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Abstract

There is evidence of severe vulnerability of the rice sector even with the remarkable importance it plays in the Philippine society and the economy. The convergence hypothesis was verified among the Philippine provinces with reference to rice production. Convergence could mean harmonized efforts among various stakeholders to increase production among low-producing provinces to be at par with the production level among those agriculturally productive provinces that can hopefully stimulate achievement of food sufficiency. Using a panel data model augmented with a spatial autoregressive term, there is empirical evidence for the need to localize rice production policy programs across the country. The spatial term also accounts for the natural endowments of the producing provinces that complement those policies in realizing progress in the sector. Rice production among

the Philippine provinces diverged in the period 1990-2002. The El Nino episode of 1998 pulled down rice yield further aggravating the divergence among provinces.

Keywords: spatial-temporal model, backfitting, autoregression, random effect model, agricultural growth

Introduction

The Family Income and Expenditures Survey (FIES) in 2003 estimated that 79% of agricultural households fall among the four lowest income deciles (bottom 40% of the population) in the Philippines. On the other hand, only 30% of the non-agricultural households are in the bottom 40% of the population. This provides evidence of vulnerability of those in the agriculture sector in the Philippines. Furthermore, within the agriculture sector, those engaged in crop production are more disadvantaged with an average annual income in 2003 of PhP 59,999 compared to the rest in the agriculture sector with an average income of PhP 68,703.

The strong El Nino (a global weather anomaly whose effect in the Philippines is prolonged dryspell) episode of 1998 [6] expectedly affected the agriculture sector the most. The marginalization of grain farmers, specifically, those planting rice can be gauged from the gross value added (GVA) of the rice sector that declined by as much as 24% while the other crops sector were able to keep the decline to within single digit levels. Although a majority of agricultural land devoted to rice farming benefits from irrigation systems, due to the non-sustainable water source and frequent damage to the physical infrastructure caused by harsh weather conditions, rice farming still maintained the same marginalization due to the volatile weather conditions and poor policy measures towards the sector.

While the world is focusing on productivity growth to fuel agricultural growth, the Medium Term Philippine Development Plan 2004-2010 targets expansion of cultivation area as the source of agricultural growth for the Philippines. Expansion of production areas can only be secondary to a more important tool in policy making in Philippine agriculture, i.e., an assessment of the robustness of the sector to internal and external shocks. This assessment shall provide a good instrument in the development of policies and intervention strategies to avert the vulnerability of the rice sector.

The paper postulates a spatio-temporal model with spatial externalities accounted for in the model through sparse spatial autoregression to explain the dynamics of growth in yield of rice production in the Philippines. The model is then used in the verification of the convergence hypothesis with provinces as the units. Provinces are said to converge if growth in yield for the slow-growing provinces becomes faster than the growth in yield among the fast-growing provinces, and eventually achieve growth equilibrium. Convergence implies that there is enough intervention for the slow-growing (in terms of rice yield) provinces to catch up with the fast-growing provinces, further implying the appropriateness of intervention strategies intended to improve growth in yield of rice production among the provinces. Evidence of convergence will also be supported by equity among the stakeholders, that there is equity in the distribution of the needed intervention across the provinces. Furthermore, convergence may imply that the present production areas are indeed suitable for rice production. This could also mean harmonized efforts among various stakeholders in the rice sector towards a common goal of food sufficiency at the least. Divergence on the other hand, could mean that there is a need for a massive structural assessment of the sector and the goals of the different stakeholders to be able to identify an optimal strategy leading towards increase in growth of rice yield and subsequently abating the rice shortage problem confronting the Philippines and many Asian countries.

Rice Production in Philippines

Patterns of Rice production in the Philippines vary tremendously across provinces and over different periods. Rice is typically planted twice a year, one cycle during the wet months (May-October), and one cycle during the dry months (November-April). Production cycle varies across the provinces, with the southern provinces usually planting ahead of the other provinces since the onset of rainy season varies from north to south. During the period 1990-2002, quarterly growth (present quarter relative to same quarter previous year) averaged 62% across all provinces. The yield (indicating both technology advancement and production efficiency) has grown at an average of 4% per quarter. For the same reference period, the average yield is 2.78 metric tons per hectare (±0.81). Vulnerability of production activities to weather conditions is reflected in production area with an average quarterly growth rate of 61% (negative for some provinces on some quarters). Growth in production is high usually during the second quarter coming from very low (no production in some provinces) production in the fourth and first quarter. Yield has been growing until a decline in 1998 (El Nino year), but it recovered shortly thereafter. Production exhibits similar average pattern across province per quarter. See Figures 1 and 2 for details.

[Figure 1 Here]

Convergence and Agricultural Growth

With motivations from the Solow economic growth model, the concept of convergence has emerged from the literature for a relatively long period now. As noted by [3], the Solow model predicts that economies converge to a steady state, where the key force that underlies the convergence effect is diminishing returns to reproducible capital. Furthermore, steady state growth rate (zero growth) is explained by the growth model and it is only possible to obtain continued growth in output if there is exogenous technical progress or production efficiency.

Several convergence models appear in the literature. As discussed by [1] and [9], there are initially two types of convergence: unconditional or absolute β-convergence and σ-convergence. If there is a tendency for poor economies to grow at a faster rate than the richer ones, then there is absolute β-convergence. Specifically, if β > 0 in the following regression equation from [9], $\gamma_{i,t,t+T} = \alpha - \beta \log(y_{i,t}) + \varepsilon_{i,t}$, where $\gamma_{i,t,t+T}$ is the annual growth rate of GDP of the i^{th} economy between time t and t + T and log $(y_{i,t})$ be the logarithm of the i^{th} economy's GDP per capita at time t, then there is absolute β-convergence. On the other hand, if $\sigma_{t+T} < \sigma_t$, where σ_t is the standard deviation at time t of $\log(y_{i,t})$ across all economies, then the economies are σ-converging. Thus, σ-convergence implies a decreasing trend in the dispersion of per capita GDP or income over time. It refers to the inter-temporal gradual development of the dispersion of world income. These two kinds of convergence are in a way related. [9] noted that β-convergence is a necessary but insufficient condition for sustained σ-convergence. [2] pointed out that convergence is necessary since the level of inequality will grow indefinitely when β is negative (i.e. when richer economies grow faster than the poorer economies).

Absolute convergence can only be expected or anticipated exclusively among economies which are structurally homogenous and the only difference across economies is their initial levels of capital. This insight is instrumental in the formulation of the concept of conditional convergence. This model allows for the differential determinants of the steady state levels (e.g. technological level, propensity to save, or population growth rate) of the economies under study. To verify existence of conditional convergence, [1] suggested to estimate the equation $\gamma_{i,t,t+T} = a - b\log(y_{i,t}) + \psi X_{i,t} + \varepsilon_{i,t,t+T}$ where $X_{i,t}$ is a vector of variables that hold constant the steady state of economy i, and $b = (1 - e^{-\beta T})/T$. If the resulting β is positive for $X_{i,t}$ which is held constant, then there is conditional convergence. This seems to be a more realistic model since it is possible for economies to differ in varying technological and behavioral parameters which in turn translates to different levels of equilibrium.

Absolute convergence implies a tendency for differences in per capita income to wear off within the sample over time. In the long run, expected per capita income is the same for all members of the group, independently of its initial value. As explained by [2], this does not mean that inequality will disappear completely, for there will be random shocks with uneven effects on the different areas. With conditional β-convergence, on the other hand, each economy converges only to its own steady state but these can be very different from each other. Hence, a high degree of inequality could persist, even in the long run, and will be observed with high persistence in the relative positions of the different economies. In other words, rich economies will generally remain rich while the poor continue to lag behind.

This leads us to the question of interpretability of the parameter β from the two models. β shows how fast the economies approach their steady state levels. It can help in the analysis of economic growth as it gives the rate or speed of convergence. [2] further noted that there is no contradiction between these estimates once it is recognized that they are measuring different things. While the unconditional parameter measures the overall intensity of a process of income convergence which may work in part through changes over time in various structural characteristics, the conditional parameter captures the speed at which the economy would be approaching a "pseudo steady state" whose location is determined by the current values of the conditioning variables.

Agriculture has a vital role to play in contributing to an economy's development. According to [4], agricultural growth is central to development and the implication of the model on structural transformation (i.e., a declining role for agriculture) can be a threat to development. The model actually shows a connection of agricultural growth to industrial development. Those countries which are experiencing increases in agricultural productivity will have a shift of workers from the agricultural to nonagricultural sector. That low agricultural productivity can substantially delay industrialization among these countries. This delay might result into low per capita income of the country compared to that of the leader. Greater understanding of the determinants of agricultural productivity will improve the understanding of the development process among poor nations.

[9] cited that increases in agricultural production, both from crops and animals, initially were attributed to increases in the area cultivated but towards the end of the twentieth century, growth is coming from increases in land productivity (output per acre or hectare of cultivated area). Growth in total factor productivity in agriculture

has made an important contribution to economic growth within rural areas and this has led to poverty reduction. There are several constraints on agricultural productivity: resource and environmental, scientific and technical, and institutional. These will have differential effects on economies having such constraints and specific actions can be taken to facilitate growth in each economy.

Model Specification and Estimation

This paper uses quarterly rice production data aggregated at the provincial level for the period 1990 to 2002 in the Philippines. Rice production is characterized by pronounced seasonality, having only two complete production cycles within a year.

A spatial autoregression term accounting for spatial externalities (natural endowments, localized policies, local climate, etc.) is embedded in the spatial-temporal growth model similar to [7], postulated as follows:

$$\begin{aligned} \Delta p_t &= \beta_0 + \beta_1 \log(y_t) + \beta_2 \log(a_t) + \beta_3 \log(c_t) \\ &\quad + \delta\left(\Delta p_t - \beta_0 - \beta_1 \log(y_t) - \beta_2 \log(a_t) - \beta_3 \log(c_t)\right)D + u + e_t \qquad (1) \end{aligned}$$

$$e_t = \rho e_{t-1} + z_t$$

Where Δp_t is a vector of growth rates in quarterly yield of rice for the provinces at time t, computed both from the original and the deseasonalized data. Deseasonalization is used to eliminate the effect of strong seasonality in rice production. Presence of pronounced seasonality can conceal the structural relationship among time series.

Deseasonalization can also provide an alternative method of computing growth rates (quarter of the current year relative to the same quarter of the previous year). y_t is the vector of yield of rice of the provinces at time t, a_t is the vector of harvest area for rice, c_t is the vector of harvest area for corn. Following [5], the neighborhood system used is the region composed of several provinces. Agriculture planning and the subsequent programs are implemented at the regions, hence, it is expected that there is some homogeneity of rice production among provinces in the same region. A neighborhood is composed of provinces in the same region who are beneficiaries of similar agricultural policies and programs. Thus, the matrix $D = [(d_{ij})]$ is defined as

$$d_{ij} = \begin{cases} \frac{1}{m_R}, \text{ if province i and j are neighbors (in the same region)} \\ 0, \text{ otherwise} \end{cases} \qquad (2)$$

a spatial autoregression indicator matrix, m_R is the number of provinces in a region and can possibly vary across the regions. $u = (u_1, u_2, .., u_k, .., u_P)^T$ is a vector of random effect component that will account for productivity endowments specific to the provinces and constant over time, P is the number of provinces and $u_k \sim NID(0, \sigma_u^2)$. e_t is the vector of autocorrelated errors for the provinces at time t, and $z_t \sim N(0, \sigma^2)$. The effect of D is to average initial residuals of provinces in the same region (neighborhood). The residuals, after accounting for the covariates, are attributed to the spatial externalities common among provinces in the same region. The spatial externalities can serve as aggregate proximate indicators of the viability of the area in growing the crop (natural endowments) as well as policies and programs supporting local rice production.

The model is estimated using a generalized least squares procedure in two backfitting steps similar to the one proposed by [5]. Step 1 considers a linear model to compute the initial residuals. The residuals are then aggregated with D before the second generalized least squares is applied to the whole model with estimated residuals from Step 1. See [5] for details of the estimation procedure.

The effect of El Nino episode of 1998 is assessed using a dummy variable in the model above. Interactions of this dummy variable with all the terms in the model, including that of spatial autoregression, are also included in the model.

Convergence in Rice Yield

The likelihood ratio rest show that random effect model with spatial-temporal autoregression for both the original data and the deseasonalized rice yield data significantly fits (p<0.0000) to the provincial data (see Tables 1 and 2). Parameter estimates for both growth equations (original and deseasonalized) are similar. The effect of deseasonalization can be observed only in the magnitude of the spatial parameter.

Adjusting for spatial effect (spatial autoregression) of the regions, the model is significant (p<0.0000) in Table 1 (lower part). Furthermore, the good fit of the model to the data is supported by the low value of the mean absolute percentage error

(MAPE) at 0.83%. In model (1), $\beta_1<0$ would imply convergence. From Table 1 however, $\beta_1=0.2629$, a positive value indicating that the provinces failed to exhibit convergence in rice yield. This can be interpreted in two ways. First, the natural endowments of the provinces are distinctly varied so that even with interventions in farming systems and introduction of technological innovations, yield still vary significantly across the provinces in the same region. This empirically proves that zoning of agricultural areas in the Philippines is an important strategy towards the identification of optimal production areas for certain crops, especially rice. An intensive advocacy campaign among farmers to consider a crop more suitable to their soil type is needed, and that rice is not really ideal for all provinces. The second interpretation of divergence is that the agricultural interventions are not tailor-fitted to the needs of the provinces benefiting from such.

The negative effect of area on growth in yield (-0.0102) implies declining returns to scale and an indication that the newly developed production areas are not necessarily optimal for rice production. While many arable lands are still available in various parts of the country, it cannot be cultivated for rice production. For the rice sector, expansion of harvest area seems not feasible to drive growth. Corn production area does not significantly contribute to yield of rice. This means that either there is not enough crop rotation between rice and corn, or that rice farmers do not give up production area for corn and vice versa.

[Table 1 Here]

[Table 2 Here]

The autoregression parameter estimate is only 0.1014 in Table 1 (lower part). This means that random shocks in yield in the previous quarter influences only about 10% of the random shocks in yield for the present quarter. Thus, that rice farming has become more intensive, and the present random shocks like technology application dominated soil and weather endowments, are usually inherited across neighboring quarters.

The random effect due to the provinces accounts for a little more 2% (Table 1, lower part) of the aggregate of spatial and temporal variance (excluding the effect of the spatial parameter). This is an indication that spatial dependency is better accounted for by the spatial autoregression component than by simply postulating a random component for the provinces. Since the sign of the spatial effect is negative, if the value of the average residuals in a neighborhood is positive, then there will be a reduction in the prediction of yield, indicating that spatial externalities contributed negatively to yield. On the other hand, negative average residual (autoregressive term) means that the spatial externalities are positive contributions to yield.

The spatial externalities associated with a region include, but are not limited to, natural endowments due to ideal weather and soil fertility as well as the implementation of programs geared towards enhancing productivity. In Table 1 (lower part), the coefficient for spatial autoregression is -1.6889. The spatial distances were evaluated among the neighbors (regions) and the effect of the negative coefficient is noted. A majority of the regions yield positive effects for spatial externalities with Central Luzon and Davao regions benefiting the most from spatial externalities. Davao region is one region that benefit from almost uniform distribution of rainfall throughout the year, in addition to the good quality of soil suited for grains production. Central Luzon on the other hand, includes the most fertile land ideal for crop production (including rice). It also has the most advanced irrigation systems in the region complementing several demonstration farms of different agricultural research institutions. In 2002, of the 16 rice-producing regions, Central Luzon produced 17% of total rice production in the country. Three regions yield negative effect of spatial externalities, including ARMM, Central Visayas, and Eastern Visayas, where some of the lowest rice production can be observed in the period 1990-2002.

Effect of the 1998 El Nino on Convergence

The effect of the 1998 El Nino episode was accounted into the model using a dummy variable. Including further the interaction of this dummy variable with other terms in the model fits significantly as well, as supported by the likelihood ratio test ($p<0.0000$), see Table 3 for details. The MAPE is 0.81%, further validating adequacy of the model. The 1998 El Nino contributed further in the divergence of rice yield among the provinces. Magnitude of the effect of drought varies across the provinces. Some provinces were able to adjust to mitigate the ill-effects of the weather anomaly, further pushing them away from other provinces that were not able to cope with the drought while having lower productivity to start with. Provinces across the country generally experienced reduction in yield as an effect of the drought. The interactions of El Nino with all the other terms in the model are not significant. The El Nino episode of 1998 does not contribute significantly to the temporal variation and well as the provincial random effects.

[Table 3 Here]

Conclusions

Growth in rice yield in many Asian countries, the Philippines specifically, is an important social, economic, and political issue that needs to be resolved. Considering the fast-growing population and the limited arable land in the region, the only possible solution to abate the potential food shortage is to drive growth in yield of rice, a staple in the region.

Growth in yield can be achieved through technological innovations and production efficiency. In the Philippines, there is empirical evidence that growth in rice yield diverges among the provinces. This indicates that current policies aimed towards improving yield in slow-growing areas does not suffice for these provinces to catch up with the growth in yield among the more agriculturally advanced provinces. More localized (regional) policies and appropriate zoning of provinces are needed to stimulate growth among the provinces towards the steady-state growth level. The El Nino episode in 1998 further aggravated the divergence among the provinces, an evidence of the vulnerability of the rice sector to weather anomalies. The less agriculturally advanced provinces failed to adopt mechanisms that will mitigate the ill-effect of such conditions.

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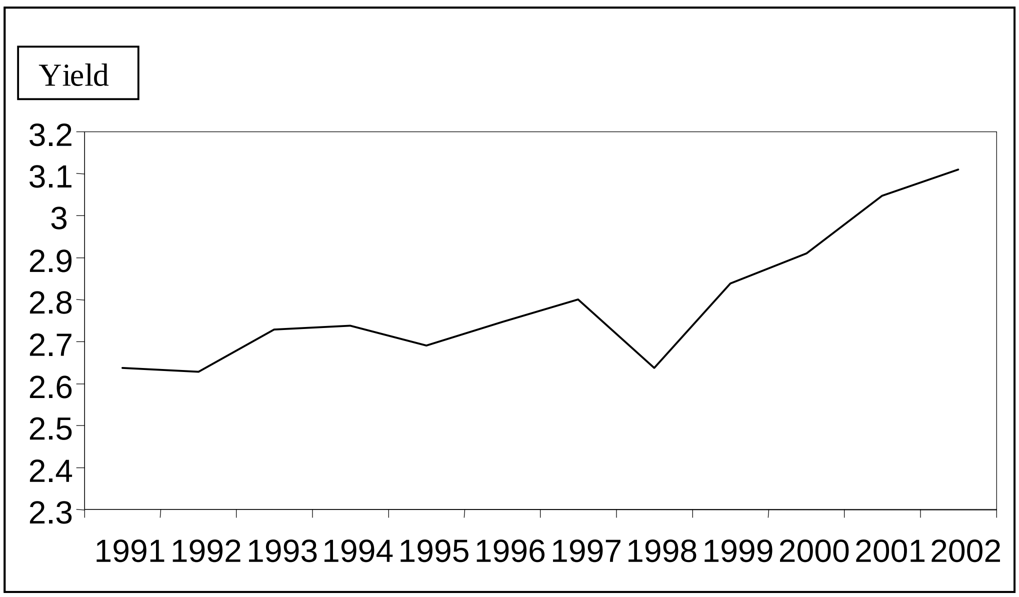
Figure 1: Average Rice Yield and Production Across Provinces By Calendar Year



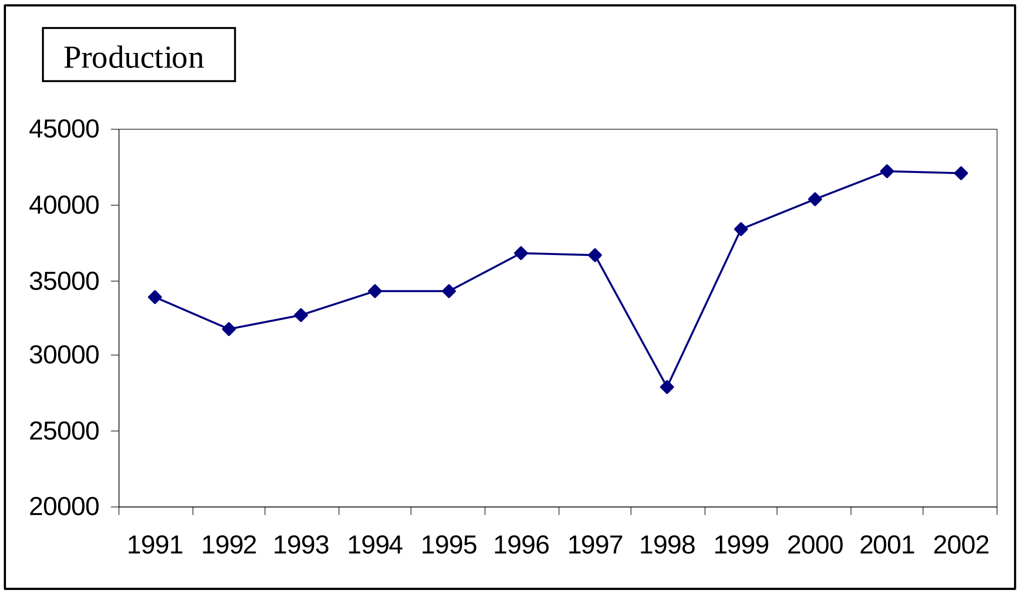


Table 1: Convergence in Quarterly Growth in Yield of Rice

Random Effect Model				
Overall Fit p-value*	0.0000	Determinant	Coefficient	p-value
ρ	0.1014	Constant	-0.0462	0.166
σ_u	0.0327	Log(Yield)	0.1889	0.000
σ_ε	0.2243	Log(Area)	-0.0107	0.001
$\sigma_u/(\sigma_u+\sigma_\varepsilon)$	0.0208	Log(CornArea)	-0.0010	0.652
Random Effect Model Adjusted with Spatial Autoregression				
Overall Fit p-value	0.0000	Determinant	Coefficient	p-value
ρ	0.1014	Constant	-0.0503	0.134
σ_u	0.0347	Log(Yield)	0.2629	0.000
σ_ε	0.2216	Log(Area)	-0.0102	0.002
$\sigma_u/(\sigma_u+\sigma_\varepsilon)$	0.0239	Log(CornArea)	-0.0018	0.439
		Spatial Neighborhood	-1.6889	0.000

**Goodness-of-fit test*

Table 2: Convergence in Quarterly Growth in Deseasonalized Yield of Rice

Random Effect Model				
Overall Fit p-value*	0.0000	Determinant	Coefficient	p-value
ρ	-0.1557	Constant	-0.1376	0.000
σ_u	0.0294	Log(Yield)	0.2649	0.000
σ_ε	0.2108	Log(Area)	-0.0137	0.000
$\sigma_u/(\sigma_u+\sigma_\varepsilon)$	0.0190	Log(CornArea)	0.0022	0.341
Random Effect Model with Spatial Autoregression				
Overall Fit p-value	0.0000	Determinant	Coefficient	p-value
ρ	-0.1557	Constant	-0.1766	0.000
σ_u	0.0290	Log(Yield)	0.3285	0.000
σ_ε	0.2079	Log(Area)	-0.0130	0.000
$\sigma_u/(\sigma_u+\sigma_\varepsilon)$	0.0190	Log(CornArea)	0.0022	0.318
		Spatial Neighborhood	-1.3433	0.000

**Goodness-of-fit test*

Table 3: Convergence in Quarterly Growth in Yield of Rice
(Effect of El Nino)

Random Effect Model with Spatial Autoregression				
Overall Fit p-value *	0.0000	Determinant	Coefficient	p-value
ρ	0.1003	Constant	-0.0160	0.645
σ_u	0.0331	Y98	-0.1052	0.238
σ_ε	0.2205	Y98* Log(Yield)	0.0838	0.116
$\sigma_u/(\sigma_u+\sigma_\varepsilon)$	0.0220	Y98*Log(Area)	-0.0163	0.098
		Y98*Log(Corn Area)	0.0104	0.117
		Log(Yield)	0.2425	0.000
		Log(Area)	-0.0094	0.007
		Log(Corn Area)	-0.0033	0.170
		Spatial Effect	-1.7515	0.000
		Y98*Spatial Effect	0.2745	0.645

**Goodness-of-fit test*