AUTHOR ACCEPTED MANUSCRIPT

FINAL PUBLICATION INFORMATION

Too Little Too Late : Welfare Impacts of Rainfall Shocks in Rural Indonesia

The definitive version of the text was subsequently published in

Bulletin of Indonesian Economic Studies, 48(3), 2012-11-20

Published by Taylor and Francis

THE FINAL PUBLISHED VERSION OF THIS ARTICLE IS AVAILABLE ON THE PUBLISHER'S PLATFORM

Too Little Too Late: Welfare Impacts of Rainfall Shocks in Rural Indonesia[1]

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Manuscript ID: CBIE-2010-0031
1st Resubmission: March 15, 2011
2nd Resubmission: November 1, 2011

Abstract

Abstract: We consider two shocks: (i) a delay in the onset of monsoon and (ii) a significant shortfall in rainfall in the 90 day post-onset period. Focusing on households with family farm businesses, we find that a delay in the monsoon onset does not have a significant impact on the welfare of rice farmers. However, rice farm households located in areas exposed to low rainfall following the monsoon are negatively affected. Rice farm households appear to be able to protect their food expenditure in the face of weather shocks at the expense of lower nonfood expenditures per capita. We also use propensity score matching to identify community programs that might moderate the welfare impact of this type of shock. Access to credit and public works projects in communities were among the programs with the strongest moderating effect. This is an important consideration for the design and implementation of adaptation strategies.

[1]We wish to thank Will Martin, Syud Amer Ahmed, William Wallace, and two anonymous referees for useful comments in an earlier version of this paper. The findings, interpretations, and conclusions are entirely those of the authors. They do not necessarily represent the view of the World Bank, its Executive Directors, or the countries they represent.

1. Introduction

In Indonesia, annual rainfall patterns are critical to agricultural output and rural livelihoods. In the cultivation of rice, the country's most important crop, farmers typically grow seedlings in a small plot and then transplant them to flooded paddy fields when rainfall is sufficient. Thus, low cumulative rainfall at the beginning of the wet season can delay transplanting and subsequently the harvests (Heytens 1991). Such climate-induced delays in crop harvests can mean an extended hungry season for poor farmers with limited savings or stocks. Furthermore, these delays can also undermine the prospects for a descent second harvest later in the year.

Empirical studies have shown that in Indonesia the amount of rainfall in September to December, the period encompassing the early portion of the wet season, has a strong positive correlation with rice production output through the area planted and the area harvested in January to April. Between 1971 and 1998, the rainfall in the September to December period explained over 80% of the variation in both the planted and harvested rice area in January to April (Naylor et al. 2001, 2002). These same studies made further linkages to sea-surface temperature anomaly (SSTA) and to El Nino / La Nina climate patterns and proposed forecasting models to inform food policy planning. Falcon et al. (2004) extended climate-production models down to the province level and suggested that with improved forecasting models and timely dissemination, farmers could be notified of recommended cropping patterns to adapt to changing conditions, and agencies could be better positioned to mobilize relief efforts to assist poor and near poor households impacted by the shocks.

While there has been extensive research on the rainfall-production linkages at the aggregate level, very little is known about the welfare losses that households experience from the rainfall shocks, irrespective of whether the shocks are induced by El Nino or not. Households at low levels of income are believed to be the most vulnerable to the impacts of negative shocks, including the rainfall shocks discussed above. This is due to their geographical locations, limited assets, limited access to resources and services, low human capital and high dependence upon natural resources for income and consumption. While there is wide recognition of the threat of climate-induced shocks upon the poor, limited attention has been given to quantifying the household level effects of rainfall shocks. Our analysis considers the household welfare

implications of both a late monsoon onset and low level of rainfall. As we note later, a certain amount of rainfall is needed in the 90 day post-onset period for rice to grow properly.

With future projections pointing to a greater probability of rainfall shocks[2], policy makers will need to know what policies can either mitigate the impacts or help households cope with the shocks. As various social safety nets and other social assistance programs are already in place, an assessment of their role in assisting households cope with the impacts of rainfall shocks or in mitigating the impacts would be a good place to start. For instance, programs that provide households with greater access to credit may help them cope with delayed or poor harvests. If community block grants are used to invest in more advanced irrigation infrastructure, they could potentially help mitigate the impacts of the rainfall shocks. Or, if the grants support public works projects, they may generate nonfarm employment opportunities in the community. Evidence from within Indonesia confirming or refuting such claims could help policy makers identify instruments to help protect vulnerable households. Using available data, we explore the potential moderating effects of various programs.

The purpose of this paper is to analyze the potential welfare impacts of rainfall shocks in rural Indonesia, and to draw relevant policy lessons. The paper is organized as follows. Section 2 presents the methodology focusing on the estimation of the impacts of rainfall variability on household expenditure per capita, our measure of welfare. The guiding view here is that the distribution of welfare losses associated with such events depends on the degree of household and community level vulnerability and the moderating impact of existing assets and social protection institutions. Understanding these factors plays an important role in designing policies to minimize exposure to and the impact of these shocks. Section 3 describes the available data while analytical results are presented in section 4. Concluding remarks are made in section 5.

2. Methodology

This section describes the methodology and analytical frameworks used to estimate the impacts of rainfall variability on household welfare in rural Indonesia and the potential moderating effects of community-based programs. We need to make our analytical framework

[2] Adapting projections by the IPCC to local conditions, Naylor et al (2007) predict that by 2050 the probability of a 30-day delay in monsoon will increase from 9-18 percent currently to 30-40 percent. This delay combined with increased temperature could reduce the yield of rice and soybean by as much as 10 percent.

consistent with the logic of vulnerability, the bedrock concept for the study of the welfare impacts of weather shocks. The distribution of economic welfare in any given society hinges crucially on individual endowments and behavior and the socio-political arrangements that govern social interaction. These factors (endowments, behavior and social interaction) also determine the distribution of vulnerability[3]. Adger (1999) emphasizes the connection between individual and collective vulnerability because it is impossible to consider individual achievement in isolation from the natural and social environment. Vulnerability of an individual or a household to livelihood stress depends crucially on both exposure and the ability to cope with and recover from the shock. Exposure is a function of, *inter alia*, climatic and topographical factors and the extent to which livelihoods are dependent on the weather. The ability to cope is largely determined by access to resources, the diversity of income sources and social status within the community[4]. Increased exposure combined with a reduced capacity to cope with, recover from, or adapt to any exogenous stress on livelihood leads to increased vulnerability.

Given the data limitations we face, we focus our strategy to exploiting cross-sectional variation in the data and linking our welfare indicator, real per capita expenditures, or some component thereof (food versus non-food expenditure) to a rainfall shock defined on the basis of available rainfall data focusing mainly on rural households. As noted earlier, the yield of crops such as rice and soybean can be very much affected by changes in precipitation patterns.

Given the importance of rice farming in the rural economy of Indonesia, we define rainfall shocks with reference to this activity. Naylor et al. (2007), in their study of the delay in monsoon onset, define "onset" as the number of days after August 1 when cumulative rainfall reaches 20 cm [5], and "delay" as the number of days above the mean onset date over a 25 year period from 1979 to 2004. Since farmers will typically begin planting after monsoon onset, late onset may affect prospects for a second harvest later in the season and possibly change crop combinations, with potentially significant consequences on production and market prices.

While delayed onset is an important determinant of harvest, we also need to consider the amount of rainfall after the onset. After farmers plant the rice fields, 60-120 cm of rainfall are

[3] Vulnerability is usually taken as the likelihood that, at a given point in time, individual welfare will fall short of some socially acceptable benchmark (Hoddinott and Quisumbing 2008).

[4] Hoddinott and Quisumbing (2008) make essentially the same point by noting that, at the household level, vulnerability is determined by the nature of the shock, the availability of additional sources of income, the functioning of labor, credit and insurance markets, and the extent of public assistance.

[5] This is the amount of rainfall needed to moisten ground sufficiently for planting. It is believed that about 100 cm of rain are needed throughout the season for cultivation.

needed during the 3-4 month grow-out period (Naylor et al. 2002). Thus, the second dimension of our shock involves the deviation of the amount of post-onset rainfall from the 25 year mean for each weather station. We define the amount of post-onset rainfall as the total amount of rainfall during the 90 day period following the monsoon onset date.

[Figure 1 around here]

The timing of these events in relation to the 2000 IFLS3 survey is illustrated in Figure 1. Considering that the degree of rainfall variability can differ across areas and that households may adjust farming practices accordingly, we use standard deviations from the inter-temporal mean to help account for such spatial differences. In terms of delay of monsoon onset, we define a negative shock as being more than one standard deviation above the 25 year mean. In terms of the amount of post-onset rainfall, we define a negative shock as being more than two standard deviations below the 25 year mean.

Given the interconnection between individual and collective vulnerability and adaptive capacity, our empirical analysis uses regression analysis to link an indicator of household welfare, that is, real per capita total expenditure or its food and nonfood components, to some rainfall shock while controlling for household characteristics, and for the province of residence. We estimate a regression equation of the form,

$$y_{ij} = \beta_0 + \beta_1 X_i + \beta_2 S_j + \beta_3 (S_j * F_i)$$

where Y_{ij} represents per capita household expenditure of household *i* in community *j*, and X_i represents various control variables. S_j represents the covariate rainfall shocks, and F_i is a binary variable representing rice farming households. Standard errors accounted for clustering at the community level and stratification by province and urban/rural sector in line with the complex survey design of the IFLS.

After analyzing the effects of rainfall shocks on welfare, we consider the potential moderating effect of various community level programs. Ideally, we would like to measure, for the same household, per capita expenditures with and without the program of interest at a particular point in time. This is not possible though, so we must seek alternatives. If program

placement had been done randomly, simply comparing average per capita household expenditure between communities with and without the program could be a good option for evaluating whether a certain program assisted households exposed to shocks.

However, the placement of government programs is not likely to be random (Pitt et al., 1993). Many of the social safety net programs that emerged following the 1997 financial crisis were intended to protect the poor and were thus targeted to poorer communities and households, albeit with high leakage rates (Sumarto et al., 2002). Given this potential for selection bias in program placement, the distribution of community and household characteristics is likely to be different between communities that have and do not have the program. One consequence of the endogeneity in program placement is that if this issue is not addressed in the analysis, it is likely to result in biased estimates of program effects, especially when using cross-sectional data.

Recognizing that government assistance programs are often targeted to poor areas, we use propensity score matching (PSM) to investigate the role that various social programs (e.g. safety nets, credit) in the community could play in moderating the impact of the shock on household welfare, most likely by aiding affected households cope with the shock. The PSM method is comprised of two main steps. The first step is the propensity score model, which is used to predict the likelihood of a household or community receiving treatment, in this case, one of the social assistance programs. The predicted values are commonly referred to as the propensity scores. Assuming that conditional on observable community characteristics program placement is as good as random, we can consider two households with the same propensity score as observationally equivalent. The second step is the process of matching each household from the group with the program to equivalent households in the group without the program. This is performed based on the propensity scores such that the group constructed from matched households is comparable to the other. Hereafter, we will refer to the group of households that reside in communities with a specific program as the “treatment group” and the constructed comparison group of households without the program as the “control group”. With the treatment and control groups defined, the average difference in the outcome variable can then be estimated.

We estimate propensity scores on covariates using probit regressions and retrieve their predicted values to allow for the matching of “treated” observations with those in the comparison group. For each program, a separate stepwise estimation of the probit specification was performed such that variables with a p-value less than 0.2 were added to the right hand side. The

dependent variable was a binary variable indicating whether a household resided in a community with the specific program of interest. The list of possible right hand side variables for the stepwise estimation included household and community variables, and binary variables for the different provinces. The household variables always included in the model were: household size, age of head, education level of head, household use of electricity, ownership of farmland, household nonfarm business, and household farm business. Candidate household variables were: marital status of head and gender of head. The candidate community variables were: availability of public transport, availability of piped water, predominance of asphalt roads, share of households with electricity, distance to provincial capital, distance to district capital, and the shares of household heads with elementary, junior high, high school, and university level education, and share of households with a "letter of the poor". All rural households were part of the sample for the probit regressions.

After the propensity scores are estimated, observations in the treatment and control groups were trimmed to obtain a common support for the propensity scores. In terms of the matching procedure, we match each treatment household to its "nearest neighbor" based on propensity scores. For each household in the treatment group, 3 households from the control group are matched with replacement based on the propensity score. To adjust for inexact matches of the propensity score, regression adjustments were performed as in Abadie et al. (2004). We then compare average outcome for households in the treatment group (i.e. in communities with a specific program) to the average outcome for similar households in the control group (i.e. living in communities without the program under consideration).

To describe this somewhat more formally, let Y_i (1) denote the per capita expenditure outcome of household i in the presence of some "treatment" attribute in the local community, such as a safety net program or type of infrastructure, and Y_i (0) denote the per capita expenditure outcome of household i in the absence of the attribute in the local community. As both Y_i (1) and Y_i (0) are not observable, we must construct a counterfactual group of households in communities that do not have "treatment" attribute of interest but have a similar probability of having the attribute based on observable community characteristics. Through a matching process, we define bias-corrected matching estimators, $\hat{Y}_i(0)$, in place of Y_i (0) (see Abadie and Imbens, 2002, and Abadie et al., 2004 for details) and estimate the sample average treatment effect for the subpopulation of the treated (SATT):

$$SATT = \frac{1}{n_1} \sum_{i|W_i=1} \left\{ Y_i(1) - \hat{Y}_i(0) \right\},$$

where W_i=1 indicates that a household is in a community with the treatment attribute, and n_1 is the sample size of the treated.

3. *Data*

We are able to study the impacts of extreme weather events on rural households by merging household and community level data from the Indonesian Family Life Survey (IFLS) with daily rainfall data covering a 25 year period. The combined data set contains information on rainfall, household expenditures, household level socio-economic characteristics, and community level attributes. The IFLS3 household and community surveys were fielded from late June to the end of October 2000. The community surveys include data on whether various social programs were presently conducted on a routine basis or recently conducted in 1999/2000 in the community. It should be noted that the data do not indicate which households actually participated in the programs.

The household level data contains the consumption aggregate and its food and nonfood components. The food component consists of 37 food items (purchases and the value of own production or gifts) consumed within the last week. The nonfood component consists of frequently purchased goods and services (utilities, personal toiletries, household items, domestic services, recreation and entertainment, transport, sweepstakes), less frequent purchases and durables (clothing, furniture, medical, ceremonies, tax), housing, and educational expenditures for children living in the household. Transfers out of the household were excluded. All values are monthly figures and are in real terms. To obtain real values, both temporal and spatial deflators were used, using prices in December 2000 in Jakarta as the base.[6]

Using daily rainfall data from 1979 to 2004, we calculated the 25 year mean and standard deviations for monsoon onset and the amount of post-onset rainfall for 32 weather stations. The rainfall data from these weather stations were then matched to communities in IFLS. Weather data were merged with household survey data at the community level based on proximity. Only

[6] The spatial deflator used is the ratio of the location (province, urban/rural area) poverty line (in December 2000 prices) to the Jakarta poverty line. Thus the spatial deflator used converts the local December 2000 values into Jakarta December 2000 values.

weather stations with complete data for the 25 year period were used. The matched data contained a total of 267 communities and 32 WMO stations. In rural areas, 106 communities in 9 provinces were matched to 27 stations. In rural Java, 66 communities in 4 provinces were matched to 18 stations. The number of communities per WMO station ranged from 1 to 10 in rural areas. 3,290 households were matched to 27 stations in rural areas, and 2,159 households were matched to 18 stations in rural Java.

After merging available precipitation data and dropping observations with missing data, the sample size in the 2000 IFLS3 for our analysis was reduced to 6,188 households from a total of 10, 292. 3,290 households in our 2000 sample were located in rural areas, and of these 2,159 were located on Java. Data from additional weather stations would benefit this analysis by improving the level of disaggregation of weather data, but this data could not be obtained.

[Figure 2 around here]

Figure 2 shows variation by province in monsoon onset and post-onset rainfall in 1999/2000. With respect to delays in monsoon onset, only provinces in Java experienced a delay greater than one standard deviation from the 25 year mean. As for the amount of rainfall during the 90 day post-onset period, again only provinces in Java experienced rainfall below two standard deviations from the 25 year mean.

[Table 1 around here]

The summary statistics of household expenditures, household characteristics, and rainfall shock exposure in rural Java are shown in Table 1. The majority of household heads were married males who did not have more than an elementary education. The vast majority of households utilized electricity. Half of the households owned farmland, and 44% were engaged in non-farm businesses. Nearly 60% of households were engaged in a farm business, 38% with rice as the most valuable crop and 22% with another crop as the most valuable. 34% of households in our sample were exposed to the delay of onset shock and 45% were exposed to the post-onset low rainfall shock. The correlation coefficient between these two shock variables for our sample was not large at 0.38.

4. *Empirical* Results

We present our findings on (i) the impact of rainfall shocks on per capita household consumption levels and (ii) the role that various social programs may have played in assisting households cope with the negative welfare impacts of rainfall shocks. For the first part, we used regression analysis to quantify the average reduction in household welfare levels for those exposed to low rainfall shocks. For the second part, we used propensity score matching to estimate the extent of the moderating effects offered by the various community-based programs.

Welfare Impacts of Rainfall Shocks

Given the importance of rain-fed agriculture, in particular rice farming, to rural livelihoods in Indonesia, we study the potential impact of rainfall shocks on per capita total household expenditure, and its food and nonfood components. We focus on rural Java, the predominant rice production area in Indonesia, and use regression analysis to estimate the impacts on household expenditures.

We include in our regressions two binary variables representing the two rainfall shocks defined earlier, delayed monsoon onset and post-onset low rainfall. We interact these shock variables with a binary variable for rice farming households, specifically households engaged in a farm business with rice as the most valuable crop. This is done to differentiate the effect of the shocks between households that have and do not have a farm business with rice as the most valuable crop. In the regressions, we control for various household characteristics: household size, age of household head, sex and marital status of head, level of education of the head (binary variables for elementary, junior high, high school, and university), access to electricity, ownership of farm land, and household farm and nonfarm business activity, whether or not rice is the most valuable crop, and province of residence. The reference case is a household in rural West Java province, with an uneducated, single, male head, that has no access to electricity, no farm land, and no household farm or nonfarm businesses.

Using the two rainfall shock variables separately as well as together, we used three different specifications for our regressions. The first includes a binary variable for delayed monsoon onset along with its interaction term with the binary variable for rice farming household. The second substitutes the post-onset low rainfall variable as the shock variable. The

third includes both rainfall shocks along their interaction terms. This third variation was used with different dependent variables, that is, per capital total household expenditure and its food and nonfood components.

As might have been expected, there is a strong positive correlation between household per capita expenditure and assets, namely education and ownership of farmland. All education coefficients are positive and significantly different from zero. For all five of the regressions reported in Table 2, the magnitude of these coefficients increase with the level of education up to high school, but the coefficients for university education are less than those associated with high school, which is a rather unusual. In general, the province of residence does not seem to matter in the explanation of variations in household welfare as the associated coefficients are not significantly different from zero. Having electricity is certainly an indication of wealth. This is manifested by a positive and significant effect on per capita expenditure. Similarly, owning farmland or a non-farm business has a positive and significant impact on household expenditure and its components (food and nonfood).

In the absence of a weather shock, our results show that there is no statistically significant difference between the average welfare of households for which rice is the most valuable crop and that of the reference household (Table 2). On the other hand, we find that households running a farm business with non-rice crops as the most valuable had per capita nonfood expenditures about 12 percent lower than the reference household.

The definition of the rainfall shock variable is important in our specifications. While a shock defined by the delay in the monsoon onset has a negative effect on the per capita total expenditures of rural households of Java, it is not statistically significant. This is contrary to that reported in Korkeala et al. (2009) based on panel data. However, when we look at the food component of expenditures, a delay of monsoon onset shock is associated with a 13 percent drop in per capita food expenditures relative to the reference household.

If the amount of rainfall during the 90 day post-onset period is below 2 standard deviations away from the 25 year mean, the coefficients associated with the interaction between the post-onset low rainfall shock and rice farming are negative and significantly different from zero (at a 5 percent level of significance) for total and nonfood expenditures. With exposure to the low rainfall shock, the per capita total expenditure of households engaged in rice farming is 12 to 14 percent lower than that of the reference household and the per capita nonfood

expenditure is 26 percent lower, controlling for household attributes and province of residence. In contrast, we find that the interaction of the low rainfall shock with the binary variable identifying households engaged in rice farming does not have a statistically significant effect on food consumption. This result, which is frequently observed among rural households in different countries (Skoufias, and Quisumbing, 2005), suggests that rice farm households are able to protect their food consumption in the face of weather shocks. Thus, households manage to protect their food consumption at the expense of nonfood consumption. To the extent that reduced expenditures on nonfood are accompanied by lower expenditures on children's education, weather-related shocks may also be associated with reduced investment in the human capital of children (Jacoby and Skoufias, 1997).

[Table 2 around here]

Role of Community Programs

As noted earlier, vulnerability of an individual or a household to livelihood stress depends on both exposure and the ability to cope with and recover from the shock. The ability to cope is largely determined by access to resources, including savings and cash and in-kind transfers as part of some social assistance programs. We explored the role of the following six social assistance programs in mitigating potential negative welfare impacts of shocks in rural areas of Java: (1) availability of credit through the INPRES Poor Villages Program, (2) Kampung Improvement Program, an informal housing area upgrading program that provided basic services and infrastructure through community based organizations, (3) Infrastructure Development Program, a community-based infrastructure development program, and (4) Padat Karya program, a loose collection of labor-intensive workfare programs sponsored by various government departments (Sumarto et al. 2002), (5) PDM-DKE (Regional Empowerment to Overcome the Impact of Economic Crisis) program, a block grant program for villages to support revolving funds for credit or public works projects that offer nonfarm employment opportunities (Sumarto et al. 2002), and (6) the Inpres Desa Tertinggal (IDT) (Program for Underdeveloped Villages), another block grant program targeting extremely poor villages (Sumarto et al. 2002). These programs may assist households cope with the loss of farm income,

smaller harvests, or higher prices by enhancing access to credit, providing cash or in-kind transfers, and labor opportunities.

As discussed earlier, recognizing that government assistance programs are often targeted to poor areas, we use propensity score matching to infer the moderating impact of some community level interventions on the impact of the shock. For each of the community-based programs, we estimate the average treatment effect of the intervention on per capita household expenditures components among households exposed to the shock and located in communities with the program of interest (i.e. SATT, or the sample average treatment effect for the treated). To assess whether the potential program benefits differ according to the presence or absence of a shock, we also estimated the SATT among households not exposed to the shock. In addition, we repeated the procedures using another variation of the PSM specification as well as limited the sub-sample to rural households engaged in a farm business. The results in Table 3 are shown as the percent difference in mean per capita expenditures between the treatment and control groups. The panel on the left side of Table 3 relates to the sample of households of rural Java that were exposed to the post-onset low rainfall shock regardless of occupational status, while the panel on the right focuses on the sub-sample of households exposed to the shock that were engaged in a farm business.[7]

[Table 3 around here]

The results for the INPRES Poor Villages Program and the IDT Program indicate positive and significant average treatment effects that are greater among rural households engaged in farm businesses vis-a-vis all rural households. Households in communities with the INPRES credit program and exposed to a low rainfall shock had an average of 15.7% higher per capita expenditure than the control group (i.e. without INPRES). Among communities not exposed to the shock, the INPRES program did not show any significant difference in average treatment effects. For the sub-sample engaged in farm businesses and hit by a rainfall shock, average per capita expenditure levels in communities with the program was 24.9% greater than in communities without the program. Among households not exposed to the shock, the average

[7] We also attempted to extend this analysis to only farmers indicating rice as the most valuable crop, but the data thinned out and precluded application of this approach to this sub-sample.

treatment effects was -13.4% and statistically significant at 95% confidence level. These results suggest that the greater access to credit furnished by the INPRES program may have allowed households to borrow to maintain household consumption levels in cases where rainfall shocks might have diminished harvests, constituting an important coping mechanism for households affected by the shocks.

Similarly, the average treatment effects of the IDT program, which provided block grants for underdeveloped villages, were 16.0% and 23.3% among all rural households exposed to the shock and among the sub-sample engaged in farm businesses, respectively. Both of these results were significant at the 95% confidence level. On the other hand, the corresponding treatment effects among households not exposed to the shock were smaller (-2.2% and 5.3%) but not statistically significant. This suggests that the IDT block grant program may have helped provide some relief to rural households hit by the rainfall shock, in particular to farming households, likely by generating employment opportunities locally through various public works projects.

The Kampung Improvement Program results indicate positive average treatment effects of 24.8% and 16.6% for the sample of rural households, and 19.3% and 12.2% for the sub-sample limited to households engaged in farm businesses. Unlike the case of INPRES and IDT, the average treatment effect is smaller for the sub-sample engaged in farm businesses, albeit the 19.3% result is only weakly significant at the 90% confidence level. The ATT for the sub-samples not exposed to shock were smaller than corresponding results for the sample with shock. The exact mechanisms by which this program might have yielded these results are not apparent, but one might venture to guess that the improvements in infrastructure might help mitigate the impacts of a low rainfall shocks. Given the positive results, further investigation would be worthwhile.

The Padat Karya safety net program had an average treatment effect of 13.3% among rural households exposed to the low rainfall shock, but this was only weakly significant at the 90% confidence level. The other results for the Padat Karya program were statistically insignificant. However, this labor intensive workfare program appears to exhibit potential as an effective safety net in alleviating the stress that may have been induced by a rainfall shock.

The results for the Infrastructure Development Program and PDM-DKE (public works / credit) safety net program were statistically insignificant. It is not possible to say much about the effectiveness of these programs in the context of rainfall shocks.

The results above suggest that access to credit and public works projects in communities can help households cope with shocks and thereby play a strong protective role during times of crisis. On the other hand, infrastructure improvement programs in communities may help mitigate the impacts of the shocks. In light of these findings, these policy instruments should be given due consideration in the design and implementation of adaptation strategies.

5. Concluding Remarks

Very little empirical evidence exists on the welfare losses that households experience as a consequence of weather shocks. In principle, households at low levels of income are most vulnerable to the impacts of weather extremes given their geographical locations, limited assets and access to resources and services, low human capital and high dependence upon natural resources for income and consumption. While there is wide recognition of the threat of climate-induced shocks upon the poor, limited attention has been given to quantifying the effects of weather extremes and identifying targeted measures that could mitigate the poverty impacts. This paper seeks to make a contribution by analyzing the potential welfare impacts of rainfall shocks in rural Indonesia with a focus on households engaged in family farm businesses, in particular rice farming. It also attempts to identify community interventions with the potential capable of dampening the adverse impact of climate change and extremes. The focus on rice farming is due to the fact that rice is a staple food in Indonesia.

The basic approach adopted here is to exploit cross-sectional variation in the data and link a welfare indicator, real consumption per capita, or some component thereof (i.e. food versus non-food expenditure) to a weather shock defined on the basis of available rainfall data focusing mainly on rural households. In particular, we consider two types of shocks: delayed onset of monsoon and rain shortfall in the 90 day period following monsoon onset. We find that delay in the monsoon onset does not have a significant impact on the welfare of rural households. However, rice farm households located in areas experiencing low rainfall following the monsoon onset are negatively affected by the low rainfall shock. Nonfood expenditure per capita is the most affected component. This suggests that rice farm households protect their food expenditure in the face of weather shocks. Further study is needed to better understand these choices and their implications for adaptation strategies.

To identify potential policy instruments that might moderate the welfare impact of weather shocks, we use propensity score matching to evaluate various social assistance programs. Our results indicate that credit availability, the existence of safety nets and public works programs offer the strongest cushion for these types of shocks. This is an important consideration for the design and implementation of strategies to protect poor vulnerable households. Indeed, individual ability to cope with and recover from crises hinges critically on available social support. Taken together with other emerging evidence on the long lasting effects of rainfall shocks on human capital, our findings highlight the urgent need for effective adaptation strategies.

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Figure 1: Timing of typical climate events and the IFLS3

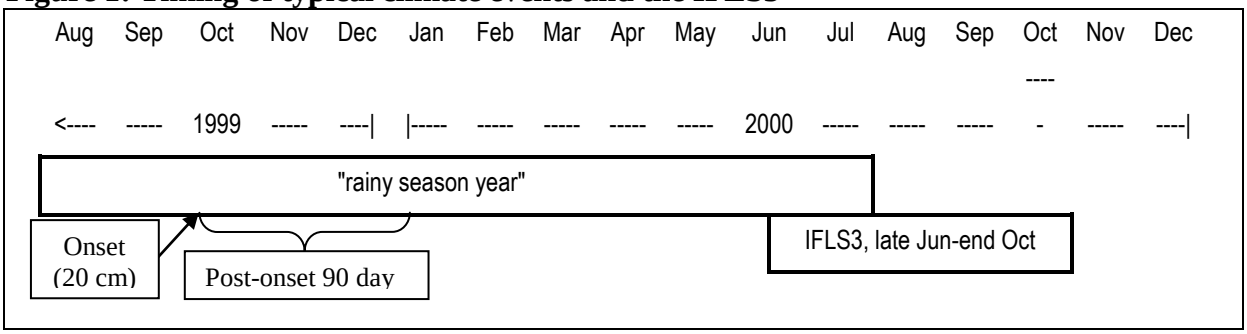

Figure 2: Variation in monsoon onset and post-onset rainfall (1999/2000)

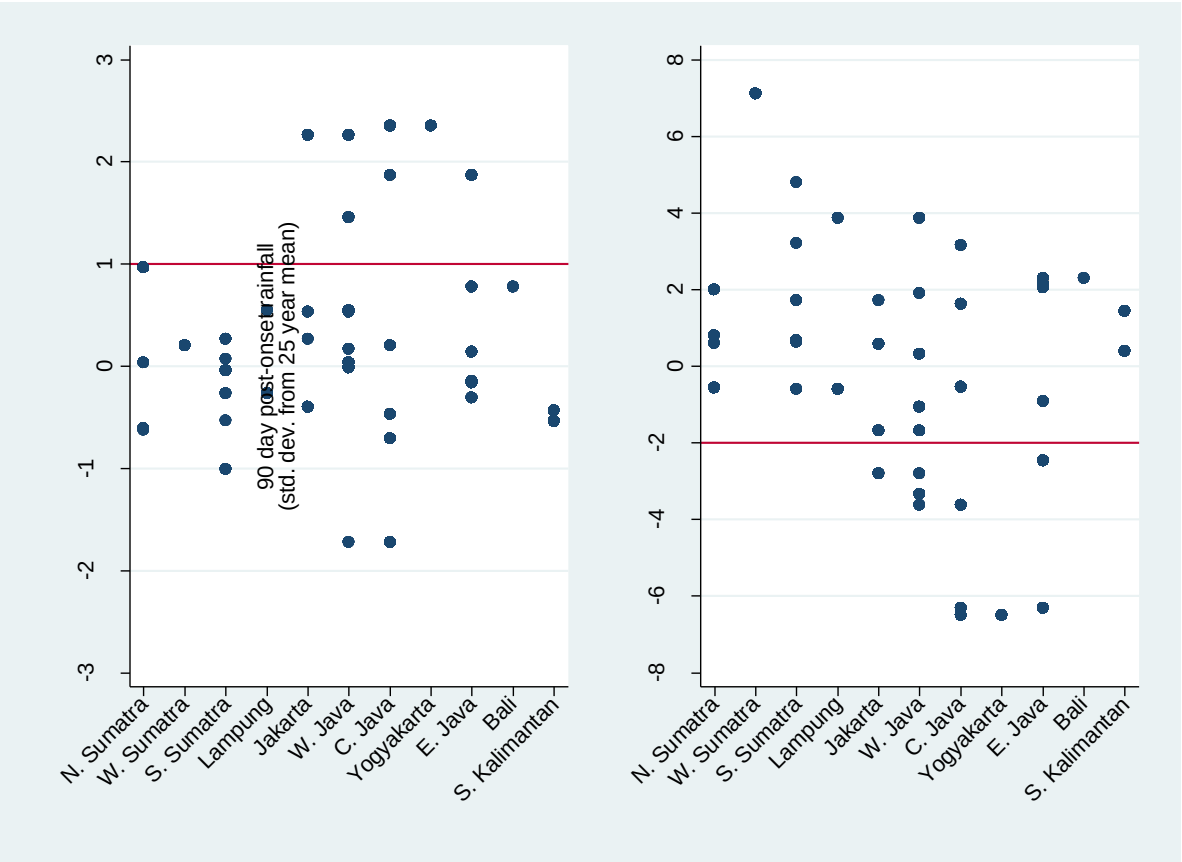

Table 1: Summary Statistics for Households in Rural Java (1999/2000 IFLS)

Variables	Mean	Std. Err.
total pce (Rupiah per capita per month)	257273	7660
food pce (Rupiah per capita per month)	154389	4332
nonfood pce (Rupiah per capita per month)	102885	4745
household size	3.06	0.09
age of head	48.41	0.45
married head	0.84	0.01
female head	0.18	0.01
highest education of head: elementary	0.58	0.02
highest education of head: jr. high school	0.07	0.01
highest education of head: high school	0.05	0.01
highest education of head: university	0.08	0.01
hh utilizes electricity	0.90	0.03
hh owns farmland	0.50	0.03
hh non-farm business	0.44	0.03
hh farm business - rice most valuable crop	0.38	0.03
hh farm business - other crop most valuable	0.22	0.03
shock: delay of monsoon onset (>1 sd)	0.34	0.06
shock: delay of monsoon onset (>2 sd)	0.16	0.04
shock: post-onset low rainfall (<-1 sd)	0.57	0.06
shock: post-onset low rainfall (<-2 sd)	0.45	0.06
N=2159		

Table 2: Regression Results of Shocks on Household Consumption in Rural Java, 1999/2000

Dependent Variable (log):	total pce						nonfood pce		food pce	
	delay of onset shock (1)		post-onset low rainfall shock (2)		both shocks (3)		both shocks (4)		both shocks (5)	
hh farm business - rice most valuable crop	0.002		0.056		0.041		0.072		0.034	
	(0.042)		(0.047)		(0.046)		(0.065)		(0.042)	
hh farm business - other crop most valuable	-0.046		-0.047		-0.046		-0.117	**	0.003	
	(0.044)		(0.046)		(0.045)		(0.054)		(0.048)	
shock: delay of monsoon onset (>1sd)	-0.042				-0.035		0.103		-0.132	**
	(0.064)				(0.065)		(0.084)		(0.061)	
shock: post-onset low rainfall (<-2sd)			-0.036		-0.027		-0.034		-0.019	
			(0.054)		(0.055)		(0.076)		(0.049)	
hh farm rice X delay shock	0.024				0.072		0.037		0.118	*
	(0.062)				(0.072)		(0.114)		(0.063)	
hh farm rice X low rainfall shock			-0.120	**	-0.142	**	-0.256	**	-0.083	
			(0.059)		(0.067)		(0.104)		(0.057)	
household size	-0.145	***	-0.145	***	-0.145	***	-0.136	***	-0.148	***
	(0.008)		(0.009)		(0.008)		(0.011)		(0.008)	
age of head	0.015	**	0.015	**	0.015	**	0.017	**	0.016	***
	(0.006)		(0.006)		(0.006)		(0.008)		(0.006)	
age of head^2 (1/100)	-0.015	***	-0.015	***	-0.015	***	-0.019	**	-0.015	***
	(0.005)		(0.005)		(0.005)		(0.007)		(0.005)	
married head	0.036		0.042		0.041		0.016		0.102	
	(0.077)		(0.076)		(0.077)		(0.086)		(0.078)	
female head	-0.019		-0.015		-0.016		0.007		0.012	
	(0.077)		(0.076)		(0.076)		(0.079)		(0.079)	
highest education of head: elementary	0.091	**	0.086	**	0.087	**	0.172	***	0.039	
	(0.044)		(0.042)		(0.042)		(0.051)		(0.045)	
highest education of head: jr. high school	0.214	***	0.206	***	0.207	***	0.358	***	0.123	
	(0.071)		(0.070)		(0.070)		(0.085)		(0.075)	
highest education of head: high school	0.506	***	0.502	***	0.503	***	0.786	***	0.300	***
	(0.084)		(0.083)		(0.083)		(0.093)		(0.087)	
highest education of head: university	0.212	**	0.205	**	0.205	**	0.350	***	0.098	
	(0.099)		(0.095)		(0.095)		(0.117)		(0.088)	
Central Java province (33)	-0.072		-0.055		-0.057		-0.007		-0.075	
	(0.076)		(0.073)		(0.073)		(0.097)		(0.068)	
Yogyakarta province (34)	-0.038		0.004		0.005		0.044		-0.023	
	(0.114)		(0.106)		(0.112)		(0.134)		(0.115)	
East Java province (35)	-0.071		-0.063		-0.061		-0.016		-0.106	**
	(0.058)		(0.057)		(0.056)		(0.088)		(0.047)	
hh utilizes electricity	0.158	**	0.188	***	0.188	***	0.441	***	0.060	
	(0.066)		(0.062)		(0.062)		(0.106)		(0.063)	
hh owns farmland	0.114	***	0.117	***	0.116	***	0.131	***	0.080	**
	(0.032)		(0.032)		(0.032)		(0.046)		(0.033)	
hh non-farm business	0.172	***	0.170	***	0.170	***	0.228	***	0.131	***
	(0.035)		(0.034)		(0.034)		(0.044)		(0.034)	
constant	11.972	***	11.946	***	11.952	***	10.431	***	11.574	***
	(0.199)		(0.193)		(0.191)		(0.277)		(0.170)	
N	2159		2159		2159		2159		2159	
r2	0.196		0.2		0.201		0.189		0.175	

legend: p<0.10 *, p<0.05 **, p<0.01 * ; standard errors in parentheses above**

Table 3: Moderating Effects of Community-Based Programs for Rural Households Exposed to Post-Onset Low Rainfall Shocks: Average Treatment Effects based on Propensity Score Matching

		All rural households				Rural households engaged in farm business			
	Low rainfall shock:	Yes		No		Yes		No	
INPRES Poor Villages Program (credit)	att	15.7	**	-5.9		24.9	**	-13.4	***
	n1	245		604		136		398	
	n0	299		1305		165		857	
IDT Program (block grants)	att	16.0	**	-2.2		23.3	**	5.3	
	n1	231		198		145		161	
	n0	489		323		299		197	
Kampung Improvement Program (community-based)	att	24.8	***	16.6	**	19.3	*	12.2	
	n1	287		280		167		205	
	n0	406		527		289		336	
Infrastructure Development Program (community-based)	att	4.9		21.4	*	-10.9		5.3	
	n1	168		61		78		56	
	n0	447		32		279		23	
Padat Karya Program (public works)	att	13.3	*	10.9		-3.7		-10.4	
	n1	167		168		64		71	
	n0	499		518		308		210	
PDM-DKE Program (block grants)	att	0.4		-8.1		15.0		5.4	
	n1	137		485		55		216	
	n0	565		1199		371		758	

Legend: att = average treatment effect on the treated, expressed as the percent difference in average per capita total household expenditure between treatment and control groups; $p < 0.1$ *, $p < 0.05$ **, $p < 0.01$ ***; n1=number of households in treatment group after trimming; n0=number of households in control group after trimming.