Journal of Agribusiness and Social Sciences 1 (2026)

Journal of Agribusiness and Social Sciences (JASS)

https://journals.ageconfrontiers.com/jass

Technology Innovation and Agricultural Emissions: Evidence on Environmental Sustainability in China

Sadaf Shahab, Muhammad Tariq Mahmood [a, *]

[a] *Department of Economics, Federal Urdu University of Arts, Science & Technology, Islamabad, Pakistan*

A R T I C L E I N F O

Article History:
Received 16 March 2026
Accepted 2 April 2026
Available online 11 May 2026

Keywords:
Sustainability
Agricultural emissions
Technological innovation
EKC
Agro Machinery

A B S T R A C T

The objective of this paper is to identify the impact of technical innovation in the agricultural sector on the agricultural carbon intensity in China. The study uses data from 1990 to 2021 and employs multiple time-series techniques to do a robust analysis. The results indicate that the technical innovation has helped reduce the negative externality of agricultural output in China, with the presence of a significant environmental Kuznets curve (EKC). Further, it finds the years 2005-06 to be a turning point for the EKC. The study used technical innovation as a binary variable to identify the impact on agricultural production and emissions. The Standard VAR and Causality tests imply a significant role technology plays in helping the masses in increasing their output, with less harm to the environment. The study concludes that for sustainable agro growth, the technological innovations should help the peasant sector in applications through training and awareness.

Introduction

Accelerating low-carbon development has grown in importance for many nations throughout the world as the effects of global warming issues. Farmers and agribusinesses may expand food production and take part in value-added processing due to access to clean, dependable electricity. Additionally, it enables farmers operating in remote locations to replace costly diesel generators with more modern and eco-friendly equipment like solar food dryers and solar water irrigation. The market for solar agricultural technologies is still in its infancy, and obstacles include relatively high technology costs, a lack of widespread knowledge of the advantages, a lack of effective policy incentives, and restricted access to financing for farmers and suppliers to make solar technologies more affordable. Carbon intensity of electricity is a gauge of its cleanliness. It expresses of the amount of carbon dioxide (CO_2) that is released in order to generate one kilowatt hour (kWh) of electricity. Fossil fuels are used to generate electricity, which has a higher carbon footprint because CO_2 emissions are produced during the generation process. The carbon intensity value of renewable energy sources, such as wind, hydro, or solar power, is significantly lower and frequently zero because they emit almost no CO_2. If electricity is used with a low-carbon intensity throughout the day when the cleanest electricity is being produced, it can reduce overall carbon emissions.

The Chinese government publicly announced its long-term plans to reach carbon neutrality by 2060 and reach a peak in carbon emissions by 2030 (Wu et. al. 2021). This ambitious objective pushes China's growth toward a low-carbon economy and has the potential to considerably decrease global warming (Liu & Yang, 2021). With 17% of the nation's overall emissions coming from agriculture, China has much greater carbon emissions than the worldwide average of 11% (Huang, et. al. 2019). In addition to being a crucial component of China's "dual carbon" agenda, encouraging the reduction of carbon emissions in agriculture is also essential to expediting the development of an agricultural ecological civilization. Farmers in China can gain access to a vast and helpful ecosystem with the aid of agro-tech and a new business model that is driven by digital innovation throughout the entire agricultural value chain. Modern agriculture platforms and smart farming technology such as drone and satellite imagery and pattern modelling can help transform farmers' mobile phones into knowledgeable environmental tools and resources.

The future of global agricultural growth lies not just in making agricultural production more ecologically responsible and sustainable, but also in linking farmers and the people who eat their food digitally. Li, and Qin, (2019) suggest an emission permit allocation model that is based on efficiency and energy conservation and emission reduction technologies as a solution to this issue. Because China is such a large country, regional economic progress is unevenly distributed. It is impossible to distribute the burden of the emission reductions made by each region evenly.

* Corresponding author. *E-mail address:* mahmoodtariq@fuuast.edu.pk (Muhammad Tariq Mahmood).

Farmers and agribusinesses may expand food production and take part in value-added processing thanks to access to clean, dependable electricity. Additionally, it enables farmers operating in remote locations to replace costly diesel generators with more modern and environmentally friendly equipment like solar food dryers and solar water irrigation. The market for solar agricultural technologies is still in its infancy, and obstacles include relatively high technology costs, a lack of widespread knowledge of the advantages, a lack of effective policy incentives, and restricted access to financing for farmers and suppliers to make solar technologies more affordable.

In this paper we investigate the relationship between changes in agricultural technology and the emission intensity. We also estimate the turing point for so-called Environmental Kuznets Curve (EKC) to find the level of output to be significant for ecological improvement. For this paper we have used emission intensity of agriculture sector and can easily proxy it for carbon intensity factor used in some earlier literature (see for example: Hatfield et al., 2020; Smith et al., 2014; Tongwane and Moeletsi, 2020).

Review of Literature

Numerous research on the assessment of agricultural carbon emissions have been conducted during the last 20 years. Dalgaard et al. (2011) used the Intergovernmental Panel on Climate Change's technique to estimate agricultural GHG emissions in Denmark. Based on earlier research, Tian et al. (2014) computed China's agricultural carbon emissions from 1995 to 2010. However, the outcomes of various estimating techniques could vary. Bell et al. (2014) compared the new strategy adopted by the Scottish Government with the IPCC guidelines and national communications and questioned the IPCC guidelines for GHG inventories, believing that the IPCC guidelines ignored soil emissions during agricultural land-use change in its agricultural inventory. The intensity of GHG emissions from worldwide agricultural output was assessed by Bennetzen et al. (2016).

The assessment of agricultural carbon emissions has benefited significantly from these research. Since Kraft and Kraft's (1978) groundbreaking exploration, the connection between energy use and economic growth has gained popularity. The majority of empirical findings show a positive correlation between energy use and economic growth (Mahmood et. al., 2019; Gozgor et al., 2018; Odhiambo, 2009; Tang et al., 2016; Zhixin and Xin, 2011). However, with the nation's economy growing quickly, issues with energy scarcity and pollution have made it difficult for the economy to grow sustainably. Additionally, it has been established that energy consumption is a link between environmental sustainability and economic growth (Mahmood and Shahab, 2014; Mahmood et. al., 2022).

However, Edoja et al. (2016) looked at the dynamic relationship between carbon output, agricultural performance, and food security for Nigeria. The findings of the vector autoregressive model and the impulse response functions show that the short-run relationships between CO2 emissions and food security and agricultural production are inverse and statistically significant. Furthermore, according to the variance decomposition results, CO2 emissions are responsible for around 23% and 22% of the variations in agricultural output and food security, respectively. Additionally, the Granger causality test findings show a one-way causation between CO2 emissions and food security as well as between CO2 emissions and agricultural production. According to simulation studies by Mulatu et al. (2016), CO2 emissions have a negative impact on family wellbeing and agricultural output.

The use of fossil fuel-based industrial fertilizers and machinery, particularly motorized pumps, allowed for the elimination of key constraints related to soil nutrients, labour and water supplies. Agricultureal land efficiency was increased by innovations in the nitrogen fertilizer, irrigation, and other technology industries (Burney et al., 2010). However, such innovations did not always result in input cost reductions (Pellegrini and Fernandez, 2018; Hamant, 2020). Consequently, even if food output has increased globally over the past few decades, this has had a significant negative impact on the ecosystem. Environmental degradation brought on by CO2 and "greenhouse" gas (GHG) emissions increases heat intensity, which contributes significantly to a decline in agricultural produce (Hatfield et al., 2020).

The decoupling approach can identify the relationships among the elements, and is widely used to investigate the relationship between energy use, CO2 emissions, and economic growth (Wang and Feng, 2019). For instance, Zhang and Wang (2013) use the decoupling model to explore how China's economic development and CO2 emissions are related. In China's Shandong province, Wang and Liu. (2017) found a link between power output and CO2 emissions; Zhang et al. (2018) looked at the degree of decoupling between economic growth and coal use. To examine the relationship between industrial outputs and fossil fuel use in China, Meng et al. (2017) evaluated the decoupling approach.

According to Khan et al. (2020) for the Nordic nations, the renewable energy not only improves air quality but also does not hinder economic growth. Sharif et al. (2020) investigate the connection between environmental deterioration and renewable energy consumption in the most polluted ten nations and reveal a significant connection between these variables. Additionally, nuclear and renewable energy considerably lower emissions while adjusting for trade liberalisation and the environmental Kuznets curve.

However, the results are comparable in SAARC nations; the use of renewable energy reduces emissions. Quantile autoregressive distributed lag was used by Aziz et al. (2020) to evaluate the EKC hypothesis based on quantile behaviour of the relationship between economic growth, renewable energy, agricultural production, environmental deterioration, and forest area (QARDL). They discovered that the production of agriculture had a detrimental impact on ecological footprints. Using a panel vector error correction model (VECM) for the lucky-seven countries, Eyuboglu and Uzar (2020) examined the interrelationships between the consumption of renewable energy, carbon emissions, and agriculture. They found that agriculture improves renewable energy and CO2 emissions help to reduce CO2 emissions.

Numerous investigations have been made to explore the connection between the volume of output and CO2 emissions in the context of several nations. Markedly, Omri [2013] showed that in the situations of some middle east economies CO2 emissions and the scale of production are monotonically linked, holding other parameters constant. Similar evidence was discovered in several other research, including those by Ang [2008] for Malaysia, Pao and Tsai [2011] for Brazil, Alam et al. [2011] for India and Lotfalipour et al. [2010] for Iran. However, a number of studies show that the relationship between production and CO2 emissions for various countries follows an inverted U-shaped EKC, including Al-Mulali et al. [2015] for high- and upper-middle-income countries, Acaravci and Ozturk [2010] for Denmark and Italy and Shahbaz et al. [2014] for Tunisia. There are two other studies that concentrate on Saudi Arabia: Liu et al. (2012) and Taher and Hajjar (2014) which are helpful in determining in determining a future energy policy for Saudi Arabia.

The research on the EKC hypothesis has recently been expanded to cover several more crucial elements, such financial development. Some researcher argue that absence of this key variable might produce false findings (Dasgupta et al., 2001; Tamazian et al., 2009; Islam et al., 2013; Shahbaz et al., 2013; Jiang and Xiaoxin, 2019). An improved financial system serves as a catalyst for the advancement of environmentally friendly industrial technologies, which in turn leads to better energy infrastructure and lower CO2 emissions.

Agriculture value-added is cited in the literature as having a significant impact on environmental deterioration (Mahmood et al., 2019; Duxbury et al., 1993). However, the research on the potential connection between the value-added to agriculture and CO2 emissions is still ambiguous. According to Mahmood et al. (2019), the agriculture industry contributes to lowering carbon emissions, which helps slow down environmental deterioration. On the other hand, according to Duxbury et al. (1993), the livestock and agricultural industries are significant producers of methane and nitrogen emissions. According to a research by the World Bank (2018), the agriculture sector accounts for 73% of the world's nitrous oxide emissions and is a significant contributor to environmental deterioration. Overuse of natural resources contributes to major environmental problems including deforestation and global warming.

Keeping in view the existing literature on the interplay between economic globalization and CO2 emissions, in this paper we hypothesize that as agriculture plays a significant role in combating CO2 emissions, rather more easily than any other source of emissions, there must be a turning point of production that may identify optimal level of emissions.

Material and Method

In this section we will highlight that how the structure of the model is developed to investigate the relationship between the agriculture value added output and the emissions, particularly nitrous oxide and methane. Theoretically, one can imagine that increase in agriculture activities affect the environment in two ways; (i) through its impact by emitting more pollution to the economy due to use of agriculture machinery, e.g., tractors, harvesters, etc; (ii) through its environment friendly nature of output, by reducing chances of urbanization, reducing air pollution, etc. Both these channels help us understanding that the agricultural-environment circa may be twofold. Similarly, there are equal chances that the pollution can reduce the agriculture output due to many biological and other factor. Keeping this in mind we develop following background for hypotheses 1 and 2 below.

That although agriculture may emit pollution, but due to its natural phenomenon, it will reduce emissions in long run. As a result there is possibility of an inverted U-shaped EKC. This shape of EKC is predominantly possible due to improved agriculture technology and reduced energy intensity. The two way relation of agriculture and environment is affected by number of other factors, including carbon intensity, energy intensity, and agriculture technology,

Hypothesis 1. The digital economy has an inhibitory effect on agricultural carbon intensity.

Hypothesis 2. Digital economy can reduce agricultural carbon intensity by boosting agricultural technology.

The model

The possible trend in time-series make it skeptical to use any sophisticated econometric technique. In the foregoing, we can symbolize the model as:

$$Et = f(Yt, Kt, At) \qquad (1)$$

Where, Et denotes emission intensity, Yt output, Kt capital (includes embodied technologies), and At are disembodied technologies. We assume that output is function of K and L according to a usual production function (eq. 2 below)

$$Yt = f(AtKt, Lt) \qquad (2)$$

Assuming fixed land in agriculture, we also assume fixed agriculture labor proportion in total population. This system of equations can be written in following VAR specification. We use VAR, because due to possible trend and unit root in the time-series variables, the VAR model incorporates all possible order of integrations. It also addresses the simultaneity issue that may arise from two way causality between output and emissions.

$$E_t = \alpha_{10} + \theta_{11}E_{t-1} + \theta_{12}Y_{t-1} + \theta_{13}EnIn_{t-1} + \theta_{14}M_{t-1} + \theta_{15}Tn_{t-1} + \upsilon_{1t} \qquad (3)$$

$$Y_t = \alpha_{20} + \theta_{21}E_{t-1} + \theta_{22}Y_{t-1} + \theta_{23}EnIn_{t-1} + \theta_{24}M_{t-1} + \theta_{25}Tn_{t-1} + \upsilon_{2t} \qquad (4)$$

$$EnIn_t = \alpha_{30} + \theta_{31}E_{t-1} + \theta_{32}Y_{t-1} + \theta_{33}EnIn_{t-1} + \theta_{34}M_{t-1} + \theta_{35}Tn_{t-1} + \upsilon_{3t} \qquad (5)$$

$$M_t = \alpha_{40} + \theta_{41}E_{t-1} + \theta_{42}Y_{t-1} + \theta_{43}EnIn_{t-1} + \theta_{44}M_{t-1} + \theta_{45}Tn_{t-1} + \upsilon_{4t} \qquad (6)$$

$$E_t = \alpha_{50} + \theta_{51}E_{t-1} + \theta_{52}Y_{t-1} + \theta_{53}EnIn_{t-1} + \theta_{54}M_{t-1} + \theta_{55}Tn_{t-1} + \upsilon_{5t} \qquad (7)$$

Where EnIn is energy intensity in agriculture, M is agriculture machinery, Tn is proxy for use of improves technology factor in agriculture sector. After estimation of this reduced form VAR, the impulse response functions and Variance Decomposition of each series is done. This complete VAR system also includes an exogenous binary variable of technological progress since year 2005. This structural break point was identified through EKC estimated through following model;

$$E_t = B_0 + B_1Y_t + B_2Y_t^2 + B_3Y_t^3 + \mu_t \qquad (8)$$

Where Et are emissions, Yt is agriculture output. In this equation for EKC to hold, requires B1>0, B2<0 and B3>0. Many studies put details on it, including Mahmood & Shahab (2014), Mahmood et. al., (2019) Shahbaz et.al (2018) and Farhani and Ozturk, (2015) for example.

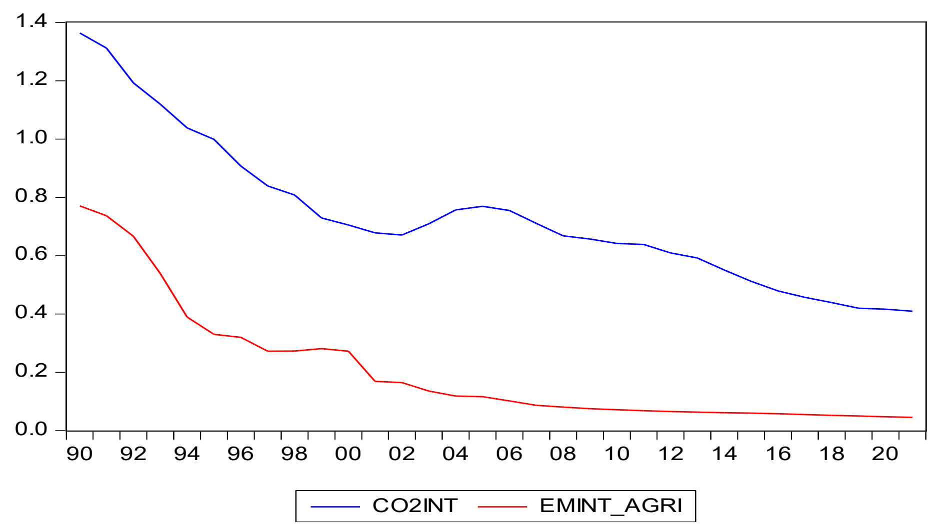
Data and Methods

For the present study we relied on the latest dataset of World Development Indicators, EnerData and NBS China, spanning 1990-2021. Agricultural Emission Intensity (AEI) Measurement: following Zhou, et al. (2019) we calculated agricultural intensity using following formula.

$$Et = AEt/AVt \qquad (9)$$

In figure (1) the upper line shows the carbon intensity of whole economy whereas the lower line represents the AEI only. It is obvious that the emission intensity of agriculture sector was more than half of the total intensity in 1990, reduced to 10 percent of the total emissions in 2020. Further the drop in ACI is leading factor to drop in total Emission intensity.

Figure1. Comparison of AEI to Overall EI



Results and Analysis

Like every other research using timeseries data, this study also uses unitroot test to find the possible order of integration. Table (2) shows the results of Augmented Dickey & Fuller test.

Table 1 Unit root test

Variable Name	Symbol	ADF Stat	Order
Emissions in Agri	E	-5.314521	I(0)
Agri Output	LY	-4.75913	I(1)
Agri Machinery	LM	-3.263004	I(1)
Energy Intensity	ENIN	-2.070332	I(0)
Technology Use	LTN	-2.924961	I(1)
Argi Emission Intensity	AEI	-2.469799	I(0)

As table (1) shows the variables have mixed order of integration, inferring that the robust techniques to do further analysis are potentially vector auto regressive (VAR) approach or autoregressive distributed lag (ARDL) model. But as it is obvious, the potential dependent variables of the model Et or AEIt are integrated of order 1, so using ARDL approach may not be appropriate one (Pesaran, et. al., 2001). Thus we are left with the no other choice to use simple VAR model for further analysis. This will provide use with the impulse response functions (IRF) and Variance decomposition of the model. Before doing VAR analysis we first estimate the EKC for China's agriculture to find out the turning point and the technical binary variable.

EKC Estimation

We estimate equation (8) by applying OLS on the Chinese data and find the results as given in table (2). All the parameters are statistically significant with reasonable value of R2. This confirms that at initial level of agriculture output, the amount of emissions increase whereas at a point when it reaches its maximum, corresponds to a high output growth. Figure 2 and 3 are based on the results of equation (8). In figure (2), it can be observed clearly that the estimated level of emissions peaked in 2005 and then after started declining, though passively. A trend line passing through the estimated data is based on two-period-ahead forecast shows that there is an indication of turning point of the EKC. Figure (3) presents the EKC for the China'a agricultural sector following Grossman and Krueger (1995). The turning point is found where agricultural value added output was ¥ 5931.13 Billion, equivalent to $ 560.84 per capita. At that point the PPP value of GDP per capita in china was 5053.681. This means that China's agricultural started reducing pollutants before reaching the USD 8000 per capita GDP as suggested by Grossman and Krueger (1995).

Table 2 Estimation of EKC

Dependent variable - Emissions		
Variable	Coefficient	t-stat
Y_t	2.032344	18.56553
Y_t^2	-0.094961	-6.559112
Y_t^3	0.001277	2.676140
R^2	0.726	

Figure 2. EKC China Agri - With Time

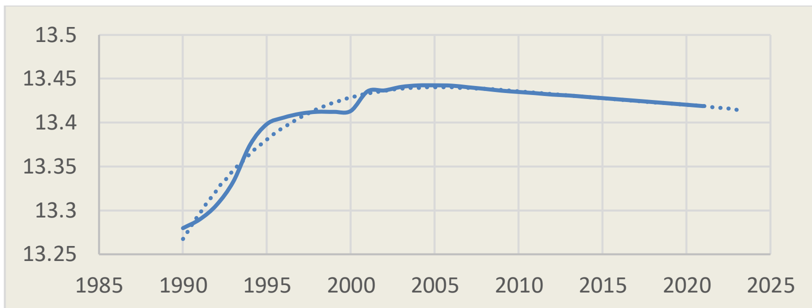
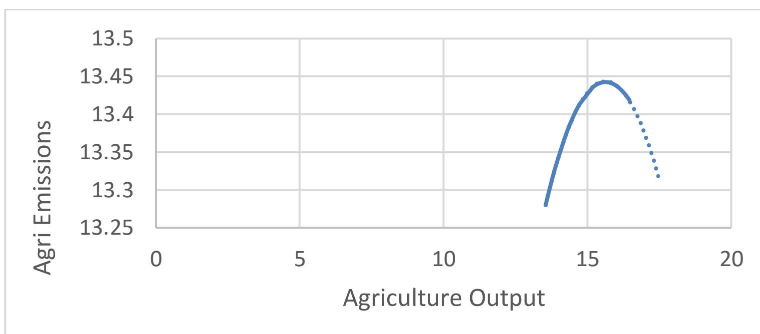


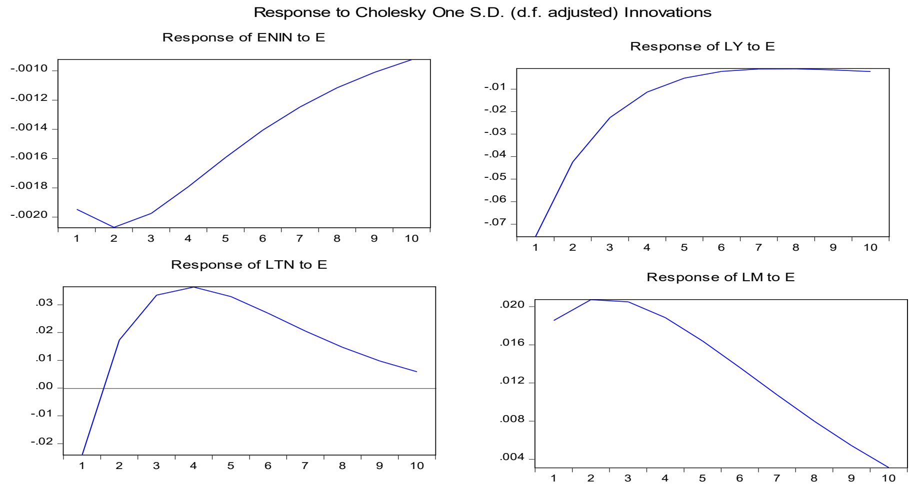
Figure 3. EKC China Agri- Output Model



Vector Autoregressive Approach

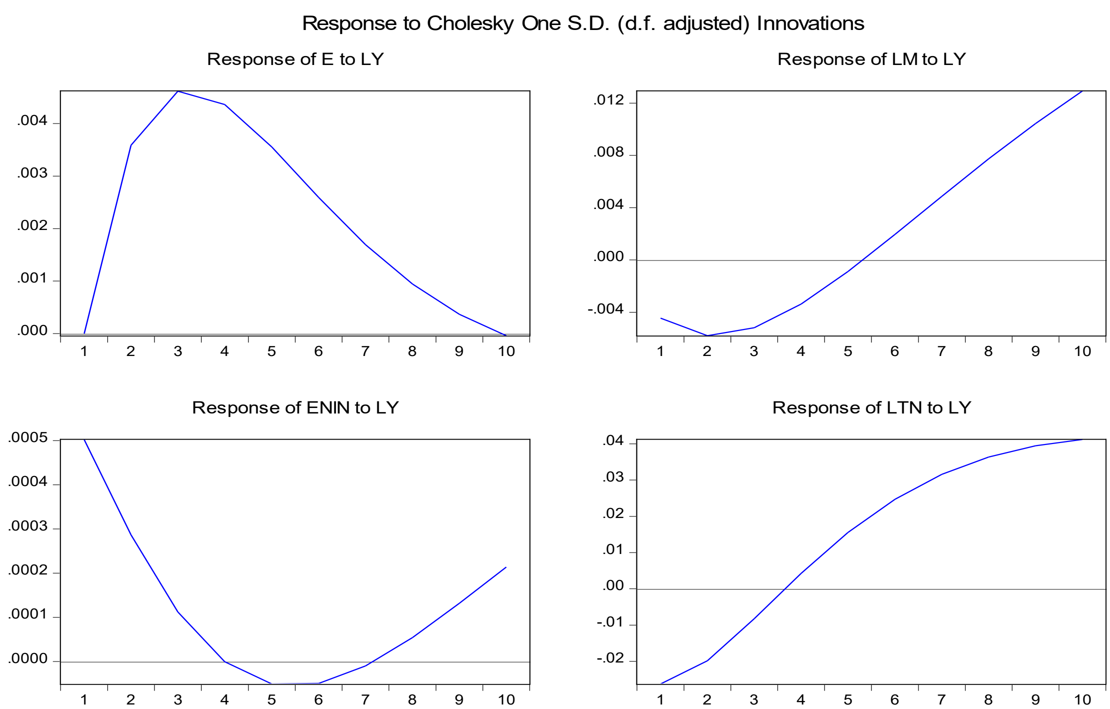
Next we estimate equations 3-7 using simple VAR and get IRFs presented in figures 4 to 8. We discuss each figure turn by turn. In figure 4, the estimated response of energy intensity to emission is initially positive, reduces for short run, then bounces back and increase at a decreasing pace. Output response to emissions is also positive though initially zero, converges after sixth period. Technology response to emission seems like EKC, initially negative, converges quickly. Finally, an increase in emissions results in increase in use of agro machinery.

Figure 4: Response to Emissions



In figure 5, one standard deviation shock to output results in increase in emissions, i.e., standard to theory; reaches it peak in third period and then converges in 10th period. Initially, agriculture machinery use responds negatively to output, then after second period, it bounces, converges to zero in 6th period and then increase up to 1.2 percent. Energy intensity response to output is seemingly zero bound. Technology response to output shock, initially negative, increases to 4% in 10th period. It means one percent shock to agricultural output, increase the technology use in the long run.

Figure 5: Response to Output



With initially zero response to energy intensity, the emissions increase with a positive shock to energy intensive production in agriculture sector. Output and machinery use response positively to an energy intensive farming in China. Technology is needed to grow, with a passive decrease in energy intensity. These results are made further clear though the use of standard causality tests.

Figure 7 shows that a shock to machinery use results in a zero initial response to negative for five periods. However, this stable response is zero bound for all future periods. Output response to machinery is mirror image of that was by the emissions. Thus if machine use shock results in higher output and lower emission in the short run, then for longer run, it is reversed. Energy intensity reduce despite its positive initial response due to a shock to the machinery use in agriculture sector. Technology reacts zero to negative to a shock to machinery use.

Emission response to technology is negative, means innovation in agriculture technology, reduces the emission and hence the carbon intensity of agriculture sector in China. Output and machine use respond positive to technological shocks. However, surprisingly the reaction of energy intensity is zero bound but positive. This may be due to advancement in technology leads to lower energy intensity, making energy technologically neutral. The increase in use of renewable energy in China in past decade or more is a significant cause of this.

In short run the variance of emissions is self-determined, however, in long run, output and technology play significant role. Emission play very significant role in determining the variation in output, both in short run and long run, although for case of Chinese agriculture, the ro le of emission reduces, whereas clean technological innovation's role increases from zero percent in one period to 24 percent in 10th period. The variance of machinery use is mostly self-determined in short run, however emissions play a persistent role in determination of its variance. Technology and energy int ensity play more pivotal role in long run. Energy intensity variation is influenced by machinery use and pollution in the short run. However, the role of m achinery increased over 10th period, while that of emissions reduced. The variation in technology is brought through by all variables in short run, but ou tput and emissions play more role. However, the machinery and output play relatively higher role (tables A1 to A5). There exist a statistically significant two-way causality between pollution and output; between pollution and technology; and between Output and technology in Chinese agriculture Table (A-6 in appendix). However, a unidirectional causation runs from energy intensity to emissions, output to machinery use, technology to machine use and ener gy intensity to technology use. These results confirm that the there is significant role that green technology innovations can play to mitigate the dual problems: of economic inefficiency and environmental degradation.

Figure 6: Response to energy Intensity

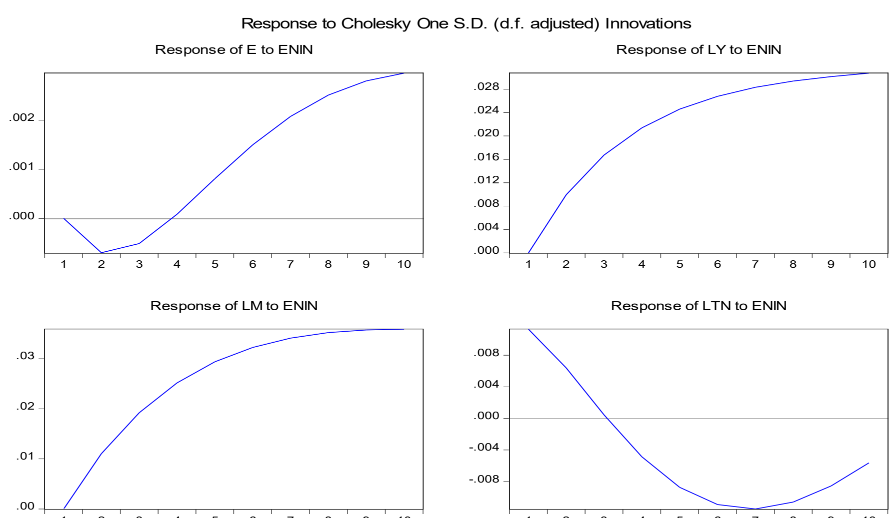


Figure 7: Response to Machinery

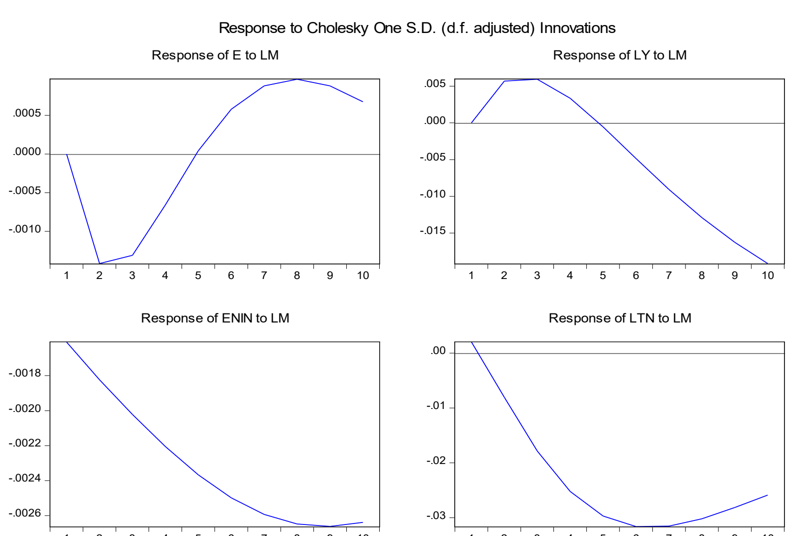
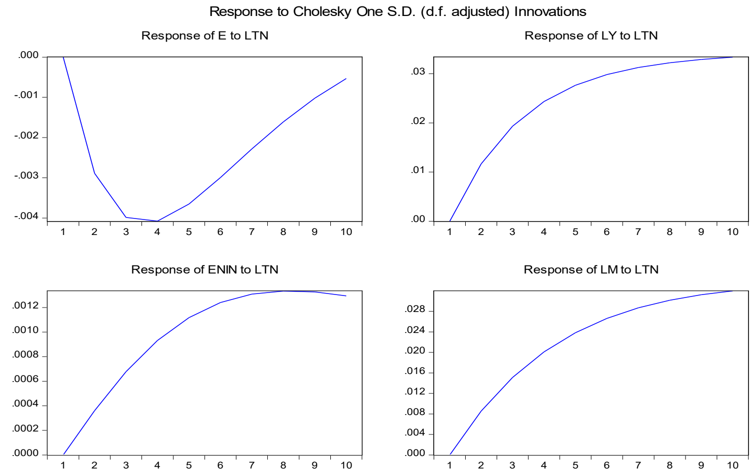


Figure 8: Response to Technology



Conclusions and Implications

In this paper we have identified the relationship between technological innovations, agricultural output value addition and emissions generated by agricultural activity in China. For empirical analysis the use of standard VAR, estimation of EKC and Granger causality is applied to annual Chinese data. We find that the technological progress, or use, can affect dual problems of economic efficiency and pollution reduction. An estimated downward trend is found in case of agriculture sector. The use of machinery like tractors, harvesters, etc. play pivotal role in environmental degradation, but due to climate-smart technology changes, the resource allocation and efficiency can be improved. China can give farmers across the nation the support they need by utilizing modern agriculture platforms and smart farming technology, such as drone and satellite imagery and pattern modelling, and converting farmers' mobile phones into knowledgeable environmental tools and resources. Small farmers can gain access to a vast and helpful ecosystem with the aid of agri-tech and a new business model that is driven by digital innovation throughout the entire agricultural value chain. Using scientific and technological research and development, it is crucial to scale up training and capacity building projects all over the world. This will enable farmers to respond quickly to issues that arise in agricultural production, such as how to deal with climate change, unusual weather, and other difficulties.

References

Acaravcı, A., and I. Ozturk. 2010. "On the Relationship between Energy Consumption, CO2 Emissions and Economic Growth in Europe." Energy 35 (12): 5412–5420.

Alam MJ, Begum IA, Buysse J, Rahman S, Van Huylenbroeck G. Dynamic modeling of causal relationship between energy consumption, CO2 emissions and economic growth in India. Renew Sustain Energy Rev 2011;15(6):3243–51.

Ang JB (2008). Economic development, pollutant emissions and energy consumption in Malaysia. J Policy Model; 30(2):271–8.

Aziz, N., Sharif, A., Raza, A., Rong, K., 2020. Revisiting the role of forestry, agriculture, and renewable energy in testing environment Kuznets curve in Pakistan: evidence from Quantile ARDL approach. Environ. Sci. Pollut. Res. 27, 10115–10128.

Azlina AA, Mustapha NN. Energy, economic growth and pollutant emissions nexus: the case of Malaysia. Procedia-Social Behav Sci 2012;65:1–7.

Bell, M.J., Cloy, J.M., Rees, R.M., 2014. The true extent of agriculture's contribution to national greenhouse gas emissions. Environ. Sci. Pol. 39, 1–12.

Bennetzen, E.H., Smith, P., Porter, J.R., 2016. Decoupling of greenhouse gas emissions from global agricultural production: 1970–2050. Glob. Chang. Biol. 22, 763–781.

Burney, J.A., Davis, S.J. and Lobell, D.B. (2010), "Greenhouse gas mitigation by agricultural intensification", Proceedings of the National Academy of Sciences USA, Vol. 107, pp. 12052-12057.

Dalgaard, T., Olesen, J.E., Petersen, S.O., Petersen, B.M., Jorgensen, U., Kristensen, T., et al., 2011. Developments in greenhouse gas emissions and net energy use in Danish agriculture - how to achieve substantial CO(2) reductions? Environ. Pollut. 159, 3193–3203

Dasgupta, S., Laplante, B., Mamingi, N., 2001. Pollution and capital markets in developing countries. J. Environ. Econ. Manag. 42, 310–335, 2001.

Duxbury, J. M., Harper, L. A., & Mosier, A. (1993). Contributions of agro ecosystems to global climate change. Agricultural ecosystem effects on trace gases and global climate change, 55, 1-18.

Edoja, P.E., Aye, G.C. and Abu, O. (2016), "Dynamic relationship among CO2 emission, agricultural productivity and food security in Nigeria", Cogent Economics & Finance, Vol. 4 No. 1, 1204809, doi: 10.1080/23322039.2016.1204809

Eyuboglu, K., Uzar, U., 2020. Examining the roles of renewable energy consumption and agriculture on CO2 emission in lucky-seven countries. Environ. Sci. Pollut. Res. 27, 45031–45040. https://doi.org/10.1007/s11356-020-10374-2.

Gozgor, G., Lau, C. K. M., & Lu, Z. (2018). Energy consumption and economic growth: New evidence from the OECD countries. Energy, 153, 27-34.

Grossman, G. M., & Krueger, A. B. (1995). Economic growth and the environment. The quarterly journal of economics, 110(2), 353-377.

Hamant, O. (2020), "Plant scientists can't ignore Jevons paradox anymore", Nature Plants, Vol. 6 No. 7, pp. 720-722.

Hatfield, J.L., Antle, J., Garrett, K.A., Izaurralde, R.C., Mader, T., Marshall, E., Nearing, M., Robertson, G.P. and Ziska, L. (2020), "Indicators of climate change in agricultural systems", Climatic Change, Vol. 163, pp. 1719-1732.

Islam, F., Shahbaz, M., Ahmed, A.U., Alam, M.M., 2013. Financial development and energy consumption nexus in Malaysia: a multivariate time series analysis. Econ. Modell. 30, 435–441, 2013.

Jiang, C., Xiaoxin, M., 2019. The impact of financial development on carbon emissions: a global perspective. Sustainability 11, 5241.

Khan AG, Hossain MA, Chen S (2021) Do financial development, trade openness, economic development, and energy consumption affect carbon emissions for an

emerging country? Environ Sci Pollut Res. https://doi.org/10.1007/s11356-021-13339-1
Kraft, J., Kraft, A., 1978. On the relationship between energy and GNP. J. Energy Dev. 3, 401–403.
Li, H. and Qin, Q. (2019), "Challenges for China's carbon emissions peaking in 2030: a decomposition and decoupling analysis", Journal of Cleaner Production, Vol. 207, pp. 857-865.
Liu H, Tellez BG, Atallah T, Barghouty M. The role of CO2 capture and storage in Saudi Arabia's energy future. Int J Greenh Gas Control 2012;11:163–71.
Liu, M., & Yang, L. (2021). Spatial pattern of China's agricultural carbon emission performance. Ecological Indicators, 133, 108345.
Lotfalipour MR, Falahi MA, Ashena M. Economic growth, CO2 emissions and fossil fuels consumption in Iran. Energy 2010;35(12):5115–20.
Mahmood, M. T., & Shahab, S. (2014). Energy, emissions and the economy: empirical analysis from Pakistan. The Pakistan Development Review, 383-400.
Mahmood, M. T., Shahab, S., & Hafeez, M. (2020). Energy capacity, industrial production, and the environment: an empirical analysis from Pakistan. Environmental Science and Pollution Research, 27(5), 4830-4839.
Mahmood, M. T., Shahab, S., & Shahbaz, M. (2022). The relevance of economic freedom for energy, environment, and economic growth in Asia-Pacific region. Environmental Science and Pollution Research, 29(4), 5396-5405.
Meng M, Fu Y, Wang X (2017) Decoupling, decomposition, and forecasting analysis of China's fossil energy consumption from industrial output. J Clean Prod 177:752–759.
Mulatu, D.W., Eshete, Z.S. and Gatiso, T.G. (2016), "The impact of CO2 emissions on agricultural productivity and household welfare in Ethiopia: a computable general equilibrium analysis", Environment for Development- Discussion Paper Series March 2016 EfD DP 16-08,
Odhiambo, N.M., 2009. Energy consumption and economic growth nexus in Tanzania: An ARDL bounds testing approach. Energy Policy 37, 617–622.
Omri A. CO2 emissions, energy consumption and economic growth nexus in MENA countries: evidence from simultaneous equations models. Energy Econ 2013;40:657–64.
Pao HT, Tsai CM. Modeling and forecasting the CO2 emissions, energy consumption and economic growth in Brazil. Energy 2011;36(5):2450–8.
Pellegrini, P. and Fernandez, R.J. (2018), "Crop intensification, land use and on-farm energy-use efficiency during the worldwide spread of the green revolution", Proceedings of the National Academy of Sciences USA, Vol. 115, pp. 2335-2340.
Shahbaz M, Khraief N, Uddin GS, Ozturk I. Environmental Kuznets curve in an open economy: a bounds testing and causality analysis for Tunisia. Renew Sustain Energy Rev 2014;34:325–36.
Shahbaz, M., Tiwari, A.K., Nasir, M., 2013. The effects of financial development, economic growth, coal consumption and trade openness on CO2 emissions in South Africa. Energy Pol. 61, 1452–1459.
Smith, P., Clark, H., Dong, H., Elsiddig, E.A., Haberl, H., Harper, R., House, J., Jafari, M., Masera, O., Mbow, C. and Ravindranath, N.H. (2014), "Chapter 11 - Agriculture, forestry and other land use (AFOLU)", Climate Change 2014: Mitigation of Climate Change, IPCC Working Group III Contribution to AR5, Cambridge University Press.
Taher, N., Hajjar, B., Taher, N., & Hajjar, B. (2014). Environmental concerns and policies in Saudi Arabia. Energy and Environment in Saudi Arabia: Concerns & Opportunities, 27-51.
Tamazian, A., Chousa, J.P., Vadlamannati, K.C., 2009. Does higher economic and financial development lead to environmental degradation: evidence from BRIC countries. Energy Policy. 37, 246–253.
Tang, C.F., Tan, B.W., Ozturk, I., 2016. Energy consumption and economic growth in Vietnam. Renew. Sust. Energ. Rev. 54, 1506–1514.
Tian, Y., Zhang, J.-b., He, Y.-y., 2014. Research on spatial-temporal characteristics and driving factor of agricultural carbon emissions in China. J. Integr. Agric. 13, 1393–1403.
Tongwane, M.I. and Moeletsi, M.E. (2020), "Emission factors and carbon emissions of methane from enteric fermentation of cattle produced under different management systems in South Africa", Journal of Cleaner Production, Vol. 265, 121931
Wang, M. and Feng, C. (2019), "Decoupling economic growth from carbon dioxide emissions in China's metal industrial sectors: a technological and efficiency perspective", Science of The Total Environment, Vol. 691, pp. 1173-1181.
Wang, S., and X. Liu. 2017. "China's City-Level Energy-Related CO2 Emissions: Spatiotemporal Patterns and Driving Forces." Applied Energy 200: 204–214.
Wei Wei, Wen Changcun, Cui Qi, et al. The impact of agricultural technology progress on agricultural energy use and carbon emissions-based on the GTAP-E model analysis. Agricultural Technology and Economy, 2018(2): 30-40.
Yilmaz, S.; Haynes, K.E.; Dinc, M. Geographic and Network Neighbors: Spillover Effects of Telecommunications Infrastructure. J. Reg. Sci. 2002, 42, 339–360.
Zhang, Pengyan, Jianjian He, Xin Hong, Wei Zhang, Chengzhe Qin, Bo Pang, Yanyan Li, and Yu Liu. 2018. "Carbon Sources/Sinks Analysis of Land Use Changes in China Based on Data Envelopment Analysis." Journal of Cleaner Production 204: 702–711. doi:10.1016/j. jclepro.2018.08.341.
Zhixin, Z., Xin, R., 2011. Causal relationships between energy consumption and economic growth. Energy Procedia 5, 2065–2071.

Appendix

Table A1: Variance Decomposition of E

Period	S.E.	E	LY	LM	ENIN	LTN
1	0.026367	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.029193	97.22001	1.508384	0.235549	0.057872	0.978186
3	0.030062	93.04117	3.782996	0.411828	0.083758	2.680251
4	0.030661	89.46937	5.662187	0.441887	0.081276	4.345276
5	0.031178	87.07868	6.775477	0.427550	0.145754	5.572539
6	0.031599	85.58969	7.270762	0.449699	0.366733	6.323117
7	0.031926	84.59148	7.403945	0.516826	0.782344	6.705409
8	0.032184	83.80147	7.371758	0.599028	1.379165	6.848581
9	0.032396	83.07868	7.288457	0.665202	2.109384	6.858279
10	0.032580	82.37406	7.206583	0.700768	2.910875	6.807717

Table A2: Variance Decomposition of LY

Period	S.E.	E	LY	LM	ENIN	LTN
1	0.088875	72.01192	27.98808	0.000000	0.000000	0.000000
2	0.104829	68.08504	29.48134	0.295799	0.898908	1.238905
3	0.112966	62.64281	29.85987	0.532816	2.968759	3.995741
4	0.119771	56.61544	29.30893	0.552378	5.830784	7.692465
5	0.126791	50.68420	28.23205	0.494807	8.963771	11.62517
6	0.134320	45.18764	26.98137	0.571609	11.96610	15.29327
7	0.142333	40.24829	25.77216	0.913674	14.61701	18.44885
8	0.150741	35.88777	24.70567	1.546109	16.83632	21.02413
9	0.159449	32.08349	23.81320	2.422869	18.62888	23.05156
10	0.168368	28.79165	23.08991	3.468243	20.04203	24.60816

Table A3: Variance Decomposition of LM

Period	S.E.	E	LY	LM	ENIN	LTN
1	0.109464	2.874076	0.165531	96.96039	0.000000	0.000000
2	0.143214	3.773838	0.260156	95.01683	0.592137	0.357044
3	0.162935	4.499123	0.302270	92.21568	1.847088	1.135841
4	0.175737	5.017744	0.296759	88.76408	3.637988	2.283432
5	0.184767	5.327903	0.270725	84.85110	5.819268	3.731004
6	0.191789	5.449130	0.261615	80.66802	8.229111	5.392129
7	0.197863	5.415327	0.306526	76.40514	10.70354	7.169473
8	0.203621	5.267650	0.433822	72.23545	13.09603	8.967049
9	0.209420	5.047516	0.658561	68.29666	15.29440	10.70286
10	0.215432	4.791061	0.982149	64.68055	17.22892	12.31733

Table A4: Variance Decomposition of ENIN

Period	S.E.	E	LY	LM	ENIN	LTN
1	0.006537	8.864824	0.590742	6.049168	84.49527	0.000000
2	0.009184	9.570942	0.396726	7.008088	82.87021	0.154032
3	0.011122	9.676205	0.280640	8.082438	81.48433	0.476388
4	0.012658	9.473255	0.216657	9.273926	80.12698	0.909185
5	0.013917	9.143967	0.180557	10.56363	78.71527	1.396581
6	0.014967	8.788055	0.157206	11.91985	77.24079	1.894094
7	0.015850	8.454182	0.140212	13.30456	75.73009	2.370960
8	0.016597	8.162265	0.128942	14.67883	74.22116	2.808804
9	0.017230	7.917244	0.125495	16.00716	72.75120	3.198905
10	0.017767	7.716887	0.132514	17.26026	71.35105	3.539290

Table A5: Variance Decomposition of LTN

Period	S.E.	E	LY	LM	ENIN	LTN

1	0.095076	6.358570	7.611893	0.044899	1.412076	84.57256
2	0.131551	5.049668	6.256532	0.398093	0.973703	87.32200
3	0.158847	7.909815	4.559654	1.534410	0.668622	85.32750
4	0.179979	10.25439	3.608781	3.158855	0.593408	82.38456
5	0.196695	11.38960	3.647985	4.925490	0.693303	79.34362
6	0.210340	11.60250	4.571461	6.564701	0.875042	76.38629
7	0.221841	11.28823	6.138425	7.922784	1.053323	73.59724
8	0.231793	10.74136	8.087737	8.952754	1.173023	71.04513
9	0.240582	10.13638	10.19774	9.678860	1.214860	68.77216
10	0.248483	9.558351	12.30633	10.15863	1.190102	66.78660

Table A6: Pairwise Granger Causality Tests

Sample: 1990 2021

Null Hypothesis:	Obs	F-Statistic	Prob.
LY does not Granger Cause E	30	2.88226	0.0748
E does not Granger Cause LY		2.86892	0.0756
LM does not Granger Cause E	30	1.04946	0.365
E does not Granger Cause LM		2.72034	0.0853
ENIN does not Granger Cause E	30	2.58109	0.0957
E does not Granger Cause ENIN		1.34845	0.2779
LTN does not Granger Cause E	30	11.7824	0.0002
E does not Granger Cause LTN		9.39287	0.0009
LM does not Granger Cause LY	30	0.67729	0.5171
LY does not Granger Cause LM		3.592	0.0425
ENIN does not Granger Cause LY	30	0.78824	0.4656
LY does not Granger Cause ENIN		1.92555	0.1668
LTN does not Granger Cause LY	30	3.58189	0.0429
LY does not Granger Cause LTN		4.05443	0.0299
ENIN does not Granger Cause LM	30	1.12865	0.3394
LM does not Granger Cause ENIN		0.76561	0.4756
LTN does not Granger Cause LM	30	3.19786	0.058
LM does not Granger Cause LTN		0.42245	0.66
LTN does not Granger Cause ENIN	30	0.34578	0.711
ENIN does not Granger Cause LTN		3.51349	0.0452