Feed the Future Innovation Lab for Food Security Policy

Research Paper 137 July 2019

DO CROP INCOME SHOCKS WIDEN DISPARITIES IN SMALLHOLDER AGRICULTURAL INVESTMENTS? PANEL SURVEY EVIDENCE FROM ZAMBIA

By

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Food Security Policy *Research Papers*

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Authors' Acknowledgment:

This study was made possible by the generous support of the American people provided to the Feed the Future Innovation Lab for Food Security Policy (FSP) through the United States Agency for International Development (USAID) under Cooperative Agreement No. AID-OAA-L-13-00001 (Zambia Buy-In). Additional funding support was also provided by the Swedish International Development Agency (SIDA), the USAID Mission to Zambia [grant number 611-A-00-11-00001-00], Michigan State University (MSU), and the U.S. Department of Agriculture (USDA) National Institute of Food and Agriculture and Michigan AgBioResearch [project number MICL02501]. The contents are the sole responsibility of the authors and do not necessarily reflect the views of USAID, USDA, the United States Government, SIDA, MSU, or Michigan AgBioResearch.

This paper is also published as IAPRI Working Paper No. 116, December 2016.

This study is made possible by the generous support of the American people through the United States Agency for International Development (USAID) under the Feed the Future initiative. The contents are the responsibility of the study authors and do not necessarily reflect the views of USAID or the United States Government

Published by the Department of Agricultural, Food, and Resource Economics, Michigan State University, Justin S. Morrill Hall of Agriculture, 446 West Circle Dr., Room 202, East Lansing, Michigan 48824, USA.

EXECUTIVE SUMMARY

We investigate whether the effects of negative crop income shocks in one season persist in subsequent seasons due to reductions in crop inputs. If bad seasons cause household cash constraints to bind, and this results in the scaling back of the next season's production, the next season's crop income is also compromised, potentially creating a poverty trap. Troublingly, households most susceptible to such a poverty trap mechanism are likely to be those that rely the most on own-farm production and have the fewest sources of liquidity—in other words, the poorest.

We use data from a three-wave (2001, 2004, and 2008), nationally-representative survey of smallholder farm households in Zambia to test for the effect of rainfall shocks—interacted with measures of household liquidity—on investment in maize production in the following season. We focus specifically on the ability (or inability) of farm households to invest in own-farm maize production in the form of mineral fertilizer use, improved seed use, and area allocated to maize. We use three liquidity measures: livestock, regular off-farm wage employment, and access to subsidies/loans for fertilizer purchase. A priori, we predict that the presence of such liquidity sources will protect maize investments from negative income shocks in the previous seasons.

These liquidity measures may be endogenous to the input decisions; we therefore use panel data methods and an instrumental variables/control function approach. Additionally, we test whether reduced maize inputs do indeed cause reduced maize income and, ultimately, total income.

Our results show that the effects of rainfall shocks in one agricultural season persist into the subsequent season in the form of reduced maize inputs. The estimated effect of reduced inputs on the following season's income, however, is modest. However, we must keep in mind that this estimated modest effect is the *average* effect across all sampled households. Whether this mechanism constitutes a poverty trap for a *particular* household depends on that household's overall reliance on farm production, as well as the distribution of rainfall shocks that it faces. For households that rely overwhelmingly on crops and typically experience multiple deficit periods in bad years, even two or three consecutively bad years could still pose a poverty trap.

Surprisingly, liquidity—as measured by livestock, salaried household members, and fertilizer subsidy access—does not increase households' ability to smooth inputs. It is important to note, however, that livestock and salaried household members may not be appropriate liquidity measures for the poorer households in the sample.

Given that inputs decrease as a result of (negative) rainfall shocks in previous seasons, and given the ability to observe rainfall shocks over Zambia at a fine scale, input divestment might be predicted, geographically, based on rainfall patterns. On a season-to-season basis, the allocation of resources through programs such as the Farmer Input Support Program (FISP) could be informed by these predictions of input divestment. That way, programs such as the FISP would pose less of a crowding-out threat to existing sources of fertilizer, and more effectively target the neediest communities each season.

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ACRONYMS

APE	Average Partial Effect
CFA	Control Function Approach
CRE	Correlated Random Effects
CSA	Census Supervisory Area
CSO	Central Statistics Office
FISP	Farmer Input Support Program
FSP	Fertilizer Support Program
FSRP	Food Security Research Project
IV	Instrumental Variable(s)
kg	kilogram
MACO	Ministry of Agriculture and Cooperatives
POLS	Pooled Ordinary Least Squares
SEA	Standard Enumeration Area
TAMSAT	Tropical Applications of Meteorology using SATellite data and ground-based observations

1. INTRODUCTION

Smallholder farm households face a myriad of potential negative income shocks, including weather shocks. In the wake of such a shock, we think of households as reallocating and transacting their many types of assets—including livestock, land, labor, and cash—with the dual objectives of maintaining minimum levels of current consumption and protecting prospects for future consumption. Very poor households face the unenviable task of choosing between present consumption and future production. Clearly, the inability of a household to maintain a subsistence level of consumption represents an immediate catastrophe. On the other hand, permitting shocks to compromise prospects for future consumption threatens a household in a different way: if such shocks occur with regularity, each event can slowly drag the household (deeper) into poverty. Households cutting back on production inputs in response to bad years may comprise a particular poverty trap mechanism.

The persistence of negative effects from past agricultural and weather shocks on consumption has been well documented (e.g., Dercon (2004); Dercon, Hoddinott, and Woldehanna (2005)). Negative shocks will obviously have lasting effects if they force households to liquidate savings—as this will make them less able to deal with future shocks. Severe shocks have also been shown to cause households to disinvest in human capital (e.g., Kinsey, Burger, and Gunning (1998)) and to draw down productive assets below critical levels.

Studies linking shocks to year-to-year own-farm investment and input use decisions, however, remain comparatively rare. The question merits attention for several reasons. First, the risky nature of farming means that many farm households—especially poorer ones— experience volatile income streams. Second, for the poorest rural households, own-farm production is often the primary income source. In the case of Zambia, Chapoto et al. (2011) note, "On average, non-poor households earn 74-77% of their income from off-farm activities compared to only 26-34% amongst the chronically poor households". For these households, how much cash and labor to invest in production is potentially the most important financial decision made each year. Finally, following negative income shocks, own-farm productivity the next season will be an important determinant of the speed of the household's recovery. If households reduce their agricultural inputs following negative shocks, this increases the likelihood that they will be even more cash-constrained in future seasons and therefore more likely to reduce inputs down the road. The troubling implication of such a mechanism is that, for these households, periodic shocks may perpetuate poverty.

Theory suggests that it is the cash-constrained households (i.e., those with less liquidity) that are susceptible to such a poverty trap mechanism (e.g., Kusunose and Lybbert 2014). Using household-level panel data from rural Zambia, we test for differential effects—by household liquidity level—of negative crop income shocks on input investments in own-farm production. We focus specifically on the ability (or inability) of farm households to invest in own-farm maize production in the form of mineral fertilizer use, improved seed use, and area allocated to maize. In this setting, maize is a staple food crop that is grown by the vast majority of households; it also serves to generate cash when needed. Among poorer farm families who are oriented toward producing sufficient food, maize production typically constitutes the single most important activity in terms of labor and value of farm earnings (Smale and Mason 2014).

Our concern is that poorer households may be responding to negative cash shocks by cutting back on cash investments in maize and diverting labor towards comparatively-labor-intensive-but-cash-sparing crops such as cassava. Generally, reduced investment in maize production may lead, in turn, to reductions in future household income, consumption, and savings (Smale and Mason 2014). In contrast, richer households are more likely to cover cash deficits via savings and/or credit, leaving investment in maize production unaffected. In other words, we hypothesize that liquidity serves the function of shielding household investments and future productivity from negative income shocks.

In this study, we use data from a three-wave (2001, 2004, and 2008), nationally-representative survey of smallholder farm households in Zambia to test for the effect of rainfall shocks—by themselves and also interacted with measures of household liquidity—on investment in maize production in the subsequent season. We use three liquidity measures: livestock, regular off- farm wage employment, and access to subsidies/loans for fertilizer purchase. These liquidity measures may be endogenous to the input decisions; we, therefore, use panel data methods and an instrumental variables/control function approach. Additionally, we test whether reduced maize inputs do indeed cause reduced maize income and, ultimately, total income.

Our results show that the effects of rainfall shocks in one agricultural season persist into the subsequent season in the form of reduced maize inputs. The estimated effect of reduced inputs on the following season's income, however, is modest. Surprisingly, liquidity—as measured by livestock, salaried household members, and fertilizer subsidy access—does not increase households' ability to smooth inputs. In the next section, we describe the salient features of the rural Zambian context. In section 3, we briefly explain our methodology. In section 4, we discuss our findings, and section 5 concludes with policy implications.

2. CONTEXT

Assets can, to some extent, predict the welfare trajectories of households. Theoretical models of asset dynamics suggest the existence of critical asset thresholds, above and below which household behavior bifurcates: above the threshold asset level, households' production activities are safe from random shocks; below the threshold, households begin converting productive assets into consumption, compromising future production. The existence of such critical asset thresholds has been documented in various contexts. In this study, we propose and test a specific mechanism through which asset holdings may predict Zambian smallholders' short-term responses (and, eventually, long-term vulnerability) to negative shocks. For a detailed description of the mechanism, we direct the reader to Kusunose and Lybbert (2014).

We characterize rural Zambia as a setting in which crop production provides the main source of income but is supplemented with off-farm wages and livestock production. Responses to shocks will primarily manifest themselves in the (re)allocation of household labor and cash between immediate consumption and investment in own-farm production. If a household's reserve of cash (or any fungible asset) is so low that the shock makes it cash constrained, we predict that it will disinvest from its own-farm production, meaning it will allocate its labor to sources of immediate income and, simultaneously, spend less cash on production. In the case of rural Zambia, labor may be allocated away from maize production to activities such as day labor and/or harvesting cassava. Assuming limited substitutability between labor and other inputs to maize production such as purchased seed and fertilizer, investments in these inputs may also decline. In contrast, households that are not constrained—either because they have sufficient fungible assets and/or because they can borrow—are not forced to disinvest, and can plant as usual.

There is some evidence for such a mechanism at work among Zambian smallholders. A field experiment conducted by Fink, Jack, and Masiye (2014) showed that easing credit constraints reduces households' participation in off-farm work during the hungry season. While this study did not directly address the effect of this labor-market participation on on-farm investments, the observation of workers laboring off their own farms during critical agricultural periods, combined with the assumption of limited substitutability between labor and other inputs, suggests that some households respond to shocks by generally divesting from agricultural production.

3. METHODS

If our proposed poverty trap mechanism exists, then we should observe among cash-constrained households that i) lower crop incomes cause fewer cash inputs to be invested in the subsequent season's crop, and ii) lower cash inputs in that (subsequent) year will result in lower crop income (in that subsequent year). The first hypothesis is more important from a theoretical standpoint, but testing the second hypothesis is also necessary to empirically establish our poverty trap mechanism. Of additional interest is the relative scale of the respective effects.

The most intuitive approach is to estimate the recursive system of equations

$$inputs_{t+1} = f(income_t, liquidity_t; \boldsymbol{X}) \quad (1)$$
$$income_t = g(rainfall_t, inputs_t; \boldsymbol{X}) \quad (2)$$

where *income* is maize income, total crop income, or total household income (we test all three). However, the three waves of our panel (2001, 2004, and 2008) are not back-to-back years, meaning that we are unable to observe the crop inputs in the season immediately following the (observed) income. Thus, the only hypothesis that can be tested directly is the second hypothesis, using equation 2 above. Moreover, in equation 1, the endogeneity of income and liquidity is problematic. And this endogeneity will contaminate equation 2 through the inputs variable.

These concerns, as well as the shape of our data, suggest the following alternative system:

$$inputs_{t+1} = f(rainfall_t, liquidity_t; \boldsymbol{X}) \quad (1')$$
$$income_t = g(rainfall_t, inputs_t; \boldsymbol{X}) \quad (2')$$

In the new equation 1 (1'), income in time *t* has been replaced with rainfall in *t*. The availability of rainfall data for all seasons—sampled or not—permits an indirect test of the key first hypothesis: Rainfall deficits, acting through reduced income, reduce the next season's inputs. Rainfall is an attractive proxy for income in that it is an important determinant, while also being exogenous to the household and thus uncorrelated with unobserved factors that may also influence investment behavior (Dell, Jones, and Olken 2014). It is important to note that Chapoto et al. (2011) and Mason et al. (2010) have previously documented insufficient and/or ill-timed rains as causing negative income shocks for smallholder farm households in Zambia (with Chapoto et al. 2011 using the same data as we use here).

3.1. Empirical Specification and Identification

3.1.1. Inputs Equation

Our primary goal is to identify the effect of liquidity on disrupting the link between rainfall in season *t* and crop inputs in season *t + 1*. We therefore require a specification that can test whether households with less access to sources of liquidity respond differently to rainfall hocks than those that are liquidity-unconstrained. Representing household *i*'s maize input (be it fertilizer, land, or improved seed) in season *t* as I_{it}, the Standard Enumeration Area (SEA)-level[1] severity of rainfall deficits as R_{vt}, measures of household liquidity (or sources of liquidity) as the vector L_{it}, and other covariates as the vector X_{it}, our general specification of the inputs equation is:

$$I_{it} = \beta_R R_{vt-1} + \beta_{RL}'(R_{vt-1}L_{it}) + \beta_X' X_{it} + c_i + \varepsilon_{it} \tag{3}$$

The inclusion of c_i makes explicit the existence of (time-constant) unobserved household-level heterogeneity that could be correlated with the observed covariates and bias our results. *Ceteris paribus*, we expect rainfall deficits to reduce cash investments in maize (β_R < 0). However, we predict that this response will be muted for households with sufficient liquidity, suggesting positive elements in the vector of coefficients β_{RL}. We use this same general specification for four maize inputs—basal fertilizer, top dressing fertilizer, improved maize seed (hybrid and improved, open-pollinated varieties), and area allocated to maize. We expect that the first three inputs will be affected directly by cash constraints. Maize area, we predict, will be indirectly affected by cash constraints. If it is a substitute for cash inputs, rainfall deficits could result in increases in area planted in maize (for example, if households have minimum subsistence levels of maize production that must be produced). If it is a complementary input, the area response should be similar to that predicted for the cash inputs.

We contend with two issues. First, our three liquidity variables—i) the number of household members with regular, salaried jobs, ii) livestock holdings, and iii) participation in the Fertilizer Support Program (FSP), a fertilizer subsidy program—are likely endogenous. (This, of course, renders our liquidity-rainfall interaction variables endogenous as well.) Second, both the liquidity variables and the input variables have high proportions of zero values. For example, pooling data from all three survey waves, 86% of households use no (mineral) basal fertilizer, 64% use no top dressing, and 63% do not use improved maize seed. We therefore estimate all four input equations using the Control Function Approach (CFA), a two-step instrumental-variables approach that can accommodate censoring in both the outcome variable of interest (inputs) and the endogenous explanatory variables (liquidity). The reader is directed to Wooldridge (2015) for additional detail and caveats of using this methodology. Additionally, we leverage the panel-nature of the data by using the correlated random effects (CRE) approach to control for time-constant unobserved heterogeneity that may be correlated with the observed covariates. For details on the CRE approach, the reader can refer to Chamberlain (1984) and Mundlak (1978).

Specifically, for each of the four input equations, in a series of first-stage CRE regressions, each of the three liquidity variables is regressed on the covariates **X** and at least as many instrument variables (IVs) as potentially endogenous liquidity terms (Rivers and Vuong 1988; Vella 1993). In the case of censored liquidity variables, this first-stage equation is a Tobit specification; in the case of binary liquidity variables, it is a probit specification. The IVs and other covariates are described in greater detail in the Variables section below. Then, in a series of second stage CRE Tobit regressions, each input is regressed on the lagged rainfall shocks, the three liquidity variables, control variables, and the generalized residuals from the three first stage regressions (Wooldridge 2015). The inclusion of these residuals allows us to simultaneously test and correct for the potentially endogenous nature of the liquidity variables.

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[1] A standard enumeration area typically contains about 150-200 households, or 2 to 4 villages. Multiple SEAs comprise a district.

3.1.2. Income Equation

We estimate the income equation (2') using the following log-linear specification:

$$lnY_{it} = \alpha_R R_{vt} + \alpha'_{vt} I_{it} + \alpha'_X \boldsymbol{X}_{it} + d_i + u_{it} \quad (4)$$

We use the CFA in combination with CRE pooled OLS (CFA-CRE POLS). In first -stage CRE Tobit regressions, we regress each of the four inputs on lagged rainfall, liquidity instruments, and the other exogenous control variables, which we describe below. In the second stage, we estimate the income equation above via CRE POLS, including as additional regressors the generalized residuals from the four input first stage regressions. Standard errors are bootstrapped. Because of the log-linear specification, all coefficients (multiplied by 100) can be interpreted as percentage changes in income (maize, crop, and total) due to one-unit increases in the inputs and rainfall shocks, other factors constant.

3.2. Data

The data on inputs, liquidity, income, and household characteristics were collected in 2001, 2004, and 2008 by the Central Statistical Office and Ministry of Agriculture and Cooperatives of Zambia in collaboration with Michigan State University and the Food Security Research Project. The 2001 survey data capture the 1999-2000 agricultural year (October-September), including the harvest and additional income (wages, livestock sales, crop marketing decisions, etc.) during the subsequent 2000- 2001 crop marketing year (May-April). Similarly, the 2004 survey captures the 2002-2003 agricultural year and 2003-2004 crop-marketing year; and the 2008 survey captures the 2006-2007 agricultural year and 2007-2008 crop-marketing year. These data are nationally representative of smallholder farm households (i.e., those cultivating less than 20 ha of land). Nine provinces and 70 districts are represented in the sample. These districts are further broken into 394 SEAs. As mentioned above, our rainfall data are matched to these household data at the SEA level. The sampling framework and survey instrument are described in greater detail in CSO/MACO/FSRP (2008).

This study is based on the subset of households that meet the dual criteria of being successfully interviewed in all three years, and having grown maize in all three years. Table 1 shows summary statistics of these households, by survey year. Of the 6,922 households sampled in 2001, 5,358 were successfully re-interviewed in 2004, and 4,286 were interviewed across all three years. Of these, 68% planted maize all three years. Our balanced panel of maize-growing households comprises 2,933 households across 199 SEAs. More detailed information about the sampling and attrition of households can be found in the data section of Mason, Jayne, and Mofya-Mukuka (2013).

For the rainfall shocks, we use dekadal (10-day period), geo-referenced data from Tropical Applications of Meteorology using SATellite and ground-based observations (TAMSAT) data (Grimes, Pardo-Igúzquiza, and Bonifacio 1999; Maidment et al. 2014; Milford and Dugdale 1990; Tarnavsky et al. 2014). The resolution of these data is $4km^2$.

3.3. Variables

3.3.1. Inputs

This study considers four maize inputs: basal fertilizer, top dressing fertilizer, improved seed, and land.[2] *Basal fertilizer* is the total amount, in kilograms (kg), of any mineral basal fertilizer applied to a household's maize crop. While there is some variation in the type of fertilizer used for this purpose, across the three seasons, over 95% of farmers applying basal fertilizer report using *Compound D* (N:P:K = 10:20:10). Therefore, this variable can effectively be thought of as the total amount of Compound D applied to maize in a season. Similarly, the vast majority (93%) of households that apply top dressing use urea; *top dressing* can be practically thought of as the total amount of urea, in kilograms, applied to maize. As mentioned above, the use of any mineral fertilizer is far from universal. Therefore, the sample means for fertilizer shown in Table 1 understate the amounts applied by fertilizer-using households.

Improved seed is the total amount (in kilograms) of purchased hybrid or improved open- pollinated varieties of maize seed. This variable includes all maize seed other than local seed, recycled hybrid seed, and seed of unknown/uncertain provenance. *Area* is the total area, in hectares, planted in maize. Table 1 shows summary statistics for these variables as well.

3.3.2. Rainfall Shocks

Following Chapoto et al. (2011), we use the number of 20-day periods during the growing season (November through March) with cumulative rainfall of less than 40 mm. This mea- sure partially captures the timing of rainfall throughout the season, as well as amounts. For example, as Table 1 shows, many households typically experience one 20-day period in which rainfall totals less than 40 mm; this is typically in November, the beginning of the rainy season when rainfall is generally less. However, if a household experiences three or more such intervals, it indicates lack of rain in periods when more rain is expected and needed by crops—for example, in late December and January. Thus, the higher number of deficit periods, the more likely it is that a household's crops are compromised.

3.3.3. Liquidity

We simultaneously test the effect of three types/sources of liquidity: animals owned, salaried household members, and FSP participation. *Animals owned* is measured in tropical livestock units and includes cattle (bulls, heifers, steers, cows, and calves), sheep, goats, pigs, and chickens. *Salaried members* is the number of household members in off-farm, non- agricultural jobs with regular salaries. These occupations include teachers, nurses, and civil servants. Note that this does not include wages for harvesting forest products. Unsurprisingly, most households have no such salaried members and those that do typically have just one (Table 1). Our choice of *salaried members* reflects our belief that due to high entry costs into such professions, it is more exogenous than, say, hours worked or total

[2] While labor is clearly an important input, measures of labor (such as the number of weedings and hired labor) showed so little variation that they did not permit estimation.

income. *FSP participation* is a binary variable that indicates whether a household acquired fertilizer through FSP.

Table 1. Summary Statistics

	Variable name	Description	2001	2004	2008
Maize inputs	*basal fertilizer*	total basal fertilizer applied to maize (kg)	56.84	60.76	88.28
			(157.65)	(176.00)	(271.55)
		% using	28.9	36.2	38.7
	top dressing	total top dressing applied to maize (kg)	58.33	62.47	90.78
			(176.46)	(176.52)	(267.75)
		% using	30.2	38.0	40.9
	improved seed	total improved maize seed (kg)	6.02	15.23	18.95
			(20.67)	(52.76)	(49.09)
		% using	20.2	40.6	45.0
	area	total area sown in maize (ha)	1.43	1.14	1.38
			(1.74)	(1.43)	(2.19)
Income	*maize income*	maize income (mill. ZMK)	0.55	0.97	1.57
			(1.07)	(2.07)	(3.63)
	crop income	all crop income (mill. ZMK)	0.85	1.71	2.33
			(1.40)	(2.82)	(5.46)
	total income	total income (mill. ZMK)	1.97	3.87	6.29
			(4.35)	(9.79)	(14.88)
Liquidity	*salaries*	household members with regular salaries	0.04	0.05	0.04
			(0.23)	(0.24)	(0.21)
	livestock	livestock (TLU)	2.56	4.88	4.96
			(7.09)	(22.16)	(15.21)
	FSP	FSP/FCP participation (bin.)	0.09	0.13	0.16
			(0.28)	(0.33)	(0.37)
Instruments	*allocated fertilizer*	district-level fertilizer allocation	39.53	44.62	46.15
		(kg/agricultural household)	(68.32)	(22.42)	(35.37)
	voted for president	ruling party won HH's constituency	0.93	0.29	0.61
		in last presidential election (bin.)	(0.25)	(0.46)	(0.49)
	district-level livestock	district-level mean of livestock (TLU)	1.75	3.83	4.25
			(1.25)	(3.88)	(3.86)
	settlement year	household's year of settlement in locality	1985.95	1985.95	1985.95
			(14.34)	(14.34)	(14.34)
	headman tie	head closely related to headman when	0.32	0.32	0.32
		household originally allocated land (bin.)	(0.47)	(0.47)	(0.47)
	local	head belongs to clan that originally	0.80	0.80	0.80
		settled area (bin.)	(0.40)	(0.40)	(0.40)
Covariates	*fertilizer price*	fertilizer price at point-of-purchase	733.98	1529.65	2113.81
		(ZMK/kg)	(98.43)	(185.77)	(356.19)
	maize price	prior-season maize price (ZMK/kg)	240.63	626.98	556.74
			(35.31)	(74.45)	(102.68)
	transportation cost	cost to transport 50kg of fertilizer (ZMK,		3533.20	12235.77
		mean of 2004 and 2008 used in analysis)		(20980.15)	(52166.60)
	head age	age of head	47.27	49.72	52.72
			(15.27)	(14.88)	(14.71)
	adults	adults 15-59 years of age	3.08	3.30	3.14
			(1.93)	(1.99)	(1.88)
	female head	female-headed (bin., as of 2008)			0.22
					(0.41)
	distance	distance to the nearest town	32.80		
		(km, as of 2001)	(21.27)		
	CSA-level credit	formal credit use	0.13	0.14	0.11
		(CSA-level mean used in analysis.)	(0.11)	(0.11)	(0.11)

Table 1, cont.

			2001	2004	2008
Rainfall shocks	*rain shocks, prior*	Rainfall shocks, prior season			
		% experiencing			
		no deficit periods	13.91	44.53	47.12
		1 deficit period	64.17	19.47	34.81
		2 deficit periods	15.92	11.29	17.70
		3 deficit periods	4.50	21.07	0.38
		4 or more deficit periods	1.50	3.65	0
	rain shocks, current	Rainfall shocks, current season			
		% experiencing			
		no deficit periods	12.62	20.93	59.32
		1 deficit period	55.20	10.67	33.41
		2 deficit periods	29.15	44.26	6.07
		3 deficit periods	3.03	23.32	10.60
		4 or more deficit periods	0	0.82	0.14

The FSP participation variable has a slightly different interpretation in the context of the 1999/2000 agricultural season: at that time, the FSP proper did not exist. For households in 1999/2000, the FSP variable captures fertilizer acquisition through the Fertilizer Credit Program, the fertilizer subsidy program that FSP replaced in 2002. See Mason, Jayne, and Mofya-Mukuka (2013) for in-depth descriptions of these programs. Finally, these three liquidity measures are interacted with the lagged rainfall shock variable described above.

Ideally, we would observe each of these three liquidity variables at the time of (or just before) the input acquisition decisions. Unfortunately, the surveys were designed so that two out of three—animals owned and salaried members—are observed immediately *following* the input decisions. Therefore, correlation between inputs and liquidity observed in the same survey wave may be spurious or, at worst, due to reverse causality. To gauge any such bias, we test for our key relationships using two second-best alternatives for the *animals owned* and *salaried members* variables. The first alternative is to use, for all three seasons, animals owned (salaried members) in 2000. While this does not mitigate the possibility of spurious correlation for observations in the first survey wave, for the input decisions made in 2002 (which appear in the 2004 survey round) and 2006 (which appear in 2008), the two liquidity variables are pre-determined. The second alternative is to use the liquidity variables observed in the preceding survey wave. That is, we explain input decisions in 2002 (2006) as a function of livestock in 2000 (2004). We do the same for salaried household members. Here, the drawbacks are that we lose the 1999 cross-section of input variables and, as with the previous alternative, the interpretation of the coefficient on liquidity-rainfall is awkward; here it must be interpreted as the effect of having an additional unit of liquidity two years prior to the input decision.

We obtain similar results across all three versions of liquidity measures. For this reason, we include and discuss only results from the original specification that uses the contemporaneous liquidity measures—that is, results estimated using the liquidity data from the same survey year as the input data (using all three survey years).

3.3.4. Income

Our three *income* variables are maize income, crop income, and total income. Maize income is the gross value of the household's maize harvest in a particular year. Similarly, crop income is the gross value of all crops harvested over the year. Total income is the household's gross income from all documented sources over the survey year. This includes crops, agricultural (wage) work, in-kind payments, and non-farm work, remittances, and business income.

3.3.5. Instrumental Variables and Other Exogenous Variables

The CFA, as applied to the inputs equations, relies on first-stage regressions of the suspected endogenous liquidity measures on the exogenous variables from the second-stage regression and the instrumental variables (which, by definition, are excluded from the second stage regression). Our excluded IVs are: *social capital* (whether the household is related to the headman of the village; whether it is considered *local*[3]; how long the household has resided in the village; the district-level mean of livestock holdings (excluding the household); the district-level administrative allocation of FSP fertilizer (in kilograms per agricultural household); and whether the household's constituency had voted for the winning candidate in the past presidential election. *A priori*, we believe that our measures of social capital influence all three liquidity measures (livestock levels, salaried household members, and FSP participation), while not directly influencing the level of maize inputs. Ruminants, for example, require land (or access to land), which is facilitated by being established in the community. Similarly, having extensive ties to the community and being considered a local family are likely to aid in obtaining salaried jobs. And social clout may facilitate access to government programs, such as FSP. Maize inputs, by contrast, require physical capital but this is plausibly independent of social capital. In using the district-level FSP fertilizer allocation and past presidential election outcome variables to explain FSP participation, we follow Mason and Ricker-Gilbert (2013).

We use as control variables the district-level prices of fertilizer, the district-level lagged producer price of maize (to proxy for the expected maize price), the gender of the household head, the reported cost of transporting home 50 kg of fertilizer from the closest point of purchase, the distance to the closest town, and the Census Supervisory Area (CSA) -level mean of credit use,[4] the age of the household head, and the number of working-age adults in the household. Of these, we treat the transportation cost, distance to the closest town, and the gender of the household head as time invariant.

[3] More precisely, local indicates that the household head belongs to the clan that originally settled the locality.
[4] This variable is computed as the mean (across the CSA) of a binary variable that indicates whether the household borrowed money from a formal institution.

4. RESULTS

4.1. Input Equations

Table 2 shows select results from the input regressions for basal fertilizer, top dressing, improved maize seed, and maize area—the first, second, third, and fourth columns, respectively. Specifically, the table shows the average partial effects of rainfall shocks on these inputs (specifically, the partial first derivative of the input level with respect to rainfall shocks), the effect that liquidity variables have on this rainfall effect (that is, partial derivatives of the rainfall effect with respect to liquidity—thus partial second derivatives), the effect of control variables (first derivatives), as well as the effect or correlation of the generalized residuals of the liquidity variables (also first derivatives).

Two general patterns emerge across all inputs. First, prior-season rainfall shocks negatively affect inputs, as expected. This is based on the significantly negative Average Partial Effects (APEs) of rainfall shocks, or $\frac{\partial I}{\partial R}$. The one exception is improved seed, which appears not to be affected by rainfall. The relative magnitude of the rainfall shock effect differs by input. The effect on area planted is estimated between -0.044 and -0.056 ha (3 to 4% of average maize area) per rainfall deficit period. The estimated effect of rainfall shocks on basal fertilizer application is between -3.6 and -4.4 kg per rainfall deficit period, or 5 to 6% of the sample mean; that for top dressing ranges between -3.2 and -4.2 kg (4 to 6% of the sample mean). Given that sampled households experience, on average, approximately 1 rainfall deficit period, the effect of rainfall shocks appears to be modest.

The second consistent pattern is that the estimated effect of FSP—calculated as the partial derivative of the rainfall effect with respect to FSP participation ($\frac{\partial^2 I}{\partial R \partial FSP}$)—is unexpectedly negative, and significantly so. The implication is that FSP participation *exacerbates* the reduction in maize inputs in response to rainfall deficit periods. We have no intuitive explanation as to why this would be the case, particularly in the case of basal fertilizer and top dressing. One lingering concern, however, is that the presence of an unobserved household- or region-level characteristic, not captured by the CREs, makes it more likely that a household receives FSP inputs *and* that it cuts back on maize inputs following shocks. Finally, the estimated effects of livestock and salaried household members are, on the whole, insignificant. However, these last results should be interpreted with caution. Recall that it was not possible to observe livestock and salaries just prior to planting time. Given our contemporaneous livestock and salary measures, the general insignificance and inconsistency (across specifications) of the estimated effects does not necessarily constitute a rejection of the hypothesized poverty trap mechanism.

To summarize, we find that rainfall shocks reduce fertilizer use and planted maize area, but not the use of improved maize seed. One explanation is that quality seed—while absolutely crucial—represents a small portion of the cash expenses, relative to the amounts spent on mineral fertilizer and labor, which, in turn, likely influences the area planted. Households may be cutting back proportionately on the relatively big expenses, but may not think to do so for seed. However, without a way to formally test the relative sizes of the effects across inputs, this discussion should be viewed as speculative.

Table 2. Determinants of Maize Inputs, Select Average Partial Effects

	basal fertilizer		top dressing		hybrid seed		area	
rain shocks, prior	-4.211	***	-3.753	***	-0.343		-0.044	***
	(1.305)		(1.300)		(0.293)		(0.011)	
salaries (second deriv.)	-9.427	**	-8.033	*	-0.948		0.028	
	(4.415)		(4.484)		(0.772)		(0.044)	
livestock (second deriv.)	-0.010		-0.042		-0.006		-0.002	*
	(0.116)		(0.109)		(0.016)		(0.001)	
FSP (second deriv.)	-18.318	***	-17.288	***	-2.446	***	-0.166	***
	(1.879)		(1.910)		(0.546)		(0.034)	
fertilizer price	0.004		0.005		0.006	***	-0.000	
	(0.004)		(0.004)		(0.001)		(0.000)	
maize price	-0.007		-0.013		-0.009	***	-0.000	***
	(0.014)		(0.014)		(0.003)		(0.000)	
head age	0.178		0.106		-0.026		0.005	***
	(0.219)		(0.216)		(0.046)		(0.002)	
adults	8.746	***	8.491	***	1.331	***	0.093	***
	(0.919)		(0.982)		(0.183)		(0.009)	
female head	-15.859	***	-14.209	***	-3.441	***	-0.185	***
	(3.096)		(3.046)		(0.693)		(0.022)	
transportation cost	-0.014	***	-0.015	***	-0.005	***	-0.000	***
	(0.002)		(0.002)		(0.001)		(0.000)	
distance	-0.547	***	-0.597	***	-0.044	***	-0.000	
	(0.063)		(0.065)		(0.013)		(0.000)	
CSA-level credit	22.049	*	23.874	*	-9.023	**	-0.139	
	(13.179)		(13.296)		(3.539)		(0.114)	
residual, salaries	5.727	***	5.335	***	0.781	**	-0.008	
	(1.756)		(1.814)		(0.350)		(0.020)	
residual, livestock	0.293		0.328		0.022		0.004	
	(0.333)		(0.338)		(0.043)		(0.004)	
residual, FSP	51.963	***	51.560	***	6.235	***	0.279	***
	(2.825)		(2.818)		(0.669)		(0.036)	
Wald Chi-sq. statistic	539.34		542.34		436.28		656.16	

Notes:
All APEs, unless otherwise noted, are first derivatives.
Standard errors in parentheses, clustered at household level, obtained by bootstrap.
* p<.1; ** p<.05; *** p<0.01

4.2. Income Equations

Table 3 shows results from the regressions for maize income, crop income, and total income. Two inputs significantly predict maize, crop, and total income: top dressing and maize area. A one-hectare increase in maize area increases maize income by 60% (or approximately 600,000 Zambian Kwacha (ZMK), given the sample mean of maize income) and crop income by 20% (330,000 ZMK). And a one-kilogram increase in top dressing (urea, for nearly all households) increases maize income by 0.2% (or approximately 2,000 ZMK). Combined with results from the input equations above, this implies that rainfall shocks are transmitted to income in subsequent seasons in the form of reduced maize area and top dressing. Simple first-order approximations of the input effects of each rainfall shock on maize income are 2.6% via area reductions[5] and 0.6% via reduced top dressing.[6] A crude estimate of the total effect of a single rainfall shock on income the following season is 3.2%. These percentage effects are approximately halved when we consider the effect of rainfall shocks on total income, rather than maize income.

Our inputs analysis above rests on the assumption that rainfall shocks over a season will diminish maize (crop, total) income from that season. This is, after all, our hypothesized pathway by which lagged rainfall shocks reduce maize inputs. It is therefore surprising that our analysis here does not bear this out. We find no discernible relationship between current-season rainfall shocks and income. This, combined with the findings above, would seem to imply that rainfall shocks in a particular season do *not* affect the income from that (same) season, but still cause divestments in the *following* season's crop. If inputs and income were estimated as functions of the same set of rainfall shocks, this would constitute a major, troubling, inconsistency in our findings. Recall, however, that our income equations are estimated using rainfall shocks over the agricultural seasons 1999/2000, 2002/2003, and 2006/2006; whereas the input equations are functions of rainfall shocks in the 1998/1999, 2001/2002, and 2005/2006 seasons. While there is clearly variation in rainfall across regions, it is dwarfed by the variation across time. Using only three seasons to estimate rainfall effects is likely to introduce *small sample* bias, a concern that may be relevant for both sets of estimates.

[5] -0.044 ha x 60% maize income/ ha = 2.6% change in maize income.

[6] -3.2 kg x 0.2% maize income / kg = 0.64% change in maize income.

Table 3. Determinants of Maize, Crop, and Total Income

	(ln) maize income		(ln) crop income		(ln) total income	
rain shocks, current	0.005		-0.004		0.004	
	(0.014)		(0.014)		(0.018)	
basal fertilizer	-0.001		-0.000		0.000	
	(0.000)		(0.000)		(0.000)	
top dressing	0.002	***	0.001	***	0.001	***
	(0.000)		(0.000)		(0.000)	
improved seed	-0.001		-0.001	*	0.001	
	(0.001)		(0.001)		(0.001)	
area	0.620	***	0.205	***	0.383	***
	(0.073)		(0.064)		(0.089)	
fertilizer price	0.000	*	0.000		0.000	
	(0.000)		(0.000)		(0.000)	
maize price	0.000	***	0.000	***	0.000	**
	(0.000)		(0.000)		(0.000)	
transportation cost	-0.000		-0.000	***	-0.000	
	(0.000)		(0.000)		(0.000)	
head age	0.001		0.003		-0.001	
	(0.003)		(0.003)		(0.003)	
adults	0.031	***	0.087	***	0.106	***
	(0.011)		(0.011)		(0.014)	
female head	-0.138	***	-0.287	***	-0.278	***
	(0.032)		(0.035)		(0.040)	
distance	-0.001		0.001	**	-0.001	
	(0.001)		(0.001)		(0.001)	
CSA-level credit	0.093		0.391	***	0.553	***
	(0.121)		(0.117)		(0.156)	
residual, basal fert.	0.000	**	0.000	*	0.000	
	(0.000)		(0.000)		(0.000)	
residual, top dress.	0.000		0.000		0.000	
	(0.000)		(0.000)		(0.000)	
residual, seed	0.001	***	0.001	***	0.000	*
	(0.000)		(0.000)		(0.000)	
residual, area	-0.255	***	0.083		-0.207	**
	(0.066)		(0.064)		(0.086)	
Observations	8479		8536		8577	
Chi-sq. statistic, regression	3608.45		4495.68		4201.83	
Partial Chi-sq. stat., inputs	112.65	***	47.87	***	75.37	***

NOTES: * p<.1; ** p<.05; *** p<0.01.

Standard errors in parentheses, clustered at household level, obtained by bootstrap.

5. CONCLUSIONS AND POLICY IMPLICATIONS

We find evidence of a poverty trap mechanism in which rainfall shocks cause households to disinvest from staple crops. Using nationally representative panel data on smallholder farm households in Zambia, we first test for the relationship between prior-season rainfall and inputs, and next between inputs and income. From the first set of tests, we find that households reduce maize area, basal fertilizer, and top dressing in response to rainfall deficits from the previous season. Results from the second set of tests, however, do not provide evidence for our hypothesized pathway—rainfall shocks tightening household budgets.

Keeping this caveat in mind, we combine our findings from the two sets of tests and calculate a simple first-order approximation of the effect of rainfall shocks on income, as a result of input divestment. With each rainfall shock, following-season maize income falls by approximately 3%. Given that the average number of rainfall deficit periods experienced by households is 1.2, the estimated divestment effect is modest. Liquidity—measured here in terms of livestock, salaried household members, and access to fertilizer subsidies—does not appear to counteract this effect. However, we place less confidence in this last result since two out of three liquidity variables were measured with error, and since there are likely to be other important (but unobservable) sources of liquidity.

In summary, the effect of a bad season persists in the form of a modest reduction in inputs for the following season's crop. The presumed relationship is via reduced income, although this does not appear in our data. Given that the typical Zambian farm household draws income from non-agricultural activities as well as farm production, it is not surprising that the average household shows only a modest response to bad harvests. The key word here is average. Whether this mechanism constitutes a poverty trap for a particular household depends on that household's overall reliance on farm production, as well as the distribution of rainfall shocks that it faces. For households with non-farm income-generating activities, a bad rainfall year may not influence the following season's production decisions at all. Similarly, if rainfall patterns are random across seasons (i.e., not autocorrelated) and if the household can expect to have the (sample) average number of rainfall deficit dekads each year (approximately 1.2) then input reductions following bad years will likely be compensated by increased inputs (and production) in relatively good years. However, for households that rely overwhelmingly on crops and typically experience multiple deficit periods in bad years, even two or three consecutively bad years could pose a poverty trap. Given that the hallmark characteristic of climate change is increased variance in weather patterns (i.e., more extreme events), such households warrant extra attention, as they may be a harbinger of things to come.

When taken together, our findings point to three courses of action. Unsurprisingly, the first two speak to the need for more empirical analysis. First, there is a need to implement similar studies by household *subsamples*. We find here significantly negative effects on investments arising from rainfall shocks, using the entire sample of smallholders. Within smallholders, however, there is a wide range of households. Given the theoretical possibility of critical asset thresholds, future vulnerability analysis should test for responses, by group. Theory suggests that the severity of divestment would be even greater for the poorest households. If policies are to be targeted to the neediest, it is imperative that research focus particularly on the poorest households, rather than the average household.

Second, this analysis—with its non-intuitive result regarding the role of liquidity—highlights the need to think about meaningful markers of liquidity *among the poorest*. Our counter-intuitive results—that liquidity exacerbates divestment in seasons following bad harvests—is driven by the responses of households that happen to have *any* livestock, salaried household members, and/or access to the FSP, because these are the households that showed variation in these data. The poor, by typically having zero livestock and salaried members, showed little to no variation. That is, our measures of liquidity were such that the responses of the richer households disproportionately drove our findings with respect to the effects of liquidity. However, it is precisely the poorer households with which we are more concerned. This highlights the need to find markers of liquidity that would vary, even when considering the poorer households in the sample.

The third recommendation pertains to policy. This and previous studies imply that rainfall patterns matter. If, in fact, rainfall deficit periods cause significant input divestment, and we find the effect to be even greater for the poorest segments of the population, programs such as the FSP (now the Farmer Input Support Program, FISP) could consider dynamically targeting the areas that are likely to see the most divestment. The availability of high-resolution dekadal rainfall records means that it is possible to identify potential regions that experience back-to-back years with poor rainfall. Input subsidies might be targeted to those regions; such a dynamic formula, articulated ex ante, might increase the efficacy of a limited budget, while lowering the possibility of crowding out commercial fertilizer purchases.

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