The Link between Agricultural Output and the States of Poverty in the Philippines: Evidence from Self-Rated Poverty Data

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The Link between Agricultural Output and the States of Poverty in the Philippines: Evidence from Self-Rated Poverty Data[1]

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ABSTRACT

The high poverty incidence in the county is a concern that needs to be addressed by our policy makers. Official poverty statistics from the National Statistical Coordination Board (NSCB) shows that the reduction in poverty over the past two decades has been quite dismal from 38% in 1988 to 26% in 2009 or less than one percent reduction per year. Since poverty incidence has dynamic patterns, studies using official poverty data encounter difficulty because of limited number of data points. This study builds econometric models in analyzing the movement of poverty in the country using the quarterly self-rated poverty series of the Social Weather Stations. The first model uses Markov Switching to determine the states of poverty. It assumes two states: *high* and *moderate states of poverty*. A high 61% of the population considered themselves as poor when the country is in the state of *high poverty*. In times of *moderate poverty*, 49.5% of the population considered themselves as poor. The result shows that once the country is in the state of *high poverty*, it stays there for an average of 24 quarters, or six years, before moving out. The paper then builds a logistic regression model to show what determines the states of high poverty. The model shows that a one-percent increase in agricultural output in the previous quarter reduces the probability of being in the *high state* of poverty by about 8 percentage points, all things being the same. The study shows that poverty incidence in the country is dynamic and frequent monitoring through self-rated poverty surveys is important in order to assess the effectiveness of the government programs in reducing poverty. The self-rated poverty surveys can complement the official statistics on poverty incidence.

Keywords: Markov Switching, Logistic Regression, Self-Rated Poverty

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1. INTRODUCTION

The high poverty incidence in the country continues to be a major concern for policy makers, researchers and students interested in study of the country's development. Official poverty statistics from the National Statistical Coordination Board (NSCB) shows that the reduction in poverty over the past two decades has been quite dismal from 38% in 1988 to 26% in 2009 or less than one percent reduction per year.

What might explain such dismal performance in poverty reduction effort through these years? A quick answer is the country's poor economic growth performance. The Philippines' economic growth performance is no match relative to its East Asian neighbors, as shown in Table 1 below. While the neighboring economies, such as Thailand and Indonesia, have been growing by an average of about 6 to 8 percent in per capita Gross Domestic Product (GDP) from 1961 to 2009, the Philippines only managed to grow at about 4 percent during the same period (Mapa, and Balisacan (2011).[5] Moreover, studies (Balisacan and Fuwa (2004) and Balisacan (2007)) have also shown a weak response of poverty reduction to economic growth for the country. In particular, a one percent increase in per capita income growth results in about 1.3 percent to 1.6 percent reduction in poverty incidence for the Philippines. The comparative figures for other countries are 2.3 percent for Indonesia, 4.9 percent for Thailand and an average of 2.1 percent for countries in East Asia.

Table 1. Comparative Economic Performance for Selected Countries in East Asia

	Per capita GDP (in US $ PPP)					Per capita GDP growth		
	1980	1990	2000	2009		1961-70	1971-90	1991-2009
China	524	1,101	2,667	6,200		4.65	7.82	10.47
Japan	18,647	25,946	28,605	29,688		10.47	4.22	0.9
Korea, Rep.	5,544	11,383	18,730	25,493		8.26	8.02	5.11
Hong Kong SAR, China	13,945	23,697	29,785	40,599		10.19	8.24	4.25
Philippines	2,618	2,385	2,587	3,216		4.93	3.86	3.71
Thailand	2,231	3,961	5,568	7,258		8.17	7.39	4.32
Indonesia	1,361	2,087	2,727	3,813		4.18	7.14	4.75

Source: World Development Indicators (WDI), World Databank http://databank.worldbank.org/ddp/home.do; PPP is Purchasing Power Parity

[5] For the period 1988 to 2009, the country's real GDP grew by about 3.92 percent while the Agricultural sector only grew by about 2.36 percent (in 2000 constant prices; NSCB)

The latest poverty estimates, for the year 2009, also indicate that poverty continues to be concentrated in the rural areas where 40% of the population is considered poor, while the figure is only 12% in the urban areas. Hence, the rural sector contributes to about three-fourths of the total poor in the country. The disaggregation by sectors would show that the poverty incidence in the agriculture sector is about 48% and contributes to about two-thirds of the country's poor (Balisacan, et.al, 2011).

A study of Reyes, Tabuga, Mina, Asis and Datu (2010) also provided some explanations linking the increase in poverty incidence in 2006 to the lack of increase in the real income in the agricultural sector. In explaining the increase of poverty incidence in 2006, the authors decomposed the percentage change in poverty into the effect of real income and redistribution. The results indicate that the increase of poverty incidence in 2006 can be attributed to the lack of real income growth and dismal income distribution, even at the time of high economic growth. High output growth, furthermore, only had an impact on non-agricultural sector and its effect did not trickle down to rural areas where most of the poor people are located. Thus, the authors are in support of policies in increasing the real income of households with effective redistributive efforts.

In another paper, the same authors, Reyes, Tabuga, Mina, Asis and Datu (2011), distinguished the characteristics of the transient poor, "refer to those who are classified as poor during a given point in time but were previously non-poor for at least one year during the period under study," and the chronic poor, "those that are consistently income poor during the period under study." The authors used a panel data set constructed from 2003, 2006 and 2009 Family Income and Expenditure Surveys (FIES) and found that there is a greater proportion of chronic poor involved in the agricultural sector than the transient poor.

The global financial crisis (GFC) that started in 2008 also had a significant impact in increasing poverty incidence in the country. Reyes, Sobrevina and de Jesus (2010) looked at the impact of the GFC on the Philippines at the household and community level. The analysis is through the data on the different dimensions of poverty obtained from the community-based monitoring systems (CBMS) being implemented in the Philippines. The channels through which the global crisis could affect households are through overseas employment and remittances. The authors covered 10 selected sites distributed all over the Philippines with a total of 3499 households. The CBMS data reveals that there were some OFWs (12.9% of all households interviewed) who were retrenched during the period November 2008 to April 2009. A large proportion (25%) of OFWs who were retrenched came from Saudi Arabia. About 9.3% of the households with OFW reported that their OFW experienced wage reduction during the period. Moreover, 71.4% of the OFWs who experienced wage reduction are working in Asian countries. An estimated 7.1% of all households experienced a decline in the frequency of receipt of remittances. Majority of these households (79.1%) reported a decline in their monthly income from the business. Some of the employed individuals also experienced a reduction in wage, number of working hours, and employment benefits. Results show that poverty incidences in most of the sites have increased in 2009 as compared to their previous CBMS round. Results of this study showed that the potential impact of the crisis varies across different groups of households. The crisis has affected the households in terms of OFW remittances and local employment. This may, therefore, result in an increase in poverty incidence, albeit modestly. In response to the crisis, households adopted various coping strategies which may be damaging and counter-productive in the long run (such as withdrawal of children from school). Although the government has identified and implemented some programs that could mitigate the impact of the crisis, more efficient targeting is necessary.

Balisacan, Piza, Mapa, Abad Santos and Odra (2010) showed that the impact of the GFC on the economy and the social sector is severe and may linger for many years to come. The study showed that the GFC pushed down the GDP growth rate from its long-term trend (of about 4.7%) by 1.0 percentage point in 2008 and 3.8 percentage points in 2009. Moreover, the authors showed that if there was no GFC and the economy moved along its long-term growth path, average household income would have increased by 1.8% between 2008 and 2009, causing poverty to fall, rather than increase (from 2006 to 2009), by about 0.4 percentage points during the same period. Given these estimates and current population growth projections, nearly 2 million Filipinos were pushed to poverty owing to the GFC.

This paper examines the dynamic patterns of poverty incidence and the economic factors that determines poverty incidence using the quarterly time series data from the Social Weather Stations (SWS) national poverty surveys. A Markov switching model is used to determine the "states" of poverty incidence, classified as "moderate" and "high" states. The paper then builds a logistic regression model to show what economic factors determine the states of high poverty. An important feature of this paper is the mainstreaming of the time series data on poverty incidence from the SWS into the econometric model. The organization of the paper is as follows: section 2 discusses the different methods of measuring poverty incidence in the Philippines. Section 3 presents the econometric models using the Markov switching and the logistic regression models for poverty incidence and section 4 concludes.

2. MEASURES OF POVERTY INCIDENCE

2.1. National Measures of Poverty

Poverty is a complex phenomenon and a multi-dimensional concept. In the Philippines, there are several existing measures of hunger incidence. At the national level there are two commonly reported measures of poverty: (1) the number of poor families and individuals reported by the National Statistical Coordination Board (NSCB) and; (2) the self-rated poverty incidence collected by the Social Weather Stations (SWS). The NSCB statistics on the number of poor families and individuals are measured from the FIES and available every three years are also the official statistics on poverty in the country. The SWS measure of poverty incidence is collected every quarter and is referred to as the direct measure of poverty since this is compiled on the basis of responses of individuals to questions about their experiences about poverty.

2.1.1. National Statistical Coordination Board (NSCB) Measure of Subsistence Incidence

The official statistics on poverty incidence is the number of families that are considered as poor. In accordance with NSCB Resolution No. 1, Series of 2003, Approving the Proposed Methodology for Computation of Provincial Poverty Statistics, estimation of poverty starts with the computation of the food threshold, which is determined by using regional menus priced at the provincial level. The one-day menus were determined by the Food and Nutrition Research Institute (FNRI) using low-cost, nutritionally adequate food items satisfying basic food requirements of 2,000 calories, which are 100 percent adequate for the Recommended Energy and Nutrient Intake (RENI) for energy and protein and 80 percent adequate for the RENI for vitamins, minerals and other nutrients. These menus were used to estimate the per capita per day food cost. This is then multiplied by 30.4 (approximate number of days per month) to get the monthly food threshold or by 365 days (30.4 days/month x 12 months) to get the annual per capita food threshold. After the computation of the food threshold, the estimation of the poverty threshold to include the additional income required for the sustenance of the minimum non-food basic needs follows. Non-food basic needs include the following: clothing and footwear; fuel, light and water; housing maintenance and other minor repairs; rental or occupied dwelling units; medical care; education; transportation and communications; non-durable furnishing; household operations; and personal care and effects. Hence, to compute for the poverty threshold, the food threshold is divided by the proportion of the food expenditures (FE) to total basic expenditures (TBE) derived from the latest FIES using the FE/TBE's of families within the +/- ten percentile of the food threshold. The resulting estimate is the annual per capita poverty threshold (NSCB, 2007). The official poverty incidence in 2009 is about 26.5 percent of the total population or around 23.14 million Filipinos that are considered as poor. The figures in Table 2 below showed an increasing percentage of Filipinos who are poor from 2003 to 2009.

Table 2. Official Poverty Incidence among Population (2003, 2006 and 2009)

Major Island Group	Poverty Incidence among Population (%)			Magnitude of Poor Population			Share to Total Poor Population (%)		
	2003	2006	2009	2003	2006	2009	2003	2006	2009
PHILIPPINES	**24.9**	**26.4**	**26.5**	**19,796,954**	**22,173,190**	**23,142,481**	**100**	**100**	**100**
Luzon	16.7	18.6	17.9	7,564,531	8,857,020	8,850,387	38.2	39.9	38.2
Visayas	34.8	34.9	35.2	5,447,582	5,839,316	6,213,233	27.5	26.3	26.8
Mindanao	36.8	37.8	39.6	6,784,840	7,476,854	8,078,861	34.3	33.7	34.9

Source: National Statistical Coordination Board (NSCB)

2.1.2 Social Weather Stations (SWS) Measure of Poverty Indicator

One criticism of the official statistics for measuring poverty by the NSCB is that "being infrequently applied, (it) has fostered an illusion that poverty steadily declines" (Mahangas, 2009). On the one hand, the FIES is conducted only once every three years and the official hunger and poverty incidence statistics were reported only nine times from 1985 to 2009. The poverty and hunger incidence statistics from the 2012 FIES will only be released in 2013. Due to the lack of a frequent measure of poverty incidence in the country, government officials depend on the national quarterly surveys on poverty conducted by the SWS, particularly during periods between the FIES years.[6] The SWS is a private, non-profit scientific institute established in 1985 to generate social survey data. In the SWS approach, the poverty self-rating does not depend on any predetermined or top-down poverty line. In each survey, the household head -- the respondent for poverty and hunger questions, speaking in behalf of the entire family -- is asked to point to where he/she thinks the household fares in a showcard featuring only the word POOR, the *negative* (not the opposite) term NOT POOR, and a line in-between. Half of the sample uses the left showcard, and the other half uses the right showcard, in order to eliminate positioning-bias. The word consistently used for POOR, *mahirap*, expresses the least degree of hardship among various Tagalog terms for poverty. The terms for POOR in other Philippine languages used in the SWS surveys are in the panel below the showcards. The SWS Self-Rated Poverty incidence is the proportion of household heads who point to word *mahirap* or POOR, when presented with the showcard by the survey interviewer. This measure of poverty uses the subjective view of the household head, speaking in behalf of the family. *Yet it is characterized by objectivity, because it can be validated by independent surveys using the same approach, just as the subjective expression of voting intentions in one survey can be validated by other independent surveys* (Mangahas, 2009). The SWS quarterly survey has 1,200 respondents from various parts of the country. The SWS quarterly hunger indicator is reported beginning April 1983 and was measured 99 times until the 2nd quarter of 2012.

Figure 1 below shows the plot of the SWS self-rated poverty incidence (SRP) from the 1st quarter of 1992 to the 2nd quarter of 2012. In addition the Hodrick-Prescott (HP) filter estimate of the long term trend, denoted by TREND_SRP, in the self-rated poverty is also reported.[7] The long term trend estimate shows that self-rated poverty incidence is generally declining from the 65 to 70 percent level in 1992 to the 50 percent level in 2012. However, the SRP movement is quite volatile fluctuating from a lower level (around the 50 percent) to a relatively high level (60

[6] Government agencies involved in the Poverty Mitigation efforts such as the Department of Social Work and Services (DSWD), National Anti-Poverty Commission (NAPC) and the National Economic and Development Authority (NEDA) make use of the SWS poverty incidence indicator to gauge the effectiveness of the strategies.

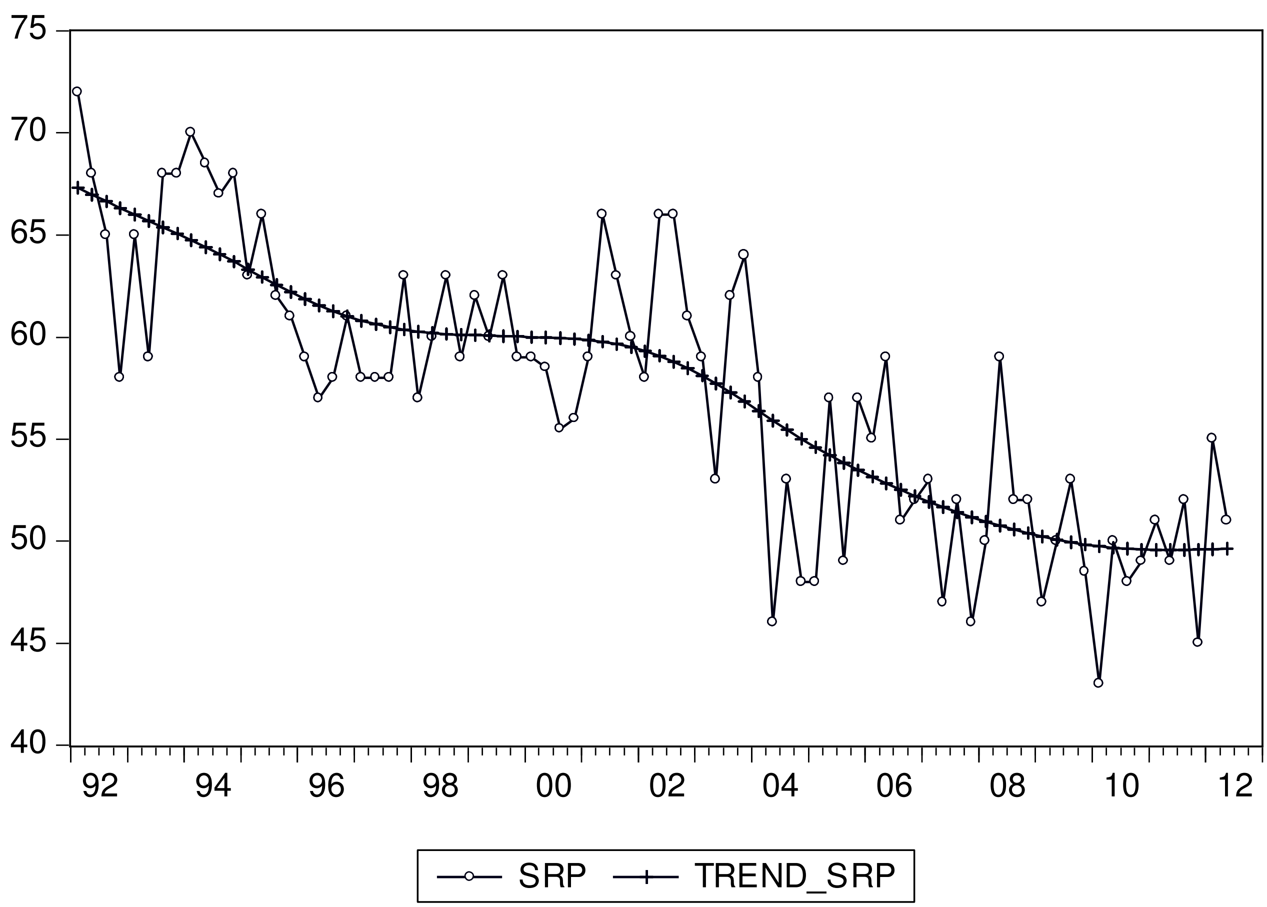
[7] The HP filter, first proposed by Hodrick and Prescott (1997) uses a smooting method to obtain an estimate of the long-term trend component of a time series. The HP filter computes the permanent trend component of a time series y_t by minimizing the variance of y_t around the trend component, subject to a penalty that constrains the second difference of the trend component.

percent) over the entire period showing that poverty incidence, as measured by the SRP of the SWS, is very dynamic. The general decline in the SRP incidence is further highlighted in Table 3 where the average SRP incidence across different administrations exhibits a decreasing but gradual trend.

Table 3. Average Self-Rated Poverty (SRP) Incidence through Different Administration

President/Administration	Average SRP
Benigno S. Aquino III (2010-2012)	50.00
Gloria Macapagal Arroyo (2001-2010)	54.38
Joseph E. Estrada (1998-2001)	59.55
Fidel V. Ramos (1992-1998)	62.44
Corazon C. Aquino (1986-1992)	63.46

Figure 1. Self-Rated Poverty (SRP) and Long-Term Trend
from 1st Quarter 1992 to 2nd Quarter 2012



Source: Self Rated Poverty (SRP) from Social Weather Stations (SWS) and Authors' Computation of the Long Term Trend

In addition to the NSCB's official measure of poverty and the SWS self-rated poverty incidence, there are authors that proposed different measures of poverty. One of the more promising measures is suggested by Balisacan (2011) using the multidimensional poverty index (MPI). This measure treats poverty as being a multidimensional phenomenon, with education, health and standard of living as its dimensions, rather than being determined by income (or expenditure) alone. The MPI is computed as,

$$M_0 = \frac{\sum_{n=1}^{N} I(c_n \geq k)\, c_n}{DN}$$

where D is the number of attainment dimensions, c_n is the weighted number of deprivations suffered by and individual n and $I(.)$ is an indicator that takes the value of 1 if the expression in the parenthesis is true, otherwise it takes the value of 0. Among the advantages of this measure is its convenience in identifying the most vulnerable people, showing aspects in which they are deprived, and revealing the interconnections among deprivations. This is so because the MPI can systematically assess the magnitude, intensity and sources of multidimensional poverty. The study seeks to assess the nature, intensity and sources of multidimensional poverty in the Philippines. One important result of the study is that, unlike income poverty, MPI responds to growth. Moreover, all three sources (FIES, APIS, and NDHS) of the MPI estimate (all three of these sources have the data necessary for the computation of MPI) show continued reduction in multidimensional poverty. In other words, MPI actually declined as the economy expanded in the past decade. The diversity of both deprivation intensity and magnitude of poverty across geographic areas and sectors of the Philippine society is enormous, suggesting that, beyond growth, much needs to be done to make development more inclusive. Another remarkable result is that all three data sets provide the same ranking of the three broad dimensions of poverty. Standard of living contributed the most to aggregate poverty, followed by health and education. The study also showed that the poverty profiles are robust to assumptions about the poverty cutoff.

3. ECONOMETRIC MODELS

3.1. Markov Switching Model

In modeling the dynamic movement of the SRP incidence, the authors used a nonlinear time series model known as the Markov Switching Model proposed by Hamilton (1989). The Markov switching model uses the idea of the Markov process. Consider the stochastic process $\{S_t\}_{t\in A}$ where *A* is a subset of the real numbers. Then $\{S_t\}_{t\in A}$ is a *Markov process* if, for any $s_1 < s_2 < s_3 < \cdots < s_n < s$,

$$P\left(a < S_t \leq b | S_{t_1} = s_1, S_{t_2} = s_2, \ldots, S_{t_n} = s_n\right) = P(a < S_t \leq b | S_{t_n} = s_n). \qquad (1)$$

If, in addition to being a Markov process, $\{S_t\}_{t\in A}$ is a discrete-time (A is a countable set) and discrete valued (the range of S_t is countable) stochastic process, then $\{S_t\}_{t\in A}$ is called a *Markov chain*. The range of S_t is called the *state space* of S_t. Any element in the range of S_t is called a *state* of S_t. It is necessary to define the one-step transition probability:

$$p_{ij}^{t,t+1} = P(S_{t+1} = j | S_t = i) \qquad (2)$$

If $\{S_t\}$ is a Markov chain and $p_{ij}^{k,k+1} = p_{ij}^{n,n+1}$ for all *n* and *k*, then $\{S_t\}$ is called a *stationary* Markov chain. For such Markov chains, the superscripts appearing in the one-step transition probabilities may be omitted. That is, $p_{ij} = p_{ij}^{t,t+1}$ for all *t*. The transition probabilities of a stationary Markov chain may be represented by a matrix $\{P_{ij}\}$, called the *transition probability matrix*. If all the states of a Markov chain are accessible from any given state, then the Markov chain is said to be *irreducible*. Lastly, if all the states of the Markov chain satisfy the condition $P_{ii} > 0$ (that is, it is possible for the process to remain in the state where it is) then the Markov chain is said to be *aperiodic*.

This study uses the simplest form of the model, where the transition is driven by a two state Markov chain. A time series $\{x_t\}$ follows an Markov Switching Auto-Regressive (MSA) model (with two regimes) if it satisfies:

$$x_t = \begin{cases} c_1 + \sum_{i=1}^{p} \emptyset_{1,i} x_{t-i} + a_{1t} & if S_t = 1 \\ c_2 + \sum_{i=1}^{p} \emptyset_{2,i} x_{t-i} + a_{2t} & if S_t = 2 \end{cases} \qquad (3)$$

Or, in shorthand notation,

$$x_t = \emptyset_{s_t,0} + \sum_{i=1}^{p} \emptyset_{s_t,i} x_{t-i} + a_{s_t,t} \tag{4}$$

In the above model, $\{S_t\}$ assumes values in the state space {1, 2} and is a stationary, aperiodic, and irreducible Markov chain with transition probabilities

$$P(S_t = 2|S_{t-1} = 1) = p_{12} \;\; and \;\; P(S_t = 1|S_{t-1} = 2) = p_{21} \tag{5}$$

The transition probabilities can be written in the form of a transition probability matrix:

$$P = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix}$$

where, $\sum_{j=1}^{2} p_{ij} = 1$

Since the process $\{S_t\}$ is assumed to be irreducible and aperiodic, once it is in any given state, it may move to the other state in the next transition, or it may stay in its current state. Each element in the transition probability matrix gives the probability that state i is followed by state j. The process is assumed to depend on the past values of x_t and s_t only through s_{t-1}. Only the time series $\{x_t\}$ is observed, not the states of poverty. Therefore, a way must be found to form optical inferences about the current state based on the observed values of x_t. Given the number of states, Hamilton (1989) shows how to estimate the parameters of the model and the transition probabilities governing the motion of poverty. Franses and van Dijk (2000) describe the estimation procedure for a two-regime Markov Switching model, and the authors present it here. Under the assumption that $a_{s_t,t}$ in (1) is normally distributed, the density of x_t conditonal on the regime s_t and the information set I_{t-1} is a normal distribution with mean $\emptyset_{s_t,0} + \sum_{i=1}^{p} \emptyset_{s_t,i} x_{t-i}$ and variance σ^2,

$$f(x_t|s_t = j, I_{t-1};\ \theta) = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left\{\frac{-\left(x_t - (\emptyset_{s_t,0} + \sum_{i=1}^{p} \emptyset_{s_t,i} x_{t-i})\right)^2}{2\sigma^2}\right\} \tag{6}$$

Given that the state $s_t$is unobserved, the conditional log likelihood for the t^{th} observations $l_t(\theta)$ is given by the log of the density of x_t conditional only upon I_{t-1}. That is,

$l_t(\theta)$ = ln $f(x_t|\, I_{t-1}, \theta)$. The density $f(x_t|\, I_{t-1}, \theta)$ can be obtained from the joint density of x_t and s_t as follows:

$$f(x_t|\, I_{t-1};\, \theta) = f(x_t, s_t = 1|I_{t-1}; \theta) + f(x_t, s_t = 2|I_{t-1}; \theta)$$

$$= \sum_{j=1}^{2} f(x_t|s_t = j, I_{t-1}; \theta) \cdot P(s_t = j|I_{t-1}; \theta) \qquad (7)$$

In order to be able to compute the above density, it is necessary to quantify the conditional probabilities of being in either regime given the history of the process, $P(s_t = j|I_{t-1}; \theta)$. Intuitively, if the regime that occurs at time t - 1 were known and included in the information set I_{t-1}, the optimal forecasts of the regime probabilities are simply equal to the transition probabilities of the Markov process s_t. More formally,

$$\widehat{\xi_{t|t-1}} = P \cdot \xi_{t-1} \qquad (8)$$

where $\widehat{\xi_{t|t-1}}$ denotes the 2 × 1 vector containing the conditional probabilities of interest. That is, $\widehat{\xi_{t|t-1}} = (P(s_t = 1|I_{t-1}; \theta),\ P(s_t = 2|I_{t-1}; \theta))'$, $\xi_{t-1} = (1{,}0)'$ if $s_{t-1} = 1$ and $\xi_{t-1} = (0{,}1)'$ if $s_{t-1} = 2$, and P is the transition probability matrix. In practice, however, the regime at time t – 1 is unknown, as it is unobservable. The best one can do is replace ξ_{t-1} in (2) by an estimate of the probabilities of each regime occuring at time t – 1 conditional upon all information up to and including the observation at t – 1 itself. Denote the 2 × 1 vector containing the optimal inference concerning the regime probabilities as $\widehat{\xi_{t-1|t-1}}$. Given a starting value $\widehat{\xi_{1|0}}$ and values of the parameters contained in θ, one can compute the optimal forecast and inference for the conditional regime probabilities by iterating on the pair of equations

$$\widehat{\xi_{t|t}} = \frac{\hat{\xi}_{t|t-1} \odot \boldsymbol{f}_t}{1'(\hat{\xi}_{t|t-1} \odot \boldsymbol{f}_t)} \qquad (9)$$

$$\widehat{\xi_{t+1|t}} = P \cdot \widehat{\xi_{t|t}} \qquad (10)$$

for t = 1,⋯,n, where $\boldsymbol{f}_t$ denotes the vector containing the conditional densities for the two regimes and ⨀ denotes element by element mulitplication. The necessary starting values $\widehat{\xi_{1|0}}$ can either be taken to be a fixed vector of constants which sum to unity or can be included as separate parameters that need to be estimated.

Finally, let $\widehat{\xi_{t|n}}$ denote the vector which contains the smoothed inference on the regime probabilities, that is, the estimates of the probability that regime *j* occurs at time *t* given all available observations, $P(s_t = j|I_n; \theta)$. Kim (1993) developed an algorithm to obtain these regime probabilities from the conditional probabilities $\widehat{\xi_{t|t}}$ and $\widehat{\xi_{t+1|t}}$ given in (9) and (10).

Returning to (9), the denominator of the right-hand side expression actually is the conditional log likelihood for the observation at time t, which follows directly from the definitions of $\widehat{\xi_{t|t-1}}$ and $\boldsymbol{f}_t$. As shown in Hamilton (1989), the maximum likelihood estimates of the transition probabilities are given by:

$$\widehat{p_{ij}} = \frac{\sum_{t=2}^{n} P(s_t=j, s_{t-1}=i|I_n;\hat{\theta})}{\sum_{t=2}^{n} P(s_{t-1}=i|I_n;\hat{\theta})} \tag{11}$$

where $\hat{\theta}$ denotes the maximum likelihood estimates of θ. Moreover, the estimates $\widehat{\emptyset_j}$ of $\emptyset_j$ can be obtained from a weighted least squares regression of y_t on x_t, with weights given by the smoothed probability of regime *j* occurring. Putting all of the above elements together suggests an iterative procedure to estimate the parameters of the Markov switching model. This procedure turns out to be an application of the Expectation Maximization (EM) algorithm developed by Dempster, Laird and Rubin (1977). It can be shown that every iteration increases the value of the likelihood function, and thus the final estimates are ML estimates. McCulloch and Tsay (1994) also considered a Markov Chain Monte Carlo (MCMC) method to estimate a general MSA model. The MSA model can easily be generalized to the case of more than two states. The computational intensity increases rapidly, however. For simplicity and easy interpretation of results, this paper works on only two states. The innovational series $\{a_{1t}\}$ and $\{a_{2t}\}$ are sequences of independent and identically distributed random variables with mean zero and finite variance and are independent of each other. A small p_{ij} means that the model tends to stay longer in state *i*. In fact, $1/\ p_{ij}$ is the expected duration of the process to stay in state *i*. In this paper, the authors extend the methodology by modeling the unconditional probability of being in the state of high poverty using the logistic regression model. This model has as its response variable a binary variable whose corresponds to the two states generated by the Markov Switching model (the states of *"high"* and *"moderate"* poverty). The explanatory variables examined may then be considered potential determinants of poverty in the Philippines.

3.1.1 Empirical Results of the MSA Model

In this study the authors made use of the Markov Switching Auto-Regressive (MSA) model to determine two states of poverty incidence in the country using the quarterly SWS self-rated poverty incidence data. The authors utilized the SWS survey data from the 1st quarter of 1994 up to the 4th quarter of 2009. The estimation procedure was done using the R language. A maximum likelihood estimation procedure was used to estimate the parameters of the model and the results are shown in Table 4 below.

Table 4. Estimation Results of a Markov Switching Auto-Regressive for the Self-Rated Poverty Series

State 1(High Poverty Incidence)					
Parameter	c_1	Φ_1	Φ_2	σ_1	p_{12}
Estimate	19.17	0.49	0.19	4.13	0.04
Standard Error	6.543	0.115	0.108	0.356	
State 2 (Moderate Poverty Incidence)					
Parameter	c_2	Φ_1	Φ_2	σ_2	p_{21}
Estimate	68.84	-0.40	0.014	1.63	0.31
Standard Error	5.95	0.097	0.108	0.599	

The figures from table 4 show that the mean percentage of poor households in state 1 (high poverty) is about 61.1% (computed as 19.17 / (1 – 0.49 – 0.19)), while the mean percentage of more households is state 2 (moderate poverty) is about 49.5% (computed as 68.84 / (1 – (–0.40 + 0.014)). Moreover, the transition probabilities (p_{12} and p_{21}) are different in both states. On the one hand, the transition probability from a moderate state of poverty to a high state of poverty is rather high at 0.31. On the other hand, the transition probability from a high state of poverty to a moderate state of poverty is only 0.04. The transition probabilities show that it is more likely to enter into a state of high poverty than to get out of that state. Probing into these transition probabilities, we can calculate the expected duration in each state. The expected duration in a state of high poverty is about 24 quarters. This means that, on the average, the state of high poverty in the Philippines lasts around 24 quarters, or six years. Moreover, the expected duration of a period of low poverty is about 3.22 quarters. That is, when the country is in the moderate state of poverty, the condition is expected to last for about three quarters only, or less than a year. The results from the MSA model shows that the country tends to stay longer in high poverty than out of it. The coefficients of both AR (1) and AR (2) differ largely between the two regimes, indicating that the dynamics of poverty in the Philippines are different for the moderate and high poverty levels.

Figures 2 and 3 below are the filtered and smoothed probabilities, respectively. The graphs show the dominance of state 1 (high poverty) over state 2 (moderate poverty) in most of the data points in the series. This confirms the results suggesting that the series stays longer in state 1 (high poverty) than in state 2 (moderate poverty). However, there is a silver lining: the graph shows that in the last quarters, the series has a high probability to be in state 2 (moderate poverty) than in state 1 (high poverty).

Figure 2. Filter Probabilities for State 1 (High Poverty) and State 2 (Moderate Poverty)

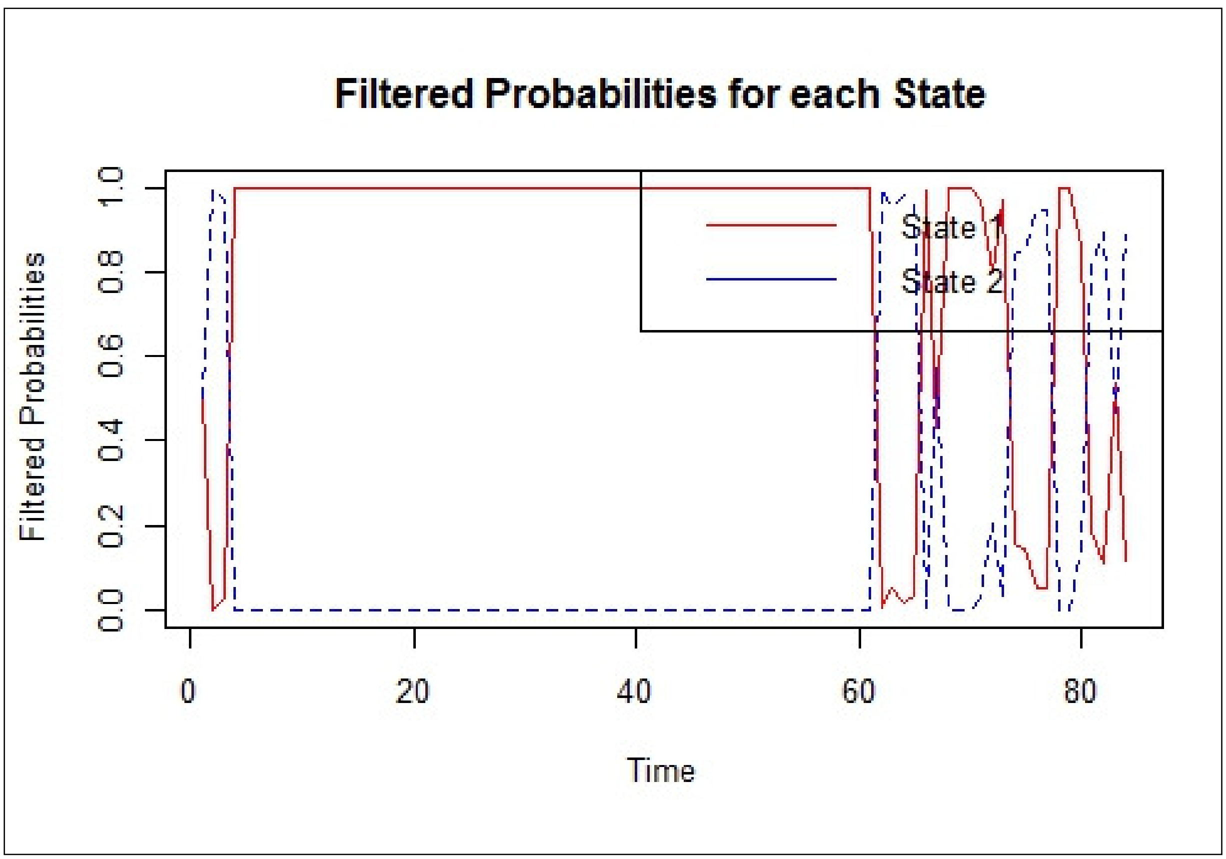
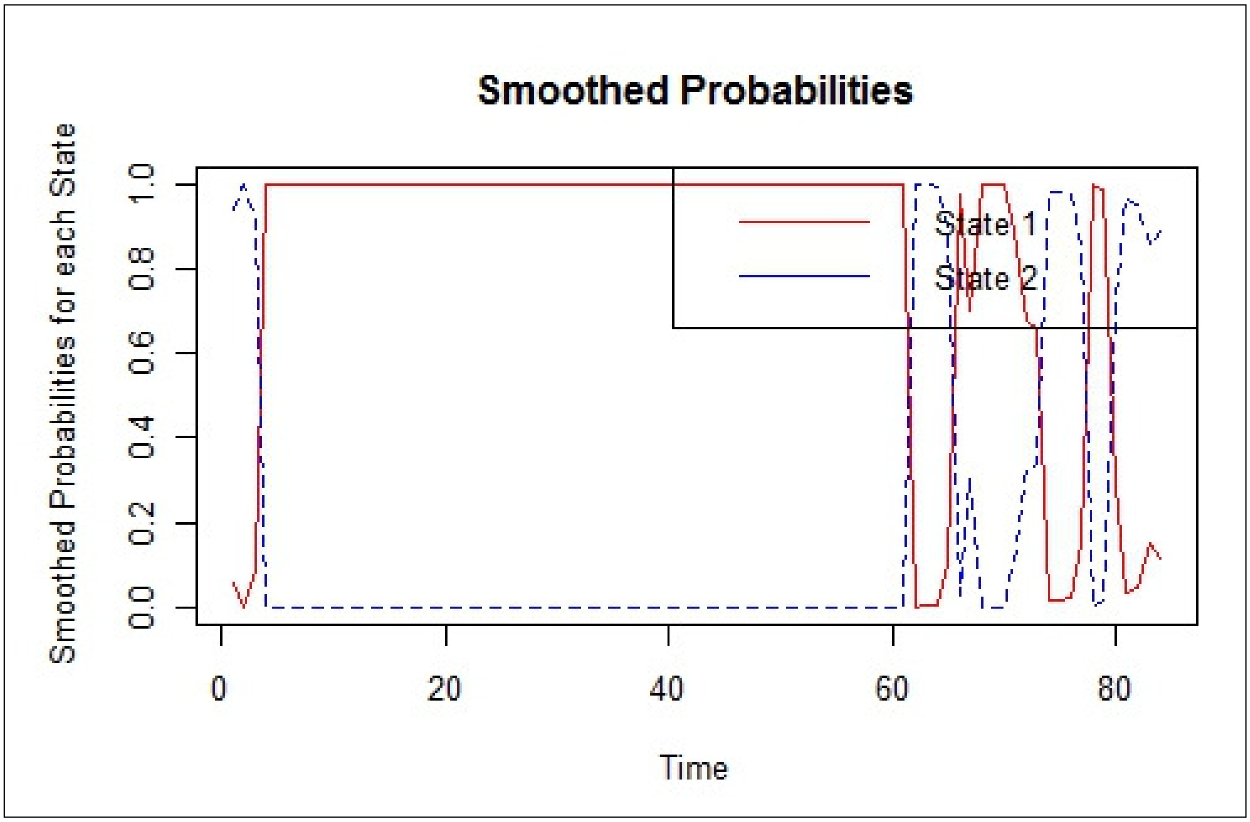


Figure 3. Filter Probabilities for State 1 (High Poverty) and State 2 (Moderate Poverty)



3.2. Logistic Regression Model (Determinants of the High State of Poverty)

The econometric model used in analyzing the determinants of the high state of poverty is the *logit model*. Consider the linear model,

$$y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki} + \varepsilon_i \qquad i = 1,2,\ldots,n \qquad (12)$$

where the variable of interest, y_i, takes on the value 1 if the SRP incidence in the high state and value 0 if the SRP incidence is in the moderate state. The X_1, X_2,…, X_k represent the determinants of the high state of poverty incidence.

Note that y_i is a Bernoulli random variable with probability of success, π, or $y_i \sim Be(\pi)$. The problem in economics is that most likely π is unknown and not constant across the observations. The solution is to make π dependent on X_i. Thus, we have,

$$y_i \sim Be\left(F\left(\beta_o + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki}\right)\right) \qquad (13)$$

where the function F(·) has the property that maps $\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta_kX_k$ onto the interval [0,1]. Thus, instead of considering the precise value of y, we are now interested on the probability that y = 1, given the outcome of $\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta_kX_k$, or,

$$\Pr\left(y_i = 1 \mid \underline{\beta}, \underline{x_i}\right) = F(\underline{x_i}\,\underline{\beta}) \qquad (14)$$

where F is a continuous, strictly increasing function and returns a value ranging from 0 to 1. The choice of F determines the type of binary model. Given such a specification, the parameters of this model (the betas) can be estimated using the method of maximum likelihood. Once the identifiable parameters are established, the likelihood function is written as,

$$L(y;\beta) = \prod_{i=1}^{n} \left\{ \left[F(x_i\beta)\right]^{y_i} \left[1 - F(x_i\beta)\right]^{1-y_i} \right\} \qquad (15)$$

In the case of the LOGIT model with a single explanatory variable the probability of success is given by,

$$\Pr(y_i = 1 \mid x_i) = \frac{\exp(\beta_0 + \beta_1 x_i)}{1 + \exp(\beta_0 + \beta_1 x_i)} \qquad (16)$$

The parameters of the model are estimated using Maximum Likelihood (ML). Using the likelihood function,

$$L(y;\beta) = \prod_{i=1}^{n} \left\{ \left[F(x_i\beta)\right]^{y_i} \left[1 - F(x_i\beta)\right]^{1-y_i} \right\} \qquad (17)$$

We can obtain an expression for the log-likelihood,

$$\log(L) = \sum_{i=1}^{n} y_i \log[F(x_i'\beta] + (1-y_i)\log[1-F(x_i'\beta)]$$
$$= \sum_{i:y_i=1}^{n} \log[F(x_i\beta] + \sum_{i:y_i=0}^{n} \log[1-F(x_i\beta)] \qquad (18)$$

Differentiating the log-likelihood function with respect to the parameter vector β and set the vector of derivatives equal to zero:

$$\frac{\partial \log L}{\partial \beta} = \sum_{i:y_i=1} \frac{f(x_i\beta)}{F(x_i\beta)} x_i' - \sum_{i:y_i=0} \frac{f(x_i\beta)}{1-F(x_i)} x_i' = 0 \qquad (19)$$

where f(.) is the probability density function associated with the F(.). Simplifying, we have,

$$0 = \sum_{i=1}^{n} \left[\frac{y_i}{F(x_i\beta)} - \frac{1-y_i}{1-F(x_i\beta)} \right] f(x_i\beta) x_i' \qquad (20)$$

Combining the two terms inside the brackets, we have,

$$0 = \sum_{i=1}^{n} \frac{y_i - F(x_i\beta)}{F(x_i\beta) - [1-F(x_i\beta)]} f(x_i\beta) x_i' \qquad (21)$$

In the *logit* model we can simplify the last equation using the fact that,

$$f(x) = F(x)[1-F(x)] = \frac{\exp(-x)}{(1+\exp(-x))^2} \qquad (22)$$

The simplification yields:

$$0 = \sum_{i=1}^{n} [y_i - F(x_i\beta)] x_i' \quad or \quad \sum_{i=1}^{n} y_i x_i' = \sum_{i=1}^{n} F(x_i\beta) x_i' \qquad (23)$$

The likelihood equations associated with the *logit* models are non-linear in the parameters. Simple closed-form expressions for the ML estimators are not available, so they must be solved using numerical algorithms.

Marginal Effects

Interpretation of the coefficient values is complicated by the fact that estimated coefficients from a binary model cannot be interpreted as marginal effect on the dependent variable. The marginal effect of X_j on the conditional probability is given by,

$$\frac{\partial E\left(y \mid \underline{X}, \underline{\beta}\right)}{\partial X_j} = f(\underline{x}_i' \underline{\beta})\beta_j \qquad (24)$$

where f(·) is the density function corresponding to F(·). In here, β_j is weighted by a factor f(·) that depends on the values of all the regressors in X̲. The direction of the effect of a change in X_j depends only on the sign of the β_j coefficient. Positive values of β_j imply that increasing X_j will increase the probability of the response, while negative values of β_j will decrease the probability of the response. The marginal effect is usually estimated using the average of all the values of the explanatory variables (**X̲**) as the representative values in the estimation.

Average Marginal Effect

Some researchers (particularly Bartus (2005)) argue that it would be more preferable to compute the *average marginal effect*, that is, the average of each individual's marginal effect. The marginal effect computed at the *average X* is different from the average of the marginal effect computed at the individual X.

Explanatory Variables (Determinants of Poverty Incidence in Elderly-Headed Households)

The explanatory variables (**X̲**) used to explain the high state of poverty incidence include: (a) the quarterly Agricultural output (in natural logarithm), (b) the quarterly Government expenditures (in natural logarithm), (c) quarterly underemployment rate and (d) the quarterly food component of the consumer price index (in natural logarithm).

3.2.1. Empirical Results from the Logistic Regression Model

The figures in Table 5 show the percentage of quarters that exhibited a high state of poverty from 1994 to 2009. Out of the 64 quarters, the country experienced a high state of poverty in 47 quarters (73%) and only 17 quarters in the moderate state of poverty (27%).

Table 5. Frequency Distribution of the States of Poverty (1st Quarter 1994 to 4th Quarter 2009)

State of Poverty	Frequency	Percent
Moderate State	17.00	26.56
High State	47.00	73.44
Total	64.00	100.00

The results of the logistic regression model are shown in Table 6 below. The sign of the estimated coefficients of the explanatory variables are consistent with expectations. The results show that increasing output in Agriculture (1 quarter ago) decreases the probability that the country will be in the "High" state of poverty. In particular, a one-percent increase in Agricultural output in the last quarter decreases the probability of "HIGH" State of Poverty by about 8 percentage points. Increasing Government Spending (1 quarter ago) decrease the probability that the country will be in the "High" state of poverty. A one-percent increase in government spending in the last quarter decrease the probability of "HIGH" State of Poverty by about 11 percentage points. Higher underemployment rate in the current quarter increases the probability that the country will be in the "high" state of poverty. For every one percentage point in current underemployment rate increases the probability of "HIGH" State of Poverty by about 4 percentage points. Higher food prices in the current quarter also increases the probability that the country will be in the "high" state of poverty. For every one percentage point in Food Inflation increases the probability of "HIGH" State of Poverty by about 4 percentage points.

The logistic regression model shows that government spending and expansion in agriculture are two crucial components that will reduce the probability of a high state of poverty in the country.

Table 6. Estimated Coefficients of the Logistic Regression Model

Variables	Estd. Coeff.	Std. Err.	z-stat	P-value
Agricultural Output (in log; lag 1)	-0.9318 ***	0.2245	-4.1500	0.0000
Underemployment Rate	0.0370 **	0.0174	2.1200	0.0340
Government Expenditures (in log; lag 1)	-1.4771 ***	0.3780	-3.9100	0.0000
Food CPI (in log)	0.0426 *	0.0288	1.4800	0.1380

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level (one-sided alternative)

The figures in Table 7 show the forecasting performance of the logistic regression model. Out of the 46 quarters that are classified as in the high state of poverty, the model was able to correctly predict 44 quarters, or a sensitivity value of 96 percent. Moreover, out of the 17 quarters that are classified as in the moderate state of poverty, the model was able to correctly predict 13 quarters or a specificity value of 76 percent. Overall, the model was able to correctly classify 90 percent of the quarters into either high or moderate state of poverty.

Table 7. Percentage of Correct Prediction of the Logistic Regression Model

	Actual Outcome		
Model Classification	High Poverty	Moderate Poverty	Total
High Poverty	44 (96%)	4	48
Moderate Poverty	2	13 (76%)	15
	46	17	63

4. CONCLUSIONS

This paper examined the dynamics of poverty incidence in the Philippines using the self-rated poverty incidence data of the SWS and found that poverty incidence can be classified (using the Markov switching model) as either a high state of poverty, occurring at the 60 percent level, or a moderate state of poverty, occurring at around the 50 percent level. The results also show that it is more likely for the country to be in the high state of poverty than in the moderate state of poverty. Moreover, once in high state of poverty the country stays there for a long time (about 24 quarters). On the contrary, once it experiences a moderate state of poverty it lasts for only three quarters. The results suggest that the high state poverty in the Philippines is persistent.

The logistic model has identified four important determinants of the high state of poverty in the country. On the one hand, increasing the output of the agricultural sector (lag 1 quarter) and the level of government expenditures (lag 1 quarter) reduces the probability that the country will be in the high state of poverty. On the other hand, increasing underemployment rate and food prices increases the probability of being in the high state of poverty. This study shows the relative importance of agriculture in output on poverty reduction. Government programs to alleviate poverty should focus on boosting the agricultural sector's productivity and mobilizing the labor force to reduce the level of underemployment, another important factor in reducing poverty incidence.

5. REFERENCES

Balisacan, A.M. (2007), "Local Growth and Poverty Reduction." In A. M. Balisacan and H. Hill, eds., *The Dynamics of Regional Development: The Philippines in East Asia*. Cheltenham: Edward Elgar.

Balisacan, A.M. (2011), "What Has Really Happened to Poverty in the Philippines? New Measures, Evidence, and Policy Implications." UPSE Discussion Paper 2011-14. School of Economics, University of the Philippines Diliman.

Balisacan, A.M. and N. Fuwa. (2004), "Going beyond Cross-country Averages: Growth, Inequality and Poverty Reduction in the Philippines," *World Development*, 32(11): 1891–1907.

Balisacan, Arsenio M., Sharon Piza, Dennis Mapa, Carlos Abad Santos, and Donna Odra (2010), "The Philippine Economy and Poverty During the Global Economic Crisis" The Philippine Review of Economics, Vol. XLVII, No.1, June 2010, pp.1-37.

Bartus, Tomas (2005), "Estimation of marginal effects using margeff" The Stata Journal, Vol. 5, No. 3, pp. 309-329.

Hamilton, J.D. (1989), "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle," *Econometrica* , March 1989.

Hodrick, R. and E. C. Prescott, 1997, "Postwar U.S. Business Cycles: An Empirical Investigation," *Journal of Money, Credit, and Banking*, **29**: 1-16.

Mangahas, M., 2009 "The Role of Civil Society in Poverty Monitoring: The Case of the Philippines." *A paper presented on The Impact of the Global Economic Situation on Poverty and Sustainable Development in Asia and the Pacific, September 28-30, 2009, Hanoi, Vietnam.*

National Statistical Coordination Board (2007), "Frequently Asked Questions on Poverty Statistics http://www.nscb.gov.ph/poverty/FAQs/default.asp.

National Statistical Coordination Board (2011), "2009 Philippines Poverty Statistics." http://www.nscb.gov.ph/poverty/default.asp

Reyes, Celia, Alellie Sobrevina and Jeremy de Jesus (2010), "The Impact of the Global Financial Crisis on Poverty in the Philippines." PIDS Discussion Paper 2010-04, Philippine Institute for Development Studies.

Reyes, Celia, Aubrey Tabuga, Christian Mina, Ronina Asis and Maria Blesila Datu (2010), "Are We Winning the Fight against Poverty?: An assessment of the Poverty Situation in the Philippines. " PIDS Discussion Paper 2010-26, Philippine Institute for Development Studies.

Reyes, Celia, Aubrey Tabuga, Christian Mina, Ronina Asis and Maria Blesila Datu (2011), "Dynamics of Poverty in the Philippines: Distinguishing the Chronic from the Transient Poor." PIDS Discussion Paper 2011-31, Philippine Institute for Development Studies.

Social Weather Stations (2012), "Second Quarter 2012 Social Weather Survey: Families rating themselves as Mahirap or Poor abate to 51%." http://www.sws.org.ph/