Analyzing dynamic impacts of deagriculturalization on CO2 emissions in selected Asian economies: a tale of two shocks

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Abstract
The study investigates the symmetric and asymmetric impact of agriculturalization on CO2 emissions in a sample of selected Asian economies for time period 1985 to 2019. For empirical analysis, the study adopted panel linear and nonlinear autoregressive distributed lag (ARDL) approaches. The long-run findings of panel ARDL reveal that agriculturalization contributes to environmental quality by mitigating CO2 emissions. The panel nonlinear results clearly indicate that the effects of agriculturalization on CO2 emissions are asymmetric. The findings demonstrate that agriculturalization improves environmental quality and de-agriculturalization mitigates environmental quality. Our empirical results are also robust to alternative model specifications. Based on these findings, the study recommends that the relevant authorities should formulate reforms in the agriculture sector that controls and reduces carbon emissions in Asian economies.

Keywords CO2 emissions · Deagriculturalization · GDP · Asian economies · NARDL

Introduction

World’s population has grown from 1 billion in 1800 to 7.9 billion in 2020. This massive rise in the population has increased the demand for food manifold. Consequently, the importance of the agriculture sector has also increased as it provides food to billions of people. Moreover, agriculture has become an essential factor in achieving sustainable economic development, and Higgs (1897) also supported this claim. In the literature, Sertoglu et al. (2017) and Victor Bekun and Akadiri (2019) provide strong enough evidence to support the idea that agriculture is crucial for economic growth. However, finding the path through which agriculture can help achieve long-term economic growth is an important question that still needs an appropriate answer from academics, empirics, and policymakers.

Several pieces of empirical evidence are available that sustain the idea that agriculture is vital in the long-term economic growth of the economy by selling agricultural products to other economies (Balassa 1978; Voivodas 1973; Chandio et al. 2021). Conversely, some studies do not support the favorable impact of agriculture on economic growth. For instance, Tiffin and Irz (2006) gathered data for 85 countries over the period 1960–1971 and confirmed the positive effects of the agriculture sector on the economic growth. However, finding the path through which agriculture can help achieve long-term economic growth is an important question that still needs an appropriate answer from academics, empirics, and policymakers.

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Moreover, due to the rising population, the demand for agricultural products is also on the rise. Consequently, the energy demand also rises in a bid to produce agricultural products for the rising population. As far as developing economies are concerned, their energy mix is primarily composed of non-renewable energy (Majeed and Luni 2019), the main source of increased greenhouse gas (GHG) emissions in the ecosystem. Therefore, the progress of the agriculture sector is not free of cost, instead comes at the expense of environmental degradation (Gokmenoglu and Taspinar 2018). Food and Agricultural Organization (FAO) highlighted that the agricultural sector is responsible for almost one-third of the total worldwide GHG emissions; hence, it has a vital role in degrading the environment (FAO, 2016). The adverse effects of the agricultural sector have further escalated after the food crisis of 2006–2008, and this sector ranked second among the contributors of global GHG emissions. One of the most significant consequences of agriculture is deforestation which degrades the environment significantly. Forest provides the wood for cooking and heating purposes in the rural areas of developing economies, emitting CO₂ emissions. Moreover, the agricultural sector involves activities such as burning bushes and biomass (Ramachandra et al., 2015; Rehman et al., 2021a). However, according to a report published by FAO in the year 2016, the agriculture sector has the ability to cut down its currently produced GHG emissions by 20–60% at the end of the year 2030. The harmful effects of the agriculture sector on environmental quality can be reduced by discouraging deforestation, using innovative varieties of plants, applying good quality fertilizers, and adopting green and renewable energy (Reynolds et al. 2015; Mohamad et al. 2016; Liu et al. 2017).

Existing literature on the nexus between environment and agriculture pointed out a variety of agricultural practices that can affect environmental quality. Pretty (2008) highlighted that the association between environment and agriculture relies on the techniques used in the agricultural sector. Cultivation can upsurge CO₂ releases if biological leftover increases in the land. On the other side, instead of burning the waste, we can use it to produce renewable energy that would help to mitigate CO₂ emissions in the environment. Besides, sustainable agricultural methods have various advantages, such as a rise in per acre yield, a decline in pesticide use, and low carbon emissions in the atmosphere.

A plethora of studies is available that have examined the role of the agricultural sector as a determinant of environmental quality in various economies. Couwenberg et al. (2010) analyzed the influence of peat soil, rice paddy, and fertilizers on the ecological quality of the countries of Southeast Asia by employing meta-analysis. Their findings confirmed that peatland rewetting upsurged methane and carbon discharges. Hughes et al. (2011) observed that fungicide therapy helps improve environmental quality in the United Kingdom. In the context of China, Zhang et al. (2015), tried to investigate the effects of various crop traits such as harvest, residues, and its process on CO₂ emissions by using the symmetric framework. Their outcomes suggested that remainders of crops degraded the environmental quality. Similarly, Zahoor et al. (2015) highlighted that nitrous oxide (N₂O) emissions increased due to agricultural activities and contributes to environmental pollution and global warming. Hou et al. (2015) pointed out that livestock activities enhance CO₂ emissions; however, its effects can be mitigated through effective farm management. Likewise, Mariantonietta et al. (2018) also supported the idea that efficient farm management can help reduce livestock-related carbon emissions.

Although the previous literature provided enough evidence on the relationship between agriculture and environmental quality, the findings are inconclusive. The implied reasons could be the application of different data sets and estimation techniques. Furthermore, the results are sensitive to the difference in agricultural methods observed in various countries. All the previous studies have one thing in common: they ignore the agricultural variables’ nonlinear behavior, which is very common in the agriculture sector due to its vulnerability to external shocks. Lastly, most studies have ignored the Asian economies, which heavily rely on the agriculture sector. Hence, this study is an effort to find the dynamic impacts of de-agriculturalization on the CO₂ emissions in selected Asian economies. However, in this study, we have focused on the asymmetric effects of de-agriculturalization on the environmental quality in selected Asian economies. To that end, we have employed linear and nonlinear panel ARDL techniques, which are robust to find the asymmetric effects of the variables and provide efficient results even if the sample size is small. This study will also provide essential policy directives for all stakeholders.

The selection of Asian economies is not by chance but instead based on the fact that the contribution of agriculture to the total GDP of Asian economies is about 10–15%. However, agricultural production in Asian regions is severely threatened due to climate change, mainly in tropical areas. Per acre, yields are anticipated to decline rapidly in tropical regions such as South and Southeast Asia in the current century. According to Asian Development Bank (ADB, 2009), there is a fear that per acre yield will decline by 50% at the end of the 21st century compared to the yield in the 1990s. And the agriculture sector itself is a significant contributor to global GHG emissions; hence, studying the impact of the agriculture sector on the CO₂ emissions in Asian economies is pertinent from the point of view of food security and sustainable economic development. Hence, the contribution of the study to the current can be elaborated in the following ways. Firstly, the study relies on the asymmetric
assumption, which enables us to capture the positive and negative changes in the independent variables (agriculturalization) on the dependent variable (CO₂ emissions). The asymmetric assumption implies that if a positive change in the agriculturalization positively impacts the CO₂ emissions, the negative change in the agriculturalization may impact the CO₂ emissions negatively, positively, or insignificantly. To estimate the model empirically, we have employed the NARDL-PMG model. Secondly, the study provides both short and long-run estimates as opposed to the previous studies, which only focus on the long-run estimates. Finally, the set of countries used in the analysis is quite unique, which most past studies ignore.

**Literature review**

The association between deagriculturalization and CO₂ emissions and the resultant impact on climate change is not well recognized around the globe. The agriculture sector is considered susceptible to CO₂ emissions (Zhou et al., 2022). The contribution of the agricultural sector to worldwide CO₂ emissions ranges from 1/3 to 1/4 (World Bank, 2013). The contribution of the agricultural sector to worldwide CO₂ emissions is relatively lesser than the industrial sector. Agri-cultural economists and environmentalists denoted that there is a need to implement less-polluted agricultural techniques that protect the environment and enhance economic growth (Rehman et al. 2019; Chandio et al. 2021). The agricultural sector is not only enhancing the economic development of the economy but also enhanced food security. Moreover, it generates various environmental and social problems in the economy. A bulk of literature is available that has explored the determining factors of environmental quality but the association between deagriculturalization and CO₂ emissions is still unexplored. Rehman et al. (2017) explored the impact of livestock feed and crop yield on greenhouse gas emissions in the case of developing economies. The study concluded that after decreasing the 25 percent and 50 percent yield gaps in livestock and crops, respectively, 8 percent reduction will occur in agriculture-based GHG emissions by 2050.

Zhang et al. (2015) examined the impact of crop processes, crop remainders, and crop harvests on CO₂ emissions. The study concluded that crop remainder intensifies CO₂ emissions, hence environmental quality declines. Rehman et al. (2022) explored the nexus between agriculture productivity and CO₂ emissions and reported a negative association between them. Gul et al. (2021) explored the nexus between agriculturalization and global warming and reported that any negative shock in agricultural activity significantly influences global warming. Rehman et al. (2019) examined the effect of agriculturalization on CO₂ emissions in the case of Pakistan. The findings suggest that use of fertilizers, energy consumption, water availability, and per capita income significantly intensifies CO₂ emissions in the country. Ullah et al. (2021) explored the impact of deagriculturalization on GDP and environmental quality in the case of Pakistan. The findings infer that their agriculturalization reports a negative impact on economic growth; while, deagriculturalization reports an insignificant effect on economic growth. In contrast, both agriculturalization and deagriculturalization result in improving environmental quality in Pakistan.

A bulk of existing literature reports the negative impact of agriculture farming on environmental quality. It is argued that soil quality gets deteriorated due to land use ignoring the conservation techniques of soil and overgrazing as well. Upsurge in agriculture activity enhances energy consumption, contributing to the high absorption of CO₂ emissions, deteriorating water quality, causing global warming, and deforestation (Chandio et al. 2020; Rehman et al. 2020). Kim et al. (2016) denoted that a positive increase in agriculturalization triggers CO₂ emissions and global warming. Previously, studies investigated the association between fertilizers, peat soil, and CO₂ emissions (Rehman et al. 2016; Chandio et al., 2019a) and reported that peat soil reduces pollution emissions. Another study done by Hughes et al. (2011) investigated the impact of fungicides on CO₂ emissions and concluded that treatment of fungicides reduces CO₂ emissions. Chandio et al. (2019b) explored the effect of agricultural soil on CO₂ emissions and revealed that it intensifies CO₂ emissions. Afterward, Rehman et al. (2021a) explore the nexus between agriculture, livestock, and pollution emissions. The results indicate that livestock is positively linked with CO₂ emissions, while well-organized farm management is negatively associated with CO₂ emissions. Mohamad et al. (2016) explore the effect of agriculturalization on pollution emissions. The findings display that agriculturalization is positively linked with CO₂ emissions, thus deteriorating environmental quality.

Mariantonietta et al. (2018) reported a positive linkage between livestock activities and pollution emissions. Moreover, Vetter et al. (2017) denoted that agriculturalization is the major cause of global warming. The upsurge in population raises the demand for agriculturalization which cause a significant rise in pollution emissions. Findings also reveal that livestock and rice cultivation are major contributors of CO₂ emissions compared with other cereal cultivation. Rehman et al. (2021b) explored the effect of the use of nitrous fertilizer in cultivation on CO₂ emissions. The findings display that nitrous fertilizers increase pollution emissions and global warming. Reynolds et al. (2015) investigated the nexus between agriculturalization and carbon emissions for South Asian economies and sub-Saharan Africa. The study concluded that agriculturalization is negatively linked.
with CO₂ emissions. The results further added that a proper management system, proper harvest system, and proper cultivation of crops enhance the quality of the environment in developing countries. Önder et al. (2011) denoted that agriculturalization exerts a positive and negative influence on environmental quality. Stolze et al. (2000) concluded that agriculturalization tends to increase pollution emissions and intensifies environmental degradation.

The literature review summarized the ambiguous relationship between agriculturalization and CO₂ emissions. One strand of literature discloses a positive association between agriculturalization and CO₂ emissions, while the other strand reports a negative linkage between agriculturalization and CO₂ emissions. Thus, it is necessary to further explore the nexus between agriculturalization and CO₂ emissions for the Asian economies. Moreover, the existing literature provides symmetric relationship between agriculturalization and CO₂ emissions. However, the novelty of our study is that it provides an asymmetric association between agriculturalization and CO₂ emissions considering the impact of positive and negative shocks in agriculturalization.

**Study methods and data**

To analyze the impact of agriculturalization on the environmental quality in selected Asian economies, we have borrowed the following long-run model from past studies.

\[
\Delta CO_{2,t} = \varphi_0 + \varphi_1 AVA_t + \varphi_2 GDP_t + \varphi_3 EC_t + \varphi_4 Urb_t + \varphi_5 FD_t + \varepsilon_t
\]

Where agriculturalization (AVA), gross domestic product (GDP), energy consumption (EC), urbanization (Urb), and financial development (FD) are used as a determinant of carbon emissions (CO₂) in selected Asian economies. Equation (1) limits itself to long-run estimates; however, the analysis tries to capture short- and long-run estimates. Hence, we have redefined the above model (1) into the form of an error correction model as specified underneath:

\[
\Delta CO_{2,t} = \alpha_0 + \sum_{i=1}^{p} \pi_{1i} \Delta CO_{2,t-i} + \sum_{i=0}^{p} \pi_{2i} \Delta AVA_{t-i} \\
+ \sum_{i=0}^{p} \pi_{3i} \Delta GDP_{t-i} + \sum_{i=0}^{p} \pi_{4i} \Delta EC_{t-i} \\
+ \sum_{i=0}^{p} \pi_{5i} \Delta Urb_{t-i} + \sum_{i=0}^{p} \pi_{6i} \Delta FD_{t-i} \\
+ \omega_1 CO_{2,t-1} + \omega_2 AVA_{t-1} \\
+ \omega_3 GDP_{t-1} + \omega_4 EC_{t-1} \\
+ \omega_5 Urb_{t-1} + \omega_6 FD_{t-1} + \lambda.ECM_{t-1} + \varepsilon_t
\]

Redefining Eq. (1) into error correction format (2) leads us to the ARDL-PMG model of Pesaran et al. (1999, 2001). The method is considered superior to other panel data techniques in many ways. Firstly, this method is superior because we do not need to put any extra effort while generating short and long-run estimates, and this method estimates them simultaneously with single regression. The short-run results can be inferred from coefficient estimates of first-differenced variables, and the long run results are to be represented through coefficient \(\omega_2 - \omega_4\) normalized on \(\omega_1\). Most of the panel cointegration methods require that data must be stationary at first difference. However, if the variables included in the analysis are a mixture of I(0) and I(1), the ARDL-PMG model provides the solution in this situation. The ARDL-PMG has the power to deal with integrating properties of the variables; therefore, it can handle the variables that are either stationary at level or first difference. Since a limited number of observations can provide unbiased and inefficient estimates with other estimation techniques, the ARDL-PMG can also deal with this problem and deliver efficient results. Finally, the issue of endogeneity is a severe concern of the panel data analysis, whereas the ARDL-PMG can perform well in the presence of endogeneity due to the inclusion of a short-run dynamic process. As mentioned above, our analysis also focuses on the asymmetric assumption. To that end, we have divided the variable of agriculturalization into their positive and negative components by using the partial sum procedure of Shin et al. (2014). We have decomposed the only focused variable (AVA) for nonlinear analysis.

\[
AVA^+_{t} = \sum_{i=1}^{p} \Delta AVA^+_{t-i} = \sum_{i=1}^{p} \max (\Delta AVA^+_{t-i}, 0)
\]

(3)

\[
AVA^-_{t} = \sum_{i=1}^{p} \Delta AVA^-_{t-i} = \sum_{i=1}^{p} \min (\Delta AVA^-_{t-i}, 0)
\]

(4)

Equations (3) and (4) represent the positive and negative changes in the AVA variables, respectively. Putting these variables in place of the original variables in Eq. (2) will convert it into the NARDL-PMG model as shown below:

\[
\Delta CO_{2,t} = \alpha_0 + \sum_{i=1}^{p} \pi_{1i} \Delta CO_{2,t-i} + \sum_{i=0}^{p} \pi_{2i} \Delta AVA^+_{t-i} \\
+ \sum_{i=0}^{p} \pi_{3i} \Delta GDP_{t-i} + \sum_{i=0}^{p} \pi_{4i} \Delta EC_{t-i} \\
+ \sum_{i=0}^{p} \pi_{5i} \Delta Urb_{t-i} + \sum_{i=0}^{p} \pi_{6i} \Delta FD_{t-i} \\
+ \omega_1 CO_{2,t-1} + \omega_2 AVA^+_{t-1} \\
+ \omega_3 GDP_{t-1} + \omega_4 EC_{t-1} \\
+ \omega_5 Urb_{t-1} + \omega_6 FD_{t-1} + \lambda.ECM_{t-1} + \varepsilon_t
\]

(5)
The NARDL-PMG model shown in Eq. (5) is an extended version of the ARDL-PMG model, and the same methods and procedures of the linear model are also applicable in the non-linear model. However, the short-run asymmetric effects are confirmed through short-run and long-run WALD tests. The short-run asymmetric effects are validated if the sum of short-run estimates attached to \( \Delta AVA^+ \) and \( \Delta AVA^- \) are significantly different from each other. In the same way, if the long-run estimate of \( AVA^+ \) is different from the long-run estimate of \( AVA \), this indicates the long-run asymmetric effects. In the end, FMOLS, DOLS, and panel quantile regression are also used for robustness.

### Data

Our data sample consists of panel data of nine selected Asian countries (India, Japan, Korea, China, Pakistan, Thailand, Philippines, Vietnam, and Indonesia), covering the period 1985–2019, which are obtained from the World Development Indicators (WDI) by the World Bank (2020). Notably, we consider the \( CO_2 \) emissions in kilotons as the dependent variable, while the independent key factor is agriculturalization. As Ullah et al. (2021) used agricultural value-added as a proxy for agriculturalization, we have used the same definition for our study.

While, the control variables are GDP, energy consumption, financial development, and urbanization. GDP impact is expected positive on \( CO_2 \) emissions by promoting economic activity. Therefore, following Aslam et al. (2021), we use GDP per capita (current US$) as an indicator of economic progress. Theoretical and empirical literature posits that energy consumption has a positive influence on \( CO_2 \) emissions. Following the standard practice (Sohail et al. 2021), we used an energy use (kg of oil equivalent per capita) as an indicator of energy consumption. The nexus between financial development and environmental performance is also well documented (Li et al. 2022). Various studies adopted different proxy measures to capture the impact of financial development. Following the study of Yang et al. (2020), domestic credit to the private sector (% of GDP) is used to measure financial development. Urbanization has increased \( CO_2 \) emissions by rising energy demand. Hence, the urban population (% of total population) is a key factor of \( CO_2 \) emissions (Ullah et al. 2020). For better estimates and expressing large numbers, all variables are converted to the logarithmic form in this study. The descriptive statistics are reported in Table 1, which specify that the average values of \( CO_2 \), \( AVA \), \( GDP \), \( EC \), \( FD \), and \( Urb \) are 10.56, 0.875, 9.356, 10.25, 7.325, and 10.25, respectively.

### Results and discussion

In this study, our goal is to estimate the effects of deagriculturalization on \( CO_2 \) emissions in selected Asian economies. Table 2 reports the results of cross-sectional dependence tests. The findings confirm the presence of cross-sectional independence in main variables among selected economies. For that purpose, we have applied two-panel unit root tests Im–Pesaran–Shin (IPS) and ADF-Fisher. From Table 3, we deduce that both the tests confirm that most of the selected

### Table 1  Variable description

| Variables                  | Symbol | Definitions                                                                 | Mean   | Std. Dev. | Min    | Max    | Sources                                      |
|----------------------------|--------|-----------------------------------------------------------------------------|--------|-----------|--------|--------|----------------------------------------------|
| \( CO_2 \) emissions (kt)  | \( CO_2 \) | \( CO_2 \) emissions (kt)                                                   | 10.56  | 0.875     | 9.356  | 13.56  | WDI, 2020                                   |
| Agriculturalization        | \( AVA \) | Agriculture, forestry, and fishing, value added (% of GDP)                  | 10.25  | 7.325     | 0.870  | 25.02  | https://databank.worldbank.org/source/world-development-indicators#advancedDownloadOptions |
| Gross domestic product     | \( GDP \) | GDP per capita (current US$)                                                | 7.501  | 1.021     | 4.982  | 9.985  |                                             |
| Energy consumption         | \( EC \) | Energy use (kg of oil equivalent per capita)                                | 6.659  | 0.785     | 4.658  | 7.987  |                                             |
| Financial development      | \( FD \) | Domestic credit to private sector (% of GDP)                                | 3.987  | 0.789     | 1.879  | 4.658  |                                             |
| Urbanization               | \( Urb \) | Urban population (% of total population)                                    | 44.02  | 20.01     | 21.23  | 86.01  |                                             |

### Table 2  Cross-sectional dependence test

|                  | \( CO_2 \) | \( AVA \) | \( GDP \) | \( EC \) | \( FD \) | \( Urb \) |
|------------------|-------------|-----------|-----------|---------|---------|----------|
| Pesaran’s test   | 0.036       | −1.118    | 6.886***  | 0.544   | 0.394   | −0.586   |
| Prob.            | 0.971       | 0.263     | 0.000     | 0.586   | 0.693   | 0.557    |
| Off-diagonal     | 0.273       | 0.363     | 0.430     | 0.263   | 0.271   | 0.520    |

1 WDI, 2020 https://databank.worldbank.org/source/world-development-indicators#advancedDownloadOptions
variables are a mixture of \(I(0)\) and \(I(1)\); thus, panel-ARDL is justifiable. To that end, we have applied linear and nonlinear panel ARDL-PMG as baseline models. Then, to check the robustness of our results, we have used linear and nonlinear FMOLS and DOLS, and lastly, the asymmetric quantile regression analysis. However, before applying ARDL and NARDL-PMG, we need to confirm the stationarity of our variables. Next, as our data is annual, the analysis applied a maximum of two lags, and to select appropriate lags, we imposed Akaike Information Criterion (AIC).

**Table 3** Panel unit root tests

|       | ADF          | IPS          |
|-------|--------------|--------------|
|       | \(I(0)\)    | \(I(1)\)    | Decision |
| \(I(0)\) | \(I(1)\) | \(I(0)\) | \(I(1)\) | Decision |
| CO\(_2\)  | \(-0.354^{**}\) | \(-2.790^{***}\) | \(I(1)\) | \(-0.570\) | \(-2.581^{***}\) | \(I(1)\) |
| AVA      | \(-2.598^{***}\) | \(I(0)\) | \(-2.601^{***}\) | \(I(0)\) |
| GDP      | \(0.437\) | \(-6.014^{***}\) | \(I(1)\) | \(-0.970\) | \(-4.318^{***}\) | \(I(1)\) |
| EC       | \(-0.785\) | \(-9.208^{***}\) | \(I(1)\) | \(-1.730\) | \(-5.039^{***}\) | \(I(1)\) |
| FD       | \(-0.099\) | \(-3.678^{***}\) | \(I(1)\) | \(-1.595\) | \(-3.557^{***}\) | \(I(1)\) |
| Urb      | \(-2.657^{***}\) | \(I(0)\) | \(-2.190^{**}\) | \(I(0)\) |

\(***p<0.01\), \(**p<0.05\), and \(*p<0.1\)

**Table 4** ARDL and NARDL estimates

|       | ARDL-PMG |           | NARDL-PMG |           |
|-------|----------|-----------|-----------|-----------|
|       | Coefficient | Std. error | \(t\)-statistic | Coefficient | Std. error | \(t\)-statistic |
| Long run |          |           |          |          |           |          |
| AVA    | \(-0.045^{***}\) | 0.012 | 3.689 | \(-0.047^{***}\) | 0.005 | 7.610 |
| AVA_POS | 0.534^{***} | 0.092 | 5.732 | 0.449^{***} | 0.026 | 17.26 |
| AVA_NEG | 0.323 | 0.322 | 0.996 | 0.846^{***} | 0.050 | 16.91 |
| GDP    | 0.154 | 0.143 | 1.060 | 0.117^{***} | 0.048 | 2.437 |
| EC     | 0.009^{***} | 0.002 | 2.681 | 0.056^{***} | 0.003 | 18.52 |
| Short run |          |           |          |          |           |          |
| D(AVA) | 0.003 | 0.015 | 0.111 | 0.041 | 0.070 | 0.556 |
| D(AVA_POS) | 0.017 | 0.054 | 0.281 | 0.015 | 0.050 | 0.285 |
| D(AVA_NEG) | 0.013 | 0.023 | 0.561 | 0.013 | 0.023 | 0.561 |
| D(GDP) | \(-0.031^{*}\) | 0.016 | 1.674 | \(-0.134^{*}\) | 0.079 | 1.663 |
| D(FD) | 0.695^{***} | 0.156 | 4.419 | 0.182 | 0.514 | 0.351 |
| D(URB) | 0.117^{*} | 0.069 | 1.666 | \(-0.174^{*}\) | 0.100 | 1.740 |
| D(Urb) | \(-0.153\) | 0.135 | 1.119 | \(-0.221\) | 0.272 | 0.805 |
| C      | 1.553^{***} | 0.316 | 4.897 | 2.188 | 1.361 | 1.609 |
| Diagnostics | F-test | 5.678^{***} | 7.665^{***} | 342.5 | 365.5 | 5.356^{***} |
|       | ECM(−1) | \(-0.192\) | 0.036 | 5.156 | \(-0.349\) | 0.194 | 1.776 |
|       | Wald-LR | 365.5 | 1.325 | 3.556^{***} | 1.325 |
Table 4 provides the estimate of linear and nonlinear ARDL estimates alongside the estimate of cointegration tests. The validity of long-run results depends on the outcomes of cointegration tests, namely ECM, and $F$-test. Both the tests confirm that our variables are cointegrated; in other words, the long-run relationship between CO$_2$, AVA, GDP, EC, FD, and Urb is not spurious.

From Table 4, we can infer that the estimated coefficient of AVA in the linear ARDL-PMG is negatively significant, implying that a 1% rise in AVA decreases the CO$_2$ emissions. Similarly, in the nonlinear ARDL-PMG, the estimates attached to AVA_POS and AVA_NEG are negatively significant. Numerically, we can say that a 1% rise in AVA causes the CO$_2$ emissions to decrease by 0.047%, whereas a 1% decline in the AVA causes the CO$_2$ emissions to rise by 0.021%. Both linear and nonlinear findings complement each other and the magnitude of both the linear and nonlinear estimates are almost similar. However, the nonlinear estimates provide an additional estimate that gives us information regarding the effect of negative shock in AVA on environmental quality. The size of negative shock is less than the positive shock, which implies that a rise in AVA will improve the environmental quality more as compared to the degradation in the environmental quality caused by the negative shock in AVA. Seeing the behavior of asymmetric estimates, we can confirm that CO$_2$ emissions respond asymmetrically to the positive and negative shocks, and the asymmetric effects are also confirmed via a significant estimate of WALD-LR reported in Table 4.

Generally, our findings suggest that excessive deagriculturalization improves the environment of selected Asian economies; however, deagriculturalization degrades the environmental quality by increasing CO$_2$ emissions. The agriculture sector can either improve or degrade the environmental quality. According to FAO, agriculture-driven GHG emissions are about one-third of the total global emissions (FAO, 2016). However, FAO also highlighted that the agriculture sector has the ability to reduce its currently produced CO$_2$ emissions down by 20–60% at the end of the year 2030. The agriculture sector can improve the environmental quality by using renewable energy sources (Reynolds et al. 2015; Mohamad et al. 2016; Liu et al. 2017) as it requires energy for plowing, irrigation, harvesting, and livestock activities. Instead of burning the crops residues, bushes, and wastes, farmers can use them to produce renewable energy, which helps to reduce CO$_2$ emissions. Increased agriculturalization can increase plantation and crops, which speed up photosynthesis and consequently mitigate CO$_2$ emissions. Furthermore, improvement in agriculture-related infrastructures such as water reservoirs, agricultural transmission amenities, commodities production base, and rural weather casting framework can help modernize the rural areas, eventually improving the rural economy without exerting more burden on the environment (Dhehibi et al. 2016). Better farm management can also help to reduce livestock-related CO$_2$ emissions (Hou et al. 2015 and Mariantonietta et al. 2018).

The findings of the study illustrate that deagriculturalization reduces energy consumption which leads to a reduction in CO$_2$ emissions. It is also argued that technology-based agriculturalization intensifies green production. The findings also infer that the phenomenon of deagriculturalization is rising in Asian economies that slowing down economic growth and industrialization thus improving environmental quality. Major sources of carbon emissions in the agricultural sector are the burning of crop remainders, chemical fertilizer, enteric fermentation, manure management, soil management, rice cultivation, and livestock. The findings of our study are supported by Alhassan et al. (2021), who state that agriculturalization can control GHG emissions due to the extreme use of cleaner energy sources during the process of production. It is justified as many events of cultivation, such as irrigation, are driven by renewable and clean energy sources. Moreover, it is further justified as the agriculture sector in Asian economies is transforming towards environment-friendly technologies by accumulating positive externalities and endorsing environmental quality. Our findings are congruent with the outcomes of Lin and Xu (2018), who conclude that modern biofuels, for example, biogas and bioethanol, and various other agricultural deposits such as wheatgrass, grain powder, and coverings of hazelnut could be used in the agricultural sector that reduces CO$_2$ emissions. Xu and Lin (2016) further added that cleaner energy sources enhance productivity in the agriculture sector and thus improve environmental sustainability in the long run. Ullah et al. (2021) study support our findings by claiming that the green economic activities significantly control CO$_2$ emissions. Moreover, Lin and Xu (2018) further argued that organic farming in the livestock and agriculture sector is getting enlarged in Asian economies resulting in improving environmental health and human health as well.

The estimates attached to the control variables of GDP are positively significant in linear and nonlinear ARDL-PMG, suggesting the supporting role of economic activities on CO$_2$ emissions. However, the estimates of EC and FD are also positive in both the base models, however, significant in NARDL-PMG and insignificant in ARDL-PMG. However, URB exerts a positive and significant impact on CO$_2$ emissions in both the linear and nonlinear base models. Overall, we can say that energy consumption, financial development, and urbanization contribute to environmental degradation, in Asian economies, besides GDP growth and agriculturalization.

The results of robust models are displayed in Table 5. The estimates attached to AVA in the linear FMOLS and DOLS are negatively significant. In a more precise way, we can say that a 1% rise in agriculture-related activities in the selected Asian economies reduces the CO$_2$ emissions by 0.02% in both FOLS and DOLS models. When we turn our attention to the nonlinear FMOLS and DOLS models, we can see that the estimated coefficients of AVA_POS and AVA_NEG are asymmetric in
More specifically, a 1% rise or positive shock in agricultural activities reduces the CO₂ emissions by 0.03% in FMOLS models and 0.04% in the DOLS model. Conversely, a 1% fall or negative shock in the agriculture sector increases the CO₂ emissions by 0.02% in FMOLS and 0.13% in the DOLS model. The findings of our robust model support the outcomes of our basic model, and both suggest that agriculturalization improves environmental quality in selected Asian economies; whereas, deagriculturalization degrades the environmental quality. Moreover, the size of the estimates in the baseline models and robust models are also similar, which further confirms the results of the baseline models. Like our baseline models, the estimated coefficients of GDP, EC, FD, and Urb are positively significant in the linear and nonlinear FMOLS and DOLS models, implying an increase in economic activities, urbanization, energy consumption, and financial development all degrade the environmental quality.

Table 6 portrays the results of quantile regression estimates. Although we have presented the complete results of all our variables; however, to save space, we only discuss the results of our primary variable. In total, we have included 11 quantiles. The estimates of AVA_POS and AVA_NEG are insignificant from the 5th quantile to the 40th quantile. However, for the rest of the quantiles, the estimates of AVA_POS are significant and negative, but the estimates of AVA_NEG are significant and positive. As far as the effects of AVA_POS on the CO₂ emissions are concerned, the estimates are continuously rising from 0.425% in the 50th quantile to 0.556% in the 95th quantile. Generally speaking, the higher will be agriculture-related activities will be the improvement in the environmental quality. On the other side, the estimates of AVA_NEG decrease from 50th quantile to 60th quantile. It increases again in the 70th quantile, and after that, it decreases continuously till the 95th quantile. The results of AVA_NEG suggest that deagriculturalization degrades the environmental quality; however, its impact is most severe in the 70th quantile and least in the 60th quantile.

### Conclusion and implications

The existing literature on agriculturalization and environmental pollution has been overwhelmed with ambiguous findings. As several studies reveal a clear association between agriculturalization and degradation of environment which provides no clear discrepancy between carbon emissions stemming from agricultural modernization and pollution emissions persuaded by various cultivation strategies and practices. The study makes an effort to explore the asymmetric impact of agriculturalization on CO₂ emissions in nine Asian economies for time horizon 1985 to 2019. For conducting regression analysis, the study employed ARDL-PMG and NARDL-PMG techniques. The long-run outcomes of ARDL-PMG infer that agriculturalization...
has a significant negative impact on CO₂ emissions revealing that in response to an increase in agricultural activities, the quality of the environment will rise. The findings of NARDL-PMG deduce that positive shock in agriculturalization infer a significant negative impact on CO₂ emissions and negative shock in agriculturalization (i.e., de-agriculturalization) has a significant positive impact on CO₂ emissions. In short, according to NARDL-PMG findings, agriculturalization tends to enhance environmental quality and de-agriculturalization leads to diminishing the quality of environment in the long run. The study also incorporated the impact of some important control variables such as GDP, energy use, financial development, and urbanization on carbon emissions in selected Asian economies. The NARDL-PMG findings of these control variables demonstrate that all these factors significantly increase carbon emissions in the long run in these economies. However, the findings do not report any symmetric and asymmetric association between agriculturalization and CO₂ emissions in the short run. For robustness testing, the study employed FMOLS and DOLS regression techniques. The empirical outcomes of robust models are quite similar to the findings of ARDL-PMG and NARDL-PMG approaches.

Given our empirical results, the government and policymakers need to emphasize organic farming in selected Asian economies. The governments should emphasize zero tillage, organic farming, irrigation monitoring, drones, and biotechnology that would help in the reduction of environmental pollution in Pakistan. The policymaker should use more clean energy consumption in agricultural activities. The Asian governments can encourage green agricultural revolution by adopting an incentive mechanism. The outcomes of the empirical study can be a guideline and blueprint for other agrarian countries to tackle the problem of deagriculturalization for the creation of effective policies around environmental quality. Government should be established and empowered to control and reduce agriculture-based pollution in Asian economies. Asian governments should increase environmental quality by improving green agriculturalization.

This study is not free from shortcomings, and the major limitation of the study is that it does not consider the cross-sectional dependence while analyzing the impact of deagriculturalization on CO₂ emissions. The method applied in the analysis does not accommodate the cross-sectional dependence among the selected economies. Further, the data set is limited to a few Asian economies; therefore, the inferences drawn from the study are limited in their impacts. There are still several avenues for future research. The present study is done for Asian economies at the aggregate level; in the future, the same study can also be done for disaggregated levels considering these economies. Furthermore, the same model can be tested for other regions and developing economies, especially for newly emerging economies.

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

Author contribution This idea was given by Siyuan Lin. Siyuan Lin, Ning Zhou, and Junaid Jahangir analyzed the data and wrote the complete paper, while Sidra Sohail read and approved the final version.

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Declarations

Ethics approval Not applicable

Consent to participate I am free to contact any of the people involved in the research to seek further clarification and information.

Consent for publication Not applicable

Competing interests The authors declare no competing interests.

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