Impact of Extreme Rainfall Days on the Welfare of Households in the Formal and Informal Sectors

Majah-Leah V. Ravago[a], Gerald Gracius Pascua[a], Loubill Dayne Aceron[a], Emilio Gozo[b], Faye Cruz[b], and Gemma Narisma[b,c]
[a]*Department of Economics, Ateneo de Manila University, Quezon City, Philippines*
[b]*Regional Climate Systems Laboratory, Manila Observatory, Quezon City, Philippines*
[c]*Atmospheric Science Program, Physics Department, Ateneo de Manila University, Quezon City, Philippines*

Majah-Leah V. Ravago (Corresponding author) | Department of Economics, Ateneo de Manila University, Rm 400 4/F Leong Hall, Katipunan Ave, Loyola Heights, 1108 Quezon City, Philippines | Email: mravago@ateneo.edu ORCID iD: 0000-0001-8031-9502

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Abstract

We examine the impact of a weather shock, specifically extreme rainfall days, on the welfare of the households in the formal and informal sectors. We combine the theoretical framework of household production model in the presence of weather shocks with the dual economy model where sector choice is endogenous. We model the informality or formality of the households as endogenous regimes depending on the net benefits they are likely to get from being in a specific sector. We then estimate a simultaneous equation model with endogenous switching to account for the heterogeneity in the decision to be in the informal or formal sector. This allows us to assess the impact of extreme rainfall days on income and expenditure. We take the case of the Philippines by utilizing household data in 2006 to 2015.

Keywords: Extreme weather events; informality; switching regressions; informal sector; Philippines

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1. Introduction

Households from low socio-economic backgrounds often face greater disaster risks but are least prepared for disaster events due to several factors including housing affordability, low income, and low literacy levels, among others. These factors are reflective of the characteristics of the informal segment of the economy, which is largely composed of poor households.

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. 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 (Cinco et al., 2016). From 2011 to 2018, the World Risk Report (Heintze et al., 2018) has consistently ranked the Philippines among the top three countries in the world at high disaster risk, along with Vanuatu and Tonga. In 2019, the country registered an improvement placing ninth in the ranking (Behlert et al., 2019).

With climatic changes that are expected to result in shifting precipitation patterns and potentially fewer but slightly stronger tropical cyclones affecting the Philippines (Gallo et al., 2019), understanding its impact not only on the welfare of the formal, but more importantly on the poorer informal sector is crucial for the appropriate design of policy instruments and social protection.

In this context, we aim to assess and differentiate the impact of extreme weather events on the welfare of the formal and informal sectors of the economy using household level survey data from the Philippines. We consider the annual number of extreme rainfall days as an indicator of extreme weather events that occur in each municipality. We contribute to the literature in two ways. First, we provide a theoretical framework that combines the dual economy model where sector assignment is endogenous and the model of household utility maximization in the presence of weather shocks to differentiate the impact of extreme weather events on the welfare of households in the formal and informal sectors. Our second contribution is the empirical evidence that we provide on the vulnerability of the informal and the formal households by estimating a switching regression model using the full information maximum likelihood (FIML) method.

We find that the household's welfare is adversely affected by extreme rainfall days regardless of which sector they belong to. For the two welfare indicators, expenditures and income, the negative impact is bigger for the formal than the informal sector by as much as 17.4 and 11.9 percent, respectively. This is intuitive given that the households in the formal sector have larger income and have more to lose than households in the informal sector. However, the adverse impact to informal households may be irreversible given their limited capability to recover and their ability to smooth out consumption even during years considered as normal. Moreover, given this negative result, there is a potential for households in both sectors to slide into poverty when they are affected by extreme weather events.

The paper is organized as follows. Section 2 reviews related literature. Section 3 presents our theoretical framework and empirical specification. Section 4 discusses our data sources and documents stylized facts on the formal and informal sector and statistical relationship with rainfall data. Section 5 presents our empirical estimation and discussion of results. The last section provides conclusions and policy implications.

2. Review of Related Literature

Disasters due to natural hazards have become a pressing development concern due to its unfortunate capability to negate development gains, push households deeper into poverty, and exacerbate inequality (Beg et al., 2002; Karim, 2018; McGuigan, Reynolds, & Wiedmer, 2002; Organisation for Economic Co-operation and Development, 2003). A household's socio-economic status influences its vulnerability to a disaster, and their resilience in its aftermath (Arouri, Nguyen, & Youssef, 2015; Teo, Goonetilleke, Ahankoob, Deilami, & Lawie, 2018). Poorer households, especially those in rural areas, are more likely to suffer from disasters (De Haen & Hemrich, 2007; Ludwig et al., 2007), and are more vulnerable (Dintwa, Letamo, & Navaneetham, 2019; Fothergill & Peek, 2004).

Informal households, where most of the urban and rural poor belong, tend to be in hazardous areas, increasing their disaster risk profiles. The International Labour Organization (ILO) defines informal economy as consisting of independent, self-employed small-scale producers and distributors of goods and services. Some workers may be doing the same work as those in the formal sector but does so in an unregulated and unprotected environment.

Disasters caused by natural hazards increase the probability of informal workers to remain informal, while also increasing the risk that formal workers will fall into informal sector. Studies suggest that formal workers forced to leave their jobs due to external shocks prefer to become informal workers rather than becoming unemployed. This could happen in an economy, especially those that are very dependent on the services sector, especially tourism (Pecha, 2017). Informality aggravates the socioeconomic costs incurred by households during disasters. The marginalization of this sector to public systems worsens their ability to cope with shocks compared to formal sector. The potential lack of health insurance may increase the costs of accessing good health centers, reducing the possibility of this population to receive proper health services, and worsening their productivity. Hallegatte, Vogt-Schilb, Bangalore, & Rozenberg (2017) points out the importance of protecting vulnerable populations from natural shocks since they lack the formal financial instruments to cope with the risk. Informal households do not have access to financial tools to overcome the negative effects of natural disasters including no access to credit, lack of savings and non-existent formal insurance. Their lack of access to financing in the event of a disaster shock compels informal workers to use their own (usually scarce) savings to recover or even relying financially on family or friends (Patankar & Patwardhan, 2015).

Given its geographical location and associated risks to disasters, the Philippines has attracted the interest of researchers in examining the nexus between disasters due to natural hazards and welfare. Examples include studies investigating rainfall shocks and poverty (Bayudan-Dacuycuy & Baje, 2019; Skoufias, Kawasoe, Strobl, & Acosta, 2019); drought and poverty (Datt & Hoogeveen, 2003); flood disasters and welfare (Yonson & Noy, 2019); typhoon and its welfare impacts on the rich and poor (Sakai, Estudillo, Fuwa, Higuchi, & Sawada, 2017); farmer's welfare and meteorological shocks (Ravago, Roumasset, & Jandoc, 2016); typhoon and death (Anttila-Hughes & Hsiang, 2013); and extreme weather and inequality (Bayani-Arias & Palanca-Tan, 2017).

To the best of our knowledge, none of the existing studies have explicitly modelled the impact of extreme weather events on the welfare of the informal and formal sectors. Given the size of the informality in the country and their characteristics, it is important to understand and differentiate the impacts of extreme weather events based on informality so that appropriate policy instruments can be developed.

3. Economic Framework

3.1. Theoretical framework

We differentiate the impact of extreme weather events, specifically the number of extreme rainfall days per year, on the welfare of the households in the formal and informal sectors of the economy. We combine the theoretical framework of household utility maximization in the presence of weather shocks (Dercon, 1996; Rosenzweig & Binswanger, 1993) with the dual economy model where sector employment is endogenous (Günther & Launov, 2012; Harris & Todaro, 1970; Maloney, 2004; Stiglitz, 1976). The theoretical basis of the formal-informal sectors is the dual market theories of Lewis (1954) followed-up by Harris-

Todaro (1970) and Stiglitz (1976). A distinction in these body of literature is that the formal sector is subject to taxation and regulatory law, while the informal sector is largely outside of it (implicitly illegal). However, there is not a sharp divide between formal and informal, some firms may be formal in some respects and informal in others (Gërxhani, 2004; Guha-Khasnobis, Kanbur, & Ostrom, 2006). Nonetheless, a bifurcation is a useful hypothetical construct that can serve as a guide in improvements of statistical databases; and formulation and implementation of policies.

The seminal papers above hold the view that workers choose the disadvantaged informal sector to escape unemployment once they are rationed out of the formal sector. While the informal sector is associated with lower earnings (and income), the observed lower wages coupled with lower returns to education do not necessarily imply market segmentation (Heckman & Hotz, 1986; Pratap & Quintin, 2006). If agents were free to move between two sectors with two earnings equation (Basu, 2003), this implies a voluntary choice of agents to work in the informal sector (Maloney, 2004). However, this does not necessarily imply that they are not poor but rather they would not be better off working in the formal sector. We take this view in modelling the endogeneity to total income of the formal and informal sectors.

A household faces a choice between the informal (I) and formal (F) sectors. It weighs the costs and expected benefits before arriving at a decision. Assuming that the expected benefits are equal to the income differentials between the formal (π_F) and informal (π_I), sectors, it will choose to be in the informal sector if the expected benefits are greater than the cost, that is:

$$\pi_I(\mu_I, \sigma_I) - \pi_F(\mu_F, \sigma_F) > f(s). \tag{1}$$

The income function of the households choosing I or F sector, respectively, is a function of the mean (μ_I), (μ_F) and standard deviation (σ_I), (σ_F) of incomes in the respective sector. The cost function $f(s)$, with $f'(s)$> 0 is increasing with search intensity s. Choosing the informal sector may be due to the non-wage features of the informal sector, such as households maximizing utility rather than earnings (Maloney, 2004). How are π_I and π_F determined?

We follow the set-up of household utility maximization in the presence of weather shocks (Asiimwe & Mpuga, 2007; Dercon, 1996; Rosenzweig & Binswanger, 1993). Each of the household has total assets (A), representing its stock of wealth. It is assumed that households allocate (n) shares of the assets to produce output that maximizes consumption needs prior to the realization of either a good or bad state associated with weather (w). Household maximizes the following utility function:

$$U_j = V(\mu_c, \sigma_c); V_\mu > 0, V_\sigma < 0 \ldots j = 1,2 \ldots N \quad (2)$$

where μ_c and σ_c are the mean and standard deviation of consumption. The function in equation (2) is quasi-concave to ensure convexity of preferences. The utility function is strictly quasi-concave ensuring a unique solution.

Household maximizes its utility as defined in Equation (2) by either choosing an appropriate suite of production investments or units of labour to supply when I or F sector is considered. If I sector is considered, its profit function is assumed to exhibit a constant return to scale in the inputs. The mean (μ_I) and standard deviation (σ_I) of the profits of household, its productive investment portfolio vector S_i, and the mean (μ_ω) and standard deviation (σ_ω) of the stochastic weather distribution are related via the following:

$$\mu_I = Af(S_i)\mu_\omega \quad (3)$$

$$\sigma_I = Al(S_i)\sigma_\omega \ , \ f_{ss}, l_{ss} < 0 \quad (4)$$

When F sector is considered, its income function is assumed to exhibit a constant returns to scale (CRS). The mean (μ_F) and standard deviation (σ_F) of the income of household, its units of labour L_i, and the mean (μ_ω) and standard deviation (σ_ω) of the stochastic weather distribution are related via the following:

$$\mu_F = Ad(L_i)\mu_\omega \tag{5}$$

$$\sigma_F = Ak(L_i)\sigma_\omega\ ,\ d_{LL}, K_{LL} < 0 \tag{6}$$

CRS assumption in the mean and standard deviation of the weather distribution is due to homogeneity of degree 0 in A of the mean and standard deviations in income per unit of wealth (Asiimwe & Mpuga, 2007) in Equations (3) to (6). Assuming only one source of variability in output and earnings, the mean consumption is given by:

$$\mu_{Ic} = \mu_I \text{ and } \mu_{Fc} = \mu_F \tag{7}$$

Mapping the standard deviation in income of households in I and F sectors depends on the constraints in capital markets. If there is an absence of borrowing and constraint in selling assets, then $\sigma_{Ic} = \sigma_I$ and $\sigma_{Fc} = \sigma_F$, similar to the assumptions in risk studies. However, if there is an insurance market then we have a case where $\sigma_{Ic} = \sigma_{Fc} = 0$, akin to savings in permanent income hypothesis. The standard deviation lies somewhere in between in empirical research (Asiimwe & Mpuga, 2007). Moreover, the relationships between consumption and profit variable of households in I sector and the consumption and earnings variability of households in F sector are given by:

$$\sigma_{Ic} = \kappa(A)\sigma_{I\,,}\ \ \kappa'(A) < 0 \tag{8}$$

$$\sigma_{Fc} = \rho(A)\sigma_{F\,,}\ \ \rho'(A) < 0 \tag{9}$$

The set of first-order conditions are given by:

$$V_\mu f_{S_i} = -V_\sigma l_{S_i}\sigma_\omega\kappa\ \ i = 1,2..,n-1 \text{ for } I \tag{10}$$

$$V_\mu d_{L_i} = -V_\sigma k_{L_i}\sigma_\omega\rho\ \ i = 1,2..,n-1 \text{ for } F \tag{11}$$

where $f_{S_i} = f_i - f_n$ and $l_{S_i} = l_i - l_n$, with f_i and l_i as the marginal contribution of the j_{th} production capital to the mean and standard deviation of profits, respectively, and $d_{L_i} = d_i - d_n$ and $k_l = k_i - k_n$, with d_i and k_i as the marginal contribution of the j_{th} labour units to the mean and standard deviation of earnings, respectively. The implication of the investment equilibrium characterized by risk aversion can then be tested. For the case of households in the

I sector, it's the positive association across all production assets between the marginal contributions to the mean and to the variability of profits for any two assets i and m. For the case of F, it's the positive association across all labour units between the marginal contributions to the mean and to the variability of earnings between two units of labour i and m.

$$\frac{f_{s_i}}{f_{s_m}} = \frac{l_{s_i}}{l_{s_m}} \text{ and } \frac{d_{s_i}}{d_{s_m}} = \frac{k_{s_i}}{k_{s_m}} \tag{12}$$

The implication of extreme weather disturbance on the riskiness of household's portfolios and profitability or earnings can be derived (Rosenzweig & Binswanger, 1993). An increase in the standard deviation of weather distribution σ_ω, leads to a decrease in l and k, and therefore to profitability and earnings of households in I and F sectors, respectively. That is, the size of the effect of increased risk due to weather disturbances decreases with the household's total wealth, if there is post consumption smoothing. Relatively wealthier households are likely to be more efficient than poor ones, even if wealth is independent of risk aversion (see Ravago, Roumasset, & Jandoc, 2016 for an example of a numerical illustration). Wealthier households are assumed to be found in the F sector and thus can better smooth consumption. This we show empirically in the next section.

3.2. Empirical Methods

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. The basic approach in examining the difference in the welfare of the formal and informal households would be the inclusion of a dummy variable equal to one if the household is classified as informal, and then, apply the ordinary least squares (OLS). However, this leads to a biased estimate due to the assumption that informality is exogenously determined, when in fact it can be potentially endogenous. Being in the informal sector may be voluntary based on households' self-selection. Households belonging to the informal sector may have systematically distinct characteristics and chose to be in the informal sector due to their expected benefits, thereby also influencing their income as noted in Section 3.1.

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. To address this endogeneity bias, we estimate a switching regression model by using maximum likelihood methods (Lee & Trost, 1978). We test the hypothesis that extreme rainfall days depress profits and earnings of households and therefore lower their income and consumption. Further, we examine the difference in the decline in income and expenditure of households in the informal and formal sectors.

We set up the econometric model by highlighting the difference between the total income in the informal and formal sectors as the main factor influencing sector choice. The difference can be interpreted as expected benefits and the desirability of being in either informal or formal sector. Due to limited data, we abstract from the role of lifetime income or other characteristics such as job security and other benefits in the sector of choice.

As presented in Section 3.1, a household faces a choice between the formal and informal sector. Households' characteristics and cost of seeking employment determine the expected net benefits of being in one sector. The difference in the net benefits determines the sector of choice. We have the following specification:

$$\log Y_{Ii} = \beta_0 + \beta_{It} D_{Ii-t} + \boldsymbol{\beta_I X}_{Ii} + \varepsilon_{Ii} \tag{13}$$

$$\log Y_{Fi} = \beta_0 + \beta_{Ft} D_{Fi-t} + \boldsymbol{\beta_F X}_{Fi} + \varepsilon_{Fi} \tag{14}$$

$$\mathrm{I}_i^* = \delta(\log Y_{Ii} - \log Y_{Fi}) + \gamma \boldsymbol{Z}_i + \eta_i \tag{15}$$

I_i^* is a latent variable that determines the sector chosen by the households (i) ; Y_{Ii} and Y_{Fi} are income of households in the informal (I) and formal (F) sectors, respectively. Households expenditure will also be used as left-hand side variable since it is empirically a better measure of welfare (Balisacan, 1993; Deaton, 1997). $\boldsymbol{Z}_i$ is a vector of characteristics influencing the decision regarding the sector of choice. D_{i-t} stands for an extreme weather event, i.e., the number of extreme rainfall days in a year experienced by the households in a municipality, in lags by $t = 1,2,3$ years. This variable is lagged by at least one year since timing of data collection matters in capturing any potential impact of this variable. We include lagged by two- and three-year values of this variable (D_{i-2} and D_{i-3}) to test any lingering effects of earlier experience. $\boldsymbol{X}_i$ is a vector of households' characteristics that influence income (or expenditures). The vector of parameters is β_0, β_{It}, β_{Ft}, $\boldsymbol{\beta_I}$, $\boldsymbol{\beta_F}$, and γ. The error terms are ε_I, ε_F, and η. The observed value outcome I_i of latent variable I_i^* of whether the household chooses a sector has the following form:

$$\begin{aligned} I_i &= 1 \; if \; I_i^* > 0 \\ I_i &= 0 \; Otherwise \end{aligned} \tag{16}$$

Our vector of household characteristics includes sex of household head, age of household, square of the age of household head, marital status of the household head, educational attainment of the household head, and household size. Our identifying variables for the sector selection equation are urbanity and being poor or non-poor. Urban-rural municipality classification is a proxy for location. Households' residential location may affect sector choice but not necessarily income. Being poor or non-poor is classification according to the standard of living set by the government. Having these variables in our switching regressions improves identification relative to OLS.

The error terms in Equations (13), (14), and (15) are assumed to have a trivariate normal distribution with zero mean and covariance matrix $\sum$, (i.e. $(\eta, \varepsilon_I, \varepsilon_F)' \sim N(0, \sum)$), with:

$$\sum = \begin{matrix} \sigma_\eta^2 & \sigma_{\eta I} & \sigma_{\eta F} \\ \sigma_{I\eta} & \sigma_I^2 & . \\ \sigma_{F\eta} & . & \sigma_F^2 \end{matrix}$$

where σ_η^2 is the variance of the error term in the selection equation (15-16), (which can be assumed to be equal to 1, since the coefficients are estimable only up to a scale factor (Di Falco, Veronesi, & Yesuf, 2011; Maddala, 1983), σ_I^2 and σ_F^2 are the variances of the error terms in the welfare equations (13) and (14), and $\sigma_{I\eta}$and $\sigma_{F\eta_\eta}$ represent the covariance of η_i and ε_{Ii} and ε_{Fi}. Since Y_{Ii} and Y_{Ii} are not observed simultaneously the covariance between ε_{Ii} and ε_{Fi} is not defined, indicated as dots in the covariance matrix. Moreover, since the error term of the selection equation (15-16) is correlated with the error terms of the welfare equations (13) and (14), the expected values of ε_{Ii} and ε_{Fi} conditional on the sample selection are non-zero and are defined as:

$$E[\varepsilon_{Ii}|I_i = 1] = \sigma_{I\eta}\frac{\phi(\gamma \boldsymbol{Z}_i)}{\Phi(\gamma \boldsymbol{Z}_i)} = \sigma_{I\eta}\lambda_{Ii} \tag{17}$$

$$E[\varepsilon_{Fi}|I_i = 0] = -\sigma_{F\eta}\frac{\phi(\gamma \boldsymbol{Z}_i)}{1-\Phi(\gamma \boldsymbol{Z}_i)} = \sigma_{F\eta}\lambda_{Fi} \tag{18}$$

where $\phi(.)$ and $\Phi(\gamma \boldsymbol{Z}_i)$ are the standard normal probability density function and standard normal cumulative density function, respectively; and $\lambda_{Ii} = \frac{\phi(\gamma \boldsymbol{Z}_i)}{\Phi(\gamma \boldsymbol{Z}_i)} = \sigma_{I\eta}$ and $\lambda_{Fi} = \frac{\phi(\gamma \boldsymbol{Z}_i)}{1-\Phi(\gamma \boldsymbol{Z}_i)}$. It is noteworthy that if the estimated covariances $\hat{\sigma}_{I\eta}$ and $\hat{\sigma}_{F\eta}$ are statistically significant, then the decision to be in the informal sector and the level of income (or expenditure) are correlated. This implies evidence of endogenous switching, and we can reject the null hypothesis of the absence of sample selectivity bias.

If selectivity effects are ignored, estimates of the relative income of the households in the two sectors are biased. The full- information maximum-likelihood (FIML) method corrects for the selection bias in income (or expenditure) estimates by accounting for correlation between the errors (η_i) in the selection equation (15-16) and the errors in separate income equations estimated for the households in the informal (ε_I) and formal sectors (ε_F) (Di Falco et al., 2011; Lokshin & Sajaia, 2004; Maddala, 1986; Nelson, 1984). Given the assumptions regarding the distribution of the error terms, the logarithmic likelihood function is:

$$\ln L_i = \sum_{i=1}^{N} I_i \left[ln\phi\left(\frac{\varepsilon_{Ii}}{\sigma_I}\right) - ln\,\sigma_I + ln\Phi(\theta_{Ii}) \right] + (1 - I_i) \left[ln\phi\left(\frac{\varepsilon_{Fi}}{\sigma_F}\right) - ln\,\sigma_F + ln(1 - \Phi)(\theta_{Fi}) \right] \quad (19)$$

where $\theta_{Ii} = \frac{\gamma \boldsymbol{Z}_i + \rho_j \varepsilon_{ji} / \sigma_j}{\sqrt{1-\rho_j^2}}, j = I, F$ with ρ_j denoting correlation coefficient between the error term η_i of the selection equation (15-16) and the error term $\varepsilon_{ji}$of equations (13) and (14), respectively.

3.2.1. Conditional Expectations, Treatment and Heterogeneity Effects

The endogenous switching regression model can be used to compare the observed and counterfactual levels of income (or expenditures). Hence, we can compare four cases. Compare Case (a) the expected income (or expenditures) of a household in the informal sector with Case (b) the expected income (or expenditures) of a household in the formal sector. Then, we compare the expected income (or expenditures) in the counterfactual hypothetical scenario. We compare Case (c), which is a household in the informal sectors but their expected income (and expenditure) is as if they are in formal sector hypothetically with Case (d), which is a household in the formal sector but their expected income (and expenditure) is as if they are in the informal sector hypothetically. The conditional expectations of the welfare equations for income (expenditure) in the four cases are presented in Table 1 and defined as follows:

$$E(Y_{Ii} |\, I_i = 1) = \beta_{It} D_{Ii-t} + \boldsymbol{\beta}_I \boldsymbol{X}_{Ii} + \sigma_{I\eta} \lambda_{Ii} \quad (20a)$$

$$E(Y_{Fi} |\, I_i = 0) = \beta_{Ft} D_{Fi-t} + \boldsymbol{\beta_F} \boldsymbol{X}_{Fi} + \sigma_{F\eta} \lambda_{Fi} \quad (20b)$$

$$E(Y_{Fi} |\, I_i = 1) = \beta_{Ft} D_{Ii-t} + \boldsymbol{\beta_F} \boldsymbol{X}_{Ii} + \sigma_{F\eta} \lambda_{Ii} \quad (20c)$$

$$E(Y_{Ii} |\, I_i = 0) = \beta_{It} D_{Fi-t} + \boldsymbol{\beta_I} \boldsymbol{X}_{Fi} + \sigma_{I\eta} \lambda_{Fi} \quad (20d)$$

Table 1. Conditional expectation, treatment, and heterogeneity effects.

Subsample	Decision Stage		Treatment Effects
	Informal	Formal	
Informal	(a) $E(Y_{Ii}\vert\, I_i = 1)$	(c) $E(Y_{Fi}\vert\, I_i = 1)$	TT
Formal	(d) $E(Y\vert\, I_i = 0)$	(b) $E(Y_{Fi}\vert\, I_i = 0)$	TU
Heterogeneity Effects	BH_I	BH_F	TH

Notes:
(a) and (b) represent observed expected income (or expenditure); (c) and (d) represent counterfactual expected income (or expenditure);
$I_i = 1$ if household is in the informal sector; $I_i = 0$ if household is in the formal sector;
Y_{Ii}: Log of real per capita income (or expenditure) if households choose to be in the informal sector;
Y_{Fi}: Log of real per capita income (or expenditure) if households choose to be in the formal sector;
TT: the effect of the treatment (i.e., being in the informal sector) on the treated (i.e., households are in the informal sector);
TU: the effect of the treatment (i.e., being in the informal sector) on the untreated (i.e., households are in the formal sector);
BH_I, BH_F: the effect of base heterogeneity for households that are in the informal sector (I), and formal sector (F); and
TH = (TT - TU): transitional heterogeneity.

Following Akpalu & Zhang, 2014; Di Falco et al., 2011; J. Heckman, Tobias, & Vytlacil, 2001, we calculate the following effects:

$$TT = E(y_{Ii}\vert\, I_i = 1) - E(y_{Fi}\vert\, I_i = 1) = (\beta_{It} - \beta_{Ft})D_{Ii-t} + (\boldsymbol{\beta_I} - \boldsymbol{\beta_F})\boldsymbol{X}_{Ii} + (\sigma_{I\eta} - \sigma_{F\eta})\lambda_{Ii} \quad (21a)$$

$$TU = E(y_{Ii}\vert\, I_i = 0) - E(y_{Fi}\vert\, I_i = 0) = (\beta_{It} - \beta_{Ft})D_{Fi-t} + (\boldsymbol{\beta_I} - \boldsymbol{\beta_F})\boldsymbol{X}_{Fi} + (\sigma_{I\eta} - \sigma_{F\eta})\lambda_{Fi} \quad (21b)$$

$$BH_I = E(y_{Ii}\vert\, I_i = 1) - E(y_{Ii}\vert\, I_i = 0) = (D_{Ii-t} - D_{Fi-t})\beta_{It} + (\boldsymbol{X}_{Ii} - \boldsymbol{X}_{Fi})\boldsymbol{\beta_I} + (\lambda_{I\eta} - \lambda_{F\eta})\sigma_{I\eta} \quad (21c)$$

$$BH_F = E(y_{Fi}\vert\, I_i = 1) - E(y_{Fi}\vert\, I_i = 0) = (D_{Ii-t} - D_{Fi-t})\beta_{Ft} + (\boldsymbol{X}_{Ii} - \boldsymbol{X}_{Fi})\boldsymbol{\beta_F} + (\lambda_{I\eta} - \lambda_{F\eta})\sigma_{F\eta} \quad (21d)$$

Conditions in Equations (21a)–(21d) can be described as follows:

(21a) Effect of the treatment on the treated. This is the effect of being in the informal sector in the presence of weather shock on the income (or expenditure) of the households that are in the informal sector.

(21b) The effect of the treatment on the untreated, i.e. households in the formal sector, given by the difference between cases (d) and (b).

(21c) The effect of heterogeneity of households in the informal sector is the difference between cases (a) and (d). Households in the informal sector may have lower income (or expenditure) than households in the formal sector regardless of their decision to be in the informal sector due to unobservable characteristics. This is the effect of base heterogeneity.

(21d) Similarly for the group of households that decided go to the formal sector, "the effect of base heterogeneity" is the difference between (c) and (b).

Transitional heterogeneity" (TH) in Table 1 is if the effect of going to the informal sector is larger or smaller for the households that actually go to the informal sector or for the households that did not relative to their counterfactual cases, that is the difference between equations (TT) and (TU).

4. Data, Sources, and some Stylized Facts

4.1. Household Data

We utilized two nationwide survey of households conducted by the Philippine Statistics Authority (PSA), namely the Family Income and Expenditure Survey (FIES) and the Labor Force Survey (LFS) in 2006, 2009, 2012, and 2015 (Philippine Statistics Authority, 2015a, 2018). These surveys use the same master sample based on the 2000 Census of Population and Housing (Philippine Statistics Authority, 2003) and follow a multistage sampling design that are representative of the population. We applied sampling weights in the estimation to adjust for disproportionate sampling and non-response.[1] This ensures that our estimates of the total number of households and population are consistent with the PSA's "high assumption" population projection. While both surveys are based on the same master sample, only a part of

[1] We used *rfactor* (raising factor) as the probability weight in 2006, 2009, and 2012 dataset. In 2015 data, the probability weight is equal to the product of *rfactor* and *pop_adj* (population adjustment).

the master sample is retained for the succeeding survey years, and thus it is only a cross section data and not a panel. The FIES and LFS are merged annually at the household level by the PSA and this is the dataset that we used. The data for households' income, expenditure, and households' characteristics are obtained from these two surveys.

4.2. Who are the informal sectors in the Philippines?

The PSA does not issue official statistical counts of formal and informal household shares in the country; however, it defines the informal sector as those households' unincorporated enterprises, which consists of the following: (1) informal own-account enterprises and (2) enterprises of informal employers. Informal own-account enterprises may employ unpaid family workers as well as occasionally or seasonally hired workers but do not employ employees on a continuous basis. Enterprises of informal employers are the own- and operated by own-account workers, which employ employees on a continuous basis. Acknowledging the differences in the implicit distinction in the dualism literature (Harris & Todaro, 1970; Lewis, 1954; Stiglitz, 1976) and the distinction used in the data, we offer an estimate of household informality using the PSA definition as a basis. Small businesses that are unincorporated but still pay taxes and in the government database for regulations may be considered formal.

The LFS classified employed persons according to seven categories, namely (1) Worked for private household, (2) Worked for private establishment, (3) Worked for government or government-controlled corporation, (4) Worked with Pay in Own Family-Operated Farm or Business, (5) Self-Employed, (6) Employers, and (7) Worked without pay in own family-operated farm or business. We classified households as formal or informal based on the class of work of the household head: informal if class of work falls under classification 5, 6 or 7; otherwise, formal. Based on the above definition, Table 2 presents the distribution of households by type of economy, formal and informal. The proportion of informal households has decreased, from 43 percent in 2006 down to 36 percent in 2015. There are more informal than formal households from 2006 to 2009 but we see a reversal in the numbers starting 2012.

Table 2. Distribution of Households by Class of Work of Household Head (in 000)

Category	Class of Work	2006	2009	2012	2015
	Formal	6,695 (38.47)	7,176 (38.89)	9,022 (42.31)	9,335 (42.47)
1	Private Household	250 (1.44)	321 (1.74)	385 (1.80)	461 (2.10)
2	Private Establishment	5,313 (30.53)	5,606 (30.38)	7,279 (34.14)	7,450 (33.89)
3	Gov or Gov-controlled Corporation	1,110 (6.38)	1,245 (6.75)	1,355 (6.35)	1,419 (6.45)
4	Own Family-Operated with Pay	21 (0.12)	4 (0.02)	4 (0.02)	5 (0.02)
	Informal	7,439 (42.75)	7,545 (40.89)	7,828 (36.71)	7,926 (36.06)
5	Self-Employed	6,101 (35.06)	6,193 (33.56)	6,430 (30.16)	6,611 (30.08)
6	Employer in Own Family-Operated Farm/Business	1,215 (6.98)	1,224 (6.63)	1,282 (6.01)	1,167 (5.31)
7	Own Family-Operated without Pay	123 (0.71)	129 (0.70)	116 (0.54)	148 (0.67)
	Total employed	14,134 (81.22)	14,721 (79.78)	16,851 (79.03)	17,261 (78.53)
	Non-Working	3,268 (18.78)	3,731 (20.22)	4,472 (20.97)	4,719 (21.47)
	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. We used *rfactor* (raising factor) as the probability weight in 2006, 2009, and 2012 dataset. In 2015, the probability weight is equal to the product of *rfactor* and *pop_adj* (population adjustment). Total number of households using these weights are consistent with the PSA's "high assumption" population projection. Source of basic data: FIES-LFS.

Where do the informal households live? Table 3 distinguishes the informal and formal households based on the areas where they lived, either urban or rural and whether they are poor or non-poor. The literature has documented that the common features of informal households are that they are mostly in the rural areas and most of them are poor. Municipality is defined 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. A household is considered poor if its total income is less than the provincial threshold of poverty set by the government. Table 3 highlights the intersection of informality in the Philippines and these characteristics.

Table 3. Distribution of Households by Urban-Rural and Formal-Informal Classifications (in 000)

Classification	2006	2009	2012	2015
Rural Non-poor	7,101	7,510	9,348	10,147
	(41)	(41)	(44)	(46)
Formal	2,370	2,546	3,473	3,854
	[33]	[34]	[37]	[38]
Informal	3,503	3,550	3,923	4,146
	[49]	[47]	[42]	[41]
Non-working	1,228	1,414	1,952	2,147
	[17]	[19]	[21]	[21]
Rural Poor	3,097	3,188	3,429	3,062
	(18)	(17)	(16)	(14)
Formal	981	1,076	1,326	1,234
	[32]	[34]	[39]	[40]
Informal	1,827	1,758	1,698	1,469
	[59]	[55]	[50]	[48]
Non-working	289	355	405	359
	[9]	[11]	[12]	[12]
Urban Non-poor	6,621	7,105	7,865	8,168
	(38)	(39)	(37)	(37)
Formal	3,087	3,228	3,897	3,952
	[47]	[45]	[50]	[48]
Informal	1,871	2,017	1,959	2,107
	[28]	[28]	[25]	[26]
Non-working	1,663	1,860	2,009	2,109
	[25]	[26]	[26]	[26]
Urban Poor	584	649	681	604
	(3)	(4)	(3)	(3)
Formal	257	327	327	295
	[44]	[50]	[48]	[49]
Informal	238	221	248	205
	[41]	[34]	[36]	[34]
Non-working	88	101	106	105
	[15]	[16]	[16]	[17]
Total Number of Households in Population	17,403	18,452	21,323	21,980
	(100)	(100)	(100)	(100)

Authors' calculation. Numbers in parenthesis are percentage shares. Sampling weights are applied to reflect the number of households in the population. We used *rfactor* (raising factor) as the probability weight in 2006, 2009, and 2012 dataset. In 2015, the probability weight is equal to the product of *rfactor* and *pop_adj* (population adjustment). Total number of households using these weights are consistent with the PSA's "high assumption" population projection. Poor/Non-poor are households whose income fall below the provincial minimum standard set by the PSA (Philippine Statistics Authority, 2015b). 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. Source of basic data: FIES-LFS and PSA.

Poverty is still a rural phenomenon in the country. There are more poor households in the rural areas than in the urban areas. 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. On the other hand, the urban poor households comprised only about 3 percent of the total number of households. The proportion of the informal households is lower compared with the formal sector. The trend from 2006 to 2015 is also decreasing following the overall trend we observed in the proportion of informal households.

4.3. ***Rainfall Data and Extremes Index***

In this study, 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. Its spatial coverage at 0.25° (approximately 25 km) grid resolution addresses constraints posed by the limited number of weather stations in the Philippines.

Different indices based on intensity, frequency, accumulation, and duration have been used in other studies to describe rainfall extremes at seasonal and annual timescales (Cheong et al., 2018; Endo, Matsumoto, & Lwin, 2009; Villafuerte et al., 2014; Zhang et al., 2011). We define extreme rainfall day as a day with rainfall equal to or exceeding the baseline threshold value of 95th percentile of rainfall from all days across the 1998 to 2018 period. Counting the number of extreme rainfall day in a year yields an annual number of extreme rainfall days where some years may have more or fewer extreme rainfall days than other years. This definition is similar with one of the extreme precipitation indices in Villafuerte et al. (2014) but differs in considering all days instead of only wet days when deriving the 95th percentile threshold value. Although a higher percentile threshold, e.g. 99th percentile, could be used to describe extreme rainfall, this can result in a smaller sample size; hence, the 95th percentile threshold was selected in this study, which encompasses both heavy and extreme rainfall. Also, note that this baseline threshold value is determined at each grid box of the dataset because of the localized nature of rainfall. Then, the maximum number among all grid boxes within each municipal boundary is used to define the number of extreme rainfall days per municipality for each year. Figure 1 illustrates the maximum annual number of extreme rainfall days within the period from 1998 to 2018 wherein the year with the maximum annual number differs per municipality.

Each year, we distinguished municipalities as experiencing "normal" or "extreme" rainfall. A municipality is tagged under "extreme" when the number of extreme rainfall days for the year exceeds the 75th percentile of the annual number of extreme rainfall days across the 1998-2018 period. Since there is no weight assigned to a particular extreme rainfall event, e.g. in terms of disastrous impacts, each extreme rainfall day is treated equally such that if there are few extreme rainfall days in that year, then it would be possible that the year is considered as "normal".

It would be important to note some caveats. First, the extreme characteristic is defined here in terms of the frequency of intense rainfall. Thus, events that may be extreme due to prolonged rainfall duration albeit with moderate intensity, as well as intense typhoons with moderate rainfall, may have been excluded in this definition. The choice of thresholds for both definitions of extreme rainfall day (i.e. 95th percentile) and extreme year (i.e. 75th percentile) can also give different results. Another consideration would be limitations in the dataset itself. Although the TRMM data has been shown to be able to capture extreme precipitation in the Philippines, the skill can vary per region, e.g. better skill in the northern and eastern regions than in the southern parts of the country (Jamandre & Narisma, 2013; Peralta, Narisma, &

Cruz, 2020). Extreme rainfall due to localized thunderstorms may also be underestimated given the spatial resolution of the dataset.

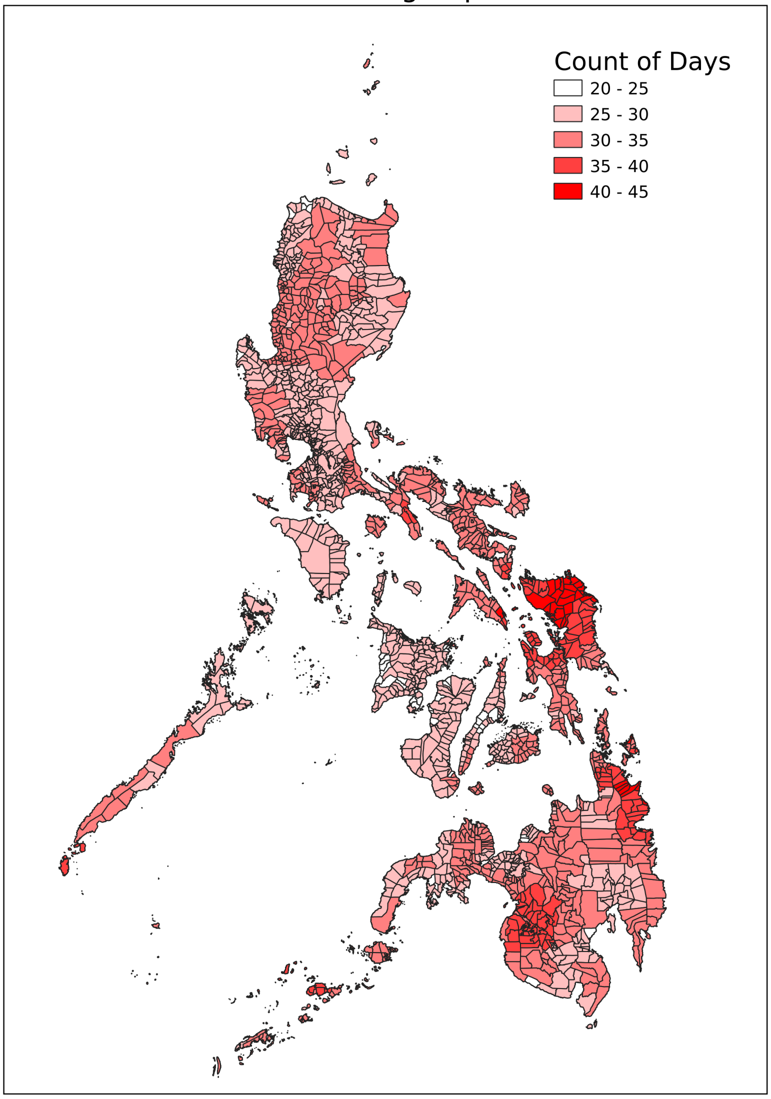

Figure 1. Map of the maximum annual number of extreme rainfall days within the 1998 to 2018 period

4.4. Extreme weather events and welfare

Since our interest is on the impact of extreme weather events on the welfare of the informal and formal households, a simple comparison of welfare indicators combined with information on their experience of annual number of extreme rainfall days is informative. We compare the average income and expenditure of households in areas that experienced an extreme year vis-à-vis areas that had a normal year. As defined, a municipality is considered to have experienced an extreme rainfall year when the number of extreme rainfall days for that year exceeds the 75th percentile of the annual number of extreme rainfall days across the 1998-2018 period.

Figure 2 shows the municipalities that experienced an extreme year for the years 2005, 2008, 2011, and 2014. Since the impact of extreme rainfall would manifest on welfare measures in the year after it was experienced, we used the one-year lag of the data. For welfare indicators, we used average per capita real income and expenditure.

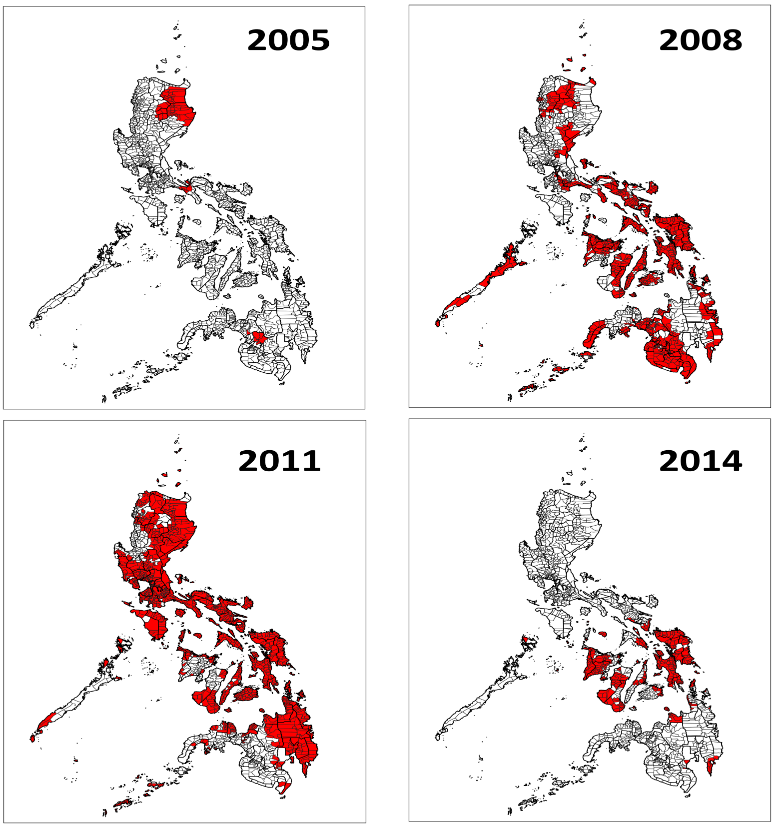

Figure 2. Areas that experienced an "extreme" year (in red) during the years: 2005, 2008, 2011, and 2014.

Table 4 presents the comparison and shows that for both households experiencing normal and extreme years, per capita expenditures and income are lower among informal households compared to formal households. Informal households, where most of the urban and rural poor belong, tend to be in hazardous areas, increasing their disaster risk profiles.

Table 4. Real Incomes and Expenditures per Capita, by Informality and by Extremity of Rainfall (Using 2000 Prices)

		Normal		Extreme		P-Values			
		Formal	Informal	Formal	Informal				
		(a)	(b)	(c)	(d)	(a,b)	(c,d)	(a,c)	(b,d)
2006	Income	33,152	25,099	24,979	21,489	0.0000	0.0320	0.0004	0.0064
	Expenditures	27,976	21,284	20,705	17,866	0.0000	0.0132	0.0000	0.0001
	N (by sector)	13,363	16,328	471	809				
	N, total	30,971							
2009	Income	35,366	31,954	29,213	24,969	0.0002	0.0002	0.0000	0.0000
	Expenditures	30,306	25,724	25,214	20,470	0.0000	0.0000	0.0000	0.0000
	N (by sector)	7,786	7,895	6,337	8,429				
	N, total	30,447							
2012	Income	28,659	25,162	33,780	28,785	0.0001	0.0000	0.0000	0.0000
	Expenditures	22,613	19,721	28,038	22,498	0.0000	0.0000	0.0000	0.0000
	N (by sector)	4,795	5,344	11,220	10,271				
	N, total	31,630							
2015	Income	34,132	30,489	27,243	25,423	0.0000	0.0973	0.0000	0.0000
	Expenditures	27,576	23,384	21,619	20,149	0.0000	0.0125	0.0000	0.0000
	N (by sector)	13,980	13,268	2,575	2,709				
	N, total	32,532							

Authors' calculations. The numbers are per capita real household incomes and expenditures computed using year 2000 prices. The reported P-value is from the t-test between populations means. N is the total number of households with observations in the sample data. Extreme rainfall day is defined 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. Sources of basic data: FIES-LFS 2006 to 2015, PSA.

Table 5 presents the same comparison with 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. These welfare indicators show that the average per capita expenditure and income of households in areas with extremely high rainfall are lower compared with their counterparts in areas experiencing normal rainfall. Exemption is agricultural income, where the informal households have higher income than the households in the formal sector. This is expected since agriculture is dependent on rainfall and a substantial proportion of informal households are engaged in agriculture. This does not mean that agricultural income is higher than income non-agricultural income.

Table 5. Disaggregated Real Incomes and Expenditures per Capita (Using 2000 Prices)

	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. Extreme rainfall day is defined 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. Sources of basic data: FIES-LFS 2006 to 2015, PSA.

4.5. Descriptive Statistics

Table 6 present some descriptive statistics that we used in the empirical estimation. Appendix Table A1 has the variable definition and Table A2 has descriptive statistics with complete list of variables. In terms of family characteristics, on the average, informal household heads were observed to be older than those in the formal sector. The sex and marital status of household heads are comparably similar. Educational attainment of the household head is defined as a dummy variable equal to one if the head finished high school or higher, and zero otherwise. Using this categorization, majority of household heads among the formal sector finished secondary education, while the same cannot be said among informal households. This can be indicative of the disparity in the accessibility of education where those in the informal sector have less resources and opportunities to sustain receiving education. This observation is consistent in poverty and urban-rural indicators. A household is considered poor if its total current income is lower than its provincial annual per capita poverty threshold (Philippine Statistics Authority, 2015b). On the average, a higher share of informal households are poor compared to those in the formal sector. The urban-rural indicator is also observably higher among formal households than among informal households.

Table 6. Descriptive Statistics

Description	Total (n = 125,533)		Formal (n = 60,512)		Informal (n = 65,041)	
	Mean	SD	Mean	SD	Mean	SD
Real Income per capita	30,034	48,440	32690	42543	27564	53226
Real Expenditure per capita	24,540	29,069	27147	31222	22116	26684
Number of Extreme Rainfall days, previous year	21.61	5.8	21.60	5.6	21.63	5.9
Number of Extreme Rainfall days, two years ago	17.86	4.7	17.57	4.7	18.13	4.7
Number of Extreme Rainfall days, three years ago	21.10	4.8	21.19	4.8	21.02	4.8
Informality dummy = 1 if informal, 0 if formal	0.52	0.5	0.00	0.0	1.00	0.0
Sex of HH dummy = 1 if male, 0 if female	0.86	0.3	0.88	0.3	0.84	0.4
Age of HH	47.5	12.4	44.6	11.0	50.3	12.9
Age of HH Squared	2,413	1,240	2106	1027	2698	1349
Marital status of HH dummy = 1 if household head is married, 0 otherwise	0.17	0.4	0.16	0.4	0.18	0.4
Educational attainment of HH dummy = 1 if household head finished high school or higher, 0 otherwise	0.43	0.5	0.52	0.5	0.35	0.5
Household Size	4.85	2.2	4.86	2.1	4.83	2.2
Poverty indicator dummy = 1 if poor, 0 if non-poor	0.24	0.4	0.20	0.4	0.28	0.4
Urban Municipality dummy = 1 if urban, 0 if non-urban	0.32	0.5	0.41	0.5	0.24	0.4

Authors' calculations. Figures are real household incomes and expenditures computed using 2000 prices. Extreme rainfall days are defined as days with rainfall exceeding the 95th percentile over the 1998-2018 period in each year per location. Poverty is defined by comparing household's total income on the provincial annual per capita poverty threshold. Municipality is defined as urban if more than 60 percent of the households is categorized as urban in the FIES urban/rural classification. Sources of basic data: FIES-LFS 2006 to 2015, PSA.

5. Empirical estimation and results

Using the number of extreme rainfall days in a year as indicator for extreme weather event, Table 7 presents the estimates using OLS and the endogenous switching regression model estimated by full information likelihood (FIML). Columns (a) and (e) present the estimation by ordinary least squares (OLS) of the welfare equation using expenditure and income, respectively. This specification has no switching and with a dummy variable equal to one if the household is observed to be in the informal sector, zero otherwise. However, informality is not exogenous since classification may be due to self-selection and thus estimates may be inconsistent and biased.

Table 7. Parameter Estimates of Sector Choice and Welfare Equations, Pooled data

		Endogenous Switching Regression[a] (EXPENDITURE)				Endogenous Switching Regression[a] (INCOME)		
Model	**OLS**		**Formal**	**Informal**	**OLS**		**Formal**	**Informal**
Dependent Variable	**Log (Per Capita Expenditure)**	**Informality**	**Log (Per Capita Expenditure)**		**Log (Per Capita Income)**	**Informality**	**Log (Per Capita Income)**	
	(a)	**(b)**	**(c)**	**(d)**	**(e)**	**(f)**	**(g)**	**(h)**
Informality dummy = 1 if informal, 0 if formal	-0.067***				-0.069***			
	(0.004)				(0.004)			
Log of Number of Extreme Rainfall days, previous year	-0.096***	-0.125***	-0.162***	-0.106***	-0.084***	-0.132***	-0.172***	-0.119***
	(0.010)	(0.013)	(0.010)	(0.009)	(0.010)	(0.013)	(0.011)	(0.011)
Log of Number of Extreme Rainfall days, two years ago	-0.197***	0.100***	-0.177***	-0.107***	-0.162***	0.076***	-0.157***	-0.064***
	(0.011)	(0.013)	(0.010)	(0.010)	(0.011)	(0.013)	(0.010)	(0.011)
Log of Number of Extreme Rainfall days, three years ago	-0.027**	-0.143***	-0.113***	-0.077***	0.037***	-0.113***	-0.046***	(0.009)
	(0.011)	(0.015)	(0.011)	(0.011)	(0.011)	(0.015)	(0.012)	(0.012)
Sex of HH dummy = 1 if male, 0 if female	-0.126***	-0.226***	-0.204***	-0.204***	-0.148***	-0.217***	-0.233***	-0.241***
	(0.007)	(0.013)	(0.010)	(0.009)	(0.007)	-0.013	(0.011)	(0.011)
Age of HH	0.019***	0.000	0.024***	0.033***	0.021***	0.008***	0.029***	0.034***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Age of HH Squared	-0.000***	0.000***	-0.000***	-0.000***	-0.000***	0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Marital status of HH dummy = 1 if household head is married, 0 otherwise	-0.012*	-0.181***	-0.075***	-0.136***	-0.019***	-0.184***	-0.093***	-0.163***
	(0.006)	(0.013)	(0.009)	(0.009)	(0.007)	(0.012)	(0.010)	(0.011)
Educational attainment of HH dummy = 1 if household head finished high school or higher, 0 otherwise	0.494***	0.022***	0.645***	0.384***	0.509***	0.068***	0.721***	0.370***
	(0.005)	(0.007)	(0.005)	(0.006)	(0.005)	(0.007)	(0.006)	(0.006)
Household Size	-0.083***	-0.055***	-0.141***	-0.114***	-0.076***	-0.067***	-0.150***	-0.115***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Poverty indicator dummy = 1 if poor, 0 if non-poor	-0.769***	0.831***			-0.957***	0.953***		
	(0.004)	(0.006)			(0.004)	(0.006)		
Urban Municipality dummy = 1 if urban, 0 if non-urban		-0.445***				-0.339***		
		(0.005)				(0.005)		
Constant	10.712***	0.366***	11.236***	9.433***	10.430***	0.146*	10.992***	9.083***
	(0.057)	(0.082)	(0.062)	(0.059)	(0.057)	(0.080)	(0.068)	(0.068)
R-squared	0.537				0.554			
Sigma			-0.767	0.762			0.803	0.889
Rho			0.805	0.947			0.814	0.972
Observations	125553	125553	125553	125553	125553	125553	125553	125553
LR test of indep. eqns. :	chi2(2) = 32186.05	Prob > chi2 = 0.0000			chi2(2) = 25885.27	Prob > chi2 = 0.0000		

Notes: [a] Estimation by Full Information Maximum Likelihood using "movestay" command of STATA. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. *Sigma* is the square-root of the variance of the error terms (ε_{Ii} and ε_{Fi}) in the welfare equations (13) and (14), respectively. *Rho* is the correlation coefficient between the error term (η_i) in the selection equation (15) and the error terms (ε_{Ii} and ε_{Fi}) in the welfare equations (13) and (14), respectively. *Rho* confidence interval: column (c) is 0.80 – 0.81; (d) is 0.945 – 0.949; (g) is 0.81 – 0.82 ; and (h) 0.971 – 0.973. Thus, all *Rho*s are significantly different from zero.

To address endogeneity, we implemented endogenous switching regression using Stata's "movestay" command (Lokshin & Sajaia, 2004, 2008). We estimated the coefficients in the specification given in equations (13) and (14) using two welfare indicators, log of real per capita expenditure (columns c and d) and log of per real capita income (columns g and h). Columns (b) and (f) present the estimated coefficients of selection equation (15) and equation (16), i.e., choosing either informal or formal sector.

The results of the selection equation in columns (b) and (f) shows that each identifying variable has a significant effect on the likelihood of being in the informal sector. The results suggest that poverty and urban-rural classification of municipality where the households reside 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.

The estimated coefficients of the correlation terms (Rho) are positive using both expenditure and income. The Rho values which measure the correlation coefficients between the error terms (η_i) in the selection model and the error terms (ε_{Ii} and ε_{Fi}) in the welfare equations (13) and (14), are all statistically significantly different from zero. This implies that we fail to reject the null hypothesis of sample selection bias. This shows that being in the informal sector may not have the same effect as being in the formal sector if they choose informal sector. Thus, the switching regression is more appropriate than the OLS regression. The likelihood ratio test of independence of the selection and outcome equations indicate that we can reject the null hypothesis of no correlation between informality and income or expenditure.

The positive sign of the Rho values indicate negative bias. Those who are informal are likely to have lower expenditure or income than any random household in the sample. This implies that informal households tend to have unobserved characteristics ("ability") that lower expenditure and income. Not controlling for this, for example in the OLS models, will bias upwards the estimates of the impact of formal-informal classification on expenditure.

Focusing now on the implication of informality on welfare in the presence of a weather shock (number of extreme rainfall days), the most obvious approach is to estimate the income or expenditure equation using OLS that includes a dummy variable equal to one if the household is informal, and zero otherwise (Table 7, columns (a) and (e)). The estimated parameters for informality are as expected, negative and significant. The results also show that being informal compared to formal sector decreases expenditure and income by around 7 percent, respectively, holding other things constant and significant at one percent level. Consistent with the literature, OLS estimates show that one added day of extreme rainfall in the previous year adversely affect the households' income by negative 8.4 percent and households' expenditure negative 9.6 percent. However, this approach assumes that informality is exogenously determined, while it can be potentially endogenous. Thus, OLS estimates may be biased and inconsistent. The approach also does not distinguish the potential difference in the welfare function of the households in the informal and formal sectors.

The coefficient estimates in Table 7, columns (c) (d), (g), and (h) consider the endogenous switching in the welfare function. In terms of the coefficients of the welfare function for the informal and formal households, the estimates of the one-year lag of the number of extreme rainfall days for income or expenditure equations are negative and significant. Higher number of extreme rainfall days experienced by the households one year ago significantly lowers expenditure of households 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. The coefficients of the two- and three-year lagged extreme rainfall variable are all negative and significant, with the magnitude getting smaller the earlier the experience of extreme rainfall.

This shows that households, regardless of which sector they belong, are still reeling from the negative effects of experiencing extreme rainfall from three and two years ago.

Adding the coefficient estimates of the three lagged variables gives the value of the impact of persistent experience of extreme rainfall days. Using expenditure as welfare indicator, the impact on the formal and informal sectors are -0.45 and -0.29, respectively. Using income, the impact on the formal and informal sectors are -0.38 and -0.19, respectively. This is intuitive given that the households in the formal sector has larger income and expenditure 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 limited capability to recover and their ability to smooth out consumption even during years considered as experiencing normal rainfall. Figure 3 plots the lag distribution of the β_{jt} coefficients of the extreme rainfall days variable (with expenditure as the welfare indicator). 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.

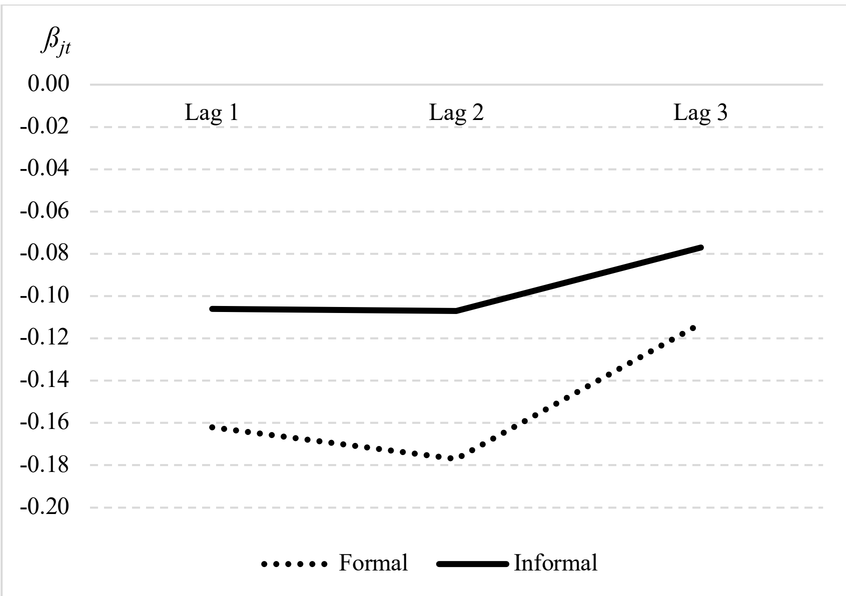

Figure 3. Lag distribution of the extreme rainfall days variable, D_{ji-t}.

In appendix Tables A3 and A4, we report the regression results with one-year lag only and with both one- and two-year lags of the variable number of extreme rainfall days, respectively.

Table 8 reports the conditional expectation, treatment and heterogeneity effects or the expected income and expenditure in the presence of weather shock under actual and counterfactual conditions as provided in Table 1.

Table 8a. Conditional expectation, treatment and heterogeneity effects, Income (in PhP) 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

Table 8b. Conditional Expectation, Treatment and Heterogeneity Effects, Expenditure (in PhP) as Dependent Variable

Subsample	Decision Stage		Treatment effects	
	Informal	Formal		
Informal	(a) 16,999	(c) 19,082	TT	-2,083
Formal	(d) 5,648	(b) 44,540	TU	-38,892
Heterogeneity Effects	BH_I 11,352	BH_F -25,458	TH	36,810

Notes: Author's calculation. Since the specification is in logs, reported numbers above are $exp(\hat{y}_j)$ to get the levels per capita in PhP. See Table 1. (a) and (b) represent the observed expected value of welfare indicators, income, and expenditure in PhP. (c) and (d) represent the counterfactual expected value. Being observed to be in the informal sector is like being treated, with informality as the treatment. TT is the treatment effect on the treated. TU is treatment effect on the untreated. The heterogeneity effect is the effect of base heterogeneity for households that went to informal sector and those that went to formal sector. TH = TT-TU is the transitional heterogeneity.

In Table 8a, 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. 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 where they choose the formal sector. In the second case where the counterfactual of formal households being informal, (cells b vs. d), households in the formal sector would have income lower by PhP 51,500 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 49,591 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). 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. The results also show that households in the informal sector are worse off choosing to be in the informal sector than formal sector. Finally, in the counterfactual case (d), that the formal households become informal, they would have income much lower than households that are in the informal sector. Table 8b has similar interpretation using expenditure as the dependent variable.

6. Concluding Remarks

Our goal is to examine whether there are differences in the effects of extreme weather events as defined by the number of extreme rainfall days in a year on households considered as informal or formal. In our analysis, we combine the framework of household production model in the presence of weather shocks with the dual economy model where sector choice is endogenous. We estimate a simultaneous equations model with endogenous switching to account for the heterogeneity in the decision to be in the informal and formal sector.

Our analysis suggest that household's characteristics influence the choice of being in either the informal or formal sector. Being poor and living in the rural areas significantly increase the likelihood of being in the informal sector.

On the implication of informality on welfare in the presence of a weather shock, we find that the household's welfare is adversely affected by frequent extreme rainfall days regardless of what sector they belong to. For the two welfare indicators, expenditures and income, the negative impact is bigger for the formal than the informal sector by as much as 17.4 and 11.6 percent, respectively. The higher percentage loss by "formal" households is probably because a higher percentage of their income is measured by the data. Households in the formal sector have also 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 limited capability to recover and their ability to smooth out consumption even during years considered as normal. Moreover, given this negative result, there is a potential for households in both sectors to slide into poverty when they are affected by extreme weather events. 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.

With the foregoing, targeted social protection coverage to households near the poverty line can help soften the blow of a weather shocks. Policies on poverty alleviation should include attention to its stochastic aspects (Anderson & Roumasset, 1996). 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.

References

Akpalu, W., & Zhang, X. (2014). Fast-Food Consumption and Child Body Mass Index in China. Helsinki, Finland: UNU-WIDER.

Anderson, J., & Roumasset, J. (1996). Food Insecurity and Stochastic Aspects of Poverty. *Asian Journal of Agricultural Economics*, *2*(2), 53–66. Retrieved from https://econpapers.repec.org/RePEc:pra:mprapa:13323

Anttila-Hughes, J., & Hsiang, S. (2013). Destruction, Disinvestment, and Death: Economic and Human Losses Following Environmental Disaster . *SSRN*. https://doi.org/dx.doi.org/10.2139/ssrn.2220501

Arouri, M., Nguyen, C., & Youssef, A. Ben. (2015). Natural Disasters, Household Welfare, and Resilience: Evidence from Rural Vietnam. *World Development*, *70*, 59–77. https://doi.org/https://doi.org/10.1016/j.worlddev.2014.12.017

Asiimwe, J. B., & Mpuga, P. (2007). Implications of rainfall shocks for household income and consumption in Uganda. In *Conference Proceedings*. Retrieved from https://www.africaportal.org/publications/implications-of-rainfall-shocks-for-household-income-and-consumption-in-uganda/

Balisacan, A. M. (1993). Agricultural Growth, Landlessness, Off-Farm Employment, and Rural Poverty in the Philippines. *Economic Development and Cultural Change*, *41*(3), 533–562. Retrieved from http://www.jstor.org/stable/1154315

Basu, K. (2003). *Analytical Development Economics: The Less Developed Economy Revisited* (Vol. 1). The MIT Press. Retrieved from https://econpapers.repec.org/RePEc:mtp:titles:0262523442

Bayani-Arias, J. K., & Palanca-Tan, R. (2017). Analyzing the Relationship Between Exposure to Extreme Weather and Economic Inequality in the Philippines. *Journal of Economics, Management & Agricultural Development*, *3*, 27–39. Retrieved from https://cem.uplb.edu.ph/jemad-volume-3-number-1/finish/5-journals/289-jemad-volume-3-number-1

Bayudan-Dacuycuy, C., & Baje, L. K. (2019). When It Rains, It Pours? Analyzing the Rainfall Shocks-Poverty Nexus in the Philippines. *Social Indicators Research: An International and Interdisciplinary Journal for Quality-of-Life Measurement*, *145*(1), 67–93. https://doi.org/DOI: 10.1007/s11205-019-02111-,

Beg, N., Morlot, J. C., Davidson, O., Afrane-Okesse, Y., Tyani, L., Denton, F., … Atiq Rahman, A. (2002). Linkages between climate change and sustainable development. *Climate Policy*, *2*(2), 129–144. https://doi.org/https://doi.org/10.1016/S1469-3062(02)00028-1

Behlert, B., Diekjobst, R., Felgentreff, C., Manandhar, T., Mucke, P., Pries, L., … Weller, D. (2019). *World Risk Report 2020*. *n/a*. Bündnis Entwicklung Hilft and Ruhr University Bochum Institute for International Law of Peace and Armed Conflict (IFHV) URL - https://weltrisikobericht.de/wp-content/uploads/2020/09/WorldRiskReport-2020.pdf. https://doi.org/n/a

Cheong, W. K., Timbal, B., Golding, N., Sirabaha, S., Kwan, K. F., Cinco, T. A., … Han, S. (2018). Observed and modelled temperature and precipitation extremes over Southeast Asia from 1972 to 2010. *International Journal of Climatology*, *38*(7), 3013–3027. https://doi.org/10.1002/joc.5479

Cinco, T. A., de Guzman, R. G., Ortiz, A. M. D., Delfino, R. J. P., Lasco, R. D., Hilario, F.D., Juanillo, E.L., Barba, R. & Ares, E.D. (2016). Observed trends and impacts of tropical cyclones in the Philippines. *International Journal of Climatology*, *36*(14), 4638–4650. https://doi.org/10.1002/joc.4659

Datt, G., & Hoogeveen, H. (2003). El Niño or El Peso? Crisis, Poverty and Income Distribution in the Philippines. *World Development*, *31*(7), 1103–1124. https://doi.org/https://doi.org/10.1016/S0305-750X(03)00060-3

De Haen, H., & Hemrich, G. (2007). The economics of natural disasters: implications and challenges for food security. *Agricultural Economics*, *37*(s1), 31–45. https://doi.org/10.1111/j.1574-0862.2007.00233.x

Deaton, A. (1997). *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*. The World Bank. https://doi.org/DOI:

Dercon, S. (1996). Risk, Crop Choice, and Savings: Evidence from Tanzania. *Economic Development and Cultural Change*, *44*(3), 485–513. Retrieved from http://www.jstor.org/stable/1154463

Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective from Ethiopia. *American Journal of Agricultural Economics*, *93*(3), 829–846. https://doi.org/10.1093/ajae/aar006

Dintwa, K. F., Letamo, G., & Navaneetham, K. (2019). Quantifying social vulnerability to natural hazards in Botswana: An application of cutter model. *International Journal of Disaster Risk Reduction*, *37*, 101189. https://doi.org/https://doi.org/10.1016/j.ijdrr.2019.101189

Endo, N., Matsumoto, J., & Lwin, T. (2009). Trends in Precipitation Extremes over Southeast Asia. *SOLA*, *5*, 168–171. https://doi.org/10.2151/sola.2009-043

Fothergill, A., & Peek, L. A. (2004). Poverty and disasters in the United States: A review of recent sociological findings. *Natural Hazards*, *32*(1), 89–110. https://doi.org/10.1023/B:NHAZ.0000026792.76181.d9

Gallo, F., Daron, J., Macadam, I., Cinco, T., Villafuerte II, M., Buonomo, E., … Jones, R. G. (2019). High-resolution regional climate model projections of future tropical cyclone activity in the Philippines. *International Journal of Climatology*, *39*(3), 1181–1194. https://doi.org/10.1002/joc.5870

Gërxhani, K. (2004). The Informal Sector in Developed and Less Developed Countries: A Literature Survey. *Public Choice*, *120*(3), 267–300. https://doi.org/10.1023/B:PUCH.0000044287.88147.5e

Guha-Khasnobis, B., Kanbur, R., & Ostrom, E. (2006). *Linking the Formal and Informal Economy: Concepts and Policies*. *WIDER Studies in Development Economics*. Oxford: Oxford University Press. https://doi.org/10.1093/0199204764.001.0001

Günther, I., & Launov, A. (2012). Informal employment in developing countries: Opportunity or last resort? *Journal of Development Economics*, *97*(1), 88–98. https://doi.org/https://doi.org/10.1016/j.jdeveco.2011.01.001

Hallegatte, S., Vogt-Schilb, A., Bangalore, M., & Rozenberg, J. (2017). *PUnbreakable : Building the Resilience of the Poor in the Face of Natural Disasters*. Retrieved from http://documents.worldbank.org/curated/en/512241480487839624/pdf/110618-PUB-Box396333B-PUBLIC-PUBDATE-11-24-16-UNIT-ITSKI.pdf

Harris, J. R., & Todaro, M. P. (1970). Migration, Unemployment and Development: A Two-Sector Analysis. *The American Economic Review*, *60*(1), 126–142. Retrieved from http://www.jstor.org/stable/1807860

Heckman, J., & Hotz, J. (1986). An Investigation of the Labor Market Earnings of Panamanian Males Evaluating the Sources of Inequality. *The Journal of Human Resources*, *21*(4), 507–542. https://doi.org/10.2307/145765

Heckman, J., Tobias, J. L., & Vytlacil, E. (2001). Four Parameters of Interest in the Evaluation of Social Programs. *Southern Economic Journal*, *68*(2), 211–223. https://doi.org/10.2307/1061591

Heintze, H.-J., Kirch, L., Küppers, B., Mann, H., Mischo, F., Mucke, P., … Weller, D. (2018). *World Risk Report*. Bündnis Entwicklung Hilft and Ruhr University Bochum – Institute for International Law of Peace and Armed Conflict (IFHV). Retrieved from https://reliefweb.int/sites/reliefweb.int/files/resources/WorldRiskReport-2018.pdf

Huffman, G. J., Bolvin, D. T., Nelkin, E. J., Wolff, D. B., Adler, R. F., Gu, G., … Stocker, E. F. (2007). The TRMM Multisatellite Precipitation Analysis (TMPA): Quasi-Global, Multiyear, Combined-Sensor Precipitation Estimates at Fine Scales. *Journal of Hydrometeorology*, *8*(1), 38–55. https://doi.org/10.1175/JHM560.1

Jamandre, C. A., & Narisma, G. (2013). Spatio-temporal validation of satellite-based rainfall estimates in the Philippines. *Atmospheric Research*, *122*, 599–608. https://doi.org/10.1016/j.atmosres.2012.06.024

Karim, A. (2018). The Household Response to Persistent Natural Disasters: Evidence from Bangladesh. *World Development*, *103*, 40–59. https://doi.org/https://doi.org/10.1016/j.worlddev.2017.10.026

Lee, L.-F., & Trost, R. P. (1978). Estimation of some limited dependent variable models with application to housing demand. *Journal of Econometrics*, *8*(3), 357–382. https://doi.org/https://doi.org/10.1016/0304-4076(78)90052-0

Lewis, W. A. (1954). Economic Development with Unlimited Supplies of Labour. *The Manchester School*, *22*(2), 139–191. https://doi.org/10.1111/j.1467-9957.1954.tb00021.x
Lokshin, M., & Sajaia, Z. (2004). Maximum Likelihood Estimation of Endogenous Switching Regression Models. *The Stata Journal*, *4*(3), 282–289. https://doi.org/10.1177/1536867X0400400306
Lokshin, M., & Sajaia, Z. (2008, April 22). MOVESTAY: Stata module for maximum likelihood estimation of endogenous regression switching models. Retrieved from https://econpapers.repec.org/RePEc:boc:bocode:s456710
Ludwig, F., van Scheltinga, C. T., Verhagen, J., Kruijt, B., van Ierland, E., Dellink, R., … Kabat, P. (2007). *Climate change impacts on developingcountries – EU accountability*. Retrieved from http://www.europarl.europa.eu/RegData/etudes/etudes/join/2007/393511/IPOL-ENVI_ET(2007)393511_EN.pdf
Maddala, G. S. (1983). *Limited-Dependent and Qualitative Variables in Econometrics*. *Econometric Society Monographs*. Cambridge: Cambridge University Press. https://doi.org/DOI: 10.1017/CBO9780511810176
Maddala, G. S. (1986). Disequilibrium, self-selection, and switching models. In Z. Griliches† & M. D. Intriligator (Eds.) (Vol. 3, pp. 1633-1688 BT-Handbook of Econometrics). Elsevier. Retrieved from https://econpapers.repec.org/RePEc:eee:ecochp:3-28
Maloney, W. F. (2004). Informality Revisited. *World Development*, *32*(7), 1159–1178. https://doi.org/https://doi.org/10.1016/j.worlddev.2004.01.008
McGuigan, C., Reynolds, R., & Wiedmer, D. (2002). *Poverty and Climate Change: Assessing Impacts in Developing Countries and the Initiatives of the International Community*. Retrieved from http://www.odi.org/sites/odi.org.uk/files/odi-assets/publications-opinion-files/3449.pdf
Merged Family Income and Expenditure Survey (FIES) and Labor Force Survey (LFS). (2006). Retrieved from https://psa.gov.ph/
Nelson, F. D. (1984). Efficiency of the two-step estimator for models with endogenous sample selection. *Journal of Econometrics*, *24*(1), 181–196. https://doi.org/https://doi.org/10.1016/0304-4076(84)90078-2
Organisation for Economic Co-operation and Development, O. (2003). *Poverty and Climate Change: Reducing the Vulnerability of the Poor through Adaptation*. Retrieved from http://www.oecd.org/env/cc/2502872.pdf
Patankar, A., & Patwardhan, A. (2015). Estimating the uninsured losses due to extreme weather events and implications for informal sector vulnerability: a case study of Mumbai, India. *Natural Hazards*, *80*. https://doi.org/10.1007/s11069-015-1968-3
Pecha, C. (2017). *The Effects of Natural Disasters on the Labour Market: Do Hurricanes Increase Informality?* (IDB Publications (Working Papers)). Inter-American Development Bank. https://doi.org/DOI:
Peralta, J. C., Narisma, G., & Cruz, F. (2020). Validation of Satellite and Ground Station-based High-Resolution Rainfall Gridded Datasets over the Philippines. *Journal of Hydrometeorology*. https://doi.org/10.1175/JHM-D-19-0276.1
Philippine Statistics Authority. (2003). Master Sample Brochure. Retrieved from https://psa.gov.ph/sites/default/files/attachments/hsd/article/2003%2520master%2520sample.pdf
Philippine Statistics Authority. (2015a, February 15). Family Income and Expenditure Survey (FIES). Retrieved from https://psa.gov.ph/content/family-income-and-expenditure-survey-fies-0
Philippine Statistics Authority. (2015b, February 15). Official Poverty Statistics of the Philippines. Retrieved from https://psa.gov.ph/sites/default/files/2015 Full Year Official Poverty Statistics of the Philippines Publication.pdf
Philippine Statistics Authority. (2018, February 15). Labor Force Survey (LFS). Retrieved from https://psa.gov.ph/statistics/survey/labor-force
Pratap, S., & Quintin, E. (2006). Are labor markets segmented in developing countries? A semiparametric approach. *European Economic Review*, *50*(7), 1817–1841. https://doi.org/https://doi.org/10.1016/j.euroecorev.2005.06.004
Ravago, M.-L. V, Roumasset, J., & Jandoc, K. (2016). Risk management and coping strategies: climate change and agriculture in the Philippines. *Philippine Review of Economics*, *53*(2), 66–104. https://doi.org/DOI: ,

Rosenzweig, M. R., & Binswanger, H. P. (1993). Wealth, Weather Risk and the Composition and Profitability of Agricultural Investments. *The Economic Journal*, *103*(416), 56–78. https://doi.org/10.2307/2234337

Sakai, Y., Estudillo, J. P., Fuwa, N., Higuchi, Y., & Sawada, Y. (2017). Do Natural Disasters Affect the Poor Disproportionately? Price Change and Welfare Impact in the Aftermath of Typhoon Milenyo in the Rural Philippines. *World Development*, *94*, 16–26. https://doi.org/https://doi.org/10.1016/j.worlddev.2016.12.036

Skoufias, E., Kawasoe, Y., Strobl, E., & Acosta, P. A. (2019). *Identifying the Vulnerable to Poverty from Natural Disasters : The Case of Typhoons in the Philippines* (Policy Research Working Paper Series). The World Bank. https://doi.org/DOI:

Stiglitz, J. (1976). The Efficiency Wage Hypothesis, Surplus Labour, and the Dirstribution of Income in L.D.C.s. *Oxford Economic Papers*, *28*(2), 185–207. https://doi.org/10.1093/oxfordjournals.oep.a041340

Teo, M., Goonetilleke, A., Ahankoob, A., Deilami, K., & Lawie, M. (2018). Disaster awareness and information seeking behaviour among residents from low socio-economic backgrounds. *International Journal of Disaster Risk Reduction*, *31*, 1121–1131. https://doi.org/https://doi.org/10.1016/j.ijdrr.2018.09.008

Villafuerte, M. Q., Matsumoto, J., Akasaka, I., Takahashi, H. G., Kubota, H., & Cinco, T. A. (2014). Long-term trends and variability of rainfall extremes in the Philippines. *Atmospheric Research*, *137*, 1–13. https://doi.org/https://doi.org/10.1016/j.atmosres.2013.09.021

Yonson, R., & Noy, I. (2019). Disaster Risk Management Policies and the Measurement of Resilience for Philippine Regions. *Risk Analysis*, *0*(0). https://doi.org/10.1111/risa.13394

Zhang, X., Alexander, L., Hegerl, G. C., Jones, P., Tank, A. K., Peterson, T. C., … Zwiers, F. W. (2011). Indices for monitoring changes in extremes based on daily temperature and precipitation data. *WIREs Climate Change*, *2*(6), 851–870. https://doi.org/10.1002/wcc.147

Appendices

Table A1. Variable Definitions

Variable Name	Definition
Real Income per capita	Real Income per capita
Real Expenditure per capita	Real Expenditure per capita
Extreme Rainfall Lag (1)	Number of Extreme Rainfall days, previous year
Extreme Rainfall Lag (2)	Number of Extreme Rainfall days, two years ago
Extreme Rainfall Lag (3)	Number of Extreme Rainfall days, three years ago
Informality (1/0)	Informality dummy = 1 if informal, 0 if formal
Sex of Household Head (HH)	Sex of HH dummy = 1 if male, 0 if female
Age of HH	Age of HH
Age of HH Squared	Age of HH Squared
Marital Status of HH (1/0)	Marital status of HH dummy = 1 if household head is married, 0 otherwise
Educ. Attainment of HH (1/0)	Educational attainment of HH dummy = 1 if household head finished high school or higher, 0 otherwise
Household Size	Household Size
Poverty Indicator (1/0)	Poverty indicator dummy = 1 if poor, 0 if non-poor
Urban-Rural Indicator (1/0)	Urban Municipality dummy = 1 if urban, 0 if non-urban
Year	year of household observation
Total Income	total household income, in nominal terms
Income Per Capita	total household income divided by the household size
Real Income Per Capita	total household income, in real terms
Log of Real Income Per Capita	logarithm of real household income per capita
Total Expenditure	total household expenditure, in nominal terms
Expenditure Per Capita	total household expenditure divided by the household size
Real Expenditure Per Capita	total household expenditure, in real terms
Log of Real Expenditure Per Capita	logarithm of real household expenditure per capita
GDP Deflator	GDP deflator with respect to 2000 prices

Table A2. Complete Summary Statistics

Description	Total Sample			Formal			Informal		
	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD
Total Income	125,553	197,125	263,669	60512	214998	234368	65041	180496	287273
Total Expenditure	125,553	162,069	161,082	60512	179278	172216	65041	146059	148201
Real per capita Income	125,553	30,034	48,440	60512	32690	42543	65041	27564	53226
Real per capita Expenditures	125,553	24,540	29,069	60512	27147	31222	65041	22116	26684
log (Real per capita Income)	125,553	9.8	0.7	60512	9.9	0.8	65041	9.7	0.7
log (Real per capita Expenditures)	125,553	9.8	0.7	60512	9.9	0.8	65041	9.7	0.7
Number of Extreme Rainfall days, previous year	125,553	21.6	5.8	60512	21.6	5.6	65041	21.6	5.9
Number of Extreme Rainfall days, two years ago	125,553	17.9	4.7	60512	17.6	4.7	65041	18.1	4.7
Number of Extreme Rainfall days, three years ago	125,553	21.1	4.8	60512	21.2	4.8	65041	21.0	4.8
log (Number of Extreme Rainfall days, previous year)	125,553	3.0	0.3	60512	3.0	0.3	65041	3.0	0.3
log (Number of Extreme Rainfall days, two years ago)	125,553	2.8	0.3	60512	2.8	0.3	65041	2.9	0.3
log (Number of Extreme Rainfall days, three years ago)	125,553	3.0	0.2	60512	3.0	0.2	65041	3.0	0.2
Extreme Rainfall Indicator, previous year dummy = 1 if anomalous, 0 if normal	125,553	0.3	0.5	60512	0.3	0.5	65041	0.3	0.5
Extreme Rainfall Indicator, two years ago dummy = 1 if anomalous, 0 if normal	125,553	0.1	0.2	60512	0.1	0.2	65041	0.1	0.3
Extreme Rainfall Indicator, three years ago dummy = 1 if anomalous, 0 if normal	125,553	0.3	0.4	60512	0.3	0.4	65041	0.2	0.4
Informality dummy = 1 if informal, 0 if formal	125,553	0.5	0.5	60512	0.0	0.0	65041	1.0	0.0
Sex of HH dummy = 1 if male, 0 if female	125,553	0.9	0.3	60512	0.9	0.3	65041	0.8	0.4
Age of HH	125,553	47.5	12.4	60512	44.6	11.0	65041	50.3	12.9
Age of HH Squared	125,553	2,413	1,240	60512	2106	1027	65041	2698	1349
Marital Status of HH dummy = 1 if household head is married, 0 otherwise	125,553	0.2	0.4	60512	0.2	0.4	65041	0.2	0.4
Educ. Attainment of HH dummy = 1 if household head finished high school or higher, 0 otherwise	125,553	0.4	0.5	60512	0.5	0.5	65041	0.4	0.5
Household Size	125,553	4.8	2.2	60512	4.9	2.1	65041	4.8	2.2
Poverty Indicator dummy = 1 if poor, 0 if non-poor	125,553	0.2	0.4	60512	0.2	0.4	65041	0.3	0.4
Urban-Rural Indicator dummy = 1 if urban, 0 if non-urban	125,553	0.3	0.5	60512	0.4	0.5	65041	0.2	0.4
Year	125,553	2,011	3	60512	2011	3	65041	2010	3

Table A3. Parameter Estimates of Sector Choice and Welfare Equations Using Lagged Previous Year Extreme Rainfall Days as Extreme Weather Event, Pooled data

		Endogenous Switching Regression: EXPENDITURE				Endogenous Switching Regression: INCOME		
Model	OLS		Formal	Informal	Model	OLS		Formal
Dependent Variable		Informality	Log (Expenditure)			Dependent Variable		
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Informality dummy = 1 if informal, 0 if formal	-0.072***				-0.074***			
	(0.004)				(0.004)			
Number of Extreme Rainfall days, previous year	-0.047***	-0.149***	-0.118***	-0.099***	-0.041***	-0.152***	-0.130***	-0.113***
	(0.010)	(0.013)	(0.010)	(0.009)	(0.010)	(0.012)	(0.011)	(0.010)
Sex of HH dummy = 1 if male, 0 if female	-0.129***	-0.227***	-0.211***	-0.206***	-0.151***	-0.219***	-0.211***	-0.206***
	(0.007)	(0.013)	(0.010)	(0.009)	(0.007)	(0.013)	(0.010)	(0.009)
Age of HH	0.018***	0.000	0.024***	0.033***	0.020***	0.008***	0.024***	0.033***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Age of HH Squared	-0.000***	0.000***	-0.000***	-0.000***	-0.000***	0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Marital status of HH dummy = 1 if household head is married, 0 otherwise	-0.013*	-0.183***	-0.078***	-0.137***	-0.019***	-0.186***	-0.078***	-0.137***
	(0.006)	(0.013)	(0.009)	(0.009)	(0.007)	(0.012)	(0.009)	(0.009)
Educational attainment of HH dummy = 1 if household head finished high school or higher, 0 otherwise	0.501***	0.019***	0.650***	0.388***	0.514***	0.067***	0.650***	0.388***
	(0.005)	(0.007)	(0.005)	(0.006)	(0.005)	(0.007)	(0.005)	(0.006)
Household Size	-0.083***	-0.055***	-0.141***	-0.114***	-0.076***	-0.067***	-0.141***	-0.114***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Poverty indicator dummy = 1 if poor, 0 if non-poor	-0.778***	0.832***			-0.965***	0.953***		
	(0.004)	(0.006)			(0.004)	(0.006)		
Urban Municipality dummy = 1 if urban, 0 if non-urban		-0.454***				-0.344***		
		(0.005)				(0.005)		
Constant	9.931***	0.303***	10.281***	8.870***	9.958***	0.086	10.281***	8.870***
	(0.039)	(0.061)	(0.047)	(0.044)	(0.038)	(0.059)	(0.047)	(0.044)
R-squared	0.532				0.552			
sigma			0.736	0.764			0.809	0.891
rho			0.811	0.003			0.817	0.973
Observations	125,553	125,553	125,553	125,553	125,553	125,553	125,553	125,553
LR test of indep. eqns. :		chi2(2) = 26575.79 Prob > chi2 = 0.0000				chi2(2) = 32934.55 Prob > chi2 = 0.0000		

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table A4. Parameter Estimates of Sector Choice and Welfare Equations, Using Lagged Two Years Extreme Rainfall Days as Extreme Weather Event, pooled data

		Endogenous Switching Regression: EXPENDITURE				Endogenous Switching Regression: INCOME		
Model	OLS		Formal	Informal	Model	OLS		Formal
Dependent Variable		Informality	Log (Expenditure)			Dependent Variable		
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Informality dummy = 1 if informal, 0 if formal	-0.067***				-0.070***			
	(0.004)				(0.004)			
Number of Extreme Rainfall days, previous year	-0.099***	-0.138***	-0.173***	-0.112***	-0.081***	0.066***	-0.136***	-0.111***
	(0.010)	(0.013)	(0.010)	(0.009)	(0.010)	(0.012)	(0.012)	(0.010)
Number of Extreme Rainfall days, two years ago	-0.202***	0.075***	-0.195***	-0.120***	-0.155***	0.102***	-0.368***	-0.306***
	(0.011)	(0.013)	(0.009)	(0.009)	(0.011)	(0.004)	(0.012)	(0.011)
Sex of HH dummy = 1 if male, 0 if female	-0.126***	-0.227***	-0.205***	-0.204***	-0.148***	-0.081***	0.012	-0.150***
	(0.007)	(0.013)	(0.010)	(0.009)	(0.007)	(0.013)	(0.012)	(0.011)
Age of HH	0.018***	0.000	0.024***	0.033***	0.021***	-0.038***	0.054***	0.048***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Age of HH Squared	-0.000***	0.000***	-0.000***	-0.000***	-0.000***	0.001***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Marital status of HH dummy = 1 if household head is married, 0 otherwise	-0.012*	-0.183***	-0.075***	-0.137***	-0.019***	-0.173***	0.123***	-0.008
	(0.006)	(0.013)	(0.009)	(0.009)	(0.007)	(0.012)	(0.011)	(0.010)
Educational attainment of HH dummy = 1 if household head finished high school or higher, 0 otherwise	0.494***	0.021***	0.643***	0.383***	0.509***	-0.627***	0.846***	0.889***
	(0.005)	(0.007)	(0.005)	(0.006)	(0.005)	(0.007)	(0.007)	(0.006)
Household Size	-0.083***	-0.055***	-0.141***	-0.114***	-0.076***	0.062***	-0.122***	-0.134***
	(0.001)	(0.002)	(0.001)	(0.001)		(0.002)	(0.002)	(0.001)
Poverty indicator dummy = 1 if poor, 0 if non-poor	-0.769***	0.832***			-0.958***	-0.771***		
Urban Municipality dummy = 1 if urban, 0 if non-urban		-0.444***				0.102***		
		(0.005)				(0.004)		
Constant	10.652***	0.050	10.984***	9.259***	10.510***	-0.258***	9.771***	10.663***
	(0.051)	(0.075)	(0.057)	(0.054)	(0.050)	(0.073)	(0.069)	(0.062)
R-squared	0.537				0.554			
sigma			0.727	0.763			0.968	0.814
rho			0.806	0.948			-0.981	-0.767
Observations	125,553	125,553	125,553	125,553	125,553	125,553	125,553	125,553
LR test of indep. eqns. :		chi2(2) = 25980.97 Prob > chi2 = 0.0000				chi2(2) = 15389.41 Prob > chi2 = 0.0000		

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1