, followed by the bank of Jiangsu on January 20, 2017, the bank of Huzhou on July 24, 2019, and recently Chongqing rural commercial bank on February 27, 2020, and Mian Yang City Commercial on July 20, 2020, respectively. Due to the dominant banking sector in the Chinese financial system (consolidated banking system assets of around 240 % of GDP and domestic credit equivalent to 145 % of GDP in 2011, Turner et al. 2012), green credit remains the main form of green finance in China, allowing financial institutions and government to implement regulatory policies and macro-control to meet the need for financing of renewable energy companies. According to the People's Bank of China (2015), "*Green finance policy refers to a series of policy and institutional arrangements to attract private capital investments into green industries such as environmental protection, energy conservation, and clean energy through financial services – including lending, private equity funds, bonds, shares, and insurance.*"

[1] http://awsassets.panda.org/downloads/stimulus_final_en_lr_edit_fin.pdf
[2] https://www.irena.org/IRENADocuments/Statistical_Profiles/Asia/China_Asia_RE_SP.pdf
[3] https://www.iea.org/reports/global-energy-co2-status-report-2019/emissions#abstract

Green credits (loans) usually represent a set of supporting financial products and policies, such as corporate loans and preferential interest rates, among others, offered by banks to green industries with eco-friendly projects or restrictions on projects having adverse effects on the environment. Green credits also include home mortgages, motor vehicle loans, and green credit card services, as well as project finance, equipment leasing, and construction loans for companies in the industries of energy conservation and environmental pollution control. Green securities are also an alternative funding mechanism helping companies to secure the sustainability of venture capital for their green projects. They consist of funds and investors (retail and institutional investors) that directly invest in private firms in environmental pollution control, energy conservancy, and related sectors. Chinese venture capital and private equity funds made up to 694 lots of investments in the clean energy industry totalizing over US$8.2 billion, resulting in successful initial public offerings of many firms in China and abroad during the period 2007-2012 (Zero2IPO 2012).

Growing concern about global warming has sparked interest in more specific green policies by paying attention to green financial products and renewable energy in day-to-day business. To reduce the high levels of carbon dioxide emissions and pollution from the world's second-largest economy, but also the world's largest emitter[4], more and more studies have started to examine the relationship between green finance, investments in renewable energies, ecological efficiency, and economic growth in China (Aizawa and Yang 2010; Zhang et al. 2011; Wang and Zhi 2016; Liu et al. 2017; Peng 2018; Wang et al. 2019a; Wang et al. 2019b; He et al. 2019a; He et al. 2019b; Zhou et al. 2020). For instance, He et al. (2019a) analyzed the effects of green finance and debt credit on renewable energy investment efficiency in 141 listed companies in the renewable energy industry in China from 2011 to 2016 using a panel fixed-effect model. They found that green finance positively affected renewable energy efficiency in China. Besides, He et al. (2019b) examined the impact of renewable energy investment on green economy development based on the threshold value of green credit in 150 companies of the green industries listed in the Chinese A-share market during the 2004-2015 period. They revealed that renewable energy investment positively affected green economy development when the green credit level is lower than 132.31 kM CNY. Still, the detrimental effect occurred when the green credit level exceeded its threshold value. They measured green credit by bank loans to the energy conservancy and environmental protection industries.

Overall, most of these studies have overlooked the likelihood of asymmetrical effects of short-term lending and long-term lending to green industries on environmental quality, as well as the impact of the capital market, i.e., green securities, on reducing carbon emissions in China. These studies also did not provide a comparative analysis of these effects on the quality of the environment while considering the size of the indicators of green credits and green securities in the different Chinese provinces. Moreover, they also ignored the heterogeneous characteristics between the variables, i.e., the entirety of their conditional distributions, since most of the studies above focused on traditional econometric methods (*OLS, FE, ARDL, FMOLS, and DOLS* estimators, among others) relying on conditional means (*CM*).

Therefore, this study fills these gaps by investigating the effects of green credits (short-term loans and long-term loans) and green securities on environmental quality in multivariate models under the EKC

[4] https://www.iea-coal.org/china-top-global-emitter-aims-to-go-carbon-neutral-by-2060/

framework in the Chinese provinces from 1992Q1 to 2020Q4. We also consider the influences of renewable energy consumption, oil prices, urbanization, trade openness, and foreign investments on environmental quality in the Chinese provinces. This study employs both CM-based estimators and the method of moments-quantile regression (MM-QR) with fixed effects considering the entire conditional distribution of variables at various quantiles. The MM-QR considers the initial levels of carbon emissions (environmental quality) across Chinese provinces in our comprehensive analysis. Based on the findings of this study, we derive policy implications for improving environmental quality for sustainable development in the Chinese provinces.

The other parts of this paper are structured as follows. Section 2 reviews the literature on the topic, whereas section 3 describes the methodology and data of this paper. Section 4 reveals the results and presents the related discussion of our findings. Section 5 summarizes our study and explains its policy implications.

## 2. Literature review

Growing concerns about global warming and environmental degradation have drawn much attention to the search for mechanisms that promote economic growth while improving the quality of the environment. In this regard, green lending policies, one of the main instruments of green finance, have recently emerged as a promising alternative for sustainable development by inducing companies and governments to turn to more renewable energy sources in their production process to curb rising carbon emissions around the world, unlike the effects of traditional financing mechanisms on environmental quality.

Liu et al. (2017) and He et al. (2019a) revealed four mechanisms from which green finance may influence renewable energy development and indirectly affect environmental quality, namely, *resources allocation*, *capital support*, the *monitoring of enterprises*, and the *innovation-driven effect*. He et al. (2019a) highlighted the likely complex effects of green finance on investments in renewable energy industries due to its dual characteristics of "green" and "finance." The attributes "finance" or "financial development" include several functions such as mobilization and allocation of resources, capital support, and monitoring and supervision of activities, among others. *Resource mobilization and allocation* imply that the financial system can effectively direct financial resources to productive and competitive industries for optimal use and efficient distribution of resources. Green policies through financial institutions will allocate funds from high-pollution, and low-efficiency industries to low-pollution and high-efficiency industries, promoting the optimization and improvement of the industrial and energy system to increase economic growth and ameliorate environmental quality.

The *capital support* function refers to providing financial resources and improving financial services and the business environment through the financial system. It increases the capital needed for low-energy consumption, low-carbon, and high-efficiency industries, which may reduce the financial constraints of green enterprises and improve the efficiency of their natural and financial resources.

*Monitoring and controlling enterprises* means that the financial system must provide technical assistance and financing services to enterprises enabling them to manage and supervise their investments efficiently. Due to the maximization of bank interests, renewable energies may face funding constraints at an early stage. The renewable energy industry requires high and long initial investments to become profitable in return on investment. Therefore, the renewable energy industry requires effective management and supervision of investments to benefit from the financial system's support. The green finance system necessitates that financial institutions effectively evaluate the social and environmental impacts of companies in their financing routine. The supervision and regulations of enterprises' activities will oblige them to improve their production system and productivity, reducing environmental pollution. Liu et al. (2017) emphasize that green finance stimulates technological innovation (*innovation-driven-effect*) by supporting emerging technology companies, expanding the scale of their capital investment, and enhancing the efficiency of utilization of existing resources. It improves environmental quality by upgrading and optimizing industrial and energy systems. Hence, green finance can promote the deployment of renewable energy projects because they are innovative, low-carbon, competitive, and conducive to sustainable development.

He et al.(2019a) analyzed the effects of green finance and debt credit on renewable energy investment efficiency in 141 listed companies in the renewable energy industry in China from 2011 to 2016 using a panel fixed-effect model. They used several financial indicators such as green credit, green securities, green insurance, green investment, and carbon finance to draw an index of green finance (green financial development). They found that green finance positively affected renewable energy efficiency in China. Besides, He et al. (2019b) examined the impact of renewable energy investment on green economy development based on the threshold value of green credit in 150 companies of the green industries listed in the Chinese A-share market during the 2004-2015 period. They revealed that renewable energy investment positively affected green economy development when the green credit level is lower than 132.31 kM CNY. Still, the detrimental effect occurred when the level of green credit exceeded its threshold value. They measured green credit by bank loans to the energy conservancy and environmental protection industries.

In addition, Ho (2018) analyzed the potential for environmental risk monitoring of banks in China based on data from twenty-one banks at the forefront of green finance guidelines from 2012 to 2017. His study showed that major Chinese banks are improving their abilities to incorporate environmental requirements into credit risk assessment in line with regulatory guidelines, but barriers to effective pricing and efficient monitoring of credit risk related to environmental issues subsist. Ren et al. (2022) also found that green investment can decrease China's environmental pollution. They employed a dynamic threshold model and a spatial Durbin model to reveal that institutional quality moderated the nonlinear effect of green investment on environmental pollution from 2006 to 2017.

Using the gray correlation analysis and the fixed effect model, Zhang et al. (2021) analyzed the effects of green credit on environmental quality in Chinese provinces during the 2007-2016 period. They showed that green credit improved the quality of the environment in resource-based provinces more than in non-resource-based provinces. The authors found that green credit policies had significant effects only in provinces with developed financial markets. Qi (2021) revealed that the green credit guidelines policy significantly reduced environmental pollution in the Chinese provinces under better financial and ecological conditions by improving the investment efficiency of companies. The author employed the PSM-DID model on A-share listed firms' data over the 2008-2017 period. Ji et al. (2021) also indicated that the Green Credit Guidelines in 2012, as well as the green fiscal policy and the level of financial development, helped heavy pollution industries to increase their environmental protection investments in China from 2009 to 2017. Through the propensity score matching and difference-in-difference method (PSM-DID), Xiao et al. (2022) showed that the green credit policy reduced sulfur dioxide emissions in China significantly in companies located in the eastern provinces by improving energy consumption intensity and increasing environmental investment from 1999 to 2013. Using the rolling window and recursive evolving methods, Madaleno et al. (2022) found bidirectional causalities between green finance, environmental responsibility, clean energy, and green technology in specific periods of the daily data from July 31, 2014, to October 12, 2021.

Based on the studies cited above (Liu et al. 2017; He et al. 2019a; He et al. 2019b; Zhang et al. 2021; Xiao et al. 2022), we formulate the following hypotheses:

*Hypothesis 1a: green credits improve environmental quality in the Chinese provinces in the short term.*

*Hypothesis 1b: green credits improve environmental quality in the Chinese provinces in the long term.*

The development of stock markets has also played an essential role in the quality of the environment in the world. On the one hand, stock markets are primarily attractive for companies because they give them access to equity financing, debt financing, and various funding sources. In the absence of green policy guidelines, substantial business growth can lead to more polluting (fossil) energy consumption and increased carbon emissions. In addition, the development of stock markets allows risk diversification mechanisms that can generate a wealth effect for market players. This wealth effect further stimulates demand for goods and services, especially in manufacturing industries, intensifying carbon emissions (Sadorsky 2011, Mankiw and Scarth 2008).

On the other hand, well-developed stock markets can establish stricter regulations and ESG compliance mechanisms for listed companies. These policies, along with mandatory disclosures and stock market rankings of corporate environmental performance, can compel companies to reduce carbon emissions and improve environmental quality to attract more sustainable finance. Due to the growing concern about global warming, new developments in the stock markets are gradually incorporating green finance policies that encourage and facilitate more funding sources for investments in green industries, which are a promising alternative to reduce carbon emissions and improve the quality of the environment.

In a comparative analysis, Paramati et al. (2018) found that stock market indicators reduced carbon emissions in developed countries, unlike in emerging economies. They employed the common correlated effects mean group estimator (CCE-MG) on data regarding total market capitalization per capita, the total value of stocks traded per capita, energy efficiency, population density, GDP per capita, and carbon dioxide emissions from 1992 to 2011. Zhang (2011) revealed that the scale of the stock market (i.e., the ratio of stock market capitalization to GDP) had a relatively greater effect on carbon emissions in China compared to its efficiency (i.e., the ratio of stock market turnover to GDP) from 1980 to 2009. Using the NARDL models, Mhadhbi et al. (2021) pointed out that negative and positive shocks on stock market indicators (shares traded per capita and market capitalization per capita) increased carbon emissions in 19 emerging countries over the long term from 1995-to 2014. Nevertheless, developed stock markets are needed to reduce private and public sector financing costs, minimize energy intensity and consumption and improve energy efficiency. This scenario helps promote energy-saving technologies and betters the quality of the environment (Yue et al. 2019). Similarly, Paramati et al. (2016) showed the positive effect of stock market development on clean energy utilization in 20 emerging countries from 1991 to 2012. Recent developments in stock markets show that ESG requirements and green policies are being considered in allocating financial resources between listed companies (equity financing and debt financing) due to the potential benefits of renewable energies in reducing carbon emissions and global warming. Based on this perspective and considering the empirical literature documented above (Paramati et al. 2016; Liu et al. 2017; He et al. 2019a; He et al. 2019b; Yue et al. 2019), we assume the following hypothesis:

*Hypothesis 2: green securities enhance environmental quality in the Chinese provinces.*

The nexus between finance and environmental quality has also been examined within the environmental Kuznets curve (EKC) framework developed by Grossman and Krueger (1991) and vulgarized by Shafik (1994) and Selden and Song (1994).

Under the EKC hypothesis, per capita income has an inverted U-shaped effect on environmental degradation. This hypothesis assumes that environmental quality declines as carbon emissions rise in the early phases of economic growth. This trend is reversed when the level of income (GDP per capita) exceeds an optimal threshold as economic activities develop in a country. Hence, Shahbaz et al. (2017) validated the EKC hypothesis in China from 1970 to 2012 using the autoregressive distributed lag (*ARDL*) method. Khan et al. (2019) investigated the nexus between economic growth, energy consumption, financial development, and carbon dioxide emissions ($CO_2$) in 193 nations during the 1990-2017 period. They confirmed the *EKC* hypothesis using the three-stage least squares (*3SLS*), generalized method of moments (*GMM*), and a seemingly unrelated regression (*SUR*). Other studies also corroborated the *EKC* hypothesis in several countries while considering the effects of participation in global value, energy consumption, green finance, and governance quality on environmental quality (Assamoi et al. 2020a; Wen et al. 2021; Chen and Chen 2021; Kassi et al. 2022). Nevertheless, the findings of a few studies do not confirm the *EKC* hypothesis in China (Gui et al. 2019; Yilanci and Pata 2020). For instance, Gui et al. (2019) employed a spatial panel method for 285 cities but failed to support the EKC hypothesis for solid waste generation in China from 2006 to 2015.

In most cases, studies proved that renewable energy consumption reduced carbon emissions, thereby improving environmental quality (Dong et al. 2018; Yu et al. 2020; Li et al. 2021; Anwar et al. 2021; Kassi et al. 2022; Ehigiamusoe and Dogan 2022). Using a series of econometric methods, Dong et al. (2018) revealed the beneficial influence of renewable energy consumption on $CO_2$ emissions from 1965 to 2016. Li et al. (2021) highlighted the threshold effect of renewable energy consumption on the low-carbon economy in China from 2000 to 2017, arguing that the positive effect only occurs when renewable energy consumption reaches high levels. Anwar et al. (2021) also showed that renewable energy consumption decreased $CO_2$ emissions at all quantiles in Asian countries using the MM-QR method on data from 1990 to 2018.

A series of empirical studies also underlined the impacts of oil prices (Zhang and Zhang 2016; Saboori et al. 2017; Bilgili et al. 2020; Kassi et al. 2022), urbanization (Du et al. 2012; Sheng and Guo 2016; Li et al. 2021; Kassi et al. 2022), foreign direct investment (Sun et al. 2017; Wang et al. 2019; Assamoi et al. 2020b; Wang et al. 2021) and trade openness (Li and Tu 2014; Sousa et al. 2015; Fan et al. 2019; Zugravu-Soilita 2019; Assamoi et al. 2020a) on environmental quality.

Using the ARDL method with the EKC framework, Saboori et al. (2017) indicated that oil prices decreased environmental degradation by negatively affecting the ecological footprint of the Organization of Petroleum Exporting Countries (OPEC) from 1977 to 2008. Bilgili et al. (2020) analyzed the co-movements between oil prices and $CO_2$ emissions in China through wavelet coherence techniques. They found that oil prices have significant adverse effects on $CO_2$ emissions in China at high frequencies during the periods 1960-2014 and 1971-2014. According to Du et al. (2012), the urbanization level increased carbon emissions in the Chinese provinces during the 1995-2009 period. Li et al. (2021) confirmed the positive effect of urbanization on the degree of China's low-carbon economy over the 2000-2017 period. In contrast to the inhibiting effect of renewable energy consumption on $CO_2$ emissions, Kassi et al. (2022) indicate that oil prices and urbanization increase $CO_2$ emissions from 1990 to 2017. In a multivariate EKC framework, the authors used the DOLS and FMOLS estimators and the moments-quantile regression (MM-QR) method with fixed-effects models on panel data from 123 countries.

Using the ARDL method with structural breaks, Assamoi et al. (2020b) revealed that foreign direct investment (FDI) favored the increase in $CO_2$ emissions in Cote d'Ivoire during the 1980-2014 period, confirming the pollution haven hypothesis (PHH) of a positive effect of FDI inflows on $CO_2$ emissions. Sun et al. (2017) also confirmed the PHH hypothesis in China from 1980 to 2012. Wang et al. (2021) found an inverted U-shaped effect of FDI on $CO_2$ emissions in 30 Chinese provinces by employing the STIRPAT model with the EKC framework over the 2004-2016 period. They argue that FDI promotes energy intensity which raises $CO_2$ emissions, but the emission trading system (ETS) mitigates the influence of FDI on $CO_2$ emissions in China. Ahmad et al. (2021) also confirmed the inverted U-shaped effect of FDI on $CO_2$ emissions in China during the 1998-2016 period, but they found heterogeneous influences at the provincial levels using the dynamic common correlated effects mean group (DCCEMG). Lan et al. (2011) also confirmed the PHH hypothesis only in Chinese provinces with low levels of human capital.

Additionally, Fan et al. (2019) showed that greater trade openness reduced CO2 emissions in low-carbon sectors, unlike the case of high-carbon sectors in China from 2000 to 2014. Through the GMM estimators, Zugravu-Soilita (2019) pointed out that the direct, indirect, and total effect of trade openness on environmental pollution depended on the net trade status of countries during the 1996-2011 period. Assamoi et al. (2020a) support the idea that trade openness improves environmental quality. Using the DOLS and FMOLS methods, the authors found a negative link between trade openness and $CO_2$ emissions in selected Asian economies from 1995q1 to 2014q4.

Similarly, Dogan and Seker (2016b) revealed that trade openness, financial development, and renewable energy consumption reduced $CO_2$ emissions in the top renewable energy nations, unlike non-renewable energy consumption.

## 3. Data and Methodology of the study

### *3.1. Data*

This study examines the effects of green credits and securities on environmental quality in China over 1992Q1-2020Q4. We considered this period due to the availability of accurate data for the main variables of interest. We mainly used unbalanced panel data from 29 provinces and municipalities grouped into three regions, namely those in eastern, central, and western China. Table 1 presents the list of provinces and municipalities according to their geographical repartition following the National Bureau of Statistics of China in 2018[5]and Moody's Analytics (Cochrane et al. 2019). Furthermore, we measured green credits and green securities by financial indicators of listed companies in A-shares on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE) from the energy savings and environmental protection industries (renewable energy enterprises).

**Table 1. List of selected provinces and municipalities in Mainland China**

| Eastern (12) | Central (6) | Western (11) |
|---|---|---|
| Heilongjiang | Anhui | Chongqing *a* |
| Jilin | Henan | Gansu |
| Liaoning | Hubei | Guangxi *b* |
| Beijing *a* | Hunan | Guizhou |
| Fujian | Jiangxi | Inner Mongolia *b* |
| Guangdong | Shanxi | Ningxia *b* |
| Hebei | | Qinghai |
| Jiangsu | | Shaanxi |
| Shandong | | Sichuan, |
| Shanghai *a* | | Xinjiang *b* |
| Tianjin *a* | | Yunnan |
| Zhejiang | | |

Note: The symbols *a* and *b* denote municipalities and autonomous regions in China, respectively.

Following He et al. (2019b) and based on the industry classification guidelines of the China Securities Regulatory Commission (CSRC) in 2012, we chose 152 renewable energy enterprises listed in A-shares in 29 Chinese municipalities and provinces from the industries of mechanical, electrical, and equipment manufacturing (code C38), the industries of electricity, gas, heat, water production and supply (codes D44, D45, and D46), and the industries of ecology and environmental governance (code N77).
Following He et al. (2019a), we only considered the listed companies in the Chinese A-share market before December 31, 2010, and excluded enterprises under special financial treatment to reduce highly

[5] http://www.stats.gov.cn/tjsj/ndsj/2018/indexeh.htm

**Table 2. Description of the variables**

| Variables | Measurement | Empirical literature | Expected signs | Source |
|---|---|---|---|---|
| *CE* | It measures carbon emissions (total consumption, kt CO2) of province *i* at time *t*. Low carbon emission (*CE*) values indicate good environmental quality, while high values do not. | Sheng and Guo 2016; He et al. 2019; Assamoi et al. 2020a; Li et al. 2021; Wang et al. 2021 ; Kassi et al. 2022 | | Wind |
| *STL* | A measure of short-term green credit, indicating the ratio of short-term loans to total assets in green industries registered in province *i* at time *t*. | He et al. 2019; Zhou et al. 2020 ; Qi 2021 ; Zhang et al. 2021 | - | Wind |
| *LTL* | A measure of long-term green credit, denoting the ratio of long-term loans to total assets in green industries registered in province *i* at time *t*. | He et al. 2019; Zhou et al. 2020 ; Ji et al. 2021 ; Xiao et al. 2022 | - | Wind |
| *CAP* | It denotes a proxy of green securities, representing the ratio of market capitalization to GDP (CNY 1000) in green industries of province *i* at time *t*. | Paramati et al. 2016 ; He et al. 2019; Yue et al. 2019 ; Zhou et al. 2020 | - | CSMAR |
| *Controls* | | | | |
| *RENC* | Renewable energy consumption (percentage of total energy) | Apergis et al. 2018; Khan et al. 2020; Kassi et al. 2020; Kassi et al. 2021. | - | Wind |
| *GDPC* | It indicates the gross domestic product (GDP, in CNY) per capita of province *i* at time *t,* an indicator of economic growth. | Kassi et al. 2017 ; Apergis et al. 2018 ; Le et al. 2020 ; Abbasi et al. 2020 | + | Wind |
| $(GDPC)^2$ | It denotes the square of the GDP per capita of province *i* at time *t* | Gani 2012; Dogan and Seker 2016a; Danish et al. 2019; Kassi et al. 2021 | | Wind |
| *FDI* | It is the ratio of the total fixed assets investment of a foreign-funded economy to provincial GDP. It is used to measure foreign direct investment in province *i* at time *t.* | Hao and Liu 2015; Wang et al. 2019; Zhang et al. 2020 | +/- | Wind |
| *TRA* | It represents the total import & export value (percentage of GDP), a measure of trade openness of province *i* at time *t.* | Gani 2012; Dogan and Seker 2016a; Song et al. 2021 | +/- | Wind |
| *URB* | It shows the urbanization rate in each province, measured by the proportion of people living in urban cities (percentage of the total population) of province *i* at time *t*. | Sheng and Guo 2016; Abbasi et al. 2020; Anwar et al. 2020; Khan et al. 2020; | + | Wind |
| *OIL* | Crude oil prices (USD/barrel) | Saboori et al. 2016; Katircioglu 2017; Abumunshar et al. 2020. | - | Wind |

Note: *Wind*: China's Wind database; *NBSC*: National Bureau of Statistics of China; *CSMAR*: China Stock Market & Accounting Research database.

unbalanced panel data. We also excluded all B, H, and N shares to avoid the effect of issuing either overseas stocks or domestic foreign shares on companies' investment behavior. Finally, we excluded some companies with highly incomplete data in the sample. Furthermore, we converted the annual data into quarterly data by utilizing the low-to-high frequency technique to increase the number of observations for reliable results in the comparative analysis across regions. Following previous studies, we chose the quadratic-match average option of the low-to-high frequency method (Kassi et al. 2019a, b).

This method applies a local quadratic interpolation of the annual data to supplement quarterly observations so that the average value over four adjacent periods is equivalent to the data observed in the corresponding year. We measured green credits by the listed firms' loan ratios in energy saving and environmental protection industries, whereas green securities indicate their total stock market capitalization. Based on the studies of He et al. (2019) and Zhou et al. (2020), Table 2 describes the related green financial variables, the indicator of environmental quality, and the control variables. The database of this study was derived from the China Stock Market & Accounting Research database (CSMAR), the National Bureau of Statistics of China (NBSC), and the Wind database. We then transform all variables into the logarithmic form.

### *3.2. Specification of the model*

Several empirical studies have validated the EKC framework using a quadratic model in which economic growth had an inverted U-shaped impact on carbon emissions (Gani 2012; Dogan and Seker 2016a; Hunjra et al. 2020; Zhou et al. 2020). Following these studies, we propose an updated multivariate model by examining the effects of green credits (*STLs* and *LTLs*) and green securities (*CAPs*) on environmental quality (*CE*). We also investigated the impacts of renewable energy consumption (*RENC*), oil prices (*OIL*), urbanization (*URB*), trade openness (*TRA*), and foreign direct investments (*FDI*) on environmental quality (*CE*) within the EKC framework as follows:

$$\begin{aligned}\ln CE_{it} = {} & \beta_0 + \beta_1 \ln RENC_{it} + \beta_2 \ln STL_{it} + \beta_3 \ln LTL_{it} + \beta_4 \ln CAP_{it} + \beta_5 \ln GDPC_{it} + \beta_6 \ln GDPC^2_{it} \\ & + \beta_7 \ln OIL_{it} + \beta_8 \ln URB_{it} + \beta_9 \ln TRA_{it} + \beta_{10} \ln FDI_{it} + \theta_i + \varepsilon_{it} \qquad (1)\end{aligned}$$

Where $\beta_k (1 \leq \text{k} \leq 10)$ shows the estimated impacts of the underlying variables (see Table 2) on carbon emissions (*CE*); $\beta_0$ is a constant term, and $\theta_i$ and $\varepsilon_{it}$ are the fixed effects of each province *i* and the error term at time *t*, respectively. The symbol *ln* denotes the variables' logarithmic transformation.

Renewable energy is energy from sources that regenerate naturally but whose flow is limited; renewable resources are practically inexhaustible in duration but limited in the quantity of energy available per unit of time. They are different from fossil fuels owing to their availability, diversity, and abundance around the world, as well as their potential not to contribute to climate change. Renewable energies are essential in the fight against environmental degradation because they minimize or do not generate polluting emissions (greenhouse gases) during the energy production process. Renewables are helpful for sustainable development by reducing energy dependence on fossil fuels and their imports which drastically hurt environmental quality. Hence, renewable energy consumption is expected to decrease carbon emissions $(\beta_1 < 0)$ and enhance the environmental quality across provinces.

Green credits (short-term loans, *STLs*, and long-term loans, *LTLs*) usually represent a set of supporting financial products and policies, such as corporate loans and preferential interest rates, among others, offered by banks to green industries with eco-friendly projects or restrictions on projects having adverse effects on the environment. In addition, green securities represent the trading of shares of listed companies engaged in conserving natural resources and promoting environmentally friendly business practices. They are denoted by the total stock market capitalization (*CAP*). Green credits and securities remain the primary forms of green finance in China, allowing financial institutions and the government to implement regulatory and macro-control policies to meet the financing need of renewable energy companies to combat global warming and environmental pollution. Following He et al. (2019) and Zhou et al. (2020), we assume $\beta_2 < 0, \beta_3 < 0\, and \quad \beta_4 < 0$, respectively.

According to EKC's hypothesis, economic growth is expected to contribute to environmental deterioration $(\beta_5 > 0)$ due to the expansion of energy-intensive activities that significantly increases carbon emissions in the early stages of development. Under this hypothesis, we also postulate that economic growth only improves the quality of the environment when the level of income reaches an optimal threshold beyond which nations or local authorities may have enough financial resources to implement environmentally friendly policies, decreasing carbon emissions $(\beta_6 < 0)$.

Based on previous studies, Table 2 summarizes the expected effects of all variables on environmental quality measured by the level of carbon emissions.

### *3.3. Methods and estimation techniques*

#### *3.3.1. Preliminary analysis*

Our analysis started with evaluating the characteristics of the variables via their descriptive statistics, correlation analysis, and multicollinearity tests. For reliable results, we performed the variance inflation factor (VIF) to ensure that the models were free from multicollinearity problems between variables. The VIF reveals how much the variance of an estimated parameter is inflated when multicollinearity exists in a multivariate model. Based on previous studies, we assume there is no multicollinearity problem in the models if the VIF is less than 10 (Marquardt 1970; Hair et al. 1995; El-Bannany 2017, Kassi et al. 2021). Moreover, we analyzed the stationarity of the variables at their levels and first differences using the panel unit root tests in Im et al. (2003), Levin et al. (2002), Phillips and Perron (1988), and Dickey and Fuller (1981). The null hypothesis states that all variables are not stationary at their levels, instead of the alternative hypothesis of stationary variables in their first differences. Unlike the other three tests, Levin et al. (2002) suppose a standard unit root process.

We concluded the preliminary analyses by the cointegration test in Kao (1999) to examine the long-term nexus between variables. In the first-stage regression, Kao (1999) specifies section-specific intercepts and homogeneous coefficients. The null hypothesis supposes the absence of cointegration, unlike the alternative hypothesis of a long-term nexus among the variables.

*3.3.2. FMOLS and DOLS estimators*

In the case of cointegrated variables, fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS) are the most widely used benchmark estimators in empirical analyses. Under the assumption of integrated variables at the first difference I (1), Phillips and Hansen (1990) proposed the FMOLS estimator, a nonparametric method, to derive asymptotically normal and unbiased long-term estimates robust to any problem of endogenous variables. The FMOLS technique presumes a unique vector of cointegration among the variables. The DOLS estimator developed by Saikkonen (1991) is a parametric method that provides more features by including lags and leads of the first-differenced predictors in the models. Most studies confirmed the superiority of the FMOLS and DOLS methods over the ordinary least squares (OLS) estimator (Li and Maddala 1997; Khalaf and Urga 2014). For instance, they consider the endogeneity and small sample biases in the regression, unlike the OLS estimator. Nevertheless, according to Kao and Chiang (2001), the DOLS estimator outperforms the FMOLS method because the DOLS estimator is less biased and does not require a kernel estimator and nonparametric heterogeneous methods for the covariance matrix.

*3.3.3. Quantiles via moments under panel data with fixed effects*

In order to perform further investigations and alternative approaches for robust analyses, we first tested the heterogeneity of the slopes across panel units in the models through a test described in Bersvendsen and Ditzen (2021). They derived a standardized method from the slope homogeneity test of Pesaran and Yamagata (2008). The test's null hypothesis imposes slope homogeneity via a weighted fixed-effect estimator, whereas the alternative hypothesis supposes slope heterogeneity under a cross-sectional specific OLS model. After confirming the existence of slope heterogeneity in the models, we analyzed the effects of green credits and securities, along with the control variables, on the entire distribution of carbon emissions using the method of moments-quantile regression (*MM-QR*) with fixed effects models developed by Machado and Santos Silva (2019). In order to assess the robustness of our findings, we compared the results obtained from the *MM-QR* method with those of the traditional fixed-effects models (*FE*) with Driscoll-Kraay's standard errors robust to cross-sectional dependence across panel units. Most traditional methods, such as the OLS, FE, FMOLS, and DOLS estimators, rely on conditional means (CM) by deriving the mean value of the estimated parameters from the models. These estimators do not wholly describe the relationships between the variables due to this restriction on their entire distributions. However, the MM-QR method describes how the regressors influence the entire conditional distribution of the explained variable (CE). Moreover, MM-QR is an improved version of panel quantile regression (QR) developed by Koenker and Bassett (1978), as it also deals with endogenous predictors in FE models.

Based on the moment conditions of Machado and Santos Silva (2019), the MM-QR model with panel fixed effects is formulated as follows:

$$Q_Y(\theta|X_{it}) = \lambda_i(\theta) + X_{it}^{'}\beta + Z_{it}^{'}\omega q(\theta) \qquad with \quad \lambda_i(\theta) \equiv (\lambda_i + \phi_i q(\theta)) \qquad (2)$$

Where *Y* and *X* denote the explained variable (*lnCE*) and the predictors defined in equation (1), respectively, and *Z* indicates a vector of known differentiable transformations of the elements of *X*. The symbol $\lambda_i(\theta)$ represents the quantile (θ) fixed effect of panel unit *i* at time *t,* and $\beta$ and $\omega$ are parameters.

Machado and Santos Silva (2019) documented the steps through which the one-step GMM estimator of Hansen (1982) can be computed sequentially via the estimation of q (θ) by the solution $\hat{q}$ to

$$\min_q \sum_i \sum_t \psi_\tau(\hat{\Omega}_{it} - (\hat{\phi}_i + Z_{it}^{'}\hat{\omega})q) \quad with \quad \psi_\tau(B) = (\theta-1)BI\{B \le 0\} + \theta BI\{B > 0\}, \text{and } \hat{\Omega}_{it} = Y_{it} - \hat{\lambda}_i - X_{it}^{'}\hat{\beta} \quad (3)$$

Where $\psi_\tau(B)$ is the check function, and $\hat{\omega}, \hat{\phi}, and\ \hat{\Omega}$ are the estimated parameters and residuals.

In addition, the *MM-QR* is convenient with endogenous variables, nonlinear models, and cross-sectional models. It is based on moment conditions and identifies conditional means under exogeneity. Unlike the *CM* methods, the fixed effects in the *MM-QR* framework affect the entire distribution instead of location shifters (Koenker 2004). Also, it does not rely on distributional assumptions (that is, normal distribution) and handles outliers (Akram et al. 2021). Finally, the *MM-QR* accounts for the unobserved and distributional heterogeneities in the models at different quantiles.

## 4. Results and discussion

### *4.1. Preliminary results*

Our empirical analysis started by presenting the descriptive statistics of the variables. Thus, Table 3 shows that all the variables are right-skewed, i.e., their distributions have longer right tails than left tails. Most variables have leptokurtic distributions with kurtosis >3, indicating a higher likelihood of extreme outlier values or heavier tails, except for *RENC, OIL*, and *URB*.

In addition, Table A.1 shows the distributions of the average values of carbon emissions (*CE*) in the Chinese provinces according to their geographical locations (see Appendices) during the 1992Q1-2020Q4 period. We found that the Eastern region had the most significant average value of carbon emissions (292703.56 kt of $CO_2$) compared to the Central region (257435.36 kt of $CO_2$) and the Western region (163028.47 kt of $CO_2$) of China.

At the provincial level, Shandong contributed the most to carbon emissions (588635.42 kt of $CO_2$), unlike Beijing (87016.96 kt of $CO_2$) in the Eastern region. Similarly, Inner Mongolia (387251.60 kt of $CO_2$) and Henan (373724.46 kt of $CO_2$) had the highest average contributions of *CE,* but Qinghai

(31530.58 kt of CO2) and Jiangxi (134838.34 kt of CO2) registered the lowest values of *CE* in the Western and Central regions of China, respectively.

**Table 3. Descriptive Statistics**

| Variables | Obs | Std. Dev. | Mean | Max | Min | Kurt. | Skew. |
|---|---|---|---|---|---|---|---|
| *CE* | 2656 | 182000 | 237000 | 937000 | 11500 | 4.897 | 1.465 |
| *RENC* | 3132 | 8.226 | 20.779 | 32.931 | 11.338 | 1.248 | 0.189 |
| *STL* | 3108 | 0.089 | 0.138 | 0.742 | 0.001 | 7.918 | 1.624 |
| *LTL* | 3004 | 0.188 | 0.223 | 1.376 | 0.0004 | 6.077 | 1.387 |
| *CAP* | 2916 | 0.014 | 0.01 | 0.113 | 0.001 | 15.45 | 3.118 |
| *GDPC* | 3364 | 28413.19 | 28135.65 | 165000 | 1034 | 5.995 | 1.616 |
| *OIL* | 3364 | 27.12 | 44.123 | 106.52 | 9.39 | 2.422 | 0.713 |
| *URB* | 3044 | 17.026 | 49.179 | 89.6 | 16.18 | 2.72 | 0.42 |
| *TRA* | 3108 | 0.383 | 0.306 | 2.138 | 0.007 | 7.173 | 2.139 |
| *FDI* | 2544 | 0.015 | 0.016 | 0.123 | 0.0001 | 11.692 | 2.351 |

Note: See Table 2 for the description of variables. The symbols *Obs., Std. Dev* and *Mean* indicate the number of observations, the standard deviations, and the average values of the variables, respectively. *Max, Min, Kurt*, and *Skew* denote the maximum and the minimum values, the kurtosis, and the skewness of all variables, respectively.

On the other hand, Table A.2 indicates weak correlations (less than 0.70) between the variables in most cases, which are acceptable values according to Mukaka (2012). Above all, there are weak correlations between the indicators of green credits (*STLs* and *LTLs*) and green securities (*CAPs*), which imply the absence of problems of multicollinearity between the variables (Cf. Appendices).

About the unit root tests described in section 3.3, we found that most variables are stationary at the 1% level of significance at the first difference (these results are available upon request). Finally, the results of the cointegration test are presented in Table 4. The *ADF* t-statistics are significant at the 5% level in all models at the provincial level and at the 10% level in the model, including all provinces. Therefore, there was a long-term relationship between the variables across the Chinese provinces from 1992Q1 to 2020Q4.

### *4.2. Results of the FMOLS and DOLS estimators*

In a comparative analysis, we initially estimated the basic model [1] to examine the effects of green credits and green securities on carbon emissions in the three selected Chinese regions using the FMOLS and DOLS estimators for robustness checks, respectively.

The results of the FMOLS method in panel A of Table 4 show that the two indicators of green credits, namely short-term loans (*STLs*) and long-term loans (*LTLs*), reduce carbon emissions (*CE*) in the Eastern region at 1% and 5% levels, but also in the Central region of China at the 5% and 10% levels of significance, respectively. However, although *STLs* had a negative effect on *CE*, *LTLs* instead increased *CE* in China's western region.

**Table 4. Results of the *FMOLS* and *DOLS* estimators**

| | Panel A: Fully modified least squares (FMOLS) | | | | Panel B: Dynamic ordinary least squares (DOLS) | | | |
|---|---|---|---|---|---|---|---|---|
| Variables | Eastern | Central | Western | All provinces | Eastern | Central | Western | All provinces |
| *lnRENC* | -0.281*** | -0.286*** | -0.837*** | -0.233*** | -0.275*** | -0.428*** | -0.743*** | -0.309*** |
| | (0.048) | (0.107) | (0.088) | (0.038) | (0.051) | (0.090) | (0.086) | (0.039) |
| *lnSTL* | -0.049*** | -0.032** | -0.020*** | -0.029*** | -0.044*** | -0.024** | -0.015** | -0.020*** |
| | (0.006) | (0.014) | (0.007) | (0.005) | (0.006) | (0.012) | (0.007) | (0.005) |
| *lnLTL* | -0.009** | -0.015* | 0.029*** | 0.010*** | -0.008** | -0.006 | 0.023*** | 0.009** |
| | (0.004) | (0.007) | (0.006) | (0.003) | (0.004) | (0.006) | (0.005) | (0.003) |
| *lnCAP* | -0.047*** | -0.072*** | -0.023** | -0.060*** | -0.041*** | -0.047*** | -0.020* | -0.044*** |
| | (0.006) | (0.015) | (0.010) | (0.006) | (0.007) | (0.012) | (0.010) | (0.006) |
| *lnGDPC* | 2.118*** | 2.201*** | -1.743*** | 0.444*** | 2.019*** | 1.554*** | -1.535*** | 0.632*** |
| | (0.173) | (0.548) | (0.249) | (0.094) | (0.180) | (0.442) | (0.240) | (0.101) |
| *lnGDPC2* | -0.090*** | -0.094*** | 0.106*** | -0.007 | -0.085*** | -0.064*** | 0.098*** | -0.017*** |
| | (0.008) | (0.025) | (0.011) | (0.004) | (0.008) | (0.020) | (0.010) | (0.004) |
| *lnOIL* | 0.039*** | -0.021 | -0.008 | 0.046*** | 0.037*** | -0.017 | -0.003 | 0.036*** |
| | (0.010) | (0.017) | (0.017) | (0.008) | (0.010) | (0.014) | (0.016) | (0.009) |
| *lnURB* | 0.584*** | -0.008 | -0.338** | 0.429*** | 0.571*** | 0.100 | -0.364*** | 0.379*** |
| | (0.031) | (0.133) | (0.131) | (0.032) | (0.031) | (0.114) | (0.123) | (0.032) |
| *lnTRA* | -0.121*** | 0.037 | -0.211*** | -0.158*** | -0.094*** | 0.027 | -0.189*** | -0.137*** |
| | (0.019) | (0.023) | (0.017) | (0.012) | (0.021) | (0.020) | (0.017) | (0.012) |
| *lnFDI* | 0.051*** | -0.005 | 0.057*** | 0.097*** | 0.058*** | -0.006 | 0.045*** | 0.074*** |
| | (0.010) | (0.010) | (0.011) | (0.007) | (0.010) | (0.008) | (0.010) | (0.007) |
| R-squared | 0.985 | 0.978 | 0.961 | 0.970 | 0.991 | 0.984 | 0.976 | 0.981 |
| Observations | 807 | 473 | 616 | 1896 | 786 | 466 | 600 | 1852 |
| Cointegration test | | | | | | | | |
| *ADF* statistics | -2.152** | -1.991** | -1.972** | -1.624* | -2.152** | -1.991** | -1.972** | -1.624* |
| P-values | 0.015 | 0.023 | 0.026 | 0.052 | 0.015 | 0.023 | 0.016 | 0.052 |

Note: See Table 2 for the definition of variables. *ADF* denotes the augmented Dickey-Fuller statistics in the cointegration test. Numbers in parentheses represent the standard errors of the estimated parameters. ***p < 0.01, **p < 0.05, *p < 0.1.

The effects of *STLs* and *LTLs* were significant at the 1% level in this region. On the other hand, green securities (*CAPs*) adversely influenced carbon emissions in all regions. The effect of *CAPs* on *CE* was significant at the 1% level in the Eastern and Central regions and at the 5% level in China's Western region. Furthermore, economic growth (*GDPC*) had an inverted U-shaped effect on *CE* only in the Eastern and Central regions of China, significant at the 1% level. Conversely, *GDPC* had a U-shaped effect on *CE* in the Western region, significant at the 1% level.

Concerning the control variables, Table 4 indicates that renewable energy consumption (*RENC*) significantly decreases carbon emissions in all regions at the 1% level. The results revealed that oil prices (*OIL*) and urbanization (*URB*) significantly increased carbon emissions only in the Eastern region at the 1% level, unlike the other two regions. Furthermore, trade openness (*TRA*) lowered *CE* in the Eastern and Western regions to the significance level of 1%, as opposed to its positive effect on *CE* in the Central China region. Nevertheless, foreign direct investment (*FDI*) raised *CE* in the Eastern and Western regions at the significance level of 1%, unlike its negative influence on *CE* in the Central region of China. Concerning the DOLS method, panel B of Table 4 provides essentially similar results to those of the FMOLS technique in panel A.

In contrast to the results from the FMOLS method, we found that the adverse effects of *STLs*, *CAPs*, and *URB* on *CE* were significant at the 5%, 10%, and 1% levels in the western region with the DOLS method, respectively. However, Panel B of Table 4 indicates that *LTLs* decrease *CE* in central China, as opposed to the effect of *URB*. These estimates were not significant in the DOLS method. At the aggregate level, the FMOLS and DOLS revealed that *STLs, CAPs, RENC,* and *TRA* decreased *CE* in all provinces, unlike the effects of *LTLs, OIL, URB,* and *FDI.*

### *4.3. Results of the panel fixed-effects models.*

We first tested the null hypothesis of homogeneous slope coefficients in all models using the procedure described in Bersvendsen and Ditzen (2021). Table 5 shows that the unadjusted delta and adjusted delta statistics are significant in all cases at the 1% level.

**Table 5. Testing for slope heterogeneity in the models across regions and provinces**

| Regions | Delta | Adjusted Delta. |
|---|---|---|
| Eastern | 28.125*** | 30.944*** |
| | (0.000) | (0.000) |
| Central | 13.938*** | 15.118*** |
| | (0.000) | (0.000) |
| Western | 19.506*** | 21.729*** |
| | (0.000) | (0.000) |
| All provinces | 56.759*** | 62.491*** |
| | (0.000) | (0.000) |

Note: See Pesaran and Yamagata (2008) for the complete description of the test statistics. Values in parentheses indicate the tests' p values. ***p < 0.01, **p < 0.05, *p < 0.1.

Therefore, we rejected the null hypothesis of slope homogeneity in all models. These results confirm the heterogeneity of the slopes and the presence of fixed effects in the models.

Next, Table 6 indicates that the statistics of the Breusch and Pagan (1980)'s LM test and Friedman (1937)'s test for cross-sectional dependence (CD) are significant at the 1% level in all models, except for those of the Pesaran (2004)'s CD test in most cases.

**Table 6. Results of the panel fixed-effects models.**

| Variables | Eastern | Central | Western | All provinces |
|---|---|---|---|---|
| *lnRENC* | -0.290*** | -0.288*** | -0.888*** | -0.352*** |
| | (0.026) | (0.090) | (0.073) | (0.037) |
| *lnSTL* | -0.049*** | -0.025*** | -0.012 | -0.019*** |
| | (0.008) | (0.008) | (0.008) | (0.006) |
| *lnLTL* | -0.008*** | -0.006 | 0.026*** | 0.007** |
| | (0.003) | (0.006) | (0.004) | (0.003) |
| *lnCAP* | -0.042*** | -0.049*** | -0.017** | -0.041*** |
| | (0.007) | (0.010) | (0.007) | (0.007) |
| *lnGDPC* | 1.978*** | 2.221*** | -1.913*** | 0.658*** |
| | (0.143) | (0.541) | (0.198) | (0.067) |
| *lnGDPC2* | -0.084*** | -0.095*** | 0.116*** | -0.019*** |
| | (0.007) | (0.025) | (0.009) | (0.004) |
| *lnOIL* | 0.034*** | -0.014 | -0.024** | 0.024*** |
| | (0.009) | (0.012) | (0.011) | (0.008) |
| *lnURB* | 0.575*** | -0.035 | -0.396*** | 0.376*** |
| | (0.035) | (0.100) | (0.114) | (0.035) |
| *lnTRA* | -0.092*** | 0.035* | -0.169*** | -0.128*** |
| | (0.013) | (0.020) | (0.012) | (0.008) |
| *lnFDI* | 0.060*** | -0.003 | 0.010 | 0.056*** |
| | (0.012) | (0.010) | (0.008) | (0.010) |
| Constant | -0.970 | 0.474 | 22.963*** | 6.682*** |
| | (0.710) | (2.847) | (1.019) | (0.287) |
| R-squared | 0.950 | 0.966 | 0.939 | 0.926 |
| F-stat | 3644.46*** | 5538.45*** | 3204.25*** | 3437.07*** |
| [Prob>F] | [0.000] | [0.000] | [0.000] | [0.000] |
| Observations | 828 | 480 | 680 | 1,988 |
| Mean VIF | 5.04 | 9.33 | 6.69 | 5.08 |
| CD tests | | | | |
| Pesaran test | 1.294 | -2.068 | -2.163 | 7.211*** |
| | [0.195] | [1.961] | [1.969] | [0.000] |
| Friedman test | 100.811*** | 64.032*** | 28.058*** | 138.530*** |
| | [0.000] | [0.000] | [0.001] | [0.000] |
| LM test | 834.312*** | 134.095*** | 435.837*** | 6356.676*** |
| | [0.000] | [0.000] | [0.000] | [0.000] |

Note: See Table 2 for the definition of variables. The standard errors of Driscoll and Kraay (1998) and the P-values are reported in parentheses and brackets, respectively. *CD* tests show the results of the cross-sectional dependence tests of Friedman (1937), Pesaran (2004), and the Lagrange Multiplier (LM) test of Breusch and Pagan (1980). *Mean VIF* indicates the average values of the variance inflation factor for the test of multicollinearity. *** p<0.01, ** p<0.05, * p<0.1

These outcomes reject the null hypothesis of independent cross-sectional errors in the models. Hence, we applied the standard errors of Driscoll and Kraay (1998) to the FE models because they are robust to heteroscedastic and cross-sectionally dependent residuals across panel units.

Table 6 also displays the results of the fixed-effects (FE) models for each region and in all provinces. The findings of the FE models corroborate those of the DOLS and FMOLS estimators. Although the signs of the estimates remained unchanged, the FE models improved the significance of the results in several cases. The low values of the average VIF (less than 10)
confirm the absence of multicollinearity problems in the models (Marquardt 1970; Hair et al. 1995; El-Bannany 2017, Kassi et al. 2021).

Furthermore, we examined the effects of the size of the green credits (*STLs* and *LTLs*) and green securities (*CAPs*) on carbon emissions in Table 7.

We categorized provinces that had mean values of *STLs*, *LTLs*, and *CAPs* below the medians of their distributions (less than the 50th percentile) as *small,* while *large* referred to those with high mean values of *STLs*, *LTL*s, and *CAPs* (greater than or equal to their 50th percentile) during the 1992Q1-2020Q4 period.

Panel A of Table 7 compares the effects of small and large numbers of *STLs* on *CE* in all provinces. Although *STLs* had significant adverse effects on *CE* at the 1% level in both scenarios, high levels of *STLs* (*large STLs*) substantially reduced *CE* compared to their low levels (*small STLs*). The impacts of the control variables on *CE* are unchanged, except for the contrasting effects of *FDI* on *CE* in Panel A. In addition, Panel B reveals that *small LTLs* significantly decrease *CE*, unlike the positive effect of *large LTLs*. We noted only two main differences between the two scenarios, namely the insignificant U-shaped effect of *GDPC* and the negative impact of *OIL* on *CE* in the case with *small LTLs*, as opposed to the results with *large LTLs*.

Finally, Panel C of Table 7 shows that *small CAPs* and *large CAPs* significantly lower *CE* at the 1% level, but *large CAPs* have the greatest impact on *CE*. The effects of *RENC* and *GDPC* on *CE* are contrasted in the two scenarios, unlike those of the other control variables. Table 8 also reports similar results of the effects of *small* and *large STLs, LTLs,* and *CAPs* on *CE* in all provinces using the *DOLS* and *FMOLS* estimators in Panel A and Panel B, respectively. These results confirmed our previous findings in Table 7 under the *FE* model. Although most of the results remained the same in terms of signs and levels of significance, the estimates from the *FMOLS* method were higher than those from the *FE* and *DOLS* estimators. The magnitudes of the effects of *STLs, LTLs*, and *CAPs* on *CE* vary slightly from the *FE* model (Panels B and C) in Table 7 to the *DOLS* model in Table 8.

In the last stages of the empirical analyses, we present the results of the quantiles via moments regressions with fixed effects in Table 9 across the Chinese regions and provinces. Among the similarities, Table 9 mostly confirms the negative effects of *RENC, STLs*, and *CAPs* on *CE* in the Chinese regions and provinces in all the different quantiles. Panel A and Panel B show that *LTLs* reduce *CE*, whereas *GDPC* has an inverted U-shaped effect on *CE* in the Eastern and Central regions in all quantiles. We also observe a downward trend in the impacts (in absolute values) of *STLs*, *LTLs, CAPs,* and *RENC* on *CE* in most cases across all provinces as the quantiles increase (i.e., from low to high initial levels of *CE* in all provinces), especially in the central and western regions of China. However, the estimated coefficients of *STLs* and *LTLs* were stable in the eastern region, while those of *LTLs* (in absolute values) increased throughout the conditional distribution of *CE* (i.e., as the quantiles widened) in the central region of China.

**Table 7. Effects of *small* and *large* levels of green credits and green securities on carbon emissions**

| | Panel A | | | Panel B | | | Panel C | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variables** | ***Small STL*** | ***Large STL*** | ***All STL*** | ***Small LTL*** | ***Large LTL*** | ***All LTL*** | ***Small CAP*** | ***Large CAP*** | ***All CAP*** |
| *lnRENC* | -0.390*** | -0.611*** | -0.460*** | -0.803*** | -0.083* | -0.424*** | -0.880*** | 0.058 | -0.334*** |
| | (0.036) | (0.031) | (0.029) | (0.043) | (0.043) | (0.030) | (0.023) | (0.048) | (0.035) |
| *lnSTL* | -0.033*** | -0.041*** | -0.023*** | | | | | | |
| | (0.009) | (0.003) | (0.005) | | | | | | |
| *lnLTL* | | | | -0.012*** | 0.044*** | 0.010*** | | | |
| | | | | (0.003) | (0.006) | (0.002) | | | |
| *lnCAP* | | | | | | | -0.017** | -0.030*** | -0.036*** |
| | | | | | | | (0.008) | (0.008) | (0.007) |
| *lnGDPC* | 0.399*** | 0.251** | 0.826*** | -0.026 | 0.857*** | 0.721*** | -0.615*** | 1.593*** | 0.810*** |
| | (0.102) | (0.113) | (0.076) | (0.118) | (0.102) | (0.073) | (0.101) | (0.114) | (0.071) |
| *lnGDPC2* | -0.005 | -0.002 | -0.028*** | 0.008 | -0.025*** | -0.023*** | 0.034*** | -0.053*** | -0.025*** |
| | (0.005) | (0.005) | (0.004) | (0.006) | (0.005) | (0.004) | (0.005) | (0.005) | (0.004) |
| *lnOIL* | 0.025*** | 0.009 | 0.016*** | -0.005 | 0.046*** | 0.019*** | 0.017** | 0.021** | 0.019*** |
| | (0.007) | (0.008) | (0.006) | (0.009) | (0.005) | (0.006) | (0.007) | (0.009) | (0.007) |
| *lnURB* | 0.444*** | 0.244*** | 0.338*** | 0.421*** | 0.445*** | 0.424*** | 0.386*** | 0.074 | 0.328*** |
| | (0.063) | (0.025) | (0.013) | (0.034) | (0.057) | (0.035) | (0.016) | (0.069) | (0.019) |
| *lnTRA* | -0.134*** | -0.065*** | -0.115*** | -0.068*** | -0.114*** | -0.118*** | -0.078*** | -0.132*** | -0.120*** |
| | (0.016) | (0.008) | (0.009) | (0.015) | (0.021) | (0.009) | (0.015) | (0.008) | (0.007) |
| *lnFDI* | 0.159*** | -0.012* | 0.058*** | 0.014 | 0.091*** | 0.056*** | 0.057*** | 0.054*** | 0.052*** |
| | (0.010) | (0.007) | (0.009) | (0.010) | (0.009) | (0.009) | (0.009) | (0.010) | (0.009) |
| Constant | 8.262*** | 10.373*** | 6.573*** | 12.190*** | 4.631*** | 6.789*** | 16.056*** | 0.631 | 5.973*** |
| | (0.479) | (0.581) | (0.376) | (0.672) | (0.398) | (0.340) | (0.545) | (0.517) | (0.329) |
| R-squared | 0.926 | 0.952 | 0.929 | 0.956 | 0.911 | 0.924 | 0.962 | 0.924 | 0.927 |
| F-stat | 3565.80*** | 7293.56*** | 4170.13*** | 5240.03*** | 5461.81*** | 2963.60*** | 6516.79*** | 2952.24*** | 3642.76*** |
| [Prob>F] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] |
| Observations | 1,012 | 1,072 | 2,084 | 948 | 1,068 | 2,016 | 964 | 1,080 | 2,044 |
| Mean VIF | 7.66 | 5.06 | 5.19 | 7.97 | 5.68 | 5.74 | 7.89 | 5.37 | 5.42 |

Note: *Small* denotes the lowest values (less than the 50th percentiles) in the distribution of the average levels of *STLs*, *LTLs,* and *CAPs* of the provinces over the 1992-2020 period, as opposed to *Large* (equal to or greater than the 50th percentiles). We used the fixed-effects models with Driscoll-Kraay (1998)'s standard errors**.** Standard errors are reported in parentheses, and P-values are in brackets. *** p<0.01, ** p<0.05, * p<0.1.

**Table 8. Robustness analysis of the effects of *small* and *large* levels of green credits and securities on carbon emissions**

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | **Panel A: Results of the DOLS estimator** | | | | | |
| **Variables** | ***Small STL*** | ***Large STL*** | ***All STL*** | ***Small LTL*** | ***Large LTL*** | ***All LTL*** | ***Small CAP*** | ***Large CAP*** | ***All CAP*** |
| *lnSTL* | -0.027*** | -0.038*** | -0.017*** | | | | | | |
| | (0.007) | (0.005) | (0.005) | | | | | | |
| *lnLTL* | | | | -0.014*** | 0.046*** | 0.010*** | | | |
| | | | | (0.003) | (0.006) | (0.003) | | | |
| *lnCAP* | | | | | | | -0.019*** | -0.029*** | -0.037*** |
| | | | | | | | (0.006) | (0.007) | (0.006) |
| Controls | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| R-squared | 0.975 | 0.991 | 0.983 | 0.988 | 0.975 | 0.979 | 0.987 | 0.982 | 0.983 |
| Observations | 974 | 1026 | 2000 | 860 | 1020 | 1880 | 924 | 1036 | 1960 |
| | | | | **Panel B: Results of the FMOLS estimator** | | | | | |
| **Variables** | ***Small STL*** | ***Large STL*** | ***All STL*** | ***Small LTL*** | ***Large LTL*** | ***All LTL*** | ***Small CAP*** | ***Large CAP*** | ***All CAP*** |
| *lnSTL* | -0.043*** | -0.048*** | -0.028*** | | | | | | |
| | (0.008) | (0.006) | (0.005) | | | | | | |
| *lnLTL* | | | | -0.017*** | 0.049*** | 0.012*** | | | |
| | | | | (0.004) | (0.007) | (0.004) | | | |
| *lnCAP* | | | | | | | -0.021*** | -0.039*** | -0.046*** |
| | | | | | | | (0.006) | (0.008) | (0.006) |
| Controls | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| R-squared | 0.961 | 0.987 | 0.974 | 0.982 | 0.960 | 0.968 | 0.981 | 0.972 | 0.975 |
| Observations | 993 | 1049 | 2042 | 880 | 1044 | 1924 | 944 | 1058 | 2002 |

Note: See Table 7. *Controls* and *yes* indicate that all other (control) variables were included in the *DOLS* and *FMOLS* models, as in Table 7.
For page saving reasons, we do not report the complete results, which are available on request. Standard errors are indicated in parentheses.
***p<0.01, **p<0.05, *p<0.1.

Table 9 reveals that *STLs* and *CAPs* stimulate *CE* only at the 90th quantile in the central and western regions, respectively, while the positive effect of *LTLs* on *CE* at the lowest quantiles becomes negative at the 70th, 80th, and 90th quantiles of *CE* in all provinces of China.

This pattern of decreasing impacts of the estimates (in absolute values) on *CE* across quantiles was also found in the cases of *GDPC* and *GDPC2* in all provinces, unlike those located in China's western region. Moreover, the magnitude of the effects of *OIL* and *URB* on *CE* widens in all provinces as the quantiles increase, except for the cases in the western region, while this trend is reversed in the cases of *TRA* and *FDI* across quantiles.

Finally, Panel B of Table 9 reveals that the adverse effects of *URB*, *FDI,* and *TRA* on *CE* at the lowest quantiles turn out to be positive at the highest quantiles (70th, 80th, and 90th) in the central region.

### *4.4. Discussion of the findings*

Our analysis reveals several findings on the effects of green credits (*STLs* and *LTLs*) and green securities (*CAPs*) on carbon emissions (*CE*) across 29 selected Chinese provinces grouped into three main regions from 1992Q1 to 2020Q4. First, the negative effect of *STLs* on *CE* in all provinces validates *hypothesis 1a*, i.e., the beneficial impact of short-term loans to green industries on environmental quality in China. However, the positive effect of *LTLs* on *CE* in all provinces, which does not support *hypothesis 1b*, originates only from China's western region.

These results show that long-term loans reduce environmental quality by increasing carbon emissions only in the western region, as opposed to the eastern and central regions of China. These results indicate the ineffective use of long-term loans intended to promote environmentally friendly activities in the Western region. This poor allocation of loans creates a crowding-out effect of green investments and damages long-term environmental quality. Unlike the eastern and central regions, the structure or maturity of loans (i.e., short-term versus long-term loans) to green industries can play an essential role in understanding the sustainability of the beneficial effects of green credits on the quality of the environment in the Chinese provinces, especially those located in the western region. The pressure of loan repayment deadlines and the constraint of respecting the ecological and profitability clauses and objectives assigned to green companies contracting short-term loans oblige them to adopt more efficient and effective strategies for productive investments to improve environmental quality. This scenario also helps these green industries meet their financial constraints by ameliorating their credit rating to qualify for new loans, which are contingent on the performance of previous short-term loans. The dominant banking sector in the Chinese financial system creates many challenges in financing green projects, such as the relatively high propensity of banks to provide short-term loans with strong regulatory and supervisory policies. Most banks face a maturity mismatch for green loans, as their interest or ability to provide long-term loans for green projects is limited by the relatively short maturity of their on-balance sheet commitments and the need for avoiding excessive transformation of deadlines

Additionally, green businesses that take out short-term loans are often subject to strict regulatory policies and good governance practices. The supervision and regulation of their activities will compel

**Table 9. Quantile regressions using the method of moments with fixed-effects models**

| | Panel A: Eastern | | | | | | Panel B: Central | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **Q.30** | **Q.40** | **Q.50** | **Q.70** | **Q.80** | **Q.90** | **Q.30** | **Q.40** | **Q.50** | **Q.70** | **Q.80** | **Q.90** |
| *lnRENC* | -0.344*** | -0.309*** | -0.287*** | -0.216*** | -0.195*** | -0.161** | -0.333*** | -0.320*** | -0.287*** | -0.249** | -0.232* | -0.198 |
| | (0.069) | (0.063) | (0.061) | (0.065) | (0.068) | (0.076) | (0.092) | (0.090) | (0.093) | (0.109) | (0.119) | (0.143) |
| *lnSTL* | -0.049*** | -0.049*** | -0.049*** | -0.049*** | -0.049*** | -0.049*** | -0.044*** | -0.039*** | -0.025** | -0.009 | -0.003 | 0.012 |
| | (0.009) | (0.008) | (0.008) | (0.008) | (0.009) | (0.010) | (0.012) | (0.012) | (0.013) | (0.015) | (0.016) | (0.019) |
| *lnLTL* | -0.009* | -0.009* | -0.008* | -0.008* | -0.008 | -0.008 | -0.001 | -0.002 | -0.007 | -0.011 | -0.013 | -0.017 |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.006) | (0.008) | (0.007) | (0.008) | (0.009) | (0.010) | (0.012) |
| *lnCAP* | -0.050*** | -0.045*** | -0.041*** | -0.030*** | -0.027*** | -0.022** | -0.061*** | -0.058*** | -0.049*** | -0.039** | -0.034** | -0.025 |
| | (0.009) | (0.008) | (0.008) | (0.008) | (0.009) | (0.010) | (0.013) | (0.013) | (0.013) | (0.016) | (0.017) | (0.020) |
| *lnGDPC* | 2.274*** | 2.085*** | 1.962*** | 1.578*** | 1.462*** | 1.278*** | 2.723*** | 2.582*** | 2.212*** | 1.796*** | 1.615** | 1.238 |
| | (0.274) | (0.249) | (0.241) | (0.254) | (0.267) | (0.299) | (0.488) | (0.481) | (0.497) | (0.576) | (0.629) | (0.754) |
| *lnGDPC2* | -0.098*** | -0.089*** | -0.083*** | -0.064*** | -0.059*** | -0.050*** | -0.118*** | -0.112*** | -0.094*** | -0.075*** | -0.066** | -0.048 |
| | (0.013) | (0.012) | (0.011) | (0.012) | (0.013) | (0.014) | (0.023) | (0.022) | (0.023) | (0.027) | (0.029) | (0.035) |
| *lnOIL* | 0.019 | 0.029** | 0.035*** | 0.055*** | 0.061*** | 0.071*** | -0.030** | -0.025* | -0.014 | -0.000 | 0.006 | 0.018 |
| | (0.013) | (0.012) | (0.011) | (0.012) | (0.013) | (0.014) | (0.014) | (0.014) | (0.014) | (0.016) | (0.018) | (0.021) |
| *lnURB* | 0.513*** | 0.552*** | 0.578*** | 0.658*** | 0.682*** | 0.720*** | -0.183 | -0.141 | -0.032 | 0.091 | 0.145 | 0.256 |
| | (0.069) | (0.063) | (0.061) | (0.064) | (0.068) | (0.076) | (0.125) | (0.124) | (0.128) | (0.148) | (0.161) | (0.193) |
| *lnTRA* | -0.096*** | -0.094*** | -0.092*** | -0.087*** | -0.085*** | -0.082*** | -0.021 | -0.005 | 0.035 | 0.081*** | 0.101*** | 0.143*** |
| | (0.025) | (0.022) | (0.022) | (0.023) | (0.024) | (0.027) | (0.021) | (0.021) | (0.022) | (0.024) | (0.027) | (0.031) |
| *lnFDI* | 0.062*** | 0.061*** | 0.060*** | 0.058*** | 0.057*** | 0.056*** | -0.013 | -0.010 | -0.003 | 0.006 | 0.010 | 0.017 |
| | (0.015) | (0.014) | (0.013) | (0.014) | (0.015) | (0.017) | (0.010) | (0.010) | (0.010) | (0.012) | (0.013) | (0.015) |
| Constant | -2.113 | -1.381 | -0.907 | 0.574 | 1.022 | 1.732 | -1.744 | -1.123 | 0.513 | 2.352 | 3.155 | 4.822 |
| | (1.448) | (1.322) | (1.279) | (1.348) | (1.420) | (1.586) | (2.504) | (2.462) | (2.543) | (2.954) | (3.224) | (3.868) |
| Observations | 828 | 828 | 828 | 828 | 828 | 828 | 480 | 480 | 480 | 480 | 480 | 480 |

Note: See Table 7. Standard errors are indicated in parentheses. ***p<0.01, **p<0.05, *p<0.1.

**Table 9. Quantile regressions using the method of moments with fixed-effects models (Cont.)**

| | Panel C: Western | | | | | | Panel D: All provinces | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **Q.30** | **Q.40** | **Q.50** | **Q.70** | **Q.80** | **Q.90** | **Q.30** | **Q.40** | **Q.50** | **Q.70** | **Q.80** | **Q.90** |
| *lnRENC* | -0.979*** | -0.942*** | -0.895*** | -0.803*** | -0.751*** | -0.654*** | -0.435*** | -0.396*** | -0.350*** | -0.271*** | -0.237*** | -0.194*** |
| | (0.128) | (0.118) | (0.111) | (0.118) | (0.132) | (0.172) | (0.120) | (0.099) | (0.076) | (0.051) | (0.052) | (0.065) |
| *lnSTL* | -0.014 | -0.013 | -0.012 | -0.009 | -0.008 | -0.006 | -0.023 | -0.021 | -0.019* | -0.016** | -0.014** | -0.012 |
| | (0.011) | (0.010) | (0.009) | (0.010) | (0.011) | (0.014) | (0.016) | (0.013) | (0.010) | (0.007) | (0.007) | (0.009) |
| *lnLTL* | 0.032*** | 0.030*** | 0.027*** | 0.021*** | 0.018** | 0.011 | 0.014 | 0.011 | 0.006 | -0.001 | -0.004 | -0.008 |
| | (0.007) | (0.007) | (0.006) | (0.007) | (0.008) | (0.010) | (0.011) | (0.009) | (0.007) | (0.005) | (0.005) | (0.006) |
| *lnCAP* | -0.028** | -0.024** | -0.018 | -0.007 | -0.001 | 0.011 | -0.045*** | -0.043*** | -0.040*** | -0.036*** | -0.034*** | -0.031*** |
| | (0.013) | (0.012) | (0.011) | (0.012) | (0.013) | (0.017) | (0.017) | (0.014) | (0.011) | (0.007) | (0.008) | (0.009) |
| *lnGDPC* | -1.793*** | -1.842*** | -1.904*** | -2.028*** | -2.096*** | -2.226*** | 0.661** | 0.660** | 0.658*** | 0.654*** | 0.653*** | 0.651*** |
| | (0.389) | (0.359) | (0.337) | (0.357) | (0.401) | (0.523) | (0.315) | (0.259) | (0.199) | (0.133) | (0.136) | (0.169) |
| *lnGDPC2* | 0.109*** | 0.112*** | 0.116*** | 0.123*** | 0.128*** | 0.136*** | -0.020 | -0.019 | -0.019** | -0.017*** | -0.017*** | -0.016** |
| | (0.017) | (0.016) | (0.015) | (0.016) | (0.018) | (0.023) | (0.015) | (0.012) | (0.009) | (0.006) | (0.006) | (0.008) |
| *lnOIL* | -0.027 | -0.026 | -0.024 | -0.021 | -0.019 | -0.016 | 0.019 | 0.021 | 0.024 | 0.028** | 0.030*** | 0.032** |
| | (0.024) | (0.022) | (0.021) | (0.022) | (0.025) | (0.032) | (0.026) | (0.021) | (0.016) | (0.011) | (0.011) | (0.014) |
| *lnURB* | -0.434** | -0.418** | -0.399** | -0.360** | -0.338* | -0.298 | 0.343*** | 0.358*** | 0.377*** | 0.409*** | 0.422*** | 0.439*** |
| | (0.183) | (0.168) | (0.158) | (0.168) | (0.188) | (0.245) | (0.118) | (0.097) | (0.075) | (0.050) | (0.051) | (0.063) |
| *lnTRA* | -0.156*** | -0.161*** | -0.168*** | -0.181*** | -0.188*** | -0.202*** | -0.131*** | -0.130*** | -0.128*** | -0.124*** | -0.122*** | -0.120*** |
| | (0.022) | (0.020) | (0.019) | (0.020) | (0.023) | (0.029) | (0.033) | (0.027) | (0.021) | (0.014) | (0.014) | (0.018) |
| *lnFDI* | 0.007 | 0.008 | 0.010 | 0.013 | 0.015 | 0.019 | 0.074*** | 0.066*** | 0.055*** | 0.037*** | 0.029*** | 0.019 |
| | (0.011) | (0.010) | (0.010) | (0.010) | (0.011) | (0.015) | (0.024) | (0.019) | (0.015) | (0.010) | (0.010) | (0.013) |
| Constant | 22.820*** | 22.879*** | 22.952*** | 23.098*** | 23.178*** | 23.332*** | 7.126*** | 6.917*** | 6.673*** | 6.246*** | 6.064*** | 5.834*** |
| | (2.116) | (1.950) | (1.831) | (1.942) | (2.180) | (2.843) | (1.747) | (1.435) | (1.101) | (0.737) | (0.757) | (0.938) |
| Observations | 680 | 680 | 680 | 680 | 680 | 680 | 1,988 | 1,988 | 1,988 | 1,988 | 1,988 | 1,988 |

Note: See Table 7. Standard errors are indicated in parentheses. ***p<0.01, **p<0.05, *p<0.1.

them to improve their production system and productivity, reducing the environmental pollution. Liu et al. (2018) point out that green credit stimulates technological innovation by supporting emerging technology firms, expanding the scale of their capital investments, and enhancing the efficiency of using existing resources. It improves the quality of the environment by modernizing and optimizing industrial and energy systems. Thus, green credits promote the deployment of renewable energy projects because they are innovative, low carbon, competitive, and conducive to sustainable development.

The contrasting effects of long-term loans (*LTLs*) on carbon emissions (*CE*) between Chinese regions may indicate that many asymmetries exist within provinces and are related to inefficiency, misallocation of loans, energy structure, and governance quality in the western region.

Figure 1 reveals that several provinces in the western region, which represent the least polluting area, received a high proportion of long-term loans (*large LTLs*) compared to the other regions. The detrimental impact of long-term loans to the green industries on environmental quality (i.e., a positive effect of *LTLs* on *CE*) in the western region reflects a lack of effective green policy implementation for which these loans were granted. It also points to a lack of efficiency in renewable energy investments and internal management in the long term, unlike in the eastern and central regions of China. Similar to He et al. (2019a), we believe that green credits may not be effective in mitigating long-term underinvestment scenarios in renewable energy technologies in some Chinese provinces, especially in the western region, unless the banking system and the provincial government firmly establish appropriate policies for oversight, coordination and good governance in green industries.

Furthermore, we found that green securities (*CAPs*) improved environmental quality by decreasing carbon emissions (*CE*) in all Chinese provinces. This finding, which is consistent with *hypothesis 2*, may imply that the capital market is more efficient than the banking system in assessing the risks associated with evolving and highly complex green projects and thereby structuring contracts and mechanisms that bind the green industries to achieve their primary goal of sustainable development in all provinces over the long-term. The ability of banks to assess the environmental risks associated with complex corporate financing and projects may be limited by the lack of data (information asymmetries) on the environmental profiles of borrowers (i.e., data on environmental technologies and carbon emissions). It is difficult for banks alone to effectively analyze business and environmental risks of the green industries in the absence of centralized data collection and collaboration in some provinces when green policies on disclosure of corporate environmental information come from various private and public institutions. Therefore, the stock markets can promote good environmental quality by establishing regulations and requirements for listed companies to constrain them to use greener technologies and further develop sustainable practices of corporate social responsibility that reduce industrial pollution and ensure environmental sustainability, bringing greater high energy efficiency in their production process (Lanoie et al. 1998). In line with the Sustainable Development Goals and the growing awareness of global warming, recent stock market developments favor financing channels for structured investments in cleaner energy projects to reduce carbon emissions (Paramati et al. 2016; Paramati et al. 2017).

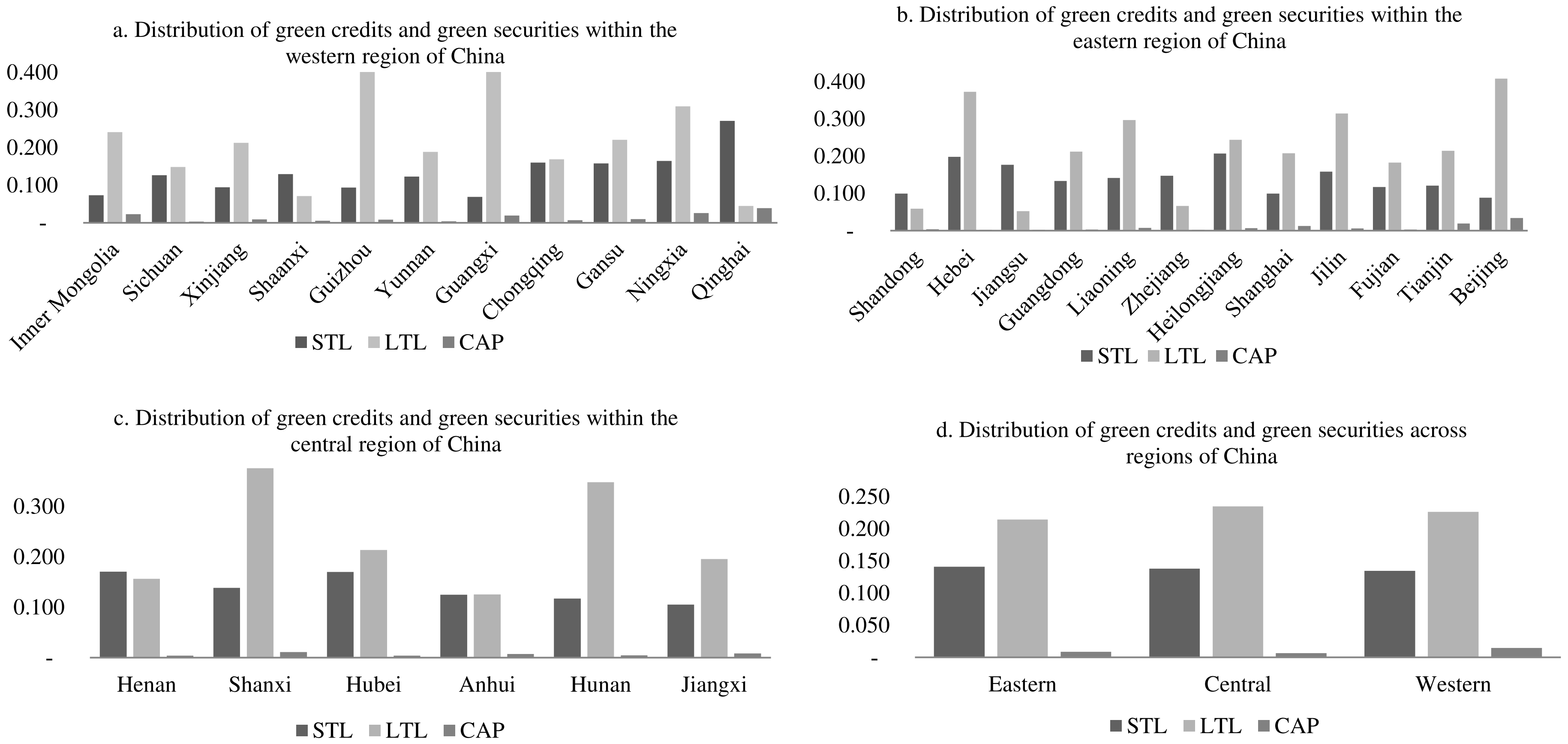
In addition, the long-term analysis reveals that green credits only improve environmental quality in

Chinese provinces with low proportions of long-term loans (*small LTLs*), unlike those with the highest shares (*large LTLs*). However, short-term green credits (*small STLs* and *large STLs*) and green securities (*small CAPs* and *large CAPs*) reduce carbon emissions in all provinces, regardless of size. In particular, Chinese green enterprises with large market capitalizations (*large CAPs*) and a large number of short-term credits *(large STLs*) have the greatest impact on improving the quality of the environment compared to their counterparts (*small CAPs* and s*mall STLs*). For instance, Table 7 indicates that a 10% increase in *large STLs* and *large CAPs* significantly diminishes *CE* by 0.41% and 0.30%, compared to 0.33% and 0.17% with *small STLs* and *small CAPs*, respectively. As noted earlier, these results confirm that, unlike the capital market, the banking system may not be efficient and well-equipped with analytical capabilities to assess and monitor long-term lending to green businesses in some provinces (particularly the western region) due to their weak regulation, risk management and disparate levels of governance quality among Chinese provinces.

Although *STLs* and *CAPs* enhance environmental quality by decreasing *CE* in all regions of China, their negative impacts on *CE* weaken in the most polluting provinces (i.e., the 70$^{th}$, 80$^{th}$, and 90$^{th}$ quantiles of *CE*), but they remain relatively higher in the eastern and central regions in the short-term, respectively. On the other hand, we note that non-significant adverse effects of *LTLs* on *CE* can only occur in the most polluting provinces in the long term, coming mainly from the central region where the impacts of *LTLs* on *CE* increase at the highest quantiles. However, the long-term analysis indicates that *LTLs* significantly improve environmental quality only in the eastern region, namely in provinces with initially lower carbon emissions (i.e., the lower quantiles of *CE*). This evidence shows that modern renewable energy is not yet well entrenched in the production process of companies in some provinces as they still depend on fossil fuels or traditional renewable energy. These results underline that the beneficial effects of green credits on the quality of the environment in the short term may fade in the long term in most polluting provinces. These effects may gradually reverse over the long term, particularly in the western region, if there are no prudential mechanisms for monitoring green investments. Our results complement those of He et al. (2019b), who proved the double-threshold effects of green credits on the relationship between renewable energy investment and green economic development in China during the 2004-2015 period. Thus, they showed that these threshold effects of green credits condition investments in renewable energies to favor and slow down green economic development in three successive stages. The authors argued that small and medium-sized enterprises were the main driving forces in promoting the development of a green economy than large enterprises due to their inefficient use of funds. Nevertheless, we show that green credits and green securities effectively promote good environmental quality by supporting the development of green industries in eastern and central regions of China through their relatively strict legal framework, economic environment, and better allocation of these loans for the sustainable development of green technologies to combat environmental degradation. Our findings are also similar to those of Chen and Chen (2021), who proved the negative effect of green finance on carbon emission in the Chinese provinces during the 2005-2018 period.

In addition, our finding of the inverted U-shaped effect of economic growth on carbon emissions in all Chinese provinces, except those in the western region, aligns with the results of most previous related

**Figure 1: Distribution of the average proportions of green credits and securities in the Chinese regions and provinces during the 1992Q1-2020Q4 period.**




Note: *STL and LTL* denote green credits, i.e., short-term and long-term loans, while *CAP* represents green securities as defined in Table 2. The horizontal axis displays the provinces of each region, from the most polluting to the least polluting. The vertical axis shows the proportion of *STL, LTL,* and *CAP*, respectively.

studies confirming the EKC hypothesis (Ren et al. 2014; Li et al. 2016; Shahbaz et al. 2017; Assamoi et al. 2020a; Kassi et al. 2022). It shows that most of the provinces of the eastern and central regions will be the catalysts for good environmental quality in China when the development of their economic activities exceeds an optimal threshold. Growing awareness of global warming in China will compel these regions to implement green policies and strong regulatory mechanisms to tackle carbon emissions. These regions are the most polluting areas due to the high concentration of energy-consuming industries and economic activities. The *GDPC*'s U-shaped effect on *CE* in western China will raise long-term environmental concerns as this less polluting region will accelerate its economic growth to catch up with other developed regions. Unless specific regulations are implemented, the western region may not reduce its carbon intensity and meet its long-term energy intensity target. This least developed region (i.e., lowest average *GDPC* compared to other regions) will attract many energy-intensive industries from eastern and central regions (Wang et al. 2011).

Regarding the control variables, the negative effect of *OIL* on *CE* in China, as suggested by previous studies (Zhang and Zhang 2016; Saboori et al. 2017; Bilgili et al. 2020), is valid only for the central and western regions. Unlike in eastern China, the substitution effect of any increase in oil prices, coupled with the growing trend to implement green regulatory policies, will drive a shift towards demands for more renewable energy sources in the process of producing goods and services, improving the quality of the environment (reducing *CE*) in the central and western regions. This study also reveals that renewable energy consumption is one of the main drivers of good environmental quality by mitigating carbon emissions in all Chinese regions, with more significant impacts in the least polluting provinces (the lowest quantiles of *CE*), especially in western China. This finding is consistent with the results of other studies (Dong et al. 2018; Yu et al. 2020; Li et al. 2021; Kassi et al. 2022). Renewable energy consumption has many benefits for sustainable development in China, but also in the world, due to its low carbon intensity, sustainability of energy supply, and increasing competitiveness (wind, hydro and solar PV) as its levelised costs are declining through innovative techniques, government subsidies and economies of scale (IEA 2020). Besides, the detrimental effect of urbanization on environmental quality in China remains one of the primary concerns regarding its sustainable development in the developed regions of eastern China and the most polluting provinces of central China (the highest quantiles of *CE*), as highlighted in previous studies (Du et al. 2012; Sheng and Guo 2016; Li et al. 2021). This result can be related to the high proportions of energy-consuming industries dependent on fossil fuels (high-carbon energy). It is also linked to population density and the agglomeration effect in the eastern and central regions with relatively high average urbanization rates (about 61.03% and 39.31%, respectively) over the study period. The beneficial effect of trade on environmental quality in most Chinese provinces is consistent with the works of Li and Tu (2014), Sousa et al. (2015), Fan et al. (2019), and Assamoi et al. (2020a). The adverse effect of foreign direct investment on environmental quality in Chinese provinces has also been confirmed in several empirical studies (Wang et al. 2019; Wawrzyniak and Doryń 2020; Assamoi et al. 2020b; Wang et al. 2021). Foreign direct investment has mainly increased the production scale of energy-intensive and energy-inefficient manufacturing industries, which has increased carbon emissions by not effectively transferring green technological progress to the Chinese provinces.

## 5. Conclusion and policy implications

The transition to cleaner energies in daily activities has become necessary to combat endemic global warming and environmental degradation. As one of the world's largest carbon emitters, China has been gradually integrating green policies into its financial system to reduce carbon emissions and improve environmental quality. In this study, we examine the effects of the leading green finance instruments, namely green credits and green securities, on environmental quality in comparative analysis across Chinese provinces from 1992Q1 to 2020Q4. We measured green credits by the ratios of short-term loans (*STLs*) and long-term loans (*LTLs*) to total assets, whereas green securities (*CAPs*) represent the ratio of market capitalization to GDP in green industries, respectively. We chose 152 renewable energy enterprises listed in A-shares on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE) in 29 Chinese municipalities and provinces. We also analyze the effects of renewable energy consumption (*RENC*), foreign direct investments (*FDI*), trade openness (*TRA*), urbanization (*URB*), and oil prices (*OIL*) on environmental quality, i.e., carbon dioxide emissions (*CE*) in a multivariate *EKC* framework. Additionally, our study used both traditional econometric methods based on conditional means (*CM*), i.e., the FMOLS, DOLS, and FE estimators, and the method of moments-quantile regression (MM-QR) with fixed-effects models. Unlike CM-based methods, the MM-QR estimator analyzes the effects of the explanatory variables on the entire conditional distribution of *CE* at different quantiles (i.e., initial levels of *CE*) across Chinese provinces.

The CM-based estimators showed that *STLs* and *CAPs* decreased *CE* in Chinese provinces. Unlike the Western region, *LTLs* improved environmental quality by reducing *CE* in the Eastern and Central regions of China. Next, we found that the size of *STLs, LTLs,* and *CAPs* have asymmetrical effects on *CE* across provinces. High levels of *STLs* and *CAPs* have greater effects on *CE* than their low levels, whereas *small LTLs* substantially reduce *CE*, unlike the detrimental effect of large *LTLs* on environmental quality in all provinces. Moreover, the MM-QR estimator revealed that *STLs* and *CAPs* were drivers of *CE* only in the most polluting provinces (i.e., at the 90th quantile) of the central and western regions, respectively, but *LTLs* improve the quality of the environment only at the highest quantiles of *CE* in all Chinese provinces.

We note a downward trend in the impacts (in absolute values) of *STLs, LTLs*, and *CAPs* on *CE* as the quantiles increase, particularly in China's central and western regions. Besides, although renewable energy consumption inhibits carbon emissions in all provinces, oil prices, urbanization, and foreign direct investments are drivers of carbon emissions only in the Eastern region in most cases. In contrast, trade openness and foreign direct investments deter environmental quality in the Central and Western regions, respectively. These effects vary across quantiles in all provinces. Finally, our findings validate the EKC hypothesis in the Eastern and Central regions, unlike the U-shaped effect of economic growth on carbon emissions found in China's western region.

This study has several policy implications for improving environmental quality in Chinese provinces. The heterogeneous effects of *STLs* and *LTLs* on *CE* imply that the structure (i.e., maturity) of lending to green industries plays a vital role in improving the environment in some provinces, particularly in the western region of China, due to inefficiencies in loan allocation, unproductive investments, and a lack of a robust regulatory framework and good governance practices. The negative effect of *STLs* on *CE* in all Chinese provinces means that Chinese financial actors should prioritize short-term lending to green industries as they compel companies operating in these sectors to make productive investments to improve their credit rating for their future loan applications. The relatively good performance of green credits on environmental quality in the short term indicates that they are one of the essential green financial mechanisms that policymakers should rely on to reduce carbon emissions in China. Short-term lending primarily reflects the short maturity of liabilities on banks' balance sheets and the need to avoid excessive maturity transformation. Short-term loans can ease financing constraints for renewable companies and make it easier to track their investments in clean projects that improve environmental quality in Chinese provinces. These short-term loans to green industries will have a greater effect on environmental quality in eastern and central China, respectively, the most polluting provinces subject to stricter environmental regulations, than in western China.

Nevertheless, we recommend that Chinese banks and relevant policymakers allocate a small number of long-term loans to finance green projects, especially in provinces located in the eastern and central regions, to reduce carbon emissions. Most banks lack the analytical capabilities and skills to assess the risks associated with evolving and complex green projects having long maturity, lower *opex,* and higher *capex* than conventional projects. In addition, there is an urgent need to incorporate good governance practices as a prerequisite for financing long-term green and innovative projects in Chinese provinces, mainly in western China. Policymakers should also pay attention to the least polluting provinces. The absence of greater enforcement of green policy guidelines and a strict monitoring framework can lead to inefficient use of these green credits in investments in long-term energy-intensive activities.

The negative influence of green securities on carbon emissions in all Chinese provinces reveals the significant role that the development of the green industry stock exchange can play in improving the quality of the environment in China. The ability of its stock market to develop an efficient allocation of financial resources, a monitoring system, a mechanism for mitigating environmental risks, and attractive investment opportunities in green industries based on investors' risk profiles make the stock market an essential alternative that public and private authorities should rely on to reduce carbon emissions in Chinese provinces. Hence, policymakers should enforce green policies guidelines in the development of the stock market by creating mechanisms that incite investors to allocate a substantial amount of funds to green projects, but also by compelling listed companies to meet specific environmental, social and responsible governance conditions as additional requirements for raising funds to support their activities. Chinese financial system regulators should facilitate listing green industries on the stock market to obtain additional financial resources that they would otherwise not obtain to finance their activities that improve the quality of the environment in all provinces. Most banks cannot effectively finance long-term green projects characterized by technical, market, and political uncertainties in which credit approval specialists and account managers lack the knowledge and skills to assess these projects appropriately. Moreover, Chinese local governments and regulators should strengthen green policy guidelines and pilot programs in the most polluting provinces while paying attention to environmental risks in underdeveloped western provinces of China, seeking to catch up with the advanced development process of other provinces.

Green credit alone may fall far short of meeting the demand for green financing. Efforts are needed to promote the direct financing markets vigorously. Policymakers should also rely on market-based tools such as structural reserve rates, fiscal discount rates, differentiated ratios of venture capital, and improved environmental disclosure to help stock markets in information screening, price discovery, and risk management of green development projects.

The Chinese government should promote modern renewable energies (modern biomass, wind, solar, hydro, geothermal, and biofuels) in daily activities in all provinces, mainly in the major carbon emitters in Eastern and Central China. Renewable energies have beneficial effects on economic growth and environmental quality, which cannot be denied because of their low polluting nature, durability, availability, and competitiveness (wind power and solar photovoltaic) compared to fossil fuels. The technological advances and the cost reduction of renewable energies make them a viable solution for enhancing environmental quality across the Chinese provinces. Moreover, there is an urgent need to gradually put in place institutional mechanisms that reduce the harmful effect of oil prices on the quality of the environment in the most polluting provinces of Eastern and Central China. Therefore, as an alternative to optimal taxation and export quotas on polluting industries, the local authorities should redistribute a significant portion of the revenue from rising oil prices to support renewable resources (i.e., solar energy, wind energy, modern biomass, hydroelectric energy, among other renewables) in Eastern and Central China, but also to improve the competitiveness of renewable energy in Western China for sustainable development in China.

In addition, China should integrate cleaner technologies and eco-friendly practices into its urbanization policy, mainly in the eastern region and the most polluting provinces in the central region, where industries in these densely populated areas, with a high concentration of economic activity, still depend on non-renewable energy sources to meet the daily needs of households.

We also show that trade openness is one of the main strategies for reducing carbon emissions in China. The country should improve the structure of export products by promoting the export of products from low-carbon industries but prohibiting or restricting the export of carbon-intensive products through green trade policies with export tariffs, quotas, export refund policies, mainly in polluting provinces in central China. It is also essential to encourage imports of environmental technologies that promote the expansion of green industries in all Chinese provinces.

Moreover, there is an urgent need to improve the composition of *FDI* through green mechanisms that support foreign industries and technologies that are environmentally friendly but also promote their efficient use of resources in China. The Chinese government should direct *FDI* and innovation towards green industries (i.e., clean energy, environmental protection, energy conservation, and low-carbon industries) through fiscal incentives and relaxation of administrative and regulatory measures. However, local authorities must restrict foreign projects that negatively affect the environment, especially in eastern and western China.

Additionally, the validity of the EKC hypothesis in the eastern and central regions of China, mainly in low carbon emitters, reveals that policymakers should use their financial resources and economic power by shifting the energy mix toward more renewables and cleaner technologies in the production of goods and services in these regions. It means that they can continue the transition to a more environmentally friendly economy. As a late starter in China's development phase, the western region must subsidize green businesses and provide tax incentives for start-ups and industries while implementing policies that limit any reliance on non-renewable energy sources and carbon-intensive activities in the long term. Overall, the asymmetrical effects of green credits and green securities, among other factors, on environmental quality across quantiles imply that policymakers should adjust their green policies according to the individual characteristics of Chinese provinces at the regional level. This study can also help the international community to consider market-based instruments and the structure of lending to green industries among the main determinants of environmental quality.

## Declarations

- **Ethics approval and consent to participate:** Not applicable
- **Consent for publication:** Not applicable
- **Availability of data and materials:** The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.
- **Competing interests:** The authors have no relevant financial or non-financial interests to disclose
- **Funding:** The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.
- **Authors' contributions: DFK** designed the article, wrote the methodology, performed the econometric analysis, and discussed the results. **YL** oversaw the investigation and drafted the conclusion and policy implications. **FEG** wrote the introduction and organized the study. **SJT** has compiled the data and drafted the literature review. **RS** reviewed the literature and edited the article. All authors read and approved the manuscript.
- **Acknowledgments:** Not applicable at this stage.

## APPENDICES

Table A.1. Classification of the Chinese provinces by percentile of average values of Carbon emissions over the 1997-2020 period.

| The overall ranking of all provinces | | | | | |
|---|---|---|---|---|---|
| [1% - 30%[ [31530.58 – 141747.6[ | | [30% - 40%[ [141747.6 – 163292.8[ | | [40% - 50%[ [163292.8 – 192094[ | |
| Qinghai; Beijing; Ningxia; Gansu; Tianjin; Chongqing; Jiangxi; Guangxi | | Yunnan; Fujian; Jilin | | Shanghai; Guizhou; Shaanxi | |
| [50% - 70%[ [192094 –282085.1[ | | [70% - 80%[ [282085.1 – 373724.5[ | | [80% - 90%[ [373724.5-480763.9[ | |
| Xinjiang; Heilongjiang; Hunan; Sichuan; Anhui; Hubei | | Zhejiang; Shanxi; Liaoning | | Henan; Inner Mongolia; Guangdong; P ≥ 90% Jiangsu; Hebei; Shandong | |
| Ranking of provinces by region | | | | | |
| Western region | | Central region | | Eastern region | |
| Qinghai | 31530.58 | Jiangxi | 134838.34 | Beijing | 87016.96 |
| Ningxia | 100759.27 | Hunan | 204601.95 | Tianjin | 109380.27 |
| Gansu | 107503.07 | Anhui | 237899.36 | Fujian | 158402.16 |
| Chongqing | 113582.81 | Hubei | 246703.47 | Jilin | 162503.36 |
| Guangxi | 139000.24 | Shanxi | 346844.56 | Shanghai | 163292.77 |
| Yunnan | 141747.57 | Henan | 373724.46 | Heilongjiang | 196740.63 |
| Guizhou | 169608.52 | | | Zhejiang | 282085.06 |
| Shaanxi | 173294.94 | | | Liaoning | 357877.94 |
| Xinjiang | 192093.98 | | | Guangdong | 387872.83 |
| Sichuan | 228818.56 | | | Jiangsu | 480763.92 |
| Inner Mongolia | 387251.60 | | | Hebei | 537871.39 |
| | | | | Shandong | 588635.42 |
| Mean | 163028.47 | Mean | 257435.36 | Mean | 292703.56 |

Note: This table shows the average levels of carbon emissions (kt CO2) of the provinces in brackets at various percentiles (P) during the 1997-2020 period. It ranks the provinces from the lowest to the highest average values of carbon emissions over the studied period.

Table A.2. Pairwise correlations (All Provinces)

| Variables | *lnCO2* | *lnRENC* | *lnSTL* | *lnLTL* | *lnCAP* | *lnGDPC* | *lnOIL* | *lnURB* | *lnTRA* | *lnFDI* |
|---|---|---|---|---|---|---|---|---|---|---|
| *lnCO2* | 1.000 | | | | | | | | | |
| *lnRENC* | -0.570*** | 1.000 | | | | | | | | |
| *lnSTL* | 0.023 | -0.043** | 1.000 | | | | | | | |
| *lnLTL* | 0.157*** | -0.289*** | -0.077*** | 1.000 | | | | | | |
| *lnCAP* | -0.641*** | 0.357*** | -0.255*** | -0.041** | 1.000 | | | | | |
| *lnGDPC* | 0.571*** | -0.859*** | -0.052*** | 0.240*** | -0.291*** | 1.000 | | | | |
| *lnOIL* | 0.466*** | -0.889*** | 0.077*** | 0.257*** | -0.316*** | 0.723*** | 1.000 | | | |
| *lnURB* | 0.327*** | -0.501*** | -0.031* | 0.196*** | -0.134*** | 0.732*** | 0.411*** | 1.000 | | |
| *lnTRA* | 0.137*** | -0.008 | -0.048*** | 0.017 | -0.131*** | 0.334*** | 0.012 | 0.563*** | 1.000 | |
| *lnFDI* | 0.210*** | -0.077*** | 0.103*** | 0.031 | -0.256*** | 0.300*** | 0.115*** | 0.374*** | 0.662*** | 1.000 |

Note: See Table 2 for the description of variables. *** p<0.01, ** p<0.05, * p<0.1

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