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**Essays on the role of rural finance, green finance and digital  
financial inclusion in reducing carbon emission**

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A thesis  
submitted in partial fulfilment  
of the requirements for the Degree of  
Doctor of Philosophy

at  
Lincoln University  
by  
Die Hu

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Abstract of a thesis submitted in partial fulfilment of the  
requirements for the Degree of Doctor of Philosophy

## **Abstract**

### **Essays on the role of rural finance, green finance and digital financial inclusion on agricultural carbon emissions reduction**

by

Die Hu

Green agricultural development is significant for China against the background of carbon peak and carbon neutrality, and at the same time, it is crucial to secure China's food security. This thesis examines the influence of finance on agricultural carbon emissions, specifically focusing on the significant role of rural finance, green finance and digital financial inclusion. This thesis comprises three essays investigating whether rural finance, green finance and digital financial inclusion help to reduce agricultural carbon emissions in China. The first essay estimates China's agricultural carbon emissions from 2001 to 2020 and analyzes the temporal and spatial characteristics of agricultural carbon emissions, providing a research base for the thesis. Next, the essay examines the impacts of rural finance on agricultural carbon emissions by introducing the rural finance development indicator into the environmental Kuznets Curve Theory. This not only extends the theory but also helps validate the rural environmental Kuznets Curve in China. The findings reveal that the environmental Kuznets Curve hypothesis is invalid in rural China and that rural finance is not conducive to reducing agricultural carbon emissions.

The second essay uses a bidirectional-fixed effects regression model, a quantile regression mode, and a difference-in-differences model to investigate the impacts of green finance on agricultural carbon emissions (ACEs). The results reveal that green finance significantly negatively correlates with ACEs in the eastern and central regions but is insignificant for the whole of China. Secondly, there is significant regional heterogeneity in the impact of green finance on ACEs. The impacts of green finance on agricultural carbon emissions also vary across different quantities, showing an asymmetric impact of green finance on ACEs. Thirdly, the Green Finance Reform and Innovation Pilot Zones do not show a direct policy effect on ACEs.

The third essay investigates the combined effect of green finance and digital financial inclusion on ACEs using bidirectional fixed-effects regression, moderation mechanism analysis, and Two-Stage Least Squares instrumental methods. The finding reveals that green finance positively impacts ACEs reduction but digital financial inclusion negatively impacts ACEs' reduction. Moderation mechanism analysis shows that digital financial inclusion has a negative role in moderating the impact of green finance on ACEs, indicating uncoordinated development between green finance and digital financial inclusion in rural China. The results are robust to different methods that address the endogeneity issues.

This thesis extends the ACEs theory into the agricultural sector, not only enhancing the scope of the Environmental Kuznets Curve Theory into the agricultural sector but also addressing the omitted variables criticized by scholars by considering financial development's impact on the environment. This thesis also examines the role of green finance in reducing carbon emissions in the agricultural sector, which was overlooked in previous research. Using quantile regression to examine the asymmetric effects of green finance across different quantiles and a difference-in-differences model to examine green policy impacts provides more robust results and critical information for formulating policies. More importantly, this thesis provides a unique perspective to examine the combined effects of green finance and digital financial inclusion, offering pivotal conclusions and policy recommendations.

**Keywords:** Agricultural carbon emissions; environmental Kuznets Curve; rural finance; green finance; digital financial inclusion

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## Abbreviations

ACEs	Agricultural carbon emissions
ACEI	Agricultural carbon emissions intensity
ACEP	Agricultural carbon emissions per capita
ADF	Augmented Dickey-Fuller
AFE	Agricultural fiscal expense
AIS	Agricultural industry structure
AML	Agricultural mechanization level
ARDL	Autoregressive distributed lag model
BRIC	Brazil, Russia, India and China
CADF	Cross-sectional augmented Dickey-Fuller
CD	Cross-sectional dependence
CH <sub>4</sub>	Methane
CIPS	Cross-sectional Im Pesaran-Shin
CO <sub>2</sub>	Carbon dioxide
CO <sub>2e</sub>	Carbon dioxide equivalents
COP26	26 <sup>th</sup> conference of the Parties
DFI	Digital financial inclusion
DID	Difference-in-differences
EDU	Education level
EKC	Environmental Kuznets Curve
FD	Financial development
FE	Fixed effects
G-20	Group of Twenty
GFRIPZ	Green Finance Reform and Innovation Pilot Zones
GHG	Greenhouse gas
GMM	Generalized method of moments
GWP	Global warming potential
IPAT	Impact, population affluence and technology
IPCC	The Intergovernmental Panel on Climate Change
LLC	Levin-Lin-Chu
LMDI	Logarithmic Mean Divisia Index
ND	Natural disaster

N <sub>2</sub> O	Nitrous oxide
PGDP	Rural GDP per capital
RFs	Rural financial scale
RGDP	Rural gross domestic product
RF <sub>e</sub>	Rural financial efficiency
SYS-GMM	System-generalized method of moments
UR	Urbanization

## Introduction

The increasing severity of the global environment is compelling people to recognize the significance of mitigating climate change and protecting the environment, which also makes sustainable development common sense in the global community (Ofori et al., 2023; Tenaw & Beyene, 2021; Yu et al., 2023). Climate change, mainly caused by rising global temperatures triggered by carbon emissions, has brought a great threat to human survival as well as economic and social development (Carlson et al., 2017; Ebi et al., 2021; Zhang, 2023). Nations worldwide have taken various measures to mitigate climate change (Lee & Lee, 2022; Ofori et al., 2023). As a responsible country, China has also taken responsibility and committed to mitigating climate change by pledging to achieve a carbon peak in 2030 and carbon neutrality by 2060 (Lee & Lee, 2022; Yu et al., 2023). However, this commitment poses great challenges for all the Chinese industries, especially for the agricultural sector.

Agriculture is the most basic material production sector in the national economy of most countries in the world. It provides a material base for human survival and social development (Zhu et al., 2021) and shoulders the responsibility of feeding the growing global population. However, it is also the sector most affected by climate change. Agricultural production seriously relies on the climate (Agovino et al., 2019; Gokmenoglu & Taspinar, 2018) and agriculture is the pioneer victim. Therefore, there is a great challenge for agriculture to meet the growing global demand for food and reduce carbon emissions. Against this background, the Chinese government has proposed a green agriculture development strategy and implemented a series of policies to reduce agriculture carbon emissions (ACEs). In 2021, China issued the 14th Five-Year National Green Development Plan for Agriculture to reduce ACEs significantly by 2025 (Du et al., 2023). However, developing green agriculture requires vast investment and significant capital resources. Thus, using financial mechanisms to facilitate the development of green agriculture becomes essential.

This thesis covers three financial mechanisms potentially affecting China's sustainable agriculture development: rural finance, green finance, and digital financial inclusion. Rural finance is regarded as the core of the modern rural economy. It can help to alleviate credit constraints in rural areas and promote the development of the agricultural sector (Abate et al., 2016; Beck et al., 2015; Yaron & Mundial, 1992). A lack of funds hindering agricultural growth and development motivates the establishment of a formal rural financial system (Yaron & Mundial, 1992). Abate et al.(2016) investigated the impacts of institutional finance in Ethiopia

and found that access to institutional finance positively impacts the adoption and extent of technology use. Easy access to finance also alleviates credit constraints for microenterprises in rural areas (Beck et al., 2015). Although rural finance can provide the necessary funding for agricultural development, it focuses more on productivity and economic growth, neglecting the environmental benefits of rural areas. This particularly if more funds are used to buy machines and fertilizer, it will lead to a rise in ACEs.

As a financial instrument, green finance does not only focus on economic growth but also focuses on environmental benefits by directing the capital to support green initiatives and promote clean technologies (Hou et al., 2023). It is regarded as a financial innovation to balance economic development and environmental protection (Salazar, 1998). Thus, green finance can help to reduce ACEs by providing green technologies and sustainable agricultural practices in rural areas.

Digital financial inclusion has two characteristics: digitalization and inclusiveness. Compared to traditional finance, digital finance can help lower the financial threshold and provide convenient, cost-effective financial services and products for users with expanded coverage without geographical restrictions using digital platforms (Irfan et al., 2022; Lee et al., 2022; Liu et al., 2023). It greatly benefits farmers and businesses in rural areas with financial constraints. With expanded access to financial services, farmers and businesses in rural areas can access more funding, which can directly or indirectly facilitate green initiatives but also lead to a rise in energy-intensive input, resulting in an increase in ACEs.

Building a theoretic framework including three financial mechanisms: rural finance, green finance, and DFI, this study investigates the role and impacts of three financial mechanisms on reducing ACEs via essays. The three essays systematically explore the research questions, jointly providing a comprehensive understanding of how financial mechanisms facilitate carbon emissions reduction and promote green agriculture development. This has significant practical implications for the Chinese government and financial institutions. It also can promote China's rural green financial system development and foster sustainable agricultural development.

The first essay (Parts 1 and 2) forms the base of the thesis. It investigates ACEs and the relationship between agricultural growth and rural financial development. ACEs are the central focus of the thesis. Many researchers have measured ACEs, e.g., Li et al. (2011) measured the ACEs of China from 1993 to 2008 from six main carbon sources, including fertilizer, pesticide, agricultural film use, diesel fuel use in agricultural machinery, farmland tillage, and electricity use in agricultural irrigation. Du et al. (2023) measured ACEs in China from 2011 to 2020 using

similar carbon sources. However, their measurement methods neglect the other greenhouse gas (GHG) emissions responsible for global warming. In part 1 of the first essay, I measure the ACEs at the provincial level in China from broad carbon sources, including the carbon dioxide (CO<sub>2</sub>) from agricultural production, methane (CH<sub>4</sub>) from rice paddies, methane (CH<sub>4</sub>) and nitrous oxide (N<sub>2</sub>O) from livestock breeding from 2001 to 2020.

Following that, the structural changes and ACEs' temporal and spatial characteristics are examined using the Theil Index and Moran's I Index. The results reveal an "increase-decrease-increase-decrease" growth trend of ACEs, with livestock and land use emissions emerging as two significant contributors to the emissions. The decrease in the Theil Index shows that regional emissions disparity is diminishing. The global Moran Index shows a positive spatial autocorrelation among regions.

In part 2 of the first essay, I investigate the impact of rural financial development on the rural Environmental Kuznets Curve (EKC) hypothesis by incorporating financial development into the relationship between agricultural growth and ACEs. Empirically, I use the fixed effects (FE) model to test the EKC hypothesis and examine the impact of rural financial development on the rural EKC hypothesis. Next, I conduct a heterogeneity analysis by dividing the national sample into four regional samples: eastern, central, western and northeastern regions, to investigate regional disparities. The results reveal that the EKC hypothesis is not valid in rural China, showing an inverted N-shape relationship between agricultural growth and ACEs; financial development significantly impacts ACEs, and the regional disparities are significant. The generalized method of moments (GMM) model provides a robustness check.

In essay two, I use the entropy method to construct a comprehensive index of green finance development that can measure the development level of green finance. This approach assesses the importance of each indicator by calculating its entropy value and then determining the weight of each indicator to eliminate the drawbacks of other techniques that primarily rely on expert and personal judgments to determine the weights (Lee & Lee, 2022; Sun et al., 2023).

Many researchers believe that green finance, which can guide the flow of capital to green and environmentally friendly industries (Hussain et al., 2023), plays a significant role in reducing carbon emissions (Irfan et al., 2022; Lee et al., 2022). Based on that belief, using a bidirectional-fixed effects regression model, I examine the impact of green finance development level on ACEs using data from 31 Chinese provinces from 2007 to 2020. I also use a quantile regression to capture the impact of green finance on ACEs at different quantiles and a difference-in-differences (DID) model to investigate the policy effect of building Green Finance Reform and

Innovation Pilot Zones (GFRIPZ) on reducing carbon emission in the agricultural sector. The results show that green finance significantly negatively correlates with agricultural carbon emissions in the eastern and central regions but is insignificant for the whole of China. It also shows a significant regional heterogeneity in the impact of green finance on agricultural carbon emissions based on different regions and an asymmetric impact of green finance on agricultural carbon emissions. However, the DID approach results reveal that the policy effect of building Green Finance Reform and Innovation Pilot Zones has a limited effect in reducing rural carbon emissions.

Essay three examines the role of DFI on ACEs and investigates the interaction effects of green finance and DFI on ACEs. Much research has separately investigated the role of green finance and DFI on carbon emissions reduction. For instance, Zhang et al.(2022) used data on G-20 economies from 2008 to 2018 to examine the impact of green finance on carbon emissions. Wang et al. (2022) employed a spatial econometric model to investigate the impact of DFI on carbon emissions in 284 prefecture-level cities in China. They reveal a positive correlation between DFI and carbon emissions. However, little research has investigated the interaction effect of green finance and DFI on reducing ACEs. It is unclear whether the effects of green finance and DFI are substitutes for each other or complement each other. Therefore, in essay 3, I use a moderation mechanism analysis to analyze the interaction effects of green finance and DFI on ACEs in 31 Chinese provinces from 2011 to 2020. The results reveal a significant negative correlation between green finance and ACEs but a positive correlation between DFI and ACEs, indicating that green finance helps to reduce ACEs, but DFI increases ACEs. The results also show that DFI negatively affects the impact of green finance on ACEs. The results are verified by a series of robustness checks, including the two-stage least squares instrumental method.

The three essays complement each other and jointly provide a theoretic framework to explore the role of finance on agricultural sustainability. Essay one shows that rural finance does influence ACEs and agricultural economic growth, but its impact is relatively limited. This result emphasizes the significance of investigating how green finance can enhance its effectiveness in promoting green development in rural areas, especially in China's rural revitalization. This suggests that traditional finance alone may not be adequate to address the current issues.

Essays Two investigates the impacts of green finance on ACEs. Unlike traditional finance, green finance directs capital toward low-carbon agricultural projects, which may have a more

significant impact on reducing emissions. DFI, on the other hand, enhances the availability of financial services in rural areas. However, whether the impact is positive or negative remains controversial. Therefore, Essay Three examines the impact of DFI on ACE and investigates whether green finance and digital financial inclusion display synergistic or crowding-out effects on the reduction of ACEs.

The empirical analysis reveals how different financial tools can be used to support ACE reduction. First, governments should establish a rural green financial system, implement green policies, and provide incentives to promote green finance development in rural regions. Second, financial institutions should develop more green financial products suitable for rural green development. Thirdly, green DFI should be paid more attention, since green finance can enhance the sustainability objectives while DFI expands the financial access for green initiatives. Promoting green DFI can fully explore the advantages of green finance and DFI.

My thesis contributes to the literature in several ways. First, it extends the EKC theory to the agricultural sector and integrates financial development to examine its impact on ACEs, addressing the omitted variables that have been criticized by scholars in considering financial development's impact on the environment. Secondly, my thesis examines the impact of green finance on carbon emissions in the agricultural sector, previously overlooked, using quantile regression to examine the asymmetric effects of green finance across different quantiles and a difference-in-differences model to examine green policy impacts, providing more robust results and critical information for formulating policies. More importantly, the thesis provides a unique perspective on the interaction effect of green finance and digital financial inclusion on ACEs by using moderation mechanism analysis and so offers pivotal conclusions and policy recommendations. Finally, the thesis has significant practical value in achieving green and low-carbon agriculture against the backdrop of carbon peak and carbon neutrality.

The rest of the thesis is organized as follows. In essay 1 (parts 1 and 2), I present a study of the role of rural finance in EKC. Essay two investigates the role of green finance on ACEs, and essay three presents the interaction effects of green finance and DFI on ACEs. The final part concludes the study with recommendations.

## Essay One (Part 1)

### The Temporal and Spatial Analysis of Agricultural Carbon Emissions

#### 2.1 Introduction

Climate change, mainly caused by rising global temperatures triggered by carbon emissions, has greatly threatened human survival and economic and social development (Carlson et al., 2017; Ebi et al., 2021; Zhang, 2023). Agriculture, which provides the material for human survival (Zhu et al., 2021), is very sensitive to climate change because agricultural activities rely on climatic conditions (Agovino et al., 2019). Climate change, such as global warming, rainstorms, floods, and extreme weather events, directly impacts agriculture and threatens food security and agricultural sustainability. In addition, the global population is estimated to reach almost 10 billion in 2050, with an expected doubling of global food demand (Lindner et al., 2013; Zhu et al., 2021). It is a great challenge to feed the growing global population under climate change and rapid urbanization (Laurett et al., 2021). Conversely, agriculture also impacts and contributes to climate change by generating direct greenhouse gas (GHG) emissions (Agovino et al., 2019). GHG emissions generated by agricultural activities account for 23% of anthropogenic GHG emissions, ranking as their second most significant source (Cui et al., 2022; Wen et al., 2022).

With the substantial role of agriculture in climate change, reducing ACEs is an important way to mitigate climate change and enhance agriculture's sustainability. To reduce carbon emissions, most people focus on the industrial, energy, and transport sectors; the significant role of the agricultural sector is often neglected. Recently, more and more researchers have started to pay attention to the agricultural sector in the context of climate change. The authors measured current ACE levels (Cui et al., 2022; Huang et al., 2019; Liu & Yang, 2021; Su et al., 2023), analyzed the influencing factors of ACEs (Du et al., 2023; Li et al., 2022; Mu et al., 2023; Zhu & Huo, 2022), and examined the relationship between ACEs and agricultural development (Kwakwa et al., 2022; Xiong et al., 2016). This provides a robust theoretical foundation and empirical groundwork for research in the area. However, there are notable gaps in the literature.

First, there is a lack of a comprehensive measurement of ACEs. Many studies measured ACEs from specific or limited aspects of agricultural activities, focusing on the source of carbon dioxide (CO<sub>2</sub>), neglecting the other sources of GHG gas, such as methane (CH<sub>4</sub>) and nitrous oxide (N<sub>2</sub>O). However, ACEs include the total GHG emissions from agricultural activities, including carbon dioxide, methane, and nitrous oxide (Johnson et al., 2007). In scientific studies

and reports, carbon emissions often refer to carbon dioxide equivalents (CO<sub>2</sub>e). The other GHG emissions, such as methane and nitrous, can be converted into CO<sub>2</sub>e based on their Global Warming Potential (GWP)<sup>1</sup> coefficients (Tian & Yin, 2022).

Furthermore, many researchers cannot distinguish “carbon,” usually referring to the elemental form, from “carbon dioxide,” a GHG composed of carbon (Tian & Yin, 2022), which can lead to a systematic underestimation of a country's total ACE. Thirdly, many studies have analyzed the characteristics of ACEs, including their spatial and temporal characteristics, but few have investigated the internal structural changes of ACEs. Essay one measures the ACEs in 31 provinces and municipalities in China and attempts to investigate ACEs’ temporal and spatial evolutionary trends at the provincial level and the changes in its internal structure using the Theil Index and Moran's I Index.

Essay one contributes to the literature in several ways. First, the provincial level of ACEs in China is measured according to the most recent Intergovernmental Panel on Climate Change (IPCC) Guidelines for National GHG Inventories and China's Provincial Guidelines for GHG Inventories (Trial) in 2023, which provided a more comprehensive measurement covering broader carbon sources, including agricultural land use, the rice paddies, and livestock breeding and management often overlooked in previous studies. Secondly, in addition to the latest IPCC guidelines, ACEs’ measurement also adjusts the carbon coefficients to the local context in China. Finally, the essay categorizes ACE sources into agricultural land use, rice paddy cultivation, and livestock production to examine the structural composition of ACEs. The essay is structured as follows. Section 2 presents a literature review on ACEs. Section 3 describes the methodology and data used in the study. Section 4 presents the empirical findings, and Section 5 concludes the essay with policy implications.

## **2.2 Literature Review**

### **2.2.1 The Measurement of Agricultural Carbon Emissions**

Quantifying ACEs is important to assess agriculture’s contribution to climate change (Bell et al., 2014) and provides scope for nations to reduce ACEs. There are various methods to measure ACEs, including the life-cycle method (Wen et al., 2023). The most popular method is the IPCC emissions factor method (Cui et al., 2022; Wen et al., 2023), which has the most recognition and has been adopted by many studies (Cui et al., 2022; Du et al., 2023; Wen et al., 2022). There

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<sup>1</sup> GWP is the ability of a greenhouse gas defined by IPCC to trap heat in the atmosphere relative to carbon dioxide. It is the ratio of radiative forcing from a unit mass of the gas to a unit mass of carbon dioxide over 100 years. Usually, the GWP of carbon dioxide equals 1, methane is 21 and nitrous oxide is 310.

are two measurements of ACEs using the IPCC emissions factor method. From a narrow perspective focusing only on carbon dioxide when measuring ACEs, the ACEs are generated from direct agricultural inputs, such as fertilizers, pesticides, agricultural film, diesel, and irrigation and tillage. For example, Li et al. (2011) measured China's ACEs between 1993 and 2008 based on six key carbon sources: fertilizers, pesticides, agricultural film, irrigation, ploughing, machinery and diesel use in agricultural production. Similarly, Liu and Yang (2021) measured the ACEs in 30 Chinese provinces from 2009 to 2019 using the same six carbon sources. Du et al.(2023) measured the ACEs of prefecture-level cities from 2011 to 2020 based on the same method to explore the impact of policy on ACEs in China.

In the broader perspective, ACEs also include methane and nitrous oxide, which are responsible for the potential greenhouse effect and cause severe global warming problems (Johnson et al., 2007; Tian et al., 2014; Tian & Yin, 2022). Therefore, many researchers measure ACEs from a more extensive range of activities, covering general agricultural cultivation, rice cultivation, and livestock farming. For instance, Dalgaard et al. (2011) estimated Denmark's agricultural GHG emissions of carbon dioxide, methane, and nitrous oxide from 1990 to 2010. Tian et al. (2014) measured the ACEs of 31 Chinese provinces and cities from 23 carbon emission sources associated with agricultural inputs, rice paddies, and livestock breeding from 1995 to 2010.

### **2.2.2 The Characteristics and Influencing Factors of Agricultural Carbon Emissions**

With extensive research on carbon emissions, the research on carbon emissions shifted to ACEs' characteristics and influencing factors. For instance, Su et al. (2023) used the convergence model to investigate the convergence characteristics of ACEs using a dataset of 31 Chinese provinces from 2005 to 2020. Likewise, Cui et al. (2022) used the convergence model. They combined it with the Theil Index method to investigate the spatiotemporal heterogeneity and convergence of ACEs in 31 Chinese provinces from 1997 to 2017 to provide a comprehensive analysis of the characteristics of ACEs. However, the measurement of ACEs in their study focused only on six carbon sources in the plant industry, which underestimates the total ACEs in China. Zhang (2022) examined the spatial and temporal distribution characteristics of carbon emissions on different land use in China's Yellow River Delta from 2000 to 2019, thus enriching the research literature. However, the author's results varied based on the research areas, differences in the research period, and specific carbon emissions coefficients used. There is still a need for a comprehensive, accurate measurement of ACEs and an in-depth analysis of ACEs that can provide more accurate information and insights for policymakers to formulate robust measures to mitigate carbon emissions.

Regarding the factors influencing ACEs, some researchers use the Logarithmic Mean Divisia Index (LMDI) decomposition and decoupling analysis to examine trends and regional disparities over time. For example, Akram et al.(2019) used the LMDI model to examine the main driving force of Pakistan's carbon emissions from 1990 to 2016 to reveal that the energy structure effect is the most important driving force of carbon emissions in Pakistan. Ortega-Ruiz et al. (2020) decomposed an enlarged Kaya identity using the LMDI method to examine the evolution of the factors influencing carbon emissions in India from 1990 to 2016. Guo et al. (2021) used the Kaya identity and the LMDI method to analyze the influential factors of ACEs in the Jilin Province, China, from 1998 to 2018. Many other approaches have been used to study the factors that influence the reduction of ACEs. Ma et al. (2022) analyzed data from 31 Chinese regions from 2011 to 2019 to find that promoting digital agriculture can significantly reduce ACEs. They also found that agricultural technology, industry structure, and rural education level were crucial factors in reducing ACEs. Their study highlights regional cooperation and the integration of digital finance in reducing emissions. Du et al. (2023) assessed China's 2018 National Agricultural Sustainable Development policy and found it effectively reduced ACEs, especially in cities with a smaller urban-rural income gap and higher agricultural output. It offers valuable insights for sustainable agriculture development.

### **2.2.3 The Relationship Between Agricultural Growth and Agricultural Carbon Emissions**

Among the various factors influencing ACEs, the relationship between carbon dioxide and economic development arouses much attention in researchers. Some studies used the EKC hypothesis to investigate the relationship between agricultural growth and ACEs. For instance, Gokmenoglu and Taspinar (2018) adopted the time series method to overcome issues of cross-sectional dependence to test the agricultural EKC hypothesis for Pakistan from 1971 to 2014 and confirm the EKC hypothesis for Pakistan. Zafeiriou and Azam (2017) analyze the relationship between agricultural economic performance and carbon dioxide emissions in France, Portugal, and Spain using the auto ARDL approach to test the EKC hypothesis. Their results confirm the EKC in the long run. Zhang et al. (2019) adopted the autoregressive distributed lag (ARDL) method to test the EKC hypothesis for ACE in China's main grain-producing areas using time-series data from 1996 to 2015. Their results support the EKC hypothesis.

However, the EKC literature on agricultural growth and ACEs is limited. The empirical results are not consistent, with some research showing a positive correlation and others showing a negative correlation between agricultural growth and ACEs.

Using the EKC hypothesis to investigate the relationship between agricultural growth and ACEs, some studies analyse the relationship using Tapio decoupling methods. Xiong et al. (2016) applied the decoupling method to explore the relationships between ACEs and agricultural growth in the Hotan prefecture of China from 1999 to 2013. Their results show that there is a “decoupling, hooking, and decoupling” in a three-stage process between the ACEs and agricultural growth in Hotan. Luo et al. (2017) used panel data of 30 Chinese provinces from 1997 to 2014 to examine the decoupling relationship between agricultural growth and ACEs from agricultural production activities, farming and livestock husbandry.

In summary, current published research by scholars focusses on understanding the formation mechanisms of ACEs, accurately measuring ACEs, and the factors influencing ACEs. However, a comprehensive ACEs estimation system has not been established; there is a particular need for a dynamic analysis regarding the structure of ACEs.

## 2.3 Methodology and Data

### 2.3.1 The Measurement of Agricultural Carbon Emissions

According to the IPCC Fourth Assessment Report (IPCC, 2019), GHG such as methane and nitrous oxide produced during agricultural activities are also considered as ACEs converted to CO<sub>2</sub> equivalents. Based on China's Provincial Guidelines for GHG Inventories (2023), non-energy agriculture GHG sources include soil management, rice cultivation, enteric fermentation and livestock manure. Therefore, the ACEs in our study include: (1) carbon emissions caused by agricultural land use, (2) methane emissions produced from rice paddies, and (3) methane and nitrous oxide emissions triggered by livestock.

#### 2.3.1.1 Agricultural carbon emissions from agriculture land use

Based on the literature, carbon emissions from agricultural land use include carbon emissions produced by agricultural inputs such as chemical fertilizers, pesticides and agricultural films; carbon emissions produced by diesel fuel use in agricultural machinery; carbon emissions produced from farmland tillage; and carbon emissions from the consumption of electricity for agricultural irrigation activity. The carbon emissions from agricultural land use are obtained using equation (2.1):

$$E_{landuse} = \sum T_i \alpha_i \quad (2.1)$$

where:  $E_{landuse}$  denotes the carbon emissions from agricultural land use;  $T_i$  is the amount of chemical fertilizers, pesticides, agricultural films, diesel fuel, sown area of crops and area of irrigation; and  $\alpha_i$  is the carbon emissions of each carbon source. In this study, following Li et

al. (2011) and Luo et al. (2017), a carbon emissions factor of 4.9341 kg C/kg is set for pesticides.

Table 2.1 Carbon Emissions Factors of Agricultural Land Use

Type	Carbon emissions factor	Source
Pesticides (C kg/kg)	4.9341	Li et al.(2011); Luo et al. (2017)
Chemical fertilizers (C kg/kg)	0.8956	Li et al.(2011); Luo et al. (2017)
Agricultural films (C kg/kg)	5.18	Li et al.(2011) ;Tian et al.(2014)
Diesel (C kg/kg)	0.5927	Li et al. (2011); IPCC United Nations Intergovernmental Committee of Experts on Climate Change (2007)
Tillage (C kg/km <sup>2</sup> )	312.6	Li et al. (2011)
irrigation (C kg/hm <sup>2</sup> )	266.48	West and Marland (2002); Luo et al.(2017)

### 2.3.1.2 Agricultural carbon emissions from rice paddies

The main GHG from rice paddies is methane, which is a biological product of anaerobic environments mainly produced in various shallow bodies of water, swamps, wetlands and rice paddies. Considering the huge regional difference in hydrothermal conditions in China, the methane coefficients of rice paddies from different regions show wide variability (Min & Hu, 2012). According to the IPCC growth cycle of rice (IPCC, 2006), we divide rice into early rice, middle rice and late rice, and adopt methane emissions coefficients calculated by Min and Hu (2012). The emissions from rice paddies are estimated using equation (2.2):

$$E_{ricepaddies} = \sum P_i \beta_i \quad (2.2)$$

where:  $E_{ricepaddies}$  is the total methane emissions from rice paddies in 31 provinces and municipalities in China;  $P_i$  is the area of rice paddies in each province; and  $\beta_i$  is the coefficient of rice paddies in different provinces or municipalities.

### 2.3.1.3 Agricultural carbon emissions from livestock

ACEs from livestock include methane from enteric fermentation of ruminants and methane and nitrous oxide emissions caused by manure management (Hu & Wang, 2010; Shang et al., 2015). For China, the cultivated livestock involves cattle, horses, sheep, pigs, donkeys, mules and camels. The methane and nitrous oxide emissions can be estimated using equation (2.3):

$$E_{livestock} = \sum q_i \mu_i \quad (2.3)$$

where:  $E_{livestock}$  denotes the total methane or nitrous oxide from livestock;  $q_i$  is the quantity of each livestock type; and  $\mu_i$  is the corresponding emissions coefficient of each source of each livestock type. The relevant emissions livestock coefficients are from IPCC (2019) (see Table 2.2) e.g., the emissions coefficient of methane from enteric fermentation for cows is 59.7 kg

per head and of manure management is 8.75 kg per head. The nitrous oxide emissions coefficient for manure management for cows is 1 kg per head (Hu & Wang, 2010; Shang et al., 2015).

To facilitate the summation and to be consistent with other carbon emissions studies, we convert carbon, methane and nitros oxide emissions into standard carbon dioxide emission equivalents. According to IPCC (2019), the carbon dioxide conversion coefficients of carbon, methane and nitrous oxide are 44/12, 25 and 298, respectively (Tian & Yin, 2022).

Table 2.2 The Emissions Coefficients of Livestock and Poultry (unit: kg/head/year)

Animal	Methane emissions coefficient		Nitrous oxide emissions coefficient	Source
	Enteric fermentation	Manure management		
Cow	59.7	8.75	1	Hu & Wang (2010) Shang et al. (2015)
Mule	10	0.9	1.39	IPCC (2019), FAO, Shang et al. (2015)
Camel	46	1.92	1.39	IPCC (2019), FAO, Shang et al. (2015)
Donkey	10	0.9	1.39	IPCC (2019), FAO, Shang et al. (2015)
Horse	18	1.64	1.39	IPCC (2019) , FAO, Shang et al. (2015)
Pig	1	3.5	0.33	Hu & Wang (2010); Shang et al. (2015)
Sheep	5	0.15	0.3	IPCC (2019), Hu & Wang (2010)
Goat	5	0.17	0.2	IPCC (2019), FAO, Hu & Wang (2010)
Poultry		0.02	0.02	Shang et al. (2015)

#### 2.3.1.4 Indicators for the measurement of agricultural carbon emissions

To measure carbon emissions, two key methods are commonly used: the total carbon emissions and carbon emissions intensity, calculated as carbon emissions divided by GDP (Cui et al., 2022; Wen et al., 2022). We analyse the overall change in ACEs and the structural composition of ACEs, so the selected indicator for measuring carbon emissions in the agricultural sector is ACET, the total volume of ACEs. The ACET approach provides a comprehensive view of the environmental impact, revealing the full extent of emissions from agricultural activities. In contrast, carbon emissions intensity may not capture the agricultural sector's entire carbon footprint. This broader perspective is vital for an in-depth environmental analysis and informed policy formulation. I use equation (2.4) to calculate the total ACEs:

$$ACET = E_{landuse} + E_{ricepaddies} + E_{livestock} \quad (2.4)$$

### 2.3.2 The Theil Index Estimation Method

There is vast territory and abundant resources in China. However, significant disparities exist among regions because of differences in resource endowments, hydrothermal conditions, agricultural structure, economy and technology. Hence, it is important to examine the regional discrepancies and spatiotemporal variations in carbon emissions in Chinese agriculture (Cui et al., 2022; Liu & Yang, 2021; Wen et al., 2022). For geographical characteristics, I divide the sample into four groups to analyse the regional differences in ACEs.

According to the National Bureau of Statistics of China, our sample comprises four major regions: the Eastern, Central, Western, and Northeastern regions. The Eastern region covers 10 provinces and cities: Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan. The Central region includes six provinces: Shanxi, Anhui, Jiangxi, Henan, Hubei and Hunan. The Western region covers 12 provinces or districts: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu Province, Qinghai, Ningxia and Xinjiang. The Northeastern region consists of three provinces: Liaoning, Jilin and Heilongjiang.

When conducting regional discrepancy analysis, the regional difference decomposition analysis is commonly used because it is a great method to examine regional differences. Several methods have been used in previous studies, including the LMDI method (Akram et al., 2019; Guo et al., 2021); the Dagum Gini coefficient (Zhang et al., 2022); and the Theil Index. Compared with other methods, the Theil Index has distinct advantages in measuring within-region differences and between region differences. The Theil Index is a type of “entropy” method is obtained by setting the general entropy standard index (C) to 0 (Cui et al., 2022). The reason for setting C equal to 0 is that this can provide valuable insights when analysing the contribution rate of the differences within and between regions to overall disparities. Typically, the Theil Index ranges from 0 to 1, with a small value indicating a small difference and the greater value denoting a greater disparity (Cui et al., 2022). I use the Theil Index to examine the regional disparities. The models are as follows:

$$T = \frac{1}{k} \sum_{q=1}^k \left( \frac{C_q}{C} \times \ln \frac{C_q}{C} \right) \quad (2.5)$$

$$T_p = \frac{1}{K_p} \sum_{q=1}^{K_p} \left( \frac{C_{pq}}{C_p} \times \ln \frac{C_{pq}}{C_p} \right) \quad (2.6)$$

$$T = T_w + T_b = \frac{4}{K_p} \sum_{q=1}^{K_p} \left( \frac{k_p}{k} \times \ln \frac{\overline{C_p}}{C} \times T_p \right) + \frac{4}{K_p} \sum_{q=1}^{K_p} \left( \frac{k_p}{k} \times \ln \frac{\overline{C_p}}{S} \times \ln \frac{\overline{C_p}}{S} \right) \quad (2.7)$$

In equation (2.5),  $T$  represents the Theil index, which shows the disparity of ACEs at the national level. The values of  $T$  range from 0 to 1. A smaller  $T$  indicates lower overall disparity in ACEs and a larger  $T$  indicates greater overall disparity. Here,  $q$  represents a province,  $k$  denotes the number of provinces, and  $C_q$  signifies the ACEs for province  $q$ . In equation (2.6),  $T_p$  signifies the overall difference in the Theil index for region  $p$ ;  $K_p$  represents the number of provinces in region  $p$ ;  $C_{pq}$  stands for the agricultural carbon emissions of province  $p$  in region  $q$ ; and  $C_p$  represents the average agricultural carbon emissions for the provinces in region  $p$ . In equation (2.7),  $T_w$  indicates the within-region difference and  $T_b$  signifies the between-region difference, which is obtained by further decomposing  $T_p$ . Additionally,  $T_w/T$  and  $T_b/T$  are defined as the contributions of within-region and between-region differences to the overall difference, respectively.  $(C_p/C) \times (T_p/T)$  signifies the individual contribution of each region to the total intra-regional disparity, with  $C_p$  denoting the sum of agricultural carbon emissions in the provinces in the region and  $C$  represents the total agricultural carbon emissions for the entire country.

### 2.3.3 Spatial Correlation Analysis Index

I use Moran's I Index to investigate whether there is a spatial correlation. There are two types of Moran's I Index. One is the global Moran's I Index, which shows global spatial autocorrelation. The other is the local Moran's I Index, which examines local spatial correlation (Liu & Yang, 2021; Zhang et al., 2022). Equation (2.8) estimates local Moran's I indexes:

$$I = \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} (C_i - \bar{C})(C_j - \bar{C})}{S^2 \sum_{i=1}^n \sum_{j=1}^n W_{ij}} \quad (2.8)$$

where:  $n$  represents the number of samples under study;  $C_i$  is the ACET in region  $i$ ;  $\bar{C}$  is the sample mean;  $S^2$  is the sample variance; and  $W_{ij}$  is the element in row  $i$ , column  $j$  of the spatial matrix. The value  $I$  ranges from -1 to 1. If " $I > 0$ ", it means that there is a positive spatial correlation among the regions. Conversely, if " $I < 0$ ", it signifies a negative spatial correlation. If " $I = 0$ ", it suggests that there is a random distribution among the regions. The greater absolute value of  $I$ , the more significant the correlation of spatial distribution.

The spatial weight matrix  $W_{ij}$  can be obtained using geographical adjacency matrices, inverse distance matrices, economic distance matrices, nested economic matrices and time distance matrices. Neighboring provinces share similar natural resources and climate, which leads to a clustering of agricultural production, so I use a simple binary geographic adjacency matrix following the Queen adjacency rule to obtain the spatial matrix  $W_{ij}$ . According to the Queen adjacency rule, adjacent is identified by sharing a common edge or vertex (corner) among regions. The matrix  $W$  is constructed as follows: the values along the principal diagonal are assigned a value of 0 and, if region  $i$  is adjacent to region  $j$ ,  $W_{ij}$  is set to 1; otherwise, it is set to 0. I use Geoda software to create spatial weights, conduct related spatial analysis and Arcmap to draw spatial maps.

## **2.4 Results and Discussion**

### **2.4.1 The Temporal Characteristics of ACET**

Figure 2.1 shows China's total ACET from 2001 to 2020 has four fluctuating stages. The first stage is from 2001 to 2005, the second is from 2005 to 2007, the third is from 2008 to 2015, and the fourth is from 2016 to 2020. The general trend and peak are confirmed by Liu et al. (2021) and Yang et al. (2022). However, the specific timeline is somewhat different. In the first stage, the ACET increases from 90565.86 104 tonnes of ACEs to 99985.15 104 tonnes with an average growth rate of 2.52%. Notably, during 2004 and 2005, there is a sharp increase in ACET, with the maximum growth rate reaching 4.95%. This can be attributed to China's government policies. In 2004, the Chinese government issued the No.1 central document, with a theme focusing on agriculture, rural areas, and farmers, that emphasizes the top priority of the "three rural" issues. The policy significantly promoted farmers' enthusiasm for raising farmland (Liu & Yang, 2021; Tian et al., 2014), which led to more production materials being invested in agriculture, resulting in a significant increase in ACET (see Table 2.3). The growth rate of ACET from rice paddies reached 7.06%, and land use rose to 5.54%, contributing to most of the increase in ACET. This demonstrates that government policy promoted agricultural production. During the second stage, ACET decreased sharply, with a growth rate of -3.17% in 2006 and -3.80% in 2007 (see Table 2.3). The decline in the growth rate of livestock and poultry contributed most to the decrease in the total growth rate, with growth rates of -8.75% in 2006 and -11.85% in 2007. This decline may attributed to decreased production of livestock because of avian influenza in 2006 and the impact of natural disasters such as flooding in the Huaihe Basin in 2007 (Xu et al., 2017).

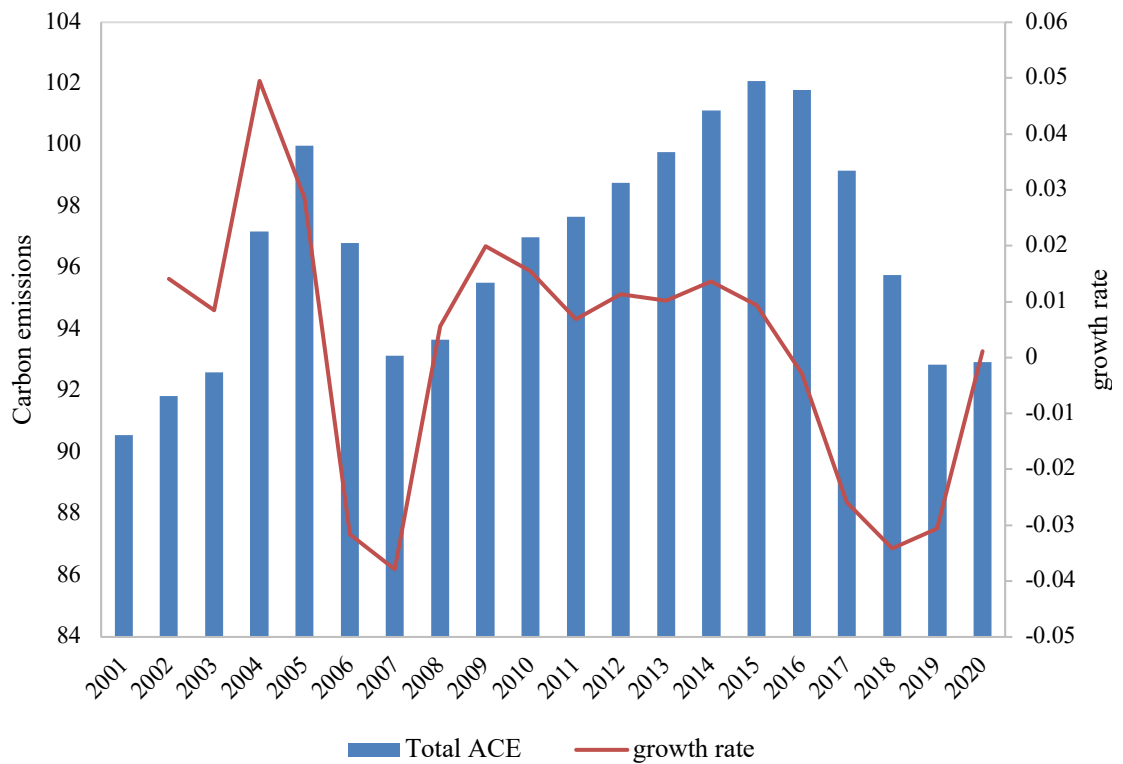


Figure 2.1 Total agricultural carbon emissions and their annual growth rate in China from 2001 to 2020 (unit 10<sup>7</sup>tonnes)

Source: Author’s calculations and compilation

During the third stage, from 2008 to 2015, the total ACEs rebound from the decline in 2007 and keep an upward trend to reach a peak in 2015. The continued rise in this period can be attributed to the large amount of agricultural inputs such as fertilizer, pesticide, and agricultural plastic film used (Yang et al., 2022). Liu et al.(2021) confirm that the amount of fertilizer, which accounted for one-third of the world's consumption in 2015, was a leading cause of the peak in carbon emissions. The fourth stage, from 2016 to 2020, shows a decline in ACET after peaking in 2015. The main reason for this decline is because of the green agriculture development strategy proposed by the Chinese government. To achieve green development of agriculture, China’s Ministry of Agriculture issued two policy documents in 2015: the *Zero Growth Action Plan for Fertilizers by 2020* and the *Zero Growth Action Plan for Pesticides by 2020*.

The Ministry of Finance and the Ministry of Agriculture jointly issued *Establishing a Reform Plan for Agricultural Subsidy System Guided by Green Ecology* in December 2016. The general office of the State Council in China issued *Opinions on Promoting the Development of Green Agriculture by Innovating Institutions and Mechanisms* in September 2017. These documents demonstrate the determination of the Chinese government to promote green agriculture.

Table 2.3 Agricultural Carbon Emissions of China from 2001 to 2020 (unit:10<sup>4</sup> tonnes)

Year	Livestock ACEs	Growth rate	Rice paddies ACEs	Growth rate	Land use ACEs	Growth rate	Total ACEs	Growth rate
2001	40228.17	-	22602.97	-	27734.73	-	90565.86	-
2002	41067.50	2.09%	22475.52	-0.56%	28294.06	2.02%	91837.08	1.40%
2003	42439.72	3.34%	21390.32	-4.82%	28782.21	1.72%	92612.25	0.84%
2004	43918.37	3.48%	22900.52	7.06%	30378.00	5.54%	97196.89	4.95%
2005	45355.53	3.27%	23299.15	1.74%	31330.47	3.14%	99985.15	2.87%
2006	41385.21	-8.75%	23164.94	-0.58%	32268.63	2.99%	96818.78	-3.17%
2007	36482.66	-11.85%	23189.12	0.1%	33478.36	3.75%	93150.15	-3.80%
2008	36250.40	-0.64%	23380.60	0.83%	34036.16	1.67%	93667.16	0.56%
2009	36812.60	1.55%	23696.86	1.35%	35018.85	2.89%	95528.32	1.99%
2010	37173.03	0.98%	23784.82	0.37%	36047.14	2.93%	97004.98	1.55%
2011	36787.92	-1.03%	23874.45	0.38%	37005.16	2.66%	97667.53	0.68%
2012	37039.30	0.68%	23843.05	-0.13%	37892.81	2.40%	98775.16	1.13%
2013	37335.02	0.80%	23956.18	0.47%	38492.69	1.58%	99783.89	1.02%
2014	37953.46	1.66%	24106.86	0.63%	39078.11	1.52%	101138.43	1.36%
2015	38333.44	1.00%	24402.47	1.23%	39351.77	0.70%	102087.67	0.94%
2016	38139.13	-0.51%	24560.48	0.65%	39096.58	-0.65%	101796.19	0.29%
2017	36050.07	-5.48%	24705.42	0.59%	38408.26	-1.76%	99163.76	-2.59%
2018	33974.32	-5.76%	24621.79	-0.34%	37185.74	-3.18%	95781.85	-3.41%
2019	32492.13	-4.36%	24419.02	-0.82%	35938.99	-3.35%	92850.14	-3.06%
2020	33189.91	2.15%	24618.93	0.81%	35141.43	-2.22%	92950.28	0.1%

Source: Author's calculations

The results show changes in total ACET from 2001 to 2020 are significantly related to government policies; agricultural input is one of the most important factors influencing the amount of ACET, which also suggests that the extensive growth model of Chinese agriculture depends mainly on agricultural inputs.

#### 2.4.2 The Regional and Structure Characteristics of Agricultural Carbon Emissions Total

The ACET varies in different regions. The ACET of the western region is the highest, followed by the central region, eastern region, and northeastern region (see Figure 2.2). The reason that the western region has the highest total ACEs is that it covers more provinces and is a more extensive geographic area (Su et al., 2023). The ACET shows similar trends for the central and western regions, with an “increase, decrease, increase and decrease” pattern, though the eastern region shows a continuing decline after 2005. In contrast, the northeastern region shows a decline from 2001 to 2016, with a slight decrease after 2016. The results are consistent with those in the study by Liu et al. (2021).

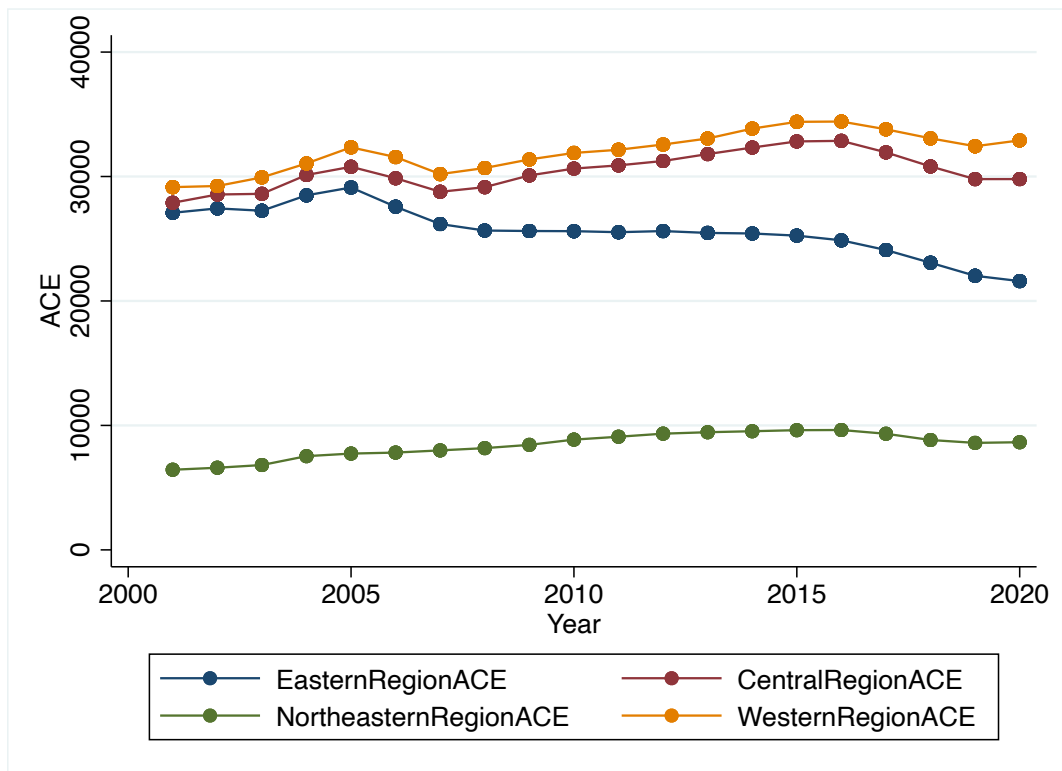


Figure 2.2 Regional areas of agricultural carbon emission in China from 2001-2020  
Source: Author's calculations

Regarding the average ACET, the central region ranks highest with an average annual of  $5073.187 \times 10^4$  tonnes, followed by the northeastern, western, and eastern regions (see Table 2.4). The reason that the central region had the highest average annual ACET is because the area covers most parts of the grain-producing provinces Anhui, Jiangxi, Henan, Hubei and Hunan. The second largest average annual ACET is for Liaoning, Jilin, and Heilongjiang provinces, which are also important grain-producing provinces.

Different regions show variations in the local ACET composition (see Table 2.4). For the eastern region, the ACEs from land use are the largest source, accounting for 45.3% of the average annual volume, followed by livestock (28.15%) and rice paddies (26.5%). For the central region, ACEs from rice paddies contribute the most significant portion of ACET (39.42%), followed by land use (32.33%) and livestock (28.25%). For the northeastern region, ACEs from livestock are  $1289.984 \times 10^4$  tonnes, accounting for 45.93%, followed by land use (44.14%) and rice paddies (9.93%). For the western region, ACEs from livestock contributed the most, 57.6% of the average annual volume, followed by land use (29.89%) and rice paddies (12.51%). The variations in the ACET composition of the different regions significantly demonstrate regional differences. The central region is China's most important rice-producing area, covering seven grain-producing provinces (Yang et al., 2022).

Table 2.4 The Agricultural Carbon Emission of China's Different Regions

Region	Stats	Livestock ACEs	Rice paddies ACEs	Land use ACEs	ACET
Eastern	N	200	200	200	200
	mean	722.2618	680.6988	1161.985	2564.946
	sd	818.6171	914.5196	1042.343	2105.251
	min	23.08907	0.03969	52.68224	75.83746
	max	3386.58	3020.568	3496.996	6784.182
Central	N	120	120	120	120
	mean	1433.103	1999.904	1640.18	5073.187
	sd	920.4908	1380.804	853.5987	1867.949
	min	447.2314	0.12578	528.8328	1103.628
	max	4397.935	3633.956	3667.531	7409.948
Northeastern	N	60	60	60	60
	mean	1289.984	278.6661	1239.912	2808.563
	sd	157.4569	264.0202	370.8764	714.6279
	min	918.3548	75.32729	730.0103	1877.882
	max	1519.062	824.4517	2052.223	4338.275
Western	N	240	240	240	240
	mean	1535.767	333.9385	797.2785	2666.984
	sd	805.7574	532.832	535.1029	1482.177
	min	254.0009	0	27.9306	432.0933
	max	3500.8	1923.48	2084.491	6176.572
Total	N	620	620	620	620
	mean	1229.69	762.8927	1120.903	3113.486
	sd	871.3554	1069.848	841.3265	1980.045
	min	23.08907	0	27.9306	75.83746
	max	4397.935	3633.956	3667.531	7409.948

Source: Author's calculations

Regarding the national ACET structure, the largest ACET source is livestock and poultry, followed by land use and rice paddies (see Table 2.5). The annual average ACET from livestock and poultry is  $38120.396 \times 10^4$  tonnes, accounting for 39.5% of the average yearly ACET. The ACET from land use is 36%, and rice paddies account for 24.2% of the annual average ACET.

Table 2.5 Descriptive Statistics of ACEs Structure

Variable	Obs	Mean	Std. Dev.	Min	Max
Livestock ACEs	20	38120.396	3389.552	32492.125	45355.527
Ricepaddies ACEs	20	23649.674	863.931	21390.316	24705.424
Landuse ACEs	20	34748.008	3811.401	27734.727	39351.766
Total ACEs	20	96518.077	3530.975	90565.859	102087.67

Source: Author's calculations

The structure of ACET changes between 2001 and 2020 with variations in proportions over the observed years (see Figure 2.3). The figure shows the proportion of ACET from livestock and poultry to total ACET declined from 2003. The percentage of ACET from land use increased

from 2005 and became the most significant percentage of total ACET from 2012 until 2020.

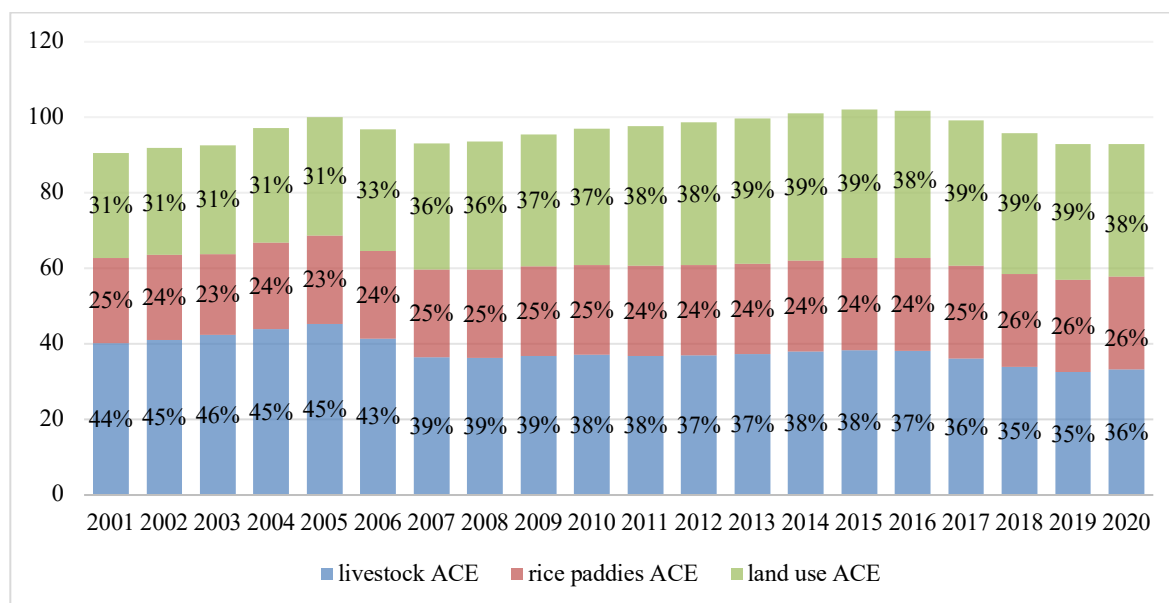


Figure 2.3 Total agricultural carbon emissions and their composition for China from 2001 to 2020 (Unit  $10^7$ tonnes)

Source: Author’s calculations and compilation

### 2.4.3 Further Analysis Results on Regional Differences

Table 2.6 presents the Theil Index of ACET and its contribution by region from 2001 to 2020. From the table, the overall and regional Theil Index and the contributions of regional Theil Index results to the overall Theil Index can be seen. Notably, the contributions within areas and between areas are provided. Table 2.6 shows that the Theil Index has a slightly fluctuating downward trend over the years, which indicates that ACEs’ inequality is declining across regions. This result is consistent with the findings of Cui et al. (2021), despite the fact that they calculated the Theil Index based on the intensity of ACEs and per capita ACEs rather than total ACEs. The Theil Index for the eastern region is far larger than for other regions, indicating a greater inequality of ACEs in this region.

Table 2.6 The Theil Index of Total Agricultural Carbon Emissions and Regional Contributions

Year	Theil Index						Contribution Rate of the Theil Index						
	Country	Eastern	Central	Northeast	West	Within areas	Between areas	Eastern	Central	Northeast	West	Within areas	Between areas
2001	0.223	0.355	0.084	0.007	0.173	0.184	0.039	0.477	0.117	0.002	0.250	0.825	0.175
2002	0.227	0.358	0.080	0.009	0.168	0.186	0.041	0.480	0.111	0.003	0.240	0.819	0.181
2003	0.224	0.364	0.082	0.007	0.162	0.185	0.039	0.481	0.114	0.002	0.234	0.826	0.174
2004	0.226	0.372	0.084	0.006	0.159	0.186	0.039	0.490	0.117	0.002	0.228	0.826	0.174
2005	0.225	0.376	0.086	0.007	0.157	0.187	0.038	0.492	0.118	0.002	0.228	0.832	0.168
2006	0.225	0.381	0.087	0.010	0.156	0.187	0.038	0.487	0.121	0.004	0.228	0.832	0.168
2007	0.221	0.374	0.088	0.012	0.154	0.183	0.038	0.471	0.123	0.005	0.224	0.829	0.171
2008	0.218	0.361	0.091	0.013	0.154	0.179	0.039	0.444	0.127	0.005	0.227	0.820	0.180
2009	0.218	0.358	0.092	0.015	0.152	0.176	0.042	0.431	0.130	0.006	0.223	0.808	0.192
2010	0.218	0.359	0.091	0.019	0.150	0.175	0.043	0.425	0.130	0.008	0.221	0.803	0.197
2011	0.217	0.361	0.090	0.023	0.148	0.174	0.043	0.424	0.128	0.010	0.219	0.800	0.200
2012	0.218	0.367	0.088	0.026	0.148	0.174	0.044	0.427	0.125	0.011	0.219	0.799	0.201
2013	0.218	0.368	0.086	0.028	0.147	0.173	0.046	0.422	0.123	0.012	0.218	0.791	0.209
2014	0.219	0.372	0.085	0.029	0.147	0.173	0.047	0.420	0.122	0.012	0.221	0.788	0.212
2015	0.221	0.378	0.085	0.028	0.147	0.173	0.048	0.420	0.123	0.012	0.222	0.782	0.218
2016	0.222	0.383	0.085	0.029	0.145	0.173	0.050	0.420	0.123	0.012	0.220	0.777	0.223
2017	0.223	0.389	0.084	0.036	0.143	0.174	0.049	0.424	0.121	0.015	0.219	0.779	0.221
2018	0.224	0.396	0.083	0.043	0.141	0.175	0.049	0.429	0.120	0.018	0.219	0.781	0.219
2019	0.222	0.399	0.082	0.039	0.139	0.173	0.049	0.425	0.118	0.016	0.218	0.778	0.222
2020	0.220	0.399	0.081	0.043	0.135	0.170	0.050	0.416	0.116	0.018	0.214	0.772	0.228

Source: Author's calculations

Figure 2.4 shows how regional disparities in ACEs changed across the various Chinese regions from 2001 to 2020. There are four different lines: a red dotted line, a purple dashed line, a solid purple line, and a light blue dash-dotted line, showing the evolving trends of the Theil Index in eastern, central, northeastern, and western regions, respectively, in China. There are two other lines: a dark blue dashed line and a yellow dashed line, representing the Theil Index of intra-regional and inter-regional inequality. The index figure reveals a decreasing trend from the eastern, western, and central to the northeastern region. This result is different from the findings in Cui et al. (2022), where the Theil Index shows a different trend, with the western region highest, followed by the central, eastern and northeastern regions. The different choices of proxy ACEs compared with total ACEs in this study and the carbon emissions intensity in their study contribute to the inconsistent results between the studies. Additionally, the reason that the eastern region exhibits the most significant Theil Index is that the eastern region covers a large north-south span including Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan, that have significant differences in natural endowments, resource conditions, and agricultural cultivation patterns, resulting in substantial variations in total carbon emissions among the provinces, leading to considerable internal disparities.

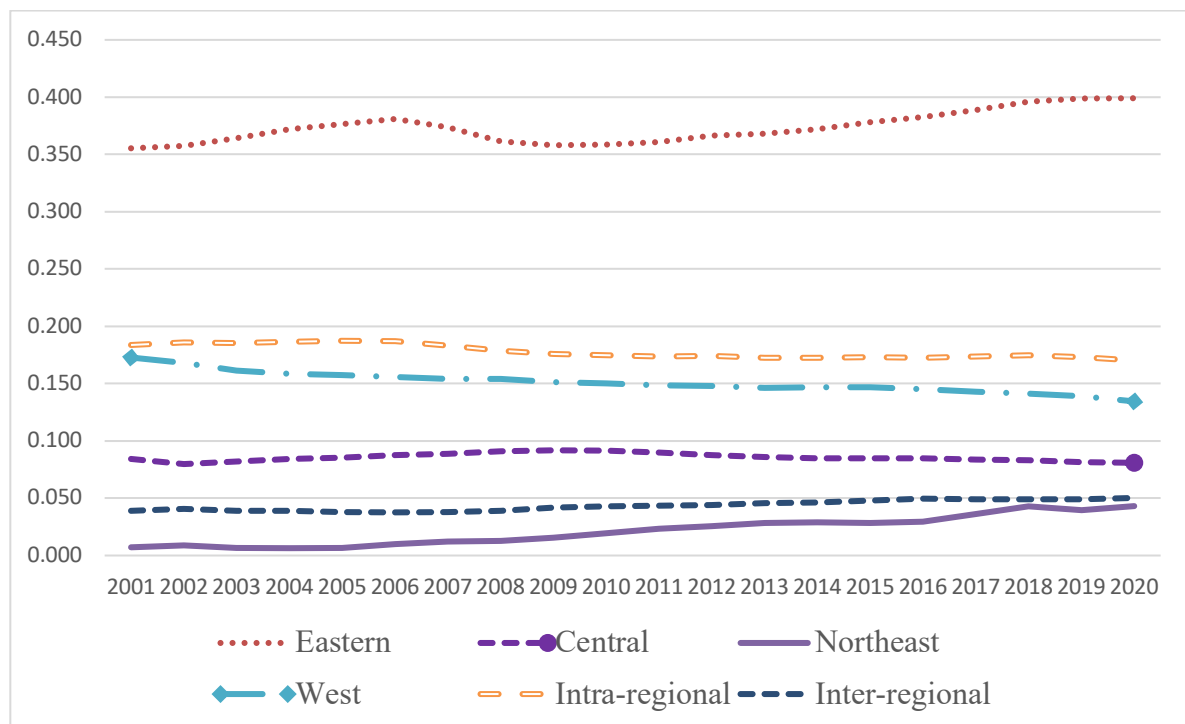


Figure 2.4 Trends in the Theil Index of total agricultural carbon emissions in China’s regions from 2001-2020

Source: Author’s calculations

Figure 2.5 presents the regional contribution rates to the Theil Index, showing the individual contribution of each region to the total disparity. The eastern region has the most significant rate, followed by the western, central, and northeastern regions. Despite being ranked first in contribution rate, the eastern region has a fluctuating downward trend. Notably, the contribution rate of the northeastern region is the lowest among the four regions, remaining below 0.1 from 2001 to 2020. The contribution rates of the central and western regions show a similar trend, with the rates remaining relatively stable.

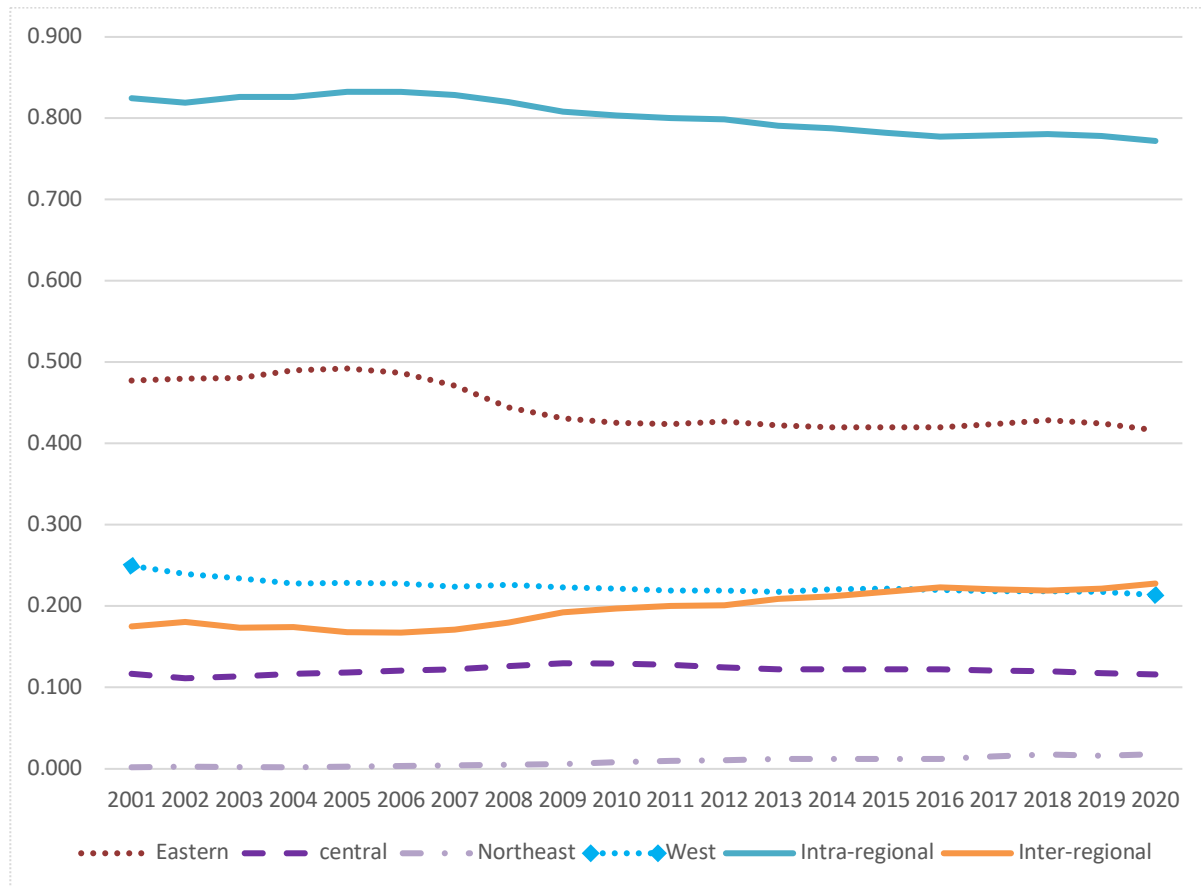


Figure 2.5 Trends in Theil Index contribution rate of total agricultural carbon emissions of China's regions from 2001-2020

Source: Authors' calculations

#### 2.4.4 The Spatial Characteristics of Total Agricultural Carbon Emissions

Table 2.7 presents the global spatial autocorrelation analysis of ACET across 31 Chinese provinces over two decades using an adjacency matrix. The Global Moran Index remains positive during the period, indicating a positive spatial correlation. This result is consistent with the findings in Liu and Yang (2021) and Zhang et al. (2022) who also report positive spatial correlations in their studies. However, the positive spatial trend is not statistically significant in all years. Notably, from 2001 to 2006, the p-values were below the 0.05 threshold, which

indicates significant spatial clustering of ACET. In contrast, from 2007, the p-values rose above 0.05, indicating a lack of statistical significance in spatial autocorrelation. There is a general declining trend in Moran's I values over time, suggesting a gradual decrease in spatial clustering among the regions. The finding aligns with Su et al. (2023).

Table 2.7 Global Moran's I Index of Carbon Emissions Intensity

Year	Moran's I	P-value	Year	Moran's I	P-value
2001	0.2385	0.016	2011	0.1444	0.076
2002	0.2347	0.017	2012	0.1420	0.079
2003	0.2150	0.033	2013	0.1413	0.081
2004	0.1828	0.044	2014	0.1326	0.088
2005	0.1589	0.062	2015	0.1316	0.088
2006	0.1412	0.080	2016	0.140	0.080
2007	0.1240	0.104	2017	0.1346	0.086
2008	0.1307	0.098	2018	0.1237	0.101
2009	0.1373	0.087	2019	0.1194	0.105
2010	0.1415	0.082	2020	0.115	0.108

Source: Author's calculations

Figure 2.6 reports the results of Local Moran's I scatterplots for 2001 and 2020. It compares the changes in spatial autocorrelation of ACET at the local level. A Moran's scatterplot consists of four quadrants divided by horizontal and vertical axes. The horizontal axis shows the standardized value of ACET and the vertical axis indicates the standardized spatial lag of ACET. The spatial lag is the average value of the ACET for neighboring areas. In the two scatterplots, there is a decrease in spatial autocorrelation over time, with a drop from 0.238 in 2001 to 0.115 in 2020, indicating a reduced emissions clustering. This decrease in emissions clustering may be attributed to the spread of low-carbon technologies that can weaken the spatial concentration of ACET (Liu & Yang, 2021). The scatter in the first quadrant scatterplot in 2001 refers to the Hubei, Anhui, Shandong, etc., provinces revealing a significant high-high cluster in these areas. In contrast, the third quadrant displays low-low clusters that include Neimenggu, where lower emissions are regionally grouped. In the 2020 scatterplot, there is a high-high cluster for Hubei, Anhui, and Shandong, but the low-low cluster is not obvious for Neimenggu.

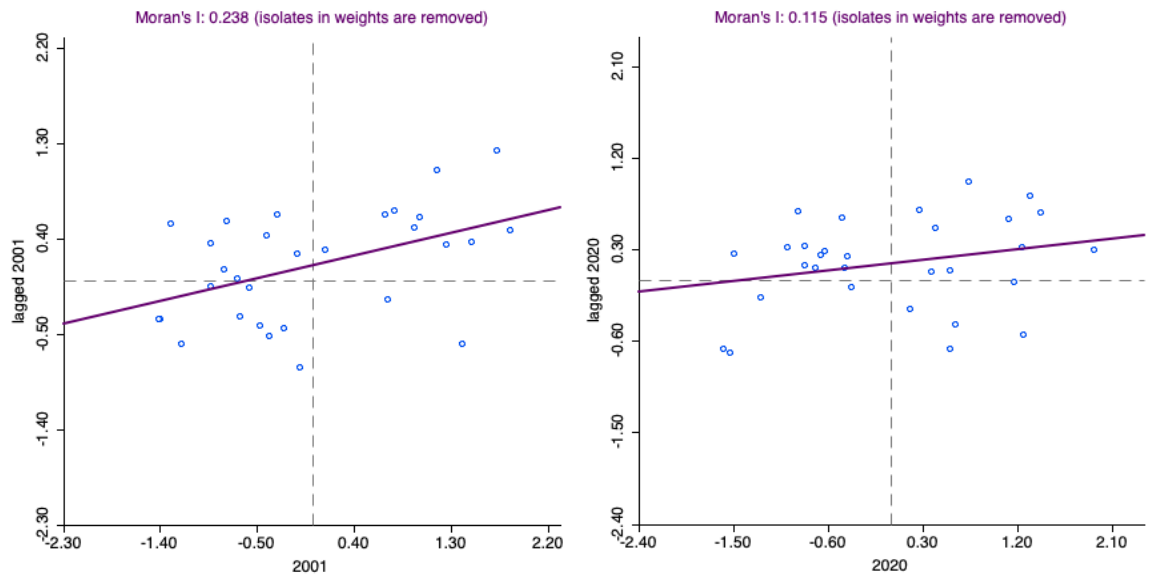


Figure 2.6 Local Moran cluster diagrams of China's provincial agricultural carbon emissions in 2001 and 2020  
 Source: Author's calculations

Figure 2.7 shows the average ACET of each province in China from 2001 to 2020. The figure shows that the highest ACET appears in Henan province, followed by Hunan, Sichuan, Shandong, and Hubei, which are major grain-producing regions in China.

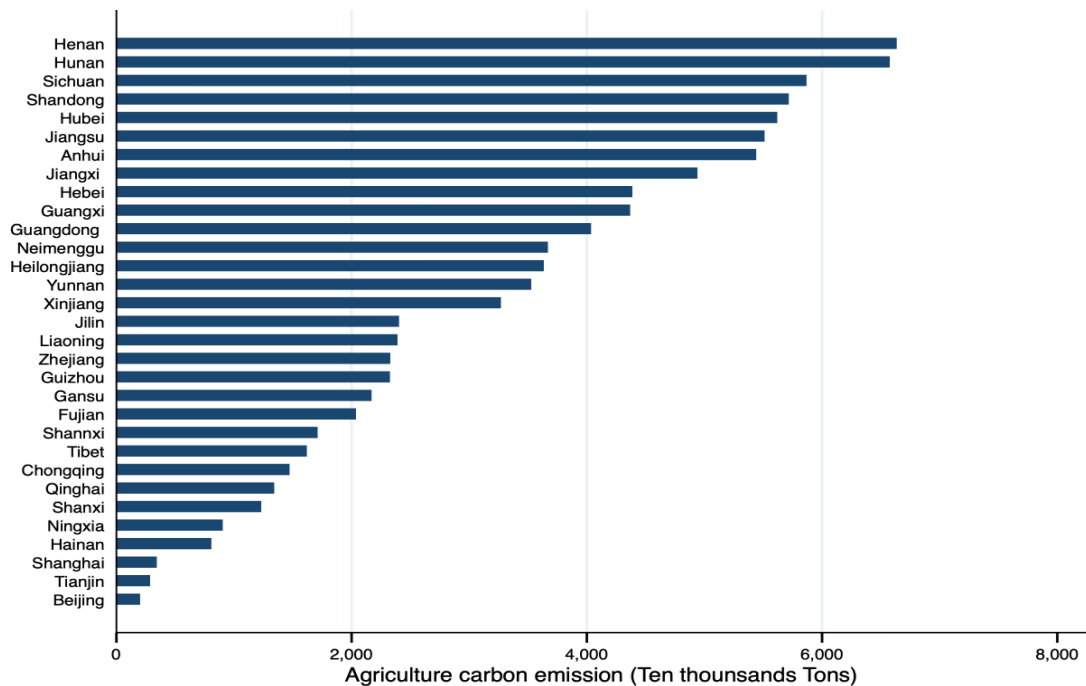


Figure 2.7 The average agricultural carbon emissions of each Chinese province from 2001 to 2020  
 Source: Author's calculations

## 2.5 Conclusion and Recommendations

Based on the panel data for 31 provinces in China, I measured the provincial level of ACEs from three carbon sources: agricultural land use, rice paddy cultivation, and livestock production by referring to the IPCC Guidelines for National GHG Inventories and China's Provincial Guidelines for GHG Inventories (Trial) in 2023 from 2001 to 2020. I use the statistical methods of the Theil Index and Spatial Moran's Index to explore ACEs' temporal, regional, structural, and spatial characteristics in China. The results contribute to the literature by providing a more comprehensive measurement of ACEs covering broader carbon sources, including agricultural land use, rice paddies cultivation, and livestock production, which are often overlooked in previous studies. I also provide a more comprehensive description of provincial ACEs' various characteristics: temporal, regional, structural, and spatial. The results give policymakers more insights on ACEs to help formulate more robust emissions reduction policy measures.

The main results of the study are as follows. First, China's total ACEs show a fluctuating downward trend, with an increase from 2001 to 2005 followed by a decline until 2007 and then a steady rise to a peak in 2015, and then they decrease. Government policies play an important role in the changes in the total amount of ACEs. Secondly, livestock production is the most significant contributor to total emissions, accounting for about 40%, followed by land use emissions caused by pesticides, fertilizers, and agricultural films, representing 36% of the average annual ACET. However, for the central region, the main grain-producing region in China, the ACEs from rice paddies' cultivation account for the most significant proportion. Thirdly, the national Theil Index has a fluctuating downward trend, and the regional Theil Indexes show that the eastern region is significantly higher than the western, central, and northeastern regions. Finally, the Global Moran Index shows spatial autocorrelation in the observed years, but the local Moran's I scatterplots show a decline in spatial autocorrelation.

The study's results provide significant policy implications for the Chinese government to formulate differential carbon emissions reduction policy measures. First, the Chinese government or related organizations must develop a standardized measurement system for ACEs to ensure the consistent, accurate assessment of ACEs. Although the academic community is paying more attention to measuring ACEs, there is no unified opinion on a measurement standard, which is not conducive to long-term tracking and comparison of ACEs. Therefore, it is important to develop a standardized measurement system for ACEs.

Second, since different regions have different ACE structures, formulating a unified ACE reduction policy is not conducive to regional ACE reduction. It is necessary to establish ACE reduction policy measures tailored to local conditions. Different regions should develop their own measures according to their local geographical characteristics and natural endowments, thereby combating climate change. The central region, mainly focused on the plant industry, should optimize farmland management by improving fertilizer use efficiency, reducing the amount of chemical fertilizers used, and using conservation tillage. For the western region, improving livestock management, such as optimizing feed formulations and manure management, is crucial to reducing ACEs.

Finally, considering the decrease in regional disparity indicated by the Theil Index and the spatial autocorrelation of ACEs, it is important to formulate region-specific strategies and emphasize regional cooperation in ACEs reduction. For neighboring regions with the same natural endowments and economic structures, building a knowledge and technology-sharing system to share successful emission reduction technologies and management practices is important. Coordinating policies and incentives in the neighboring regions will create a supportive environment for sustainable development in rural communities that benefits all.

## Essay One (Part 2)

# The Nexus of Agricultural Growth, Financial Development and Agricultural Carbon Emissions

### 3.1 Introduction

Climate change from carbon emissions severely impacts the global environment and poses significant threats to economic and social development (Pata, Dam, et al., 2023; Yang et al., 2021). Agriculture, a prominent source of carbon emissions, plays a substantial role in climate change by directly generating GHG but is also severely impacted by climate change (Agovino et al., 2019; Yang et al., 2022). On the one hand, agricultural activities significantly contribute to carbon dioxide, methane, and nitrous oxide levels (Duxbury, 1994; Johnson et al., 2007; Smith et al., 2008). The GHG emissions generated by agricultural activities, such as livestock and arable farming, account for 23% of anthropogenic GHG emissions, the second largest source of GHG (Cui et al., 2022; Wen et al., 2022). Conversely, agriculture is profoundly impacted by climate change (Agovino et al., 2019; Gokmenoglu & Taspinar, 2018); extreme weather caused by climate change poses significant challenges to sustainable agricultural production.

With increasing recognition of the significant role of agriculture in climate change, the global community is committed to reducing carbon emissions from the agricultural sector (Bell et al., 2014). Agriculture in China has seen great developments since the reform and opening of China. However, these developments came at a huge loss of natural resources and environmental quality. Regarding carbon emissions, the agriculture sector alone contributes 17% of the country's total carbon emissions (Yu et al., 2023). Against the backdrop of the “dual carbon” strategy, that is, the carbon peak and carbon neutrality strategy, Chinese agriculture faces great challenges in reducing carbon emissions while meeting the food demands of its vast population. In the context of rural revitalization, securing the food demand alone is insufficient; pursuing the sustainability of agriculture is the priority goal. The sustainability of agriculture includes agriculture growth and environmental protection. In terms of environmental performance, reducing ACEs becomes essential due to climate change. Therefore, how to achieve agricultural growth and reduce ACEs becomes a critical issue for sustainable development.

However, many studies have investigated the relationship between economic growth and carbon emissions reduction (e.g., Khan et al., 2021; Mahmood et al., 2023; Pata & Caglar, 2021).

Some studies use EKC Theory to investigate the relationship between the two, but there is limited research on agricultural growth and ACEs (Xiong et al., 2016). Currently, few studies have investigated the relationship between agricultural growth and ACEs (Zafeiriou & Azam, 2017).

Furthermore, the EKC Theory is frequently used as a basic theory to investigate the relationship between growth and environmental pollution, is criticized by many scholars for omitting some important variables, such as energy consumption, foreign trade, and technological progress. To improve study robustness and accuracy, many studies have investigated the nexus of growth-carbon emissions by incorporating other crucial factors, among which, the nexus of growth-energy-carbon emissions is an important literature strand (Acheampong, 2018; Narcisse et al., 2023; Zhang et al., 2019). For instance, Narcisse et al.(2023) empirically examined the N-shaped relationship between economic growth and carbon emissions by incorporating energy use and domestic government health expenditure in China. Considering the significant role of financial development in the nexus between growth and carbon emissions, there is a need for research on the impact of financial development on the EKC Theory.

This essay aims to fill the literature gap by including financial development and analysing the relationship between agricultural growth, ACEs and rural financial development. This essay makes several contributions. First, it extends the EKC framework to the agricultural sector, which has been neglected for a long period compared with the industrial sector. Second, this essay mitigates omitted variable bias in the EKC hypothesis by including financial development in the EKC framework, contributing to the literature, and provides practical policy insights for reducing ACEs. Lastly, the essay improves methodological accuracy by addressing heterogeneity and cross-sectional dependence in the panel data analysis, which were neglected in similar studies. By doing so, the essay provides more robust, reliable empirical results.

The essay is structured as follows: Section 2 reviews the related literature. Section 3 outlines the data and methodology used in the study. Section 4 presents and discusses the empirical findings. Section 5 concludes the study with policy recommendations.

## **3.2 Literature Review**

### **3.2.1 The Relationship Between Economic Growth and Carbon Emissions**

The relationship between environmental quality and economic growth has been extensively discussed with intensified recognition of environmental protection. Against this background, the EKC Theory gained global acceptance as an important theory for investigating this

relationship. The pioneering study by Grossman and Krueger (1991) posited that the relationship between income and environmental pollution showed a non-linear inverted U-shaped relationship. Initially, an increase in income led to an increase in environmental pollution. After achieving a threshold, pollution declined as income rose, producing an inverted U-shape. Shafik and Bandyopadhyay (1992) tested this relationship for 10 environmental indicators across 149 countries from 1960 to 1990. Panayotou (1993) used cross-sectional data to investigate the EKC Theory using four different environmental indicators against nominal GDP in the late 1980s. The author's findings confirm the EKC Theory across all examined indicators. Panayotou (1995) posits that technological innovations and strict environmental regulations were crucial factors in shaping the relationship. The EKC Theory is supported by both empirical studies and theoretical research. For instance, some studies adopted the green Solow model and macroeconomic production and utility functions to validate the theory (Tenaw & Beyene, 2021). Table 3.1 summarises studies that investigate the relationship between income and carbon emissions.

Table 3.1 A Summary of the Environmental Kuznets Curve Literature

Study	Data set	Period	Methodology	Results
Ozturk & Acaravci (2013)	Time series data for Turkey	1960-2007	ARDL model	Confirm EKC
Heidari et al. (2015)	Panel data of five ASEAN countries	1980-2008	PSTR model	Confirm EKC
Dogan & Seker (2016)	Panel data for OECD countries	1975-2011	Dynamic seemingly unrelated cointegrating regressions	Confirm EKC
Gokmenoglu & Taspinar (2018)	Time series data for Pakistan	1971-2014	FMOLS model	Confirm EKC
Pata (2019)	Time series data for Turkey	1969-2017	ARDL model	Confirm EKC
Tenaw & Beyene (2021)	Panel data for 20 Sub-Saharan African countries	1990-2015	ARDL	Confirm EKC
Thio et al. (2023)	Panel data for 10 countries	2000-2014	Panel quantile regression	Confirm EKC
Farooq et al. (2022)	Panel data for 180 countries	1980-2016	Panel quantile regression	Confirm EKC
Wang, Zhang, et al. (2022)	Time series data for China	1995-2017	VECM model	Confirm EKC
Jahanger et al. (2023)	Panel data for top 9 thermonuclear energy-producing countries	1990-2017	Moments quantile regression	Confirm EKC
Pata et al. (2023)	Time series data for German	1974-2018	FMOLS model	Confirm EKC

Despite the EKC Theory gaining wide acceptance, some scholars still challenged it, arguing that there may be other forms of relationship, such as a U-shape and N-shape, between income and carbon emissions (Martino & Nguyen-Van, 2016; Özokcu & Özdemir, 2017; Tenaw & Beyene, 2021). Additionally, the omitted variable bias is a critical issue that must be addressed when analysing the relationship (Javid & Sharif, 2016; Kirikkaleli & Kalmaz, 2020; Sarkodie & Strezov, 2019).

To explore the complex relationship between economic growth and carbon emissions, a cubic functional form was widely used by scholars to determine whether an inverse relationship emerges (Akboştancı et al., 2009; Dinda, 2004; Grossman & Krueger, 1995; Özokcu & Özdemir, 2017; Panayotou, 1997). Grossman and Krueger (1995) argue that a cubic functional form is adaptable enough to capture the diverse, fluctuating patterns between GDP and pollution, particularly when applying flexible dummy variables to different GDP intervals.

To address the issue of omitted variable bias, many studies incorporated more variables into the EKC framework (Javid & Sharif, 2016), including natural resources, energy consumption, globalization, technological innovation and environmental regulations (Jahanger et al., 2023; Khan et al., 2021; Leal & Marques, 2020; Pata & Caglar, 2021). This provides better validation of the EKC hypothesis. However, there is a need for more research to investigate the impact of financial development on the EKC curve, since financial development (FD) is an important factor affecting economic growth and carbon emissions.

### **3.2.2 The Relationship Between Financial Development and Carbon Emissions**

Despite extensive research on the relationship between economic growth and carbon emissions, there is a lack of studies that investigate the impact of FD on EKC curves. Further, the limited research presents conflicting results, with some studies arguing that FD significantly enhances environmental sustainability by reducing carbon emissions (Adams & Klobodu, 2018; Dar & Asif, 2018; Khan et al., 2021) whereas others suggest a negative impact of FD on environmental quality (Ahmad et al., 2022; Javid & Sharif, 2016).

According to the literature, FD can help reduce carbon emissions. It contributes to carbon emissions reduction through two mechanisms. First, FD facilitates investment in clean energy and environment-friendly technology, leading to improved energy efficiency and reduced carbon emissions (Dogan & Seker, 2016; Hussain et al., 2023; Saidi & Mbarek, 2017). For example, Khan et al. (2021) investigated the impacts of FD and energy consumption on carbon emissions using panel data from 1990 to 2017 in 184 countries and indicated that FD can help reduce carbon emissions. Secondly, FD directly impacts the structure of industries, influencing carbon emissions through changes in the consumption of materials and the generation of waste (Hussain et al., 2023). Others argue that FD can negatively impact environmental quality by increasing the ecological footprint (Ahmad et al., 2022) or increasing emissions (Javid & Sharif, 2016; Sehrawat et al., 2015; Shahbaz et al., 2016). For instance, Acheampong's (2019) study used 46 Sub-Saharan African countries' panel data from 1980 to 2015 to investigate the impact of FD. The author's results show that FD raises carbon emissions. Similarly, Shahbaz et al. (2016) find that increased emissions is often associated with financial increases in the Pakistan's banking sector from 1985 to 2014. Javid and Sharif (2016) reveal a correlation between Pakistan's financial development and increased emissions from 1972 to 2013.

### **3.2.3 The Relationship Between Agricultural Growth, Financial Development and Agricultural Carbon Emissions**

Although substantial research has examined the relationship between economic growth and carbon emissions, there is a notable lack of emphasis on investigating the relationship between agricultural growth, ACEs and FD in rural areas. Several researchers have explored the relationship between agricultural growth and ACE (Luo et al., 2017; Wang & Lv, 2022; Xiong et al., 2016; Zafeiriou & Azam, 2017; Zhang et al., 2019). Xiong et al. (2016) conducted a decoupling relationship analysis to find that economic growth is the primary driver of increased ACEs. In contrast, efficiency was regarded as a crucial factor in reducing ACEs in Hotan Prefecture, China. Zafeiriou and Azam (2017) validated the EKC hypothesis for France, Portugal and Spain, however, in the short run, the EKC hypothesis for Spain still needs to be confirmed. Zhang et al. (2019) adopted the autoregressive distributed lag (ARDL) method to validate the EKC hypothesis for ACE in China's main grain-producing areas using time-series data. Similarly, Wang and Lv (2022) validated the EKC hypothesis for Henan Province, China.

However, previous studies have focused on local areas rather than the provincial or national level. Some studies primarily focus on overall carbon emissions rather than ACEs, whereas others focus on carbon emissions from traditional crop farming, neglecting the substantial contribution of livestock farming to ACEs. Furthermore, many studies failed to pay attention to the significant role of FD. This essay uses China's provincial-level panel data to bridge these gaps to investigate the relationship between agricultural growth, rural FD and ACEs from 2001 to 2019. This provides a more comprehensive understanding of the relationships between agricultural growth, ACEs, and FD in rural China.

## **3.3 Methodology and Data**

### **3.3.1 The Theoretical Framework and Model Construction**

The EKC Theory provides a significant framework for investigating the relationship between agriculture growth and ACEs. According to the theory, economic development is the top priority in the initial stage of economic growth. However, this development comes at a huge cost to resources and the environment. With economic growth, carbon emissions rise significantly. However, when economic growth reaches a certain level, people are more concerned about environmental quality. With the development of green technology, carbon emissions decrease because of the double effect of growing awareness and green technology development (Pata, Kartal, et al., 2023). The green Solow model (Brock & Taylor, 2005) and macroeconomic production and utility functions (Kijima et al., 2010) support the EKC

relationship theoretically (Tenaw & Beyene, 2021). Thus, I hypothesize the following relationship:

*H1: there is a nonlinear relationship between agricultural growth and ACEs in China with an inverted U-shaped relationship.*

However, some research challenges the EKC hypothesis by proposing that there is omitted variable bias in the EKC framework, since there are many other significant factors simultaneously impacting economic growth and the environment (Jahanger et al., 2023; Khan et al., 2021; Leal & Marques, 2020; Pata & Caglar, 2021). Notably, FD, as an important influencing factor on economic growth (and also carbon emissions level), has received great attention worldwide (Ahmad et al., 2022; Javid & Sharif, 2016; Khan et al., 2017; Shahbaz et al., 2016). FD impacts carbon emissions in several ways. First, a well-developed financial system can provide funds for green technology development and promote green innovation, contributing to decreased carbon emissions (Ahmad et al., 2022; Dogan & Seker, 2016; Shahbaz et al., 2016). Secondly, a developed financial system can provide high-quality financial services to environmental protection programs at a lower cost and, thereby, reduce carbon emissions (Shahbaz et al., 2013; Tamazian & Bhaskara Rao, 2010). Thirdly, a developed financial system can use the capital market to force companies to issue environmental performance reports and guide investors to adopt environment-friendly technology and reduce carbon emissions (Shahbaz et al., 2013). Further, a developed financial system can directly reduce carbon emissions by promoting a carbon trading market (Shahbaz et al., 2013). However, financial development can also help boost economic growth and increase energy consumption, leading to a substantial increase in carbon emissions (Ahmad et al., 2022; Shahbaz et al., 2016).

In the context of the Chinese agriculture sector, FD can impact ACEs through two mechanisms. On the one hand, FD can improve farmers' access to credit, enabling investments in environmentally sustainable technologies such as precision agriculture and renewable energy, contributing to decreased ACEs. On the other hand, FD may elevate ACEs by increased use of inputs such as fertilizers, pesticides, and energy-intensive machinery, which can enhance productivity while increasing ACEs. However, because of the limited development of the capital and carbon trading markets and the particularity of China's rural financial system, which mainly relies on the rural financial banking system, the impact of rural finance on ACEs is mainly through providing funds and promoting green technology development. Additionally, because of the characteristics of dispersed small-scale farmers of China's agriculture, investment in green technology innovation is limited, which greatly decreases the impact of financial development on carbon emissions reduction in rural areas. In addition, with a

generally weak environmental protection awareness of farmers, the funds provided by the rural financial system go to energy-consuming and input-intensive agricultural activities that increase ACEs (Guo et al., 2022). Thus, I hypothesize the following relationship:

*H2: Rural financial development is not conducive to reducing ACEs.*

Because of China's vast territory, there are great differences in natural endowments, agricultural structure, economic development and technology development in different regions (Cui et al., 2022). The impacts of financial development and agricultural growth on ACEs may vary across regions. Thus, I hypothesize the following relationship:

*H3: The impacts of agriculture growth and rural financial development vary across regions.*

This study incorporates FD into the rural EKC framework for *H1* and *H2* using the cubic term that can provide more accurate information and capture the diverse patterns among agricultural growth and ACEs. This methodology is based on the previous studies such as Grossman and Krueger (1995), Panayotou (1997), Dinda (2004), Akbostancı et al. (2009) and Özokcu and Özdemir (2017). The specific equation in the context of our study is constructed as follows:

$$\begin{aligned} \ln ACET_{it} = & \alpha_i + \beta_1 RGDP_{it} + \beta_2 \ln GDP_{it}^2 + \beta_3 \ln GDP_{it}^3 + \beta_4 RFS_{it} + \beta_5 RFE_{it} \\ & + \sum_{k=6}^9 \beta_k \text{Control}_{it} + \mu_{it} \end{aligned} \quad (3.1)$$

where:  $\ln ACET_{it}$  is the logarithmic form of the core explained variable, ACET, measuring the total carbon emissions in the agricultural sector;  $\ln GDP_{it}$  is the logarithm of PGDP, which indicates the level of agricultural growth, defined by per capita of the rural GDP (RGDP) in rural areas; RFS and RFE are proxy indicators of FD, representing the scale and efficiency of rural finance development;  $i$  represents the different provinces; and  $t$  indicates the year. The intercept term,  $\alpha_i$ , indicates individual regional effects;  $\beta_1$  to  $\beta_9$  are the coefficients to be estimated;  $\text{Control}_{it}$  refers to a set of control variables, such as urbanization (UR), agricultural mechanization level (AML), agricultural industry structure (AIS), and agricultural fiscal expenditure (AFE); and  $\mu_{it}$  is the random error term.

When  $\beta_1 > 0$  and  $\beta_2 = \beta_3 = 0$ , it suggests a monotonically increasing relationship between agricultural growth and ACEs. If  $\beta_1 > 0$ ,  $\beta_2 < 0$ , and  $\beta_3 = 0$ , it shows an inverted U-shape, which validates the EKC hypothesis. When  $\beta_1 < 0$ ,  $\beta_2 > 0$ , and  $\beta_3 = 0$ , this denotes a U-shape, suggesting that the ACEs decrease with the development of agricultural growth at the initial stage and, after a threshold level, it increases with the agricultural growth. When  $\beta_1 > 0$ ,  $\beta_2 < 0$ , and  $\beta_3 > 0$ , it indicates an N-shape, with ACE increasing, decreasing, then increasing again

with GDP; when  $\beta_1 < 0$ ,  $\beta_2 > 0$ , and  $\beta_3 < 0$ , it indicates an inverted N-shape, with ACE decreasing, increasing, then decreasing again with GDP (Akboştañcı et al., 2009; Dinda, 2004; Özokcu & Özdemir, 2017).

To test *H3*, I conduct a regional heterogeneity analysis by dividing the sample into four groups based on the classification by the National Bureau of Statistics of China: the eastern, central, western and northeastern regions. A group regression analysis is performed to obtain robust results. Additionally, I use the system GMM (SYS-GMM) estimation method as a further check of the reliability of the estimates.

Considering that ACET may have path dependence, ACET in the next period may have been affected by ACEs in the current period. Therefore, I introduced a lagged period of ACEs as an explanatory variable into the model to capture the dynamic effect and perform robust checks with equation (3.2):

$$\begin{aligned} \ln ACET_{i,t} = & \alpha_i + \gamma \ln ACE_{it-1} + \mu_1 RGDP_{it} + \mu_2 \ln GDP_{it}^2 + \mu_3 \ln GDP_{it}^3 + \mu_3 RFS_{it} \\ & + \mu_4 RFE_{it} + \sum_{k=5}^8 \mu_k \text{Control}_{it} + \mu_{it} \end{aligned} \quad (3.2)$$

where:  $\ln ACE_{it-1}$  is the lagged period of the  $\ln ACE_{it}$ , and  $\gamma$  is the coefficient of the lagged ACE to be estimated.

### 3.3.2 Estimation Strategy

I test the EKC Theory and examine the impact of FD on ACEs using panel data from China's 31 provinces. Since many panel data studies analysis suggest that panel-data models are prone to significant cross-sectional dependence in errors (De Hoyos & Sarafidis, 2006; Dogan & Seker, 2016; Pesaran, 2021), this may arise from unobserved shocks, unobserved components, and local spillover effects among regions (Dogan & Seker, 2016; Pesaran, 2021). I adopt an appropriate method to test for the existence of cross-sectional dependence. Since the data show large cross-sectional dimensions (N) and short time dimensions (T), it is reasonable to adopt the cross-sectional dependence (CD) test, which applies to data with large N and small T (Pesaran, 2021).

If the issue of CD and heterogeneity exist in the data, the first-generation unit root tests, such as the Dickey-Fuller (ADF) test and Levin-Lin-Chu (LLC) test (Zhang et al., 2019), will not be effective and may lead to misleading results (Dogan et al., 2017; Pesaran, 2007). The cross-sectional augmented Dickey-Fuller (CADF) and Im Pesaran-Shin (CIPS) panel unit root tests, which consider the existence of possible CD, are preferred to traditional panel unit root tests

(Pesaran, 2007). Therefore, I use the CADF and CIPS methods to conduct panel unit root tests to ensure valid regression results.

Next, the F and LM tests are conducted to detect the presence of individual effects. If individual effects exist, the Hausman test will be conducted to determine which model should be chosen between the fixed effects and random effects model. After selecting the appropriate model, the estimator will be conducted to test hypotheses (1) and (2). Next, I conduct a regional heterogeneity analysis to test hypothesis (3). Finally, a series of robustness checks, including SYS-GMM method, are conducted to test the reliability of empirical results. The reasons I employ SYS-GMM estimator are as follows. Firstly, it enhances the precision of estimators in the context of dynamic panel data. In contrast to Difference GMM, which depends on first-differencing to remove individual effects, SYS-GMM significantly improves asymptotic efficiency by combining differenced and level equations to produce more instruments. This increases overall efficiency and improves instrument validity (Blundell & Bond, 1998; Khan et al., 2021; Sun & Chen, 2022). Furthermore, SYS-GMM can be useful in panel data analysis, especially when considering individual heterogeneity, since it can address unobserved individual-specific effects that could bias ordinary least squares (OLS) estimates. Additionally, the SYS-GMM estimator helps account for autocorrelation (Khan et al., 2021) and addresses endogeneity using lagged values as instruments (Acheampong, 2018; Blundell & Bond, 1998).

### 3.3.3 Data and Variables

To systematically examine the impact of agricultural growth and rural financial development on ACEs, I use a panel dataset of China's 31 provinces from 2001 to 2019. The key variables with their descriptions, measurements and data sources are now described next.

#### 3.3.3.1 *Agricultural Carbon Emissions*

ACET, the dependent variable, measures the total carbon emissions of the agricultural sector. Traditional ACEs measurement methods mainly focus on carbon dioxide, often overlooking the significant contributions of methane and nitrous oxide to global warming (Cui et al., 2022; Su et al., 2023). I include these emissions to address the gap, providing a more comprehensive understanding of the impact of ACEs.

In line with standard scientific practice, I convert emissions into carbon dioxide equivalents (CO<sub>2</sub>e) based on their global warming potential (GWP), facilitating a consistent comparison and a comprehensive environmental evaluation. Specifically, the ACEs here include carbon dioxide emissions from agricultural land use, methane emissions from rice paddies, and

methane and nitrous oxide emissions from livestock. I calculate the total amount of ACEs using the strategies recommended by the IPCC (2019) and the Provincial Guidelines for GHG Inventories (Trial) of China (2023). The primary data to estimate the ACEs are from the China Statistical Yearbook, ensuring reliable estimates for the analysis.

In my analysis, carbon emissions from agricultural land use cover a range of sources including agricultural inputs, diesel fuel used in machinery, emissions from farmland tillage, and electricity consumption for irrigation. I adopt a specific carbon emissions factor of 4.9341 kg C/kg for pesticides, based on Li et al. (2011) and Luo et al. (2017). Table 3.2 presents the various carbon emissions factors used in the study.

Table 3.2 Carbon Emissions Factors from Agriculture Land Use

Type	Carbon emissions factor	Source
Pesticides (C kg/kg)	4.9341	Li et al. (2011); Luo et al. (2017)
Chemical fertilizer (Ckg/kg)	0.8956	Li et al. (2011); Luo et al. (2017)
Agricultural films (C kg/kg)	5.18	Li et al. (2011); Tian et al.(2014)
Diesel (C kg/kg)	0.5927	Li et al. (2011); IPCC United Nations Intergovernmental Committee of Experts on Climate Change (2019)
Tillage (C kg/km <sup>2</sup> )	312.6	Li et al. (2011)
irrigation (C kg/hm <sup>2</sup> )	266.48	West and Marland (2002); Luo et al. (2017)

Rice paddies are a significant source of methane emissions (Qian et al., 2023). They are categorized into early, middle and late rice with corresponding emissions coefficients based on the research of Min and Hu (2012). Livestock contributes to ACEs through methane emissions from ruminant enteric fermentation and methane/nitrous oxide emissions from manure management. The emissions coefficients for the different livestock species are from the Intergovernmental Panel on Climate Change (2019). The total agricultural carbon emissions of each province can be estimated using equation (3.3):

$$E_{ACEs} = \sum_1^k E_i = \sum_1^k T_i \delta_i \quad (3.3)$$

where:  $i$  represents the type of carbon source;  $k$  is the total number of carbon sources;  $E_{ACEs}$  is the overall carbon emissions;  $E_i$  is the carbon emissions of each specific carbon source;  $T_i$  is the quantity of each specific carbon source; and  $\delta_i$  denotes the carbon emissions coefficient for each specific carbon source. From 2001 to 2019, China's total ACEs fluctuated through four distinct phases (see Figure 3.1).

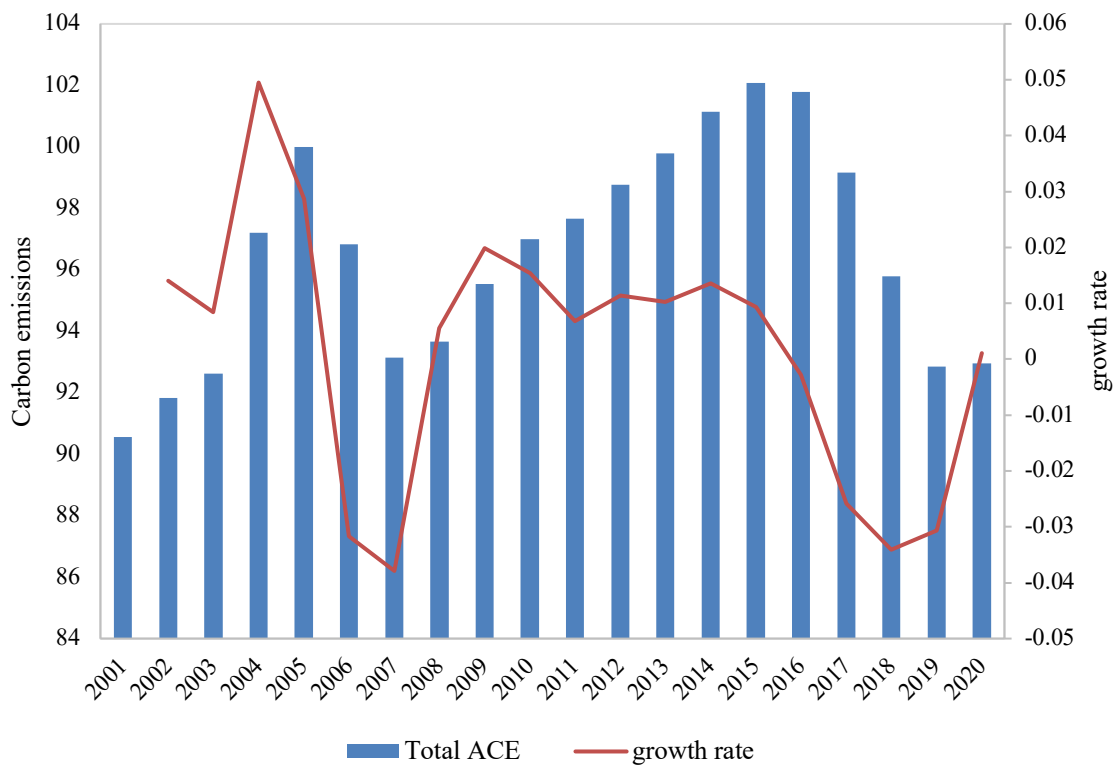


Figure 3.1 Total ACEs and the annual growth rate of China's ACEs from 2001 to 2020 (unit 10<sup>7</sup>tonnes)

Source: Author's calculations and compilation

### 3.3.3.2 Core Explanatory Variables

The core explanatory variables are PGDP and rural financial development. PGDP is agricultural growth, defined by the rural GDP (RGDP) per capita in rural areas. RGDP is the total value of agriculture, forestry, animal husbandry and fisheries. These data are from the China Rural Statistical Yearbook. The year 2001 is used as the base for the non-valence of the calendar year data. Financial development is defined as enhancing the quality and quantity of financial intermediary services (Muhammad et al., 2016), measured by various indicators such as the liquid liabilities to GDP ratio (Adams & Klobodu, 2018; Jalil & Feridun, 2011), deposit money bank assets to GDP ratio, stock market capitalization to GDP ratio (Abbasi & Riaz, 2016) and the ratio of private credit to GDP (Dogan & Seker, 2016; Javid & Sharif, 2016; Khan et al., 2021). However, because of the characteristics of China's financial system in that a significant part of deposits has been "sleeping", which means that the deposits remain unused or inactive in banks (Zhang, 2011), the ratio of deposits or the sum of deposits and loans to GDP, frequently used in previous studies (Abbasi & Riaz, 2016; Tamazian & Bhaskara Rao, 2010), does not

accurately measure financial development in China. Additionally, previous studies failed to distinguish financial scale and efficiency (Zhang, 2011).

The main financial capital comes from local financial institutions and the development of other markets, such as stocks and bonds, is limited in rural China (Mei et al., 2022). Therefore, I follow previous studies and use rural financial scale (RFs), calculated as the ratio of rural loans (RL) to rural GDP (RGDP), and rural financial efficiency (RFe), calculated as the ratio of rural loans (RL) to rural GDP (RGDP), to measure rural financial development. RFs denotes the rural financial intermediation scale and RFe reflects rural financial intermediation efficiency, which is the ability to allocate financial resources effectively (Liu et al., 2021; Zhang, 2011).

### *3.3.3.3 Control Variables*

The control variables are: urbanization, agricultural mechanization, agriculture structure and agricultural fiscal expenses, denoted by UR, AML, AIS, and AFE. Urbanization refers to the process of the rural labour force shifting to urban areas. Reducing the labour force in rural areas leads to a change in agricultural production toward intensification, specialization and low carbon, thereby reducing ACEs (Han et al., 2021; Su et al., 2023). I use the ratio of the urban population to the total population to measure the urbanization level. The agricultural mechanization level is the input of agricultural machinery in the agricultural sector. A high agricultural machinery input means high energy consumption, producing more ACEs. It is proxied by the total power of agricultural machinery in each province (Ma et al., 2023). Since planting and animal husbandry are the main sources of ACEs for this study, the ratio of planting and animal husbandry output value to total agricultural output value is used to indicate the agricultural structure. Agricultural fiscal expense refers to the government's financial support for the agricultural sector. Table 3.3 presents the study variables - the logarithmic form is used to eliminate heteroscedasticity in the data.

## **3.4 Results and Discussion**

### **3.4.1 Pre-estimation Diagnostics**

Table 3.4 provides the descriptive statistics of the main study variables. ACEs represent the yearly total ACEs of each province from 2001 to 2019, with the maximum value observed in Henan province in 2005 and the minimum value in Beijing in 2019. PGDP represents per capita agricultural GDP of each province from 2001 to 2019 adjusted to constant prices in 2001.

Table 3.3 Definitions of the Study Variables

Variable	Definition	Unit	Time	Data source
ACET	Total ACEs	10 <sup>3</sup> tonnes	2001-2019	Estimated by author
PGDP	Rural GDP per capital	Constant 2001 Chinese Yuan	2001-2019	China Rural Statistical Yearbook
RFs	Agricultural loan/RGDP	% of RGDP	2001-2019	China Rural Financial Services Report China Rural Statistical Yearbook
RFe	Agricultural loan/rural household deposits	%	2001-2019	China Rural Financial Services Report; China Financial Statistics Yearbook
UR	Urban population/Total Population	%	2001-2019	China Rural Statistical Yearbook
AML	Total power of agricultural machinery in each area	million kilowatts	2001-2019	China Rural Statistical Yearbook
AIS	output value of farming industry and animal husbandry industry / RGDP	% of RGDP	2001-2019	China Rural Statistical Yearbook
AFE	Fiscal expense on agriculture	¥ 10 <sup>8</sup> Yuan	2001-2019	China Rural Statistical Yearbook

Source: Author's compilation

Table 3.4 Descriptive Statistics

Variable	Obs	Mean	Std Dev.	Min	Max
ACET	589	3119.569	1985.643	81	7410
ACEI	589	1.814	1.284	0.294	7.608
PGDP	589	6998.156	3835.733	1384	24010
RFs	589	0.354	0.245	0.011	1.737
RFe	589	0.414	0.255	0.003	1.266
UR	589	0.514	0.157	0.168	0.896
AML	589	2785.798	2703.728	94	13353
AIS	589	0.834	0.103	0.538	0.988
AFE	589	291.397	282.344	1	1311

Source: Author's compilation

Table 3.5 presents the Pearson correlation matrix of the study variables. There are significant correlations between the dependent variable lnACE and most variables at the 1% significance level (RFs, RFe, UR, lnAML, AIS, and lnAFE). The highest correlation is between lnACE and lnAML (0.838) followed by UR (0.519), RFs (0.30), and lnAFE (0.293). For the different forms of income variables, lnPGDP, lnPGDP2 and lnPGDP3, significant correlations are at the 10%, 5% and 5% significance levels, respectively. This suggests that models' variables are free from multicollinearity issues.

Table 3.5 The Correlation Matrix of the Study Variables

	lnACE T	lnPGD P	lnPG DP2	lnPGD P3	RFs	RFe	UR	lnA ML	AIS	lnA FE
lnACET	1.00									
lnPGDP	-0.078 *	1.00								
lnPGDP2	-0.083 **	0.99 ***	1.00							
lnPGDP3	-0.089 **	0.99 ***	0.99 ***	1.00						
RFs	-0.30 ***	-0.02	-0.02	-0.02	1.00					
RFe	0.199 ***	-0.23 ***	-0.23 ***	-0.23 ***	0.15 ***	1.00				
UR	-0.52 ***	0.70 ***	0.70 ***	0.69 ***	0.15 ***	-0.42 ***	1.00			
lnAML	0.84 ***	0.11 ***	0.10 **	0.10 **	-0.09 **	0.13* **	-0.28 ***	1.00		
AIS	0.11 ***	-0.44 ***	-0.44 ***	-0.43 ***	0.08 **	0.25 ***	-0.43 ***	0.12 ***	1.00	
lnAFE	0.29 ***	0.54 ***	0.53 ***	0.52 ***	0.22 ***	-0.26 ***	0.33 ***	0.48 ***	-0.11 ***	1.00

Note: \*\*\*, \*\* and \* indicate statistical significance at the 1%, 5 % and 10% level respectively.

Table 3.6 presents the Pesaran CD test results for each variable's cross-sectional dependence. The results show that all variables are statistically significant at the 1% level, rejecting the null hypothesis of no interdependence, i.e., cross-sectional dependence exists among the variables.

Table 3.6 Pesaran Cross Sectional Dependence Test Results of the Variables

Variable	Test stat.	Prob.
lnACET	13.7***	0.000
lnGDP	71.81***	0.000
lnGDP2	71.77***	0.000
lnGDP3	71.73***	0.000
RFs	18.25***	0.000
RFe	34.95***	0.000
UR	87.33***	0.000
lnAML	54.52***	0.000
lnAFE	92.18***	0.000
AIS	36.69***	0.000

Note: \*\*\* indicates statistically significant at the 1% level.

Since cross-sectional dependence exists in the panel data, CADF and CIPS are used to address the cross-sectional dependence and guarantee the robustness of the unit root test. Table 3.7 presents the results of the panel unit root tests. According to the CADF test, UR, lnAFE, and

AIS are stationary at level, whereas the other variables are not stationary at level but, after first differencing, they become stationary. Similarly, the results from CIPS test show that UR, lnAML, lnAFE, and AIS are stationary at level, and the other variables become stationary after first differencing. Notably, all the variables become stationary after first differencing, rejecting the null hypothesis at the 1% significance level, which implies that all variables are integrated in order (I (1)). This demonstrates that there is a long-run equilibrium relationship between the variables, ensuring the reliability and effectiveness of the subsequent estimates (Dou et al., 2021).

Table 3.7 Panel Unit Root Test of the Variables for Stationarity

	Level		First difference	
	Intercept	Intercept & trend	Intercept	Intercept & trend
Cross-sectionally Augmented Dicky-Fuller (CADF)				
lnACET	-1.283	-2.236	-2.32***	-2.837***
lnGDP	-1.785	-1.577	-2.431***	-2.93***
lnGDP2	-1.765	-1.918	-2.483***	-2.924***
lnGDP3	-1.749	-2.19	-2.617***	-2.909***
RFs	-1.842	-2.446	-2.865***	-2.93***
RFe	-1.881	-2.039	-2.707***	-2.797***
UR	-2.239***	-2.798***	-2.609***	-2.714***
lnAML	-1.717	-2.389	-2.604***	-2.795***
lnAFE	-2.657***	-3.06***	-3.254***	-3.796***
AIS	-2.44***	-3.237***	-3.759***	-3.547***
Cross-sectionally Augmented IPS(CIPS)				
lnACET	-2.005	-2.493	-3.379***	-3.804***
lnGDP	-1.794	-1.636	-3.052***	-3.346***
lnGDP2	-1.746	-1.836	-3.062***	-3.301***
lnGDP3	-1.686	-2.070	-3.178***	-3.258***
RFs	-1.984	-2.901***	-3.870***	-3.964***
RFe	-1.848	-2.371	-3.701***	-3.618***
UR	-2.045*	-2.709**	-3.170***	-3.169***
lnAML	-2.093*	-2.582*	-3.625***	-3.573***
lnAFE	-2.621***	-3.141***	-3.968***	-4.494***
AIS	-2.468***	-3.184***	-4.269***	--4.289***

Note: \*\*\*, \*\* and \*, indicate  $P < 0.01, 0.05, 0.10$ , respectively.

### 3.4.2 Baseline Regression Results

Table 3.8 presents the baseline regression results of Models (1), (2), and (3), which display the results without control variables, with control variables, and including fixed effects, respectively. The results reveal an inverted “N” shaped relationship between agricultural growth and ACEs in all models indicated by the models' negative linear, positive squared and negative cubic terms. This rejects our hypothesis (1), which posits a nonlinear relationship between agricultural growth and ACEs in China with an inverted U-shaped curve. The EKC curve is absent in rural China.

Table 3.8 Baseline Regression Results of the Factors Affecting Agricultural Carbon Emissions

Variable	(1) lnACET		(2) lnACET		(3) lnACET	
lnPGDP	-13.755*	(6.81)	-17.973***	(6.11)	-16.389**	(6.43)
lnPGDP2	1.600**	(0.78)	2.161***	(0.71)	1.971**	(0.75)
lnPGDP3	-0.061**	(0.03)	-0.084***	(0.03)	-0.077**	(0.03)
RFs			-0.026	(0.06)	-0.015	(0.06)
RFe			0.165**	(0.07)	0.146**	(0.06)
UR			-1.279***	(0.42)	-1.183**	(0.44)
lnAML			0.154***	(0.05)	0.135**	(0.05)
AIS			0.711**	(0.32)	0.679*	(0.37)
lnAFE			-0.048***	(0.01)	-0.012	(0.02)
_cons	46.729**	(19.74)	55.129***	(17.53)	50.712***	(18.42)
N	589.000		589.000		589.000	
r2_a	0.113		0.578		0.618	
year	No		No		Yes	
F	3.322		12.680		47.974	

Notes: Standard errors are in parentheses; \*\*\*, \*\* and \*, indicate  $P < 0.01, 0.05, 0.10$ , respectively

The results from model (1) show that, initially, when RGDP increases by 1%, it leads to a 13.755% decrease in ACEs. However, after a threshold level, a 1% increase in RGDP leads to a 1.6% increase in ACEs and then, at another threshold a 1% increase in RGDP causes a decline in ACEs of 0.061 %. After introducing the control variables into model (2), the results still show an inverted ‘N’ shape that is statistically significant at the 1% level. Model (3), which includes fixed effects after controlling some influencing variables, also reveals an inverted ‘N’ shape but at the 5% significance level. These findings reject hypothesis (1), indicating that the EKC curve does not exist in rural China.

Several factors contribute to the inverted “N” shaped relationship. During the initial stage, an increase in RGDP is not mainly caused by agricultural production but also by non-agricultural activities since, during this stage, the trade-off between revenue and the high cost of farming activities leads farmers into the non-farming sector, leaving farmland abandoned, which causes a decrease in ACEs. Since the issue of the No.1 Central Document in 2004, which emphasizes the top priority of the “three rural” issue, farmers’ enthusiasm for using farmland and other agricultural activities was extensively promoted (Liu et al., 2021; Tian et al., 2014), which led to more production materials invested into agricultural use, resulting in a significant increase in ACEs.

Models (2) and (3), which include financial development indicators, demonstrate that RFe significantly contributes to the increased ACEs at the 5% level in both models, whereas RFs negatively impacts on ACEs but it is not statistically significant, which confirms our hypothesis

(2), suggesting that financial development in rural areas is not conducive to reduce ACEs. Specifically, a 1% increase in RFe leads to a 0.165% increase in ACEs in model (2) at a 5% significance level. In contrast, RFe negatively impact ACEs; every 1% increase in RFe leads to a 0.026% decrease in ACEs but with no statistical significance. Model (3) shows similar results even when controlling for individual and time-fixed effects.

RFe is the rural financial scale, a financial scale that indicates that more funds can be invested into all kinds of economic activity. The results from Models (2) and (3) reveal that RFe may reduce ACEs despite no statistical significance. This suggests that rural financial development can provide more financial resources for agricultural production and promote green technology in rural areas, thereby lowering emissions (Liu et al., 2021). Conversely, RFe reflects the efficiency of the financial system in allocating financial resources; it shows an increase in ACEs. A possible reason is that environmental protection awareness in rural areas is not strong, leading to more funds being invested in energy-consuming and input-intensive agricultural operations. This finding is consistent with the study by Acheampong et al. (2019) who argue that FD can provide greater access to high-energy consumption activities that impact environmental quality negatively.

For the control variables in model (2), the results present a positive impact of lnAML and AIS on ACEs. Specifically, a 1% increase in the agricultural mechanization level is accompanied by a 0.154% increase in ACEs (significant at the 1% level), suggesting that higher agricultural machinery use contributes to increased carbon emissions. Similarly, a 1% increase in AIS leads to a 0.711% increase in ACEs. In contrast, UR and lnAFE show a significant negative impact on ACEs at the 1% level, suggesting that urbanization and government financial support to the agriculture sector can help to reduce ACEs. The possible reason that government financial support can mitigate ACEs could be attributed to the government's allocation of funds to eco-friendly agricultural programmes and investment in agricultural technology and infrastructure that reduce ACEs. Model (3) produces similar results, which supports model (2)'s findings.

### **3.4.3 Heterogeneity Analysis**

Table 3.9 displays the findings of the heterogeneity analysis, which strongly supports our hypothesis 3. Hypothesis 3 posits that impacts of agricultural growth and rural financial development vary by region. First, the impact of agricultural growth varies across regions, with an inverted "N" shape appearing for the eastern, central and northeastern regions at a 1% significance level, confirming the consistency of the inverted "N" shaped relationship. The relationship fails to have statistical significance in the west despite negative linear, positive

quadratic and negative cubic terms.

Table 3.9 The Effects of Heterogeneity on the Effects of Rural Economic Growth and Financial Development on Total Agricultural Carbon Emissions

Variable	Whole country lnACE	Eastern region lnACE	Central region lnACE	Western region lnACE	Northeastern region lnACE
lnPGDP	-16.398*** (2.80)	-84.286*** (12.71)	-44.336*** (7.53)	-1.296 (5.30)	-87.701*** (31.30)
lnPGDP2	1.972*** (0.33)	9.113*** (1.39)	5.438*** (0.91)	0.099 (0.63)	9.831*** (3.50)
lnPGDP3	-0.077*** (0.01)	-0.328*** (0.05)	-0.219*** (0.04)	0.002 (0.02)	-0.364*** (0.13)
RFs	-0.015 (0.02)	-0.243*** (0.04)	0.023 (0.05)	0.100*** (0.03)	-0.610* (0.31)
RFe	0.145*** (0.03)	0.480*** (0.06)	0.333*** (0.09)	-0.060 (0.05)	0.309** (0.13)
UR	-1.183*** (0.22)	0.474 (0.32)	-1.287** (0.53)	-1.536*** (0.58)	0.564 (0.97)
lnAML	0.135*** (0.02)	0.207*** (0.03)	0.117*** (0.03)	-0.015 (0.05)	0.027 (0.07)
AIS	0.678*** (0.12)	0.497*** (0.18)	-0.375 (0.23)	0.412 (0.26)	0.168 (0.96)
lnAFE	-0.013 (0.01)	-0.020 (0.02)	0.024 (0.02)	0.028 (0.02)	-0.050* (0.03)
_cons	50.738*** (8.01)	264.461*** (38.77)	126.730*** (20.89)	11.020 (14.79)	265.885*** (93.42)
N	589.000	190.000	114.000	228.000	57.000
r2_a	0.597	0.866	0.690	0.490	0.955
year					
F	34.310	46.511	10.506	9.499	45.464

Note: Standard errors in parentheses, \*\*\*, \*\* and \*, indicate  $P < 0.01$ ,  $0.05$ ,  $0.10$ , respectively

Secondly, the impact of FD varies across regions. The results show RFs had a significant negative impact on ACEs in the eastern and northeastern regions at the 1% and 10% level, respectively, but a significant positive impact in the western region at the 1% level and in the central region no statistically significant impact. RFe positive impacts ACEs in the eastern, central, and northeastern regions with a significance level of 1%, 1%, and 5%, respectively, which is consistent with the results of the national sample. However, it shows a negative impact for the western region, but not statistically significant.

The reason that the impact of rural FD on ACEs differs between the western region and other regions could be attributable to differences in development level. The eastern, northeastern, and central regions are more developed than the western region regarding economic growth and FD level. Xu et al.'s (2022) finding supports this result by revealing that there is an inverted U-

shaped relationship between rural FD and ACEs, suggesting that ACEs initially increase with FD growth, but eventually decrease with FD growth because more capital is invested in agricultural green technology.

### 3.4.3 Robustness Check

Several robustness tests were conducted to ensure the validity and accuracy of the empirical results on the relationship between agricultural growth, rural financial development and ACEs.

#### 3.4.3.1 GMM Regression

The SYS-GMM method is commonly used to overcome the weakness of first difference GMM to maximize the use of instruments and improve estimation precision (Acheampong, 2018; Adams & Klobodu, 2018). The SYS-GMM is superior to the first difference GMM in controlling for endogeneity by including lagged dependent variables as instruments in both the level and first difference equations, providing consistent, efficient estimators (Acheampong, 2018; Blundell & Bond, 1998).

Table 3.10, Column (3), shows the results of SYS-GMM; the current period of ACEs is significantly, positively impacted by lagged ACEs at the 1% level and the inverted “N” shaped relationship is confirmed by the negative first-degree term, positive quadratic term and negative cubic term. RFs has a significant negative impact on ACEs at the 1% and RFe has a significant positive impact on ACEs but only at the 10% level. Table 3.10 also compares the SYS-GMM estimates with the pooled OLS regression and two-way fixed-effects models and shows consistent results.

Table 3.10 Robustness Check: A Comparison of the GMM Regression Results

Variable	(1) OLS	(2) FE	(3) GMM
L.lnACE	1.006*** (0.01)	0.869*** (0.02)	0.937*** (0.03)
lnPGDP	-1.090 (1.52)	-5.255*** (1.60)	-0.204*** (0.08)
lnPGDP2	0.140 (0.18)	0.632*** (0.19)	0.038** (0.02)
lnPGDP3	-0.006 (0.01)	-0.025*** (0.01)	-0.002** (0.05)
RFs	-0.029*** (0.01)	-0.024** (0.01)	-0.095*** (0.03)
RFe	0.028*** (0.01)	0.009 (0.02)	0.039* (0.02)
UR	-0.009 (0.03)	0.017 (0.13)	-0.003 (0.10)
lnAML	0.003 (0.00)	0.040*** (0.01)	0.041** (0.02)
AIS	0.070*** (0.02)	0.337*** (0.06)	0.389*** (0.005)
lnAFE	-0.012*** (0.00)	-0.015** (0.01)	0.005 (0.01)
_cons	2.723 (4.37)	14.592*** (4.62)	-55.555* (30.94)
ar2p			0.087
hansenp			1.000
N	558.000	558.000	558.000

Notes: Standard errors in parentheses; \*\*\*, \*\* and \*, indicate P < 0.01, 0.05, 0.10,

respectively

### 3.4.3.2 The explained variable is advanced by one period

To account for the lagged effects of agricultural growth and rural FD on ACEs, the explained variable is forwarded by one period to address the endogeneity issue caused by reverse causality. The result is shown in Column (1) of Table 3.11.

Table 3.11 Robustness Check: Shifting the Dependent Variable One Period Forward and Alternative Variable for Agricultural Carbon Emission

Variable	(1) f.lnACE	(2) lnACEI	(3) f.lnACEI
lnPGDP	-17.903** (6.54)	-11.806 (8.81)	-14.173 (8.48)
lnPGDP2	2.161*** (0.76)	1.450 (1.05)	1.748* (1.01)
lnPGDP3	-0.085*** (0.03)	-0.056 (0.04)	-0.068* (0.04)
RFs	-0.031 (0.07)	-0.036 (0.08)	-0.051 (0.08)
RFe	0.142** (0.07)	0.163* (0.08)	0.162** (0.07)
UR	-0.995** (0.45)	0.011 (0.59)	-0.004 (0.59)
lnAML	0.154** (0.06)	0.121* (0.06)	0.136** (0.06)
AIS	0.624 (0.38)	0.195 (0.41)	0.218 (0.41)
lnAFE	-0.025 (0.02)	-0.042* (0.02)	-0.051** (0.02)
_cons	54.657*** (18.66)	29.347 (24.78)	35.514 (23.82)
N	558.000	589.000	558.000
r2_a	0.607	0.834	0.831
year	Yes	Yes	Yes
F	39.897	133.030	238.666

Notes: Standard errors in parentheses. \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01

### 3.4.3.3 Alternative Variable for Agricultural Carbon Emissions

Considering that there are two methods: the total ACEs and ACEs' intensity, to measure the carbon emissions level in the agricultural sector, to ensure the validity of results, I use ACEs intensity and forward period of ACEs intensity as alternative variables to examine the impact of agricultural growth and rural FD on ACEs. The results are shown in Column (2) and (3) of Table 3.11. The results of Columns (2) and (3) are not as significant as in Column (1), but they still provide robustness for the baseline results. Additionally, the forward period of ACEs intensity is also used to conduct heterogeneity analysis, which further provides the robustness test (see Table 3.12).

Table 3.12 The Effects of Heterogeneity in the Effects of Rural Economic Growth and Financial Development on ACE Intensity

Variable	(1) Whole country F.lnACEI	(2) Eastern region F.lnACEI	(3) Central region F.lnACEI	(4) Western region F.lnACEI	(5) Northeastern region F.lnACEI
lnPGDP	-14.173*** (3.14)	-113.493*** (14.05)	-68.570*** (9.47)	9.239** (4.61)	-101.395*** (26.34)
lnPGDP2	1.748***	12.381***	8.353***	-1.087**	11.460***

	(0.37)	(1.54)	(1.15)	(0.55)	(2.95)
lnPGDP3	-0.068***	-0.449***	-0.335***	0.048**	-0.429***
	(0.01)	(0.06)	(0.05)	(0.02)	(0.11)
RFs	-0.051**	-0.234***	-0.088	0.060**	-1.137***
	(0.03)	(0.04)	(0.06)	(0.03)	(0.25)
RFe	0.162***	0.382***	0.334***	-0.008	0.445***
	(0.03)	(0.06)	(0.11)	(0.04)	(0.11)
UR	-0.004	2.998***	0.235	-0.380	2.308**
	(0.24)	(0.34)	(0.62)	(0.49)	(0.87)
lnAML	0.136***	0.263***	0.095***	-0.089**	0.085
	(0.02)	(0.03)	(0.03)	(0.04)	(0.06)
AIS	0.218	0.370*	-0.738***	0.182	0.437
	(0.14)	(0.21)	(0.27)	(0.21)	(0.80)
lnAFE	-0.051***	-0.038	0.030	0.002	-0.027
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
_cons	35.514***	342.561***	185.476***	-27.608**	295.305***
	(8.95)	(42.74)	(26.15)	(12.82)	(78.43)
N	558.000	180.000	108.000	216.000	54.000
r2_a	0.821	0.894	0.932	0.897	0.989
year					
F	100.274	59.334	57.929	73.323	184.826

Notes: Standard errors in parentheses; \*\*\*, \*\* and \*, indicate  $P < 0.01$ ,  $0.05$ ,  $0.10$ , respectively

### 3.5 Conclusion and Recommendations

To systematically examine the impact of agricultural growth and rural financial development on ACEs, this essay uses a panel dataset of the 31 Chinese provinces from 2001 to 2019 to test the EKC Theory. I examine the impact of FD on ACEs in rural China using the fixed effects method, the SYS-GMM method, and alternative variable methods used to provide a robustness check to ensure the validity of the results. Cross-sectional dependence in the data is also considered to confirm the results' accuracy.

The main findings of the study are as follows. First, the EKC Theory does not apply in rural China, but an inverted "N" shape curve appears for the relationship between agricultural growth and ACEs. Secondly, the role of rural FD in China's agricultural sector in reducing ACEs has not been thoroughly used. RFe is significantly positively correlated with ACEs, and RFs are negatively correlated with ACEs, but the relationship is not insignificant. Thirdly, there is a heterogeneous impact on agricultural growth and FD on ACEs.

Based on the findings, several policy implications can be drawn to reduce ACEs for Chinese agriculture. First, regarding the impact of policies contributing to the inverted "N" relationship between agricultural growth and ACEs, more policies to reduce ACEs are needed because economic growth cannot automatically resolve environmental issues. Secondly, since the role

of rural FD has not been fully studied for the agricultural sector, more measures, especially environmentally friendly measures such as green finance, should be promoted in rural areas. Green finance not only provides financial resources to environmentally friendly programmes and green agricultural practices but also helps promote environmental protection awareness in rural areas. Thirdly, given the significant role of fiscal expenses in agriculture, more targeted fiscal policies and green agricultural investments should be promoted to contribute to environmental sustainability. Finally, regional variation emphasizes the need for each region to formulate differentiated ACEs' reduction policies based on regional characteristics.

### **3.6 Limitations and Future Research**

This study has several limitations. First, the data sample includes only 31 Chinese provinces because of the data availability. If there were a higher density data, such as county-level data, then the heterogeneity of ACEs and the impacts of financial development on ACEs could provide more insights for policymakers. Second, because this study analyses only the impact of financial development on ACEs, we need more mechanism analysis on how it impacts ACEs. Finally, this study uses mainly macro-level data for empirical analysis. However, farmers' green behaviours, such as adopting green agricultural practices, also impact ACEs but this lacks analysis at the micro level. Further research can focus on micro-level analysis to investigate the impact of financial development on ACEs. If a higher-density dataset can be obtained, an in-depth analysis can be conducted.

## Essay Two

# The Impact of Green Finance Development on Agricultural Carbon Emissions

### 4.1 Introduction

A carbon emissions reduction target has been proposed because of the increasing severity of the global environment in recent years, making green development a common sense approach for the global community (Ofori et al., 2023; Tenaw & Beyene, 2021; Yu et al., 2023). For example, in 2015, the Paris Climate Agreement Conference set emissions reduction targets to limit global warming (Lan et al., 2023). In 2020, the European Union issued the European Green Deal with the goal of achieving carbon neutrality by 2050 (Zhang, 2023). The United Nations Climate Change Conference of the Parties (COP26) in 2021 was to promote efforts to achieve net-zero emissions by 2050 (Ofori et al., 2023).

However, how to achieve green development and reduce carbon emissions has become a significant global issue (Lee & Lee, 2022; Zhang, 2023). The literature shows that green finance, which aims to address environmental and sustainable issues by leading the capital from carbon-intensive and polluting businesses to low carbon industry, has been considered an effective way to reduce carbon emissions and achieve green development (Lan et al., 2023; Liu & Wang, 2023; Zhang et al., 2022). Green finance, including all kinds of green financial instruments, such as green credit, green bonds, green insurance and green funds, emerges as an important green innovation to foster the growth of environmentally friendly projects while minimizing the negative environmental effects (Zhang, 2023). For the mechanism of how green finance can contribute to carbon emissions reduction and achieve green development, scholars have analyzed the topic from different perspectives. For example, Lee et al. (2023) argue that green finance contributes to carbon emissions reduction by promoting economic growth, technical innovation, industrial upgrading, and renewable energy transition. The role of green finance in promoting green development and carbon emissions reduction has not only been emphasized by the research community but also by international organizations and most of the world's governments. For example, the European Union initiated carbon emissions trading in 2005, the world's first emissions trading system (Zhang, 2023).

China has achieved remarkable economic development as the largest developing and transition country. However, that development came at a huge cost such as environmental pollution with

the extensive growth (Shahbaz et al.,2022; Zhang, 2023; Zhou et al.,2022). As a responsible country, China pledged to achieve a carbon peak in 2030 and carbon neutrality by 2060 (Lee & Lee, 2022; Yu et al., 2023). Green finance became an important means to achieve sustainable development for China. Compared with other countries, the development of green finance started later but has shown rapid development (Hou et al., 2023) because of great efforts by the Chinese government. As early as 2012, China issued the Green Credit Guidelines that greatly promoted the green credit market in China (Qin & Cao, 2022; Zhang et al., 2022). In 2016, the document "*Guiding Opinions on Establishing a Green Financial System*" was jointly issued by seven departments of the Chinese government, which made China the first country to establish such a system. In 2017, eight green financial innovation reform pilot zones in five Chinese provinces were established (Hou et al., 2023; Zhang, 2023). Thus, China became the largest green bond market in the world (Zhang, 2023).

Extensive research on the role of green finance in China has focused on the relationship between green finance and green growth (Taghizadeh-Hesary et al., 2022; Zhang et al., 2022; Zhou et al., 2022). Some studies investigated the effects of green finance policies, including the pilot zone (Hou et al., 2023; Liu & Wang, 2023; Zhang, 2023) and green credit policies (Qin & Cao, 2022; Zhang et al., 2022). Some studies investigated the relationship between green finance, renewable energy investment, and green innovations (Mngumi et al., 2022; Sun et al., 2022; Zhang et al., 2022). Much research on the relationship between green finance and carbon emissions reduction has been conducted (Lee et al., 2023; Sharif et al., 2022; Zhang et al., 2022). However, there is limited research on green finance and ACEs, given the significant role of green finance in green agricultural development in the context of rural revitalization.

This essay bridges that gap by exploring the nexus between green finance and ACEs using quantile regression and a panel dataset of 31 Chinese provinces from 2007 to 2020 to analyze the asymmetric effect of green finance on ACEs. The study uses the DID model to empirically examine the effects of green finance policies on ACEs and provide comprehensive insights for policymakers to formulate different policies tailored to the agricultural sector. There are three contributions from the study. First, the study examines the role of green finance in reducing carbon emissions in the agricultural sector, a previously overlooked sector compared with the industry and energy sectors. Secondly, the study uses quantile regression to examine the asymmetric effects of green finance across different quantiles, providing more robust results and critical information for formulating policies. Finally, the study provides a new perspective on the effects of the Green Finance Reform and Innovation Pilot Zones.

The essay two is structured as follows. Section 2 provides the relevant literature review. Section 3 provides the theoretical background and develops the hypotheses. Section 4 discusses the methodology and data. Section 5 presents the empirical results, and Section 6 concludes the essay with policy implications.

## **4.2 Literature Review**

### **4.2.1 Research on Green Finance**

Green finance originates from the growing awareness of environmental protection and the recognition of the necessity for the financial system to consider environmental risk (Irfan et al., 2022). It was first proposed by Salazar (1998) but emerged then as “ environmental finance.” Salazar (1998) believes environmental finance is financial innovation to balance economic development and environmental protection. Cowan (1999) argues that environmental finance, which is part of sustainability, is designed to pay for an environmental protection level. Labatt and White (2002) posited that environmental finance avoids environmental risks and addresses environmental challenges. In China, green finance is defined by the Guidelines for Establishing the Green Financial System (2016) as economic activities to provide financial services for project investment, financing, operation and management in environmental protection (Hou et al., 2023).

Despite there being no unified definition of green finance (Irfan et al., 2022; Shi et al., 2022), topics on green finance have been extensively discussed. Scholars have studied green finance from different perspectives, such as how to measure green finance development (Lv et al., 2021), the significant role of green finance contributing to green growth (Desalegn & Tangl, 2022; Sadiq et al., 2022; Taghizadeh-Hesary, et al., 2022), the relationship between green finance and green innovation (Yu et al., 2021), green finance and renewable energy (Li & Umair, 2023; Mngumi et al., 2022; Zhang et al., 2022) , and the significant role of green finance policies (Shi et al., 2022; Sun et al., 2022; Yan et al., 2022; Zhang, 2023). For instance, Lv et al.(2021) established a green financial development index to measure the development level of 31 provinces in China from 2010 to 2019. Using the DID model, mediation effects, and the panel vector autoregression model, Irfan et al.(2022) used panel data on China to test how green finance impacts green innovation. The results show that green finance promotes green innovation in economic growth, industry structure, and research and development in investment.

#### **4.2.2 Research on the Relationship between Green Finance and Carbon Emissions**

Despite numerous studies on green finance from different perspectives, research on the relationship between green finance and carbon emissions is quite limited, only a few studies have investigated this relationship (Lee et al., 2023; Liu & Xia, 2022; Zhang et al., 2022). Meo and Karim (2022) used a quantile regression model to investigate the relationship between green finance and carbon emissions in 10 countries. The authors reveal that green finance exerts a negative impact on carbon emissions, but the impact varies across different quantiles. Zhang et al. (2022) used panel data on G20 economies to investigate the impacts of green finance and digital finance on carbon emissions. They show that green finance, renewable energy investment, and technology innovation decrease carbon emissions, and economic growth, energy consumption, trade, and foreign direct investments increase carbon emissions. Sharif et al. (2022) examined the impact of green technology innovation and green finance on carbon emissions in G7 countries from 1995 to 2019. They show that green finance decreases carbon emissions. However, some studies show different results regarding the relationship between green finance and carbon emissions. For instance, using the Hansen threshold regression model to analyze the impact of provincial-level green finance in China, Bai et al. (2022) reveal a non-linear relationship between green finance and carbon emissions.

#### **4.3 The Theoretical Framework and Research Hypotheses**

Under the EKC framework, the relationship between carbon emissions and economic growth has an initial increase in carbon emissions with economic growth followed by a decrease after achieving a threshold level of economic growth (Grossman & Krueger, 1991; Panayotou, 1993; Shafik & Bandyopadhyay, 1992). However, the impact of FD in driving economic growth, according to the financial intermediation growth theory, makes FD an intermediate factor in the relationship between carbon emissions and economic growth (Durusu-Ciftci et al., 2017; Ofori et al., 2023). Tamazian et al. (2009) pioneered the investigation of the impact of FD on carbon emissions, economic growth, and energy consumption. Their results reveal that FD and economic growth are key factors in carbon emissions levels in BRIC economies. However, the impact of FD on carbon emissions remains controversial since it also exerts negative impacts on environmental quality and contributes to the carbon emissions level by providing more financial resources for some high-energy consuming and high-emissions industries (Shahbaz et al., 2016; Zhang, 2011).

Green finance aims to promote green development and address environmental challenges; it has a more obvious environmental protection function. Compared with traditional finance, green finance serves as an institutional arrangement to green the economy (Zhang, 2023). There are three channels in which green finance plays a role in reducing carbon emissions. First, green finance can directly provide financial support and capital to green industries, restraining the high-pollution and energy-consuming industries (Hussain et al., 2023; Lee et al., 2023), thereby contributing to reduced carbon emissions. Secondly, because of inherent characteristics such as high risk and low return of green innovation (Xiang et al., 2022), it always faces great financial constraints, but green finance can help alleviate these constraints and promote green technical innovations. Thirdly, green finance can upgrade industry structure by optimizing resource allocation and guiding consumption and investment, thus playing a significant role in carbon emissions reduction (Mo et al., 2023).

Agriculture, as the base production sector of national economies (Zhu et al., 2021), can be transformed toward green development by promoting green finance. Green finance can provide financial support and capital to technologies and agricultural practices that are more environmentally friendly to achieve the sustainable development of agriculture. As an institutional arrangement (Zhang, 2023), it can promote the awareness of environmental protection in farmers by encouraging farmers to adopt more sustainable agricultural practices. Thus, I hypothesize the following relationship:

*H1: Green finance development negatively impacts the level of ACEs.*

Given the vast territory and great geographical diversity of China, different regions have different natural endowments, agricultural structures, production modes, economic development levels and technology development levels (Cui et al., 2022), which leads to greater regional heterogeneity both in green finance development and the levels and patterns of ACEs. The factors influencing ACEs, including government policies, research, and developments in investment in green technologies, also vary across different regions. Thus, I hypothesize the following relationships:

*H2: The impact of green finance on ACEs shows regional heterogeneity.*

*H3: The impacts of green finance on different levels of ACEs vary.*

Brock and Taylor (2005) propose that there are three effects: the scale effect, technological progress effect, and structural transformation effect, of FD to promote economic growth. However, as an institutional arrangement, green finance is designed, and serves, as a policy tool and comprehensive financial service guided by the government to promote green development

and address environmental challenges. Therefore, it has a fourth effect compared with traditional finance, the policy effect. Thus, I hypothesize the following relationship:

*H4: Green finance has a positive policy effect on ACEs.*

## 4.4 Methodology and Data

### 4.4.1 The Baseline Model

Essay two follow the studies by Dogan and Seker (2016) and Javid and Sharif (2016) in using provincial level panel data of China to investigate the impact of green finance on ACEs. To test hypothesis (1), a two-way fixed effects model pted as follows:

$$\ln ACET_{it} = \alpha_i + \alpha_1 \ln GDP_{it} + \alpha_2 \ln GDP_{it}^2 + \alpha_3 \ln GDP_{it}^3 + \alpha_4 GF_{it} + \alpha_k X_{it} + \mu_{it} \quad (4.1)$$

where:  $\ln ACET_{it}$  indicates the carbon emissions level of the agricultural sector;  $\ln GDP_{it}$  measures the level of agricultural development, proxied by the rural GDP per capita in rural areas (the rural GDP refers to the gross output value of farming, forestry, animal husbandry, and fishery by province);  $GF_{it}$  represents the development level of green finance;  $i$  represents the different provinces and regions;  $t$  represents the year;  $\alpha_i$  is the intercept term that does not change with time; and  $X_{it}$  denotes a series of control variables including urbanization, agricultural mechanization level, agricultural industry structure, agricultural fiscal expense, agricultural education level and agricultural natural disasters.

### 4.4.2 Heterogeneity Analysis

To test hypothesis (2), group regressions for regional heterogeneity analysis are conducted by dividing the national sample into four subgroups based on geographical characteristics: the eastern, central, western and northeastern regions. To test hypothesis (3), quantile regression is used to ensure a robust result and to explore a more complex relationship by investigating the asymmetric effects of green finance across different quantiles of ACEs. There are distinct advantages in adopting quantile regression, since it can capture the variability and heterogeneity of green finance's impacts on ACEs by not only considering the average value but also the data distribution. It also can overcome the problems of homoscedasticity, zero mean and normal distribution, providing more robust results (Zhang et al., 2022).

### 4.4.3 The Policy Effect Test

In 2017, eight Green Finance Reform and Innovation Pilot Zones (GFRIPZ) in five provinces (Zhejiang, Jiangxi, Guangdong, Guizhou and Xinjiang) were established by the Chinese government to promote sustainable development (Hou et al., 2023; Zhang, 2023). To test hypothesis (4), I conduct a quasi-natural experiment using the DID model, following the studies by Irfan et al. (2022) and Liu and Wang (2023), to examine the policy effects of green finance on ACEs. The model is as follows:

$$\ln ACET_{it} = \beta_0 + \beta_1 Treat_i * Post_t + \alpha_1 \ln GDP_{it} + \alpha_2 \ln GDP_{it}^2 + \alpha_3 \ln GDP_{it}^3 + \alpha_4 GF_{it} + \alpha_k X_{it} + \mu_{it} \quad (4.2)$$

where:  $Treat_i$  indicates whether a GFRIPZ is built in area  $i$  during the study period. If a GFRIPZ was built in area  $i$ ,  $Treat_i = 1$ ; otherwise,  $Treat_i = 0$ .  $Post_t$  indicates the year before or after the year of establishing a GFRIPZ.

### 4.4.4 Variables

#### 4.4.3.1 Explanatory Variable

ACET is the explanatory variable. It measures the total ACEs in the agricultural sector. ACEs includes carbon dioxide emissions from agricultural land use, methane emissions from rice paddies and methane and nitrous oxide emissions from livestock. I measure the total amount of ACEs by following the strategies recommended by the IPCC (2019) and by referring to the Provincial Guidelines for GHG Inventories (Trial) of China (2023). The primary data for estimating ACEs were sourced from the China Statistical Yearbook to ensure a reliable, robust analysis. The ACET can be estimated by:

$$E_{ACET} = \sum_1^k E_i = \sum_1^k T_i \delta_i \quad (4.3)$$

where:  $i$  is the type of carbon source;  $k$  is the total number of carbon sources;  $E_{ACET}$  is the overall carbon emissions;  $E_i$  is the carbon emissions of each specific carbon source;  $T_i$  is the quantity of each specific carbon source; and  $\delta_i$  is the carbon emissions coefficient for each specific carbon source. Figure 4.1 shows the temporal trend in ACEs from 2007 to 2020 in each Chinese province.

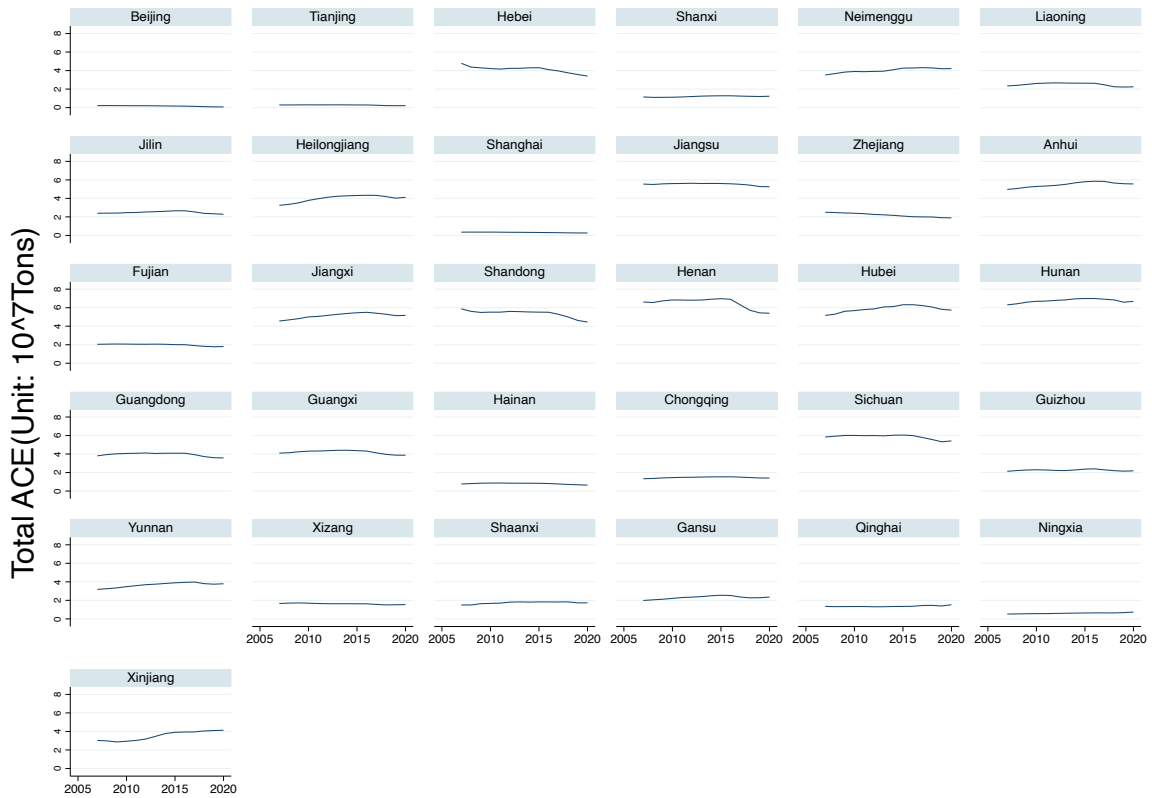


Figure 4.1 The total ACEs changing trend from 2007-2020 for each province.  
Source: Author’s calculations

#### 4.4.3.2 Green Finance Index

Following the studies by Lee and Lee (2022), Sun et al. (2023) and Zhang et al. (2022), the three main financial products: green credit, green investment and green insurance, and government support for green development proxied by fiscal environmental protection expenditure, are used as secondary indicators to the construct green finance index using the entropy method. Table 4.1 defines the four indicators in the green finance index.

Table 4.1 shows that green credit is a negative indicator indicated by the proportion of interest expenditure in high-energy-consuming industries. The reason for choosing this as the proxy of green credit is that there are no national statistics for green credit balance from 2007 to 2020. Green investment is described as the proportion of investment in environmental pollution control of the GDP (Sun et al., 2023; Zhang et al., 2022). Green insurance includes ecological environmental liability insurance and agricultural insurance. Because of a late start, there is a lack of provincial data for ecological environmental liability insurance in China. I use agricultural insurance indicators to measure the development of green insurance. Government

support mainly refers to financial support for environmental protection, expressed as the proportion of fiscal environmental protection expenditure to the government's general budget expenditure.

Table 4.1 Green Finance Index

Primary index	Secondary indicator	Indicator description	Indicator properties
Green credit	Proportion of interest expenditure of high energy-consuming industries	Interest expense of six high energy consuming industries/Industrial interest expense	negative
Green investment	Proportion of investment in environmental pollution control	Investment in environmental pollution control/GDP	positive
Green insurance	Depth of agricultural insurance	Agricultural insurance income/Gross agricultural output value	positive
Green Support	Proportion of fiscal environmental protection expenditure	Fiscal environmental protection expenditure/General fiscal budget expenditure	positive

Source: Author's calculations

In constructing the green finance index, I need to determine the weights of the secondary indicators, which is a significant issue that can affect measurement accuracy. I adopt the entropy method to determine the weight since it does not require subjective weighting but determines the weight based on the information provided by the observed value, providing more objective results. The specific calculation of the entropy process is as follows.

First, I standardize the data of each indicator, i.e., for the given year  $t$ , the  $i$  province's  $j$  indicator  $X_{\lambda ij}$ , assuming that the standardized value is  $Z_{\lambda ij}$ , then equation (4.4) is given as:

$$Z_{\lambda ij} = \frac{X_{\lambda ij} - \text{Min}X_{\lambda ij}}{\text{Max}X_{\lambda ij} - \text{Min}X_{\lambda ij}} \quad (4.4)$$

where:  $i=1, 2, 3, \dots, n$ ,  $j=1, 2, 3, \dots, m$ , respectively, represent the total number of evaluation objectives, that is the province and indicators;  $X_{\lambda ij}$  is the value of indicator  $j$  for  $i$  province in year  $\lambda$ ; and  $\text{Max}X_{ij}$  and  $\text{Min}X_{ij}$  are the maximum and minimum values for different indicator  $j$  in all evaluation objects.

Second, I normalize the indicators using equation (4.5):

$$P_{\lambda ij} = \frac{Z_{\lambda ij}}{\sum_{\lambda=1}^t \sum_{i=1}^m Z_{\lambda ij}} \quad (4.5)$$

Next, I calculate the information entropy of the  $j$  indicator using equation (4.6):

$$E_j = -k \sum_{\lambda=1}^t \sum_{i=1}^m P_{\lambda ij} \ln P_{\lambda ij} \quad (4.6)$$

where:  $\kappa = 1/\ln(t \times m)$ .

Finally, I determine the weight of the j indicator. According to equation (4.7), the information entropy of j indicator is calculated, and the weight is:

$$W = \frac{1 - E_j}{k - \sum E_j} \quad (4.7)$$

I then multiply the calculated weight by the score of each indicator to get the development level score of the green finance development level:

$$GF_{\lambda i} = P_{\lambda ij} \times W_j \quad (4.8)$$

#### 4.4.3.3 Control Variables

To ensure the accuracy of regression results, a set of variables that can influence provincial level ACEs are controlled in the model. The control variables are: urbanization (UR), agriculture mechanization level (AML), agricultural industry structure (AIS), agricultural fiscal expense (AFE), agricultural working force education level (EDU), and natural disaster (ND).

UR refers to a process of the rural labour force shifting to urban areas and is indicated by the ratio of urban population to the total population as an indicator of urbanization level. AML indicates the machinery use that impacts and ACEs in the agricultural sector. It is proxied by the total power of the agricultural machinery in each province. AIS is the composition of the agricultural sector, expressed as the proportion of output value of farming industry and animal husbandry industry to the gross output value of farming, forestry, animal husbandry and fisheries. AFE refers to government spending for the agricultural sector. AHC is the education level of the rural population, indicated by the average years schooling of residents. ND measures natural impacts on the ACEs level. Table 4.2 presents the descriptive statistics of the study variables.

#### 4.4.4 Data

I use a provincial-level dataset of 31 Chinese provinces from 2007 to 2020. The primary data are from the China Statistical Yearbook, China Financial Statistics Yearbook, China Environmental Statistics Yearbook and the China Rural Statistical Yearbook.

Table 4.2 The Descriptive Statistics of the Study Variables

Variables	Definition	N	Mean	Std. Dev	Mini	Max
ACET	Total ACE(10 <sup>4</sup> tonnes)	434	3137	1976	75.84	6994
ACEI	ACE intensity	434	2.955	3.479	0.445	24.88
ACEP	ACE per capita	434	1.932	1.329	0.278	7.507
PGDP	Rural GDP per capita	434	8372	4083	2053	24704
GF	Green finance index	434	0.306	0.155	0.0510	0.838
GC	Green credit	434	0.539	0.150	0.0280	0.906
GI	Green investment	434	0.0150	0.00800	0	0.0460
GINSUR	Green insurance	434	0.00500	0.00600	0	0.0380
GFS	Proportion of fiscal environmental protection expenditure	434	0.0300	0.0110	0.00800	0.0680
AML	million kilowatts	434	3152	2865	93.97	13353
AIS	% of RGDP	434	0.664	0.139	0.355	0.971
FAE	Fiscal agriculture expense (¥ 10 <sup>8</sup> Yuan)	434	433.2	287.5	22.96	1339
UR	Urbanization rate	434	0.482	0.156	0.168	0.896
EDU	Average schooling years of residents	434	7.484	0.948	3.549	10.75
ND	Damage area by disaster/ total planted area of crops	434	0.186	0.144	0	0.696

Note: Std = standard deviation

Source: Author's calculations

## 4.5 Results and Discussion

### 4.5.1 Baseline Results

Table 4.3, Columns (1) to (7), shows the regression results from adding control variables one at a time - an insignificant negative impact of green finance across all columns. This fails to confirm hypothesis (1) that green finance has a significant negative effect on ACEs, i.e., reduces carbon emissions in rural China. Specifically, without considering the control variables, a 1% increase in green finance decreases ACEs by 7.2% but insignificant. When considering AML, proxied by agriculture machinery, a 1% increase in green finance leads to a 7.6% decrease in ACEs. Even considering all control variables, the result is still insignificant. My findings contradict the study by Ren et al. (2020) who argue that green finance reduces carbon intensity and by Mo et al.(2023) who posit that developing green finance can significantly reduce China's ACEs intensity. A possible reason for the inconsistency is that the indicators used are different, with total ACEs here and ACE intensity in their studies. The result also indicates that, though green finance has made great achievements in China, most are not directed at the agricultural

sector, so it has no impact on ACEs. Also, agricultural growth impacts ACEs. However, the relationship between agricultural growth and ACEs is an inverted “N” shape.

The agricultural mechanization level contributes to the increase in ACEs, at a statistically significant 1% level across Table 4.3, Columns 2-7. The finding shows that, with an increase in the level of machinery, ACEs increase, since there is substantial consumption of fossil fuels, suggesting that the use of technologies in rural areas is not environmentally friendly or energy efficient. The findings also show that urbanization positively impacts ACEs, at the 1% significance level, which is consistent with previous studies (Ma et al., 2023; Su et al., 2023).

Table 4.3 Stepwise Fixed-Effects Regressions on the Impact of Green Finance on Agricultural Carbon Emissions

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	lnACET	lnACET	lnACET	lnACET	lnACET	lnACET	lnACET
lnPGDP	-5.245*** (1.39)	-7.560*** (1.90)	-7.189*** (2.00)	-6.806*** (1.99)	-9.611*** (2.36)	-9.594*** (2.26)	-9.458*** (2.41)
lnPGDP2	0.645*** (0.15)	0.912*** (0.21)	0.874*** (0.22)	0.825*** (0.22)	1.142*** (0.26)	1.143*** (0.25)	1.128*** (0.27)
lnPGDP3	-0.024*** (0.01)	-0.035*** (0.01)	-0.033*** (0.01)	-0.031*** (0.01)	-0.043*** (0.01)	-0.043*** (0.01)	-0.043*** (0.01)
GF	-0.072 (0.08)	-0.076 (0.09)	-0.072 (0.09)	-0.109 (0.11)	-0.140 (0.11)	-0.126 (0.13)	-0.127 (0.13)
lnAML		0.134*** (0.03)	0.137*** (0.03)	0.130*** (0.03)	0.125*** (0.03)	0.128*** (0.03)	0.128*** (0.03)
AIS			0.077 (0.05)	0.139** (0.05)	0.117** (0.04)	0.110** (0.04)	0.117** (0.05)
lnFAE				0.073 (0.05)	0.072 (0.05)	0.071 (0.05)	0.072 (0.05)
UR					0.418* (0.20)	0.408* (0.20)	0.399* (0.19)
lnEDU						-0.071 (0.12)	-0.069 (0.12)
ND							-0.014 (0.04)
_cons	20.294*** (4.17)	26.169*** (5.81)	24.918*** (6.15)	23.658*** (6.10)	31.638*** (7.02)	31.629*** (6.70)	31.242*** (7.12)
N	434	434	434	434	434	434	434
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	1.4e+10	3.6e+09	5.5e+09	758.530	4296.832	5952.513	5685.977

Notes: Driscoll-Kraay standard errors in parentheses. Considering the cross-section independence, self-correlation, and heteroscedasticity exist in the data, Driscoll-Kraay standard errors are used in the regression. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively.

Source: Author's calculations

## 4.5.2 Heterogeneity

Table 4.4 displays the varying impacts of green finance on total ACEs across different regions in China. The results confirm our Hypothesis (2), which posits that the impact of green finance on ACEs shows regional heterogeneity. A 1% increase in green finance is associated with a decrease of 12.7% in ACEs in the national sample, but this is insignificant. For the central and eastern regions, a 1% increase in green finance leads to a 43.9% and 116.5% decrease in ACEs, significant at 10% and 1%, respectively. In the western and northeastern regions, the impacts are positive but not significant. The western and northeastern regions show a positive relationship between green finance and ACEs, but again it is not statistically significant. The possible reason could be that green finance is mainly used in other sectors rather than the agricultural sector, leading to less support for agricultural green initiatives.

Table 4.4 The Impact of Green Finance on the Total Agricultural Carbon Emissions in Different Regions of China

Variables	(1) Whole country	(2) Eastern region	(3) Central region	(4) Western region	(5) Northeastern region
	lnACET	lnACET	lnACET	lnACET	lnACET
lnPGDP	-9.458*** (2.41)	-69.061** (31.84)	-37.057** (13.10)	-1.815 (6.17)	-1.087 (3.11)
lnPGDP2	1.128*** (0.27)	7.503** (3.37)	4.425** (1.52)	0.147 (0.70)	0.406 (0.67)
lnPGDP3	-0.043*** (0.01)	-0.271** (0.12)	-0.172** (0.06)	0.001 (0.03)	-0.020 (0.03)
GF	-0.127 (0.13)	-0.439* (0.21)	-1.165*** (0.34)	0.108 (0.11)	0.008 (0.15)
lnAML	0.128*** (0.03)	0.341*** (0.09)	0.077** (0.03)	0.006 (0.06)	-0.227*** (0.06)
AIS	0.117** (0.05)	0.345 (0.22)	-0.238 (0.46)	-0.366 (0.24)	0.344 (1.27)
lnFAE	0.072 (0.05)	0.011 (0.06)	0.018 (0.04)	-0.050* (0.02)	0.040 (0.10)
UR	0.399* (0.19)	0.691* (0.36)	0.380 (0.35)	1.591*** (0.34)	2.287* (1.23)
lnEDU	-0.069 (0.12)	-0.614** (0.24)	-0.299** (0.11)	0.080 (0.07)	-0.693*** (0.15)
ND	-0.014 (0.04)	0.040 (0.04)	-0.087* (0.04)	0.034 (0.05)	0.008 (0.08)
_cons	31.242*** (7.12)	216.561** (99.60)	109.026** (37.32)	11.484 (17.81)	0.000 (.)
N	434.000	140.000	84.000	168.000	42.000
F	5685.977	626.237	89.826	870.110	375.943

Notes: Driscoll-Kraay standard errors in parentheses. Considering cross-section independence, self-correlation and heteroscedasticity exist in data, Driscoll-Kraay standard errors are used in the regression. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively. Source: Author's calculations

At the national level, factors such as agricultural mechanization level, agricultural structure, and urbanization increase ACEs. It can be seen in the eastern region that urbanization and AML significantly contribute to increased ACEs. In the central region, the agricultural mechanization level contributes to the increase in ACEs with a significance level of 5%. The agricultural workforce education level, indicated by average schooling years, is related to a decrease in ACEs at the 5% significance level. In the western region, urbanization contributes to increased ACEs at the 1% significance level. In the northeastern region, agricultural mechanization and education levels are key factors in decreasing ACEs. These findings show that the impacts of green finance on ACEs vary across the different regions.

Green finance significantly contributes to ACEs reduction in the central and eastern regions while showing no impact in the western and northeastern regions. There are several reasons for this phenomenon. First, the levels of economic and financial development in the eastern and central regions are higher than the other regions, which leads to a disparity in the levels of green finance development (Sun et al., 2023; Zhou et al., 2022). Second, compared to other regions, the eastern and central regions possess geographical advantages, resource endowments, and early start in economic development, which provide a greater base for green technology development. It is essential for mitigating carbon emissions (Zhang et al., 2023).

#### **4.5.3 The Quantile Regression Results**

Table 4.5 presents the results of the unconditional panel quantile regression analysis. The results show a negative impact of green finance on ACEs at the lower (10<sup>th</sup>-30<sup>th</sup>) and higher (80<sup>th</sup>-90<sup>th</sup>) quantiles. However, there is no statistical significance for higher quantiles. In contrast, significant positive impacts of green finance are observed at the middle quantiles (40<sup>th</sup>-60<sup>th</sup>) at the 5%, 1%, and 1% levels, respectively. This confirms hypothesis (3) that the impacts of green finance on different levels of ACEs vary. This study's finding is consistent with the results of Zhang et al. (2022) on the impact of green finance on carbon emissions in G-20 economies. They reveal that the impact of green finance is negative at lower (10<sup>th</sup>-25<sup>th</sup>) and higher quantiles (60<sup>th</sup>-90<sup>th</sup>), like in this study, though the quantiles are different. In the middle quantiles (30<sup>th</sup>-50<sup>th</sup>), their results show a significant positive impact, which is similar to this study. It is worth noting that the quantile regression for the agricultural mechanization level shows a significant positive impact across all quantiles, implying that the increased use of agricultural mechanization is an important driver for increased ACEs. Though education level is an important factor that can help to reduce ACEs, the effects are prominent only in low quantiles.

Despite the rapid development of green finance, the application and distribution of green finance in different regions may have to have different focuses. The Green Finance Reform and Innovation Pilot Zones in China have different focuses. Some regions tend to provide green finance resources to favor the green transformation of the industry or energy sector, neglecting the green demands of the rural green industry. This could be the reason that the impact of green finance is different across quantiles and factors influencing ACEs show different effects on ACEs.

Table 4.5 Unconditional Panel Quantile Regression: The Asymmetrical Impact of Green Funds on Agricultural Carbon Emissions

Factor	Q10 lnACET	Q20 lnACET	Q30 lnACET	Q40 lnACET	Q50 lnACET	Q60 lnACET	Q70 lnACET	Q80 lnACET	Q90 lnACET
lnPGDP	179.864 (135.46)	92.384 (61.87)	-40.379 (44.78)	40.893 (47.46)	-39.481 (51.12)	31.642 (43.71)	2.957 (43.69)	-81.117* (41.86)	28.329 (37.94)
lnPGDP2	-20.562 (14.88)	-9.540 (6.80)	4.800 (4.92)	-3.939 (5.21)	4.926 (5.62)	-3.227 (4.80)	0.046 (4.80)	9.331** (4.60)	-2.886 (4.17)
lnPGDP3	0.784 (0.54)	0.327 (0.25)	-0.187 (0.18)	0.125 (0.19)	-0.200 (0.21)	0.109 (0.18)	-0.015 (0.18)	-0.356** (0.17)	0.097 (0.15)
GF	-2.609** (1.27)	-0.669 (0.58)	-1.327*** (0.42)	0.991** (0.44)	2.364*** (0.48)	1.502*** (0.41)	0.170 (0.41)	-0.215 (0.39)	-0.329 (0.35)
lnAML	1.642*** (0.17)	0.832*** (0.08)	0.822*** (0.06)	0.930*** (0.06)	1.064*** (0.06)	0.809*** (0.05)	0.540*** (0.05)	0.351*** (0.05)	0.206*** (0.05)
AIS	-3.871*** (0.89)	-1.619*** (0.41)	-1.621*** (0.30)	-1.118*** (0.31)	-2.172*** (0.34)	-1.572*** (0.29)	-0.584** (0.29)	-0.393 (0.28)	-0.492** (0.25)
lnFAE	-0.379* (0.22)	0.411*** (0.10)	0.467*** (0.07)	0.211*** (0.08)	0.020 (0.08)	-0.039 (0.07)	-0.033 (0.07)	0.069 (0.07)	-0.036 (0.06)
UR	-11.260*** (1.30)	2.899*** (0.59)	3.130*** (0.43)	3.106*** (0.45)	2.888*** (0.49)	1.740*** (0.42)	0.614 (0.42)	0.551 (0.40)	-0.415 (0.36)
lnEDU	-5.226*** (1.42)	-7.249*** (0.65)	-3.442*** (0.47)	-3.007*** (0.50)	-2.631*** (0.53)	-1.073** (0.46)	-0.286 (0.46)	-0.330 (0.44)	0.605 (0.40)
ND	5.679*** (0.83)	0.537 (0.38)	1.113*** (0.28)	1.098*** (0.29)	0.158 (0.31)	-0.697*** (0.27)	-0.734*** (0.27)	-0.639** (0.26)	-0.273 (0.23)
Constant	-511.318 (410.36)	-284.128 (187.43)	116.143 (135.67)	-135.976 (143.77)	106.659 (154.85)	-98.383 (132.40)	-13.834 (132.36)	240.478* (126.81)	-84.877 (114.94)
N	434.000	434.000	434.000	434.000	434.000	434.000	434.000	434.000	434.000
R <sup>2</sup>	0.742	0.619	0.702	0.639	0.598	0.516	0.379	0.291	0.135
F	125.795	71.458	102.804	77.710	65.401	47.126	27.381	18.777	7.784

Notes: Standard errors in parentheses. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively

Source: Author's calculations.

#### 4.5.4 The Policy Effects Results

The "parallel trend test" is a method to evaluate the effectiveness of the DID model in determining the consistency of trends before and after the implementation of GFRIPZ in the experimental area where GFRIPZ is constructed and the control group is where GFRIPZ is not constructed. The trend is different following the establishment of the GFRIPZ based on the parallel hypothesis. I conduct a parallel trend test and comparatively analyse the trends in both groups before and after the establishment of GFRIPZ. The results can be inferred from the parallel trend plot in Figure 4.5. Before 2017, when the GFRIPZ was implemented, both groups had a consistent, parallel trend in ACEs. However, it is interesting to find that, after 2017, the trends do not show a divergence, which is inconsistent with the parallel trend hypothesis. This suggests that there is no policy effect on the reduction of ACEs, which is also demonstrated by the results of DID regression analysis (see Table 4.6).

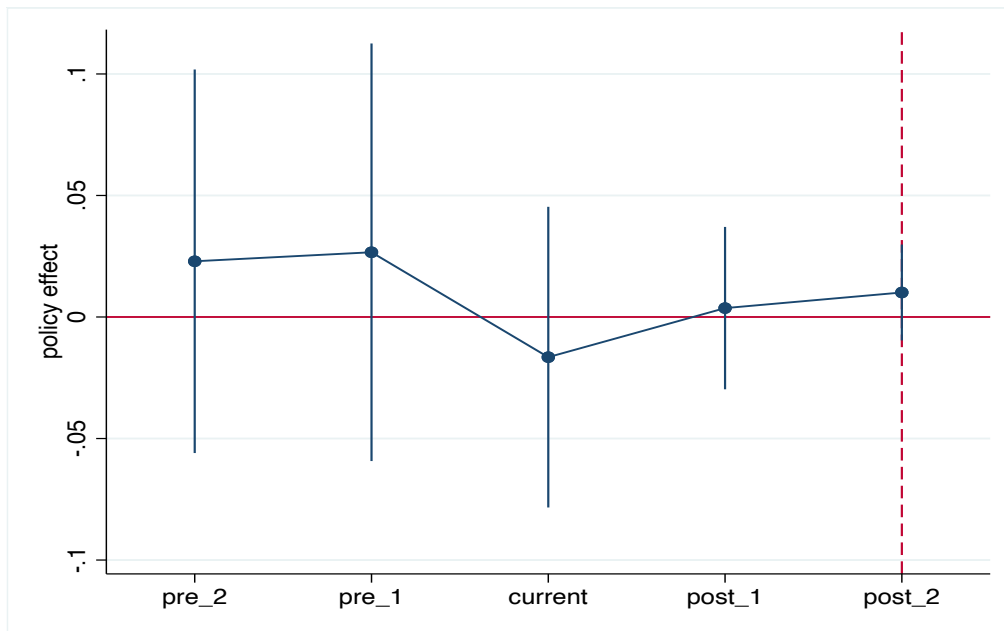


Figure 4.2 Parallel trend test  
Source: Author's calculations

Table 4.6 presents the results of the DID regression analysis with model (1) not considering regional effects and time effects, model (2) controlling the regional effects but not the time effects, and model (3) controlling both regional and time effects to evaluate the impact of GFRIPZ on the ACEs level. The results in Table 4.6 show no significance with the coefficients of DID across three models, suggesting that the implementation of GFRIPZ does not affect the ACEs. This contradicts expectations and indicates that the green finance policy does not show a policy effect in rural areas, which rejects our hypothesis (4).

The reason there is no policy effect on ACEs could be that most green finance policies focus on the green transformation of the industrial and energy sectors rather than the agricultural sector. For instance, Liu and Wang (2023) employ DID method to examine the effects of establishing PZGFRI on the development of green patent applications. The authors' results show that establishing PZGFRI significantly increases the number of green patent applications, mostly due to higher research and development input. Furthermore, previous research has demonstrated that the establishment of these experimental areas has a beneficial impact on the decrease of regional pollution emissions (Huang and Zhang, 2021) and improves the overall productivity of urban green ecosystem by promoting green innovation and decreasing energy consumption in cities (Zhang et al., 2023).

It can also be inferred from the specific measures of building PZGFRI, which include supporting the aggregation of talents, funds, and technology for green industries, promoting the establishment of green financial institutions, developing green credit and financing systems, initiating pilot markets for trading pollution, water, and energy rights, offering policy support, and establishing a risk prevention mechanism for green finance (Liu and Wang, 2023). This suggests that there are deficiencies in the impact of PZGFRI on rural green financial development. It emphasizes the need for the promotion of green technology, green financial products, and green knowledge in rural areas to meet the requirement of green industry in rural areas to support rural revitalization.

Table 4.6 Policy Effects of Green Finance Regressions

Variables	(1)		(2)		(3)	
	lnACET		lnACET		lnACET	
did	-0.072	(0.11)	0.003	(0.06)	0.049	(0.05)
lnPGDP	7.218	(17.50)	-16.362	(13.23)	-8.151	(12.76)
lnPGDP2	-0.563	(1.93)	1.946	(1.45)	0.977	(1.39)
lnPGDP3	0.013	(0.07)	-0.075	(0.05)	-0.037	(0.05)
GF	-0.427*	(0.22)	-0.480***	(0.15)	-0.114	(0.13)
lnAML	0.722***	(0.03)	0.203**	(0.07)	0.126*	(0.07)
AIS	-1.231***	(0.16)	0.362	(0.31)	0.167	(0.34)
lnFAE	0.115***	(0.04)	-0.009	(0.02)	0.075	(0.05)
UR	0.589**	(0.28)	1.250**	(0.51)	0.362	(0.48)
lnEDU	-2.460***	(0.26)	0.069	(0.09)	-0.055	(0.11)
ND	0.553***	(0.15)	0.010	(0.03)	-0.013	(0.03)
cons	-21.555	(52.84)	49.891	(39.99)	27.194	(38.74)
N	434		434		434	
R <sup>2</sup>	0.863		0.520		0.996	
Province FE	No		Yes		Yes	
Year FE	No		No		Yes	
F	.		7.535		8.513	

Notes: Standard errors in parentheses. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively. Model (1) does not control regional effects and time effects,

model (2) controls regional effects but not time effects, and model (3) controls both regional effects and time effects.

Source: Author's calculations

#### 4.5.5 Robustness Check

To ensure the robustness and validity of the results, the ACEs intensity and ACEs per capita (ACEP) used to measure ACEs are used to proxy ACEs as the dependent variable in the robustness check. Table 4.7 shows the results of three regression models, revealing that green finance has insignificant negative impacts across the three models. These findings confirm the consistent, insignificant impact of green finance on reducing carbon emissions across different model specifications, providing robustness and validity. The secondary indicators of the green finance index are also used to conduct robustness checks. The results in Table 4.8 show that green investment and government financial support on environmental protection negatively correlate with ACEs whereas green credit and green insurance positively correlate with ACEs levels. It is notable that green credit increases ACEs at the 1% significance level. Government finance support reduces ACEs at the 1% significance level.

Table 4.7 Fixed Effects Regression by ACET, ACEI and ACEP Respectively

	(1) lnACET		(2) lnACEI		(3) lnACEP	
lnPGDP	-9.458***	(2.41)	-1.198	(2.85)	-0.198	(2.85)
lnPGDP2	1.128***	(0.27)	0.111	(0.31)	0.111	(0.31)
lnPGDP3	-0.043***	(0.01)	-0.005	(0.01)	-0.005	(0.01)
GF	-0.127	(0.13)	-0.249	(0.15)	-0.249	(0.15)
lnAML	0.128***	(0.03)	0.083**	(0.03)	0.083**	(0.03)
AIS	0.117**	(0.05)	0.401***	(0.06)	0.401***	(0.06)
lnFAE	0.072	(0.05)	0.058	(0.04)	0.058	(0.04)
UR	0.399*	(0.19)	-0.247	(0.20)	-0.247	(0.20)
lnEDU	-0.069	(0.12)	-0.073	(0.15)	-0.073	(0.15)
ND	-0.014	(0.04)	-0.005	(0.04)	-0.005	(0.04)
Constant	31.242***	(7.12)	4.952	(8.61)	-4.259	(8.61)
N	434.000		434.000		434.000	
year	Yes		Yes		Yes	
F	5685.977		2069.734		2809.769	

*Note: Driscoll-Kraay standard errors in parentheses. Considering the cross-section independence, self-correlation, and heteroscedasticity exist in data, Driscoll-Kraay standard errors are used in the regression. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively.*

Table 4.8 Impact of Green Finance Secondary Indicators on Agricultural Carbon Emission

Variables	(1) lnACET		(2) lnACET		(3) lnACET		(4) lnACET	
lnPGDP	-9.466***	(2.25)	-9.212***	(2.64)	-9.393***	(2.32)	-10.723***	(2.36)
lnPGDP2	1.128***	(0.25)	1.100***	(0.29)	1.119***	(0.26)	1.257***	(0.26)
lnPGDP3	-0.042***	(0.01)	-0.042***	(0.01)	-0.042***	(0.01)	-0.047***	(0.01)
GC	0.490***	(0.14)						
GI			-0.336	(0.37)				
GINSUR					0.007	(0.11)		
GFS							-0.621***	(0.12)
lnAML	0.137***	(0.03)	0.136***	(0.04)	0.132***	(0.03)	0.116***	(0.03)
AIS	0.122*	(0.06)	0.118**	(0.05)	0.125**	(0.05)	0.146*	(0.08)
lnFAE	0.059*	(0.03)	0.069	(0.04)	0.059	(0.04)	0.059	(0.04)
UR	0.326	(0.21)	0.275	(0.24)	0.296	(0.19)	0.360	(0.25)
lnEDU	-0.091	(0.10)	-0.060	(0.13)	-0.103	(0.12)	-0.115	(0.11)
ND	-0.014	(0.04)	-0.018	(0.03)	-0.014	(0.04)	-0.010	(0.03)
Constant	31.240***	(6.66)	30.465***	(7.88)	31.166***	(6.84)	35.585***	(7.02)
N	434		434		434		434	
year	Yes		Yes		Yes		Yes	
F	2059.706		2316.675		3678.502		4022.371	

Note: Driscoll-Kraay standard errors are in parentheses. Considering cross-section independence, self-correlation, and heteroscedasticity exist in the data, Driscoll-Kraay standard errors are used in the regression. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% levels, respectively.

Source: Author's calculations

## 4.6 Conclusion and Policy Recommendations

To investigate the impact of green finance on ACEs in rural China, this study constructs a panel dataset of China's 31 provinces from 2007 to 2020 using a fixed effects method, a quantile regression method, and a DID method. Robustness checks are conducted to confirm the validity of the results.

The main findings of the study are as follows. First, green finance does not play a significant role in reducing ACEs in the whole of China, but it significantly decreases the ACEs in China's eastern and central regions. As one dimension of green finance development, government financial support significantly reduces ACEs, but green credit significantly increases ACEs. Using agricultural machinery contributes to increased ACEs. Second, the impact of green finance on ACEs has a regional heterogeneity in China. Different focuses and initiatives of green finance in different regions lead to different impacts of green finance on ACEs across different quantiles of green finance. Third, the Green Finance Reform and Innovation Pilot Zones do not show a direct policy effect on ACEs.

Based on the study's findings of this study, several policy implications can be drawn to enhance the effectiveness of green finance in reducing ACEs in China. First, since the role of green

finance in reducing ACEs has not been fully adopted in rural China, it is important to promote rural green finance development by providing more green financial products tailored to rural areas and directing capital towards green agricultural programs and practices. Second, it is essential to consider regional heterogeneity in developing policies to reduce ACEs across various regions. Strategies must be tailored to each region, considering their distinct economic, geographic, and environmental contexts. For instance, the eastern and central regions, characterized by advanced green finance and technological innovation, should enhance their green finance initiatives. Conversely, the western and northeastern regions necessitate foundational support in green finance infrastructure and capacity-building efforts. Third, promoting green agricultural technologies is essential for enhancing the energy efficiency of agricultural machinery, which is crucial in agricultural and environmental contexts. This involves investing in cleaner, renewable energy sources for agricultural production and offering subsidies or incentives for farmers to adopt these technologies, especially in areas with higher ACEs. Finally, policies to enhance rural green finance development should be broadened to support sustainable agricultural practices and promote green development in rural regions. Potential measures may include financial incentives, low-interest green loans, and the creation of rural green finance service platforms. Integrating digital financial inclusion with green finance initiatives can enhance access to financial resources for smallholder farmers, facilitating more significant participation in green projects and supporting a more sustainable rural economy.

#### **4.7 Limitations and Future Research**

This study has several limitations. First, because of data availability, the lack of data on rural green finance makes it impossible to understand the development of rural green finance and its impact on ACEs. Second, the study lacks a mechanism analysis of how green finance impacts ACEs. Finally, the study focuses only on the agricultural sector in China in investigating the impact of green finance on carbon emissions, which may differ from developed countries or other developing countries. Further research could focus on mechanism analysis to investigate how green finance impacts ACEs. Transnational research can be conducted by adding samples from other countries, which can help achieve carbon neutrality and sustainable agricultural development worldwide.

## Essay Three

# The Nexus of Digital Finance, Green Finance and Agricultural Carbon Emissions

### 5.1 Introduction

Global warming, mainly caused by carbon emissions, has been recognized as a significant threat to human survival since the Industrial Revolution, giving way to green and sustainable development as the global consensus (Wang et al., 2022; Wei et al., 2019). The industrial and energy sectors are identified as the primary contributors to carbon emissions. However, carbon emissions from the agricultural sector cannot be neglected since they also are significant contributors to global warming, the second largest source accounting for about 30% of the world's total carbon emissions (Ma et al., 2022; Xu et al., 2022). Therefore, it is a global issue, and there is a concern to reduce carbon emissions from the agricultural sector to address the challenges of global warming (Zhao et al., 2023).

As the largest emitter in the world, China faces great pressure to reduce carbon emissions and achieve carbon neutrality by 2060. To achieve carbon peak and carbon neutrality, the Chinese government has implemented many policies and has proposed a green development strategy. Agriculture, an important part of the Chinese economy and a significant carbon source plays a substantial role in achieving green development and reducing carbon emissions that account for 17% of China's total carbon emissions (Yu et al., 2023). Thus, the Chinese government proposed green development goals for the agricultural sector in China's Central Document No.1 in 2021. The following year's Central Document No. 1 again highlighted "green" as a crucial focus and emphasized how to use financial instruments to promote green development in the agricultural sector. Against this background, the role of green finance has drawn great attention in reducing ACEs and achieving green development in rural China because of the link between economic growth and environmental protection.

Conversely, because of the rapid development of digital technologies, digitalization has become a trend in society and a new growth engine of economic development. The financial sector has also been transformed by digital technologies such as big data, blockchain, and artificial intelligence. Against this background, digital financial inclusion (DFI) has gained remarkable development because of its advantages, such as convenience, cost-effectiveness, and no geographical restrictions (Liu & Ren, 2023; Mukalayi & Inglesi-Lotz, 2023; Wang et al., 2023).

Its role in carbon emissions reduction has also gained attention (Khan et al., 2023; Wang, et al., 2022).

Many studies have explored the relationship between all kinds of finance and carbon emissions, including the impact of green finance on carbon emissions (Ahmad et al., 2022; Dogan & Seker, 2016; Hussain et al., 2023; Ofori et al., 2023; Saeed Meo & Karim, 2022). Tamazian et al. (2009) investigated the effects of FD on carbon emissions in BRIC economies. Following that, many studies were conducted, but the impact of FD on carbon emissions remains controversial. Some research posits that FD significantly enhances environmental sustainability by reducing carbon emissions, (Adams & Klobodu, 2018; Dar & Asif, 2018; Khan et al., 2021) whereas others argue that FD contributes to carbon emissions (Javid & Sharif, 2016; Shahbaz et al., 2016). Studies on green finance and carbon emissions are limited, but some significant studies provide a platform for further studies. Saeed Meo and Karim (2022) used a quantile regression model to investigate the relationship between green finance and carbon emissions in 10 countries. Sharif et al. (2022) examined the impact of green finance on carbon emissions in G7 countries from 1995 to 2019 and showed that green finance decreases carbon emissions. However, the study of the relationship between green finance and ACEs is under-explored.

Many studies have explored the impacts of DFI on carbon emissions (Khan et al., 2023; Mukalayi & Inglesi-Lotz, 2023; Wang et al., 2023). For instance, Khan et al. (2023) used GMM estimation to investigate the effect of digital financial inclusion on carbon emissions in emerging and developing economies and revealed a significantly positive relationship. Wang et al. (2023) used an IPAT model to investigate the spatial spillover impacts of DFI on carbon emissions in 284 cities in China from 2011 to 2016. The results indicate that carbon emissions exert substantial spatial spillover impacts, and DFI decreases carbon emissions in Chinese cities. There is a lack of investigations of DFI's effect on carbon emissions in the agricultural sector. The literature shows both green finance and DFI significantly impact ACEs. However, most studies have investigated the relationship between ACEs and green finance and ACEs and DFI separately (Pan, 2022). No study has thoroughly examined the relationships between green finance, DFI, and ACEs. This study addresses this gap by investigating the relationships and provides more valuable insights and new perspectives for further research.

This study makes several contributions. First, it is the first to investigate the combined effects of green finance and DFI on ACEs, providing a more comprehensive understanding of the relationship and analyzing the underlying mechanisms. Secondly, this study uses moderation mechanism analysis to reveal that DFI restrains the effects of green finance and that a crowding

out effect of DFI on green finance in rural areas during the study period. Finally, this study not only provides new perspectives and frameworks for theoretical study but also offers practical guidance for policymakers to effectively address climate change and achieve green development by effectively using financial tools.

This essay is structured as follows. Section 2 reviews the literature. Section 3 provides the theoretical background and develops the hypothesis. Section 4 details the methodology and data. Section 5 presents the empirical results and discussion, and Section 6 concludes the study with policy implications.

## **5.2 Literature Review**

### **5.2.1 Research on the Relationship Between Green Finance and Agricultural Carbon Emissions**

Green finance emerged from growing concerns about environmental protection and the intensified recognition of using finance tools to mitigate climate change and achieve green development (Irfan et al., 2022). The idea was first proposed by Salazar (1998) and, after that, green finance gained worldwide attention. Green finance has been extensively discussed from different perspectives, such as the significant role of green finance in promoting green growth (Desalegn & Tangl, 2022; Sadiq et al., 2022; Taghizadeh-Hesary, et al., 2022), the relationship between green finance and green innovation (Fang & Shao, 2022; Irfan et al., 2022; Wang, 2022; Yu et al., 2021), green finance and renewable energy (Li & Umair, 2023; Mngumi et al., 2022; Zhang et al., 2022), and green finance and carbon emissions (Ren et al., 2020; Sharif et al., 2022; Zhang et al., 2022). However, these studies did not extend to the relationships among green finance, agricultural growth, and ACEs. Only limited research has paid attention to this area. For instance, Mo et al. (2023) used a panel dataset of 30 Chinese provinces to investigate the impact of green finance on ACEs from 2011 to 2020 and revealed that green finance significantly decreases ACEs' intensity. Further mediation analysis indicates that green finance reduces ACEs by optimizing agricultural industry structure and promoting green technology. Guo et al. (2022) investigated the long-term equilibrium relationship between green finance and ACEs to draw the same conclusion that green finance reduces ACEs.

## **5.2.2 Research on the Relationship Between Digital Financial Inclusion and Agricultural Carbon Emissions**

DFI has gained much attention because of its advantages, such as convenience, cost-effectiveness, and without geographical restrictions, compared with traditional finance in promoting economic development (Liu & Ren, 2023; Mukalayi & Inglesi-Lotz, 2023; Wang et al., 2023). Many studies have examined the role of DFI either from the perspective of promoting agricultural green total factor productivity (Gao et al., 2022; Hong et al., 2022; Shen et al., 2023; Xiao et al., 2023) or the relationship between green finance and carbon emissions (Khan et al., 2021; Mukalayi & Inglesi-Lotz, 2023; Wang et al., 2023; Zheng & Li, 2022). However, the findings from these studies are mixed. Some assert that DFI has a negative correlation with carbon emissions, highlighting the role of DFI in reducing carbon emissions. For instance, Khan et al. (2023) investigated the impact of DFI on carbon emissions in emerging and developing economies and revealed that DFI can reduce carbon emissions. Zheng and Li (2022) investigated the impact of DFI in 30 Chinese provinces from 2013 to 2020 and found that DFI reduced ACEs in use depth and digitization level. Others posit that DFI increases carbon emissions. For instance, Ozturk and Ullah (2022) examined the impacts of DFI both on economic growth and carbon emissions in 42 countries from 2007 to 2019 and found that DFI promoted economic growth but increased carbon emissions.

With the intensified challenge of climate change and food security issues faced by the agricultural sector, more and more studies have paid attention to the relationship between DFI and ACEs. Liu and Zhou (2023) used a dataset of 31 Chinese provinces from 2011 to 2020 to investigate the relationship between digital finance and ACEs. They indicate that digital finance can reduce ACEs by facilitating agricultural green innovation. Liu et al. (2022) used a fixed effects model to investigate the significant role of DFI on ACEs in 30 Chinese provinces from 2011 to 2019. The results show that DFI can effectively decrease ACEs levels. However, Chang (2022) posited a non-linear relationship, indicating an inverted "U" shape curve relationship between digital finance and ACEs. This study uses a dataset of 31 Chinese provinces from 2011 to 2020 to investigate the impact of digital finance and explores the mechanisms using fixed effects, threshold effects, mediating effects, and moderating effects models.

## **5.3 The Theoretical Framework and Research Hypothesis**

Many researchers have demonstrated that finance can have a significant impact on carbon emissions because of its contribution to economic expansion, which makes it an intermediate

factor under the EKC framework (Ofori et al., 2023). However, the effects of FD on carbon emissions remain controversial, whether it brings a positive or negative impact on carbon emissions reduction has not achieved a consensus. The effect depends on where the financial resources go. If the financial resources are invested in the green industry, they could yield a positive impact, but if the financial resources are invested into so-called “dirty industries”, such as high-emissions, high-energy consuming, high-pollution industries, they could lead to increased carbon emissions. As an institutional arrangement (Zhang, 2023), green finance could guide capital to green industries, providing more financial resources for green projects at lower financing costs (Jalil & Feridun, 2011). This acts as a link between economic growth and the environment designed to address climate change and achieve green development.

There are several channels through which green finance impacts ACEs. First, it can directly provide financial support and capital for the development of rural green industries. By providing capital to rural green projects, such as renewable energy firms, sustainable agricultural practices, and carbon sequestration programmes at a lower cost, it can help reduce ACEs (Mo et al., 2023). Secondly, green finance can help alleviate the financial constraints on technology innovation and promote agricultural green production efficiency, thereby reducing ACEs. Thirdly, the popularization of knowledge related to green finance when promoting green finance and implementing green finance policies can help improve farmers’ environmental awareness, encouraging them to adopt more sustainable agricultural practices. Drawing from these insights, I hypothesize the following relationship:

*Hypothesis 1: Green finance development negatively impacts the level of ACEs.*

Financial inclusion originated from the link of financial exclusion and poverty proposed by some scholars (Chibba, 2009; Fareed et al., 2022; Khan et al., 2023). It enables individuals and business to achieve their financial goals by providing a wide range of financial products and services including transactions, payments, savings, credit, and insurance (Fareed et al., 2022; Khan et al., 2023; Said & Acheampong, 2024). With the booming of digital technology and widely use of big data platforms, DFI has more advantages in promoting information sharing and decreasing transaction cost by reducing geographic constraints compared to financial inclusion (Lee et al., 2022; Wang et al., 2023). Many studies have investigated DFI focusing on economic growth (Ahmad et al., 2021; Liu et al., 2021), sustainable development (Ozturk & Ullah, 2022; Tay et al., 2022), consumption transformation (Lai et al., 2020), carbon emissions reduction (Mukalayi & Inglesi-Lotz, 2023; Wang et al., 2023; Zhang et al., 2023). However, few studies have focussed on DFI and ACEs and no study pays attention to the relationship between green finance development and DFI in rural China.

DFI can provide easily accessible loans and financial products for farmers to adopt low-emissions agricultural technologies and practices, thereby reducing ACEs. This benefits farmers in remote areas by providing wide access to financial products at low cost through mobile payments and internet banking. DFI can also help mitigate the risks associated with technology innovation through information-sharing technology and cloud computing technology, thereby promoting green technology innovation and achieving a reduction in ACEs (Sun et al., 2022). Conversely, since there are financial constraints and limited environmental protection awareness in rural areas, the availability of access to more funds provided by DFI may possibly be used to expand production, leading to increased ACEs. DFI also provides easy access for households to purchase energy-intensive products that can increase carbon emissions (Khan et al., 2023).

Since there are financial constraints in rural areas, it remains to be seen if the role of green finance and DFI can reduce ACEs in rural areas. Can DFI help expand the reach of green financial resources in rural areas, thereby enhancing the environmental impact of green finance? Or does it cause crowding-out effects to green finance, leading to a deterioration of the environment and an increase in ACEs? These questions are critical for green development in rural areas and they are associated with the realization of carbon peak and carbon neutrality. To explore the combined impacts of green finance and DFI on ACEs, I propose the following hypothesis:

*Hypothesis 2: DFI moderates the impact of green finance on ACEs level.*

China is a vast country with great geographical diversity; each region has its own characteristics regarding natural endowments, agricultural structure, production mode, economic development, and technology development (Cui et al., 2022), which leads to great regional heterogeneity in green finance development. Different levels in green finance development reflect the determinations and ability of local governments to control environmental pollution, since green finance is an institutional arrangement (Zhang, 2023). A high level of green finance development indicates more remarkable ability to allocate green financial resources. Regions with high developed green finance implies more green financial resources can be allocated to green industries, contributing to ACEs' reduction. In contrast, regions with less developed green finance may not have enough funds to channel towards projects that effectively reduce ACEs. Therefore, different levels of green finance development may cause different impacts on ACEs. Therefore, I hypothesize the following relationship:

*H3. The impacts of green finance and DFI vary with the development level of green finance.*

## 5.4 Methodology and Data

### 5.4.1 Empirical Model

#### 5.4.1.1 Baseline model

I use the fixed effects regression model to investigate the impact of green finance and DFI on the ACEI of 31 Chinese provinces from 2011 to 2020 to test hypothesis (1). The basic regression model is given equation (5.1):

$$\ln ACEI_{it} = \alpha_i + \alpha_1 GF_{it} + \alpha_2 DFI_{it} + \alpha_k X_{it} + \mu_{it} \quad (5.1)$$

where:  $\ln ACEI_{it}$  represents ACEs' intensity (ACEs divided by rural GDP);  $GF_{it}$  represents the green finance index, the level of green finance development;  $i$  represents the different provinces and regions;  $t$  is the year;  $\alpha_i$  is the intercept term representing the individual effect; and  $X_{it}$  is a series of control variables such as GDP, urbanization (UR), agriculture mechanization development level (AML), agricultural industry structure (AIS), agricultural fiscal expense (AFE), agricultural education level (EDU), and agricultural natural disasters.

#### 5.4.1.2 Moderation model

To further explore the impact of DFI on ACEs and investigate the moderating effects of DFI on the relationship between green finance and ACEs (which helps determine whether there is complementary or substitution effects between green finance and DFI in rural China), I include an interaction term,  $GF*DFI$ , in the model (equation (5.2)):

$$\ln ACEI_{it} = \alpha_i + \alpha_1 GF_{it} + \alpha_2 DFI_{it} + \alpha_3 (GF_{it} * DFI_{it}) + \alpha_k X_{it} + \mu_{it} \quad (5.2)$$

where:  $GF*DFI$  is the interaction term between green finance and DFI. When the coefficient of  $GF$  is positive and the coefficient of interaction term is negative, DFI helps alleviate the adverse effects of  $GF$ . When the coefficient of  $GF$  is negative and the coefficient of interaction term is positive, it suggests that DFI inhibits the positive effects of green finance on ACEs. Hence,  $\alpha_1$  and  $\alpha_3$  are the core coefficients to be estimated by the model. The other variables are consistent with equation (5.1).

#### 5.4.1.3 Group regression model

Different levels of green finance development are determined by many factors including government policy, determinants and the financial resource allocation ability to control environmental pollution, which also impact ACEs' levels. To explore the heterogeneity of the impact of different levels of green finance development on ACEs, I use the median value to

divide the whole sample into two groups: high level of green finance development and low level of green finance development.

$$\ln ACEI_{it} = \alpha_i + \alpha_1 GF_{it} + \alpha_2 DIF_{it} + \alpha_3 (GF_{it} * DFI_{it}) + \alpha_k X_{it} + \mu_{it} \quad (GF < 0.264) \quad (5.3)$$

$$\ln ACEI_{it} = \alpha_i + \alpha_1 GF_{it} + \alpha_2 DIF_{it} + \alpha_3 (GF_{it} * DFI_{it}) + \alpha_k X_{it} + \mu_{it} \quad (GF > 0.264) \quad (5.4)$$

The variables are consistent with equation (5.2) and 0.264 is the median of GF that divides the sample into two groups.

## 5.4.2 Variables

### 5.4.2.1 Explained variable

ACEI is the explained variable. Three indicators can be used to measure the ACEs level. One is the total amount of carbon emissions (ACET), another is agricultural carbon emissions intensity (ACEI) (calculated as total carbon emissions divided by GDP) and a third is ACEP (calculated as total carbon emissions divided by population) (Cui et al., 2022; Wen et al., 2022). I choose ACEI as the explained variable to measure the ACEs' level since it represents the carbon missions caused by the growth of each unit of agricultural output, which offers an additional viewpoint by considering emissions in relation to productivity compared to the first two essays. It facilitates an in-depth understanding of the relationship between financial mechanisms and ACEs, especially in regions where emissions intensity may provide greater insight into environmental efficiency than total emissions alone. To obtain ACEI, the total ACEs should first be estimated. The total ACEs include the carbon dioxide emissions from agricultural land use, methane emissions from rice paddies, and methane and nitrous oxide emissions from livestock. Following the IPCC (2019) approach, the total ACEs can be estimated as follows:

$$E_{ACET} = \sum_1^k E_i = \sum_1^k T_i \delta_i \quad (5.5)$$

where:  $i$  represents the type of carbon source;  $k$  represents the total number of carbon sources;  $E_{ACET}$  represents the total carbon emissions;  $E_i$  represents the carbon emissions of each specific carbon source;  $T_i$  represents the quantity of each specific carbon source; and  $\delta_i$  is the carbon emissions coefficient for each specific carbon source. After calculating total ACEs, ACEI can be obtained by equation (5.6):

$$ACEI = ACET / GDP \quad (5.6)$$

### 5.4.2.2 Explanatory variable -green finance

Green finance includes a wide range of green financial products, such as green credit, green securities, green insurance, green investment and carbon finance (Zhang et al., 2022).

Following Lee and Lee (2022), Sun et al. (2023) and Zhang et al. (2022), I construct a comprehensive index of green finance development using three main financial products: green credit, green investment, and green insurance, as well as government support to measure the development of green finance. The entropy method is used to determine the weight of each secondary indicator. Table 5.1 presents definitions of the four secondary indicators of the green finance development index.

Table 5.1 The Green Finance Development Index

Primary index	Secondary indicator	Indicator description	Indicator properties
Green credit	Proportion of interest expenditure of high energy-consuming industries	Interest expense of six high energy consuming industries/Industrial interest expense	negative
Green investment	Proportion of investment in environmental pollution control	Investment in environmental pollution control/GDP	positive
Green insurance	Depth of agricultural insurance	Agricultural insurance income/Gross agricultural output value	positive
Green Support	Proportion of fiscal environmental protection expenditure	Fiscal environmental protection expenditure/General fiscal budget expenditure	positive

Author's compilation

#### 5.4.2.3 Digital financial inclusion

DFI data are from The Peking University Digital Financial Inclusion Index of China. The DFI index designed by the Peking University Digital Finance Research Center is widely recognized and used since it displays the development of DFI comprehensively, objectively, and representatively (Liu & Ren, 2023; Wang et al., 2022). The index consists of three sub-indicators: coverage breadth, depth of use and digitalization degree, covering provincial, city and county levels of China. Because of its authority, popularity and other advantages, I use it as an indicator to measure the DFI level.

#### 5.4.2.4 Control variables

I include a set of control variables that can influence provincial-level ACEs to enhance the accuracy of the results. The control variables are urbanization (UR), agriculture mechanization level (AML), agricultural industry structure (AIS), agricultural fiscal expense (AFE), agricultural workforce education level (EDU), and natural disaster (ND). UR is the ratio of the urban population to the total population, reflecting the shift in the rural labor force to urban areas (Mo et al., 2023). AML is the machinery use, which impacts productivity and ACEs in

the agricultural sector. It is proxied by total power of agricultural machinery in each province. AIS is the share of the farming industry and animal husbandry industry output value to the gross output value. AFE is government spending on the agricultural sector. EDU measures the education level of the rural population by the average schooling years of residents. ND measures natural impacts on ACEs' levels.

### 5.4.3 Data

I use regional data on 31 Chinese provinces from 2011 to 2020. The primary data are from China Statistical Yearbook, China Financial Statistics Yearbook, China Environmental Statistics Yearbook, and China Rural Statistical Yearbook, and EPS database. Table 5.2 presents the descriptive statistics of the variables.

Table 5.2 Description of the Variables

Variable	Variable indicator	Variable symbol	Source
ACEI	Agricultural Carbon Emissions Intensity	ACEI	Calculation by author
ACET	Total Agricultural Carbon Emissions	ACET	Calculation by author
ACEP	Agricultural Carbon Emissions Per Capita	ACEP	Calculation by author
Green finance	Green finance Index	GF	Calculation by author
Digital financial inclusion	Digital Finance Index	DFI	The Peking University Digital Financial Inclusion Index of China
Economic growth	GDP Per Capita	PGDP	China Statistical Yearbook
Urbanization	Rural population/ total population	UR	China Financial Statistics Yearbook
Agriculture mechanization development level	million kilowatts	AML	China Financial Statistics Yearbook
Agricultural industry structure	output value of farming industry and animal husbandry industry/RGDP	AIS	China Financial Statistics Yearbook
Agricultural fiscal expense	government spending on agriculture	AFE	China Financial Statistics Yearbook
Agricultural education level	Average schooling years of residents	EDU	China Financial Statistics Yearbook
Agricultural natural disasters	Damage area by disaster/ total planted area of crops	ND	China Statistical Yearbook

Source: Author's compilation

## 5.5 Results and Discussion

### 5.5.1 Descriptive Statistics

Table 5.3 presents the descriptive statistics of study variables. The mean and median of lnACET are 7.732 and 7.880, respectively, indicating the total ACEs of some regions are notably lower than the median. The minimum and maximum values of GF are 0.104 and 0.773, respectively, indicating a big difference in green finance development level across regions. The standard deviations of lnACET, lnACEI, and lnDFI are notably higher than for the other variables, indicating the wide spread of these variables.

Table 5.3 The Descriptive Statistics of the Study Variables

Variable	N	Mean	P50	SD	Min	Max
lnACET	310	7.732	7.880	0.979	4.329	8.853
lnACEI	310	0.0960	0.00900	0.638	-1.119	2.721
lnACEP	310	0.540	0.479	0.552	-1.281	1.944
GF	310	0.248	0.214	0.112	0.104	0.773
lnDFI	310	5.212	5.410	0.677	2.786	6.068
lnPGDP	310	9.655	9.654	0.446	8.429	10.69
lnAML	310	7.637	7.829	1.125	4.543	9.499
lnFAE	310	6.137	6.212	0.584	4.519	7.200
lnEDU	310	2.014	2.015	0.116	1.489	2.375
UR	310	0.459	0.430	0.157	0.168	0.893
AIS	310	0.662	0.669	0.144	0.355	0.971
ND	310	0.150	0.121	0.118	0	0.696

Note: Author's calculations

Table 5.4 reports the results of two types of correlation test: Pearson's correlation coefficients and Spearman's rank correlation. In both tests, the maximum correlation is between urbanization and education level, with Pearson's correlation coefficient value of 0.83 and a Spearman's rank correlation value of 0.78. These results indicate that there is no significant multicollinearity issue in the dataset.

Table 5.4 The Correlation Matrix

	GF	lnDFI	lnPGDP	lnAML	lnFAE	lnEDU	UR	AIS	ND
GF	1	0.23*	0.00	-0.23*	-0.12*	0.19*	0.12*	0.25*	-0.05
lnDFI	0.23*	1	0.38*	-0.05	0.50*	-0.13*	-0.08	-0.12*	-0.43*
lnPGDP	-0.11*	0.37*	1	0.34*	0.34*	0.11*	0.20*	0.16*	-0.05
lnAML	-0.49*	-0.06	0.33*	1	0.69*	-0.19*	-0.28*	0.39*	0.08
lnFAE	-0.09*	0.45*	0.32*	0.67*	1	-0.22*	-0.29*	0.09	-0.13*
lnEDU	0.21*	-0.05	0.18*	-0.30*	-0.16*	1	0.78*	0.01	0.07
UR	0.29*	0.00	0.11*	-0.52*	-0.30*	0.83*	1	0.03	0.05
AIS	0.03	-0.10*	0.14*	0.38*	0.09	-0.06	-0.03	1	0.13*
ND	-0.10*	-0.33*	-0.04	0.03	-0.20*	0.06	-0.04	0.06	1

Notes: Lower-triangular cells report Pearson's correlation coefficients, upper-triangular cells are Spearman's rank correlation. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Source: Author's calculations

## 5.5.2 Baseline Regression Analysis

I use a panel dataset of 31 Chinese provinces from 2011 to 2020 to investigate the impact of green finance on ACEI to test hypothesis (1). The results are presented in Table 5.5. Table 5.5, Column (1), shows the impact of green finance on ACEI without considering the impact of DFI and time effects. Column (2) incorporates DFI to investigate the impact of DFI on ACEI without considering time trends. Columns (2) and (3) consider time effects, which can help to address the time varying omitted variables problems.

Table 5.5 Benchmark Regression: The Impact of GF and DFI on ACEI

Variables	(1)		(2)		(3)	
GF	-0.585***	(0.18)	-0.585***	(0.19)	-0.430***	(0.15)
lnPGDP	-0.451***	(0.10)	-0.455***	(0.10)	-0.360**	(0.17)
lnAML	0.092	(0.08)	0.089	(0.08)	0.047	(0.07)
lnFAE	0.007	(0.04)	-0.010	(0.05)	0.092	(0.07)
lnEDU	0.287**	(0.13)	0.302**	(0.13)	0.534***	(0.15)
UR	0.616	(0.47)	0.653	(0.47)	-0.243	(0.49)
AIS	0.437	(0.38)	0.408	(0.39)	0.328	(0.35)
ND	0.087	(0.05)	0.091*	(0.05)	0.073	(0.05)
lnDFI			0.012	(0.02)	0.089*	(0.05)
_cons	2.684**	(1.31)	2.767*	(1.38)	1.347	(1.32)
N	310.000		310.000		310.000	
r2_a	0.825		0.825		0.871	
year					Yes	
F	43.813		45.275		69.392	

Notes: Robust standard errors in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  Column (1) investigates the impact of green finance on ACEI without considering the impact of DFI and time effects. Column (2) includes DFI into regression model but does not consider time effects. Model (3) both consider the impact of DFI and time effects.

Source: Author's calculations

The results in Table 5.5. Column (1) indicate that green finance negatively impacts ACEI at the 1% significance level. This suggests that green finance can help decrease ACEI, validating hypothesis (1). The results in Column (2) show consistency in the negative relationship between green finance and ACEI. At the same time, DFI is positively correlated with ACEI but insignificant, indicating that the development of DFI may lead to an increase in ACEI. Table 5.5, Column (3) shows similar results to Column (2), with a significant negative impact of green finance at a 1% significance level and a positive impact of DFI on ACEI at the 10% level. The findings align with previous studies (Guo et al., 2022; Mo et al., 2023). The results reveal a negative relationship between green finance and ACEs, demonstrating the significant role of green finance in ACEs' reduction. The finding is similar to that in Tong et al. (2022), which indicates that the development of green finance can promote green growth by improving green

total factor productivity. Using the Super-SBM model to investigate the impact of green finance in 30 Chinese provinces from 2006 to 2018, Lee and Lee (2022) show that green finance significantly improves green productivity.

DFI has a positive impact on ACEI, indicating that DFI tends to increase ACEI. This result differs from the previous studies by Chang (2022), Liu and Ren (2023) and Sun et al. (2022). Specifically, based on panel data of 31 Chinese provinces from 2011 to 2020, Chang (2022) reveals that digital finance has a non-linear relationship with ACEs with two thresholds. The reduction effects of DFI can be achieved by promoting farmers' entrepreneurship and technological innovation, and urbanization can amplify the reduction effects. Liu and Ren (2023) investigated the relationship between DFI and the coordinated development of food security and ACEs' reduction in China's grain production system. The authors show that an increase in DFI leads to an increase in the level of coordinated development of food security and a reduction in ACEs. Sun et al. (2022) used a super slacks-based measure model to measure ACEs performance in China from 2011 to 2020. Their results reveal that DFI can significantly improve ACEs' performance. The possible reason for the difference in the results could be the different indicators used in the models, such as digital finance in Chang's (2022) study and DFI in this study, different samples, and different measurements of ACEs levels.

Despite the differences in the above studies, the findings support Jin et al. (2023). Their study shows that DFI inhibits the improvement of ACEs' efficiency. They defend their conclusion by positing that DFI mainly helps individual farmers and small businesses in rural areas, but because of a limited production scale, they cannot afford low-emissions and high-energy efficient technologies to reduce ACEs. This study's results align with the study by Mukalayi and Inglesi-Lotz (2023), who argue that higher DFI is associated with higher energy consumption, which may lead to increased carbon emissions.

### **5.5.3 Moderating Effects Analysis**

In this part of the study, the moderating mechanism of how DFI influences the impacts of green finance development on ACEs is analyzed. The commonly used moderating regression model, which incorporates an interaction term of green finance and DFI, is used to conduct the analysis. Table 5.6 presents the results, with columns (1) and (2) showing the results of ACEI as the dependent variable, columns (3) and (4) showing the results of ACET as the dependent variable, and columns (5) and (6) showing the results of ACEP as the dependent variable. Columns (1), (3), and (5) show the results that do not incorporate the interaction term, reflecting the effects of green finance on ACEs, whereas columns (2), (4), and (6) include the interaction term. The

negative coefficient of green finance and the positive coefficient of the interaction term suggest that DFI inhibits the impacts of green finance on ACEs, which confirms our hypothesis (2), suggesting that there is a crowding-out effect of DFI on green finance in terms of ACEs reduction. The crowding-out effect of DFI on green finance regarding the reduction of ACEs arises from the fact that, although DFI improves financial accessibility, it does not inherently allocate financial resources to green or sustainable agricultural practices. This finding aligns with previous studies (Jin et al., 2023; Ozturk & Acaravci, 2013; Wang et al., 2022), suggesting that DFI increases carbon emissions. Jin et al. (2023) show that DFI contributes to increased ACEs efficiency because it does not support technological progress in green agricultural production.

Table 5.6 Regression of Green Finance on Agricultural Carbon Emissions and the Moderating Effect of Digital Financial Inclusion)

Variable	(1) lnACEI	(2) lnACEI	(3) lnACET	(4) lnACET	(5) lnACEP	(6) lnACEP
GF	-0.392** (0.15)	-0.526*** (0.14)	-0.265* (0.15)	-0.371** (0.15)	-0.392** (0.15)	-0.526*** (0.14)
lnPGDP	-0.299** (0.17)	-0.285 (0.18)	0.487*** (0.18)	0.504** (0.20)	0.701*** (0.15)	0.715*** (0.18)
lnAML	0.051 (0.07)	0.046 (0.06)	0.080 (0.07)	0.076 (0.06)	0.051 (0.07)	0.046 (0.06)
lnFAE	0.101 (0.07)	0.083 (0.07)	0.142* (0.07)	0.127* (0.07)	0.101 (0.07)	0.083 (0.07)
lnEDU	0.439*** (0.13)	0.659*** (0.17)	0.293* (0.17)	0.464** (0.20)	0.439*** (0.13)	0.659*** (0.17)
UR	-0.169 (0.48)	-0.379 (0.45)	-0.093 (0.48)	-0.258 (0.48)	-0.169 (0.48)	-0.379 (0.45)
AIS	0.288 (0.37)	0.409 (0.31)	0.051 (0.40)	0.146 (0.35)	0.288 (0.37)	0.409 (0.31)
ND	0.065 (0.05)	0.043 (0.05)	0.034 (0.05)	0.015 (0.05)	0.065 (0.05)	0.043 (0.05)
lnDFI		0.070 (0.05)		0.049 (0.05)		0.070 (0.05)
interact		0.284** (0.11)		0.232** (0.11)		0.284** (0.11)
Constant	1.192 (1.29)	0.540 (1.38)	1.233 (1.82)	0.688 (1.94)	-8.019*** (1.29)	-8.670*** (1.38)
N	310	310	310	310	310	310
r2_a	0.868	0.880	0.647	0.666	0.756	0.778
year	Yes	Yes	Yes	Yes	Yes	Yes
F	67.579	49.667	37.072	22.597	49.571	47.293

Notes: Robust standard errors in parentheses. \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01

Source: Author's calculations

Instead, it encourages the wide use of traditional high-energy technologies. However, the results for the relationship between green finance and DFI have not yet been found. The possible reason

that DFI inhibits the impacts of green finance could be attributed to the relatively backward, imperfect rural financial system (Pan, 2022). The difficulties in financing and the high cost of financing seriously restrict the development of rural areas. When facing the provision of green finance and DFI, individual farmers and small businesses tend to use funds to expand the scale and promote the efficiency of agricultural production rather than considering environmental outcomes. The support and incentives provided by the green policy are insufficient to support farmers and rural businesses to overcome the negative externalities of traditional agricultural production.

#### 5.5.4 Heterogeneous Analysis

The impacts of green finance and DFI on ACEs are confirmed by the baseline results. To further explore the heterogeneity of the effects of different levels of green finance development on ACEs, I conduct subgroup regressions. The main results are presented in Table 5.7. Column (1) shows low green finance development, Column (2) shows the results of high green finance development, and Column (3) shows the whole samples.

Comparing the results of the two groups, we find that the group with a low green finance level shows a significantly negative impact of green finance on ACEs at a 5% level in Column (1) of Table 5.7. However, the group with a high green finance level shows an insignificant negative impact on ACEs. The coefficients of DFI in all three columns are insignificant, indicating that DFI does not exert a significant effect on ACEs. However, the coefficient in Column (1) is negative, while in Column (2), it is positive, suggesting that DFI is conducive to ACE reduction in the regions with low green finance development despite insignificance. This is an interesting finding, which implies that there is an uncoordinated development of green finance and DFI. The results validate hypothesis (3) that the impacts of green finance and DFI vary with the development level of green finance.

Table 5.7 The Heterogeneous Effect of GF and DFI on ACEI

Variable	(1) Low		(2) High		(3) Full	
GF	-2.073**	(0.91)	-0.040	(0.89)	-2.008***	(0.61)
lnDFI	-0.022	(0.03)	0.111	(0.08)	-0.001	(0.06)
interact	0.394**	(0.17)	-0.108	(0.16)	0.284**	(0.11)
lnPGDP	-0.252**	(0.10)	-0.337*	(0.17)	-0.285	(0.18)
lnAML	-0.003	(0.03)	0.047	(0.07)	0.046	(0.06)
lnFAE	-0.071*	(0.04)	0.248***	(0.08)	0.083	(0.07)
lnEDU	0.044	(0.22)	0.491*	(0.24)	0.659***	(0.17)
UR	-0.599*	(0.33)	-0.218	(0.66)	-0.379	(0.45)
AIS	0.682**	(0.27)	0.185	(0.41)	0.409	(0.31)
ND	0.009	(0.02)	-0.051	(0.09)	0.043	(0.05)
cons	2.921**	(1.21)	0.536	(1.38)	0.908	(1.36)

N	155.000	155.000	310.000
r2_a	0.973	0.798	0.880
year	Yes	Yes	Yes
F	1.7e+04	251.810	49.667

Notes: Robust standard errors in parentheses. \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01

Source: Author's calculations

Regarding the moderating effects of DFI, in both Column (1) with low green finance development level and Column (3) with full samples, the interaction term is significantly positive, and the coefficients of GF are negative, suggesting that the joint effects of green finance and DFI increase the ACEs. However, in Column (2), the joint effects of green finance and DFI do not significantly impact ACEs. This suggests a more uncoordinated development in regions with low green finance development levels.

### 5.5.5 Endogeneity Analysis

Endogeneity is a significant issue in empirical studies that should be addressed to obtain more robust results. In this study, there are several potential causes of endogeneity. First, there may be reverse causality because of the complex relationships among the variables. The previous analysis in this chapter shows that green finance exerts a significant impact on ACEs. However, when the ACEs are too high in some regions, it compels the local government to promote green finance development to address the issue. Green finance and DFI, as new financial forms, influence each other. Secondly, I control many factors influencing ACEs to address the omitted variables issue and use the bi-directional fixed effects model to control the individual effects and time effects to alleviate the issue; eliminating the omitted variables issue is unrealistic. To address the endogeneity, I adopt two methods. The first is to shift the dependent variable forward by one period to address reverse causality. The results of this method are reported in Table 5.8.

Table 5.8 Regression Results after Shifting Dependt variable Forward by One Period

Variable	(1)		(2)	
	F.lnACEI		F.lnACET	
GF	-1.992***	(0.53)	-1.457**	(0.56)
lnDFI	0.015	(0.06)	0.029	(0.05)
interact	0.292***	(0.10)	0.216**	(0.10)
lnPGDP	-0.300	(0.20)	0.496**	(0.23)
lnAML	0.053	(0.06)	0.089	(0.06)
lnFAE	0.049	(0.07)	0.080	(0.07)
lnEDU	0.869***	(0.18)	0.551**	(0.21)
UR	-0.466	(0.47)	-0.299	(0.53)
AIS	0.374	(0.29)	0.151	(0.36)
ND	0.038	(0.04)	0.008	(0.04)
Constant	0.710	(1.54)	0.935	(2.15)
N	279.000		279.000	

r2_a	0.876	0.669
year	Yes	Yes
F	201.648	18.066

Notes: Robust standard errors in parentheses. \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01.

Source: Author's calculations

The second method is two-stage least squares estimation(2SLS), which is conducted with the average green finance level in that year as an instrument variable (IV). This IV is highly relevant to green finance but not relevant to ACEs, satisfying the requirements of the 2SLS model. The results of 2SLS method are presented in Table 5.9.

Table 5.9 Regression Results Using the Instrumental Variable Method

Variable	(1) lnACEI		(2) lnACET	
GF	-1.447***	(0.32)	-1.042***	(0.39)
lnDFI	0.010	(0.06)	0.003	(0.06)
interact	0.200***	(0.06)	0.138*	(0.07)
lnPGDP	-0.247	(0.17)	0.513**	(0.21)
lnAML	0.042	(0.06)	0.069	(0.06)
lnFAE	0.065	(0.06)	0.111*	(0.07)
lnEDU	0.229	(0.21)	0.257	(0.24)
UR	-0.369	(0.45)	-0.303	(0.47)
AIS	0.432	(0.31)	0.194	(0.36)
ND	0.045	(0.04)	0.014	(0.04)
Constant	1.884	(1.48)	1.728	(2.01)
N	300.000		300.000	

Notes: Robust standard errors in parentheses. \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01

Source: Author's calculations

### 5.5.6 Robustness Test

There are three critical metrics used to assess ACEs: ACEI, ACET, and ACEP (Cui et al., 2022; Wen et al., 2022). ACET is the total ACEs, and ACEP is the per capita carbon emissions. I use ACEI as the dependent variable in the study's baseline model since it can offer an in-depth comprehension of emissions efficiency. However, ACET also offers a comprehensive perspective on total emissions, ensuring the results are valid at an aggregate level. ACEP facilitates a per capita analysis, which can illuminate emissions associated with individual productivity or consumption behaviors. Thus, ACET and ACEP are used as alternative variables for robustness checks. The results are presented in Table 5.6, Columns (3), (4), (5), and (6) and Table 5.9, Column (2). The results in Table 5.6 demonstrate that green finance has a negative impact on ACEs, including using the alternative ACET and ACEP, which validates hypothesis (1). The results of 2SLS method in Table 5.9 reinforce the validity of those results.

## 5.6 Conclusions and Policy Recommendations

The study uses a fixed effects regression model to investigate the impact of green finance and DFI on the ACEs of 31 Chinese provinces from 2011 to 2020, conducts a moderation mechanism analysis to explore the combined effects of green finance and DFI on ACEs, and uses a group regression method to examine the heterogeneity of the impact of green finance on ACEs. One period forward of the dependent variable and 2SLS regression methods are used to address endogeneity issues in the model. The instrumental variable method is also used to ensure the validity of the results.

The main findings are as follows. First, green finance development is conducive to reducing agricultural carbon emissions, but digital financial inclusion tends to increase carbon emissions in rural China. Secondly, the promotion of digital financial inclusion has an inhibiting effect on the impact of green finance on agricultural carbon emission reductions, indicating uncoordinated development between green finance and digital financial inclusion in rural China. Thirdly, the effects of green finance and digital financial inclusion vary with the development level of green finance; green finance and digital financial inclusion show a more uncoordinated development in regions with low green finance development levels.

Based on the results, there are several policy recommendations. First, considering the significant role of green finance in reducing carbon emissions in rural China, governments must establish a rural green financial system, implement more green policies, and provide more incentives to promote green finance development in rural areas. Currently, the lack of green financial products for rural restricts agricultural green development. Accelerating the development of rural green finance is of great significance to realizing rural revitalization policies and carbon neutrality goals in China. Secondly, green finance and digital financial inclusion should be integrated for coordinated development. The development of green finance can help digital financial inclusion realize sustainable goals and digital financial inclusion can provide more financing channels and financial resources for green finance, extending market reach. Therefore, the integration of green finance and digital financial inclusion's development should be promoted by encouraging financial institutions to develop more green digital financial inclusion products that can meet green standards in an extensive market. Thirdly, when formulating policies to promote the development of green finance and digital financial inclusion, 'one-size-fits-all' policies should not be advocated. The formulated policies should be tailored to regional characteristics, accounting for local economic growth, natural endowments and industry structure.

## **5.7 Limitations and Future Research**

This study has several limitations. First, it lacks data on rural green finance, so cannot provide an overall understanding of its development in rural areas and propose targeted rural green finance development measures. Second, the study period is not long because of data availability. The results would be more robust if an extended study period on the relationships among green finance, DFI and ACEs could be analysed. Thirdly, I use only China as a sample to investigate the relationships among green finance, DFI and ACEs, which cannot provide a universal conclusion. If more samples from other regions, such as Asia, Europe and North America, can be added, it will provide more in-depth analysis, general conclusions and implications. Future research could obtain more available data to do transnational research, analyse the relationships among green finance, DFI and ACEs at a national level.

## Conclusion

### 6.1 Main Findings of the Research

This thesis consists of three essays investigating how the financial system can reduce carbon emissions in rural China. The first essay investigates the role of rural financial development on the relationship between agricultural growth and ACEs. The second essay examines the role of green finance in ACE reduction. The third essay examines the role of DFI and its moderating effects on the impact of green finance on ACEs.

The first essay comprises two parts. Part one measures the agricultural carbon emissions and analyses the structure changes and the temporal and spatial characteristics using the Theil Index and Moran's I Index. The results show a fluctuating growth trend of ACEs characterized by an "increase-decrease-increase-decrease" pattern, with livestock and land use emissions emerging as the two major contributors to carbon emissions. The decreasing Theil Index shows that the regional emissions disparity is diminishing. The Moran Index shows positive spatial autocorrelation among regions. Part two, based on the EKC Theory, investigates the impact of agricultural growth and rural financial development on agricultural carbon emissions in 31 Chinese provinces from 2001 to 2019. The results reveal that the theory is not valid in rural China, with an inverted "N" shape relationship between agricultural growth and ACEs; financial development is not conducive to carbon emissions reductions in rural areas, since rural financial efficiency is significantly positively correlated with ACEs and regional disparities are obvious.

The second essay investigates the impact of green finance on ACEs in 31 Chinese provinces from 2007 to 2020 using fixed effects, quantile regression and DID methods. The results reveal that green finance does not play a significant role in reducing ACEs in the whole of China, but it significantly decreases the ACEs in eastern and central China. As one dimension of green finance development, government finance support substantially reduces ACEs whereas green credit increases ACEs. The use of agricultural machinery contributes to increased ACEs. The impact of green finance on ACEs displays regional heterogeneity in China and different impacts of green finance on ACEs are observed across different the quantiles because of different focusses and initiatives of green finance in the different regions. Third, the Green Finance Reform and Innovation Pilot Zones has no policy effect on ACEs.

The third essay examines the impact of green finance and DFI on the ACEs of 31 Chinese provinces from 2011 to 2020 and explores the mechanism of how DFI moderates the impact of green finance on ACEs. I use a group regression method to examine heterogeneity in the impact of green finance on ACEs. The results indicate that green finance development plays a crucial role in reducing ACEs whereas DFI increases carbon emissions in rural China. Additionally, DFI has an inhibiting effect on the impact of green finance on ACEs' reduction, indicating uncoordinated development between green finance and DFI. Thirdly, the impacts of green finance and DFI vary with the development level of green finance; green finance and DFI show a more uncoordinated development in regions with low green finance development levels.

Overall, the studies provide a comprehensive insight into the emissions reduction effects of financial development and the mechanism of how financial development impacts carbon emissions reduction in rural China.

## **6.2 The Implications of the Research**

The studies' results provide significant policy implications for the Chinese government to formulate differential carbon emissions reduction policy measures. First, since green finance plays a significant role in ACEs reduction, it is crucial to promote rural green finance development, which is very significant to realizing rural revitalization policies and carbon neutrality goals in China. To this end, it is necessary for governments to establish a rural green financial system, implement more green policies, and provide more incentives to promote green finance development in rural areas. For financial institutions, it is necessary to develop and provide more green financial products tailored to rural areas, directing the capital toward green agricultural programs and practices since green industries development in rural areas is restricted by the lack of green financial products. For individuals, it is essential to enhance public awareness about the environmental impacts of agriculture production in rural communities.

Secondly, green finance and DFI should be integrated for coordinated development in China. The development of green finance can help DFI realize sustainable goals and DFI can provide more financing channels and financial resources for green finance, extending its market reach. Therefore, the integration of green finance and DFI development should be promoted by encouraging financial institutions to develop more green DFI products that can meet green standards and target an extensive market.

Thirdly, given the substantial role of policies on the reduction of ACEs, the development of green finance and DFI in China, governments need to play a significant role in building a standardized measurement system for ACEs that can ensure consistent, accurate assessment of ACEs. This includes formulating more targeted fiscal policies and green policies on the reduction of ACEs and promoting the development of green finance and DFI. However, it is worth noting that, when formulating policies, it is essential to formulate region-specific policies, ‘one-size-fits-all’ policies should not be advocated because of regional heterogeneity.

In conclusion, green financial innovations and targeted policy interventions are essential to support green finance and DFI development, thereby reducing carbon emissions in rural areas by utilizing financial resources.

### **6.3 Contributions of the Research**

Given China’s significant contribution to global warming and its commitment to mitigating climate change by reducing carbon emissions, carbon emissions reduction has become an essential task for every sector in China. Many studies have focused on the industry, energy, and transport sectors but have neglected the agricultural sector for a long time. Against the background of rural revitalization and green agricultural development, how the financial system can help reduce carbon emissions and facilitate the development of green agriculture is essential.

This thesis bridges a literature gap by investigating the role of rural finance, green finance, and DFI in reducing ACEs. The possible contributions are as follows. First, this thesis provides a more comprehensive measurement of ACEs by covering more carbon sources, including agricultural land use, rice paddies, and livestock management, which were often overlooked in previous studies. Since the measurement of ACEs follows the latest IPCC guidelines and accounts for the actual situation in China by adjusting the carbon coefficients to the local context, it provides an improved measurement of provincial-level ACEs in China.

Secondly, this thesis extends the EKC Theory framework to the agricultural sector and overcomes the omitted variable bias in the hypothesis by integrating financial development into the EKC framework, which not only contributes to the literature but also provides practical policy insights for reducing ACEs, especially with a background of the “dual carbon” strategy. Thirdly, this thesis examines the role of green finance in reducing carbon emissions in the agricultural sector, which was previously overlooked compared to the industry and energy sectors. The study uses quantile regression to examine the asymmetric effects of green finance

across different quantiles, providing new insights to enable reduced carbon emissions and valuable information for formulating policies to achieve green development.

Fourthly, this thesis is pioneering in investigating the combined effects of green finance and DFI on ACEs, thus providing a more comprehensive understanding of the relationships and analysing the underlying mechanisms. It also reveals an interesting result that DFI restrains the effects of green finance, indicating a crowding out effect of DFI on green finance in rural areas during the study period.

Overall, this thesis not only provides new perspectives and frameworks for theoretical study but also offers practical guidance for policymakers to help them effectively address climate change and achieve green development using financial tools.

#### **6.4 Limitations and Future Research**

Overall, there are several limitations. First, for the ACEs research, the data sample includes only 31 Chinese provinces, so it cannot provide more county- or household-level insights. Since the influencing factors on ACEs include macro- and micro-level factors, such as farmers' green behaviors, financial literacy, and digital capability, macro and micro analysis can be combined to get a more robust result.

Second, for green finance research, the lack of data on rural green finance makes it impossible to provide an overall understanding of its development in rural areas and so propose targeted rural green finance development measures. Knowledge of the mechanism analysis on how green finance impacts ACEs is lacking.

Thirdly, the study focuses on only the agricultural sector in China to investigate the relationships among green finance, DFI and ACEs, which may differ from developed countries or other developing countries and cannot provide a universal conclusion. Future research can obtain available household-level data using field surveys to conduct microanalysis on how green finance and DFI impact ACEs and determine the relationship between green finance and DFI in rural areas. Future research can also focus on a more expanded area by conducting transnational research, analysing the relationships among green finance, DFI and carbon emissions at the national level.

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