News from the Sky: An Empirical Test of Forward-Looking Behavior among Zambian Farmers

by Ken Miura and Takeshi Sakurai

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Abstract

This paper proposes a novel test of consumption responses to new information by building on a buffer stock saving model with borrowing constraints. While the consumption responses of asset-poor and asset-rich households are close to zero or modest, the middle asset group reacts to advance information the most. We test this hump-shaped relationship with weekly household data combined with daily plot-level rainfall records from rural Zambia. The empirical analysis first confirms that rainfall works as a good predictor of future maize harvests in the sample villages. Then, the regression results show that weekly household consumption responds to rainfall in certain months, which has sufficient predictive power for future harvests. Furthermore, the response is heterogeneous according to the level of grain inventories, consistent with the proposed model. Our results suggest that while even constrained households can change their consumption schedules before income shocks happen by adjusting their buffer stocks, welfare gains from advance information depend on the available asset levels.

Keywords: Household consumption, grain storage, seasonality, Africa

JEL Classification: D15, O13, Q12

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1 Introduction

Forward-looking decision-making by individuals and firms is a central assumption of many economic models in a dynamic setting. On the empirical side, the incorporation of anticipation effects into the analysis is critical for evaluating a wide range of economic policies, since their neglect produces biased estimates for the true treatment effects on the behavior of interest. Given the importance of these issues, the rich literature on consumption behavior has developed the excess sensitivity test of consumption responses to anticipated income changes or has examined the "saving for a rainy day" implication of the permanent income hypothesis (Jappelli and Pistaferri, 2010).[1] In addition, recent empirical studies have exploited episodes in which future income changes are predictable for households and have provided convincing evidence.[2]

While evidence has been gradually gathered on consumers in developed countries, empirical investigations of forward-looking consumption behavior in developing countries are scarce. Underlying this lacuna are difficulties in identifying expected income changes as well as finding a convincing empirical proxy for this type of signal. Such a proxy needs to be exogenous, observable for both households and researchers, and sufficiently correlated with future income. Another practical reason is the lack of long panel data on signals and the consumption decisions made in response to them. However, once these challenges are circumvented, we can expect rich implications for a vast array of development policies. For example, understanding the exact timing of consumption responses is essential for calculating accurate welfare costs of income fluctuations in less-developed countries in which households have limited strategies to cope with uncertain income.

We challenge this issue by using weekly agricultural household panel data combined with daily rainfall records from rural Zambia in 2007–2011. The sequential and seasonal nature of agricultural production provides a good setting for empirically examining how farmers react to signals and change their behavior accordingly.[3] In the study area (as well as in other rural areas of sub-Saharan

[1]The idea behind the excess sensitivity test is that any past predictor of future income should not predict either consumption changes or consumption growth, since economic agents have already incorporated the expectation of income changes into their optimal consumption schedule before actual occurrence. The excess sensitivity test is an indirect and weak test of forward-looking behavior because it seeks to find evidence against such behavior and its rejection does not tell us anything about possible constraints. As an alternative approach to testing forward-looking behavior, the "saving for a rainy day" hypothesis proposed by Campbell (1987) suggests that economic agents save when they expect future income to decline. The important applications of this test to an African context are Deaton (1992) for Côte d'Ivoire and Udry (1995) for Nigeria, both of who find that household saving responds in anticipation of future income shocks. However, data constraints prevent them from investigating household consumption behavior extensively. Indeed, Deaton (1992) uses a short rotating panel with only two data points for each household and Udry (1995) lacks consumption and income data.

[2]The examples of such episodes include tax rebates (Johnson et al., 2006; Heim, 2007), expected tax changes(Mertens and Ravn, 2012; Kueng, 2014), unemployment insurance benefit exhaustion, and fiscal stimulus programs (Parker et al., 2013; Agarwal and Qian, 2014). Among them, Heim (2007) estimates the effect of state tax rebates in the United States and differentiates between responses to the announcement and those to the actual receipt of rebates by exploiting the different timings of their signing across states. He finds weak announcement effects on overall consumption, whereas households might alter the composition of spending in anticipation of the rebate. Another important exception is Agarwal and Qian (2014), who detect a sizable announcement effect from a growth dividend program in Singapore.

[3]Some studies incorporate sequential production processes in developing countries into their analytical frameworks and discuss their implications on economic outcomes including farm labor (Fafchamps, 1993; Skoufias, 1993) and

Africa) where irrigation is rare and agriculture is rain-fed, crop harvests received as an annual lump sum at harvest time are highly sensitive to climate conditions such as rain. The key observation of this study is that information about exogenous rainfall shocks is gradually revealed over the agricultural season. Given this feature, farmers may revise their expectations of final crop harvests by observing current rainfall patterns in a crop season, thereby adjusting their consumption and saving behavior before it is fully realized. For example, if farmers experience a severe drought at some point in the planting stage, then they will expect crop harvests to be low. In response to the decline in expected future income, they may then start reducing consumption levels to increase saving in preparation for this future negative situation. On the contrary, households may increase current consumption after observing "good" rainfall within a crop season since they expect good harvests. As such, rainfall patterns can make farmers' expectations of future harvests sufficiently updated to induce subsequent behavioral changes.

Based on this idea, we explore the extent to which poor agricultural households in sub-Saharan Africa respond to anticipated income changes under borrowing constraints. As a key driver changing expected income, this study employs information on plot-level rainfall. To formally check the validity of rainfall as an informative signal of the future, we first confirm the statistically significant relationship between the amount of rainfall in the planting/weeding periods (November to March) and household maize harvests in the harvesting period (March to June) in the survey villages. The regression results show that rainfall in November and January has a positive and linear association with final maize harvests.[4] They also show that weekly rainfall does not have any immediate impact on current cash flow during the planting/weeding periods, which rules out simple income effects. Furthermore, the descriptive evidence shows that most of the rain in the planting/weeding periods does not have any relationship with the variation in final maize yields. This finding implies that rainfall can be considered to be a predictor of the first moment of future harvest incomes, rather than their second moment.

The main outcome variable is household consumption. Whether households change consumption in response to rainfall signals depends on their ability to finance consumption, and hence the structure of the credit and insurance markets. For example, the presence of borrowing constraints would dampen consumption responses to news, since constrained households are not allowed to borrow against future income in anticipation of increases in future income.[5] Reflecting the environment faced by sample households, we extend Deaton's (1991) buffer stock saving model with borrowing constraints by introducing information shocks. The proposed model assumes that whereas farmers cannot borrow money for consumption purposes, they can borrow against future income by adjusting asset stocks such as grain inventories. The main theoretical implication from the model is that the impact of advance information on consumption growth has a hump-shaped

calorie consumption (Behrman et al., 1997). However, no empirical research has thus far examined consumption responses in anticipation of income changes.

[4]This result is consistent with local information about climate and local proverbs on weather forecasts in the study site (Kanno et al., 2013).

[5]Models that make different assumptions on how well these markets function provide distinct implications. If insurance markets are complete, no effect of household-specific news on consumption is expected since all the shocks are fully insured *ex ante* through transactions of contingent claims across different states of nature. On the contrary, a small consumption response is expected under the permanent income hypothesis with complete credit markets because the change in discounted lifetime income is spread across the remaining periods.

relationship with the level of available asset stocks, conditional on the size of changes in expected income: while the consumption responses of asset-poor and asset-rich households are close to zero or modest, the middle asset group reacts to new information the most.

This result can be interpreted as follows. Asset-poor households can do nothing after receiving informative signals because of borrowing constraints and the small amount of available buffer stocks. The reaction of asset-rich households is limited because the marginal utility from changes in future income is smaller than that of other households. Their response is well approximated by the permanent income hypothesis, since they behave as though the borrowing constraints were not binding thanks to the ample amount of stocks. As a result, the greatest beneficiary from advance information is the middle asset group. The convexity of future marginal utility explains these asset-differentiated impacts of information shocks between middle-asset and asset-rich households. We empirically examine this intuitive but important implication in the Euler equation framework by relating rainfall amount to household consumption growth at the weekly level.

The empirical results show that weekly rainfall during the planting/weeding periods has a statistically significant effect on household consumption growth, suggesting that sample households behave in a forward-looking way on average. In particular, a one-standard-deviation increase in weekly rainfall results in a 3.0% rise in total household consumption per adult equivalent. More importantly, household consumption responds only to weekly rainfall in January, which has sufficient predictive power for future maize harvests. This main finding is robust to alternative explanations, including rainfall-induced changes in family labor demand, income variability, and returns to holding grain stocks. We detect this significant relationship only for food consumption. Since the consumption of maize (the staple food in Zambia) comprises the largest share of food consumption, these results indicate that agricultural households respond to rainfall signals in a crop season by simply adjusting maize grain stocks. This view is also supported by another finding that net saving in the form of other assets including cash and livestock reacts little to weekly rainfall.

By constructing a series of maize stocks for every household/week, we also test the asset-differentiated response predicted by the theoretical model. Non-parametric specifications find a hump-shaped relationship between the size of the response to rainfall signals and maize stocks. Overall, these findings are consistent with the buffer stock saving model with borrowing constraints. Our results suggest that while even constrained households can change their consumption schedule upon the arrival of new information by adjusting grain inventories, welfare gains from advance information depend largely on the available asset levels.

This study is one of the first empirical examinations of forward-looking behavior on the consumption side in developing countries. Chaudhuri (1999) is a notable complementary study, as it tests the same idea for farm households using ICRISAT data from India. However, we extend his work in two important dimensions. The first difference is in the asset-based sample separation rule. Since he splits the sample into two categories (poor and rich), his empirical method cannot detect the hump-shaped relationship, an important implication of the buffer stock saving model, as highlighted above. The striking empirical result of the wealth-differentiated impacts of this study is a unique contribution to the literature. The second related distinction is that we use an estimated series of maize inventories and allows for time-varying constraints on the consumption plan, while his categorization is based on initial wealth at the beginning of the survey and remains fixed throughout the estimation. The non-parametric technique used in this study also helps find the flexible relationship between the degree of forward-looking behavior and wealth.

The present study is related to three main threads of the literature. First, we propose a new theoretical restriction for the buffer stock saving model: the impact of information shocks has a hump-shaped relationship with cash-on-hand. This prediction cannot be generated by either myopic consumption models (Berg, 2013) or the permanent income model with complete credit markets. Among the few empirical examinations of the model, Carroll (1992) treats unemployment fear as an important source of income uncertainty confronted by households and relates its proxies to aggregate consumption growth in the United States. While the proposed test based on changes in the first moment of future income does not capture an important aspect of precautionary saving, it would be easier to apply this restriction to many settings than use the proxy of income risk. Another type of test for the buffer stock model relies on Carroll's (1997) implication of target net wealth (e.g., Jappelli et al., 2008). For rural areas characterized by subsistence farming and incomplete credit markets, Deaton's (1991) version of the buffer stock saving model with explicit borrowing constraints would be more appropriate to capture reality.

This study also makes a novel contribution to the literature on the risk-coping behavior of low-income households. The high-frequency survey data used in this study offer a unique opportunity to differentiate advance information shocks from actual income shocks. In the literature on consumption smoothing, rainfall data have been used as an instrument to estimate transitory income shocks (e.g., Paxson, 1992; Fafchamps et al., 1998) or as its proxy (e.g., Hoddinott, 2006). In the current study, we use daily rainfall records as an empirical measure of news about future income. The notable difference between these two distinct shocks is that the poor rarely react to news because of borrowing constraints. While some previous studies have reported different degrees of consumption insurance by wealth (e.g., Jalan and Ravallion, 1999; Carter and Lybbert, 2012), the hump-shaped relationship is a distinguishing feature of consumption responses to information shocks. This contrast suggests that even if annual differences find a change in consumption of equal size, one household's consumption path over a year might be smoother than the other's because of the lack of available assets. The evaluation of welfare costs needs to take this aspect into account. This also implies that using asset levels after income shocks as a proxy for credit constraints may be misleading because they reflect the previous adjustment in response to information shocks.

Third, this study is connected to the burgeoning literature that investigates responsiveness to climate information in several dimensions of household production decisions in the developing world. Empirical examples include irrigation investment (Taraz, 2017), crop choice (Miller, 2015), and planting-stage investment (Rosenzweig and Udry, 2013; Giné et al., 2017; Kala, 2017). Unlike existing work that focuses on the role of expectations on the production side, we examine their role in the framework of an intertemporal optimization problem regarding the resource allocation between consumption and saving.

The rest of this paper is organized as follows. The next section describes the data used in the estimation and confirms that rainfall patterns serve as a good proxy for news about future harvests. Section 3 presents the theoretical framework used to guide the subsequent empirical analyses and discusses its theoretical implications. The estimation results on the impact of information shocks on consumption behavior and their robustness are presented in Section 4. Section 5 concludes.

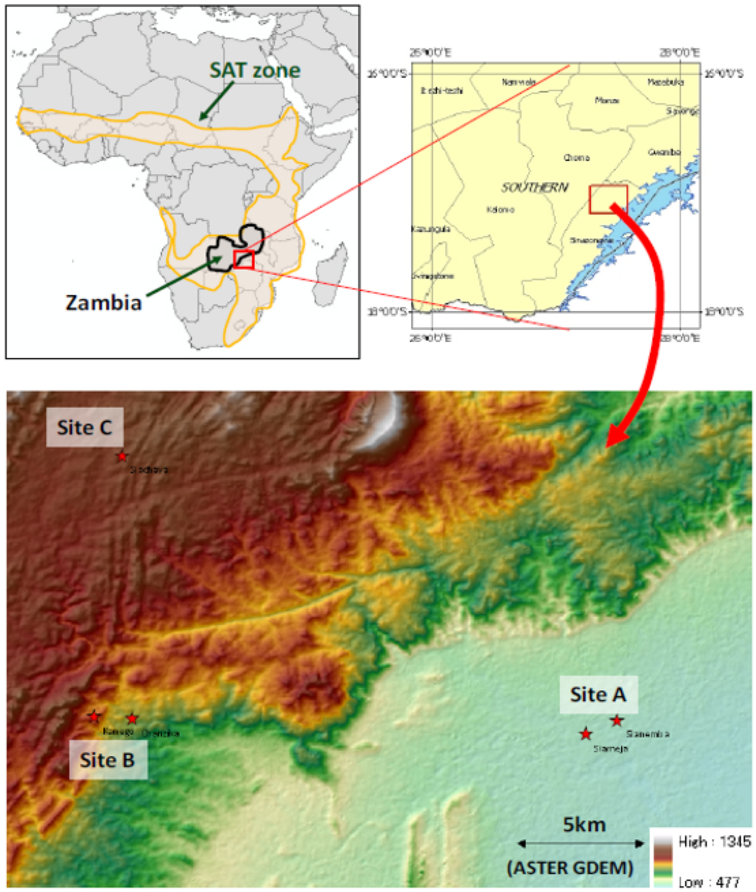

Figure 1: Study area

Source: Resilience project

2 Settings and data

This study uses household panel data collected by the Research Institute for Humanity and Nature (RIHN). The data were collected from Southern Province in Zambia. Zambia is situated in the semi-arid tropics, and climatic variation, especially with regard to rainfall, is a substantial covariate risk that threatens the subsistence of small-scale farmers. In particular, Southern Province is the most drought-prone area in the country; however, as most local farmers lack access to irrigation, agriculture is completely rain-fed.

The main agricultural season in Southern Province coincides with the rainy season (November to April). According to the general agricultural cycle, this study defines the following three periods: the planting period (November and December), weeding period (January to March), and harvesting period (April to June). During the rainy season, farmers in the region grow maize, cotton, sweet potatoes, and various vegetables. Since it does not rain at all in the dry season (May to October), their agricultural activities are limited. In the dry season, livelihoods rely on grain stock from previous maize harvests and earnings from non-agricultural (e.g., working as coal miners and fishers) and self-employment (e.g., collecting stones and making furniture for sale) activities.

In Southern Province, the RIHN selected three agro-ecologically distinctive locations alongside Lake Kariba for the household survey (Figure 1). The three locations are a lower flat lake-side area (site A), a middle escarpment area (site B), and an upper terrace on the Zambian plateau (site C). As shown in Figure 1, these three sites, all of which are within a 25-km radius, are relatively close to each other. In each site, 16 households were randomly selected for the interviews based on the village census in July 2007, providing a total sample of 48 households.

The household survey began with an annual interview in November 2007, followed by weekly interviews. Data collection continued until November 2011. The annual interviews were carried out at the start of each crop year to collect information on households' demographic characteristics and asset holdings. The main information came from the weekly interviews which asked about all the economic activities conducted and shocks experienced by households in the week before the interview date. In particular, the dataset included detailed information on the time use patterns and health status of family members, household agricultural production, self-employment activities, livestock transactions, money and gift transfers, and household consumption.

This section discusses the characteristics of the data on rainfall, income, and consumption. To check whether rainfall serves as a signal of future harvests, the regression results for the relationship between rainfall and maize production follow.

2.1 Rainfall

To test whether households behave in a forward-looking way, signals that have good predictive power for future incomes need to be specified. This study uses plot-level rainfall as such a signal for the following reasons. First, the relationship between rainfall and crop production has been established by previous empirical studies in developing countries (e.g., Fafchamps et al., 1998). As will be seen, the association is also confirmed by the data used in this study. Second, anecdotal evidence from the study site indicates that local farmers also realize that rainfall amount and its pattern are the most important determinants of crop harvests (Kanno et al., 2013). Third, rainfall is exogenous and observable to both farmers and researchers.

The dataset includes plot-level rainfall data from the main field of each survey household. These were recorded by automatic rain gauges installed for the purpose of this study. Table 1 summaries the recorded rainfall amounts.[6] Table 1 indicates that rainfall amounts often differ from one site to another because of geographical differences, particularly elevation-based differences, in this small area.

To confirm the intra-annual rainfall patterns, Figure 2 shows the averages of weekly rainfall and local maize prices during the survey period.[7] Although the study area is often hit by severe drought,

[6]Because no previous records of rainfall were available, we had no information on normal annual rainfall levels for the study site.

[7]The maize prices were calculated based on information from the consumption module of the weekly survey. In the module, respondents were asked to provide the volume and value of the food the household consumed in the previous week. For purchased food, they replied with purchase prices in the local market. For self-produced food, respondents estimated the values based on the market price at the time of the survey. Hence, the calculated maize prices may reflect household characteristics, although market transactions of maize are active and its market price would be common

Table 1: Annual rainfall by crop year

	2007/08	2008/09	2009/10	2010/11
Site A (16 households)	1596	1312	1687	1155
	(40)	(78)	(69)	(72)
Site B (16 households)	1574	1383	1455	1365
	(59)	(50)	(166)	(128)
Site C (16 households)	1404	1377	1358	1107
	(65)	(66)	(116)	(67)
Total (48 households)	1525	1358	1500	1209
	(102)	(72)	(185)	(145)

Notes: The numbers represent the average annual rainfall in millimeters. Standard deviations in parentheses.

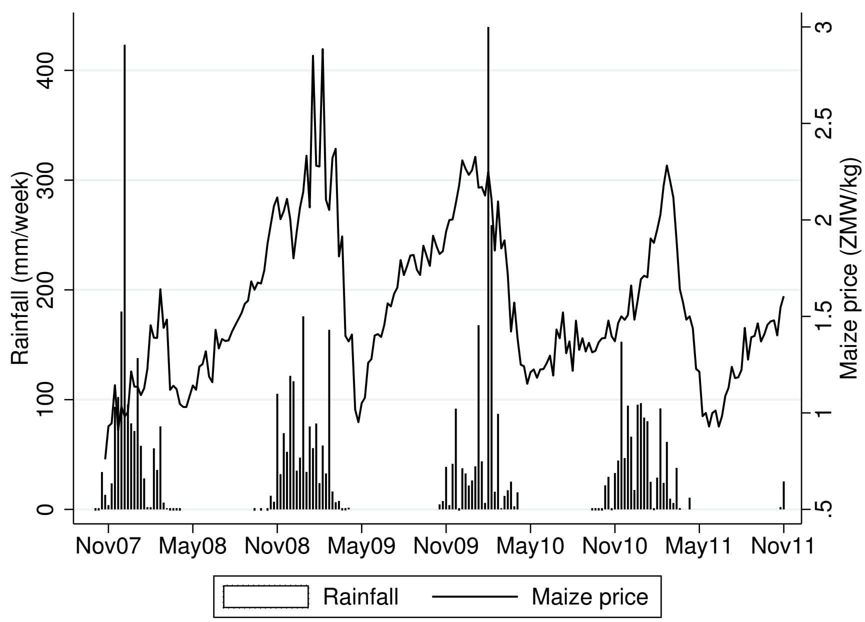

Figure 2: Weekly rainfall and local maize price

Notes: The figure presents weekly averages for local maize prices and plot-level rainfall amounts.

heavy rainfall was observed twice during the sample period: in the final weeks in December 2007 and during February 2010. No damage to fields or infrastructure was observed in 2009/10 despite the high volumes of rainfall observed, especially in site A. On the contrary, the heavy rain in December 2007 damaged crops, inundated fields, and destroyed infrastructure such as roads and bridges.[8] According to the villagers in the study site, such an event is rare and occurs only once

knowledge among local farmers.

[8]The shock caused by the heavy rainfall in December 2007 can be observed in the movement of the local maize price. As shown in Figure 2, the price increased after the rainy season of 2007/08 and continued to rise until the harvest

in several decades. The abnormality of the weather in December 2007 was also confirmed by the long-term data from the closest weather station (see Appendix Figure B1). Given the uncommon nature of these data, special attention should thus be paid to the week of heavy rainfall in December 2007 in the main analysis.

Before introducing the income and consumption data, we discuss the formal weather forecasts available to local farmers. Official forecasts of an upcoming rainy season are mainly available through radio broadcasts, and these are usually issued and distributed at the beginning of the rainy season. However, they only provide rough predictions (e.g., a "good" year or a "drought" year) and say nothing about the timing of the rainfall. More importantly, since these forecasts are made at regional levels, the information may not be as valuable as at the local level because of the existence of salient micro-climates.

2.2 Consumption, cash flow, and grain stocks

The consumption section of the weekly interviews asked respondents what kinds of agricultural products the household consumed in the week before the survey date and their prices. The food includes not only self-produced food, but also food purchased, received as public food aid or a gift, and collected in the field. For purchased food, they provided the purchase prices in the local market. For self-produced food, the values were estimated based on respondents' subjective judgment and the market price. In addition to food consumption, household expenditure for non-food and services in the previous week was provided. Using this information, we calculate the total value of consumption per adult equivalent for every week during the survey period. To calculate adult equivalent units, scales are adopted from the Living Conditions Monitoring Survey report (Central Statisitcal Office, 2011).[9] We deflate the resultant nominal values by the standardized version of area-specific maize prices.[10]

Using the information from the module of agricultural practices, weekly cash flow from crop production is calculated by summing the value from the sales of harvested crops, net of all expenses of agricultural inputs (e.g., seeds, chemical fertilizer, and hired labor) except for family labor. The input costs are entered into the calculation at the time of their application rather than their purchase. We also compute wage income from employment and earnings from piecework and other self-employment activities for each survey week. The sum of these is defined as cash flow of off-farm work. The other minor income sources are revenue from sales of natural resources such as firewood and sales of livestock products such as eggs and milk. This study defines a household's total cash flow as the sum of these four types of net cash flow.

Table 2 summarizes weekly consumption and cash flow during the survey period. Table 2 shows

of the 2008/09 crop in March and April 2009. In each crop season, the price declined after the harvest, but the decline was much smaller after the harvest of the 2007/08 crop season than after the harvests of the other years, indicating a poor harvest in 2007/08.

[9]Appendix Table C1 shows the scales. For this calculation, the number of family members in each age category is based on the information at the start of the crop season.

[10]Setting the price of maize as of November 2007 in site A as 1, we calculate the relative maize prices for every week.

Table 2: Consumption and cash flow per week during the survey period

	Planting/weeding	Harvesting	Dry season
Weekly consumption			
Total consumption	4.32	5.46	5.10
	(4.08)	(5.47)	(4.31)
Food consumption	3.68	4.36	4.08
	(2.67)	(2.96)	(2.49)
Luxuary goods consumption	0.03	0.03	0.05
	(0.17)	(0.18)	(0.27)
Household goods consumption	0.43	0.77	0.71
	(2.22)	(3.44)	(2.71)
Medical expenditure	0.02	0.02	0.01
	(0.12)	(0.11)	(0.10)
Other service expenses	0.17	0.28	0.25
	(1.01)	(1.42)	(0.97)
Weekly cash flow			
Total cash flow	1.66	6.00	5.60
	(12.87)	(28.72)	(27.42)
Cash flow of agriculture	-0.28	2.08	1.23
	(5.40)	(17.69)	(10.98)
Cash flow of off-farm work	1.81	3.79	4.23
	(10.47)	(14.61)	(20.48)
Revenue of natural resource sales	0.07	0.05	0.06
	(0.51)	(0.37)	(0.42)
Revenue of livestock product sales	0.05	0.08	0.08
	(0.28)	(0.36)	(0.31)
Observations	4029	2264	3027

Notes: The values are expressed per adult-equivalent in Zambian kwacha, deflated by the local maize price index obtained from the household survey data. US$ 1.00 = ZMW 3.7. Luxury goods include alcohol, tobacco, and snacks. Household goods include tableware, clothes, and necessities such as soap and candles. Medical expenditure consists of medical fees and expenditure on medicine. Other services include fees involving maize-milling, schooling, transportation, and mobile phones, among others. The planting/weeding period corresponds to November-March. The Harvesting period corresponds to April-June. The dry season corresponds to July-October.

that the average weekly food consumption per adult equivalent unit is about ZMW 4.3 (approximately USD 1.2) in the planting and weeding periods, indicating that the sample consists of very low-income households.[11] The corresponding median values are much lower, namely ZMW 3.4, ZMW 4.4, and ZMW 4.1 for the planting/weeding periods, harvesting periods, and dry seasons,

[11] Zambia implemented a new currency system on January 1, 2013. The new Zambian kwacha (ZMW) was introduced at the rate of 1,000 old kwacha = ZMW 1. Throughout this study, we use the current description of Zambian Kwacha. In November 2007, USD 1 was equal to approximately ZMW 3.7.

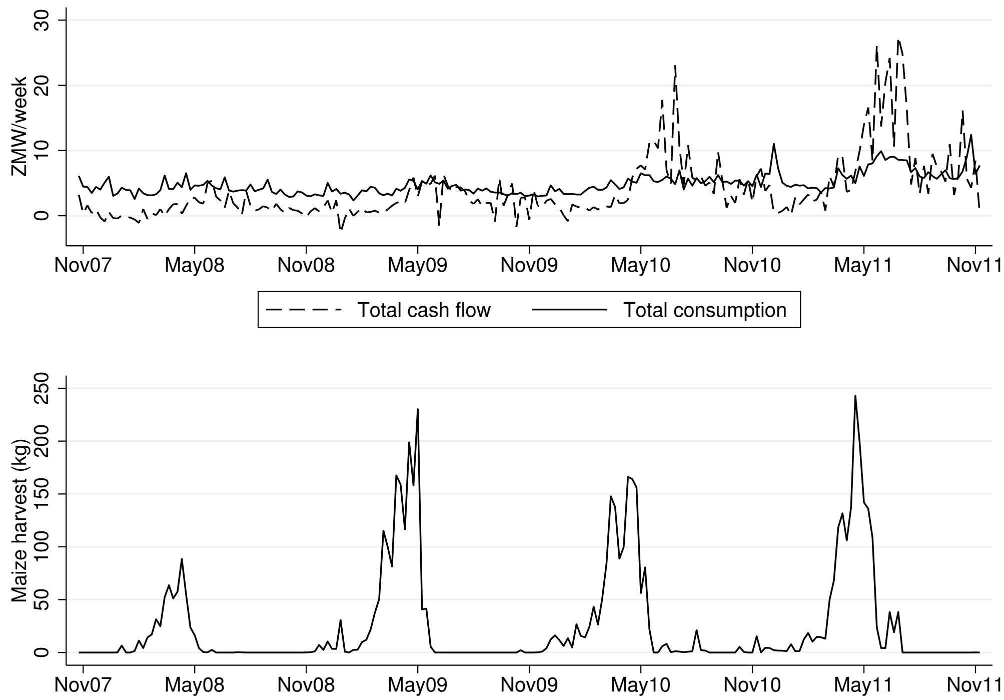

Figure 3: Seasonality in consumption, cash flow, and maize production

respectively. Table 2 also shows that weekly consumption per adult equivalent varies by season. Average consumption in the planting/weeding periods is approximately 21% lower than that in the harvesting period. Seasonal fluctuations are more salient in household cash flow. Table 2 suggests that opportunities for non-agricultural work are relatively limited in the planting/weeding periods. Indeed, the average cash flow of agricultural activities is negative in these periods. Figure 3 illustrates their fluctuations along with the timing of maize harvests over the survey period, suggesting that consumption does not balance out within the agricultural cycle.

To understand the maize market position of survey households. Sales and purchases. The Zambia Food Reserve Agency (FRA) buys maize from farmers at a higher price than market prices. (Fung et. al. 2020, *Agricultural Economics*) How to source grain. (Table 1 and Footnote 6 of Fung et. al. 2020)

Because formal saving and borrowing opportunities are limited in the survey area, sample farm households report dissaving grain stock against future income to shield consumption from seasonal fluctuations in cash flow. Although the survey did not directly ask farmers about their grain inventories, weekly data on maize harvests and transactions are available. Using this information, we construct a series of maize grain stock for each week using two methods. The first method (Method 1) computed the stock of maize in kilograms as of the first week of July 2008 by adding the maize grain harvested and received as a gift and deducting the maize consumed and given as a gift between March and June 2008. We replaced a negative initial value with 0 under the assumption that

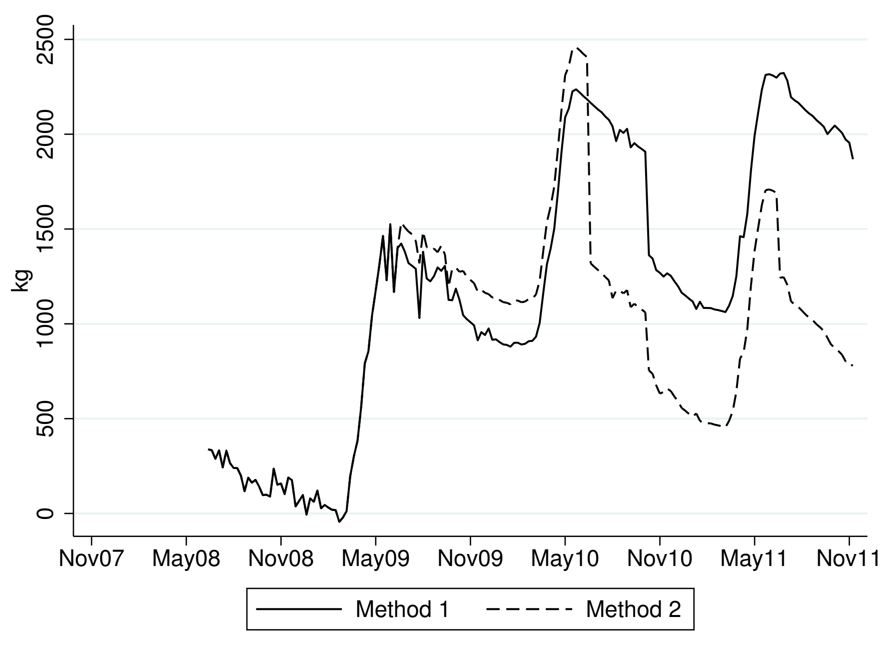

Figure 4: Maize stock

maize transactions at least balance out in the harvesting period. For each week after July 2008, the amount of harvested and received maize was added to and the amount of maize consumed and sent out subtracted from the lagged stock amount, and this routine was repeated until the end of the survey. There are two concerns about the accuracy of maize stocks based on Method 1. The first concern is that this method is sensitive to the number of surveys conducted. Weekly data are missing at some points because, for instance, every family member was absent when the enumerator visited. Although the following analyses limit the sample based on the available number of weekly surveys, important records (e.g., harvests) might be insufficiently captured and these missing values may then affect the subsequent estimates of maize inventories. The second concern is that owing to the nature of the stock variable, any measurement errors in a previous survey would accumulate and the estimated maize stocks in the latter part of the survey period might have considerable noise.

To check the robustness of the maize stock measure, other estimates of maize stocks were constructed following Method 2. Like Method 1, initial maize inventories in the first week of July 2008 were calculated for each household and these were then adjusted based on maize transactions up to June 2009. The difference from Method 1 is that the initial maze stock in the first week of July 2009 was recalculated and defined as the sum of the maize grain harvested and received as a gift minus the maize consumed and given out as a gift between March and June 2009. Then, a subsequent series of maize stocks until June 2010 was constructed by taking into account all maize transactions. The stock series after July 2010 were computed in a similar way. Although the calculated maize inventories based on Method 2 are discontinuous at the beginning of July, this methodology is less sensitive to missing data and accumulated noise in principle. In addition, the estimates are more comparable among agricultural years because they follow the same calculation method. On the contrary, Method 2 cannot reflect the maize stocks carried over from before the harvesting period, which is its main drawback. Both methods might underestimate the series of maize inventories in the first year of measurement since the amounts carried over from before March 2008 are not incorporated into the calculation.

Figure 4 plots the weekly series of the average maize stocks constructed using Methods 1 and 2. If the estimates based on Method 1 were perfectly accurate, the disparity among the two methods would imply that the amount of maize grain carried over from the previous crop season was not negligible. As shown in the latter part of the survey period, there are stark differences between the two estimates, which suggests that the Method 2 stock series might be underestimated. However, these differences could simply reflect the accumulation of noise, which is the main concern of Method 1. Keeping this in mind, Figure 4 shows that, on average, maize grain stocks did not run out except in the lean season before the harvest period in 2009. This fact implies that the average household can intertemporally transfer resources by flexibly adjusting maize grain stocks.

2.3 Does rainfall work as a signal of future harvests?

The basic idea behind this study is that rainfall in the planting and weeding periods is a predictor of future cash flow in the harvesting period. To verify whether rainfall works as such an informative signal for farmers in practice, the following conditions need to be checked:

> Condition 1: rainfall does not have an immediate impact on a household's current cash flow during the planting and weeding periods.
>
> Condition 2: rainfall during the planting and weeding periods has a statistically significant relationship with future maize harvests.
>
> Condition 3: rainfall during the planting and weeding periods does not affect the variability of future maize harvests.

Condition 1 should be verified to rule out simple income effects. The most important condition for a signal is having sufficient power to predict future income, which represents condition 2.[12] Condition 3 concerns the effect of weekly rainfall on the second moment, which complicates the subsequent analysis.

To validate condition 1, we estimate the weekly-level relationship between rainfall and household cash flow in a reduced-form framework.[13] Specifically, the net cash flow earned by household i in week t (π_{it}) during the planting/weeding periods (November to March) is specified in a linear form as

$$\pi_{it} = \alpha_1 \mathrm{RAIN}_{i,t-1} + \alpha_2 \mathrm{RAIN}^2_{i,t-1} + \alpha_3 L_{iy} + \alpha_4 X_{it} + \gamma_i + \gamma_m + \gamma_y + \epsilon_{it} \tag{1}$$

[12] The direct effect of rainfall shows up when rainfall in a particular week during these periods has an independent and significant impact on future crop harvests. In addition, rainfall can have indirect impacts through changes in expectations of future rainfall conditions, which consequently relate to harvests. The current study does not differentiate these two channels. In other words, only the combination of these two channels is of interest.

[13] Although the immediate impact of weekly rainfall on income earnings is insignificant in the general setting, it might be important in rural areas of sub-Saharan Africa. Possible examples include high demand for piecework labor to carry out weeding in the week after heavy rain.

where RAIN_{it} stands for the rainfall measured in household i's main field in week t, L_{iy} represents a vector of the demographic variables at the beginning of crop year y, X_{it} stands for a vector of controls that determine the level of income, γ_i is the household fixed effect, γ_m (γ_y) captures the calendar-month (year) fixed effects, and ϵ_{it} represents a random shock to cash earnings. This empirical specification relates cash flow in week t to the rainfall amounts recorded in week $t-1$, since lagged rainfall is treated as the potential signal that affects the consumption growth between weeks t and $t-2$ in the main empirical specifications (Section 4). To capture the available labor force in household i, the demographic variables include the numbers of men, women, boys (aged 6 to 15), and girls (aged 6 to 15) in L_{iy}. These demographic variables are obtained from the annual survey to circumvent issues related to endogenous changes in household composition (as in the calculation of adult equivalent units), and thus they are fixed throughout crop year y. The number of days for which family members were ill in the previous week is also added into X_{it} to take into account those factors varying the available labor force. In addition, self-reported episodes of non-rainfall shocks on sample households' plots are added as a control. Examples of field-level shocks include insect infestations, plant diseases, and animals trampling crops.[14] To incorporate the information into the empirical analysis, we construct a dummy variable taking 1 if any non-rainfall shock was observed in the previous week. Finally, to control for general seasonality, the regression equation also includes the calendar-month dummies and crop year dummies. The estimation sample is limited to the planting and weeding periods (November to March).[15]

Table 3 presents the estimates of Equation (1). The estimation results show that rainfall in the previous week during the planting and weeding periods does not have a statistically significant impact on total cash flow (columns (1) and (2)). As shown in columns (3) and (4), this basic pattern does not change when controlling for rainfall in the current week. Put differently, the data suggest that the simple income effect induced by weekly rainfall cannot be the main driver of changes in current household consumption levels.

The empirical analyses now turn to verify condition 2. In general, rainfall has a concave relationship with harvests.[16] However, the timing of rainfall is more important for local farmers than its total amount. To investigate whether rainfall amounts in distinct agricultural stages have different

[14] Among these, the most frequently reported shock during the survey period was crop damage by animals and birds. Adverse occurrences affecting crop production might be considered to be a signal employed by farmers to predict future income. However, such field-level shocks would have immediately raised the demand for cash to purchase chemicals to address insect infestations and/or hire labor to erect a fence to prevent intrusion by animals. In addition, such shocks are endogenous to household investments in prevention. Hence, the empirical analysis focuses on rainfall as the signal.

[15] All the regressions in this study control for the corresponding survey days because weekly interviews sometimes cover a period of less than or more than seven days.

[16] The concave relationship between annual rainfall and harvests is also confirmed in the current data. Appendix Figure B2 links total rainfall between November and February to the yield of harvested maize aggregated over March to June in the same year. To obtain more precise estimates, we regress the maize yields measured in the harvesting period of crop year y on total rainfall between November and February. Appendix Table C3 reports the estimation results, while Appendix Table C2 presents descriptive statistics of the empirical variables. Depending on the estimation method, we find that the relationship between total rainfall in the rainy season and maize yields is concave with a peak of 1000–1100 millimeters, although the estimates of the fixed effects model are imprecisely estimated.

Table 3: Determinants of weekly cash flow during planting and weeding periods

	(1)	(2)	(3)	(4)
Rain (100mm), t-1	-0.11	0.05	0.05	0.06
	(0.10)	(0.32)	(0.31)	(0.30)
Rain (100mm), t-1 squared		-0.04	-0.04	-0.04
		(0.06)	(0.06)	(0.06)
Rain (100mm), t			-0.09	-0.12
			(0.14)	(0.45)
Rain (100mm), t squared				0.01
				(0.10)
Field-level shock dummy, t	-0.86	-0.86	-0.87*	-0.87
	(0.52)	(0.52)	(0.51)	(0.52)
Total sick days adults, t	0.17*	0.17*	0.17*	0.17*
	(0.09)	(0.09)	(0.09)	(0.09)
Total sick days children, t	0.00	0.00	0.00	0.00
	(0.10)	(0.10)	(0.10)	(0.10)
Log maize price, t	-0.54	-0.51	-0.54	-0.55
	(1.11)	(1.11)	(1.11)	(1.14)
Total survey days, t	0.87	0.87	0.88	0.88
	(0.69)	(0.69)	(0.69)	(0.69)
Land size (ha), y	0.53	0.53	0.53	0.53
	(0.58)	(0.58)	(0.58)	(0.58)
Number of adult males, y	0.59	0.59	0.59	0.59
	(0.54)	(0.54)	(0.54)	(0.54)
Number of adult females, y	-0.05	-0.05	-0.05	-0.05
	(0.51)	(0.51)	(0.51)	(0.51)
Number of boys, y	0.01	0.01	0.01	0.01
	(1.16)	(1.16)	(1.16)	(1.16)
Number of girls, y	1.48	1.48	1.48	1.48
	(1.43)	(1.43)	(1.43)	(1.43)
Household FE	YES	YES	YES	YES
Crop year FE	YES	YES	YES	YES
Calendar-month FE	YES	YES	YES	YES
Dependent variable mean	1.66	1.66	1.66	1.66
Dependent variable SD	12.87	12.87	12.87	12.87
R^2	0.12	0.12	0.12	0.12
N	4029	4029	4029	4029

Notes: Robust standard errors clustered by household in parentheses. *** denotes significance at 1% level, ** at 5% level, and * at 10% level. The dependent variable is weekly cash flow per adult equivalent. The estimation sample is limtied to the planting and weeding periods (November to March). Examples of field-level shocks include insect infestations, plant diseases, and animals trampling crops.

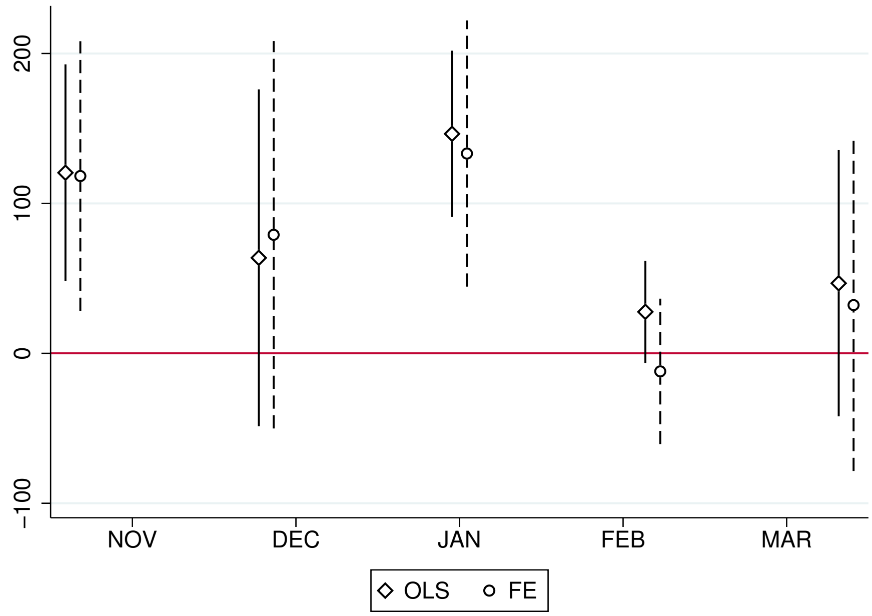

Figure 5: Estimated impacts of rainfall on maize yield by calendar-month

Notes: Point estimates of rainfall impacts on maize yield and their 95% confidence intervals are presented for each calendar-month.

predictive powers for future harvests, the following regression equation is estimated:

$$HV_{iy} = \alpha_1 \text{RAIN in month m}_{iy} + \alpha_2 \text{CUMRAIN up to month m}_{iy} + \alpha_3 L_{iy} + \alpha_4 X_{iy} + \gamma_i + \gamma_y + \epsilon_{iy} \quad (2)$$

where HV_{iy} is household i's maize yield measured in the harvesting period of crop year y. The first coefficient α_1 measures the impact of the total rainfall in month m on the maize yields in the corresponding crop year. The important assumption here is that impacts from rainfall are homogeneous in the same month. In addition to these month-specific rainfall amounts, Equation (2) controls for cumulative rainfall amounts earlier in the same crop year. Since rainfall from between November and March is separately examined, the number of regressions is five.

Figure 5 presents the estimated coefficients on rainfall amounts in each calendar-month.[17] The estimation results reveal that rainfall in November and January has statistically significant predictive power for maize harvests in the corresponding harvesting period. These effects make sense in the current context, because November is the first peak of planting activities and January corresponds to the second peak. Since a large amount of rainfall in the week after sowing is necessary for seeds to germinate, the productivity impacts of rainfall in these months would be higher than that in the other months.[18] The coefficient on December rainfall is also positive, although the impacts

[17] Appendix Table C4 provides the full estimation results.

[18] This finding is consistent with the experimental results from a controlled agricultural trial in the same study site (Shimono et al., 2012). They show that delaying sowing by 10–20 days can reduce maize yields by 19%, or 125 kg/ha, compared with the control plots sowed on a "normal" date based on the decisions of local farmers.

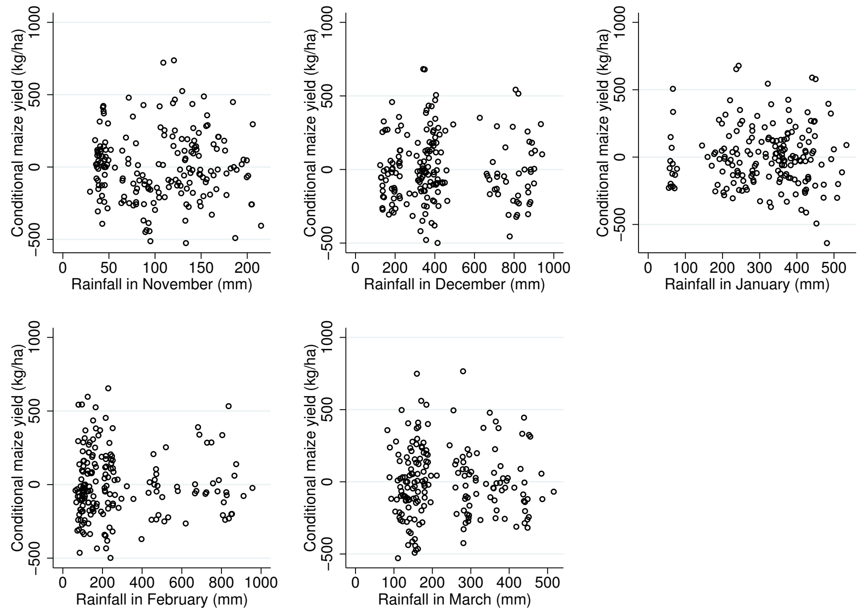

Figure 6: Effects on the variance in maize yields

Notes: For each month, this figure shows a plot of rainfall and the resulting residuals from Appendix Table C4.

are imprecisely estimated mainly because of the small sample for this month.[19] For November and December, the squared terms of rainfall do not have predictive power and only the linear rainfall terms are sufficient to capture the impacts on future harvests in the current specification.[20] Based on these results, this study assumes that higher weekly rainfall during the agricultural season leads to greater maize harvests after conditioning on cumulative rainfall amounts up to the current week.

Finally, condition 3 is checked. The discussions have thus far focused on the impact of rainfall on the first moment of future maize harvests. In addition, the arrival of new climate information might lessen the uncertainty surrounding crop harvests. To investigate this possibility, Figure 6 shows the relationship between rainfall and the residuals from the regressions in Figure 5 by month. The width of the residuals seems to be even across most rainfall ranges for all months and thus rainfall generally has no relationship with yield variability. More formally, Appendix Table C4 presents the results of the Breusch–Pagan test, which finds no heteroscedasticity in a linear form of rainfall.[21] Thus, weekly rainfall is unlikely to convey decisive information about the second

[19] As mentioned in Section 2, the uncommon heavy rainfall in December 2007 makes the estimates unstable. For that month, Figure 5 shows the estimated coefficients based on a sample excluding the 2007/08 crop year.

[20] This result can thus be understood given that the length of time of rainfall used in Figure 5 is different from the estimates in Appendix Table C3. As Appendix Table C3 shows, rainfall has a positive relationship with maize yields up to 1000–1100 millimeters. In an average year, monthly rainfall in any month does not exceed this threshold.

[21] The Breusch–Pagan test examines the null hypothesis that the variance in the error term cannot be written by a linear form of rainfall. As shown in Appendix Table C4, the null hypotheses are not rejected for every month. Nevertheless, Section 4.5 touches upon the possibility that the heavy rainfall in December 2007 might have reduced

moment of future harvests.

3 Theoretical framework

To guide how household consumption responds to advance information, this section derives testable implications for the subsequent empirical analyses. The seminal study by Deaton (1991) develops the buffer stock saving model with borrowing constraints. His model shows that precautionary motives interact with borrowing constraints because the inability to borrow when times are bad provides an additional motive for accumulating assets when times are good, even for impatient consumers. In his model, the main assumptions are (1) impatient agents whose discount rates exceed the interest rates of risk-free assets, (2) the constant relative risk aversion (CRRA) preference, and (3) the presence of borrowing constraints. Maintaining these assumptions, this section presents a theoretical framework that incorporates the gradual realization of income uncertainty. The proposed model predicts that the impact of information shocks has a hump-shaped relationship with the level of cash-on-hand. This is a unique feature of the buffer stock saving model with borrowing constraints, which contrasts with the predictions that a complete credit market model makes about the response to information shocks.

In what follows, Section 3.1 presents the theoretical set-up in the general form. The details in the derivation of the approximate solution for consumption growth are relegated to Appendix Section A. Section 3.2 illustrates how current consumption reacts to changes in income expectations after receiving new information. Section 3.3 numerically solves a simple dynamic model to present a theoretical prediction of the relationship between the degree of forward-looking behavior and asset stock levels, which offers the primary hypothesis of this study.

3.1 Theoretical set-up and approximate solutions

This section provides a simple three-period model outlining a decision-making process to clarify how the revelation of information observed by a small-scale farmer influences his/her current consumption choices in the presence of borrowing constraints. While the basic structure builds on the theoretical model developed by Blundell and Stoker (1999), we extend their model by introducing information shocks and explicit borrowing constraints. The three periods (denoted by t=1, 2, 3) correspond to the planting period, weeding period, and harvesting period in the empirical settings. In particular, the farmer solves the following problem at the beginning of period 1:

$$\max \quad u_1(c_1) + \frac{1}{1+\delta_2}E_1(u_2(c_2)|I_1) + \frac{1}{(1+\delta_2)(1+\delta_3)}E_1(u_3(c_3)|I_1)$$

with instantaneous utility u_t defined over the consumption of a single commodity c_t and a period-specific discount rate $0 < \delta_t < 1$. E_t is the expectation operator based on the information set I_t available to the household at time t. The farmer receives income y_t in each period t. For instance, y_3 is crop harvest income. The only uncertainty in this model lies in y_3, and that uncertainty is not

uncertainty about future maize harvests.

resolved until the beginning of period 3. The model introduces the important assumptions that (1) the farmer enters the first period with information I_1 about y_3 and (2) he/she receives an informative signal, denoted by θ_2, about y_3 before choosing his/her second-period consumption c_2. Assuming that there is no bequest motive, the ex-post lifetime budget constraint over the three periods is

$$c_1 + \frac{1}{1+r_2}c_2 + \frac{1}{(1+r_2)(1+r_3)}c_3 = A_1 + y_1 + \frac{1}{1+r_2}y_2 + \frac{1}{(1+r_2)(1+r_3)}y_3 \tag{3}$$

where A_1 is an exogenously given initial asset and r_t is the risk-free interest rate.

It is useful to distinguish beginning-of-period wealth X_t from end-of-period wealth W_t. Beginning-of-period wealth (i.e., cash-on-hand) X_t evolves over time as $X_{t+1} = (1+r_{t+1})(X_t - c_t) + y_{t+1}$ for t = 1 and 2. Initial cash-on-hand X_1 is assumed to be the sum of initial assets A_1 and first-period income y_1, that is, $X_1 = A_1 + y_1$. To guarantee positive consumption in the first period, the model assumes that the farmer enters the period with positive cash-on-hand X_1. On the contrary, end-of-period W_t is defined as $W_t = X_t - c_t$. In our model, assets are not productive and do not determine income y_t.

In each period, the farmer faces the following type of borrowing constraint:

$$W_t \geq 0$$

In other words, assets carried over to the next period must be non-negative.

This intertemporal optimization problem is solved by backward induction. First, c_3 is easily determined since the farmer simply spends whatever is left after y_3 is realized. Using the ex-post identity of the lifetime resources, third-period consumption is expressed as

$$c_3^* = (1+r_3)(X_2 - c_2) + y_3$$

Given c_1 and the optimal third-period consumption c_3^*, the farmer solves the following maximization problem in period 2 after receiving information θ_2:

$$\begin{array}{ll} \max_{c_2} & u_2(c_2) + \frac{1}{1+\delta_3} E_2[u_3((1+r_3)(X_2 - c_2) + y_3)|I_1, \theta_2] \\ \text{subject to} & W_2 = X_2 - c_2 \geq 0 \end{array} \tag{4}$$

The first-order conditions are

$$\begin{aligned} u_2^{'}(c_2) = \frac{1+r_3}{1+\delta_3} E_2[u_3^{'}((1+r_3)(X_2 - c_2) + y_3)|I_1, \theta_2] + \lambda_2 \\ \lambda_2(X_2 - c_2) = 0 \\ \lambda_2, \quad X_2 - c_2 \geq 0 \end{aligned}$$

where $u_t^{'}(*)$ represents the marginal utility function and λ_2 is the Lagrange multiplier attached to the second-period borrowing constraint. These conditions suggest two types of consumption behavior under borrowing constraints. First, $\lambda_2 = 0$ implies that the farmer puts aside a share of cash-on-hand as saving for future consumption, and his/her consumption path follows the standard

Euler equation. Thus, the farmer behaves as if he/she was not subject to any borrowing constraints at all. Second, the optimal condition requires the farmer to set consumption c_2 as high as cash-on-hand X_2 if the borrowing constraint is binding. Combining these, the condition for intertemporal optimization can be written in a uniform way:

$$u_2^{'}(c_2) = \max[u_2^{'}(X_2), \ \ \frac{1+r_3}{1+\delta_3}E_2[u_3^{'}((1+r_3)(X_2-c_2)+y_3)|I_1,\theta_2]] \tag{5}$$

As shown in Equation (5), cash-on-hand X_2 directly enters the Euler equation. The solution to this problem c_2^* is

$$c_2^* = \begin{cases} X_2 & if \ \ c_2^{**} \geq X_2 \\ c_2^{**} & if \ \ c_2^{**} < X_2 \end{cases}$$

where c_2^{**} is the solution to $u_2^{'}(c_2^{**}) = \frac{1+r_3}{1+\delta_3}E_2[u_3^{'}((1+r_3)(X_2-c_2^{**})+y_3)|I_1,\theta_2]$. As such, consumption can be expressed as a function of two state variables, cash-on-hand and the information set available to the household at the beginning of the second period. Cash-on-hand at the beginning of period 2 is determined by the level of first-period consumption c_1 since $X_2 = (1+r_2)(X_1-c_1)+y_2$. Thus, c_2^* can be written as $c_2^*(c_1, I_1, \theta_2)$.

Returning to the first period, the farmer solves for c_1 given the optimal choices c_2^* and c_3^*, both of which are a function of c_1. In particular, c_1 is chosen to maximize the constrained optimization problem as below:

$$\begin{aligned} \max_{c_1} \ \ & u_1(c_1) + \frac{1}{1+\delta_2}E_1[u_2(c_2^*(c_1,I_1,\theta_2)|I_1] \\ & + \frac{1}{(1+\delta_2)(1+\delta_3)}E_1[u_3((1+r_3)((1+r_2)(X_1-c_1)+y_2-c_2^*(c_1,I_1,\theta_2))+y_3)|I_1] \\ \text{subject to} \ \ & W_1 = A_1 + y_1 - c_1 \geq 0 \\ & W_2 = (1+r_2)(X_1-c_1)+y_2-c_2^*(c_1,I_1,\theta_2) \geq 0 \end{aligned}$$

Both θ_2 and y_3 are uncertain at this point.

The solutions depend on the level of optimal consumption in period 2. In the first scenario in which the borrowing constraint is binding in period 2, the farmer knows that he/she will spend his/her entire cash-on-hand (i.e., $c_2^* = X_2$) in the next period and only consume income received in period 3 (i.e., $c_3^* = y_3$). Given this future plan, the optimal condition for first-period consumption should be

$$u_1^{'}(c_1) = \max[u_1^{'}(X_1), \ \ \frac{1+r_2}{1+\delta_2}u_2^{'}((1+r_2)(A_1+y_1-c_1)+y_2)] \tag{6}$$

Since the marginal utility from second-period consumption is certain, the optimal level of consumption in period 1 can be expressed as

$$c_1^{BC*} = \begin{cases} X_1 & if \ \ c_1^{BC**} \geq X_1 \\ c_1^{BC**} & if \ \ c_1^{BC**} < X_1 \end{cases}$$

where c_1^{BC**} is the solution to $u_1^{'}(c_1^{BC**}) = \frac{1+r_2}{1+\delta_2}u_2^{'}((1+r_2)(A_1+y_1-c_1^{BC**})+y_2)$ and $X_1 = A_1+y_1$.

On the contrary, consider the case in which c_2^* is an interior solution. Under the assumption that the conditional variance in y_3 does not vary with signals θ_2, Section A.1 shows that the intertemporal optimal consumption plan between periods 1 and 2 should satisfy

$$u_1^{'}(c_1) = \max[u_1^{'}(X_1), \;\; \frac{1+r_2}{1+\delta_2}E_1[u_2^{'}(c_2^*(c_1, I_1, \theta_2))]] \tag{7}$$

in which $c_2^*(c_1, I_1, \theta_2)$ is a solution to $u_2^{'}(c_2^*) = \frac{1+r_3}{1+\delta_3}E_2[u_3^{'}((1+r_3)(X_2-c_2^*)+y_3)]$. Denote c_1^{NC*} as the solution to the first-period problem, conditional on $c_2^* = c_2^{**}$. Then, we have

$$c_1^{NC*} = \begin{cases} X_1 & if \;\; c_1^{NC**} \geq X_1 \\ c_1^{NC**} & if \;\; c_1^{NC**} < X_1 \end{cases}$$

where c_1^{NC**} is the solution to $u_1^{'}(c_1^{NC**}) = \frac{1+r_2}{1+\delta_2}E_1[u_2^{'}(c_2^*(c_1^{NC**}, I_1, \theta_2))]$.

Given the above set-up, Section A.2 introduces the CRRA preference assumptions and derives the Euler equation in the case of no borrowing constraints. With the CRRA utility form, closed-form solutions for the consumption function or consumption growth are not available. Following Blundell and Stoker (1999), approximate solutions are instead derived. As a result, the growth in consumption between periods 1 and 2 is shown to have the following form:

$$\triangle \ln c_2 \approx -\frac{1}{\rho}\ln(\frac{\alpha_1}{\alpha_2})(\frac{1+\delta_2}{1+r_2}) + \frac{\zeta_2^*}{(1+r_2)(1-\omega_1^*)\tilde{X}_1} + \ln(\omega_2^*) + \ln\Sigma \tag{8}$$

where ζ_2^* represents the changes in expected income after observing signal θ_2, defined as $\zeta_2^* = \frac{E_2[\zeta_3|I_1,\theta_2]}{1+r_3}$ with $\zeta_3 \equiv y_3 - E_1[y_3|I_1]$, and $\tilde{X}_t$ is the present value of expected wealth in period t. In particular, $\tilde{X}_1 \equiv A_1 + y_1 + \frac{1}{1+r_2}y_2 + \frac{1}{(1+r_2)(1+r_3)}E_1[y_3|I_1]$. ω_t^* represents the approximate solution of the optimal consumption share to available wealth in period t. The last term in Equation (8) captures the effect of income variance on growth in consumption. Equation (8) provides a theoretical basis for the empirical specification.

The Euler equation suggests that while the household responds to changes in expected income, its impact on consumption growth is attenuated by the increase in the level of cash-on-hand ($\frac{\partial \triangle \ln c_2}{\partial \zeta_2^*} = \frac{1}{(1+r_2)(1-\omega_1^*)\tilde{X}_1}$). One important implication is that wealthy households respond less to signals of future income than poor households because the increment in expected future income for the rich does not have a significant effect on their overall lifetime resources. On the contrary, households with low cash-on-hand face a much more complicated problem because of the possibility of binding borrowing constraints in the future. The next two sections explore the implications for asset-poor households further.

3.2 Graphical interpretations

The Euler equation in the presence of liquidity constraints has the forms shown in Equations (5), (6), and (7). Owing to borrowing constraints, consumption in any period cannot exceed cash-on-hand, and this upper bound on consumption levels implies a lower bound for marginal utility. Exploring these Euler equations to examine the optimal relationship between consumption in adjacent periods provides the intuition for how information shocks, if any, alter subsequent optimal consumption paths. The following discussions based on graphical visualization stress that initial wealth plays an important role in response to information shocks under borrowing constraints.

Note that y_3 can be decomposed into expected y_3 as of period 1 ($E_1[y_3|I_1]$), which is an updated forecast error ζ_3 as of period 2 ($E_2[\zeta_3|I_1, \theta_2]$), and the remaining forecast error ζ_3^* as of period 2, that is, $y_3 = E_1[y_3|I_1] + E_2[\zeta_3|I_1, \theta_2] + \zeta_3^*$. For illustration purposes, define $\zeta_2^* = \frac{E_2[\zeta_3|I_1,\theta_2]}{1+r_3}$ and denote $\frac{1+r_3}{1+\delta_3} E_2[u_3^{'}((1+r_3)(X_2 - c_2) + y_3)|I_1, \theta_2]$ in Equation (5) as $f(\zeta_2^*)$.

Figure 7 graphically shows Equation (5) and describes the comparative statics of c_2 with respect to changes in expected income due to information shocks θ_2. Panel (a) of Figure 7 depicts the Euler equation in the case of low cash-on-hand, X_2. The farmer's optimal consumption is at the intersection of $u_2^{'}(c_2)$ and $f(\zeta_2^*)$ in the case of no borrowing constraints, whereas that level of consumption is not feasible in practice because of the binding constraint. In this case, the farmer consumes his/her entire cash-on-hand. Suppose that the farmer receives good news at the beginning of period 2. After receiving this news, $f(\zeta_2^*)$ shifts downward to $f(\zeta_2^{*high})$ in Panel (a), and the optimal consumption level rises. However, he/she can do nothing in response to good news, making his/her consumption level unchanged, which implies positive news does not affect c_2^* if cash-on-hand is relatively low at the start of period 2. Similarly, relatively small negative changes in expected income shift $f(\zeta_2^*)$ upward, which does not have any impact until the optimal consumption level c_2^{**} reaches X_2. These observations imply that resource transfers over time are restricted for these types of households.

The more interesting case is observed after receiving significant negative information on upcoming harvest incomes. In Figure 7, $f(\zeta_2^{*low})$ illustrates this case. Here, expected future marginal utility rises sufficiently to change the optimal consumption plan and start saving a part of cash-on-hand for (expected) future bad harvests. These observations lead to the conclusion that while positive news shocks should have no effect on current consumption, the impact of negative news shocks depends on the magnitude of changes in expected income when the farmer enters the period with relatively low cash-on-hand.

Panel (b) of Figure 7 illustrates the case in which the farmer enters period 2 with relatively high cash-on-hand. In this case, the impact of positive news depends on the size of changes in expected income due to new information. The same consideration indicates that positive information shocks increase current consumption until assets are drawn down to zero and the farmer's optimal behavior thereafter is to be a hand-to-mouth consumer. As Deaton (1991) shows, there is a threshold level of cash-on-hand below which consumption just follows cash-on-hand ($c = X$) and above which consumers start accumulating assets ($c < X$). As such, a farmer with cash-on-hand slightly above the threshold level cannot fully use positive information shocks because of the binding borrowing constraints once his/her assets are stocked out. On the contrary, current consumption responds to negative news shocks in a more flexible way by reducing consumption to increase asset stocks. Therefore, farmers exhibit asymmetric responses to information shocks (Chaudhuri, 1999).

In summary, information shocks should not affect current consumption when cash-on-hand is low except for the case of significantly negative news, which causes the household to start accu-

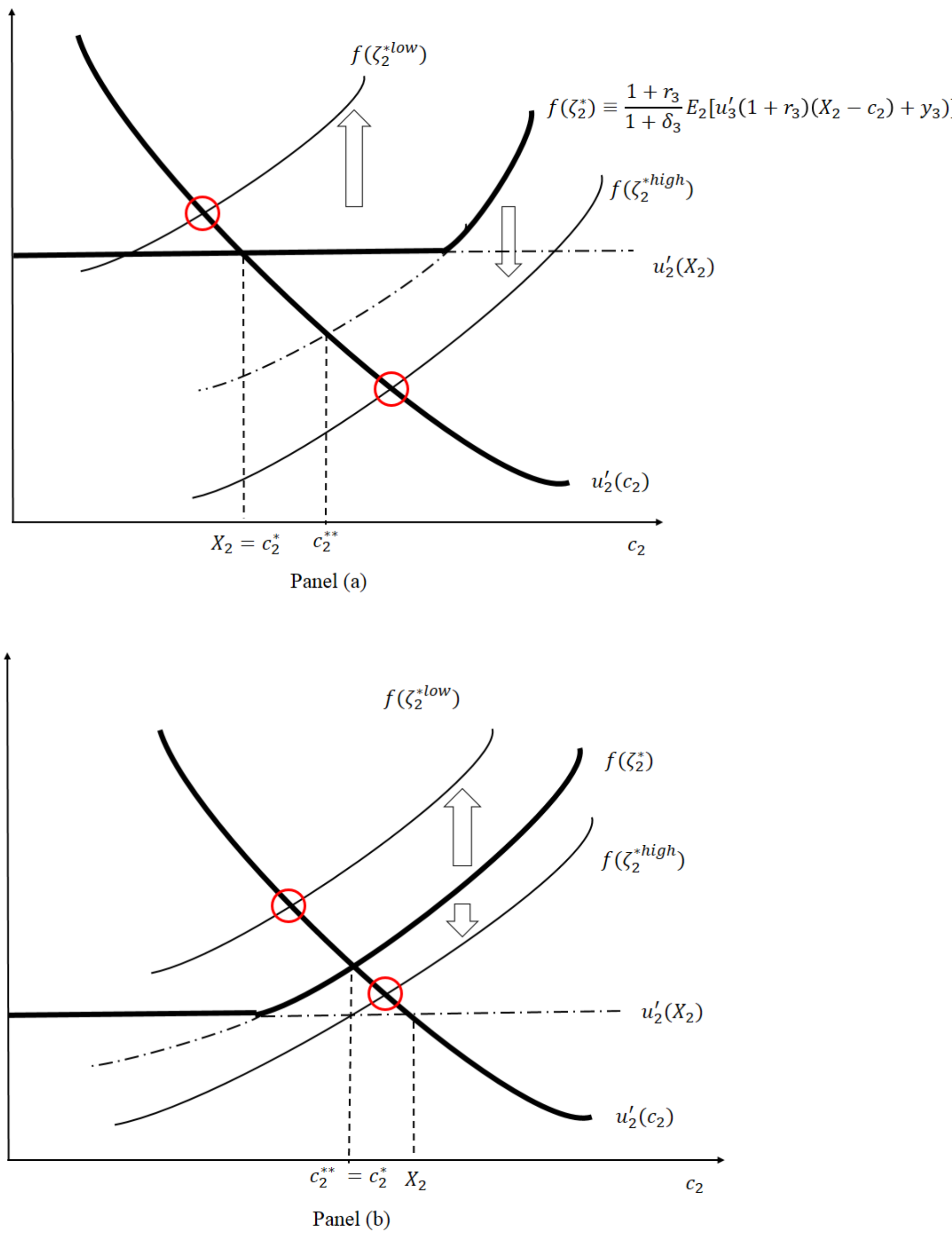

Figure 7: Comparative statics based on Equation (5)

Notes: Panel (a) for a farmer with low cash-on-hand and Panel (b) for a farmer with high cash-on-hand.

Table 4: Parameter values for the numerical model

	u(c)	$\frac{1}{1+\delta}$	1+r	y_2	y_3^h	y_3^l	$Pr(y_3^h)$
Log utility	$\ln c$ if c>0, -1000 otherwise	0.95	1	40	335	85	0.5
Quadratic utility	$c - \frac{c^2}{2000}$ if c>0, -1000 otherwise	0.95	1	40	335	85	0.5

mulating assets in preparation for the expected bad state of the world. When beginning-of-period wealth is sufficiently high, the farmer fully responds to negative information shocks and partially responds to positive information shocks. The main point of these discussions is that the impact of information shocks depends on the amount of liquidity assets available to the household at the time of decision-making.

3.3 Numerical exercise

The above comparative statics reveal some insights into how information shocks affect consumption behavior for asset-poor and asset-rich households. However, this discussion gives rise to the question of when the household starts responding to advance information. To demonstrate how the degree of forward-looking behavior differs with initial asset levels more clearly, a simple dynamic programming model of the second-period consumption choice is solved using numerical methods. The basic structure is the choice of second-period consumption c_2 after observing information θ_2, as formalized in Equation (4). To extend this static model to a dynamic setting, the model here assumes that the household repeatedly faces this second-period problem.

The numerical analysis of this model consists of two parts. The first part investigates how the agent evaluates utility from future consumption. In doing so, we define the Bellman equation as $V(X_2) = \max u(c_2) + \frac{1}{1+\delta} E[V((1+r_3)(X_2 - c_2) + y_3)]$. $V(X_2)$ represents the maximum expected discounted present value when the household enters period 2 with asset stocks X_2. The value function is formed before the arrival of information. The shape of the true value function is obtained by the value function iteration. The tolerance for when to stop the iteration is measured by the norm of the difference between $V^{t-1}(X)$ and $V^t(X)$, namely, $tol = \sqrt{\sum_{i=1}^{n}(V^t(X) - V^{t-1}(X))^2}$, where n is the number of grids in the asset space and t is the number of iterations. We set the maximum tolerance at 0.001. The asset space covers a range between 0 and 1000, and thus 1001 grids are assigned.

Table 4 summarizes the parameter values used for the iteration. For signal θ_2, the model assumes only two possible signals about the state of the world (good news and bad news); these signals are directly linked to the states, represented by h and l. In this simple setting, we assume that signal θ_2 tells the agent precise information about which state will arise in period 3. To reflect the economic environment, we parameterize income values for the numerical solution based on the estimates of a household's harvest earnings from the current dataset. In particular, the household predicts that future income will be $y_3^h = 335$ after observing good news. The probability of receiving good news is set at 0.5. On the contrary, bad news indicates that future income will be $y_3^l = 85$ with certainty. The difference between the two income values is generated from the two standard deviations of rainfall amounts in the planting/weeding periods based on the estimates; thus, y_3^h and y_3^l are respectively close to the 75th and 25th distributions of cash flow per adult equivalent during the harvesting period. In the second step of the exercise, using the converged form of the value function, we calculate the differences in the optimal consumption levels between the two states for each level of initial cash-on-hand.

Figure 8 shows the differences in consumption after receiving good news and after receiving bad news for each level of stock under the assumption of log utility preferences. Two features are noteworthy. First, the impact of information depends on the initial asset stock levels, and the relationship between the extent of forward-looking behavior and buffer stocks has a hump-shaped form. This important result can be interpreted as follows. Asset-poor households can do nothing after observing a signal because of the borrowing constraints and low level of asset stocks available. Once buffer stocks become available to the household, it starts responding to new information. The initial responses are small since they are still bounded by the available stock levels. Their reactions are gradually increasing, and the effect is the largest for a household with an intermediate level of buffer stocks. After the point, it falls to a smaller constant level over a range of a high volume of stocks since asset-rich households can behave as if they were the permanent income hypothesis consumers. This hump-shaped form does not rely on the functional form of the utility function.[22] Indeed, the key driver of this asset-differentiated effect is the concave form of the value function with respect to cash-on-hand: the marginal utility from future consumption is much larger for the less wealthy than the rich.

The second point can be made by comparing the implication of the permanent income hypothesis. Figure 9 depicts the case of the quadratic utility form without borrowing constraints. Specifically, we extend the minimum asset level to -1300 so that the household can borrow up to this point. With access to credit markets, the reaction of the asset-poor is as high as that of the asset-rich. Interestingly, buffer-stock savers above the middle-asset level in Figure 8 is more sensitive to advance information than the similar households with the credit access in Figure 9. For the buffer stock savers, the receipt of good news means that the negative impact of borrowing constraints eases in the subsequent future periods thanks to the increase in available resources. Thus, they would feel free to increase consumption like non-constrained households, although the increment is still constrained by current buffer stocks. After the receipt of bad news, on the contrary, they know that they will face the same situation in the future. In this case, they choose lower consumption than the corresponding household with access to credit. Given these two speculations, the difference in consumption between the two states can be larger for buffer stock savers.

Overall, the hump-shaped relationship between consumption responses to news and initial asset stock levels is a unique prediction. This implication can distinguish the buffer stock saving model with borrowing constraints from alternative ones such as the permanent income hypothesis and myopic consumer behavior in which the household consumes a fixed share of current income.[23] In addition, this feature should not be observed in the case of consumption responses to actual income shocks. This remarkable asset-differentiated impact of information shocks is subject to empirical testing with the data in Section 4.

[22] The assumption of the quadratic utility form produces a similar picture (Appendix Figure B3).

[23] However, the acceptance of the null cannot discern alternative preference assumptions (e.g., the quadratic form) from the constant relative risk aversion (CRRA) form on which the buffer stock saving model relies. These produce similar predictions (Figure 8 and Appendix Figure B3).

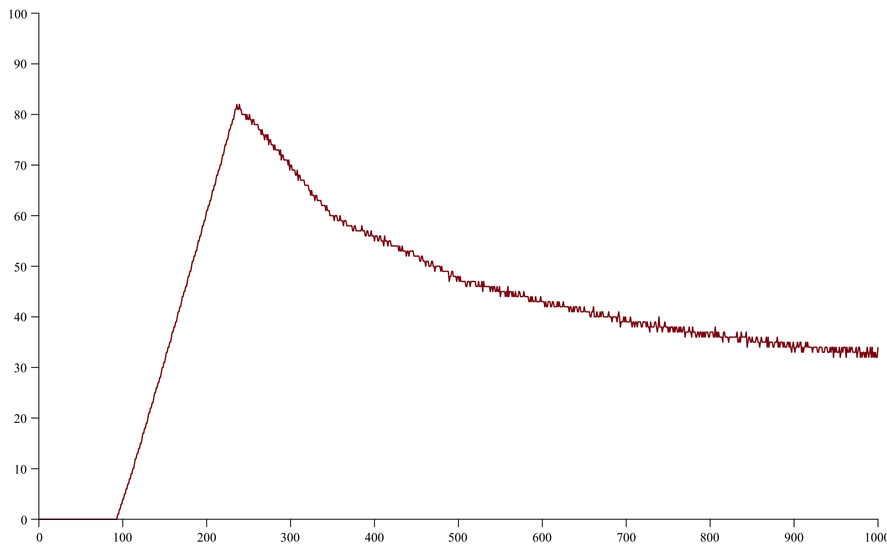

Figure 8: Changes in consumption by initial assets: log utility

Notes: The y-axis measures the difference in consumption between after the receipt of good news and after the receipt of bad news. The x-axis measures initial asset levels.

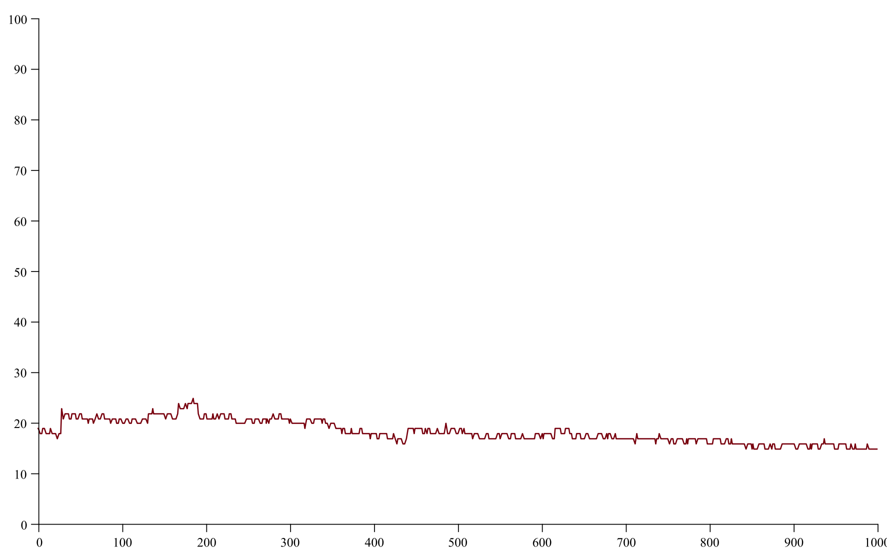

Figure 9: Changes in consumption by initial assets: quadratic utility without borrowing constraints

Notes: The y-axis measures the difference in consumption between after the receipt of good news and after the receipt of bad news. The x-axis measures initial asset levels.

4 Does household consumption respond to news?

4.1 Empirical strategy

The main empirical specification for fluctuations in household consumption builds on the Euler equation in Equation (8). In the baseline regression, the dependent variable is the difference in the log of real consumption per adult equivalent between weeks t and $t-2$, denoted by $\triangle \ln c_{it} = \ln c_{it} - \ln c_{i,t-2}$. Assuming the rational expectations hypothesis such that $E_t(\zeta_t | I_{t-1}, \theta_t) = \gamma_1 \theta_t + \gamma_2 \theta_t I_{t-1}$, we formulate the main empirical specification as

$$\begin{aligned}\triangle \ln c_{it} = \beta_1 \mathrm{RAIN}_{it-1} + \beta_2 \mathrm{CUMRAIN}_{i,t-2} + \beta_3 \mathrm{RAIN}_{i,t-1} \times \mathrm{CUMRAIN}_{i,t-2} \\ + \gamma_X \triangle X_{it} + \gamma_m I_m + \varepsilon_{it}\end{aligned} \tag{9}$$

where RAIN_{it} represents the rainfall amounts observed by household i in week t, $\mathrm{CUMRAIN}_{it}$ is the cumulative rainfall observed by household i up to week t, $\triangle$ is an operator that returns the difference in a variable between weeks t and $t-2$, X_{it} is a vector of the household controls, I_m is a calendar-month fixed effect, and ε_{it} is an error term that may include measurement error in consumption.

Remember that Equation (8) also has a term that captures effects from income variance. Since no plausible proxies for the household-specific variance in crop harvests are available, the specification assumes that rainfall signals do not convey significant information on the variability of harvest income and that its impact, if any, is uniform among sample households. Under this assumption, time-invariant variance is captured by the observable characteristics, whereas the effects from the time-varying part are subsumed into the calendar-month dummies. Although Figure 6 presents descriptive evidence that rainfall during the agricultural season alters volatility in final outputs only slightly, Section 4.5 checks the robustness of estimation results to this variance effect.

Because the main regressions are at the weekly level, general seasonality in household consumption needs to be controlled for. For example, if prices systematically fluctuate across seasons, it is optimal to consume more in periods of low prices relative to periods of high prices despite incentives to smooth consumption. As shown in Figure 2, the survey area experiences substantial seasonality in maize prices, as in other rural areas of sub-Saharan Africa (Gilbert et al., 2017; Burke et al., 2019). Similarly, if marginal returns to nutrition are considerably high in busy periods relative to other periods, it would pay to increase consumption in these labor-peak periods (Dercon and Krishnan, 2000). The systematic occurrence of illness[24] and credit market access (Foster, 1995; Fink et al., 2020) across periods are other factors that might create seasonal fluctuations in household consumption. To control for seasonal effects from price fluctuations and disease environment, the vector of the controls (X_{it}) includes total sick days for the family members of household i in week t and the maize price observed in site v in week t.[25] While the first differences in consumption wipe out seasonal factors such as periodic taste changes and time-invariant household features,

[24] Empirical studies of human biology have reported that seasonal declines in nutritional status and the peak in mortality rates coincide with the period of food scarcity before the harvest season.

[25] Since maize consumption amounts to more than half of the typical budget of households, the maize price is a representative measure of the variation in the cost of consumption.

we also include calendar-month dummies to control for any remaining seasonal aspects that might affect consumption growth.[26]

We estimate Equation (9) by ordinary least squares with robust standard errors clustered at the household level. The coefficient of interest is β_1, capturing the effect of new information, represented by rainfall amount, on consumption growth. Because this study focuses on household responses to rainfall signals in an agricultural season, the estimation sample is restricted to the five months from November to March. As a result, the structure of the data set for this empirical regression is an unbalanced panel of the 48 agricultural households for 91 weeks.[27]

Equation (8) builds on the assumption that households do not face borrowing constraints. Thus, the estimated coefficients would be underestimated because of the presence of constrained households. Indeed, the more interesting theoretical prediction from Section 3.3 claims that the impact of rainfall signals depends on asset levels and that their relationship is hump-shaped: households with an intermediate level of buffer stocks more respond to information shocks than the poor and the rich. To test this, the following model is also estimated:

$$\triangle \ln c_{it} = \beta_0 \mathrm{RAIN}_{i,t-1} + f(\mathrm{RAIN}_{i,t-1}, \mathrm{MS}_{i,t-2}) + \gamma_1 \mathrm{MS}_{i,t-2} + \gamma_X \triangle X_{it} + \varepsilon_{it} \tag{10}$$

where MS_{it} is the estimated maize stocks in kilograms at the beginning of week t. As a robustness check, we also use the maize harvest of household i in year $y-1$ ($\mathrm{HV}_{i,y-1}$) instead of MS_{it}. The proposed hump-shaped relationship can be expressed as

$$\frac{d \triangle \ln c_{it}}{d\,\mathrm{RAIN}_{i,t-1}} = \beta_0 + \beta_1 f(\mathrm{MS}_{i,t-2}) \tag{11}$$

To capture the flexible form, a natural cubic spline is fit to the data.[28] Suppose that the number of knots is n and denote knots as t_j for j=1...n. In particular, Equation (11) is assumed to have the following form using truncated power basis functions:

$$\frac{d \triangle \ln c_{it}}{d\,\mathrm{RAIN}_{i,t-1}} = \beta_0 + \beta_1 \mathrm{MS}_{i,t-2} + \sum_{j=2}^{n-1} \beta_j V_j \tag{12}$$

where the basis function V_j is defined as

$$V_j = \frac{(\mathrm{MS}_{i,t-2} - t_{j-1})^3_+ - (t_n - t_{n-1})^{-1}[(\mathrm{MS}_{i,t-2} - t_{n-1})^3_+ (t_n - t_{j-1}) - (\mathrm{MS}_{i,t-2} - t_n)^3_+ (t_{n-1} - t_{j-1})]}{(t_n - t_1)^2}$$

[26] One implicit assumption here is that the seasonal factors affecting consumption growth over the weeks within a certain month do not differ. While some weeks may have special meaning for local farmers (e.g., Christmas), this assumption holds in the study area.

[27] If the panel was completely balanced, we would have 4,368 household/week observations for the estimation sample. In practice, the number of available observations is 4,054 household/week observations, which indicates that the proportion of missing data is 7.2%.

[28] A natural cubic spline adds to a piecewise cubic polynomial the two additional constraints that the estimated relationship is linear beyond the first and last knots in which outliers affect the results the most.

for j=2,...,n-1 and $(x)_+ = \max(x, 0)$.[29] A natural cubic spline with n knots can be represented as n basis functions. For example, if the number of knots is determined to be 4, basis functions are a constant term, $\text{MS}_{i,t-2}$ itself, V_2, and V_3. Under this specification, the main regression equation (10) can be written as

$$\begin{aligned}\triangle \ln c_{it} = \beta_0 \text{RAIN}_{i,t-1} + \beta_1 \text{RAIN}_{i,t-1} \times \text{MS}_{i,t-2} + \sum_{j=2}^{n-1} \beta_j \text{RAIN}_{i,t-1} \times V_j \\ + \gamma_1 \text{MS}_{i,t-2} + \gamma_X \triangle X_{it} + \varepsilon_{it}\end{aligned} \tag{13}$$

The marginal effects presented in Equation (12) are predicted based on the estimates of the coefficients β_j for j=0...n-1 in Equation (13). To construct the corresponding confidence interval for Equation (12), we calculate the estimated standard errors of the predicted marginal effects using the delta method.

The practical challenge is choosing the number of knots n in advance. In general, the variance in the estimated function rises as the number of knots increases. To select the number of knots based on the comparison among specifications with a different number of knots, we conduct a five fold cross-validation (CV). Then, we choose the specification with the smallest CV estimate as the empirical model for Equation (13).[30]

4.2 Baseline results

Table 5 presents the baseline regression results of Equation (9) for total household consumption and food consumption.[31] The estimation result in column (1) indicates that rainfall in the previous week of the crop season has a statistically significant and positive impact on total household

[29] If linear splines are instead applied, the corresponding specification would be

$$\frac{d \triangle \ln c_{it}}{d\,\text{RAIN}_{i,t-1}} = \beta_0 + \beta_1 \text{MS}_{i,t-2} + \sum_{j=2}^{n-1} \beta_j (\text{MS}_{i,t-2})_+$$

The preferred spline is a natural cubic spline, since it can achieve local polynomial representations in segments. In particular, the advantage over a linear spline is that a natural cubic spline has continuous first and second derivatives at pre-defined knots.

[30] The k-fold CV randomly splits the estimation sample set into k non-overlapping parts of equal size, and the model of interest is fit to k-1 sets to assess the i-th out-of-sample data. The resulting fitted model is used to predict the dependent variable on the i-th part of the data held out. Then, we evaluate the performance of the prediction model based on the mean squared error (MSE), denoted by MSE_i. This process is repeated k times for the k different folds. The k-fold CV estimate of the prediction error is then calculated by averaging the MSE estimates across the k portions:

$$CV_k = \frac{1}{k} \sum_{i=1}^{k} \text{MSE}_i$$

The CV estimates differ across applications because of randomness in the sample splits.

[31] To avoid disturbance from outliers, the top 1% and bottom 1% of household food consumption are dropped from the estimation sample.

Table 5: OLS estimates of the determinants of growth in consumption per adult equivalent

	(1) Total	(2) Total	(3) Food	(4) Food
Rain (100mm), t-1	0.039***	0.091***	0.040***	0.078***
	(0.010)	(0.024)	(0.009)	(0.022)
Cumurative Rain (100mm) up to t-2	-0.000	0.005	-0.002	0.002
	(0.003)	(0.004)	(0.003)	(0.004)
× Rain (100mm), t-1		-0.010**		-0.008*
		(0.004)		(0.004)
Field-level shock dummy, t-1	0.027	0.025	0.029	0.027
	(0.030)	(0.030)	(0.029)	(0.030)
△ Total sick days adults, t, t-2	0.011**	0.011**	0.006	0.006
	(0.005)	(0.005)	(0.004)	(0.004)
△ Total sick days children (6 to 15) t, t-2	0.006	0.006	0.013	0.012
	(0.010)	(0.010)	(0.009)	(0.009)
△ Total sick days children (0 to 5) t, t-2	0.012***	0.012***	0.008*	0.008*
	(0.004)	(0.004)	(0.004)	(0.004)
△ Log maize price t, t-2	-0.795***	-0.797***	-0.821***	-0.822***
	(0.064)	(0.065)	(0.055)	(0.055)
△ Survey dates t, t-2	0.100***	0.100***	0.100***	0.100***
	(0.024)	(0.023)	(0.021)	(0.021)
Land size (ha), y	0.000	0.000	-0.001	-0.000
	(0.003)	(0.002)	(0.002)	(0.002)
Adult equivalent units, y	-0.003	-0.003	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Calendar-month FE	YES	YES	YES	YES
R^2	0.09	0.09	0.11	0.11
N	3322	3322	3322	3322

Notes: Robust standard errors clustered by household in parentheses. *** denotes significance at 1% level, ** at 5% level, and * at 10% level. The dependent variable is the difference in the log of consumption per adult equivalent between weeks t and t-2. The estimation sample is limtied to the planting and weeding periods (November to March).

consumption in the current week: a one-standard-deviation increase in weekly rainfall by 75 millimeters induces a 3% (=exp(0.75×0.039)-1) rise in total weekly consumption per adult equivalent. A similar pattern can be confirmed for food consumption in column (3). Overall, the effect is relatively small. Nevertheless, changes in consumption after observing rainfall signals should not be overlooked for the following two reasons. First, the survey sample consists of very low-income households: average real weekly consumption per adult equivalent is ZMW 4.4 (=USD 1.2) during the sample period. As shown in Section 2, median consumption is much lower than average consumption. Thus, even increases (decreases) in consumption by 3% may imply substantial welfare gains (losses) for sample farmers. Second, this estimate shows an average effect because whether farmers change consumption levels in response to news depends on their ability to finance consumption. For example, about 60% of household/week observations record a negative or zero cash flow in the planting and weeding periods. In this sense, the estimation results are a combination of unconstrained and constrained behavior by farmers.

Regression equation (9) relies on the assumption that households do not face borrowing constraints. If this is the case, past information should not affect current consumption growth because farmers have already incorporated previous changes in their expectations, driven by past information, into their optimal consumption plan. This theoretical implication is violated if the borrowing constraints are binding because constrained households cannot optimally adjust their consumption plans in the past. The estimated coefficients on cumulative rainfall amounts provide evidence that past information does not affect current growth in total household consumption, suggesting that average farm households can transfer resources across periods in some way.

Additional evidence is presented in the even columns in which the interaction term between one-period lagged rainfall and cumulative rainfall is added into the regressors. The estimated coefficients on this interaction term are significantly negative, consistent with the concave relationship between annual rainfall and maize yields (Appendix Table C3): local farmers—after observing higher rainfall in the previous week of the agricultural season—expect the maize harvest be high, but this favorable effect is attenuated if previous rainfall amounts are also high because of the underlying substitute relationship.

As shown in Figure 5, the impacts of rainfall on future maize harvests are not uniform across months. Specifically, rainfall amounts from November and January are found to have a statistically significant effect on maize yields. If sample farmers take advantage of advance information in their decision-making process by observing rainfall patterns, household consumption growth would be more responsive to rain in November and January. This is tested by replacing $\text{RAIN}_{i,t-1}$ with the interaction terms between $\text{RAIN}_{i,t-1}$ and a monthly dummy for the corresponding previous week (i.e., week t-1). The control variables are the same as those in Table 5. The estimation results in Table 6 show that the main effect comes from January rainfall. Although not significant at any conventional statistical level, the effect sizes of November rainfall are also remarkable.[32] Thus, Table 6 supports the main story of this study.

4.3 Asset-differentiated impacts

To test the main prediction that the impact of advance information has a hump-shaped relationship with asset stock levels, Equation (13) is run using weekly maize inventories ($\text{MS}_{i,t-2}$). To select the number of knots, five-fold CV is performed on Equation (13). Based on the result shown in Appendix Figure B4, the following empirical analyses use four knots.[33] Following Harrell's (2015)

[32] One possible explanation for the imprecise estimates of November rainfall might be that cash demand is comparatively high in this month because of purchases of agricultural inputs such as fertilizer and seeds whose application timing is presumably correlated with weekly rain. As another speculation, some farmers do not think of November rainfall as a decisive signal of final maize outputs, even though the production data reveal the statistically significant association (Figure 5).

[33] Appendix Figure B4 presents the typical CV estimates by the number of knots. For comparison purposes, the CV estimate based on Equation (13) only with the interaction term between $\text{HV}_{i,y-1}$ and $\text{RAIN}_{i,t-1}$ is also reported at the

Table 6: Rainfall impacts on consumption growth by month

	(1) Total	(2) Food
Rain (100mm), t-1 × November, t-1	0.096	0.068
	(0.099)	(0.090)
Rain (100mm), t-1 × December, t-1	0.017	0.021
	(0.025)	(0.024)
Rain (100mm), t-1 × January, t-1	0.087*	0.081**
	(0.049)	(0.039)
Rain (100mm), t-1 × February, t-1	0.013	0.008
	(0.016)	(0.015)
Rain (100mm), t-1 × March, t-1	-0.037	-0.002
	(0.032)	(0.028)
Cumurative Rain (100mm) up to t-2	0.005	0.003
	(0.004)	(0.004)
Calendar-month FE for week t	YES	YES
Calendar-month FE for week t-1	YES	YES
R^2	0.11	0.14
N	3322	3322

Notes: Robust standard errors clustered by household in parentheses. *** denotes significance at 1% level, ** at 5% level, and * at 10% level. The dependent variable is the difference in the log of consumption per adult equivalent between weeks t and t-2. The estimation sample is limtied to the planting and weeding periods (November to March). The same set of controls as in Table 5 are included but not reported.

recommended percentiles, the knot locations are chosen as the 5th, 35th, 65th, and 95th percentiles of the distribution of $\text{MS}_{i,t-2}$.

Based on the estimation results of Equation (12) with $\text{MS}_{i,t-2}$, Figure 10 presents the estimated marginal effect of rainfall on consumption growth, represented by Equation (13), for each stock level.[34] As shown in Panel (a) of Figure 10 using maize stocks based on Method 1, the marginal effects have a hump-shaped relationship, consistent with the earlier theoretical prediction. However, the relationship is imprecisely estimated for households with a high volume of maize grain stocks.

To check the robustness, we run the same regressions with a series of maize grain inventories computed by Method 2. The results summarized in Panel (b) of Figure 10 show more striking results: households with an intermediate level of maize stocks respond to rainfall signals the most, whereas those with more grain stocks do not react to them. For example, the 95% confidence interval does not contain zero over a region between 200 kg and 1,100 kg, suggesting that households

point in which the number of knots is zero. Appendix Figure B4 shows that the models based on cubic splines have smaller MSEs than the model with only an interaction term. Although there are no substantial differences between three and seven knots, the model with four knots tends to take the smallest MSE.

[34] A natural cubic spline with the full sample poorly behaves in the tails of the asset variables. To increase the precision of the estimates, the estimation sample is limited to 10–90% of maize stocks for Figure 10 and 5–95% of the last year's maize harvests for Appendix Figure B5. Only for graphical purposes, the minimum amount is added for each stock variable since some values take negative values.

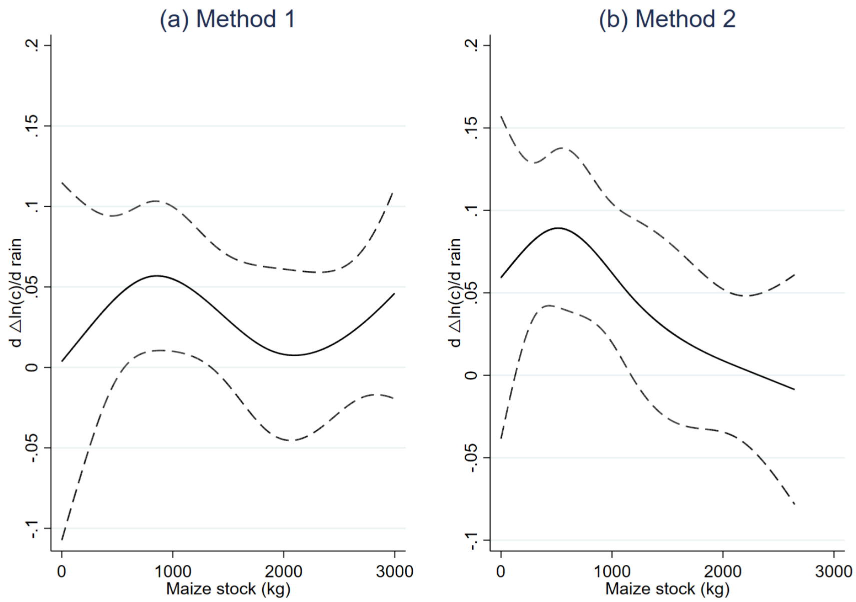

Figure 10: Impacts of weekly rainfall by maize stocks

Notes: The dashed and solid lines respectively show the 95% confidence intervals and estimated marginal effect.

that had these levels of grain inventories respond to rainfall signals on average but households with 450 kg maize harvests react to those the most.[35]

The estimated maize stock based on Method 1 is less reliable over a range of high volumes of stock due to potential accumulated measurement errors. On the contrary, Method 2 has less ability to capture relatively small amounts since carrying stock over from before harvest is not allowed. Combining results from Panels (a) and (b) of Figure 10, our data fairly well confirm the theoretically predicted relationship.

One may concern that current asset stock levels are endogenous since those are reflected by household behavior in the past. Because the maize harvests in the previous year can a good approximation of current maize stocks, Appendix Figure B5 shows the same result except for using the previous year's maize harvests. In similar to Figure 10, a hump-shaped relationship is detected although the relationship is less clear because of less time-variations in the previous year's maize harvests.

Overall, the main results presented so far provide evidence that while even constrained households can change their consumption schedules in advance of the actual occurrence of income shocks, responses to advance information depend greatly on the available buffer stock levels.

[35]The same patterns are also confirmed by the specifications based on linear splines (results not shown).

4.4 Alternative explanations: Non-separable preferences with leisure

We examine alternative hypotheses. The previous analysis rested on the assumption that leisure is not an argument of the utility function. In the survey area, however, treating labor and leisure as choice variables may be important for two competing reasons. One is the complementarity between consumption and leisure. If high rainfall saves working hours for any reason, farmers can enjoy more leisure time and increase consumption levels because of the complementarity. For instance, in the study villages, rainwater is stored and used for water to drink and wash dishes and clothes, which suggests that households can save the time usually spent fetching water after a rainy week. The second reason reflects the reality of an agrarian economy characterized by incomplete labor markets. The underlying idea is the nutrition–productivity link: better nutritional status leads to higher productivity.[36] Since most work in the economy is physically demanding, the nutritional status of workers can positively influence time worked and labor productivity in principle (de Janvry and Sadoulet, 2006). Under this assumption, returns to investments in nutrition significantly change in accord with the agricultural cycle. For example, food demand would be high to boost labor productivity in the peak season of production. Whereas the calendar-month dummies in the main regression control for the usual seasonal differences in labor demand, weekly rainfall can affect the return on labor inputs and immediately change labor demand, which may increase household consumption through the proposed nutrition–productivity link. Indeed, anecdotal evidence indicates that local farmers plant maize seeds after receiving a "good" amount of rain at the beginning of the crop season to avoid the failure of the seed to germinate because of the lack of subsequent rainfall (Shimono et al., 2012). Furthermore, time spent weeding could increase if high rainfall promotes weeds on fields. Thus, the possible relationship between rainfall shocks and labor demand is the central threat to the main story of this study.

We check this alternative channel using the weekly time use data by examining the effect of weekly rainfall on household working hours. If the complementarity between leisure and consumption plays an important role, working hours would respond to weekly rainfall in a different direction to consumption. On the contrary, consumption and working hours would change in the same direction if the nutrition–productivity link drives the baseline results.[37]

Replacing the dependent variable with changes in total working hours between weeks t and t-2, we estimate Equation (9) separately for male and female family labor.[38] We define total working hours as the sum of time spent on agricultural work, non-agricultural work, and household chores. The results in columns (1) and (2) of Table 7 support the first possibility: when it rains in the

[36] Empirical support for this productivity effect of calorie consumption is weak in the literature (Strauss, 1986; Deolalikar et al., 1988; Behrman et al., 1997). Nevertheless, discussions on the nutrition–productivity link are essential since this possibility is the main threat to our central claim.

[37] This testable hypothesis is similar to Kazianga and Udry (2006)'s result. They discuss the nutrition–productivity link in the context of consumption smoothing and claim that if households smooth perfectly, consumption and farm labor demand must move in the same direction in response to transitory shocks. The same interpretation would be applied to the farmer's response to information shocks.

[38] Market wage rates are not controlled for since they are not available in the dataset. For consistency, the sample restriction rule (see Footnote 31) is the same as in Table 5.

Table 7: Determinants of changes in working hours per capita

	(1) Total	(2) Total	(3) Domestic work	(4) Domestic work
Rain (100mm), t-1	-0.498	-0.478	-0.245*	-0.287
	(0.399)	(0.383)	(0.136)	(0.176)
Cumurative Rain (100mm) up to t-2	-0.096	0.209	-0.048	0.017
	(0.120)	(0.139)	(0.034)	(0.060)
Field-level shock dummy, t-1	0.116	-0.338	-0.004	-0.210
	(0.686)	(0.640)	(0.190)	(0.365)
△ Total sick days adults, t, t-2	-0.326**	-0.544***	0.043	-0.359***
	(0.122)	(0.180)	(0.049)	(0.076)
△ Total sick days children (6 to 15) t, t-2	-0.130	-0.192	-0.133***	-0.231*
	(0.197)	(0.229)	(0.049)	(0.117)
△ Total sick days children (0 to 5) t, t-2	-0.080	-0.217*	0.058*	-0.074
	(0.089)	(0.123)	(0.031)	(0.066)
△ Log maize price t, t-2	4.006**	1.605	0.206	-0.230
	(1.588)	(2.194)	(0.752)	(0.825)
△ Survey dates t, t-2	1.730**	2.993***	0.342	2.475***
	(0.801)	(0.871)	(0.248)	(0.552)
Land size (ha), y	0.089	-0.042	-0.021	-0.051
	(0.059)	(0.076)	(0.020)	(0.036)
Adult equivalent units, y	0.030	0.057	0.014	0.035
	(0.058)	(0.042)	(0.014)	(0.025)
Sample	Male adults	Female adults	Male adults	Female adults
Calendar-month FE	YES	YES	YES	YES
R^2	0.02	0.03	0.01	0.05
N	3003	3295	3003	3295

Notes: Robust standard errors clustered by household in parentheses. *** denotes significance at 1% level, ** at 5% level, and * at 10% level. The dependent variable is the change in total working hours per capita between weeks t and t-2. The estimation sample is limtied to the planting and weeding periods (November to March).

previous week, adults work less and thus enjoy more leisure time. The reduction in total household working hours mainly comes from the decrease in time spent on domestic work, as shown in columns (3) and (4) of Table 7.[39] These findings are consistent with the first possibility that rainfall in the previous week reduces demand for household chores and increases leisure time for family members, thereby increasing household food consumption through the possible complementarity between consumption and leisure. However, estimated coefficients are insignificant or marginally significant at most.

[39]The regressions using time spent on either agricultural activities or non-agricultural work find that coefficients on rainfall are not statistically significant at any conventional level.

Table 8: Rainfall impacts on changes in working hours by month

	(1) Total	(2) Total	(3) Domestic work	(4) Domestic work
Rain (100mm), t-1 × November, t-1	0.832	2.319	0.121	-0.212
	(2.229)	(1.769)	(0.950)	(0.759)
Rain (100mm), t-1 × December, t-1	-2.179*	-0.779	-0.427*	-0.305
	(1.166)	(0.857)	(0.247)	(0.479)
Rain (100mm), t-1 × January, t-1	1.096	0.865	-0.476	-0.574
	(0.978)	(1.229)	(0.460)	(0.891)
Rain (100mm), t-1 × February, t-1	-0.094	-0.995**	-0.176	-0.290
	(0.476)	(0.449)	(0.105)	(0.202)
Rain (100mm), t-1 × March, t-1	-1.027	-0.392	0.019	-0.289
	(1.253)	(1.213)	(0.399)	(0.618)
Cumurative Rain (100mm) up to t-2	-0.109	0.174	-0.016	0.057
	(0.149)	(0.170)	(0.038)	(0.073)
Sample	Male adults	Female adults	Male adults	Female adults
Calendar-month FE for week t	YES	YES	YES	YES
Calendar-month FE for week t-1	YES	YES	YES	YES
R^2	0.02	0.03	0.01	0.05
N	3003	3295	3003	3295

Notes: Robust standard errors clustered by household in parentheses. *** denotes significance at 1% level, ** at 5% level, and * at 10% level. The dependent variable is the change in total working hours per capita between weeks t and t-2. The estimation sample is limtied to the planting and weeding periods (November to March). The same set of controls as in Table 5 are included but not reported.

If this effect is sizeable despite their statistical significance, it may be concluded that households may adjust consumption because of changes in leisure time thanks to rainfall instead of changes in their expectations of future maize harvests. However, the following three pieces of evidence suggest that this competing possibility is not the main driver of the change in consumption in the study villages. First, Table 8 reports the results from the same exercise as Table 6 except using changes in total working hours as the dependent variable to examine the impact of rainfall on labor hours by timing. As shown in Table 8, no statistically significant impacts are found for January rainfall. Second, Appendix Table C7 tests whether the coefficients on rainfall remain significant in the consumption growth regressions even after controlling for changes in the total working hours of male and female adults. Although the changes in the total working hours of men and women are clearly endogenous, this regression offers a rough test of the over-identification restriction. As shown in Appendix Table C7, the estimated coefficients on the rainfall signal are similar to the results of the baseline specification (Table 5) in terms of both magnitude and statistical significance. As further checks from a different angle, Appendix Figures B6–B8 replicate Figure 10 for the total working hours of men and women. They show no significant impact at any local level of asset stocks, and the patterns are not comparable to those for consumption growth. Taken together, the main results are robust to the possibility of non-separable preferences with leisure.

4.5 Alternative explanations: Variance

An additional concern is raised by the discussions presented in Section 2.3: rainfall signals may convey information on the variability of future harvests. The reason for changes in household consumption could be that the household expects future maize harvests to be more certain after the receipt of new information. The reduction in yield uncertainty will decrease the precautionary saving motive and lead risk-averse households to increase consumption. In the above regressions with the level of rainfall as the main independent variable, these effects on the second moment might contaminate the effects on the first moment. However, the primary finding is from January in which volatility in maize yields seems to be fairly constant across different rainfall ranges (see Figure 6). In addition, the same regression equation (9) after dropping the extremely high rainfall in December still finds the comparable result with Table 5 (results not shown).[40] Thus, the baseline results still hold even after taking into account the impact of rainfall signals on variability in maize harvests.

4.6 Alternative explanations: Returns to grain stocks

High rainfall can cause the direct loss of stored grain inventories due to a great incidence of mold and insect pests (Kadjo et al., 2018). As such, rainfall patterns during the agricultural season may affect returns to holding maize grain in food storage.[41] We cannot separate this possibility from the effect of rainfall signals through changes in expectations of future harvests, since they basically work in the same direction. However, if the changes in returns to holding grains drive the main results, other food consumption would not respond to rainfall signals. To test this idea, livestock self-consumption provides a good opportunity, since livestock is also an important buffer stock in the study site (Miura et al., 2012). While returns to keeping livestock presumably depend on recent weather patterns in the short run, the underlying assumption of this exercise is that the impact of rainfall on returns to keeping livestock does not match the impact on returns to grain holdings exactly. If rainfall works as an informative signal of future harvests, households would increase the self-consumption of livestock as well as maize consumption.

Replacing the dependent variable with changes in the value of livestock self-consumed between weeks t and t-2, Equation (9) is re-estimated.[42] The results in Tables 9 and 10 indicate that livestock self-consumption indeed reacts to rainfall in January, which provides evidence to reject the possibility that the changes in returns to holding grain stocks lead to the main results.

[40] More precisely, the estimation sample excludes observations with weekly rainfall above 132.5 millimeters in the planting period. This threshold value of rainfall corresponds to the 95th percentile of the distribution for the period.

[41] Returns to grain stocks are also dependent on seasonal changes in grain prices. This effect is directly controlled by the changes in maize prices in the vector of the control variables.

[42] Like the estimation with total consumption growth, we drop the top and bottom 1% of the dependent variable from the estimation sample.

Table 9: Determinants of livestock self-consumption

	(1)	(2)
Rain (100mm), t-1	0.029**	0.070**
	(0.011)	(0.026)
Cumurative Rain (100mm) up to t-2	-0.002	0.002
	(0.003)	(0.004)
× Rain (100mm), t-1		-0.008**
		(0.004)
Calendar-month FE	YES	YES
R^2	0.02	0.02
N	3383	3383

Notes: Robust standard errors clustered by household in parentheses. *** denotes significance at 1% level, ** at 5% level, and * at 10% level. OLS is used for the estimation. The dependent variable is the change in livestock self-consumption per adult equivalent between weeks t and t-2. The estimation sample is limtied to the planting and weeding periods (November to March). The same set of controls as in Table 5 are included but not reported.

Table 10: Rainfall impacts on livestock self-consumption by month

	(1)
Rain (100mm), t-1 × November, t-1	-0.032
	(0.097)
Rain (100mm), t-1 × December, t-1	0.018
	(0.039)
Rain (100mm), t-1 × January, t-1	0.095**
	(0.047)
Rain (100mm), t-1 × February, t-1	-0.001
	(0.015)
Rain (100mm), t-1 × March, t-1	-0.007
	(0.028)
Cumurative Rain (100mm) up to t-2	0.004
	(0.004)
Calendar-month FE for week t	YES
Calendar-month FE for week t-1	YES
R^2	0.05
N	3383

Notes: Robust standard errors clustered by household in parentheses. *** denotes significance at 1% level, ** at 5% level, and * at 10% level. OLS is used for the estimation. The dependent variable is the change in livestock self-consumption per adult equivalent between weeks t and t-2. The estimation sample is limtied to the planting and weeding periods (November to March). The same set of controls as in Table 5 are included but not reported.

Table 11: Determinants of changes in weekly non-food consumption levels

	(1) Luxury goods	(2) Household goods	(3) Medical expenditure	(4) Other services
Rain (100mm), t-1	0.003	0.050	0.002	0.010
	(0.005)	(0.040)	(0.003)	(0.034)
Cumurative Rain (100mm) up to t-2	0.000	0.011	-0.000	0.010
	(0.001)	(0.009)	(0.001)	(0.008)
Field-level shock dummy, t-1	-0.001	0.011	-0.011	0.005
	(0.007)	(0.037)	(0.008)	(0.038)
△ Total sick days adults, t, t-2	0.002	0.035	0.009***	0.026
	(0.003)	(0.033)	(0.003)	(0.021)
△ Total sick days children (6 to 15) t, t-2	0.007	-0.024	0.007	-0.024
	(0.007)	(0.018)	(0.005)	(0.019)
△ Total sick days children (0 to 5) t, t-2	0.002	0.009	0.005***	0.010*
	(0.001)	(0.013)	(0.002)	(0.006)
△ Log maize price t, t-2	-0.011	0.326	0.013	0.089
	(0.028)	(0.229)	(0.019)	(0.172)
△ Survey dates t, t-2	-0.011*	-0.020	-0.008	0.070
	(0.006)	(0.028)	(0.006)	(0.065)
Land size (ha), y	-0.001	0.010	0.000	-0.003
	(0.001)	(0.010)	(0.000)	(0.004)
Adult equivalent units, y	0.001*	0.004	-0.000	0.001
	(0.001)	(0.009)	(0.000)	(0.001)
Calendar-month FE	YES	YES	YES	YES
R^2	0.01	0.00	0.03	0.01
N	3322	3322	3322	3322

Notes: Robust standard errors clustered by household in parentheses. *** denotes significance at 1% level, ** at 5% level, and * at 10% level. The dependent variable is the change in consumption levels of each category between weeks t and t-2. The estimation sample is limtied to the planting and weeding periods (November to March).

4.7 Additional evidence

The main story of this study is that farm households in rural Zambia can change consumption in response to advance information before income changes actually happen by adjusting buffer stocks, especially grain inventories. We present additional supporting evidence in this final subsection.

The previous empirical regressions showed that higher rainfall in the previous week leads to higher household consumption, particularly food consumption. Is there any effect on consumption in other categories? To answer this question, we examine changes in expenditure in the categories of luxury goods, household goods, medical expenditure, and other services.[43] The estimation re-

[43]Luxury goods include alcohol, tobacco, and snacks. Examples of household goods are tableware, clothes, and

Table 12: Rainfall impacts on non-food consumption by month

	(1) Luxury goods	(2) Household goods	(3) Medical expenditure	(4) Other services
Rain (100mm), t-1 × November, t-1	0.050*	0.161	-0.028	-0.019
	(0.029)	(0.413)	(0.018)	(0.082)
Rain (100mm), t-1 × December, t-1	-0.000	0.056	0.004	0.023
	(0.017)	(0.070)	(0.003)	(0.045)
Rain (100mm), t-1 × January, t-1	-0.045	0.132	-0.016	0.073
	(0.049)	(0.092)	(0.016)	(0.119)
Rain (100mm), t-1 × February, t-1	0.007	0.034	0.012	0.005
	(0.005)	(0.056)	(0.007)	(0.022)
Rain (100mm), t-1 × March, t-1	0.009	-0.144**	-0.004	-0.079**
	(0.007)	(0.069)	(0.009)	(0.039)
Cumurative Rain (100mm) up to t-2	0.003**	0.012*	0.001	0.010
	(0.001)	(0.006)	(0.001)	(0.007)
Calendar-month FE for week t	YES	YES	YES	YES
Calendar-month FE for week t-1	YES	YES	YES	YES
R^2	0.01	0.01	0.03	0.01
N	3322	3322	3322	3322

Notes: Robust standard errors clustered by household in parentheses. *** denotes significance at 1% level, ** at 5% level, and * at 10% level. The dependent variable is the difference in the log of consumption per adult equivalent between weeks t and t-2. The estimation sample is limtied to the planting and weeding periods (November to March). The same set of controls as in Table 5 are included but not reported.

sults in Table 11 show that no commodity group has a relationship with lagged-period rainfall. According to Table 12 that investigates the effects of the timing of rainfall, only household spending on luxury goods reacts to rainfall amounts in November (note that November rainfall has certain predictive power for future maize harvests, as shown in Figure 5). These findings suggest that the positive impact of rainfall on household consumption is driven mainly by increases in food consumption, which typically has a large share of survey households' budgets. In addition, these results are consistent with the main idea of the buffer stock saving model that households can borrow and save against future income by adjusting the level of buffer stocks in general and grain inventories in particular. One possible explanation for the limited evidence on the impacts on the other consumption categories is the non-negligible transaction cost incurred when households sell grain maize in local markets.

Except for stock adjustments, agricultural households may have alternative ways to source consumption upon the arrival of new information. As important examples, we examine the roles of cash and gift transactions with relatives and friends and livestock transactions in local markets.

necessities such as soap and candles. Medical expenditure consists of medical fees and expenditure on medicine. Finally, other services include fees involving maize-milling, schooling, transportation, and mobile phones, among others.

Table 13: Determinants of net saving

	(1) Net cash transactions	(2) Net gift transactions	(3) Livestock net saving
Rain (100mm), t-1	0.003	-0.217	-0.139
	(0.054)	(0.129)	(0.215)
Cumurative Rain (100mm) up to t-2	-0.057*	-0.050	0.280
	(0.029)	(0.045)	(0.253)
Field-level shock dummy, t-1	0.077	0.489	0.533
	(0.081)	(0.368)	(0.971)
△ Total sick days adults, t, t-2	0.057	0.023	-0.372
	(0.046)	(0.016)	(0.280)
△ Total sick days children (6 to 15) t, t-2	0.043	-0.030	0.039
	(0.047)	(0.021)	(0.048)
△ Total sick days children (0 to 5) t, t-2	0.049	0.033	-0.023
	(0.063)	(0.031)	(0.075)
△ Log maize price t, t-2	-0.183	1.172	-4.982
	(0.306)	(1.177)	(3.738)
△ Survey dates t, t-2	-0.180	-0.102	-0.964**
	(0.133)	(0.061)	(0.411)
Land size (ha), y	-0.012	-0.006	-0.012
	(0.008)	(0.005)	(0.099)
Adult equivalent units, y	0.011	0.009	-0.076
	(0.009)	(0.010)	(0.080)
Calendar-month FE	YES	YES	YES
R^2	0.00	0.01	0.01
N	3208	3322	3322

Notes: Robust standard errors clustered by household in parentheses. *** denotes significance at 1% level, ** at 5% level, and * at 10% level. OLS was used for the estimation. The dependent variable is the change in net saving of the specified assets between weeks t and t-2. The estimation sample is limtied to the planting and weeding periods (November to March).

The net saving equations for transactions involving livestock and cash are estimated by replacing the dependent variable with changes in net saving between weeks t and t-2 in Equation (9). Since negative values stand for dissaving, the coefficients on rainfall are expected to be negative if these assets are used to finance household consumption after observing positive information shocks.

Table 13 summarizes the estimation results for net saving in the form of cash, gifts, and livestock. We define net saving through cash transactions as the value of cash sent to relatives and friends, net of the value of cash received from them. Net saving in the form of gifts is defined similarly. Table 13 may indicate that sample households receive gifts in response to high rainfall in the planting/weeding periods. However, the effect is not economically significant. A one-standard-deviation increase in rainfall by 75 millimeters in the previous week induces households to receive more gifts worth approximately ZMW0.16 (= 0.217×0.75) per household in the planting/weeding periods. Thus, the effect does not solely account for the corresponding increase in food consumption. Finally, we define net saving in the form of livestock as the value of livestock purchased and given as a gift, net of the value of livestock sold and given as a gift. As shown in column (3) of Table 13, the estimates for net saving in the form of livestock do not show any significant results.

Combining these results with the previous finding that rainfall in the previous week only affects food consumption, we can conclude that sample households behave in a forward-looking way in response to the arrival of new information by simply adjusting grain inventories. Since maize consumption accounts for a large share of food consumption, adjustments to maize stocks serve as a primary mechanism through which agricultural households use the new information fully. The observed asset-differentiated impact also suggests that the degree of forward-looking behavior is significantly limited by the level of available grain inventories. Overall, the empirical results presented in this study are consistent with the buffer-stock saving model with borrowing constraints.

5 Conclusions

This study tests farmers' forward-looking consumption behavior by exploiting the sequential nature of agricultural production in rural Zambia. Using high-frequency household data, the empirical results reveal that poor agricultural households indeed behave in a forward-looking fashion by responding to new information on future crop harvests. Another important finding is that their responses differ according to the level of buffer stocks such as grain inventories, consistent with the prediction by the buffer stock saving model with borrowing constraints.

The asset-differentiated effects have rich implications for a wide array of development policies. For instance, Rosenzweig and Udry (2013) report that planting investment decisions by Indian farmers respond to official weather forecasts, especially when they are accurate. The empirical evidence from this study suggests that the provision of formal weather forecasts also has favorable impacts on consumption behavior, especially for households in the middle asset group. For asset-poor households, another policy intervention such as timely credit provision would be more effective by enhancing their ability to transfer resources over time.[44]

From a more general policy perspective, understanding how local farmers take advantage of natural signals (e.g., rainfall) to predict the state of the world is particularly important for areas in which people have limited access to formal weather forecasts and still follow indigenous knowledge, including the sample area of this study (Luseno et al., 2003; Lybbert et al., 2007). For example, if households react to weather conditions and change their behavior before the harvesting period, the timing of the announcement of food aid delivery needs to take immediate household consumption responses into consideration.

The main contribution of this study is the provision of empirical evidence on forward-looking behavior in developing countries. Given the scarcity of analysis in the literature because of the lack of high-frequency data on signals and the responses to them, the evidence presented in this paper is expected to shed light on a new aspect of the consumption behavior of small-scale farmers living

[44] Alternative explanation for the null reactions of asset-poor households to new information is that their decision-making is psychologically biased by scarce grain reserves per se (Fehr et al., 2019).

in a highly uncertain world. However, this study captures only one type of information shock on household income and relies on data drawn from a small sample. To examine whether these results have external validity, the further collection of high-frequency data is desirable.

References

Agarwal, S. and Qian, W. (2014). Consumption and debt response to unanticipated income shocks: Evidence from a natural experiment in singapore. *American Economic Review*, 104(12):4205–30.

Behrman, J. R., Foster, A. D., and Rosenzweig, M. R. (1997). The dynamics of agricultural production and the calorie-income relationship: Evidence from pakistan. *Journal of Econometrics*, 77(1):187–207.

Berg, E. (2013). Are poor people credit-constrained or myopic? evidence from a south african panel. *Journal of Development Economics*, 101:195–205.

Blundell, R. and Stoker, T. M. (1999). Consumption and the timing of income risk. *European Economic Review*, 43(3):475–507.

Burke, M., Bergquist, L. F., and Miguel, E. (2019). Sell low and buy high: arbitrage and local price effects in kenyan markets. *The Quarterly Journal of Economics*, 134(2):785–842.

Campbell, J. (1987). Does saving anticipate declining labor income? an alternative test of the permanent income hypothesis. *Econometrica*, 55(6):1249–73.

Carroll, C. (1992). The buffer-stock theory of saving: Some macroeconomic evidence. *Brookings Papers on Economic Activity*, 23(2):61–156.

Carroll, C. (1997). Buffer-stock saving and the life cycle/permanent income hypothesis. *Quarterly Journal of Economics*, 112(1):1–55.

Carter, M. R. and Lybbert, T. J. (2012). Consumption versus asset smoothing: testing the implications of poverty trap theory in burkina faso. *Journal of Development Economics*, 99(2):255–264.

Central Statisitcal Office (2011). Living conditions monitoring survey report 2006.

Chaudhuri, S. (1999). Forward-looking behavior, precautionary savings, and borrowing constraints in a poor, agrarian economy: tests using rainfall data. *Columbia University Department of Economics Working Paper*, (9899-10).

de Janvry, A. and Sadoulet, E. (2006). Progress in the modeling of rural households' behavior under market failures. In *Poverty, inequality and development*, pages 155–181. Springer.

Deaton, A. (1991). Saving and liquidity constraints. *Econometrica*, 59(5):1221–48.

Deaton, A. S. (1992). Saving and income smoothing in cote d'ivoire. *Journal of African Economies*, 1(1):1–24.

Deolalikar, A. B. et al. (1988). Nutrition and labor productivity in agriculture: Estimates for rural south india. *The Review of Economics and Statistics*, 70(3):406–413.

Dercon, S. and Krishnan, P. (2000). Vulnerability, seasonality and poverty in ethiopia. *The Journal of Development Studies*, 36(6):25–53.

Fafchamps, M. (1993). Sequential labor decisions under uncertainty: An estimable household model of west-african farmers. *Econometrica*, 61(5):1173–97.

Fafchamps, M., Udry, C., and Czukas, K. (1998). Drought and saving in west africa: are livestock a buffer stock? *Journal of Development Economics*, 55(2):273–305.

Fehr, D., Fink, G., and Jack, K. (2019). Poverty, seasonal scarcity and exchange asymmetries. Technical report, National Bureau of Economic Research.

Fink, G., Jack, B. K., and Masiye, F. (2020). Seasonal liquidity, rural labor markets, and agricultural production. *American Economic Review*, 110(11):3351–92.

Foster, A. D. (1995). Prices, credit markets and child growth in low-income rural areas. *The Economic Journal*, 105(430):551–570.

Gilbert, C., Christiaensen, L., and Kaminski, J. (2017). Food price seasonality in africa: Measurement and extent. *Food Policy*, 67:119–132.

Giné, X., Townsend, R. M., and Vickery, J. (2017). Forecasting when it matters: Evidence from semi-arid india.

Harrell, F. E. (2015). *Regression modeling strategies: with applications to linear models, logistic and ordinal regression, and survival analysis*. Springer.

Heim, B. (2007). The effect of tax rebates on consumption expenditures: Evidence from state tax rebates. *National Tax Journal*, 60(4):685–710.

Hoddinott, J. (2006). Shocks and their consequences across and within households in rural zimbabwe. *Journal of Development Studies*, 42(2):301–321.

Jalan, J. and Ravallion, M. (1999). Are the poor less well insured? evidence on vulnerability to income risk in rural china. *Journal of Development Economics*, 58(1):61–81.

Jappelli, T., Padula, M., and Pistaferri, L. (2008). A direct test of the buffer-stock model of saving. *Journal of the European Economic Association*, 6(6):1186–1210.

Jappelli, T. and Pistaferri, L. (2010). The consumption response to income changes. *Annual Review of Economics*, 2(1):479–506.

Johnson, D. S., Parker, J. A., and Souleles, N. S. (2006). Household expenditure and the income tax rebates of 2001. *American Economic Review*, 96(5):1589–1610.

Kadjo, D., Ricker-Gilbert, J., Abdoulaye, T., Shively, G., and Baco, M. N. (2018). Storage losses, liquidity constraints, and maize storage decisions in benin. *Agricultural Economics*, 49(4):435–454.

Kala, N. (2017). Learning , adaptation , and climate uncertainty : Evidence from indian agriculture.

Kanno, H., Sakurai, T., Shinjo, H., Miyazaki, H., Ishimoto, Y., Saeki, T., Umetsu, C., Sokotela, S., and Chiboola, M. (2013). Indigenous climate information and modern meteorological records in sinazongwe district, southern province, zambia. *Japan Agricultural Research Quarterly: JARQ*, 47(2):191–201.

Kazianga, H. and Udry, C. (2006). Consumption smoothing? livestock, insurance and drought in rural burkina faso. *Journal of Development Economics*, 79(2):413–446.

Kueng, L. (2014). Tax news: The response of household spending to changes in expected taxes. Technical report, National Bureau of Economic Research.

Luseno, W. K., McPeak, J. G., Barrett, C. B., Little, P. D., and Gebru, G. (2003). Assessing the value of climate forecast information for pastoralists: Evidence from southern ethiopia and northern kenya. *World development*, 31(9):1477–1494.

Lybbert, T. J., Barrett, C. B., McPeak, J. G., and Luseno, W. K. (2007). Bayesian herders: Updating of rainfall beliefs in response to external forecasts. *World Development*, 35(3):480–497.

Mertens, K. and Ravn, M. O. (2012). Empirical evidence on the aggregate effects of anticipated and unanticipated us tax policy shocks. *American Economic Journal: Economic Policy*, 4(2):145–81.

Miller, B. (2015). Does validity fall from the sky?observant farmers and the endogeneity of rainfall.

Miura, K., Kanno, H., and Sakurai, T. (2012). Shock and livestock transactions in rural zambia: a re-examination of the buffer stock hypothesis. *Japanese Journal of Rural Economics*, 14:20–34.

Parker, J. A., Souleles, N. S., Johnson, D. S., and McClelland, R. (2013). Consumer spending and the economic stimulus payments of 2008. *American Economic Review*, 103(6):2530–53.

Paxson, C. (1992). Using weather variability to estimate the response of savings to transitory income in thailand. *American Economic Review*, 82(1):15–33.

Rosenzweig, M. and Udry, C. R. (2013). Forecasting profitability. Technical report, National Bureau of Economic Research.

Shimono, H., Miyazaki, H., Shinjo, H., Kanno, H., and Sakurai, T. (2012). Do zambian smallholders choose the optimal sowing date for high maize productivity? *Tropical Agriculture and Development*, 56(2):62–70.

Skoufias, E. (1993). Seasonal labor utilization in agriculture: theory and evidence from agrarian households in india. *American Journal of Agricultural Economics*, 75(1):20–32.

Strauss, J. (1986). Does better nutrition raise farm productivity? *Journal of Political Economy*, 94(2):297–320.

Taraz, V. (2017). Adaptation to climate change: Historical evidence from the indian monsoon. *Environment and Development Economics*, 22(5):517–545.

Udry, C. (1995). Risk and saving in northern nigeria. *American Economic Review*, 85(5):1287–1300.

A Approximate solutions

A.1 Derivation of Equation (7)

If $c_2^*(c_1, I_1, \theta_2)$ is an interior solution, it is a solution to $u_2^{'}(c_2^*) = \frac{1+r_3}{1+\delta_3} E_2[u_3^{'}((1+r_3)(X_2(c_1) - c_2^*) + y_3)|I_1, \theta_2]$. Denote this equation as Equation (*). Then, the first-order condition with respect to c_1 can be written as

$$
\begin{aligned}
&u_1^{'}(c_1) + \frac{1}{1+\delta_2} E_1[\frac{\partial c_2^*(c_1, I_1, \theta_2)}{\partial c_1} u_2^{'}(c_2^*(c_1, I_1, \theta_2))|I_1] \\
&\quad - \frac{(1+r_2)(1+r_3)}{(1+\delta_2)(1+\delta_3)} E_1[u_3^{'}((1+r_3)(X_2(c_1) - c_2^*) + y_3)|I_1] \\
&\quad - \frac{1+r_3}{(1+\delta_2)(1+\delta_3)} E_1[\frac{\partial c_2^*(c_1, I_1, \theta_2)}{\partial c_1} u_3^{'}((1+r_3)(X_2(c_1) - c_2^*) + y_3)|I_1] \\
&\quad - \lambda_1 - E_1[\lambda_2((1+r_2) + \frac{\partial c_2^*(c_1, I_1, \theta_2)}{\partial c_1})|I_1] = 0
\end{aligned} \tag{14}
$$

Hence, the complication comes from conditional covariances Cov$(\frac{\partial c_2^*(c_1,I_1,\theta_2)}{\partial c_1}, u_2^{'}(c_2^*(c_1, I_1, \theta_2)))$ and Cov$(\frac{\partial c_2^*(c_1,I_1,\theta_2)}{\partial c_1}, u_3^{'}((1+r_3)(X_2(c_1) - c_2^*) + y_3))$. However, $\frac{\partial c_2^*(c_1,I_1,\theta_2)}{\partial c_1}$ does not depend on a random variable θ_2 with the standard preference assumptions. In fact, Section A.2 shows this under the assumption of Var$(\zeta_3^*|I_1, \theta_2) =$ Var$(\zeta_3^*|I_1)$ and CRRA preferences. Thus, $\frac{\partial c_2^*(c_1,I_1,\theta_2)}{\partial c_1}$ and marginal utilities are independent at least under these assumptions.

In addition, by taking expectations conditional on I_1 for both sides of Equation (*), we have

$$E_1[u_2^{'}(c_2^*(c_1, I_1, \theta_2))|I_1] = \frac{1+r_3}{1+\delta_3} E_1[u_3^{'}((1+r_3)(X_2(c_1) - c_2^*) + y_3)|I_1]$$

Using these, the second and forth terms of Equation (14) are cancelled out, and the third term can be expressed as $-\frac{1+r_2}{1+\delta_2} E_1[u_2^{'}(c_2^*)|I_1]$. Thus, Equation (14) reduces to

$$u_1^{'}(c_1) - \frac{1+r_2}{1+\delta_2} E_1[u_2^{'}(c_2^*)|I_1] - \lambda_1 - E_1[\lambda_2((1+r_2) + \frac{\partial c_2^*(c_1, I_1, \theta_2)}{\partial c_1})|I_1] = 0$$

c_2^* is assumed to be an interior solution to the period 2 problem, which implies $\lambda_2 = 0$ for sure. Thus, Equation (14) is re-written as $u_1^{'}(c_1) = \frac{1+r_2}{1+\delta_2} E_1[u_2^{'}(c_2^*)|I_1] + \lambda_1$, and the inter-temporal optimal consumption plan between periods 1 and 2 should satisfy

$$u_1^{'}(c_1) = \max[u_1^{'}(X_1), \ \ \frac{1+r_2}{1+\delta_2} E_1[u_2^{'}(c_2^*(c_1, I_2))|I_1]]$$

This corresponds to Equation 7.

A.2 Consumption and income innovations

Section 3.1 derived the Euler equations in a general form. In order to derive an exact relationship between changes in prediction toward harvest income and consumption innovations under the buffer-stock saving model with borrowing constraints, the assumption of constant relative risk aversion preferences (CRRA) is additionally imposed on the general model. Specifically, the model assumes that the instantaneous utility has the following form:

$$u_t = \begin{cases} \alpha_t \frac{c_t^{1-\rho}}{1-\rho} & if \;\; \rho > 0, \;\; \rho \neq 1 \\ \alpha_t \ln c_t & if \;\; \rho = 1 \end{cases}$$

in which ρ measures the relative risk aversion. Because the model with CRRA preferences does not yield the closed-form solutions of consumption, approximate solutions are derived following Blundell and Stoker (1999). It is easier to work with the expected available wealth, denoted by $\tilde{X}_t$, instead of actual cash-on-hand X_t. The ex-post identity regarding the life-time resources in Equation (3) can be reformulated as

$$c_1 + \frac{1}{1+r_2}c_2 + \frac{1}{(1+r_2)(1+r_3)}c_3 = \tilde{X}_1 + \frac{1}{(1+r_2)(1+r_3)}\zeta_3$$

where $\tilde{X}_1$ is the expected available wealth at period 1, that is $\tilde{X}_1 \equiv A_1 + y_1 + \frac{1}{1+r_2}y_2 + \frac{1}{(1+r_2)(1+r_3)}E_1[y_3|I_1]$ and ζ_3 is a forecast error from the vantage point of period 1, that is $\zeta_3 \equiv y_3 - E_1[y_3|I_1]$. The point to make is that the budget constraint is different period by period. When the farmer observes θ_2 at the start of period 2, the expected value of y_3 will be revised as $E_2[y_3|I_1,\theta_2] = E_1[y_3|\theta_1] + E_2[\zeta_3|I_1,\theta_2]$ and a remaining forecast error can be written as $\zeta_3^* = y_3 - E_1[y_3|\theta_1] - E_2[\zeta_3|I_1,\theta_2]$. The rational expectations assumption implies $E_1[\zeta_3|I_1] = E_2[\zeta_3^*|I_1,\theta_2] = 0$. Given these notations, the budget constraint in period 2 can be written as

$$c_2 + \frac{c_3}{1+r_3} = (1+r_2)(\tilde{X}_1 - c_1) + \frac{E_2(\zeta_3|I_1,\theta_2)}{1+r_3} + \frac{\zeta_3}{1+r_3} \equiv \tilde{X}_2 + \frac{\zeta_3}{1+r_3}$$

where $\tilde{X}_2 = (1+r_2)(\tilde{X}_1 - c_1) + \zeta_2^*$ with $\zeta_2^* = \frac{E_2[\zeta_3|I_1,\theta_2]}{1+r_3}$.

Using the defined $\tilde{X}_t$, the Euler equation in period 2 can be written as:

$$\alpha_2 c_2^{-\rho} = \frac{(1+r_3)^{1-\rho}}{1+\delta_3}\alpha_3(\tilde{X}_2 - c_2)^{-\rho}E_2[(\frac{\tilde{X}_2 - c_2}{\tilde{X}_2 - c_2 + \frac{\zeta_3^*}{1+r_3}})^{\rho}|I_1,\theta_2] + \lambda_2 \tag{15}$$

This equation implicitly defines c_2 as a function of the exogenous variables. However, there is no analytical solution for this consumption function. Following Blundell and Stoker (1999), the strategy here is to approximate the E_2 term in Equation (15) by a second-order Taylor expansion of the integrand around optimal consumption levels in a perfectly certain world without any borrowing constraints. By expressing the integrand as a percentage of initial available wealth $\tilde{X}_1$, the E_2 term is rewritten as:

$$E_2[(\frac{\Omega_3}{\Omega_3+\phi_3})^\rho] \tag{16}$$

in which $\Omega_3 = \frac{\tilde{X}_2-c_2}{\tilde{X}_1(1+r_2)}$ and $\phi_3 = \frac{\zeta_3^*}{\tilde{X}_1(1+r_2)(1+r_3)}$. Denote Ω_3^o and ϕ_3^o as the same expressions in a certain world without borrowing constraints. Since there is no uncertainty in y_3 in this alternative world, ϕ_3^o should be 0 with a probability of 1. Because of $E_2[\phi_3|I_1,\theta_2] = 0$ by assumption in the main setting, the second-order expansion of Equation (16) around the perfect certainty values $(\Omega_3,\phi_3) = (\Omega_3^o, 0)$ yields

$$E_2[(\frac{\Omega_3}{\Omega_3+\phi_3})^\rho|I_1,\theta_2] \approx 1+\frac{\rho(1+\rho)}{2}\frac{1}{(\Omega_3^o)^2}\sigma_{3|2}^2 \tag{17}$$

where $\sigma_{3|2}^2 \equiv \text{Var}(\phi_3) = \frac{\text{Var}[\zeta_3^*|I_1,\theta_2]}{(\tilde{X}_1(1+r_2)(1+r_3))^2}$ captures income risk relative to available wealth. In the certain world without any borrowing constraints, optimal consumption levels can be expressed as fixed shares of assets in each period:

$$\begin{aligned}
c_1^o &= \frac{1}{1+(1+r_2)^{\frac{1-\rho}{\rho}}(\frac{\alpha_2}{\alpha_1})^{\frac{1}{\rho}}(\frac{1}{1+\delta_2})^{\frac{1}{\rho}}[1+(\frac{\alpha_3}{\alpha_2})^{\frac{1}{\rho}}(\frac{1}{1+\delta_3})^{\frac{1}{\rho}}(1+r_3)^{\frac{1-\rho}{\rho}}]}\tilde{X}_1^o \equiv \omega_1^o\tilde{X}_1^o \\
c_2^o &= \frac{1}{1+(\frac{\alpha_3}{\alpha_2})^{\frac{1}{\rho}}(\frac{1}{1+\delta_3})^{\frac{1}{\rho}}(1+r_3)^{\frac{1-\rho}{\rho}}}\tilde{X}_2^o \equiv \omega_2^o\tilde{X}_2^o \\
c_3^o &= (1-\omega_2^o)(1+r_3)\tilde{X}_2^o
\end{aligned}$$

in which $\tilde{X}_1^o = A_1+y_1+\frac{1}{1+r_2}y_2+\frac{1}{(1+r_2)(1+r_3)}y_3$ and $\tilde{X}_2^o = (1+r_2)(\tilde{X}_1^o-c_1^o)$. Substituting these optimal solutions under a certain world into Ω_3^o yields

$$\Omega_3^o = \frac{\tilde{X}_2^o-c_2^o}{\tilde{X}_1^o(1+r_2)} = (1-\omega_1^o)(1-\omega_2^o)$$

Then, Equation (17) can be approximated as

$$E_2[(\frac{\Omega_3}{\Omega_3+\phi_3})^\rho] \approx 1+\frac{\rho(1+\rho)}{2}\frac{\sigma_{3|2}^2}{(1-\omega_1^o)^2(1-\omega_2^o)^2}$$

As a result, the Euler equation (15) can be expressed as

$$\begin{aligned}
\alpha_2 c_2^{-\rho} &\approx \frac{(1+r_3)^{1-\rho}}{1+\delta_3}\alpha_3(\tilde{X}_2-c_2)^{-\rho}(1+\frac{\rho(1+\rho)}{2}\frac{\sigma_{3|2}^2}{(1-\omega_1^o)^2(1-\omega_2^o)^2})+\lambda_2 \\
&= \frac{(1+r_3)^{1-\rho}}{1+\delta_3}\alpha_3^*(\tilde{X}_2-c_2)^{-\rho}+\lambda_2
\end{aligned}$$

where $\alpha_3^* = \alpha_3(1+\frac{\rho(1+\rho)}{2}\frac{\sigma_{3|2}^2}{(1-\omega_1^o)^2(1-\omega_2^o)^2})$. The main difference with the perfect certainty case is that marginal utilities from future consumption are adjusted by the variance of future income and wealth stock levels ($\sigma^2_{3|2}$). From this, the approximate solutions when borrowing constraints are not binding can be shown as:

$$\begin{aligned} c_2 &= \omega_2^*((1+r_2)(\tilde{X}_1 - c_1) + \zeta_2^*) \\ c_3 &= (1+r_3)(1-\omega_2^*)((1+r_2)(\tilde{X}_1 - c_1) + \zeta_2^*) + \zeta_3^* \end{aligned} \tag{18}$$

in which $\omega_2^* = \frac{(1+\delta_3)^{\frac{1}{\rho}} \alpha_2^{\frac{1}{\rho}}}{(1+\delta_3)^{\frac{1}{\rho}} (\alpha_2)^{\frac{1}{\rho}} + (1+r_3)^{\frac{1-\rho}{\rho}} (\alpha_3^*)^{\frac{1}{\rho}}}$. This suggests that the household adjusts for income risk by spending the fraction ω_2^* of available wealth in period 2. The relationship between consumption and income innovations can be derived from the Euler equation relating the second-period consumption to the third-period consumption. The Euler equation between periods 2 and 3 is

$$\frac{\alpha_2}{c_2^\rho} = \frac{1+r_3}{1+\delta_3} \alpha_3 E_2[\frac{1}{c_3^\rho} | I_1, \theta_2] + \lambda_2$$

Consider the case when borrowing constraints are not binding. Define the consumption innovation μ_3 as $\mu_3 \equiv (\frac{c_3}{c_2})^\rho \frac{\alpha_2}{\alpha_3} \frac{1+\delta_3}{1+r_3} = \frac{1}{1+\epsilon_3}$. Substituting the approximate solution c_3 in Equation (18) into this and rearranging,

$$\mu_3 \approx (\frac{c_3}{c_2})^\rho \frac{\alpha_2}{\alpha_3} \frac{1+\delta_3}{1+r_3} = (1 + \frac{\zeta_3^*}{(1+r_3)(\tilde{X}_2 - c_2)})^\rho (1 + \frac{1+\rho}{2} \frac{\sigma^2_{3|2}}{(1-\omega_1^o)^2 (1-\omega_2^o)^2})$$

Taking logs and using the approximation of $\ln(1+x) \approx x$ for a small x,

$$\triangle \ln c_3 \approx -\frac{1}{\rho} \ln(\frac{\alpha_2}{\alpha_3})(\frac{1+\delta_3}{1+r_3}) + \frac{\zeta_3^*}{(1+r_3)(\tilde{X}_2 - c_2)} + \frac{1+\rho}{2} \frac{\sigma^2_{3|2}}{(1-\omega_1^o)^2(1-\omega_2^o)^2} \tag{19}$$

in which $\triangle$ is the first-differencing operator. Note that ζ_3^* represents unexpected income shocks which actually happen in period 3.

If the borrowing constraint is binding in period 2, the growth in consumption between periods 2 and 3 is

$$\triangle \ln c_3 = \ln y_3 - \ln X_2$$

As for the maximization problem of period 1, the first-order condition, conditional on that the borrowing constraint is not binding in period 2, can be written as

$$\begin{aligned} \frac{\alpha_1}{c_1^\rho} = & \frac{\alpha_2}{1+\delta_2} (\omega_2^*)^{1-\rho} (1+r_2)^{1-\rho} (\tilde{X}_1 - c_1)^{-\rho} E_1[(\frac{\Omega_2}{\Omega_2 + \phi_2})^\rho] + \\ & \frac{\alpha_3}{(1+\delta_2)(1+\delta_3)} (1-\omega_2^*)^{1-\rho} (1+r_2)^{1-\rho} (1+r_3)^{1-\rho} (\tilde{X}_1 - c_1)^{-\rho} E_1[(\frac{\Omega_2}{\Omega_2 + \phi_2 + \frac{\phi_3}{1-\omega_2^*}})^\rho] + \lambda_1 \end{aligned} \tag{20}$$

in which $\Omega_2 = \frac{\tilde{X}_1 - c_1}{\tilde{X}_1}$ and $\phi_2 = \frac{\zeta_2^*}{\tilde{X}_1(1+r_2)}$. Note that $E_1[\phi_2|I_1] = 0$ by the rational expectations assumption. As before, the second-order Taylor expansion around $(\Omega_2, \phi_2) = (\Omega_2^o, 0)$ yields

$$E_1[(\frac{\Omega_2}{\Omega_2 + \phi_2})^\rho] \approx 1 + \frac{\rho(1+\rho)}{2}\frac{1}{(\Omega_2^o)^2}\sigma_{2|1}^2$$

and,

$$E_1[(\frac{\Omega_2}{\Omega_2 + \phi_2 + \frac{\phi_3}{1-\omega_2^*}})^\rho] \approx 1 + \frac{\rho(1+\rho)}{2}\frac{1}{(\Omega_1^o)^2}(\sigma_{2|1}^2 + \frac{\sigma_{3|2}^2}{(1-\omega_2^*)^2})$$

where $\sigma_{2|1}^2 \equiv \text{Var}(\phi_2) = \frac{\text{Var}(\zeta_2^*|I_1)}{(\tilde{X}_1(1+r_2))^2}$. The derivation builds on the assumption that the variance of ζ_3^* is not affected by ζ_2^* (and hence θ_2), that is $\text{Var}(\zeta_3^*|I_1, \theta_2) = \text{Var}(\zeta_3^*|I_1)$. Without this assumption, ω_2^* also depends on the updated ζ_2^*, which adds additional non-linearities to the approximation. Because $\Omega_2^o = \frac{\tilde{X}_1^o - c_1^o}{\tilde{X}_1^o} = (1 - \omega_1^o)$, the Euler equation can be rewritten as

$$\frac{\alpha_1}{c_1^\rho} = \frac{(1+r_2)^{1-\rho}}{1+\delta_2}(\omega_2^*)^{1-\rho}(\tilde{X}_1 - c_1)^{-\rho}\alpha_2^{**} + \frac{(1+r_2)^{1-\rho}(1+r_3)^{1-\rho}}{(1+\delta_2)(1+\delta_3)}(1-\omega_2^*)^{1-\rho}(\tilde{X}_1 - c_1)^{-\rho}\alpha_3^{**} + \lambda_1$$

in which $\alpha_2^{**} = \alpha_2(1 + \frac{\rho(1+\rho)}{2}\frac{1}{(1-\omega_1^o)^2}\sigma_{2|1}^2)$ and $\alpha_3^{**} = \alpha_3(1 + \frac{\rho(1+\rho)}{2}\frac{1}{(1-\omega_1^o)^2}(\sigma_{2|1}^2 + \frac{\sigma_{3|2}^2}{(1-\omega_2^*)^2}))$. Thus, if $\lambda_1 = 0$, we have an approximation solution of first-period consumption:

$$c_1 = \frac{1}{1+\Gamma}\tilde{X}_1 \equiv \omega_1^*\tilde{X}_1$$

where $\Gamma = \frac{(1+r_2)^{\frac{1-\rho}{\rho}}}{((1+\delta_2)\alpha_1)^{\frac{1}{\rho}}}[(\omega_2^*)^{1-\rho}\alpha_2^{**} + \frac{(1+r_3)^{1-\rho}}{1+\delta_3}(1-\omega_2^*)^{1-\rho}\alpha_3^{**}]^{\frac{1}{\rho}}$. On the other hand, if $\lambda_1 \neq 0$, $c_1 = X_1$.

In the case in which borrowing constraints are binding in period 2, it can be shown that the consumption function has the form of

$$c_1 = \frac{1}{(\frac{\alpha_2}{\alpha_1})^{\frac{1}{\rho}}(\frac{1+r_2}{1+\delta_2})^{\frac{1}{\rho}} + (1+r_2)}[(1+r_2)X_1 + y_2]$$

if borrowing constraints are not binding in period 1, and $c_1 = X_1$ if borrowing constraints are binding in this period.

The Euler equation between periods 1 and 2 has the form of $\frac{\alpha_1}{c_1^\rho} = \frac{1+r_2}{1+\delta_2}\alpha_2 E_1[\frac{1}{c_2^\rho}] + \lambda_1$. In the case of non-binding borrowing constraints in period 1, the consumption innovation μ_2 is defined as

$$\mu_2 \equiv \frac{c_2^\rho}{c_1^\rho}\frac{\alpha_1}{\alpha_2}(\frac{1+\delta_2}{1+r_2}) = \frac{1}{1+\epsilon_2}$$

Substituting Equations (18) and (20) generates

$$\mu_2 \approx (\frac{c_2}{c_1})^\rho \frac{\alpha_1}{\alpha_2}(\frac{1+\delta_2}{1+r_2}) = (1+\frac{\zeta_2^*}{(1+r_2)\tilde{X}_1 - c_1})^\rho(\omega_2^*)^\rho\Sigma$$

.[45] Taking logs and using the approximation of $\ln(1+x) \approx x$,

$$\triangle \ln c_2 \approx -\frac{1}{\rho}\ln(\frac{\alpha_1}{\alpha_2})(\frac{1+\delta_2}{1+r_2}) + \frac{\zeta_2^*}{(1+r_2)(1-\omega_1^*)\tilde{X}_1} + \ln(\omega_2^*) + \ln\Sigma \tag{21}$$

in which ω_1^* is the share of first-period consumption at the optimal allocation conditional on that borrowing constraints are not binding in period 2.

If the borrowing constraints are binding in period 1, then c_1 equals X_1, not $\tilde{X}_1$. In this case, when borrowing constraints are not binding in period 2, we have

$$\triangle \ln c_2 \approx \ln(\omega_2^*) + \ln(y_2 + \zeta_2^* + \frac{E_1[y_3|I_1]}{1+r_3}) - \ln(X_1)$$

On the other hand, c_2 equals $X_2 = y_2$ when the household faces a borrowing constraint. Then, the growth in consumption can be expressed as

$$\triangle \ln c_2 = \ln(y_2) - \ln(X_1)$$

[45] $\Sigma = (1+\frac{\alpha_3}{\alpha_2}\frac{(1+r_3)^{1-\rho}}{1+\delta_3}(\frac{1-\omega_2^*}{\omega_2^*})^{1-\rho})(1+\frac{\rho(1+\rho)}{2}\frac{\sigma_{2|1}^2}{(1-\omega_1^o)^2})(\omega_2^*)^{1-\rho}+\frac{\alpha_3}{\alpha_2}\frac{(1+r_3)^{1-\rho}}{1+\delta_3}(1-\omega_2^*)^{1-\rho}\frac{\rho(1+\rho)}{2}\frac{1}{(1-\omega_1^o)^2}\frac{\sigma_{3|2}^2}{(1-\omega_2^*)^2})$.

B Appendix figures

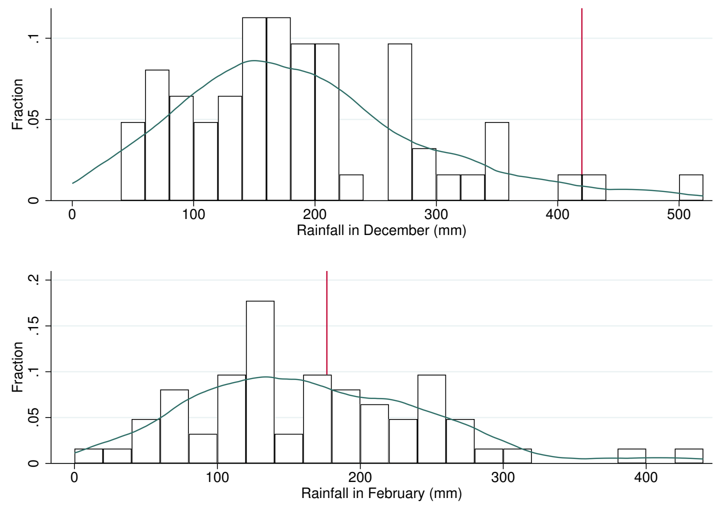

Figure B1: Distributions of historical rainfall at the Choma weather station

Notes: The figure shows the distributions of rainfall in December and February recorded by the Choma weather station between the crop years 1950/51 and 2011/12. The red lines show recorded monthly rainfall of the weather station in December 2007 (419.9 millimeters) and in February 2010 (176.6 millimeters).

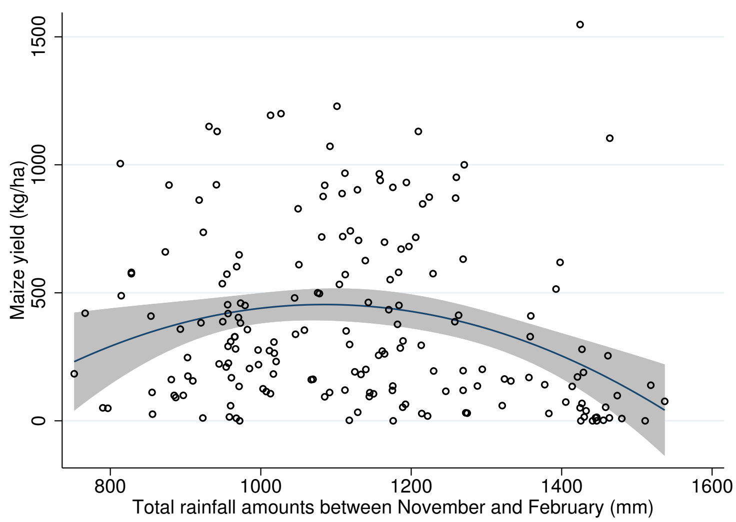

Figure B2: Unconditional scatter plot for the relationship between rainfall (November-February) and maize yield (March-June)

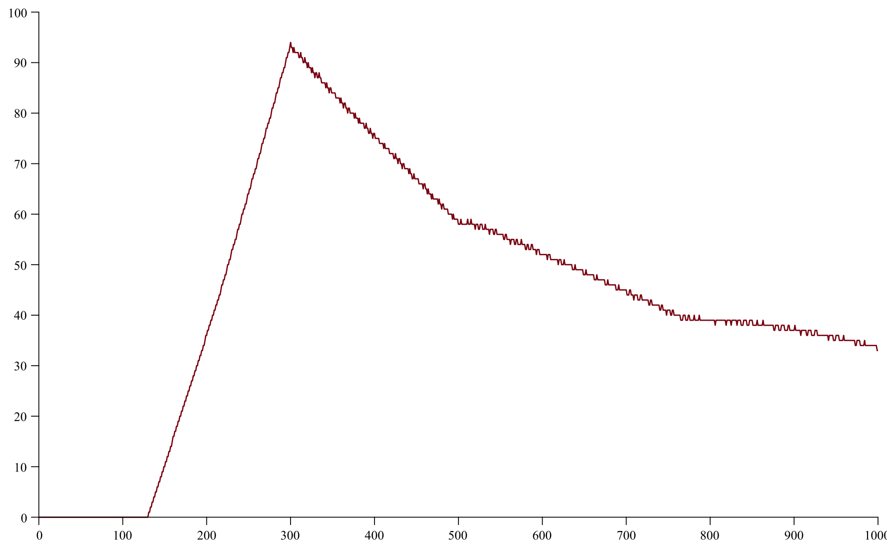

Figure B3: Changes in consumption by initial assets: quadratic utility

Notes: y-axis measures a difference in consumption between after the receipt of good news and after the receipt of bad news. x-axis measures initial asset levels.

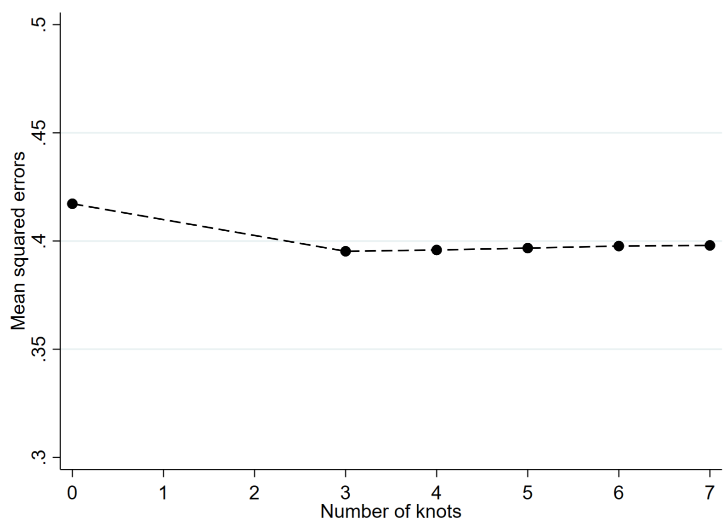

Figure B4: 5-fold cross-validation

Figure B5: Impacts of weekly rainfall by maize harvest of last year

Notes:The dashed and solid lines respectively show the 95% confidence intervals and estimated marginal effect.

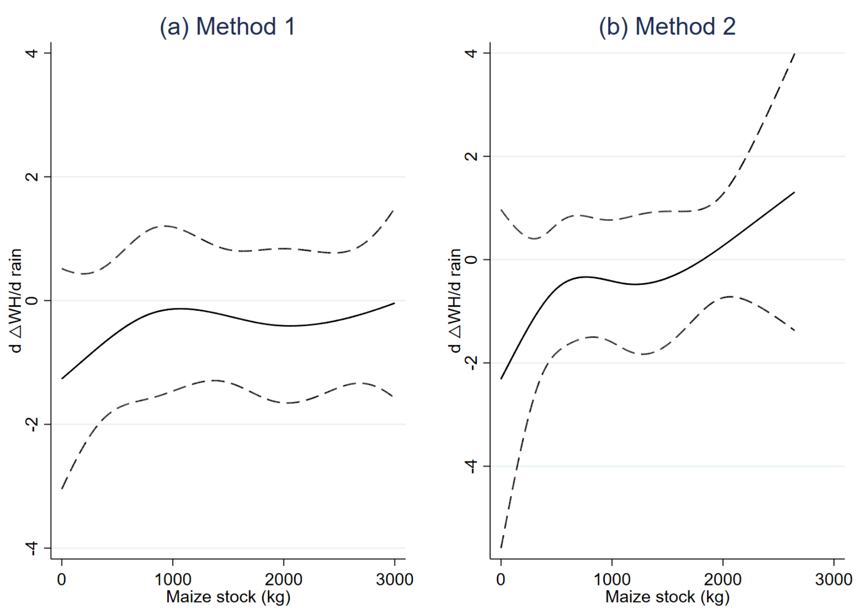

Figure B6: Impacts of weekly rainfall on working hours of male adults by maize stocks

Notes: The dashed and solid lines respectively show the 95% confidence intervals and estimated marginal effect.

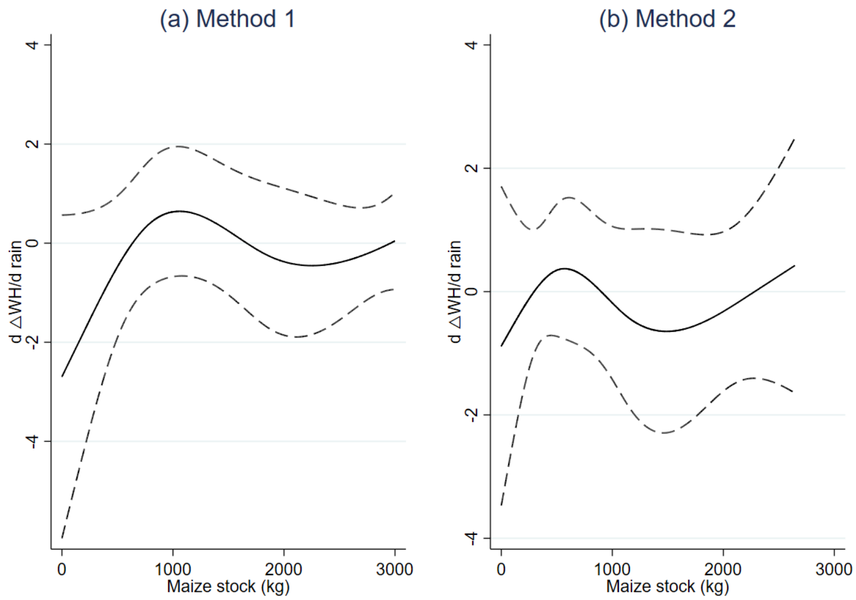

Figure B7: Impacts of weekly rainfall on working hours of female adults by maize stocks
Notes: The dashed and solid lines respectively show the 95% confidence intervals and estimated marginal effect.

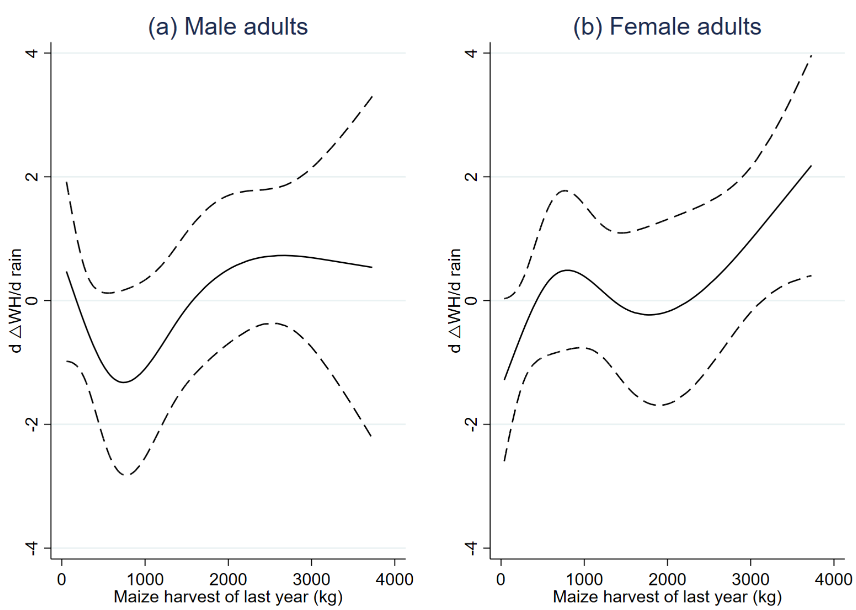

Figure B8: Impacts of weekly rainfall on working hours by previous maize harvests
Notes: The dashed and solid lines respectively show the 95% confidence intervals and estimated marginal effect.

C Appendix tables

Table C1: Adult equivalent scales

Age category	Adult equivalent scale
Child 0-3 year	0.36
Child 4-6 year	0.62
Child 7-9 year	0.78
Child 10-12 year	0.95
Adult female (age 13 and above)	1.00
Adult male (age 13 and above)	1.00

Source: Central Statisitcal Office (2011).

Table C2: Summary statistics for annual-level regressions

	Mean (SD)
Rainfall	
Rainfall in planting/weeding periods (100mm)	11.29
	(1.88)
Rainfall in November (100mm)	1.05
	(0.50)
Rainfall in December (100mm)	4.26
	(2.33)
Rainfall in January (100mm)	3.13
	(1.14)
Rainfall in February (100mm)	2.84
	(2.39)
Rainfall in March (100mm)	2.34
	(1.12)
Controls	
Field-level shocks	5.42
	(5.14)
Total sick days, adults	24.31
	(23.43)
Total sick days, children	5.20
	(9.27)
Land size (ha)	3.65
	(2.48)
Adult equivalent units	6.77
	(3.35)
Total number of survey days for March-June	125.05
	(21.21)
Observations	183

Table C3: Determinants of maize yield

	(1)	(2)
Rainfall in planting/weeding periods (100mm)	395.08***	276.72
	(144.65)	(190.63)
Rainfall in planting/weeding periods (100mm), squared	-17.97***	-13.99
	(6.41)	(8.35)
Field-level shocks	1.06	-0.34
	(4.84)	(6.15)
Land size (ha)	-43.59***	-48.06***
	(9.71)	(15.91)
Adult equivalent units	-4.56	8.14
	(7.44)	(15.86)
Total sick days, adults	1.02	2.03
	(0.93)	(2.00)
Total sick days, children	-0.63	0.46
	(1.65)	(1.82)
Total number of survey dates	5.02***	1.99
	(1.08)	(1.75)
HH FE	NO	YES
Dependent Variable Mean	379.28	379.28
Dependent Variable SD	335.98	335.98
R^2	0.25	0.55
N	183	183

Notes: The dependent variable is maize yield in kilograms per hectare. Robust standard errors clustered by household are in parentheses. *** denotes significance at 1% level, ** at 5% level, and * at 10% level.

Table C4: Rainfall impacts on maize yield by month

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Nov	Nov	Dec	Dec	Jan	Jan	Feb	Feb	Mar	Mar
Rainfall (100mm)	120.47***	118.26**	63.71	79.08	146.41***	133.28***	27.68	-12.03	46.75	32.18
	(35.96)	(44.72)	(55.82)	(64.19)	(27.59)	(44.16)	(16.95)	(24.12)	(44.17)	(55.03)
Cumulative rainfall	0.00	0.00	-10.22	-57.85	-83.14***	-83.83***	76.20**	-30.22	-22.00	-13.97
	(.)	(.)	(105.78)	(116.86)	(15.40)	(22.26)	(34.39)	(56.51)	(19.50)	(23.89)
Breusch-Pagan test (p-value)	0.78	0.37	0.61	0.58	0.90	0.26	0.71	0.19	0.51	0.37
HH FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Mean of rainfall	1.05	1.05	3.07	3.07	3.13	3.13	2.84	2.84	2.34	2.34
SD of rainfall	0.50	0.50	0.99	0.99	1.14	1.14	2.39	2.39	1.12	1.12
R^2	0.23	0.52	0.22	0.61	0.33	0.58	0.23	0.49	0.21	0.49
N	183	183	139	139	183	183	183	183	183	183

Notes: The dependent variable is maize yield in kilograms per hectare. Robust standard errors clustered by household are in parentheses. *** denotes significance at 1% level, ** at 5% level, and * at 10% level. Regressions include controls for field-level shocks, land size, adult equivalent units, total sick days of adults, total sick days of children, and the total number of days covered by the survey.

Table C5: Rainfall impacts on maize yield by month

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Nov	Nov	Dec	Dec	Jan	Jan	Feb	Feb	Mar	Mar
Rainfall (100mm)	120.47***	118.26**	-7.77	-7.77	138.91***	166.72***	-25.19	-59.60**	77.63*	57.18
	(35.96)	(44.72)	(91.55)	(91.55)	(44.72)	(51.81)	(21.47)	(25.59)	(41.75)	(52.54)
rainint	0.00	0.00	76.01	76.01	3.29	-21.02	31.87***	33.31***	-22.48**	-24.66**
	(.)	(.)	(67.63)	(67.63)	(13.59)	(16.02)	(8.60)	(10.86)	(9.45)	(11.35)
Cumulative rainfall	0.00	0.00	-248.73	-248.73	-96.68*	7.47	7.13	-72.34	71.02	89.73
	(.)	(.)	(215.06)	(215.06)	(53.27)	(70.47)	(39.26)	(55.01)	(47.54)	(57.70)
B-P test (p-value)	0.78	0.37	0.49	0.26	0.98	0.48	0.77	0.43	0.64	0.57
HH FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Mean of rainfall	1.05	1.05	3.07	3.07	3.13	3.13	2.84	2.84	2.34	2.34
Std. dev. of rainfall	0.50	0.50	0.99	0.99	1.14	1.14	2.39	2.39	1.12	1.12
R squared	0.23	0.52	0.22	0.22	0.33	0.59	0.27	0.53	0.23	0.51
N	183	183	139	139	183	183	183	183	183	183

Notes: The dependent variable is maize yield in kilograms per hectare. Robust standard errors clustered by household are in parentheses. *** denotes significance at 1% level, ** at 5% level, and * at 10% level. Regressions include controls for field-level shocks, land size, adult equivalent units, total sick days of adults, total sick days of children, and the total number of days covered by the survey.

Table C6: Summary statistics of explanatory variables

	Mean (SD)
Signals	
Rain (100mm), t-1	0.6177
	(0.7729)
Cumurative Rain (100mm) up to t-2	4.5893
	(4.4629)
Controls	
Field-level shock dummy, t-1	0.1507
	(0.3562)
$\triangle$ Total sick days adults, t, t-2	-0.0011
	(2.4563)
$\triangle$ Total sick days children (6 to 15) t, t-2	0.0194
	(1.1062)
$\triangle$ Total sick days children (0 to 5) t, t-2	0.0506
	(2.2318)
$\triangle$ Log maize price t, t-2	0.0270
	(0.1586)
$\triangle$ Survey dates t, t-2	-0.0277
	(0.5178)
Land size (ha), y	3.6833
	(2.5463)
Adult equivalent units, y	6.7154
	(3.3601)
Observations	3322

Notes: The sample is limited to the planting and weeding periods (November-March).

Table C7: Test of complementarity between consumption and leisure

	(1) Total	(2) Total	(3) Food	(4) Food
Rain (100mm), t-1	0.036***	0.094***	0.038***	0.078***
	(0.011)	(0.027)	(0.010)	(0.025)
Cumurative Rain (100mm) up to t-2	0.000	0.006	-0.002	0.002
	(0.003)	(0.004)	(0.003)	(0.004)
$\times$ Rain (100mm), t-1		-0.012**		-0.008*
		(0.005)		(0.004)
$\triangle$ Total working hours male adults t, t-2	0.000	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
$\triangle$ Total working hours female adults t, t-2	-0.000	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Calendar-month FE	YES	YES	YES	YES
R^2	0.08	0.08	0.10	0.10
N	2990	2990	2990	2990

Notes: Robust standard errors clustered by household in parentheses. *** denotes significance at 1% level, ** at 5% level, and * at 10% level. The dependent variable is the difference in the log of consumption per adult equivalent between weeks t and t-2. The estimation sample is limtied to the planting and weeding periods (November to March). The same set of controls as in Table 5 are included but not reported.