SCHOOL OF STATISTICS
UNIVERSITY OF THE PHILIPPINES DILIMAN

WORKING PAPER SERIES

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Need to Track Few More Statistical Indicators for the Poor

by

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UPSS Working Paper No. 2015-01
February 2015

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Dennis S. Mapa[1], Kristelle M. Castillo[2] and Krizia DR. Francisco[2]

ABSTRACT

Reducing hunger incidence in the country is still the major policy challenge confronting our leaders today. Statistics on hunger produced by both government and private institutions show a very slow reduction in hunger incidence over the last five years. Official data from Philippines Statistics Authority (PSA) show the percentage of Filipinos experiencing extreme poverty (hunger) decreased only slightly from 10.9 percent of the population in 2009 to 10.4 percent in 2012 and increasing marginally to 10.7 percent during the 1st semester of 2013. The results of the 8th National Nutrition Survey (NNS) of 2013 conducted by the Food Nutrition and Research Institute (FNRI) show the same small reduction in the proportion of children aged 0-5 years who are underweight (indirect measure of hunger) from 20.7 percent in 2008 to 19.8 percent in 2013. Self-rated hunger incidence data from the Social Weather Stations (SWS) also reveal a similar bleak picture, where hunger incidence in households averaging at 19.5 percent in 2013 from 19.1 percent in 2009, slowing down slightly to an average of 18.3 percent in 2014. This slow reduction in hunger incidence is a puzzle considering the country's respectable economic growth performance, with Real Gross Domestic Product (GDP) growing at an annual average of 6.3 percent during the period 2010-2014.

This paper looks at the factors that influence the dynamic nature of hunger incidence in the Philippines using the data from the SWS quarterly surveys on hunger. Variables identified as potential determinants of hunger incidence are, among others, changes in the price of rice and job misery index (sum of the employment and unemployment rates). A Vector AutoRegressive (VAR) model is used to determine the effect of a shock to the possible determinants on total hunger. Results show that a shock (increase) in the price of rice at the current quarter tends to increase hunger incidence in the succeeding quarter. A shock (increase) in job misery index at the current quarter also increases the hunger incidence in the next quarter. Further analysis using the time-varying parameter (TVP) model shows a higher effect of changes in the price of rice to hunger incidence after the global rice crisis in 2008. This shows that hunger incidence is becoming very sensitive to changes in the price of rice.

Keywords: Hunger Incidence, Vector AutoRegressive (VAR) model, State Space, Time-Varying Parameters (TVP) model

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I. INTRODUCTION

Hunger is the "the most cruel and concrete sign of poverty," a statement made by pontiff Pope Benedict XVI during a summit of the United Nations' Food and Agriculture Organization (FAO) in November 2009 in Rome. Moreover, the current pontiff Pope Francis calls the high incidence of hunger as a global scandal, saying that "the world can no longer turn away from millions of people who are suffering from hunger."[3] The two pontiffs have reason to raise such alarm. The FAO latest 2012-2014 estimates on world hunger pegged about 805 million people suffering from hunger daily. While the number is about 100 million lower compared to the figures a decade ago, the current world hunger incidence still represents about 11.3 percent of the global population and about 13.5 percent of the population of the developing countries (FAO, 2014).

In the Philippines, reducing hunger incidence is still the major policy challenge confronting our leaders. Statistics on hunger produced by both government and private institutions show a very slow reduction in hunger incidence over the last five years. This seems to be a puzzle considering the respectable growth of the economy averaging at 6.3 percent per year, measured by the Real GDP (RGDP), during the same period. Official data from Philippines Statistics Authority (PSA) show the percentage of subsistence poor (or extremely poor) in the population decreased only slightly from 10.9 percent of the population in 2009 to 10.4 percent in 2012 and increasing marginally to 10.7 percent during the 1st semester of 2013.[4]

The results of the 8th National Nutrition Survey (NNS) of 2013 conducted by the Food Nutrition and Research Institute (FNRI) show the same small reduction in the proportion of

[3] Message of Pope Francis to the Caritas Internationalis' global campaign "*One Human Family, Food for All*." (2013)

[4] Comparative figures on subsistence poor during the first semesters are from the Philippine Statistics Authority (PSA) are: 14.2 percent (for 2006), 13.3 percent (2009), 13.4 percent (2012) and 10.7 percent (2013)

children aged 0-5 years who are underweight (indirect measure of hunger) from 20.7 percent in 2008 to 19.8 percent in 2013. Moreover, the same report shows that the proportion of children who are under-height for age (stunted) also decreased marginally from 32.3 percent in 2008 from 30.3 percent in 2013. Given the slow progress in reducing the number of households living below the subsistence or food threshold and in minimizing the number of underweight children, the Philippines will most likely miss its Millennium Development Goal (MDG) target of halving the proportion of poor households living below the food threshold and halving the proportion of underweight children below 5 years old from 1991 to 2015.[5]

In addition to government data on hunger incidence, the Social Weather Stations (SWS) also reports quarterly hunger incidence since July 1998. The Social Weather Stations (SWS) is a private, non-profit scientific institute established in 1985 to generate social survey data. The SWS hunger indicator is defined as the proportion of household heads reporting that their families have experienced hunger, without having anything to eat, at least once in the last three months (Mangahas, 2009). The SWS quarterly survey has 1,200 respondents from various parts of the country. The respondents are asked if they have experienced hunger in the past three months. If the respondent answers yes, a second question is then asked regarding the frequency of the experience. The SWS further classifies hunger into moderate if it happened "only once" or "a few times" and severe if it happened "often" or "always" (SWS, 2014).[6] The self-rated hunger incidence data from the SWS also reveal a similar bleak picture, where hunger incidence in households averaging at 19.5 percent in 2013 from 19.1 percent in 2009, slowing down slightly

[5] The MDG targets are 13.3 percent in the prevalence of underweight children under 5 years old and 8.8 percent for the percentage of population below the national subsistence (food) threshold.

[6] While the SWS hunger indicator reports the total hunger incidence as well as the moderate and severe hunger incidence, this paper focuses only on the total hunger incidence for its analysis.

to an average of 18.3 percent in 2014.[7] Maligalig (2008) in her review of the various measures of hunger (direct and indirect) in the Philippines raised the issue of underestimation in the SWS hunger incidence figures due to potential sources of bias from its survey design components.[8] The author pointed out that while the sampling error from the SWS quarterly survey is about 2.83 percent, the non-sampling error due to potential problems with the sampling frame and sampling strategy can increase the over-all sampling and non-sampling error.[9]

There are many possible causes hunger and very often these causes are interrelated. According to the World Food Programme (WFP), an agency under the United Nations system and the largest humanitarian agency fighting global hunger, there are six (6) important factors causing hunger: (1) poverty, (2) lack of investment in agriculture, (3) natural disasters, (4) war and displacement, (5) unstable prices of food products, and (6) food wastage (WFP, 2014). The Nobel Prize Laureate Amartya Sen argued that in order to conquer hunger we need to tackle "all the causes of hunger simultaneously particularly poverty, and not just concentrate on producing more food" (Sen, 2013).

In the Philippines, a study by Mapa, Han and Estrada (2011) showed that food prices and underemployment rate (the authors' proxy for quality of jobs) are important factors affecting involuntary hunger using the SWS quarterly data. The authors show that, on the one hand, an increase in food prices at the current quarter will increase hunger incidence in the next five quarters, that is, higher food prices have lingering effect on hunger incidence. On the other hand,

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[7] The last reported hunger incidence during the 4th quarter of 2014 is 17.2 percent

[8] The impact of the bias in the estimated parameters of the econometric model, such as the Vector Auto-Regressive (VAR) model, will depend on the variance of the error, the gap between the "true" hunger incidence and the estimated value. When one would like to measure the (partial) effect of a variable, X_t, but we can only observe an imperfect measure $\tilde{X}_t$, where $\tilde{X}_t = X_t + w_t$, one can show that the least squares estimator $\hat{\beta}_1$ has probability limit $\beta_{1*}(\sigma^2_X / (\sigma^2_X + \sigma^2_w))$ and is biased toward zero. However, if the error (w_t) is constant, the variance, σ^2_w is zero and the estimator is still consistent.

[9] The readers are referred to Maligalig's 2008 paper "Examining the Existing Direct Measures of Hunger in the Philippines" for an extensive discussion on the sampling and estimation issues.

shocks to underemployment also increase hunger incidence but the effects last for only two quarters.

This paper examines the dynamic patterns of hunger incidence and the effects of the determinants of hunger using the quarterly time series data from the SWS national surveys on hunger, covering the period 2000-2013. Two econometric models are used to determine the link of the price of rice and job misery index (sum of the unemployment and underemployment rates) on the current and future hunger incidence in the country: (a) vector autoregressive (VAR) and time varying parameter (TVP) models.

The main motivation of the paper is to examine the impact two major recent shocks on hunger incidence, the food crisis in 2008 resulting in high prices of basic commodities, particularly rice, and the global financial crisis causing the rise in unemployment and underemployment among Filipino workers.

The organization of the paper is as follows: this section serves as the introduction, section 2 discusses the trend in hunger incidence using SWS quarterly data, the price of rice, inflation rate and job misery index using the official statistics in the Philippines, section 3 presents the results of the vector autoregressive (VAR) and time varying parameter models for hunger incidence and section 4 concludes.

II. TRENDS IN HUNGER INCIDENCE, RICE PRICE AND JOB MISERY INDEX

2.1. SWS Quarterly Hunger Incidence Report

The SWS reports that about 17.2 percent of the families in the Philippines experienced involuntary hunger during the 4th quarter of 2014. The 17.2 percent is equivalent to about 3.8 million families. For the full year 2014, the average hunger incidence is relatively lower at 18.3

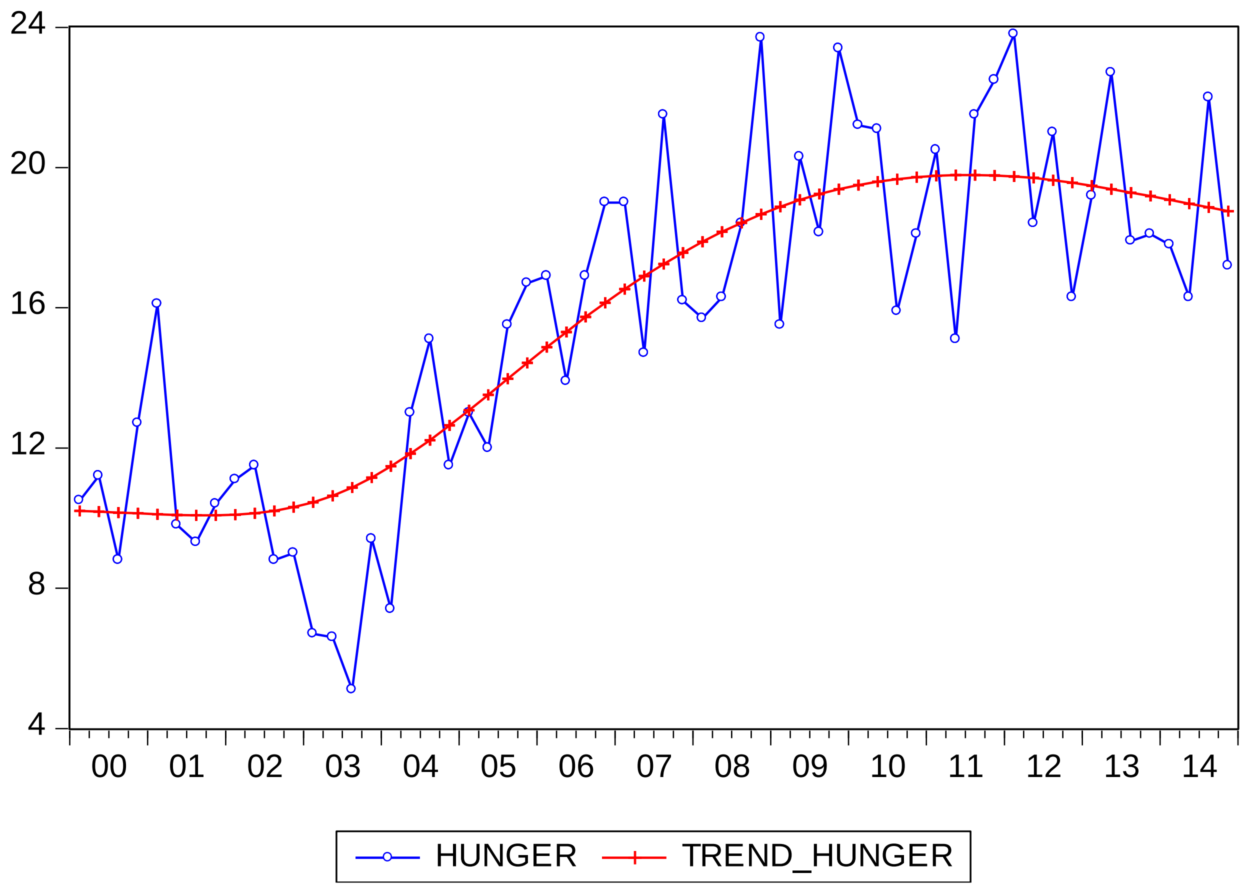
percent, compared to the 2013 full year average of 19.5 percent. Indeed, the trend in quarterly hunger incidence using SWS data is on the decline as shown in figure 1, which provides the time plot of the percentage of families experiencing hunger from the 1st quarter of 2000 to the 4th quarter of 2014 together with the estimate of the long-term trend of the percentage of hunger incidence computed using the Hodrick-Prescott (HP) filter.[10]

The long run trend exhibited a downward pattern starting the 4th quarter of 2011, which means the peak (highest point) of the HP filter occurred during the 3rd quarter of 2011. The downturn in the long run trend of hunger incidence, albeit slow, is good news considering the slope of the long-term trend component shifted during the 3rd quarter of 2003 and became steeper, indicating a relatively faster increase in the percentage of families that experienced hunger after the 3rd quarter of 2003 compared to the period before it.

The slow reduction in hunger incidence happens during the period of relatively high economic growth, measured by the Real GDP. The average annual growth in the RGDP during the period 2010-2014 (Aquino administration) is 6.3 percent, significantly higher compared to the annual average growth of 4.8 percent during the period 2001-2010 (Arroyo administration). It shows that high economic growth, while a necessary condition, is not sufficient to accelerate the reduction in hunger incidence.

[10] 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 component (TR_t) of a time series y_t by minimizing the variance of y_t around TR_t, subject to a penalty that constrains the second difference of TR_t.

Figure 1. Hunger Incidence and Long Run Trend (Hodrick-Prescott Filter)
1st Quarter 2000 to 4th Quarter 2014 (SWS Data)



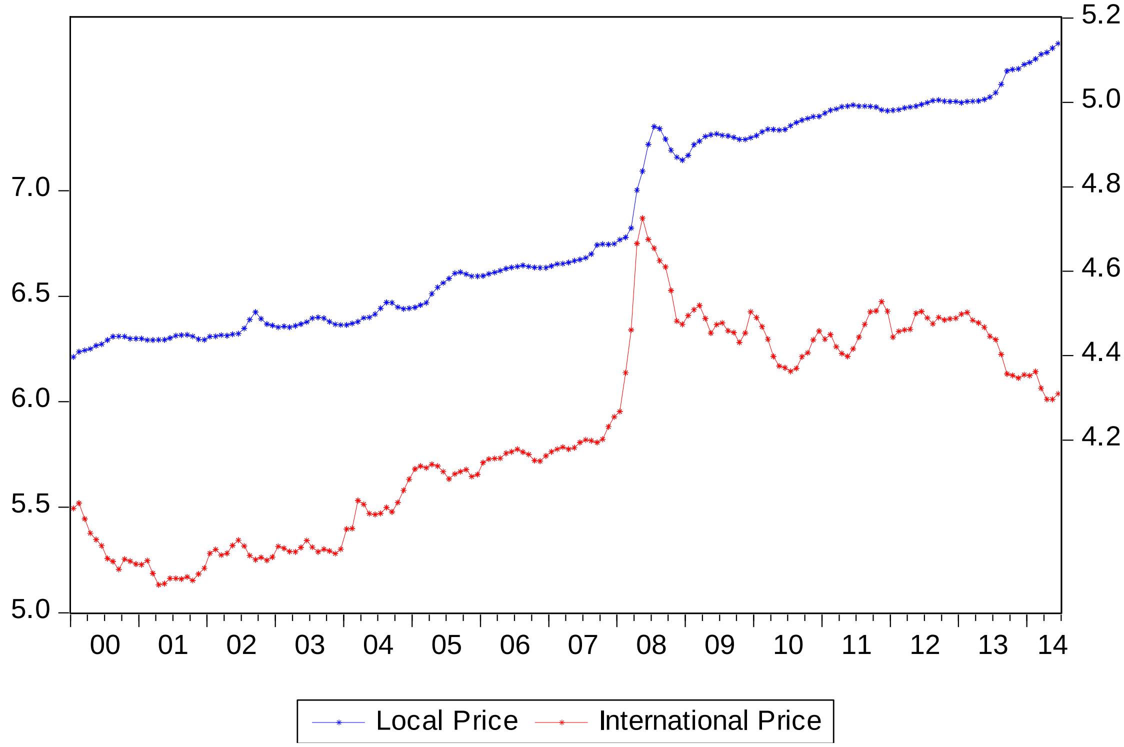
2.2. The Global Rice Price Crisis of 2007-2008 and Shift in the Local Rice Price

The world rice prices surged in 2007-2008, with prices tripled during a short span of time – about 6 months. According to the FAO, the policy measures made by the different governments (both rice producers and consumers) exacerbated the rice price crisis. These policies include restricting the rice supplies to the world market by large producers, particularly Vietnam and India, in order to avoid shortages for their own consumers, such as banning rice exports and increasing the minimum export prices. The responses of rice importing countries neither help in mitigating the rice price crisis, such as making public purchases at a price higher than the prevailing market prices at the time, creating further uncertainty in the rice market (FAO, 2011). The impact of the rice price crisis is outright felt by poor households in the developing countries.

The local rice price index, as reported by the Philippine Statistics Authority (PSA), together with the price of Thailand's 100% 2nd Grade Rice (in US$/Ton), from January 2000 to June 2014, are presented in figure 2 below. The price of Thailand's rice increased to US$ 963/ton in May 2008 coming from US$ 324/ton in May 2007, increasing by almost 200 percent in a span of 12 months. The immediate impact of the rice price crisis was felt in poor households where rice is the staple food, causing hunger incidence to spiked up during the last quarter of 2008.

The country's annual headline inflation rate reached 8.3 percent in 2008, coming from a low of 2.9 percent in 2007. During the peak of the rice price crisis in the 3rd quarter 2008, the inflation rates reached double digits averaging at 10.3 percent. Not known to many, however, is the fact that the inflation rate of the poorest 30 percent of the Filipino households reached 19.3 percent during the same quarter (almost double that of the headline inflation rate) and full year inflation rate reaching a high of 13.9 percent in 2008, 67 percent higher than the popularly reported headline inflation rate! As a result, the hunger incidence as reported by the SWS spiked during the 4th quarter of 2008, reaching 23.7 percent (the second highest reported number since the hunger incidence data was collected in 1998).

Figure 2. Monthly Averages Rice Price Index (PHIL) and Thailand 100%, 2nd Grade Rice (in US$/Ton)
January 2000 to June 2014 (in natural logarithm)



The difference between the headline inflation rate (inflation rate for all households) and the inflation rate for the poorest 30 percent of the households is basically the composition of the consumption basket. On the one hand, for the poorest 30 percent of the households, the food expenditures account for about 70 percent of the consumption basket, with rice accounting for 23 percent of the entire consumption basket. On the other hand, food expenditures account for only 39 percent of the consumption basket for all households, where the headline inflation is generated. The expenditure for rice accounts to less than 10 percent of the consumption basket for all households.[11]

[11] It should be noted that the headline inflation rate and the inflation rate for the poorest 30 percent are reported using difference base year and difference frequency. The headline inflation rate is reported monthly with 2006 as base year, while the inflation rate for the poorest 30 percent of households is reported quarterly with 2000 as base year. Given the implications of this important indicator on the welfare of the poor households, it will benefit the

Since the price of rice has been continuously increasing even when the international prices are on the decline, as shown in figure 2, the inflation rate for the poorest 30 percent of the households has been higher relative to the more popularly reported headline inflation rate.

The graphs in figure 3 show a comparison of the headline inflation rate and the inflation rate for the poorest 30 percent of households. There is still a substantial gap between the two inflation rates and while the government is declaring a relatively low headline inflation rate, this is not being felt by the poorest 30 percent of the households which are continuously experiencing higher prices of commodities, particularly rice. For 2014, while the headline inflation rate is reported at an average of 4.1 percent, the inflation rate for the poorest 30 percent of households is still about 2 percentage point higher at 6 percent.

In response to the possibility of another rice price crisis, the Aquino administration through the Department of Agriculture crafted the Food Staples Sufficiency Program for 2011-2016 (FSSP 2011-2016). The FSSP is a coherent plan toward achieving rice self-sufficiency or zero importation starting 2013. This government policy is aimed towards securing the national demand for rice at affordable and stable prices and targets self-sufficiency in food staples towards ensuring food security. To achieve the goals of the rice-sufficiency program, the budget for the Department of Agriculture sharply increased to Php 55 Billion in 2013 from Php 33 Billion in 2010 to cover the budgetary requirement such as improving irrigation, sustaining research and development for new crop varieties, promoting mechanized on-farm and postharvest strategies, and harnessing the potential of high-elevation and upland rice ecosystems.

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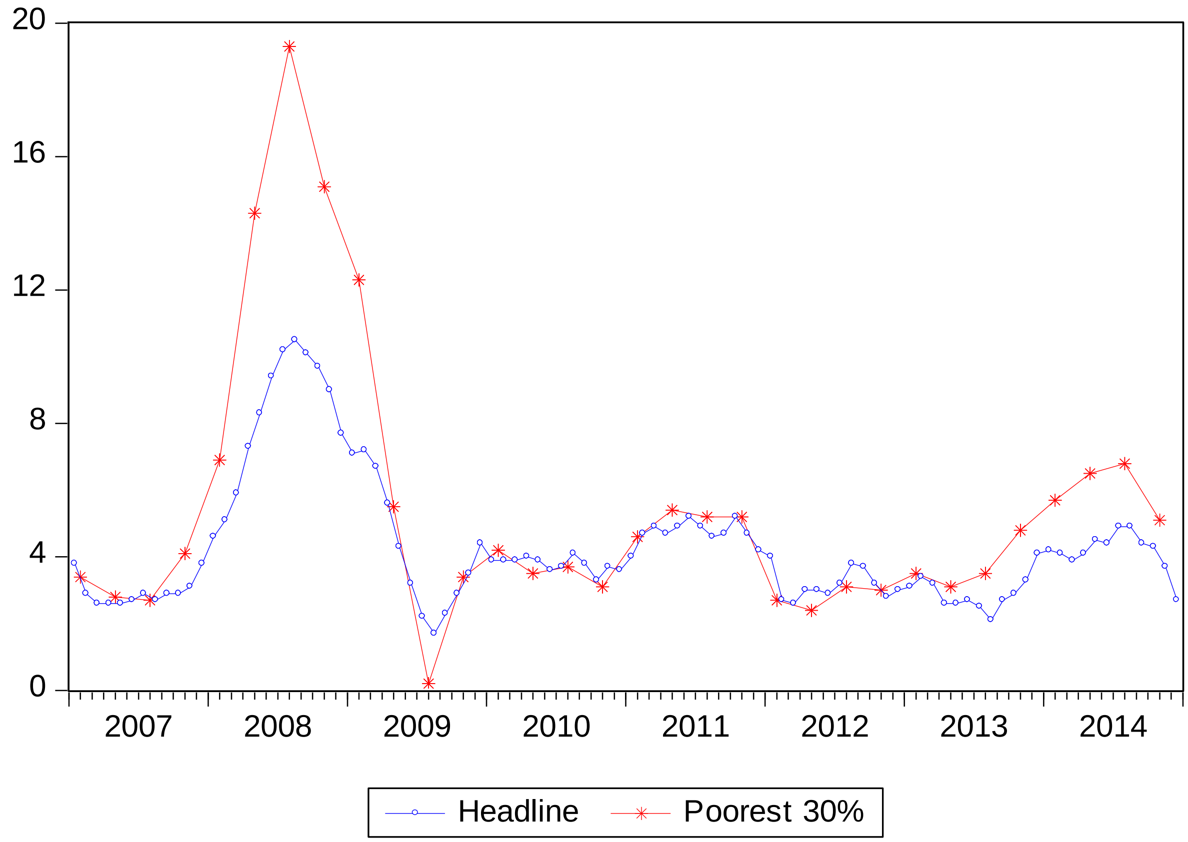
public and our policy makers if the PSA reviews the reporting mechanism of the inflation rate for the poorest 30 percent of households and perhaps report this number together with the headline inflation rate on a monthly basis.

Figure 3. Headline Inflation Rate and Inflation Rate of the Poorest 30 Percent of Households
(1st Quarter 2007 to 4th Quarter 2014)



In a study of Briones and Galang (2014), the authors argued that rice self-sufficiency target is unlikely to be achieved, whether in 2013 or even through the course of the decade to 2020. The authors added that in spite of the efforts of the rice-sufficiency program, the goals are simply untenable due to the highly ambitious and unrealistic projections of *palay* yield under the FSSP, from 3.78 ton per hectare to 4.53 ton per hectare, and production from 17.0 to 22.7 million tons, over the period 2011 to 2016, corresponding to annual growth rates of 3.8 and 6.3 percent, respectively. The authors doubt the DA's growth projections which are significantly higher compared to the historical yield and production growth rates of 1.5 and 3.2 percent, respectively, from 1994 to 2010. Recent developments proved the authors correctly since the country continued to import rice in 2014 due to another spike in the local rice prices during the period. In fact the DA may have unwittingly created the spike in the rice prices in 2013-2014 because of the department's underestimation of the country's rice consumption.[12]

2.3. The Job Misery Index

While the economy grew at a respectable rate of 6.3 percent in 2014 the number of newly created jobs remains wanting, growing at a slower pace of 2.8 percent. The number of employed persons in 2014 reached 37.31 million from 36.29 million in 2013, or about additional 1,024,000 jobs. The number of newly created jobs is slightly higher compared to the number of new workers entering the labor force, reaching about 958,000 in the same year. This brought down the country's annual unemployment rate to 6.8 percent in 2014, from 7.3 percent in 2013. Still, the Philippines unemployment rate is the highest when compared to other countries in the ASEAN-5, as shown in table 1 below.

Table 1. Annual Unemployment Rate of Countries in the ASEAN 5, 2010-2014

Country	Annual Unemployment Rate				
	2010	2011	2012	2013	2014
Indonesia	7.1	6.6	6.1	6.0	5.7p
Malaysia	3.4	3.1	3.0	3.2	3.3p
Philippines	7.3	7.0	7.0	7.3	6.8f
Singapore	3.1	2.9	2.8	3.1	1.9p
Thailand	1.0	0.7	0.7	0.8	0.9p

Source: International Labor Organization (ILO); Department of Labor and Employment (DOLE)
p – preliminary estimate; f – final estimate

In the Philippines, there is seems to be disconnect between output growth and growth in employment due to an incongruence between real GDP and employment with respect to the

[12] Presidential Assistant for Food Security and Agricultural Modernization Francis Pangilinan said, in an interview with the media, that the Department of Agriculture may have underestimated rice consumption to 11 million tons instead of 12 million tons, leading to a hike in prices.

sectoral structures (Peralta, 2013). It is observed that while the unemployment rate is at single digit, the underemployment rate (a good proxy for quality of available jobs) is relative high. The Philippine Statistics Authority (PSA) has the following definition of unemployed and underemployed persons:

a. Unemployed persons include all those who, during the reference period are 15 years old and over as of their last birthday who have no job/business and actively looking for work. Also considered as unemployed are persons without a job or business who are reported not looking for work because of their belief that no work was available or because of temporary illness/disability, bad weather, pending job application or waiting for job interview.

b. Underemployed persons include all employed persons who express the desire to have additional hours of work in their present job or an additional job, or to have a new job with longer working hours. Visibly underemployed persons are those who work for less than 40 hours during the reference period and want additional hours of work.

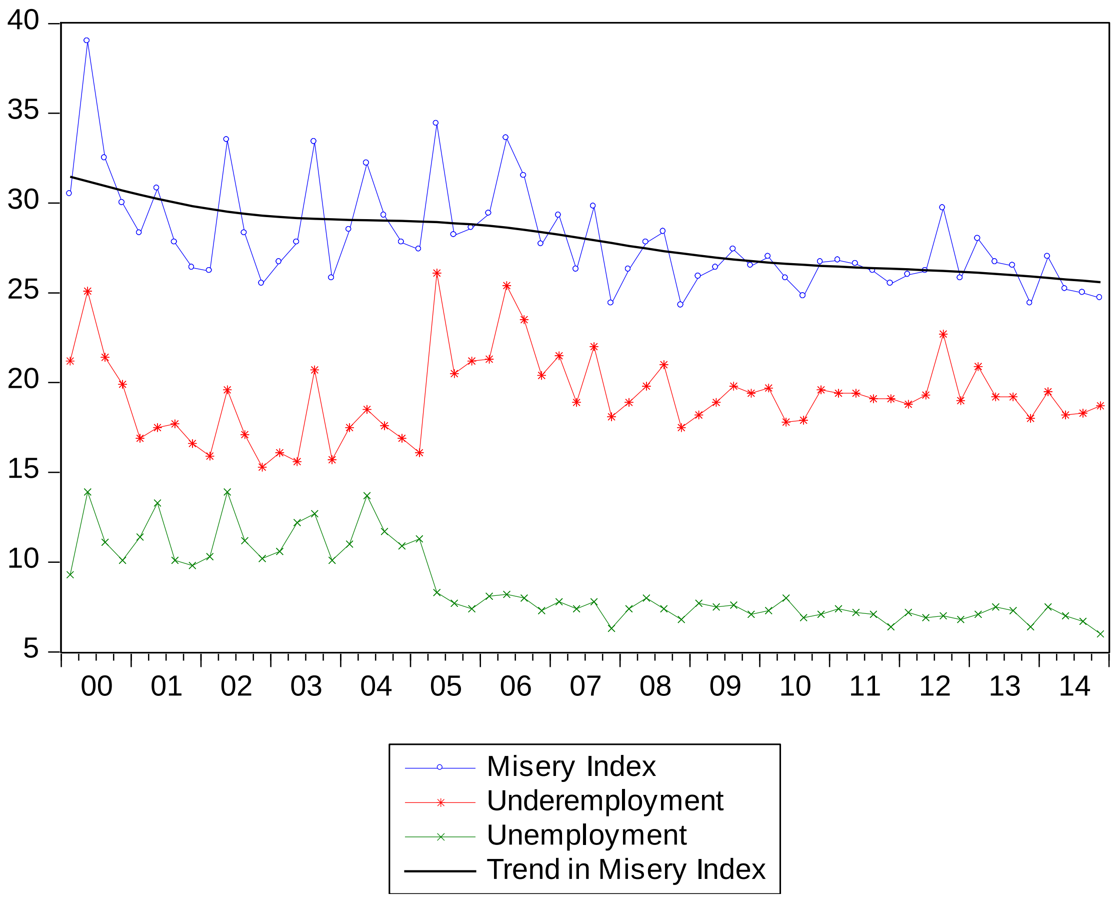
To analyze the dynamics of the labor sector and its impact on hunger incidence, the paper used an index called the *job misery index*, defined as the sum of the unemployment rate and underemployment rate. The *job misery index* can be quickly computed from the statistics reported in the quarterly Labor Force Survey (LFS) conducted by the PSA. It is also quick measure of the *labor underutilization rate* defined as the sum of the unemployed and the underemployed persons (the underutilized population), expressed as a proportion of the labor force. The *job misery index* is a better way of measuring the extent of underutilized labor resources in an economy, compared to the unemployment rate, which excludes underemployed workers.[13]

Figure 4 presents the quarterly unemployment rate, underemployment rate and the *job misery index* in the country during the period 2000-2014. The long run trend of the misery index,

[13] The PSA may perhaps, in the future, also report the labor underutilization rate together with the unemployment and underemployment rates.

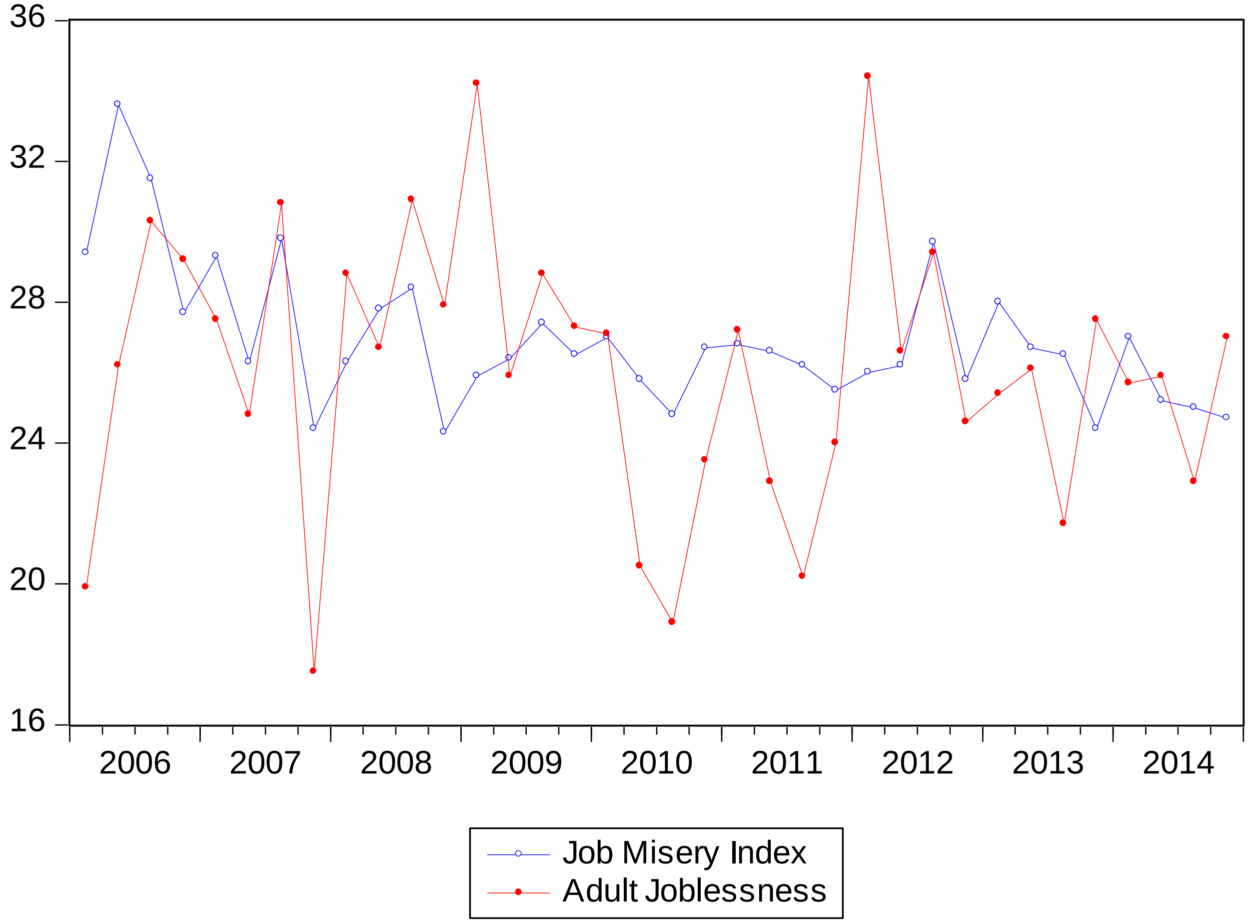
computed using the Hodrick-Prescott Filter, is high (between 25 to 26 percent) and dropping at a relatively slow pace signifying a relatively high underutilization of the labor resources.

Figure 4. Unemployment Rate, Underemployment Rate, Job Misery Index and its Long Run Trend
1st Quarter 2000 to 4th Quarter 2014



Coincidentally, the SWS also reports a quarterly series related to the labor sector known as the Adult Joblessness. The adult joblessness series is based on two traditional qualifications: without a job at present and looking for a job. Persons not working, without a job but not looking for one (e.g. housewives, students, etc.), are excluded from the adult joblessness. Aside from the difference in definition with the PSA on unemployment, the SWS respondents are at least 18 years old compared to the lower official boundary used by the PSA of 15 years of age. In the SWS survey, persons with jobs are those currently working, including unpaid family members.

Figure 5. Job Misery Index and Adult Joblessness
1st Quarter 2006 to 4th Quarter 2014



Analysis of the two series, adult joblessness and the job misery index, shows high correlation and co-movement for both series beginning the 1st quarter 2006 up to the 4th quarter of 2014, shown in figure 5.[14] The correlation between the quarter-to-quarter changes of the two series is 0.49 for the period 2006Q1 to 2014Q4, significantly higher than the correlation of 0.13 for the entire sample period 2000Q1 to 2014Q4. Moreover, the two series exhibit relatively strong co-movement around the trend, moving together (same upward/downward movements) in

[14] Comparative analysis was made for the period 1st quarter 2000 to 4th quarter 2014. However, the link between the two series is weaker for the longer sample (2000-2014) compared to the shorter sample (2006-2014). One plausible explanation is the change in the definition of unemployment of the PSA starting April 2005.

23 out of 36 quarters. In other words, the fluctuations of the two series around a trend are the same in 6 out of every 8 quarters.

III. ECONOMETRIC MODELS: VAR and TVP

3.1. The Vector AutoRegressive (VAR) Model

The vector autoregressive (VAR) is commonly used for forecasting systems of interrelated time series and for analyzing the dynamic impact of random disturbances (or shocks) on the system of variables. The main distinction of the VAR approach, compared to the other econometric models, is that it treats every endogenous variable in the system as a function of the lagged values of all endogenous variables in the system. When we are not confident that a variable is actually exogenous, we can treat each variable symmetrically. In the three-variable case order one VAR (or VAR (1)) model we have,

$$
\begin{aligned}
y_t &= \beta_{10} - \beta_{12} z_t - \beta_{13} w_t + \gamma_{11} y_{t-1} + \gamma_{12} z_{t-1} + \gamma_{13} w_{t-1} + \varepsilon_{yt} \\
z_t &= \beta_{20} - \beta_{21} y_t - \beta_{23} w_t + \gamma_{21} y_{t-1} + \gamma_{22} z_{t-1} + \gamma_{23} w_{t-1} + \varepsilon_{zt} \\
w_t &= \beta_{30} - \beta_{31} y_t - \beta_{32} z_t + \gamma_{31} y_{t-1} + \gamma_{32} z_{t-1} + \gamma_{33} w_{t-1} + \varepsilon_{wt}
\end{aligned}
\qquad (1)
$$

where y_t is say total hunger incidence, z_t is the price of rice and w_t is the misery index, all at quarter t. The $\varepsilon_{yt,}$, ε_{zt} and ε_{wt} are white noise disturbance terms with means 0 and standard deviations σ_y, σ_z and σ_w, respectively. The equations in (1) are called the structural equations of the VAR. The parameters, β_{12}, β_{13}, β_{21}, β_{23}, β_{31} and β_{32} measure the contemporaneous effects while the γ's measure the lag 1 effects. The equations are not in reduced form since, for example, y_t has contemporaneous effect on z_t and w_t. Isolating the time t variables on the left-hand side, we have,

$$
\begin{aligned}
y_t + \beta_{12} z_t + \beta_{13} w_t &= \beta_{10} + \gamma_{11} y_{t-1} + \gamma_{12} z_{t-1} + \gamma_{13} w_{t-1} + \varepsilon_{yt} \\
\beta_{21} y_t + z_t + \beta_{23} w_t &= \beta_{20} + \gamma_{21} y_{t-1} + \gamma_{22} z_{t-1} + \gamma_{23} w_{t-1} + \varepsilon_{zt} \\
\beta_{31} y_t + \beta_{32} z + w_t &= \beta_{30_t} + \gamma_{31} y_{t-1} + \gamma_{32} z_{t-1} + \gamma_{33} w_{t-1} + \varepsilon_{wt}
\end{aligned}
\qquad (2)
$$

In matrix form,

$$\begin{bmatrix} 1 & \beta_{12} & \beta_{13} \\ \beta_{21} & 1 & \beta_{23} \\ \beta_{31} & \beta_{32} & 1 \end{bmatrix}\begin{bmatrix} y_t \\ z_t \\ w_t \end{bmatrix} = \begin{bmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \end{bmatrix}\begin{bmatrix} y_{t-1} \\ z_{t-1} \\ w_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \\ \varepsilon_{wt} \end{bmatrix}$$

Simplifying, we have,

$$\begin{aligned} B\underline{x}_t &= \Gamma_0 + \Gamma_1 \underline{x}_{t-1} + \underline{\varepsilon}_t \\ \underline{x}_t &= B^{-1}\Gamma_0 + B^{-1}\Gamma_1 \underline{x}_{t-1} + B^{-1}\underline{\varepsilon}_t \qquad (3) \\ \underline{x}_t &= A_0 + A_1 \underline{x}_{t-1} + \underline{e}_t \end{aligned}$$

where $\underline{x}_t = \begin{bmatrix} y_t \\ z_t \\ w_t \end{bmatrix}$, $B = \begin{bmatrix} 1 & \beta_{12} & \beta_{13} \\ \beta_{21} & 1 & \beta_{23} \\ \beta_{31} & \beta_{32} & 1 \end{bmatrix}$, $\Gamma_0 = \begin{bmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \end{bmatrix}$, $\Gamma_1 = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \end{bmatrix}$, $\varepsilon_t = \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \\ \varepsilon_{wt} \end{bmatrix}$

The equations in (3) are called the reduced-form representation of a VAR (1) model. We can generalize the mathematical representation of the reduced-form VAR model as,

$$\underline{x}_t = A_0 + A_1 \underline{x}_{t-1} + A_2 \underline{x}_{t-2} + \ldots + A_p \underline{x}_{t-p} + \underline{e}_t \qquad (4)$$

where $\underline{\mathbf{x}}_{\mathbf{t}}$ is a (k x 1) vector of endogenous variables, $\underline{\mathbf{A}}_1$, $\underline{\mathbf{A}}_2$,…, $\underline{\mathbf{A}}_p$ are matrices of coefficients to be estimated, and $\underline{e}_t$ is a (k x 1) vector of forecast errors that may be contemporaneously correlated but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables. The error vector $\underline{e}_t$ is assumed to be normally distributed with mean $\underline{\mathbf{0}}$ and covariance matrix $\underline{\mathbf{\Sigma}}$. The order of the VAR model (p) is determined using the information criteria (Akaike, Schwarz and the Hannan-Quinn).

3.2. Summary Statistics

The figures in table 2 show the summary statistics of the variables used in the study. These summary statistics are presented for the full data 2000-2013 and for the period 2008-2013, during and after the global rice price crisis. The average year-on-year rice price inflation, as reported by the PSA, is higher from 2008-onwards at 7.26 percent, compared to the entire sample period where the average rice price inflation is only 4.91 percent.

As shown in figure 2, the local price of rice experienced a jump, to a higher level, during the global rice price crisis and remained high even after the crisis when the international rice prices are going down. The current high prices of rice that Filipino consumers are experiencing now can no longer be attributed to the changes in the international prices.

The average annual hunger incidence is also higher during the period 2008-2013 at 19.49 percent compared to the period 2000-2013 where hunger incidence is 15.70 percent. The econometric models will show that such increase in the hunger incidence is largely explained by the increase in the price of rice.

The job misery index remained almost the same for the two periods averaging at between 27 to 28 percent, while the average inflation rate for the housing, water, gas, electricity and fuel index decreased slightly for period 2008-2013 to 4.04 percent, from 4.91 percent for the entire sample.

Table 2. Summary Statistics of the Variables

	Full Data (2000 to 2013)				After 2008			
	Hunger	Job Misery	Rice	HWGEF	Hunger	Job Misery	Rice	HWGEF
Statistics	Incidence	Index	Price Inf	Price Inf	Incidence	Index	Price Inf	Price Inf
Mean	15.70	27.87	4.91	4.53	19.49	26.58	7.26	4.04
Median	16.15	27.40	3.22	4.76	19.75	26.45	3.78	4.76
Maximum	23.80	34.40	33.18	7.99	23.80	29.70	33.18	5.86
Minimum	5.10	24.30	-1.15	0.80	15.10	24.30	-1.15	0.80
Std. Dev.	4.99	2.42	6.81	1.88	2.87	1.18	9.53	1.50
No. of Quarters	50	50	50	50	22	22	22	22

HWGEF is Housing, Water, Gas, Electricity and Fuel Price Index as Reported by the PSA, together with the Rice Price Index; Job Misery Index is computed from Unemployment and Underemployment Rates as reported by the PSA; Social Weather Stations (SWS) provided the Hunger Data

3.3. Augmented Dickey-Fuller (ADF) Tests for Presence of Unit Roots

The quarterly time series data on hunger incidence, rice price index, job misery index and the HWGEF price index are tested for presence of unit root(s) using the Augmented Dickey-Fuller (ADF) test prior to building the VAR model. The results in table 3 show that the time series hunger incidence, rice price and the HWEGF price indices are non-stationary, The ADF test for the job misery index and the seasonally-adjusted job misery index are both stationary with deterministic trend.[15]

Table 3. Results of the Augmented Dickey Fuller (ADF) Tests for Presence of Unit Root

Variable	Test Statistic	p-value	Remarks
HWEGF Price Index (in nat. log.)	-2.85	0.19	I(1)
Job Misery Index (in nat. log.)	-6.55	0.00	Stationary*
Job Misery Index (seasonally adjusted; in nat. log.)	-3.46	0.05	Stationary*
Rice Price Index (in nat. log.)	-2.56	0.30	I(1)
Hunger Incidence (in nat. log.)	-2.81	0.20	I(1)

* Stationary with Deterministic Trend

3.4. Empirical Results from the VAR Model

The results of the VAR (1) model using the quarterly time series data on hunger incidence, price of rice index, job misery index and the HWEGF index are reported in table 4 below. The paper is interested in the first equation of the VAR model where the dependent variable is the change in the quarterly hunger incidence, under the column DLOG(HUNGER). The change in hunger incidence at quarter t can be explained significantly by the lag 1 change in hunger incidence (own lag), rice price inflation at lag 1, job misery index at lag 1 and the HWEGF inflation also at lag 1.

[15] The seasonally-adjusted series of the job misery index is used in the econometric models. The series is adjusted using the X-12 procedures in Eviews 8.0.

The VAR model in table 4 is a reduced-form VAR and can only be used to forecast future hunger incidence. The dynamic relationship of the VAR model is derived using the Impulse Response Function (IRF).

Table 4. VAR Model for Hunger Incidence, Rice Price, Job Misery and HWEGF Indices

	DLOG(HUNGER)	DLOG(RICE)	DLOG(HWEGF)	LOG(MISERY_SA)
DLOG(HUNGER(-1))	-0.432***	-0.003	-0.003	0.010
	(0.123)	(0.016)	(0.005)	(0.041)
	[-3.505]	[-0.202]	[-0.565]	[0.239]
DLOG(RICE(-1))	2.043**	0.180	-0.020	0.018
	(1.065)	(0.139)	(0.0430)	(0.358)
	[1.919]	[1.301]	[-0.463]	[0.051]
DLOG(HWEGF(-1))	-5.661*	0.711	0.297*	0.637
	(3.507)	(0.456)	(0.142)	(1.179)
	[-1.614]	[1.558]	[2.096]	[0.541]
LOG(MISERY_SA(-1))	0.685*	-0.068	0.009	0.381*
	(0.375)	(0.049)	(0.015)	(0.126)
	[1.825]	[-1.401]	[0.602]	[3.017]
C	-2.228*	0.230	-0.023	2.054
	(1.247)	(0.162)	(0.050)	(0.419)
	[-1.786]	[1.415]	[-0.448]	[4.898]
R-squared	0.3068	0.1172	0.1024	0.1831
Adj. R-squared	0.2478	0.0421	0.0260	0.1136
*Std Errors are in ( ) and t-statistics in [ ]; *** significant at 1%; ** significant at 5%; * significant at 10%*				

3.5. Impulse Response Function (IRF)

The impulse response function of a variable due to a change in another variable is the primary method used to analyze the macroeconomic dynamics captured by the VAR system. A shock to the i^{th} variable (e.g. increase in rice price inflation or job misery index) not only directly affects the i^{th} variable but is also transmitted to all the other endogenous variables, in particular hunger incidence, through the dynamic (lag) structure of the VAR. An impulse response function traces the effect of a one-time shock to one of the innovations (error terms) on the current and future values of the endogenous variables. If the error terms are contemporaneously uncorrelated, then the i^{th} innovation (ε_{it}) is simply a shock to y_{it} or what is referred to as "shock to itself."

3.5.1. Response of Hunger Incidence to a Shock in Rice Price Inflation

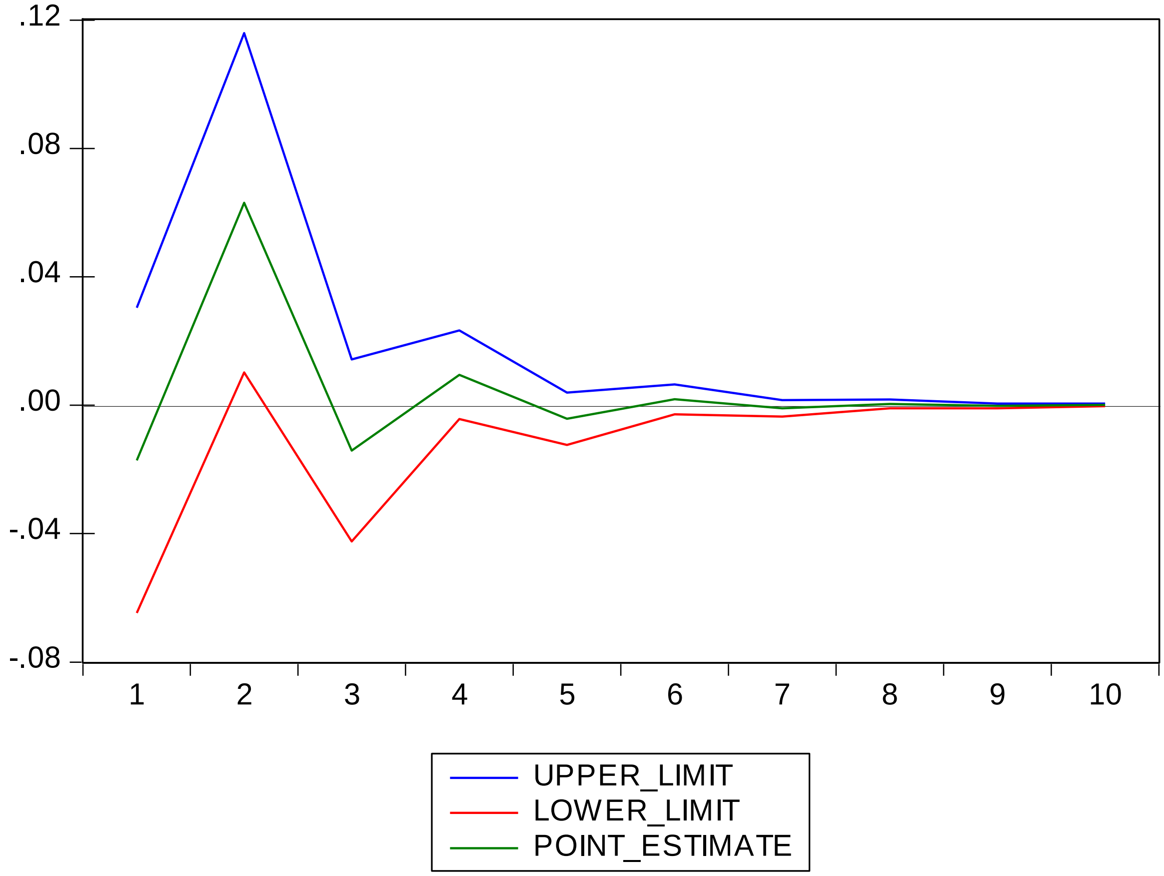
The response of the change in hunger incidence to a shock in rice price inflation is given in table 5 and figure 4 below. The IRF shows that a one-time shock (or increase) to rice price inflation at quarter t will have a significant effect on total hunger incidence in the succeeding quarter t+1. In particular, a one standard deviation increase to rice price (about 2.8 percentage points using the sample data) at quarter t will increase total hunger by about 6 percentage points in the next quarter, all things being the same. After quarter (t + 1), the effect of this one-time shock to the rice price inflation on hunger incidence decays to zero. The result shows that hunger incidence is sensitive to changes in rice prices for one quarter.

Table 5. Impulse Response Function – Response of Change in Hunger Incidence to a One-Standard Deviation increase in Rice Price Inflation at Quarter 1

Quarter	Point Estimate	Standard Error.	Confidence Interval (+/- 1.64 SD)	
			Lower Limit	Upper Limit
1	-0.017	0.029	-0.065	0.030
2	**0.063**	**0.032**	**0.010**	**0.116**
3	-0.014	0.017	-0.042	0.014
4	0.009	0.008	-0.004	0.023
5	-0.004	0.005	-0.012	0.004
6	0.002	0.003	-0.003	0.006
7	-0.001	0.002	-0.003	0.002
8	0.000	0.001	-0.001	0.002

Cholesky Ordering: dlog(hwegf) log(misery_sa) dlog(rice) dlog(total)

Figure 4. Response of Hunger Incidence to One Std Dev increase in Rice Price Inflation



3.5.2. Response of Hunger Incidence to a Shock in the Job Misery Index

The response of the change in hunger incidence to a shock in the job misery index is given in table 6 and figure 5 below. The IRF shows that a one-time shock (or increase) to the job misery index at quarter t will have a significant effect on total hunger incidence in the succeeding quarter t+1. In particular, a one standard deviation increase to the job misery index (about 8 percent using the sample data) at quarter 1 will increase total hunger by about 4.2 percentage points in the next quarter, all things being the same. After quarter (t + 1), the effect of this one-time shock to the job misery index on hunger incidence decays to zero. The result shows changes in the job misery index is also influencing hunger incidence, albeit at a lower magnitude when compared to the impact of the price of rice.

Table 6. Impulse Response Function – Response of Change in Hunger Incidence to a One-Standard Deviation increase in the Job Misery Index Quarter 1

Quarter	Point Estimate	Standard Error.	Confidence Interval (+/- 1.64 SD)	
			Lower Limit	Upper Limit
1	0.020	0.029	-0.018	0.057
2*	**0.042**	**0.031**	**0.003**	**0.082**
3	-0.012	0.014	-0.031	0.006
4	0.006	0.008	-0.004	0.016
5	-0.003	0.004	-0.008	0.002
6	0.001	0.002	-0.001	0.004
7	-0.001	0.001	-0.002	0.001
8	0.000	0.001	0.000	0.001

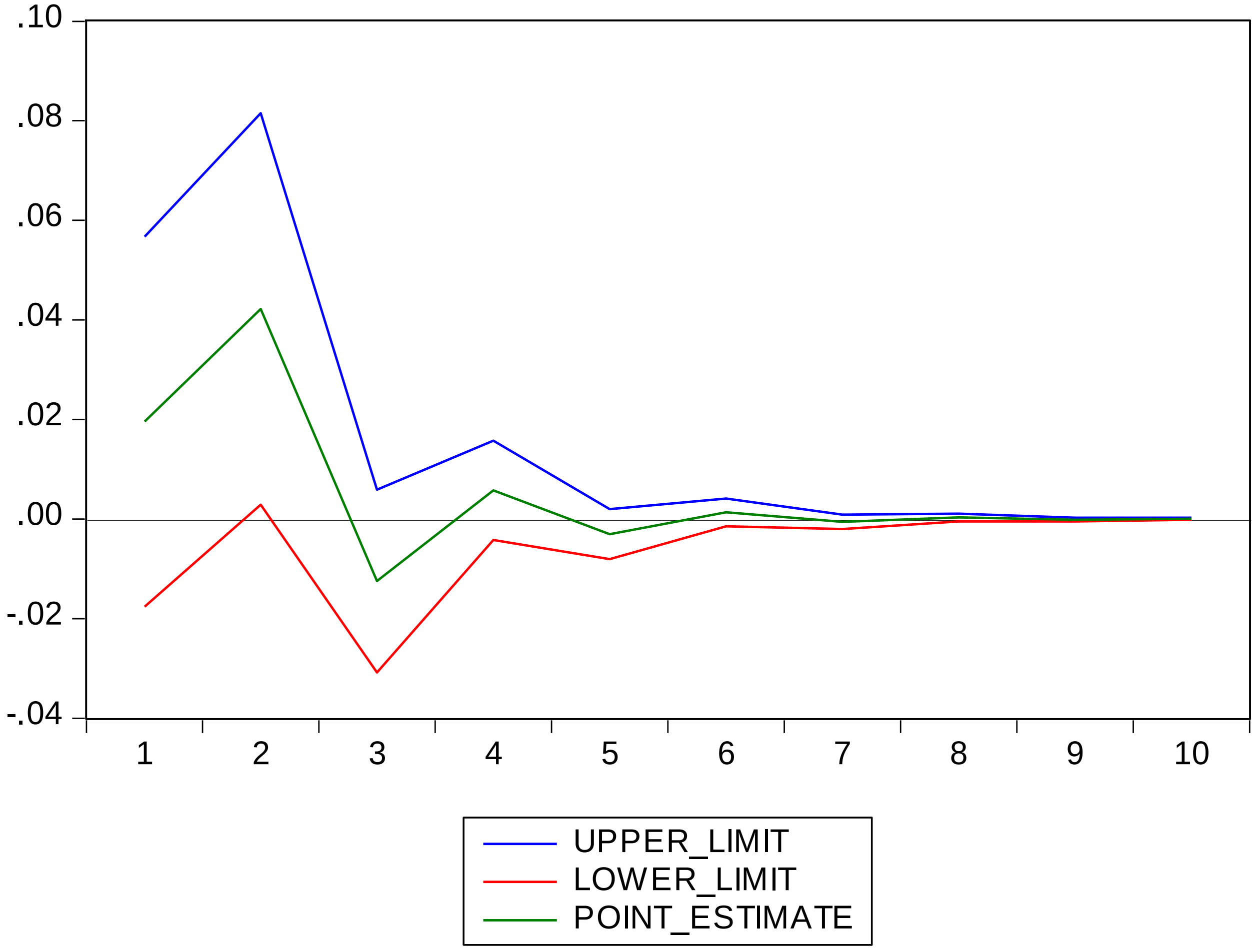
*Cholesky Ordering: dlog(hwegf) log(misery_sa) dlog(rice) dlog(total); *significant at the 10% level one-sided test*

Moreover, analysis of the forecast error variance of hunger incidence shows that shocks in the price of rice explain about 7 percent of the variation in the forecast errors of hunger incidence. The shocks to the job misery index explains about 4 percent of the variation in the forecast erros of hunger ncidence.[16]

The impact of the shocks to the rice prices and job misery index on hunger incidence are lasting for only one quarter. This is relatively a shorter immediate effect on hunger incidence when compared to the results of the previous study by Mapa, Han and Estrada (2011) where the authors find that shocks to the more broader food inflation affect hunger incidence in the next five (5) quarters. Moreover, the impact of shocks to underemployment in the same study affects hunger incidence in the next two quarters. One plausible explanation to this shorter impact of shocks is the relative success of the hunger mitigation programs of the Aquino administration such as the expansion of the number of households benefiting from the conditional cash transfer (CCT) program.

[16] A one-time increase in HWEGF Price Inflation does not affect changes in hunger incidence for the 10 immediate quarters and is no longer reported.

Figure 5. Response of Hunger Incidence to One Std Dev increase in the Job Misery Index



3.6. Time-Varying Parameter (TVP) Models

One important motivation of this paper is to examine the impact of the shocks to the rice price following the global rice price crises of 2008 on hunger incidence. As shown in figure 2 the local rice price exhibited a structural change after the global rice crisis. The trend of the rice price in the country has been increasing despite the downward movement of prices in the international market. The authors would like to determine the link between rice price and hunger incidence during and after the global rice price crisis. The authors' hypothesis is that hunger incidence is becoming more sensitive to changes in the price of rice after the rice crisis. To prove this empirically, the authors build a time-varying parameter (TVP) model for hunger incidence.

Consider the following regression model, in which the regression coefficients are time-varying with specific dynamics,

$$y_t = \underline{x}_t'\underline{\beta}_t + \varepsilon_t, \qquad \varepsilon_t \sim \text{i.i.d } N(0, R) \qquad (5)$$

$$\underline{\beta}_t = \underline{c}_t + \underline{F}\underline{\beta}_{t-1} + \underline{v}_t, \qquad \underline{v}_t \sim \text{i.i.d. } N(\underline{0}, \underline{Q}) \qquad (6)$$

where y_t is a (1x1) scalar of response; $\underline{x}_t$ is a (k x 1) vector of exogenous or predetermined variables; ε_t and v_t are independent; $\underline{\beta}_t$ is (k x 1) vector of time-varying coefficients; $\underline{F}$ is (k x k); and $\underline{Q}$ is (k x k); t = 1, 2, …, T.

The $\underline{F}$, $\underline{c}$ and $\underline{Q}$ may be defined according to a model specification such as a time-varying parameter (TVP) modes with random walk coefficients and TVP models with auto-regressive order 1 or AR(1) coefficient. When $\underline{c} = \underline{0}$ and $\underline{F} = \underline{I}_k$, each of the regression coefficient in β_t follows a random walk. If $\underline{F}$ is a diagonal matrix and the absolute values of its diagonal elements are less than 1, each regression coefficient follows a stationary AR(1) process.

3.6.1. State Space Models

State space models deal with dynamic time series involving unobserved variables. State Space is used to represent models that are more complex than common or mainstream models because it can capture unobserved components. In principle, it can be any model that includes an observation process and a state process. Econometric models (in particular time series models) including Auto-Regressive Moving Average (ARMA) model, linear regression models, and spline models can be considered as special cases and may be written in state space forms. Some applications of SSM are extracting trend, modeling time-varying parameters and capturing dynamic factors. An example is the extracted trend is the one utilizing the Kalman Filter as the estimation procedure. Kalman Filter, derived by Kalman (1960), is an algorithm used to solve state space models in the linear case. A linear (Gaussian) state space representation of the dynamics of the (n x 1) vector $\underline{y}_t$ is given by the system of equations,

$$\underline{y}_t = \underline{X}_t\underline{\beta}_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \Sigma_\varepsilon) \qquad \text{measurement equation} \qquad (7)$$

$$\underline{\beta}_t = \underline{c}_t + \underline{F}\underline{\beta}_{t-1} + \underline{\nu}_t \qquad \underline{\nu}_t \sim N(0, \Sigma_\nu) \qquad \text{transition equation} \qquad (8)$$

The first equation (7), referred to as the "signal" or "observation" or "measurement" equation, describes the relationship between the observed time series $\underline{y}_t$ and the (possibly unobserved) state $\beta_{t.}$ The second equation (8), known as the "state" or "transition" equation, describes the evolution of the state variables as being driven by the stochastic process of innovations ν_t (Pichler, 2007). The transition equation has the form of a first-order difference equation in the state vector. Kalman Filter fully explores this dynamic structure for filtering, smoothing and forecasting (Kim and Nelson, 1989).

3.6.2. Model Parameter Estimation using Kalman Filter

After defining the model, the next task is the estimation of model parameters given the time series of observations. There are two unknowns, the model state variables and the parameters that define the model error covariance matrix. When the system is linear and errors are Gaussian, Kalman (1960) filter estimation can be used to estimate the states because of the sequential nature of the equations. The Kalman filter is an iterative computational algorithm involving the following steps: initialization, prediction, correction and likelihood construction. The recursive Kalman Filter formula depend on known distribution for the initial time uncertainty. In using the standard recursive algorithm, initial conditions for the mean and variance values must be established to complete the recursion. It is known that the initial mean value does not influence the smoothing estimates provided that a sufficiently large value is chosen for the initial variance. The Kalman filter the computes recursively the optimal state predictions of y_t which is conditional on past information and also on the variance of their prediction error (Saini and Mittal, 2014). A good exposition of the Kalman Filter algorithm in the State Space problems can be found in Kim and Nelson (1989).

3.6.3. State Space Model Specification and Results

To determine the changes (if there are any) in the relationship between the price of rice on hunger incidence before and after the global rice price crisis, the authors build a TVP with the following specifications,

$$\Delta LOGTOTAL_t = \beta_{0,t} + \beta_{1,t}\,\Delta LOGRICE_{t-1} + \beta_{4,t}\,LOGMISERY\_SA_{t-1} + \beta 4{,}t\,\Delta LOGHWEGF_{t-1} + \beta_{5,t}\,\Delta LOGTOTAL_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim \text{i.i.d. } N(0, \sigma^2) \qquad (9)$$

where $\beta_{i,t} = \beta_{i,t-1} + v_{it}\,, v_{it} \sim$ i.i.d. $N(0, \sigma^2{}_i)$ $\quad i = 0, 1, 2, 3, 4, 5$

The parameters in the regression model in (9) are all treated as time-varying. The model consists of one signal equation and five state equations. The estimated time-varying parameters associated with the changes in the price of rice are table 7 below.

Table 7. Summary of the Impact of the Rice Price Inflation (Lag 1) on Hunger Incidence

	Sample Periods	
Summary Statistics	2003 to 2008	2009 to 2013
Mean	1.02	1.88
Median	0.72	1.88
Std. Dev	1.40	0.04
Number of Quarters	26	18

On the one hand, the impact of the rice price inflation on hunger incidence using the time-varying parameter (TVP) model varies significantly before and after the global rice price crises. Before and during the crisis period (2003-2008),[17] the model estimates that a one-percentage point increase in the rice price inflation in the previous quarter will increase the average hunger incidence by about one-percentage point in the current quarter, all things being the same. This average effect of the rice price inflation on hunger incidence jumped to 1.88 percentage points during the period 2009 to 2013. In other words, a one-percentage point increase in the rice price inflation in the previous quarter results in an average 1.88 percentage points increase in hunger incidence in the current quarter. The results show that hunger incidence is becoming more sensitive to change in the price of rice after the global rice price crisis.[18] The results of the TVP model, particularly for the period after the crisis, are consistent with the results of the impulse response function (IRF) in the VAR model.

On the other hand, the estimated coefficients of the job misery index (lag 1) do not differ significantly before and after the global rice price crisis. The result shows that the link between job misery index and hunger incidence remains constant throughout the sample period.

IV. CONCLUSIONS and RECOMMENDATIONS

This paper examines the dynamics of hunger incidence in the country using the quarterly survey data generated by the Social Weather Stations (SWS). It also identifies the factors that can help determine hunger incidence such as rice price, an indicator in the labor market using the job misery index or the sum of the unemployment and underemployment rates, and housing, water, electricity, fuel and gas (HWEFG) price index. To pin down the relationship of the variables empirically, the paper used the vector autoregressive (VAR) and time-varying parameter (TVP) models. The results of the analysis show that a shock (increase) in the price of

[17] The first few time-varying estimates (10 estimates in this case) are discarded since these are usually affected by the initial values in the estimation. This a common practice when reporting results of the Kalman Filter.
[18] The difference of the two means, 1.88 versus 1.02, is significantly different from zero using the t-test, with p-value of 0.0041

rice at the current quarter tends to increase hunger incidence in the succeeding quarter. Moreover, a shock (increase) in the job misery index at the current quarter also increases the hunger incidence in the next quarter. Further analysis using the time-varying parameter (TVP) model shows a higher effect of changes in the price of rice to hunger incidence after the global rice crisis of 2008. The impact of the change in the price of rice on hunger incidence almost doubled after the global rice price crisis than before it. This means that hunger incidence is becoming very sensitive to changes in the price of rice. This is because the poor households consume a large percentage of their budget on rice expenditures relative to the non-poor households. Institutional reform measures must be implemented to alleviate the impact of high price of rice in the country. The rice self-sufficiency program of the government must be reviewed in the light of the studies pointing to the program as one of the culprits resulting in the continuing increases in the price of rice in the local market. Another key factor affecting hunger incidence is the availability (quantity) and the quality of jobs. The relatively fast pace in economic growth experienced by the country during the last five years, unfortunately, only resulted in marginal increases in number of new jobs created. The job misery index remains high which means that a large percentage of the country's labor resources is underutilized. The objective of having inclusive growth will not materialize if the growth rates in the quantity and quality of available jobs will not improve.

It is also important that the public and the policy makers are provided with relevant information and indicators that affect the welfare of the general population, but more specially, the poor households. As the central authority of the Philippine government on primary data collection, it is the responsibility of the Philippine Statistics Authority (PSA) to inform our policy makers on the welfare of the marginalize sector of the population through relevant statistical indicators. In the case of inflation rate, it is high time that the PSA gives equal importance to the inflation rate for the poorest 30 percent of the households, similar to the headline inflation rate (for all households), particularly during periods when there are substantial gaps/differences in the two inflation figures. At present, the public is given the impression that inflation rates (headline inflation) are low, without knowing much that the inflation of the poorest households remains high due to the continuing increases in the price of rice. The inflation rate for the poorest 30 percent of the households should also be reported monthly, rather than quarterly, together with the headline inflation rate. The PSA, together with the Department of Labor and Employment (DOLE), should also report the quarterly *labor underutilization rate* (or perhaps the job misery index) to provide the public and policy makers with a clearer picture of the labor situation in the country. While the PSA and the DOLE both report the unemployment and underemployment rates, importance in this quarterly labor sector report is given to the unemployment rate which tends to underestimate the underutilization of the country's labor resources. As Amartya Sen said *"in order to conquer hunger, we must tackle all the causes of hunger simultaneously."* In order to tackle these causes of hunger and provide the right solution to alleviate the condition of the poor, we must have the correct and relevant information on these causes. We need to track a few more statistical indicators for the poor.

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