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Transient poverty, poverty dynamics, and vulnerability to poverty: An empirical analysis using a balanced panel from rural China

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Abstract

China's economic reforms starting in the late 1970s have resulted in rapid economic growth, with annual growth in gross domestic product averaging greater than 10 percent per year for more than thirty years. Accompanying this rapid growth in national accounts have been rapid and widespread reductions in poverty. With these reductions in poverty, however, there has often been observed an increase in income inequality, both between as well as within rural and urban sectors. This rising income gap challenges the notion that economic reforms in China have been as successful as the poverty statistics would suggest.

In this paper, we suggest that an alternative view would be to consider the effects of these reforms on changing the chronic nature of poverty and reducing household vulnerability to poverty. Using a balanced panel from rural China from 1991 through 2006, we find that most poverty among our sample has shifted from being chronic in nature to being transient, with households either shifting into a state of being non-poor moving in and out of poverty. Among our sample, vulnerability to poverty has been declining over time, but the declines are not uniform over time or space. We decompose household vulnerability status into two proximate causes: low expected income and high income variability, finding vulnerability increasingly due to income variability. Additionally, we demonstrate that vulnerable households have very different characteristics than non-vulnerable households.

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Keywords

vulnerability; poverty; China; panel data

1. Introduction

China's economic reforms starting in the late 1970s have resulted in rapid economic growth, with annual growth in gross domestic product (GDP) averaging greater than 10 percent per year for more than thirty years (National Bureau of Statistics of China, 2014). Accompanying this rapid growth in national accounts have been rapid and widespread reductions in poverty. According to official statistics, the poverty headcount rate (i.e., the proportion of the total population with income levels below the official poverty line) fell from over 30 percent in 1978 to just over 3 percent by 2000 (Park and Wang, 2001). While these official poverty statistics are regarded as somewhat controversial, China's progress on poverty reduction is well-documented, and almost all sources demonstrate incredible reductions in poverty.[1] But while the income gains have been rapid and have benefited both rural and urban sectors, the ensuing poverty reductions have not been particularly smooth nor equal. Rural poverty headcounts, for example, reduced rapidly in the early years of reforms, before increasing slightly in the late 1980s and early 1990s, after which time it began another period of rapid declines. Additionally, with the overall dramatic reductions in poverty headcounts has come an increase in income inequality, which has arisen within as well as between urban and rural sectors. The overall increase in income inequality is such that, over the course of two decades, China has evolved from one of the most egalitarian societies to being on par with some of the most unequal societies in all of Asia (Naughton, 2007). This rise in income inequality and widening disparities between rural and urban sectors has led some to question the ultimate success of China's market-oriented reforms, particularly in light of the government's desire to promote a "harmonious society", which has sometimes been interpreted as referring to a narrowing of the income gap.[2]

Despite these concerns, there may be reasons to believe that poverty headcount and income inequality indicators may not be the most appropriate with which to assess the societal outcomes of China's economic reforms. Despite its widespread use, the poverty headcount (or poverty gaps, or other such measures) is merely one metric for gauging socioeconomic status. Furthermore, the poverty headcount is based on assessment of households' aggregate poverty status, which can itself be a problematic measure of a household's actual status for several key reasons. First, poverty is an ex post indicator of well-being. For the purposes of evaluating economic policies, however, it may be preferable to assess the ex ante possibilities that a household will be poor in the future. Second, the income or consumption outcomes by which poverty status is determined are themselves the results of stochastic as well as deterministic forces (Morduch, 1994). While it may be true that "the poor shall never

[1]For example, using a modified poverty line meant to better reflect the costs of achieving a 2,100 kCal/capita/day consumption bundle, and furthermore reflecting differences in the costs of achieving this bundle in rural and urban settings, Ravallion and Chen (2007) estimate that the national poverty headcount fell from 53 percent in 1981 to 8 percent by 2001.

[2]The objective of a harmonious society was introduced by President Hu Jintao in 2002, and was later included in the country's eleventh five-year plan (2006–2010).

cease out of the land," economic development may succeed in removing structural or institutional barriers that trap households in chronic or persistent poverty, such as low levels of education, poor health, limited access to capital, economic policies, etc. As Jalan and Ravallion (1998) note, however, at any point in time, some portion of those observed to be in poverty are only transient, experiencing some type of short-term, unanticipated shock resulting in their income or consumption shortfall, even when their characteristics are such that they would not, under normal conditions, be in poverty. In the case of China, this seems to be a particularly salient concern. The nature of poverty–whether it is more chronic or more transitory–has important implications for development policies: If poverty is more of a temporary phenomenon, then policies aimed at stabilizing short-term income fluctuations (such as increasing rural credit or providing social safety net programs) may be more appropriate; if poverty is more persistent, then policies should address concerns of a more structural nature (such as addressing labor markets or increasing rates of capital accumulation, including human capital) (Glauben et al., 2012). There have been several studies that have examined the effects of economic reforms on the persistence of poverty in China, often largely concluding that poverty is more transient in nature, but with some variability across provinces (e.g., Jalan and Ravallion, 1998; McCulloch and Calandrino, 2003; Glauben et al., 2012).

Differentiating between whether poverty is largely transient or chronic has implications when assessing overall progress towards development goals (Jalan and Ravallion, 1998). If poverty is largely a transitory phenomenon, then poverty indicators are snapshot summaries of a stochastic process, representing an observed sample of $n = 1$ from a distribution of potential outcomes. It is our contention in this paper that this summary may be an inaccurate description of a household's true level of well-being. What is important in this regard is not so much the observed outcome but the distribution of potential outcomes from which the observed outcome was drawn. Framing well-being in terms of a distribution of potential income or consumption outcomes suggests an alternative metric by which to gauge the effectiveness of development policy: a household's vulnerability to poverty. Because vulnerability gauges a household's susceptibility to adverse socioeconomic outcomes, it is a forward-looking, ex ante measure.

In this paper, we will apply a methodology for quantifying vulnerability to income poverty as the probability that a household's income will fall below a pre-specified poverty line in the future. A household's vulnerability is dependent the parameters of its specific income distribution, specifically the expected real income level as well as its variance. With estimates of these parameters, we are able to characterize a given household's real income probability density function, quantify their vulnerability to income poverty, and ascertain whether households are vulnerable due to the level or variability of income or expected income.

2. The Measurement of Vulnerability

Poverty analysis allows development practitioners and policymakers to evaluate the effects of a given program or policy after the fact. But there is strong justification for development and other poverty-reduction strategies to be more forward-looking and consider what their impacts or outcomes might be in the future (Naudé et al., 2009; Haughton and Khandker, 2009). This logic forms the foundation for considering vulnerability as itself an indicator of policy effectiveness, since vulnerability relates to an ex ante susceptibility to an undesirable outcome, such as poverty, food insecurity, or natural hazards (Naude et al., 2009). Vulnerability analysis provides a way of identifying those households or individuals whose livelihoods are likely to be adversely affected by a particular policy Most early attempts at analyzing vulnerability tended to involve more or less qualitative assessments, sometimes encompassing different dimensions of vulnerability A nice feature of this approach is that it explicitly recognizes there are different manifestations of vulnerability, and this analytical toolbox may be particularly useful for isolating the most vulnerable groups within a society for the purposes of prioritizing or targeting development programs. Like poverty assessments, however, these qualitative measurements of vulnerability merely summarize ex post observations of outcomes, rather than providing any form of ex ante assessment of how likely these households or individuals are to suffer welfare declines.

Perhaps the most widely used approach considers vulnerability as expected poverty (see, for example, early contributions by McCulloch and Calandrino, 2003; Kamanou and Morduch, 2005; Christiaensen and Subbarao, 2005 and Günther and Harttgen, 2009).[3] Since poverty is such a widely used and recognized indicator of socioeconomic status, and because expected poverty has a cardinal interpretation and is more easily interpretable than utility-based measures (e.g., the measure proposed by Ligon and Schechter, 2003), conceptualizing vulnerability in terms of expected poverty seems a reasonable route to take in assessing ex ante household welfare. Using the poverty headcount ratio introduced in Foster et al. (1984), it can be shown that vulnerability as expected poverty reduces to simply the cumulative distribution of income below the poverty line, or simply the probability of poverty. Our measure of vulnerability as the probability of poverty captures the likelihood that incomes fall below the poverty line at some point in the future:

$$\upsilon_{it}=\Pr(y_{i,t+\Delta} \leq z_{t+\Delta}) \quad (1)$$

where $y_{i,t+\Delta}$ is household *i*'s income at period $t + \Delta$ (for any non-negative incremental time step Δ), and $z_{t+\Delta}$ is a poverty line. This measure considers vulnerability as an ex ante measure of the household's well being, since it is the state of the household at time *t*, which is prior to the realization of the outcome at time $t + \Delta$. The practical problem, of course, is that $y_{i,t+\Delta}$ is not observable, so this approach requires predictions to be made about the household's future income prospects. To arrive at an estimate of future household income, we begin by specifying the determinants of income and allowing predicted changes in these various determinants to condition our expectation for future income. We can write household income at period *t* as

$$y_{it}=y\left(X'_{it}, \beta_t, \alpha_i, \delta_t, \varepsilon_{it}\right) \quad (2)$$

[3]Much of the literature treating vulnerability as expected poverty can ultimately be traced back to working papers by Christiaensen and Boisvert (2000) and Chaudhuri et al. (2002).

where X_{it} is a vector of observable time-varying household characteristics, β_t is a vector of parameters describing the state of the economy at period t, α_i captures unobservable household-specific factors that condition income, δ_t captures the effects of the passage of time, and ε_{it} is a time-varying idiosyncratic (i.e., household-specific) disturbance, presumably capturing unobservable shocks (both positive and negative) that lead to perturbations of observed income from expected income. In other words, ε_{it} contributes to the differentiation in welfare for households that are otherwise observationally equivalent. Assuming parametric heterogeneity over time (i.e., $\beta_t = \beta$), we can then re-write equation (1) as

$$\upsilon_{it}=\Pr\left[y_{i,t+\Delta}=y\left(E\left[X'_{i,t+\Delta}\right],\beta,\alpha_i,\delta_{t+\Delta},E[\varepsilon_{i,t+\Delta}]\right)\leq z|X'_{it},\beta,\alpha_i,\varepsilon_{it}\right] \quad (3)$$

Any approach to estimating vulnerability in this fashion requires some assumption (or estimation) of the underlying distribution of household income (i.e., its mean and variance), some specification of the income poverty line, and the interpretation requires the establishment of some threshold probability above which households are deemed to be vulnerable. With a sufficiently long data series, and under the assumption that the error terms are independent and identically distributed over time, recovering the distribution of household consumption is a relatively straightforward procedure. But this is a restrictive assumption, especially given a longitudinal data structure. For regressions involving income as the dependent variable, it is very probable that the errors will fail to be homoskedastic, and this form of this heteroskedasticity can largely be attributable to household characteristics. To correct for this heteroskedasticity, many applications use the generalized least squares estimator introduced in Amemiya (1977) (see, for example, Chaudhuri et al., 2002. Given that incomes are typically assumed to be lognormally distributed, we begin by considering a household income generating process as a two-way error component permanent income function (c.f. Bhalla, 1980)

$$\ln y_{it}=X'_{it}\beta+\alpha_i+\delta_t+\varepsilon_{it} \quad (4)$$

The predicted values from this regression provide us with an estimate of household permanent income, which serves as our expectation for income at period $t + \Delta$. Income and consumption data gathered from household surveys likely contain measurement error which will (among other potential biases) overstate the variance of our outcome measure and, other things equal, result in inflated estimates of household vulnerability (Baulch and Hoddinott, 2000; Kamanou and Morduch, 2005). Because regressions using longitudinal data are able to control for household-specific effects (either fixed or random), it is likely that measurement error will be subsumed into the a_i error component, which results in a consistent estimate of the income variance.

Christiaensen and Subbarao (2005) have suggested that, if available, shock data should be included in X_{it} as conditioning explanatory variables. Insofar as the inclusion of shocks in these income regressions provides unbiased estimates for the marginal effects of the other explanatory variables included in the model, then including shocks is appropriate. But the ultimate objective for these income regressions is not the estimation of the marginal effects, per se, but rather using the marginal effects to create an estimate of household expected income at period $t + \Delta$. If shocks are unanticipated perturbations, then it seems reasonable to assume that, in any given period, the expected value of a shock is zero. So while our income function may be re-specified as $\ln y_{it}=X_{it}^{'}\beta+\theta_{it}^{'}\gamma+\alpha_i+\delta_t+\varepsilon_{it}$, where θ_{it} is a vector of shocks observed for household *i* in period *t*, the *expected* income should be calculated as $E[\ln y_{i,t+\Delta}]=X_{i,t+\Delta}^{'}\hat{\beta}+\hat{\alpha}_i+\hat{\delta}_{t+\Delta}$. This underlies the frequent assumption that ε_{it} is a mean-zero disturbance term that captures idiosyncratic factors that contribute to different consumption levels for households that are otherwise observationally equivalent. When we estimate income regressions and construct our measure of vulnerability in the following sections, we consider shocks to condition observed income-which will increase the precision of estimated marginal income effects-but we will not include the shocks when we generate our ex ante estimates of conditional expected income.

Within the context of cross-sectional data, it is often assumed that the ε_{it} component also reflects intertemporal variance in consumption. But this requires the strong assumption that the error terms are independently distributed over time, and that there is no serial correlation in the error terms. This assumption makes it acceptable to assume, therefore, that the cross-sectional variability is a good proxy for intertemporal variation. For studies using simple cross-sectional data, this assumption may be a matter of necessity as well as a matter of convenience. For data with a sufficiently long longitudinal structure, one is able to more easily obtain empirical estimates for the expected level and variance of household income. We can use these estimates of expected income to derive an estimate for the household's underlying income variance, computed as the average squared deviation of observed income from expected income.

$$\mathrm{Var}[\ln y_{it}|X_{it}^{'},\hat{\beta},\hat{\alpha}_i,\hat{\delta}_t]=\hat{\sigma}_{y_i}^2=T_i^{-1}\sum_{t=1}^{T_i}\left(\ln y_{it}-E[\ln y_{it}|X_{it}^{'},\hat{\beta},\hat{\alpha}_i,\hat{\delta}_t]\right)^2 \quad (5)$$

Implicitly, the variance of household income estimated via this procedure takes into consideration household characteristics, since these characteristics condition expected household income, which is then used in the construction of the income variance term. We are therefore able to generate a measure of income variability that is conditional upon household characteristics without necessarily assuming that cross-sectional variation proxies for intertemporal variation.

With these two moments for the household income distribution estimated, we are able to generate a measure of vulnerability, proxied by the probability that household income will fall below the poverty line:

$$\hat{v}_i=\Phi\left(\frac{\ln z-E[\ln y_{it}|X_{it}^{'},\hat{\beta},\hat{\alpha}_i,\hat{\delta}_t]}{\sqrt{\mathrm{Var}[\ln y_{it}|X_{it}^{'},\hat{\beta},\hat{\alpha}_i,\hat{\delta}_t]}}\right) \quad (6)$$

where Φ is the normal cumulative distribution function.

3. Data

The data used in this study come from the China Health and Nutrition Survey (CHNS), a longitudinal household survey conducted by the Carolina Population Center at the University of North Carolina, Chapel Hill and the National Institute of Food Safety at the Chinese Center for Disease Control and Prevention. The survey was designed to examine the effects of health, nutrition, and family planning policies implemented by various local and national governmental organizations, as well as to examine the economic and social transformations of Chinese society and how these transformations are manifesting themselves in the health and nutritional status of the population. For the present study, we use data from five survey waves from 1991 through 2006, drawing a balanced sample of households from seven provinces (Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi, and Guizhou). A multistage, random cluster process was used to draw the samples in each province. Within each province, counties were stratified by income and a weighted sampling scheme was used to select four counties in each province.

Panel data have the advantage that they allow the researcher to control for unobserved sources of heterogeneity. In many instances, however, panel data are not available–especially in developing countries. To date, many researchers exploring vulnerability to poverty have relied upon cross-sectional data, simply due to a dearth of available panel data. Other recent applications have used pseudo-panels from repeated cross-sections (Échevin, 2013). Where panel data are available in developing countries, there is often a non-trivial issue of respondent attrition, which can be problematic when those who leave the sample are differently vulnerable from those who remain in the sample (Kamanou and Morduch, 2005). Households that migrate, for example, may do so because they are among the most vulnerable or, since migration may be a means of smoothing total household income, those who have migrated may have more stable incomes and, as a result, be less vulnerable than those who have not migrated. If attrition arises due to either of these causes, resulting estimates will be biased in one direction or another. There are a few possible routes that could be followed in this regard. First, one could simply treat the data as repeated cross-sections. The problem with this, of course, is that this approach imposes strong distributional assumptions on the error terms, cannot control for unobservable sources of heterogeneity and assumes that intertemporal variation in income is reasonably proxied by cross-sectional variation. A second approach is to use the unbalanced panel to form pseudo-panels, (e.g., Zhang and Wan, 2006). A final approach–which we ultimately chose to follow–is to use a balanced sample of households that appear in each survey wave. Reducing the total sample into a balanced panel requires trade offs between the number of households observed and the length of time over which each household is observed. In order to focus on poverty and vulnerability dynamics, we wanted track the same households across survey waves to ensure that our aggregated figures were not simply capturing the entry or exit of different households from the sample. We have therefore restricted our sample to those households who participated in the survey in every wave from 1991 through 2006. Since there is a great deal of attrition among urban households in the survey, which is perhaps indicative of a greater degree of household mobility, and since the urban households that remained in the survey throughout our specified time period are likely not representative of the larger population of urban households in China, we have restricted our sample to rural households. We were able to extract a balanced sample of 375 households that remained as survey respondents from 1991 through 2006, yielding 2,250 total observations. While the small sample severely limits the extent to which the study's findings can be generalized beyond the sample households, we note that many of general observations (increased wealth, dramatic reductions in poverty, absorption into stable non-poverty status, reduced vulnerability) are consistent with the familiar narratives of China's economic development in the post-reform era (e.g., Park and Wang, 2001; Lin et al., 2003; Naughton, 2007; Glauben et al., 2012; Ward, 2014).

Summary statistics for the households used in this analysis are reported in Table 1. The variables chosen for inclusion in the income regression specified in equation (4) include a combination of household demographic characteristics, household socioeconomic characteristics, community characteristics, and a series of exogenous shocks: age of the household head (and its square), the number of dependents (those household members younger than 15 or older than 65), the number of working-age household members, a binary variable to capture the household's status as being female-headed (=1), the education of the household head, the average education level of household members, household physical capital, a binary variable capturing whether the community is near a free trade area, the proportion of community laborers involved in agriculture, the proportion of community laborers who migrate outside the community to earn income, and a series of seasonal rainfall shocks. To create our measures of agricultural and commercial capital, we use principal component analysis (PCA) methods to create asset indices.[4] These indices are based on either binary or quantitative indicators of household ownership of various types of capital, and are normalized relative to period-specific means and standard deviations. The agricultural assets used in constructing the agricultural capital index include large (four-wheel) tractors, small (two-wheel) tractors (or power tillers), power threshers, irrigation equipment, and water pumps. The business assets used in constructing the commercial capital index include commercial cooking equipment, commercial sewing equipment, commercial carpentry equipment, and other commercial equipment.[5] These two asset categories are productive assets which, in addition to being stores of wealth, are also income-generating forms of capital. To generate a measure of weather shocks, we consider deviations in seasonal observed rainfall (at the county level, with measurements from the prior year) relative to long-term averages, which proxy for expected rainfall.[6] Our shock measure is a hybrid of the measures used by Mangyo (2008) and Paxson (1992), where the

[4]As suggested by an anonymous reviewer, households may accumulate physical capital in response to a state of vulnerability, wherein the capital can be viewed as a sort of precautionary savings. While we acknowledge this possibility, isolating the causal relationship between household physical wealth and vulnerability is beyond the scope of the present study.

[5]The CHNS distinguishes between ownership of some assets for personal use and ownership for business activities. We only consider households to own commercial capital if the equipment is used in an income-generating activity.

[6]The long-term averages that serve as expected rainfall were computed using province-level rainfall measurements for the period 1951 through 2000. These province-level measurements were based on publicly available weather station data that were used to construct a month-by-month, year-by-year continuous rainfall distribution map for all of China using an inverse distance-weighted spatial interpolation algorithm. These measurements were then spatially- and temporally-aggregated up to generate a single long-term, province-level average. Based on an analysis of deductive disclosure risks, it was not possible to merge the long time series with the CHNS household survey data at the county level.

seasonal shocks are represented as a *z*-score. The vector of rainfall shocks can be written as $\Lambda_{kt}=[\lambda_{kt}^1, \lambda_{kt}^2, \lambda_{kt}^3, \lambda_{kt}^4]$, where

$$\lambda_{kt}^j = \left| \frac{r_{k,t-1}^j - \overline{r}_k^j}{\sigma_{r_k^j}} \right|, j=1, \ldots, 4 \quad (7)$$

where $r_{k,t-1}^j$ represents the observed rainfall in county *k* during season *j* of year *t*, $\overline{r}_k^j$ represents the expected rainfall in county *k* for season *j*, and $\sigma_{r_k^j}$ represents the standard deviation of rainfall for county *k* during season *j*. Since these shocks are computed as absolute values, it allows for excessive rainfall and drought conditions to be considered a shock.

Based on our balanced longitudinal sample of 375 households across 6 survey waves, Figure 1 reports sample poverty headcounts based on the official Chinese poverty line, the $1.25 per day poverty line, and the $2.00 per day poverty line.[7] While this figure supports the notion that China has made significant progress in reducing poverty headcounts, at least among our balanced sample, it highlights the extent to which the choice of poverty line can lead to potentially erroneous judgments about the degree of this success. For example, judging by the official poverty line, one would conclude that poverty within our rural sample was virtually eradicated by 2006, since estimates based on our balanced panel from the CHNS suggest that only 0.4 percent of the sample had incomes below the official income poverty line in 2006. This contrasts with estimated poverty headcounts of 7.5 percent and 21.9 percent within our sample using the $1.25 per day and $2.00 per day PPP poverty lines that are perhaps more reflective of the true state of income poverty.

The role of China's growth-oriented, anti-poverty policies has received considerable attention in the literature. Montalvo and Ravallion (2010) highlight the importance of the primary sector (particularly agriculture) in driving down absolute poverty in China. While migration to urban areas has helped in reducing poverty nationally, the bulk of the reduction in poverty came from rural areas (see also Ravallion and Chen, 2007). The role of agrarian reforms implemented in China cannot be understated. De-collectivization of agriculture and the privatization of land-use rights under the Household Responsibility System in 1980's played an important role in increasing the primary output and hence, contributing towards poverty reduction (Lin et al., 2003; Ravallion and Chen, 2007). Collective farming ended in almost all of China and family farms emerged as the dominant system of farming. Chinese land reforms have been credited to be the most egalitarian land reforms in history and barely created any landlessness which is considered as a major hindrance in crushing poverty in other developing countries. Other reforms, like raising the food grain procurement prices

[7]The real incomes used to construct this figure are in 2006 RMB, and have been converted to per capita terms to create poverty headcounts. For the official poverty line, we have inflated the nominal poverty lines to 2006 using community-specific price indices provided by the CHNS, resulting in a series of community- and time-specific poverty lines. Based on material supplemental to 2008 *World Development Indicators*, the 2005 $1.25 per day poverty line in local currency was 5.11 RMB per day, with an implicit private consumption PPP conversion factor of 4.088. We re-scaled the local currency equivalent poverty line based on differences in private consumption PPP conversion factors between 2005 and 2006 and arrived at a 2006 local currency poverty line of 5.02 RMB per day). Since the income levels used are in 2006 RMB, no inflation adjustments have been made. These poverty lines are national averages, and do not take into consideration cost-of-living differences between urban and rural areas.

and increasing the supply of modern inputs to farmers also helped improving the terms of trade of agriculture. Evidence also suggests that migration played an important role in escaping poverty for some households despite the existence of constraints on labor mobility.

The structure of tax system in China also underwent a historic change. Wang and Shen (2014) observe that the regressive tax system in China has slowly improved and helped in reducing the differences in the tax burden between rural and urban households. The tax system in China was previously structured such that the rural households had to pay a disproportionately high share of taxes in the form of agricultural tax (Tao and Liu, 2005). In 2000, the central government launched a rural tax-and-fee reform where all agricultural taxes and fees were to be replaced by a uniform agricultural tax until 2003, after which it was exempted in most provinces by 2005 and waived across the country in 2006 (Wang and Shen, 2014). Although poverty headcounts have reduced dramatically, Imai et al. (2010) argue that the regressive tax system has actually hindered poverty-reduction efforts, and suggest that recent tax reforms may signal further reductions in poverty in the future.

As we have argued previously, such poverty statistics represent an ex post summary of an observed outcome. Household welfare encompasses more than just its present income or consumption, and households that are poor today may not necessarily be poor tomorrow (Baulch and Hoddinott, 2000). The nature and dynamics of poverty has received much attention in the poverty literature. The distinction between transient and chronic poverty is very important, especially from a policy perspective, as different responses and measures are likely to be appropriate for each (Baulch and Hoddinott, 2000; Jalan and Ravallion, 1998, 2000; McKay and Lawson, 2003). The nature of poverty has significant implications for the appropriateness of poverty reduction policies. Barrett (2005) for example, distinguishes between the role of safety nets (which include programs such as emergency feeding programs, crop or unemployment insurance, disaster assistance, etc.) and cargo nets (which include land reforms, targeted microfinance, targeted school feeding program, etc). While the former prevents non-poor and transient poor from becoming chronically poor, the latter is meant to lift people out of poverty by changing societal or institutional structures. Using a panel from four provinces in China from 1985–1990, Jalan and Ravallion (1998) find evidence that much of the poverty in China is transient, with much of the squared poverty gap due to variability in consumption. They also demonstrate that the relative share of transient poverty differs between relatively well-off and relatively deprived provinces: in relatively well-off provinces, poverty is more likely to be transient than in relatively deprived provinces. Furthermore, they argue that the transient nature of much of China's poverty is likely to limit the effectiveness of anti-poverty policies which are too narrowly focused on structural sources of poverty. Jalan and Ravallion (2000) provide evidence that the factors that determine transient poverty are different from those that determine chronic poverty in China, and that many of the factors that contribute to chronic poverty have little or even opposite effects on transient poverty. McCulloch and Calandrino (2003) find a great deal of movement in and out of poverty in rural Sichuan province over 1991–1995, with only 2.4 percent of households poor for all five years. Duclos et al. (2010) find high prevalence of transient poor representing two-thirds of total poor in their sample of rural China from 1987–2001. Glauben et al. (2012) also explore the dynamic nature of poverty in China and find that the majority of population in their sample from 1991–2005 seems to be temporarily poor, and furthermore suggest that policy measures should focus at institutions to manage price and income fluctuations.

We illustrate the transient nature of poverty in our sample by the poverty transition matrix reported in Table 2 based on the $2.00 per day PPP poverty line. Very few households in our sample remain poor from one period to the next, and with the passage of time, the proportion of households who are poor in two consecutive survey waves diminishes dramatically. For example, there were 53.6 percent of households who were poor in 1991 and remained poor into 1993, while there were only 7.2 percent of households who were poor in 2004 that remained poor into 2006. These transition probabilities, particularly those between adjacent survey waves, suggest that the majority of poverty from our sample in rural China is largely transient, as there were only 8 households in our sample who were poor (by the specified poverty line) in all six sample periods. The transient nature of poverty reflects the importance of the shape of a household's income distribution. We now consider a measure of vulnerability, which uses information about the household's income distribution to inform a conditional probability that the household will fall into income poverty in the future.

4. Estimation of Vulnerability

4.1. Determinants of Household Income

To estimate household vulnerability as expected poverty, we begin by estimating the two-way error component income regression model (allowing for both household and time effects) specified by equation (4).[8] Table 3 presents the results of both fixed effects and random effects estimation for purposes of comparison. We employ a Hausman test to determine the appropriate model specification; the Hausman test statistic of 123.78 suggest a clear rejection of the random effects estimator. As we progress with estimating the parameters of the households' income distributions, we will rely on the results of the fixed effects estimation, taking into consideration the estimates of the household- and time-specific effects in constructing our expected income and income variance terms.

Classical regression models assume that the disturbance terms are independently and identically distributed across observations. With a longitudinal data structure, however, it is typically observed that the disturbances are independently distributed across households (i.e., the cross-sectional unit), but are neither identically distributed across households nor independently distributed across time periods for the same household. The failure of this assumption will lead to biased estimates of the variance-covariance matrix, which will invalidate inferences based on the standard errors derived from this matrix.[9] While our ultimate objective is to generate estimates of household vulnerability to poverty, and not to perform hypothesis tests on the parameter estimates resulting from these regressions, we are

[8]We performed a Honda Lagrange Multiplier test for two-way effects based on the results of a pooled OLS regression of equation (4). The test statistic of 26.20 indicates a rejection of the null hypothesis of no individual or time effects. In addition, because the data have a time-series component, we test for the presence of a unit root using an Augmented Dickey-Fuller (ADF) test using two period lags. Based on the estimated ADF test statistic −26.03 , we conclude that the data do not exhibit a unit root. This is fortuitous not only because it implies that real household incomes per person are stationary, but also because this particular vulnerability estimator performs better than other vulnerability estimators when the data are stationary.

nevertheless interested in understanding the relationships between real household income per person and the selected regressors. Since these explanatory variables condition household income, and since expected household income relative to the poverty line is an important component of our vulnerability measure, understanding how these variables influence income may have some direct implications for how these variables influence vulnerability. For this reason, we report standard errors that are robust to unknown sources of heteroskedasticity and serial correlation. Arellano (1987) proposed an asymptotic variance-covariance matrix that satisfies this property within a fixed effects regression model. The standard errors for the fixed effects model reported in Table 3 have been adjusted using this approach. This adjustment is inappropriate for random effects estimators, so we have adjusted the standard errors in the random effects model to control for heteroskedasticity only, but we restrict the error variances for a particular household to be the same.

4.2. Analysis of Household Vulnerability to Poverty

Based on the methodology outlined above, we construct estimates of household vulnerability to poverty. Figure 2 plots the average probabilities that a household will fall into poverty, delimited by region and survey wave. While levels of vulnerability were rather high in the early years of the survey (a 0.6 probability of poverty or higher in 1991), by 2006 the levels of vulnerability had been dramatically reduced in all provinces covered by the CHNS. This is perhaps not surprising given a similar situation was observed with poverty headcounts over time. This figure illustrates that vulnerability to poverty varies a great deal over time and space. Nonetheless, several general trends can be detected. First, in all regions we generally observe vulnerability either declining or remaining flat from one survey wave to the next. Second, we find that sample households in Jiangsu province has the lowest average level of vulnerability in all survey waves. This finding is consistent with the findings of Imai et al. (2010). Part of the explanation for this lies in that, from our balanced sample, average household real incomes per person are higher in Jiangsu than in any of the other provinces for which we have data. There may be a geographic explanation for this. Jiangsu is located on the eastern coast of China, adjacent to Shanghai, and has a dynamic economy with prominent industries such as plastics, semiconductors, petrochemicals and automobiles. It's proximity to Shanghai and its broad industrial base may contribute to an average share of migrant workers in households' communities of 29.7 percent. While the households in our sample come from communities that are rural, they nevertheless demonstrate very urbane characteristics. The communities from Jiangsu have the lowest average community-level employment in agriculture, with, on average, just over 50 percent of the labor force employed in agriculture (based on responses from community leaders). Sample households from Jiangsu have, on average, fewer than one dependent per household and among the provinces in our sample, it is the only one in which sample households have fewer than one dependent on average. The average dependency ratio (i.e., the ratio of

[9]For example, from our fixed effects regression, we compute a Breusch-Pagan heteroskedasticity test statistic of 90.83, indicating a rejection of homoskedastic errors, and a Breusch-Godfrey/Wooldridge serial correlation test statistic of 351.40, indicating a rejection of serially uncorrelated errors. Because of the uneven spacing of our longitudinal data, however, it is difficult to identify the nature of the serial correlation (i.e., it is difficult to estimate an autoregressive correlation coefficient given the differences in the temporal spacing between survey waves) as well as to correct for it (e.g., by using a Cochrane-Orcutt transformation).

dependents to working-age individuals) among sample households in Jiangsu is 0.41, less than that observed among sample households from any other province, suggesting that sample households in Jiangsu have a higher proportion of economically active household members relative to non-productive household members.

4.3. Identifying the Vulnerable

Identifying “vulnerable” groups is an important exercise that can have important implications for the targeting of development assistance or for understanding how vulnerable households respond to the inherent risks they face. Generally speaking, we require a threshold probability of poverty above which a household is qualified as vulnerable, which is essentially a poverty line defining a poverty of household security or stability Unlike income poverty lines, however, there is not a clear minimum amount of security below which households are security-poor. The most commonly used threshold in the existing literature is a probability of poverty of 0.5: households with at least 50 percent chance of poverty are considered vulnerable.[10] This vulnerability threshold has been used extensively in the literature (e.g., Christiaensen and Subbarao, 2005; Zhang and Wan, 2006; Imai et al., 2010; Échevin, 2013. The use of this line has been defended based on several features. First, this threshold defines the point in equation (6) where expected income exactly equals the poverty line. Second, a 50/50 chance of falling into poverty seems a reasonable threshold to demarcate the vulnerable from those not vulnerable. Additionally, if a household is currently exactly at the poverty line and faces a zero mean shock, then the household has a vulnerability of 0.5, implying that as the time interval goes to zero the statuses of “currently poor” and “currently vulnerable to poverty” coincide (Pritchett et al., 2000). While we agree that this latter feature is attractive, we find the other two features decidedly unattractive. Defining a poverty threshold of 0.5 implies that only those households with $\upsilon_{it} \geq 0.5$ are considered vulnerable. In order for $\upsilon_{it} \geq 0.5$, it must be the case that $(\ln z_{it} - E[\ln y_{it}|X_{it}^{'}])/\hat{\sigma}_i \leq 0$, and since $\hat{\sigma_i} > 0$ by definition, only those households with $\ln z_t - E[\ln y_{it}|X_{it}^{'}] \leq 0$ are considered vulnerable; in other words, only those households that are currently expected to be poor are considered vulnerable. This definition seems to only consider vulnerability to chronic or structural poverty; it ignores the possibility that there are some households who expect to be above the poverty line but who have highly variable incomes. This group might be adequately described as being vulnerable to transient poverty, since they are sufficiently exposed to shocks that have the potential of pushing them over the poverty line, while structurally they are not particularly susceptible to chronic poverty. Additionally, setting the vulnerability threshold at 0.5 implies a dramatically low level of security: households are equally as likely to be poor as they are to be non-poor. This elicits imagery of households living on a knife’s edge, where even the smallest negative perturbation can result in poverty. We prefer a more conservative vulnerability threshold, where households are more likely than not to remain out of poverty, but who–because of variability in their income distribution–have a nontrivial risk of poverty.

[10]Inherently, defining a vulnerability threshold is arbitrary (Haughton and Khandker, 2009). An alternative threshold that is often used is the observed poverty headcount rate. In some cases, the observed poverty rate threshold is used in conjunction with the 0.5 threshold, where the 0.5 vulnerability line is used to define the lower bound for the “highly vulnerable” and the headcount poverty rate is used to define the lower bound for the “relatively vulnerable.” It is common for both vulnerability thresholds to be reported (e.g., Zhang and Wan, 2006).

We choose to set the vulnerability threshold at 0.333, implying that vulnerable households are those that have a one-in-three chance of falling into poverty. Figure 3 plots the vulnerable headcount ratio among sample households throughout the period covered by the survey. This figure illustrates the dramatic reduction in vulnerability that occurred in the most recent decade. The proportion of the sample with a probability of poverty in excess of 0.333 fell from 0.71 at the beginning of the decade to 0.26 by 2006.

4.4. Categorization of poverty and vulnerability

We are able to categorize our sample of households based on income and vulnerability characteristics.[11]. This categorization is illustrated by Figure 4, which allows us to closely examine the various manifestations of current poverty, future expected poverty, and current vulnerability status.

We focus on six overlapping categories of households. Specifically, we focus on the chronic poor and transient poor, high vulnerability non-poor and low vulnerability non-poor, and then distinguishing those households who are vulnerable due to low expected income and those who are vulnerable due to highly variable income. In this figure, for example, currently poor households (those households whose current per capita income falls below the $2.00 per day poverty threshold) are represented by area A + B + C, while non-poor households are represented by area D + E + F. We can further decompose the poor households into those that are structurally (or chronically) poor (i.e., those households that are currently poor and whose structural characteristics suggest that the household expects poverty; these households are represented by area A) and those that are transitorily poor (i.e., those households whose characteristics would not otherwise lead to an expectation of poverty, but who nonetheless are currently poor; these households are represented by area B + C). We are also able to identify those households that are vulnerable to poverty yet not currently poor (areas D+E) as well as those households that are currently poor but not vulnerable (area C). Vulnerable households are represented by area A + B + D + E; for these households, the probability of poverty is at least as great as our vulnerability threshold of 0.333. We can decompose vulnerable households into those that are vulnerable due to low expected income (i.e., area A + D) and those that are vulnerable due to highly variable income (i.e., area B + E). A summary of these six household categories by survey wave is shown in Table 4.[12]

These figures provide some interesting insight into poverty and vulnerability dynamics in rural China during the period in question. We have previously observed a sharp decline in poverty in rural China during the survey period. We see from this table that much of the declines in poverty can be attributed to declines in chronic poverty. These figures suggest that chronic poverty among our sample households has been virtually eliminated during the fifteen years spanned by our data. But while there has been significant progress in reducing chronic poverty, the proportion of the sample that is transitorily poor has been steadily

[11]This categorization follows along the lines introduced by Suryahadi and Sumarto (2003))

[12]Note that, because these categories overlap, the rows do not sum to one. However, since poor and non-poor are mutually exclusive and exhaustive categorizations, the sum of the entries for the first four columns will sum to one. The final two columns sum to the headcount ratio of vulnerable households, and the table entries represent the relative contribution of the two proximate causes to the overall headcount ratio.

increasing, from about 6 percent in 1991 to 13 percent in 2006. If we subscribe to the notion that chronic poverty is primarily due to structural characteristics of the household, while transient poverty has more to do with the effects of unanticipated shocks, then these figures suggest that the structure of rural organization has improved, though despite these improvements there remains residual risk that could potentially nudge households below the poverty line. Among the non-poor, there has been a significant improvement in terms of vulnerability. In the early years of the survey, a relatively constant proportion of the sample was significantly vulnerable to poverty, even though their resulting status was not, in fact, poverty. Since 2000, however, the proportion of the non-poor who were vulnerable to poverty has declined, from 24.8 percent in 2000 to 10.4 percent in 2006. Throughout the sample period, the proportion of the sample that was non-poor and who were not vulnerable to poverty (based on our vulnerability threshold) has increased. In tandem, these figures suggest an increasingly secure income situation for non-poor households.

The figures in the last two columns of Table 4 report the share of the total sample (in each survey wave) that is vulnerable due to either low expected income or high income variability. A clear pattern that emerges is that, over time, the proportion of our sample that is vulnerable due to low expected income has fallen significantly, virtually in step with the declines in chronic poverty. The proportion of the sample that is vulnerable to poverty due to highly variable incomes increases through 2000, and then begins to decline in the latter waves. This, too, is consistent with our observations regarding the constancy of transient poverty: income variability remains of concern, though the evidence suggests that income variability has become less of a concern in recent years. We can also examine patterns in the proximate causes of a household's status in being vulnerable or not. Initially, most vulnerable households were vulnerable due to low expected income rather than highly variable incomes (89.5 percent in 1991). Over time, as structural transformations raised expected incomes above the poverty line, the share of vulnerable households attributable to low expected income diminished. By 2004, more than half of the vulnerable were vulnerable to poverty not because of low expected incomes, but rather because of high income variability (by 2006, 56.2 percent of vulnerable households were so because of high income variance).

4.5. Characteristics of the Vulnerable

Development policies may wish to specifically target vulnerable households, so it is important to be able to identify the characteristics that condition or are symptomatic of vulnerability. Because the vulnerability measure is derived based on the results of an income regression, attempts to regress vulnerability on income-generating variables (or variables highly correlated with income-generating variables) runs the risk of simply re-creating the underlying data generating process used to create the vulnerability measure in the first place. To avoid this potential pitfall while still attempting to extract important information regarding the impacts of various terms on household vulnerability, we examine and compare the sample characteristics of households that are classified as vulnerable with the characteristics of those that are not. The comparison takes the form of a *t*-test of sample means, which requires the assumption that the two samples are random, independent, and come from normally distributed populations. We relax the assumption that the samples have equal variances, and allow for different sample variances between the two groups. Since our measure of vulnerability is in terms of income poverty, we are of course interested in understanding how the determinants of income vary between vulnerable and non-vulnerable households. Based on the results of our fixed effects income regression (Table 3), we are able to ascertain how these determinants affect household income, but the test of sample means allows us to determine whether vulnerable households are sufficiently different from non-vulnerable households in these regards. In addition to these determinants of household income, there are other factors that may not necessarily affect incomes but may be manifestations of underlying household vulnerability. In this regard, we specifically consider households' asset ownership (by various categories of assets, including housing capital, transportation capital, and household durable goods capital) in addition to the sources of household income included in the income regression. To illustrate the relationship between poverty status and vulnerability, we also include a characterization of poor households, which very clearly suggests that many of the characteristics of poor households are largely similar to the characteristics of vulnerable households.

These sample means and the resulting *t*-statistics are reported in Table 5. For almost all of the characteristics observed, there is a significant difference between vulnerable and non-vulnerable households (at the 10 percent level or better). Most of the significant differences are unsurprising, especially when taken in light of the results of the income regression reported in Table 3. For example, vulnerable households have lower observed incomes, lower expected incomes, and greater income variability. These are almost definitively indicative of vulnerability, given our methodology for estimating vulnerability. But vulnerable households do not only have generally lower incomes, they are also less diversified. Vulnerable households derive, on average, nearly 65 percent of their income from agriculture, whereas non-vulnerable households derive only about 45 of their income from agriculture. Non-vulnerable households derive a significantly greater share of their income from formal wage employment and unearned sources (including remittances) than do vulnerable households (30 percent and 15 percent, respectively, for non-vulnerable households as compared with 15 percent and 10 percent, respectively, for vulnerable households). This demonstrates how powerful off-farm formal sector employment and remittances can be as instrument of rural development, not only in terms of raising total household incomes, but also in terms of reducing overall household vulnerability to poverty (see also de la Fuente, 2010).

In terms of demographic characteristics, vulnerable households are younger, with more than twice as many dependents and 20 percent fewer working age household members. Vulnerable household heads have less education, as do vulnerable household members in general. The community characteristics also imply that vulnerable households are more likely to come from communities that are heavily dependent upon agriculture, and who have fewer members (or at least a lower proportion of community members) that leave the community on a periodic or permanent migratory basis to seek off-farm employment. Households that live in communities near open trade zones are less likely to be vulnerable, as 44 percent of non-vulnerable households come from such areas, compared with only 28 percent of vulnerable households.

Vulnerable households have significantly lower levels of asset ownership, including the important income-generating agricultural assets and commercial capital, but also the other forms of assets such as housing capital, transportation capital, and durable goods. While these are highly correlated with incomes, they may be used in a consumption smoothing capacity in the event that a household experiences a shock since they can be considered stores of wealth.

Somewhat surprisingly, the one characteristic for which there is not a statistically significant difference between vulnerable and non-vulnerable households is whether the household is female-headed. A priori, one might assume that female-headed households were more likely to be vulnerable (though the results from our income regressions reported in Table 3 suggest that female-headed status does not necessarily imply lower real per capita incomes). At least in our sample, however, female-headed households are no more likely to be vulnerable than they are to be non-vulnerable. Part of the explanation for this surprising finding could be that female-headed households have remittance income arising from spouses or children who have migrated from the countryside to urban areas. Indeed, Ward and Shively (2015) reported that female-headed households did, in fact, have a larger number of migrants in their house- hold than male-headed households. This could also be partially responsible for our finding that vulnerable households have fewer household migrants than non-vulnerable households. There are a couple ways of interpreting these results. A priori, one might hypothesize that vulnerable households would perceive their vulnerability and diversify their income sources by increasing their supply of migrants, thereby smoothing their income against potential shocks. At face value, the statistics reported in Table 5 would appear to contradict this hypothesis. However, given the dramatic differences in the average number of migrants between vulnerable and non-vulnerable households, we suggest that these statistics might be indicative of causality flowing in the opposite direction: migration and the resulting remittances to family members in the countryside may actually be a determinant of why households are not vulnerable. This has been observed in other contexts, such as Mexico, for example, where de la Fuente (2010) find a negative and statistically significant relationship between receipt of remittances and a rural household's probability of experiencing a spell of poverty. Nguyen et al. (2015), on the other hand, find no statistically significant relationship between migration and reduction in vulnerability to poverty, but this could be linked to their finding that migration and ensuing remittances have societal benefits that extend beyond just the receiving household, but also to rural areas more generally. So while we cannot say that vulnerability increases the flow of migration, these results suggest that households are less vulnerable because they have more migrants supplying the household with remittances. If urban incomes are indeed higher than rural incomes (as would be suggested in a standard Harris-Todaro framework), then migrant income and remittances not only provides the remaining household members with an income source that not only supplements agricultural profits, but which is also sufficiently de-coupled from agriculture. These remittances, therefore, presumably contribute to both higher and less variable incomes. Since these two factors are important determinants of the households income distribution and our resulting measure of vulnerability, participation in migration may be an important step in reducing household vulnerability to poverty.

5. Concluding Remarks

The notion of vulnerability as a characteristic of well-being is one of high importance to policy-makers and development practitioners wishing to more effectively target populations-at-risk with assistance in order to prevent–or at least mitigate–welfare losses in the future. In this paper, we have demonstrated a methodology for estimating household vulnerability to poverty using longitudinal data from rural China, where vulnerability is quantified as the probability that household income will fall below a specified poverty line in the future. The longitudinal structure of the data allow us to directly estimate the parameters of each household's income distribution and track the evolution of poverty and vulnerability over time.

Our results suggest that, at least for our sample drawn from a balanced panel of households in rural China, economic developments over from as late as the early 1990s through 2006 have dramatically reduced chronic poverty, such that, by the year 2006, most of the poverty observed in our sample is the result of transitory shocks that perturb household incomes below the poverty line. By considering poverty transitions across survey waves, staying non-poor from one year to the next is increasingly becoming the norm (67 percent of households remained non-poor from 2004 to 2006, compared with only 15 percent who remained non-poor from 1991 to 1993), while remaining entrenched in poverty is increasingly becoming a rarity (only 7 percent of households remained in poverty from 2004 to 2006, compared with 54 percent who remained poor from 1991 to 1993). This largely translates into reduced vulnerability to poverty, as more and more households escape the chronic, structural poverty that would persist from year to year. While restricting our sample to a balanced panel reduces the total sample size and limits our ability to make generalizable observations regarding our findings, these findings are largely consistent with general observations regarding reduced poverty and increased well-being that have occurred throughout China since the beginning of economic reforms in the late 1970s.

While the reduction in chronic poverty and the overall decline in vulnerability to poverty are no doubt positive developments, there are questions that remain regarding the persistence of transitory poverty. In other words, why have policies and reforms not been more successful in insulating households from the sort of shocks that can tip them into spells of poverty? Despite the relatively long time period covered by our panel, this answer remains elusive.

While many commentators have often interpreted President Hu's desire for a "harmonious society" to be one of narrowing income inequality; after all, the policy focus has largely shifted towards an agenda emphasizing equitable growth rather than sole reliance on growth oriented anti-poverty policies as it did prior to 2003 (Sicular, 2013). But the "harmonious society" may be better understood as attempting to address some of the social conflicts that have arisen through the course of development. Certainly, one could argue that widening income gaps such as those often observed in post-reform China could generate this sort of social discord (as happened in the United States beginning in 2011 during the so-called "Occupy Wall Street" movement). But social harmony may largely be the result of individual harmony, which is ultimately a subjective perception about one's own well-being. Studies of subjective well-being have found that, over the last two decades, life satisfaction has either remained rather stagnant or slightly declined, though satisfaction seems to be increasing in recent years, following a decline in the late 1990s and early 2000s (Easterlin et al., 2012). This pattern is somewhat mirrored by the pattern of unemployment, suggesting that aggregate levels of life satisfaction increase with aggregate employment. Clearly securing employment has psychological benefits, not least in that one feels that the income generated from their employment at least partially insulates them from other sorts of perturbations, which may result in perceptions of greater resilience or reduced vulnerability. Perceiving one's self as less vulnerable to poverty may be of greater subjective value than perceiving a widening gap between one's income and the income of complete strangers, especially for risk averse individuals who value the reduction in vulnerability perhaps more so than they would a secular increase in income. The incorporation of behavioral characteristics into studies of vulnerability may be a fruitful area of inquiry, such as the recent work by Gloede et al. (2015), and may provide the basis for new ways of contemplating rural households' decisionmaking processes.

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Highlights

- We use a balanced panel of households in rural China from 1991 through 2006 to study poverty dynamics and vulnerability to poverty.
- Over time, the structure of poverty has changed from being mostly chronic to mostly transitory.
- Vulnerability to poverty has been declining steadily over time, with much of this reduction due to increasing real incomes.
- As of 2006, high income variability is the source of most vulnerability to poverty.

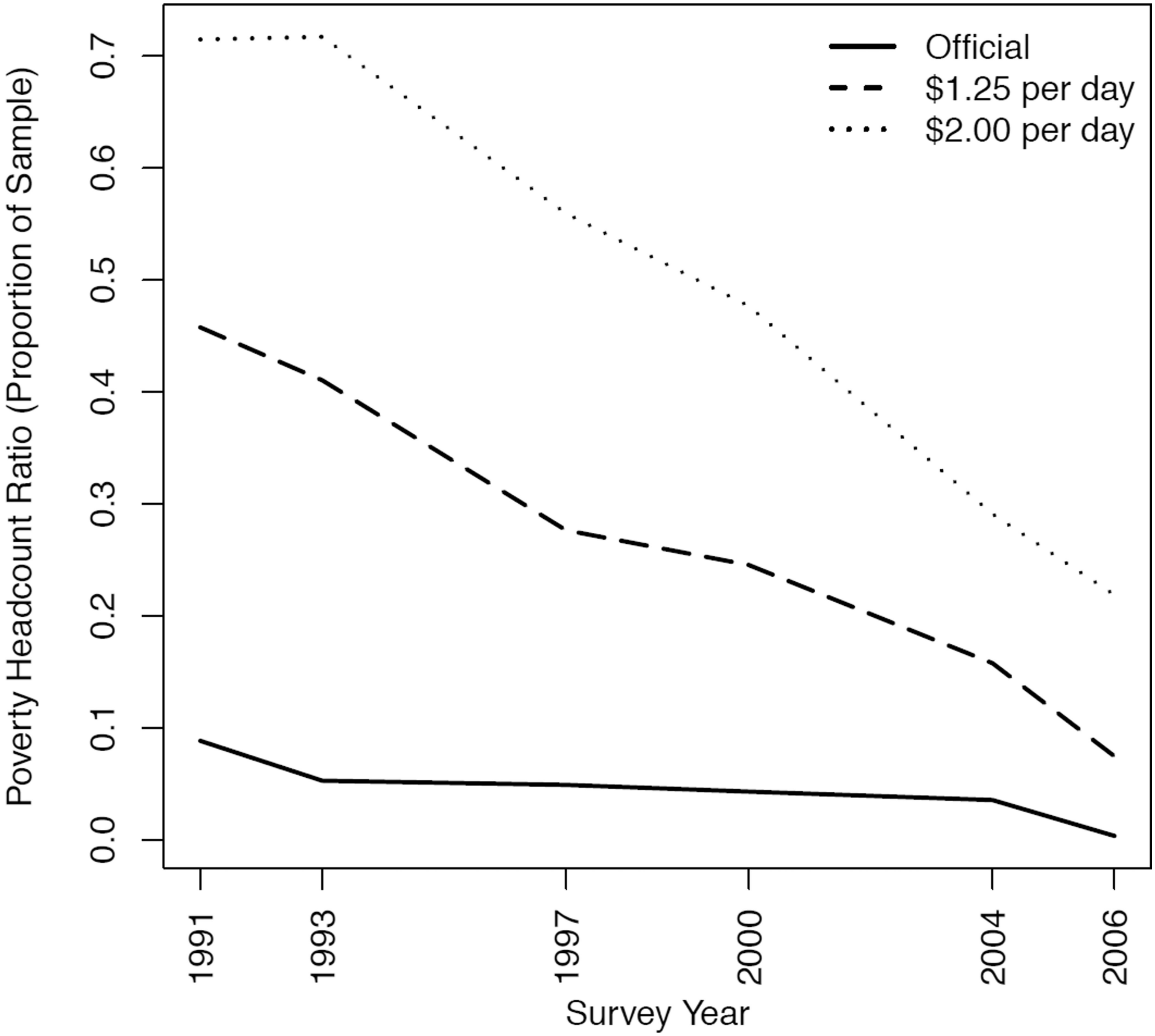

Figure 1.

Trends in poverty headcounts based on balanced sample of 375 households in CHNS (by survey wave and over different poverty lines)

Note: Official poverty lines have been converted to real terms using community specific price indices provided by Carolina Population Center as part of CHNS data. International standard poverty lines based on $1.25 per day converted to local currency using private consumption PPP conversion factor included in the World Bank's *World Development Indicators*.

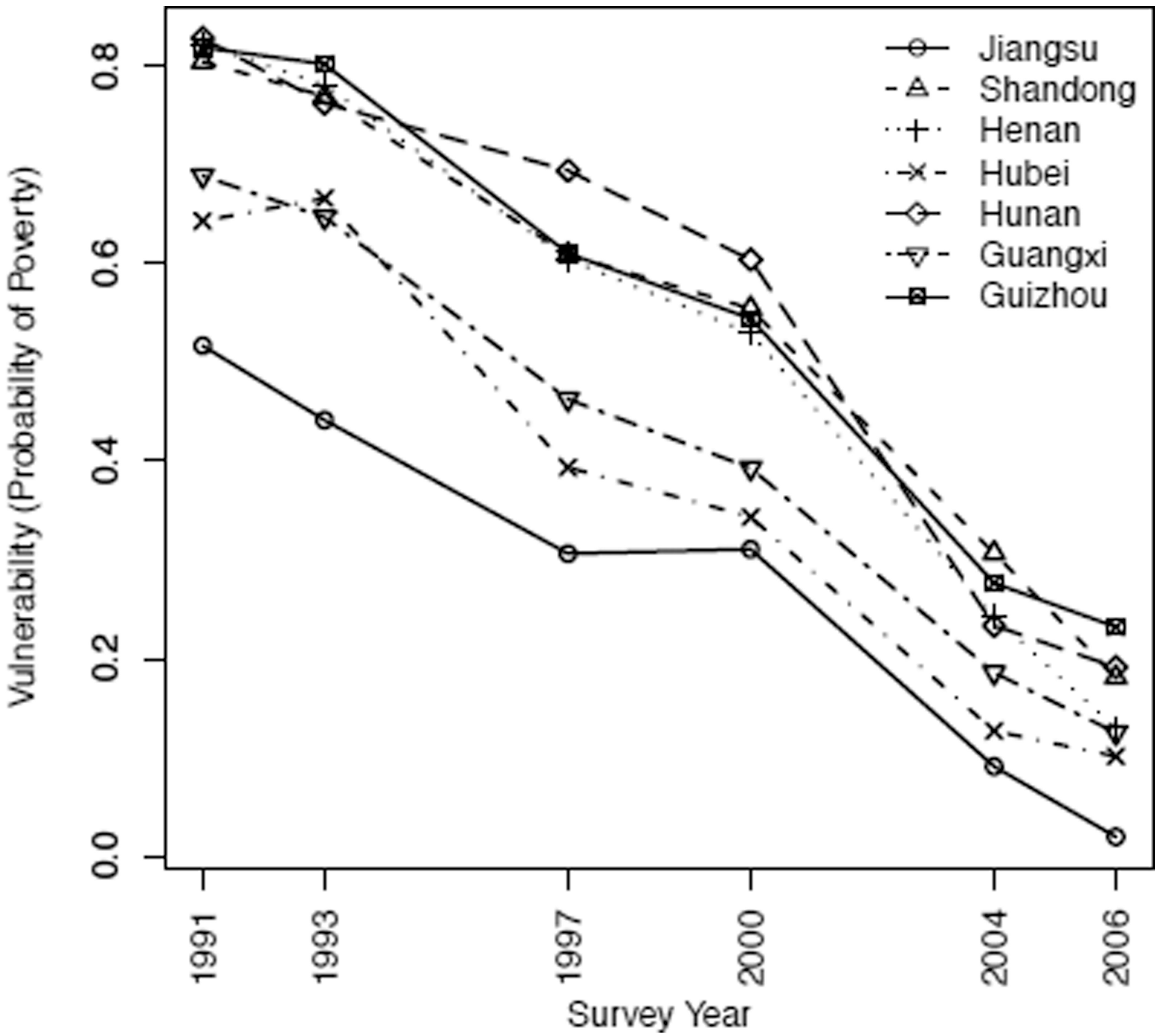

Figure 2.
Household vulnerability to poverty by region and survey Wave

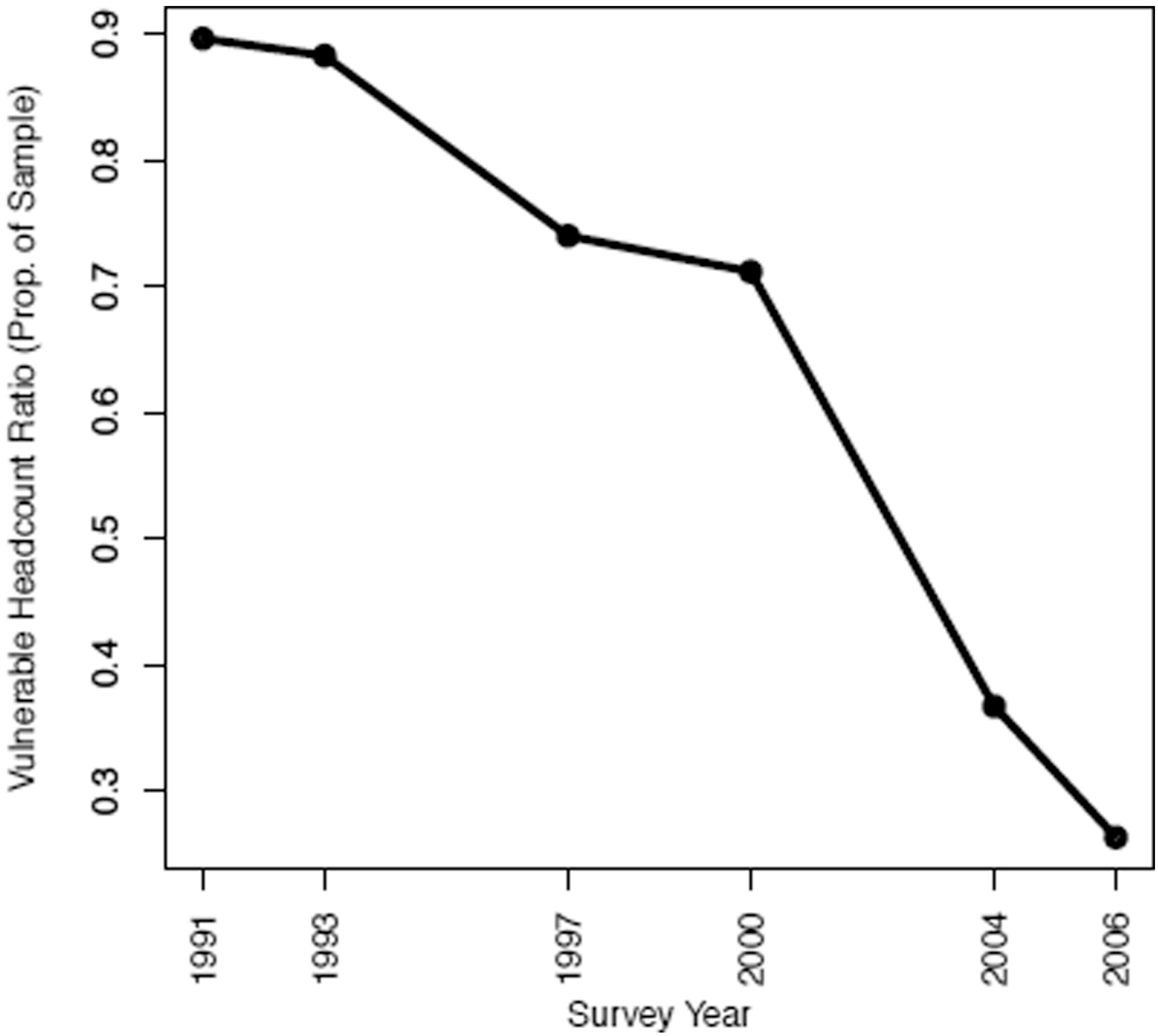

Figure 3.
Proportion of sample individuals vulnerable to income poverty by survey wave, based on \$2.00 per day poverty line and 33.3 percent probability of poverty used in determining vulnerability

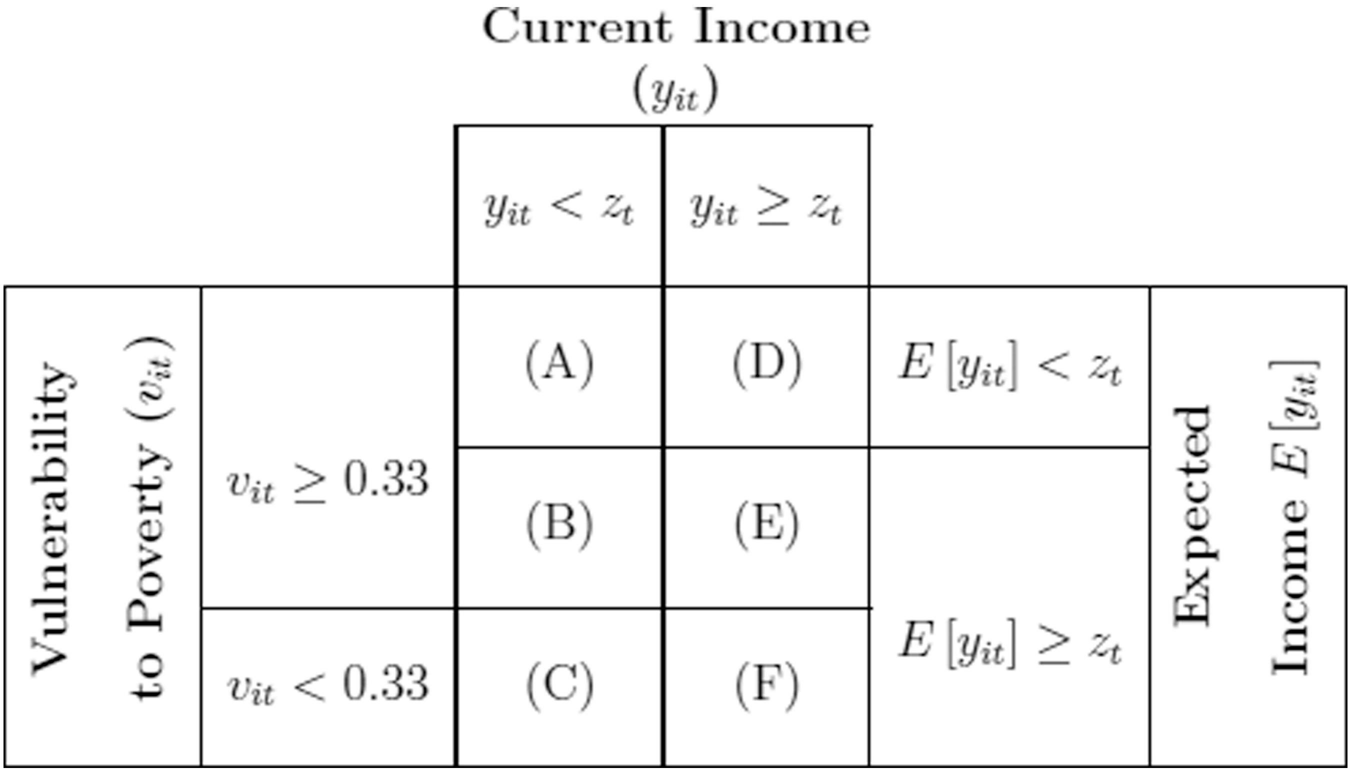

Figure 4.
Poverty and vulnerability categories

Table 1

Summary Statistics by Survey Wave

	1991	1993	1997	2000	2004	2006
ln(HH Income per Person)	7.617 (0.723)	7.687 (0.664)	8.025 (0.775)	8.180 (0.849)	8.550 (0.883)	8.794 (0.862)
Age of HH Head	41.211 (10.526)	43.216 (10.620)	46.251 (9.893)	48.670 (9.627)	53.123 (10.155)	55.105 (9.884)
Number of Dependents	1.739 (1.195)	1.691 (1.208)	1.475 (1.188)	1.288 (1.122)	1.013 (1.076)	1.019 (1.148)
Number of Working Age HH Members	2.837 (1.203)	2.880 (1.208)	3.205 (1.262)	3.333 (1.203)	3.637 (1.290)	4.264 (1.474)
Female-Headed HH (=1)	0.048 (0.214)	0.069 (0.254)	0.096 (0.295)	0.077 (0.267)	0.096 (0.295)	0.096 (0.295)
Education of HH Head	5.784 (3.579)	5.803 (3.666)	6.008 (3.618)	6.323 (3.544)	6.357 (3.506)	5.931 (3.877)
Avg. Education of HH Members	4.594 (2.179)	4.979 (2.072)	5.349 (2.078)	6.015 (2.216)	5.805 (2.148)	5.490 (2.209)
ln(Land Area Cultivated)	1.358 (0.640)	1.416 (0.671)	1.342 (0.642)	1.292 (0.683)	1.242 (0.753)	1.214 (0.777)
Agricultural Capital Index	0.591 (1.242)	0.584 (1.073)	0.760 (1.574)	0.859 (1.487)	1.012 (1.672)	1.052 (1.516)
Business Capital Index	0.248 (0.985)	0.316 (1.115)	0.270 (0.880)	0.321 (1.110)	0.364 (1.312)	0.262 (0.863)
Comm. Near Open-Trade Area (=1)	0.160 (0.367)	0.189 (0.392)	0.384 (0.487)	0.387 (0.488)	0.467 (0.500)	0.451 (0.498)
Pct. Ag. Employment in Comm.	78.341 (20.162)	70.267 (23.786)	66.469 (20.523)	66.813 (20.120)	56.637 (23.383)	50.141 (24.531)
Pct. Migrants in Comm.	15.059 (16.264)	18.851 (15.772)	25.024 (19.207)	28.360 (22.384)	29.701 (23.679)	30.528 (20.112)
No. Observations	375	375	375	375	375	375

Note: Standard deviations in parentheses.

Table 2

Poverty Transition Matrix: Empirical Probability of Transitions Poverty Status from One Period to Later Period(s)

		1993		1997		2000		2004		2006	
Poverty Status:		**Poor**	**Non-Poor**	**Poor**	**Non-Poor**	**Poor**	**Non-Poor**	**Poor**	**Non-Poor**	**Poor**	**Non-Poor**
1991	Poor	0.54	0.15	0.41	0.29	0.34	0.35	0.19	0.50	0.13	0.56
	Non-Poor	0.15	0.15	0.09	0.22	0.08	0.23	0.04	0.27	0.04	0.27
1993	Poor			0.40	0.29	0.33	0.36	0.16	0.53	0.14	0.55
	Non-Poor			0.10	0.21	0.09	0.22	0.07	0.24	0.03	0.27
1997	Poor					0.27	0.22	0.17	0.33	0.10	0.39
	Non-Poor					0.15	0.35	0.06	0.45	0.07	0.43
2000	Poor							0.13	0.30	0.11	0.31
	Non-Poor							0.10	0.48	0.07	0.51
2004	Poor									0.07	0.15
	Non-Poor									0.10	0.67

Note: Empirical probabilities are computed as sample averages for each of the particular transition categories.

Table 3

Fixed and Random Effects Panel Income Regressions: Dependent Variable is the Natural Logarithm of Real Household Income Per Person

	Fixed Effects	Random Effects
Age of HH Head	0.018 (0.014)	0.011 (0.010)
Age of HH Head^2	−0.023 * (0.013)	−0.011 (0.010)
Number of Dependents	−0.166 *** (0.021)	−0.180 *** (0.015)
Number of Working Age HH Members	−0.031 (0.023)	−0.019 (0.017)
Female-Headed HH (=1)	0.097 (0.088)	0.060 (0.056)
Education of HH Head	0.006 (0.011)	0.011 (0.007)
Avg. Education of HH Members	0.020 (0.014)	0.050 *** (0.010)
ln(Land Area)	0.179 *** (0.039)	0.175 *** (0.029)
Agricultural Capital Index	0.019 (0.013)	0.013 (0.011)
Business Capital Index	0.052 *** (0.014)	0.071 *** (0.013)
Near Open Trade Area (=1)	0.000 (0.043)	0.041 (0.037)
Pct. of Workers in Agriculture	0.001 (0.001)	−0.001 * (0.001)
Pct. of Migrant Workforce	0.004 *** (0.001)	0.004 *** (0.001)
Jan-Mar Rainfall Shock	0.060 (0.047)	0.009 (0.041)
Apr-Jun Rainfall Shock	0.212 ** (0.088)	0.297 *** (0.085)
Jul-Sep Rainfall Shock	0.306 ** (0.124)	0.298 ** (0.118)
Oct-Dec Rainfall Shock	−0.134 (0.085)	−0.215 *** (0.082)
No. Observations		
Households (*n*):	375	375
Periods (*T*):	6	6
Total Observations (*N*):	2250	2250
R^2 (within)	0.38	0.37
R^2 (between)	0.27	0.39
R^2 (overall)	0.35	0.37

*Note: Significant at 10% level

** Significant at 5% level

*** Significant at 1% level. Standard errors in parentheses. In the fixed effects model, standard errors have been adjusted according to the method proposed by Arellano (1987). This adjustment results in standard errors that are robust to the existence of heteroskedasticity and/or serial correlation in the disturbances. Standard errors in the random effects model have been adjusted using a variant of White's heteroskedasticity-robust variance-covariance matrix, where the error variances are restricted to be the same for all observations derived from a particular household.

Table 4

Poverty and vulnerability categorization

	Poor		Non-Poor		Vulnerable	
Wave	**Chronic Poor (A)**	**transient Poor (B+C)**	**High Vulnerability (D+E)**	**Low Vulnerability (F)**	**Low Expected Income (A+D)**	**High Income Variability (B+E)**
1991	0.63	0.06	0.21	0.10	0.79	0.09
1993	0.60	0.09	0.20	0.11	0.75	0.11
1997	0.39	0.11	0.23	0.27	0.55	0.14
2000	0.32	0.10	0.25	0.33	0.45	0.20
2004	0.11	0.11	0.14	0.64	0.17	0.14
2006	0.05	0.13	0.10	0.72	0.09	0.12

Note: Figures represent sample proportions. The first four columns correspond to the underlying sample for the given year, while the last two columns correspond to only the vulnerable subsample.

Table 5

Characteristics of vulnerable, non-vulnerable, and poor households

Characteristic	Vulnerable Households	Non-Vulnerable Households	Poor Households
ln(Real Household Income per Person)	7.682	8.839 ***	7.366 ***
Expected ln(Real Household Income per Person)	7.615	8.726 ***	7.588
Household Income Variance	0.391	0.329 ***	0.383
Age of Household Head	46.395	50.252 ***	45.868
Number of Dependents	1.776	0.756 ***	1.799
Number of Working Age Household Members	3.056	3.819 ***	3.030
Female-Headed Household (=1)	0.082	0.078	0.066
Education of HH Head	5.514	6.822 ***	5.599
Avg. Education of Household Members	4.824	6.201 ***	4.715
ln(Land Area)	1.277	1.362 ***	1.268
Agricultural Capital Index	0.689	0.991 ***	0.683
Business Capital Index	0.193	0.454 ***	0.195
Near Open Trade Area (=1)	0.275	0.438 ***	0.268
Pct. of Workers in Agriculture	71.212	55.038 ***	71.348
Pct. of Migrant Workforce	20.611	30.607 ***	20.445
Housing Capital Index	3.703	4.278 ***	3.662
Transportation Capital Index	0.902	1.458 ***	0.849
Household Durables Index	1.801	2.272 ***	1.795
Household Ag Income	3357.408	6594.763 ***	2516.786 ***
Household Wage Income	744.282	4379.465 ***	249.469 ***
Household Side Income	665.633	2328.836 ***	232.915 ***
Household Unearned Income	514.820	1850.092 ***	324.226 ***
Number of HH Migrants	0.328	1.010 ***	0.250 ***
Jan-Mar Rainfall Shock	0.588	0.512 ***	0.584
Apr-Jun Rainfall Shock	0.232	0.330 ***	0.224
Jul-Sep Rainfall Shock	0.230	0.200 ***	0.227
Oct-Dec Rainfall Shock	0.317	0.413 ***	0.318

* Note: Significant at 10% level

** Significant at 5% level

*** Significant at 1% level based on *t*-test of sample means compared with vulnerable households.