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Effect of Green Finance on Rural Revitalization in Guangxi Zhuang Autonomous Region

Dansha Zhang[1*], Tajul Ariffin Masron[2], Xinming Du[1], Xueping Lu[1]

[1] Nanning Vocational and Technical University, China
[2] Universiti Sains Malaysia, Malaysia

* Corresponding Author: 331784004@qq.com

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Abstract: *Using panel data from 14 prefecture-level cities in Guangxi Zhuang Autonomous Region, China, from 2013 to 2021, this study applies the Generalized Method of Moments (GMM) model to examine the impact of green finance, represented by green credit and agricultural insurance, on rural revitalization with digitalization moderation. The results indicate that green finance has a significant positive impact on rural revitalization across most dimensions with digitalization moderation, although it may cause short-term decrease in rural per capita disposable income. This study proposes digital leasing platforms, insurance incentives, and training to boost rural revitalization.*

Keywords: Green Finance, Digitalization, Rural Revitalization, GMM

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1. Introduction

Green finance has emerged as a critical instrument for cultivating environmentally sustainable and inclusive economic systems (Zhao et al., 2024; Lv et al., 2021). The integration of digital technological advancements has significantly expanded green finance applications within rural revitalization frameworks (Bhatnagar & Sharma, 2022), positioning this financial innovation as a pivotal mechanism for funding ecological initiatives (Berrou et al., 2019). However, the inherent characteristics of environmental projects—characterized by substantial capital intensity, extended investment cycles, and suboptimal economic returns (Bakry et al., 2023)—impose substantial fiscal constraints on participating enterprises, thereby constraining the broader implementation of green finance strategies in rural development contexts. This challenge persists despite China's multidimensional rural revitalization objectives that simultaneously pursue environmental conservation, economic growth, and sustainable development targets (Geng et al., 2024).

Notwithstanding Guangxi's policy interventions employing fiscal subsidies and tax incentives to promote green finance, empirical outcomes remain suboptimal. As evidenced in Figure 1, the regression analysis reveals a positive yet statistically weak association between green insurance (GF02) and the Rural Revitalization Index ($\beta=0.18$, $p<0.05$), with a flatter regression slope suggesting policy efficacy limitations. Similarly, green credit (GF01) demonstrates a modest correlation with rural development indicators ($R^2=0.32$), underscoring the necessity for enhanced policy enablers. Drawing upon Sustainable Development Theory (Daly, 1996), this study posits digitalization as a catalytic moderator capable of amplifying green finance effectiveness through technological innovation and optimized resource allocation—a mechanism hypothesized to strengthen the finance-revitalization transmission channel.

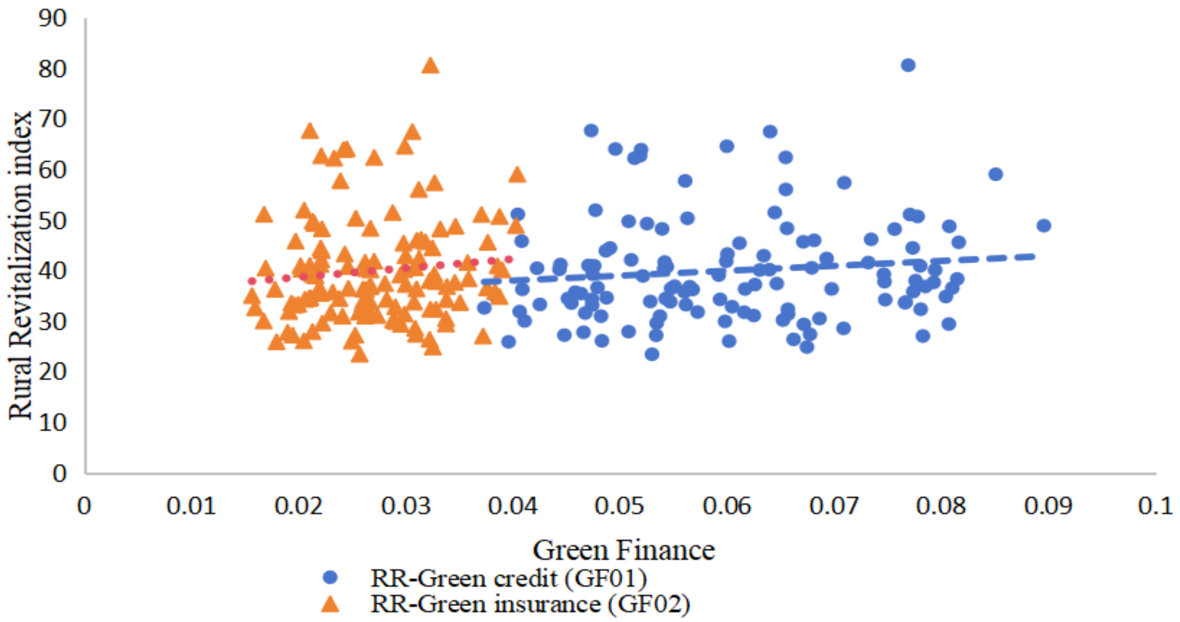

Figure 1: Rural Revitalization vs Green Finance

This investigation systematically examines the dual mechanisms through which green finance influences rural revitalization: 1) facilitating industrial green transformation, 2) augmenting agricultural income streams, and 3) improving ecological governance. Furthermore, it quantitatively assesses digitalization's moderating effects on these pathways. Employing mixed-methods research combining theoretical modeling and empirical verification, the study aims to derive evidence-based policy recommendations for three key stakeholders: 1) policymakers in green finance strategy formulation, 2) financial institutions in product innovation, and 3) local governments in incentive structure optimization.

Theoretical contributions manifest in addressing critical research gaps regarding the digital moderation mechanism within green finance-rural revitalization dynamics, thereby advancing financial innovation literature. Practically, the findings provide actionable insights for 1) designing tiered green finance products aligned with rural economic realities, 2) developing digital infrastructure to enhance fund allocation efficiency, and 3) formulating composite policy packages integrating fiscal and technological instruments. These outcomes hold particular relevance for developing economies pursuing SDG-aligned rural transformation.

2. Literature Review

Speaking of green finance, Raman et al. (2025) use a hybrid approach to study the contribution of sustainable finance to the Sustainable Development Goals (SDGs) and find that green finance innovation plays a great role in driving investment in renewable energy and reducing environmental impact. However, they also point out that high transaction costs and inadequate institutional frameworks faced by developing countries are stumbling blocks to the adoption of green financial instruments. The study by Zhang et al. (2022) is also interesting, finding that green finance investment and technological progress together can significantly improve renewable energy efficiency and play an important role in achieving the Sustainable Development Goals, particularly climate action (SDG 13) and affordable and clean energy

(SDG 7). But to realize these benefits, challenges such as regulatory shortcomings and market barriers must be addressed. These findings coincide with discussions on the relationship between green finance and sustainable development, as highlighted by Scholtens (2006). Green finance is seen not only as an important tool for protecting the environment, as stated by Wang et al. (2022) and Zhang et al. (2021), but also as a driver of sustainable economy (Wu, 2023) and social development (Dai & Chen, 2023). However, when promoting rural revitalization, green finance encounters many problems, such as policy gaps, product shortages, and supply-demand imbalances, which greatly reduce its role. Zhao (2024) describes these challenges in detail.

Many studies use green credit to measure green finance performance, such as those by Wang et al. (2021) and Lu et al. (2022). Additionally, agricultural insurance is also a very important part of green finance. The long-term effect of agricultural insurance is particularly critical, as it can stabilize farmers' income expectations without worrying about a return to highly polluting and energy-intensive production methods due to short-term risks, as Hou and Wang (2022) mention. Moreover, green agricultural technologies, such as water-saving irrigation and organic farming, are expensive and risky at first. Farmers will not dare to try them without some kind of security.

Green finance can promote the green transformation and upgrading of rural industries. Research by Hao et al. (2024), Soundarrajan and Vivek (2016), and Yang et al. (2021) supports that green finance has a role that goes beyond environmental protection and can reduce pollution and conserve resources while boosting economic growth by developing green industries and creating jobs. In rural revitalization, it can bring many benefits, such as encouraging investment in environmental projects, mitigating environmental risks for rural enterprises, and increasing access to green financing. Based on these findings, we propose the following hypothesis:

Hypothesis 1: Green finance has a positive impact on promoting rural revitalization in Guangxi.

Digital technologies are reshaping how green finance works. Research shows that from big data risk control to AI intelligent advisors, digital tools are breaking through the service boundaries of traditional finance (Wen et al., 2022; Wang & Shao, 2024). This is not just a technological upgrade, but more like a genetic reorganization of financial service models. What's more, digital technologies are also leading to innovation and diversification of green financial products.

However, research on the empowerment of digitalization for green finance is only just beginning. Jiang et al. (2024) look at data from 30 Chinese provinces from 2014 to 2021. They find that combining digitalization with green finance can boost financial service access and efficiency, and help agriculture go green and grow sustainably through tech and better infrastructure. Recent research shows digital agri-insurance is key for protecting the environment and lifting rural living standards. Dong et al. (2025) find that digital agricultural insurance increase farmers' willingness to adopt new technology compared to traditional insurance because it reduces information asymmetry, and financial constraints.
Based on these findings, we feel it is necessary to propose a hypothesis:

Hypothesis 2: Digitalization positively moderates the impact of green finance on promoting rural revitalization in Guangxi.

Although green finance has great potential, it also faces some thorny problems. For example, information asymmetry and inadequate risk management capabilities can easily lead to inefficient resource allocation, which will drag down rural revitalization. This is mentioned in Jiakui et al. (2023). And despite its environmental and economic benefits, green finance on its own may not be enough to drive sustainable rural development, as Lingmin (2024) also points out.

Interestingly, although digitalization may help green finance better serve rural revitalization, there is little research on it. This is exact the problem we want to solve in this paper. We intend to fill this gap by analyzing how digitalization can support green finance in rural revitalization. We will put forward practical strategies based on the actual situation of Guangxi, hoping to provide a scientific basis for policy formulation, help rural revitalization, and develop in a greener and more sustainable direction.

3. Methodology

To better understand the role of green finance in rural revitalization, we construct a baseline regression model (equation (3)). The theoretical basis of this model is the theory of sustainable development (Daly, 1996), which emphasizes that economic growth should not only focus on immediate interests, but also take into account environmental sustainability and social equity. Green finance acts as a guidance that directs funds to projects that are beneficial to sustainable rural development. These could include developing eco-agriculture, building green infrastructure, or promoting resource-efficient industries. In this way, green finance not only promotes economic growth, but also ensures that this growth is eco-friendly.

In building the model, we also consult a large amount of existing literature to select the control variables. Specifically, we refer to the study by Zhang et al. (2024) and include entrepreneurial activity (NSE) as a control variable; Fiscal transparency (FTP) is added based on the research of de Mendonpada & Baca (2022); Chen's (2016) research leads us to include foreign direct investment (FDI); The study by Li et al. (2018) prompts us to consider urbanization (URBP) as a factor. These control variables make our model more comprehensive in assessing the contribution of green finance to rural revitalization. Equation (3) is shown as follows:

$$RR_{it} = \alpha + \beta_1 GF_{it} + \beta_2 DIG_{it} + \beta_3 NSE_{it} + \beta_4 FTP_{it} + \beta_5 FDI_{it} + \beta_6 URBP_{it} + \varepsilon_{it} \quad (3)$$

In equation (3), i denotes each city and t denotes time. α is the intercept, β represents the coefficients of the independent variables. RR_{it} is the rural revitalization level indicator, DIG_{it} is the digitalization level indicator, GF_{it} is the green finance level, and ε_{it} is the random disturbance term. To control data dispersion and reduce the impact of outliers, all variables are transformed using the natural logarithm.

Building on Equation (3), an extended model incorporating the moderating variable (DIG_{it}) is established as Equation (4) to explore whether digitalization can moderate the relationship between green finance and rural revitalization:

$$RR_{it} = \alpha + \beta_1 GF_{it} + \beta_2 DIG_{it} + \beta_3 (DIG_{it} \times GF_{it}) + \beta_4 X_{it} + \varepsilon_{it} \quad (4)$$

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Traditional panel data methods like pooled OLS, random effects, and fixed effects can be biased and inconsistent because lagged dependent variables might correlate with error terms (Ibrahim & Law, 2014). To fix this, we use a two-step Generalized Method of Moments (GMM) for panel data. It deals with endogeneity and bias from non-exogenous variables. This method follows what Holtz-Eakin et al. (1988), Arellano and Bond (1991), and Arellano and Bover (1995) suggested. The dynamic panel model can be written simply as Equation (5):

$$RR_{it} = \alpha + \gamma RR_{it-1} + \beta X_{it} + \varepsilon_{t} \quad (5)$$

Here, γ is the coefficient of the lagged dependent variable. In dynamic models, the inclusion of the lagged dependent variable (RRi_{t-1}) helps to more accurately understand and predict the time-dependent nature of economic phenomena while accounting for the persistence of economic activities.

Construction of Rural Revitalization Index and Digitalization Index

In constructing the measurement index system for the level of rural revitalization, this study carefully considers the principles of data availability and accuracy. Accordingly, the Rural Revitalization Index (RR) is chosen as the core dependent variable. For the selection of dimensions, this study builds on the work of Geng et al. (2023, 2024), who propose a comprehensive framework for assessing rural revitalization through three key dimensions: industrial prosperity, improved livelihoods, and ecological livability. The specific sub-indicators for each dimension are detailed in Table 1. Following the methodology of the United Nations Development Programme (UNDP) in developing the Human Development Index (HDI), each sub-indicator is standardized to construct the Rural Revitalization Index (RR).

Table 1 Rural Revitalization Level Indicator System

Rural Revitalization Sub-Indicators	Indicator Type	Specific Indicator Measurement	Sub-Indicators Proxy Variable
Industrial Prosperity	Positive Indicator	Total output value of agriculture, forestry, animal husbandry, and fisheries	Subr1
	Positive Indicator	Per capita total agricultural machinery power	Subr2
	Positive Indicator	Rural residents' value added in primary industry	Subr3
Enriched Livelihoods	Positive Indicator	Per capita disposable income of rural residents	Subr4
Ecological Livability	Negative Indicator	Pesticide and fertilizer usage	Subr5

To ensure consistency and comparability, this study standardizes each indicator following the approach used by the United Nations in constructing the Human Development Index (HDI). Each indicator is converted into a standardized value using Equation (6):[1].

$$\text{Sub - Indicator} = \frac{\text{Actual Value - Minimum Value}}{\text{Maximum Value - Minimum Value}} \quad (6)$$

After standardizing all sub-indicators, this study applies the Human Development Index calculation method outlined in the United Nations Development Programme (UNDP) 2021–

2022 Human Development Report (UNDP, 2021; 2022) to derive the composite Rural Revitalization Index (RR) using the following formula:

$$RR = \frac{Subr1 + Subr2 + Subr3 + Subr4 + Subr5}{5} \quad (7)$$

The Digitalization Index (DIG) is the moderating variable in this study. Its calculation follows the methodology proposed in the United Nations Development Programme (UNDP) 2021-2022 Human Development Report (UNDP, 2022) for the Human Development Index. This study selects six core sub-indicators that comprehensively reflect the level of digitalization, as shown in Table 2. The Digitalization Index is constructed in a manner similar to the Rural Revitalization Index (RR), using a similar calculation approach.

Table 2 Digitalization Level Indicator System

Digitalization Sub-Indicator	Indicator Description	Explanation
INT	Internet Penetration Rate	The number of internet users per 100 people.
COM	Proportion of Employees in Computer Services and Software Industries	The number of employees in the computer services and software industries per 100 people.
TEL	Total Telecommunications Services	The total amount of telecommunications services used per 100 people.
POS	Postal Service Usage	The amount of postal services used per 100 people.
MPH	Mobile Phone User Penetration Rate	The proportion of mobile phone users per 100 people.
SCE	Research and Development Investment	Public funding invested by the government in scientific research and technological development.

Data Sources

The study analyzes data from all 14 cities in the Guangxi Zhuang autonomous region in China from 2013 to 2021. Green credit is measured as the difference between total industrial interest expenses and interest expenses of six energy-intensive industries, divided by total industrial interest expenses (Wang et al., 2021; Liu & He, 2021). This ratio reflects the share of interest expenses outside high-energy-consuming sectors, indirectly indicating the scale of green credit. Green insurance is assessed through the ratio of agricultural insurance claim payments to premium income. This claims ratio is a key indicator of risk coverage and financial sustainability in the insurance sector, with higher ratios suggesting effective compensation for farmers' environmental risks (Hou & Wang, 2022; Zou et al., 2022; An et al., 2023). Table 3 details the variables, descriptions, and data sources.

Table 3. List of Variables, Descriptions, and Sources.

Variables	Proxy	Descriptions	Sources
RR	Rural Revitalization Index	RR has three key dimensions: industrial prosperity, enriched livelihoods, and ecological livability	Guangxi statistical yearbook [2] and the statistical yearbook of each prefecture-level city
GF01	Green Credit	The difference between total industrial interest expenditure and interest expenditure of the six energy-intensive industries, divided by the total industrial interest expenditure	Statistical yearbook of each prefecture-level city
GF02	Green Insurance	The ratio of agricultural insurance claims paid to agricultural insurance premium income	Guangxi statistical yearbook and China National Financial Regulatory Administration
DIG	Digitalization Index	Digitalization Index is calculated by United Nations Development Programme method from six sub-indicators	China City Statistics Yearbook[3]
NSE	Entrepreneurship	The number of new private enterprises in a city is divided by the number of labor force to obtain the number of new startups per 100 people	Qixinbao database[4] which uses China National Enterprise Credit Information Publicity System as the data source
FTP	Fiscal Transparency	A comprehensive evaluation of the fiscal transparency of local governments	Research Reports on Fiscal Transparency of Chinese Municipal Government by Tsinghua University[5]
FDI	Foreign direct investment	The proportion of utilized foreign direct investment to GDP	China City Statistics Yearbook
URBP	Urbanization	Proportion of permanent urban residents in the city's population	

4. Results and Discussion

This study employs a two-step system GMM model to conduct a thorough analysis of data from 14 prefecture-level cities in Guangxi. The validity of the model has been confirmed. The AR(1) test significantly indicates the presence of first-order autocorrelation, while the AR(2) test shows no significant second-order autocorrelation, effectively ruling out the possibility of second-order autocorrelation. The Hansen test further validates the appropriateness of the instrument variables, ensuring the robustness and reliability of the model.

Green finance are under two proxies: GF01 for green credit and GF02 for green insurance (see Table 1 for indicator definitions). Table 4 shows the direct effects of green finance on rural revitalization sub-indicators, while Table 5 illustrates the moderating effect of digitalization on the relationship between green finance and rural revitalization. The results indicate that with digitalization as a moderator, both green credit (GF01) and green insurance (GF02) generally have a significant positive impact on rural revitalization, though they may cause some fluctuations in rural per capita disposable income.

Table 4: Regression results of the direct impact of green finance on rural revitalization

	model 1.1 RR=RR	model 1.2 RR=subr1	model 1.3 RR=subr2	model 1.4 RR=subr3	model 1.5 RR=subr4	model 1.6 RR=subr5		model 1.7 RR=RR	model 1.8 RR=subr1	model 1.9 RR=subr2	model 1.10 RR=subr3	model 1.11 RR=subr4	model 1.12 RR=subr5
RR_{t-1}	0.336**	0.654***	-0.224**	0.992***	0.843***	0.297	RR_{t-1}	0.328**	0.631***	-0.252**	0.985***	0.843***	0.138
	(0.013)	(0.000)	(0.044)	(0.000)	(0.000)	(0.110)		(0.025)	(0.000)	(0.025)	(0.000)	(0.000)	(0.371)
GF01	-0.048	-0.104	-0.090	0.044	0.024*	0.100	GF02	-0.097	-0.230***	-0.106	0.012	0.025**	0.033
	(0.521)	(0.128)	(0.296)	(0.112)	(0.083)	(0.456)		(0.223)	(0.000)	(0.215)	(0.604)	(0.035)	(0.283)
DIG	0.367***	0.336***	0.341***	0.081***	0.040***	0.129***	DIG	0.387***	0.394***	0.335***	0.091***	0.039***	0.163***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)
NSE	0.024	-0.008	0.039	-0.030*	-0.007	0.076***	NSE	0.027	-0.001	0.051	-0.027	-0.007	0.055
	(0.773)	(0.813)	(0.266)	(0.089)	(0.407)	(0.001)		(0.749)	(0.986)	(0.175)	(0.127)	(0.372)	(0.259)
URBP	0.106	0.032	-0.022	0.171	0.075	-0.074	URBP	0.141	0.055	-0.022	0.150	0.075*	-0.039
	(0.823)	(0.862)	(0.892)	(0.129)	(0.112)	(0.497)		(0.762)	(0.806)	(0.895)	(0.185)	(0.091)	(0.874)
FDI	-0.038	0.019	-0.075**	-0.010**	0.006**	-0.014	FDI	-0.046*	0.006	-0.077*	-0.011***	0.006**	-0.024*
	(0.124)	(0.271)	(0.044)	(0.012)	(0.023)	(0.233)		(0.080)	(0.781)	(0.068)	(0.009)	(0.043)	(0.070)
FTP	-0.014	0.156***	-0.132***	-0.026*	0.019***	-0.054**	FTP	-0.020	0.138***	-0.126***	-0.026*	0.019***	-0.035
	(0.503)	(0.000)	(0.000)	(0.058)	(0.002)	(0.011)		(0.333)	(0.000)	(0.000)	(0.065)	(0.001)	(0.104)
Model criteria													
Cities	14	14	14	14	14	14		14	14	14	14	14	14
AR(1)	0.00321	0.000396	0.0785	0.00922	0.00313	0.0156		0.00311	0.000615	0.0521	0.00719	0.00581	0.0262
AR(2)	0.585	0.0205	0.183	0.426	0.660	0.801		0.462	0.0326	0.167	0.210	0.714	0.821
Hansen	0.695	0.462	0.872	0.601	0.521	0.878		0.674	0.465	0.826	0.560	0.513	0.712

Note: p-values are shown in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively. The model is estimated using the two-step system GMM. AR and Hansen show p-values.

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The left half of Table 4 presents the regression results for green finance and rural revitalization, represented by green credit (GF01) in Models 1.1 to 1.6, while the right half (Models 1.7 to 1.12) shows the results for green insurance (GF02) on rural revitalization. The results in Table 4 indicate that the direct effect of green credit (GF01) on the overall rural revitalization index (RR) is mostly statistically insignificant. However, for the sub-indicator of rural per capita disposable income (model 1.5, subr4), green credit shows a significant positive effect ($p < 0.1$), suggesting that green credit directly contributes to raising rural income levels.

In Table 4, Model 1.5, a 1% increase in green credit (GF01) corresponds to an average 0.024% rise in rural per capita disposable income (subr4) ($p < 0.1$). This suggests that the direct effect of green credit primarily boosts agricultural productivity and rural income through increased capital investment. But in Model 1.8, a 1% rise in the agricultural insurance claims ratio (GF02) correlates with an average 0.23% decline in the total output value of agriculture, forestry, animal husbandry, and fisheries (subr1). This may indicate that the claims process increases production costs through time and resource demands or that payouts do not immediately translate into productivity gains. A high claims ratio might also lead to risk-avoidance behaviors, with insurers adjusting premiums or policy terms to limit support for high-risk agricultural activities, potentially discouraging farmers from expanding production. Additionally, strict risk management measures, like restricting high-risk or high-pollution practices, could further reduce total output, which effects discussed by Just & Pope (2003) and Goodwin & Smith (2013). However, in Model 1.11, the claims ratio shows a positive impact on rural per capita income, suggesting that despite short-term production constraints, higher claims payouts can enhance long-term income stability. By providing financial security, green insurance helps farmers better cope with natural disasters and market fluctuations, stabilizing their long-term income expectations.

Although the direct impact of green finance on rural revitalization is not statistically significant in Table 4, introducing digitalization as a proxy for technological progress brings new dynamics. When digitalization moderates the relationship between green finance and rural revitalization, their interaction generates better effects across various aspects, as further explored in Table 5, which follows a similar format to Table 4.

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Table 5: Regression results of the impact of green finance on rural revitalization with digitalization moderation

	model 2.1 RR=RR	model 2.2 RR=subr 1	model 2.3 RR=subr 2	model 2.4 RR=subr 3	model 2.5 RR=subr 4	model 2.6 RR=subr 5
RR_{t-1}	0.526***	0.678***	-0.313**	0.991***	0.876***	0.095
	(0.001)	(0.000)	(0.028)	(0.000)	(0.000)	(0.646)
GF01*DIG	1.653***	0.936**	0.677***	0.100**	-0.090**	-0.193
	(0.000)	(0.013)	(0.000)	(0.036)	(0.042)	(0.190)
GF01	-4.905***	-2.872***	-1.941***	-0.239	0.289**	0.624
	(0.000)	(0.004)	(0.000)	(0.143)	(0.021)	(0.151)
DIG	4.936***	2.914***	2.232***	0.350***	-0.242**	-0.395
	(0.000)	(0.004)	(0.000)	(0.004)	(0.035)	(0.353)
NSE	0.284***	0.137	0.239***	-0.002	-0.028**	0.098**
	(0.006)	(0.112)	(0.000)	(0.915)	(0.020)	(0.027)
URBP	-0.329	-0.040	-0.601	0.082	0.068	-0.355
	(0.459)	(0.920)	(0.104)	(0.423)	(0.214)	(0.164)
FDI	-0.073**	-0.006	-0.087***	-0.011**	0.011***	-0.025
	(0.034)	(0.790)	(0.005)	(0.028)	(0.001)	(0.184)
FTP	-0.109***	0.109***	-0.110**	-0.023	0.023***	-0.002
	(0.008)	(0.007)	(0.011)	(0.120)	(0.000)	(0.910)
Model criteria						
Cities	14	14	14	14	14	14
AR(1)	0.0389	0.00324	0.0984	0.00512	0.00656	0.0646
AR(2)	0.229	0.316	0.654	0.176	0.920	0.416
Hansen	0.858	0.609	0.996	0.624	0.607	0.939

	model 2.7 RR=RR	model 2.8 RR=subr 1	model 2.9 RR=subr 2	model 2.10 RR=subr 3	model 2.11 RR=subr 4	model 2.12 RR=subr 5
RR_{t-1}	0.719***	0.732***	-0.435**	0.990***	0.868***	0.623**
	(0.003)	(0.000)	(0.018)	(0.000)	(0.000)	(0.026)
GF02*DIG	0.945***	0.883***	0.632**	0.099**	-0.113**	-0.420***
	(0.000)	(0.001)	(0.012)	(0.018)	(0.026)	(0.001)
GF02	-2.735***	-2.794***	-1.897**	-0.248*	0.358**	1.301***
	(0.000)	(0.000)	(0.013)	(0.056)	(0.011)	(0.001)
DIG	3.656***	3.449***	2.615***	0.429***	-0.398**	-1.436***
	(0.000)	(0.000)	(0.006)	(0.004)	(0.017)	(0.003)
NSE	0.159	0.124**	0.177***	-0.002	-0.029**	0.044
	(0.140)	(0.026)	(0.000)	(0.922)	(0.017)	(0.147)
URBP	-0.454	0.009	-0.053	0.107	0.070	-0.391**
	(0.313)	(0.979)	(0.792)	(0.255)	(0.526)	(0.031)
FDI	-0.026	-0.020	-0.093***	-0.014**	0.012*	0.006
	(0.462)	(0.300)	(0.009)	(0.042)	(0.065)	(0.734)
FTP	-0.070*	0.120***	-0.103**	-0.028*	0.024***	-0.044*
	(0.071)	(0.005)	(0.017)	(0.081)	(0.000)	(0.059)
Model criteria						
Cities	14	14	14	14	14	14
AR(1)	0.0680	0.00297	0.0317	0.00485	0.0212	0.0958
AR(2)	0.496	0.140	0.367	0.180	0.974	0.251
Hansen	0.926	0.613	0.981	0.652	0.584	1.000

Note: p-values are shown in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively. The model is estimated using the two-step system GMM. AR and Hansen show p-values.

As can be seen from Table 5, digitalization has a significant role in improving the effect of green finance in helping rural revitalization. Specifically, green credit (GF01) and green insurance (GF02), with the helping of digitalization, have a more obvious positive impact on rural revitalization and its sub-indicators. The reason behind this is not difficult to understand, digitalization has expanded the coverage of green credit, but also increased the proportion or effectiveness of agricultural insurance claims, thus making green finance more effective in promoting rural revitalization. Which is also supported by studies by Fu and Niu (2023) and Ye et al. (2023).

In models 2.1 and 2.7, we focus on the overall Rural Revitalization Index (RR). The results show that the interaction term of green credit and digitalization (GF01*DIG) and the interaction term of green insurance and digitalization (GF02*DIG) have a significant positive impact on rural revitalization. This shows that the role of green finance is further amplified when digitalization acts as a moderating factor. However, in models 1.1 and 1.7 (Table 4), digitalization is not taken into account as a moderating factor, and the results are less significant.

Moreover, the results indicate that the moderating effect of digitalization on green credit (GF01) consistently enhances rural revitalization indicators in Models 2.2, 2.3, and 2.4. This positive influence is reflected in the total output value of agriculture, forestry, animal husbandry, and fisheries, as well as in per capita agricultural machinery power and the added value of the primary industry. For example, digital inclusive finance can improve resource allocation by facilitating access to agricultural equipment through digital rental platforms, allowing rural areas to enhance effective agricultural machinery power. Scholtens and Dam (2007) highlight that the Equator Principles enable measurable and verifiable environmental benefits through technological progress, reducing information asymmetry between financial institutions and project parties. It can be inferred that the advancement of digitalization not only enhances financial institutions' ability to assess green credit risks but also strengthens the effectiveness of green finance policies in promoting rural revitalization by improving information transparency and data verification. Furthermore, agricultural big data platforms connect green finance providers, such as banks and funds, with demand-side entities, such as ecological farms and clean energy projects. This reduces intermediary costs, improves the efficiency of fund utilization, and provides stronger financial support for the agricultural green industry.

For green insurance (GF02), the direct impact of green insurance is not significant in Model 1.9 and Model 1.10 of Table 4, while the digitalization moderated green insurance in Table 5 has a significant positive impact on rural revitalization as shown in Models 2.9, and 2.10 in Table. Comparing Model 1.8 in Table 4 with Model 2.8 in Table 5, the positive impact of the agricultural insurance claim ratio on total agricultural output becomes significant at the 1% level after digitalization moderation. This suggests that digitalization significantly mitigates the negative direct effect of the agricultural insurance claim ratio. This could be due to the enhanced risk assessment and pricing accuracy through big data and blockchain technology, which reduce information asymmetry and increase insurance companies' willingness to support agriculture (Yekimov et al., 2023). Digitalization can also improve insurance claim efficiency, alleviating farmers' liquidity constraints and accelerating their recovery from losses (Benami & Carter, 2021). Additionally, smart agriculture and monitoring systems enhance risk management, minimizing potential losses (Said Mohamed et al., 2021). Moreover, digital empowerment enables green finance to provide more effective financing and insurance support for the primary industry, thereby promoting industrial value-added (Xiao et al., 2024; Jiang et al., 2024).

For the negative indicators of rural revitalization as pesticide and fertilizer usage (Models 2.6 and 2.12), while Model 2.6, which represents the interaction between green credit and digitalization, is not significant, Model 2.12 shows a negative significant interaction between digitalization and green insurance, which helps reduce pesticide and fertilizer usage. The coefficient of the interaction term in Model 2.12 is -0.420, significant at the 1% level. This suggests that for every 1% increase in the agricultural insurance payout rate with digitalization, pesticide and fertilizer usage decreases by an average of 0.42%, promoting agricultural production in a more environmentally friendly and sustainable direction, aligning with sustainable development goals, and consistent with Dong et al. (2025). In traditional agriculture, farmers may overuse pesticides and fertilizers to maximize yields and avoid production losses, leading to excessive fertilization and pesticide application. Digital tools enhance risk identification, making agricultural insurance more precise. When the payout rate increases, farmers know that they will receive reasonable compensation in case of natural disasters or pest outbreaks, reducing the need to rely on excessive pesticide and fertilizer use as self-protection measures. Local governments may leverage digital platforms to link insurance policies, guiding insured farmers to reduce pesticide and fertilizer usage, for example, by offering insurance discounts to encourage environmentally friendly agricultural practices.

However, after digital empowerment, the moderating effect of digitalization on green finance can cause some income fluctuations. As shown in Table 5, the coefficients for the interaction terms between green credit, green insurance, and digitalization in rural per capita disposable income (Models 2.5 and 2.11) are -0.090 and -0.113 ($p<0.05$), respectively, indicating a negative impact from the moderating effect of digitalization to income. This may be because, after digital empowerment, the scale of green credit and the insurance payout rate have higher usage thresholds, such as the need to learn how to use smartphones or computers for loan and insurance information access. This leads to increased adaptation costs for some agricultural workers in the short term, which in turn affects their short-term income levels (Rotz et al., 2019; Guo et al., 2024). Therefore, while promoting digitalization and green finance, corresponding training and support measures should be implemented to ensure rural residents have the ability to learn new technologies and truly benefit from the progress in digitalization.

5. Conclusion and Policy Recommendations

This study analyzes panel data from 14 prefecture-level cities in Guangxi from 2013 to 2021 and finds that as a moderating variable, digitalization significantly enhances the positive impact of green credit and insurance on rural revitalization, especially in areas like industrial prosperity and ecological livability, but it can cause fluctuations in rural per capita disposable income in the short run. Several policy recommendations are offered as follows:

Governments should encourage collaboration between financial institutions and technology companies to develop digital platforms for agricultural equipment leasing, with governments investing more in rural digital infrastructure as the basis for the operation of the platform. These platforms can optimize resource allocation, enhance machinery utilization efficiency, and reduce idle resources and waste. By precisely matching supply and demand, the platform can lower leasing costs and boost farmers' productivity.

Given the regression results show a negative correlation between digitalization-moderated agricultural insurance payouts and pesticide and fertilizer usage, local governments could leverage digital platforms to align insurance policies with rural revitalization. For example, digital platforms can monitor farmers' pesticide and fertilizer usage, allowing those who reduce inputs to receive lower premiums or faster claims processing.

To mitigate the short-term income volatility caused by the moderating effect of digitalization on green finance, governments, and relevant institutions should provide digital skills training for farmers, helping them master basic operations like using smartphones or computers to access loan and insurance information. Financial institutions should also simplify the digital processes for green credit and agricultural insurance, reducing technical barriers and learning costs. Additionally, the government could offer short-term economic subsidies or loan support to help farmers navigate the transition period.

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There are no potential conflicts of interest.

Data availability statement
The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

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