Vulnerability in Pakistan, 2001 - 2004*

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March 2009

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*Draft prepared as a background paper for the Pakistan Poverty Assessment Project, the World Bank. The author is very grateful to comments and advice from Ethan Ligon, Alain de Janvry, Nobuo Yoshida, and Tomo Sho.

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Abstract

This paper addresses the question: What kind of households are vulnerable and how are they vulnerable in Pakistan? This question is investigated using two-period panel data (surveyed in 2001 and 2004) covering about 1,600 households in rural Punjab and Sindh, and four rounds of nationally-representative, repeated cross-section data, covering about 15,000 households in each round of 1998/99, 2001/02, 2004/05, and 2005/06. During this period, average consumption initially decreased and then increased. Associated with this change, poverty increased initially and then decreased, and inequality decreased initially and then increased. The vulnerability analysis in this paper focuses on the second period when poverty decreased. Five measures of vulnerability are employed: transient poverty components of observed poverty, decreases in consumption levels, sensitivity of consumption changes to village-level shocks, variance of consumption changes, and the welfare cost of risk simulated under the assumption of a specific utility function.

Empirical results are summarized as follows. Important physical assets in Pakistan, i.e., farmland, livestock, and durable goods, are vulnerablity-reducing in general. The landed households, however, may have difficulty in catching up with the macroeconomic growth rate in a boom. Access to non-farm employment is vulnerablity-reducing. In contrast, access to credit and remittance has mixed effects, probably due to the reverse causality that households hit by adverse shocks seek credit or remittance more eagerly. Education is weakly associated with higher vulnerability. This could be because the welfare level of educated households is higher than uneducated households in general, implying that educated households have larger room for consumption curtailment when hit by an adverse shock. Households with more dependent members are less vulnerable, suggesting the existence of an informal social support or implicit contract for households with more children. Larger households suffer from a larger welfare cost of risk than smaller households do.

Geographically, residents in rural Sindh are more subject to various types of vulnerability than those in rural Punjab, especially northern districts of Punjab. Across the country, however, residents in NWFP and Balochistan suffer a larger cost of welfare loss due to risk, making the difference between rural Sindh and rural Punjab a minor one, and urban residents in Punjab and Sindh are less subject to vulnerability than all others, although we have to be careful since the regional contrasts in vulnerability across Pakistan are not based on panel data. To estimate the welfare cost of risk from repeated cross-section data, we impose restrictions that correspond to the permanent income hypothesis with perfect credit markets, but the dynamics of consumption inequality is not wholly consistent with these restrictions.

1 Introduction

In attacking poverty in developing countries, due considerations need to be paid to the dynamics of income and consumption at the household level, because poor households are likely to suffer not only from low income and consumption on average but also from fluctuations of their welfare. These households are vulnerable to a decline in their welfare level because they have limited ability to cope with shocks and also they are subject to substantial shocks, such as weather variability (Dercon, 2005; Fafchamps, 2003). This concern has led to an emerging literature on vulnerability measures in development economics (Ligon and Schechter, 2003; 2004; Kamanou and Morduch, 2005; Calvo and Dercon, 2005; Kurosaki 2006a). We broadly think people as vulnerable when (i) they cannot mitigate income volatility and (ii) their consumption expenditure is volatile over time (they lack reliable coping mechanisms). Thus vulnerability is a forward-looking concept.

As an example of low-income countries subject to substantial vulnerability, this paper examines the case of Pakistan. Pakistan is located in South Asia, where more than 500 million people or about 40% were estimated to live below the poverty line at the turn of the century (World Bank, 2001). Economic development in South Asia has been characterized 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 Pakistan (World Bank, 2002). Although the overall economic growth rates were improved during the 2000s, poverty reduction was slower than expected. Using a two-period panel dataset spanning three years from the North-West Frontier Province (NWFP), one of the four provinces comprising Pakistan, Kurosaki (2006a) and Kurosaki (2006b) show that rural households were indeed vulnerable to substantial welfare fluctuations. Using a three-year panel dataset from Pakistan's Punjab, Kurosaki (1998) shows that farmers' consumption was excessively sensitive to idiosyncratic shocks to their non-farm income. The aggregate numbers hide these welfare fluctuations. Therefore, it is of vital importance for poverty assessment in Pakistan to address the question: What kind of households are vulnerable and how are they vulnerable?

This paper investigates this question using two types of datasets: two-period panel data (surveyed in 2001 and 2004) covering about 1,600 households in rural Punjab and Sindh, and, four rounds of nationally-representative, repeated cross-section data, covering about 15,000 households in each round of 1998/99, 2001/02, 2004/05, and 2005/06. During this period, average consumption initially decreased and then increased. Associated with this change, poverty increased initially and then decreased, and inequality decreased initially and then increased. The vulnerability analysis in this paper focuses on the second period when poverty decreased. Data used in this paper are described in Section 2, with trends in poverty and inequality calculated from these data .

Five measures of vulnerability are employed: transient poverty components of observed poverty, decreases in consumption levels, sensitivity of consumption changes to village-level shocks, variance of consumption changes, and the welfare cost of risk simulated under the assumption of a specific utility function. The analytical framework underlying these measures is explained in Section 3. Some of these vulnerability measures are defined using the poverty line as a threshold while others are defined without using the poverty line. To focus on the vulnerability problems faced by poor households, the correlates of the five measures of vulnerability were analyzed using the subsample excluding rich households. Then in each section from Section 4 to Section 8, the five measures are estimated using the two period panel data from Pakistan.

One shortcoming of the analysis in Sections 4-8 is that the panel data are not nationally representative and the sample size is not very large. If we can utilize nationally-representative, repeated cross-section data, with a large number of sample observations, for a vulnerability analysis, our understanding of vulnerability in Pakistan can be enhanced substantially. In the literature, Ligon (2008a) presents a methodology to estimate a version of the vulnerability measure proposed by Ligon and Schechter (2003), by imposing a dynamic restriction derived from the permanent-income-hypothesis with perfect credit markets. Section 9 applies this methodology to the case of Pakistan. The final section concludes the paper.

2 Poverty and Inequality in Pakistan

2.1 Data

2.1.1 Characteristics of Pakistan's economy

Pakistan is a federal state comprising four provinces of Punjab, Sindh, NWFP (North-West Frontier Province), and Balochistan. In general, Punjab and Sindh are regarded as economically advanced provinces, while NWFP and Balochistan are regarded as backward provinces. One difficulty in comparing the four provinces is the imbalance in their sizes. In terms of population as well as production, Punjab is the largest, occupying more than a half of the national economy. Sindh is the second largest accounting for 23% of the national population, followed by NWFP, accounting for 14%. Balochistan is the largest in terms of area (about 45% of Pakistan's area) but the smallest in terms of population (only 4% of the national population). The isolation and remoteness of Balochistan makes it difficult to obtain reliable data on this province.

Another dimension of spatial disparity in Pakistan is the difference in living standards between urban and rural areas. About 30% of the Pakistani population live in urban areas. Even after adjusting for differences in prices, income and expenditure levels in urban areas are much higher than in rural areas. Urban Punjab and urban Sindh are thus regarded as the most advanced regions. Urban-rural disparity is the largest in Sindh, whose rural regions are lagging behind in various aspects, characterized by a few big landlords and numerous landless sharecroppers.

Although declining, the share of agriculture in Pakistan's GDP is still high at over 20% (Government of Pakistan, various issues). There are two crop seasons: *Kharif* and *Rabi*.[1] Since Pakistan is mostly located in semi-arid and arid zones, crop production in both seasons is highly dependent on irrigation. In spite of the fact that Pakistan has the largest irrigated agriculture in the world in terms of acreage, agricultural output fluctuates substantially (Kurosaki, 1998). This is because the canal water availability depends on rainfall in the Himalaya, which fluctuates every year, and the irrigation water availability at the farm level is disrupted frequently due to management problems in the irrigation system. In addition to the agricultural sector, agro-industries (such as cotton-based textiles) and agro-services (such as trade of agricultural produce) are important in non-agricultural sectors. Because of this, Pakistan's macroeconomy as a whole also fluctuates substantially, depending on the weather.

2.1.2 PIHS/PSLM: Nationally-representative, repeated cross-section data

The Federal Bureau of Statistics, the Government of Pakistan, has been conducting household income and expenditure surveys on a regular basis. In this paper, microdata from four, most recent surveys are employed. In 1998/99 and 2001/02,[2] these surveys were called *Pakistan Integrated Household Survey* (PIHS), while in 2004/05 and 2005/06, they were conducted as a part of *Pakistan Social and Living Standards Measurement Survey* (PSLM). The subsample of PSLM were asked additional questionnaires corresponding to the household income and expenditure surveys. The pooled dataset is called "PIHS/PSLM data" below.

In each survey, a nationally representative sample was drawn in two stages: primary sampling units (PSU) with different sampling probabilities were randomly chosen in the first stage; twelve (or eleven in the 2005/06 survey) households were randomly chosen from each PSU in the second stage. The sample size for our analysis is approximately 15,000 households in all four surveys. Since the simple average of household size among the sample households is

[1] *Kharif* is a monsoon season whose harvests come in September-November, while *Rabi* is a dry season whose harvests come in March-June. Rice, cotton, and maize are major crops in *Kharif* while wheat and gram pulse are major crops in *Rabi*.

[2] The years are the reference year for the survey, corresponding to a period from July 1 to June 30.

about seven in all four surveys, the micro dataset for each year covers approximately 105,000 individuals. The variables in the dataset include household roster, education, income and employment, consumption quantity and expenditure, assets, etc.

In the PIHS/PSLM dataset, nominal consumption expenditure[3] per capita[4] in Pakistan Rupees is calculated and then converted into a real term by dividing by the official poverty line. This is the concept known as the "welfare ratio" and denoted as c_{it}, where subscript i refers to individual i and t refers to the survey year. In a static analysis of poverty, individuals with $c_{it} \geq 1$ are classified as non-poor and those with $c_{it} < 1$ are classified as poor. The official poverty line of Pakistan is close to the level of 1 PPP$/day (1.25 PPP$/day in 2005 price), which is adopted widely in the international comparison.

2.1.3 PRHS panel data

Pakistan Institute of Development Economics (PIDE) and the World Bank jointly conducted a panel survey called "Pakistan Rural Household Survey." The first round (PRHS-I) was surveyed from September 2001 to January 2002, collecting information on agricultural related activities for the crop seasons of *Kharif* 2000 and *Rabi* 2000/01, and consumption information corresponding to the month preceding the survey. About 2,700 households living in rural areas were surveyed, spreading all four provinces of Pakistan.

Three years after, the second round (PRHS-II) was surveyed from August 2004 to October 2004, covering agricultural crop seasons of *Kharif* 2003 and *Rabi* 2003/04, and consumption in the month preceding the survey. Because of security problems and other reasons, sample households in NWFP and Balochistan were not re-surveyed. We calculate from the PRHS panel data the welfare ratio (c_{it}) in exactly the same way as we did from the PIHS/PSLM data.[5]

In this paper, the balanced panel of 1,609 households (929 in Punjab and 680 in Sindh) are employed, for which complete consumption information was available in both surveys. In

[3]Since many farm households in Pakistan are subsistence-oriented and many rural laborer households are paid sometimes in kind, the value of these in-kind transactions were carefully imputed in calculating the consumption expenditure.

[4]To be precise, "per capita" means "per adult equivalence unit," which is the unit adopted by the Government of Pakistan to establish the official poverty line. Individuals who are 18 years old or above are assigned the weight of 1.0 and others are assigned that of 0.8.

[5]The official poverty line was converted into the poverty line for each PRHS round in four steps: First, the poverty headcount rate for rural Punjab and Sindh was estimated at 38.5% using PIHS 2001/02 data and the official poverty line. Second, the poverty line for PRHS-I was fixed to generate the same poverty headcount rate using PRHS-I data for rural Punjab and Sindh, including the households who dropped out in the re-survey. Third, an inter-temporal inflation rate of 15.2% between PRHS-I and PRHS-II was estimated by weighting monthly CPIs by the number of observations for each corresponding month for PRHS-I and PRHS-II data. Fourth, the poverty line for PRHS-II was fixed by multiplying the PRHS-I poverty line by the inflation rate. Since most of the main analysis of this paper does not depend on the poverty line, the results in Sections 4-9 are robust to this procedure.

PRHS-I, the number of sample households in Punjab and Sindh with complete consumption information was 1,874, implying the attrition rate at 14%. The panel dataset is called "PRHS panel" below.

In PRHS-I, the sample households were randomly drawn from sample villages and the sample villages were chosen as broadly representative of each province. Therefore, if the attrition was purely random, the PRHS panel data are broadly representative of rural Punjab and Sindh. Comparing the panel households with those who dropped out of PRHS, we found that the average of c_{it} in PRHS-I among the attritted sample was 12% lower than that among the panel sample, and the difference was statistically significant (p value = 0.029). On the other hand, household size and compositions were similar between the two groups (the difference was statistically insignificant). This suggests a possibility of weak attrition bias in that initially poor households were more likely to drop out of the sample.

2.2 Trends in poverty and inequality measures

Using the four rounds of PIHS/PSLM data, the average consumption expenditures are calculated and summarized in Table 1. The average welfare ratio (average of c_{it} across i for each t) declined initially, followed by increases in the next two periods (see Figure 1 also). The level in 2005/06 at 1.681 is only 15% higher than the 1998/99 level but 21% higher than the 2001/02 level. The annual growth rate (exponential) from 1998/99 to 2005/06 was 1.56% while that from 2001/02 to 2005/06 was 4.80%. The movement of average welfare ratios is closely related with agricultural production in Pakistan. Agricultural value-added (real terms) in the national account statistics[6] declined in 2000/01 and experienced zero growth in the next year. Thus the year 2001/02 was associated with the worst agricultural output in recent years. The agricultural production recovered in the next two years, culminating in 2004/05, the bumper harvest year in recent years.

Table 2 summarizes FGT poverty measures.[7] Changes in the poverty measures are just the opposite of changes in the average means reported in Table 1, as shown more clearly in Figure 1. The robust standard errors reported in Table 2 show that at the national level, changes in poverty measures were all statistically significant at the 5% level.[8] Among regions reported in Table 2, urban and rural Punjab and rural NWFP were most successful in reducing poverty continuously, while rural Sindh and urban/rural Balochistan experienced

[6]Data sources are Government of Pakistan (various issues).

[7]Since c_{it} is normalized by the poverty line, the FGT class of poverty measures can be defined as: $P_t(\alpha) = \frac{1}{n_t}\sum_{i\in\{c_{it}<1\}}(1-c_{it})^{\alpha}$, where α is a non-negative number. In Table 2, headcount index ($\alpha = 0$), poverty gap index ($\alpha = 1$), and squared poverty gap index ($\alpha = 2$) are reported.

[8]Two-sample t tests on the equality of means allowing for unequal variances were conducted and the null hypothesis was statistically rejected.

volatile changes in poverty measures. The headcount index in Balochistan nearly doubled in one year between 2004/05 and 2005/06. On average, poverty in urban areas had been less volatile than in rural areas. The overall trends, however, look mostly similar across urban and rural areas for all four provinces. Furthermore, the spatial disparity in poverty across provinces and between urban/rural areas remains substantial (Figure 2).

Table 3 reports inequality measures proposed by Atkinson (1970).[9] The inequality aversion parameter is set at 3, because it will be used as the intermediate parameter in estimating the welfare cost of risk in Section 9. Figure 1 shows that inequality decreased from 1998/99 to 2001/02, then it increased rapidly from 2001/02 to 2004/05. The first decrease and the second increase were both statistically significant at the 1% level. In contrast, the increase of inequality from 2004/05 to 2005/06 was only marginally significant (p-value was 0.051 for the two-sample t tests on the equality of means). Furthermore, according to some other inequality measures, such as Gini coefficient, inequality slightly increased from 2004/05 to 2005/06. In all four provinces, inequality in urban areas is higher than in rural areas.

Since all three measures of mean consumption, poverty, and inequality are summary statistics characterizing the distribution of c_{it}, it is informative to examine the exact shape of its distribution graphically. Therefore, Figure 3 shows univariate kernel density estimation results[10] for the natural logarithm of c_{it}. First, in all four years, the density curve is a smooth one, with its peak slightly higher than the poverty line (i.e., $\ln(1) = 0$). This implies that a slight shift of the whole distribution can change poverty measures substantially in Pakistan. Second, the growth pattern from 2001/02 to 2004/05 and that from 2004/05 to 2005/06 are different. From 2001/02 to 2004/05, the whole distribution seems to have shifted to the right, while from 2004/05 to 2005/06, the distribution became more skewed, with those population with $-0.6 \leq \ln(c_{it}) \leq -0.3$ decreased (poverty was reduced) and those population with $\ln(c_{it}) \geq 1.5$ increased (the rich population became larger).

The trends in poverty and inequality between PIHS 2001/02 and PSLM 2004/05 are similar to those between PRHS-I (2001) and PRHS-II (2004), as shown in Table 4. The poverty measures decreased substantially from 2001 to 2004. The decrease was slightly larger in Sindh, reducing the gap between the two provinces. In both Punjab and Sindh, inequality increased during this period. This is similar to the change observed in nationally representative household surveys between 2001/02 and 2004/05 (Table 3).

[9] A standard bootstrap approach was adopted to estimate the standard errors of Atkinson's inequality measures. The number of bootstrap replications to be performed was specified at 100 and the size of the samples to be drawn as the same as the data. The results reported in this paper were stable with respect to the number of replications around 100.

[10] The Epanechnikov kernel was used and the optimal bandwidth that would minimize the mean integrated square error if the data were Gaussian was employed to produce Figure 3. The shape of the figure was sensitive neither to the choice of kernel nor to different bandwidths around the adopted one.

2.3 Poverty transition at the household level

The change in poverty measures in Table 2 cannot show how many households experience a "fall into poverty" when the average poverty headcount ratio decreases. To examine the change at the individual level, we need a panel data. Table 5 thus employs the PRHS panel data and classifies each household's status of poverty transition.

Out of 1,609 households, 182 were below the poverty line in both periods ("chronically poor"), 342 were below the poverty line in PRHS-I but above it in PRHS-II ("getting out of poverty"), 176 were above the poverty line in PRHS-I but below it in PRHS-II ("falling into poverty"), and 904 were equal to or above the poverty line in both periods ("never poor"). In terms of individual population, 13.4% of the PRHS-I individuals belonged to the "chronically poor" households, 23.7% to the "getting out of poverty" households, 11.6% to the "falling into poverty" households, and 51.2% to the "never poor" households.

In terms of transition probability, 65.3% of households who were initially poor became non-poor in PRHS-II, while 16.2% of households who were initially non-poor became poor three years after. Therefore, we observe high level of poverty mobility. The vulnerability measured by the incidence of falls into poverty is thus very high in rural Pakistan. The transition probability from non-poor to poor was higher in Sindh (23.5%) than in Punjab (12.5%). In this sense, dwellers in rural Sindh were more vulnerable than those in rural Punjab. Whether this regional contrast will hold after difference in household endowments and household characteristics is left for other reports under preparation for the Pakistan Poverty Assessment Project.[11]

3 Analytical Framework

The empirical analyses of this paper are based on a standard model of a household (denoted i), which optimizes its forward looking welfare defined as

$$W_{it} = U(c_{it}) + E_t \left[\sum_{\tau=1}^{T} \left(\frac{1}{1+\delta} \right)^{\tau} U(c_{i,t+\tau}) \right], \tag{1}$$

where $U(.)$ is an instantaneous utility function that satisfies $U'(.) > 0, U''(.) < 0$, δ is the subjective discount rate, and $E[.]$ is an expectation operator. In period t, household i allocates resources across consumption, investment, production, etc., in order to maximizes W_{it} subject to endowments and technology constraints. Although the functional form of $U(.)$ and δ may differ from household to household, they are assumed to be the same for simplicity (or we implicitly assume a social welfare function).

[11] See Arif and Bilquees (2008) for such an analysis by applying a multinomial logit model to the two-period panel data of Pakistan Socio-Economic Survey (1998/99 and 2000/01).

The key assumption is risk aversion ($U''(.) < 0$). Because of risk aversion, households would choose a completely smoothed consumption path even if their income path is fluctuating, when the income path is exogenous and pre-determined (no uncertainty) and when they are faced with perfect credit markets (i.e., they can borrow or lend any amount of money at the same interest rate). Under perfect credit markets, when there is exogenous but stochastic fluctuation in the income levels, their consumption path is fairly smoothed and responsive to income shocks only partially to the uninsured idiosyncratic risk. On the other hand, when households are faced with credit (or liquidity) constraint, which is likely to be binding when the households' cash in hand is low, their consumption path cannot be smoothed from the current period to the next period (Deaton, 1991).

The most important implication of this dynamic model to the vulnerability analysis is that the household welfare declines when households face greater consumption risk in the future. As a measure of the future risk, the past variability of consumption is informative. We therefore use panel data of individual-level consumption to infer the welfare loss due to risk. This is the main approach adopted in this paper. The methodologies can be further classified into two.

The first group of methodologies is a reduced-form approach. Depending on the availability of variables in the PRHS panel data, we adopt four measures for the reduced-form approach: transient poverty components of observed poverty according to the decomposition proposed by Ravallion (1988) (the larger the transient poverty, the more vulnerable, *ceteris paribus*), changes in consumption (the more negative, the more vulnerable, *ceteris paribus*); sensitivity of consumption changes to income shocks (the more sensitive, the more vulnerable, *ceteris paribus*); and the variance of consumption changes (the higher the variance, the more vulnerable, *ceteris paribus*). These methodologies are applied to the Pakistan PRHS panel data and examined in each of Sections 4-7.

The second group of methodologies is more structural. One problem for the first group of vulnerability measures is that the *ceteris paribus* condition is never met in the real data so that if different measures of vulnerability are associated with a variable with the opposite signs, we cannot infer the sign of the net effect of that variable on vulnerability. To solve this problem, we can numerically calculate the value of W_{it} in equation (1) for the default case corresponding to the data and for some counterfactual cases, by specifying/calibrating/estimating the stochastic process of c_{it} and the form of utility function $U(.)$. The two sets of numerical values are aggregated across individuals and the difference between the two can be normalized into monetary values, showing the (net) welfare cost of uninsurable idiosyncratic risk, for example. As an application in this direction, Section 8 employs a simplified version of Ligon and Schechter's (2003) model and applies it to the

PRHS panel data. Unlike the reduced-form methodologies examined in Sections 4-7, the structural approach can be applicable to repeated cross-section data if we impose additional assumptions on the stochastic process of c_{it}. Following Ligon (2008a), Section 9 attempts this approach, applying it to the PIHS/PSLM dataset.

These vulnerability measures can be classified by another aspect, i.e., whether a measure is defined using the poverty line as a threshold. The transient/chronic poverty decomposition by Ravallion (1988) (Section 4) and the transition matrix approach in Subsection 2.3 are typical examples to define vulnerability measures using the poverty line.[12] The key assumption there is that we take into account the welfare cost of consumption variation only when the consumption change occurs below the poverty line. Since we judge that consumption variation that occurs slightly higher than the poverty line is also a serious problem for non-rich households in Pakistan, the emphasis of this paper is on the methodologies that measure vulnerability without using the poverty line as a threshold (Sections 5-9).

In principle, the measures of vulnerability that do not use the poverty line as a threshold can be examined for the whole population or the whole sample. However, since the objective of this paper is to contribute to the understanding of poverty in Pakistan, it is better to exclude rich households from the analysis of vulnerability. Therefore, in all econometric analyses of this paper, households whose c_{it} was more than four were excluded from the analysis.[13] There is another advantage of using this subsample because it is suspected that consumption expenditure data for richer population are more subject to measurement error than those for poorer population. Households whose size changed by more than three persons were also excluded, because most of them experienced split or drastic re-formation of household structure and per-capita consumption levels in the two periods were not very comparable. After this selection, the number of observations was reduced from 1,609 (Table 5) to 1,293. We believe that this sub-sample is more homogenous than the whole sample.

The vulnerability measures are compared with potential correlates of vulnerability. As such correlates, regional fixed effects and initial household characteristics (X_i) are adopted. Vector X_i includes variables such as physical assets owned by the household (farmland,

[12] Another methodology often adopted in the literature defines the vulnerability as the probability for future consumption to fall below the poverty line (Chaudhuri et al., 2002; Pritchett et al., 2000; Mansuri and Healy, 2001). Although this is an interesting methodology, the analysis of this probability tends to yield results very similar to the analysis of static poverty when the time dimension of the panel data is short. In the case of the PRHS panel dataset (its time dimension is only two), this was indeed the case. For this reason, this paper does not attempt to estimate the probability for future consumption to fall below the poverty line. For the correlates of this probability, see other reports in the Pakistan Poverty Assessment Project on the correlates of static poverty.

[13] Remember that our measure of c_{it} is the welfare ratio, implying that the cut-off point at c_{it}=4 is that those households whose consumption is more than four times the poverty line are excluded from the analysis in this paper. The results reported in this section remained qualitatively the same when the cut-off point was changed marginally.

livestock, the sum of the value of durable consumption goods, transportation equipment, house buildings, etc.), income sources (number of male working members engaged in non-farm work, existence of remittance receipt, etc.), credit access, education level of the household head, and demographic composition (number of household members, female ratio among them, and dependency ratio among them).[14] Definition and summary statistics of empirical variables are summarized in Table 6.

4 Correlates of Transient Poverty

4.1 Ravallion's decomposition into chronic and transient poverty

As shown in Table 5, a cross section of individuals in the PRHS dataset could be divided into four categories: "chronically poor," "getting out of poverty," "falling into poverty," and "never poor." Although useful, this analysis may not be satisfactory since the welfare cost of consumption variability for the chronically poor is completely ignored. This argument is a dynamic extension of the criticism against the (static) headcount index for its tendency to ignore the depth of poverty below the poverty line.

Ravallion (1988) proposed a powerful alternative to the categorical analysis. He examined the response of the expected value of a poverty measure to changes in the variability in consumption. If there is no fluctuation in consumption due to risk, the time average of a poverty measure becomes equivalent to the value of a poverty measure corresponding to the time average of individual consumption. Since individual consumption always fluctuates across time in the actual panel data, the time average of a poverty measure is always larger than the value of a poverty measure corresponding to the time average of individual consumption, when we use poverty measures that are sensitive to inequality among the poor (such as the squared poverty gap index). The value of a poverty measure corresponding to the time average of individual consumption is a measure of chronic poverty while the additional poverty due to consumption variability is a measure of transient poverty. More concretely, from the PRHS panel data, we calculate

$$P_i^T = \frac{p(c_{i,t-1}) + p(c_{i,t})}{2} - p\left(\frac{c_{i,t-1} + c_{i,t}}{2}\right), \tag{2}$$

where c_{it} is the welfare ratio calculated from the PRHS panel data with $t-1$ corresponding to PRHS-I and t corresponding to PRHS-II, $p(.)$ is a poverty score function satisfying $p(c) = 0$ when $c \geq 1$; $p(c) > 0$, $\partial p/\partial c < 0$ and $\partial^2 p/\partial c^2 > 0$ when $c < 1$.

[14] Regarding education and landholding, dummy variables distinguishing zero and positive years of education or positive acreage of owned land were attempted as well, yielding results very similar to those reported in this paper. Regarding the access to non-farm jobs, variables characterizing female workers engaged in non-farm jobs were not included because the average was close to zero and the variation was very small.

Ravallion's (1988) transient/chronic poverty decomposition analysis has been applied to a number of household datasets from developing countries to analyze vulnerability (Ravallion, 1988; Jalan and Ravallion, 1998; Baulch and Hoddinott, 2000; Kurosaki, 2006b). These studies have shown that vulnerability measured by the size of transient poverty is important in general and its relative importance differs across regions and across social strata. Although the squared poverty gap index has been the most popular functional form for $p(.)$ in the previous studies, this paper employs Clark=Watts' poverty measure with parameter -2, because Kurosaki (2006b) found that this measure is superior to the squared poverty gap index both theoretically and empirically. Clark=Watts poverty index is defined as $p(c) = \frac{1}{\beta}(1 - (\frac{c}{z})^{\beta})$, where β (< 1) is the inequality sensitivity parameter, which is set at -2 in the empirical analysis for Pakistan.

Intuitively, the value of P_i^T shows the additional poverty that is attributable to the fact that consumption fluctuated (i.e., the fact c_{it} was not equal to $c_{i,t-1}$). It usually takes a positive value for "chronically poor" households, correctly showing that consumption fluctuation below the poverty line had affected their welfare adversely. It is zero for the "never poor." Therefore, it is a useful measure of vulnerability holding the average consumption level constant. We regress P_i^T on X_i and regional fixed effects to infer what kind of household characteristics are correlated with this measure of vulnerability. The empirical model is

$$P_i^T = X_i\beta + \mu_v + u_i, \tag{3}$$

where β is a vector of parameters to be estimated, μ_v is village fixed effects, and u_i is a zero-mean error term.

4.2 Estimation results

Table 7 shows the estimation results. Since our focus is on the welfare at the individual level, the houseohld-level regression was weighted by the number of household members. Since the household size for some households changed between the two surveys, we report results based on two weights (initial and subsequent household size).

Specification (i) shows basic estimation results for equation (3). Among household characteristics, the size of owned land and the size of livestock (large animals) have a negative coefficient with statistical significance. These asset-rich households are thus less subject to transient poverty, consistent with findings by Kurosaki and Fafchamps (2002) that such households in Pakistan Punjab are more insured against fluctuations in farming income. Elder households also are less subject to transient poverty. In contrast, households with access to formal credit and larger households were more subject to transient poverty. Regarding the impact of credit access, the sign is the opposite of what we expect if access to credit contributes to consumption smoothing. The positive coefficient may reflect the fact that formal credit in rural Pakistan is usually provided only for production purposes to borrowers with sufficient collateral. Such households may have larger room for curtailing consumption when hit by negative income shocks.

The pattern remains the same when we use alternative weights (specification (ii) using household size in PRHS-II) or when we combine the village fixed effects into three regional dummies[15] (specification (iii)). The coefficients on the regional dummies suggest that dwellers in rural Sindh suffered from larger transient poverty than those in Punjab. In specifications (ii) and (iii), the remittance dummy becomes significant with a negative coefficient. This suggests that remittance is an effective tool to reduce transient poverty. The impact of household head's age is not very robust, resulting in insignificant results under specification (iii).

The results in Table 7 were found robust to changes in the choice of poverty measures, as long as the inequality sensitivity parameter was sufficiently high. When Clark=Watts measures were employed, $\beta = 0$ or -1 resulted in results very similar to those in Table 7. When FGT poverty measures were employed, $\alpha = 3$ or 4 resulted in results very similar to those in Table 7. In contrast, FGT poverty measures with $\alpha = 2$ (squared poverty gap index) led to completely insignificant regression results.

5 Correlates of Changes in Consumption

5.1 Empirical model

One shortcoming of the transient poverty analysis above is that it does not take into account changes in consumption that occurred above the poverty line. The consumption level of some of the "never poor" might have been very stable while that of others might have been fluctuating year by year. Then it could be better to regard the latter type as (potentially) more vulnerable than the former type. Another issue is that some of the observed change in consumption levels would have been anticipated by the household. If this is the case, we need to decompose the observed changes in consumption into anticipated and unanticipated components. The correlates of the observed changes in consumption and those of the variances of consumption growth residuals are thus analyzed in Sections 5-7.

First, in this section, to account for the vulnerability associated with continuous changes

[15] There is no official division of Punjab into North Punjab and South Punjab. Among 35 districts in Punjab, six districts were surveyed in PRHS, from which three districts of Attock, Faisalabad, and Hafizabad are classified as "Northern Punjab" and three districts of Bahawalpur, Muzaffargarh, and Vehari are classified as "Southern Punjab" in this paper. Out of 22 districts in Sindh, the PRHS data cover four districts of Badin, Larkana, Mirpur Khas, and Nawabshah.

in consumption, we estimate an empirical model

$$\Delta \ln c_{it} = X_i \beta + \mu_v + \Delta u_{it}, \tag{4}$$

where $\Delta \ln c_{it}$ is log change of consumption for household i from period $t-1$ (PRHS-I) to period t (PRHS-II), and Δu_{it} is an error term. Since there are only two periods in our panel dataset, equation (4) is estimated as a cross-section regression model.

This empirical model shows what kind of household attributes in X_i are associated with a larger decline in consumption. In this sense, this is one measure of vulnerability. Similar specification was adopted in empirical studies on vulnerability such as Ravallion (1995), Jalan and Ravallion (1999), and Glewwe and Hall (1998).

5.2 Estimation results

Table 8 shows the estimation results for equation (4). Since the regression results are not sensitive to the choice of weights, we only report results using the initial household size as the weight (this applies to later sections as well).

The basic result under specification (i) shows that the within-village variation in X_i does not explain well the variation in consumption growth. Among household characteristics, three variables are found to have statistically significant coefficients: the size of owned land (negative), the number of male household members who were employed permanently in regular non-farm jobs (positive), and the dependency ratio (positive). The finding that households with larger landholding were lagging behind in consumption growth seems to suggest that growth from 2001 to 2004 was not very land-based. We might be tempted to interpret that the second finding to show that households with more access to non-farm permanent employment were less vulnerable to stochastic consumption decline. However, the positive coefficient may simply reflect the life-cycle improvement in earnings associated with non-farm permanent jobs (e.g., regular promotion). The third finding that households with more dependent household members experienced higher growth in consumption may simply reflect the fact that children (the majority among the dependent members) require larger amount of consumption after they become three years older.[16] All other variables are insignificant. The proxy variables for informal credit constraints have a positive sign, as expected from the theoretical model (Deaton, 1991), but the coefficients were statistically significant only at the 15% level.

The impact of household characteristics remains qualitatively the same when we combine the village fixed effects into three regional dummies. The remittance dummy now has

[16] When we subdivide the sample into the relatively rich and the relatively poor by the median of the welfare ratio, *depratio* has a positive and significant coefficient only among the former. It is negative and statistically insignificant among the poor. This seems to support the life cycle interpretation.

a marginally significant, positive coefficient but it turns out that this is not robust (see specification (iii)). The coefficients on the regional dummies under specification (ii) suggest that dwellers in rural Sindh experienced higher consumption growth than those in Northern Punjab and those in Southern Punjab experienced slower consumption growth than those in Northern Punjab. The narrowing gap between Sindh and Punjab was suggested from tables in Section 2. An important finding from Table 8 is that the regional contrast is statistically significant even after controlling for the difference in household characteristics and the difference is more striking if we compare Sindh and Southern Punjab.

6 Sensitivity of Consumption Changes to Village-level Shocks

6.1 Empirical model

The direct cause of consumption decline could be a decline in income. Therefore, one useful way of quantifying vulnerability is to examine the sensitivity of household-level consumption changes to household-level income changes after controlling for village-level aggregate shocks (Townsend, 1994; Kurosaki, 2006a). This literature is based on the theory of risk-sharing where villagers attempt to smooth their consumption through pooling the idiosyncratic component of their income with fellow villagers. At the same time, the extent to which household consumption responds to income shocks is itself an interesting parameter, and can be interpreted as a measure of vulnerability (Amin et al., 2003; Skoufias and Quisumbing, 2005).

However, information on household income in PRHS is not in detail and not comparable between the first and the second round. Therefore, it is not feasible to apply models like Townsend (1994) or Kurosaki (2006a) using the household-level income change as an explanatory variable for the household-level consumption change. Furthermore, information on idiosyncratic income shocks such as livestock death or plot-level production problems (e.g, see Dercon and Krishnan, 2000) is also lacking in our dataset. On the other hand, we have village-level shock variables. Therefore, we revise the empirical model (4) as

$$\Delta \ln c_{it} = X_i\beta + Z_v Z_i \gamma + \Delta u_{it}, \tag{5}$$

where Z_v is a vector of village-level production shock variables for household i living in village v, Z_i is a subset of X_i used as a shifter for the household's ability to cope with production shocks, and γ is a vector of parameters to be estimated. Vector γ is of main interest, which shows which of household attributes Z_i is associated with a larger decline in consumption if the village is hit by a production shock Z_v.

As proxy for Z_v, 24 variables were available in PRHS-II, all of which assessed the negative impact due to natural disasters in five points: 0 ("No effect": no report for the crop damage), 1 ("Little effect": yield loss up to 10%), 2 ("Moderate": 10-25% loss), 3 ("Severe": 25-50%

loss), and 4 ("Disaster": more than 50% loss). Three types of disasters were investigated: drought; flooding; and pest attack. Eight cropping seasons up to the survey reference period (i.e., from *Kharif* 2000 to *Rabi* 2003/04) were covered. After attempting several ways of aggregating the twenty-four variables, we report the results with three aggregated variables for drought, flood, and pest in the agricultural year of 2003/04, each taking an integer value from 0 to 8 (Table 6). Since the consumption data in PRHS-II were collected in August-October 2004, the agricultural output in 2003/04 should have affected the consumption most directly. Nationally, 2003/04 was a normal harvest year. Nevertheless, this does not mean that all villages experienced a normal harvest. As shown in Table 6, several villages suffered from drought and pest attack and fewer villages suffered from floods. How responsive to these shocks was the consumption of residents in these villages, relative to villages that did not report such shocks? This question is addressed in this section.

6.2 Estimation results

Table 9 shows the estimation results. All estimation specifications include the fifteen explanatory variables in Table 8. Since their coefficients are very robust to the revision of model (4) into model (5), they are not reported in Table 9 for brevity.

In specification (i), no cross term was included. Three village-level shock variables were added and their coefficients were negative as expected. However, only the effects of drought and pest were statistically significant. Nevertheless, the size of coefficients was substantial. For instance, the coefficient of -0.016 on drought shock implies that consumption growth rate is reduced by 9.8 percentage point (where the average consumption growth rate was 17.3%, Table 6), if both *Kharif* and *Rabi* crops were destroyed by "Severe" droughts, in comparison with the case of "No effect" of drought (-0.098=-0.01632*6). The impact of flood is estimated at a value similar to that of drought but not statistically significant, possibly due to the smaller number of villages affected by floods in our sample (flood damages were reported from villages in Northern Punjab only). On the other hand, the impact of pest is slightly larger than that of drought and statistically significant.

To examine whether regional difference exists regarding the extent of consumption smoothing ability against village-level agricultural shocks, specification (ii) allows the slope of Z_v for drought and pest attack to differ across three regions (Northern Punjab as the reference). Regarding the effect of drought, the negative impact was significant for Northern Punjab, while it was mitigated in both Southern Punjab and Sindh. In Southern Punjab, the net effect (-0.029+0.040) is slightly positive, though not significantly different from zero. One interpretation is that since drought is an every-day occurrence in Southern Punjab and Sindh, villagers have institutionalized a means to isolate their consumption from the ill-effects of drought on farm income. Candidates for such a means may include inter-village transfers, credit transactions, and migration. This is a topic worth further investigation.

Regarding the effect on consumption of pest attack in the farm, the impact in Northern Punjab was almost zero, while it was negative in Southern Punjab. This seems to reflect the importance of cotton crops (inherently vulnerable to pest attacks) in Southern Punjab. Southern Punjab residents are thus highly vulnerable to pest attacks.

In specification (iii) of Table 9, household-level characteristics (those explanatory variables reported in Table 8) were interacted with the village-level farming shocks. Statistically insignificant interaction terms were deleted from the regression model. The results show that households with many dependent members were able to more isolate their consumption from drought-driven income decline, the ill-effects of flooding are mitigated if a household is more landed and the household head is younger (unexpectedly, household head's education is associated with a severer impact of flood), and households with problems to formal credit access were subject to larger decline in consumption when hit by pest shocks. On the ill-impact of pest attacks, household's access to remittance receipt and informal credit has the effect opposite to the expectation: households with remittance (or access to informal credit) experienced a larger decline in consumption when hit by pest attacks. Regarding the impact of remittance, the reverse causality may be suspected since the variable was calculated from households' income sources in 2003/04, not in PRHS-I — Because households were hit by pest attack, they received more remittance but the increased remittance was not sufficient to cancel its damage.

To sum up, the sensitivity of consumption changes to village-level farm production shocks differs across regions, depending upon the nature of shocks and the characteristics of households. Elder households seem to be more vulnerable to these shocks and land is effective in mitigating the ill-effects of flood. Consumption levels of Northern Punjab villagers are more vulnerable to drought and flood than those in Sindh. Judging from the fact that the average c_{it} is much higher in Northern Punjab than in Southern Punjab and Sindh, we speculate that risk-coping measures against drought in Southern Punjab and Sindh could be very expensive, sacrificing the expected income.

7 Correlates of the Variance of Consumption Changes

7.1 Empirical model

If we interpret the fitted value $X_i\hat{\beta}$ from model (4) or (5) as the expected growth rate for household i, the vulnerability to risk should be better captured by the variances of the residual term. With this motivation, this section extends the empirical model (4) as

$$\Delta \ln c_{it} = X_i\beta + \mu_v + (Z_i\gamma)^{\frac{1}{2}}\Delta u_i. \tag{6}$$

where γ is a vector of parameters to be estimated. This specification allows the variance of consumption changes to be a function of Z_i (the subset of X_i and/or village fixed effects) (see Just and Pope, 1978). Vector γ is of main interest, which shows which of household attributes Z_i is associated with higher volatility of consumption changes relative to the village average, thus providing an interesting measure of vulnerability (Pritchett et al., 2000).

Equation (6) can be estimated in two steps or in an iterative way. The first step of the two-step approach is to estimate (6) ignoring the heteroskedasticity, which is what we have already done in specification (i) in Table 9. The second step is to regress the square of its fitted residuals on variables Z_i. This is econometrically inefficient, although it is unbiased and consistent. If we believe that the structure of heteroskedasticity specified in the second step is a correct one, we can iterate re-estimating equation (6) using weighted least squares to incorporate the heteroskedasticity structure, until the estimated coefficients of β and γ converge to some fixed points. By iterating this procedure, an efficiency gain is obtained.

7.2 Estimation results

Table 10 shows the estimation results for parameter γ, based on the two-step procedure. The iteration was not converging when village fixed effects were included, while, when regional dummies were included, it converged to estimates for β very similar to those reported in Table 8, and to estimates for γ very similar to those reported in Table 10. Therefore, two-step estimation results are reported in this paper.

When region-specific intercepts are included (specification (ii) in Table 10), four variables have significant coefficients: households with a larger number of livestock animals (cattle and buffalo), households owning more assets (durable consumption goods, transportation equipment, house buildings, etc.), and households who have a larger number of dependent family members were associated with smaller variance in consumption innovation, while households with a larger number of small livestock animals were associated with larger variance in consumption innovation. All of Tables 8-10 thus show that households with higher dependency ratio are less vulnerable in various aspects. This is against intuition if we focus on the possibility that households with lower dependency ratio can diversify their risk and can cope with risk better through labor market participation than other households (Kochar, 1999; Ito and Kurosaki, forthcoming). On the other hand, this is consistent with intuition that some sort of reciproicity-based risk-sharing arrangements exists in rural Pakistan for households with more children because these children can repay in the future the benefit they receive today.

Among three regions, the Sindh dummy is associated with a positive coefficient on the consumption variance. The difference between Sindh and Northern Punjab (or Southern Punjab) is highly significant. Therefore, rural dwellers in Sindh are more vulnerable in the sense that they are subject to larger variance in innovation to individual-level consumption after controlling for the household characteristics.[17] On the other hand, the variances in levels of consumption (c_{it}) across households are much larger in Punjab (especially in Northern Punjab) than in Sindh. Therefore, among non-rich households (remember that these analyses excluded households whose c_{it} was greater than four), those in rural Sindh are more equal but associated with higher volatility than rural Punjab counterparts.

Regarding the effect of large animals, it is consistent with the finding by Kurosaki and Fafchamps (2002) that rural households with larger livestock in Pakistan behave in a less risk-averse way because their ex post consumption smoothing ability is higher. However, as shown in specification (i) in Table 10, the negative coefficient on large animals becomes statistically insignificant and the positive coefficient on small animals remains statistically significant (although marginally so), when we use village fixed effects. When insignificant variables are deleted (specification (iii) in Table 10), both livestock variables remain statistically significant. It could be possible that small livestock animals were decumulated to compensate income shocks, resulting in the opposite sign of the coefficient on the small livestock variable.

8 Welfare Cost of Risk Using PRHS Panel Data

8.1 Model specification

In this section, as a more comprehensive measure of vulnerability, we simulate the welfare cost of risk based on a specific form of utility function, *a la* Ligon and Schechter (2003), using the PRHS panel data. First, a model assuming homoskedastic innovations to individual consumption is employed, which is estimable from repeated cross-section datasets if supplemented by additional assumptions, as proposed by Ligon (2008a), and applied to the PIHS/PSLM data in Section 9. Second, the individual-level consumption dynamics model estimated in Table 10 is directly incorporated into the estimation of the welfare cost of risk,

[17]This interpretation is based on an implicit assumption that the fitted residual in equation (4) shows innovation to consumption that is unexpected by the household. It is also possible that the fitted residual shows innovation to consumption that is completely anticipated by the household but unobservable to the econometrician. If the latter case is true, the interpretation should be that rural dwellers in Sindh were heterogenous in terms of anticipated changes in consumption, and therefore not necessarily vulnerable. From the information included in the PRHS panel data, it is impossible to distinguish the two. In the recent literature, an attempt has been made to identify the two using direct information on households' expectation. See for example, Kaufmann and Pistaferri (2009).

allowing for heterogeneity in both level and variance of consumption changes.

We focus on the quantification of the welfare loss due to risk factors that would happen between period $t-1$ (PRHS-I) and t (PRHS-II), looking from period $t-1$. For this purpose, equation (1) is revised as

$$W_{i,t-1} = (1+\delta)U(c_{i,t-1}) + E_{t-1}U(c_{i,t}), \tag{7}$$

which is used as the default value of welfare. The default value of welfare is compared with a counterfactual where there is no risk in period t, i.e.,

$$W^*_{i,t-1} = (1+\delta)U(c_{i,t-1}) + U(E_{t-1}c_{i,t}). \tag{8}$$

By subtracting (7) from this equation, the individual-level welfare cost of risk[18] can be defined as

$$\begin{aligned} V^i_{t-1,t} &= W^*_{i,t-1} - W_{i,t-1} = U(E_{t-1}c_{i,t}) - E_{t-1}U(c_{i,t}) \\ &= [U(E_{t-1}c_{it}) - E_{t-1}U(E_{t-1}[c_{it}|\bar{x}_t])] + [E_{t-1}U(E_{t-1}[c_{it}|\bar{x}_t]) - E_{t-1}U(c_{it})] \\ &= AggregateRisk^i_{t-1,t} + IdiosyncraticRisk^i_{t-1,t}, \end{aligned} \tag{9}$$

where $\bar{x}_t$ is the vector of macroeconomic variables. The first term of the last expression shows the welfare cost of aggregate risk and the last shows the welfare cost of idiosyncratic risk (possibly including measurement error as well).[19]

In the empirical analysis, the utility function is specified as a constant relative risk aversion (CRRA) utility function, namely,

$$U(c) = \frac{c^{1-\gamma}-1}{1-\gamma}, \tag{10}$$

where γ (>0) is the coefficient of relative risk aversion. As shown by Ligon (2008a), this specification is closely related with Atkinson's (1970) inequality measures. In addition, the CRRA utility corresponds to Clark=Watts poverty measures, which satisfy various desirable properties in conducting transient poverty analysis (Kurosaki, 2006b). Following Ligon (2008a), γ is set at 2 and consumption c is defined relative to the period average among the

[18] As is clear from this definition, $V^i_{t-1,t}$ does not take into account the expected income loss due to income smoothing (e.g., income diversification). In other words, $V^i_{t-1,t}$ as the welfare cost of risk treats the flow of income as exogenous. If income smoothing is important, $V^i_{t-1,t}$ defined in this paper is an underestimate for the real welfare cost of risk. For farmers in Pakistan's Punjab, Kurosaki and Fafchamps (2002) estimated the size of foregone income due to diversification at 2.0% of farmers' income, which is not negligible.

[19] Ligon and Schechter's (2003) decomposition includes the poverty factor in addition to the decomposition (9), since their counterfactual corresponds to a case where households were assured the minimum consumption level at the poverty line or the national average consumption. To focus on the welfare cost of risk and to be consistent with the exercises in Section 9, this additional term is not analyzed in this paper. Ligon and Schechter (2003) further decomposes the last term of (9) into the welfare cost of observable idiosyncratic risk and that associated with unexplained risk and measurement error. Due to the absence of variables that proxy idiosyncratic shocks in our data, this decomposition is not attempted in this paper.

population. This has an advantage that numbers measured in utility units are proxy for the amount measured as a proportion of expenditure the household would be willing to sacrifice to eliminate risk.

In order to estimate the welfare cost of risk following (9), we need to estimate the period $t-1$ forecast of the stochastic distribution of c_{it}. For this purpose, we assume

$$\ln c_{it} = \ln c_{i,t-1} + \mu_{it} + \epsilon_t + u_{it}, \tag{11}$$

where μ_{it} is the expected growth rate, ϵ_t is an aggregate shock to consumption, u_{it} is an idiosyncratic shock to consumption, and (ϵ_t, u_{it}) are jointly normally distributed with zero means, zero correlation, and variances of σ^A, σ_i^I, respectively.[20] With these assumptions and using moment generating functions, we can obtain a closed-form solution for the welfare cost of risk when $\gamma = 2$, as

$$\begin{aligned} AggregateRisk_{t-1,t}^i &= \frac{\bar{c}_{t-1}}{c_{i,t-1}} \left[\exp(-\mu_{it} + \frac{\sigma^A}{2} - \frac{\sigma_i^I}{2}) - \exp(-\mu_{it} - \frac{\sigma^A}{2} - \frac{\sigma_i^I}{2}) \right], \\ IdiosyncraticRisk_{t-1,t}^i &= \frac{\bar{c}_{t-1}}{c_{i,t-1}} \left[\exp(-\mu_{it} + \frac{\sigma^A}{2} + \frac{\sigma_i^I}{2}) - \exp(-\mu_{it} + \frac{\sigma^A}{2} - \frac{\sigma_i^I}{2}) \right], \end{aligned} \tag{12}$$

Two approaches are adopted to estimate μ_{it} and σ_i^I from the PRHS panel data. The first one uses the observed mean of $\ln c_{it} - \ln c_{i,t-1}$ as the estimate for μ and the observed variance of $\ln c_{it} - \ln c_{i,t-1}$ as the estimate for σ^I. In other words, expected growth rates of consumption are assumed to be homogenous and idiosyncratic shocks to consumption growth are assumed to be homoskedastic. In the second approach, we use equation (6) to construct the period $t-1$ forecast of the stochastic distribution of c_{it}. Namely,

$$\begin{aligned} \mu_{it} &= E_{t-1}[\ln c_{it}] - \ln c_{i,t-1} = X_i\hat{\beta} + \hat{\mu}_v, \\ \sigma_i^I &= Z_i\hat{\gamma}. \end{aligned} \tag{13}$$

In this specification, expected growth rates of consumption are assumed to be heterogenous and idiosyncratic shocks to consumption growth are assumed to be heteroskedastic.

Finally, we calibrate σ^A in two ways. First, since we cannot estimate it from the PRHS panel data with its time dimension of only two, the time series data of the log of real per-capita GDP from 1998/99 to 2005/06[21] are regressed on a linear time trend and σ^A is estimated by the regression standard error. Since regional GDP data do not exist in Pakistan, the same procedure cannot be adopted if we want region-specific σ^A. Therefore, in the second approach, the national estimate for σ^A in the first approach was multiplied

[20] We investigated whether the assumption of log-normality of errors to the individual-level consumption process is appropriate by plotting fitted residuals from equations (4) and (6). It was found that the fitted residuals were reasonably well-approximated by a normal distribution.

[21] Data sources are Government of Pakistan (various issues).

by the region-specific factors that were calculated from the PIHS/PSLM data using similar regression models.

8.2 Simulation results

Table 11 shows the estimation result of welfare costs. First, when we assume homogenous growth rates, homoskedastic idiosyncratic shocks, and the aggregate risk at the national level, the welfare cost of total risk is estimated at 0.294, implying that PRHS consumers (excluding the richer households whose welfare ratio is greater than four) would have been willing to collectively sacrifice 29.4% of 2001 expenditure to eradicate risk that occurred between 2001 and 2004. This is decomposed into aggregate and idiosyncratic factors, whose estimated standard errors are much smaller than the estimated coefficient, implying that the contribution of each risk factor ("the willingness to pay to eliminate risk") was also statistically significant. The idiosyncratic risk factor dominates the aggregate risk factor, accounting for 99.7% of the total welfare cost. This is because the estimate for idiosyncratic shocks ($\hat{\sigma}^I$) is much larger than that for aggregate shocks ($\hat{\sigma}^A$). The point estimate underlying Table 11, part 1.1 is: $\hat{\sigma}^I$=0.29765 and $\hat{\sigma}^A$=0.00102. Both aggregate and idiosyncratic risk costs are higher in rural Sindh than in rural Punjab.

Replacing the national aggregate risk by the regional aggregate risk or introducing heterogeneity in expected growth rates and $\hat{\sigma}^I_i$ does not alter the results qualitatively. Since the aggregate consumption growth rates in rural Sindh were more volatile than in rural Punjab (see Table 1), the assumption of the regional aggregate risk results in higher share of aggregate risk cost in the overall risk cost in rural Sindh. Even then, the contribution of the aggregate risk factor is less than 1%. Therefore, PRHS households in Pakistan are subject to high variability in consumption, mostly due to idiosyncratic shocks.[22]

Table 12 investigates whether the welfare cost of risk differs according to explanatory variables adopted in Tables 7-10. In interpreting Table 12, it should be noted that the regional (socio-economic) contrasts in Table 12 are different from those among similar variables in Tables 7-10. In Tables 7-10, the regression coefficient shows partial correlation of each of these variables with a particular measure of vulnerability. In Table 12, the reported numbers show bivariate correlation of each variable with the estimated welfare cost of risk. Therefore, for example, even though the initial household size was never significant in Tables 8-10, it shows a significant difference of the welfare cost of risk depending on the household size in Table 12, since the household size is correlated with other household-level variables.

Among different comparisons, the regional contrast is the clearest: Northern Punjab is the least vulnerable, followed by Southern Punjab, and Sindh is the most vulnerable to risk.

[22] However, a reservation similar to footnote 16 applies here as well.

The difference is statistically significant at the 1% level.

Physical assets are weakly correlated with the aggregate risk cost while they are negatively and strongly correlated with the idiosyncratic risk cost. Landless, livestock-poor, or durable asset-poor households are more vulnerable to idiosyncratic shocks than landed, livestock-rich, or asset-rich households (the difference is statistically significant at 1%), consistent with findings of risk-aversion heterogeneity among Pakistani farmers by Kurosaki and Fafchamps (2002). The contrast in landholding is clearer than suggested by Tables 7-10.

In contrast, income sources, credit access, and education of household heads matter in the bivariate comparison of the welfare loss due to idiosyncratic shocks not as strong as asset variables do. These variables are associated with the welfare cost of aggregate risk more significantly. The finding that landed and educated households absorbed more of the welfare cost of aggregate risk than other households seems consistent with the theory of efficient risk-sharing when households are heterogenous in their capacity to bear risk (Kurosaki, 2001). Under such settings, the efficient resource allocation requires that the consumption of households who are more able to bear risk should be more responsive to the aggregate income shock than that of other households, because such households serve as an implicit insurer. Two dummy variables for remittance and formal credit access are associated with low exposure to idiosyncratic risk and the difference was statistically significant at 1%. This is consistent with the view that access to credit and remittance outside villages contribute to consumption smoothing.

Among demographic characteristics, the impact of female household head is not shown in the table since the number of female headed households is too small, and the impact of female ratios is not shown since this variable was not significant at all. The dependency ratio is associated with larger aggregate risk cost but not associated with idiosyncratic risk cost, in contrast to findings in Tables 8-10. Finally, the household size is associated positively to vulnerability both aggregate and idiosyncratic, with the 1% level of statistical significance. Therefore, larger households were found more vulnerable than smaller households.

Table 12 was simulated under the assumption of heterogenous growth rates and heteroskedastic idiosyncratic shocks, with regional estimates for the aggregate risk. When other three specifications in Table 11 were adopted, the regional and socio-economic contrasts become less clear. The socio-economic contrast with respect to the welfare cost of aggregate shocks becomes weaker when homogenous growth rates and homoskedastic idiosyncratic shocks were assumed (corresponding to part 1.1 or 1.2 in Table 11), as expected. However, the results remain qualitatively the same with respect to those socio-economic variables with the 1% level of significance in Table 12. On the other hand, the regional contrast with respect to the welfare cost of aggregate shocks becomes statistically insignificant when the regional estimates for the aggregate risk were replaced by the national estimate (corresponding to part 1.1 or 2.1 in Table 11).

9 Welfare Cost of Risk Using PIHS/PSLM Repeated Cross-Section Data

9.1 Estimating the welfare cost of risk using repeated cross-section data

9.1.1 Overview of the empirical strategy

The analysis in the previous section showed regional and socio-economic contrasts in the welfare loss due to uninsurable risk. However, because the sample size is not very large and geographical coverage was limited to rural Punjab and Sindh, we were not able to obtain the national picture. If we can utilize the PIHS/PSLM data, with a larger number of sample observations, for a vulnerability analysis, our understanding of vulnerability in Pakistan can be enhanced substantially.

In general, most of the existing vulnerability measures attempt to quantify or to approximate the welfare cost of risk using panel data of individual-level consumption. Therefore, data requirement often inhibits the applicability of vulnerability measures, because the existing panel datasets from developing countries are either small in the cross-section sample size and geographical coverage (e.g., India's ICRISAT data) or short in the time-series sample size (e.g., LSMS two-period panel data from Peru, Vietnam, or Cote d'Ivore). To overcome this difficulty, there have been several methodologies proposed, in which a variant of vulnerability measures is estimated from cross-section or repeated cross-section datasets. For instance, Chaudhuri et al. (2002) propose a framework to estimate the probability for future consumption to fall below the poverty line using cross-section data, and they apply the framework to Indonesian data. However, their methodology is based on a highly *ad hoc* assumption that the time-series variance of individual-level consumption is similar to its cross-section variance in a period. This assumption is hard to be justified because the larger cross-section variance around the estimated consumption levels may simply suggest that the cross-section model does not capture the underlying data generating process.

On the other hand, Ligon (2008a) presents a methodology to estimate a version of the vulnerability measure proposed by Ligon and Schechter (2003). An advantage of Ligon's (2008a) measure is that the time-series variance of individual-level consumption is not the same as its cross-section variance and can be estimated from repeated cross-section data of households. In addition, Ligon (2008a) shows that this methodology can be related to Atkinson's (1970) family of inequality measures, which is another advantage of this methodology. From these reasons, this paper attempts to apply and extend Ligon's (2008a) methodology for the case of Pakistan to estimate the welfare cost of risk. A cost of Ligon's (2008a) measure is that a restrictive assumption is required on the dynamics structure of individual-level consumption, i.e., the future consumption is determined by the current consumption multiplied by the aggregate growth rate and idiosyncratic shocks, which are orthogonal not only to the aggregate growth rate but also to the household's initial consumption level.

We start with the model in Section 8. Our goal is to quantify the welfare loss due to risk factors that would happen between period $t-1$ (one of the PIHS/PSLM years) and t (the round of the PIHS/PSLM after the first one), looking from period $t-1$. Therefore, the decomposition is the same as (9), which results in equation (12) under the assumption of the risk (inequality) aversion parameter γ of two. Three parameters remain to be specified: μ_{it} (expected growth rate of consumption), σ_i^I (variance of the idiosyncratic innovation to consumption), and σ^A (variance of the aggregate risk). Regarding σ^A, the values calibrated in Section 8 are used. The parameter μ_{it} is estimated as the difference between $\ln \bar{c}_t$ and $\ln \bar{c}_{t-1}$ in the PIHS/PSLM data. We calculate it at the regional level, i.e., provinces distinguished by urban and rural areas. The last parameter to be specified is σ_i^I.

9.1.2 Methodology to estimate the variance of idiosyncratic components of consumption change using repeated cross-section data

Without panel information at the individual level, we need to impose a restriction on the dynamics structure of individual-level consumption. As a starting point, we adopt the permanent income hypothesis with perfect credit markets but with no insurance markets (we call this regime "PIH-UC," where UC stands for "unconstrained in credit markets"). As shown by Deaton (1991) and others, the consumption dynamics at the individual level under PIH-UC should satisfy the following Euler equation:

$$U'(c_{i,t-1}) = E_{t-1}\left[\frac{R_{t-1,t}}{1+\delta}U'(c_{i,t})\right], \tag{14}$$

where $R_{t-1,t}$ is the gross return in the credit market from $t-1$ to t. One of the specifications that approximate the above Euler equation under the assumption of consumption preference (10) is the model of (11) with additional restriction that u_{it} is orthogonal to $\ln c_{i,t-1}$. The additional restriction implies that $\ln c_{it}$ follows a random walk with drift at the rate of the aggregate growth rate.[23] It should be noted that this specification does not assume that individual-level incomes follow a random walk with drift. It is likely that individual incomes are highly autocorrelated. Nevertheless, the consumers' optimization under PIH-UC results in a random walk property of consumption.

[23]Strictly speaking, the aggregate growth rate here is not the same as the aggregate growth rate usually defined as $\ln(\bar{c}_t/\bar{c}_{t-1})$. The aggregate growth rate here is analogous to the cross-section average of $\ln(c_{it}/c_{i,t-1})$.

Given the consumption dynamics of (11), the additional orthogonality condition explained above, the consumption preference of (10), the assumption of homogenous risk and time preference, and the moment generating function for a normal distribution, σ^I can be approximated as[24]

$$\frac{\sigma^I}{2} = \frac{1}{\gamma} \ln \left[\frac{1 - A_{t-1}(1+\gamma)}{1 - A_t(1+\gamma)} \right], \tag{15}$$

where $A(.)$ is Atkinson's inequality measure:

$$A(\alpha) \equiv 1 - \frac{1}{\bar{c}} \left[\frac{1}{n} \sum_i c_i^{1-\alpha} \right]^{\frac{1}{1-\alpha}}, \tag{16}$$

where α is the parameter for society's inequality aversion.

The key relationship implicit in (15) is that the estimate for σ^I is positive only when $A_{t-1}(1+\gamma) < A_t(1+\gamma)$. This is because under PIH-UC with homogenous preference, idiosyncratic income shocks to individuals will be accumulated over time while aggregate shocks are equally shared among all households. In other words, under the PIH-UC regime, we should observe that cross-section consumption variance among households in the same cohort should be increasing over time. In the real data, however, $A_{t-1}(1+\gamma) < A_t(1+\gamma)$ may not hold for some group or for some period. We examine if this is a serious problem in our datasets and thereby examine whether the PIH-UC regime with homogenous preference is a relevant approximation for Pakistan.

9.2 Simulation results

9.2.1 Variance of idiosyncratic components of consumption change

As shown in Table 3, the overall inequality in Pakistan decreased from 1998/99 to 2001/02, then it increased rapidly from 2001/02 to 2004/05. Unlike Ligon's (2008a) variance estimates for Ecuador, which were all positive, three out of six potential periods between two rounds of PIHS/PSLM would be associated with negative estimates for the variance. To avoid the negative estimate for σ^I and to facilitate comparison with Section 8 using the PRHS panel data, the welfare cost of risk is estimated in this section only for the period from 2001/02 to 2004/05.[25] As a policy oriented research, the focus on the period from 2001/02 to 2004/05

[24] This is derived by aggregating the Euler equation across i, using the definition of Atkinson's inequality measures and the law of large numbers. See Appendix in Ligon (2008a).

[25] To test clearly whether or not the PIH-UC assumption is accepted, we need to control for demographic factors, because in the repeated cross-section data, elder households who tend to have larger variance due to the accumulated idiosyncratic shocks are gradually replaced by younger households with smaller variance. If the cohort composition effect is important, $A_{t-1} < A_t$ need not to hold for the whole sample even under PIH-UC. Cohort analysis results show that the dynamics of consumption inequality from 2001/02 to 2004/05 is more compatible with the PIH-UC model than other periods. These results are available on request from the author.

will shed light on questions such as how large was vulnerability throughout Pakistan and which regions were more vulnerable amidst the overall growth and growing inequality.

Table 13 shows the region-wise estimates for growth rates (μ) and variances (σ^I) for the period from 2001/02 to 2004/05. Although the estimate for σ^I is positive for all regions in Pakistan, it is not significantly different from 0 in Sindh. This is because the change in inequality was small in urban Sindh while the inequality in rural Sindh, 2004/05, was estimated with large standard error (Table 3).

9.2.2 Welfare cost of risk

Table 14 reports the estimates for the welfare cost of risk following equation (12) using the repeated cross-section data. When we calculate these figures, we use regional growth rates and regional estimates for σ^I (differentiated by provinces and urban/rural areas). To make the estimates comparable with those in Tables 11-12 of Section 8, only those households whose welfare ratio is smaller than four are included.

The welfare cost of risk is estimated at 0.061, implying that Pakistani consumers would have been willing to collectively sacrifice 6.1% of 2001/02 expenditure to eradicate risk that occurred between 2001/02 and 2004/05. This is a non-negligible number, though we suspect that it is an underestimate (see below). About 98% of this welfare cost of risk is attributable to idiosyncratic shocks.

Region wise, the welfare cost of aggregate risk is the largest in rural Balochistan and rural Sindh, followed by urban Balochistan and urban Punjab. The welfare cost of aggregate risk was estimated to be the smallest in rural Punjab followed by urban Sindh and rural NWFP. Pooling rural and urban areas, residents in NWFP and Punjab are less vulnerable to aggregate risk than those in Sindh and Balochistan. However, these regional contrasts in the welfare cost of aggregate risk are completely dominated by the regional contrasts in that of idiosyncratic risk. The welfare cost of idiosyncratic risk is the largest in urban NWFP, followed by rural Balochistan and rural NWFP. It is the smallest in urban Sindh followed by rural Punjab. The estimated standard errors are generally small, making most of the interesting regional contrast statistically significant as well.

Although the absolute magnitudes of the idiosyncratic risk factor is much smaller than those based on panel data (Table 11) and those estimated for Ecuador (Ligon, 2008a), the contrast across regions within Pakistan shown in Table 14 confirms the expectation as a whole. The idiosyncratic risk factor is more important than the aggregate risk factor. Economically smaller and more backward provinces of Balochistan and NWFP are more vulnerable to idiosyncratic risk than Sindh and Punjab.

9.3 Comparison with the results using the PRHS panel data

The welfare costs of risk for rural Punjab and rural Sindh in Table 14 are directly comparable with those in Table 11. The estimates for aggregate risk are very similar between the two tables, because we use the same estimates for σ^A (variance of the aggregate risk). It is striking to see that the estimates for idiosyncratic risk in Table 14 are smaller than those in Table 11 by the factor of five. This is because the estimates for σ^I (variance of the idiosyncratic innovation to consumption) associated with Table 14 are much smaller than those associated with Table 11 (see the first and the second part of Table 15).

To examine whether the difference was due to data (the period coverage as well as the representativeness of each dataset are different), we apply the methodology in this section to the PRHS panel dataset, ignoring its panel information. The key parameter σ^I is now estimated using equation (15) and cross-section inequality measures reported in Table 4. If σ^I calculated in this way is close to those reported in the second part of Table 15 and the estimates for the welfare cost of risk do not change much, the difference between the first and the second part of Table 15 should be attributed to the difference in data, not to the difference in methodology.

The results are reported in the third part of Table 15. The welfare cost of aggregate risk does not change much. In sharp contrast, the welfare cost of idiosyncratic risk becomes much smaller by the factor of 2.1. This is because σ^I is underestimated when panel information is not utilized: the estimates based on differences in Atkinson's inequality measures were around 0.135. In contrast, when we calculate the variance of $\ln c_{it} - \ln c_{i,t-1}$ using the panel information, we obtained the estimate at 0.297. Therefore, the repeated cross-section data approach underestimates the vulnerability due to the idiosyncratic risk factor and the bias is substantial. This bias occurs because the idiosyncratic innovation to log consumption in the actual data is not orthogonal to the initial level of consumption. Particularly, the pattern shows mean-reversion of consumption at the individual level. This is not consistent with the PIH-UC assumption.

Since the idiosyncratic variance (σ^I) is underestimated by the factor of 2.2, we re-simulate the welfare cost of risk using the PIHS/PSLM data, with σ^I inflated by 2.2 for both rural Punjab and rural Sindh. As expected, this adjustment increases the estimates for the welfare cost of idiosyncratic risk. The difference between the second and the fourth part of Table 15 might have been attributed to the difference in the period and geographic coverage.

With the same spirit, the welfare costs of risk in Table 15 were re-simulated with σ^I inflated by the factor of 2.2 for all regions in Pakistan. The results are reported in Table 16.

The regional contrast as well as the relative magnitudes of aggregate and idiosyncratic factors remain qualitatively the same. The re-simulation makes the results more consistent with findings from Section 8. In absolute terms, the welfare cost of total risk is now estimated at 0.133 (Pakistani consumers would have been willing to collectively sacrifice 13.3% of 2001/02 expenditure to eradicate risk that occurred between 2001/02 and 2004/05). Judging from the comparison with results in Section 8 and findings in the existing studies on Pakistani economy, we conclude that Table 16 would have been closer to the reality than Table 14.[26]

A serious caveat of Table 16 is that there is no theoretical reason to apply the same inflating factor to all regions of Pakistan. The estimate for σ^I is underestimated if estimated using equation (15) because the idiosyncratic innovation to log consumption is not orthogonal to the initial level of consumption (violation of the PIH-UC model with homogenous preference). There is no *a priori* reason to believe that the level of divergence from the PIH-UC assumption is similar across Pakistan. Furthermore, as shown in Table 3, three out of six time differences in the four rounds of the PIHS/PSLM data were associated with a decrease in inequality. A cohort analysis shows that this anomaly cannot be due to the changes in age composition in the sample and that there were periods and regions with a decrease in inequality, some of which were statistically significant.[27]

These results thus suggest that the applicability of the PIH-UC model to Pakistan is not very high. For a more comprehensive vulnerability analysis covering other sub-periods and using regional parameters for regional decomposition, a more flexible model of households' consumption dynamics is required. In the literature, four important models have been proposed, between the two extreme cases of the model of full risk-sharing (or Arrow-Debreu complete markets model) and the model of autarky with no saving technology. The first is the PIH-UC model. The second model, which is a straightforward extension of the PIH-UC model in the direction of the autarky model, is to incorporate credit constraints (e.g., Deaton, 1991). Between the two polar cases of the full risk-sharing model and the autarky model also lie models of risk-sharing under private information (Ligon, 1998) and risk-sharing with limited commitment (Ligon et al., 2002). Another dimension that should affect consumption dynamics is the possibility of mis-specification of preferences. As Deaton and Paxson (1994) pointed out, the prediction that the inequality in consumption increases with age is based on the assumption that preferences across individuals and across the family cycle are homogenous. When heterogeneity is allowed, we cannot obtain an unambiguous

[26] As another robustness check, a subset of households that belonged to the same cohort groups was used to re-estimate Tables 14 and 16. The results were very similar to Tables 14 and 16, but the risk contribution slightly larger (not reported). Therefore, the decomposition results for the period from 2001/02 to 2004/05 are robust.

[27] See footnote 25.

prediction regarding the relation between inequality and age. Some of the anecdotal observations from Pakistan are compatible with predictions from some of these models while other observations are compatible with predictions from other models. Exploring for the appropriate microeconomic model for Pakistani consumers is thus left for further research.

10 Summary and Conclusion

In Pakistan, what kind of households are vulnerable and how are they vulnerable? This question was investigated in this paper using two-period panel data (PRHS: surveyed in 2001 and 2004) and four rounds of nationally-representative, repeated cross-section data (PIHS/PSLM in 1998/99, 2001/02, 2004/05, and 2005/06). Since vulnerability is a concept closely associated with changes in welfare status, most of vulnerability measures proposed in the literature have been applied to panel data, using direct information on consumption changes at the individual level. From these measures, five were applied to the PRHS panel data: (i) transient poverty components of observed poverty, (ii) decline in consumption levels, (iii) sensitivity of consumption changes to village-level shocks, (iv) the variance of consumption changes, and (v) the welfare cost of risk simulated under a specific form of utility function. Among them, the last measure can be estimated from repeated cross-section data if additional restrictions that correspond to the permanent income hypothesis with perfect credit markets are employed. This methodology was applied to the PIHS/PSLM repeated cross-section data for the period from 2001/02 to 2004/05.

The empirical results are summarized in Table 17, which shows whether a particular correlate is vulnerability-increasing or vulnerability-reducing. The most important physical assets in Pakistan, i.e., farmland, livestock, and durable goods, are vulnerablity-reducing in general. The landed households, however, may have difficulty in catching up with the macroeconomic growth rate in a boom. Access to non-farm employment is vulnerablity-reducing. In contrast, access to credit and remittance has mixed effects, probably due to the reverse causality that households hit by adverse shocks seek credit (remittance) more eagerly. Education was not significantly correlated with vulnerability, but when it was, the direction was to increase vulnerability. This could be because the welfare level of educated households is higher than uneducated households in general, resulting in larger room for consumption curtailment when hit by an adverse shock, as demonstrated by Kurosaki (2006a) for households in rural NWFP. Households with more dependent members are less vulnerable, suggesting the existence of an informal social support or implicit contract for households with more children. Larger households suffer from a larger welfare cost of risk than smaller households do.

In rural areas covered by the PRHS surveys, Sindh was found to be more subject to various types of vulnerability than Northern Punjab, with Southern Punjab in between. Across the country, however, residents in NWFP and Balochistan suffer a larger cost of welfare loss due to risk, making the difference between rural Sindh and rural Punjab a minor one, and urban residents in Punjab and Sindh are less subject to vulnerability than all others, although we have to be careful since the regional contrasts in vulnerability across Pakistan are not based on panel data. To estimate the welfare cost of risk from repeated cross-section data, we imposed restrictions that correspond to the permanent income hypothesis with perfect credit markets and homogenous preference, but the dynamics of consumption inequality is not wholly consistent with these restrictions. The regional contrast between rural Punjab and rural Sindh shows that the divergence from the PIH-UC regime is more frequent in rural Sindh, where financial development is lagging behind Punjab. This could be the reason for higher vulnerability of Sindh villagers than of Punjab villagers. Rigorous tests to identify the regime characterizing consumption dynamics are left for further research.

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Figure 1. Trends in mean consumption (green: right axis), poverty (red), and inequality (blue) in Pakistan

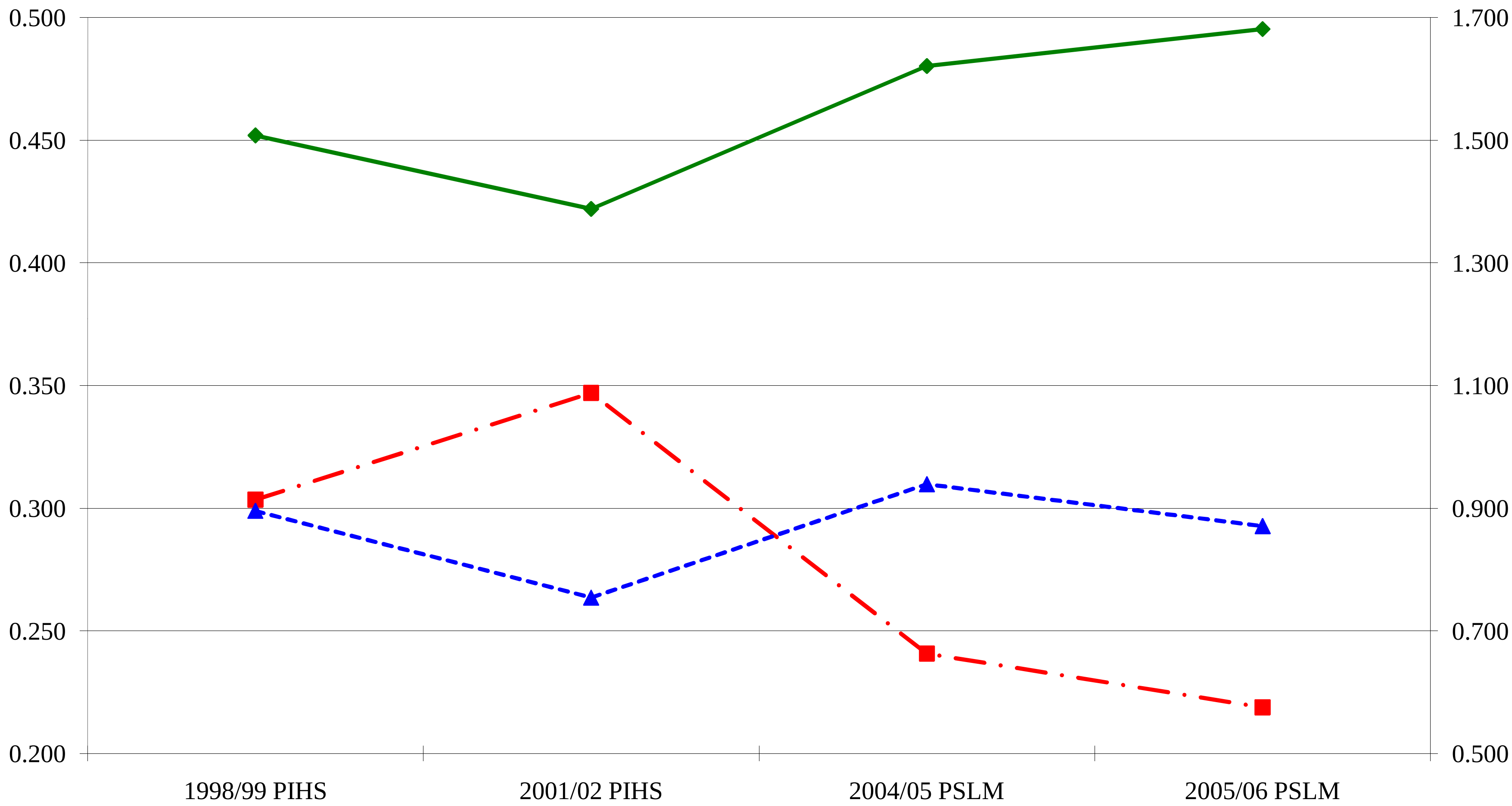

Figure 2. Regional disparity in poverty headcount ratio, Pakistan, 2004/05 PSLM

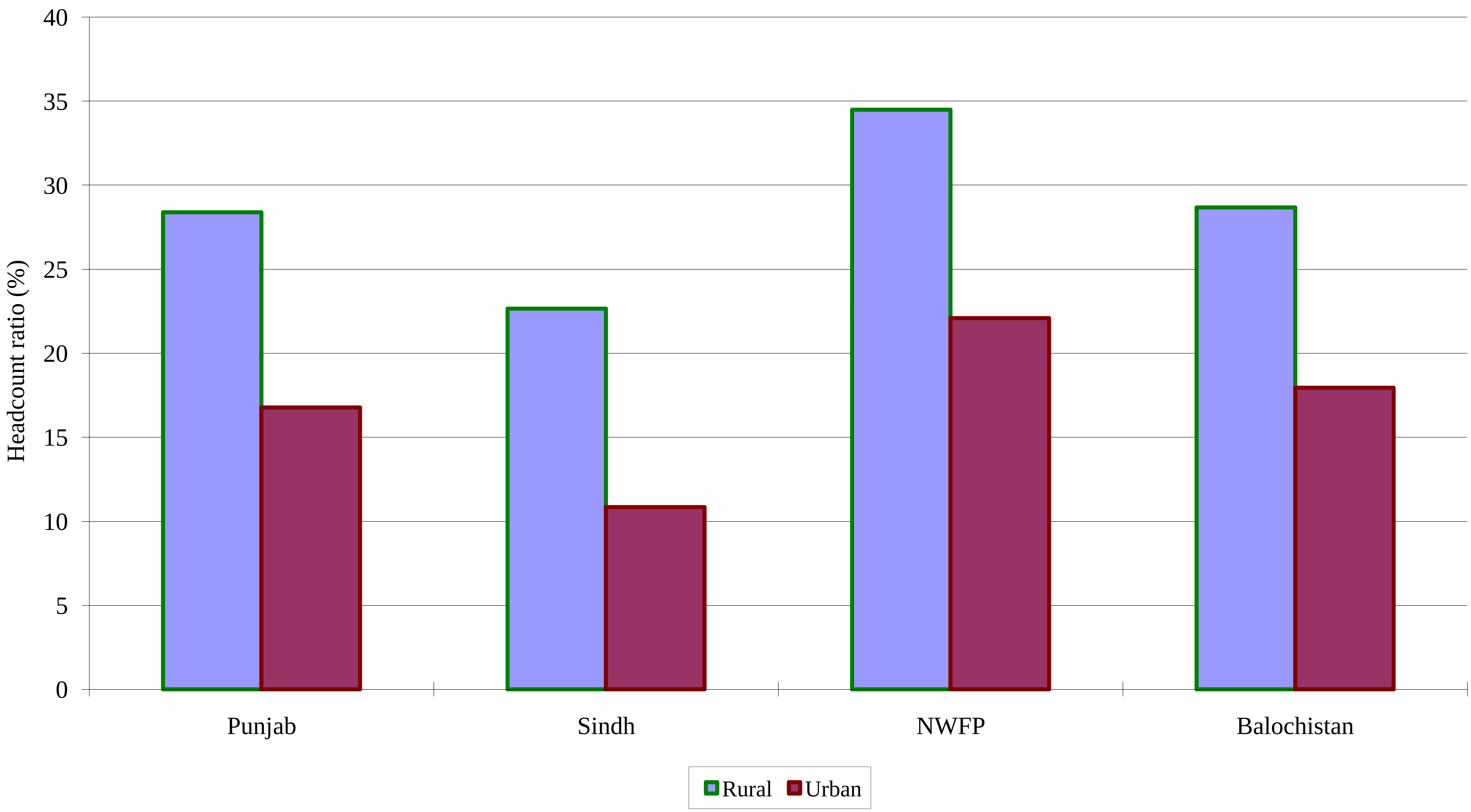

Figure 3. Distribution of the welfare ratio, Pakistan

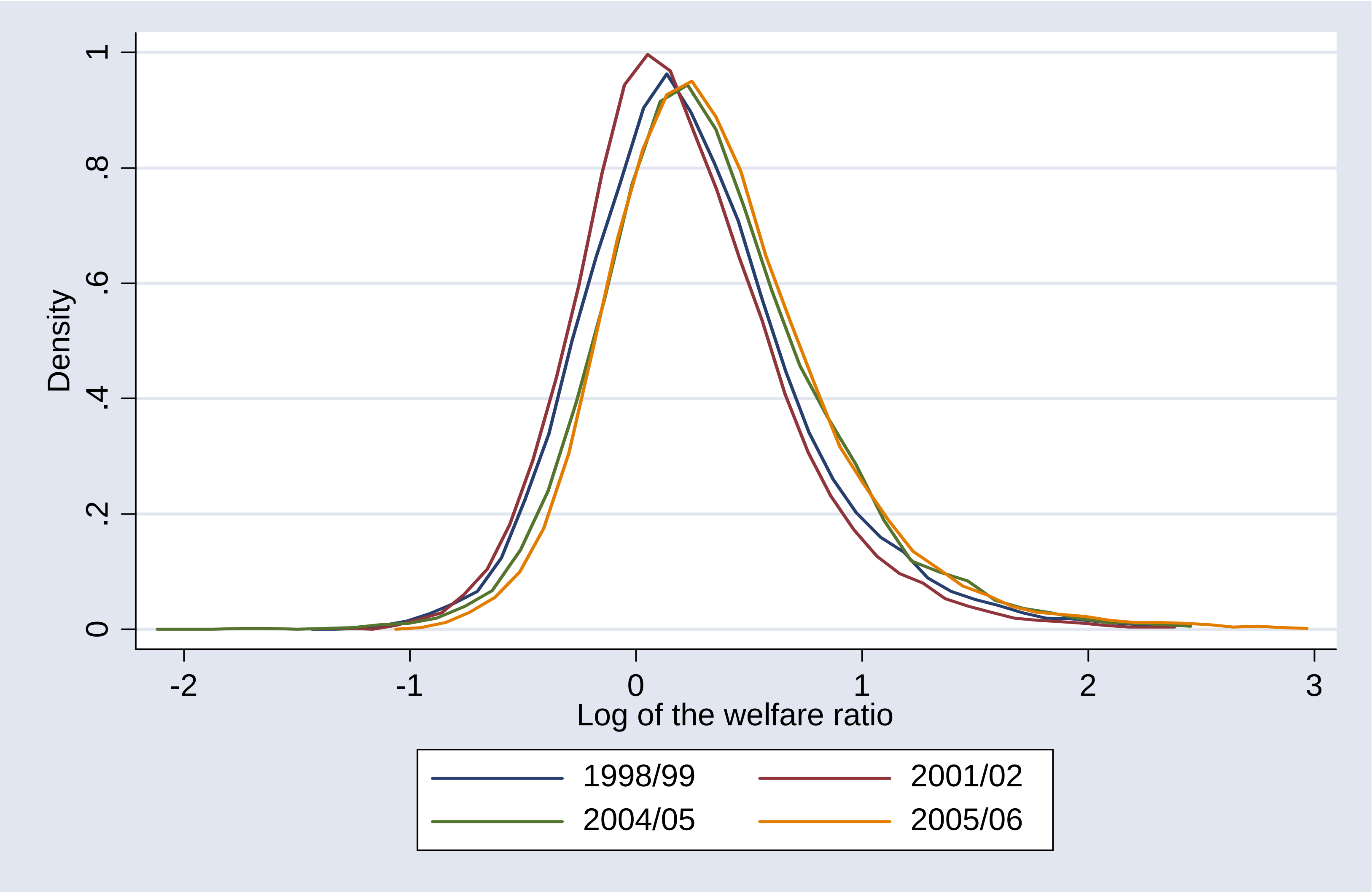

Table 1. Mean expenditures in Pakistan

	1998/99PIHS	2001/02PIHS	2004/05PSLM	2005/06PSLM
All Pakistan				
Number of sample households	14,670	14,705	14,704	15,439
Nominal monthly expenditure	1,016	1,004	1,424	1,588
per capita (Rs.)	(799)	(685)	(1,055)	(1,278)
Welfare ratio	**1.508**	**1.388**	**1.621**	**1.681**
	(1.187)	(0.947)	(1.200)	(1.353)
By regions (mean of welfare ratio only)				
Punjab	**1.529**	**1.432**	**1.637**	**1.764**
Urban	1.942	1.676	2.008	2.216
Rural	1.362	1.333	1.468	1.550
Sindh	**1.597**	**1.407**	**1.757**	**1.723**
Urban	1.966	1.866	2.217	2.162
Rural	1.314	1.113	1.414	1.294
NWFP	**1.291**	**1.222**	**1.373**	**1.477**
Urban	1.762	1.490	1.779	1.798
Rural	1.209	1.176	1.292	1.418
Balochistan	**1.464**	**1.239**	**1.410**	**1.130**
Urban	1.536	1.454	1.739	1.383
Rural	1.453	1.194	1.325	1.051

Notes: Numbers in parenthesis show standard deviations. Both means and standard deviations are weighted to reflect the sampling probability and difference in household sizes so that the estimated figures are unbiased estimates for the national (regional) means among individuals.

Source: Calculated by the author from the PIHS/PSLM data.

Table 2. FGT poverty measures based on expenditures in Pakistan

	1998/99PIHS	2001/02PIHS	2004/05PSLM	2005/06PSLM
All Pakistan				
Headcount index	**0.304**	**0.347**	**0.241**	**0.219**
	(0.00860)	(0.00883)	(0.00834)	(0.00787)
Poverty gap index	0.0638	0.0712	0.0478	0.0385
	(0.00266)	(0.00268)	(0.00223)	(0.00232)
Squared poverty gap index	0.0198	0.0217	0.0149	0.0105
	(0.00116)	(0.00110)	(0.00094)	(0.00095)
Headcount index by regions				
Punjab	**0.304**	**0.315**	**0.247**	**0.181**
Urban	0.239	0.234	0.168	0.121
Rural	0.330	0.348	0.284	0.210
Sindh	**0.259**	**0.372**	**0.176**	**0.213**
Urban	0.149	0.203	0.108	0.115
Rural	0.343	0.480	0.227	0.310
NWFP	**0.413**	**0.422**	**0.324**	**0.273**
Urban	0.261	0.304	0.221	0.236
Rural	0.439	0.443	0.345	0.280
Balochistan	**0.215**	**0.370**	**0.265**	**0.508**
Urban	0.245	0.273	0.179	0.324
Rural	0.211	0.390	0.287	0.566

Notes: All poverty measures are weighted to reflect the sampling probability and difference in household sizes so that the estimated figures are unbiased estimates for the national (regional) poverty measures. Robust standard errors reflecting PSU are reported in parenthesis.

Source: Calculated by the author from the PIHS/PSLM data.

Table 3. Atkinson's inequality measures in Pakistan

	1998/99PIHS	2001/02PIHS	2004/05PSLM	2005/06PSLM
All Pakistan	**0.299**	**0.264**	**0.310**	**0.293**
	(0.0050)	(0.0037)	(0.0074)	(0.0046)
By regions				
Punjab	**0.309**	**0.271**	**0.313**	**0.293**
	(0.0076)	(0.0055)	(0.0061)	(0.0059)
Urban	0.403	0.329	0.370	0.365
	(0.0119)	(0.0127)	(0.0096)	(0.0098)
Rural	0.249	0.239	0.268	0.233
	(0.0066)	(0.0066)	(0.0069)	(0.0073)
Sindh	**0.308**	**0.295**	**0.324**	**0.302**
	(0.0078)	(0.0078)	(0.0230)	(0.0082)
Urban	0.335	0.343	0.356	0.345
	(0.0114)	(0.0126)	(0.0116)	(0.0118)
Rural	0.239	0.193	0.243	0.176
	(0.0109)	(0.0055)	(0.0331)	(0.0062)
NWFP	**0.254**	**0.189**	**0.262**	**0.233**
	(0.0112)	(0.0060)	(0.0191)	(0.0071)
Urban	0.376	0.258	0.350	0.331
	(0.0209)	(0.0116)	(0.0244)	(0.0139)
Rural	0.219	0.171	0.233	0.209
	(0.0120)	(0.0071)	(0.0222)	(0.0072)
Balochistan	**0.211**	**0.163**	**0.238**	**0.227**
	(0.0099)	(0.0052)	(0.0118)	(0.0102)
Urban	0.243	0.221	0.285	0.237
	(0.0201)	(0.0127)	(0.0249)	(0.0116)
Rural	0.206	0.146	0.214	0.207
	(0.0103)	(0.0055)	(0.0145)	(0.0123)

Notes: The inequality aversion parameter for Atkinson's inequality measure is set at 3. Bootstrapped standard errors are reported in parenthesis.

Source: Calculated by the author from the PIHS/PSLM data.

Table 4. Poverty and inequality measures based on expenditures in the PRHS panel data

	PRHS-I (2001)	PRHS-II (2004)
1. Poverty Measures		
Sum of Punjab and Sindh (rural only)		
Headcount index	**0.372**	**0.259**
	(0.01381)	(0.01278)
Poverty gap index	0.0950	0.0680
	(0.00475)	(0.00434)
Squared poverty gap index	0.0354	0.0260
	(0.00233)	(0.00215)
Headcount index by regions		
Rural Punjab	**0.272**	**0.207**
	(0.01675)	(0.01511)
Rural Sindh	**0.490**	**0.318**
	(0.02188)	(0.02088)
Ratio: Sindh/Punjab	1.800	1.537
2. Atkinson inequality measures		
Sum of Punjab and Sindh (rural only)	**0.359**	**0.425**
	(0.0120)	(0.0122)
By regions		
Rural Punjab	**0.357**	**0.438**
	(0.0169)	(0.0184)
Rural Sindh	**0.305**	**0.392**
	(0.0155)	(0.0150)

Notes: The inequality aversion parameter for Atkinson's inequality measure is set at 3. Conventional standard errors are reported in parenthesis for poverty measures, while bootstrapped standard errors are reported in parenthesis for inequality measures.

Source: Calculated by the author from the PRHS panel data.

Table 5. Poverty transition in the PRHS panel data

Status in PRHS-I (2001)	Status in PRHS-II (2004) Below *z*	Above *z*	Total
Punjab and Sindh pooled			
Number of sample households			
Below *z*	182	342	524
Above *z*	176	909	1,085
Total	358	1,251	1,609
Transition probability (%)			
Below *z*	34.7	65.3	100.0
Above *z*	16.2	83.8	100.0
Rural Punjab			
Number of sample households			
Below *z*	77	138	215
Above *z*	89	625	714
Total	166	763	929
Transition probability (%)			
Below *z*	35.8	64.2	100.0
Above *z*	12.5	87.5	100.0
Rural Sindh			
Number of sample households			
Below *z*	105	204	309
Above *z*	87	284	371
Total	192	488	680
Transition probability (%)			
Below *z*	34.0	66.0	100.0
Above *z*	23.5	76.5	100.0

Note: "*z*" is the poverty line estimated by the World Bank research group following the procedure explained in footnote 5.

Source: Calculated by the author from the PRHS panel data.

Table 6. Summary statistics of empirical variables used in regression analyses

Variable	Definition	NOB	Mean	Std.Dev.	Min	Max
Dependent variable						
transpov	Value of transient poverty using Clark=Watts poverty measure with parameter -2.	1,293	0.116	0.309	0	4.747
dlnc	Log difference of the welfare ratio between PRHS-I and PRHS-II.	1,293	0.169	0.606	-1.767	2.299
resfitsq	Square of the fitted residual from regressing dlnc on the explanatory variables.	1,241	0.275	0.369	0.000	3.190
Explanatory variables: Household characteristics						
landacre	Size of farmland owned by the household (acres).	1,293	4.947	11.679	0	102
livslrg	Number of large livestock animals owned by the household.	1,293	2.496	3.019	0	21
livssml	Number of sheep and goats owned by the household.	1,293	1.816	3.935	0	50
assets	Value of assets (durable consumption goods, transportation equipment, house buildings, etc.) owned by the household (Rs.1,000).	1,293	20.000	56.992	0	2001
nfe_perm	Number of male household members who were employed permanently by the private sector, government, or police.	1,293	0.239	0.561	0	5
nfe_casl	Number of male household members who were employed in non-farm activities on daily or contract basis.	1,293	0.429	0.742	0	4
remit	Dummy for a household who received remittances from family members living separately.	1,293	0.055	dummy	0	1
cc_fml	Dummy for a household who were constrained to the formal credit access.#	1,290	0.682	dummy	0	1
cc_inf	Dummy for a household who were constrained to the informal credit access.#	1,290	0.101	dummy	0	1
head_age	Age of household head (years).	1,293	47.639	14.283	14	99
head_sch	Education level of household head (completed years of schooling).	1,243	2.791	3.849	0	21
head_fem	Dummy for a female-headed household.	1,293	0.018	dummy	0	1
femratio	The ratio of females in the household size.	1,293	0.482	0.143	0	1
depratio	The ratio of dependent members (aged <15 and >60) in the household size.	1,293	0.476	0.186	0	1
popwt1	Household size (Nos.).	1,293	8.957	4.443	1	42
Explanatory variables: Village-level agricultural production shocks						
drought	Index variable* for crop damage due to drought in Kharif 2003 and Rabi 2003/04.	1,293	2.447	2.430	0	8
flood	Index variable* for crop damage due to flood in Kharif 2003 and Rabi 2003/04.	1,293	0.481	1.511	0	8
pest	Index variable* for crop damage due to pest attack in Kharif 2003 and Rabi 2003/04.	1,293	2.165	2.461	0	8

Notes: #Households were regarded as constrained if they needed to borrow from the formal (informal) sector and applied to the loan but rejected; or, if they needed to borrow from the formal (informal) sector but did not apply to the loan because the credit institutions are too far away, no guarantee available, no collateral, too much procedures, etc. The corresponding period for the formal loan is "ever until 2000/01" while that for the informal loan is "during 2000/01".

*The sum of index variables for the two seasons. Each variable takes 0 ("No effect": no report for the crop damage), 1 ("Little effect": yield loss up to 10%), 2 ("Moderate": 10-25% loss), 3 ("Severe": 25-50% loss), and 4 ("Disaster": more than 50% loss). Therefore, the combined variable takes an integer values from 0 (no report for the crop damage in both seasons) to 8 (more than 50% loss in both seasons).

(1) The subsample used in the regression analyses is those households whose welfare ratio was smaller than four in both PRHS-I and PRHS-II and whose size changed by less than or equal to three persons during the two surveys. Because of this selection, the number of househlds in this table is at most 1,293, against 1,609 in Table 5.

(2) Means and standard deviations (Std.Dev.) are weighted by the household size in PRHS 1 in order to obtain individual-level summary statistics.

(3) All household-level variables are taken from the PRHS-I dataset, except for "remit", which corresponds to the remittance receipt in the agricultural year of 2003/04.

Source: Calculated by the author from the PRHS panel data.

Table 7. Correlates of transient poverty

	Dependent variable: *transpov* (value of transient poverty score based on Clark=Watts poverty measure)								
	(i) With village f.e., weight=PRHS-I			(ii) With village f.e., weight=PRHS-II			(iii) With regional f.e., weight=PRHS-I		
Explanatory variables	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.
landacre	-0.00131	*	(0.00068)	-0.00138	**	(0.00070)	-0.00157	**	(0.00070)
livslrg	-0.00985	***	(0.00251)	-0.01026	***	(0.00257)	-0.01314	***	(0.00306)
livssml	0.00211		(0.00221)	0.00206		(0.00222)	0.00048		(0.00202)
assets	-0.00007		(0.00006)	-0.00006		(0.00006)	-0.00003		(0.00006)
nfe_perm	0.02642		(0.01640)	0.02470		(0.01688)	0.01895		(0.01652)
nfe_casl	0.00696		(0.01283)	0.00683		(0.01363)	-0.00168		(0.01440)
remit	-0.04226		(0.02601)	-0.04596	*	(0.02592)	-0.04518	**	(0.02182)
cc_fml	0.03093	*	(0.01663)	0.03118	*	(0.01733)	0.03209	**	(0.01603)
cc_inf	0.04527		(0.03353)	0.04199		(0.03371)	0.03198		(0.02861)
head_age	-0.00134	*	(0.00071)	-0.00139	*	(0.00075)	-0.00098		(0.00074)
head_sch	-0.00288		(0.00218)	-0.00318		(0.00221)	-0.00274		(0.00225)
head_fem	0.03894		(0.04250)	0.04059		(0.04179)	0.03834		(0.04374)
femratio	-0.06614		(0.07900)	-0.06892		(0.08060)	-0.07472		(0.07270)
depratio	0.02720		(0.04752)	0.01030		(0.04963)	0.04013		(0.04660)
popwt1	0.00953	***	(0.00308)	0.00952	***	(0.00322)	0.00872	***	(0.00290)
fixed effects for 94 villages	(jointly significant at 1%)			(jointly significant at 1%)					
South.Punjab dummy							0.00895		(0.01988)
Sindh dummy							0.10836	***	(0.01780)
intercept							0.07181		(0.07026)
F-stat for zero slopes	2.25	***		2.25	***		4.59	***	
R-squared	0.175			0.169			0.068		

Notes: NOB is 1,241 (several households whose "head_sch" was missing were dropped). Estimated by weighted least squares with household size as weights. Huber-White robust standard errors are reported in parenthesis, with * 10%, ** 5%, and *** 1% statistical significance levels.

Source: Estimated by the author from the PRHS panel data.

Table 8. Correlates of changes in consumption

	Dependent variable: *dlnc* (change in log consumption)								
	(i) With village f.e.			(ii) With regional f.e.			(iii) With village f.e., parsimonious specif.		
Explanatory variables	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.
landacre	-0.00680	***	(0.00249)	-0.00822	***	(0.00286)	-0.00832	***	(0.00244)
livslrg	0.00014		(0.00735)	-0.00139		(0.00693)			
livssml	-0.00357		(0.00654)	-0.01048		(0.00638)			
assets	0.00009		(0.00017)	0.00026		(0.00024)			
nfe_perm	0.10056	***	(0.03741)	0.10500	***	(0.03569)	0.07260	**	(0.03651)
nfe_casl	0.01490		(0.02684)	0.00826		(0.02605)			
remit	0.09080		(0.08223)	0.14831	*	(0.07800)	0.10822		(0.08128)
cc_fml	-0.00553		(0.04117)	0.03725		(0.04192)			
cc_inf	0.08434		(0.05843)	0.05756		(0.05863)			
head_age	0.00193		(0.00129)	0.00174		(0.00131)			
head_sch	-0.00210		(0.00499)	0.00197		(0.00527)			
head_fem	0.01436		(0.11046)	-0.01705		(0.10658)			
femratio	-0.13082		(0.12124)	-0.15825		(0.12373)			
depratio	0.20674	**	(0.09116)	0.26091	***	(0.09472)	0.14990	*	(0.08613)
popwt1	-0.00584		(0.00699)	-0.00705		(0.00729)			
fixed effects for 94 villages	(jointly significant at 1%)						(jointly significant at 1%)		
South.Punjab dummy				-0.08555	*	(0.04620)			
Sindh dummy				0.15630	***	(0.04543)			
intercept				0.04195		(0.11375)			
F-stat for zero slopes	3.60	***		3.59	***		4.23	***	
R-squared	0.251			0.079			0.247		

Notes: See notes to Table 7.
Source: Estimated by the author from the PRHS panel data.

Table 9. Sensitivity of consumption changes to village-level agricultural shocks

	Dependent variable: *dlnc* (change in log consumption)								
	(i) Without cross-terms			(ii) With cross-terms with regional dummies			(iii) With cross-terms with hh. characteristics		
Explanatory variables	Coef.		S.E.	Coef.		S.E.	Coef.		S.E.
15 household-level variables	(jointly significant at 1%)			(jointly significant at 1%)			(jointly significant at 1%)		
drought	-0.01632	**	(0.00817)	-0.02944	*	(0.01583)	-0.05768	**	(0.02310)
drought*South.Punjab				0.04043	*	(0.02369)	0.04220	*	(0.02327)
drought*Sindh				0.01157		(0.01872)	0.00881		(0.01799)
drought*depr							0.06414	*	(0.03644)
flood (North.Punjab)	-0.01477		(0.01287)	-0.01770		(0.01277)	0.07924	*	(0.04250)
flood*landacre							0.00186	*	(0.00104)
flood*head_age							-0.00188	**	(0.00092)
flood*head_sch							-0.00613	***	(0.00235)
pest	-0.02014	**	(0.00862)	0.00561		(0.01515)	0.04058	**	(0.01805)
pest*South.Punjab				-0.06048	***	(0.02125)	-0.06373	***	(0.02070)
pest*Sindh				0.00621		(0.04250)	0.00557		(0.04139)
pest*remit							-0.05449	***	(0.01547)
pest*cc_fml							0.05817	**	(0.02506)
pest*cc_inf							-0.07337	**	(0.03043)
intercept	0.19814	*	(0.11013)	0.22631	**	(0.11050)	0.12628		(0.12869)
F-stat for zero slopes	2.71	***		2.75	***		3.59	***	
R-squared	0.069			0.077			0.104		

Notes: See notes to Table 7.
Source: Estimated by the author from the PRHS panel data.

Table 10. Correlates of the variance of consumption changes

Explanatory variables	Dependent variable: *resfitsq* (square of the fitted residual from specification (i) in Table 8)					
	(i) With village f.e.		(ii) With regional f.e.		(iii) With village f.e., parsimonious specif.	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
landacre	-0.00153	(0.00128)	-0.00086	(0.00113)		
livslrg	-0.00435	(0.00406)	-0.00772 **	(0.00382)	-0.00631 *	(0.00390)
livssml	0.00797 *	(0.00406)	0.00787 *	(0.00414)	0.00767 *	(0.00393)
assets	-0.00032 ***	(0.00012)	-0.00028 **	(0.00012)	-0.00031 **	(0.00012)
nfe_perm	-0.00794	(0.02238)	-0.00567	(0.02148)		
nfe_casl	-0.01101	(0.01507)	-0.01749	(0.01460)		
remit	-0.03680	(0.04032)	-0.01958	(0.03839)		
cc_fml	-0.00842	(0.02538)	0.00626	(0.02538)		
cc_inf	-0.00004	(0.03499)	-0.01169	(0.03243)		
head_age	0.00047	(0.00075)	0.00039	(0.00074)		
head_sch	0.00050	(0.00303)	-0.00042	(0.00271)		
head_fem	-0.01604	(0.07597)	0.00598	(0.07347)		
femratio	0.00734	(0.07979)	0.01429	(0.07560)		
depratio	-0.12819 **	(0.05883)	-0.12624 **	(0.05639)	-0.13424 **	(0.05752)
popwt1	-0.00295	(0.00362)	-0.00066	(0.00303)		
fixed effects for 94 villages	(jointly significant at 1%)				(jointly significant at 1%)	
South.Punjab dummy			0.02356	(0.02809)		
Sindh dummy			0.09703 ***	(0.02717)		
intercept			0.28738 ***	(0.06801)		
F-stat for zero slopes	2.63 ***		1.88 ***		2.74 ***	
R-squared	0.134		0.030		0.130	

Notes: See notes to Table 7.
Source: Estimated by the author from the PRHS panel data.

Table 11. Welfare cost of risk from 2001 to 2004, panel data

	From 2001 to 2004				
	Aggregate Risk		Idiosyncratic Risk		
		Share to the total (%)		Share to the total (%)	Total
1. Homogenous growth rates and homoskedastic idiosyncratic shocks					
1.1. National estimate for the aggregate risk					
Sum of Punjab and Sindh (rural)	0.0009	0.3	0.2928	99.7	0.2938
	(0.00001)		(0.00425)		
By regions					
Rural Punjab	0.0008	0.3	0.2560	99.7	0.2568
	(0.00001)		(0.00455)		
Rural Sindh	0.0011	0.3	0.3356	99.7	0.3367
	(0.00002)		(0.00727)		
1.2. Regional estimates for the aggregate risk					
Sum of Punjab and Sindh (rural)	0.0014	0.5	0.2929	99.5	0.2943
	(0.00004)		(0.00425)		
By regions					
Rural Punjab	0.0003	0.1	0.2559	99.9	0.2562
	(0.00001)		(0.00455)		
Rural Sindh	0.0027	0.8	0.3359	99.2	0.3385
	(0.00006)		(0.00728)		
2. Heterogenous growth rates and heteroskedastic idiosyncratic shocks					
2.1. National estimate for the aggregate risk					
Sum of Punjab and Sindh (rural)	0.0009	0.3	0.2984	99.7	0.2994
	(0.00001)		(0.00674)		
By regions					
Rural Punjab	0.0009	0.4	0.2406	99.6	0.2415
	(0.00002)		(0.00652)		
Rural Sindh	0.0010	0.3	0.3674	99.7	0.3684
	(0.00002)		(0.01226)		
2.2. Regional estimates for the aggregate risk					
Sum of Punjab and Sindh (rural)	0.0013	0.4	0.2985	99.6	0.2998
	(0.00004)		(0.00674)		
By regions					
Rural Punjab	0.0003	0.1	0.2406	99.9	0.2409
	(0.00001)		(0.00652)		
Rural Sindh	0.0024	0.7	0.3677	99.3	0.3701
	(0.00006)		(0.01227)		

Notes: Standard errors are reported in parenthesis.
Source: Estimated by the author from the PRHS panel data.

Table 12. Welfare cost and household characteristics

	From 2001 to 2004					
	Aggregate Risk			Idiosyncratic Risk		
	Welfare cost		(std.error)	Welfare cost		(std.error)
Sum of Punjab and Sindh (rural)	0.0013		(0.00004)	0.299		(0.0067)
By regions						
Northern Punjab	0.0003	(ref)	(0.00001)	0.199	(ref)	(0.0076)
Southern Punjab	0.0004	***	(0.00001)	0.286	***	(0.0103)
Rural Sindh	0.0024	***	(0.00006)	0.368	***	(0.0123)
By physical assets						
Landless households ("landacre"=0)	0.0014	(ref)	(0.00005)	0.327	(ref)	(0.0102)
Landed households ("landacre">0)	0.0011	***	(0.00006)	0.272	***	(0.0086)
Hhs with less livestock ("livslrg"<median)	0.0013	(ref)	(0.00005)	0.331	(ref)	(0.0103)
Hhs with more livestock ("livslrg">= median)	0.0013	n.s.	(0.00006)	0.271	***	(0.0087)
Hhs with less asset ("assets"<median)	0.0013	(ref)	(0.00005)	0.317	(ref)	(0.0091)
Hhs with more asset ("assets">=median)	0.0013	n.s.	(0.00006)	0.281	***	(0.0099)
By income sources						
Nonfarm permanent empl. ("nfe_perm"<=median)	0.0013	(ref)	(0.00004)	0.307	(ref)	(0.0076)
Nonfarm permanent empl. ("nfe_perm">median)	0.0012	n.s.	(0.00009)	0.261	**	(0.0139)
Nonfarm casual empl. ("nfe_casl"<=median)	0.0014	(ref)	(0.00005)	0.302	(ref)	(0.0087)
Nonfarm casual empl. ("nfe_casl">median)	0.0011	***	(0.00006)	0.292	n.s.	(0.0102)
No remittance access ("remit"=0)	0.0013	(ref)	(0.00004)	0.302	(ref)	(0.0070)
With remittance access ("remit"=1)	0.0011	*	(0.00013)	0.236	***	(0.0186)
By credit access						
Limited access to formal credit ("cc_fml"=1)	0.0013	(ref)	(0.00005)	0.311	(ref)	(0.0087)
Good access to formal credit ("cc_fml"=0)	0.0013	n.s.	(0.00007)	0.272	***	(0.0101)
Limited access to informal credit ("cc_inf"=1)	0.0009	(ref)	(0.00010)	0.290	(ref)	(0.0228)
Good access to informal credit ("cc_inf"=0)	0.0013	***	(0.00004)	0.299	n.s.	(0.0071)
By education of household heads						
No education ("head_sch=0")	0.0012	(ref)	(0.00005)	0.303	(ref)	(0.0094)
Some education ("head_sch>0")	0.0014	***	(0.00006)	0.293	n.s.	(0.0097)
By demographic characteristics						
Less dependent members ("depratio"<median)	0.0012	(ref)	(0.00006)	0.304	(ref)	(0.0097)
More dependent members ("depratio">=median)	0.0014	**	(0.00005)	0.294	n.s.	(0.0093)
Smaller households ("popwt1"<median)	0.0010	(ref)	(0.00004)	0.264	(ref)	(0.0080)
Larger households ("popwt1">=median)	0.0015	***	(0.00006)	0.322	***	(0.0109)

Notes: Simulated under the assumption of heterogenous growth rates and heteroskedastic idiosyncratic shocks, and regional estimates for the aggregate risk (corresponding to part 2.2 in Table 11). Standard errors are reported in parenthesis. *t*-test results for the equal mean (assuming unequal variance) are shown by asterisks: * 10%, ** 5%, *** 1% statistical significance levels.

Source: Estimated by the author from the PRHS panel data.

Table 13. Growth and variance of consumption expenditure in various regions in Pakistan

	From 2001/02 to 2004/05		
	Growth rates of consumption ("mu")	Variance of idiosyncratic innovation to consumption ("sigma^I")	
All Pakistan	**0.155**	**0.065**	***
By regions			
Punjab	**0.134**	**0.059**	***
Urban	0.180	0.063	***
Rural	0.096	0.040	***
Sindh	**0.222**	**0.043**	
Urban	0.172	0.020	
Rural	0.240	0.064	
NWFP	**0.117**	**0.094**	***
Urban	0.177	0.132	***
Rural	0.095	0.078	***
Balochistan	**0.129**	**0.093**	***
Urban	0.179	0.087	**
Rural	0.104	0.083	***

Notes: Asterisks show that the Atkinson inequality estimates for the two periods, which are used to calculate "sigma^I", are statistically significantly different (*=10%, **=5%, ***=1% level). Two-sample *t* tests on the equality of means allowing for unequal variances were conducted. The *t* tests were based on bootstrap standard errors of Atkinson's inequality measures reported in Table 3.

Source: Estimated by the author from the PIHS/PSLM data.

Table 14. Welfare cost of risk from 2001/02 to 2004/05, repeated cross-section data

	Number of sample households#	From 2001/02 PIHS to 2004/05 PSLM				
		Aggregate Risk		Idiosyncratic Risk		Total
			Share to the total (%)		Share to the total (%)	
All Pakistan	**14,174**	**0.0013**	**2.1**	**0.0599**	**97.9**	**0.0611**
		(0.00001)		(0.00029)		
By regions						
Punjab	**6,032**	**0.0009**	**1.8**	**0.0499**	**98.2**	**0.0509**
		(0.00001)		(0.00030)		
Urban	2,314	0.0023	3.7	0.0601	96.3	0.0624
		(0.00002)		(0.00060)		
Rural	3,718	0.0004	0.9	0.0460	99.1	0.0464
		(0.00000)		(0.00031)		
Sindh	**3,519**	**0.0020**	**3.7**	**0.0524**	**96.3**	**0.0544**
		(0.00002)		(0.00058)		
Urban	1,355	0.0007	3.6	0.0181	96.4	0.0188
		(0.00001)		(0.00020)		
Rural	2,164	0.0028	3.7	0.0729	96.3	0.0757
		(0.00002)		(0.00058)		
NWFP	**2,619**	**0.0009**	**0.9**	**0.1015**	**99.1**	**0.1024**
		(0.00001)		(0.00073)		
Urban	808	0.0018	1.4	0.1305	98.6	0.1323
		(0.00003)		(0.00184)		
Rural	1,811	0.0008	0.8	0.0966	99.2	0.0973
		(0.00001)		(0.00074)		
Balochistan	**2,004**	**0.0027**	**2.8**	**0.0951**	**97.2**	**0.0979**
		(0.00002)		(0.00069)		
Urban	609	0.0024	2.8	0.0832	97.2	0.0856
		(0.00004)		(0.00130)		
Rural	1,395	0.0028	2.8	0.0976	97.2	0.1004
		(0.00002)		(0.00081)		

Notes: Standard errors are reported in parenthesis. # The number of observations is smaller than those used in Tables 1-3 because those households whose welfare ratio is greater than four are excluded, as in Tables 6-12.

Source: Estimated by the author from the PIHS/PSLM data.

Table 15. Comparison of the welfare cost of risk using two different datasets

	From 2001 (2001/02) to 2004 (2004/05)				
	Aggregate Risk		Idiosyncratic Risk		
		Share to the total (%)		Share to the total (%)	Estimates for "sigma^I"
1. Estimated using the PIHS/PSLM repeated cross-section data (Table 14)					
Rural Punjab	0.0004	0.9	0.0460	99.1	0.0399
	(0.00000)		(0.00031)		
Rural Sindh	0.0028	3.7	0.0729	96.3	0.0638
	(0.00002)		(0.00058)		
2. Estimated using the PRHS panel data, with homogenous growth rates/idiosyncratic shocks and regional growth rates (1.2 of Table 11)					
Rural Punjab	0.0003	0.1	0.2559	99.9	0.2966
	(0.00001)		(0.00455)		
Rural Sindh	0.0027	0.8	0.3359	99.2	0.2966
	(0.00006)		(0.00728)		
3. Estimated using the PRHS panel data, but using the methodology of 1.(treating the panel data as if they are repeated cross-section data)					
Rural Punjab	0.0003	0.2	0.1207	99.8	0.1351
	(0.00001)		(0.00216)		
Rural Sindh	0.0028	1.7	0.1604	98.3	0.1344
	(0.00012)		(0.00344)		
4. Estimated using the PIHS/PSLM repeated cross-section data but with "sigma^I" adjusted					
Rural Punjab	0.0004	0.4	0.1011	99.6	0.0878
	(0.00000)		(0.00069)		
Rural Sindh	0.0027	1.6	0.1604	98.4	0.1404
	(0.00002)		(0.00129)		

Notes: Standard errors are reported in parenthesis.

Source: Estimated by the author from the PRHS panel data and the PIHS/PSLM data.

Table 16. Welfare cost of risk, repeated cross-section data
(Adjusted for underestimation of the variance of idiosyncratic innovation to consumption)

	From 2001/02 PIHS to 2004/05 PSLM				
	Aggregate Risk		Idiosyncratic Risk		Total
		Share to the total (%)		Share to the total (%)	
All Pakistan	**0.0012**	**0.9**	**0.1318**	**99.1**	**0.1330**
	(0.00001)		(0.00064)		
By regions					
Punjab	**0.0009**	**0.8**	**0.1099**	**99.2**	**0.1108**
	(0.00001)		(0.00065)		
Urban	0.0022	1.6	0.1324	98.4	0.1346
	(0.00002)		(0.00131)		
Rural	0.0004	0.4	0.1011	99.6	0.1015
	(0.00000)		(0.00069)		
Sindh	**0.0019**	**1.6**	**0.1153**	**98.4**	**0.1172**
	(0.00002)		(0.00128)		
Urban	0.0007	1.7	0.0399	98.3	0.0406
	(0.00001)		(0.00044)		
Rural	0.0027	1.6	0.1604	98.4	0.1631
	(0.00002)		(0.00129)		
NWFP	**0.0009**	**0.4**	**0.2235**	**99.6**	**0.2244**
	(0.00001)		(0.00161)		
Urban	0.0017	0.6	0.2878	99.4	0.2895
	(0.00002)		(0.00405)		
Rural	0.0007	0.3	0.2127	99.7	0.2134
	(0.00001)		(0.00164)		
Balochistan	**0.0026**	**1.2**	**0.2095**	**98.8**	**0.2121**
	(0.00002)		(0.00153)		
Urban	0.0023	1.2	0.1832	98.8	0.1855
	(0.00004)		(0.00287)		
Rural	0.0026	1.2	0.2150	98.8	0.2177
	(0.00002)		(0.00178)		

Notes: Standard errors are reported in parenthesis. The welfare cost of risk is simulated after the regional "sigma^I" in Table 12 is multiplied by 2.2.

Source: Estimated by the author from the PIHS/PSLM data.

Table 17. Summary of vulnerability measurement

	Measure of vulnerability					
	Partial impact#				Total impact#	
	Transient poverty	Change in consump-tion level	Sensitivity of consump-tion to flood, drought, pest attacks	Variance of consump-tion changes	Welfare cost of aggregate risk	Welfare cost of idiosyn-cratic risk
Regional contrast: reference=Northern Punjab, rural						
Southern Punjab, rural		-	+ (drought), - - (pest)		- -	- -
Sindh, rural	-	++		- -	- -	- -
Regional contrast: reference=All Pakistan						
Punjab, urban					-	+
Punjab, rural					++	+
Sindh, urban					+	++
Sindh, rural					- -	-
NWFP, urban					-	- -
NWFP, rural					+	- -
Balochistan, urban					-	-
Balochistan, rural					- -	- -
Wealth effect						
Farmland	++	- -	++		++	++
Livestock (large animals)	++			+		++
Durable assets				++		++
Access to non-farm or outside income sources						
Nonfarm permanent empl.		++				+
Nonfarm casual empl.					++	
Remittance	+		- -		+	++
Credit access						
Formal credit	-		- -			+
Informal credit			++		- -	
Education of household head			- -		-	
Demographic characteristics						
Head's age			- -			
More dependent members		++	+	++	-	
Larger households	- -				- -	- -

Notes: "++" ("+") means that the row variable is vulnerability-reducing strongly (weakly) when the vulnerability is measured by the column variable. "- -" ("-") means that the row variable is vulnerability-increasing strongly (weakly).

"Partial impact" shows an effect when only the row variable is changed with other row variables remaining constant (*ceteris paribus* assumption). "Total effect" shows the bi-variate relation between the row variable and the column vulnerability with other row variables possibly changing.

Source: Compiled from Tables 7-12 and Table 16.