The Importance of the Savings Device in Precautionary Savings: Empirical Evidence from Rural Bangladesh

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Abstract

We test if precautionary behavior in the consumption decisions of rural households differs across the forms of savings. Using monthly panel data from Bangladesh we find that, on average, the savings device does not matter but that the effect of income on savings indeed depends on the savings device. Precautionary savings in the form of staple grain is relatively constant across income quartiles while non-grain precautionary savings varies across income quartiles. Previous studies, which treat these two types of savings devices as fungible, misdiagnose the reasons for, and by extension the market failures behind, a large percentage of the precautionary savings held by rural households.

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1 Introduction

This article sheds new light on how rural households in developing economies attempt to self-insure against production risk by holding liquid assets. For rural households with limited access to insurance and credit markets, a key form of self-insurance is precautionary savings in anticipation of future income shocks (Jalan and Ravallion, 2001; Giles and Yoo, 2007). Precautionary savings is costly because it diverts income away from investments and into liquid but unproductive assets (Rosenzweig and Wolpin, 1993; Udry, 1995; Carroll and Kimball, 2005). However, not all forms of liquid assets are equally unproductive. An extensive literature exists regarding the value of precautionary storage of staple grains. In addition to its value as self-insurance, staple grain storage provides households with a price hedge (Park, 2006) and helps ensure food security (Renkow, 1990; Saha and Stroud, 1994; Deininger et al., 2007). These examples of what Working (1949) referred to as the convenience yield of grain storage suggest that the motivation for precautionary storage, and by extension the market failures that storage addresses, may be different from the motivation for other forms of precautionary savings.

In this paper, we examine the rate of the precautionary motive in household savings and grain storage. To do so we estimate the effects of production risk on consumption growth. We interpret change in consumption growth in response to production risk as precautionary savings. Households facing increased production risk consume less and save more in the current period in order to more easily smooth consumption if a negative shock to income materializes in the future. We use historic rainfall variability as an exogenous proxy for production risk.[1]

Our primary contribution is to disaggregate precautionary savings into non-grain savings and grain storage. Most studies on precautionary behavior and consumption lump grain storage in with other forms of unproductive liquid assets (like cash and jewelry).[2] We find that precautionary behavior manifests differently for grain storage and non-grain savings. Non-grain precautionary savings varies across income quartiles, creating a stylized inverted-U relationship in which the poorest and wealthiest households hold the lowest share of savings for precautionary purposes.[3] Households in the lowest and upper two income quartiles hold less than 10 per cent of total savings for precautionary purposes while households in the second income quartile hold nearly half of total savings for precautionary purposes. In contrast, levels of precautionary grain storage are relatively constant across income quartiles. Above a poverty threshold level, households store between 16 and 19 per cent of rice for precautionary purposes.[4] This behavior is consistent with the commodity

[1] The use of historic rainfall as a proxy for risk in agricultural production has a long history. Examples using South Asian villages coming from the same ICRISAT study we use include Wolpin (1982), Rosenzweig and Binswanger (1993), Rosenzweig and Wolpin (1993), and Chaudhuri (1999).

[2] Several previous studies (Rosenzweig and Wolpin, 1993; Udry, 1995; Kazianga and Udry, 2006) have attempted to determine if households treat precautionary savings in the form of livestock (generally cattle) differently from other forms of precautionary savings. Typically they find no difference in the way households treat these different savings devices. We hypothesize that this finding is driven by the fact that cattle are a relatively lumpy savings device and that the period of observation in these studies (annual or semi-annual) tends to be too broad to pick up intra-seasonal effects. By examining a relatively liquid asset (staple grain) across a relatively short time frame (monthly data) we are able to identify differences in precautionary savings across savings devices missed by previous studies.

[3] While this finding may be unexpected theoretically (assuming households have CRRA utility, as we assume in Section 2), it is largely supported by the empirical literature on households in developing countries. See, for example, Jalan and Ravallion (2001) and Gilligan and Hoddinott (2007). Alternatively, see Carroll and Samwick (1997, 1998) who find a positive linear relationship between precautionary savings and income for households in the United States.

[4] In Bangladesh, rice is the staple grain, accounting for 75 per cent of total agricultural production and 40 per cent of total food consumption (VDSA, 2013). In our data, this income threshold level is approximately 1,000 Taka

storage literature regarding households receiving additional benefits from the storage of staple grain beyond its role as self-insurance against production risk.[5]

To motivate our empirical analysis we develop a simple theoretical model of consumption growth based on Blundell and Stoker (1999).[6] We examine precautionary savings and storage in the context of consumption growth, instead of the dynamic programming models more typical of the commodity storage literature for two reasons. First, a consumption growth framework allows us to identify a proxy for production risk that is not correlated with other household decisions. This avoids issues of endogenous choice present in many storage models (Saha and Stroud, 1994; Park, 2006). Additionally, the model provides a mechanism for households to update their risk perceptions as income changes. Models that assume a constant stream of income (Carroll and Kimball, 2005; Mogues, 2011) fail to account for wealth effects on risk or fail to allow household precautionary behavior to change based on the wealth effects of previous shocks.[7] Second, our framework allows us to utilize monthly data to examine intra-seasonal changes in precautionary behavior. Previous studies of precautionary savings, consumption behavior, or grain storage relied on annual, semi-annual, or quarterly data.[8] Such studies are incapable of capturing how households manage consumption, savings, and storage when production and income events occur at higher frequencies. Annual data is particularly undesirable in the context of rural households whose income depends on more than one harvest per year, as in the case of Bangladesh.[9] Perceived risk to agricultural production appears throughout the several stages of the cropping season. Monthly data provides a unique look at the sensitivity of households to production risk and their ability to engage in precautionary savings.

Our empirical analysis relies on an exogenous proxy for production risk, the value of which is updated as household perceptions of risk change with the realization of new information. We follow Giles and Yoo (2007) in scaling historic rainfall variability by household income and consumption in order to allow for households to update risk assessments based on past shocks to wealth. We then use the estimated coefficient on the scaled rainfall variability term to predict the value of household precautionary savings at different levels of production risk. Additionally, we examine how household precautionary behavior changes as income changes. By allowing the coefficient on the scaled rainfall variability term to differ across income quartiles we can more closely examine

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per person per month. This is slightly less than the rural poverty line in Bangladesh calculated by Balagtas et al. (2013). Below this threshold, households have almost no precautionary savings.

[5]See Deininger et al. (2007) as an empirical example of households giving priority to self-insure caloric consumption ahead of self-insuring other forms of consumption. Intuitively, the Deininger et al. (2007) result, along with our result, is driven by households switching away from precautionary savings to other, more productive forms of insurance (formal insurance, credit), as their wealth increases. But, these same households do not switch away from precautionary storage because it provides insurance against unanticipated supply disruptions (Renkow, 1990) - a food security contingency that additional income may not alleviate.

[6]Studies that adopt a similar consumption growth approach include Giles and Yoo (2007), Lee and Sawada (2010), and Dercon and Christiaensen (2011).

[7]There is an extensive literature on the importance of wealth effects on precautionary savings. See Zeller and Sharma (2000), Jalan and Ravallion (2001), Kazianga and Udry (2006), and Gilligan and Hoddinott (2007)

[8]For studies that examine precautionary savings or consumption smoothing at the annual level see Kazarosian (1997), Jalan and Ravallion (2001), Kazianga and Udry (2006), Park (2006), Giles and Yoo (2007), Lee and Sawada (2010), Dercon and Christiaensen (2011), and Carter and Lybbert (2012). Studies that utilize semi-annual data include Jacoby and Skoufias (1998) and Mogues (2011). Saha (1994), Saha and Stroud (1994), and Hahm and Steigerwald (1999) use quarterly data.

[9]Rural households in Bangladesh are able to grow crops in three seasons. The dry, irrigated spring *Boro* season, the short summer monsoon season, *Aus*, and the post-monsoon autumn *Aman* season.

income effects on precautionary savings that might be obscured by analysis of mean effects only.[10]

Our finding that precautionary behavior manifests differently for grain storage and for non-grain savings has important implications for rural development and development policy. Greater income reduces households' precautionary savings of non-grain assets but does not do the same for grain holdings. In rural communities, poor harvests caused by drought or flooding can make staple foods unavailable in local markets at any price. In these situations, more income will not allow households to purchase staple products when those products are unavailable. The implication is that solutions to the problem of unproductive wealth tied up in precautionary savings - improved access to credit, remittances, etc. - will not work for savings in the form of stored grain. Easing liquidity constraints (Lee and Sawada, 2010) or expanding migrant labor networks (Giles and Yoo, 2007) seek to address failures in the credit or insurance market that motivate much of the precautionary savings behavior observed in rural households. However, the motivation for holding wealth in staple grain is due to a different type of market failure related to the supply and distribution of staple foods. Policies aimed at addressing the supply story are needed if households are to reduce precautionary staple grain holding.

2 Theoretical Framework

Precautionary savings differs from consumption smoothing in that consumption smoothing is a contemporaneous response to realized income shocks while precautionary saving is a response to expected future income shocks. Households who believe an income shock may occur in the future have several options. If they choose to reduce current consumption and increase current savings the household is engaging in precautionary savings. By increasing savings in expectation of an income shock, the household facilitates consumption smoothing when an income shock is realized.

Our empirical work is based on standard theoretical models of consumption growth (Jacoby and Skoufias, 1998; Blundell and Stoker, 1999). Changes to consumption behavior resulting from a shock to income will depend on the timing of those shocks and household levels of wealth and income.[11] For simplicity, we limit our theoretical analysis to a three period model which can be thought of in terms of agricultural production over multiple growing seasons. Over each period, households choose consumption expenditure, c_t, dependent upon the budget constraint:

$$c_0 + \frac{c_1}{1+r_1} + \frac{c_2}{(1+r_1)(1+r_2)} = W + \frac{\varphi_1}{1+r_1} + \frac{\varphi_2}{(1+r_1)(1+r_2)}. \tag{1}$$

Here r_t is the real interest rate and $W = A_0 + y_0 + \frac{\mathrm{E}_0[y_1]}{1+r_1} + \frac{\mathrm{E}_0[y_2]}{(1+r_1)(1+r_2)}$, which is expected wealth at $t = 0$ decomposed into initial assets, initial income, and present value of expected future income. All terms are in present value and expectations of future events are from the vantage point of the initial period.

The φ_t terms are innovations in income unknown at period $t = 0$ but realized in subsequent periods. These innovations to income are forecasting errors in future income from the vantage point

[10] We also conduct several robustness checks which we report in Appendix B.

[11] Recent work by Apps et al. (2014) has extended the model of precautionary savings to the case of the two-person household. In our data, primary income for households comes from a single source - on-farm production. Additionally, we are concerned with risk increases of the second order. Given our context, while the Apps et al. (2014) model would add complexity to our analysis the insights provided are not directly applicable. Therefore, we are confident in the efficacy of standard theoretical models of consumption growth for our context.

of $t = 0$, defined as $\varphi_t = y_t - \mathrm{E}_0[y_t]$ with $t = 1, 2$. Thus, in periods subsequent to the initial period, the household will update its expectations on future income with the realization of the innovations in income. From the perspective of $t = 0$, income innovations are jointly distributed with mean zero: $\mathrm{E}_0[\varphi_1] = 0$ and $\mathrm{E}_0[\varphi_2] = 0$. We define $\varphi_2^* = \varphi_2 - \mathrm{E}_1[\varphi_2|\varphi_1]$, where the second term is the conditional expectation of φ_2 given the realized value of φ_1 so that $\mathrm{E}_1[\varphi_2^*] = 0$. We also define

$$\varphi_1^* = \varphi_1 + \frac{\mathrm{E}_1[\varphi_2|\varphi_1]}{1 + r_2} \tag{2}$$

so that φ_1^* and φ_2^* are uncorrelated innovations to income realized in their respective time periods. We make the simplifying assumption that $\sigma_1^2 = \mathrm{Var}[\varphi_1^*]$ and $\sigma_{2|1}^2 = \mathrm{Var}[\varphi_2^*|\varphi_1]$. In words: the conditional variance of φ_2^* does not depend on φ_1^*, which reduces a source of nonlinearity in the subsequent consumption maximization problem (Blundell and Stoker, 1999).

To solve the optimal consumption problem, we assume a utility function with constant relative risk aversion (CRRA) and isoelastic preferences characterized by

$$U_t(c_t) = \alpha_t \left(\frac{c_t^{1+\lambda}}{1 + \lambda} \right) \tag{3}$$

when $\lambda < 0$ and $\lambda \neq -1$. Alternatively, when $\lambda = -1$,

$$U_t(c_t) = \alpha_t \ln(c_t), \tag{4}$$

which allows us to write the intertemporal household maximization problem, subject to the budget constraint in equation (1), in the familiar Cobb-Douglas form:

$$\max_c U(c_t) = \gamma_0 \ln(c_0) + \gamma_1 \ln(c_1) + \gamma_2 \ln(c_2) \tag{5}$$

where $\gamma_0 = \alpha_0$, $\gamma_1 = \frac{\alpha_1}{1+\delta_1}$, and $\gamma_2 = \frac{\alpha_2}{1+\delta_2}$. Without loss of generality we normalize $\gamma_0 + \gamma_1 + \gamma_2 = 1$.

Given our setup, the specific Euler equation for optimal consumption allocation between periods 1 and 2 is

$$\frac{\alpha_2}{c_2} = \frac{\alpha_1}{c_1}(1 + \varphi_2). \tag{6}$$

Using the Euler equation results in a non-linear first-order condition to the maximization problem. We can approximate the condition by using the second-order Taylor series expansion which allows us to derive the optimal consumption growth model:

$$\Delta \ln c_2 = -\ln \frac{\alpha_1}{\alpha_2} + \frac{1}{\alpha_2}\sigma_{2|1}^2 + \frac{\alpha_1}{\alpha_2}\frac{\varphi_2^*}{c_1}, \tag{7}$$

where $\sigma_{2|1}^2 = \frac{\mathrm{Var}[\varphi_2^*|\varphi_1]}{W^2}$. In words: consumption growth is a linear function of an intertemporal substitution term ($-\ln \frac{\alpha_1}{\alpha_2}$), the variance of future income innovations ($\sigma_{2|1}^2$), and the normalized value of those income innovations ($\frac{\varphi_2^*}{c_1}$). Our variable of interest is the $\sigma_{2|1}^2$, which is the variance of updated income innovations conditional on the previous period, normalized by lifetime wealth. An increase in the income variance term increases precautionary savings, resulting in an increase in consumption growth.

3 Survey Data

To conduct our empirical analysis, we use household data from 12 rice growing villages in Bangladesh collected by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) and the International Rice Research Institute (IRRI) as part of the Village Dynamics Study of South Asia (VDSA, 2013). The villages were selected randomly to be representative of the various agro-ecological zones in Bangladesh and are therefore representative of agricultural households in the country. Within villages, 40 households were randomly selected from strata based on village census listings. We utilize a balanced panel of 458 households with 32 monthly observations covering the cropping seasons from late 2009 to mid-2012.[12]

The monthly data in the VDSA study allows us to analyze intra-seasonal changes in precautionary savings decisions. Households in rural Bangladesh have the opportunity to choose among three growing seasons. Thus, annual data can miss intra-year changes in precautionary savings decisions as good and bad harvests might net out any behavioral changes. Quarterly data may better capture changes in consumption resulting from seasonal harvests yet miss intra-seasonal changes as households observe the growth of their crops. Table 1 presents descriptive statistics at the quarterly level.

3.1 Household Consumption

To calculate the change in household consumption, our dependent variable, we use monthly per capita consumption. Consumption is the sum of current non-durable goods consumed in a month as measured by market and non-market expenditures. This includes the value of household food consumption, fuel, clothing, and education, either purchased, home produced, or received as a gift or loan in kind. For goods purchased in the market the data set includes purchase price and quantity. For home produced goods we use monthly prices collected at the village level to compute the value of the goods.[13]

We add to the monthly consumption data the value of a stream of services from durable goods and housing measured annually. We use a straight line depreciation of seven years for durable goods and 20 years for housing. The per capita value of durable goods and housing make up on average 12 per cent of per capita consumption. Food constitutes 48 per cent of per capita consumption while non-durable, non-food goods make up the remaining 40 per cent of per capita consumption.

3.2 Household Income

We calculate income in net terms using net revenue from agricultural and non-agricultural production, net off-farm wage labor, and net gifts and transfers. Revenue from agricultural production includes revenue from the production of crops, livestock, and the sale of green manure. Approximately 12 per cent of the value of agricultural production comes from annual crops such as jute,

[12]The unbalanced panel data set contains 507 households. To balance the panel we drop 49 households with incomplete observations (less than 10 per cent of total households) from the analysis. The primary reason for incomplete observations is not attrition but division of households as young men leave the home to establish a new household in the village.

[13]We follow Hentschel and Lanjouw (1996) and Dercon et al. (2009) in excluding periodic expenses such as weddings, funerals, and medical expenses from the monthly consumption data. Such periodic expenses are akin to preference shocks and we would not expect households to smooth total consumption across months when there is and is not a wedding. Rather, we expect households to smooth consumption of necessities despite periodic expenses.

sugarcane, vegetables, and green manure. Among seasonal crops, the dry spring season rice, *Boro*, accounts for 49 per cent of seasonal production value. By comparison, the post monsoon autumn season, *Aman*, accounts for 38 per cent of seasonal production value. The short summer monsoon season, *Aus*, makes up the remaining 13 per cent. In addition to revenue from agricultural production, we also include wages for non-own-farm agricultural labor. Costs of agricultural production include the value of all material and labor inputs.

Off-farm labor composes 30 per cent of household income. The majority of off-farm labor occurs within five kilometers of the home, with only one per cent of off-farm laborers working further than 50 kilometers from home (and therefore qualifying as migrant labor). For off-farm labor the VDSA data includes information on the amount spent in performing the task (primarily food and transportation costs), allowing us to calculate net income.

Finally, we also include net transfers to the household. These include net measures for government transfers and informal transfers, such as gifts and remittances. Due to timing inconsistencies in the recording of farm-labor, we aggregate all net income terms to the quarterly level before determining per capita monthly income.

3.3 Household Savings

We calculate savings as the difference between monthly per capita income and consumption. Savings rates fluctuate from month to month depending on the cropping season (see Figure 1).[14] Typically, savings are positive in the months during and immediately after harvest (April to June for *Boro* and October to December for *Aman*). During the planting and growing months for *Boro* and *Aman*, savings tend to be negative, meaning households are consuming from savings or subsisting on credit in anticipation of harvest. Seasonal fluctuations in savings are primarily driven by changes in income, not changes in consumption. This is the same result Chaudhuri and Paxson (2002) found in India, where income exhibits large swings in seasonality while consumption remains fairly static across seasons.

These data demonstrate the value of conducting an analysis of precautionary savings and grain storage at a monthly level. When aggregated to the quarterly or annual level, these fluctuations are muted or disappear completely. At the quarterly level, savings are negative only in the first quarter (January to March), while savings levels are positive in all other quarters. This is due to income from *Aus* and *Aman* harvests (falling in quarters three and four respectively) off-setting the lean months earlier in the quarters. Aggregated to the annual level all signs of dis-savings disappear as, on average, household per capita income exceeds household per capita consumption.

3.4 Household Managed Land

Another independent variable in our consumption growth estimation is the area of household managed land. On average, households own twice as much land as is leased in. There is seasonal variation in managed land as households increase acreage during *Boro* and reduce acreage during *Aus*. However, there is little variation from one *Boro* season to the next or from one *Aus* season to the next. This is because most rental contracts are multi-year, with a family continually renting in or out the same parcel of land for a given season. Having agreed to farm a certain number and/or

[14]Our reliance on income aggregated to the quarterly level effectively smooths our income variable and, by extension, partially smooths our savings data. However, even with smoothed income data, the use of monthly consumption data introduces significant month-to-month variation in savings as evidenced by Figure 1.

size of plot in a given season, a household continues to farm approximately that same land area from year to year.[15]

3.5 Historic Monthly Rainfall Variability

We use village level rainfall data as an exogenous determinant of yields in agricultural production. After determining the period of rainfall most important to rice yields in our data, we us the variability in twenty years of historic rainfall as a proxy for production risk.[16]

The Bangladesh Meteorological Department provided us with monthly rainfall data from its 32 weather stations for the years 1948-2012. Of those stations, we selected the station with the shortest Euclidean distance to each of the 12 VDSA villages. Given the geographic dispersal of the 12 VDSA villages no two villages shared the closest weather station. The majority of rain in Bangladesh comes during the summer monsoon season, generally June to September, but sometimes extends into May or October. Since rice is by far the dominant crop, accounting for 75 per cent of household income from crop production, we focus our search for a proxy for production risk on rainfall events that impact rice production.

To construct a proxy for production risk we tested numerous permutations of rainfall's influence on crop production (see Appendix A). We found two equally strong indicators of agricultural production: average rainfall over the previous six months and average rainfall over the previous four months. Lacking clear statistical or agronomic reasons for choosing one candidate over the other, we selected average rainfall over the previous six months since it provides more conservative results.[17] Thus, the best indicator of yields for the *Aman* harvest in December is the average rainfall in the months July through December. Similarly, the best indicator of yields for the *Boro* harvest in May is the average rainfall in the months December through May. As a proxy for production risk we use 20 years of rainfall data to calculate the sample standard deviation of average rainfall over the six months previous to harvest for each village.[18]

While rice is the major agricultural good produced by farmers, households do not exclusively produce rice. Every household in the data set has secondary crop production. Thus, while not every household grows rice in every season, household have some agricultural production in almost every month. We therefore believe that even for households not cultivating rice in a given season our prior-six-months-rainfall variable is a good proxy for potential shocks to income.

[15] See Appendix A for more details on how cultivated land size changes from season to season and year to year.

[16] See Paxson (1992), Jacoby and Skoufias (1998), Chaudhuri (1999), Rose (2001), and Giles and Yoo (2007) for examples of this approach.

[17] We present results from our alternative proxy in Appendix B as a robustness check

[18] The sample standard deviation for each village is calculated as

$$\sigma_j = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(R_{jt} - \bar{R}_j)^2}.$$

For each monthly village observation we first calculate the average rainfall over the previous six months (R_{jt}). We then take the average of this term over the last twenty years ($\bar{R}_j$). Finally, we calculate the sample standard deviation, where $T = 20$.

4 Empirical Strategy

Our econometric model follows from equation (7) and standard Euler equation models:[19]

$$\Delta \ln C_{it+1} = \alpha + \zeta Z_{it} + \gamma G_{it} + X_{jt}\xi + u_{it+1}, \tag{8}$$

where $\Delta \ln C_{it+1}$ is the growth of consumption from period t to $t+1$; Z_{it} is the area of land managed by household i at period t; G_{it} is the scaled standard deviation of rainfall ($\pi_{it}\sigma_j$); and X_{jt} is a matrix of village-month dummy variables

To construct the scaled rainfall term we calculate $\pi_{it}\sigma_j = \frac{\sigma_j Y_{it}^2}{C_{it}^2}$ where Y_{it} is total income, including both farm and off-farm income.[20] The choice to scale our proxy for variance in income $\left(\sigma_j Y_{it}^2\right)$ is driven by theory, although theory suggests scaling by the inverse of wealth squared, as in equation (7). However, reported wealth in our data set is poorly defined and lacks standardization across households and across time. Following Giles and Yoo (2007), we resolve this practical issue by replacing the expected wealth term with consumption in period t. The scaled rainfall variability term captures changes to consumption due to production risk. These include changes in consumption due to changes in future expected yield and lifetime wealth due to rainfall. The term also accounts for changes that have a persistent effect on consumption but are not due to rainfall. Finally, scaling allows the village level shock to be idiosyncratic, with rainfall values affecting households in a village differently depending on household income and consumption.

The village-month dummies control for aggregate shocks. Since rainfall variability is perfectly collinear with the village-month dummy variables, the coefficient γ does not directly provide an estimate for the effect of rainfall shocks on consumption. Rather, the coefficient of scaled rainfall variability captures changes in consumption behavior coming from changes in income that are expected to result from the rainfall shock. Since the presence of income in the scaled rainfall variability term captures all other persistent effects on rice yields, such as education, age, access to off-farm activity, we exclude measures of household capital in our regression.

The primary focus of our empirical analysis is on the coefficient (γ) of the scaled rainfall variability term (G_{it}). We expect γ to be positive, meaning that an increase in the scaled rainfall variability term in period t leads to a decrease in current consumption, an increase in current savings, and results in an increase in consumption growth between t and $t+1$.

We first estimate equation (8) using OLS. Results are presented in column (1) of Table 2. However, OLS estimation likely suffers from two endogeneity issues. First, using current period consumption in the scaling term and in the consumption growth term means that the measurement errors in $\Delta \ln C_{it+1}$ and G_{it} are correlated. Second, using household land and a household specific scaling term introduces the potential for bias due to unobserved household heterogeneity.

We deal first with the issue of correlated measurement errors. We address this issue by following an instrumental variable approach for models with correlated random coefficients (Wooldridge, 2003, 2005). Given that the problematic term, G_{it}, is an interaction term between the exogenous rainfall variability and the potentially endogenous idiosyncratic scaling term, we follow Wooldridge (2003) in simply instrumenting for the potentially endogenous term. We estimate a version of

[19] It should be noted that there is a measure of debate regarding the appropriateness of estimating consumption Euler equations of this form. See Carroll (2001) and Ludvigson and Paxson (2001).

[20] We use the standard deviation of our income shock proxy and not the variance. This monotonic transformation is adopted simply to facilitate similarity in scale of our independent variables in our regression and has no qualitative effect on our results.

equation (8) in which the scaling term is instrumented using values from past periods' consumption. Specifically, we predict $\hat{\pi}_{it}$ from the following equation:

$$\pi_{it} = c + \beta_1 \pi_{it-1} + \beta_2 \pi_{it-2} + \zeta Z_{it} + X_{jt}\xi + e_{it}. \tag{9}$$

Results from this first stage estimation are presented in column (2) of Panel B in Table 2. We then use the Generalized Methods of Moments Instrumental Variable estimator and instrument G_{it} with $\hat{G}_{it} = \hat{\pi}_{it}\sigma_j$. Wooldridge (2003) shows that this approach produces consistent estimates and improves on efficiency.[21] Results from the GMM-IV estimation are presented in column (2) of Table 2. As one would expect if OLS estimation suffered from correlated measurement errors, the coefficient on scaled rainfall variability is smaller in the GMM-IV specification.

The second source of potential endogeneity is an unobserved heterogeneity bias resulting from persistent unobserved household effects. We address this issue by adopting a first-differenced growth model. First-differencing nets out any unobserved time constant household effects that may be correlated with both landholding and our scaled rainfall variability term.[22] Specifically, we estimate:

$$\Delta\Delta \ln C_{it+1} = c + \zeta \Delta Z_{it} + \gamma \Delta G_{it} + X_{jt}\xi + \Delta u_{it+1}. \tag{10}$$

Results from the FD estimation are presented in column (3) of Table 2. The coefficient on scaled rainfall variability in the FD specification is greater than in the OLS, suggesting that sensitivity to risk increases once we have controlled for individual life cycle effects.

To control for both potential sources of endogeneity, we estimate a model that combines both the IV and FD techniques. Following Anderson and Hsiao (1982), we construct our instrument by predicting $\Delta\hat{\pi}_{it}$ from the following:

$$\Delta\pi_{it} = c + \beta_1 \pi_{it-1} + \beta_2 \pi_{it-2} + \zeta \Delta Z_{it} + X_{jt}\xi + e_{it}. \tag{11}$$

Results from this first stage estimation are presented in column (4) of Panel B in Table 2. We then use the GMM-IV estimator and instrument ΔG_{it} with $\Delta\hat{G}_{it} = \Delta\hat{\pi}_{it}\sigma_j$. The FDIV approach is our preferred method in that it simultaneously controls for both potential sources of endogeneity. Results are presented in column (4) of Table 2. The estimated coefficient on scaled rainfall variability is significant at the 99 per cent level and, as theory predicts, has a positive effect on growth in household consumption. We interpret this to mean that households respond to an increase in production risk by reducing current consumption and increasing precautionary savings.

[21] See Dercon et al. (2009) for arguments for and an application of this approach in estimating consumption growth models with endogenous regressors.

[22] Two potentially important difference between households in Bangladesh are the ability to access credit through micro-finance institutions and the ability to enter or exit the off-farm labor market. The ability of a household to access credit is a function of a household's characteristics and the degree of market penetration at the village level. Assuming a household's access to credit is constant over the 32 months of study, first-differencing will control for this unobserved heterogeneity. The state of market penetration by micro-credit agencies, and any changes to the degree of market penetration, is controlled for by our use of 383 village-month dummy variables. Unfortunately, we are unable to control for potential changes in credit-relevant household characteristics that occur over the 32 months of study. Given the short time frame under consideration, we do not consider this issue fundamentally detrimental to our analysis but our results should be interpreted with caution in light of this fact. Regarding potential changes to off-farm labor participation, in our data there does not appear to be consistent or sizable seasonal swings in off-farm employment that would indicate households making marginal adjustments in anticipation of or response to a seasonal income shock. Even if such adjustments did exist, we include off-farm income in our scaling term for production risk. Thus, this term incorporates changes to employment and allows households to adjust consumption based on such changes. We thank two anonymous reviewers for pointing out these potential issue.

5 Effects of Production Risk on Precautionary Savings and Storage

We use our regression results and data to quantify the effect of production risk on the savings of an average household. We then disaggregate total savings into non-rice savings and rice storage to examine if households treat staple grain storage any differently than other forms of liquid assets. Finally, we explore the relationship between household income and mean production risk.

5.1 Effects of Production Risk at Mean Income

Using the coefficient on scaled rainfall variability from the FDIV regression and the distribution of the scaled rainfall variability term, we estimate the effects of changes in risk on household savings (see Table 3). To do this, we first calculate mean per capital monthly income, consumption, and total savings.

To provide an economic value to precautionary savings by households we multiple mean per capita consumption by our FDIV regression coefficient and different values for the scaled rainfall variability term drawn from the distribution of this data. To simulate changes in production risk we calculate the value of precautionary savings at the 25^{th}, 50^{th}, and 75^{th} percentile. We then calculate the percentage of total savings that can be attributed to precautionary motives. For the average household facing average production risk, we find that about 20 Taka per person per month (just under 5 per cent of total savings) is kept for precautionary purposes. An increase in production risk from the 50^{th} to the 75^{th} percentile results in a household increasing precautionary savings from about 20 to nearly 60 Taka per person per month (14 per cent of total savings). Alternatively, a decrease in production risk from the 50^{th} to the 25^{th} percentile results in a household decreasing precautionary savings from about 20 to 5 Taka per person per month (just over 1 per cent of total savings). As a point of comparison, average per capita monthly educational expenditure is 107 Taka. Thus, we conclude that precautionary savings is a small but costly expense for households, especially households facing severe production risk.

Because we are interested in determining if staple grain is treated any differently than other forms of savings we decompose total consumption and total savings into non-rice and rice components. Across the data set, monthly per capita rice consumption accounts for 17 per cent of total consumption and monthly per capita rice storage accounts for 17 per cent of total savings. We then calculate the economic value of precautionary non-rice savings and precautionary storage.

The disaggregated results are remarkably similar to the results when we examine all forms of savings combined. While the economic value for each form of precautionary savings is different, the share of precautionary savings and storage are equivalent. For an average household facing the mean level of production risk, total precautionary non-rice savings constitutes 4.75 per cent of total non-rice savings while precautionary rice storage constitutes 4.97 per cent of total rice storage. The similarity between precautionary non-rice savings and precautionary rice storage do not change with increased or decreased production risk. An increase in production risk from the 50^{th} to the 75^{th} percentile results in a household keeping 13.9 per cent of non-rice savings for precautionary purposes while storing 14.6 per cent of rice for precautionary purposes. A decrease in production risk from the 50^{th} to the 25^{th} percentile results in a household keeping 1.18 per cent of non-rice savings for precautionary purposes while storing 1.23 per cent of rice for precautionary purposes.

The results in Table 3 suggest that, on average, households do not treat staple grain storage as a unique form of precautionary savings. While the economic value of precautionary non-rice savings and precautionary storage differ, the share of savings and storage kept for precautionary purposes are equivalent. However, this result may stem from the fact that at the mean income level the share of rice consumption in rice storage (15.7 per cent) is markedly similar to the share of non-rice consumption in non-rice savings (16.4 per cent). In the next sub-section we examine the extent to which our initial results are an artifact of conducting the analysis at mean income levels by examining how precautionary savings, precautionary non-rice savings, and precautionary storage change with income.

5.2 Effects of Production Risk by Income Quartile

Households may choose to forgo precautionary savings for a number of reasons. Chief among these is that precautionary savings is costly. It ties up capital in non-productive assets to prepare for an event that might not materialize. Households may also forgo precautionary savings if consumption levels are so low that households are unable to reduce current consumption further in order to increase savings. Previous empirical work on households in developing economies has found that wealthy and poor households tend to have less precautionary savings than middle income households (Jalan and Ravallion, 2001).[23] We explore the potential for heterogeneous behavior by dividing our data into income quartiles. Across the quartiles per capita monthly income varies greatly (30 Taka at lowest to 6,557 Taka at highest). As one would expect, per capita monthly consumption is less variable (2,079 to 3,364 Taka).

In order to test the hypothesis that precautionary savings varies across income, we re-specify equation (8) as

$$\Delta \ln C_{it+1} = \alpha + \zeta Z_{it} + \gamma_q G_{qit} + X_{jt}\xi + u_{it+1}, \tag{12}$$

where q indicates the income quartile household i belongs to at time t. By allowing γ_q to vary by income quartile we can test if production risk has heterogeneous effects on changes in consumption across income.[24] We follow the same estimation procedure as outlined in Section 4.[25] Estimation results are presented in Table 4.

Examining the FDIV estimation results, scaled rainfall variability is significant for all quartiles. The point estimate for scaled rainfall variability is smallest for the lowest income quartile and largest for the second lowest income quartile. A simple Wald test allows us to reject the null hypothesis that point estimates are equal across income quartile. In a piecewise comparison of point estimates, we reject the null of equality of coefficients in all cases except between the point estimates for scaled rainfall variability for the third and fourth quartile. We interpret this to mean that while all households increase precautionary savings in response to production risk, the degree of response differs based on income. Households in the lowest and second lowest income quartile respond to production risk differently than households in the top two income quartiles, whose response is statistically indistinguishable from each other. However, the two lowest quartiles respond to production risk in contrary ways. Consumption by households in the lowest income

[23] Deininger et al. (2007) and Carter and Lybbert (2012) show something similar in regards to consumption smoothing.

[24] This method is similar to that used by Hurst et al. (2010) to test if precautionary savings rates differ between business owners and nonbusiness owners.

[25] In the case of the IV estimation, we instrument G_{qit} with $\hat{G}_{qit} = \hat{\pi}_{qit}\sigma_j$ and in the case of the FDIV estimation we instrument ΔG_{qit} with $\Delta\hat{G}_{qit} = \Delta\hat{\pi}_{qit}\sigma_j$. Results from these first stage regression are not presented but are available from the authors upon request.

quartile is less sensitive to production risk than consumption by households in the top two income quartiles.[26] By comparison, consumption by households in the second lowest income quartile is more sensitive to production risk than consumption by households in the top two income quartiles.

In Table 5 we again estimate the economic value of precautionary savings by households. Where in Table 3 we estimated the effect of different levels of production risk on a household with mean income and consumption levels, we now estimate the effects of mean production risk on households at different income levels. We find that precautionary behavior differs dramatically across income groups. Similar to Jalan and Ravallion (2001), there is evidence of an approximate inverted-U relationship between income and precautionary savings: the households in the lowest and highest income quartiles precautionary save, on average, less than those in the middle quartiles. However, an inverted-U is an imprecise description of the data. Precautionary savings makes up a much larger share of total savings in the second income quartile (46 per cent) compared to any other income quartiles. Additionally, the third income quartile keeps a share of savings for precautionary purposes only slightly higher (7 per cent) than the fourth income quartile (3.5 per cent).

When we disaggregate total savings into non-rice savings and rice storage we find that households treat these two forms of storage differently. An inverted-U relationship similar to that between total precautionary savings and income quartiles exists between non-rice precautionary savings and income quartiles. Households in the second income quartile engage in much more precautionary non-rice savings (25 per cent) when compared to other income quartiles. The lowest income quartile keeps almost no precautionary savings in non-rice form. Less than one per cent of non-rice savings is kept for precautionary purposes. The top two income quartiles keep 6 and 3 per cent of total non-rice savings for precautionary purposes - significantly more than the lowest quartile, significantly less than the second quartile, and relatively similar to each other. However, this inverted-U relationship is not present when we look at differences in precautionary storage across income quartiles. The second, third, and fourth income quartile keep about the same share of rice for precautionary purposes (18.7, 16.4, and 18.7 per cent respectively). The lowest income quartile keeps less than one per cent of rice for precautionary purposes.

Furthermore, the percentage of non-rice savings kept for precautionary purposes and the percentage of rice storage kept for precautionary purposes vary within income quartiles (see Table 5). This is in stark contrast to our results estimated at the mean income level. At the mean income level, households do not precautionary save at different rates depending on the savings device. They keep about the same share of non-rice savings as rice storage for precautionary purposes. This result did not change when we varied the degree of risk faced by the household. When we look at estimates of precautionary non-rice savings and precautionary storage within the second, third, and fourth income quartile household savings decisions differ depending on the form of savings. Only the lowest income quartile keeps rice for precautionary purposes in roughly equivalent shares as they do non-rice savings.

In order to explore these asymmetries in precautionary savings across income quartiles we graph estimated values of precautionary non-rice savings and precautionary storage for each observation in our data (see Figure 2 and Figure 3). To generate the graphs we first estimate the value of

[26] The smaller coefficient in the lowest quartile implies that the poorest households engage in less precautionary savings than other households. However, this does not imply that consumption smoothing behavior among the poorest households differs from other households. Rather, these households do not adjust consumption based on potential production risk. Like all other households, when an income shock is realized, the poorest must either reduce consumption, reduce savings, or undertake some combination of the two. Unlike all other households, though, the poorest do not reduce consumption and increase savings in anticipation of expected income shocks.

precautionary non-rice savings (rice storage) for each household in each month.[27] We then divide by observed monthly household non-rice savings (rice storage) per capita. Each dot represents the share of non-rice savings (rice storage) kept for precautionary purposes by each household in each month (left axis) with household income on the horizontal axis. We also fit an univariate non-parametric regression line via local polynomial smoothing to clarify the relationship between share of non-rice savings (rice storage) and income (right axis).

In Figure 2 we find an asymmetry in precautionary non-rice savings centered approximately around 1,000 Taka, which is slightly below the rural poverty line of 1,266 Taka (Balagtas et al., 2013). For income greater than 1,000 Taka we find a strong negative relationship between the share of precautionary non-rice savings and income. Presumably, households with more income, when faced with an income shock, can reduce consumption and/or smooth consumption by dis-investing without the need to rely on precautionary savings. In contrast, for those with income below 1,000 Taka, precautionary non-rice savings drops precipitously and remains close to zero. At low levels of income households are not engaged in precautionary savings. Households below the threshold are, on average, already consuming in excess of current income. Households in this situation are likely to be consuming near subsistence levels, and thus are unlikely to be able to reduce current consumption in anticipation of expected future shocks.

Unlike non-rice savings, rice storage does not vary greatly with income. The average value of rice storage is 75 Taka for the lowest income quartile and 85 Taka for the highest. Compare this to non-rice savings, which varies from $-2,480$ Taka for the lowest quartile to $3,109$ Taka for the highest quartile. As a result, the relationship between precautionary storage and income is less clear then it is between precautionary non-rice savings and income (see Figure 3). There is a slight positive trend in the data as very wealthy households hold more precautionary storage than very poor households. We do not find evidence of the stylized inverted-U relationship between precautionary storage and income.

These results are driven by the fact that within a given quartile the share of precautionary non-rice savings and the share of precautionary storage differ. Precautionary non-rice savings makes up about 28 per cent of total non-rice savings in the second quartile but precautionary storage makes up only about 21 per cent of total storage. For the highest income quartile, precautionary non-rice savings is only about 3 per cent of total non-rice savings while precautionary storage in about 18 per cent of total storage.[28]

To summarize, our quartile analysis brings forward two interesting results obscured by conducting an analysis of precautionary savings using mean income and consumption levels. First, similar to Jalan and Ravallion (2001), we find a stylized inverted-U relationship between income and precautionary non-rice savings as a share of total non-rice savings. However, Figure 2 provides a more detailed picture of how precautionary savings changes as income changes. There appears to be a critical lower bound on income, near the rural poverty line, below which households are unable to engage in precautionary savings. Above this critical value, precautionary savings is inversely related to income. Thus, very wealthy and very poor households precautionary save at about the same rate while precautionary savings rates are asymmetric around per capita monthly income of 1,000 Taka.

Second, the relationship between precautionary non-rice savings and income is different than

[27]T his method is the same used to generate the Value of Precautionary Non-Rice Savings and Value of Precautionary Rice Storage in Tables 3 and 5.

[28]These differences persist when we vary the percentile of scaled rainfall variability within a quartile.

the relationship between precautionary storage and income. In our mean analysis, there was no significant difference between the share of precautionary non-rice savings and the share of precautionary storage. We took this as evidence in support of the hypothesis that households treat grain storage as fungible with other types of savings when making precautionary savings decision. In our quartile analysis, there is a significant difference between the share of precautionary non-rice savings and the share of precautionary storage. This is because rice storage levels vary little across income quartiles. Thus, our quartile analysis lends support to those studies that argue grain storage is not perfectly substitutable with other stores of wealth (Renkow, 1990; Saha and Stroud, 1994; Park, 2006).

6 Conclusion

Precautionary savings accounts for about 5 per cent of total savings for the average Bangladeshi household. But, we find the income effect on precautionary savings depends on the savings instrument. Precautionary non-rice savings is not very important for the wealthiest and poorest households in the data set while households with per capita income just above the rural poverty level hold significant amounts of liquid assets for precautionary purposes. The poorest and wealthiest households exhibit similar precautionary behavior. However, we believe this is for different reasons. The poorest households are perpetually in debt and are unable to reduce current consumption to engage in precautionary savings while the wealthiest households are better able to manage production risk and invest wealth in productive assets, alleviating the need for precautionary savings. Middle quartile households engage in costly precautionary savings to self-insure and this may reinforce poverty traps, as households have fewer liquid assets to productively invest.

These observed income effects on precautionary non-rice savings do not carry over to precautionary rice storage. Across income classes, households tend to store about the same amount of rice, on a per capita basis. This finding has important implications for rural development policy and future research on precautionary savings and consumption smoothing. The market failures that motivate households to tie up wealth in unproductive liquid assets, like cash, are different from the market failures that result in the precautionary storage of staple grain. Policies aimed at reducing precautionary savings by improving credit or insurance markets may have no impact on the level of precautionary storage. Studies that treat grain storage as fungible with other forms of savings may overlook vital information in household precautionary behavior.

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Table 1: Descriptive Statistics

Variables	1^{st} Quarter	2^{nd} Quarter	3^{rd} Quarter	4^{th} Quarter
Net Income per cap (Tk)	1771	4189	2503	3033
	(5719)	(6118)	(4722)	(4469)
Consumption per cap (Tk)	2473	2332	2603	2633
	(3859)	(2510)	(2897)	(2432)
Landholding (dec)	239	226	156	160
	(268)	(270)	(234)	(209)
Prev 6 Month's Rainfall (mm)	74.4	61.0	216	225
	(48.4)	(42.1)	(68.3)	(61.6)
Scaling Term	3.34	7.91	3.54	4.55
	(10.5)	(17.7)	(12.6)	(16.3)
Scaled Rainfall Variability	102	189	163	263
	(332)	(499)	(198)	(935)
Observations	4,122	4,122	2,748	3,664

Note: Standard deviation in parenthesis. Scaling term is defined as $(\text{income/consumption})^2$ while scaled rainfall variability is defined as $(\text{income/consumption})^2 \times$ (standard deviation of rainfall).

Table 2: Precautionary Responses to Risk in Household Consumption Decisions

Panel A: Monthly Precautionary Responses to Risk				
Regressors	OLS	IV	FD	FDIV
	(1)	(2)	(3)	(4)
Landholding	$-2.30\times10^{-05*}$	-6.64×10^{-06}	6.43×10^{-05}	5.77×10^{-05}
	(1.21×10^{-05})	(5.69×10^{-06})	(7.46×10^{-05})	(7.23×10^{-05})
Scaled Rainfall Variability	$4.26\times10^{-05**}$	7.28×10^{-06}	$1.66\times10^{-04**}$	$1.34\times10^{-04**}$
	(1.83×10^{-05})	(6.55×10^{-06})	(6.77×10^{-05})	(5.68×10^{-05})
Observations	14,198	13,282	13,740	13,282
R-squared	0.25	—	0.27	—

Panel B: First Stage Instrumental Variable Regressions				
	(1)	(2)	(3)	(4)
π_{it-1}	—	0.475***	—	-0.519***
	—	(0.040)	—	(0.042)
π_{it-2}	—	0.292***	—	0.297***
	—	(0.003)	—	(0.058)
Landholding	—	0.003***	—	-0.001
	—	(0.001)	—	(0.002)
Observations	—	13,740	—	13,740
R-squared	—	0.54	—	0.31

Note: Panel A: dependent variable is the change in household consumption from period t to period $t+1$. Scaled rainfall variability is defined as (income/consumption)^2 $\times$ (standard deviation of rainfall). IV and FDIV estimation is by GMM and utilize instrumental variables based on $t-1$ and $t-2$ periods of the scaling term. Panel B: dependent variable is scale term (π_{it-1}) defined as (income/consumption)^2. Column (1) and (2) report results using monthly data from first stage IV estimation and first stage of first differenced IV estimation, respectively. Column (3) and (4) report results using quarterly data from first stage IV estimation and first stage of first differenced IV estimation, respectively. All specifications include jointly significant village-month dummy variables to control for village level aggregate shocks. Cluster corrected robust standard errors are reported in parentheses. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 3: Estimated Effect of Precautionary Behavior on Saving and Storage

Average Income, Consumption, Savings, & Storage	
Per Capita Net Income of Rural Household (A)	2904
Per Capita Consumption of Rural Household (B)	2498
Per Capita Savings ($C = A - B$)	406
Per Capita Value of Rice Consumption (F)	433
Per Capita Value of Stored Rice (G)	67.8
Precautionary Savings & Storage at Different Levels of Rainfall Variance	
(Coef)*75th Percentile of Scaled Rainfall Variability (D)	0.023
Value of Precautionary Savings ($E = D * B$)	57.03
Value of Precautionary Non-Rice Savings ($H = D * (B - F)$)	47.15
Value of Precautionary Storage ($I = D * F$)	9.88
(Coef)*50th Percentile of Scaled Rainfall Variability (D)	0.008
Value of Precautionary Savings ($E = D * B$)	19.45
Value of Precautionary Non-Rice Savings ($H = D * (B - F)$)	16.08
Value of Precautionary Storage ($I = D * F$)	3.37
(Coef)*25th Percentile of Scaled Rainfall Variability (D)	0.002
Value of Precautionary Savings ($E = D * B$)	4.83
Value of Precautionary Non-Rice Savings ($H = D * (B - F)$)	4.00
Value of Precautionary Storage ($I = D * F$)	0.84
Precautionary Savings as a Share of Total Savings ($E/(C)$)	
At 75th Percentile of Scaled Rainfall Variability	14.0%
At 50th Percentile of Scaled Rainfall Variability	4.79%
At 25th Percentile of Scaled Rainfall Variability	1.19%
Precautionary Non-Rice Savings as a Share of Non-Rice Savings ($H/(C - G)$)	
At 75th Percentile of Scaled Rainfall Variability	13.9%
At 50th Percentile of Scaled Rainfall Variability	4.75%
At 25th Percentile of Scaled Rainfall Variability	1.18%
Precautionary Storage as a Share of Stored Rice (I/G)	
At 75th Percentile of Scaled Rainfall Variability	14.6%
At 50th Percentile of Scaled Rainfall Variability	4.97%
At 25th Percentile of Scaled Rainfall Variability	1.23%

Note: Per capita income, consumption, savings, rice consumption, and rice storage are taken at the mean of the data. Income and rice storage are measured quarterly and monthly averages are calculated. Consumption and rice consumption are measured monthly. The term (Coef) comes from FDIV method for estimating the coefficient on scaled rainfall variability in Table 2, column (4). This coefficient is 1.31×10^{-04}. Scaled rainfall variability is defined as (income/consumption)^2 $\times$ (standard deviation of rainfall). All values are in Taka.

Table 4: Monthly Precautionary Responses to Risk in Household Consumption by Income Quartile

Regressors	OLS	IV	FD	FDIV
Landholding	$-3.22\times10^{-05***}$	-6.75×10^{-06}	8.56×10^{-05}	7.67×10^{-05}
	(1.02×10^{-05})	(5.80×10^{-06})	(7.42×10^{-05})	(7.25×10^{-05})
Quartile 1 Scaled Rainfall Variability	2.19×10^{-05}	9.28×10^{-06}	$8.75\times10^{-05*}$	$6.18\times10^{-05*}$
	(1.41×10^{-05})	(1.00×10^{-05})	(7.01×10^{-05})	(3.56×10^{-05})
Quartile 2 Scaled Rainfall Variability	$2.81\times10^{-04***}$	2.57×10^{-06}	$8.45\times10^{-04***}$	$6.40\times10^{-04***}$
	(3.85×10^{-05})	(2.76×10^{-05})	(1.30×10^{-04})	(1.07×10^{-04})
Quartile 3 Scaled Rainfall Variability	$1.64\times10^{-04***}$	-1.96×10^{-06}	$4.95\times10^{-04***}$	$3.37\times10^{-04***}$
	(3.41×10^{-05})	(1.78×10^{-05})	(1.14×10^{-04})	(8.57×10^{-05})
Quartile 4 Scaled Rainfall Variability	$6.78\times10^{-05***}$	7.49×10^{-06}	$2.54\times10^{-04***}$	$2.20\times10^{-04***}$
	(1.97×10^{-05})	(6.51×10^{-06})	(5.15×10^{-05})	(6.81×10^{-05})
Observations	14,198	13,282	13,740	13,282
R-squared	0.26		0.28	

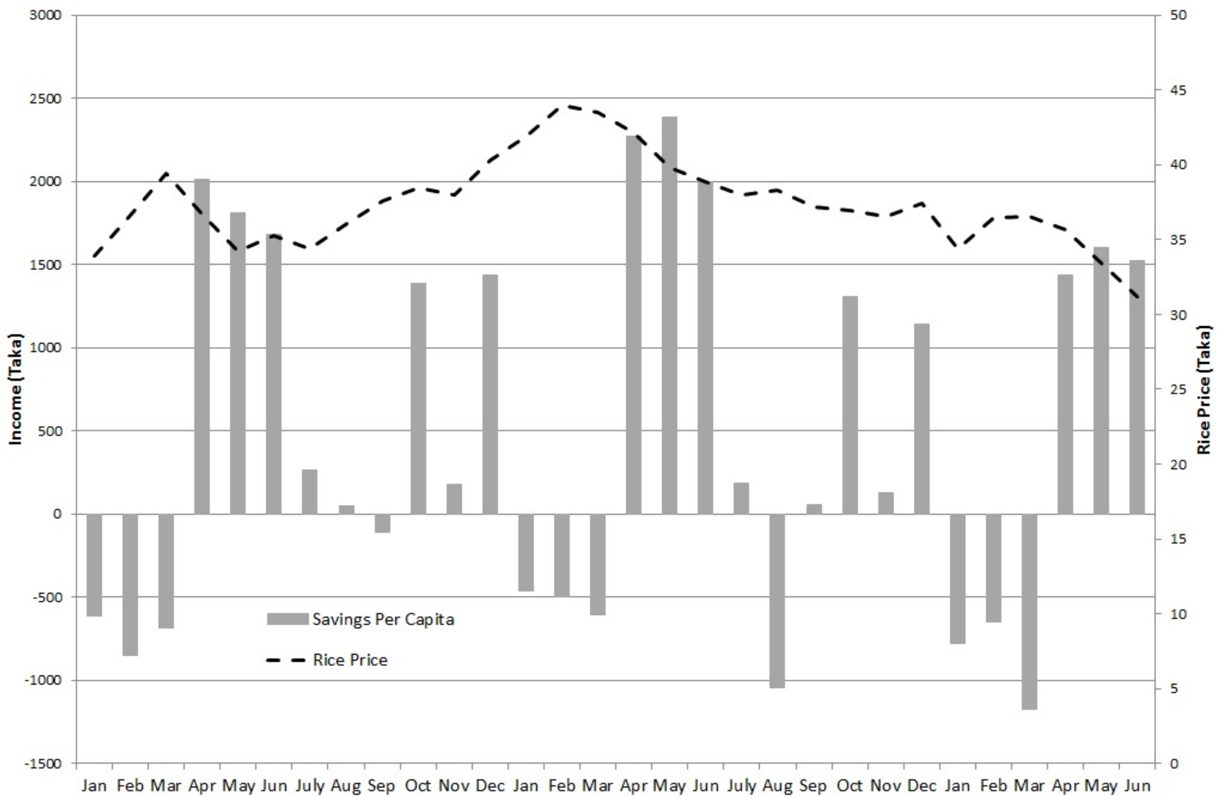
Note: Dependent variable is the change in household consumption from period t to period $t+1$. Scaled rainfall variability is defined as (income/consumption)^2 $\times$ (standard deviations of rainfall) $\times$ (income quartile indicator). IV and FDIV estimation is by GMM and utilize instrumental variables based on $t-1$ and $t-2$ periods of the scaling term. All specifications include jointly significant village-month dummy variables to control for village level aggregate shocks. Cluster corrected robust standard errors are reported in parentheses. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 5: Estimated Effect of Precautionary Behavior on Saving and Storage by Income Quartile, in Taka

	Income Quartile			
Average Income, Consumption, Savings, & Storage	**First**	**Second**	**Third**	**Fourth**
Per Capita Net Income of Rural Household (A)	29.9	1960	3045	6557
Per Capita Consumption of Rural Household (B)	2435	2079	2110	3364
Per Capita Savings ($C = A - B$)	-2405	-119	936	3194
Per Capita Value of Rice Consumption (F)	410	403	437	491
Per Capita Value of Stored Rice (G)	74.6	56.8	81.4	84.8
Predicted Precautionary Savings				
(Coef)*50th Percentile of Scaled Rain Var (D)	0.001	0.026	0.031	0.033
Value of Precautionary Savings ($E = D * B$)	2.26	54.8	64.5	110
Value of Precautionary Non-Rice Savings ($H = D * (B - F)$)	1.88	44.2	51.1	95.0
Value of Precautionary Storage ($I = D * F$)	0.38	10.6	13.4	15.8
Precautionary Savings Share of Total Savings				
Precautionary Savings Share of Total Savings ($E/(C - G)$)	0.09%	46.1%	6.89%	3.47%
Precautionary Non-Rice Savings Share of Non-Rice Savings ($H/(C - G)$)	0.08%	25.1%	5.99%	3.06%
Precautionary Storage Share of Stored Rice (I/G)	0.51%	18.7%	16.4%	18.7%

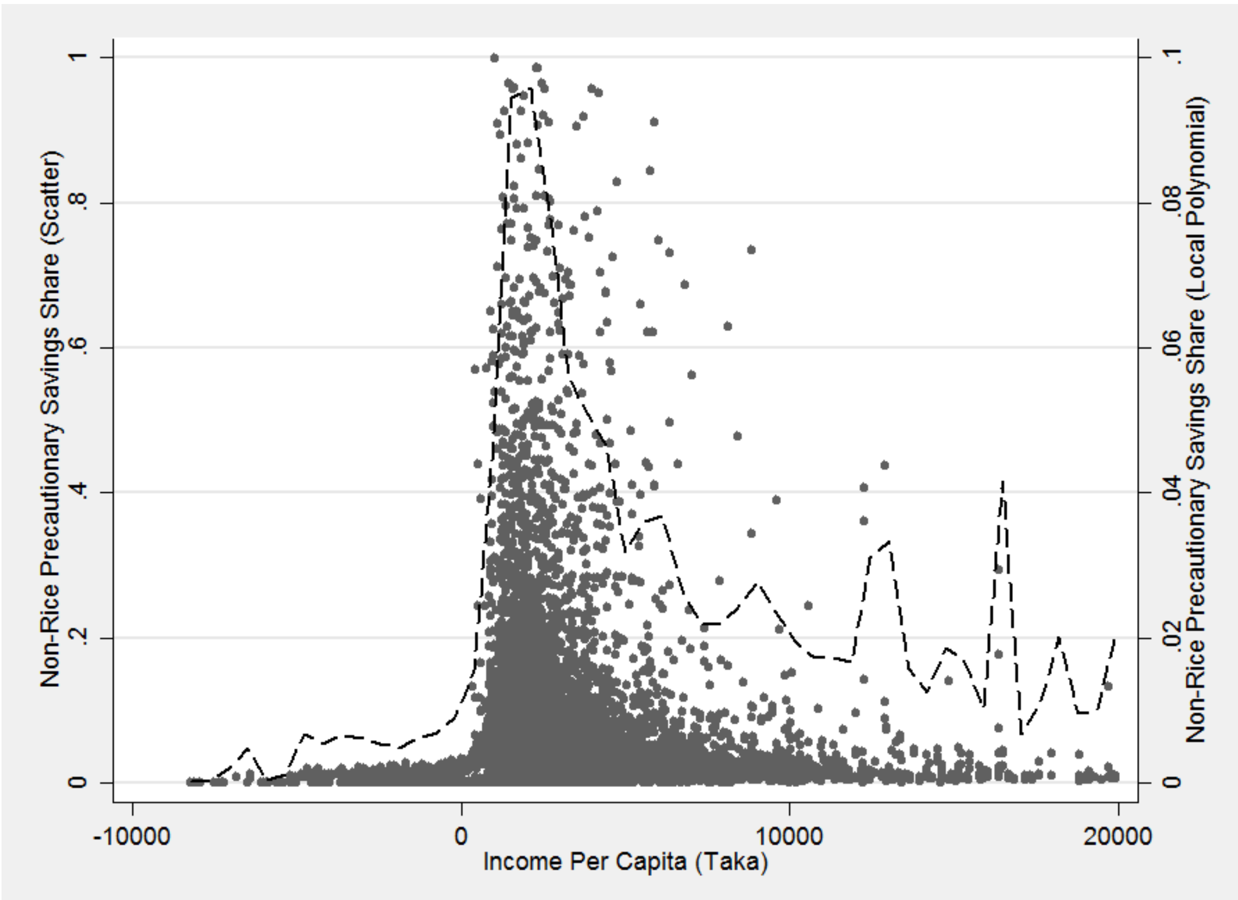
Note: Per capita income, consumption, savings, rice consumption, and rice storage are taken at the mean of each income quartile. Income and rice storage are measured quarterly and monthly averages are calculated. Consumption and rice consumption are measured monthly. The term (Coef) comes from FDIV method for estimating the coefficient on scaled rainfall variability in Table 4. This coefficient is 6.18×10^{-05} for households in the lowest income quartile, 6.40×10^{-04} for households in the second income quartile, 3.37×10^{-04} for households in the third income quartile, and 2.20×10^{-04} for households in the highest income quartile. Scaled rainfall variability is defined as (income/consumption)^2 $\times$ (variability rainfall) $\times$ (income quartile indicator). All values are in Taka.

Figure 1: Mean Savings and Rice Price, January 2010 - June 2012



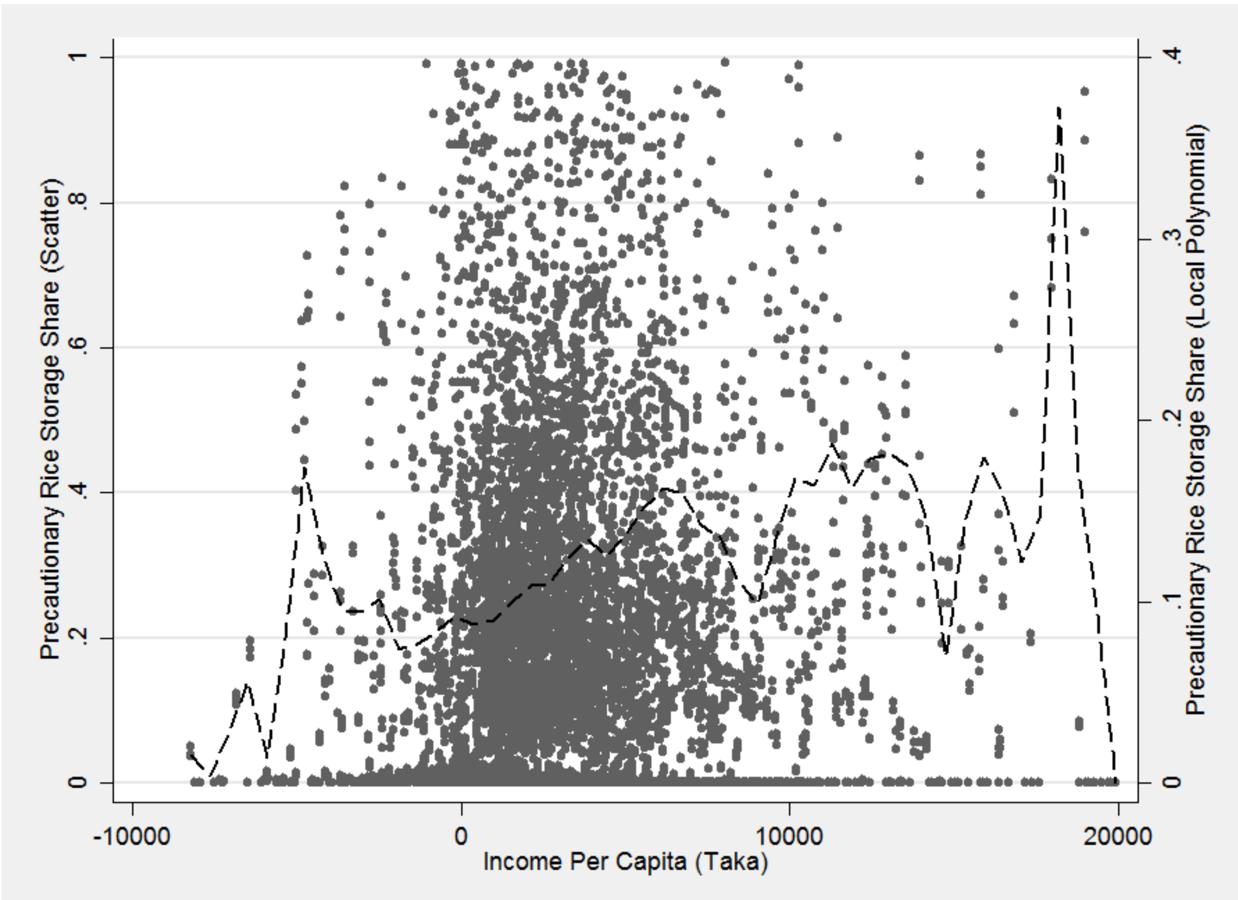
Note: Monthly per capita savings rate is calculated as the difference between average monthly per capita income and average monthly per capita consumption. Rice price is the average market price paid by households for one kilo of rice.

Figure 2: Share of Non-Rice Precautionary Savings and Income



Note: Non-Rice Precautionary Savings Share is calculated by multiplying observed monthly household non-rice consumption per capita by (Coef)*50th percentile of scaled rainfall variability for the relevant income quartile and dividing by observed monthly household non-rice savings per capita. (Coef)*50th percentile of scaled rainfall variability comes from Table 5 and is 0.001 for the lowest income quartile, 0.026 for the second quartile, 0.031 for the third income quartile, and 0.033 for the highest income quartile. Each dot represents the share of non-rice savings kept for precautionary purposes by each household in each month (left axis). We also include an univariate non-parametric regression line fitted via local polynomial smoothing (right axis).

Figure 3: Share of Precautionary Rice Storage and Income



Note: Precautionary Rice Storage Share is calculated by multiplying observed monthly household rice consumption per capita by (Coef)*50th percentile of scaled rainfall variability for the relevant income quartile and dividing by observed monthly household rice savings per capita. (Coef)*50th percentile of scaled rainfall variability comes from Table 5 and is 0.001 for the lowest income quartile, 0.026 for the second quartile, 0.031 for the third income quartile, and 0.033 for the highest income quartile. Each dot represents the share of rice storage kept for precautionary purposes by each household in each month (left axis). We also include an univariate non-parametric regression line fitted via local polynomial smoothing (right axis).

A For Online Publication: Rainfall and the Crop Cycle

Our empirical test utilizes rainfall variability as a proxy for production risk and requires that we first establish which periods of rainfall are most important for agricultural production. In Bangladesh, 88 per cent of agricultural output is from seasonal crops which are grown across three period: *Boro*, *Aman*, and *Aus*. Since rice accounts for 85 per cent of seasonal production (75 per cent of total agricultural production), we focus our analysis of rainfall and the crop cycle on rice.

The majority of rain in Bangladesh comes during the summer monsoon season, generally June-September but sometimes extending into May or October. Despite the geographically small size of Bangladesh and the concentration of precipitation to the summer months there is significant variation in rainfall between villages as well as between months (see Table A1). While the majority of rainfall is concentrated over the four summer months, the two primary rice growing seasons (*Aman* and *Boro*), are non-monsoon crops (see Table A2). *Aman* rice is planted in the second half of the monsoon (July-August) with the moisture and temperature sensitive heading stage occurring in the cool but dry late autumn (October-November). Thus, monsoon rains prior to heading; rains that refill reservoirs, raise river levels, and ensuring adequate moisture content in the soil, are important to ensuring a healthy *Aman* crop. *Boro* rice is planted early in the new year (January-February) and primarily relies on groundwater irrigation. However, late monsoon and autumn rains are important in determining moisture content in the soil, which can limit the need for costly groundwater irrigation. Only the short summer monsoon season, *Aus*, relies directly on rainfall during the season.

Since the crop cycle is spread across three seasons we infer that no single month's or set of months' rainfall will play a vital role in determining yields for all three seasons. Rather, we hypothesis that rainfall in the months immediately preceding cultivation will be important in crop production. We performed numerous regressions of household rice production on various lags of monthly rainfall. We found two equally strong indicators of agricultural production: average rainfall over the previous four months and average rainfall over the previous six months (see Table A3). Both of these candidates make agronomic sense and absent any clear criteria we choose previous six months rainfall for our proxy since it yields the more conservative results in our subsequent empirical analysis. We use as a proxy for production risk the standard deviation of our indicator over the last 20 years.

Beyond the issue of correlation between the prior six months rainfall and rice yields is a deeper question regarding the justification of using our proxy for households that may not grow rice in a given season. Here we highlight three points. First is that, while 87% of households in our data set grow rice, the remaining 13% of households engage in non-rice cultivation which is affected by rain in that six month window. This is most commonly pre- or post-monsoon crops such as wheat, maize, and legumes, or monsoon crops like jute and betel nut. Thus, while not every household grows rice in every season, every household in our data set has secondary crop production, meaning that in almost every month a household will have some agricultural production. We therefore believe that even for households cultivating a crop other then rice in a given season our prior-six-months-rainfall variable is a good proxy for potential shocks to income.

Second, in Bangladesh, we observe very little of this type of adjustment by rice farmers in our data. The concern here is that households might alter which of the growing seasons they cultivate rice in, making our proxy uninformative if the households suddenly stops cultivation in a given season.[29] However, in our data, we do not find empirical evidence of this type of behavior. Tracking households across time we only observe 28 households (7%) that cultivate rice in one season and then fail to cultivate rice in that same season the following year (See Table A4). The vast majority of households have chosen to cultivate in some combination of the three growing seasons (*Boro-Aman*, *Aus-Boro*, *Aman-Aus*, or in just a single season). Once this decision has been made households rarely alter which one or two of the three growing seasons they actually plant rice. Since we do not see households adjusting if they do or do not cultivate in a season, we believe that our rainfall proxy is a strong candidate for production risk for the vast majority of households in our data set.

Finally, regarding the relevance of our proxy for households who at the moment are not cultivating any crop, the purpose of the proxy is to trigger a behavior response not a production response. This change in behavior occurs regardless of whether or not a household produces rice in the relevant season (though the above evidence demonstrates that not producing rice on at least one plot in a given season is rare). If the household has rice in the ground, an increase in production risk will change the household's behavior so that it eats less and saves more today in the now more likely event that the crop will be bad. If the households does not happen to cultivate rice (or any other crop) in the relevant season, an increase in production risk will still elicit a behavioral response. In this case, the household will see that the crops in the area are more likely to be bad. Since market areas tend to be small in geographical scope, this will likely increase the price of rice in the future. In anticipation of this, households will eat less and save more (either cash or through buying rice to store) in anticipation of higher staple grain prices in the future. Our proxy is based on production but it is designed to elicit a behavioral response.

B For Online Publication: Alternative Specifications

In order to verify the validity of our results to changes in our specification we conduct two robustness checks. First, we test if our qualitative results fundamentally change when we use an alternative proxy for production risk (previous four months of rainfall). Second, we estimate the model on our data aggregated up to quarters, the typical unit of observation in studies of consumption smoothing and precautionary savings. We compare the quarterly results to both our monthly results and results cited in similar analysis by Giles and Yoo (2007).

B.1 Alternative Rainfall Proxy

The crop calendar for rice in Bangladesh, as well as our estimation of the production function, yield two equally strong indicators of production: the average rainfall over the previous six months and the average rainfall over the previous four months. In the previous sections we conducted our analysis using the sample standard deviation of average rainfall over the previous six months for each village as our proxy for production risk. Our preference for the previous six months as a proxy is in large part due to it generating more conservative results than the previous four month proxy. As a robustness check we present regression results using the the sample standard deviation of rainfall over the previous four months for each village as a proxy for production risk.

[29]We thank an anonymous reviewer for pointing out this potential issue.

We follow the same empirical estimation procedure as discussed in Section 4.[30] Results from these regressions are presented in Panel A of Table A5. Focusing on the FDIV procedure, the coefficient on scaled rainfall variability using the six month proxy is 1.34×10^{-04} while the coefficient on scaled rainfall variability using the four month proxy is 1.57×10^{-04}. The relatively larger point estimate using the four month proxy results in larger predicted effects for the value of per capita precautionary savings (see Table A6). Using the six month proxy, the average household facing average production risk saves 20 Taka per person per month (just under 5 per cent of total savings) for precautionary purposes. Using the four month proxy, the per capita value of precautionary savings is 24 Taka a month, or just under 6 per cent of total savings. Differences between these values increase as production risk increases.

Comparing results, we see that the alternative proxy for production risk yields slightly larger precautionary savings effects, suggesting that our approach is conservative. The average household in Bangladesh, facing the mean level of production risk, keeps between 5 and 6 per cent of total savings for precautionary purposes.

B.2 Quarterly Aggregation and Comparison

As an second robustness check, and to facilitate comparison of our results to other studies on the role of precautionary savings among rural households, we aggregate our monthly data to the quarterly level. When we estimate our model using the quarterly data, scaled rainfall variability is significant only in the OLS and FD models (see Panel B in Table A5). As stated previously, one of the benefits of monthly data is that it has the potential to reveal intra-seasonal changes in consumption behavior that might be lost in quarterly or annual data. This appears to be the case with household data in Bangladesh. The presence of three growing seasons distributed across four quarters results in an uneven distribution of income across those quarters. Monthly changes in consumption tend to net out when aggregated, resulting in little quarterly variation (see Table 1).

Although the coefficient on scaled rainfall variability is not significant in the FDIV model, we calculate the value of total precautionary savings and present it in Table A6 for purposes of comparison. As one would expect, the precautionary savings motive is very low at the quarterly level, about half of what it was when using monthly data. This result is due to a lack of variation in consumption behavior between quarters, not because of any change in savings as a percentage of income, which is around 15 per cent regardless of data frequency.

A comparison of Bangladeshi households to the rural Chinese households studied in Giles and Yoo (2007) reveals that Chinese households save much more of their income (27-29 per cent).[31] In the Chinese data, precautionary savings as a share of total savings is almost always triple that of Bangladesh. These relatively high levels of precautionary savings are despite Giles and Yoo using annual data. It is likely that, had Giles and Yoo access to quarterly or monthly data, precautionary savings would make up an even larger percentage of total savings.

The relatively low precautionary savings rate of Bangladesh compared to China may be explained by two contributing factors. First is the relative wealth of rural Bangladeshi households today compared to rural Chinese households 15-25 years ago. To facilitate this comparison, we

[30] Since rainfall variability is exogenous we use the same instrument so that the first stage regression results presented in Columns (2) and (4) of Panel B in Table 2 are unchanged.

[31] Giles and Yoo conduct their analysis using household level panel data from 44 villages. They have annual observations from 1986-1991 and again from 1995-2000. Instead of conducting their analysis on the entire panel and accounting for a structural break, they divide the panel into two panels.

aggregate the Bangladesh data to annual amounts and convert the values to dollars.[32] Per capita income in Bangladesh is about three times higher than per capita income was in China over the study period. Thus, the relative wealth of Bangladeshi households compared to Chinese households means that Bangladeshi households have less of a need for precautionary savings. Second, rice is the primary source of income for Bangladeshi households while in Giles and Yoo's area of study wheat and corn production dominates rice production. Variations in rice yields in Bangladesh are smaller, and therefore production is less risky, when compared to variations in wheat and corn yields in China. Thus, precautionary savings in Bangladesh may be less important than in China because production is less risky.

[32]We use the same Yuan-USD exchange rate as Giles and Yoo and then adjust the results (which are in 1986 USD) to 2012 USD.

Table A1: 20 Year Average Monthly and Annual Rainfall (mm)

Weather Station	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Bogra	8.3	11.6	19.1	75.0	186	298	346	294	292	144	5.5	7.5	141
Chuadanga	11.9	19.4	27.4	44.1	142	226	334	215	300	126	13.2	8.5	122
Comilla	8.5	22.8	72.6	127	310	378	400	275	241	171	28.8	9.5	170
Chandpur	6.2	23.8	55.3	99.6	234	316	398	294	269	178	27.0	4.3	159
Khulna	14.7	35.7	51.8	51.2	163	306	327	288	294	164	28.0	4.1	144
Rangpur	10.1	9.8	24.7	119	259	433	404	342	358	181	5.4	4.7	179
Madaripur	7.1	22.7	49.1	101	216	333	362	292	258	162	30.7	4.2	153
Mymensingh	7.5	18.3	39.7	133	297	406	431	324	300	201	12.0	7.5	181
Tangail	6.9	20.4	48.0	99.1	251	304	312	265	281	168	18.4	8.9	149
Dhaka	7.2	20.4	57.0	119	262	311	384	299	313	181	20.0	8.9	165
Patuakhali	7.1	26.5	48.3	90.7	199	486	570	428	371	252	30.2	2.9	209
Dinajpur	9.3	9.8	12.5	69.0	203	381	380	324	361	148	5.7	5.6	159

Note: Data is from daily rainfall observations aggregated to the monthly level. Averages are take of monthly rainfall from 1992-2012. Data is from the Bangladesh Meteorological Department, Climate Division, Dhaka.

Table A2: Crop Calendar for Rice Production

Month	Stages of Crop Development		
	Boro	*Aus*	*Aman*
January	Planting		
February	Planting		
March	Vegetative		
April	Heading	Planting	
May	Harvesting	Planting/Vegetative	
June	Harvesting	Vegetative/Heading	
July		Heading/Harvesting	Planting
August		Harvesting	Planting
September			Vegetative
October			Heading
November			Harvesting
December			Harvesting

Source: Crop Calendar of Bangladesh, Agriculture and Food Security Programme, BRAC, Dhaka.

Table A3: Effects of Rainfall on Rice Production

Regressors	(1)	(2)
ln(Previous 4 Months Rain)	0.097^{**}	
	(0.039)	
ln(Previous 6 Months Rain)		0.075^{**}
		(0.030)
ln(Labor)	1.795^{***}	1.795^{***}
	(0.161)	(0.161)
ln(Fertilizer)	0.092^{**}	0.092^{**}
	(0.048)	(0.048)
ln(Irrigation)	-0.016	-0.016
	(0.017)	(0.017)
ln(Mechanization)	0.227^{***}	0.227^{***}
	(0.047)	(0.047)
ln(Pesticide)	0.021^{**}	0.021^{**}
	(0.001)	(0.001)
Fixed Effects	yes	yes
Observations	7,052	7,052
R-squared	0.43	0.43

Note: Dependent variable is log yield. Observations are at the parcel level. Regressions include parcel level fixed effects and jointly significant village-season dummy variables to control for village level aggregate shocks. Parcel level cluster corrected robust standard errors are reported in parentheses. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A4: Number of Households Cultivating Rice

Season	2010	2011	2012
Boro	281	281	272
Aus	81	94	
Aman	324	322	

Note: Each cell represents the number of households in our rice production data set that cultivate rice in a given season in a given year. Total number of households in the data set is 399.

Table A5: Alternative Specifications of Precautionary Responses to Risk in Household Consumption Decisions

Panel A: Monthly Precautionary Responses to Risk in Household Consumption				
Regressors	OLS (1)	IV (2)	FD (3)	FDIV (4)
Landholding	$-2.02\times10^{-05*}$	-5.16×10^{-06}	7.39×10^{-05}	8.98×10^{-05}
	(1.06×10^{-05})	(4.89×10^{-06})	(7.47×10^{-05})	(7.53×10^{-05})
Scaled Rainfall Variability	$2.88\times10^{-05**}$	2.96×10^{-06}	$1.15\times10^{-04***}$	$1.57\times10^{-04***}$
	(1.34×10^{-05})	(2.90×10^{-06})	(4.51×10^{-05})	(5.27×10^{-05})
Observations	14,198	13,282	13,740	13,282
R-squared	0.25		0.26	

Panel B: Quarterly Precautionary Responses to Risk in Household Consumption				
Regressors	OLS (1)	IV (2)	FD (3)	FDIV (4)
Landholding	-1.37×10^{-06}	4.73×10^{-06}	$5.28\times10^{-05*}$	$7.94\times10^{-05**}$
	(4.84×10^{-05})	(5.04×10^{-06})	(3.03×10^{-05})	(3.14×10^{-05})
Scaled Rainfall Variability	$2.96\times10^{-05**}$	1.56×10^{-05}	$8.53\times10^{-05**}$	7.94×10^{-05}
	(1.28×10^{-05})	(1.78×10^{-05})	(3.75×10^{-05})	(6.82×10^{-05})
Observations	4,580	3,664	4,122	3,664
R-squared	0.16		0.12	

Note: Dependent variable is the change in household consumption from period t to period $t+1$. Scaled rainfall variability is defined as (income/consumption)^2 $\times$ (standard deviation of rainfall). IV and FDIV estimation is by GMM and utilize instrumental variables based on $t-1$ and $t-2$ periods of the scaling term. Panel A presents results from monthly data using the standard deviation of the previous 4 months rainfall over the last 20 years. Panel B aggregates monthly data into quarters prior to estimation and uses the standard deviation of the previous 6 months rainfall over the last 20 years. All specifications include jointly significant village-month dummy variables to control for village level aggregate shocks. Cluster corrected robust standard errors are reported in parentheses. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table A6: Estimated Effect of Precautionary Behavior & Comparison to Giles & Yoo (2007)

	China		Bangladesh	
	1986-91	**95-2000**	**Month**	**Quarter**
Average Income, Consumption, & Savings				
Per Capita Net Income	525	720	2904	8573
Per Capita Consumption	372	523	2498	7264
Per Capita Savings	153	197	406	1309
Predicted Precautionary Savings				
(Coef)*75th Percentile of Scaled Rain Var	0.081	0.093	0.032	0.012
Value of Precautionary Savings	30.1	48.6	78.8	88.2
(Coef)*50th Percentile of Scaled Rain Var	0.040	0.039	0.010	0.004
Value of Precautionary Savings	14.9	20.4	23.9	30.4
(Coef)*25th Percentile of Scaled Rain Var	0.018	0.015	0.002	0.001
Value of Precautionary Savings	6.70	7.85	5.08	7.69
Precautionary Savings as a Share of Total Savings				
At 75th Percentile of Scaled Rain Var	19.7%	24.7%	19.4%	6.73%
At 50th Percentile of Scaled Rain Var	9.73%	10.4%	5.88%	2.32%
At 25th Percentile of Scaled Rain Var	4.38%	3.98%	1.25%	0.59%
Annualized US Dollar Equivalent Value				
Average Annual Income, Consumption, & Savings				
Per Capita Earned Income	$118	$162	$467	$474
Per Capita Consumption	$83.6	$118	$395	$408
Per Capita Savings	$34.4	$44.3	$71.3	$66.3
Predicted Value of Precautionary Savings				
Precautionary Savings At 75th Percentile	$6.77	$10.9	$12.9	$4.80
Precautionary Savings At 50th Percentile	$3.34	$4.58	$3.90	$1.65
Precautionary Savings At 25th Percentile	$1.50	$1.76	$0.79	$0.42

Note: Per capita income, consumption, savings, rice consumption, and rice storage are taken at the mean of the data. Income and rice storage are measured quarterly. Consumption and rice consumption are measured monthly and then aggregated into quarters. The term (Coef) in calculating monthly values comes from FDIV method for estimating the coefficient on scaled rainfall variability where rainfall variability is calculated using the previous 4 months rainfall proxy. This coefficient, presented in Table A5, Panel A, is 1.57×10^{-04}. The term (Coef) in calculating quarterly values comes from FDIV method for estimating the coefficient on scaled rainfall variability in Table A5, Panel B. This coefficient is 7.94×10^{-05}. Scaled rainfall variability is defined as $(\text{income/consumption})^2$ $\times$ (standard deviation of rainfall). All values for China in 1986 Yuan and Bangladesh in Taka. 1986 Yuan-USD exchange rate used then inflated to 2012 USD. Contemporaneous Taka-USD exchange rate used.