Why are Filipinos hungry: Econometric analyses on possible determinants of hunger incidence in the Philippines

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ABSTRACT

Widespread hunger among Filipinos is a critical problem that should be urgently dealt with by the government. In fact, 9.9 percent or almost 10 million Filipino families are experiencing hunger based on the March 2018 Social Weather Station (SWS) quarterly hunger incidence report, whereas data from the Philippine Statistics Authority (PSA) show that subsistence incidence, or the proportion of families' income that fall below the food threshold is at 5.7 percent. Possible reasons to this increase in hunger incidence include the inflating prices of basic commodities such as rice, housing, water, electricity, gas and other fuels. Inadequate employment can also be associated with this aggravating phenomenon. Thus, this study aims to unveil the influence on hunger incidence of these determinants: job misery index, as the sum of unemployment and underemployment rates, Consumer Price Index (CPI) components such as rice, and housing, water, electricity, gas, and other fuels (HWEGF) using the quarterly time series data of SWS on hunger from the first quarter of 2000 until the first quarter of 2018. Also, the relationship between hunger incidence and regional subsistence incidence is investigated using the same three determinants. Three econometric models, vector autoregressive (VAR), time varying parameter (TVP), and two-way random effects (RE) are used in determining the link of hunger to the rice, HWEGF, and job misery indices. models. The VAR model shows that rice index significantly affects hunger incidence, as well as shocks to rice and HWEGF indices. The TVP model also suggests the significant impact of rice and HWEGF indices on hunger incidence. Meanwhile, the random effects model shows that the subsistence incidence across regions is affected by the rice index. Based on the results of the three models, rice index has a significant impact on self-rated hunger incidence and subsistence incidence among Filipinos.

Keywords: Self-rated hunger, Subsistence incidence, Vector AutoRegressive (VAR) model, State space, Time Varying Parameters (TVP) model, Two-way Random Effects model

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I. INTRODUCTION

A total of 815 million people worldwide or 11 percent of the global population experienced hunger in 2016, a 38 million increase from 2015. Large parts of this hungry population come from Africa with 20 percent of the proportion, followed by Asia with 11.7 percent, and 6.6 percent from the Latin America and Caribbean (World Food Programme, 2017)**.**

The population of the Philippines continues to grow rapidly, currently at 100,981,437 as of August 2015 (Philippine Statistics Authority, 2018) and its consequences are being more evident, specifically the incidence of hunger in the country. SWS reported that 2.7 million families or 11.8 percent has experienced hunger for the third quarter of 2017, a significant 2.3 percentage increase from the reported 9.5 percent for the second quarter of 2017 (Philippine Star, 2017). Given this continuing increase of population, different solutions to increasing hunger incidences were sought after by the Philippine administration.

A solution provided by the Arroyo administration which is still implemented as of writing is the Pantawid Pamilyang Pilipino Program or more commonly known as the 4Ps. The 4Ps provides cash assistance to the poorest of the poor aiming to improve health, nutrition, and the education for children aged 0 to 18. This program was patterned from the conditional cash transfer scheme from the Latin American and African countries, with the same hopes of lifting lives away from poverty. The 4Ps is also the government's way of fulfilling its commitment to the Millennium Development Goals, particularly in eradicating extreme poverty and hunger, achieving universal primary education, promoting gender equality, reducing child mortality, and improving maternal health care (Official Gazette of the Philippines, 2015).

The cash benefit from the 4Ps can be used to pay for basic commodities such as rice, water, housing, among others. Even though that the prices of basic goods are constantly increasing, the subsidy received by 4Ps beneficiaries has remained the same at Php2,400 a month (Santos-Recto, 2016; Rey, 2018). These price changes in basic goods is reflected through the Consumer Price Index (CPI). CPI is defined by the PSA as the change of average retail prices of a fixed basket of good commonly purchased by households relative to a base year. Since using the whole CPI would underestimate certain goods that may be of relevance for hunger, only the Rice component and Housing, Water, Electricity, Gas and Other Fuels (HWEGF) component was checked. Rice has been a pivotal political commodity ever since because of its importance as a staple food for the majority of the population, especially in the low-income Filipinos, and as a source of employment and income to a wide range of people (Intal & Garcia, 2005). The 2010 Census of Population and Housing reported that majority of the fuel for cooking used was wood at 44.1 percent of the total households, followed by Liquified Petroleum Gas (LPG) at 36.9 percent. In order to avoid underestimating other households that uses other types of gases and fuels and to also include index for housing and the essential resource water, the aggregated HWEGF was used as a measure.

Aside from the 4Ps, the government, through the National Nutrition Council established the Action Against Hunger Philippines. This institution aims to instill resilience in poor families by providing them avenues for growth through capacity building activities (National Nutrional Council, 2014).

Another repercussion of the increasing population is unemployment. The unemployment rate for the first quarter of 2018 as reported by the Philippine Statistics Authority (PSA) was recorded to be at 5.3 percent, or 2.32 million Filipinos without jobs, a 0.3 percent increase from the reported unemployment rate on the last quarter of 2017 (Philippine Statistics Authority, 2018).

In the pursuit to increase the employment rate, the government implemented several programs. The most successful of which is the Technical Education and Skills Development Authority (TESDA). TESDA started in 1994 and ever since then has been set to be the leader in the technical education and skills development of the Filipino workforce. This agency was set to increase the number of Filipinos with work without compromising its quality (TESDA, 2014).

Besides unemployment, another measure of job inadequacy that is often overlooked is underemployment. Underemployed persons are defined by the PSA as workers who express their desire to have additional hours of work in their present/additional job or have a new job with longer working hours. For the first quarter of 2018, the underemployment rate of the Philippines was recorded at 18.0 percent which is a 2.1 percent increase from the last quarter of 2017 (Philippine Statistics Authority, 2018).

All of these factors, unemployment, underemployment, and components of the Consumer Price Index (CPI) specifically the Rice component and Housing, Water, Electricity, Gas, and Other Fuels (HWEGF) component could influence the prevalence of hunger in the country. This paper aims to unveil the dynamic patterns of hunger incidence and the effects of these chosen determinants of hunger using the quarterly time series data of SWS national surveys on hunger from the first quarter of 2000 until the first quarter of 2018.

Three models are built to determine the link of hunger to the index of rice, index of HWEGF, and the job misery index, the sum of the unemployment and underemployment rates made by Mapa, Castillo, & Francisco (2015) on their working paper entitled “Rice Price, Job Misery, Hunger Incidence: Need to Track Few More Statistical Indicators for the Poor”. These econometric models are vector autoregressive (VAR), time varying parameter (TVP), and the random effects (RE) models.

This paper also makes comparisons on self-rated hunger garnered by the SWS national surveys with the regional subsistence incidence, a statistic that is derived from the Family Income and Expenditure Survey (FIES) by the PSA on the averages of years 2004-2006 (labeled 2006), 2007–2009 (labeled 2009), 2010–2012 (labeled 2012), and 2013–2015 (labeled 2015) using the same three determinants mentioned earlier.

The flow of this paper is as follows: Section I is the introduction, Section II are the measures for hunger incidence, Section III presents the descriptive statistics, Section IV shows the model building procedure, and lastly, Section V concludes the findings of this study.

II. HUNGER INCIDENCE VS. SUBSISTENCE INCIDENCE

2.1 SWS Hunger Incidence Report

The researchers explored hunger incidence provided by the SWS quarterly survey on self-rated hunger. Hunger incidence is a direct measure of an individual’s experience on hunger itself by answering questions regarding the topic (Maligalig, 2008).

2.2 PSA Subsistence Incidence Report

Another measure of hunger discussed is the subsistence incidence reported by the PSA by using the data gathered from the FIES. Subsistence incidence, as defined by the PSA, is the proportion of families or individuals whose per capita income or expenditure is less than the per capita food threshold to the total number of families or individuals (Philippine Statistics Authority, 2017).

III. TRENDS IN HUNGER INCIDENCE AND SUBSISTENCE INCIDENCE

3.1 Trends in SWS' Quarterly Hunger Incidence and Its Possible Determinants

The SWS's latest quarterly hunger incidence during the first quarter of 2018 reported 9.9 percent of families were experiencing hunger which is equivalent to almost 10 million Filipino families in the country. In 2017, the annual hunger incidence report stated that 12.3 percent of the Philippines' population were experiencing hunger. This is lower than the average hunger incidence in 2015 and 2016 which are both at 13.4 percent.

Table 1 shows that the average hunger incidence from 2000 to 2018 is at 15 percent. Data for the determinants, sourced from FIES, indicated that the rice index has a large spread across quarters, whereas the HWEGF index across the country ranges from 71.73 to 136.67. Lastly, the average job misery index, one of the possible determinants of hunger is at 27.21, based from the Labor Force Survey of the PSA.

Table 1. Descriptive Statistics of SWS Quarterly Hunger Incidence and its Possible Determinants

Statistic	Hunger Incidence	Rice Index	HWEGF Index	Job Misery Index
Mean	15.1144	127.4849	107.5288	27.2110
Median	15.5000	136.2000	108.3000	26.6
Maximum	23.8000	180.4000	136.6667	39
Minimum	5.1000	81.9667	71.7333	20.9
Std. Deviation	4.5957	35.025	19.9650	3.1465
No. of Quarters	73	73	73	73

Figure 1 gives us the time series table for the quarterly hunger incidence report of SWS from the first quarter of 2000 until the latest report released on the first quarter of 2018. Using the Hodrick-Prescott filter[4], the long-run trend of the quarterly data is also computed and presented which showed that the hunger incidence sharply increases from

[4] The Hodrick-Prescott (HP) filter is a model-free based approach to decomposing time series into its trend (and cyclical) components. It is an algorithm that smoothens the time series y_t into a long-term trend τ_t. The smoothened series τ_t is obtained by minimizing $\sum_{t=1}^{T}(y_t - \tau_i)^2 + \lambda \sum_{t=1}^{T}[(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2$ The parameter λ is called the smoothing parameter. The rule of thumb for the λ is 100 for annual, 1600 for quarterly, and 14,400 for monthly data.

the first quarter in 2003 until the last quarter in 2008. The highest reported hunger incidence is during the first quarter of 2012 and it started to decline in the second quarter of 2011.

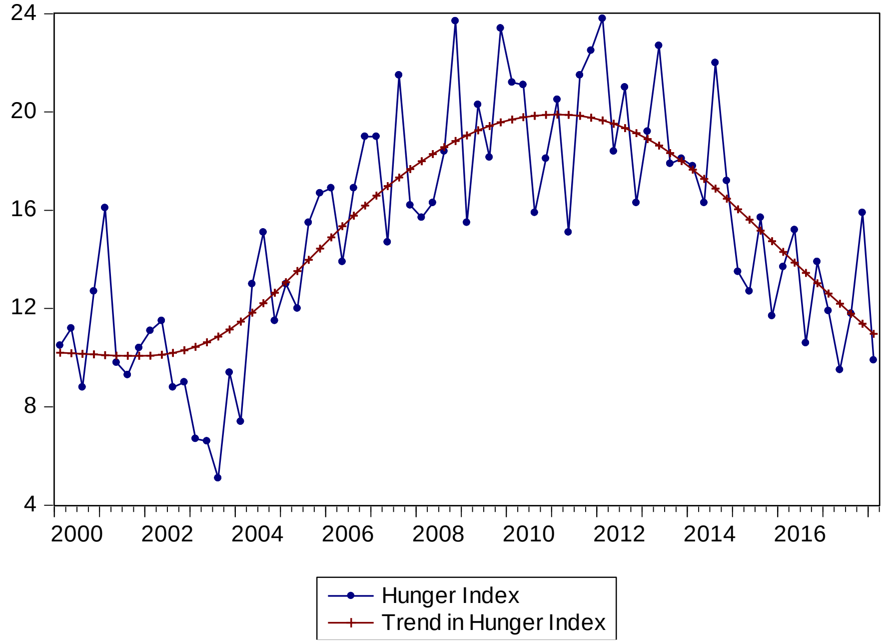

Figure 1. Hunger Incidence and its Long-Run Trend (Hodrick-Prescott Filter) for First Quarter 2000 to First Quarter 2018

On the other hand, the rice index as of the first quarter of 2018 is equal to 180.4. As shown in Figure 2, the long-run trend showed an inclination starting the first quarter of 2005. Moreover, the index, starting in the second quarter of 2008, jumped to 126.9 from the previous quarter's index of 108.4. This sudden increase is attributed to the food crisis in 2008. Since then, the rice index has continued to increase.

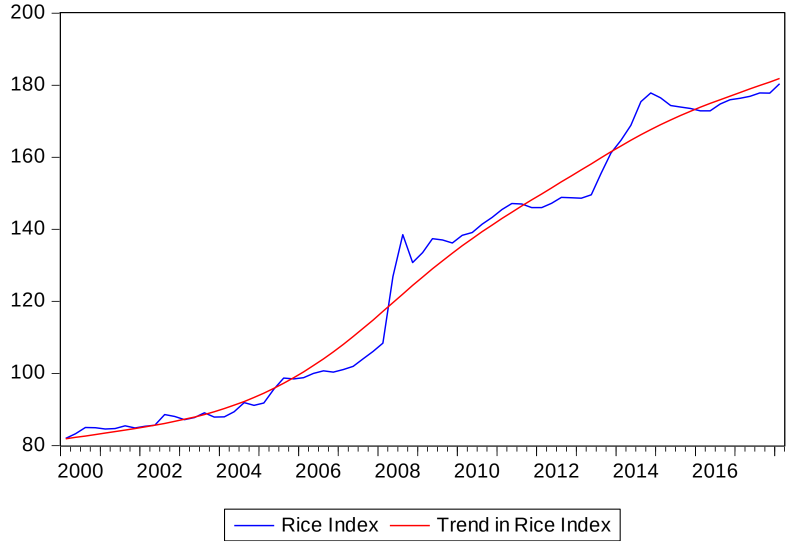

Figure 2. Rice Component and its Long-Run Trend (Hodrick-Prescott Filter) for First Quarter 2000 to First Quarter 2018

Meanwhile, the unemployment and underemployment rate in the Philippines for the first quarter of 2018 is 5.3 percent and 18 percent, respectively. This is equal to 2.32 million unemployed Filipinos, and 7.49 million underemployed Filipinos. The unemployment and underemployment rates, together with the computed job misery index and its corresponding long-term trend from 2000 to 2018 is graphed in Figure 3. It is evident that the long-term trend has high fluctuations between the years 2000 to 2006 compared to the succeeding years.

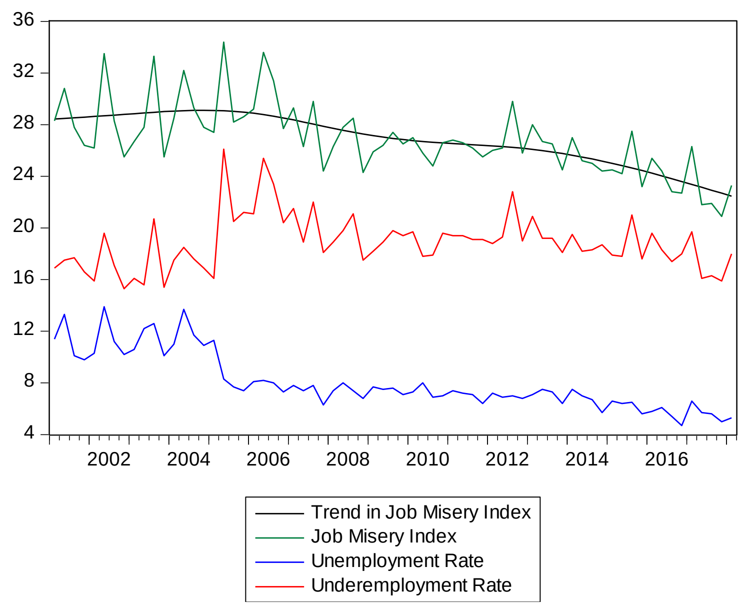

Figure 3. Unemployment and Underemployment Rates, Job Misery Index and its Long-Run Trend (Hodrick-Prescott Filter) for First Quarter 2000 to First Quarter 2018

Lastly, the HWEGF index from the first quarter of 2018 is highest at 136.7. Figure 4 shows that since the first quarter of 2000, the long-run trend of the HWEGF from the Hodrick-Prescott Filter showed that there was a steep incline until the second quarter of 2014 but showed slight decrease of HWEGF in the following quarters. After which, the trend started to exhibit slow increase.

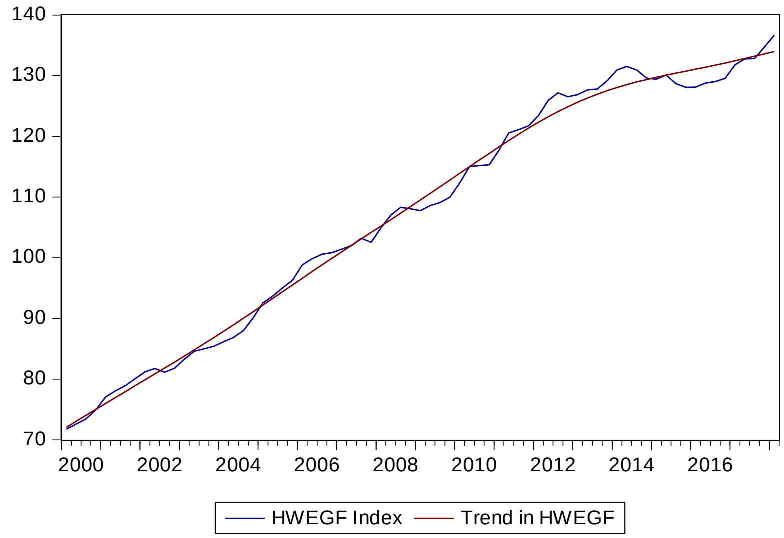

Figure 4. Housing, Water, Electricity, Gas, and Other Fuels Index and Long-Run Trend (Hodrick-Prescott Filter) for First Quarter 2000 to First Quarter 2018

3.2 Trends in PSA's Subsistence Incidence and Its Possible Determinants

Based from the measures of central tendencies shown in Table 2, subsistence incidence values are extremely varying across regions. Central Luzon recorded the highest rice index at 139.75 in 2015. On the other hand, HWEGF index is at its highest at the Caraga region. The determinants in this panel data show smaller spread compared to viewing the data per quarter. Ranges are also relatively smaller since the study considered the year 2006 as the base year for the CPI components. The average job misery index across the panel data exhibits almost the same mean at 27.75 with the quarterly data examined on the previous section.

Table 2. Overall Descriptive Statistics of Subsistence Incidence and its Possible Determinants (per Region; using the years 2006, 2009, 2012, and 2015)

Statistic	Subsistence Incidence	Rice Index	HWEGF Index	Job Misery Index
Mean	9.805587	137.9235	118.8926	27.1471
Median	9.962655	139.7500	120.6000	26.7
Maximum	24.55616	189.3000	164.1000	41.9
Minimum	0.300360	100.0000	100.0000	15.2
Std. Deviation	5.996477	27.46147	16.09773	6.0950
No. of Obs.	68	68	68	68

Figure 5 showed that across the years 2006, 2009, 2012, and 2015, in some regions specifically NCR, region III, IV-A, VI, subsistence incidence did not vary. However, in Caraga Region, together with region IX, there is a very high subsistence incidence in comparison to other regions. NCR and region IV-A remains to have the lowest subsistence incidence across the country. Overall, subsistence incidence continues to decline in almost all the regions.

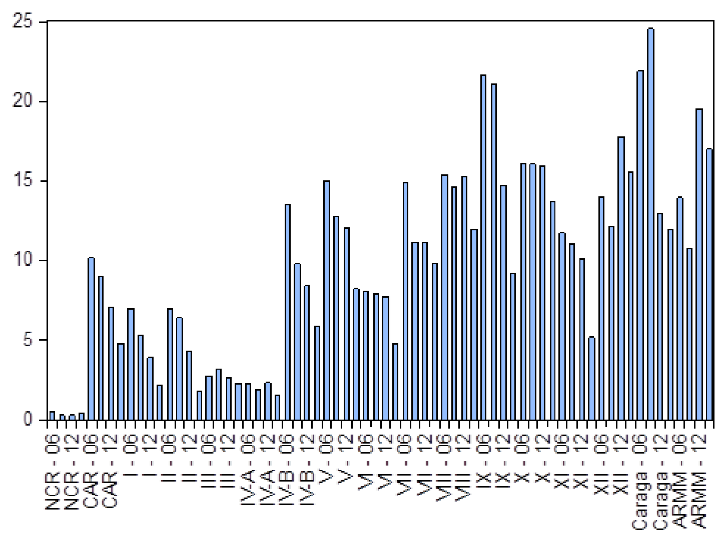

Figure 5. Subsistence Incidence per Region (2006, 2009, 2012, and 2015)

Regional data for the rice index is seen in Figure 6. The rice index is constant at 100 across all regions in 2006. Moreover, the rice index in all regions continue to increase in the succeeding years. For all regions, there is a huge increase in the rice index in 2015 compared to 2012.

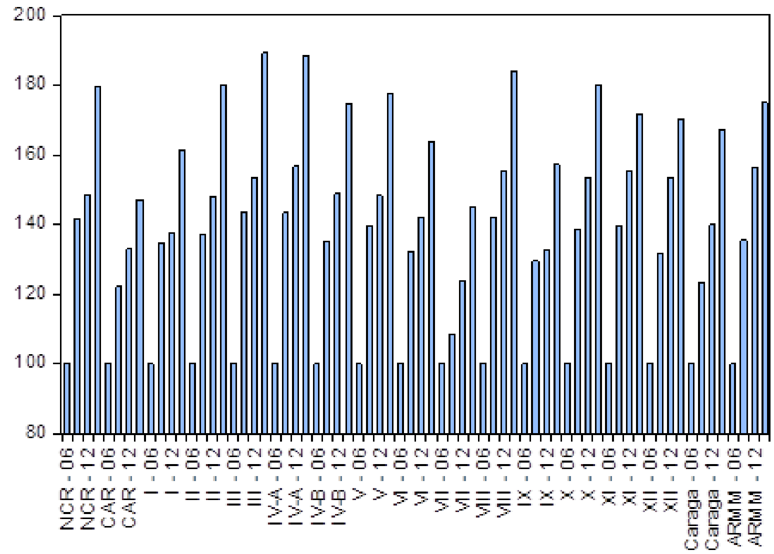

Figure 6. Regional Rice Index (2006, 2009, 2012, and 2015)

Figure 7 shows that across regions, the job misery index is relatively in Region V, Region X, and Caraga through the years that were included in the analysis. Region III has the lowest values for the job misery index, indicating low underutilization rate in that region.

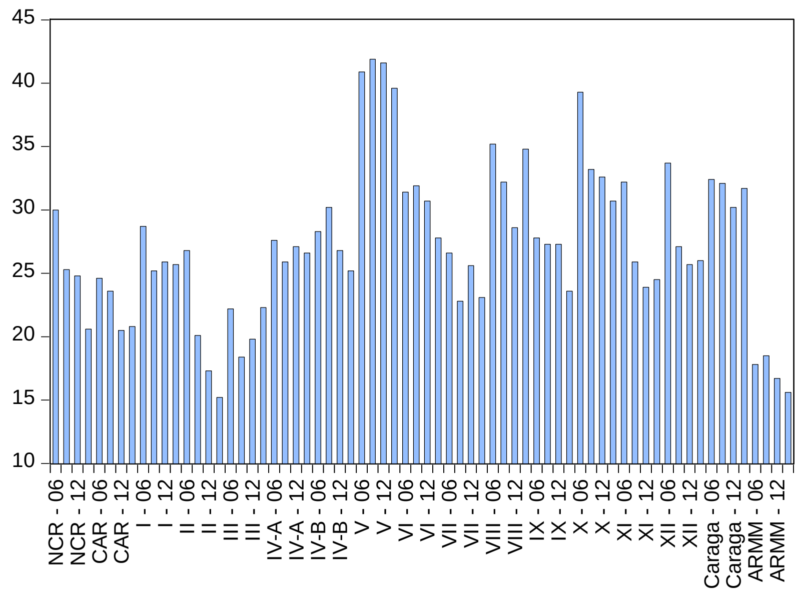

Figure 7. Job Misery Index per Region (2006, 2009, 2012, and 2015)

The regional HWEGF index for years 2006, 2009, 2012, and 2015 varies from region to region. Figure 8 shows that in 2015, almost all regions have increased HWEGF indices. The

Caraga Region, Region XII, X, and XI, have relatively higher HWEGF indices compared to other regions like Region V, ARMM, and IV-A, and NCR with low HWEGF indices.

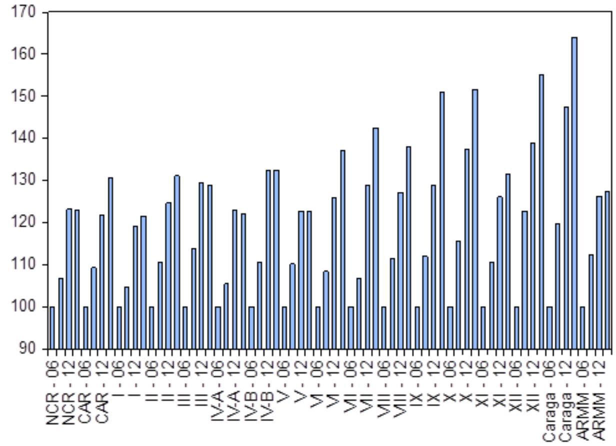

Figure 8. Housing, Water, Electricity, Gas, and Other Fuels (HWEGF) Index per Region (2006, 2009, 2012, and 2015)

For better visualization on the current condition of the response variable and its possible determinants, a heat map is presented for each variable. Darker shade corresponds to higher values of the different variables.

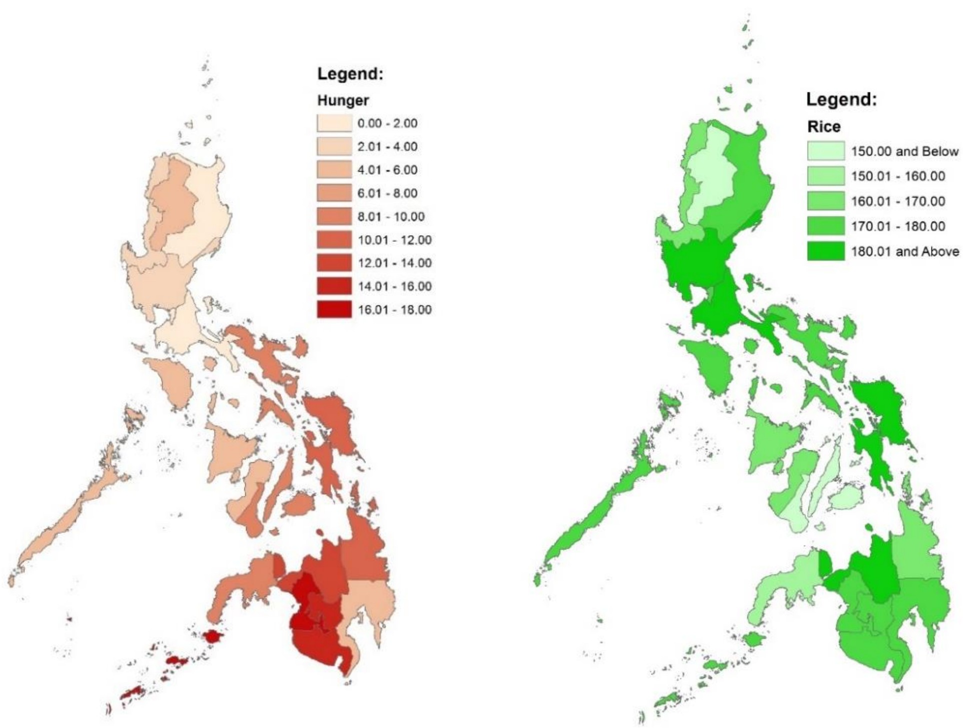

Figure 9. Distribution of Subsistence Incidence and Rice Index Across Regions (2015)

As shown in Figure 9, high values of subsistence incidence are evident in Mindanao area except the Davao Region. Specific regions that showed poor subsistence are Autonomous Region of Muslim Mindanao, Northern Mindanao, and SOCCSKARGEN. Meanwhile, regions in Luzon reported lower subsistence, the lowest of which was recorded in the Cagayan Valley. Visayas shows midrange values for subsistence. This goes to show that people in Luzon earn more than enough for what they consume for food contrary to those in Visayas or Mindanao. Figure 10 also shows that the rice indices in Luzon regions, especially in Central Luzon, National Capital Region, and CALABARZON, are relatively high. Moreover, Northern Mindanao also showed high rice index, which is problematic since subsistence in that area is high. Lesser Filipino households are seen to be incapable of eating the right amounts of food for themselves, given their present income generation.

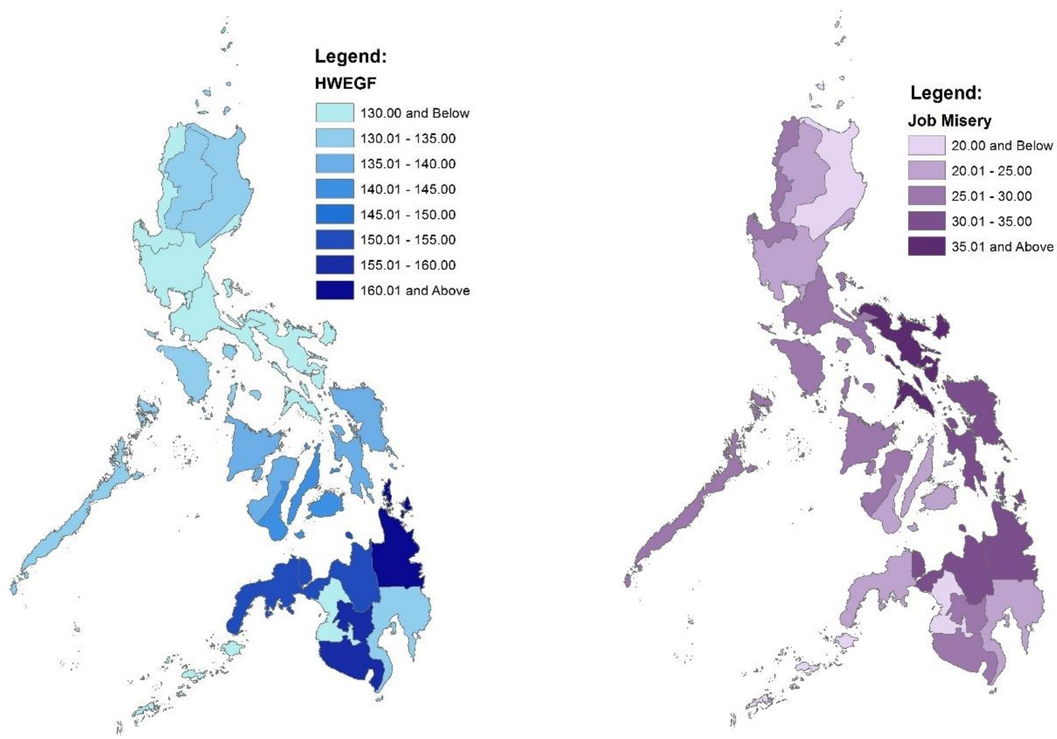

Figure 10. Distribution of HWEGF Index and Job Misery Across Regions (2015)

Figure 10 shows high HWEGF indices in regions of Mindanao, especially in Caraga, SOCCSKSARGEN, and the Zamboanga Peninsula. HWEGF indices in Luzon are the lowest among the three island groups. Job misery in region in Visayas are the highest, most especially in Eastern and Central Visayas. One must note that even when some regions exhibit both low rice and HWEGF indices, a high job misery index value is still alarming for this part of the country since they have middling values for subsistence. Caraga and the Bicol Region also exhibited high values for job misery. It is also worth noting that job misery is low in the Cagayan Valley, alongside its low subsistence.

IV. MODEL BUILDING PROCESS: VAR, TVP, and FE Models

4.1 Vector AutoRegressive (VAR) Model

The VAR Model

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 four-variable case of VAR order 1 (or VAR (1)) model we have,

$$\begin{aligned}
y_t &= \beta_{10} - \beta_{12}z_t - \beta_{13}w_t - \beta_{14}x_t + \gamma_{11}y_{t-1} + \gamma_{12}z_{t-1} + \gamma_{13}w_{t-1} + \gamma_{14}x_{t-1} + \varepsilon_{yt} \\
z_t &= \beta_{20} - \beta_{21}y_t - \beta_{23}w_t - \beta_{24}x_t + \gamma_{21}y_{t-1} + \gamma_{22}z_{t-1} + \gamma_{23}w_{t-1} + \gamma_{24}x_{t-1} + \varepsilon_{zt} \\
w_t &= \beta_{30} - \beta_{31}y_t - \beta_{32}z_t - \beta_{34}x_t + \gamma_{31}y_{t-1} + \gamma_{32}z_{t-1} + \gamma_{33}w_{t-1} + \gamma_{34}x_{t-1} + \varepsilon_{wt} \\
x_t &= \beta_{40} - \beta_{41}y_t - \beta_{42}z_t + \beta_{43}w_t + \gamma_{41}y_{t-1} + \gamma_{32}z_{t-1} + \gamma_{33}w_{t-1} + \gamma_{34}x_{t-1} + \varepsilon_{xt}
\end{aligned} \qquad (1)$$

where y_t is say SWS self-rated hunger, z_t is the rice index and w_t is the job misery index, all at quarter t. The ε_{yt}., ε_{zt}, ε_{wt} and ε_{xt} are white noise disturbance terms with means 0 and standard deviations $\sigma_y, \sigma_z, \sigma_w$ and σ_x, respectively. The equations in (1) are called the structural equations of the VAR. The parameters, β_{12}, β_{13}, β_{14}, β_{21}, β_{23}, β_{24}, β_{31}, β_{32}, β_{33}, β_{41}, β_{42} and β_{43} measure the contemporaneous effects while the $\gamma's$ measure the lag 1 effects. The equations are not in reduced form since, for example, y_t has contemporaneous effect on z_t, w_t and x_t . Isolating the time t variables on the left-hand side, we have,

$$\begin{aligned}
y_t + \beta_{12}z_t + \beta_{13}w_t + \beta_{14}x_t &= \beta_{10} + \gamma_{11}y_{t-1} + \gamma_{12}z_{t-1} + \gamma_{13}w_{t-1} + \gamma_{14}x_{t-1} + \varepsilon_{yt} \\
\beta_{21}y_t + z_t + \beta_{23}w_t + \beta_{24}x_t &= \beta_{20} + \gamma_{21}y_{t-1} + \gamma_{22}z_{t-1} + \gamma_{23}w_{t-1} + \gamma_{24}x_{t-1} + \varepsilon_{zt} \\
\beta_{31}y_t + \beta_{32}z_t + w_t + \beta_{34}x_t &= \beta_{30} + \gamma_{31}y_{t-1} + \gamma_{32}z_{t-1} + \gamma_{33}w_{t-1} + \gamma_{34}x_{t-1} + \varepsilon_{wt} \\
\beta_{41}y_t + \beta_{42}z_t + \beta_{43}w_t + x_t &= \beta_{40} + \gamma_{41}y_{t-1} + \gamma_{32}z_{t-1} + \gamma_{33}w_{t-1} + \gamma_{34}x_{t-1} + \varepsilon_{xt}
\end{aligned} \qquad (2)$$

In matrix form,

$$\begin{bmatrix} 1 & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & 1 & \beta_{23} & \beta_{24} \\ \beta_{31} & \beta_{32} & 1 & \beta_{34} \\ \beta_{41} & \beta_{42} & \beta_{43} & 1 \end{bmatrix} \begin{bmatrix} y_t \\ z_t \\ w_t \\ x_t \end{bmatrix} = \begin{bmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \\ \beta_{40} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & \gamma_{34} \\ \gamma_{41} & \gamma_{41} & \gamma_{43} & \gamma_{44} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ z_{t-1} \\ w_{t-1} \\ x_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \\ \varepsilon_{wt} \\ \varepsilon_{xt} \end{bmatrix}$$

Simplifying, we have,

$$\begin{aligned} \mathrm{B}\underline{x_t} &= \Gamma_0 + \Gamma_1 \underline{x_{t-1}} + \underline{\varepsilon_t} \\ \underline{x_t} &= \mathrm{B}^{-1}\Gamma_0 + \mathrm{B}^{-1}\Gamma_1 \underline{x_{t-1}} + \mathrm{B}^{-1}\underline{\varepsilon_t} \qquad (3) \\ \underline{x_t} &= A_0 + A_1 \underline{x_{t-1}} + \underline{e_t} \end{aligned}$$

$$\text{where } \underline{x_t} = \begin{bmatrix} y_t \\ z_t \\ w_t \\ x_t \end{bmatrix}, \ \mathrm{B} = \begin{bmatrix} 1 & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & 1 & \beta_{23} & \beta_{24} \\ \beta_{31} & \beta_{32} & 1 & \beta_{34} \\ \beta_{41} & \beta_{42} & \beta_{43} & 1 \end{bmatrix}, \ \Gamma_0 = \begin{bmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \\ \beta_{40} \end{bmatrix}$$

$$\Gamma_1 = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & \gamma_{34} \\ \gamma_{41} & \gamma_{41} & \gamma_{43} & \gamma_{44} \end{bmatrix}, \ \underline{\varepsilon_t} = \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \\ \varepsilon_{wt} \\ \varepsilon_{xt} \end{bmatrix}$$

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,

$$\underline{x_t} = A_0 + A_1 \underline{x_{t-1}} + A_2 \underline{x_{t-2}} + \cdots + \mathrm{A}_p \underline{x_{t-\mathrm{p}}} + +\underline{e_t} \qquad (4)$$

where $\underline{\boldsymbol{x_t}}$ is a $(k \ x \ 1)$ vector of endogenous variables, $\underline{\boldsymbol{A_1}}, \underline{\boldsymbol{A_2}}, \dots, \underline{\boldsymbol{A_p}}$ are matrices of coefficients to be estimated, and $\underline{\boldsymbol{e_t}}$ 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 $\underline{\boldsymbol{e_t}}$ is assumed to be normally distributed with mean $\underline{\mathbf{0}}$ and covariance matrix $\underline{\boldsymbol{\Sigma}}$. The order of the VAR model (p) is determined using the information criteria (Akaike, Schwarz and the Hannan-Quinn).

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

The Augmented-Dickey Fuller Test was used to test the presence of unit root among the variables before estimating the VAR model. As seen from the table, the hunger incidence, rice component of CPI, and HWEGF Index are non-stationary unlike the job misery index which is stationary and has a deterministic trend.

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

Variable	Test Statistic	p-value	Remarks
Hunger incidence (in nat. log)	-2.35	0.40	I(1)
Rice Component of CPI (in nat. log.)	-2.56	0.30	I(1)
HWEGF (in nat. log)	-0.98	0.94	I(1)
Job Misery Index (in nat.log)	-7.66	0.00	Stationary*
Job Misery Index (seasonally adjusted; in nat.log)	-3.67	0.03	Stationary*

* Stationary with Deterministic Trend

VAR Model Estimation and Results

Using the VAR(1) specification $\underline{x}_t = A_0 + A_1\underline{x}_{t-1}$ where $\underline{x}_t = \begin{bmatrix} y_t \\ z_t \\ w_t \\ x_t \end{bmatrix}$, y_t= Δlog(Hunger$_t$), z_t= Δlog(Rice Index$_t$), w_t= Δlog(HWEGF Index$_t$), and x_t= log(seasonally-adjusted Job Misery index$_t$), the results of the model using the quarterly time series data are on Table 4. DLOG(HUNGER), the dependent variable is the quarterly change in hunger incidence, whereas the job misery index (DLOG(JOB_MISERY_SA(-1)), HWEGF index, and rice index, all at lag 1, will serve as the explanatory variables. The reduced-VAR model will only be used to predict for future hunger incidence. This goes show that for the present time, the rice index is a significant determinant for the hunger incidence reported by the SWS.

Table 4. VAR Model for SWS Hunger Incidence, Rice Index, HWEGF Index, and Job Misery Index

	Hunger	Rice Index	HWEGF Index	Job Misery Index
Hunger (lag 1)	-0.4411***	-0.0014	-0.0015	0.0060
	(0.1105)	(0.0124)	(0.0043)	(0.0371)
	[-3.9925]	[-0.1140]	[-0.3441]	[0.1620]
Rice Index (lag 1)	1.7517 *	0.2325**	-0.0172	0.0689
	(1.0369)	(0.1163)	(0.0407)	(0.3479)
	[1.6894]	[2.0003]	[-0.4216]	[0.1981]
HWEGF Index (lag 1)	-3.5354	0.6820**	0.3806***	1.2805
	(2.9834)	(0.3345)	(0.1172)	(1.0009)
	[-1.1850]	[2.0388]	[3.2491]	[1.2794]

Job Misery Index (lag 1)	0.4219	-0.0350	0.0124	0.6304***
	(0.2769)	(0.0311)	(0.0109)	(0.0929)
	[1.5235]	[-1.1265]	[1.1439]	[6.7849]
C	-1.3785	0.1177	-0.0353	1.2008***
	(0.9064)	(0.1016)	(0.0356)	(0.3041)
	[-1.5210]	[1.1579]	[-0.9920]	[3.9492]
R-squared	0.2513	0.1243	0.1867	0.4706
Adj. R-squared	0.2059	0.0712	0.1374	0.4385

Std Errors are in ( ) and t-statistics in [ ]; *** significant at 1%; ** significant at 5%; * significant at 10%

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 $i^{\underline{th}}$ variable (e.g. increase in rice index inflation or job misery index) not only directly affects the $i^{\underline{th}}$ 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 $i^{\underline{th}}$ innovation (ε_{it}) is simply a shock to y_{it} or what is referred to as "shock to itself."

As seen from the Figure 11 below, the effect of increase in rice index on hunger incidence is significant at 10% level. A one-time increase in rice index at quarter t will only have significant effects on hunger incidence on quarter t+2. Specifically, a one standard deviation increase to rice index at the first quarter will increase the total self-rated hunger by 0.0516 standard deviation, or equivalently 5 percentage points in the next quarter, holding all other variables constant. After the second quarter, there will be no more significant effects of one-time shock to the rice index inflation on hunger incidence. The effect will slowly decay to zero. From the graph below, hunger incidence is sensitive to the changes in rice index for only one quarter.

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

Impact of an Increase in Rice Index to Hunger Incidence			**90% Confidence Interval**	
Quarter	Point Estimate	Std. Error	Lower Limit	Upper Limit
1	-0.02127	0.02511	-0.0626	0.0200
2	0.05159	0.02763	0.0061	0.0970
3	-0.01089	0.01199	-0.0306	0.0088

4	0.00798	0.00631	-0.0024	0.0184
5	-0.00305	0.00358	-0.0089	0.0028
6	0.00140	0.00198	-0.0019	0.0047
7	-0.00067	0.00107	-0.0024	0.0011
8	0.00028	0.00059	-0.0007	0.0012
9	-0.00014	0.00032	-0.0007	0.0004
10	0.00006	0.00019	-0.0003	0.0004
11	-0.00003	0.00011	-0.0002	0.0002
12	0.00001	0.00007	-0.0001	0.0001

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

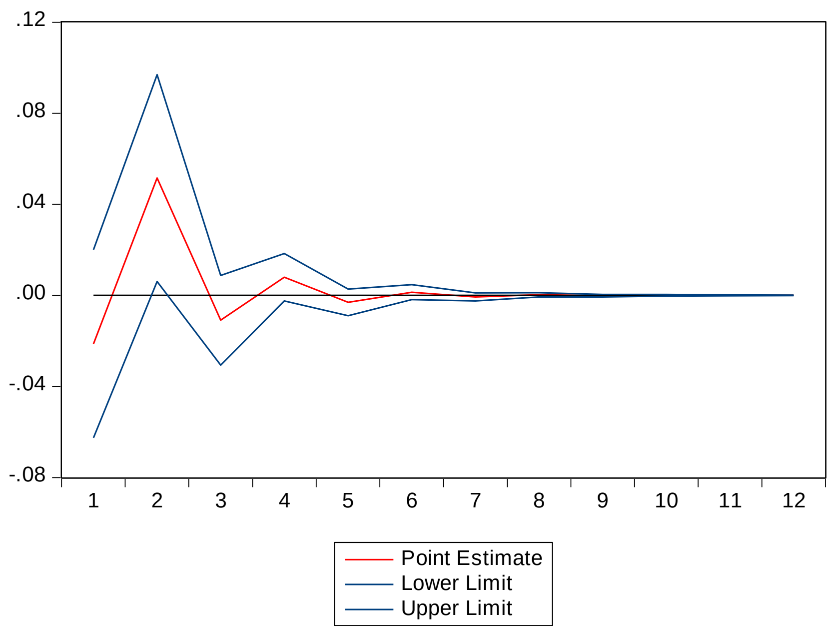

Figure 11. Response of Hunger Incidence to
One Std. Dev. Increase in Rice Index (in nat. logarithm)

The Impulse Response Function of change in hunger incidence with respect to a shock in change in HWEGF index is given below. A one-time increase in HWEGF index at quarter t will only have significant effects on hunger incidence on quarter t +3. This effect is significant at 10% level. A one standard deviation increase to HWEGF at the second quarter will increase the total self-rated hunger by 0.01207 standard deviation, or equivalently 2 percentage points in the next quarter, holding all other variables constant. Moreover, there will be no more significant effects of one-time shock to the HWEGF index inflation on hunger incidence as it slowly decays to zero, as seen from the Figure 12.

Table 6. Impulse Response Function – Response of Change in Hunger Incidence to a One-Standard Deviation increase in HWEGF Index Inflation at Quarter 1

Impact of an Increase in HWEGF Index to Hunger Incidence			**90% Confidence Interval**	
Quarter	Point Estimate	Std. Error	Lower Limit	Upper Limit
1	0.02262	0.02554	-0.0194	0.0646
2	0.03457	0.02793	-0.0805	0.0114
3	0.02048	0.01207	0.0006	0.0403
4	0.00257	0.00733	-0.0146	0.0095
5	0.00558	0.00408	-0.0011	0.0123
6	0.00010	0.00258	-0.0041	0.0043
7	0.00153	0.00158	-0.0011	0.0041
8	0.00030	0.00104	-0.0014	0.0020
9	0.00051	0.0007	-0.0006	0.0017
10	0.00020	0.00048	-0.0006	0.0010
11	0.00020	0.00034	-0.0004	0.0008
12	0.00011	0.00024	-0.0003	0.0005

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

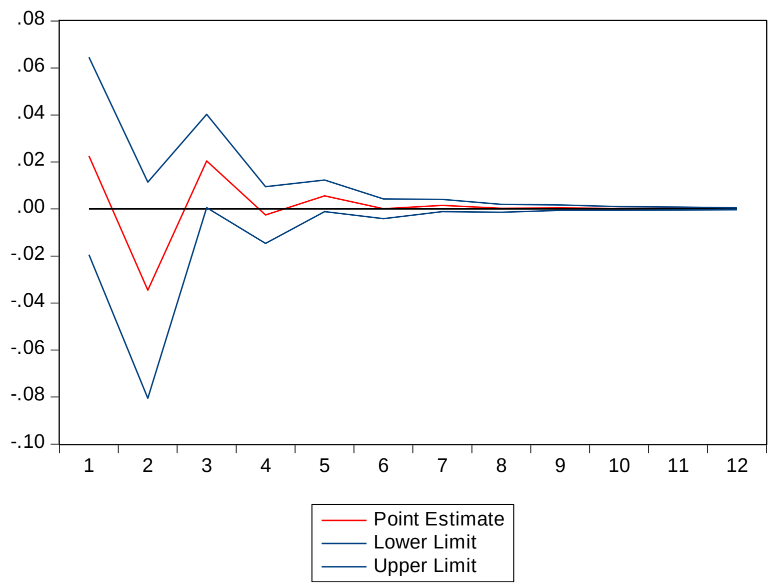

Figure 12. Response of Hunger Incidence to One Std. Dev. Increase in HWEGF (in nat. logarithm) Index

However, by looking at the response of change in hunger incidence to a one-standard deviation increase in Job Misery Index in Figure 13, there are no significant effects, as seen from the graph. The one-sided interval is also included in the table below, giving us 1.2737 which is below the cut-off, making it insignificant.

Table 7. Impulse Response Function – Response of Change in Hunger Incidence to a One-Standard Deviation increase in Job Misery Index at Quarter 1

Impact of an Increase in Seasonally Adjusted Job Misery Index to Hunger Incidence			**90% Confidence Interval**		**One-Sided Interval**
Quarter	Point Estimate	Std. Error	Lower Limit	Upper Limit	
1	0.03225	0.02532	-0.0094	0.0739	1.2737
2	0.01902	0.02372	-0.0200	0.0580	0.8019
3	0.00417	0.00909	-0.0108	0.0191	0.4587
4	0.00484	0.00742	-0.0074	0.0170	0.6523
5	0.00224	0.00392	-0.0042	0.0087	0.5714
6	0.00211	0.00315	-0.0031	0.0073	0.6698
7	0.00125	0.00202	-0.0021	0.0046	0.6188
8	0.00097	0.00154	-0.0016	0.0035	0.6299
9	0.00062	0.00107	-0.0011	0.0024	0.5794
10	0.00045	0.00079	-0.0009	0.0017	0.5696
11	0.00030	0.00056	-0.0006	0.0012	0.5357
12	0.00021	0.00041	-0.0005	0.0009	0.5122

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

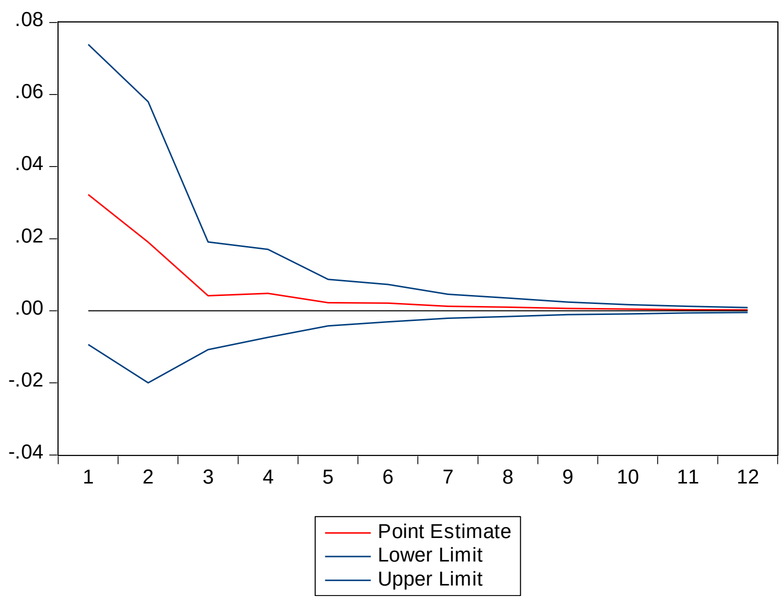

Figure 13. Response of Hunger Incidence to One Std. Dev. Increase in Job Misery Index (in nat. logarithm)

Forecast Error Variance Decomposition

Forecast Error Variance Decomposition tells us the proportion of the movements in a sequence due to its "own" shocks versus the shocks to the other variable. If ε_{zt} shocks explain none of the forecast error variance of $\{y_t\}$ at all forecast horizons, we can say that the $\{y_t\}$ is exogenous. At the other extreme, ε_{zt} shocks could explain all of the forecast error variance in $\{y_t\}$ sequence at all horizons, so that $\{y_t\}$ would be entirely exogenous. The variance decomposition provides information about the relative importance of each random innovation in affecting the variables in the VAR.

Table 8 shows the forecast error variance decomposition of hunger incidence with Cholesky Ordering: dlog(hwegf) log(misery_sa) dlog(rice) dlog(hunger). It shows how much of the future error variance of hunger incidence can be explained by its possible determinants: rice index, HWEGF index, and Job Misery Index. The past values for hunger incidence, has the greatest effect on the variability of its future values with around 96 percent of variability in the first quarter. However, the rice index does not have any significant effect on variability on quarter t. Eventually, in the second quarter, the variability of the hunger incidence explained by rice index will now increase at 5 percent, HWEGF index at 2.87 percent, and Job Misery Index at 2.36 percent. This indicates that these variables have a significant effect on the variability of hunger incidence. Still, roughly 90 percent of the variability of hunger incidence will still be explained by the previous hunger incidence values.

Table 8. Forecast Error Variance Decomposition of Hunger Incidence

Period	Std Error	Hunger Incidence	Rice Index	HWEGF Index	Seasonally Adjusted Job Misery Index
1	0.215756	95.69498	0.971394	1.099314	2.234311
		(5.08273)	(3.40549)	(2.41684)	(3.50557)
2	0.243796	89.5306	5.2386	2.871987	2.358815
		(6.72102)	(5.83784)	(4.27678)	(3.21837)
3	0.24854	89.02753	5.232556	3.442142	2.297771
		(7.02672)	(5.86098)	(4.47654)	(3.31287)
4	0.249466	88.95836	5.296025	3.427201	2.318419
		(7.10006)	(5.93301)	(4.51798)	(3.39784)
5	0.249704	88.90649	5.300803	3.470633	2.322073
		(7.16853)	(5.94662)	(4.55318)	(3.45084)
6	0.249748	88.90006	5.302087	3.469442	2.328406
		(7.19122)	(5.9511)	(4.56096)	(3.48785)
7	0.249762	88.8944	5.302184	3.472779	2.330641
		(7.21506)	(5.95367)	(4.56972)	(3.51223)
8	0.249766	88.89293	5.302158	3.472827	2.33209

		(7.22686)	(5.95365)	(4.57295)	(3.52853)
9	0.249768	88.89199	5.302121	3.473205	2.332681
		(7.23713)	(5.9538)	(4.57652)	(3.53933)
10	0.249768	88.89165	5.302103	3.473257	2.332991
		(7.24322)	(5.95359)	(4.5783)	(3.54652)
11	0.249768	88.89147	5.302093	3.473316	2.333127
		(7.24814	(5.95353)	(4.58012)	(3.55132)
12	0.249768	88.89139	5.302088	3.473332	2.333193
		(7.25136)	(5.95341)	(4.58129)	(3.55454)

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

4.2 Time-Varying Parameter Model

TVP Models

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

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

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

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

The $\underline{F}$, $\underline{c}$ and $\underline{Q}$ may be defined according to a model specification such as a time-varying parameter (TVP) models with random walk coefficients and TVP models with auto-regressive order 1 or AR(1) coefficient. When $\underline{c} = 0$ and $\underline{F} = \underline{I}_k$, each of the regression coefficient in $\underline{\beta}_t$ 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.

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, modelling 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 $(n \times 1)$ vector $\underline{y_t}$ is given by the system of equations,

$$\underline{y_t} = X_t\beta_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \Sigma_\varepsilon) \qquad \text{measurement equation} \qquad (7)$$

$$\underline{\beta_t} = \underline{c_t} + \underline{F_t}\underline{\beta_{t-1}} + \underline{v_t}, \qquad \underline{v_t} \sim N\left(\underline{0}, \underline{\Sigma_y}\right) \qquad \text{transition equation} \qquad (8)$$

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 β_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 v_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).

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).

TVP Model Specification and Results

To check if the TVP model coincides with the VAR(1) model, the researchers compared the results from VAR to the estimates of rice index from the TVP model. In addition, the TVP model was used to identify if there is a change in rice index before 2008, from 2008 to 2014, and 2014 onwards wherein there is a spike, or sudden increase in rice index in 2008 and 2014. It is important to note that during 2008, there is a crisis in the country, leading to higher food prices. In 2014, the National Food Authority and the Bureau of Custom Insiders announced that there is an overpricing of as much as 8254 Million Pesos of imported rice from Vietnam in 2013 (Esplanada, 2014). This might have an effect on the rice price on the following year.

The specification for the created TVP model is:

$$\begin{aligned}\Delta \log(Hunger_t) &= \beta_{0,t} + \beta_{1,t}\Delta \log(Hunger_{t-1}) + \beta_{2,t}\Delta \log(Rice_{t-1}) + \beta_{3,t}\Delta \log(HWEGF_{t-1}) \\ &+ \beta_{4,t} \log(seasonally\ adjusted\ Job\ Misery_{t-1}) + \varepsilon_t\end{aligned}$$

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

From Figure 14, the DLOG(RICE(-1)) coefficient from the VAR(1) model was compared to the TVP estimate on DLOG(RICE(-1)). The TVP estimate for rice index at Lag 1 shows that it varies from 2003 to 2008, having very high estimates at 2004, and low estimates at 2005 to 2008. At 2009, the rice index started to coincide with the VAR model, showing positive impact on hunger incidence. Furthermore, the mean impact of log(rice index) at lag 1 estimate from the TVP model is 1.44 before the 2008 crisis, 1.82 for the years 2009-2013, and 1.7 for 2015 and onwards. After the crisis in 2008, there is an increase in the rice index. However, the average rice index after the rice price surge in 2014 is lower than the average rice index in 2009-2013.

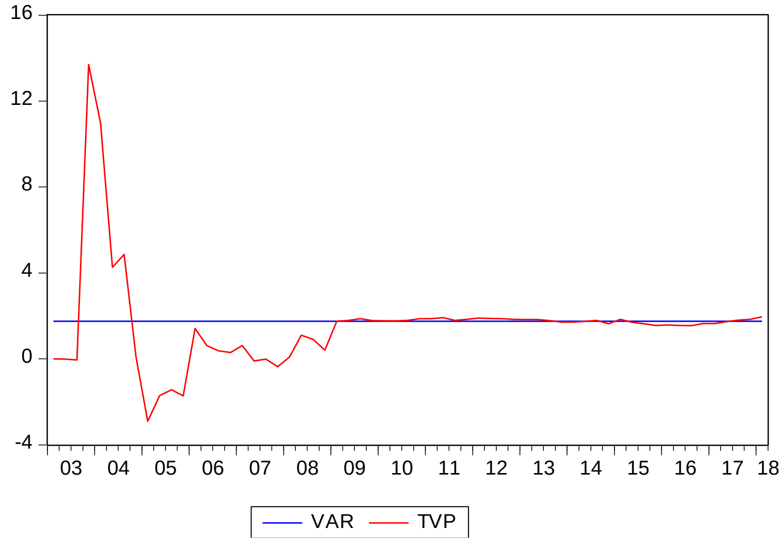

Figure 14. Rice Index (at Lag 1) Impact on Hunger Incidence

4.3 Panel Data Analysis: Two-Way Fixed and Random Effects Model

Panel data or longitudinal data (the older terminology) refer to a data set containing observations on multiple phenomena over multiple time periods. Thus, it has two dimensions: spatial (cross-sectional) and temporal (time series).

In Panel Data Regression, let us consider the following cross-sectional multiple regression with two explanatory variables, X_1 and X_2:

$$Y_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + u_i \; ; \; i = 1, 2, \ldots, N \qquad (1)$$

Consider the following time series multiple regression with two explanatory variables, X1 and X2:

$$Y_t = \alpha + \beta_1 X_{1t} + \beta_2 X_{2t} + u_t \; ; \; t = 1, 2, \ldots, T. \ldots. (2)$$

Combining (1) and (2), we get a pooled data set, which forms a panel data with the following panel regression:

$$Y_{it} = \alpha + \beta_1 X_{1it} + \beta_2 X_{2it} + u_i \; ; \; i = 1, 2, \ldots, N \; ; \; t = 1, 2, \ldots, T. \ldots. (3)$$

Random and Fixed Effects

Consider the basic unobserved effects model that can be written for a randomly drawn cross section observation i: $y_{it} = \beta_0 + \beta_1 x_{it1} + \cdots + \beta_k x_{itk} + u_i + \varepsilon_{it}$ where u_i is called the unobserved effect (also known as unobserved heterogeneity); the ε_{it} are called the idiosyncratic errors or idiosyncratic disturbances because these changes across t as well as across i. In the traditional approach to panel data models, u_i is called a "random effect" when it is treated as a random variable and a "fixed effect" when it is treated as a parameter to be estimated for each cross section observation i. In modern econometric parlance, "random effect" is synonymous with zero correlation between the observed explanatory variables and the unobserved effect: $Cov(x_{it}, u_i) = 0$ for $i = 1,2, \dots, N$ and $t = 1,2, \dots, T$.

Fixed Effects

The Fixed Effects (FE) model relaxes the assumption that the regression function is constant over time and space by allowing each cross-sectional unit to have its own constant term while the slope estimates (betas) are constrained across units, as is the variance of the error term. A two-way FE model, on the other hand, can be fitted by creating a set of time indicator variables and including all but one in the regression.

Random Effects

The Random Effects model specifies the individual effect as a random draw that is uncorrelated with the regressors and the overall disturbance term.

Hausman Test

In choosing what model to use, the Hausman Test can be utilized to test the null hypothesis that the extra orthogonality conditions imposed by the Random Effects estimator are valid. The Hausman tests the null hypothesis that estimates of Fixed Effects and Random Effects does not differ meaningfully. If the regressors are correlated with the u_i (the null hypothesis is rejected), the Fixed Effects estimator is consistent, but the Random Effects estimator is not consistent.

The p-value of the Hausman Test with chi-square 6 degrees of freedom is equal to 0.9796, concluding that the Random Effects estimator is consistent, and the Random Effects model should be used on the given data.

Panel Data Results

Before proceeding with the results, one must note that the job misery index is made by averaging the sum of unemployment and underemployment rate of the years 2004–2006 (labeled 2006), 2007–2009 (labeled 2009), 2010–2012 (labeled 2012), 2013–2015 (labeled 2015).

The Two-Way Fixed Effects Model results in measuring the effects of rice index, job misery index, and HWEGF index on total subsistence incidence is seen in Table 9. The variables are not significant.

Table 9. Panel Data Fixed Effects Model Coefficients

Variable	Coefficients	Std. Error	p-value
Rice Index (in nat. logarithm)	34.03146	20.41714	0.106
HWEGF Index(in nat. logarithm; lag 1)	-5.103157	17.42271	0.772
Job Misery Index (lag 1)	-.0775181	.2431126	0.752
Year			
2012 (3)	-3.35067	2.126139	0.126
2015 (4)	-10.39634	4.927704	0.044

Based on the result of the Hausman Test, the researchers will use the Two-Way Random Effects Model in measuring the effects of rice index, job misery index, and HWEGF index including their first lag on total subsistence incidence, we get the results given on the Table 10:

Table 10. Panel Data Random Effects Model Coefficients

Variable	Coefficients	Std. Error	p-value
Rice Index (in nat. logarithm)	24.96503	14.13896	0.077
HWEGF Index(in nat. logarithm; lag 1)	-.6567077	15.05813	0.965
Job Misery Index (lag 1)	.0041947	.1712623	0.980
Year			
2012 (3)	-2.810663	1.90689	0.140
2015 (4)	-8.98724	4.251221	0.035

At 10% level of significance, there is an effect of rice index to subsistence. This is in line with the VAR model that there is a positive effect of rice index to measures of hunger. However, the HWEGF index and the job misery index are not significant. Testing for time effects, the time indicator variables 2015 is significant at 5% level. However, the year 2012 is not significant.

The Random Effects Model for the regional panel data of subsistence incidence is consistent with the created VAR (1) Model that the rice index positively affects total self-rated hunger and total subsistence incidence – both a measure of total food hunger in the Philippines. In addition, both models do not find HWEGF index and Job Misery index significant in affecting self-rated hunger and subsistence incidence.

V. CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

Through the different econometric models, measures of hunger such as SWS hunger incidence and PSA subsistence incidence were analyzed and linked to three determinants: rice, housing, water, electricity, gas and other fuels, and job misery indices. All models (VAR, TVP, Two-way RE) show that rice index was consistently significant in determining hunger. Furthermore, HWEGF index and job misery index showed to be not significant in determining hunger in the VAR and random effects models but HWEGF proved to be significant in the TVP model. From the literature review, though overpopulation may both give hunger and job misery as repercussions, one must note that the literature showed that other similar places in the world with Asia (where the Philippines belongs), i.e., Latin Americas and the Caribbean, and Africa may have hunger reports that are similar to us but have entirely different backgrounds on unemployment and underemployment. The insignificance that the model building procedure showed may be attributed to spurious assumptions between the connection of the two variables. By also looking at the heat map, subsistence in Mindanao areas are high but show low job misery values. HWEGF index also showed to be not much of significance in this time in the country compared to when this was first examined in 2015, indicating that expenditure on housing, water, electricity, gas, and other fuels no longer helps in determining hunger.

From the heat map of the subsistence incidence in 2015, the government needs to focus in eradicating hunger most especially in areas in Mindanao, since this area showed high subsistence incidence and rice index. Maintenance in the Cagayan Valley's state should also be considered and maybe, adapt whatever system they have in tempering the prices of commodities and maintaining low subsistence.

For policymakers, it is recommended that the Philippines should focus on rice production more to lessen importation of a commodity that we can provide for ourselves. Moreover, the price of rice needs to stabilize together with the intensified rice production for the affordability of a common Filipino. Enhancing the agricultural sector in our country will also provide more jobs for lower class Filipinos, which in turn will provide them a chance to lift them up from the hunger that they experience. Furthermore, this will make the supply of rice cheaper in the country and also prevent rice shortage, which is one of the primary causes for high price of rice.

For future researchers, test once again the three possible determinants here in this paper to see if these will still be significant or not through time. It is also highly recommended to add more indicators of hunger, to provide a better measure for policymakers in this field and to fulfill the long-term goal of eradicating hunger in the Philippines. One example of which is to measure the on-going policies of the government for eradicating hunger and poverty such as the 4Ps, the PSA can include in the questionnaire for next census of population indicators if the family is a beneficiary or not, in order to have data accessible for the next set of researchers.

REFERENCES

Esplanada, J. (2014). *Rice imports overprice reach P825 million - NBI,BOC.* Retrieved from Inquirer.net: http://newsinfo.inquirer.net/569719/rice-imports-overprice-reached-p825-million-nbi-boc

Maligalig, D. (2008). Examining the Existing Direct Measures of Hunger in the Philippines. *The Philippine Statistician, 57*, 93-124.

Mapa, C. D., Castillo, K., & Francisco, K. (2015). Rice Price, Job Misery, Hunger Incidence: Need to Track A Few More Statistical Indicators for the Poor.

National Nutrional Council. (2014). *Action Against Hunger Urges Pres Duterte To Drive Change On Development Issues In The Philippines*. Retrieved from National Nutritional Council: http://nnc.gov.ph/39-featured-articles/1636-action-against-hunger-urges-pres-duterte-to-drive-change-on-development-issues-in-the-philippines

Official Gazette of the Philippines. (2015). *Official Gazette.* Retrieved from Pantawid Pamilyang Pilipino Program: http://www.officialgazette.gov.ph/programs/conditional-cash-transfer/

Philippine Star. (2017). *SWS: More Filipino families experienced hunger*. Retrieved from Philippine Star: https://www.philstar.com/headlines/2017/12/07/1766160/sws-more-filipino-families-experienced-hunger

Philippine Statistics Authority. (2009). *Underemployed Women*. Retrieved from Philippine Statistics Authority: https://psa.gov.ph/content/underemployed-women

Philippine Statistics Authority. (2017). *Subsistence incidence (S)*. Retrieved from Philippine Statistics Authority: https://psa.gov.ph/content/subsistence-incidence-s-0

Philippine Statistics Authority. (2018). *January 2018 Labor Force Survey*. Retrieved from Philippine Statistics Authority: https://www.psa.gov.ph/content/january-2018-labor-force-survey

Philippine Statistics Authority. (2018). *National Quickstat April 2018.*

Pillai, V, N. (2016). Panel Data Analysis with Stata Part 1. *Munich Personal RePEc Archive*. Retrieved from https://mpra.ub.uni-muenchen.de/76869/1/MPRA_paper_76869.pdf

Rey, A. (2018). 1.8M 4Ps beneficiaries receive P2,400 each to offset effects of tax reform. Retrieved from https://www.rappler.com/nation/197462-pantawid-pamilya-pilipino-program-subsidy-tax-reform

Santos-Recto, V. (2016). An act institutionalizing a conditional cash transfer program providing for the automatic indexation of cash grants and for other purposes. Retrieved from www.congress.gov.ph/legisdocs/basic_17/HB00017.pdf

TESDA. (2014). *Vision, Mission, Value and Quality Statement*. Retrieved from TESDA: http://www.tesda.gov.ph/About/TESDA/11

World Food Programme. (2017). *World Hunger Again On The Rise, Driven By Conflict And Climate Change, New UN Report Says*. Retrieved from World Food Programme: https://www.wfp.org/news/news-release/world-hunger-again-rise-driven-conflict-and-climate-change-new-un-report-says