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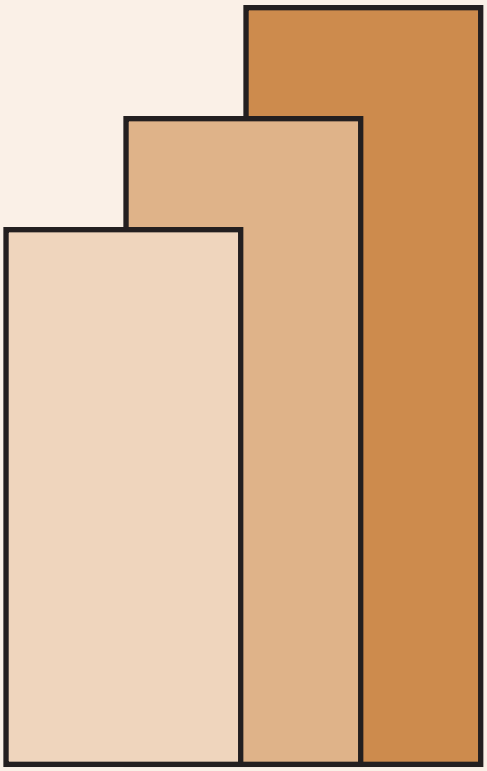

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Chronic and transient poverty and weather variability in the Philippines: Evidence using components approach

Connie Bayudan-Dacuycuy and Lora Kryz Baje[1]

Weather is an integral part of our life and weather shocks can have severe implications on income and on household consumption. Given evidence that points to altered patterns of weather parameters resulting from climate change, this paper aims to contribute to poverty studies in the Philippines by analyzing the effects of geographic attributes, like weather variability, on chronic and transient poverty. Based on the estimates of the generalized linear model, higher than normal rainfall contributes to a modest increase in chronic total and chronic food poverty in both urban and rural areas. In addition, asset ownership and college education have the most impact on the reduction of both types of poverty.

Keywords: poverty dynamics, weather variability, components approach, Philippines

I. Introduction

The Philippines has a long history of battle against poverty through the government's various anti-poverty programs. Corazon Aquino's government (1986-1992) had three major programs namely, the Comprehensive Agrarian Reform, the Community Employment and Development, and the *Tulong sa Tao* (Help the People). During Fidel Ramos' government (1992-1998), Social Reform Agenda had focused on countryside development by identifying the basic sectors and the twenty poorest provinces. Joseph Estrada's administration (1998-2001), *Lingap Para sa Mahirap* (Care for the Poor) program had identified the 100 poorest families in each local government unit. Gloria Arroyo's term (2006-2010) had the Kapit Bisig Laban sa Kahirapan–Comprehensive and Integrated Delivery of Social Services (KALAHI–CIDSS) project, which aimed for the improvement of human development services and economic opportunities and for the acceleration of asset reform among others. KALAHI-CIDSS–National Community-Driven Development Program (KC–NCDDP) seeks to empower communities to attain better access to basic services and to participate in inclusive local planning and budgeting. KC-NCDDP will be implemented from 2014 to 2019. The Conditional Cash Transfer program, locally known as the Pantawid Pamilyang Pilipino Program (4Ps), was piloted in 2017 and has since then gained momentum in scale and scope during Benigno Aquino's time (2010-2016). Currently, the Department of Social Welfare and Development (DSWD) has the Sustainable Livelihood Program. It consists of Microenterprise Development track and Employment Facilitation track, which are designed to provide 4Ps beneficiaries economic opportunities that will facilitate self-sufficiency. The 4Ps, SLP, and KC-NCDDP are still part of the core social protection programs of Rodrigo Duterte's administration. Rice subsidy of PhP600 is now included as part of the 4Ps grant.

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Despite these efforts, the country has missed its Millennium Development Goal (MDG) target of halving its 1990 poverty level by 2015. As of May 2016, the proportion of population below national poverty threshold is at 25.2%, 8 percentage points higher than the MDG target. Poverty studies in the Philippines abound but most of these use cross-section data (see for example, Balisacan, 2003a, 2003b; Balisacan and Pernia, 2002; Intal, 1994). As such, they only identify the poor at a given point in time and provide inadequate insights on the chronic and transient components of poverty and on the characteristics of economic units experiencing these types of poverty. Aldaba (2009) finds that chronic poverty in the Philippines has become a major constraint in achieving high levels of sustained growth and highlights the importance of additional research on chronic poverty. In recent years, there are efforts to make some survey data longitudinal that paved the way for the analysis of poverty dynamics in the Philippines. Using the Family Income and Expenditure Survey in 2003, 2006, and 2009 and a variant of spells aproach, Reyes et al (2010) find that at least half of households below the official poverty line are chronically poor. Using components approach, Bayudan-Dacuycuy and Lim (2013, 2014) corroborate the findings that chronic poverty is higher than transient poverty. Mina and Imai (2016) find that majority of the poor and 18% of the non-poor are vulnerable to unobservable shocks.

This paper aims to contribute to poverty studies in the Philippines by analyzing the effects of geographic attributes like weather variability on chronic and transient poverty. This paper is relevant in several ways. *One*, weather is an integral part of our life and weather shocks can have severe implications on income (see for example, Schlenker, Hanemann and Fisher, 2006; Deschenes and Greenstone, 2007). It can also have an impact on household consumption. For example, Bayudan-Dacuycuy (2017) specifically relates energy use and variability in heat index and finds that heat index fluctuation has the highest effects on the electricity consumption of balanced and female-majority households that are female headed and in rural areas.

Two, climate change and its adverse effects have received significant attention from local and international communities. This is in the light of evidence that points to altered patterns of weather parameters such as wild swings in rain and snow, melting glaciers, and rising temperatures resulting in drying out of some areas and in increased precipitation in others. There are several studies that analyze the effects of weather events on agricultural profit or output (Schlenker, Hanemann and Fisher, 2006; Deschenes and Greenstone, 2007), migration (Yang and Choi, 2007; growth (Dell, Jones and Olken, 2009); Skidmore and Toya, 2002; Noy and Vu, 2010) and health (Murray et al, 2000; Thai and Falaris, 2014). None to our knowledge has analyzed the effects of weather events on poverty and this is a gap that the paper attempts to address.

This paper uses the components approach to measure chronic and transient poverty and the generalized linear model (GLM) to investigate the effects of key variables including geographic attributes like urbanity, presence of armed conflict, and weather deviations on chronic and transient poverty in the Philippines. Results show that chronic poverty is affected by the characteristics of the household head, household's demographic composition, and labor market participation. However, transient poverty has fewer determinants. It is affected by some characteristics of the household head, asset score, and geographic attributes. Predicted total poverty and predicted food poverty indicate that asset ownership and college education have the

most impact on the reduction of both types of poverty. Higher than normal rainfall contributes to a modest increase in chronic total and chronic food poverty in both urban and rural areas.

This paper is organized as follows: section II discusses data sources, section III provides a brief discussion of the components approach and of the poverty dynamics in the Philippines, section IV outlines the empirical strategy and discusses the key variables used, section V discusses the results, and section VI summarizes, concludes, and suggests some policies for government action.

II. Data and sources

Annual Poverty Indicator Survey (APIS) and Family Income and Expenditure Survey (FIES)

The main datasets to be used are the Annual Poverty Indicator Survey (APIS) in 2004, 2007, and 2008 and the Family Income and Expenditure Survey (FIES) in 2003, 2006, and 2009 collected by the Philippine Statistics Authority (PSA) in the Philippines. APIS and FIES can be merged to form a panel dataset since there is a master sample based on the results of the Census of Population and Housing and a portion of the master sample is retained that the PSA re-surveys for some period. These samples are replaced by another set of samples to be tracked again after some period. PSA has four replicates and each of these replicates possesses the properties of the master sample.

For the purpose of this research, PSA has provided us the second rotation of replicate four of the datasets. Merging of these datasets is done by creating a household identification number through the concatenation of geographical variables such as region, province, municipality, *barangay*[2], enumeration area, sample housing unit serial number and household control number. There are 6517 samples that are common to the five datasets. An issue that needs to be addressed in using this panel data is that households are the units of observation and it is possible that household members in one year are not the same household members in the following year. This is the case when families migrate or when the household surveyed is composed of non-related members (e.g. the house is for rent). To ensure that the samples are the same households tracked down from 2003 to 2009, samples are further limited to households that satisfy two criteria: the sex of the household head should be the same throughout the period and the age of the household head should be consistent as well. For example, the age difference of the household head in 2003 FIES and 2004 APIS should be either zero or one while the age difference of the household head between 2004 APIS and 2006 FIES should be either two or three. There are 1954 samples left when these additional restrictions have been imposed.

APIS and FIES follow a multi-stage sampling design to make the sample representative of the population. However, the panel data constructed for the current research do not make use of the sampling weights since the weights differ across the survey data. This is a limitation that we acknowledge at the outset. However, this research is a step towards a deeper understanding of poverty in the Philippines while PSA still has to collect genuine longitudinal survey data.

Poverty Thresholds for non-FIES years

The PSA releases official poverty thresholds for the FIES years, which is made up of the food and the non-food thresholds. Since no thresholds have been released for 2004, 2007, and

[2] This is the basic political unit in the Philippines, equivalent to a village.

2008, the poverty thresholds for these years are therefore projected using the poverty threshold in 2003 and the provincial consumer price index in that year. Similar projection is done for the food thresholds. All the relevant APIS incomes and expenditures are multiplied by two since the reference period of APIS is past six months while the reference period of FIES is one year.

Weather data

Weather data, such as temperature represented by dry bulb readings (in degrees Celsius), relative humidity (in percent), and average rainfall (in millimeters), are collected by the Philippine Atmospheric and Geophysical Astronomical Services Administration (PAGASA) weather stations spread across the Philippines. All parameters have been measured, compiled, and disseminated through a public use file containing 50 PAGASA weather stations. To map the weather information with the APIS-FIES dataset, we use the province of residence as the merging variable. There are 83 provinces in the APIS-FIES dataset.

The PAGASA datasets have the following features: First, there are several provinces that host multiple weather stations. Second, there are several provinces that have no weather station but are assigned weather stations based on the relative distance between the province and the location of the weather station. In merging the PAGASA dataset with the APIS-FIES dataset, we address the first feature by selecting the weather station that is located in or in close proximity to the provincial capital. As an illustration, Palawan province, located in Luzon's Region 4A, has three stations, namely, Coron, Cuyo and Puerto Princesa. In this case, Puerto Princesa is chosen.

Second, in view of the importance of accounting for similar weather patterns and enhancing data variability, households in provinces without weather stations are not automatically removed. For example, Mountain Province and the provinces of La Union and Ifugao are assigned the weather station in Baguio City, Benguet while Tarlac is assigned the weather station in Cabanatuan, Nueva Ecija. Assigning adjacent weather stations to provinces without one maximizes the number of households included in the estimation sample. Without this assignment, 28 provinces will be dropped out of the sample. This translates to a reduction of 658 households. Table 1A provides the mapping of the respective weather stations to provinces and cities. The first column lists the provinces in APIS-FIES while the second column lists the PAGASA weather station assigned to it. For provinces without weather stations, the air/straight distance between their capital and the nearby weather stations is computed using the following website: *http://distancecalculator.globefeed.com/Philippines_Distance_Calculator.asp*. The fourth column shows the distance corresponding to the third column. Out of the 83 provinces, there are 24 that have weather stations, 57 that are assigned nearby weather stations, and 2 that could not be reasonably mapped. Guimaras and Batanes are two provinces where a match could not be found in the PAGASA weather data.

There are three weather parameters used in this paper, namely, temperature (dry bulb), heat index, and rainfall. Increased precipitation results to floods that aid the proliferation of vector-borne or water-borne diseases while extreme hot or cold temperature increases mortality. Both affects food security by altering the production patterns involving agriculture and environment, fisheries, and resources sectors. To come up with proxies for weather variabilities/fluctuations, the three weather parameters are compared to their normal values, which are defined as the 30-year average and are compiled for the period 1971-2000.

Based on the consultation with the PAGASA personnel, rainfall is highly localized and matching the rainfall data with the provinces can introduce substantial measurement error. To mitigate measurement error, we use three samples: households in provinces that are at most 40, 20, and 10 kilometers away from the assigned weather station. The PAGASA personnel has affirmed that weather measurements such as temperature and relative humidity are relatively stable across provinces. This means that the temperature and relative humidity data measured in another province can be used for adjacent provinces that do not have weather stations.

Griffiths et al (2005) show that changes in the mean temperature have effects on changes in extreme temperature in Asia–Pacific. Specifically, for the Philippines, it is found that significant correlation exists between the mean temperature and the frequency of extreme temperature. However, relative humidity can interact with temperature to form the heat index. Heat index is a human discomfort index that measures the temperature that the human body perceives or feels. Since climate in the Philippines is characterized by high temperature, high humidity, and abundant rainfall[3], heat index is a variable that can affect energy consumption. For example, Bayudan-Dacuycuy (2017) finds that heat index positively affects electricity and charcoal consumption and negatively affects LPG consumption. Fluctuations in heat index from its normal value have the highest effect on female headed households in rural areas as well.

Heat index (HI) is computed using the average of relative humidity and temperature collected by PAGASA. The temperature data are converted into Fahrenheit using $T_{(^0F)} = T_{(^0C)} * 9/5 + 32$. Heat index is then generated using the following formula[4]:

$$\begin{aligned} HI = {} & 42.379 + 2.04901523 * T` + 10.14333127 * R - 0.22475541 * TR - 6.83783 * (10\wedge(-3)) * Tsq \\ & -5.481717 * (10\wedge(-2)) * Rsq + 1.22874 * (10\wedge(-3)) * TsqR \\ & + 8.5282 * (10\wedge(-4)) * TRsq - 1.99 * (10\wedge(-6)) * TsqRsq \end{aligned}$$

where *T* is temperature in Fahrenheit, *Tsq* is squared temperature, *R* is relative humidity in percentage, and *Rsq* is squared relative humidity. Heat index deviation is the difference between HI and normal HI.

III. Chronic and transient poverty in the Philippines

There are several methodologies to analyze chronic and transient poverty. The model-based approach uses the estimation of components-of-variance to derive the probabilities of time sequences of poverty (Duncan and Rodgers, 1991; Lillard and Willis, 1978). The spells approach uses the construction of transition matrix to track down the movement of economic units into and out of poverty and effectively derives the 'distribution of time spent poor' (Devicienti, 2002). The components approach measures chronic and transient poverty in relation to the intertemporal mean of per capita welfare indicator. In this approach, transient poverty is the variability in consumption relative to the mean welfare indicator overtime while chronic poverty is the poverty that persists in mean consumption overtime (see for example. Jalan and Ravallion, 1998).

Our research adopts a variant of the component approach, which is introduced by Duclos, Araar and Giles (2010, DAG). The starting point of the DAG approach is the components

[3] http://www.pagasa.dost.gov.ph/

[4] Taken from the National Weather Service-National Oceanic and Atmospheric Administration website.

approach proposed by Jalan and Ravallion (1998, JR), which measures chronic and transient poverty in relation to the intertemporal mean of per capita welfare indicator. In this approach, transient poverty is the variability in consumption relative to the mean welfare indicator overtime while chronic poverty is the poverty that persists in mean consumption overtime. Later, Duclos, Araar and Giles (2010) have noted some problems with the JR approach. One, the total poverty decreases with the aversion to poverty in the JR approach. Since chronic poverty is the poverty that persists in mean consumption overtime, households who are poor most of the time may not be chronically poor if these households have a very high income level in the one period they are observed to be non-poor. DAG improved on the JR approach by developing a new set of poverty measure that addresses these problems. DAG approach utilizes the equally-distributed equivalent poverty gap or the level of individual ill-fare which, if assigned equally to all individuals and in all periods, would produce the same poverty measure as that generated by the distribution of normalized poverty gaps.[5]

Applying the DAG components approach to the APIS-FIES data, our research aims to analyze the effects of geographic attributes, such as urbanity, presence of armed conflict, and weather variability, on chronic and transient poverty. Weather variability can also be considered as a shock. As such this paper is closely related to Bayudan-Dacuycuy and Lim (2013) who use the components approach to analyze chronic and transient poverty in the Philippines. They find that shocks to labor market such as job loss or income reduction affect chronic poverty while natural disasters such as droughts affect transient poverty. They also find that a higher dependency burden due to many young children positively affects chronic poverty but not transient poverty.

Table 1 presents chronic and transient poverty statistics at the national and rural-urban level using two welfare indicators. In the left panel, chronic total and transient total poverty are computed by comparing total expenditure against the poverty threshold while in the right panel, chronic food and transient food poverty are computed by comparing food expenditure against the food threshold. From table 1, using total expenditure as welfare indicator show that chronic total poverty accounts for the large portion of total poverty. At the national level, chronic poverty comprises 85% of the total poverty. It accounts for 86% of total poverty in rural areas and for 78% of total poverty in urban areas. Similar trend is observed using food expenditure as welfare indicator, although the numbers are higher by 1-2 percentage points. The same trend is observed using the data without imposing restrictions on the age and sex of the household head.

Table 2 presents mean chronic and transient poverty statistics based on some household attributes. Chronic poverty is higher for households headed by persons with lower than a college degree compared to households headed by persons with at least a college degree. Chronic poverty decreases with the age of the household head and those headed by persons less than 40 years old have the highest while those headed by persons above 60 have the lowest chronic poverty. Chronic poverty is the highest for large households. Looking at the demographic compositions, households with high dependency burden have higher chronic poverty. This is shown in the high chronic poverty of households with members less than 1-year old, households with at least two members between 1-6 years old, and households with at least two members between 7-14 years old. Households with older, presumably economically productive members

[5] See appendix for details.

have low chronic poverty. Chronic poverty of households without social networks is higher compared to households with members who are part of non-governmental organizations or cooperatives. Looking at geographical attributes, households located in areas with armed conflict have higher chronic poverty. Households that experience above normal temperature have the highest chronic poverty. Those that experience above normal heat index have the highest chronic poverty. Households that experience above normal rainfall have higher chronic poverty. Similar trends are observed for transient poverty.

IV. Empirical strategy

To analyze the determinants of chronic and transient poverty, we assume that $y = f(x, z; e)$. The dependent variable *y* is either chronic or transient poverty. Both chronic and transient poverty are bounded between 0 and 1. Buis (2016) argues that the effect of explanatory variables tends to be nonlinear and the variance tends to decrease when the mean gets closer to the boundaries. These violate Ordinary Least Squares (OLS) assumptions of normality and homoscedasticity and using OLS would lead to biased estimates. In addition, the predicted values resulting from OLS estimates can be outside the 0-1 interval. Therefore, we adopt the generalized linear model (GLM), which is an estimator for bounded dependent variables.

Several specifications are explored to establish the effects of weather fluctuations on the poverty components. Specification 1 includes the proxy for weather variability only and results show that weather parameters significantly explain the components. Specification 2 enhances specification 1 by including the squared term of weather deviation to account for nonlinear effects. However, estimates pertaining to the squared term are not significantly different from zero and the results are not substantially different from specification 1. The final specification used includes the interaction between the urban dummy and the weather parameter. By doing this, we recognize that the effect of weather deviations may differ by geographic locations, an idea that is common in the literature. For example, Deschenes and Greenstone (2007) find that the effect of weather events on agricultural profits in the US is small but that there is heterogeneity across counties with some counties more adversely affected than others. Levine and Yang (2014) find deviations from mean local rainfall are positively associated with district-level rice output in Indonesia. Chronic total and transient total poverty refer to poverty components computed based on the per capita expenditure and poverty threshold while chronic food and transient food poverty refer to poverty components computed based on the per capita food expenditure and food threshold.

The variable *x* is a vector of head's attributes such as age, education, and marital status, demographic composition, labor market participation, and membership in NGO and/or cooperatives. The variable *z* refers to geographical characteristics including a dummy for areas with armed conflict, dummy for urban areas, and weather variables. The variable *e* is assumed to be an independently and identically distributed error term. GLM is used on three samples: households in provinces that are at most 40, 20, and 10 kilometers away from the assigned weather station. This is done due to the measurement error that can arise from the assignment strategy of weather stations to provinces we discuss above. While the measurement error is most likely to occur for the localized weather parameter like rainfall, such error is mitigated for stable weather parameters like temperature and relative humidity. Estimations are done using two

welfare indicators. The per capita expenditure is compared against the poverty threshold and the food per capita is compared against the food threshold.

Explanatory variables

To control for the heterogeneity in the capacity to pay/purchase, a score to proxy for asset ownership is generated by the principal component analysis (PCA). The PCA is a technique to reduce the dimension of the data by creating uncorrelated indices or components, where each component is a linear weighted combination of the initial variables. The variance of each of the component is generated such that the first component contains the largest variation in the original data; the second explains additional but less variation and so on[6]. An application of PCA is on household assets to create an indicator for socioeconomic status in the absence of income and expenditure data (see for example, Filmer and Pritchett, 2001). Positive scores generated by the PCA are associated with higher socioeconomic status (Vyas and Kumaranayake, 2006).

While FIES has detailed data on asset ownership, the assets included in the PCA are those that are collected in both APIS and FIES. These include radio, television, component, refrigeration, washing machine, air conditioning unit car, landline, personal computer, and gas range. The overall Kaiser-Meyer-Olkin measure of sampling adequacy is around 0.86 in each year, which indicates that these assets contain enough similar information to warrant the factor analysis[7]. Based on the score generated by the PCA, a dummy is created equal to 1 if the score is positive in all years and 0 otherwise. Following Vyas and Kumaranayake (2006), this dummy variable proxies for high socioeconomic status.

The labor market participation of the head and the spouse are also included as explanatory variables. A dummy equal to 1 is created if the head/spouse is employed in all the survey years and 0 otherwise. Variables like family size and demographic composition are averages from 2003 to 2009.

Attrition bias

A problem common to the use of any longitudinal data is that the sample collected becomes smaller in succeeding survey years. This problem is serious when non-participants have systematic characteristics that are related to poverty. If households with high opportunity costs are likely to drop out of the succeeding surveys and these households happen to be nonpoor, then estimates based on the remaining samples are likely to be bias upward.

Attrition bias, a case of selection bias, arises from the non-participation of respondents in succeeding survey years. It can affect the external and internal validities of multiwave studies (Miller and Hollist, 2007). External validity means that the characteristics of the subsequent samples are generalizable to the initial samples. Internal validity means that the correlations among the variables are similar across survey years. While the PSA has ensured that each

[6] For technical details, see Filmer and Pritchett (2001).

[7] The KMO statistic is a test if the data are suited for factor analysis by measuring the sampling adequacy for 1) each variable and 2) for the complete model (Kaiser, 1970). This statistic is a summary of how small the partial correlations are relative to the original correlations. If the variables share common factor/s, then the partial correlations should be small and the KMO should be close to 1.0 (http://www-01.ibm.com/support/docview.wss?uid=swg21479963).

replicate of the APIS and FIES possesses the properties of the master sample, we have imposed additional restrictions based on the head's age and sex to ensure that the same families are tracked down throughout the survey years. These restrictions could be a possible window for attrition bias.

Following Miller and Wright (1995) to test for attrition bias, we run a logit regression on 'stayers'[8] using the independent variables extracted from 2003. 'Stayers' is equal to 1 if the sample participated in the succeeding wave and equal to 0 otherwise. Independent variables include the characteristics of the household head, household assets, demographic composition, and geographical location dummies. These should not be statistically significant to rule out attrition bias. Result indicates that the characteristics of the household head, the asset score, urban dummy, and some of the regional dummies are statistically significant determinants of participation in the entire survey wave[9]. Box M-test is used to check for internal validity and tests for the equality of the two covariance matrices for the samples observed only in the first period and for the samples observed in all periods using the Box M-test. The null hypothesis using this test is that the two covariance matrices are equal indicating no threats to internal validity. The p-value computed using the Box M-test is 0.00, which indicates rejection of the null hypothesis.

Following Heckman (1979) to correct for attrition bias, the inverse Mills' Ratio or $IMR = \frac{\phi(\beta x)}{\Phi(\beta x)}$ [10], is computed from the probit regression of the 'stayers' against the characteristics of the household head, asset index, households' demographic composition, and geographical location dummies. IMR is included as one of the explanatory variables in the estimations done below.

V. Discussion of results

GLM estimates using *per capita expenditure and per capital food expenditure as welfare indicators* are presented in tables 2A-4A. Estimates using temperature deviation as proxy for weather variability are presented in table 2A. Chronic total poverty is negatively affected by the household's age and college education, membership in cooperatives or non-governmental organizations, number of older household members¸ always positive asset score, employment of the head's spouse, and urbanity. Chronic total poverty is positively affected by family size, number of young family members, armed conflict, and temperature deviation. Transient total poverty has fewer significant determinants. It is negatively affected by the head's college education, always positive asset score, and urbanity. Results using heat index deviation as a proxy for weather variability are presented in tables 3A and 4A. Most of the observations above are also noted. Both heat index and rainfall deviations positively affect chronic total poverty in urban areas.

Trends on the results above are also observed on GLM estimates using *per capita expenditure as welfare indicator*. However, there are some departures. Comparing the results on

[8] Equal to1 if participated in the succeeding wave and equal to 0 if not.

[9] Results are available from the author upon request.

[10] $\phi(\beta x)$ is the probability density function and $\Phi(\beta x)$ is the cumulative density function.

total poverty versus food poverty, college education is not a significant determinant of transient food poverty while it is a significant determinant of transient total poverty. Armed conflict is not a significant determinant of transient food poverty while it is a significant determinant of transient total poverty. Similar observation is noted on the effect of urban dummy. Deviations in the weather variables positively affect chronic food poverty in urban areas.

Based on the GLM estimates, total poverty and food poverty components are predicted. To do this, total poverty and food poverty are predicted for a household headed by a person who is married, is not always employed, has less than a college degree, and has a spouse who is not always employed. Households are also assumed to have two members who are less than 1-year old, one member who is between 1 to 6-year-old, with asset scores less than zero at times, and located in an area with armed conflict. Temperature and heat index deviations are assumed to be equal to 2 degrees Centigrade while rainfall deviation is assumed to be equal to 200 millimeters. These constitute the benchmark characteristics[11]. To assess the contribution of different variables, total poverty and food poverty are predicted by changing one attribute in the benchmark characteristics each time. Comparisons of predicted total poverty are presented in figures 1-3. Comparisons of predicted food poverty are presented in figures 4-6.

From figures 1-3, chronic total poverty using benchmark characteristics in the rural areas is around twice as high as in the urban areas. Using benchmark characteristics, transient total poverty is substantially lower than chronic total poverty. The disparity between chronic total and transient total poverty is more pronounced in rural areas.

Figure 1 shows the predicted total poverty from the estimates that use temperature deviation as a proxy for weather fluctuation. Relative to the benchmark attributes in urban areas, chronic total poverty is around five times lower for households that always have positive asset score. It is two times lower for households headed by persons with at least a college degree. Households with no young members, households where heads' spouses are always employed, and households in non-conflict areas have lower chronic total poverty than the benchmark although the reduction is not as pronounced as in the case of asset ownership and college education. Zero temperature deviation has a minimal contribution to chronic total poverty reduction. Similar observations are noted on the chronic total poverty in urban areas. There is minimal difference on the transient total poverty in urban and rural areas.

Figures 2 and 3 shows the predicted total poverty from the estimates that use heat index and rainfall deviations as proxies for weather variability. Similar to the temperature deviation, the absence of heat index deviation has a minimal contribution to the reduction of chronic total poverty. On the other hand, chronic total poverty of households that experience zero rainfall deviation in urban (rural) areas is 5 (9) percentage points lower than the chronic total poverty of similar households that experience rainfall deviation. Results on other key variables are similar to the observations noted in figure 1.

[11] Evaluating the marginal effects using benchmark characteristics, or marginal effects calculated at representative values (MER), is different from the marginal effects at the means (MEM) and the average marginal effects (AME) in that the latter two rely on averages.

From figures 4-6, chronic food poverty using benchmark characteristics in the rural areas is around twice as high as in the urban areas. Using benchmark characteristics, transient food poverty is substantially lower than chronic food poverty. The disparity between chronic food and transient food poverty is more pronounced in rural areas.

Predicted total poverty and predicted food poverty are compared and some observations are noted here. *One*, the predicted food poverty is higher than the predicted total poverty. Both total poverty and food poverty are higher in rural areas. *Two*, similar to total poverty, food poverty has the most reduction when households have positive asset score always and when households are headed by persons with at least a college degree. The absence of armed conflict reduces chronic food poverty more than continuous employment and more than the absence of young members do. *Three*, similar to total poverty, zero temperature and heat index deviations have minimal effect on food poverty reduction. However, the absence of rainfall deviation contributes to around 5 percentage points reduction in chronic food poverty in both urban and rural areas.

VI. Summary and conclusions

This paper uses a generalized linear model to investigate the effects of various geographic attributes like urbanity, presence of armed conflict, and weather deviations on the chronic and transient poverty in the Philippines. It uses deviations of temperature, heat index, and rainfall from their normal values (30-year average from 1971-2000) as proxies for weather variability. Three samples are used: households in provinces that are at most 40, 20, and 10 kilometers away from the assigned weather station. This is done due to the assignment strategy of weather stations to provinces, which can be a source of measurement errors. Using different samples allows us to check for the robustness of estimates in terms of significance and magnitude. Per capita expenditure is compared against poverty threshold and the resulting poverty components are referred to as chronic total and transient total poverty. Food per capita is compared against food threshold and the resulting poverty components are referred to as chronic food and transient food poverty.

Results indicate that, *one*, chronic total poverty is affected by the characteristics of the household head, household's demographic composition, and labor market participation. However, transient total poverty has fewer determinants. It is affected by some characteristics of the household head, asset score, and geographic attributes. *Two*, college education, armed conflict and urbanity are not significant determinants of transient food poverty but are significant determinants of transient total poverty. *Three*, the prediction of total poverty and food poverty based on the GLM estimates indicate that asset ownership and college education have the most impact on the reduction of both types of poverty. *Four*, among the three proxies for weather fluctuations, rainfall deviation has the more substantial effect on chronic total and chronic food poverty in both urban and rural areas.

While the discussion above pertains to factors that affect chronic poverty, it should be emphasized that transient poverty is just as important. For example, job layoffs may create new packets of poverty, which can be transient or can become chronic depending on the ability of households to smooth consumption and on the social protection in place. We devote the

succeeding discussion on existing or possible policies related to education, asset ownership, dependency burden, and weather shocks since these affect both types of poverty.

First, the bill seeking to institutionalize a tuition-free policy in SUCs was already ratified by the House of Representatives and the Senate. However, tuition fee is just a portion of education-related expenditures. Assistance to address daily expenditures like meals and transportation should also be strengthened as these expenses are equally important to ensure that students from poor households will finish college and that public investments in their education are not wasted.

Second, the possible role of assets in consumption-smoothing should be emphasized. Accumulation of assets, not only financial, but social and human capital, is assured when livelihoods are stable. Along this line, the government should explore the role of Social Enterprises (SE), which use local knowledge and local resources to address not only financial but social and environmental issues within the community. Ballesteros and Llanto (2017) identify the following government support for SEs: 1) legal/regulatory framework to facilitate experimentation and innovation, 2) incentives for mixed financing, and 3) improving the suitability of the environment for grants, international aid, and venture capitalists.

Third, armed conflict contributes to the destruction of different assets. It damages human assets by disrupting schooling and worker's mobility. It displaces people so it damages social assets such as informal network within the community. It disrupts the delivery of social protection programs to the affected communities, which drives the poor further down the poverty line. Resolving conflict is complex since it is an outcome resulting from the interactions of various factors and finding solutions are unlikely to be easy. But a good first step is to engage stakeholders not only to understand the needs of the community and to come up with feasible initiatives but to develop strong ownership for these initiatives. The former Department of Environment and Natural Resources secretary's plan to involve the New People's Army into its projects is a step towards achieving multiple objectives: sustainable use of the environment for livelihood, end armed conflict, and eventually address chronic poverty.

Fourth, the country is on the right track to address poverty resulting from high dependency burden. With the Magna Carta for Women (MCW) and Convention on the Elimination of all Forms of Discrimination Against Women (CEDAW) as legal frameworks, the Responsible Parenthood and Reproductive Health Act (RH Law or RA 10354) was enacted in 2012[12]. However, it has several setbacks: the issuance of a temporary restraining order on government's procurement, selling, distribution, and promotion of Implanon[13], the voiding of

[12] The RH Law iterates the State's duty to eradicate discriminatory practices, laws, and policies that violate a person's exercise of reproductive rights and to provide comprehensive health services and programs to address women's mortality and morbidity. In terms of health care, the RH Law iterates the State's duty to provide services on maternal and infant care, family planning, and youth sexuality education. It also iterates the State's duty to provide services for the elimination of violence against women and children, the prevention/treatment/management of reproductive tract infections and sexually transmittable infections, and infertility and sexual dysfunction, and the management of abortion complications.

[13] Implanon is preferred by most women since its effect lasts for three years. However, with the TRO in place, Implanon shots are no longer free and this has affected the most number of women in the informal sector and in the poor urban areas.

eight key provisions of the RH Law[14], and the fragmented support of LGUs[15]. The current administration, showing full support to the RH Law, signed in early 2017 Executive Order No. 12, which aims to intensify and accelerate the implementation of programs to attain zero unmet need for modern family planning by 2018.

Fifth, weather-related events also affect chronic total and chronic food poverty. Majority of calamity funds are appropriated for reconstruction and rehabilitation and for disaster and risk reduction programs[16]. Slow-onset weather phenomenon, such as increasing precipitation and volatility in temperature, is equally damaging and can have severe consequences on social and economic outcomes. Weather events like increasing temperature and precipitation are likely results of climatic shift, as suggested by PAGASA's projections using mid-range emissions scenario. This brings to the fore issues on financing projects related to climate change mitigation and adaptation. The Philippine Development Plan 2017-2022 acknowledges that especially in LGUs, funding for climate change mitigation and adaptation competes with other development priorities. Being at the frontline against the adverse effects of climatic shifts and weather events, LGUs should explore other financing funds.

One such fund is the Adaptation fund (AF), established under the Kyoto Protocol of the UN Framework Convention on Climate Change, that finances[17] adaptation programs/projects to help vulnerable communities. AF has several advantages. One, it is a direct access to international financing mechanism that enables country institutions to directly participate in the design, implementation, and monitoring of the project. Two, based on data from ICSC and Oxfam (2010), 86% of funds coming from bilateral donors to finance adaptation projects (1992-2018) are loans and 14% are grants. For mitigation projects (1992-2018) funding, 61% of the funds are loans and 39% are grants. Assistance through loans goes against the principle of common but differentiated responsibilities, which acknowledges that countries have different responsibilities and capabilities in addressing climate change. Developed countries contribute to high greenhouse gas emissions and are more capable of climate change mitigation and adaptation. If the assistance comes in the form of loans, ICSC and Oxfam (2010) argue that this "reverses the burden-sharing role and imposes new debts to those severely affected by global climate change despite having contributed less to it."

The Philippines has not yet availed AF although it is a party to the Kyoto Protocol and is therefore eligible to avail financing from the AF. AF requires a National Implementing Entity (NIE), which once accredited will be fully responsible for program/ project implementation and management. Established by Republic Act 9729 in 2009, the Climate Change Commission

[14] Includes the punishment of RH providers who fail to refer any non-life threatening case to another RH provider, the punishment of any public officer who refuses to support RH programs, the access to procedures without spousal consent, and the provision of RH services to minors without parental consent.

[15] A National Inquiry conducted by the Commission on Human Rights in early 2016 indicated that local government units have varying degrees of support for the RH Law. For example, Quezon City and the City of Marikina are in full support of the RH Law while in Sorsogon, EO 03 was declared in early 2015 that resulted in the withdrawal of all artificial contraceptives in health facilities (Commission on Human Rights, 2016).

[16] As of April 2017, around 44% of the calamity fund is appropriated for Rehabilitation and Reconstruction, 36% for the National Disaster Risk Reduction Management program, 15% for the Quick Response Fund, and 3% each for Insurance Coverage of Government Facilities and the People's Survival Fund.

[17] Small-size projects/programs up to US$1 million and regular projects/programs over US$1 million.

(CCC) formulates and implements plans on climate change and risk reduction, coordinates with LGUs to address vulnerability, and promotes and provides technical and financial support to climate change initiatives. The CCC is, therefore, the best national agency that can spearhead NIE and should start looking into how the country can tap this additional funding source. Proposals need to be evaluated for AF grant. This highlights the need for strong CCC-led capacity-building in LGUs so that LGUs can come up with community-driven and well-defined adaptation projects and programs.

In addition, the People's Survival Fund (PSF) was created through Republic Act 10174 signed on August 16, 2012 as an annual fund for LGUs to implement climate change adaptation programs/projects. Programs/projects funded by the PSF included forecasting and early warning systems, monitoring/controlling/preventing of diseases triggered by climate change, institutional development for LGUs, and establishment/strengthening of regional centers and information networks that support adaptation efforts. It also serves as a guarantee for farmers' risk insurance needs. The national government programmed PhP1 billion into the PSF, which is designed to supplement the annual appropriations allocated to projects/programs related to climate change by LGUs and other government agencies (http://climate.gov.ph/2016/11/). While there are a number of proposals submitted, only two projects are approved (one in Surigao del Sur and one in Surigao del Norte) with total requested PSF funding of around PhP120 Million. The PSF secretariat has indicated that most of the proposals submitted to the Climate Change Commission (CCC) lack the climate change adaptation component and are returned to proponents for revision. CCC can enhance their technical assistance by providing LGUs an annual technical workshop on crafting proposals with strong climate change adaptation initiatives. CCC should also improve its information dissemination campaign not only to inform the public what CCC does but to increase awareness on what climate change adaptation is and how to access the various services CCC provides.

At the national level, the National Climate Change Action Plan outlines seven strategies, namely, food security, water sufficiency, ecological and environmental stability, human security, climate smart industries and services, sustainable energy, and knowledge and capacity building, as the strategic direction for 2011 to 2028. At the local level, a well-crafted local climate change action plan (LCCAP) must reflect the varying needs of communities and the shifting and uneven effects of climate change. The LCCAP is a requirement for access to the PSF.

Convergence of climate change programs/projects with the programs/projects of other government agencies should be explored as well. For example, the implementation of LCCAP will be packaged using the concept of ecologically stable and economically resilient towns or ecotowns[18] (Climate Change Commission, 2012). Assistance in the form of immediate income to ecotowns is granted to the poor and the unemployed with the condition of protecting critical ecosystems[19]. LGUs with ecotowns should explore how to link their assistance program with the DSWD's existing 4Ps, which strengthens human capital and self-sufficiency but does not

[18] Defined as a planning unit composed of municipalities or a group of municipalities located within and in the boundaries of critical key biodiversity areas (forest, coastal/marine and fishery, or watersheds), highly vulnerable to climate change risks due to its geography, geographic location, and poverty situation.

[19] Beneficiaries may be required to protect nearby forest from illegal tree cutting, practice appropriate farming techniques, or manage household wastes.

explicitly address risks associated with climate change. For example, the conditions involving 4Ps and the conditions for helping the poor in ecotowns can be combined to come up with adaptive social protection initiatives[20]. Funds that can be freed up from rationalization of social protection programs can then be used to finance other adaptive social protection initiatives. Involvement of external stakeholders should also be explored. For example, the DSWD's Sustainable Livelihood Program through its Employment Facilitation (EF) track can be linked with Social Enterprises (SEs) by giving SEs incentives to put up enterprises for ecotowns or communities where EF is in place.

Food Security is closely related to the discussion of weather variability and climate change and poverty. In 2015, around 29% (of total employment) is still employed in agriculture, a sector that is most vulnerable to the vagaries of weather. People in rural areas can easily slip in and out of poverty since their livelihood depends on stable environments such as stable temperature and steady supply of water. To address the adverse effect of sustained weather fluctuations, LGUs should spearhead the development of a climate-smart agriculture (CSA) that fits the needs of the community. Working with the community to harness local skills and knowledge in the development of good agricultural and livelihood practices instills strong ownership among community members and adaptation is likely to be successful.

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20 These initiatives support pro-poor climate change adaptation and disaster risk reduction by strengthening the resilience of vulnerable populations to shocks (Davies et al., 2009).

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Table 1: Total poverty and its components at the national level and at the urban-rural segregation

	Per capita expenditure against poverty threshold			Per capita food expenditure against food threshold		
	Observations		% of total poverty	Observations		% of total food poverty
Using panel data with household head's age and sex restrictions						
National						
Total Poverty	1954	21.13		1954	29.87	
Total Chronic		17.87	85		25.74	86
Transient total		3.26	15		4.13	14
Rural						
Total Poverty	1266	26.45		1266	35.07	
Total Chronic		22.76	86		30.99	88
Transient total		3.69	14		4.08	12
Urban						
Total Poverty	688	11.34		688	20.31	
Total Chronic		8.88	78		16.08	79
Transient total		2.46	22		4.23	21
Using panel data without household head's age and sex restrictions						
National						
Total Poverty	5927	22.13		5927	30.98	
Total Chronic		18.76	85		26.70	86
Transient total		3.37	15		4.28	14
Rural						
Total Poverty	3721	28.20		3721	36.86	
Total Chronic		24.46	87		32.69	89
Transient total		3.74	13		4.17	11
Urban						
Total Poverty	2206	11.88		2206	21.07	
Total Chronic		9.14	77		16.61	79
Transient total		2.75	23		4.45	21

Authors' calculations based on the merged APIS-FIES dataset.

Table 2: Mean chronic and transient poverty, by socioeconomic characteristics

	Per capita expenditure against poverty threshold		Per capita food expenditure against food threshold	
	Mean chronic	Mean transient	Mean chronic	Mean transient
Household Head Age				
Between 17 and 30	23.04	3.89	31.04	4.42
Between 31 and 40	23.45	3.19	30.37	3.77
Between 41 and 50	16.41	3.16	25.21	4.19
Between 51 and 60	13.12	3.08	21.19	4.15
Above 60	11.33	3.33	18.84	4.53
Civil status of household head				
Single/Widowed/Divorced	10.62	3.15	17.30	4.37
Married	18.86	3.27	26.89	4.10
Educational attainment of household head				
Less than college graduate	21.05	3.65	29.17	4.18
At least college graduate	5.24	1.70	12.12	3.94
Average family size				
Between 1 and 5 members	12.51	3.29	20.19	4.55
Between 6 and 10 members	27.00	3.21	35.15	3.44
Between 11 and 15 members	30.78	2.96	42.40	2.60
Organizational membership of household members in NGOs/Cooperatives				
Not member in any organization	19.11	3.42	26.90	4.15
Member of 1 organization	16.00	3.01	23.94	4.03
Member of 2 organizations	10.56	2.23	19.82	5.50
Ave. number of household members less than 1 year				
0	16.62	3.21	24.68	4.14
1	30.84	3.72	36.75	4.05
Ave. number of household members less than 7 years				
0	12.01	3.06	19.99	4.28
1	19.23	3.61	27.82	4.34
2	34.46	3.43	40.73	3.38
3	48.98	2.10	52.56	1.94
4	61.76	1.03	59.81	0.96
Ave. number of household members less than 15 years				
0	10.89	3.15	18.39	4.57
1	15.24	3.47	24.02	4.59
2	25.40	3.32	32.92	3.51
3	34.20	2.99	41.54	2.65
4	42.41	2.78	50.12	2.09
5	47.13	2.88	48.21	2.61
Ave. number of household members less than 25 years				
0	17.40	3.23	24.49	4.25
1	18.04	3.17	26.19	4.08
2	17.04	3.60	26.10	4.15
3	22.62	3.25	31.56	3.42

4	18.56	2.93	28.31	4.06
5	19.19	2.13	39.29	4.52
Ave. number of household members more than 25 years				
0	8.96	3.60	16.53	5.47
1	19.61	3.25	27.25	4.00
2	12.79	3.20	21.73	4.28
3	11.46	3.41	19.93	4.85
4	10.90	2.64	20.29	4.71
5	4.85	4.29	24.56	9.76
Asset score				
Not always positive	19.78	3.55	27.85	4.18
Always positive	1.00	0.67	7.15	3.75
Job status of household head				
Never had a job	10.50	2.99	18.21	4.40
Always has a job	19.98	3.33	27.89	4.06
Employment of household head's spouse				
Never had a job	19.02	3.35	26.65	4.12
Always has a job	11.78	2.75	20.93	4.23
Armed conflict				
Areas without conflict	16.48	3.20	23.96	4.00
Areas with conflict	22.69	3.47	31.90	4.59
Dry temperature deviation				
Zero deviation	17.85	3.14	25.54	4.07
Positive deviation	18.26	3.72	26.61	4.30
Heat Index deviation				
Negative deviation	10.60	2.68	15.30	3.55
Zero deviation	16.79	2.94	23.88	4.62
Positive deviation	18.53	3.33	26.63	3.94
Rain fall deviation				
Between -31 to -40 rain deviation	18.93	3.65	29.39	3.69
Between -21 to -30 rain deviation	11.30	2.07	22.73	3.46
Between -1 to -10 rain deviation	7.14	3.69	14.99	5.57
Between 1 to 10 rain deviation	11.34	2.51	17.39	4.59
Between 11 to 20 rain deviation	23.86	3.52	31.58	3.89
Between 21 to 30 rain deviation	20.79	3.43	30.54	3.93
Between 31 to 40 rain deviation	21.36	4.07	30.38	3.88
41 and above rain deviation	18.65	3.76	25.96	4.16

Authors' calculations based on the merged APIS-FIES dataset.

Figure 1: Predicted poverty using temperature deviation

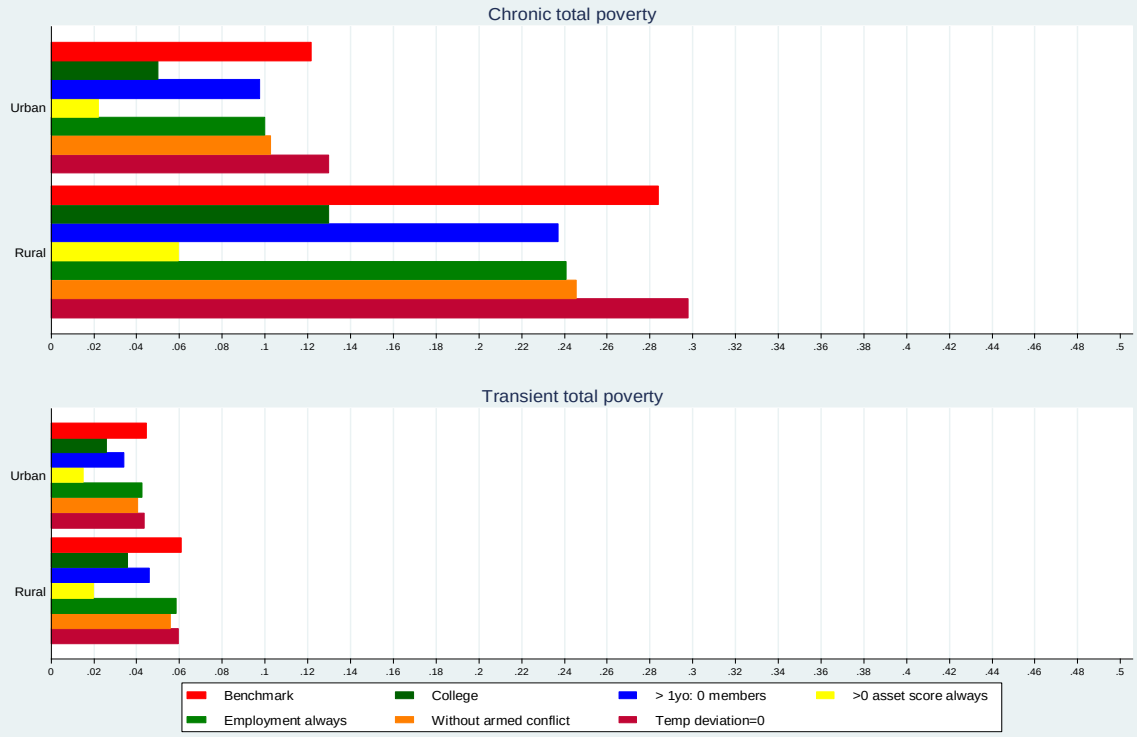


Figure 2: Predicted poverty using heat index deviation

Figure 3: Predicted poverty using rainfall deviation

Figure 4: Predicted poverty using temperature deviation

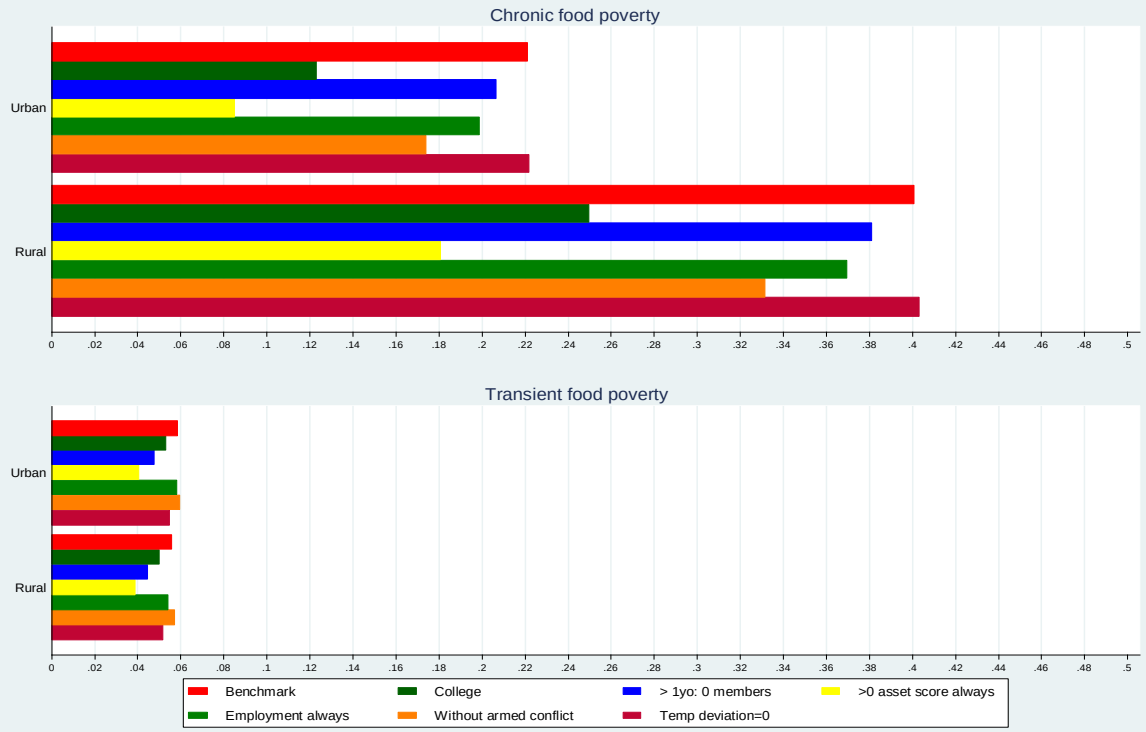
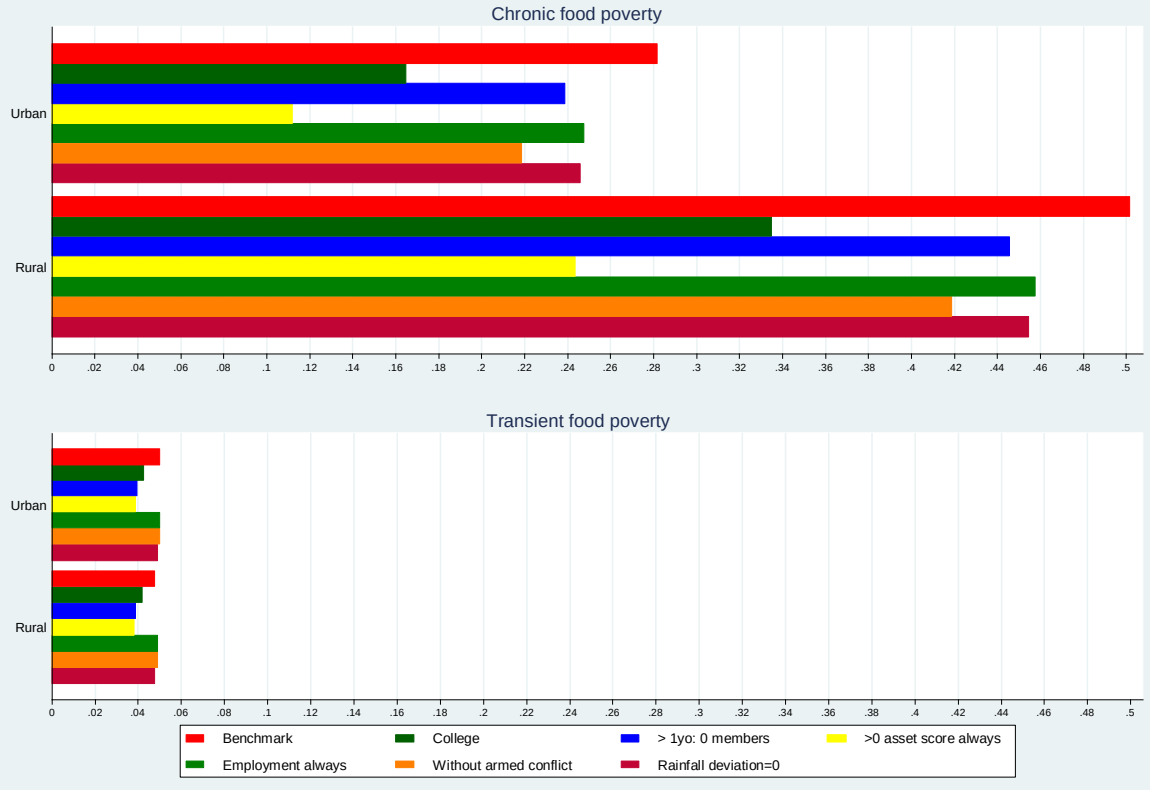


Figure 5: Predicted poverty using heat index deviation

Figure 6: Predicted poverty using rainfall deviation



APPENDIX

Table 1A: Mapping of APIS-FIES provinces with the PAGASA weather stations

APIS-FIES Province/City	Weather Station	Provincial capital to weather station	Straight line/air distance (in kms)§
Misamis Oriental	Lumbia Airport, Misamis Oriental	CDO-Lumbia Airport	5.62
Benguet	Baguio City, Benguet	La Trinidad - Baguio City	8.63
Rizal	Science Garden, Quezon City	Rizal-Quezon City	8.93
Cebu	Mactan International Airport, Cebu	Cebu City - Mactan International Airport	10.7
Pangasinan	Dagupan City, Pangasinan	Lingayen - Dagupan City	10.83
Quezon	Taybas, Quezon	Lucena-Tayabas	11.04
Nueva Ecija	Cabanatuan, Nueva Ecija	Palayan City-Cabanatuan	17.96
Agusan del Norte	Butuan City, Agusan del Norte	Cabadbaran City - Butuan City	19.42
Cavite	Sangley Point, Cavite	Trece Martirez City - Sangley Point	20.66
Sarangani	General Santos, South Cotabato	Alabel - General Santos	21.08
Abra	Sinait, Ilocos Sur (former Vigan Station)	Bangued - Sinait	32.44
Sorsogon	Legaspi City, Albay	Sorosogon City-Legaspi	33.55
La Union	Baguio City, Benguet	San Fernando City-Baguio City	33.68
Bulacan	Science Garden, Quezon City	Bulacan-Quezon City	33.76
Batangas	Ambulong, Batangas	Batangas City - Ambulong	37.13
Tarlac	Cabanatuan, Nueva Ecija	Tarlac City-Cabanatuan	40.43
Kalinga	Tuguegarao, Cagayan	Kalinga-Tuguegarao	41.23
Aklan	Roxas City, Capiz	Aklan-Roxas City	43.61
Cotabato (North)	Davao City, Davao del Sur	Cotabato-Davao City	46.85
Davao del Norte	Davao City, Davao del Sur	Tagum City - Davao City	48.41
Davao del Sur	Davao City, Davao del Sur	Digos City - Davao City	49.5
Agusan del Sur	Butuan City, Agusan del Norte	Prosperidad-Butuan City	52.88
Basilan	Zamboanga City, Zamboanga del Sur	Basilan-Zambonaga City	55.65
Lanao del Sur	Lumbia Airport, Misamis Oriental	Marawi-Lumbia Airport	56.2
Laguna	Sangley Point, Cavite	Santa Cruz-Sangley	56.87
South Cotabato	General Santos, South Cotabato	Koronadal-General Santos	58.65
Nueva Vizcaya	Baguio City, Benguet	Bayombong-Kennon Road	59.51
Isabela	Tuguegarao, Cagayan	Ilagan-Tuguegarao	61.9
Isabela City	Tuguegarao, Cagayan	Isabela City-Tuguegarao	61.9
Catanduanes	Legaspi City, Albay	Virac-Legaspi	70.46
Biliran	Tacloban City, Leyte	Naval-Tacloban City	70.51
Eastern Samar	Guiuan, Eastern Samar	Borongan-Guiuan	71.26
Compostela Valley	Davao City, Davao del Sur	Nabunturan-Davao City	72.68
Apayao	Tuguegarao, Cagayan	Apayao-Tuguegarao	73.16
Marinduque	Tayabas, Quezon	Boac-Tayabas	75.46
Zamboanga del Sur	Dipolog. Zamboanga del Norte	Pagadian City-Dipolog	75.66
Ifugao	Baguio City, Benguet	Lagawe-Baguio City	78.65
Pampanga	Iba, Zambales	San Fernando City-Iba	79.15
Surigao del Sur	Hinatuan, Surigao del Sur	Tandag City-Hinatuan	80.76
Sultan Kudarat	General Santos, South Cotabato	Sultan Kudarat-General Santos	85.54
Mountain Province	Baguio City, Benguet	Bontoc-Baguio City	87.15

Misamis Occidental	Lumbia Airport, Misamis Oriental	Oroquieta City-Lumbia Airport	89.48
Masbate	Legaspi City, Albay	Masbate City-Legaspi City	90.04
Bataan	Iba, Zambales	Balanga-Iba	91.19
Davao Oriental	Davao City, Davao del Sur	Mati-Davao City	91.54
Camiguin	Lumbia Airport, Misamis Oriental	Mambajao-Lumbia Airport	92.3
Lanao del Norte	Lumbia Airport, Misamis Oriental	Tubod-Lumbia Airport	93.21
Iloilo	Roxas City, Capiz	Iloilo City-Roxas City	94.48
Camarines Sur	Virac, Catanduanes	Pili - Virac	100.13
Negros Occidental	Roxas City, Capiz	Bacolod city-Roxas City	104.27
Zamboanga Sibugay	Zamboanga City, Zamboanga del Sur	Ipil-Zamboanga City (from Zam. Del Sur)	111.18
Occidental Mindoro	San Jose, Oriental Mondoro	Mamburao-San Jose	113.17
Maguindanao	General Santos, South Cotabato	Shariff Aguak - General Santos	118.03
Antique	Roxas City, Capiz	San Jose de Buenavista-Roxas City	124.85
Quirino	Tuguegarao, Cagayan	Quirino-Tuguegarao	134.56
Cotabato City	Davao City, Davao del Sur	Cotabato City to Davao City	135.09
Sulu	Zamboanga City, Zamboanga del Sur	Jolo-Zambonaga City	149.25

Aurora	Baler, Aurora
Oriental Mindoro	Calapan, Oriental Mindoro
Northern Samar	Catamaran, Northern Samar
Samar (Western)	Catbalogan, Western Samar
Camarines Norte	Daet, Camarines Norte
Zamboanga del Norte	Dipolog, Zamboanga del Norte
Negros Oriental	Dumaguete, Negros Oriental
Zambales	Iba, Zambales
Ilocos Norte	Laoag City, Ilocos Norte
Albay	Legaspi City, Albay
Southern Leyte	Maasin, Southern Leyte
Bukidnon	Malaybalay, Bukidnon
NCR-4th Dist.	NAIA (MIA), Pasay City
Manila	Port Area (MC), Manila
Palawan	Puerto Princesa City, Palawan
Romblon	Romblon, Romblon
Capiz	Roxas City, Capiz
NCR-2nd Dist.	Science Garden, Quezon City
NCR-3rd Dist.	Science Garden, Quezon City
Ilocos Sur	Sinait, Ilocos Sur (former Vigan Station)
Surigao del Norte	Surigao, Surigao del Norte
Leyte	Tacloban City, Leyte
Bohol	Tagbiliran City, Bohol
Cagayan	Tuguegarao, Cagayan

Batanes

Guimaras

Taken from *http://distancecalculator.globefeed.com/Philippines_Distance_Calculator.asp*

Table 2A: GLM regression estimates using dry temperature deviation as weather parameter, total poverty and food poverty

	Total poverty						Food Poverty					
Distance from the weather station	at most 40 kms		at most 20 kms		at most 10 kms		at most 40 kms		at most 20 kms		at most 10 kms	
	Chronic total	Transient total	Chronic total	Transient total	Chronic total	Transient total	Chronic Food	Transient Food	Chronic Food	Transient Food	Chronic Food	Transient Food
Attributes in 2003												
Household head age	-0.199***	-0.047	-0.199***	-0.059*	-0.211***	-0.064	-0.124***	0.01	-0.146***	-0.014	-0.163***	-0.018
	[0.042]	[0.034]	[0.043]	[0.035]	[0.052]	[0.044]	[0.031]	[0.029]	[0.033]	[0.030]	[0.041]	[0.038]
Married household head	-0.121	-0.125	-0.178	-0.165	-0.322**	-0.284**	0.006	0.024	-0.053	-0.049	-0.126	-0.086
	[0.131]	[0.107]	[0.138]	[0.109]	[0.159]	[0.130]	[0.098]	[0.089]	[0.102]	[0.092]	[0.123]	[0.114]
College graduate household head	-0.983***	-0.543***	-0.971***	-0.560***	-1.041***	-0.632***	-0.699***	-0.09	-0.700***	-0.125	-0.726***	-0.194**
	[0.140]	[0.117]	[0.145]	[0.121]	[0.186]	[0.145]	[0.086]	[0.073]	[0.090]	[0.078]	[0.112]	[0.094]
Family size	0.258***	0.044	0.272***	0.045	0.312***	-0.003	0.226***	0.032	0.234***	0.044	0.258***	0.055
	[0.053]	[0.047]	[0.057]	[0.049]	[0.075]	[0.068]	[0.040]	[0.039]	[0.042]	[0.042]	[0.056]	[0.055]
Network/membership	-0.225***	-0.036	-0.248***	-0.083	-0.304***	-0.049	-0.152***	0.02	-0.150***	-0.006	-0.176***	0.042
	[0.073]	[0.063]	[0.077]	[0.066]	[0.090]	[0.077]	[0.053]	[0.051]	[0.056]	[0.054]	[0.066]	[0.063]
Demographic characteristics												
Household members age < 1	0.151	0.16	0.123	0.151	0.025	0.068	0.044	0.13	0.042	0.111	-0.007	0.068
	[0.103]	[0.115]	[0.109]	[0.116]	[0.140]	[0.149]	[0.084]	[0.090]	[0.087]	[0.093]	[0.113]	[0.113]
Household members age ≥ 1 & age < 7	0.164**	0.003	0.125*	-0.038	0.146	0.049	0.114**	-0.089	0.078	-0.118**	0.074	-0.086
	[0.070]	[0.066]	[0.073]	[0.068]	[0.094]	[0.090]	[0.052]	[0.057]	[0.054]	[0.060]	[0.071]	[0.076]
Household members age ≥ 7 & age < 15	0.048	-0.065	0.049	-0.049	0.009	-0.024	0.019	-0.152***	0.02	-0.155***	0.008	-0.185***
	[0.060]	[0.054]	[0.065]	[0.057]	[0.087]	[0.077]	[0.046]	[0.046]	[0.049]	[0.050]	[0.065]	[0.064]
Household members age ≥ 15 & age < 25	-0.122**	0.022	-0.153**	0.005	-0.162**	0.048	-0.074*	-0.01	-0.093**	-0.031	-0.073	-0.041
	[0.059]	[0.052]	[0.063]	[0.055]	[0.082]	[0.076]	[0.044]	[0.043]	[0.047]	[0.045]	[0.060]	[0.060]
Household members age ≥ 25	-0.278***	0.041	-0.297***	0.027	-0.295***	0.115	-0.186***	0.018	-0.193***	0.001	-0.203**	0.006
	[0.083]	[0.071]	[0.090]	[0.076]	[0.112]	[0.094]	[0.059]	[0.061]	[0.064]	[0.066]	[0.081]	[0.084]
Always positive asset score	-1.891***	-1.137***	-1.825***	-1.144***	-1.674***	-1.206***	-1.019***	-0.296***	-1.111***	-0.385***	-1.155***	-0.506***
	[0.329]	[0.240]	[0.344]	[0.257]	[0.402]	[0.308]	[0.137]	[0.106]	[0.157]	[0.118]	[0.195]	[0.142]
Labor market participation												
Job status of household head	0.127	0.019	0.075	-0.036	0.139	-0.023	0.083	0.028	0.007	-0.059	0.021	-0.088
	[0.116]	[0.091]	[0.121]	[0.092]	[0.158]	[0.122]	[0.083]	[0.072]	[0.086]	[0.074]	[0.111]	[0.092]
Employment of household head's spouse	-0.179*	-0.033	-0.223**	-0.04	-0.210*	-0.036	-0.115	-0.07	-0.133*	-0.029	-0.122	-0.072
	[0.101]	[0.086]	[0.105]	[0.089]	[0.122]	[0.109]	[0.076]	[0.070]	[0.078]	[0.071]	[0.091]	[0.088]
Geographic characteristics												

Areas with conflict	0.280***	0.187***	0.195**	0.085	0.429***	0.227***	0.332***	0.039	0.298***	-0.014	0.497***	0.049
	[0.075]	[0.065]	[0.079]	[0.067]	[0.099]	[0.083]	[0.057]	[0.059]	[0.060]	[0.062]	[0.075]	[0.077]
Urban	-1.124***	-0.393***	-1.044***	-0.328***	-1.300***	-0.481***	-0.919***	0.043	-0.860***	0.059	-1.052***	0.075
	[0.098]	[0.080]	[0.103]	[0.082]	[0.135]	[0.103]	[0.071]	[0.060]	[0.074]	[0.064]	[0.095]	[0.077]
Weather variables												
Dry temperature deviation	-0.041	0.034	-0.067	0.024	0.041	0.082	0.016	0.086*	-0.007	0.086*	0.071	0.124**
	[0.082]	[0.058]	[0.086]	[0.058]	[0.094]	[0.067]	[0.052]	[0.049]	[0.055]	[0.049]	[0.058]	[0.057]
Urban*Dry temperature deviation	0.454***	0.232*	0.441**	0.210*	0.463**	0.227*	0.238*	0.058	0.223*	0.052	0.264**	0.025
	[0.172]	[0.125]	[0.179]	[0.123]	[0.189]	[0.130]	[0.123]	[0.101]	[0.129]	[0.099]	[0.133]	[0.104]

*/**/*** Significant at 10/5/1% level. Figures in brackets are robust standard errors. Inverse Mills Ratio is included as a regressor.

Table 3A: GLM regression estimates using heat index deviation as weather parameter, total poverty and food poverty

	Total poverty						**Food poverty**					
Distance from the weather station	at most 40 kms		at most 20 kms		at most 10 kms		at most 40 kms		at most 20 kms		at most 10 kms	
	Chronic total	Transient total	Chronic total	Transient total	Chronic total	Transient total	Chronic Food	Transient Food	Chronic Food	Transient Food	Chronic Food	Transient Food
Attributes in 2003												
Household head age	-0.203***	-0.049	-0.201***	-0.060*	-0.210***	-0.064	-0.130***	0.007	-0.148***	-0.015	-0.164***	-0.017
	[0.042]	[0.034]	[0.043]	[0.035]	[0.053]	[0.044]	[0.031]	[0.029]	[0.033]	[0.030]	[0.041]	[0.038]
Married household head	-0.121	-0.123	-0.176	-0.162	-0.329**	-0.288**	0.002	0.024	-0.056	-0.051	-0.137	-0.091
	[0.133]	[0.107]	[0.139]	[0.109]	[0.163]	[0.130]	[0.099]	[0.089]	[0.102]	[0.092]	[0.125]	[0.114]
College graduate household head	-0.976***	-0.547***	-0.970***	-0.567***	-1.017***	-0.635***	-0.694***	-0.095	-0.700***	-0.133*	-0.712***	-0.203**
	[0.140]	[0.117]	[0.145]	[0.121]	[0.185]	[0.145]	[0.086]	[0.073]	[0.090]	[0.078]	[0.112]	[0.094]
Family size	0.256***	0.042	0.267***	0.043	0.302***	-0.006	0.226***	0.032	0.233***	0.044	0.254***	0.055
	[0.053]	[0.046]	[0.056]	[0.049]	[0.073]	[0.068]	[0.040]	[0.039]	[0.042]	[0.042]	[0.055]	[0.056]
Network/membership	-0.234***	-0.026	-0.267***	-0.076	-0.310***	-0.036	-0.161***	0.027	-0.159***	0.001	-0.177***	0.059
	[0.071]	[0.062]	[0.076]	[0.065]	[0.088]	[0.075]	[0.052]	[0.050]	[0.055]	[0.052]	[0.064]	[0.060]
Demographic characteristics												
Household members age < 1	0.145	0.154	0.122	0.147	0.037	0.07	0.04	0.126	0.044	0.107	0.003	0.061
	[0.102]	[0.115]	[0.108]	[0.116]	[0.135]	[0.148]	[0.083]	[0.090]	[0.086]	[0.093]	[0.110]	[0.114]
Household members age ≥ 1 & age < 7	0.165**	0.006	0.127*	-0.036	0.151*	0.051	0.112**	-0.088	0.078	-0.117*	0.073	-0.083
	[0.070]	[0.066]	[0.072]	[0.068]	[0.092]	[0.090]	[0.052]	[0.057]	[0.054]	[0.060]	[0.070]	[0.076]
Household members age ≥ 7 & age < 15	0.051	-0.062	0.054	-0.047	0.032	-0.018	0.02	-0.151***	0.024	-0.153***	0.021	-0.185***
	[0.059]	[0.054]	[0.064]	[0.057]	[0.086]	[0.077]	[0.045]	[0.046]	[0.048]	[0.050]	[0.064]	[0.065]

Household members age ≥ 15 & age < 25	-0.123**	0.021	-0.152**	0.006	-0.151*	0.05	-0.076*	-0.01	-0.092**	-0.031	-0.068	-0.042
	[0.058]	[0.052]	[0.063]	[0.054]	[0.080]	[0.075]	[0.044]	[0.043]	[0.046]	[0.045]	[0.059]	[0.060]
Household members age ≥ 25	-0.273***	0.042	-0.289***	0.029	-0.281**	0.119	-0.184***	0.016	-0.189***	0.00	-0.195**	0.004
	[0.083]	[0.071]	[0.090]	[0.076]	[0.111]	[0.094]	[0.058]	[0.060]	[0.064]	[0.066]	[0.080]	[0.084]
Always positive asset score	-1.896***	-1.137***	-1.816***	-1.137***	-1.651***	-1.193***	-1.020***	-0.293***	-1.104***	-0.376***	-1.139***	-0.498***
	[0.327]	[0.240]	[0.342]	[0.258]	[0.397]	[0.309]	[0.135]	[0.106]	[0.156]	[0.118]	[0.192]	[0.142]
Labor market participation												
Job status of household head	0.123	0.02	0.076	-0.035	0.124	-0.023	0.076	0.028	0.003	-0.06	0.009	-0.084
	[0.117]	[0.091]	[0.122]	[0.092]	[0.159]	[0.122]	[0.084]	[0.072]	[0.087]	[0.074]	[0.112]	[0.093]
Employment of household head's spouse	-0.186*	-0.032	-0.231**	-0.038	-0.230*	-0.035	-0.118	-0.068	-0.136*	-0.027	-0.132	-0.068
	[0.102]	[0.086]	[0.107]	[0.089]	[0.124]	[0.109]	[0.077]	[0.071]	[0.079]	[0.072]	[0.093]	[0.088]
Geographic characteristics												
Areas with conflict	0.278***	0.183***	0.186**	0.078	0.405***	0.191**	0.330***	0.034	0.293***	-0.022	0.467***	0.009
	[0.074]	[0.065]	[0.078]	[0.067]	[0.093]	[0.079]	[0.056]	[0.059]	[0.060]	[0.062]	[0.071]	[0.075]
Urban	-1.280***	-0.429***	-1.176***	-0.345***	-1.582***	-0.551***	-1.036***	0.042	-0.957***	0.068	-1.246***	0.093
	[0.113]	[0.093]	[0.115]	[0.093]	[0.156]	[0.119]	[0.082]	[0.071]	[0.083]	[0.072]	[0.107]	[0.090]
Weather variables												
Heat index deviation	-0.026	0.005	-0.02	0.008	-0.025	0.015	-0.003	0.027*	-0.009	0.029*	-0.008	0.036**
	[0.028]	[0.018]	[0.028]	[0.018]	[0.031]	[0.019]	[0.017]	[0.015]	[0.018]	[0.015]	[0.019]	[0.017]
Urban*Heat index deviation	0.175***	0.051	0.168***	0.038	0.232***	0.075*	0.122***	0.004	0.110***	-0.004	0.159***	-0.01
	[0.048]	[0.038]	[0.049]	[0.038]	[0.055]	[0.039]	[0.034]	[0.030]	[0.035]	[0.030]	[0.040]	[0.032]

*/**/*** Significant at 10/5/1% level. Figures in brackets are robust standard errors. Inverse Mills Ratio is included as a regressor.

Table 4A: GLM regression estimates using rainfall deviation as weather parameter, total poverty and food poverty

	Total poverty						**Food poverty**					
Distance from the weather station	at most 40 kms		at most 20 kms		at most 10 kms		at most 40 kms		at most 20 kms		at most 10 kms	
	Chronic total	Transient total	Chronic total	Transient total	Chronic total	Transient total	Chronic Food	Transient Food	Chronic Food	Transient Food	Chronic Food	Transient Food
Attributes in 2003												
Household head age	-0.202***	-0.054*	-0.198***	-0.067**	-0.197***	-0.071*	-0.126***	0.003	-0.148***	-0.024	-0.160***	-0.031
	[0.041]	[0.033]	[0.043]	[0.033]	[0.052]	[0.042]	[0.030]	[0.029]	[0.032]	[0.031]	[0.039]	[0.039]
Married household head	-0.076	-0.071	-0.126	-0.126	-0.289*	-0.256**	0.015	0.048	-0.04	-0.041	-0.145	-0.077
	[0.124]	[0.101]	[0.135]	[0.105]	[0.156]	[0.122]	[0.093]	[0.084]	[0.099]	[0.088]	[0.120]	[0.109]
College graduate household head	-0.990***	-0.547***	-0.989***	-0.587***	-1.078***	-0.692***	-0.687***	-0.103	-0.692***	-0.141*	-0.735***	-0.213**

	[0.135]	[0.115]	[0.145]	[0.122]	[0.185]	[0.147]	[0.084]	[0.072]	[0.091]	[0.079]	[0.111]	[0.094]
Family size	0.254***	0.035	0.275***	0.044	0.321***	-0.001	0.212***	0.03	0.227***	0.035	0.253***	0.039
	[0.051]	[0.045]	[0.056]	[0.047]	[0.072]	[0.065]	[0.038]	[0.037]	[0.041]	[0.040]	[0.053]	[0.052]
Network/membership	-0.151**	-0.028	-0.149**	-0.055	-0.190**	-0.008	-0.095*	-0.032	-0.077	-0.05	-0.094	-0.014
	[0.069]	[0.056]	[0.075]	[0.060]	[0.089]	[0.068]	[0.051]	[0.045]	[0.055]	[0.049]	[0.065]	[0.056]
Demographic characteristics												
Household members age < 1	0.188*	0.163	0.157	0.168	0.089	0.118	0.116	0.105	0.112	0.112	0.099	0.079
	[0.099]	[0.110]	[0.105]	[0.111]	[0.130]	[0.137]	[0.082]	[0.086]	[0.087]	[0.091]	[0.110]	[0.110]
Household members age ≥ 1 & age < 7	0.124*	-0.027	0.077	-0.078	0.093	-0.014	0.096*	-0.099*	0.044	-0.124**	0.035	-0.098
	[0.069]	[0.062]	[0.071]	[0.065]	[0.090]	[0.084]	[0.050]	[0.054]	[0.052]	[0.057]	[0.067]	[0.073]
Household members age ≥ 7 & age < 15	0.047	-0.055	0.038	-0.051	-0.009	-0.03	0.028	-0.146***	0.025	-0.142***	0.01	-0.161***
	[0.058]	[0.052]	[0.064]	[0.056]	[0.084]	[0.074]	[0.044]	[0.044]	[0.048]	[0.049]	[0.063]	[0.062]
Household members age ≥ 15 & age < 25	-0.140**	0.018	-0.176***	0.003	-0.201**	0.041	-0.075*	-0.013	-0.098**	-0.022	-0.088	-0.027
	[0.058]	[0.051]	[0.063]	[0.053]	[0.082]	[0.072]	[0.043]	[0.041]	[0.045]	[0.044]	[0.057]	[0.057]
Household members age ≥ 25	-0.269***	0.05	-0.298***	0.02	-0.300***	0.101	-0.163***	0.022	-0.180***	0.009	-0.191**	0.019
	[0.079]	[0.068]	[0.087]	[0.073]	[0.107]	[0.089]	[0.057]	[0.058]	[0.062]	[0.064]	[0.077]	[0.082]
Always positive asset score	-2.016***	-1.189***	-1.929***	-1.147***	-1.842***	-1.239***	-1.062***	-0.216**	-1.137***	-0.263**	-1.214***	-0.338**
	[0.337]	[0.242]	[0.353]	[0.258]	[0.417]	[0.311]	[0.133]	[0.102]	[0.151]	[0.117]	[0.186]	[0.140]
Labor market participation												
Job status of household head	0.124	-0.008	0.058	-0.07	0.135	-0.032	0.087	0.035	0.002	-0.042	0.035	-0.049
	[0.111]	[0.086]	[0.115]	[0.086]	[0.149]	[0.116]	[0.079]	[0.071]	[0.082]	[0.074]	[0.104]	[0.095]
Employment of household head's spouse	-0.244**	-0.069	-0.295***	-0.058	-0.278**	-0.031	-0.138*	-0.028	-0.176**	0.011	-0.155*	-0.008
	[0.100]	[0.086]	[0.104]	[0.089]	[0.123]	[0.106]	[0.075]	[0.070]	[0.078]	[0.072]	[0.093]	[0.087]
Geographic characteristics												
Areas with conflict	0.379***	0.304***	0.285***	0.179**	0.304***	0.223***	0.349***	0.07	0.337***	-0.015	0.360***	0.008
	[0.084]	[0.071]	[0.098]	[0.078]	[0.100]	[0.084]	[0.062]	[0.065]	[0.071]	[0.073]	[0.074]	[0.077]
Urban	-1.259***	-0.409***	-1.175***	-0.363***	-1.460***	-0.389***	-0.982***	0.042	-0.940***	0.026	-1.122***	0.063
	[0.119]	[0.103]	[0.130]	[0.113]	[0.159]	[0.135]	[0.084]	[0.072]	[0.093]	[0.085]	[0.114]	[0.108]
Weather variables												
Rainfall deviation	0.428***	0.507***	0.359*	0.289*	-0.448	0.349	0.113	0.236*	0.188	0.013	-0.368	0.07
	[0.154]	[0.146]	[0.190]	[0.164]	[0.319]	[0.253]	[0.123]	[0.127]	[0.147]	[0.147]	[0.242]	[0.226]
Urban*Rainfall deviation	2.082***	0.673	1.909***	0.739	2.551***	0.333	1.490***	-0.316	1.533***	-0.03	1.871***	-0.285
	[0.503]	[0.443]	[0.523]	[0.466]	[0.664]	[0.602]	[0.363]	[0.297]	[0.393]	[0.353]	[0.509]	[0.503]

*/**/*** Significant at 10/5/1% level. Figures in brackets are robust standard errors. Inverse Mills Ratio is included as a regressor.

DAG components approach (Duclos, Araar and Giles, 2010)

The components approach measures chronic and transient poverty in relation to the intertemporal mean of per capita welfare indicator (Jalan and Ravallion, 1998). Let the poverty gap be

$$g_{ij} = (1 - y_{ij})_+ \qquad 1$$

where y_{ij} is the income of individual i at time j and is normalized by the poverty line in time j, then $g = (g_1, g_2, \cdots, g_n)$ and $g_i = (g_{i1}, g_{i2}, \cdots, g_{it})$ are the corresponding poverty gaps. Based on the Foster, Greer, and Thorbecke (1984) additively decomposable poverty indices, the aggregate poverty gap is

$$P_\alpha(g) = (nt)^{-1} \sum_{i=1}^{n} \sum_{j=1}^{t} g_{ij}^{\ \alpha} \qquad 2$$

and the individual poverty gap is

$$P_\alpha(g_i) = t^{-1} \sum_{j=1}^{t} g_{ij}^{\alpha} \qquad 3$$

When $\alpha = 0,1,2$, we get the typical headcount index, average poverty gap and the squared poverty gap, respectively. Jalan & Ravallion (1998) use the $P_\alpha(g)$ to construct the measures for chronic and transient poverty. Let

$$\hat{\bar{y}}_i = t^{-1} \sum_{j=1}^{t} y_{ij} \qquad 4$$

be the individual i's estimated permanent income for t periods. Individual i's chronic poverty is then

$$P_\alpha(y_i) = t^{-1} \sum_{j=1}^{t} (1 - \hat{\bar{y}})_+^{\alpha} \qquad 5$$

and aggregate chronic poverty is

$$P_\alpha(y) = n^{-1} \sum_{i=1}^{n} (1 - \hat{\bar{y}})_{i+}^{\alpha} \qquad 6$$

The aggregate transient poverty is just the difference between the aggregate and chronic poverty:

$$P_\alpha^T(y) = P_\alpha(g) - P_\alpha(y) \qquad 7$$

Transient poverty is therefore the variability in consumption relative to the mean welfare indicator overtime. Chronic poverty is the poverty that persists in mean consumption overtime.

Applying this approach, Jalan and Ravallion (2000) and Haddad and Ahmed (2003) find that transient and chronic poverty are explained by different sets of factors. Later, Duclos, Araar & Giles (2010) have noted some problems with the JR approach. One, the total poverty $P_\alpha(g)$ decreases with the aversion to poverty α in the JR approach. Since chronic poverty is the poverty that persists in mean consumption overtime, households who are poor most of the time may not be chronically poor if these households have a very high income level in the one period they are observed to be non-poor. DAG improved on the JR approach by developing a new set of poverty measures that addresses these problems.

DAG approach utilizes the equally-distributed equivalent (EDE) poverty gap, $\Gamma_\alpha(g) = P_\alpha(g)^{1/\alpha}$. EDE is the level of individual ill-fare which, if assigned equally to all individuals and in all periods, would produce the same poverty measure as that generated by the distribution g of normalized poverty gaps. The total poverty is then

$$P_\alpha(g) = n^{-1}\sum_{i-1}^{n}\Gamma_\alpha(g)^\alpha \qquad 8$$

which increases with the inequality in the distribution of gaps for $\alpha > 1$. Let

$$\gamma_\alpha(g_i) = \left(t^{-1}\sum_{j=1} g_{ij}^\alpha \right)^{1/\alpha} \qquad 9$$

be the EDE poverty gap for individual i. The transient poverty for an individual, interpreted as the amount the individual i would pay to eliminate variability in his poverty status, is

$$\theta_\alpha(g_i) = \gamma_\alpha(g_i) - \gamma_1(g_i) \qquad 10$$

where the last term is the poverty gap. The aggregate transient cost is given by

$$\Gamma_\alpha^T(g) = n^{-1}\sum_{i=1}^{n}\theta_\alpha(g_i) \qquad 11$$

which is interpreted as the cost of inequality within individuals. Chronic poverty is the residual part

$$\Gamma^*(g) = \Gamma_\alpha(g) - \Gamma_\alpha^T(g) \qquad 12$$