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Abstract

Aid from local governments can play a critical role as a risk-coping device in a post-disaster situation if the recipients have been properly targeted. Combining (i) satellite images (objective information on flood damage), (ii) administrative records (objective information on aid receipt), and (iii) sui generis survey data (self-reported information on damage assessment and aid receipt) on a large-scale flooding in the Philippines, we analyze the accuracy of disaster aid targeting and self-reporting bias in flood damage and aid receipt. We find that damage is over-reported while aid receipt is under-reported, and as a result, the estimated targeting accuracy based on self-reported information is substantially downward-biased.

Keywords: disaster, flood, *Habagat*, aid targeting, self-reporting bias, Philippines

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1. Introduction

Disasters triggered by natural hazards cause negative economic shocks to individuals and households. According to the Centre for Research on the Epidemiology of Disasters (CRED [1]), there were 335 disasters recorded in 2017, killing 9,697 people and affecting an additional 95.6 million people in the world. The CRED database shows an increasing trend in the occurrence of disasters in the past few decades, and in Asia in particular. Although disasters affect households both in the developed and developing world, Kahn [2] and Noy and Yonson [3] among others, have illustrated that households in developing countries are more vulnerable because of their limited capacity to cope with sudden negative shocks caused by disasters.

Although households and individuals in developing countries adopt various risk-coping strategies, both *ex ante* and *ex post*, their private risk-coping strategies are not always enough to compensate for the damages caused by natural hazards. For instance, Aldrich, Sawada, and Oum [4] found that only 9% of the disaster damages in Asia were insured. Since private risk-coping is insufficient, public risk-coping, particularly aid from the government, can provide be an important risk-coping device in the aftermath of disasters (Morris, et al. [5]; Shoji [6]; Strömberg [7]).

Precise targeting of aid, however, is known to be difficult. In the economics literature, targeting of food aid (e.g., Abdulai, Barrett, and Hoddinott [8]; Galasso and Ravallion [9]; Jayne, et al. [10]) and other resource transfers toward low-income households (e.g., Alatas, et al. [11]; Alderman [12]; Bardhan and Mookherjee [13]) have been investigated thoroughly, and these studies have found that targeting has been generally undermined by an inclusion error (providing transfer to those who do not need it) and an exclusion error (failing to provide transfer to those who need it). Due to such targeting errors, some researchers and policymakers argue that universal resource transfers, or universal basic income, is preferable to targeted transfers (see a recent survey by Hanna and Olken [14]). The targeting of governmental transfers is even more difficult in disaster relief and aid (e.g., Amin and Goldstein [15]; Morris and Wodon [16]; Takasaki [17]) because they have to be provided in a timely manner in the aftermath of disasters, when the government would have other responsibilities, such as reconstruction of damaged infrastructure, and where the government function itself might have been affected by the disasters.

In investigating disaster aid and its effectiveness, it is important to correctly understand the accuracy of targeting. While existing micro-level quantitative studies, including those cited above, mostly rely on self-reported information collected by household surveys, it is well-known that survey data suffers from various types of reporting biases, such as recall error and strategic misreporting (in expectation of aid, for instance) (e.g., Bound, Brown, and Mathiowetz [18]; Gibson and Kim [19]; Kennickell and Starr-McCluer [20]). A recent study suggests that the problem of reporting biases exists in survey data on disaster and aid receipt (Heltberg, Oviedo, and Talukdar [21]).

In order to correct such reporting bias and to analyze the accuracy of disaster aid targeting, we construct a sui generis dataset containing both self-reported and objective information. Our dataset is based on three different sources of information collected after a large-scale flood in the Philippines in 2012. First, we conducted a survey of 122 farmers in the affected village to collect self-reported information on flood damage and aid receipt. Second, we use satellite images that show the border of the flood submergence. The unexpected flooding resulted in within-village variations in flood damage—about half of the paddy fields were inundated. As the satellite images provide objective information on the affected fields, we can identify the intended beneficiaries of post-flood aid. More importantly, the damage is not systematically correlated with characteristics of the sample farmers, and hence, the flood damage can be considered an exogenous shock. Lastly, we create a data set from the administrative records of seed aid provided to the farmers whose agricultural land was inundated. We obtain a list of the recipient farmers from the local government office, which provides objective information on the recipients of seed aid.

Combining these data, we find that *more* farmers reported to have been affected by the flooding than those identified based on the satellite images and that *less* farmers reported to have received the seed aid than those recorded in the administrative list. In other words, the flood damage is over-reported, while the aid receipt is under-reported. Because of these two types of self-reporting bias, if we rely on the self-reported information, the exclusion error rate increases, and thus, the estimated accuracy of targeting becomes substantially lower than that based on the objective information. Our regression results show that affected farmers were only 18-20 percentage point more likely to have received aid than farmers without damage if we rely only on the subjective information. Based on the objective information, however, farmers with damage were percentage 44-47 more likely to have received aid. Although the targeting is still far from perfect, the accuracy of targeting is higher than the estimation based on self-reported data. These results suggest that aid targeting is a challenging task, but it may not be as challenging as discussed in the existing studies. Our findings support the recent trend in economics studies to combine household survey data with more objective data, such as geographical data, that are normally used in the natural science disciplines (see an excellent survey by Dell, Jones, and Olken [22]).

The remainder of this paper is organized as follows. Section 2 describes the data and Section 3 presents the descriptive analyses. Regression analyses are presented in Section 4 and summary and policy implications are discussed in Section 5.

2. Data

2.1. Typhoon *Habagat*

In August 2012, large-scale flooding occurred due to torrential monsoon rains in the Philippines. This flood is known as "*Habagat*" in Tagalog. *Habagat* started with an eight-day period of heavy rains and thunderstorms starting from August 1st, and subsequently caused typhoon-like damage, such as river overflow and landslides. Manila, the capital city of the Philippines, and surrounding provinces were severely affected. The most severe flooding took place from August 7th to August 9th, and a State of Calamity was declared on August 8th. According to the National Disaster Risk Reduction and Management Council (NDRRMC) of the Philippines, 112 people were killed and over four million people were affected. The estimated cost of damages is 651 million PHP (equivalent to 15.4 million USD as of August 2012) in infrastructural loss and 2,404 million PHP (57.0 million USD) in agricultural loss (NDRRMC [23]).

Laguna province was one of the provinces severely affected by *Habagat*. It is located at the south end of Metro Manila and alongside the Laguna Lake, the largest lake in the Philippines. *Habagat* spawned flooding, caused extreme deluges of the lake, and the outflow submerged the rice fields in its coastal area.

2.2. Study Site

We study the rice farmers in a village located in Laguna province, approximately 80 kilometers south of Metro Manila. The proximity of the village to the International

Rice Research Institute (IRRI) has enabled researchers to conduct many surveys in cooperation with IRRI. The earliest documented survey in the village dates to 1966 and 18 rounds of household surveys were conducted between 1974 and 2007.[1] Due to these numerous surveys, there is abundant available benchmark information on the village.

After *Habagat*, we visited the village, situated on the bank of the Laguna Lake, and found that the paddy fields were severely affected. During our visit, we interviewed government officials of Pila municipality, under which the village falls, and learned that 203.5 hectares out of the 367.5 hectares of the total village area were submerged. According to many farmers in the village, they had never experienced flooding of this magnitude from the lake.

2.3. Data

We employ three datasets for this study. The first is based on our sui generis survey conducted during February–March 2013. We began by identifying all the farmers in the village, using the information collected by the previous surveys and conducting interviews with the village leader and other knowledgeable villagers to update the information. We defined households that own agricultural land in the village as farmers, and found 122 rice cultivators. According to the interviews we conducted, no farmer had migrated out of the village because of *Habagat* damage. Using a questionnaire developed after our visit, we conducted a survey and interviewed all the 122 farmers (i.e., the attrition rate is zero). The subjective information for our analyses comes from this survey.

[1] The first survey was conducted by a geographer, Hiromitsu Umehara, in 1966, and subsequent surveys in the 1970s, 1980s, and 1990s were organized by agricultural economists, Yujiro Hayami and Masao Kikuchi (Hayami and Kikuchi, [24]). See Sawada, et al. [25] for the list of surveys conducted in the village.

The second data set is from the satellite images taken before and after *Habagat*. Panel (a) of Figure 1 presents a land cover before *Habagat*. The lake is on the upper left, the rice fields are in blue, and the residential area located in the center is surrounded by the paddy fields. The black lines in paddy field indicate the land plot borders created by visual interpretation of the satellite image taken on May 23rd, 2012. Panel (b) presents a land cover shortly after *Habagat*. Based on the image analysis of the satellite image taken on August 11st, 2012, we draw the border of submerged area as the red line in the figure and use it as our objective damage indicator. Figure 1 illustrates that about half of the paddy fields, located close to the lake, were inside the border of submergence.

For comparison, we overlay the plot-level subjective damage information on the satellite images in such a way that self-reported water depth before and after *Habagat* is presented using the color blue in different hues in Panels (a) and (b), respectively. Panel (b) shows that the most farms inside the red line were subjectively reported to have been submerged after *Habagat*.

The third data set is from the administrative record of seed aid distribution, obtained from the municipal government office. Soon after *Habagat*, village-level politicians went round the rice fields in the village and made a list of the affected fields. This list was submitted to the municipal government, and the municipal government distributed 1 bag (30 kilograms) of seed aid for each hectare of affected paddy for all the farmers on the list. Since the signature of each recipient farmer is placed on the list, we believe the administrative records are reliable source for objective data on aid receipt (see Figure 2). The record also has information on area size and number of bags, showing that 1 bag was indeed provided for each hectare of damaged farms.

3. Descriptive Analyses

3.1. Damage

Table 1 presents the descriptive statistics of the damage and the aid receipt. The satellite images show that 60% of the famers had their rice field affected by the flooding. We categorize the farmers as affected if their agricultural land is located within the red line shown in Panel (b) of Figure 1. According to the self-reported information, a larger proportion of farmers (76%) reported to have their rice paddy affected. We will discuss the issue of discrepancy below, but these data show that a large proportion of sample farmers were affected by *Habagat*. Because the incidence of flooding occurred just before the beginning of harvest season, many of the farmers (42%) reported that their income had declined. Based on the self-reported information on the expected and actual quantity of rice harvest and the expected and actual rice price, we compute the value of rice harvest loss. The average value of crop loss of 112,816 PHP (2,673 USD) is large in that this is equivalent to about 450 man-days earnings, considering the average daily wage for agricultural labor in this area in 2012 is about 250 PHP.

The Philippines is prone to typhoons, some of which are severe. Usually, typhoons cause damage to infrastructure, housing, and other productive assets by strong winds, but in the case of *Habagat*, only a few farmers reported house damage (2%) and asset loss (2%). In addition, the reported incidence of sickness or injury was limited (1%). Hence, our data shows that the damage by *Habagat* was mostly caused by flooding and was concentrated in agricultural land.

3.2. Disaster Aid

From the administrative records, we construct a dummy variable that takes the value of one if a farmer received the seed aid and zero, otherwise. We find that 57% of farmers were recorded to have received seed aid. From the information collected from our survey, a smaller proportion of farmers (43%) reported to have received the seed aid. While administrative records are only available for seed aid, we collected self-reported information of the receipt of other forms of aid as well. The collected information includes fertilizer aid and lump-sum aid from each organization (i.e., local government, local NGOs, church, and politicians). Five percent of the farmers reported to have received fertilizer aid, while the average value of aid received from local government amounts to 1,012 PHP, roughly equal to a four-day wage. The aid amount, however, is much less than the reported loss of 112,816 PHP, and Table 1 presents the severity of *Habagat* damage.

3.3. Self-reporting Bias

In order to analyze the discrepancy between self-reported and objective information, Table 2 presents the data from two sources on damage (Panel A) and on aid receipt (Panel B). Panel A shows that most farmers whose rice fields were affected according to the satellite images actually reported to have their paddy submerged (70 of 73). Yet, of the 49 farmers whose fields were not submerged according to the satellite images, 23 farmers reported their rice fields as submerged. While we cannot judge whether the damage was intentionally over-reported or there was actual submergence that did not appear on the satellite images, the influence of the latter is more or less random. As we will discuss in sub-section 4.1, whether a field is located within the boundary of submergence is not correlated with observable characteristics of farmers. Hence, to the extent that there is almost no under-reporting of flood damage (only 3 of 73), the flood damage was likely be over-reported.

Panel B shows that, of the 69 farmers shown on the record to have received seed aid, only 39 of them (56%) reported to have actually received it. These 39 farmers might intentionally have under-reported in the expectation of getting more aid from researchers, or they might have simply forgotten because our survey was conducted about half a year after *Habagat*. In addition to the under-reported aid receipt, 13 out of the 53 farmers (25%), who were not on the recipient list, reported having received it. They might have indirectly received seed aid from their relatives or neighbors, or they might have confused seed aid with some other forms of aid, such as fertilizer aid. Due to such reporting bias in both directions, the correlation coefficient of the objective information and the subjective information is 0.32, which is substantially less than one (see the bottom of Panel B). As the 56% under-reports and the 25% over-reports, a general tendency is under-reporting of aid reception.

3.4. Accuracy of Targeting

Table 3 reports the correlations between flood damage and seed aid receipt. Panel A is based on the objective information—the satellite images and administrative record, and Panel B is based on the self-reported, subjective information collected in our survey. Panel A shows that 74% of the sample farmers (= (55+35)/122) were properly targeted. Fourteen farmers (11%) were not affected but received aid (an inclusion error), and 18 farmers (15%) were affected but did not receive aid (an exclusion error). Since targeting was correctly done for almost three-quarters of our sample farmers, the accuracy of targeting is reasonably high, particularly given that it was done not during ordinary times but in an emergency.

In Panel B, the correct targeting rate is 53% (= (44+21)/122), the inclusion error rate is 7%, and the exclusion error rate is 40%. Due to the low accuracy of targeting, the correlation coefficient is 0.17, much less than 0.46 in Panel A. Furthermore, we cannot reject a null hypothesis that there is no correlation between the paddy submergence data and the seed aid data at the 5 percent significance level as the p-value for Pearson's chi-squared test is 0.061. The high exclusion error rate is consistent with our discussions in the previous sub-section because over-reported damage and under-reported aid receipt increases the rate. Hence, if we only rely on self-reported information, we would mistakenly conclude the accuracy of targeting to be low.

4. Regression analyses

4.1. Sample Farmer Characteristics and Exogeneity Test

Table 4 shows the comparison of characteristics of the farmers by their paddy submergence status based on the satellite images. The survey was conducted half a year after *Habagat*, but we collected data to obtain pre-disaster information. As for household composition, for example, we collected information of household members at the time of survey, members left after *Habagat*, and members joined after it. According to our survey data, 17 members left and 21 joined the household after (but not necessarily because of) *Habagat*.

Means and standard deviations of the affected farmers are presented in columns (1) and (2), means and standard deviations of the unaffected farmers in columns (3) and (4), and the p-values from the t-tests (for the null hypothesis that the mean values are the same in the two groups) are reported in column (5). Most farmers are male, in their late 50s, and secondary school graduates. Their average family size is 4 or 5 (a total of number of children, adult, and elderly in household), about 20% of them are migrant households, that is, they were not born in the village, and the average agricultural landholding size is about three hectares. Since the p-values reported in column (5) are high, the *Habagat* damage can be considered exogenous in the sample village. We use these variables as control variables in the regression analyses below.

Although we do not use consumption information as control variables because the information was missing from five sample farmers, the average food consumption value before *Habagat* was 639 PHP (15.1 USD) for the affected farmers and 702 PHP (16.6 USD) for the unaffected farmers, and the corresponding total consumption value was 1,161 PHP (27.5 USD) and 1,324 PHP (31.4 USD). Importantly, these pre-disaster consumption values are not statistically different between the two groups, and our regression results are robust to the inclusion of the pre-disaster consumption as control variables.

4.2. Regression Results

To formally analyze the accuracy of disaster aid targeting, we run regressions with a dummy variable for seed aid receipt in the left-hand side and a dummy variable for paddy submergence on the right-hand side. Table 5 shows OLS results (i.e., Linear Probability Model) and Table 6 shows Probit results. In doing so, we compare two sets of damage and aid receipt information. In columns (1) and (2), we use the objective information and in columns (3) and (4), we use subjective, self-reported information. In the odd-numbered columns, we report the benchmark results with no covariates and in the even-numbered columns, we report the results with the control variables, that is, the farmer characteristics listed in Table 4.

In Table 5, the estimated coefficient of damage is 0.44-0.47 in columns (1) and (2), suggesting that the damage significantly increases the probability of receiving seed aid by 44 to 47 percentage point. These coefficients are statistically significant at the 1 percent level. If seed aid is perfectly targeted, the estimated coefficients become one. Although we reject the null hypothesis that the coefficient is equal to one (see the p-values reported at the bottom), the point estimate is reasonably high. In contrast, the coefficient reported in columns (3) and (4) is 0.18-0.20, which is much smaller in magnitude than those reported in columns (1) and (2). In addition, the coefficient estimated with control variables is only marginally significant in column (4). The R-squared and adjusted R-squared reported at the bottom are close to zero in columns (3) and (4), which means that whether a farmer reported to have received the seed aid is not much explained by whether the same farmer reported damage from the flooding. These findings support our discussions in sub-section 3.4 that if we rely only on the self-reported information, the accuracy of disaster aid targeting is likely to be under-estimated, even after controlling for potential confounding factors.

Table 6 reports the marginal effects evaluated at the means, using Probit regressions. Column (1) shows that the farmers whose rice paddy was affected were 47 points more likely to have received seed aid. The point estimate is similar to the OLS results. Column (3) shows that the farmers with reported damage were 20 points more likely to report to have received the aid. The estimated coefficient with control variables reported in columns (2) and (4) is also similar to the OLS estimates. Hence, our results are robust to a different estimation model (without and with the control variables) and method (Liner Probability Model and Probit Model).

5. Conclusion

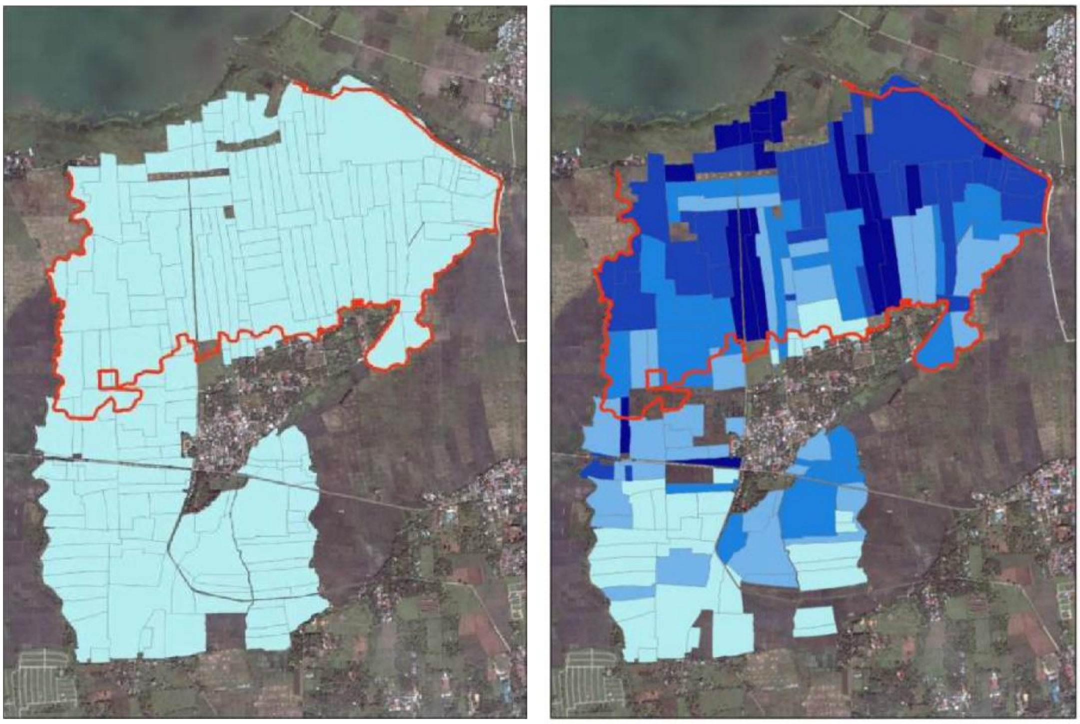
We study *Habagat* flooding as a natural experiment where rice farmers were affected by a sudden, exogenous shock by constructing sui generis datasets with three different sources of information. We find that disaster damage is over-reported and aid receipt is under-reported, and hence, there is a discrepancy in the objective information and the self-reported information. If only the subjective self-reported information is used, then the accuracy of targeting is substantially under-estimated, erroneously over-emphasizing the difficulty in disaster aid targeting. Our findings highlight importance of using objective information when researchers analyze damage and aid data from disasters.

Since the majority of farmers were severely affected, *Habagat* can be considered a covariate shock to the village. Although within-village risk sharing mechanisms may work to some extent (which is outside the scope of this paper), external supports are indispensable for such a large covariate shock. We find that the actual targeting was fairly well executed, but the null hypothesis of perfect targeting is rejected, and hence, there is room for improving the accuracy of disaster aid targeting. Based on our findings, we believe that the use of objective information can help the government improve the accuracy of targeting.

References

1. CRED (Centre for Research on the Epidemiology of Disasters). *Natural Disasters 2017*, CRED: Brussels, Belgium, 2018. Available online: https://cred.be/sites/default/files/adsr_2017.pdf (accessed on 20 December 2018)
2. Kahn, M.E. The death toll from natural disasters: The role of income, geography, and institutions. *Review of Economics and Statistics* **2005**, 87(2), 271-284.
3. Noy, I.; Yonson, R. Economic Vulnerability and Resilience to Natural hazards: A survey of concepts and measurements. *Sustainability* **2018**, 10, forthcoming.
4. Aldrich, D.P.; Sawada, Y.; Oum, S. *Resilience and Recovery in Asian Disasters*, Springer: Tokyo, Japan, 2015.
5. Morris, S.; Neidecker-Gonzales, O.; Carletto, C.; Munguia, M.; Wodon, Q. Hurricane Mitch and the livelihood of the rural poor in Honduras. *World Development* **2002**, 30(1), 49-60.
6. Shoji, M. Religious fractionalisation and crimes in disaster-affected communities: Survey evidence from Bangladesh. *Journal of Development Studies* **2018**, 54(10), 1891-1911.
7. Strömberg, D. Natural disasters, economic development, and humanitarian aid. *Journal of Economic Perspectives* **2007**, 21(3), 199-222.
8. Abdulai, A.; Barrett, C.B.; Hoddinott, J. Does food aid *really* have disincentive effects? New evidence from sub-Saharan Africa. *World Development* **2005**, 33(10), 1689-1704.
9. Galasso, E.; Ravallion, M. Decentralized targeting of an antipoverty program. *Journal of Public Economics* **2005**, 89, 705-727.
10. Jayne, T.S.; Strauss, J.; Yamano, T.; Molla, D. Targeting of food aid in rural Ethiopia: chronic need or inertia? *Journal of Development Economics* **2002**, 68, 247-288.
11. Alatas, V.; Banerjee, A.; Hanna, R.; Olken, B.A.; Tobias, J. Targeting the poor: Evidence from a field experiment in Indonesia. *American Economic Review* **2012**, 102 (4), 1206-40.
12. Alderman, H. Do local officials know something we don't? Decentralization of targeted transfers in Albania. *Journal of Public Economics* **2002**, 83 (3), 375-404.
13. Bardhan, P.; Mookherjee, D. Pro-poor targeting and accountability of local governments in West Bengal. *Journal of Development Economics* **2006**, 79(2), 303-327.
14. Hanna, R.; Olken, B.A. Universal basic incomes versus targeted transfers: Anti-poverty programs in developing countries. *Journal of Economic Perspectives* **2018**, 32(4), 201-26.
15. Amin, S.; Goldstein, M. *Data against Natural Disasters: Establishing Effective Systems for Relief, Recovery, and Reconstruction*, World Bank: Washington DC, United States, 2008.
16. Morris S.; Wodon, Q. The allocation of natural disaster relief funds: Hurricane Mitch in Honduras. *World Development* **2003**, 31(7), 1279-1289.
17. Takasaki, Y. Targeting cyclone relief within the village: Kinship, sharing, and capture. *Economic Development and Cultural Change* **2011**, 59(2), 387-416.
18. Bound J.; Brown, C.; Mathiowetz, N. Measurement error in survey data. In *Handbook of Econometrics Vol. 5.*; Heckman, J., Leamer, E., Eds.; Elsevier: Amsterdam, Netherlands, pp. 3705-3843.
19. Gibson, J.; Kim, B. Measurement error in recall surveys and the relationship between household size and food demand. *American Journal of Agricultural Economics* **2007**, 89(2), 473-489.
20. Kennickell, A.; Starr-McCluer, M. Retrospective reporting of household wealth: Evidence from the 1983-89 survey of consumer finances. *Journal of Business and Statistics Economic Statistics* **1997**, 15(4), 452-463.
21. Heltberg, R.; Oviedo, A.M.; Talukdar, F. What do household surveys really tell us about risk, shocks, and risk management in the developing world? *Journal of Development Studies* **2015**, 51(3), 209-225.
22. Dell, M.; Jones, B.F.; Olken, B.A. What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature* **2014,** 52(3), 740-798.
23. NDRRMC (National Disaster Risk Reduction and Management Council). *Update: SitRep No. 20: re Effects of South-west Monsoon Enhanced by Typhoon Haikui*, NDRRMC: Manila, Philippines, 2012.

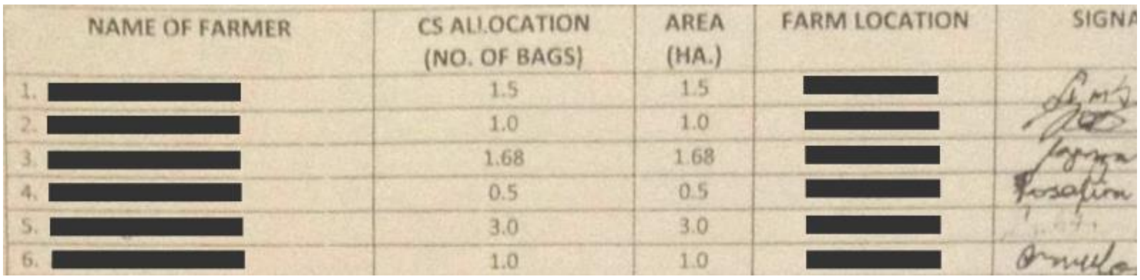
Available online: http://ndrrmc.gov.ph/2-uncategorised/2051-effects-of-southwest-monsoon-enhanced-by-tropical-storm-haikui (accessed on 20 December 2018).
24. Hayami, Y.; Kikuchi, M. *A Rice Village Saga: Three Decades of Green Revolution in the Philippines*, MacMillan Press: London, United Kingdom, 2000.
25. Sawada, Y.; Higuchi, Y.; Kajisa, K.; Fuwa, N.; Marciano, E.B.; Estudillo, J.P. The East Laguna Village: Four decades of studies in a Filipino village. *PRIMCED Discussion Paper Series No. 18*, Hitotsubashi University: Tokyo, Japan, 2012.



(**a**) (**b**)

Figure 1. Flooding border and self-reported water depth.

(**a**) Before *Habagat* in the first panel; (**b**) After *Habagat* in the second panel. The data on self-reported water depth is overlaid with five categories: lightest blue (below ankle depth <10cm), light blue (below knee depth <40cm), blue (below hip depth <80cm), dark blue (below chest depth <120cm), and darkest blue (above chest depth >120cm).



NAME OF FARMER	CS ALLOCATION (NO. OF BAGS)	AREA (HA.)	FARM LOCATION	SIGNA
1. [redacted]	1.5	1.5	[redacted]	[illegible]
2. [redacted]	1.0	1.0	[redacted]	[illegible]
3. [redacted]	1.68	1.68	[redacted]	[illegible]
4. [redacted]	0.5	0.5	[redacted]	[illegible]
5. [redacted]	3.0	3.0	[redacted]	[illegible]
6. [redacted]	1.0	1.0	[redacted]	[illegible]

Figure 2. An example of administrative record.

Table 1. Damage and Aid Receipt.

	(1) Mean	(2) SD
Damage (satellite image)		
Paddy submerged (1 = yes)	0.60	
Damage (self-report)		
Paddy submerged (1 = yes)	0.76	
Income declined (1 = yes)	0.42	
Loss from rice harvest (PHP) [1]	112,816	170,396
House submerged (1 = yes)	0.02	
Asset lost (1 = yes)	0.02	
Household member got sick/injured (1 = yes)	0.01	
Aid (administrative record)		
Seed aid (1 = yes)	0.57	
Amount of seed aid (# of bags) [2]	1.39	1.97
Aid (self-report)		
Seed aid (1 = yes)	0.43	
Fertilizer aid (1 = yes)	0.05	
Aid from local government (PHP)	1,012	2,790
Aid from local NGO (PHP)	8	91
Aid from local church (PHP)	1	14
Aid from local politician (PHP)	5	33
Number of observations	122	

Notes: 1. Loss from rice harvest is computed based on self-reported information on the expected and actual quantity of rice harvest and the expected and actual rice price. 1 USD was equivalent to 42.2 PHP as of August, 2012. 2. One bag (30 kilograms) of seed was distributed for one hectare of affected rice field.

Table 2. Relationship between Objective and Self-reported Information.

Panel A: Damage.

	Paddy submerged (self-report)		
Paddy submerged (satellite image)	Yes	No	Total
Yes	70	3	73
No	23	26	49
Total	93	29	122
Correlation coefficient		0.56	
Number of observations		122	

Panel B: Aid Receipt.

	Seed aid (self-report)		
Seed aid (administrative record)	Yes	No	Total
Yes	39	30	69
No	13	40	53
Total	52	70	122
Correlation coefficient		0.32	
Number of observations		122	

Table 3. Correlation between Damage and Aid Receipt.

Panel A: Based on Objective Information.

Seed aid (administrative record)	**Paddy submerged (satellite image)** Yes	No	Total
Yes	55	14	69
No	18	35	53
Total	73	49	122
Correlation coefficient		0.46	
p-value for Pearson's chi-squared test		0.000	
Number of observations		122	

Panel B: Based on Subjective Information.

Seed aid (self-report)	**Paddy submerged (self-report)** Yes	No	Total
Yes	44	8	52
No	49	21	70
Total	93	29	122
Correlation coefficient		0.17	
p-value for Pearson's chi-squared test		0.061	
Number of observations		122	

Table 4. Farmer Characteristics and Exogeneity Test.

Paddy submerged (satellite image)	(1)	(2)	(3)	(4)	(5)
	Yes		No		Difference
	Mean	SD	Mean	SD	*P*-value
Gender (1 = male)	0.89	0.36	0.88	0.33	0.84
Age	58.0	12.70	56.3	14.55	0.51
Schooling years	9.7	3.80	9.8	3.99	0.90
# of children (under 15) in HH	1.1	1.19	1.3	1.29	0.42
# of adult (15 to 65) in HH	2.7	1.65	3.2	1.63	0.15
# of elderly (above 65) in HH	0.4	0.75	0.5	0.71	0.70
Migrant household (1 = yes)	0.27	0.45	0.16	0.37	0.16
Land size (Ha)	3.3	4.56	2.3	3.56	0.22
Number of observations	73		49		122

Notes: *P*-values are from *t*-tests for the null hypothesis that the mean values are the same in the two groups.

Table 5. OLS results.

	(1)	(2)	(3)	(4)
	Seed aid (administrative record) (1 = yes)		**Seed aid (self-report) (1= yes)**	
Paddy submerged (satellite image)	0.47***	0.44***		
(1 = yes)	(5.66)	(5.09)		
Paddy submerged (self-report)			0.20**	0.18*
(1 = yes)			(2.00)	(1.97)
Control variables	N	Y	N	Y
R squared	0.214	0.281	0.029	0.132
Adjusted R squared	0.207	0.223	0.021	0.062
P-value for H_0: the coefficient of damage is equal to one	0.00	0.00	0.00	0.00
Number of observations	122			

Notes: Numbers in parentheses are *t*-statistics based on standard errors robust to heteroscedasticity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively. Control variables are: gender dummy, age, schooling years, numbers of children, adult, and elderly in household, migrant household dummy, and land size.

Table 6. Probit results.

	(1)	(2)	(3)	(4)
	Seed aid (administrative record) (1 = yes)		**Seed aid (self-report) (1= yes)**	
Paddy submerged (satellite image)	0.47***	0.46***		
(1 = yes)	(5.02)	(4.71)		
Paddy submerged (self-report)			0.20*	0.20*
(1 = yes)			(1.87)	(1.79)
Control variables	N	Y	N	Y
Pseudo R squared	0.161	0.231	0.022	0.064
Number of observations		122		

Notes: Marginal effects evaluated at the means are reported. Numbers in parentheses are *z*-statistics based on standard errors robust to heteroscedasticity. *** and * indicate significance at the 1% and 10% levels respectively. Control variables are: gender dummy, age, schooling years, numbers of children, adult, and elderly in household, migrant household dummy, and land size.