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

Connie Bayudan-Dacuycuy and Lora Kryz Baje[1]

Weather is an integral part of our life and weather shocks can have severe implications on welfare. Given 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. Some policy directions are provided.

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

1. Introduction

Recently, climate change has attracted attention from national and international bodies especially in the Philippines. Due to its topographic location, the country is at risk to natural disasters like tropical cyclones and storm surge and has experienced extreme shifts in weather patterns and slow-onset extreme climate events such as EL Nino and La Nina. Several studies have already provided evidence that the country is one of the most vulnerable to risks and stands to lose the most from disasters and extreme weather events (Asian Development Bank, 2017; Eckstein, Künzel and Schäfer, 2018). In fact, disasters in the Philippines from 2011-2015 have resulted in production losses and damage to infrastructure amounting to PhP 163.6 billion in agriculture (National Economic Development Authority, 2017).

Climate change and the concomitant shifts in weather patterns have implications on welfare especially for a country like the Philippines that missed its Millennium Development Goal (MDG) target of halving its 1990 poverty level by 2015. Despite its long history of battle against poverty, the proportion of population below the national poverty threshold is still high at 21.6%, 4.4 percentage points higher than the MDG target. While poverty studies in the Philippines abound, these use cross-section data and as such, only identify the poor at a given point in time. These studies are not able to analyze the movement of economic units in and out of poverty. Chronic poverty is a major constraint in achieving high levels of sustained growth Aldaba (2009) so more studies on chronic and transient poverty are needed.

Indeed, 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). Not only can weather shocks and disasters push people into poverty but it can prevent people from escaping it as well. This is because shocks can hamper asset accumulation and reduce investment in human capital (Hallegate et al, 2018). 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. Weather shocks are likely to

[1] Senior Research Fellow and Research Analyst II, respectively, Philippine Institute for Development Studies.

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 disruptions 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, which can become lower than the poverty threshold.

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, affect 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.

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. Around 26% of total employment in the Philippines in 2017 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). However, a much more informative research involves the understanding of how consumption relative to a threshold (e.g. poverty) responds 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.

2. Review of related literature

Chronic and transient poverty

Studies on poverty in the Philippines abound and common to these earlier studies is the use of cross-section dataset (Balisacan, 2003; Balisacan and Pernia, 2002; Intal, 1994), which allow the identification of poor at a given point in time only. These studies do not provide narratives on the movement of households in and out of poverty. In developed economies, there is a healthy debate on methodologies. 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 is arbitaray 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.

Natural disasters/weather shocks, consumption, and welfare

Abroad, there are many studies that investigate the natural disasters-household consumption nexus. Baez, Lucchetti, Genoni, and Salazar (2015) investigate the causal consequences of Tropical Storm Agatha in Guatemala and find that per capita consumption in urban areas has decreased, which resulted in a 5.5 percentage points increase in poverty. In Mexico, Skoufias, Vinha, and Conroy (2011) find that weather shocks have varying effects on welfare across regions, education, and gender.

There are also studies that does not automatically find a negative effect on welfare. For example, Skoufias, Katayama, and Essama-Nssah (2012) find that a delay in the onset of monsoon does not have a significant impact on the welfare of rice farmers while there is a decrease in the welfare of rice farm households in areas exposed to low rainfall after the monsoon. In the Philippines, there are studies that analyze the effects of extreme weather events on inequality (see for example, Bayani-Arias and Palanca-Tan, 2017). Safir et al (2013) analyze the effects of rainfall shocks on the consumption of Filipino households and find that negative rainfall shocks decrease food consumption

3. Research framework: Consumption, income, and shocks

How do we analyze the rainfall shock-poverty nexus? To answer this, we capitalize on Samuelson's (1974) *money metric utility*, which measures levels of living by the money required to sustain them. As Deaton and Zaidi (2002) put it: "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."

Following this reasoning, households are assumed to have a standard utility function, $u = u(Q, b, z, s, e)$, where *Q* is a vector of consumption goods, *z* is a numeraire, *b* is a vector of characteristics of *Q*, *s* is a vector of household characteristics and *e* is an unobservable component. The maximization problem involves the conditional utility function associated with a consumption good *x:*

$\bar{u}_x = \bar{u}_x(Q_x, b_x, z, s, \varepsilon)$ subject to $p_x Q_x + z \leq y$, where p_x is the price of Q_x, and *y* is income. The conditional indirect utility function in this case is $\bar{v}_x(p_x, b_x, y, s, e) = \bar{u}_x[\overline{Q}_x(p_x, b_x, y, s, e), b_x, z(p_x, b_x, y, s, e), s, e]$[2] and applying Roy's identity[3], the conditional demand for good *x* becomes $\overline{Q}_x(p_x, b_x, y, s, e)$. $\overline{Q}_x$ is typically proxied by household expenditures in empirical exercises (see for example, Deaton, 1997). Earlier investigation of welfare centers in price and expenditure elasticities. Recent studies are focused on non-price determinants of demand such as resources at marriage (Quisumbing and Maluccio, 2003), gender (Handa, 1996), and weather (Wolpin, 1982). However, a much more informative research is to analyze how consumption, $\overline{Q}_x$, relative to a threshold (e.g. minimum income required to meet food and non-food needs) responds to weather shocks and this is gap that the current study aims to address.

In the empirical implementation, we assume $q_i^w = \alpha_i + \delta Y_i + \phi k_i + \varepsilon_i$, where q^w represents poverty, *w* is either chronic or transient, and *k* is a vector of socioeconomic characteristics. ε is an unobservable shock that is assumed to be independent and identically distributed. Using OLS as an empirical strategy does not address the bias arising from endogeneity[4], which happens when there are unobservable characteristics that vary with the households' income as well. Cognitive abilities and lifelong skills that affect the state of households' poverty are most likely the same constraints that affect households' incomes. This will likely result in the effect of income that is upward bias. Hence, the modeling strategy becomes:

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

$$q_i^w = \alpha_i + \delta \hat{Y}_i + \phi k_i + \varepsilon_i \qquad (2)$$

where $\hat{Y}$ is the predicted value from equation 1. Equations 1 and 2 are simultaneously estimated using the *ivreg2* routine in Stata.

The variable *rainfall shock* is a binary variable constructed based on the values of the standard deviation (SD) of the 2003-2009 rainfall from the normal rainfall (30-year average from 1970-2000). Based on the computed values, there are three possible proxies: 1 SD above,1 SD below, and 2 SD below the normal rainfall. Three binary variables are created to represent these proxies. The use of standard deviations from a threshold 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).

In estimating equations 1 and 2, rainfall shocks are instruments for income. This follows the literature that exploits the exogeneity of weather variations to establish the causality between income and health/education (see for example, Maccini and Yang, 2009) and migration (Yang and Choi, 2007). As an instrument, rainfall shocks affect poverty only through income. In terms of relevance, rainfall shocks can drive changes in wages through disruptions in the flow of labor and through disruptions in inputs to

[2] Mansur, Mendelsohn and Morrison (2008) used this formulation in the context of energy consumption.

[3] $\overline{Q}_x(p_x, b_x, y, s, e) = -\dfrac{\partial \bar{v}(p_x, b_x, y, s, e)/\partial p_x}{\partial \bar{v}(p_x, b_x, y, s, e)/\partial y}$

[4] OLS assumption $\operatorname{cov}(Y, \varepsilon) = 0$ is violated.

entrepreneurial activities. The literature also supports the use of weather variables as instruments. Yang and Choi (2007), for example, argue that households in the Philippines are either directly or indirectly engaged in agriculture and are therefore susceptible to weather-related shocks. The validity of rainfall shocks will be formally tested using underidentification and overidentification tests.

The variable *k* 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.

The variable *Y* refers to wages or incomes while *P* is the chronic or transient poverty 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. Expenditure data are thought to provide better information on household's welfare. Its advantages include its ability to reflect households' consumption smoothing at low levels of income and its accuracy in conveying welfare information since it is not susceptible to underreporting (Safir et al, 2013). However, consumption or expenditure data from the FIES may suffer from measurement due to errors in recall. This is a limitation that we acknowledge at this point.

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.[5] 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. The interaction of weather shocks with other variables is common in the literature. Skoufias et al (2011) have interacted rainfall shocks with household attributes to assess whether the effects of shocks differ among different populations. Safir et al (2013) have interacted weather shocks with community-level characteristics to establish the welfare effects of climatic variability in the rural Philippines.

The current study interacts rainfall shocks with rural dummy and this is consistent with studies that find heterogeneity of weather shocks across geographical location. 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. 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).

[5] 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.

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 Population and Housing (CPH) 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*[6], 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 dataset 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). In order to undertake a meaningful analysis of chronic and transient poverty, there is a need to devise a way so that the samples being tracked down from 2003 to 2009 are the households of the same families. Given that households are the units of observation in FIES, the closest variables that can be used to construct the panel dataset are those that pertain to the household heads' attributes such as age and sex. Following Bayudan-Dacuycuy and Lim (2013, 2014), 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.

Admittedly, this method of constructing the panel data raises issues, which need to be addressed at this point. One, the PSA does not collect genuine longitudinal data, or data that track down the same economic unit in every survey year. As pointed out earlier, the PSA conducts the CPH such that a portion of households get retained and re-surveyed during the FIES years. Therefore, it is up to the researchers to make use of this information to come up with a dataset suitable for the analysis of poverty dynamics, which requires the tracking of the same individuals/families over time. In the case of the FIES data, households are the units of observations and another layer of restrictions is needed to ensure that the measures of chronic and transient poverty apply to the same individuals. The most feasible way to do this is to track the characteristics of the household head overtime. Hence, the dataset excludes households that have changed heads within the period and this is a limitation that we acknowledge at this juncture. Two, the selection excludes households whose heads have migrated and naturally raises concerns on the exclusion of female-headed households since there are more female overseas Filipino workers. However, only one in every five Filipino families are female-headed[7]. This is potentially due to the fact that males are typically viewed as the heads of the family in line with 'the husband is the pillar and the wife is the light' roles (Bayudan-Dacuycuy, 2013). In addition, the proportion of female-headed households are similar before and after the restrictions have been imposed (15% and 13%, respectively).

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

[7] https://psa.gov.ph/content/female-headed-families-have-more-income-male-headed-families-based-final-results-2009-family

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, Geophysical and 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. To address the 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.[8] 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.

5. Discussion of results

First-stage estimates using instrumental variable regressions are presented in the upper panel of table 3.[9] 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 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.

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[8] 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.

9 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 presented due to space considerations. The full results are available from the corresponding author upon request.

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. Based on samples using the 40 kilometers restrictions, income from the agricultural sector is negatively affected by a 1 SD deviation above the normal rainfall.

In terms of the validity of the instruments, results of the underidentification and overidentification tests are included in table 4. The null hypothesis in the former is that the equation is under-identified, $\operatorname{cov}(instrument, endogenous\ variable) = 0$. Rejection of the null hypothesis implies that the instruments are relevant; that is, the instrument induces change in the endogenous variable. The null hypothesis in the latter is that the instruments are uncorrelated with the error term, $\operatorname{cov}(instrument, error term) = 0$ and that the excluded instruments are correctly excluded from the estimated equation. Rejection of the null hypothesis implies that the instruments are valid. From columns1-4 of table 4 (chronic poverty), it can be seen that the instruments pass both tests in all specifications except for one. The rainfall shocks do not pass the overidentification tests when used as instruments for the agricultural income. Therefore, results pertaining to this outcome will not be analyzed.

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. Three, the effects of entrepreneurial 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 using the 10 kilometers restrictions 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.

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 for 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.

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 longitudinal dataset so that issues, not only concerning poverty, but also those of 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. 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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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	2675	17.93		2675	26.98	
Chronic		16.53	92		24.95	92
Transient		1.40	8		2.04	8
Rural						
Total poverty	1672	23.74		1672	33.35	
Chronic		22.09	93		31.31	94
Transient		1.65	7		2.04	6
Urban	1003	8.25		,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 2003-2009 FIES dataset.

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.

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 above 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]
1 SD below 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]
2 SD below 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 above 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*1 SD below 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*2 SD below 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

Testing 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 above 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 + 1 SD below 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 + 2 SD below 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. 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, regional dummies, and the IMR.

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, regional dummies, and the IMR.

§p-values. Tests the null hypothesis that the equation is under-identified, $\operatorname{cov}(instrument, endogenous\ variable) = 0$. 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, $\operatorname{cov}(instrument, error\ term) = 0$ and that the excluded instruments are correctly excluded from the estimated equation. Rejection of the null implies that the instruments are valid.