



POLICY BRIEF

No. 2020-24 (October 26, 2020)

Impact of Extreme Rainfall Days on the Well-being of the Households in the Formal and Informal Sectors

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The Philippines is among the most vulnerable countries to extreme weather events in the world. The geographical location of the country in the tropics and in the Pacific makes it highly exposed to extreme weather events such as typhoons, storm surges, intense flooding among others (e.g. Cinco et al. 2016). Since 2011, the World Risk Report has consistently ranked the Philippines among the top three countries in the world at high disaster risk, along with Vanuatu and Tonga, but has recently been ranked ninth since 2019.

Natural disasters can push households deeper into poverty and exacerbate inequality. Poorer households, especially those in rural areas, are more likely to suffer from disasters and are thus more vulnerable. Households from low socio-economic backgrounds often face greater disaster risks, but are also the least prepared for disaster events due to several factors including housing affordability, low income, low literacy levels, among others.

Table 1. Number of Households (in 000) in Rural Areas, by Formal-Informal Classifications

Classification	2006	2009	2012	2015
Rural Non-poor	7,101 (41)	7,510 (41)	9,348 (44)	10,147 (46)
Formal	2,370 [33]	2,546 [34]	3,473 [37]	3,854 [38]
Informal	3,503 [49]	3,550 [47]	3,923 [42]	4,146 [41]
Non-working	1,228 [17]	1,414 [19]	1,952 [21]	2,147 [21]
Rural Poor	3,097 (18)	3,188 (17)	3,429 (16)	3,062 (14)
Formal	981 [32]	1,076 [34]	1,326 [39]	1,234 [40]
Informal	1,827 [59]	1,758 [55]	1,698 [50]	1,469 [48]
Non-working	289 [9]	355 [11]	405 [12]	359 [12]
Total Number of Households in Population	17,403 (100)	18,452 (100)	21,323 (100)	21,980 (100)

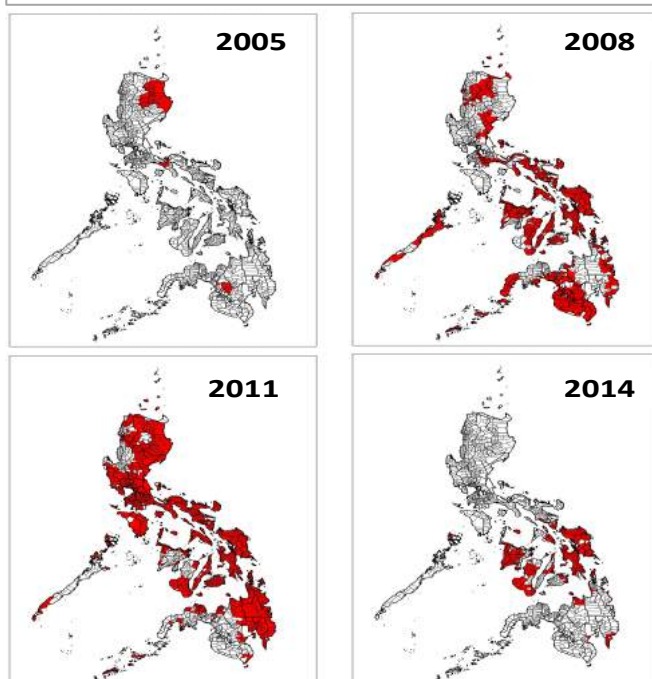
Authors' calculation. Numbers in parenthesis are percentage shares. Sampling weights are applied to reflect the number of households in the population. Poor/Non-poor are households whose income fall below the provincial minimum standard set by the PSA. A municipality is classified as rural if more than 60 percent of the households in that municipality is categorized as rural and vice versa in the FIES urban-rural classification. Note that PSA does not issue official statistical counts of formal and informal households in the country; however, it defines the informal sector as those households' unincorporated enterprises. We used this definition as basis of identifying households in the formal and formal sector. Source of basic data: FIES-LFS and PSA.

Informal households - where most of the urban and rural poor belong - tend to be located in hazardous areas, increasing their disaster risk profiles. Disasters increase the vulnerability of informal workers to remain informal, while also increasing the risk that formal workers will fall into informality. For a country

such as the Philippines, which has a large informal sector, the adverse effects of extreme weather events are not negligible, and potentially irreversible in this sector of the economy.

Informality in the country has decreased but has remained a largely rural phenomenon. From 2006 to 2015, rural poor households comprised about 16 percent of the total number of households. Of these, the proportion of informal households is larger compared with the formal households living in the same area although the proportion went down from 59 percent in 2006 to 48 percent in 2015 (Table 1)

Figure 1. Areas with above-normal number of extreme rainfall days for selected years.



We defined **extreme rainfall day** as a day with rainfall exceeding the 95th percentile over the 1998-2018 period in each year per location. Municipalities where the households live are categorized under “extreme” if the annual number of extreme rainfall days during the preceding year of the survey exceeds the 75th percentile of the annual number of extreme rainfall days across the 1998-2018 period. We utilized satellite-derived daily rainfall from the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (3B42) dataset (Huffman et al., 2007) for the years from 1998 to 2018. Figure 1 shows areas with extreme rainfall days.

Table 2 presents the disaggregation of per capita income into agriculture and non-agriculture and per capita expenditure into food, non-food, health, and education averaged over 2006-2015. **Real incomes and expenditures of informal households are significantly lower relative to formal households living in the same area.**

Table 2. Disaggregated Real Income and Expenditures per Capita, 2006-2015

	Normal				Extreme			
	Formal (a)	Informal (b)	Difference (b-a)	P-value (d)	Formal (e)	Informal (f)	Difference (f-e)	P-value (h)
Total Income	32,827	28,176	4,651	0.00	28,804	25,166	3,637	0.03
Agricultural	3,069	6,773	-3,704	0.00	3,743	7,198	-3,455	0.00
Non-agricultural	29,759	21,403	8,355	0.00	25,061	17,969	7,093	0.00
Total Expenditure	27,118	22,528	4,589	0.00	23,894	20,246	3,648	0.01
Food	10,049	8,590	1,458	0.00	8,816	8,001	814	0.03
Non-food	14,228	11,531	2,697	0.00	11,474	9,413	2,061	0.01
Health	10,049	8,590	1,458	0.00	8,816	8,001	814	0.03
Education	904	774	130	0.08	867	711	155	0.13

Authors’ calculations. Figures are real household incomes and expenditures computed using 2000 prices. The reported P-value is from the t-test between populations means using FIES-LFS data averaged over 2006-2015 period. Sources of basic data: FIES-LFS 2006 to 2015, PSA.

METHOD OF ANALYSIS: We estimate a general model of household income, production, earnings, and expenditure with households’ characteristics in the presence of a weather shock, i.e., extreme rainfall days. To assess and differentiate the impact of extreme rainfall days on the welfare of the formal and informal sectors, we first address the selectivity associated with the households being in the formal and informal sectors. Household faces a choice between the Formal and Informal sector. The difference in the net benefits determines the sector of choice. To address this endogeneity bias, we estimate a switching

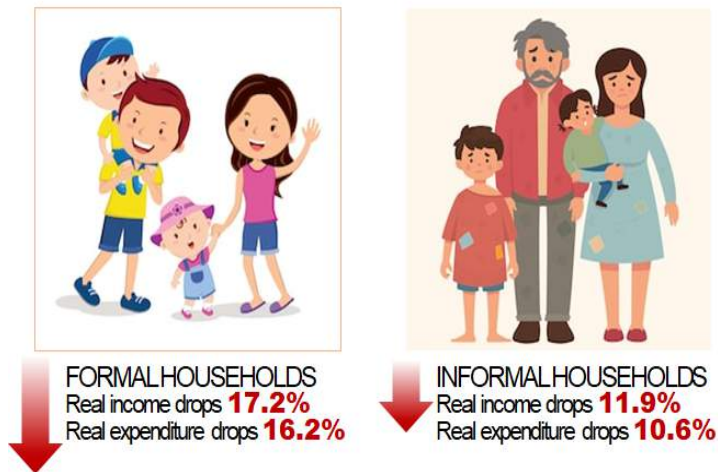
regression model by using maximum likelihood methods (Lee & Trost, 1978) and implemented using Stata's "movestay" command (Lokshin and Sajaia, 2008). We test the hypothesis that extreme rainfall days depress profits and earnings of households and therefore lower their income and consumption.

RESULT 1. Household's characteristics influence the choice of being in either the informal or formal sector. Poverty status and the urban-rural classification of municipality where the households live significantly affect the likelihood that households will be in the informal sector. Using both income and expenditure as welfare indicators, being poor significantly increases the likelihood of being in the informal sector. Living in a largely urban municipality, on the other hand, decreases the likelihood of households being in the informal sector.

RESULT 2: Household's welfare is adversely affected by extreme rainfall days regardless of which sector they belong, but the negative impact is bigger for the formal than the informal sector.

Higher number of extreme rainfall days experienced by one year ago significantly lowers household expenditures in the formal and informal sectors by 16.2 and 10.6 percent, respectively. When income is used as welfare indicator, the negative impact is slightly bigger at 17.2 percent for formal and 11.9 percent for the informal households.

Income and expenditure effects of extreme rainfall days experienced by households in the previous year



RESULT 3: The results also show that households, regardless of which sector they belong to, are still reeling from the negative effects of experiencing an extreme rainfall from three years ago (Figure 2). Thus, there is a potential for households in both sectors to slide into poverty when they are affected by extreme weather events. Households in the formal sector have larger incomes and have more to lose than the households in the informal sector. **However, the adverse impact to the informal households may be irreversible given**

their weak capability to recover and their limited ability to smooth out consumption even during days with normal rainfall.

In Figure 2, the dotted and solid line pertain to formal and informal sectors, respectively. The dotted line is more negative than the solid line. The slope of the lines can be interpreted as the speed of recovery. **The slope of the dotted line is steeper implying that the formal sector recovers faster than the informal sector.**

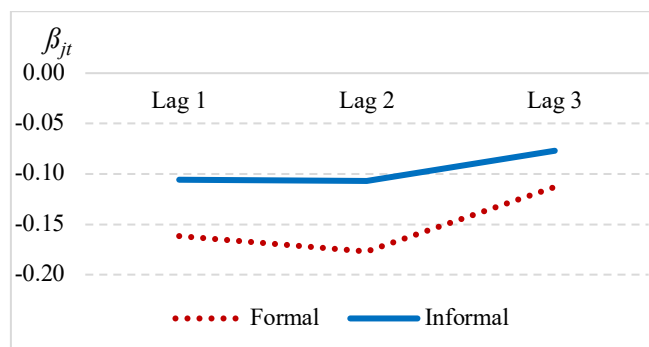


Figure 2. Lag distribution of the extreme rainfall days variable (expenditure as the welfare indicator).

RESULT 4: Households who are in the informal sector have income lower by PhP 1,909 compared to a counterfactual case where they choose the formal sector. This implies that there are other factors that explains why income of informal households are lower than the households in the formal sector regardless of the presence of weather shock.

In Table 3, cells (a) and (b) are the expected income of households in the informal sector and formal sector at PhP19,850 and PhP 56,587, respectively. To conclude that households in the formal sector do have higher income than the households in the informal sector from this comparison is misleading.

Table 3. Counterfactual comparisons, Income as Dependent Variable.

Subsample	Decision Stage		Treatment effects	
	Informal	Formal		
Informal HH	(a) 19,580	(c) 21,488	TT	-1,909
Formal HH	(d) 5,087	(b) 56,587	TU	-51,500
Heterogeneity Effects	BH _i 14,493	BH _f -35,099	TH	49,591

Note: The numbers reported are conditional expectation, treatment and heterogeneity effects.

The proper comparison should be the actual versus the counterfactual (cells a vs. c). Specifically, households who are in the informal sector have income lower by PhP 1,909 compared to a counterfactual case had they choose the formal sector. In the second comparison of actual versus the counterfactual (cells b vs. d), where the counterfactual of formal households is had they choose the informal sector. The households in the formal sector would have income lower by PhP 49,591 if they choose to be in the informal sector. These results imply that income of households choosing informal sector is further decreased in the presence of weather shock. However, transitional heterogeneity effect at PhP 36,810 is positive, which implies that the effect is significantly higher for the households that choose to be in the informal sector compared to those households that did not. The last row of Table 8 adjusts for potential heterogeneity in the sample. Households who are in the informal sector have lower income than households in the counterfactual case (c).

POLICY IMPLICATION: Targeted social protection coverage to households near the poverty line can help soften the blow of weather shocks. Policies on poverty alleviation should include attention to its stochastic aspects. This may include affordable insurance, and education campaign about the impact of disasters. In addition, specialized access to credit and insurance targeted for the poor informal sector might help households in this sector recover faster from the negative impact of a weather shocks.

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This policy brief is based on the Working Paper, **Ravago, M.V., G. Pascua, L. Acheron, E. Gozo, F. Cruz, G. Narisma, "Impact of Extreme Rainfall Days on the Welfare of Households in the Formal and Informal Sectors."**

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This transdisciplinary action research was carried out under the Coastal Cities at Risk in the Philippines: Investing in Climate and Resilience (CCAR) Project, with the aid of a grant from the International Development Resource Centre (IDRC), Canada, and implemented by the Ateneo de Manila University (ADMU), in collaboration with the Manila Observatory (MO), Ateneo Innovation Center (AIC), and the National Resilience Council (NRC).