Vulnerability and Resilience of Household Consumption and Their Determinants
-The Case of the Southern Province of Zambia-

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Abstract

Risk coping and consumption smoothing in rural areas of developing countries, where people's livelihood is often subject to various risks, have been well documented. However, the literature has not properly considered the time required for households and/or individuals to recover their level of consumption. To address the lack in the literature, we have incorporated the time dimension in the process of recovery from a shock in this paper. For this purpose, we have adapted the concept of resilience from ecology and define it in the context of consumption smoothing. Moreover, unlike most previous studies on consumption smoothing, we utilize weekly data collected before and after a covariate shock so as to provide empirical evidence of resilience.

In this paper, we provide an empirically workable definition of "resilience" at the household level. Resilience is based on the measurement of household food consumption per capita and is defined by the speed of the recovery of food consumption from a shock. Then, following the definition, we empirically estimate resilience using data collected in a rural area of Zambia, where its rain-fed agriculture is highly affected by rainfall variation. In this particular dataset, a heavy rain took place in December 2007. Resilience is measured as the speed of consumption recovery after the heavy rain shock.

Our panel data analyses reveal that the heavy rain caused a shock, i.e., reduction of food consumption, among the sample households, and it took almost one year for them to recover from the shock. Our analyses also show that household assets, such as land and livestock, have a positive effect on enhancing resilience. Then, dividing the sample into rich and poor groups based on the value of cattle holdings, we conducted similar analyses for each group separately and found that households in the rich group were more resilient than those in the poor group. The results indicate that some poor households that lack sufficient assets may not be able to recover consumption. Moreover, it is found that households in the poor group were more sensitive to the rainfall shock: they reduced consumption more quickly after the shock than did those in the rich group. We do not indicate in this paper how the sample households recover their consumption from the shock such as labor supply and livestock sales. Incorporating those coping behaviors is our next research topic as we have enough data to do it.

1. Introduction

Risks exist everywhere, and they are a part of rural life in developing countries. It is well known that rural households practice a variety of measures to manage *ex-ante* risk, such as crop and income diversification (Dercon, 2005). However, because such risk-management measures are costly and imperfect, risk events like drought often cause shocks to households, e.g., a decline of consumption. That is, shocks are almost inevitable in a risky environment. This does not necessarily imply that the impact of such shocks is significantly serious because households can mitigate the impact by undertaking various coping behaviors, such as liquidating assets, increasing labor supply, and receiving gifts (Dercon, 2002). Hence, so far as households have the capacity to cope with shocks, they can mitigate their impact, and thus their consumption is smoothed. The literature examines coping behaviors and consumption smoothing in rural areas of developing countries, generally demonstrating that rural households are usually able to smooth consumption in the case of idiosyncratic shocks, and even in the case of covariate shocks they can smooth consumption to some extent, depending on their capacity (Hoddinott and Harrower, 2005; and Dercon, Hoddinott, and Woldehanna, 2005).

However, the existing literature on consumption smoothing does not adequately consider the time required for households to recover their level of consumption. To test consumption smoothing, a panel dataset containing at least two observations at different time points is required. But because the interval between two observations is usually one or even several years, some shocks cannot be observed if consumption level recovers within the interval. This is particularly pertinent because household surveys typically ask about consumption over a recent short period, such as one month before the interview. One obvious shortcoming of such analyses is that the welfare impact of a shock can be underestimated if data collection on the risk event is conducted after the recovery or even while the recovery is in process. Another problem is that such analyses cannot exactly estimate the magnitude of the shock (i.e., reduction of consumption) and the speed of recovery (i.e., time required for recovery), if recovery has already started when *ex-post* data collection is being carried out.

To address apparent lacks in the literature on consumption smoothing, the present paper incorporates the time dimension in the process of recovery from a shock. For this purpose, we have adapted the concept of resilience from ecology and defined it in the context of consumption smoothing. Moreover, in contrast to most previous studies on consumption smoothing, the present study utilizes weekly data collected before and after a covariate shock so as to provide empirical evidence of resilience.

2. Definitions

The definitions of vulnerability and resilience are provided by Sakurai et al. (2010), based on the concept of Gunderson et al.'s engineering resilience. Gunderson et al. (2002) distinguish two ways of defining resilience in the ecological literature: one is engineering resilience, the other an ecological definition. Engineering resilience is "the speed of return to the steady state following a perturbation," conceiving ecological systems as existing close to a stable steady state. Conversely, ecological resilience assumes multiple stability domains and is measured by "the magnitude of disturbance that can be absorbed before instabilities shift or flip a system into another regime of behavior." The concept of engineering resilience fits into economics, which assumes a single stable equilibrium, while that of ecological resilience corresponds to multiple equilibria in economics.

In this paper, we adapt previous definitions and propose a new set. The definitions are schematically presented in Figure 1. The vertical axis measures the level of consumption, and the horizontal axis represents time. Figure 1 shows that the consumption level at the steady state is c_n. From time 0 to the time when a shock occurs, the consumption level remains at the steady-state level. In a short run, we can assume the consumption level to be constant. Then, owing to the shock, household consumption plunges from c_n. In this regard, two types of household are displayed in the figure. In Household A, after the shock the consumption declines to c_{sa}, a level above the threshold c_t, then it starts recovering at time t_1 and reaches the original level at time t_2. The recovery may not take place immediately after the shock; rather, the lowest level of welfare may continue for a while. But the point is that the consumption of Household A recovers within a short period of time ($t_2 - t_1$). The other type is Household B. The consumption goes down to c_{sb}, a level below the threshold c_t, after the shock. In this case, the household's consumption remains at c_{sb} for a long period—enough to allow us to consider it "permanent." The contrast in the two types of consumption dynamics is very similar to that between transitory and chronic poverty, but the threshold is not the same as a poverty line.

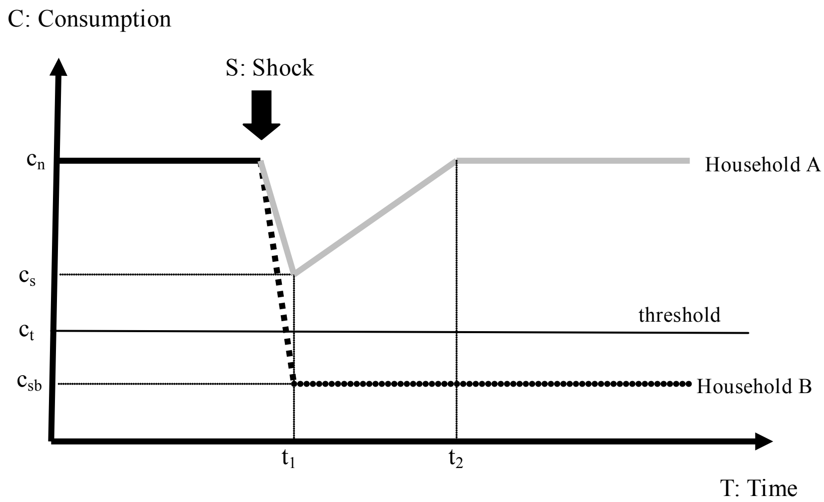

Figure 1 Schematic Definitions of Vulnerability and Resilience

Based on Figure 1, sensitivity, vulnerability, engineering resilience, and ecological resilience can be defined as follows. Sensitivity refers to the reduction of consumption against one unit of an exogenous shock: Household B is more sensitive to the shock than Household A because the former reduces consumption more than the latter, assuming the size of the shock to be the same. A household with lower sensitivity is not necessarily a better household: for example, a very poor household already below the threshold will make a very small reduction in consumption even if a shock occurs. Vulnerability is a very similar concept to sensitivity; but unlike with sensitivity, vulnerable households should be judged worse than non-vulnerable households. Thus, vulnerability can be defined as the probability that a household's consumption level will fall below the threshold level given a shock of fixed magnitude. A household whose consumption level is currently below the threshold should be excluded from the application of this definition or be considered 100% vulnerable. If we compare Household A and Household B, although the consumption level of the former is always above the threshold and that of the latter falls below the threshold, the probabilities are not 0% and 100%, respectively. We can say qualitatively that Household A is less vulnerable than Household B, but in order to obtain the probabilities we need to empirically estimate their sensitivity against a shock and the threshold.

Conversely, resilience concerns the recovery rather than the shock itself. If we assume a system with a single equilibrium, the concept of engineering resilience can be applied, and resilience can be defined as the speed of recovery of consumption from a shock. In Figure 1, the recovery speed is the slope between t_1 and t_2: it is $(c_a - c_{sa}) / (t_2 - t_1)$ in the case of Household A and 0 in the case of Household B. Thus, we can say that the resilience level of Household A is higher than that of Household B. This definition is simple, and the speed is easily calculated if the data are available, but in practice we need to control for the magnitude of shock. Otherwise, a household with less shock could be considered less resilient because there is no recovery. Finally, considering a system with multiple equilibriums, Household B is regarded as having changed its regime, e.g., from a high-consumption to a low-consumption regime, owing to the shock, and therefore we can qualitatively define Household A as resilient and Household B as not resilient. Quantitatively, ecological resilience is defined by the maximum magnitude of a shock from which a household can recover its consumption to the original level. Thus, it will be obtained by estimating the magnitude of a shock required to reduce the consumption level of a household to the threshold level. By this definition, the greater the shock, the more resilient is the household.

3. Data

This paper uses data collected as part of the Resilience Project of the Research Institute of Humanity and Nature. The project's study area is the Southern Province of Zambia, the most drought-prone zone in the country, with annual precipitation of less than 800 mm. Within the study area, three agro-ecologically distinctive sites, namely Site A, Site B, and Site C, were selected for detailed household survey, based on our own preliminary extensive survey in the study area (Sakurai, 2008). The three sites are spread over the slope adjoining Lake Kariba: Site A is located on the lower terrace of the slope on the lakeshore; Site C is on the upper terrace of the slope on the southern edge of the Zambian plateau; and Site B is located on mid-escarpment between the other two sites. Based on a village census conducted before the rainy season in 2007, 16 households in each site, thus 48 households in total, were selected for the survey.

The household survey consists of three components: (i) interview of sample households; (ii) anthropometric measurement; and (iii) rainfall measurement at the plot level. The interview was conducted every week by an enumerator, using structured questionnaires to obtain information about household agricultural production, income, consumption, and time use. For the anthropometrics, the same enumerator measured household members' body weight, height, skin-fold thickness, and upper-middle arm circumference using special instruments at the time of interview. Plot-level rainfall was recorded every 30 minutes by a rain gauge installed on a plot of each sample household. The data collection started in November 2007 at the beginning of the 2007/08 rainy season and is planned to continue until November 2011, at the end of the 2010/11 cropping season.

In December 2007, just after the beginning of the household survey, a heavy rainfall occurred at the study site. This was a very rare event in the drought-prone zone of Zambia and caused serious damage to agricultural production. Hence, this paper focuses on this heavy rain shock using data collected at site A because this site was the one most severely affected. We analyze the data covering the first two cropping years (i.e., from November 2007 to December 2009) so as to observe the heavy rain shock and the process of recovery from it. Household data were collected every week during the two-year period, but they are aggregated at the monthly level for this paper. As a result, the structure of the dataset is a panel of 16 households for 26 months. It is an unbalanced panel because some data are missing.

4. Rainfall

Following the definition of resilience given in the previous section and in Figure 1, a shock must be specified in terms of timing and magnitude. First, we confirmed the heavy rain from the rainfall pattern recorded by the rain gauges. As shown in Figure 2, there was a sharp rise in weekly rainfall in December 2007, which was not observed in December 2008 and 2009. The average rainfall of 16 rain gauge spots amounted to 473 mm in the week of December 24th, 2007. It was almost 30% of the total rainfall of the rainy season of 2007/08 (November 2007 to April 2008), and more than twice as high as the highest weekly rainfall in the rainy season of 2008/09, which was 239 mm, recorded during the week of March 12th, 2009.

Not only the rainfall during the week of December 24th, 2007, but also the total rainfall of the rainy season was much higher in 2007/08 than in 2008/09: the former was 1,596 mm and the latter 1,312 mm on average. But the difference is smaller than that of the week of December 24th (473 mm vs. 102 mm). This is because in February and March rainfall was greater in 2008/09 than in 2007/08. We cannot confirm, however, how unusual the heavy rainfall in 2007/08 was because no long-term rainfall records are available for our study sites. Nevertheless, villagers judged the heavy rain in 2007/08 to be a rare event that may happen once in several decades, and we could observe that many farmers lost maize plants, which were in the growing stage at the time of the rain, and some important infrastructure, such as roads and bridges, was lost because of floods caused by the rain. Therefore, we consider that there was a common shock in December 2007 among the sample households at site A.

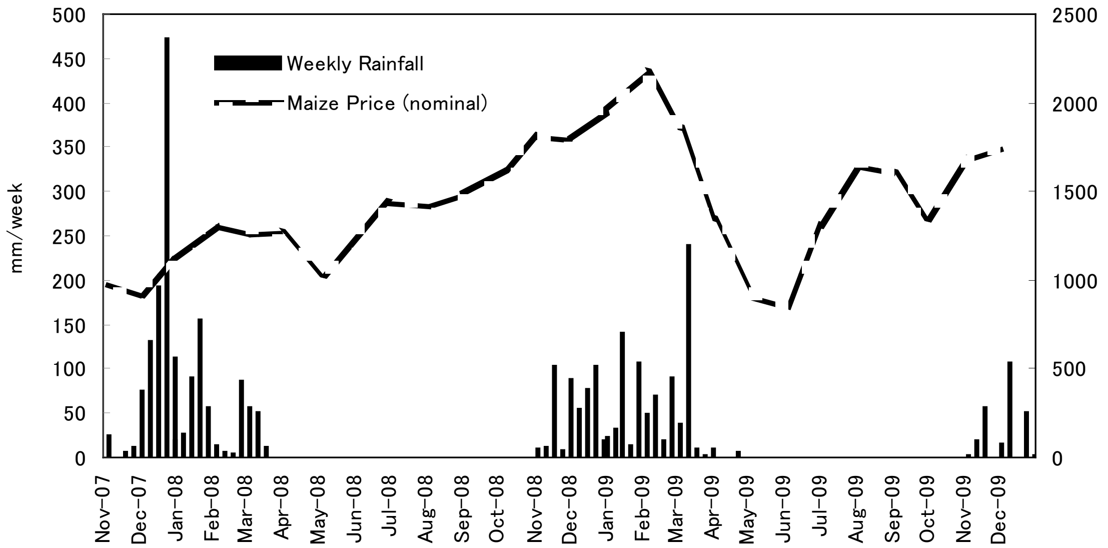

Figure 2 Average Weekly Rainfall and Maize Price

Although this report does not show any impact of the heavy rainfall on agricultural production, the aggregate impact is obvious: the price of maize, the most important staple food at the study site, increased in the local market after the rainy season of 2007/08, as shown in Figure 2, probably owing to the poor harvest that season. The nominal price continued to escalate until the harvesting of the 2008/09 crop in March 2009.

The 16 rain gauges of the sample households are distributed within just a 5-km radius. But rainfall levels among them are not uniform. As summarized in Table 1, the amount of annual rainfall was higher in 2007/08 than in 2008/09, averaged for the 16 rain gauges, but their standard deviation was lower in 2007/08 than in 2008/09. As a result, the coefficient of variation was much lower in 2007/08 than in 2008/09. We suppose that the case of 2008/09 is closer to the ordinary condition at the study site, but, as noted above, we do not have any reference with which to compare our data.

Figure 3 shows the amount of annual rainfall recorded at each sample household's plot. The household IDs on the horizontal axis are in the order of annual rainfall for 2007/08. The lowest rainfall observed at the plot of household 103 was 1,558 mm per year, while the highest rainfall was 1,698 mm per year at the plot of household 116. The annual rainfall for 2008/09 was lower than that for 2007/08 at every household, as shown in Figure 3. But the order is not the same over the two years: the lowest was 1,151 mm, recorded at household 113; the highest was 1,404 mm, recorded at household 109. The amount of rainfall in 2007/08 and 2008/09 is positively correlated, with a coefficient of 0.417, but it is not statistically significant at the 10 percent level. By comparing the two patterns of rainfall distribution among the sample households, the heavy rain in 2007/08 seemed to have been a common shock for them, though the amount of rainfall varies temporally as well as spatially. Thus, rainfall can be considered an idiosyncratic shock.

Table 1 Annual Precipitation of 2007/08 and 2008/09 Cropping Year

Cropping Year	Number of Rain Gauges	Mean (mm)	Standard Dev. (mm)	Coefficient of Variation	Maximum (mm)	Minimum (mm)
2007/08	16	1,596	40	0.025	1,698	1,558
2008/09	16	1,312	78	0.059	1,404	1,151

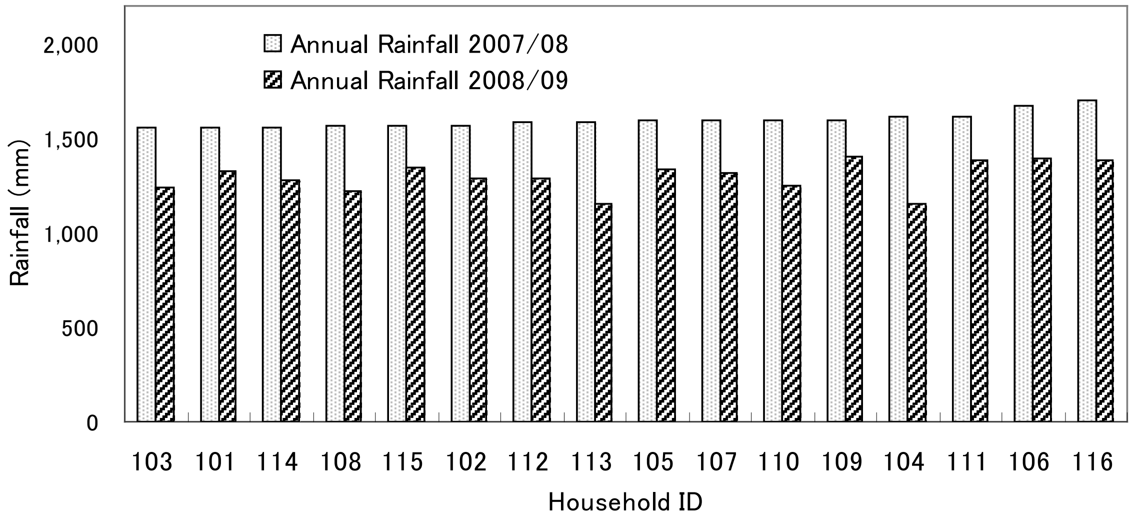

Figure 3 Distribution of Annual Rainfall among Sample Households

5. Food Consumption

Average food consumption per week per adult equivalent (hereafter, simply adult) among the sample households is calculated for every month from November 2007 to December 2009. The food includes not only self-produced food, but also food purchased, received either as public food aid or a gift, and collected/caught in the field. Except for purchased food, the values are estimated based on respondents' subjective judgment and the market price. The total value of the food consumed per week is averaged for the monthly level and then deflated by the monthly price index, based on observed prices at the local market and consumption baskets at the study sites estimated from our own data. It should be noted that because maize amounts to about half the total value of consumption, the curve of the monthly price index is quite similar to that of the nominal maize price shown in Figure 2. In addition to the real value, this paper presents the amount of food consumption in terms of its total calories. The calorific values are estimates based on the weight of food items consumed by sample households using standard coefficients given in Zambia Food Composition Tables (National Food and Nutrition Commission, 2009). They are calculated only for selected high-calorie foods, such as cereals, beans/peas, and roots/tubers. The results are given in Figure 4.

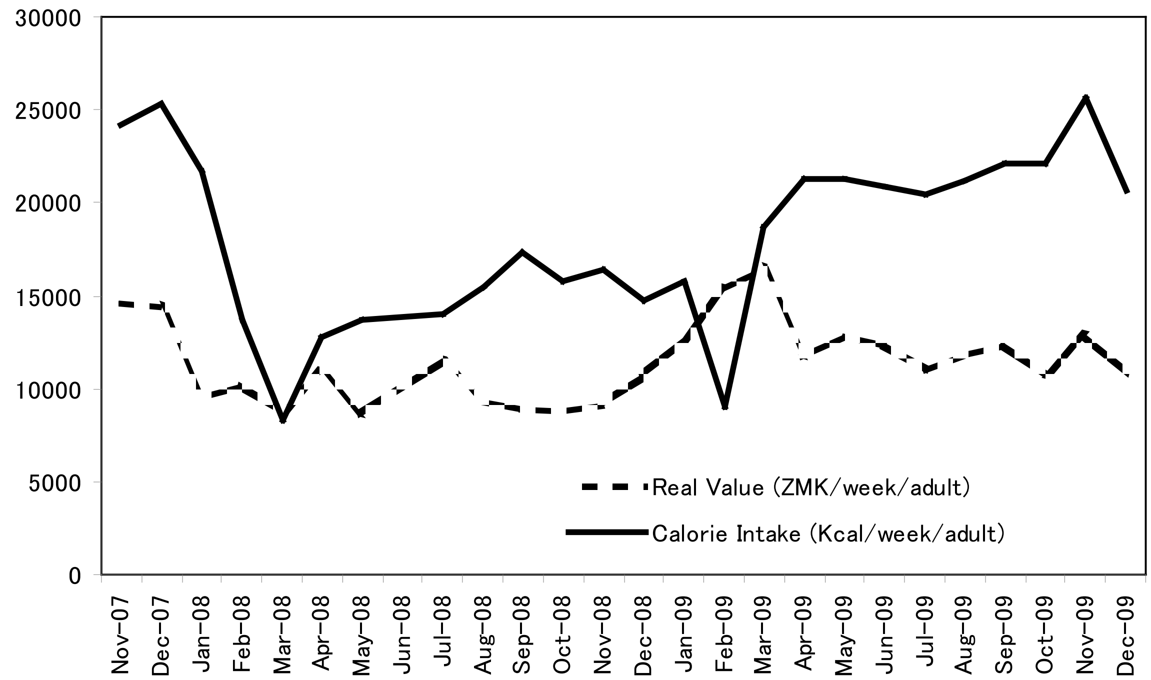

Figure 4 Average Food Consumption per Week per Adult

As shown in the figure, food consumption in terms of both real value and energy plunged in January 2008 just after the heavy rain and started recovering after March 2008. However, while we can observe a modest recovery in calorie intake after March, the recovery of food value is very slow. Considering that the maize price began to increase after the harvest season of 2007/08, the widening gap between value and calorie intake implies that villagers consumed relatively cheap, high-energy food. In fact, wheat flour and beans were distributed as food aid during that period (Kitsuki and Sakurai, 2011), and wheat flour was a cheaper energy source than maize flour in April and May 2008 (0.41 ZMK/kcal vs. 0.65 ZMK/kcal). Then, towards the end of the dry season of 2008, the maize price increased, and as a result the real value of consumption also increased, while the calorie intake decreased. This has to be another impact of the heavy rain in December 2007 through the higher market price of maize. Only after the harvest of the 2008/09 rainy season in March 2009 did calorie intake recover to a level close to that before the heavy rain, and the real value of food consumption stabilized. Applying this observed pattern to Figure 2, we could say that a shock occurred in December 2007 and recovery from the shock started in April 2008, taking one year to complete.

We can confirm that the change in calorie intake had some impact on the villagers' well-being by examining their body weight. Figure 5 is produced from the data of weekly body-weight measurement of household members and shows the ratio of deviation from the sample mean for each month. From the figure, although body weight was quite variable, we can see a small drop during the cropping season of 2007/08 and a big drop during the cropping season of 2008/09, both of which correspond to the plunge in calorie intake. Therefore, we may consider that the change in calorie intake after the heavy rain in December 2007 had a real impact on the villagers. The impact is somewhat greater with female adults than with male adults, but the pattern of the two curves is almost identical. Body-weight change is affected not only by the amount of food intake, but also by the intensity of physical activities. Based on the same weekly survey, Nasuda et al. (2011) show that males and females equally increased their working time after the heavy rain in December 2007, although females always work longer than males, including domestic chores. This observation concerning working time seems to be consistent with the body-weight change shown in Figure 5.

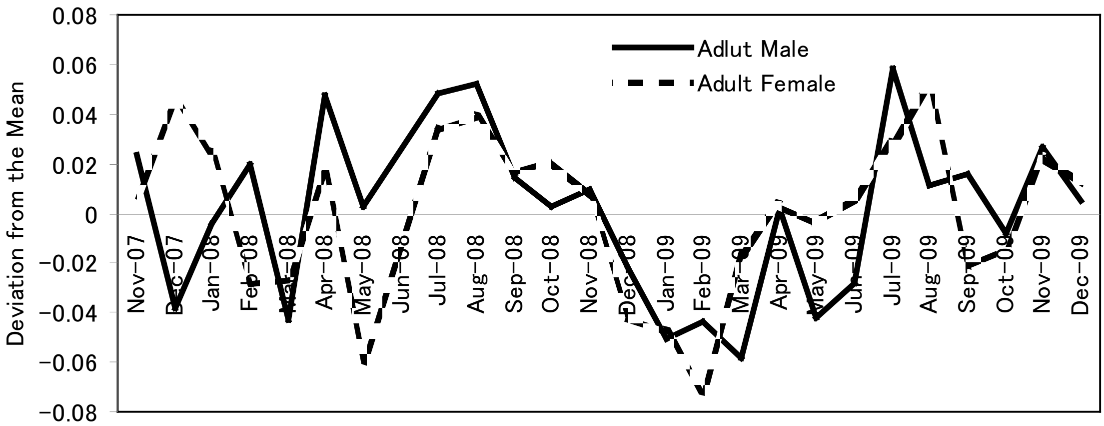

Figure 5 Monthly Body-Weight Change

6. Measuring Resilience

Following the definition of resilience discussed in section 2, engineering resilience is measured by the speed of consumption growth during the recovery period after a shock, namely from March 2008 to April 2009 according to Figure 4.

The speed of consumption growth can be written as

$$R^c_{it} = \log(C_{it}) - \log(C_{it-1}) \quad (1) \text{ or}$$

$$R^k_{it} = \log(K_{it}) - \log(K_{it-1}) \quad (2)$$

where R^c_{it} stands for resilience measured by real value of food consumption and R^k_{it} stands for resilience measured by calories for household i at time t. The former is obtained by the difference of natural logarithms of real value of food consumption per week per adult in time $t1$, C_{it} and that in time t-1, C_{it-1}. The latter, on the other hand, is obtained similarly from the difference of natural logarithms of calorie intake per week per adult, K_{it-1} and K_{it}. In our case, the unit of time is one month.

We use either consumption growth measures as the dependent variable and regress it on the explanatory variables given in Table 2.

Table 2 Explanatory Variables for Regression Analyses

Variable	Description
$RAIN_{it}$	Amount of rainfall recorded on household *i*'s plot in time *t*
$VRAIN_t$	Average amount of rainfall of sample households in time *t*
RECOV	A dummy variable for the period of recovery, i.e. from April 2008 to April 2009
$LAND_{iy}$	Total acreage of household *i*'s cropped land in agricultural year *y*
$CATL_{iy}$	Real value of cattle per adult that household *i* owns at the beginning of ag. year *y*
$SMLV_{iy}$	Real value of livestock other than cattle (small livestock such as goats and pigs) per adult that household *i* owns at the beginning of agricultural year *y*
$ASSET_{iy}$	Real value of assets other than land or livestock per adult that household *i* owns at the beginning of agricultural year *y*
AGE_{iy}	Age of the head of household *i* at the beginning of agricultural year *y*
AE_{iy}	Adult equivalent size of household *i* at the beginning of agricultural year *y*. The weight for children at and under the age of 12 is one third of adult.
D_n	Dummies for each period excluding November and December 2007 (they are assumed to be base month) and the recovery period (from April 2008 to April 2009). The subscription *n* indicates a serial number of month during the survey period: for example, *n*=3 for January 2008, *n*=4 for February 2008, *n*=25 for November 2009, *n*=26 for December 2009, and so on.

As explained above, the data-collection period was 26 months, from November 2007 to December 2009. Hence, time period t is from 1 to 26. However, the agricultural year starts in November, the onset of the rainy season, and ends in October of the following year. Therefore, the dataset covers two agricultural years fully, i.e., 2007/08 and 2008/09, plus two months in 2009/10, i.e., November and December 2009.

Among the explanatory variables listed in Table 2, *RECOV* signifies directly measuring "resilience" because the estimated coefficient for *RECOV* is the speed of recovery averaged among the sample households during the period April 2008 to April 2009. $RAIN_{it}$, household-specific rainfall, is to capture household *i* specific shocks from rainfall. As discussed earlier, rainfall is spatially variable, and we would expect its variation to be sufficient to capture a household-specific shock. Therefore, it is hypothesized that a household with a higher rainfall suffers a severer shock and hence reduces consumption more. Such an effect can be observed soon after the shock, when villagers start expecting lower income, but because the heaviest rainfall took place at the end of December 2007, we conjecture that its impact is likely to appear the following month in our monthly dataset. Therefore, lagged variables, namely $RAIN_{it-1}$ and $RAIN_{it-2}$, are used as the explanatory variables. Moreover, because the immediate effect of the heavy rain should last for a few months, interaction terms between the household-specific rainfall and dummy variables for the months after the heavy rain period (January to March 2008) are added to the explanatory variables. $VRAIN_t$ is, on the other hand, common to all the households, although it varies every month. For the same reason as with $RAIN_{it}$, $VRAIN_t$ also takes lags.

Table 3 Regression Results for Measuring Resilience

Model	RE	FE	RE	FE
Dependent Variable	R^c_{it}	R^c_{it}	R^k_{it}	R^k_{it}
Explanatory Variables	(real value)	(real value)	(calorie)	(calorie)
RECOV (n=6 – 18)	-0.17 (0.11)	-0.11 (0.19)	0.65 (0.32)*	0.62 (0.38)
$RAIN_{it-1}$ (10^{-2})	0.07 (0.16)	0.09 (0.17)	1.02 (0.42)**	1.22 (0.41)***
$RAIN_{it-2}$ (10^{-2})	-0.14 (0.18)	-0.12 (0.20)	-0.40 (0.40)	-0.24 (0.41)
$VRAIN_{t-1}$ (10^{-2})	-0.06 (0.15)	-0.10 (0.15)	-0.08 (0.04)**	-0.98 (0.40)**
$VRAIN_{t-2}$ (10^{-2})	0.13 (0.18)	0.09 (0.21)	0.26 (0.43)	0.11 (0.47)
D_3 (January 2008)	-0.13 (3.52)	-0.46 (3.37)	13.2 (5.70)**	9.84 (6.12)
D_4 (February 2008)	-8.55 (5.93)	-8.78 (6.24)	-11.2 (9.70)	-14.3 (9.79)
D_5 (March 2008)	11.4 (7.05)	12.4 (7.30)	37.0 (20.0)*	38.5 (21.3)*
$RAIN_{it-1} \times D_3(10^{-2})$	-0.13 (0.43)	-0.06 (0.42)	-1.58 (0.62)**	-1.25 (6.22)*
$RAIN_{it-2} \times D_3(10^{-2})$	1.64 (1.41)	1.54 (1.47)	-0.38 (2.35)	-0.89 (2.29)
$RAIN_{it-1} \times D_4(10^{-2})$	0.26 (1.00)	0.32 (1.07)	2.43 (1.84)	2.80 (1.98)
$RAIN_{it-2} \times D_4(10^{-2})$	8.21 (0.62)	0.85 (0.67)	0.20 (0.91)	0.32 (1.04)
$RAIN_{it-1} \times D_5(10^{-2})$	-5.04 (4.28)	-6.02 (4.70)	-12.3 (9.22)	-15.7 (10.3)
$RAIN_{it-2} \times D_5(10^{-2})$	-1.45 (1.07)	-1.46 (1.07)	-5.65 (3.19)*	-5.22 (3.26)
$LAND_{iy}$	-0.01 (0.10)	0.01 (0.17)	0.31 (0.24)	0.13 (0.34)
$CATL_{iy}(10^{-7})$	1.34 (0.99)	-0.08 (1.77)	1.89 (3.71)	0.22 (3.73)
$SMLV_{iy}(10^{-7})$	1.43 (1.24)	0.54 (1.61)	3.15 (2.51)	3.42 (4.03)
$ASSET_{iy}(10^{-6})$	-5.15 (4.06)	-3.89 (4.07)	-2.16 (1.44)	-2.53 (1.89)
$AGE_{iy}(10^{-2})$	-0.34 (0.15)**	-0.66 (2.22)	-0.04 (0.04)	-18.5 (47.5)
$AE_{iy}(10^{-1})$	-0.23 (0.22)	0.60 (0.33)*	0.29 (0.56)	-1.14 (0.63)*
D_n (n=19 – 26)	+ , - , -*	+ or -	+*** , +* or +	+* or +
Constant	0.38 (0.19)**	-4.23 (9.42)	-0.87 (0.48)*	8.23 (21.5)
Number of observations	257	257	256	256
Number of households	15	15	15	15
R^2(overall/within)	0.13	0.14	0.16	0.18

Note: Robust standard errors are in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance level respectively. The number of sample households in site A is 16 as described, but one household has been dropped from the regression because of missing data.

Because the data are panel data, we tried to estimate both fixed-effect and random-effect models, although the Hausman test generally supports the use of the random-effect model. The regression results are given in Table 3. Because the real value and calorie intake move differently, as shown in Figure 4, regression results differ between the two dependent variables. Generally, the results for calorie intake are better in terms of significance and fitness.

First of all, for the calorie intake, the sample households generally show significant "resilience" for the period April 2008 to April 2009 because the coefficient for *RECOV* is positive and significantly different from zero (random-effect model only). As for real value of food consumption, however, it is not significant. From Figure 4, it is apparent that contrasting results are plausible.

With regard to rainfall variables, the results are not so straightforward. First, household-specific rainfall has a significantly positive effect on consumption growth. If we consider that this variable is to capture the heavy rain effect, the sign is unexpected. But because we have interaction terms, rainfall without interaction should capture an ordinary relationship between rainfall and consumption via agricultural production: the better the rainfall, the better the harvest, resulting in more consumption. Second, village average rainfall has a significantly negative effect. Does it capture the heavy rainfall shock? No, it expresses a simple seasonal relationship between rainfall and consumption: during the rainy season, rainfall is high and consumption is low even without rainfall shock. Third, out of the three dummy variables for the months after the heavy rain (D_3, D_4, and D_5), two have a significantly positive sign, which is unexpected considering that consumption was declining during this period. However, the interaction terms between $RAIN_{it-1}$ and D_3 and D_5 have a significantly negative sign and cancel the positive effect of the month dummies. As a result, we can confirm that the postulated hypothesis, whereby a household with a higher rainfall suffers a severer shock and hence reduces consumption more, is supported by the data.

7. Factors Affecting Resilience

Now, our questions are who is more resilient and whether there are any households that do not recover from the shock. To identify factors affecting resilience, i.e., the speed of recovery, new interaction terms are added to the previous regression models. They are the product of *RECOV* (dummy for recovery period) and household asset variables ($LAND_{iy}$, $CATL_{iy}$, $SMLV_{iy}$, and $ASSET_{iy}$) because we expect that asset holding is the key for households to recover from a shock. Assets should include human capital and social capital, but this paper focuses only on physical assets. To see the effect of asset holdings clearly, the 16 sample households are divided into two groups based on the asset-holding level: one is rich, whose total value of cattle holdings as of October 2007 was above the median, and the other is poor, who are not in the rich group. Then, random-effect regressions are conducted for the full sample as well as each group separately.

Regarding sensitivity to rainfall shock, the regression results in Table 4 exhibit some interesting contrasts. First, the rich do not seem to be so sensitive to rainfall, while the poor are more sensitive because the coefficients for *RAIN* and *VRAIN* are significant only for the poor. In addition, the negative impact of heavy rain began appearing in January 2008 in the case of poor households, but in the case of rich households the impact was observed only after February 2008. Thus, there is one-month delay for the rich households to reduce consumption after the heavy rain.

This also implies that the poor are more sensitive to rainfall shock than the rich. As discussed in section 2, sensitivity is not the same as vulnerability, but because the poor are more sensitive to the rainfall shock than the rich, some of the poor households could easily fall below the threshold, i.e., they are vulnerable.

Table 4 Regression Results for Identifying Factors Affecting Resilience

Model	RE	RE	RE
Stratum	Full Sample	Rich	Poor
Dependent Variable	R^k_{it}	R^k_{it}	R^k_{it}
Explanatory Variables	(calorie)	(calorie)	(calorie)
RECOV (n=6 – 18)	0.62 (0.34)*	0.87 (0.53)*	0.33 (0.57)
$RAIN_{it-1}$ (10^{-2})	1.05 (0.20)**	1.03 (1.04)	1.30 (0.41)***
$RAIN_{it-2}$ (10^{-2})	-0.39 (0.19)	-0.32 (0.91)	-0.39 (0.65)
$VRAIN_{t-1}$ (10^{-2})	-0.87 (0.42)**	-0.73 (1.00)	-1.21 (0.32)***
$VRAIN_{t-2}$ (10^{-2})	0.22 (0.46)	0.06 (0.91)	0.32 (0.72)
D_3 (January 2008)	15.2 (6.01)**	8.03 (11.5)	16.0 (8.80)*
D_4 (February 2008)	-9.33 (9.98)	-17.9 (4.79)***	14.3 (10.4)
D_5 (March 2008)	38.3 (20.5)*	74.8 (20.1)***	8.33 (15.2)
$RAIN_{it-1} \times D_3 (10^{-2})$	-1.80 (0.68)***	-1.06 (1.44)	-1.87 (1.10)*
$RAIN_{it-2} \times D_3 (10^{-2})$	-0.31 (1.97)	-0.99 (9.17)	0.03 (1.94)
$RAIN_{it-1} \times D_4 (10^{-2})$	2.41 (1.91)	4.28 (2.90)	-2.52 (0.94)***
$RAIN_{it-2} \times D_4 (10^{-2})$	0.01 (1.01)	0.12 (1.47)	-0.36 (0.73)
$RAIN_{it-1} \times D_5 (10^{-2})$	-12.7 (9.50)	-27.0 (10.8)**	-3.67 (10.5)
$RAIN_{it-2} \times D_5 (10^{-2})$	-5.87 (3.17)*	-11.0 (2.44)***	-1.08 (3.42)
$LAND_{iy}$	-0.17 (0.19)	0.49 (0.15)***	0.13 (0.08)*
$CATL_{iy} (10^{-7})$	-1.50 (2.28)	-0.17 (4.51)	-6.34 (22.1)
$SMLV_{iy} (10^{-7})$	-0.38 (2.64)	4.76 (4.18)	-9.41 (26.9)
$ASSET_{iy} (10^{-6})$	-0.76 (0.50)	-0.70 (1.00)	-2.62 (25.8)
$AGE_{iy} (10^{-2})$	-0.22 (0.33)	-0.18 (0.41)	-0.08 (0.36)
$AE_{iy} (10^{-1})$	0.16 (0.43)	0.56 (0.69)	0.13 (0.26)
$RECOV \times LAND_{iy}$	0.29 (0.55)	0.30 (0.43)	0.67 (0.37)*
$RECOV \times CATL_{iy} (10^{-7})$	8.12 (4.99)*	-7.37 (7.50)	4.71 (33.2)
$RECOV \times SMLV_{iy} (10^{-7})$	6.75 (2.81)**	-3.96 (7.94)	-30.0 (85.4)
$RECOV \times ASSET_{iy} (10^{-6})$	-3.85 (2.88)	3.96 (2.77)	-5.93 (5.96)
D_n (n=19 – 26)	$+^{***}$, $+^{**}$ or +	$+^{***}$, $+^{**}$ or +	$+^{*}$ or +
Constant	-0.66 (0.36)*	-1.42 (0.68)**	-0.43 (0.69)
Number of observations	256	125	131
Number of households	15	8	7
R^2(overall)	0.18	0.34	0.21

Note: Robust standard errors are in parentheses. ***, **, and * indicate 1%, 5%, and 10% significance level respectively. The number of sample households in site A is 16 as described, but one household has been dropped.

8. Conclusions

In this paper, we first present a new, empirically workable definition of resilience in the context of consumption smoothing. Then, following the definition, we empirically estimate resilience using the data collected in a rural area of Zambia, where its rain-fed agriculture is highly affected by rainfall variation. In this particular dataset, a heavy rain took place in December 2007. Resilience is measured as the speed of consumption recovery after the heavy rain shock.

Our panel data analyses reveal that the heavy rain caused a shock, i.e., reduction of food consumption, among the sample households, and it took almost one year for them to recover from the shock. Resilience is defined as the speed of recovery, and our analyses show that household assets, such as land and livestock, have a positive effect on enhancing resilience. If we divide the sample into rich and poor groups based on the value of cattle holdings, households in the rich group are more resilient than those in the poor group on average because the coefficient of *RECOV* is significantly positive for the rich group but it is not significantly different from zero for the poor group on average. The insignificant sign for the poor implies that some of them who lack sufficient assets may not be able to recover consumption. Moreover, it is found that households in the poor group are more sensitive to the rainfall shock: they reduce consumption more quickly after the shock than those in the rich group. Following our definition, sensitivity is not the same as vulnerability, but because the poor are more sensitive to the rainfall shock than the rich, some of the poor could easily fall below the threshold, i.e., they are vulnerable.

We do not indicate how the sample households recover their consumption from the shock in this paper, although we have evidence that households increase labor supply not only in agriculture but also in non-agriculture after the shock, and households increase the sales of livestock, particularly small animals like goats and pigs, after the shock. Moreover, we find that households reduce consumption of non-food goods and services after the shock, although they maintain the level of food consumption. Incorporating those coping behaviors into analyses of factors affecting resilience is a very important research topic that we intend to tackle very soon.

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