Consumption Vulnerability to Risk in Rural Pakistan *

Takashi Kurosaki †

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†Institute of Economic Research, Hitotsubashi University, 2-1 Naka, Kunitachi, Tokyo 186-8603 Japan. Phone: 81-42-580-8363; Fax.: 81-42-580-8333. E-mail: kurosaki@ier.hit-u.ac.jp.

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Abstract

As one of the dimensions of vulnerability, this paper empirically investigates the inability of rural dwellers to cope with negative income shocks. A variable coefficient regression model is applied to a two-period household panel dataset collected in the North-West Frontier Province, Pakistan, an area with high incidence of income poverty and low human development. The empirical model allows for a different ability to smooth consumption, approximated by a linear function of households' attributes, and controls for the endogeneity of observed changes in income, using qualitative information on subjective risk assessment. Estimation results show that the ability to cope with negative income shocks is lower for households that are aged, landless and do not receive remittances regularly.

Keywords: consumption smoothing, vulnerability, poverty, risk, human capital.

JEL classification codes: I32, Q12.

1 Introduction

Interest in the dynamics of income and consumption at the household level in developing countries has increased recently, partly due to its importance in attacking poverty [*World Bank, 2000*] and partly due to the advance in theoretical modelling of household behaviour under risk and in econometric analysis based on such models [*Townsend, 1994; Udry, 1994*]. An emerging consensus is that poor households are likely to suffer not only from low income and consumption on average but also from fluctuations of their welfare. This consensus has led to a focus on 'vulnerability' in development. In the nontechnical literature, Chambers [*1989: 1*] described vulnerability as 'defenselessness, insecurity, and exposure to risk, shocks and stress,' while the World Bank [*2000: 139*] described it as 'the likelihood that a shock will result in a decline in well-being.' This paper therefore examines how negative shocks in income are transferred into a decline in consumption and how the ability to avoid such a decline is different among households.

The approach in this paper may be contrasted with related efforts in the literature on vulnerability.[1] Several authors have associated vulnerability with the exposure to observed risks: households are more vulnerable when their consumption is more variable [*Glewwe and Hall, 1998; Jalan and Ravallion, 1998, 2000*] or when their consumption shows excess sensitivity to income shocks [*Jalan and Ravallion, 1999; Dercon and Krishnan, 2000; Amin et al., 2003; Skoufias and Quisumbing, 2003; Harrower and Hoddinott, 2004*]. This paper extends the last line of research. Others have proposed measures of vulnerability as an ex ante measure of poverty, in contrast to poverty measures that are based on ex post realisation of income/consumption [*Christiaensen and Boisvert, 2000; Chaudhuri, 2000; Chaudhuri et al., 2002; McCulloch and Calandrino, 2003; Subbarao and Christiaensen, 2004; Kamanou and Morduch, 2004*]. As a more general and comprehensive measure, Ligon and Schechter [*2002, 2003*] have suggested a vulnerability measure in the utility space that quantifies the welfare loss associated with low income and various sources of income risks. Unlike these measures of vulnerability that attempt to capture the whole impact of low income and income risks, this paper attempts at a partial picture: given a negative income shock with a certain size, how much household consumption is likely to decline. In other words, this paper focuses on the inability to cope with risk. Such information can be useful in identifying particular sources of vulnerability to risk.

As an empirical attempt to quantify the inability to smooth consumption, two features

distinguish the approach in this paper from the existing literature [*Jalan and Ravallion, 1999; Dercon and Krishnan, 2000; Amin et al., 2003; Skoufias and Quisumbing, 2003*]. First, the effects of negative and positive income shocks are distinguished and the excess sensitivity parameter is allowed to vary systematically according to household characteristics.[2] This enables us to identify which households are more vulnerable to negative shocks. Second, in estimating the excess sensitivity parameter, qualitative information of the subjective assessment of risks is used as instrumental variables to control for the endogeneity of observed changes in income. As suggested by Barrett [*2004*], combining qualitative and quantitative information is an important research agenda in poverty analysis and this paper is an attempt in this direction.

The empirical part is applied to two-period household panel data collected from the North-West Frontier Province (NWFP), Pakistan. Pakistan is a part of South Asia, where more than 500 million people or about 40 per cent are estimated to live below the poverty line [*World Bank, 2000*]. Economic development in South Asia is characterised by a moderate success in economic growth with a substantial failure in human development such as basic health, education and gender equality [*Drèze and Sen, 1995*]. This characteristic is most apparent in NWFP. Furthermore, NWFP is a land scarce province with limited scope for a growth sustained by agriculture, which is more risky than in other parts of Pakistan. These additional hardships make the NWFP case study an interesting one to investigate poverty dynamics in general and consumption vulnerability in particular.

The paper is organised as follows. Section 2 specifies the empirical model of this paper. Section 3 explains the micro panel dataset used in this paper with a description of poverty transition and income/consumption dynamics. Section 4 presents estimation results. The final section summarises the paper.

2 Empirical Framework

The welfare level of an individual belonging to household i in period t is measured using real consumption, y_{it}. The most important determinant of y_{it} is household income, x_{it}. Due to exogenous shocks occurring to the income generating process, such as drought, flood, price changes in the world commodity markets, sickness/injury to the labour force and changes in policies, x_{it} fluctuates. However, y_{it} need not to be equal to x_{it}. Households can smooth consumption over time and across states of nature using various assets and

insurance arrangements ex post [*Townsend, 1994; Udry, 1994; Kurosaki and Fafchamps, 2002*]. When households' ex post risk coping measures are limited, possibly due to the underdevelopment of asset, credit and insurance markets in low income countries, they may adopt income smoothing measures, such as income diversification and asset portfolio choices [*Morduch, 1994; Kurosaki and Fafchamps, 2002*]. Since these attempts to avoid undesirable fluctuations in consumption are usually imperfect, fluctuations in y_{it} and x_{it} are commonly observed in a household panel dataset, including the one used in this study.

The variation of income and consumption in such a panel dataset can be analysed by an empirical model

$$\Delta y_{it} = \alpha_i + \beta_i \Delta \bar{x}_t + \zeta_i \Delta x_{it} + \Delta u_{it}, \tag{1}$$

where consumption changes at the individual level (Δy_{it}) are regressed on income changes at the aggregate level ($\Delta \bar{x}_t$) and income changes at the individual level (Δx_{it}). Underlying the empirical model lies a full risk sharing model analysed by Townsend [*1994*]: if the economy (say a village) achieves Pareto optimal risk sharing among villagers, Δy_{it} should respond only to the village level shocks $\Delta \bar{x}_t$ so that the size of ζ_i shows excess sensitivity of consumption to idiosyncratic income shocks. A more positive value of ζ_i indicates that individual i is less able to cope with such shocks. Several authors have thus investigated the size of ζ_i in developing countries [*Townsend, 1994; Jalan and Ravallion, 1999; Dercon and Krishnan, 2000; Amin et al., 2003; Skoufias and Quisumbing, 2003; Harrower and Hoddinott, 2004*].

As an estimation model in this paper, the model in (1) is revised in the following way. First, since parameters α_i, β_i and ζ_i cannot be estimated at the individual level when the time horizon of a panel dataset is short, it is assumed that α_i and β_i are the same across households and ζ_i can be approximated as a linear function of household attributes Z_i that are likely to affect the level of consumption smoothing at the household level. Second, since estimating (1) with both $\Delta \bar{x}_t$ and Δx_{it} as explanatory variables is subject to the endogeneity bias due to measurement errors and simultaneity in income and consumption [*Ravallion and Chaudhuri, 1997*], $\Delta \bar{x}_t$ are replaced by village dummies and Δx_{it} are replaced by their fitted values identified through instrument variables. Third, since it is more likely that a household's consumption adjustment differs depending on the sign of the shock, ζ_i in (1) is allowed to differ according to the sign of Δx_{it}.

Thus a model of consumption smoothing with variable coefficients is estimated as[3]

$$\Delta y_i = a_v + b_1 Z_i (1 - D_i) \Delta x_i + b_2 Z_i D_i \Delta x_i + u_i, \tag{2}$$

where $D_i = 1$ if $\Delta x_i < 0$, u_i is an i.i.d. error term with zero mean and a_v, b_1 and b_2 are parameters to be estimated. Parameters a_v control for village fixed effects. To facilitate intuitive interpretation, variables in vector Z_i include an intercept, dummy variables and continuous variables normalised by their village means and standard errors. Therefore, $b_{1,0}$ (the first element of vector b_1, associated with the intercept in vector Z_i) shows how much consumption increases when income increases marginally for a household with continuous Z_i variables at the village mean and dummy Z_i variables set at zero, and $b_{2,0}$ (the first element of vector b_2) shows how much consumption decreases when income decreases marginally for a similar household. Parameters $b_{2,k}$ when $k > 0$ show how different the marginal decline of consumption given a decrease of income is, depending on the household attributes.[4] The focus of this paper is on vector b_2 because it shows what kind of households were insulated from a consumption decline and what kind of households were not. This focus distinguishes the current paper from the existing studies on consumption smoothing.[5]

As instrument variables for the explanatory variables in (2), variables Z_i and dummy variables for 'reasons/factors for unanticipated positive/negative shock' are adopted. These dummies for the subjective assessment of risks are expected to capture the direction of income changes well, while households' initial attributes are expected to predict the magnitude of the changes well.

From estimation results of model (2), $\hat{\zeta}_i \equiv \hat{b}_2 Z_i$ can be calculated for each household. This parameter gives a partial information with respect to households' exposure to risk. As shown in equation (1), the size of ζ_i indicates the level vulnerability only if the sensitivity of consumption to aggregate income shocks, the size of aggregate income shocks and the size of idiosyncratic income shocks are held constant. Because of this partial nature, the approach in this paper can provide useful information to identify particular sources of vulnerability to risk. In contrast, when a comprehensive measure of vulnerability is regressed on household attributes,[6] the four sources of households' exposure to risk are not identified easily. To infer the size of exposure to risk in different ways, not only $\hat{\zeta}_i$ but also $\hat{\zeta}_i$ multiplied by the potential size of idiosyncratic income shocks are discussed in the empirical section.

3 Data

3.1 Study Region and Sample Households

This study employs a panel dataset compiled from household surveys implemented in 1996 and 1999 in three villages in the Peshawar District, NWFP, Pakistan.[7] NWFP is one of the four provinces of Pakistan. Compared with Punjab, which is the centre of agriculture and related industries, and Sind, where the metropolitan city of Karachi is located, NWFP and Baluchistan could be characterised as economically backward provinces. According to an estimate by the World Bank [*2002*], the headcount poverty index in NWFP was close to 50 per cent in the late 1990s, well above the national average.

Since NWFP is a relatively land scarce province with limited scope for a growth sustained by agriculture, human capital is expected to play an important role in poverty eradication. Yet, even in terms of human development, NWFP is behind the other two provinces. Literacy rates in NWFP, especially of females, are much lower than in Sind and Punjab, and NWFP is lagging behind Punjab and Sind in infant mortality rates also [*World Bank, 2002*]. The disparity that human development poverty is more serious than income poverty is a notorious characteristic of South Asian economies [*Drèze and Sen, 1995*]. This paper focuses on rural NWFP because it is a region where this disparity is stark.

In choosing sample villages in 1996, we controlled for village size, historical background and tenancy structure. At the same time, to ensure that the cross section data thus generated would provide dynamic implications, we carefully chose villages with different levels of economic development. The first criterion was agricultural technology: one of the three villages studied was rainfed, another semi-irrigated and the other fully-irrigated. Another criterion was that the selected villages be located along the rural/urban continuum so that it would be possible to decipher the subsistence versus market orientation of farming communities in the study area.

Table 1 summarises characteristics of sample villages and households. Village A is rainfed and is located some distance from main roads. This village serves as an example of the least developed villages. Village C is irrigated fully and is located close to a national highway, so serves as an example of the most developed villages. Village B is in between.

Out of 355 households surveyed in 1996, we were able to resurvey 304 households in 1999. Among those resurveyed, three had been divided into multiple households[8] and two had incomplete information on consumption. Therefore, a balanced panel of 299 households with

two periods is employed in this paper.[9]

Average household sizes are larger in Village A than in Villages B and C, reflecting the stronger prevalence of an extended family system in the village (Table 1). Average landholding sizes are also larger in Village A than in Villages B and C. Since the productivity of purely rainfed land is substantially lower than that of irrigated land, effective landholding sizes are comparable among the three villages. Household income and consumption were calculated including the imputed values of nonmarketed transactions, The household income includes the sum of the income from self-employed activities; wage, salary and allowance income of employed household members; net transfer receipt (public and private); net remittances receipt; and other unearned income. Average income and consumption per capita are lowest in Village A and highest in Village C, in line with our survey objective of selecting villages with different levels of economic development.

In any household survey where self-employment in agriculture is important, estimating household income and consumption is subject to measurement errors, although we did our best to minimise them [*Grosh and Glewwe, 2000*]. In our survey, a series of questions on households' adjustment to risk were also asked to the household head in the 1999 survey, such as (i) any good/bad economic year(s) in the past three years due to unanticipated shocks, (ii) associated reasons/factors thereof and (iii) possible adjustments they had to or could make to cope with the risk, such as consumption adjustments, food storage, accumulation/decumulation of productive assets (land and livestock), gold and jewellery management, mutual help and adjustment of children's schooling.

From these qualitative questions, several points were found [*Kurosaki and Khan, 2001*]. First, reasons and factors of economic shocks are heterogeneous with farming and wage labour risks ranked at the top. In each year in the same village, some farmers suffered from a crop failure while others enjoyed a regular harvest, indicating the importance of idiosyncratic farming risk in the study region. Second, the number of adjustment mechanisms cited by households was larger in Village C. In other words, economic development seems to be associated with the diversity of households' risk coping measures. Third, adjustments of children's education was rarely cited. This could be a simple reflection that there was little room to adjust education since the school enrolment ratio was very low. Villagers reported that informal credit was the most important mechanism to cope with negative income shocks.

This part of the questionnaire provides us with qualitative information on households' subjective assessment of risks, which can be used as an independent check for x_{it} and y_{it}.

For this reason, these dummy variables are used as instruments in the next section.

3.2 Poverty Transition and Income/Consumption Dynamics

Real consumption (y_{it}) was calculated by dividing the household consumption by the household size in adult equivalence units and by the consumer price index in rural areas.[10] Since food occupies the largest portion of consumption for the sample households (the average is about 60%) and the poor are more concerned with its variability than with the variability of nonfood consumption, the sensitivity of food consumption with respect to income shocks is also investigated. Real income (x_{it}) is defined similarly. During the three years since the first survey, Pakistan's economy suffered from macroeconomic stagnation, which affected NWFP's economy most severely among the four provinces. Reflecting the macro shock, the general living standard stagnated in the villages during the study period.

In addition to the macro shock, y_{it} fluctuated in an idiosyncratic way as well. Table 2 shows a transition matrix of consumption poverty with five categories of poverty status in each year. The poverty line (z) is set at Rs. 6,072 (approximately US$ 160 in 1996), which is obtained from the official poverty line.[11] Each cell in the table shows the number of households belonging to each category. Diagonal cells correspond to those households whose poverty status did not change, where 103 households are included. The number of households in cells below the diagonal is 104 and that in cells above the diagonal is 92. Therefore, the household mobility is indeed high.[12]

Out of 299 panel households, 77 (25.8%) are in the four cells in the southeast corner where $y_{it} \geq z, t = 1, 2$. They are called 'always nonpoor' households below. In contrast, the four cells in the northwest corner where $y_{it} < 0.75z, t = 1, 2$, contain 41 households (13.7%). They are called 'always very poor' households. Another group of interest is those households in six southwest cells where $y_{i1} \geq 0.75z$ and $y_{i2} < 0.75z$, where 41 households (13.7%) are included. This is a group that experienced a rapid decline in welfare and is called 'impoverished' below.

Table 3 examines the difference in consumption and income changes among these groups in more detail. Overall, consumption changed only slightly. Food consumption remained more or less constant whereas nonfood consumption declined. The overall pattern applies to 'always very poor' and 'always nonpoor' households as well. In contrast, total consumption of 'impoverished' households declined by 45 per cent or about Rs. 3,000, of which two thirds were attributable to reduction in food consumption. The welfare decline of this group was

thus substantial.

Did they need to reduce consumption substantially because they were hit by an abnormally large income shock? The last column of Table 3 shows that their income declined by almost Rs. 2,300 or by 33 per cent. This decline was similar to that experienced by other groups. It is not the case that 'impoverished' households experienced income shocks significantly larger than those experienced by others. Therefore, what distinguishes the 'impoverished' from others is not the size of an income decline but the availability of ex post consumption smoothing measures given an income decline.

As an indicator of the availability of consumption smoothing measures, Table 4 reports the change in debt and assets. The first column shows that outstanding debt increased by 5 per cent for the whole sample whereas it declined by 44 per cent for the 'impoverished. Since the majority of the outstanding debt is from informal sources, this seems to suggest that the 'impoverished' were those faced with difficulty in obtaining additional consumption credit after paying back old debt in the informal credit market. Because of this, the 'impoverished' group had to sell a larger amount of assets such as livestock and land than other households but still could not compensate for the income loss, resulting in the substantial decline in consumption.

4 Estimation Results

4.1 Determinants of Income Changes

To identify the ability to smooth consumption controlling for the endogeneity of observed changes in income, explanatory variables in equation (2) are replaced by fitted values using instrumental variables. The instruments include Z_i (household attributes that are likely to determine income changes as well as to affect the level of consumption smoothing at the household level) and the dummy variables for the subjective assessment of risks. For these variables to be valid instruments, they need to explain income changes well.

Therefore, the first stage regression results are presented for the determinants of income changes (Table 5).[13] The results themselves are also interesting because we can infer what shocks are causing income changes and to what extent. A weighted least squares method was used with the number of household members as a weight because the focus is on the individual welfare. The first two columns show determinants of income *increases* ($(1 - D_i)\Delta x_i$), which is associated with coefficient $b_{1,0}$ in equation (2), and the last two

columns show determinants of income *decreases* ($D_i\Delta x_i$), which is associated with coefficient $b_{2,0}$. Coefficients on village dummies show the average income changes for those households with their continuous variables in Z_i at village means and all dummy variables at zero (these households are called 'reference households' below). The coefficients are positive for $(1 - D_i)\Delta x_i$ and negative for $D_i\Delta x_i$ as expected.

In regression, demographic variables (household size, dependency ratio and age of household head), income sources (dummy for having household members engaged in nonfarm fulltime work and dummy for having family members who regularly remit to the household), land ownership (ownership dummy and the land asset value) and the educational status of household head were included in Z_i.[14] These variables are taken from the first survey. Although they are endogenous to household decisions in the long run, they are treated as exogenous in this paper since they are predetermined for the status in 1999 and good instrumental variables for them are not available in the dataset. Among Z_i, household size and dependency ratio reduce the size of income declines, while the age of household head and land asset values amplify the size of income declines. The effects of land is as expected because the effects of farming shocks should be larger for those households managing a larger farm.

Among the dummy variables for the subjective assessment of risks, those with statistical significance have correct signs: reports of unanticipated positive (negative) shocks amplify (reduce) the size of income increases and reduce (amplify) the size of income decreases. A report of an unanticipated decline in remittances or in nonfarm business outturn have an especially large coefficient. Such shocks are likely to reduce income substantially. Overall, the qualitative variables explain income changes well in this case.

4.2 Who Are Less Insured?

The second stage regression results for equation (2) are given in Table 6. When its constrained version that does not distinguish positive and negative shocks and ignores household heterogeneity was used, the excess sensitivity parameter, $\hat{\zeta}$, was estimated at 0.063 for total consumption and 0.055 for food consumption, both of which were not statistically significant at 5 per cent level. This implies that households on average were able to smooth consumption against idiosyncratic income shocks. However, descriptive analyses in the previous section have suggested that households are heterogeneous in their ability to cope with income risk. Allowing for heterogeneous impacts according to household attributes and dif-

ferentiated impacts depending on the sign of income changes, the results in Table 6 were obtained.[15]

The parameter of concern is b_2 (the shifter of ζ_i when $\Delta x_i < 0$). The sensitivity for the reference household (the parameter estimate for $b_{2,0}$) was 0.206 for total consumption and 0.207 for food consumption. These values decrease with household size and dependency ratio. This seems to indicate that households with more dependent members and larger size are able to reduce the ill effects of income decline, possibly through reciprocity arrangements in the region. Estimates for $b_{2,k}$ on the household head's age are significantly positive. The field survey in the villages also supports that aged households are indeed vulnerable to welfare declines if their family network is not strong.

Variables for income sources and land assets have a negative sign when $\Delta x_i < 0$. Therefore, households endowed with stable nonfarm employment, remittance sources and land assets are relatively more insulated from the perverse impacts of income declines. However, the coefficient on nonfarm employment was not significant, probably because of additional risk associated with these jobs. The coefficient on land ownership dummy was highly significant in both models, whereas that on land asset value was significant only on food consumption changes. This shows that a threshold effect of having any land is more important in smoothing consumption than a marginal effect of having additional land. The negative coefficient on regular remittance receipt suggests that remittances are important in coping with risk ex post [*Alderman, 1996; Lucas and Stark, 1985*].

The positive and significant b_2 on education is against the expectation that more educated households are more able to smooth consumption. The field survey suggests that the opposite sign could be due to a fact that households with educated heads are on average richer than others so that they have room to reduce consumption expenditure when hit by a negative shock without reducing the core components of consumption. To test this conjecture, equation (2) was reestimated with an additional variable in vector Z_i: the initial consumption level. Since this variable is clearly endogenous, the land asset value was deleted from Z_i but retained in the list of instrumental variables to improve identification, because the land asset value is one of the most important variables in determining the permanent consumption level but not robustly significant in various specifications of models corresponding to those in Table 6.

Estimation results are reported in Table 7. The coefficient on the initial consumption in b_2 is significantly positive, implying that the marginal sensitivity of consumption to an

income decline becomes larger for richer households. The coefficient is much larger for total consumption than for food consumption. These results confirm the conjecture that richer households have more room to reduce consumption (especially nonfood consumption) when hit by a negative income shock. The coefficient on education of household heads in b_2 is now significantly negative. Other variables in b_2 have slightly different coefficients in Table 7 but none of them has a statistically significant coefficient with its sign opposite to that in Table 6 with statistical significance. These results suggest that the direct role of education is to increase the ability to smooth consumption (lower ζ_i) while its indirect effect through raising the permanent consumption level is to weaken the need for households to smooth consumption (higher ζ_i). The net effect is to raise ζ_i in this case.

4.3 Exposure to Risk

To examine whether or not the results in Tables 6 and 7 are robust to alternative specifications,[16] the existence of attrition bias was tested first. A probit model for sample selection was estimated in which the probability of successful resurvey was regressed on households' initial attributes (Appendix 2). The addition of an inverse Mills ratio to equation (2) did not change the magnitudes and significance of coefficients and the inverse Mills ratio was not statistically significant at 10 per cent. Therefore, the attrition bias may not be serious in this case. Second, in calculating the household size, different equivalence scales were attempted.[17] Third, two other estimation methods were attempted: equation (2) was reestimated using the same instrumental variables method but without weighting by the number of household members; equation (2) was reestimated using a two-stage weighted least squares method with different identifying assumptions.[18]

Empirical results from other specifications are qualitatively the same with those reported in this paper. Especially robust was the effect of land ownership. The land ownership dummy had a negative coefficient in b_2 with statistical significance (mostly at 1%, in a few cases at 5%). Therefore, it can be concluded that landed households are more able to smooth consumption given the same amount of negative shocks.

As discussed in Section 2, this does not necessarily mean that landed households are less exposed to risk. Other parameters also matter, which characterise the sensitivity of consumption to aggregate income shocks, the size of the aggregate shocks and the size of idiosyncratic income shocks. To infer the size of exposure to risk in different ways, not only the fitted values of the excess sensitivity parameter ($\hat{\zeta}_i$) but also $\hat{\zeta}_i$ multiplied by the

potential size of idiosyncratic income shocks are reported in Table 8. The mean of $\hat{\zeta}_i$ is 0.107 for all households, implying that households reduce consumption by Rs. 107 given an income decline of Rs. 1,000 due to idiosyncratic shocks. The reduction of consumption given similar shocks is much smaller for landed households (Rs. 31) and much larger for landless households (Rs. 189) on average.

On the other hand, landed households tend to be subject to larger variability of their income. One of the reasons is that they depend more on farming, which is risky in the study area. In Table 8, as an indicator of the variability of household income, the variance of observed income changes around village means is shown. The mean of $(\Delta x_i/\Delta \bar{x}_v - 1)^2$ for landed households is about twice that for landless households. As an indicator of the standard deviation of income changes, squared roots of these means were calculated and multiplied by $\hat{\zeta}_i$. The result shows that the exposure to idiosyncratic risk for landed households is about 32 per cent of that for all households, while that for landless households is about 147 per cent of that for all households. Therefore, landed households are much more insured against idiosyncratic shocks than landless households.

5 Conclusion

As one of the dimensions of vulnerability, this paper empirically investigated the inability of rural dwellers to cope with negative income shocks. A variable coefficient regression model, with consumption change as a dependent variable and negative/positive income shocks distinguished, was applied to a two-period household panel dataset collected in NWFP, Pakistan, an area with high incidence of income poverty and low human development. The empirical model allowed for a different ability to smooth consumption, approximated by a linear function of households' initial attributes, and controlled for the endogeneity of observed changes in income, using qualitative information on subjective risk assessment. Estimation results showed that the ability to cope with negative income shocks is lower for households that are aged, landless and do not receive remittances regularly. In the sense that once hit by an income decline with a certain size these households had to reduce their consumption more, they were more defenceless and insecure.

The approach in this paper captures the potential degree of suffering from adverse shocks in terms of how much consumption is likely to fall when income is reduced by a fixed amount due to exogenous shocks. Because of this partial nature, the approach can provide useful

information to identify particular sources of vulnerability to risk. The size of the exogenous shocks should also matter in determining households' net vulnerability to risk. The results in this paper showed that even though landed households are subject to a larger income risk, the size of their marginal response to an income decline is so small that the net exposure to idiosyncratic risk is much smaller for them than the risk exposure for landless households. In contrast, when a comprehensive measure of vulnerability based on the consumption path is regressed on household attributes, different sources of households' exposure to risk are not identified easily.[19]

Finally, it should be noted that this paper treats both the sensitivity parameter and the size of income shocks as exogeneously fixed characteristics of a household. Under the context of households' dynamic adjustment of their assets including reciprocity networks, the two become endogenous to households' decision making in the long run. Giving micro foundations to the approach of this paper based on dynamic household models is left for a further study.[20] Another caveat is that the potential knock-on effects of cumulative shocks are not discussed in this paper due to the data limitation. This is also left for a future study using different datasets.

Notes

1 See Ligon and Schechter [*2002*] and Kamanou and Morduch [*2004*] for an overview of different means of quantifying vulnerability.

2 See Harrower and Hoddinott [*2004*] for another attempt to distinguish the effects of negative and positive income shocks and to incorporate heterogeneity in the ability to smooth consumption.

3 Since the dataset used in this paper is a two-period panel dataset and all empirical variables are in differences or initial levels, time subscripts are dropped below.

4 Equation (2) nests a model of village level consumption smoothing such as the one estimated by Townsend [*1994*]. The nested model corresponds to the case that $b_{1,k} = b_{2,k} = 0$ for all $k > 0$ and $b_{1,0} = b_{2,0}$.

5 The empirical model used by Harrower and Hoddinott [*2004*] is the closest to the one used in this paper, both allowing for different effects of income shocks depending on two factors: the sign of Δx_i and household characteristics. However, Harrower and Hoddinott [*2004*] examined the different impacts due to the two factors separately, while the model in this paper incorporates them simultaneously. Further, they employed only dummy variables in vector Z_i. In other studies, variable coefficient models differentiating positive and negative *anticipated* shocks are adopted to test for credit constraints on consumption smoothing (for example, see Garcia et al. [*1997*] and Jacoby and Skoufias [*1997*]). The model of this paper attempts to differentiate positive and negative *unanticipated* shocks because this asymmetry is an important aspect of vulnerability. Kochar [*1995, 1999*] also distinguished the impacts of negative and positive unanticipated income shocks explicitly. As a study using sources of income fluctuations rather than just income, Dercon and Krishnan [*2003*] incorporated both negative shocks (such as illness) and positive shocks (such as village aid receipt).

6 For instance, see Jalan and Ravallion [*1998, 2000*] and McCulloch and Baulch [*2000*], who regressed the household level measure of transient poverty, *a la* Ravallion [*1988*], on household attributes.

7 See Kurosaki and Hussain [*1999*] and Kurosaki and Khan [*2001*] for details of these surveys. The reference period for each survey is fiscal years 1995/96 and 1998/99 respectively (Pakistan's fiscal year is the period from July 1 to June 30).

8 In the survey, a household is defined as a unit of coresidence and shared consumption. A typical joint family in the region, where married sons live together with the household head who owns their family land along with their wives and children, is treated as one household, as long as they share a kitchen. When the household head dies or becomes aged, the land may be distributed among sons, who start to live separately on that occasion. In our survey when we encountered such cases, each family of each son was counted as one household.

9 The most frequent reason for attrition was migration. Some households had migrated out from the village and others had sent all their adult males to work in foreign countries or in Pakistani cities. As shown in Appendix 2, attrition occurred more for households living in Village A and whose heads were more educated. Education and risky environments are thus associated with higher propensity to migrate.

10 The adult equivalence scale currently adopted by the Government of Pakistan was used in calculating the size of a household, where individuals aged more than 17 years old are given the weight of 1.0 and all other individuals are given the weight of 0.8. Pakistan Rupees (Rs.) in the

empirical section of this paper are all in 1996 values.

11 The Government of Pakistan decided the official poverty line in August 2002 based on the Pakistan Integrated Household Survey, 1998/99. The poverty line corresponds to 2,350 kcal per adult per day of food intake.

12 Nevertheless, the hypothesis of an independent Markov process was rejected at 1 per cent level (χ^2 test of independence in two-way contingency tables yielded a test statistic of 51.2, whereas the 1 per cent critical value for a χ^2 variable with 16 degrees of freedom is 32.0). Therefore, there exists a tendency to remain in the same status although the transition to other statuses is frequent.

13 The first stage regression results for other explanatory variables in equation (2) are available from the author on request.

14 See Appendix 1 for the definition of these variables.

15 F-test applied to estimation results in Table 6 rejected the constrained version at 1 per cent level. The Hausman test rejected the exogeneity of explanatory variables in Table 6 and the instrumental variables listed in Table 5 passed the overidentification test (both at 5% level).

16 Results based on different specifications are available from the author on request.

17 Instead of the adult equivalence scale currently adopted by the Government of Pakistan (see note 10), the unweighted number of household members and the Government's old formula (1.0 for those aged more than 16, 0.85 for those aged between 11 and 16, 0.75 for those aged between 6 and 10 and 0.45 for individuals aged less than 6) were tried.

18 Instead of regressing all of the explanatory variables in equation (2) on instrumental variables used in Table 5 in the first stage, D_i and Δx_i in equation (2) were replaced by the fitted values of D_i and Δx_i (obtained from regressing these two variables on instrumental variables used in Table 5) in the second stage.

19 They can be identified through a comprehensive measure of vulnerability if the underlying household model of income/consumption dynamics are specified thoroughly. See Ligon and Schechter [*2002, 2003*].

20 Models by Elbers and Gunning [*2003*] and Zimmerman and Carter [*2003*] provide basic modelling ideas that are applicable to the context of this paper.

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Table 1. Sample Villages and Households (NWFP, Pakistan)

	Village A	Village B	Village C
1. Village characteristics			
Agriculture	Rainfed	Rain/irrig.	Irrigated
Distance to main roads (km)	10	4	1
Population (1998 Census)	2,858	3,831	7,575
Adult literacy rates (1998 Census)	25.8	19.9	37.5
2. Characteristics of households in the panel			
Number of households	83	111	105
Average number of household members			
in 1996	10.75	8.41	8.95
in 1999	11.13	7.86	9.30
Average farmland owned			
in 1996 (ha)	2.231	0.516	0.578
in 1999 (ha)	2.258	0.517	0.595
Average per capita income			
in 1996 (nominal US$)	194.4	231.2	336.6
in 1999 (nominal US$)	147.8	164.7	211.6
Average per capita consumption			
in 1996 (nominal US$)	134.4	157.0	200.8
in 1999 (nominal US$)	133.5	143.1	198.3

Notes: (1) 'Average per capita income (consumption)' are averages based on individuals. They were calculated as household averages with the number of household members as weights.
(2) 'Average farmland owned' is an average over all sample households.

Table 2. Transition Matrix of Consumption Poverty

	Status in 1999					
Status in 1996	$y_{it} < 0.5z$	$0.5z \leq y_{it} < 0.75z$	$0.75z \leq y_{it} < z$	$z \leq y_{it} < 1.25z$	$1.25z \leq y_{it}$	Total
Number of households						
$y_{it} < 0.5z$	2	6	4	5	0	17
$0.5z \leq y_{it} < 0.75z$	8	25	17	9	8	67
$0.75z \leq y_{it} < z$	2	14	31	11	21	79
$z \leq y_{it} < 1.25z$	4	11	15	14	11	55
$1.25z \leq y_{it}$	0	10	19	21	31	81
Total	16	66	86	60	71	299
Transition probability (%)						
$y_{it} < 0.5z$	11.8	35.3	23.5	29.4	0.0	100.0
$0.5z \leq y_{it} < 0.75z$	11.9	37.3	25.4	13.4	11.9	100.0
$0.75z \leq y_{it} < z$	2.5	17.7	39.2	13.9	26.6	100.0
$z \leq y_{it} < 1.25z$	7.3	20.0	27.3	25.5	20.0	100.0
$1.25z \leq y_{it}$	0.0	12.3	23.5	25.9	38.3	100.0

Table 3. Changes in Consumption and Income

	Consumption change (Δy_i)			Income
	Total	Food	Nonfood	change (Δx_i)
In 1996 Rs.				
All sample households	25	300	-275	-2,127
'Always very poor' households	67	201	-134	-2,169
'Impoverished' households	-3,117	-1,950	-1,167	-2,287
'Always nonpoor' households	149	351	-203	-3,199
In % change				
All sample households	0.4	6.3	-16.2	-23.0
'Always very poor' households	1.9	7.6	-15.4	-33.6
'Impoverished' households	-45.0	-38.7	-61.8	-32.6
'Always nonpoor' households	1.6	5.0	-8.2	-24.1

Notes: Since there are 140 households other than 'Always very poor' (41 households), 'Impoverished' (41 households) and 'Always nonpoor' (77 households), the weighted average of the three categories is not equal to the figures reported for 'All sample households.'

Table 4. Changes in Debt and Assets

	Outstanding debt	Livestock value	Land value
In 1996 Rs.			
All sample households	707	-5,269	-6,654
'Always very poor' households	4,187	-1,390	1,393
'Impoverished' households	-3,413	-8,220	-97,802
'Always nonpoor' households	6,880	-12,562	-21,243
In % change			
All sample households	4.6	-37.2	-1.9
'Always very poor' households	37.1	-12.3	0.4
'Impoverished' households	-44.1	-52.8	-34.3
'Always nonpoor' households	31.3	-50.9	-3.0

Note: The change in 'Land value' does not include land transactions due to inheritance among family members.

Table 5. Determinants of Income Changes

	Income increase $(1-D_i)\Delta x_i$			Income decrease $D_i\Delta x_i$		
Village dummies						
Village A	1062	(610)	*	-4274	(966)	***
Village B	1843	(841)	**	-4092	(850)	***
Village C	1096	(702)		-6178	(1029)	***
Z_i: Households' initial attributes						
Household size	-100	(206)		892	(517)	*
Dependency ratio	-23	(180)		1081	(494)	**
Age of household head	-11	(223)		-757	(368)	**
Dummy for nonfarm fulltime employees	-395	(473)		-62	(699)	
Dummy for regular remittance receipt	-1970	(1511)		-3382	(2368)	
Land ownership dummy	525	(500)		767	(758)	
Land asset value	-116	(117)		-2891	(606)	***
Education of household head	-190	(207)		-109	(376)	
Reasons/factors for unanticipated positive shock						
Good crop harvest	939	(501)	*	-306	(1000)	
Good prices for farm product	625	(725)		859	(1184)	
High wages from outside employment	99	(729)		1840	(1046)	*
Gain jobs in outside employment	-626	(759)		1951	(973)	**
Remittances increased	3435	(2867)		166	(1619)	
Good business in non-farm self-employment	2051	(1213)	*	865	(1841)	
Others	-81	(494)		1939	(773)	**
Reasons/factors for unanticipated negative shock						
Bad crop harvest	-1121	(517)	**	-1679	(834)	**
Bad prices for farm product	499	(750)		219	(1060)	
Low wages from outside employment	-1010	(389)	***	30	(1031)	
Lost jobs in outside employment	524	(610)		78	(906)	
Remittances declined	-390	(1632)		-3641	(2117)	*
Bad business in non-farm self-employment	-2637	(910)	***	-4602	(2120)	**
Others	-290	(381)		392	(826)	
R^2 based on transformed data	0.273			0.507		
F statistics for zero slope	4.06	***		8.15	***	

Notes: (1) Estimated by a weighted least squares method with the number of household members as a weight.

(2) The number of observations is 299.

(3) Continuous variables in 'Households' initial attributes' are normalised by their village means and standard errors.

(4) Huber-White heteroscedasticity consistent standard errors are reported in the parenthesis, with *** significant at 1%, ** at 5% and * at 1%.

Table 6. Consumption Changes and Households' Initial Attributes (1)

	Total consumption			Food consumption		
a_v: Village dummies						
Village A	183.5	(204.6)		613.2	(143.4)	***
Village B	309.2	(106.6)	***	509.8	(77.9)	***
Village C	957.8	(158.6)	***	893.8	(142.2)	***
b_1: Coefficients on Δx_i when $\Delta x_i > 0$						
Intercept	0.205	(0.112)	*	0.188	(0.094)	**
Household size	-0.052	(0.075)		-0.022	(0.050)	
Dependency ratio	-0.104	(0.044)	**	-0.076	(0.030)	**
Age of household head	-0.045	(0.076)		-0.042	(0.066)	
Dummy for nonfarm fulltime employees	-0.115	(0.090)		-0.107	(0.078)	
Dummy for regular remittance receipt	-0.192	(0.088)	**	-0.083	(0.073)	
Land ownership dummy	0.048	(0.104)		0.013	(0.081)	
Land asset value	0.197	(0.203)		0.138	(0.172)	
Education of household head	-0.032	(0.064)		-0.013	(0.047)	
b_2: Coefficients on Δx_i when $\Delta x_i < 0$						
Intercept	0.206	(0.051)	***	0.207	(0.044)	***
Household size	-0.060	(0.016)	***	-0.022	(0.012)	*
Dependency ratio	-0.033	(0.015)	**	-0.033	(0.013)	**
Age of household head	0.080	(0.025)	***	0.058	(0.019)	***
Dummy for nonfarm fulltime employees	-0.013	(0.044)		-0.043	(0.037)	
Dummy for regular remittance receipt	-0.116	(0.052)	**	-0.066	(0.035)	*
Land ownership dummy	-0.191	(0.044)	***	-0.168	(0.034)	***
Land asset value	-0.003	(0.003)		-0.008	(0.002)	***
Education of household head	0.069	(0.021)	***	0.053	(0.016)	***
R^2 based on transformed data	0.464			0.468		
F statistics for zero slope	10.54	***		7.09	***	

Notes: (1) Estimated by a two-stage weighted least squares method with the number of household members as a weight. Instrumental variables are the explanatory variables listed in Table 5.
(2), (3), (4) See Table 5.

Table 7. Consumption Changes and Households' Initial Attributes (2)

	Total consumption			Food consumption		
a_v: Village dummies						
Village A	153.5	(203.2)		592.0	(142.5)	***
Village B	280.7	(103.7)	***	498.8	(76.4)	***
Village C	954.1	(156.3)	***	846.9	(142.2)	***
b_1: Coefficients on Δx_i when $\Delta x_i > 0$						
Intercept	0.228	(0.097)	**	0.213	(0.075)	***
Household size	0.337	(0.141)	**	0.333	(0.133)	**
Dependency ratio	-0.085	(0.082)		-0.116	(0.075)	
Age of household head	-0.142	(0.108)		-0.154	(0.101)	
Dummy for nonfarm fulltime employees	-0.030	(0.160)		-0.031	(0.148)	
Dummy for regular remittance receipt	0.345	(0.468)		0.202	(0.294)	
Land ownership dummy	0.081	(0.139)		0.096	(0.129)	
Education of household head	-0.028	(0.068)		-0.024	(0.068)	
Initial consumption	-0.154	(0.098)		-0.058	(0.068)	
b_2: Coefficients on Δx_i when $\Delta x_i < 0$						
Intercept	-0.005	(0.055)		0.010	(0.045)	
Household size	-0.077	(0.026)	***	-0.020	(0.029)	
Dependency ratio	0.046	(0.024)	*	0.011	(0.019)	
Age of household head	0.003	(0.032)		-0.004	(0.026)	
Dummy for nonfarm fulltime employees	0.153	(0.056)	***	0.072	(0.047)	
Dummy for regular remittance receipt	-0.166	(0.073)	**	-0.113	(0.065)	*
Land ownership dummy	-0.139	(0.057)	**	-0.111	(0.046)	**
Education of household head	-0.047	(0.023)	**	-0.029	(0.018)	*
Initial consumption	0.120	(0.023)	***	0.074	(0.016)	***
R^2 based on transformed data	0.333			0.262		
F statistics for zero slope	6.82	***		4.40	***	

Notes: See Table 6.

Table 8. Inability to Smooth Consumption and Land Ownership

	All households	Landed households	Landless households
Number of households	299	154	145
Size of the excess sensitivity parameter ($\hat{\zeta}_i$)			
Mean [1]	0.107	0.031	0.189
Std. dev.	0.128	0.111	0.090
Size of idiosyncratic income shocks ($(\Delta x_i/\Delta \bar{x}_v - 1)^2$)			
Mean [2]	11.0	14.1	7.7
Std. dev.	28.8	32.4	24.1
Exposure to risk, relative to all households			
Mean [1]	1.000	0.286	1.758
Mean [1] times the squared root of mean [2]	1.000	0.324	1.469

Notes: (1) To calculate $\hat{\zeta}_i$, regression results for total consumption in Table 6 are used.
(2) 'Landless households' are those who do not own any land. Pure tenant farm households are thus included in this category.

Appendix 1. Definition and Statistics of Variables Used in Regression

Name, definition and unit	Mean	Std.Dev.
Income and consumption changes from 1996 to 1999		
Change in total consumption per adult equivalence unit (Rs.)	25.0	3462.0
Change in food consumption per adult equivalence unit (Rs.)	300.2	2744.4
Change in household income per adult equivalence unit (Rs.)	-2127.2	8096.4
Households' initial attributes (those in 1996)		
Household size (in adult equivalence units)	8.299	4.692
Dependency ratio (the number of dependents divided by the number of household members)	0.453	0.205
Age of household head (years)	49.7	16.6
Dummy for nonfarm fulltime employees	0.482	
Dummy for regular remittance receipt	0.054	
Land ownership dummy	0.515	
Land asset value (1,000,000 Rs.)	0.511	2.305
Livestock value (1,000,000 Rs.)	0.014	0.031
Net monetary asset (1,000,000 Rs.)	-0.009	0.062
Other asset value (1,000,000 Rs.)	0.019	0.077
Education of household head (years)	2.211	3.844
Reasons/factors for unanticipated positive shock		
Good crop harvest	0.278	
Good prices for farm product	0.174	
High wages from outside employment	0.070	
Gain jobs in outside employment	0.070	
Remittances increased	0.050	
Good business in nonfarm self-employment	0.067	
Others	0.050	
Reasons/factors for unanticipated negative shock		
Bad crop harvest	0.284	
Bad prices for farm product	0.137	
Low wages from outside employment	0.107	
Lost jobs in outside employment	0.107	
Remittances declined	0.023	
Bad business in nonfarm self-employment	0.030	
Others	0.217	

Notes: (1) The statistics are for the complete panel households (number of observations =299).
(2) For dummy variables, the table reports the ratio of households whose dummy variable is one.
(3) 'Rs.' denotes Pakistan Rupees in 1996 values.

Appendix 2. On Attrition Bias

Let the indicator variable $d_i = 1$ if y_{i2} is observed in period 2 and $d_i = 0$ otherwise. Suppose that y_{i2} is observed if the latent variable

$$d_i^* = \gamma R_i + \epsilon_i \geq 0, \tag{3}$$

where R_i is a vector of variables including Z_i and other identifying variables W_i and ϵ_i is a standard normal error. Then the probability of non-attrition is a probit function given by

$$Prob(d_i = 1) = \Phi(\gamma R_i), \tag{4}$$

where $\Phi(.)$ is the standard normal distribution function. The probit model was estimated by maximum likelihood, yielding the following table. Results show that attrition occurred more on households living in Village A than in Villages B and C and on households whose heads were more educated. Other household attributes are not statistically significant.

	Coef.	S.E.	dP/dX
Village dummies			
Village A	0.749	(0.260)***	0.156
Village B	1.945	(0.307)***	0.406
Village C	1.404	(0.262)**	0.293
Household's initial attributes			
Household size	-0.075	(0.142)	-0.016
Dependency ratio	0.047	(0.084)	0.010
Age of household head	-0.014	(0.102)	-0.003
Dummy for nonfarm fulltime employees	-0.045	(0.189)	-0.009
Dummy for regular remittance receipt	-0.387	(0.337)	-0.081
Land ownership dummy	-0.114	(0.205)	-0.024
Land asset value	0.319	(0.506)	0.066
Livestock value	0.197	(0.207)	0.041
Net monetary asset	-0.022	(0.125)	-0.005
Other asset value	0.388	(0.389)	0.081
Education of household head	-0.201	(0.091)**	-0.042
Number of observations	355		
Log likelihood	-133.4		
LR test for zero slopes	42.70	***	
Fraction of correct prediction	0.848		

Notes: Standard errors were computed from analytical second derivatives. Continuous variables in 'Households' initial attributes' are normalised by their village means and standard errors.