CO_2 EMISSION AND AGRICULTURAL PRODUCTIVITY IN SOUTHEAST ASIAN REGION: A POOLED MEAN GROUP ESTIMATION

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ABSTRACT

Frequent natural calamities, extreme climatic events and unexpected seasonal changes are the obvious examples of global warming. Carbon emissions by industrial units all over the world are believed to be the major contributor of the global warming that can lead to reduced agricultural productivity. This paper examines the impact of CO_2 emission on agricultural productivity in Southeast Asian countries. It investigates the dynamic relationship between CO_2 emission (along with other control-variables) and agricultural output using panel data set comprising data from Southeast Asian countries. Following the dynamic heterogeneous panel techniques developed by Pesaran and Shin (1999) for estimating the short-run and long-run effects using autoregressive distributed lag (ARDL) model in the error correction form, the study then estimated the empirical model based on pooled mean group (PMG) estimator. The study found that increased CO_2 emission resulted in higher agricultural productivity because of the fact that farmers around the globe quickly adapt to climate change. In addition, use of submersible pump and other capital machineries significantly increased agricultural yield and led to reduced dependency on human capital, while use of chemical fertilizers increased productivity in short-run but had a harmful impact in the long-run.

Keywords: *CO_2 emission, agricultural productivity, Southeast Asia, and PMG estimation.*

1. INTRODUCTION

Agriculture sector is climate dependent and sensitive to climate changes that have direct effect on its productivity. Various climatic events, such as rise in temperature, change in the frequency and intensity of rainfall and natural calamities (such as, cyclone, tornado, and tsunami) are directly linked to increased level of CO_2 emission. Extreme climatic events are likely to become more common and to have substantial effects on irrigated agriculture.

As most of the developing countries depend heavily on agriculture, the effects of CO_2 emission on productive croplands are likely to be threatening to both the welfare of the populations and the economic development of these countries. Tropical regions in the developing world are particularly vulnerable to damage from environmental changes because the unfertile soils that cover large areas of these regions already have made much of the land unusable for cultivation.

The choice of the crops cultivated and the optimal planting and harvesting times depend directly on the weather conditions in each region. This implies that the impending climate change due to increase in greenhouse gases will have direct effect on agricultural productivity, and, consequently, on farmers' incomes.

Climate change is already evident in Europe, Asia and other parts of the world, as noted by a comparison of the frequency of draughts and other extreme weather phenomena in the last half century (Olesen and Bindi, 2002). Many people believe that emissions of greenhouse gases due to anthroprogenic activities will lead to higher temperatures and increased precipitation during the 21^{st} century. Similarly, these changes are thought to have an impact on economic well being as well. The question remains: 'if such changes occur, will their economic effects be positive or negative?' A definitive answer to this question is likely to take a while, but recent research has shed light on one important aspect. Deschênes Olivier and Michael Greenstone (2007) showed that the changes in temperatures and precipitation forecast by the standard models of climate change will actually benefit agriculture in America. The most widely cited models of climate change predict that over the remainder of the century, average temperatures will rise by about 50^{o}F, and precipitation will eventually result in an average 8-inch increase in rain every year. Using these predictions, combined with the effects of past swings in temperature and precipitation, the authors concluded that agricultural productivity in the United States is likely to rise slightly (about 4 percent) due to climate change, yielding modest positive economic benefits.

In Southeast Asian region the overall agricultural productivity has shown gradual increase (Sujan, et al., 2011). The factors behind this growth are many but some are very influencing. The use of chemical fertilizers seems to have played an important role in this growth. In this paper, therefore, we examine the effect of various factors behind the increase in South Asia's agricultural productivity, and suggest appropriate policy options addressing carbon emission and agricultural productivity in Southeast Asia.

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2. LITERATURE REVIEW

Tremendous volume of research has been done in the field of climate change and global warming. However, specific studies on 'impact of carbon emission on agricultural productivity' are limited in number. Singh and Stewart (1991) examined the potential impacts of climate change resulting from an effective doubling of atmospheric CO_2 on the potential and anticipated yields of a variety of agricultural crops, including corn, soya, potatoes, wheat, phaseolus beans, sorghum, barley, oats, rapeseed and sunflowers, as well as two horticultural crops, namely apples and grapes for southern Quebec. It was found that yields would increase for some crops, such as corn, soybeans, potatoes, phaseolus beans and sorghum and would decrease for the cereal and oilseed crops, namely wheat, barley, oats, sunflowers and rapeseed. Production opportunities for apples and grapes were enhanced. Also, it appeared that the more northerly regions of Abitibi-Témiscamingue and Lac St-Jean would benefit most, in terms of agriculture, from a CO_2-induced climate change.

Olszyk, et al. (1999) estimated potential impacts of global climate change on rice yield in the Philippines and found that with ambient CO_2 and elevated temperature, both simulations and experiments generally showed no change in grain yield and biomass. But none of the responses in the experiments were statistically significant. For both elevated CO_2 and elevated temperature, simulated grain yield increased in all three seasons, whereas there were no significant effects on experimental grain yield.

Arthur, et al. (2007) investigated the environmental consequence of increased atmospheric carbon dioxide. Using a descriptive method, the study concluded that increased atmospheric carbon emission showed a marked positive effect in plant growth, and predictions of harmful climatic effects due to future increases in hydrocarbon use and minor amounts of green house gases like CO_2 do not conform to current experimental knowledge.

Daniel, et al. (2009) examined potential climate change impacts on the productivity of five major crops in the Eastern China and found that aggregate potential productivity increased 6.5% for rice, 8.3% for canola, 18.6% for corn, 22.9% for potato, and 24.9% for winter wheat. Although with significant spatial variability for each crop and without the enhanced CO_2-fertilization effect, potential productivity declines in all cases ranging from 2.5 % to 12 %.

Quiggin, et al, (2010) used a simulation model of state-contingent production to analyze the effects of climate change adaptation, which revealed that climate change will have adverse effect on irrigated agriculture in the Murray–Darling Basin in Australia, and a combination of climate mitigation and adaptation through variation in land and water uses will allow the maintenance of agricultural water use and environmental flows. Seo (2011) examined gross cell product (GCP) of Australia and New Zealand to quantify the impact of climate change and revealed that GCP falls sharply as temperature increases in the region. A 1°C increase in temperature would increase the productivity with an elasticity of -2.4, and 1 percent decrease in precipitation would decrease productivity with an elasticity of -2.3 with exception for forest vegetation on the coast that will benefit from initial warming.

Hui, et al. (2013) found that simulated productions of grain crop inherit uncertainty from using different climate models, emission scenarios and the crops simulation models. They assessed that the magnitude of change in crop production due to climate change appears within ±10% for China, and also reported that three cereal crop yields showed decline under climate change scenarios, and only wheat yields in some region showed increase. Besides, the uncertainty for crop yield projection is associated with climate change scenarios, CO_2 fertilization effects and adaptation options.

Thus, it is concluded that the literature on "CO_2 and agriculture production linkage" is not very rich and findings of previous researches cited above are mixed around the different parts of globe, perhaps because of variations in climatic conditions.

3. METHODOLOGY AND MODEL SPECIFICATION

This study has paid a sterling attention to assess the impact of CO_2 emission along with other relevant control variables, e.g., use of fertilizer, capital and population, on agriculture growth. In general, there is a consensus that panel data has fundamental advantages over a cross section or time series data, as panel estimation blends the time and cross sectional observations. Therefore, to accomplish the task panel data set has been used for 13 countries in Southeast Asia, namely Bangladesh, India, Bhutan, Nepal, Pakistan, Sri Lanka, Maldives, Thailand, Malaysia, Philippines, Lao People's Democratic Republic, Iran, and Cambodia, for a period of 37 years ranging from 1975 to 2011. Data was collected from FAO and the World Bank database and E-views 7 was used to analyze the data.

3.1 The Static Models

The traditional static models, such as pooled OLS, fixed effect and random effect have some serious limitations. For example, pooled OLS is highly restricted model since it considers the common intercept and coefficients for all cross-sectional and time series observations. In fixed effect model both the cross-sectional and time effect series can be observed, although such observation is restricted with the loss of degree of freedom due to introduction of a large number of dummy variables, especially in two way fixed models (Gujarati, 2002). In contrast to the fixed effect model, random effect is relatively less restrictive, since it considers cross sectional effects. However, random effect also has other severe limitations, i.e. the model is time invariant. This implies that the error at any period is uncorrelated with past, present and future, known as strict exogenity (Arellano, 2004). However, in real life such assumption very often rules out.

Furthermore, panel cointegration test reveals the long- run relationship, like pedroni, fisher, bretung and so on, but these models have some prerequisite conditions. For instance, all the variables have to be of the same integrated order otherwise the models would provide spurious results (Gries, et al., 2009). Moreover, there is always the possibility of multicollinearity, since most models consider a number of variables. Moreover, these models hold another assumption, i.e., the errors are conditionally homoskedastic and not serially correlated, which is very unexpected in the case of macro time series data (Arellano, 2004).

Once this assumption rules out the ordinary regression formula for estimating the within-group variance, it leads to inconsistent standard errors. On the other hand, random effect would be an appropriate specification in drawing N individuals randomly from a large population, but still the model is time invariant. Therefore, the model is unable to capture the dynamic nature of the data.

3.2 The Dynamic Panel Methodologies

One of the oldest methodologies used in panel data analysis to capture the dynamic nature of the data series is the 'GMM panel estimators', where GMM stands for Gaussian Mixture Model. This model captures the short-run dynamics. However, in this approach, the integration and the cointegration properties of the data are ignored. Thus, it is not clear whether the estimated panel models represent a structural long-run equilibrium relationship or a spurious one (Christopoulos & Tsionas, 2004). Moreover, Kiviet (1995) argued that in GMM estimation the imposition of homogeneity assumptions on the coefficients of lagged dependant variables could lead to serious biases. Moreover, the GMM and other pooled estimation models, such as the fixed effects and instrumental variables approach are intended to address potential mis-specifications and achieve consistent estimates in the presence of endogeneity.

The estimation procedures assume homogeneity in the slope coefficients. Then again, these estimation procedures are likely to produce inconsistent and misleading long-run coefficients unless the slope coefficients are indeed identical (Pesaran, et al.,1999).

Since the study focuses on identifying the long and short-run association between CO_2 and agriculture GDP, as well as to investigate the possibility of heterogeneous dynamic issues across countries, the appropriate technique to be used for the analysis of dynamic panels is autoregressive distributed lag ARDL (p,q) model in the error correction form. Then to estimate the model based on the mean group (MG) presented by Pesaran and Smith (1995) and pooled mean group (PMG) estimators developed by Pesaran, et al. (1999).

3.3 The PMG Model

Pesaran and Smith (1995), Pesaran (1997), and Pesaran and Shin (1999), present the autoregressive distributed lag (ARDL) in the error correction form as a relatively new cointegration test. Here emphasis has been laid to have simple modifications to standard methods in order to have consistent and efficient estimates of the parameters in a long-run relationship. Though Johansen (1995) and Philipps & Bruce (1990) argued that the long-run relationships exist only in the context of cointegration among integrated variables, but Pesaran and Shin (1999) argued against such assumption and presented number of econometric advantages of the PMG and MG comparing with other methods. First, the application of PMG and MG estimators do not require cointegration tests. Moreover, validity of stationarity or integration between the variables to estimate long-run relationships and of pre-testing for unit roots is no longer required, because this methodology allows estimations of different variables with different order of stationarity, i.e. it is valid whether the variables of interest are I(1) or I(0).

Moreover, this model is appropriate for the panel with large N and T dimensions, thus there is no issue of short panel or long panel. Secondly, this estimator enables us to estimate short and long-run effects simultaneously from (ARDL) model. Thirdly, failure to test hypothesis on the estimated coefficients in the long-run due to endogeneity problems in Engle Granger method can be resolved by autoregressive distributed lag approach.

Furthermore, PMG allows short-run coefficients, including the intercepts, the speed of adjustment to the long-run equilibrium values, and error variances to be heterogeneous country by country, while the long-run slop coefficients are restricted to be homogeneous across countries.

However, there are several requirements for the validity, consistency and efficiency of this methodology. First, the existence of a long-run relationship among the variables of interest requires that, the coefficient on the error–correction term has to be negative and not lower than -2. Secondly, an important assumption for the consistency of the PMG estimates is that, the resulting residual of the error-correction model be serially uncorrelated and the explanatory variables can be treated as exogenous. But these conditions can be fulfilled by including the ARDL (p,q) lags for the dependent (p) and independent variables (q) in error-correction form. Third, the relative size of T and N is crucial, since both of them are large this allows us to work on dynamic panel technique. This also helps to avoid the bias in the average estimators and resolve the issue of heterogeneity. Eberhardt and Teal (2010) argued that the treatment of heterogeneity is central to understanding the growth process. Additionally, for small N the average estimators in this approach are quite sensitive to outliers and small model permutations (Favara, 2003). Finally this estimator is particularly useful when there are reasons to expect that the long-run equilibrium relationships between variables to be similar across countries, because they might have similar nature in terms of agricultural production.

3.4 The Mean Group Estimator (MG)

The second technique (MG) introduced by Pesaran & Smith (1995) calls for estimating separate regressions for each country and calculating the coefficients as un-weighted means of the estimated coefficients for the individual countries. This does not impose any restriction. It allows for all coefficients to vary and be heterogeneous in the long-run and short-run. However, the necessary condition for the consistency and validity of this approach is to have a sufficiently large time-series dimension of the data. In addition, the cross-country dimension should also be large (about 20 to 30 countries according to Pesaran, et al.,1999) and of roughly the same order of magnitude.

3.5 Dynamic Fixed Effect (FE) Model

Finally, the dynamic FE estimator is very similar to PMG estimator in confining the coefficient of the co-integrating vector to be equal across all panels in the long-run. The FE model further restricts the speed of adjustment coefficient and the short-run coefficient to be equal. Dynamic fixed effect (DFE) model allows panel-specific intercepts. DFE model also calculates the standard error while allowing intra-group correlation. As discussed by Baltagi, Gri, and Xiong (2000), FE models are subject to a simultaneous equation bias from the endogeneity between the error term and the lagged dependent variable. The Hausman test can be easily performed to measure the extent of this endogeneity.

3.6 A Choice between MG or PMG or DFE Model

For the desired purposes under the assumption of long-run slope homogeneity, the PMG estimator offers an increase in the efficiency of the estimates with respect to mean group estimators (Pesaran, et al., 1999). This is because a homogeneous nature exists in countries under study in terms of agriculture growth and CO_2. We, therefore, expect that the long-term relationship between agriculture growth and CO_2 would be more homogenous across the middle income countries. However, short-run impacts of CO_2 on agricultural productivity may vary across countries. However, Hausman test can be used to test whether there is a significant difference between the PMG and MG. The null of this test is that the difference between PMG and MG estimations is not significant. If the null is not rejected, they are not significantly different; one uses the PMG estimator, since it is efficient. The alternative is that there is a significant difference between PMG and MG. If the null is rejected, they are significantly different, and one uses the average estimator. If there are outliers the average estimator may have a large variance and in that case the Hausman test would have little relevance.

Another important issue is that when the main interest is on the long-run parameters, and with a limited number of time series observations, ARDL lag structure should not be overextended as this imposes excessive parameter requirements on the data. The lag order can be selected either by tests, such as the Schwartz-Bayesian Criterion, or it might be imposed according to the data limitation, as is the case here that the time dimension is not long enough to over-extend the lags (Loayza and Ranciere, 2006).

Given the above discussion, the choice amongst the methodologies is a trade-off between efficiency and consistency. Therefore, at this stage the study developed the ARDL specification formulated with reference of Loayza and Ranciere (2006), which can be presented as follows:

$$\Delta(y_i)_t = \sum_{j=1}^{p-1} {}^{i}_{j}\Delta(y_i)_{t-j} + \sum_{j=0}^{q-1} {}^{i}_{j}\Delta(X_i)_{t-j} + {}^{i}[(y_i)_{t-1} - \{{}^{i}_{0} + {}^{i}_{1}(X_i)_{t-1}\}]_{it} \quad .(1)$$

where, y is agriculture GDP, X is a set of independent variables, including the CO_2, the subscripts i and t represent country and time, respectively. The term in the square brackets contains the long- run growth regression.

The equation (1) can be estimated by either PMG or MG or even DFE estimators, where all the three models consider the long-run equilibrium and the heterogeneity of dynamic adjustment process (Demetriades and Hook, 2006). Moreover, these estimators are computed by maximum likelihood estimations.

4. RESULTS AND DISCUSSION

The Table-1 summarizes the dynamic impact of CO_2 emission along with other control variables on real agriculture GDP growth. As per the PMG, MG and DFE estimators under panel ARDL(p,q) model by Pesaran, et al (2001), the error correction coefficient has to be negative and greater than -2 for the confirmation of the long-run elasticity. Expectedly, all the three estimators provide negative (greater than -2) and statistically significant coefficient. Since each model has particular features in terms of long-run and short-run homogeneity restriction, hence for this study Hausman test was conducted to evaluate the difference among PMG, MG and DFE. Here the long-run coefficients from PMG are restricted to be homogenous, while unrestricted for MG (Pesaran, Shin, and Smith, 1999). However, DFE considers all the coefficients, short-run and long-run are restricted to be same for all countries. Table-1 shows that Hausman test-1 accepts the null of coefficient restricted to be same in long-run, whereas Hausman test-2 confirms that the coefficient of both short-run and long-run are homogenous. Since the table shows DFE is consistent and efficient over PMG and MG, therefore this study emphasizes on interpreting the result from DFE as the Hausman test confirms that DFE is consistent and efficient over MG and PMG, which implies that the impact of CO_2 along with other controls follow a homogenous nature across the concerned countries in short and long-run.

It is found that CO_2 has a positive and statistically significant effect at 1% level indicating that it promoted the Agricultrual Gross Domestic Product (AGDP) despite having a lot of criticism about emission as shown by DFE estimation. This finding is not surprising since it is in line with the empirical findings of several studies including Singh and Stewart (1991). Table-1 also shows a positive and significant association between CO_2 and AGDP in short-run, though the result obtained from PMG and MG analyses showed a statistically insignificant result.

In addition, the long-run coefficient from the DFE reported that capital employed in agriculture sector has a positive and significant impact on AGDP though PMG and MG provided positive but insignificant coefficients. However, the positive sign with statistically significant coefficient of capital from all three estimators revealed that capital fostered AGDP in the short-run in countries under study.

The population involved in agriculture sector, however, does not have a significant impact on AGDP, neither in short-run nor in the long-run as provided by the DFE estimation, because farmers use more of capital equipments and depend less on human capital. Though PMG found a significant coefficient, but the study considers DFE as per Hausman confirmation of long-run and short-run homogeneity restriction.

Though chemical fertilizer is used in agriculture sector very extensively, it has a negative impact on long- run AGDP, as the coefficient of fertilizer obtained from DFE is negative and significant. However, the short-run impact of fertilizer is significantly positive for fostering the short-run AGDP.

Table-1: Impact of Carbon Emission and other Control Variables on Agricultural Productivity

	Pooled Mean Group		Mean Group		Dynamic Fixed Effect	
AGDP	**Long Run**	**Short Run**	**Long Run**	**Short Run**	**Long Run**	**Short Run**
Error Correction		-0.190***		-0.422***		-0.0666***
		(0.0662)		(0.0713)		(0.0191)
Δ Capital		0.385*		0.799***		0.450***
		(0.222)		(0.246)		(0.0941)
Δ Population		0.00306		-0.000703		5.41e-05
		(0.00406)		(0.00145)		(8.77e-05)
Δ Fertilizer		-0.000103		-8.88e-05		4.07e-05
		(0.000156)		(0.000200)		(7.07e-05)
Δ $C0_2$		0.0617		0.0589		0.0461***
		(0.0464)		(0.0504)		(0.0112)
Hausman Test 1					2.64 (0.619)	
Hausman Test 2					0.02 (0.999)	
Capital	0.269		0.309		1.287***	
	(0.182)		(0.267)		(0.323)	
Population	0.000912***		-0.000241		0.000132	
	(0.000252)		(0.00290)		(0.000575)	
Fertilizer	0.000588***		0.000830		-0.000168	
	(0.000207)		(0.000605)		(0.000571)	
$C0_2$	0.411***		0.279***		0.220***	
	(0.0436)		(0.0903)		(0.0835)	
Constant		0.356**		0.323		-0.386*
		(0.142)		(0.956)		(0.203)
Observations	468	468	468	468	468	468
Note: *** Significant at 1% level, **Significant at 5% level, *Significant at 10% level.						

5. CONCLUSIONS AND RECOMMENDATIONS

The foregoing analysis reveals that the findings are practically relevant and promising. CO_2 is the basic element of photosynthesis by which plant grows food, as a result increased CO_2 emission should lead to higher agricultural productivity, as found and claimed by this research. On the contrary, CO_2 emission has direct link with abrupt climate change like flood, drought, cyclone, etc. which surely has a negative impact on agricultural productivity. The empirical findings from this research showed higher agricultural GDP because of the fact that farmers around the globe quickly adapt to changes. They change the timing of cultivation according to the changing climate. On the other hand, use of submersible pump and other capital machineries significantly increases agricultural productivity. This fact is also demonstrated by empirical findings that use of capital increases agricultural productivity. On the other hand, now-a-days, farmers use more of machineries that reduce dependence on human capital. This fact is also proven by insignificant impact of population involved in agricultural production. Lastly, the finding regarding use of chemical fertilizers is very significant. The result showed short-term positive and long-term negative impacts that are highly significant. This means even though use of chemical fertilizer increases productivity in short-run but it has a harmful impact in the long-run.

Therefore, as the carbon emission has shown mixed effect on agriculture, it requires more investigation of the issue. Meanwhile, steps should be taken to invent climate adaptive crops. Chemical fertilizers should judiciously be used to lessen their negative impact on long-run agricultural productivity.

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