Green Technology, Agribusiness, and Rural Income Level: An Integration of Panel Data Estimation from China

Khizra Sardar[1], Zinaz Aisha[2] and Hina Ali[3]

https://doi.org/10.62345/jads.2026.15.2.8

Abstract

In recent years, the growing trend and adaptability of green technology, particularly in agribusiness, have garnered significant attention. Consequently, this research emphasises the adoption of green technology in agri-business and underscores its role in enhancing income levels. Additionally, this study aims to identify key obstacles to the sustainable adoption of green technology, including rising inflation, financial crises, and environmental emissions. To achieve this objective, a secondary dataset has been compiled from 30 different rural areas in China. For empirical analysis, time-series data spanning from 2011 to 2025 have been collected. Subsequently, the variables examined in this research include green agribusiness, gross regional product per capita, digital inclusive finance, inflation, research and development expenses, and CO2 emissions. The concluding remarks of this research suggest that green technology significantly contributes to green agribusiness and regional income per capita. Moreover, it underscores the importance of considering the role of CO2 emissions, inflation, and the adoption of modern financial mechanisms in this context."

Keywords: Green Technology, Agribusiness, Income, Rural China, CO2 Emissions, Inflation, and Digital Inclusive Finance.

Introduction

The literature has unequivocally shown a growing interest in adopting green technologies and consuming green products in recent years. Studies suggest that as the use of green products increases and advancements are made in green agribusiness, CO2 emissions are likely to decrease, thereby improving total factor productivity and, subsequently, raising the income levels of rural populations (Lee & Park, 2025). In China, a significant portion of its population is involved in agriculture and resides in rural areas. The gross agricultural production value of China was estimated to be around US$1,268 billion in 2023 (Statista, 2023), despite only 10 per cent of China's total land area being cultivated. Remarkably, China's agricultural sector ranks among the largest globally and caters to nearly 20 per cent of the world's population (Statista, 2023; FAO, 2023; Shoukat et al., 2021).

Nevertheless, this captures the attention of researchers and scholars. It fosters the critical need for further exploring & understanding the underlying contributors or influencers concerning the adoption of green technologies, green agribusinesses, income levels of rural masses, consumers

[1]*PhD Scholar, Department of Economics, The Women University Multan, Pakistan.*
Email: khizrasardar42@gmail.com
[2]*Assistant Professor, Department of Economics, Sardar Bahadur Khan Women's University Quetta, Pakistan.*
[3]*Professor, Department of Economics, The Women University Multan, Pakistan.*
Corresponding Author Email: hinaali@wum.edu.pk

Compliance with ethical standards: There are no conflicts of interest (financial or non-financial). This study did not receive any funding.

behavior towards green technology & products, and the impact of influential forces like increased inflation, carbon emissions, and antiquated mechanisms of financing (Green & Jones, 2016; Huang et al. 2019; Song et al. 2023). Furthermore, there is a literature gap in the micro-scale analysis of these forces, particularly in the examination of the agriculture sector and the green industry. By addressing these literature gaps, we can provide valuable insights into how organisations efficiently promote, implement, and manage sustainable practices to expand green agribusinesses, which, in turn, boost agricultural sector performance and raise rural households' incomes.

This research is imperative for multiple stakeholders at different levels. Firstly, organisations (or stakeholders) can benefit from empirical findings by gaining enriched insights into the adoption, promotion, and implementation of green products and technologies, consumer behaviour towards green products, and strategies to boost firm performance in the context of sustainable policies. Secondly, consumers can gain a deeper understanding of the forces influencing their actions and purchase decisions, and how their interactions influence the sustainability of the environment. Regulatory institutions and policymakers can utilise the empirical findings of this research to develop effective policies, regulations, and measures that, in turn, promote green technology adoption and support decisions on the consumption and production of green products and technologies. Besides, the research contributes significantly to the current body of knowledge by offering comprehensive and valuable insights into the complex association among green technologies, green products, consumer behaviour, and firm performance.

The central focus of this research is the interrelationship among green technologies, green products, the income levels of rural masses, and the performance of agribusinesses at the micro-scale. It encompasses thirty (30) different rural regions of China and explores the specific dynamics within the agriculture sector. The study incorporates a mixed-methods approach, including literature reviews, empirical analysis, and panel data estimation to provide a comprehensive understanding of this topic. However, it is important to acknowledge the study's limitations. The sample size (30 rural regions) may not fully represent the population, limiting the generalizability of the findings. Therefore, the limitation should be taken into consideration when interpreting and forecasting the overall results.

This research aims to achieve the following objectives:

Investigate the adoption of green technology in China's agricultural sector and identify the key challenges organisations face when implementing sustainable green agribusiness practices.

Integrate the income levels of rural China and forecast the forces that can raise rural incomes manifold.

Examine the impact of green technology adoption on firm performance, including environmental, economic, and innovation performance.

Explore the linkages between green technology, green products, income levels, and firm performance to understand their interconnected dynamics.

Literature Review

By examining the literature on agribusiness and green technologies over the past few decades, it was shown that agribusiness has increased carbon emissions in rural China. However, the performance of firms is a critical outcome affected by the adoption or effective utilisation of green technologies & products. Henceforth, it is evident that there's a need to scrutinise the influence of green technologies on environmental performance, economic stability, and firm competitiveness (Green and Jones, 2016; Song et al., 2023). Moreover, examining the linkage between green products& technologies and the performance of firms provides valuable insights into the potential benefits of linking sustainability in business strategies (Robinson & Thompson, 2015).

In this context, research and development (R&D) and technological innovations are required (Qin et al., 2023; Su et al., 2023). Sibuea and Siregar (2023) argued that green agribusiness has the capacity to raise rural communities' income levels. Similarly, consumer behaviour plays an imperative role in shaping the market for green products and affecting a firm's performance. (Ottman et al. 2025). Understanding the consumer decision-making process and the barriers to adopting green technologies helps firms overcome challenges and promote sustainable consumption (Davis & Miller, 2017; Hu & Xu, 2020).

The significance of green technologies is crucial because they can address pressing global environmental challenges and promote sustainable economic development. Green technologies offer a wide range of gains that contribute to a more sustainable and resilient future. One of the major benefits of green technologies is their role in preserving the environment (Huang et al. 2019; Chang et al. 2019). By reducing carbon emissions, minimising waste, and conserving natural resources, green technologies play an imperative role in mitigating climate change, protecting biodiversity, and preserving ecosystems. It offers innovative and effective solutions to mitigate environmental deterioration and ensure long-term global health (Wei & Su, 2019).

The contribution of green technologies and products is not limited to environmental sustainability; they also hold immense potential for accelerated economic growth and development. It signifies new industry development, job creation, and improved micro-financing opportunities and thus entails overall economic advancement (Sibuea and Siregar, 2023). The adoption and integration of green technologies open up opportunities for innovation, research and development, and the production of environmentally friendly products and services. All this not only benefits or concerns agribusinesses but indirectly stimulates economic growth and resilience (Wee & Lee, 2018).

Green technologies play an imperative role in advancing sustainable development objectives by addressing environmental, economic, and social challenges (Green & Jones, 2016; Song et al., 2023). Additionally, it presents innovative strategies to address environmental challenges, such as climate change and biodiversity, by promoting renewable energy sources, efficient energy use, waste management, and sustainable land use (Wei &Su, 2019). Regarding this, Sianturi and Feryanto (2023) argued that there's a need to control persistent inflation. Soliman et al. (2023) exhibited an asymmetric influence of increased inflation (CPI) on agricultural output.

Furthermore, the literature shows that the influence of green technology extends beyond agriculture. sector, but in turn, covers all sectors of an economy. As in the energy sector, green technology adoption has been substantial, particularly in renewable energy. The shift towards renewable energy, such as solar, wind, & hydroelectric power, has captured momentum as a static and sustainable alternative to conventional fossil-fuel-based energy generation. Green technology plays a pivotal role in harnessing and optimising renewable energy sources (Jamali & Abdallah, 2017; Wee & Lee, 2018; Wang et al., 2024).

In the transportation sector, these advancements in green technology aim to minimise environmental deterioration by improving energy efficiency and reducing reliance on fossil fuels (Wei and Su, 2019). Consequently, in the manufacturing industry, green technology adoption focuses on promoting sustainability across production processes. Manufacturers and industries are increasingly implementing green technologies (mainly in developed economies) to reduce energy consumption, enhance energy efficiency, and adopt practices to minimise environmental impacts and optimise resource utilisation. Green technology in manufacturing aims to achieve sustainable production while maintaining competitiveness and productivity (Wee & Lee, 2018; Chen et al., 2024).

Empirical Research & Statistical Examination

This research examines the relationship between green technology, green agribusinesses, and income level at the micro-level in Rural China. This research uses time-series data from 30 rural regions of China spanning 2011 to 2025. These regions include Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. Data for the examined series have been collected from well-recognised and authentic sources, such as the Statistical Yearbook of China's Economy, China's Science and Technology Statistical Yearbook, China's Rural Statistical Yearbook, and so on. Additionally, data have been collected from provincial statistical yearbooks, annual reports, statistical bulletins, and the Wind Information database to ensure comprehensive coverage and reliability.

Table 1: Variables Description and Unit of Measurement

Variables	Data Source	Relationship	Unit of Measurement
Dependent Variables :			
Log of no. of Green Agribusiness in Region	China Statistical Yearbook	+	%
Log of Gross Regional Products Per Capita	China Tertiary Industry Statistical Yearbook	+	%
Independent Variables :			
Digital Inclusive Finance Index (DIF)	Authors' on calculation China Tertiary Industry Statistical Yearbook	+	%
Consumer Price Index (CPI)	China Rural Statistical Yearbook	-	%
Ratio of Expenses on Science & Technology (R&D)	China Science and Technology Statistical Yearbook	+	%
Agriculture Co2 Emissions	Author's calculation using China Tertiary Industry Statistical Yearbook	-	%

Source: Authors Own Creation

In the above displayed table, the dependent and independent variables of this research are listed along with their data source and expected signs based on theories.

Methodological Framework

This research occupies two econometrics models. Model 1 aims to reflect the impact of green technology adoption on firm performance, including environmental performance, economic performance, and innovation capabilities.

$LGAB_{it} = \beta_0 + \beta_1 DIF_{it} + \beta_2 CPI_{it} + \beta_3 R\&D_{it} + \beta_4 ACO2_{it} + \beta_5 LGPRC_{it} + ứ_{it}$ ……………………(1)

Furthermore, the second model aimed to reflect the role of green technology in raising the income level of rural masses. Consequently, both model encompasses the key challenging forces such as inflation, CO2 emissions, and backwardness of the financial sector in agriculture. These forces hinder the implementation of sustainable practices and the attainment of overall benefits attached to green technology.

$LGPRC_{it} = \beta_0 + \beta_1 DIF_{it} + \beta_2 CPI_{it} + \beta_3 R\&D_{it} + \beta_4 ACO2_{it} + \beta_5 LGAB_{it} + \acute{r}_{it}$ …………….…..(2)

The following abbreviations replicate:

DIF = digital inclusive finance index

CPI = inflation

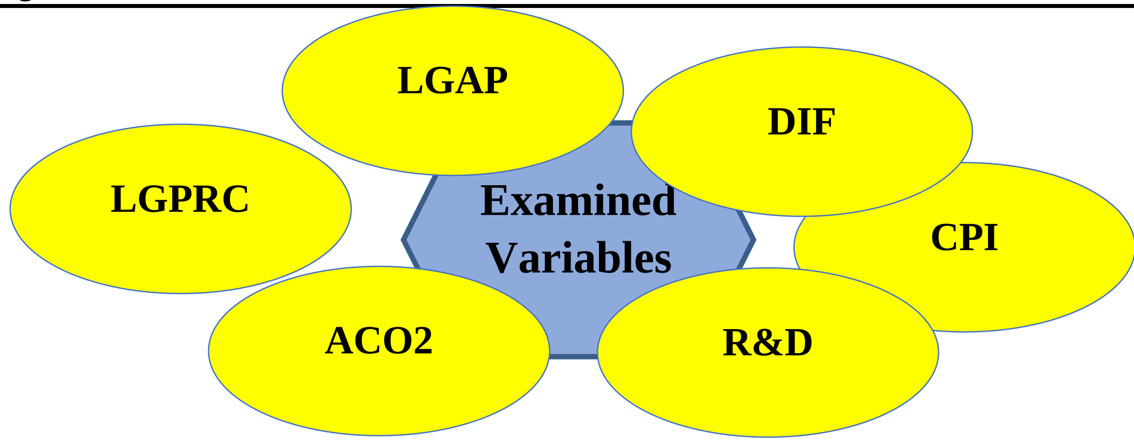
R&D = ratio of expenses on science & technology

ACO2 = agri. Co2 emissions

LGPRC = log of gross regional products per capita

LGAP = log of no. of green agribusiness

Figure 1: Models Flow Chart



Source: Authors Own Creation using MS-Word

In the above presented flow, the researcher tries to explicate all examined (dependent and independent) variables of this research.

Statistical Examination

The methodology and estimation techniques followed in this research are detailed in the following.

Table 2: Descriptive Statistics

Stat.	LGPRC	DIF	CPI	R&D	ACO2	GAB
Mean	8.524	217.246	116.527	2.093	341.442	10.840
Median	8.547	224.105	116.274	1.376	325.976	10.789
Maximum	10.375	431.930	133.613	6.756	995.752	12.013
Minimum	6.238	18.330	104.851	0.388	14.354	9.705
Std. Dev.	0.869	96.968	6.956	1.464	231.765	0.436
Skewness	-0.122	-0.285	0.159	1.256	0.740	0.362
Kurtosis	2.264	2.284	2.159	3.497	3.428	2.842
Jarque-Bera	7.505	10.461	10.095	82.045	29.735	6.870
Probability	0.023	0.005	0.006	0.000	0.000	0.032
Sum	2557.290	65173.84	34958.20	628.032	102432.8	3252.192
Sum Sq. Dev.	226.188	2811448.	14470.60	641.045	1606	56.874

Source: Author's Calculations using Eviews

In the subsequent table, descriptive statistics demonstrates a summary of salient features contained by the examined data series. As it is shown that except LGPRC and DIF all other variables are positively skewed. Consequently, all examined variables are plety-kurtic except for the case of R&D and AC02 which are lepokurtic. Jarque-bera statistics replicates the normality distribution of considered series. Additionally, based on probability values all examined variables are statistically significant. In the end, the overall number of examined observations is 300.

Table 3: Correlation matrix

variables	LGAB	DIF	CPI	R&D	AC02	LGPRC
LGAB	**1.000**					
DIF	0.549	**1.000**				
CPI	0.463	0.929	**1.000**			
R&d	0.136	0.343	0.130	**1.000**		
AC02	0.479	-0.075	-0.083	-0.156	**1.000**	
LGPRC	0.143	0.613	0.425	0.726	-0.193	**1.000**

Source: Author's Calculations using Eviews

The following table shows the correlation between the examined variables of this research. Based on these statistics, we do state that there's no multicollinearity as no variables confirm a high (severe) correlation with each other. Each variable confirmed perfect correlation with itself shown by diagonal digit. Although, correlation with other variables ranges between zero and one, and varies for each combination as shown above.

Table 4: Unit Root Test (Levin, Lin, Chu)

Variables	Level		1st Difference		Conclusion
	Intercept	Intercept & Trend	Intercept	Intercept & Trend	
LGAB	-1.039 (0.149)	-8.723* (0.000)	-4.860* (0.000)	-6.994* (0.000)	I(0,1)
GRPC	3.538* (0.019)	-4.090* (0.004)	5.238* (0.000)	5.315* (0.000)	I(0,1)
DIF	-15.570* (0.000)	-14.321* (0.000)	-14.662* (0.000)	-7.071* (0.000)	I(0,1)
CPI	-6.572* (0.000)	-14.032* (0.000)	-11.609* (0.000)	-11.528* (0.000)	I(0,1)
R&D	-1.273 (0.101)	-8.499* (0.000)	-9.334* (0.000)	-30.236* (0.000)	I(0,1)
AC02	-1.039 (0.149)	-8.723* (0.0000)	-4.860* (0.000)	-6.994* (0.0000)	I(0,1)

Source: Author's Calculations using Eviews

The following table exhibits panel unit root test estimates for considered variables of this research. The researcher utilized the "Levin, Lin, and Chu unit root test" for the above examination. Test results disclosed that all variables of this study are statistically significant. Besides, almost all variables confirmed their significance at a 1% level of significance. All variables affirmed their significance at the level which reflects that the data series does not possess any kind of trend.

However, all variables are also stationary both at the level and first difference which is shown by the cointegration level conclusion (0,1).

Table 5: Granger Causality

Pairwise Granger Causality Tests			
Lags: 2			
Null Hypothesis:	**Obs**	**F-Statistic**	**Prob.**
DIF does not Granger Cause LGAB	240	14.643	0.006
LGAB does not Granger Cause DIF		5.008	0.007
CPI does not Granger Cause LGAB	240	34.748	0.001
LGAB does not Granger Cause CPI		8.850	0.002
R&D does not Granger Cause LGAB	240	3.208	0.042
LGAB does not Granger Cause R&D		4.309	0.014
ACO2 does not Granger Cause LGAB	240	7.334	0.008
LGAB does not Granger Cause ACO2		4.659	0.010
LGPRC does not Granger Cause LGAB	240	5.396	0.005
LGAB does not Granger Cause LGPRC		0.862	0.423
CPI does not Granger Cause DIF	240	12.155	0.006
DIF does not Granger Cause CPI		19.055	0.008
R&D does not Granger Cause DIF	240	26.553	0.001
DIF does not Granger Cause R&D		1.125	0.326
ACO2 does not Granger Cause DIF	240	1.376	0.254
DIF does not Granger Cause ACO2		7.358	0.008
LGPRC does not Granger Cause DIF	240	28.932	0.001
DIF does not Granger Cause LGPRC		3.162	0.044
R&D does not Granger Cause CPI	240	0.268	0.764
CPI does not Granger Cause R&D		0.854	0.426
ACO2 does not Granger Cause CPI	240	11.033	0.005
CPI does not Granger Cause ACO2		16.729	0.007
LGPRC does not Granger Cause CPI	240	2.989	0.052
CPI does not Granger Cause LGPRC		2.377	0.095
ACO2 does not Granger Cause R&D	240	0.478	0.620
R&D does not Granger Cause ACO2		0.450	0.637
LGPRC does not Granger Cause R&D	240	0.906	0.405
R&D does not Granger Cause LGPRC		7.562	0.007
LGPRC does not Granger Cause ACO2	240	1.395	0.249
ACO2 does not Granger Cause LGPRC		0.957	0.385

Source: Author's Calculations using Eviews

The above displayed table demonstrates Granger causality between all examined variables carried out in this research. It is revealed that there's bidirectional (two way causality) between LGAB and DIF which is statistically significant. Similarly, CPI and LGAB do confirm two-way causality. Besides, R&D with LGAB and ACO2 with DIF have confirmed bidirectional causality. On the contrary, LGPRC and LGAB do confirm unidirectional (one way) causality with each other. Although, CPI confirmed bidirectional, R&D confirmed unidirectional causality with DIF. Consecutively, ACO2 also disclosed bidirectional causality with DIF. However, LGPRC replicated bidirectional causality with DIF. All remaining combinations do confirm either one-way or two-way causality with each other. Henceforth, based on this, we can conclude that there exists cause and effect relationship between all examined variables of this research.

Table 6: Robust Panel Least Square Regression (model-1)

Dependent Variable: LGAB				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
DIF	0.012	0.001	10.563	0.000
CPI	-0.072	0.014	-5.051	0.000
R&D	0.093	0.031	2.940	0.003
ACO2	0.001	0.000	13.208	0.000
LGPRC	0.428	0.123	-7.491	0.000
C	23.596	2.142	11.013	0.000
R-squared	0.655	**Durbin-Watson stat**		1.979
Adjusted R-squared	0.650	**S.E. of regression**		0.514
F-statistic	112.081	**Prob(F-statistic)**		0.000

Source: Author's Calculations using Eviews

The above exhibited table shows the robust least square estimation for examining cointegration between green agribusiness and other examined variables of this research. Despite living in today's digitalized and global world, still people, usually living in rural areas prefer and do use old ways of financing. Which is not only tedious, time consuming, but also lacks many benefits attached to digitalizing (Klerkx, Jakku, & Labarthe, 2019; Wang et al., 2023; Liu et al., 2023). Therefore, with the help of this model, the researcher tries to show that utilizing digital inclusive finance in green agribusiness will surely flourish and grow manifold. Here, DIF confirmed a statistically significant association with LGAB. A one percent increase in DIF will raise agribusiness to 0.01 percent for the case of rural China. On the contrary, an increase in the inflation rate will cause LGAB to decline by 0.07 percent. With increased inflation expenses incurred by agribusiness also increase which is why it affirms a negative association (Sianturi & Feryanto, 2023; Soliman et al., 2023). Furthermore, R&D causes a 0.09 percent increase in LGAB as increased research and development concerning agribusiness will surely bring the usage of modern technologies that'll be more effective and less costly (Su et al., 2023; Li, Gao, & Wang, 2023). On the other side, ACO2 affirmed a positive association with LGAB but the ratio is 0.001 which is also statistically significant. Carbon emissions tend to increase in rural China because of increased fertilizer usage. Therefore, in 2025, China introduced "zero-growth-fertilizers-policy". As we know, with green technology the level of CO2 emissions is reduced (Song et al., 2023; Huang et al., 2023). Therefore, the contribution of CO2 emissions here is quite low. Besides, gross regional product per capita (LGPRC) will tend to increase with the LGAB. Therefore, LGPRC and LGAB confirmed a positive association (Heberling, Templeton, & Wu 2012; Sibuea & Siregar, 2023; Nasution, Batubara, & Arif, 2023). In the end, R2 and Adjusted-R2 replicate that this model explains around 65% variation in LGAB. Therefore, we can rely on this model, for future forecasting concerning agribusiness in rural China. The F-statistics also confirmed the overall significance of the examined variable. Additionally, Durbin Watson statistics show that autocorrelation is not a leading problem in the case of our examined model.

Table 7: Robust Panel Least Square Regression (model-2)

Dependent Variable: LGPRC				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
DIF	0.004	0.004	8.695	0.000
CPI	-0.024	0.006	-3.859	0.001
R&D	0.155	0.011	13.094	0.000
ACO2	0.218	0.001	0.743	0.457
LGAB	0.172	0.023	-7.491	0.000
C	12.525	0.648	19.312	0.000
R-squared	0.745	**Durbin-Watson stat**		1. 982
Adjusted R-squared	0.723	**S.E. of regression**		0.229
F-statistic	157.183	**Prob(F-statistic)**		0.000

Source: Author's Calculations using Eviews

The above exhibited table shows the robust least square estimation for examining cointegration between rural incomes and other examined variables of this research. With the help of this model, the researcher tries to elucidate that green agribusiness can uplift rural income levels. Additionally, by using digital inclusive finance, and by controlling for inflation rural income mainly generated by agriculture can be raised manifold (Lee, Lou, & Wang, 2023. This model also controls for CO2 emissions and stresses the need for more research & development in agri. technology to boost total factors productivity and rural income level. Here, with the help of this model, the researcher tries to show that by utilizing digital inclusive finance in rural China, income levels will surely uplift (Xu & Wang, 2023). Here, LGPRC and DIF confirmed a statistically significant association. A one percent increase in DIF will raise rural income by 0.04 percent for the case of rural China. On the contrary, an increase in the inflation rate will cause LGPRC to decline by 0.02 percent. With increased inflation, it will be difficult for rural masses to utilize their incomes properly which is why it asserts a negative association with income level (Talukdar, 2012). Moreover, R&D caused a 0.15 percent increase in LGPRC as increased research and development (R&D) might result in more utilization of modern technologies that will be more effective and less costly (Qin, Zhang, & Zhao, 2023). On the contrary, ACO2 revealed a positive association with LGPRC which is statistically significant. As with increased income level, production level increases along with this, the level of CO2 emissions (that's a drastic issue for the overall globe) will also tend to increase. Therefore, there's a need to consider control over CO2 emissions by using green technologies in agribusiness (Zhang et al., 2023). Besides, LGAB affirmed a positive effect (0.17) as income level will tend to increase with LGAB. Henceforth, LGPRC and LGAB confirmed a positive association (Nasution, Batubara, & Arif, 2023). In the end, R2 and Adjusted-R2 replicate that this model explains around 74% variation in LGPRC. Therefore, we can rely on this model, for future forecasting concerning income level in rural China. The F-statistics also confirmed the overall significance of the examined variable. Additionally, Durbin Watson statistics show that autocorrelation is not a leading problem for the case of the subsequently examined model.

Diagnostic Testing

Figure 2: Residual Plot (model-1)

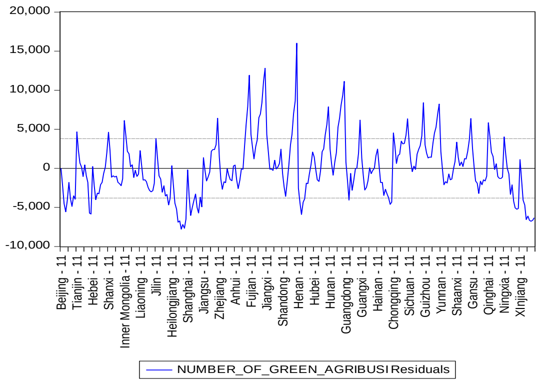
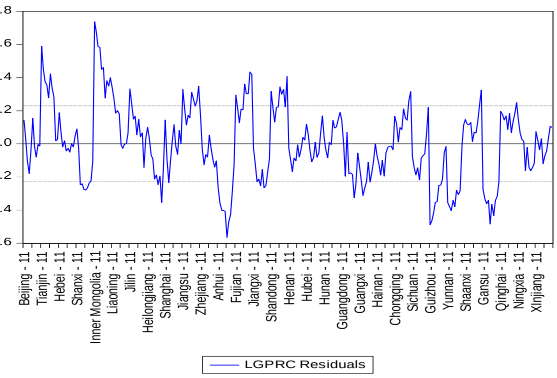


Figure 3: Residual Plot (model-2)



Source: Author's Calculations using Eviews

Subsequent residual graphs for both models replicate that residuals do not follow any consistent pattern. Hence, there's no autocorrelation and heterogeneity in the examined models.

Figure 4: Normality Tests (model-1)

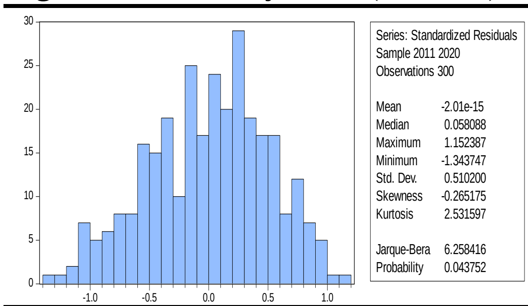
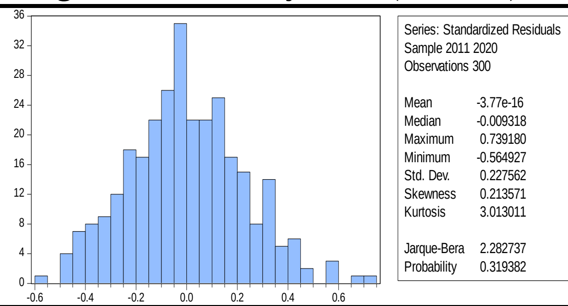


Figure 5: Normality Tests (model-2)



Source: Author's Calculations using Eviews

The following normality graphs, for both models confirmed that examined series are normally distributed towards their means.

Conclusion

In today's globalized world, where environmental degradation is a serious issue. There's a wider scope and need for the adoption of green technology and products. With the adaption of green technology in agri-business of rural areas not only firms will gain benefits but also consumers. As with increased green technology along with the firm's profit level, consumers' income level also uplifts. Therefore, this research tries to examine this intuition in the case of rural China. It is a case study of 30 different rural regions of China. The statistical examination reflects that green technology significantly contributes to or uplifts green agribusiness. Additionally, gross regional products of rural China also increased with the adoption of green technology which reflects that consumer income has increased. Consequently, financial services need to be digitalized in rural areas, the inflation level needs to be controlled, and research and development expenses need to be raised to boost obtained gains from green technology.

References

- Chen, X., Huang, Z., Luo, C., & Hu, Z. (2024). Can agricultural industry integration reduce the rural–urban income gap? Evidence from county-level data in China. *Land, 13*(3), 332.
- Davis, M., & Miller, S. (2017). Consumer decision-making process for green products: A comparative study. *Journal of Consumer Behavior, 32*(4), 145–162.
- Food and Agriculture Organization. (2023). *China at a glance*. https://www.fao.org/fao-in-china
- Green, R., & Jones, T. (2016). Green innovation and firm performance: A meta-analysis. *Journal of Business Sustainability, 21*(2), 78–95.
- Heberling, M. T., Templeton, J. J., & Wu, S. (2012). Green net regional product for the San Luis Basin, Colorado: An economic measure of regional sustainability. *Journal of Environmental Management, 111*, 287–297.
- Hu, Y., & Xu, S. (2020). Income-growth effects of rural industry integration in Zhejiang Province of China: An application of the new GRA embedded panel data regression model. *Journal of Grey System, 32*(2).
- Huang, X., Xu, X., Wang, Q., Zhang, L., Gao, X., & Chen, L. (2019). Assessment of agricultural carbon emissions and their spatiotemporal changes in China, 1997–2016. *International Journal of Environmental Research and Public Health, 16*(17), 3105.
- Jamali, D., & Abdallah, H. (2017). Green technology implementation challenges: Evidence from the energy sector. *Journal of Cleaner Production, 147*, 553–566.
- Klerkx, L., Jakku, E., & Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. *NJAS – Wageningen Journal of Life Sciences, 90*, 100315.
- Lee, C. C., Lou, R., & Wang, F. (2023). Digital financial inclusion and poverty alleviation: Evidence from the sustainable development of China. *Economic Analysis and Policy, 77*, 418–434.
- Lee, H., & Park, Y. (2025). Green technology: Definition, concepts, and applications. *Sustainability, 12*(7), 2867.
- Li, L., Gao, Y., & Wang, X. (2023). Impact of economic policy uncertainty on agribusiness technology innovation: Evidence from 231 listed firms in China. *Sustainability, 15*(13), 10037.
- Liu, D., Li, Y., You, J., Balezentis, T., & Shen, Z. (2023). Digital inclusive finance and green total factor productivity growth in rural areas. *Journal of Cleaner Production, 418*, 138159.
- Nasution, H. M., Batubara, M., & Arif, M. (2023). Rural agribusiness business development strategy in increasing farmers' income (case study of joint farmer group in Deli Serdang). *Journal of Humanities and Social Studies, 7*(1), 232–238.
- Ottman, J., Stafford, E., & Hartman, C. (2025). Green marketing and consumer behavior: Factors influencing green product purchases. *Journal of Consumer Marketing, 37*(3), 294–309.
- Qin, Z., Zhang, H., & Zhao, B. (2023). Impact of R&D investment and network penetration on human development: Evidence from China. *Social Indicators Research*, 1–25.
- Robinson, E., & Thompson, G. (2015). Economic implications of green technology adoption: Evidence from manufacturing firms. *Journal of Environmental Economics, 18*(3), 105–120.
- Shoukat, S., Ashraf, I., Ali, H., & Ali, M. Z. (2021). China's increasing investments and relationships with sea line countries of Indian Ocean: A geopolitical strategy. *Pakistan Journal of Humanities and Social Sciences, 9*(3), 555–564.

- Sianturi, E. Y., & Feryanto, F. (2023). The impact of macroeconomics and the COVID-19 pandemic on the sustainability of agribusiness companies in Indonesia. *Sustainability Science and Resources*, *4*, 7–33.
- Sibuea, F. A., & Siregar, G. (2023, May). Analysis of the contribution of agribusiness microfinance institutions on increasing farmers’ income in Serdang Bedagai District. In *Proceedings of the 3rd International Conference on Agriculture (ICA 2022)* (Vol. 33, p. 151). Springer Nature.
- Soliman, A. M., Lau, C. K., Cai, Y., Sarker, P. K., & Dastgir, S. (2023). The asymmetric effects of energy inflation, agri-inflation and CPI on agricultural output: Evidence from the NARDL and SVAR models in the UK. *Energy Economics*, 106920.
- Song, S., Zhao, S., Zhang, Y., & Ma, Y. (2023). Carbon emissions from agricultural inputs in China over the past three decades. *Agriculture*, *13*(5), 919.
- Statista. (2023). *Agriculture in China: Market forecast*. https://www.statista.com
- Su, Z., Zhang, M., Sun, J., & Wu, W. (2023). Agribusiness diversification and technological innovation efficiency: A U-shaped relationship. *Agribusiness*, *39*(2), 322–346.
- Talukdar, S. R. (2012). *The effect of inflation on poverty in developing countries: A panel data analysis* (Doctoral dissertation).
- Wang, J., Peng, L., Chen, J., & Deng, X. (2024). Impact of rural industrial integration on farmers' income: Evidence from agricultural counties in China. *Journal of Asian Economics*, *93*, 101761.
- Wang, X., Zhu, Y., Ren, X., & Gozgor, G. (2023). The impact of digital inclusive finance on the spatial convergence of green total factor productivity in Chinese cities. *Applied Economics*, *55*(42), 4871–4889.
- Wee, Y., & Lee, J. (2018). Green technology adoption in the manufacturing industry: A case study of Company XYZ. *Journal of Sustainable Engineering*, *21*(3), 124–139.
- Wei, Y., & Su, M. (2019). The importance of green technology in achieving sustainable development. *Environmental Science and Pollution Research*, *26*(14), 13633–13645.
- Xu, S., & Wang, J. (2023). The impact of digital financial inclusion on the level of agricultural output. *Sustainability*, *15*(5), 4138.
- Zhang, R., Wu, K., Cao, Y., & Sun, H. (2023). Digital inclusive finance and consumption-based embodied carbon emissions: A dual perspective of consumption and industry upgrading. *Journal of Environmental Management*, *325*, 116632.
- Герасименко, А. (2023). The influence of socio-economic factors of motivation on labor productivity in the effective agribusiness system. *Financial and Credit Activity: Problems of Theory and Practice*, *1*(48), 378–387.