Precautionary Behavior and Household Consumption and Savings Decisions: An Empirical Analysis Using Household Panel Data from Rural China

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Abstract

We develop a test of precautionary behavior in the consumption and saving decisions of rural agricultural households. We first present a constant relative risk aversion model of household consumption decisions in which consumption risk is explicitly related to yield risk. Next we discuss ways of using rainfall variance as a proxy for yield risk, and consider the possibility of using a GARCH model to estimate conditional rainfall variance. Finally, we test the empirical model using household panel data from rural China and find evidence of precautionary motives behind consumption and saving decisions.

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1. Introduction

In recent years, considerable effort has gone into understanding the nature of precautionary responses to risk and uncertainty when households make consumption and savings decisions.[3] A micro-econometric literature attempting to identify the strength of precautionary motives generally confirms the prediction that income risk plays a role in determining the timing of consumption decisions, though this literature has also produced some confusion and anomalous results due to differences in empirical strategies.[4] In this paper we first extend an analytic framework developed by Blundell and Stoker (1999) to the setting of agricultural households in the developing world, and then we develop an empirical test that avoids three common weaknesses found in the literature: (1) lack of an exogenous proxy for consumption risk; (2) lack of a mechanism for updating perceived risk as uncertainty is resolved; and (3) failure to control for the possibility that responses to risk may depend on household wealth.

If proxies for risk are endogenous with other household decisions or confounded with differences across households in the noise from income reports, then they may introduce serious bias into analyses of precautionary behavior. Jalan and Ravallion (2001), for example, test whether households hold higher shares of their wealth in liquid form when they face higher risk, and find that only a small share of unproductive liquid wealth is held as a precaution against income risk. While they employ a technically sophisticated approach to calculate income risk from a five-year panel, their measure of risk may still be endogenous for two reasons. Time-invariant sources of uncertainty will be correlated with their measure of income variance, and they make no distinction between transitory income and measurement error. Browning and Lusardi (1996) emphasize further the difficulty in using income variability as a measure of consumption risk in the absence of a long time series panel data set. Since we are also working with a

[3] See Browning and Lusardi (1996), and Carrol (2001) for useful reviews of the literature. Deaton (1992) provides an important early exposition of the precautionary motive.

[4] Lusardi (1997) and Carroll (1994) suggest that the precautionary motive may explain a significant fraction of wealth accumulation. Carroll and Samwick (1997) estimate a wealth equation with direct measures of the variance of shocks to permanent and transitory income and find some evidence of a precautionary motive, but Jappelli and Terlizzese (1992) and Dynan (1993) both produce results suggesting that precautionary motives for saving are weak or non-existent. Ludvigson and Paxson (2001) suggest that approximation error is likely to be one important factor driving anomalous results.

short panel (six years), we use rainfall variability as an exogenous and observable proxy for yield risk.[5]

Recent work in the consumption literature suggests analyses of responses to risk should reflect the plausibility that perceptions of risk change as new information is revealed.[6] For this reason, use of the conditional variance of income is preferable to the unconditional variance as a measure of income risk. One important characteristic of agricultural production is that it occurs over an extended period, and that farmers are likely to adjust consumption as new information about yield risk is revealed over the crop cycle. New information revealed through rainfall allows farmers to update assessments of risk, and when combined with historical rainfall data, rainfall can be used to construct exogenous proxies for yield risk. In order to consider the possibility that farmers might be able to update expectations about future rainfall variability and respond to these changes, we also consider the possibility of using a GARCH model to estimate conditional rainfall variances for each of the surveyed villages.[7]

In addition to failing to allow for updates in risk perceptions with information revelation, important early research in the area neglected to control for the impact of wealth toward perceptions of risk. Models using quadratic preferences (e.g., Campbell, 1987) or constant absolute risk aversion (e.g., Caballero, 1990) were tractable, but have unrealistic behavioral implications. Blundell and Stoker (1999) provide a approach to working with constrant relative risk aversion preferences in analysis of consumption decisions and the timing of income risk Banks, Blundell and Brugiavini (2001) show how to implement Blundell and Stoker (1999) empirically using quasi-panels of British household data, and find that cohort specific risk terms indeed have an impact on

[5] We use twenty years of monthy rainfall data collected at 44 different local weather stations. Rose (2001) also uses rainfall variance as a proxy for yield risk when looking at how risk influences off-farm labor supply decisions and Chaudhuri (1999) shows that rainfall patterns provide good proxies for news and uncertainty and exploits these characteristics to test for forward-looking behavior in the ICRISAT villages. It should be noted that even in developed countries, farmers continue to be concerned with factors influencing production risk. A 1996 USDA survey, for example, indicates that producers are most concerned about decreases in crop yields or livestock output (production risk), and uncertainty in commodity prices. See Harwood et al. (1999).

[6] See Blundell and Stoker (1999), Chaudhuri (1999), and Behrman, Foster, & Rosenzweig (1997).

[7] Use of historical rainfall information as an exogenous shock to agricultural production has a long history in the literature. Wolpin (1982) instruments income using information on historical regional rainfall in India, Paxson (1992) uses time-series information on regional rainfall to construct estimates of transitory income caused by rainfall shocks. Rosenzweig and Binswanger (1993) and Jacoby and Skoufias (1997) also use rainfall to proxy for risk and shock, respectively.

consumption growth. This paper extends the general approach outlined in Blundell and Stoker (1999) to environment in which income risk is driven by yield risk in agricultural production.

2. Survey Data and Rainfall Variability in China

The RCRE village and household surveys. The analyses of household consumption and saving decisions in the paper use village and household survey data provided by the Survey Department of the Research Center on the Rural Economy (RCRE) at the Ministry of Agriculture in Beijing. Annual village surveys from 44 villages of Shanxi, Jiangsu, Anhui and Henan provinces are used in conjunction with a panel data spanning the period 1986 to 1991 from roughly 3400 households per year.[8] Households are asked a range of questions regarding income from on-farm activities and household consumption, land use, asset ownership, savings, formal and informal access to and provision of credit, and transfers from both village members and friends and family outside the village. The household surveys are monitored by county agricultural research offices charged with collecting expenditure, income and labor allocation information on a monthly basis. A staff person from each office works with households to clear up inconsistencies in the survey.

In several of our empirical specifications we make use of village survey information to control for proximity to off-farm markets, local topographical characteristics, village irrigation infrastructure, and ownership structure of local enterprises. Location variables include distance to the nearest public road, and a dummy variable indicating whether the village is near a city. Indicator variables denoting village location on a plain, or in mountainous or hilly areas provide information about local topography. Share of land in the village with irrigation allows us to control for the extent to which a village exposed to risk in dry seasons. We use share of village assets owned and controlled by private sector and share of gross revenue from collective and private

[8] RCRE has collected data from a panel of households from 1986 to 2002. Survey years are missing for 1992 and 1994, and we only have rainfall information through 1997 we use the first half of the panel in the analyses of this paper. We recently learned that the data for 1992 and 1994 were actually collected in these provinces but that the forms were archived because shortages in staff and funds made it impractical to enter the data. We are now encouraging our colleagues in China to enter these data. At the least, we anticipate access to a full panel from 1995 to 2002, and so we may conduct analyses separately for early and late periods, or use procedures such as those discussed in McKenzie (2001) to use the panel with gaps.

enterprises, to control for the extent of village involvement in the local economy. Finally, share of gross revenue from non-agricultural activities and numbers of village laborers employed in local and distant labor markets may be used to control access to non-farm employment.

Historical Monthly Rainfall and Rainfall Variability in China. In addition to the RCRE survey data, enumerators working with the authors collected twenty years of monthly rainfall data (January 1978 – December 1997) from county weather stations near each village. These historical rainfall data show considerable variation across the four contiguous provinces and even across counties within provinces (summary tables and figures of village rainfall characteristics are provided in the appendix I). We next provide more information about rainfall in China and discuss way of using moments of its distribution in our analyses.

Rainfall Variability in China. Most annual precipitation in China comes during a summer rainy season, but the timing of this season in each location is not fixed. The duration of the rainy season varies from year to year, and hence the variations in annual and seasonal rainfall can be quite large. High concentrations of torrential rainfall may not only cause insufficient utilization of rainwater during the rest of the year, but also result in soil erosion, floods, and water logging.

In North China (including Henan and Shanxi provinces), where annual precipitation is lower, torrential rains make up a considerable fraction of the annual rainfall, and in some years, a few storms in summer may amount to 80 percent of total annual precipitation. While annual rainfall is lower than southern and eastern coastal areas, floods, serious soil erosion, and water logging are frequent occurrences in North China. Precipitation from summer rainstorms, however, cannot be efficiently utilized in agriculture unless it falls in areas equipped with water conservation facilities. A considerable proportion of the annual rainfall is, therefore, not necessarily beneficial for agricultural production in China's semi-arid and semi-humid regions. Furthermore, scant precipitation in winter often develops into drought conditions. China's long history of drought and flood is related, in part, to a non-uniform seasonal distribution of the rainfall.

Rainfall and the Crop Cycle in the Survey Provinces. Our empirical test uses variability of rainfall as a proxy for yield risk and requires that we first determine which months of rainfall will be most important for agricultural producers. Since we have monthly precipitation for each village, alternative specifications will employ total precipitation during important months, as well as annual precipitation.

The four provinces where our survey villages are located produce 41 percent of the wheat in China (Henan 20.4 percent, Jiangsu 9.9 percent, Anhui 7.9 percent Shanxi 3.1 percent). Most wheat is grown in eastern China, and just 5 provinces (Henan, Anhui, Jiangsu, Hebei, Shandong) account for more than 70 percent of China's total wheat output and winter wheat accounts for 90 percent of China's total wheat crop. Table 1, provided in an appendix I, shows that wheat is grown throughout the four provinces, although rice is major crop in southern Jiangsu and Anhui provinces. Wheat is one of the crops used in the two-crop-per-year and three-crops-per-year rotations for rice paddy. During the 1986-1991 period we do not have information about which crop the households cultivate, we assume here that winter wheat is the major crop in these areas.[9]

Winter wheat typically comes out of dormancy in March, at which time the demand for moisture increases significantly.[10] Rainfall and supplemental irrigation are most important in the spring when most of the crop is in a drought-sensitive heading/flowering stage. Spring droughts are one of the more serious threats for the crop. Summer rainfall is important for the following year Spring's crop because rainfall from the summer rainy season determines soil moisture, which is important during wheat planting in the winter period. For rice crops, July and September the moisture and temperature sensitive heading stages occur in July and September.[11]

From the crop cycle we infer that rainfall in March, July, and September of the year might be important for crop (wheat/rice) cultivation, though this will depend somewhat on differences across varieties. We also performed regressions of household grain production on each month of rainfall to get some idea about the importance of the

[9] The fact that these are the major grain crops in these regions is confirmed by examination of more detailed information in 1993-2002 surveys.
[10] See the crop calendar in the appendix I.

specific months of rainfall for crop production. These regression results confirm that more rain in March, July and September is beneficial for grain production. We also find that when we add rainfall from July to November of the previous year to the regression, reflecting wheat crop cycle, spring rainfall becomes relatively less significant (particularly in Shanxi, Henan provinces) and more rain during this period of the previous year is also helpful for the current year's production. This is not surprising as precipitation during the latter half of the previous year is important for determining the moisture level during the winter period and likelihood of a spring drought. From this we use the annual rainfall (sum of 12 months) as well as the selected sum of rainfall (July-November) considering the wheat and rice crop calendar to get more sensitive amount of rainfall that is possibly more closely related to crop production and yield risk.

3. Theory

The consumption growth equation behind our empirical model can be derived from a standard Euler equation for optimal consumption allocation across periods t and t+1 associated with utility maximization:

(1) $$u_C(C_t) = \beta(1+r)E\{u_C(C_{t+1}) \mid \Omega_t\}$$

where u_C is the marginal utility of consumption, r is the real interest rate, and β is a discount factor less than unity.

We assume a constant relative risk aversion (CRRA) iso-elastic utility function such as

(2) $$u(C) = \frac{1}{1-\lambda} C^{1-\lambda}$$

where λ is a coefficient of relative risk aversion independent of lifetime wealth levels. From this we can derive the specific Euler equation associated with utility maximization:

(3) $$\beta(1+r)\left\{\frac{C_{t+1}}{C_t}\right\}^{-\lambda} = 1 + e_{t+1} \text{ where } E(e_{t+1} \mid \Omega_t) = 0$$

The conditional consumption shock variance is σ_{t+1}^2, is the variance of e_{t+1} conditional on information available at time *t*. Taking logs and using a Taylor approximation for logs gives the linearized Euler equation:

$$\Delta \ln C_{t+1} = \frac{1}{\lambda}\ln\beta + \frac{1}{\lambda}\ln(1+r) + \frac{1}{2}\frac{1}{\lambda}\sigma_{t+1}^2 + u_{t+1} \tag{4}$$

where $u_{t+1} = -\frac{1}{\lambda}\{e_{t+1} - \frac{1}{2}(e_{t+1}^2 - \sigma_{t+1}^2)\}$ so that $E(u_{t+1} \mid \Omega_t) = 0$

From this we can separately identify three determinants of consumer behavior: an intertemporal substitution effect and the precautionary saving motive (and possibly, a life cycle effect reflected in the consumption path). The precautionary saving motive, captured in the third term of (4), predicts that increases in the value of the expected variance of future consumption shocks will lead to higher observed consumption growth as households save more in period *t*.

Blundell and Stoker (1999) point out that the variance term in the equation cannot be simply replaced by the conditional variance of income because the variance of the consumption shock subsequent to unexpected income changes depends on the amount of financial wealth held by household and on the magnitude of current income relative to future income. Starting from their insight, we derive a modified version of Blundell and Stoker's model that explicitly introduces yield risk from agricultural production.

The model analyzes the three-period choice of consumption expenditures c_0, c_1, c_2 by a consumer over three time periods, indexed by t=0,1,2.[12] To understand the consumer's problem, we assume a constant relative risk aversion felicity function U_t with logarithmic preferences, $U_t(c_t) = \alpha_t \ln(c_t)$. The consumer's problem is:

$$\text{Max } \lambda_0 \ln(c_0) + \lambda_1 \ln(c_1) + \lambda_2 \ln(c_2) \tag{5}$$

where we normalize $\lambda_0 + \lambda_1 + \lambda_2 = 1$ and $\lambda_0 = \alpha_0, \lambda_1 = \frac{\alpha_1}{1+\delta_1}, \lambda_2 = \frac{\alpha_2}{1+\delta_2}$

subject to the budget constraint:

[12] The basic model derivation that we used here is from Blundell & Stoker (1999).

(6) $$c_0 + \frac{c_1}{1+r_1} + \frac{c_2}{(1+r_1)(1+r_2)} = W + \frac{\varepsilon_1}{1+r_1} + \frac{\varepsilon_2}{(1+r_1)(1+r_2)}$$

where $\varepsilon_1 = y_1 - E_0 y_1$, $\varepsilon_2 = y_2 - E_0 y_2$, $W = A_0 + y_0 + \frac{E_0 y_1}{1+r_1} + \frac{E_0 y_2}{1+r_2}$.

W is expected wealth at period 0, which contains initial assets and the present value of expected income to be received over the three periods. $\varepsilon_1, \varepsilon_2$ are innovations in income that are unknown as of period of 0, ε_1 is revealed in period 1, and ε_2 is revealed in period 2. Thus it is natural to assume that information about expected innovations in income is updated in period 1.

The Euler equation for optimal allocation between period 1 and 2 is

(7) $$\frac{\alpha_2}{c_2} = \frac{\alpha_1}{c_1}(1+\varepsilon_2)$$

From which we can derive consumption growth

(8) $$\Delta \ln c_2 = -\ln \frac{\alpha_1}{\alpha_2} + \frac{1}{\alpha_2}\sigma_{2|1}^2 + \frac{\alpha_1}{\alpha_2}\frac{\varepsilon_2^*}{c_1}$$

where $\sigma_{2|1}^2 = \frac{Var(\varepsilon_2^* \mid \varepsilon_1)}{W^2}$, $\varepsilon_2^* = \varepsilon_2 - E(\varepsilon_2 \mid \varepsilon_1)$

Expected growth increases with the variance of updated income innovations conditional on the previous period, $\sigma_{2|1}^2$, and will be linear in the updated income innovation normalized by the previous wealth.

To add agricultural production to this model, assume that the households manage agricultural production like a competitive firm by hiring the needed labor inputs from the market, using their land, and selling their products on the market. Their income in this case would be agricultural profit. This assumption is introduced to rule out the endogeneity of labor supply decisions and income.[13] Thus, household profits are defined as:

(9) $y_t = p_t Q_t - w_{t-1} L_{t-1} = p_t f(L_{t-1})\eta_t - w_{t-1} L_{t-1}$ where η_t is i.i.d with mean 1.

[13] Although this assumption may be unrealistic in the real world. Chaudhuri (1999) suggests that it is not likely to change the relationship between the consumption and saving decisions, and yield risk under a more 'realistic' model specification.

We assume that period *t* production depends on inputs in period *t-1*, and that there are no changes in price and wage during the period. Taking income as profit less the value of labor input and applying these to the income innovations of the previous model, we can show that income innovation terms based on crop production will be modified like:

$$\varepsilon_1 = y_1 - E_0 y_1 = pQ_1 = pf(L_0)\eta_1$$

$$\varepsilon_2 = y_2 - E_0 y_2 = pf(L_1)\eta_2 - wL_1 - E_0(pf(L_1)\eta_2 - wL_1) \quad (10)$$

$$\varepsilon_2^* = \varepsilon_2 - E_1\varepsilon_2 = y_2 - E_o y_2 - E_1\{y_2 - E_0 y_2\}$$

Since production is realized after input decisions are determined, the conditional variance of income subsequent to shock realizations in period 1 will be: $Var(\varepsilon_2^* \mid \varepsilon_1) = \pi\tilde{\sigma}_{2|1}^2$ with $\tilde{\sigma}_{2|1}^2 = Var(\eta_2 \mid \eta_1)$ and the scaling term $\pi = (\frac{pf(L_1)}{W})^2$.

If η, the yield shock, is proxied by a rainfall shocks, it is plausible that the conditional variance of the rainfall shock will be an adequate proxy for the conditional variance of the shock, $\tilde{\sigma}_{2|1}^2 = Var(\eta_2 \mid \eta_1)$.

An empirical question arises at this point. How can we estimate the conditional variance of income innovation or yield shocks? Banks, Blundell, and Brugiavini (2001) provide one possible approach to this problem. While they estimate conditional variance of income innovations using an ARCH regression and exploiting the synthetic panel data, we apply a similar estimation method to predict the conditional variance of rainfall shocks since we have a long time series of rainfall data for each village and it is a reliable proxy for yield risk. Before applying this idea to calculate the conditional variance of rainfall, we first test whether rainfall shocks show heteroskedasticity in most villages of the survey as we expect. If we cannot reject heteroskedasticity, we can then apply the GARCH model to predict values of conditional rainfall variance. Alternatively, if we reject heteroskedasticity of rainfall then predicting the conditional rainfall variance with a GARCH model will not yield any improvements over the unconditional rainfall variance.

In our empirical discussion below, we first review our tests of the plausibility of estimating conditional rainfall variances using GARCH, and based on these results we use appropriate measure for rainfall variance. Next we discuss the empirical consumption growth model used to test for presence of a precautionary savings motive, and finally we review results of various specifications of model.

4. Empirical Strategy and Results

Do we observe GARCH effects in village rainfall time series? Since we should use the conditional variance of the yield shock, we first test the possibility of using a GARCH model to estimate the conditional variance of rainfall in each year. We thus perform autocorrelation, trend and heteroskedasticity tests with respect to rainfall data of 44 villages. The autocorrelation test confirms that neither annual (12-month) not selected month rainfall series show significant autocorrelation. Further, we confirm that there is no time trend to either rainfall series in each of the 44 villages. Finally and most important for using the GARCH model, we show that rainfall in most villages is not heteroskedastic, thus implying that variance of rainfall might not vary across the periods. Even when performing GARCH estimation for each village, these tests are confirmed. Rainfall shocks are not persistent and tend to die out rather fast, meaning that forecasted rainfall variance converges and would not vary much over our sample period (these results are summarized in Figures 4 and 5 in the Appendix II). Predictions of conditional variance would not provide additional information across the time for identifying a precautionary motive in consumption growth equation, and thus we use the unconditional variance of rainfall for each village as our proxy for yield risk.[14]

Changes in consumption exposure to yield risk are captured exclusively by a scaling term that controls for exposure to yield shocks. Since the numerator of the scaling term is the value of household grain output in period *t*, it also contains information about expectations of future yields and a possible source of information about changes in expected future income. Factors other than rainfall (e.g., expectations about future prices, or changes in quota policy) are likely to have a more persistent effect on the value of future yields, and they are likely to be captured by this term.

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[14] We calculate the sample variance of rainfall for each village, *j*, as

$$\sigma_j^2 = \left(\frac{1}{T-1} \sum_{t=1}^{T} (R - \bar{R})^2 \right)_j \quad .$$

Empirical Specification. The base specification for consumption growth is derived from our previous model although it is similar to those which are derived from the standard Euler equation (Banks, Blundell and Burgavani (2001), Ludvigson and Paxon (2001), Chaudhuri (1999), Browning and Lusardi (1996)):

(11) $$\Delta \ln C_{it+1} = \alpha + \gamma Z_{it} + \phi m_{it+1} + \delta RS_{it} + \lambda' V_{it} + \pi D_{it} + u_{it+1}$$

where $\Delta \ln C_{it+1}$: Growth in non-durable consumption from period t to t+1.

Z_t: Area of land managed by the household

m_{it+1}: Scaled unconditional variance of rainfall (= $\pi_{it}\sigma_j^2$ where $\pi_{it} = \left(\frac{\widetilde{Y}_{it}}{C_{it}}\right)^2$ & $\widetilde{Y}_{it}$ is the value of crop production in period t.[15]

RS_{it}: Rainfall shock (= $| R_{it} - R_{it-1} |$)

V_{it}: Vector of village variables such as village population, location, industry structure.

D_{it}: Province-year interaction dummies.

The coefficient on scaled rainfall variance, ϕ, in (11) is the focus of our estimation efforts, as a positive value indicates that household consumption is lower (and saving higher) in period t when households expecting that future yield shocks will have a greater potential impact on the variability of consumption. Much effort in presenting alternative specifications will center on demonstrating the robustness of this coefficient to different potential sources of bias.

Other coefficients, however, are also of potential interest. Our model predicts that households will update their expectations of earnings after realization of a period t rainfall shock, and that the impact of this shock on local agriculture will depend on levels of moisture in the soil and the previous year's rainfall shock. Given that $\Delta RS_t = RS_t - RS_{t-1} = (R_t - \overline{R}) - (R_{t-1} - \overline{R}) = R_t - R_{t-1}$, the rainfall shock term is specified as the absolute value of the difference between rainfall in period t and t-1, $R_t - R_{t-1}$ since we expect that both positive shocks (e.g. flood) and negative shocks (e.g. drought) both have unfavorable impact on the agricultural production and consumption.

[15] In empirical implementation we replace the expected wealth term (W) in the scaling factor by consumption in peirod t like Banks, Blundell and Brugiavini (2001). It may cause a measurement error problem in the estimation although we try to treat this problem with using IV method.

Strictly speaking, a positive shock means that it rained more compared to the previous year and a negative shock means that it rained less compared to the previous year. Thus shock is a relative concept here.

In the first set of specifications, we estimate (11) without separately distinguishing heavy rainfall or drought conditions and find we observe significant positive signs on the rainfall shock term (Table 1). When we estimate (11) for cases of drought and heavy rainfall separately, the coefficient on rainfall shock shows a significant positive sign in both cases, suggesting that we can interpret a current rainfall shocks as one cause of a decline in current consumption (Tables 2).

In our first extension to the base specification, we interact the scaled rainfall variance term with the share of land that is irrigated in each village, and with dummy variables for provinces other than Shanxi. Since yield risk varies regionally, and depends on soil type, climate, and the use of irrigation, we would expect that rainfall variability will be more important for consumption and saving decisions in dry regions and where less of the land is irrigated. Thus we will expect that the interaction between share of village land with irrigation and the scaled rainfall variance term to carry a negative sign. When looking province by province, we also note from Appendix I that rainfall variability appears to be more pronounced in Shanxi than in most villages of other provinces. Given that Shanxi and Henan are more arid than Jiangsu or Anhui, we also expect to find that rainfall variance has a greater impact on savings and consumption decisions in these provinces.

We next explicitly introduce additional village level variables to control for omitted village specific factors that may be correlated with consumption risk related to yield variability. These variables include village population, the dummy indicating whether the village is in a mountainous or hilly area, a dummy variable for proximity to an urban area, share of irrigated land in the village, distance to the nearest public road, share of village assets owned and controlled by private sector in the village, cadre share of village population, total land area in a village, share of gross revenue from livestock production, share of gross revenue from non-agricultural activities, and share of gross revenue from collective and private enterprises.

Finally we introduce specifications that control for access to local and migrant employment opportunities. Under the assumption that off-farm employment can be used as an alternative means for smoothing yield shocks, we assume that the precautionary motive for saving may be mitigated if households expect that they might be able to find or expand off-farm employment subsequent to experiencing a serious yield shock. We interact the scaled rainfall variance term with shares of village members employed in local and migrant labor markets, respectively, in an effort to identify this effect of access to off-farm labor markets.[16]

We have not explicitly included household demographic information because the structure of the household may itself be determined by consumption smoothing considerations (Rosenzweig, 1988; and Rosenzweig and Stark, 1989).[17] Measures of human capital, which could be constructed at the level of the household from information about numbers of individuals with different amounts of education, would also re-introduce demographic structure and potential biases in our statistical test. While not considered in this paper, it may be of use to consider specifications in which these variables are included and treated as predetermined but not strictly exogenous regressors.

Results. Table 1 summarizes results for different flavors of the base specification and Table 2 shows results when we look at negative rainfall shocks in isolation. Coefficients on the scaled rainfall variance term appear to provide strong evidence of precautionary behavior in farm households consumption decision. As weather risk increases, households depress current consumption in favor of future consumption.

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[16] These "measures of access to off-farm markets" are constructed as shares of the village with off-farm employment in either local or migrant labor markets in period t-1. These measures may be endogenous with expected growth of the local economy, and this fact is not considered when we introduce these terms. In addition, our rainfall shock term is specified as the difference in rainfall between period t and t-1. It is quite plausible that off-farm labor market participation in period t-1 is related to last years shock and our rainfall shock term. It might be better to use interactions of the scaled rainfall variance and the dummy variable for proximity to a city, or distance between the village and a major metropolitan area (e.g., the provincial capital, Beijing or Shanghai). Other village level variables may also suffer similar endogeneity problems.

[17] Kin based inter-household income transfers, 'exogamous' marriage migration and inter-household contractual arrangements are manifestations of income smoothing in an environment of spatially covariant risks.

The sign on the irrigation interaction term is in the direction that we would expect, though not significant in some specifications.[18] Interaction might be meaningful in case of the drought although we take account both flood and drought cases in the regression. Also irrigation does not necessarily make a lot of difference in summer because there is already enough rain during that season while our selected months includes these periods. Interactions between scaled rainfall variance and dummy variables for Anhui, Jiangsu, and Henan provinces carry negative coefficients, suggesting that precautionary motives are stronger in Shanxi province. Given that Shanxi is more arid but also has greater rainfall variability, this result is consistent with our expectations. Interactions with household land area, however, show significant negative signs and suggest that households with more land are less at risk from rainfall variability. Initially we expected that households with more land would be at greater risk, but this is likely a result of the constant relative risk aversion origins of the scaling term. Those households with more land are on average wealthier and are less exposed to yield variability.

Robustness Checks. The regression models shown in Tables 1 and 2 suffer from three potential problems. First, the village variables used are likely to be endogenous and may be biasing the coefficients on scaled rainfall variance terms. Second, use of household land and a household specific scaling term introduces the possibility that our results are biased by some source of unobserved heterogeneity. Third, the presence to period *t* consumption in the scaling term makes it likely that errors in the measurement of this term will be correlated with errors in the measurement of the dependent variable. Results presented in Tables 3 through 7 provide an attempt to deal with each of these issues.

Tables 3 and 4 show results from specifications in which we drop all village level variables and instead introduce village-year dummy variables to control for all aggregate shocks to villages and all fixed village effects. This exercise leads to coefficients on the scaled rainfall variance that are similar to those in our base regressions. Next, Table 5 presents results in which we first difference the data in order to control for unobserved heterogeneity. Village-year dummy variables now control for village specific

[18] A large number of reservoirs and water diversion structures have been built and many tube wells have been installed, in order to supply water for the irrigation and flood control depends on the land drainage system or water pumping station in China. Refer to Xu and Peel (1991).

occurrences with an impact on the change in growth. The first differenced scaled rainfall variance term picks up changes in risk associated with changes in the inverse of expected lifetime wealth. The higher positive coefficient indicates that those households whose consumption appears to become more at risk from yield shocks will respond by increasing the amount of consumption that they defer to future periods.

Tables 6 and 7 show our first efforts to deal with the possibility that errors in the measurement of the scaling term may be correlated with the dependent variable. In Table 6, we have estimated the growth model in levels with the scaled rainfall variance term instrumented with the period t-1 value of the scaled variance term. The results are significant at the 10 percentile, and still carry the positive sign associated with a precautionary motive. In Table 7, we show a first-differenced model in which the scaled rainfall variance term is instrumented by t-1 levels.[19] Again, we see that households respond to changes in relative consumption risk by reducing current growth in their consumption.

Other Potential Problems with Our Approach. Our model fails to consider some of the constraints faced by rural households in the developing world. By introducing yield risk in our model, we add one aspect of agricultural production, but other than this the model motivating our test is based on an exogenous income process and not endogenous agricultural income. Such standard intertemporal consumption models with exogenous income and credit constraints, though dynamic and perhaps suitable for the case where wage labor is the primary source of income, are not particularly relevant for analyzing rural households where income from farm production contributes significantly to total household income—although off-farm income is important source of household in contemporary China. As a next step, we will add risk to a dynamic model that explicitly considers these features in the spirit of dynamic household models presented in Behrman, Foster, and Rosenzweig (1997) and Saha (1994). [20]

[19] Anderson and Hsiao (1982) first suggested that instruments of this type will be valid if Δm_t is correlated with m_{t-1} but not the error term.

[20] Saha (1994) analyses a two-season agricultural household model of output and price uncertainty. Roe and Graham-Tomasi (1986) also introduce the risk into their dynamic household model. Chaudhuri (1999) exploit the inter-seasonal dimensions of household decisions to analyze the precautionary saving behavior.

How would a dynamic model help to inform our empirical analysis? And what would be the implications for our current empirical strategy? Chaudhuri (1999) suggests that the income process may be conditionally heteroskedastic when we introduce yield or price risk in an agricultural household production model and that this added complication will not pose serious problems, because even with a conditionally heteroskedastic income process, we would expect households to have the same behavioral response to risk. Still, we believe that our analyses would be stronger with formal derivation of a model incorporating both production and consumption behavior under uncertainty.

Another extension would be to place the household's optimal decision in a multi-crop framework. In our model we assume just one crop (wheat/rice) and one input, but the farm households' production revenue typically comes from multiple crops: wheat, rice, and corn. Multi-output production introduces several new dimensions to a household's choice problem. In particular, the optimal input allocation among different crops becomes an important choice that is influenced by relative profitability and perceived differences in risk. Household's optimal decisions in a multi-crop framework are complex and demand a separate analytical and empirical treatment that is beyond the scope of this paper.

Finally, although off-farm earnings are a major source of income for many farmers in China, and may be used to stabilize farm household income, our model does not explicitly include this possibility. Risk mitigation arrangements such as off-farm labor supply and on-farm storage based on inter-seasonal framework could be appropriately analyzed by introducing price and yield uncertainty in the agricultural household's optimization problem (Saha, 1994; Rose, 2001).

5. Conclusion

Traditionally farming is a risky occupation in that the consequences of decisions or events are often not known with certainty until long after they occur. While there are many sources of risk in agriculture, ranging from price and yield risk to the personal risks associated with injury or poor health we study farm household response precautionary response to identifiable yield risk related to rainfall variable.

We proceed from the assumptions that a measure of risk should be related to conditional expectations in consumption theory. Since the lack of long panels of data rules out the possibility of using conditional heteroskedasticity in income processes for identification of this effect, most analyses of the effects of income risk will be biased or endogenous. We suggest that in rural agricultural environments, a relatively long time series data of rainfall data can be an adequate proxy for yield risk. Since historical rainfall data is much less time-consuming to acquire, use of rainfall data is much less costly than execution of long panel household surveys with the explicit aim of studying precautionary behavior.

Although many caveats should be applied to both our model specification and implementation, we appear to find some evidence supporting the precautionary behavior of the household's consumption in rural China. The RCRE panel continues through 2002, and we used the early version of the data first in an effort to avoid biases introduced by missing survey years in 1992 and 1994. With updates to our rainfall information we will also estimate these models from the period 1995 to 2002. Given the increase in labor market participation between the early and later periods of the RCRE panel, it should be feasible to make useful comparisons across these periods.

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Appendix I:

Table1. Total sown areas of farm crops in 4 provinces

(units: 1000 hectares, %)

	Sown area of grain crops	Rice	Wheat	Corn
Shanxi	3128.1	6.1	951.2	822.8
Jiangsu	5994.4	2377.6	2341.4	439
Auhui	6030.6	2212.1	2137.6	512.2
Henan	8879.9	489.5	4927.3	1952.4
Shanxi	100.0	0.2	30.4	26.3
Jiangsu	100.0	39.7	39.1	7.3
Auhui	100.0	36.7	35.4	8.5
Henan	100.0	5.5	55.5	22.0

Source: China Statistical Bureau (1998) *China Statistical Yearbook 1998*.

Figure 1. Crop Calendar in China (wheat/rice):

January
- Wheat: Dormant

February
- Wheat: Dormant

March
- Early rice: Planting; Wheat: Vegetative

April
- Early & single rice: Planting; **Wheat: Heading***

May
- **Early rice: Heading***; Wheat: Filling

June
- Early rice: Maturing; Single rice: Vegetative; Wheat: Harvesting

July
- Early rice: Harvesting; **Single rice: Heading*;** Late rice: Planting

August
- Single rice: Maturing; Late rice: Vegetative

September
- Single rice: Harvesting; **Late rice: Heading***; Wheat: Planting

October
- Single rice: Harvesting; Late rice: Maturing; Wheat: Planting

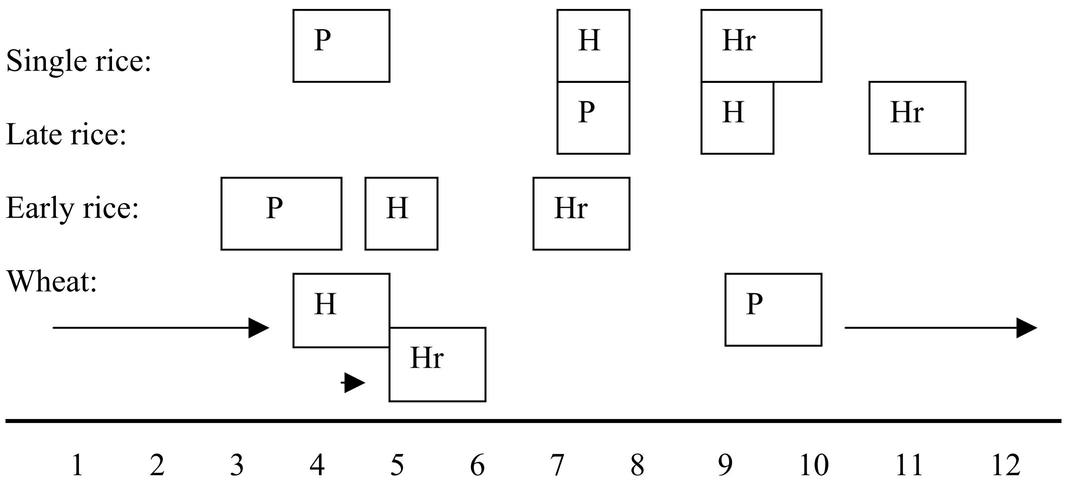
November
- Late rice: Harvesting; Wheat: Vegetative

December

- Late rice: Harvesting; Wheat: Dormant

Note: * Moisture/Temperature sensitive stage of development
Source: Production estimates and crop assessment div., FAS, USDA.

Figure 2. Crop calendar (Rice/wheat)



P: Planting, H: Heading, Hr: Harvesting

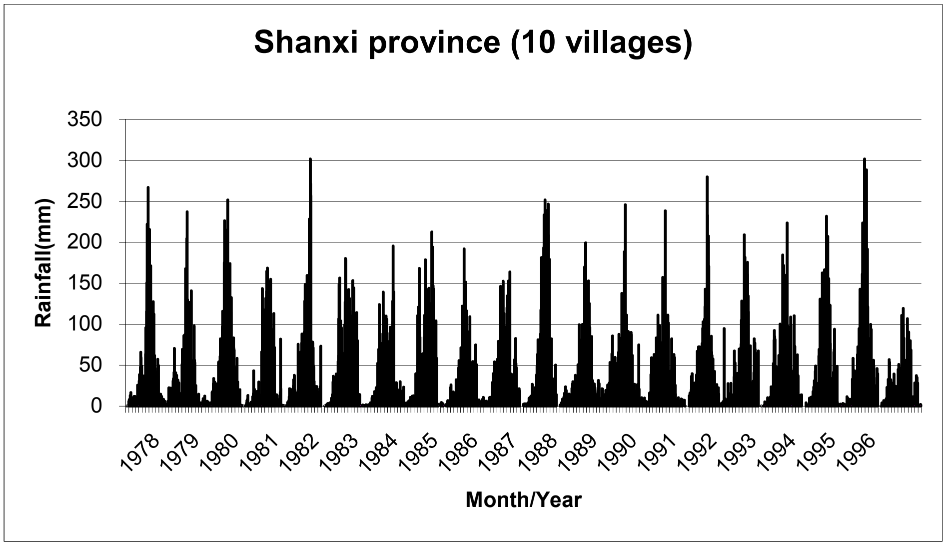
Table 2. Summary of rainfall data

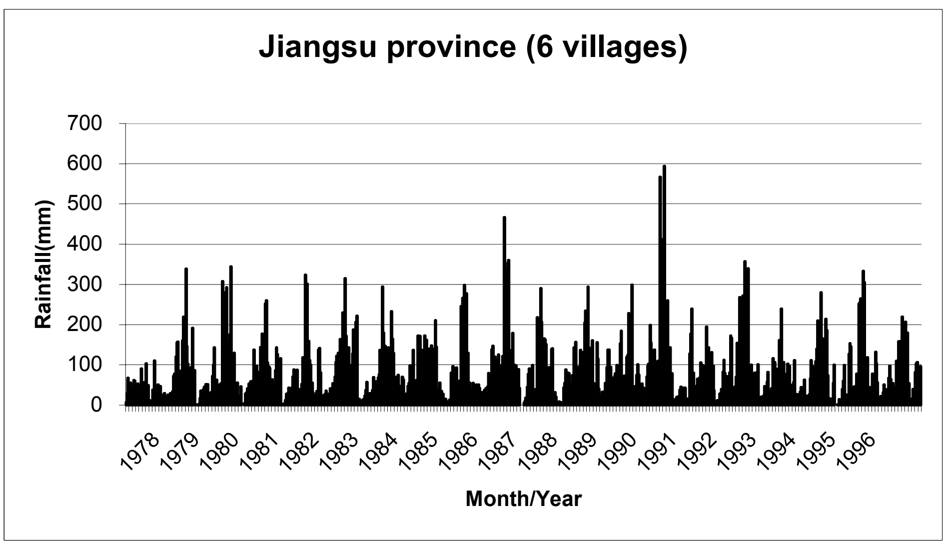
(Unit=mm)

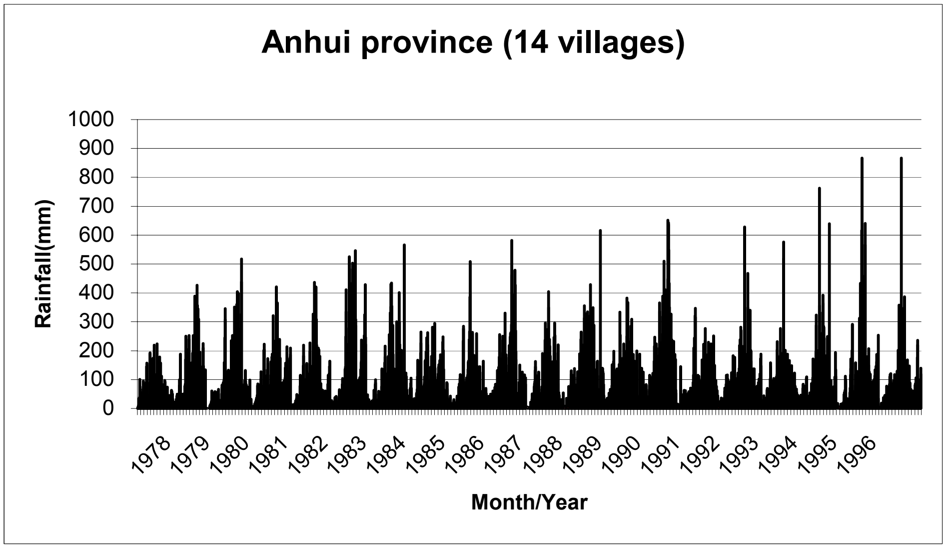
Number	Village ID	Average(village)	Average(province)
1	1401	369	Shanxi
2	1402	424	
3	1403	394	
4	1404	407	
5	1405	518	
6	1406	477	
7	1407	529	
8	1408	491	
9	1409	545	
10	1410	547	Shanxi = 470
11	3205	1013	Jiangsu
12	3206	1013	
13	3207	1024	

14	3208	1024	
15	3209	1102	
16	3210	1102	Jiangsu = 1046
17	3401	805	Anhui
18	3402	890	
19	3403	837	
20	3404	918	
21	3406	950	
22	3407	703	
23	3408	977	
24	3409	995	
25	3410	1285	
26	3412	1077	
27	3413	1097	
28	3415	1632	
29	3417	1673	
30	3418	1867	Anhui = 1122
31	4101	590	Henan
32	4102	656	
33	4103	598	
34	4104	279	
35	4105	1312	
36	4106	805	
37	4107	727	
38	4108	643	
39	4109	858	
40	4110	914	
41	4111	783	
42	4112	514	
43	4113	560	
44	4114	627	Henan = 705

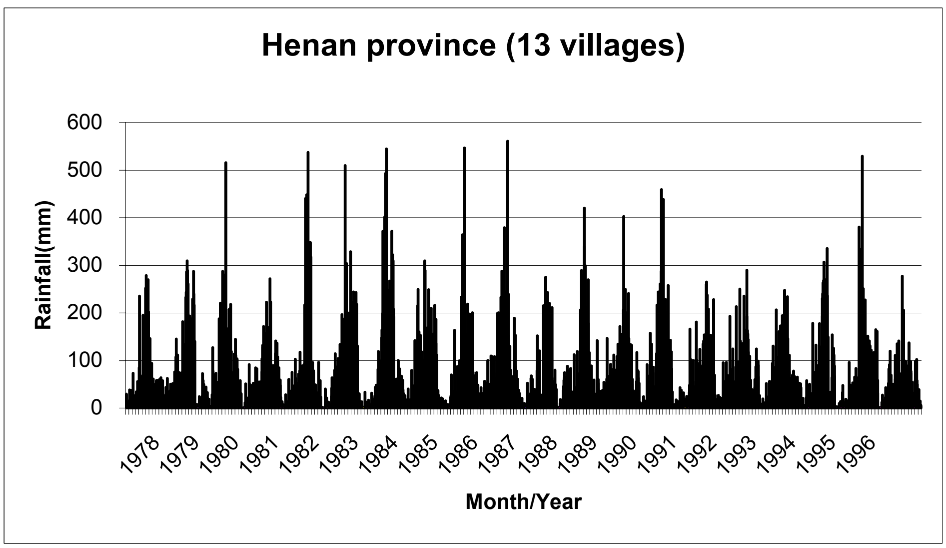
Figure 3. Rainfall pattern in each Province (1978-1997)







Anhui province (14 villages)
Rainfall(mm)
1000
900
800
700
600
500
400
300
200
100
0
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
Month/Year



Henan province (13 villages)
Rainfall(mm)
600
500
400
300
200
100
0
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
Month/Year

Appendix II. Estimation of conditional variance of rainfall using GARCH model

A standard GARCH(1,1) model with no regressors in the mean and variance equations:

Mean equation: $R_t = c + \varepsilon_t$

Variance equation: $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$

We first should study the basic statistical features of the monthly rainfall data, in order to know if it is sensible to use the GARCH model with the rainfall data. For the proper specification of the mean equation in the model we have to test autocorrelation of the coefficients for the rainfall series as well as trend. If the rainfall has strong persistence then we can use the first difference of rainfall in the mean equation.

We did the below tests for each village using annual rainfall/selected months of rainfall (sum of July through November).

1. Autocorrelation test: test for mean equation specification

$$R_t = \alpha + \rho R_{t-1} + \varepsilon_t$$

Test $H_0 : \rho = 0$

All villages could not reject the null. Thus it implies that there is no serial correlation in the rainfall in these villages.

2. Trend test: test for whether time trend exist in the rainfall

$$R_t = \alpha + \rho T + \varepsilon_t$$

Test $H_0 : \rho = 0$

All villages could not reject the null. Thus it implies that there is no trend in the rainfall in these villages.

3. Heteroskedasticity test: $(R_{it} - \overline{R}_i)^2 = \alpha + \rho(R_{it-1} - \overline{R}_i)^2 + u_{it}$

Based on our mean equation specification ($\varepsilon_t = R_t - c$) this is the same as the ARCH(1) specification test.

$$\varepsilon_t^2 = \alpha + \rho\varepsilon_{t-1}^2 + u_t$$

Test $H_0 : \rho = 0$

Regression results show that most villages could not reject the null.

4. GARCH specification test: test for whether GARCH (1,1) specification is appropriate for the data. Based on 1 and 2 results mean equation is specified like the below.

Mean equation: $R_t = c + \varepsilon_t$

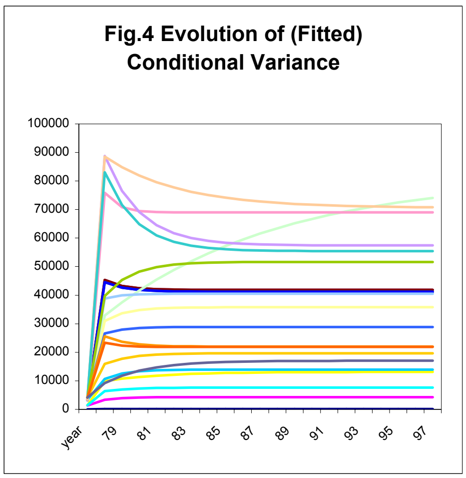
Variance equation: $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$

Test $H_0 : \alpha = 0, \beta = 0$

16 villages among 44 villages could not reject the null. Most estimation shows that $\hat{\alpha} + \hat{\beta} < 1$ so it implies that the rainfall shock cannot persist long time.

Figure 4 & 5. Evolution of (fitted) conditional variance of rainfall:

Figure 4 is based on the fitted conditional variances of the villages that would not show the GARCH effect and figure 5 is based on the fitted conditional variances of the villages that would show the GARCH effect. Since most values of conditional variance converges fast after a few years of the starting year there are little variation in the values of the conditional variance during the sample period (1986-91). For this reason the measure of the consumption shock conditional variance is replaced in the empirical regression with the interaction between the scaling factor and the measure of the income shock conditional variance.



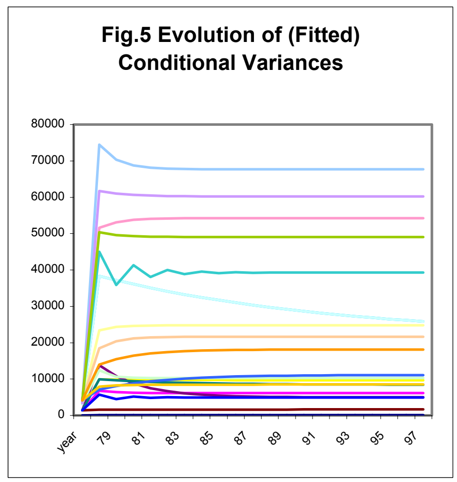


Table 1. Summary of Estimation Results Using Village Variables.

Dependent Variable: Consumption Growth from Period t to t+1, Δln(non-durable consumption per capita).

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Land_t$	-0.256	-0.241	-0.239	-0.286	-0.316	-0.113	-0.089	-0.239
	(0.089)**	(0.089)**	(0.089)**	(0.091)**	(0.093)**	(0.102)	(0.105)	(0.089)**
Scaled Rainfall Variance	1.482	1.396	1.566	2.412	3.361	1.943	4.834	1.344
	(0.102)**	(0.103)**	(0.207)**	(0.423)**	(0.607)**	(0.263)**	(0.550)**	(0.200)**
(Scaled Rainfall Variance)* (Irrigated Share of Land in $Village)_t$			-0.305		-1.318	-0.307	-1.794	-0.642
			(0.280)		(0.407)**	(0.284)	(0.422)**	(0.299)*
(Province=Jiangsu)*(Scaled Rainfall Variance)				-1.085	-0.836		-1.228	
				(0.464)*	(0.486)		(0.395)**	
(Province=Anhui)*(Scaled Rainfall Variance)				-1.002	-1.127		-1.343	
				(0.430)*	(0.475)*		(0.356)**	
(Province=Henan)*(Scaled Rainfall Variance)				-1.367	-2.014		-2.856	
				(0.459)**	(0.573)**		(0.471)**	
(Scaled Rainfall Variance)*$Land_t$						-3.866	-8.269	
						(1.255)**	(1.646)**	
(Scaled Rainfall Variance)*(Share of Village with Local $Employment)_{t-1}$								27.073
								(11.731)*
(Scaled Rainfall Variance)*(Share of Village with Migrant $Employment)_{t-1}$								80.425
								(27.901)*
ln(Village Population $_t$)	0.033	0.032	0.032	0.031	0.034	0.028	0.029	0.034
	(0.011)**	(0.011)**	(0.011)**	(0.012)**	(0.012)**	(0.012)*	(0.012)*	(0.011)**
1 if in mountains	0.039	0.025	0.029	0.031	0.05	0.025	0.049	0.035
	(0.017)*	(0.018)	(0.019)	(0.018)	(0.019)*	(0.019)	(0.019)*	(0.019)
1 if in hills	0.017	0.013	0.014	0.015	0.02	0.013	0.018	0.022
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)*	(0.010)	(0.010)	(0.010)*
1 if in near city	0.133	0.145	0.147	0.143	0.152	0.143	0.149	0.147
	(0.018)**	(0.019)**	(0.019)**	(0.019)**	(0.019)**	(0.019)**	(0.019)**	(0.019)**

Distance to Nearest Public Road (Km)	0.003	0.004	0.003	0.003	0.002	0.004	0.002	0.002
	(0.002)	(0.002)*	(0.002)*	(0.002)	(0.002)	(0.002)*	(0.002)	-0.002
(Irrigated Share of Land in Village)$_t$	0.023	0.001	0.012	-0.008	0.031	0.007	0.028	0.017
	(0.017)	(0.018)	(0.021)	(0.018)	(0.023)	(0.021)	(0.023)	(0.021)
(Share of Assets in Village Owned or Controlled by Private Sector in Village)$_t$	0.149	0.147	0.151	0.145	0.151	0.147	0.139	0.147
	(0.028)**	(0.028)**	(0.028)**	(0.029)**	(0.029)**	(0.028)**	(0.029)**	(0.028)**
(Cadre Share of Village Population)$_t$	2.339	2.984	2.98	2.531	2.702	3.103	2.983	4.051
	(1.504)	(1.496)*	(1.496)*	(1.525)	(1.528)	(1.496)*	(1.514)*	(1.513)**
(Total Land Area of Village)$_t$	2.036	1.054	1.195	0.653	0.983	1.482	1.387	1.979
	(0.992)*	(1.025)	(1.037)	(1.037)	(1.045)	(1.041)	(1.044)	(1.050)
(Access to Health Insurance (Yes=1) in Village)$_t$	-0.022	-0.021	-0.022	-0.026	-0.028	-0.018	-0.023	-0.017
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)*	(0.013)	(0.014)	(0.013)
(Share of Village with Local Employment)$_{t-1}$	-1.426	-1.508	-1.502	-1.369	-1.372	-1.63	-1.643	-2.061
	(0.515)**	(0.514)**	(0.514)**	(0.517)**	(0.517)**	(0.516)**	(0.520)**	(0.580)**
(Share of Village with Migrant Employment)$_{t-1}$	2.57	2.8	2.725	2.263	1.721	3.118	2.231	1.956
	(0.963)**	(0.961)**	(0.966)**	(0.971)*	(0.998)	(0.978)**	(0.996)*	-1.087
(Village Share of Gross Revenue from Livestock)$_t$	-0.072	-0.081	-0.078	-0.096	-0.093	-0.07	-0.079	-0.091
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.062)	(0.062)	(0.062)
(Village Share of Gross Revenue from Non-Agricultural Activities)$_t$	-0.067	-0.092	-0.083	-0.093	-0.055	-0.078	-0.035	-0.069
	(0.039)	(0.039)*	(0.041)*	(0.039)*	(0.042)	(0.041)	(0.042)	(0.041)
(Village Share of Gross Revenue from Collective & Private Enterprises)$_t$	0.115	0.14	0.134	0.128	0.088	0.141	0.078	0.117
	(0.038)**	(0.039)**	(0.040)**	(0.039)**	(0.042)*	(0.040)**	(0.042)	(0.040)**
Rainfall Shock		13.389	13.667	13.767	14.975	13.077	13.929	12.205
		(2.754)**	(2.760)**	(2.773)**	(2.798)**	(2.769)**	(2.799)**	(2.809)**
Obs.	10512	10512	10512	10512	10512	10512	10512	10512
R-squared	0.04	0.04	0.04	0.05	0.05	0.05	0.05	0.05

Notes: 1. Robust standard errors in parentheses 2. * significant at 5%, ** significant at 1% 3. All specifications include province*year dummies to control for aggregate shocks to the provincial economy.

Table 3. Summary of Estimation Results Using Village-Year Variables.

Dependent Variable: Consumption Growth from Period t to t+1, Δln(non-durable consumption per capita).

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Land_t$	-0.379	-0.366	-0.39	-0.4	-0.176	-0.136	-0.32
	(0.075)**	(0.096)**	(0.098)**	(0.099)**	(0.108)	(0.115)	(0.097)**
Scaled Rainfall Variance	2.10	2.79	2.78	3.86	3.40	5.65	2.58
	(0.101)**	(0.257)**	(0.548)**	(0.816)**	(0.331)**	(0.662)**	(0.295)**
(Scaled Rainfall Variance*(Irrigation Share of		-1.07		-1.50	-1.17	-2.11	-1.46
Land in Village)$_t$		(0.502)*		(1.398)	(0.351)**	(1.493)	(0.587)*
(Province=Jiangsu)*(Scaled Rainfall Variance)			-1.03	-0.76		-1.31	
			(0.576)	(0.608)		(0.474)**	
(Province=Anhui)*(Scaled Rainfall Variance)			-0.71	-0.83		-1.33	
			(0.563)	(0.637)		(0.471)**	
(Province=Henan)*(Scaled Rainfall Variance)			-0.40	-1.19		-2.22	
			(0.606)	(0.787)		(0.607)**	
(Scaled Rainfall Variance)*$Land_t$					-5.89	-9.03	
					(1.420)**	(1.822)**	
(Scaled Rainfall Variance*(Share of Village with							16.254
Local Employment)$_{t-1}$							(16.395)
(Scaled Rainfall Variance*(Share of Village with							102.328
Migrant Employment)$_{t-1}$							(42.86)**
Obs.	14603	12229	12229	12229	12229	12229	10962
R squared	0.11	0.13	0.13	0.13	0.13	0.14	0.13

Notes: 1. Robust standard errors in parentheses 2. * significant at 5%, ** significant at 1% 3. All specifications include village*year dummy variables to control for aggregate shocks to the village economy. Their coefficients are jointly significant.

Table 2. Summary of regression results with village variables (Absolute Value of Rainfall Shocks)
Dependent Variable: Consumption Growth from Period t to t+1, Δln(non-durable consumption per capita).

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Land_t$	-0.256	-0.521	-0.521	-0.58	-0.6	-0.426	-0.433	-0.534
	(0.089)**	(0.132)**	(0.132)**	(0.136)**	(0.138)**	(0.156)**	(0.158)**	(0.132)**
Scaled Rainfall Variance	1.482	1.662	1.557	2.752	3.199	1.828	4.116	1.333
	(0.102)**	(0.146)**	(0.287)**	(0.607)**	(0.728)**	(0.354)**	(0.803)**	(0.285)**
(Scaled Rainfall Variance)* (Irrigated Share of Land in $Village)_t$			0.185		-0.563	0.128	-0.97	-0.091
			(0.387)		(0.499)	(0.392)	(0.529)	(0.411)
(Province=Jiangsu)*(Scaled Rainfall Variance)				-0.973	-0.908		-1.076	
				(0.676)	(0.677)		-0.664	
(Province=Anhui)*(Scaled Rainfall Variance)				-1.088	-1.183		-1.269	
				(0.608)	(0.611)		(0.598)*	
(Province=Henan)*(Scaled Rainfall Variance)				-1.468	-1.795		-2.278	
				(0.675)*	(0.728)*		(0.740)**	
(Scaled Rainfall Variance)*$Land_t$						-2.482	-5.089	
						(1.790)	(2.004)*	
(Scaled Rainfall Variance)*(Share of Village with Local $Employment)_{t-1}$								27.209
								(14.423)
(Scaled Rainfall Variance)*(Share of Village with Migrant $Employment)_{t-1}$								43.677
								(37.923)
ln(Village Population $_t$)	0.033	0.017	0.018	0.019	0.02	0.014	0.015	0.022
	(0.011)**	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
1 if in mountains	0.039	-0.037	-0.041	-0.036	-0.028	-0.043	-0.028	-0.038
	(0.017)*	(0.028)	(0.030)	(0.028)	(0.030)	(0.030)	(0.030)	(0.030)
1 if in hills	0.017	0.034	0.033	0.036	0.039	0.031	0.035	0.042
	(0.010)	(0.017)*	(0.017)	(0.017)*	(0.017)*	(0.017)	(0.017)*	(0.018)*
1 if in near city	0.133	0.219	0.218	0.219	0.221	0.217	0.223	0.218
	(0.018)**	(0.029)**	(0.029)**	(0.029)**	(0.029)**	(0.029)**	(0.029)**	(0.029)**

Distance to Nearest Public	0.003	0.009	0.009	0.008	0.008	0.009	0.008	0.008
Road (Km)	(0.002)	(0.002)**	(0.002)**	(0.002)**	(0.002)**	(0.002)**	(0.002)**	(0.002)**
$(\text{Irrigated Share of Land in Village})_t$	0.023	-0.02	-0.027	-0.033	-0.018	-0.029	-0.018	-0.021
	(0.017)	(0.026)	-0.031	(0.027)	-0.032	(0.031)	-0.032	-0.031
(Share of Assets in Village Owned or Controlled	0.149	0.239	0.237	0.24	0.243	0.233	0.233	0.234
by Private Sector in Village)$_t$	(0.028)**	(0.044)**	(0.044)**	(0.045)**	(0.045)**	(0.045)**	(0.045)**	(0.045)**
$(\text{Cadre Share of Village Population})_t$	2.339	2.086	2.092	1.918	1.985	2.137	2.149	3.134
	(1.504)	(2.482)	(2.482)	(2.505)	(2.505)	(2.483)	(2.504)	(2.530)
$(\text{Total Land Area of Village})_t$	2.036	0.8	0.751	0.371	0.419	0.924	0.624	1.335
	(0.992)*	(1.416)	(1.425)	(1.436)	(1.439)	(1.426)	(1.437)	(1.438)
(Access to Health Insurance (Yes=1) in Village)$_t$	-0.022	0.007	0.007	0.001	-0.001	0.011	0.002	0.014
	(0.013)	(0.020)	(0.020)	(0.020)	(0.021)	(0.021)	(0.021)	(0.020)
(Share of Village with Local Employment)$_{t-1}$	-1.426	-3.433	-3.443	-3.293	-3.274	-3.519	-3.438	-3.914
	(0.515)**	(0.773)**	(0.774)**	(0.772)**	(0.772)**	(0.777)**	(0.776)**	(0.833)**
(Share of Village with Migrant Employment)$_{t-1}$	2.57	5.725	5.789	5.222	4.941	6.041	5.291	5.508
	(0.963)**	(1.311)**	(1.328)**	(1.322)**	(1.364)**	(1.340)**	(1.369)**	(1.506)**
(Village Share of Gross Revenue from	-0.072	-0.055	-0.056	-0.075	-0.074	-0.049	-0.059	-0.069
Livestock)$_t$	(0.061)	(0.092)	-0.093	(0.092)	-0.092	(0.093)	(0.093)	(0.094)
(Village Share of Gross Revenue from Non-	-0.067	-0.094	-0.100	-0.109	-0.095	-0.091	-0.074	-0.106
Agricultural Activities)$_t$	(0.039)	(0.061)	(0.064)	(0.062)	(0.064)	(0.065)	(0.065)	(0.064)
(Village Share of Gross Revenue from Collective	0.115	0.159	0.164	0.159	0.144	0.164	0.134	0.155
& Private Enterprises)$_t$	(0.038)**	(0.054)**	(0.056)**	(0.054)**	(0.056)*	(0.056)**	(0.056)*	(0.056)**
Rainfall Shock		5.539	5.295	6.313	7.273	4.887	6.93	3.746
		(4.092)	(4.113)	(4.118)	(4.218)	(4.119)	(4.211)	(4.157)
Obs.	10512	5203	5203	5203	5203	5203	5203	5203
R-squared	0.04	0.07	0.07	0.07	0.07	0.07	0.07	0.07

Notes: 1. Robust standard errors in parentheses 2. * significant at 5%, ** significant at 1%. 3. All specifications include province*year dummies to control for aggregate shocks to the provincial economy.

Table 4. Summary of Estimation Results Using Village-Year Dummy Variables (Absolute Value of Rainfall Shock)

Dependent Variable: Consumption Growth from Period t to t+1, Δln(non-durable consumption per capita).

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Land_t$	-0.379	-0.555	-0.619	-0.6	-0.408	-0.416	-0.5
	(0.075)**	(0.145)**	(0.152)**	(0.150)**	(0.169)*	(0.172)*	(0.146)**
Scaled Rainfall Variance	2.10	2.84	3.14	3.93	3.27	5.03	2.81
	(0.101)**	(0.338)**	(0.725)**	(0.830)**	(0.420)**	(0.935)**	(0.367)**
(Scaled Rainfall Variance*(Irrigation Share of		-0.93		-1.12	-1.07	-1.62	-1.49
Land in Village)$_t$		(0.460)*		(0.561)*	(0.469)*	(0.598)**	(0.486)**
(Province=Jiangsu)*(Scaled Rainfall Variance)			-1.07	-0.86		-1.11	
			(0.778)	(0.758)		(0.752)	
(Province=Anhui)*(Scaled Rainfall Variance)			-1.06	-1.13		-1.36	
			(0.739)	(0.719)		-0.715	
(Province=Henan)*(Scaled Rainfall Variance)			-0.47	-1.05		-1.66	
			(0.814)	(0.805)		(0.879)	
(Scaled Rainfall Variance)*$Land_t$					-3.96	-5.47	
					(1.949)*	(2.155)*	
(Scaled Rainfall Variance*(Share of Village with							-3.297
Local Employment)$_{t-1}$							(17.512)
(Scaled Rainfall Variance*(Share of Village with							139.232
Migrant Employment)$_{t-1}$							(48.885)**
Obs.	14603	5743	5743	5743	5743	5743	5384
R squared	0.11	0.12	0.11	0.12	0.12	0.12	0.13

Notes: 1. Robust standard errors in parentheses 2. * significant at 5%, ** significant at 1% 3. All specifications include village*year dummy variables to control for aggregate shocks to the village economy. Their coefficients are jointly significant.

Table 5. Summary of Estimation Results Using Village-Year Dummy Variables (First-Differenced Estimation)

Dependent Variable: First Differenced Consumption Growth, $\Delta \ln(\text{non-durable consumption per capita})_t - \Delta \ln(\text{non-durable consumption per capita})_{t-1}$.

Regressors	(1)	(2)	(3)	(4)	(5)	(6)	(7)
d($Land_t$)	-0.006	-0.005	-0.006	-0.007	-0.001	0.001	-0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
d(Scaled Rainfall Variance)	5.076	5.507	6.908	8.566	6.372	12.63	5.10
	(0.213)**	(0.508)**	(1.483)**	(1.964)**	(0.702)**	(1.411)**	(0.593)**
d((Scaled Rainfall Variance*(Irrigated Share of Land in Village)$_t$)		-0.55		-2.46	-1.02	-3.57	-2.12
		(0.484)		(1.549)	(0.513)*	(1.910)*	(0.716)**
d((Province=Jiangsu)*(Scaled Rainfall Variance))			-2.40	-1.84		-3.34	
			(1.558)	(1.57)		(1.164)**	
d((Province=Anhui)*(Scaled Rainfall Variance))			-2.09	-2.22		-3.54	
			(1.510)	(1.635)		(1.151)**	
d((Province=Henan)*(Scaled Rainfall Variance))			-2.30	-3.50		-6.08	
			(1.568)	(1.915)		(1.362)**	
d((Scaled Rainfall Variance)*Land$_t$)					-9.14	-20.24	
					(3.442)**	(4.625)**	
d((Scaled Rainfall Variance)*(Share of Village with Local Employment)$_{t-1}$)							23.976
							(41.171)
d((Scaled Rainfall Variance)*(Share of Village with Migrant Employment)$_{t-1}$)							295.709
							(123.661)*
Obs.	10960	8707	8707	8707	8707	8707	7733
R squared	0.16	0.17	0.17	0.18	0.18	0.18	0.17

Notes: 1. Robust standard errors in parentheses 2. * significant at 5%, ** significant at 1% 3. All specifications include village*year dummy variables to control for aggregate shocks to the village economy. Their coefficients are jointly significant. 4. d ( ) means first differencing.

Table 6. Summary of Estimation Results Using Village-Year Dummy Variables (IV Estimation)

Dependent Variable: Consumption Growth from Period t to t+1, Δln(non-durable consumption per capita).

Regressors	(1)	(2)
$Land_t$	-0.007	-0.009
	(0.111)	(0.111)
Scaled Rainfall Variance	0.528	1.174
	(0.287)	(0.669)
(Scaled Rainfall Variance*(Irrigated Share of Land in Village) $_t$		-0.959
		(0.842)
Obs.	10960	10960

Scaled rainfall variance term is instrumented by period t-1 level of the scaled rainfall variance.

Notes: 1.Robust standard errors in parentheses 2. * significant at 5%, ** significant at 1%

3.All specifications include village*year dummy variables to control for aggregate shocks to the village economy. Their coefficients are jointly significant.

4.d ( ) means first differencing.

Table 7. Summary of Estimation Results Using Village-Year Dummy Variables (First Differencing IV Estimation)

Dependent Variable: First Differenced Consumption Growth, Δln(non-durable consumption per capita) $_t$ - Δln(non-durable consumption per capita) $_{t-1}$.

Regressors	(1)
d($Land_t$)	-0.001
	(0.004)
d(Scaled Rainfall Variance)	3.18
	(0.300)**
Obs.	10960

The first differenced scaled rainfall variance is instrumented by period t-1 level of the scaled rainfall variance.

Notes: 1.Robust standard errors in parentheses 2. * significant at 5%, ** significant at 1%

3.All specifications include village*year dummy variables to control for aggregate shocks to the village economy. Their coefficients are jointly significant. 4.d ( ) means first differencing.