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When It Rains, It Pours? Analyzing the Rainfall Shocks-Poverty Nexus in the Philippines

Connie Bayudan-Dacuycuy and Lora Kryz C. Baje

CONTACT US:

RESEARCH INFORMATION DEPARTMENT
Philippine Institute for Development Studies

18th Floor, Three Cyberpod Centris - North Tower
EDSA corner Quezon Avenue, Quezon City, Philippines

publications@mail.pids.gov.ph
(+632) 372-1291/(+632) 372-1292

https://www.pids.gov.ph

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Abstract

Weather is an integral part of our life and weather shocks can have severe implications on welfare. Given the evidence that points to climate change resulting in altered patterns of weather parameters and given that the Philippines is one of the most vulnerable countries to climatic shifts, this paper aims to contribute to poverty studies in the Philippines by analyzing the poverty-rainfall shock nexus. The paper finds that rainfall shocks affect wages and income, which in turn, affect chronic total and chronic food poverty. Given that LGUs are in the forefront of the country's fight against the adverse effects of climate change, some policy directions are forwarded so that LGUs can better address issues on climate change. These include the development of climate-smart agriculture and the tapping of additional funding sources for projects on climate change adaptation. Partly due to exclusion errors, there are deserving households that are not part of the 4Ps. Suggestions are forwarded not only to improve the 4Ps' data management to accommodate vertical scale-up but to ensure that the program covers deserving beneficiaries as well. Policy directions on the development of adaptive social protection are also forwarded.

Keywords: rainfall shock, components approach, chronic poverty, transient poverty, Philippines

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When it rains, it pours? Analyzing the rainfall shocks-poverty nexus in the Philippines

Connie Bayudan-Dacuycuy and Lora Kryz Baje*

1. Introduction

The Philippines has a long history of battle against poverty through the government's various anti-poverty programs. Despite these efforts, the country has missed its Millennium Development Goal (MDG) target of halving its 1990 poverty level by 2015. As of 2016, the proportion of population below national poverty threshold is at 25%, 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, Intal 1994; Balisacan and Pernia, 2002; Balisacan 2003a, 2003b) and as such, only identify the poor at a given point in time. These studies are not able to analyze chronic poverty, which is found to be a major constraint in achieving high levels of sustained growth (Aldaba 2009). This highlights the importance of conducting additional researches on chronic poverty.

Recently, climate change has attracted attention from national and international bodies especially in the Philippines, which due to its topographic location, is at risk to natural disasters such as tropical cyclones and storm surge and has experienced extreme shifts in weather patterns and slow-onset extreme climate shifts such as EL Nino and La Nina. The country is the fifth most risk-prone country in the world in the period 1994–2013 (Asian Development Bank 2017) and one of the top ten countries most affected by extreme weather events in terms of fatalities and economic losses (Eckstein, Künzel and Schäfer 2018).

Weather shocks can easily affect the poor to the extent that they are faced by constraints in terms of credit, savings, and human and social capital. In fact, even modest changes in seasonality of rainfall, temperature, and wind patterns can push transient poor and marginalized people into chronic poverty as they lack access to credit, climate forecasts, insurance, government support, and effective response options, such as asset diversification (Olsson et al, 2014). In addition, climate change will make social protection goals harder to achieve, and will change the types of risks that poor people face (Kuriakose et al. 2012).

Given this backdrop, this paper aims to contribute to poverty studies in the Philippines by analyzing the effects of weather shocks 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 Deschenes and Greenstone 2007), which in turn, affects household welfare through reduced consumption. When consumption is measured against a threshold over a period of time, the analysis of chronic and transient poverty-weather shocks nexus forms part of relevant evidence needed to craft policies and programs for poverty reduction and social protection.

*Senior Research Fellow and Research Analyst II, respectively. Philippine Institute for Development Studies. Email: cdacuycuy@mail.pids.gov.ph and lbaje@mail.pids.gov.ph

Two, previous studies have established that chronic poverty is affected by shocks in the labor market and transient poverty is affected by extreme climate shifts such as El Nino and La Nina (Bayudan-Dacuycuy and Lim 2013, 2014). It is also important to analyze how different types of poverty are affected by weather shocks since around 29% of total employment in the Philippines 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. Increasing informal settlers also contributes to urban poverty.

Some studies on weather shocks in the Philippines are related to consumption (Safir et al. 2013; Bayudan-Dacuycuy 2017). However, a much more informative research involves the understanding of how consumption relative to a threshold (e.g. poverty) respond to weather shocks. To our knowledge, none so far has systematically analyzed this issue in the Philippines and this is a gap that the current research attempts to address. Given that the Philippines is at risk to natural disasters and is one of the countries that are most vulnerable to the adverse effects of climate change, it is paramount to understand how weather events can contribute to poverty. Doing so will provide better narratives to crafting policies on poverty and social protection.

This paper is organized as follows: section 2 provides a brief literature review, section 3 discusses the research framework, section 4 discusses the data and data sources, section 5 discusses the results, and section 6 summarizes and concludes.

2. Review of related literature

Studies on poverty in the Philippines abound and common to these earlier studies is the use of cross-section dataset (Intal 1994; Balisacan and Pernia 2002; Balisacan 2003), which allow the identification of poor at a given point in time only. Hence, there are no narratives that discuss the movement of households in and out of poverty. In developed economies, the study of poverty dynamics has been at the forefront of research as early as the 1970s (Lillard and Willis 1978) and there is a healthy debate on 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 (Lillard and Willi 1978; Duncan and Rodgers 1991). 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).

However, the spells approach has elements of arbitrariness in computing the transitory poverty rate since a household with two out of six poverty experiences and a household with five out of six poverty experiences are both transitory poor (Haddad and Ahmed 2003). In addition, there are households that are below but very near the poverty threshold. Owing to this, the components approach has been developed, the earlier version of which measures transient poverty as the variability in consumption relative to the mean welfare indicator overtime while chronic poverty is the poverty that persists in mean consumption overtime (Jalan and Ravallion, 1998, JR).

Later, Duclos, Araar and Giles (2010, DAG) have noted some problems with the JR approach. One, the total poverty decreases with the aversion to poverty in the JR approach. Two, 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.

In recent years, there are efforts in the Philippines to make some datasets, specifically the 2003, 2006, and 2009 Family Income and Expenditure Survey, longitudinal. This has paved the way for the analysis of poverty dynamics in the country such as Mina and Imai (2016) who use a three-level random coefficient model and find that majority of the poor and the non-poor are vulnerable to unobservable shocks.

Bayudan-Dacuycuy and Lim (2013) use the DAG approach to analyze chronic and transient poverty in the country and find that chronic poverty is higher than transient poverty. Looking at the determinants, the study finds that shocks to labor market such as job loss or income reduction affect chronic poverty while natural disasters such as droughts affect transient poverty. In addition, a higher dependency burden due to many young children positively affects chronic poverty but not transient poverty. These results are corroborated by Bayudan-Dacuycuy and Lim (2014) using a simple spells approach.

There are studies in the Philippines that analyze the effects of extreme weather events on inequality (see for example, Bayani-Arias and Palanca-Tan 2017). There are also studies that attempt to relate weather events to household welfare. Safir et al (2013) analyze the effects of rainfall shocks on the consumption of Filipino households and finds that negative rainfall shocks decrease food consumption. In addition, the consumption of households close to a highway or to a fixed-line phone appears to be fully protected from the impact of negative rainfall shocks. Bayudan-Dacuycuy (2017) finds that income is endogenous to more consumption expenditures when tropical cyclones are used as instruments than when heat index deviation is employed. This indicates that the effects of unobservable characteristics, like risk aversion toward shocks, are heightened in more destructive weather events such as tropical cyclones and the speed of adjustment to these shocks could lead to a faster revision of consumption patterns.

3. Research framework: Consumption, income, and shocks

How can a rainfall shock affect poverty? To answer this, we draw from the standard household utility maximization problem: $\max U(x)\, subject\ \ to\, px = Y$ where x and p are consumption and price of good x and Y is income. Maximization of this problem leads to a demand function $x = x(p, Y; z)$ where z is a vector of household characteristics. In the literature, consumption is a measure of welfare and is based on Samuelson's (1974) *money metric utility*, which measures levels of living by the money required to sustain them. The starting point is the standard utility maximization problem where households choose goods to maximize utility subject to a budget constraint.

Deaton and Zaidi (2002) expound that "Consumer preferences over goods are thought of as a system of indifference curves that can be labeled by taking a set of reference prices and calculating the amount of money needed to reach a utility level. The exact calculation of money metric utility requires information on preferences, which can be approximated from the cost function. By the known Shepard's Lemma, the derivative of this cost function with respect to prices is the quantity consumed." Building up on this, several studies have used household consumption as an indicator of household welfare (see for example, Deaton 1997). Due to the increasing awareness on the adverse effects of climate change and of the concomitant variabilities in weather patterns, there is a growing literature that analyzes the effects of climate/weather on various macroeconomic outcomes, such as output growth, labor productivity, conflict and political stability, and microeconomic outcomes such children's health, mortality, and IQ, and their labor market participation in later-life (see Dell et al 2014) for a comprehensive review).

There are many studies that investigate the weather shock-household consumption nexus (Thomas, Christiansen, Do and Trung 2002; Skoufias and Coady 2007; Skoufias, Katayama, and Essama-Nssa 2012).[1] However, a much more informative research involves the understanding of how consumption relative to a threshold (e.g. poverty) respond to weather shocks. While there are studies that investigate the effects of weather shocks on poverty abroad (Skoufias, Katayama, and Essama-Nssah 2012; Baez, Lucchetti, Genoni, and Salazar 2015), one is yet to be undertaken in the Philippines.

Weather shocks are likely to result in the reduction of wages and salaries and this is expected to be observed for informal workers, who comprise around 35% of the total employed in the country. For these workers, a day missed in the labor market is forgone earnings. Entrepreneurial income is likely to be affected in a similar vein. A rainfall shock, for example, interrupts the operation of enterprises through disruption in the flow of inputs and, hence, supply. The reduction in wages and income is likely to reduce welfare through the reduction in the households' expenditure per capita. In turn, the per capita expenditure can fall below the threshold that results in poverty.

As an empirical strategy, the following equations are simultaneously estimated:

$$Y_i = \varphi_i + \gamma rainfall\,shock + e_i \qquad (1)$$

$$poverty_i = \alpha_i + \delta \hat{Y}_i + \phi z_i + \varepsilon_i \qquad (2)$$

z refers to head's attributes such as age, education, and marital status, and household's demographic composition. It also includes regional dummies and proxies for labor market participation of the head and the spouse, which are equal to 1 if the head(spouse) is employed in all the survey years and 0 otherwise. Variables like demographic composition are averages from 2003 to 2009.

[1] While evidence points to the adverse effects of weather shocks, there is a strand of literature at the macroceconomic level that emphasizes creative destruction. In this literature, extreme weather events have positive impact on capital and output growth. For example, Skidmore and Toya (2002) find that climatic disasters are associated with higher long run economic growth while geologic disasters are negatively associated with growth while Noy and Vu (2010) show that disasters that destroy more properties and capital boost the economy in the short-run.

Y refers to wages and incomes. *Poverty* is the chronic and transient component computed using the DAG approach. Two welfare indicators are used, namely, the food expenditures (per capita) and the total expenditures (per capita). Per capita total expenditure is compared against the poverty threshold and the resulting poverty components are referred to as chronic total and transient total poverty. Per capita food expenditure is compared against the food threshold and the resulting poverty components are referred to as chronic food and transient food poverty.

Rainfall shock is a binary variable equal to 1 if 2003-2009 rainfall is 1 standard deviation away from the normal rainfall (30-year average from 1970-2000) and equal to 0 otherwise. Binary variables to represent 1 and 2 standard deviations below the normal rainfall are also created following similar procedures. This is a standard proxy for weather shocks used in the literature (see for example, Skoufias, Katayama, and Essama-Nssah 2012; and Baez, Lucchetti, Genoni, and Salazar 2015).

Since rainfall is highly localized and matching the rainfall data at the provincial level can introduce substantial measurement error, two samples are used in the estimation: households in provinces that are at most 40 and 10 kilometers away from the assigned weather stations. By doing this, results can be compared to establish that the signs and significance of key variables do not change across the most conservative (10 kilometers) to the least conservative (40 kilometers) samples.

Several specifications are explored to establish the effects of weather fluctuations on the components of poverty.[2] The final specification includes the interaction between the rural dummy and the rainfall shock. By doing this, we recognize that the effect of weather shocks may differ by geographic locations, an idea that is common in the literature. This follows the specifications of Skoufias et al. (2011) where rainfall shocks are interacted with household attributes to assess whether the effects of shocks differ among different populations. This is also consistent with Safir et al. (2013) who have established the welfare effects of climatic variability in the rural Philippines. In other countries, 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 while Levine and Yang (2014) find deviations from mean local rainfall are positively associated with district-level rice output in Indonesia. To test and correct for attrition bias, a problem where samples collected become smaller in succeeding years, the final specification also includes an Inverse Mills Ratio (IMR) computed following the procedure outlined in Bayudan-Dacuycuy and Lim (2013).

4. Data and sources

4.1 Family Income and Expenditure Survey (FIES)

This research uses the Family Income and Expenditure Survey (FIES) in 2003, 2006, and 2009, which are collected by the Philippine Statistics Authority (PSA). FIES can be merged to form a panel dataset since there is a master sample based on the results of the Census of

[2] Specification 1 includes the proxy for rainfall shocks only and results show that rainfall shocks significantly explain chronic and transient poverty. Specification 2 enhances specification 1 by including the squared term of rainfall shocks 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.

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*[3], enumeration area, sample housing unit serial number and household control number. There are 6311 samples that are common to the three datasets.

An issue that needs to be addressed in using this panel data is that households are the units of observation. Hence, 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. This means that the age difference of the household head in 2003 and 2006 datasets (2006 and 2009) datasets should be either two or three. There are 2715 samples left when these additional restrictions have been imposed.

FIES follows 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. Therefore, three sets of estimations are done, which separately make use of weights in 2003, 2006, and 2009.

Wage and its components, agricultural and non-agricultural, are directly extracted from the FIES datasets. On the other hand, entrepreneurial incomes are aggregated into agriculture, industry, and services. Agriculture incomes include incomes from entrepreneurial activities in farming, poultry, fishery, and forestry. Industrial incomes include incomes from trade, manufacturing, and mining while services incomes include incomes from communication, transportation, construction, and activities not elsewhere classified. All wages and incomes are expressed in logarithms of the real per capita values.

4.2 Weather data

Average rainfall data (in millimeters) are collected by the Philippine Atmospheric and Geophysical Astronomical Services Administration (PAGASA) weather stations spread across the Philippines. To map the rainfall data with the FIES dataset, the province of residence is used as the merging variable. There are 83 provinces in the FIES dataset.

The rainfall dataset has the following features: First, there are several provinces that host multiple weather stations. Second, there are several provinces that have no weather station. In merging the PAGASA dataset with the 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. To address the

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

second feature and 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 are dropped out of the sample and this translates to a reduction of 658 households.

Table 1A in the appendix provides the mapping of the respective weather stations to provinces and cities. The first column lists the provinces in 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[4] and the ones that are the closest are listed in the table. 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.

4.3 Some descriptive statistics

From table 1, chronic total poverty accounts for the large portion of total poverty. At the national level, chronic poverty comprises 92% of the total poverty. It accounts for 93% of total poverty in rural areas and for 88% of total poverty in urban areas. Similar observations are noted on figures pertaining to the food expenditure as the welfare indicator.

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

	Per capita expenditure against poverty threshold (Total)			Per capita food expenditure against food threshold (Food)		
	Observations		% of total poverty	Observations		% of total food poverty
National						
Total poverty	2,675	17.93		2,675	26.98	
Chronic		16.53	92		24.95	92
Transient		1.40	8		2.04	8
Rural						
Total poverty	1,672	23.74		1,672	33.35	
Chronic		22.09	93		31.31	94
Transient		1.65	7		2.04	6
Urban	1,003	8.25		1,003	16.37	
Total poverty		7.27	88		14.34	88
Chronic		0.99	12		2.03	12
Transient						

Authors' calculations based on the merged 2003-20009 FIES dataset.

Table 2 presents the chronic and transient poverty statistics based on some household attributes. Households whose heads are male, married, and have no college degree have higher chronic total poverty. Looking at demographic compositions, households with high

4 Computed using *http://distancecalculator.globefeed.com/Philippines_Distance_Calculator.asp*

dependency burden have higher chronic total poverty. This is shown in the high chronic total poverty of households with many young members. In terms of geographical location, households in rural areas have higher chronic total poverty than those in urban areas. Households in MIMAROPA, Zamboanga Peninsula, Northern Mindanao, Davao Region, CARAGA, and Autonomous Region of Muslim Mindanao are among the households with high chronic total poverty (between 87-89%). Households in the NCR have the lowest chronic total poverty (64%), followed by CAR, Central Luzon, and CALABARZON (72-76%). Households that experience rainfall shocks, especially the 1 SD above the normal rainfall, have higher chronic total poverty. Looking at chronic food poverty, similar trends are observed although the magnitude is higher by 2-3 percentage points.

Table 2: Chronic and transient poverty (% of total poverty), by socioeconomic characteristics

	Per capita expenditure against poverty threshold		Per capita food expenditure against food threshold	
	Chronic	Transient	Chronic	Transient
Household Head Sex				
Male	83.69	16.31	85.66	14.34
Female	76.68	23.32	79.3	20.7
Civil status of household head				
Single/Widowed/Divorced	78.46	21.54	81.1	18.9
Married	83.61	16.39	85.49	14.51
Educational attainment of household head				
Less than college graduate	83.79	16.21	86.48	13.52
At least college graduate	74.98	25.02	75.87	24.13
Ave. number of household members, less than 1 year old				
0	83	17	84.87	15.13
1	84.88	15.12	87.34	12.66
Ave. number of household members, between 1 and 6 years old				
0	80.26	19.74	82.22	17.78
1	83.42	16.58	86.04	13.96
2	88.46	11.54	90.76	9.24
3	94.01	5.99	96.55	3.45
4	99.26	0.74	99.45	0.55
Job status of household head				
Never had a job	79.74	20.26	79.21	20.79
Always had a job	83.59	16.41	86.12	13.88
Employment of household head's spouse				
Never had a job	83.54	16.46	85.46	14.54
Always had job	81.1	18.9	83.15	16.85
Geographical location				
Rural	84.99	15.01	87.57	12.43
Urban	76.86	23.14	78.73	21.27
Region I - Ilocos Region	82.18	17.82	85.15	14.85

Region II- Cagayan Valley	80.25	19.75	83.17	16.83
Region III - Central Luzon	73.72	26.28	75.84	24.16
Region IV A - CALABARZON	75.7	24.3	81.22	18.78
Region IV B - MIMAROPA	86.95	13.05	92.19	7.81
Region V - Bicol Region	85.02	14.98	89.02	10.98
Region VI - Western Visayas	79.31	20.69	82.47	17.53
Region VII - Central Visayas	85.54	14.46	87.59	12.41
Region VIII - Eastern Visayas	84.31	15.69	86	14
Region IX - Zamboanga Peninsula	88.85	11.15	90.91	9.09
Region X - Northern Mindanao	87.07	12.93	87.17	12.83
Region XI - Davao Region	87.69	12.31	87.91	12.09
Region XII - SOCCSKSARGEN	82.87	17.13	80.99	19.01
National Capital Region	64.32	35.68	64.36	35.64
Cordillera Administrative Region	72.24	27.76	78.81	21.19
Autonomous Region of Muslim Mindanao	89.11	10.89	94.89	5.11
CARAGA	87.76	12.24	89.78	10.22
Experience rainfall shock: 1 SD from the normal rainfall				
0	83.25	16.75	85.23	14.77
1	84.4	15.6	88.41	11.59
Experience rainfall shock:-1 SD from the normal rainfall				
0	82.91	17.09	85.11	14.89
1	85.28	14.72	86.18	13.82
Experience rainfall shock:-2 SD from the normal rainfall				
0	83.26	16.74	85.25	14.75
1	83.41	16.59	85.61	14.39

Authors' calculations based on the merged 2003-20009 FIES dataset.

5. Discussion of results

First-stage estimates using instrumental variable regressions are presented in the upper panel of table 3.[5] Since each of the rainfall shock are interacted with the rural dummy, the effects of each of the rainfall shocks in the rural areas are isolated by testing whether the linear combinations of these two variables are equal to zero. Results are presented in the lower panel of table 3. It can be noted that negative rainfall shocks decrease wages in rural areas more than it does in urban areas (columns 1 and 2). Agricultural wage in rural areas decreases with both positive (1 SD above the normal rainfall) and negative rainfall shocks (2 SD below the normal rainfall). Among the rainfall shocks, a 2 SD below the normal rainfall have the highest adverse effect on agricultural wages. However, this can be observed only for observations that are at most 10 kilometers away from the weather stations. This likely reflects the fact that rainfall is highly localized so that the effects of rainfall shocks on agricultural wages are isolated in specific areas. Non-agricultural wages decrease with

5 While three sets of estimations are done separately using weights in the 2003, 2006, and 2009 FIES, results presented here are estimates using the 2009 weights. Results across weights are relatively similar and estimates using the latest weights are used due to space considerations. The full results are available from the corresponding author upon request.

rainfall shocks as well (columns 5 and 6). While both negative rainfall shocks have significant effects on non-agricultural wages, a 2 SD below the normal rainfall has the bigger impact and this result is robust in observations that are at most 10 and 40 kilometers away from the weather stations.

Looking at the effects of rainfall shocks on households' entrepreneurial income, income from the services sector decreases with a 1 SD below the normal rainfall in rural areas and this effect is observed in observations that are at most 10 and 40 kilometers away from the weather stations. Income from industry decreases with rainfall shocks as well. Unlike income from the services sector, income from the industrial sector is affected by both positive and negative rainfall shocks. Among these shocks, a 1 SD above the normal rainfall has the most adverse impact. Income from the agricultural sector is negatively affected by a 1 SD deviation above the normal rainfall although this result is not robust across samples.

The effects of various types of wages and income on chronic and transient poverty are presented in table 4. Looking at the chronic total and chronic food poverty (columns 1-4), it can be seen that wage per capita (total of agriculture and non-agriculture wages) decreases both total and food poverty. A 1% increase in wages decreases both poverty measures by around 21-23%. Looking at the effects of wage components, some results are worth noting. One, chronic total poverty is affected by the agricultural wage more than by the non-agricultural wage. Chronic total poverty decreases by around 23% resulting from a 1% increase in the former while it decreases by around 16% resulting from a 1% increase in the latter. Two, agricultural wages affect chronic total poverty more than it affects chronic food poverty. On the other hand, non-agricultural wages affect chronic food poverty more than it affects chronic total poverty.

From the bottom panel of columns 1-4, test results show that the instruments did not pass the underidentification and overidentification tests for equations using the agricultural income. This puts into question the relevance and validity of the instruments. Hence, we are not going to interpret results pertaining to agricultural income. Results indicate that the effects of incomes from services sector on both chronic total and chronic food poverty are relatively similar (decline of around 11%). Similar observations in trend and magnitude are also noted on the effects of entrepreneurial incomes from the industrial sector. This is specifically observed in households that are most 10 kilometers away from the weather stations.

Looking at the transient total and transient food poverty (columns 5-8), some observations are also worth noting. One, similar to the total poverty, rainfall shocks as instruments for agriculture incomes do not pass the underidentification and overidentifcation tests. Two, results in terms of significance are not robust. This is true for transient food poverty where most estimates are not significant and/or do not pass the identification tests. Henceforth, only results that are significant and pass the identification tests are discussed. Results indicate that the effects of both wages and incomes are lower in transient total poverty than in chronic total poverty (columns 5-6 versus columns 1-2). In addition, a 1% increase in non-agricultural wages decreases transient total poverty by 1%. Similar trend and magnitude are noted on the effects of entrepreneurial incomes from both the services and industrial sectors. The effects of incomes, however, are only significantly observed in households that are most 40 kilometers away from the weather stations.

Table 3: First stage estimates, effects of rainfall shocks on wages and incomes

First stage estimates	Total wage per capita		Agricultural wage per capita		Non-agricultural wage per capita		Entrepreneurial income per capita: Services		Entrepreneurial income per capita: Industry		Entrepreneurial income per capita: Agriculture	
	10 km	40 km	10 km	40 km	10 km	40 km	10 km	40 km	10 km	40 km	10 km	40 km
Rural	-0.548***	-0.728***	-0.458**	-0.491***	-0.688***	-0.798***	-0.708**	-0.546***	-0.119	-0.663***	0.436**	0.053
	[0.125]	[0.077]	[0.206]	[0.166]	[0.141]	[0.083]	[0.333]	[0.175]	[0.276]	[0.150]	[0.194]	[0.150]
Rainfall shock												
1 SD away from normal	0.516	0.421	1.049***	1.087***	0.363	0.351	0.420	0.631	2.475***	2.117**	-0.772	-1.113*
	[0.526]	[0.517]	[0.345]	[0.368]	[0.669]	[0.653]	[0.709]	[0.638]	[0.852]	[0.915]	[0.656]	[0.607]
neg1 SD away from normal	0.21	0.053	0.393	0.557	-0.094	-0.288	0.405	0.279	1.311***	0.335	0.505	0.118
	[0.268]	[0.245]	[0.463]	[0.416]	[0.363]	[0.337]	[0.573]	[0.517]	[0.412]	[0.325]	[0.415]	[0.368]
neg2 SD away from normal	1.040*	-0.161	0.174	-0.897*	0.952*	-0.086	-1.194	-0.223	1.425	0.197	0.852***	-0.036
	[0.546]	[0.231]	[0.938]	[0.467]	[0.540]	[0.268]	[0.899]	[0.766]	[1.119]	[0.548]	[0.256]	[0.355]
Rural*1 SD away from normal	0.04	0.221	-0.556	-0.487	-0.09	-0.008	-0.219	-0.402	-1.906*	-1.324	0.657	0.938
	[0.527]	[0.513]	[0.441]	[0.427]	[0.690]	[0.668]	[0.864]	[0.793]	[1.001]	[1.056]	[0.667]	[0.627]
Rural*neg1 SD away from normal	-0.237	-0.081	-0.223	-0.408	-0.039	0.13	-0.578	-0.589	-1.186***	-0.584*	-0.710*	-0.234
	[0.253]	[0.217]	[0.453]	[0.383]	[0.324]	[0.295]	[0.532]	[0.448]	[0.415]	[0.335]	[0.414]	[0.370]
Rural*neg2 SD away from normal	-0.465	-0.029	1.741***	0.993**	-0.634	-0.206	1.850**	0.744	-1.565*	-0.519	-1.169***	0.012
	[0.464]	[0.280]	[0.473]	[0.456]	[0.474]	[0.339]	[0.862]	[0.690]	[0.923]	[0.661]	[0.316]	[0.343]
N	867	1407	357	566	776	1265	296	491	471	787	591	921

Test on the marginal effects of rainfall shock and rural dummy	Total wage per capita		Agricultural wage per capita		Non-agricultural wage per capita		Entrepreneurial income per capita: Services		Entrepreneurial income per capita: Industry		Entrepreneurial income per capita: Agriculture	
	10 km	40 km	10 km	40 km	10 km	40 km	10 km	40 km	10 km	40 km	10 km	40 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Rural + 1 SD away from normal = 0	-0.508	-0.507	-1.014***	-0.977**	-0.778	-0.806	-0.928	-0.948	-2.025**	-1.988*	1.092 *	0.991
	[0.514]	[0.508]	[0.372]	[0.392]	[0.677]	[0.664]	[0.791]	[0.771]	[0.967]	[1.047]	[0.641]	[0.612]
Rural + neg1 SD away from normal = 0	-0.785***	-0.809***	-0.681*	-0.899**	-0.727**	-0.668**	-1.287***	-1.135***	-1.305***	-1.248***	-0.274	-0.181
	[0.215]	[0.203]	[0.405]	[0.349]	[0.292]	[0.284]	[0.431]	[0.417]	[0.302]	[0.296]	[0.368]	[0.341]
Rural + neg2 SD away from normal = 0	-1.012**	-0.756***	1.283***	0.503	-1.322***	-1.004***	1.142	0.198	-1.684*	-1.182*	-0.116	0.065
	[0.446]	[0.271]	[0.438]	[0.431]	[0.452]	[0.330]	[0.812]	[0.673]	[0.882]	[0.643]	[0.326]	[0.315]

*/**/*** significant at 10/5/1% level. Figures in brackets are standard errors.

Table 4: Second stage estimates, effects of wages and incomes on chronic and transient poverty

	Chronic				Transient			
	Total poverty		Food poverty		Total Poverty		Food poverty	
	10 km	40 km	10 km	40 km	10 km	40 km	10 km	40 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total wage per capita	-0.208***	-0.195***	-0.212***	-0.228***	-0.005**	-0.006***	0.005**	-0.001
	[0.031]	[0.019]	[0.032]	[0.022]	[0.002]	[0.001]	[0.002]	[0.002]
Number of observations	867	1407	867	1407	867	1407	867	1407
Underidentification test§	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Overidentification test§§	0.846	0.781	0.819	0.691	0.115	0.067	0.242	0.016
Agricultural wage per capita	-0.233***	-0.244***	-0.162***	-0.202***	0.003	0.003	0.009***	0.007**
	[0.039]	[0.040]	[0.044]	[0.051]	[0.004]	[0.003]	[0.003]	[0.003]
Number of observations	357	566	357	566	357	566	357	566
Underidentification test§	0.009	0.006	0.009	0.006	0.009	0.006	0.009	0.006
Overidentification test§§	0.455	0.537	0.502	0.233	0.032	0.044	0.771	0.544
Non-agricultural wage per capita	-0.165***	-0.168***	-0.183***	-0.210***	-0.005***	-0.006***	0.003	-0.002
	[0.026]	[0.017]	[0.029]	[0.020]	[0.002]	[0.001]	[0.002]	[0.002]
Number of observations	776	1265	776	1265	776	1265	776	1265
Underidentification test§	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Overidentification test§§	0.39	0.533	0.35	0.706	0.614	0.147	0.165	0.045
Entrepreneurial income per capita: Services	-0.115***	-0.144***	-0.129***	-0.210***	-0.004	-0.009***	0.001	-0.004
	[0.027]	[0.033]	[0.036]	[0.051]	[0.003]	[0.003]	[0.003]	[0.003]
Number of observations	296	491	296	491	296	491	296	491
Underidentification test§	0.028	0.006	0.028	0.006	0.028	0.006	0.028	0.006
Overidentification test§§	0.575	0.939	0.391	0.902	0.357	0.526	0.662	0.083
Entrepreneurial income per capita: Industry	-0.105***	-0.134***	-0.110***	-0.170***	-0.003	-0.006***	0.002	0.000
	[0.024]	[0.022]	[0.025]	[0.027]	[0.002]	[0.002]	[0.002]	[0.002]
Number of observations	471	787	471	787	471	787	471	787
Underidentification test§	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Overidentification test§§	0.446	0.715	0.313	0.45	0.298	0.228	0.366	0.067
Entrepreneurial income per capita: Agriculture	0.158**	0.249	0.106**	0.153	-0.008*	-0.016	0.001	0.002
	[0.062]	[0.175]	[0.050]	[0.134]	[0.005]	[0.011]	[0.004]	[0.006]
Number of observations	591	921	591	921	591	921	591	921
Underidentification test§	0.215	0.923	0.215	0.923	0.215	0.923	0.215	0.923
Overidentification test§§	0.027	0.106	0.005	0.004	0.102	0.178	0.358	0.337

*/**/*** significant at 10/5/1% level. Figures in brackets are standard errors. Other regressors include the head's age, gender, educational attainment, and marital status; an indicator if the respondent(spouse) is always employed, indicators for the presence of underschool-age children, and regional dummies.

§p-values.Tests the null hypothesis that the equation is under-identified, $\mathrm{cov}(instrument, endogenous\,\mathrm{var}iable) = 0$. Rejection of the null implies that the instruments are relevant; that is, the instrument induces change in the endogenous variable.§§ p-values.Tests the null hypothesis that the instruments are uncorrelated with the error term, $\mathrm{cov}(instrument, error\ term) = 0$ and that the excluded instruments are correctly excluded from the estimated equation. Rejection of the null implies that the instruments are valid.

6. Summary and conclusions

This paper analyzes the effects of rainfall shocks on chronic and transient poverty in the Philippines. To do this, we follow the literature that exploits the exogeneity of rainfall shocks and use these as instruments. In this paper, proxies for rainfall shocks are constructed such that provinces that experience 1 SD above, 1 SD below, and 2 SD below the normal mean are assigned 1 and 0 otherwise. Two samples are used: households in provinces that are at most 40 and 10 kilometers away from the assigned weather stations. 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 rainfall shocks are valid instruments of various wages and incomes. In particular, both agricultural and non-agricultural wages are adversely affected by shocks although households that experience stronger rainfall shocks are more adversely affected in terms of wages. The effects of rainfall shocks on entrepreneurial incomes are also evident and are fairly robust on services and industrial incomes. In turn, wages and incomes negatively affect chronic poverty. Specifically, agricultural wage decreases chronic total poverty more than non-agricultural wages do. On the other hand, non-agricultural wage matters to chronic food poverty more than it does to chronic total poverty. Entrepreneurial incomes from services and industry have similar effects on both categories of chronic poverty. The effects of wages and incomes are not as robust as in the chronic poverty. Only the transient total poverty is observed to decrease with non-agricultural wages and entrepreneurial incomes from services and industry.

The Philippines is one of the countries that are most vulnerable to climate change. Based on PAGASA's projections using midrange emissions scenario, extreme weather events and weather shocks are likely results of climatic shift. Given these, it is imperative to provide evidence for narratives aimed at addressing the adverse effects of climatic shifts and the concomitant shocks to weather patterns. Hence, the succeeding discussion focuses on climate change adaptation and social protection.

First, there is a need for LGUs to be more active in developing and promoting climate-smart agriculture 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, making adaptation more likely to be successful.

Second, there is a need to tap additional adaptation funding that are available to the national government or to LGUs. The Philippine Development Plan 2017-2022 acknowledges that especially in LGUs, funding for climate change adaptation competes with other development priorities. However, there are some adaptation funds that remain untapped. One, 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[6]. PSF is appropriated PhP1 Billion per year. While there are a number of proposals submitted to CCC for PSF grant, only two projects are approved (one in Surigao del Sur and one in Surigao del Norte) with total requested PSF funding of around PHP 120 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.

Other than the PSF, another financing alternative is the Adaptation fund (AF), which is established under the Kyoto Protocol of the UN Framework Convention on Climate Change. AF is a direct access to international financing mechanism that enables country institutions to directly participate in the design, implementation, and monitoring of the project. To avail of the fund, the country must designate a National Implementing Entity (NIE), which once accredited will be fully responsible for program/project implementation and management. CCC can be the best national agency that can spearhead NIE and should start looking into how the country can tap this additional adaptation funding source. Proposals need to be evaluated for AF grant. This, again, 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.

Third, the government should also explore Adaptive Social Protection (ASP) initiatives. 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). One ASP initiative that can be explored is to integrate environmental protection into 4Ps. 4Ps strengthens human capital and self-sufficiency but does not explicitly address risks associated with climate change and with resulting shifts in weather patterns. Without adaptation, those who are at risk of being food poor are most vulnerable to extreme shifts in weather patterns. The program has to evolve with the needs arising from climate change. ASP can take the form of including environmental protection such as planting x number of trees each year, beach reforestation, or the management of household solid wastes, as part of 4Ps.

Fourth, the 4Ps should be continued given previous evidence that the program has been successful in strengthening the self-sufficiency of poor households through positive outcomes in education and health. However, people move in and out of poverty and there is a need to regularly assess whether existing beneficiaries are still qualified to be part of the program. In addition, 4Ps does not cover all poor people due to exclusion errors, which can also arise from misinformation and inadequate information dissemination when the 2009 *Listahanan,* or the system used by the Department of Social Welfare and Development (DSWD) to

[6] The AF has several disadvantages. 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. 61% of funds coming from bilateral donors to finance mitigation projects (1992-2018) are loans and 39% 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."

identify poor households based on proxy indicators of income for targeting 4Ps beneficiaries, was conducted (Albert and Dacuycuy 2017). Inclusion errors can also be a challenge. Albert and Dacuycuy (2017), for example, find that there are well-off families opting to live simple lives and are beneficiaries of the program. Given these, there is a need to revisit the basis of targeting and selecting 4Ps beneficiaries and to explore the complementary use of other community-based information such as those collected by the Community-based Monitoring System.

When typhoon Yolanda has struck, the existing data management and payment systems of 4Ps have accommodated emergency cash transfers and have facilitated horizontal scale-up, or the expansion of financial assistance to beneficiaries. However, weather shocks can create new packets of poverty since it affects the income of the near poor population as well. Given these, there is a need to improve the 4Ps' data management so it can accommodate vertical scale-up, or the expansion through enrollment of new beneficiaries. To do this, the DSWD can identify areas that are vulnerable to extreme weather events and maintain monitoring initiatives for non-beneficiaries but near poor and vulnerable households.

This paper is one of the few attempts to provide evidence on the role of rainfall shocks in chronic and transient poverty and is relevant given that the Philippines is one of the most vulnerable countries to climate change, which can manifest itself as weather shocks. Moving forward, there is a need for the PSA to collect a genuine panel dataset so that issues, not only in poverty, but also in inequality and mobility can be better analyzed.

At this point, we acknowledge that the paper has several limitations that future research can address. One, the paper has not analyzed the lagged effects of weather shocks. Two, weather stations are assigned to provinces that are located in or in close proximity to the provincial capital. This method can result in measurement errors. This method can result in measurement errors. Interpolation techniques, such as the Kriging interpolation technique, is one option that future research can use so that data in all weather stations are considered. Third, this paper uses the Inverse Mills Ratio, which is based on unobservable attributes, to correct for attrition bias. Future work can explore methods that use observable characteristics such as the one found in Fizgerald et al. (1998).

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APPENDIX

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

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			

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