Do crop income shocks widen disparities in smallholder agricultural investments? Panel survey evidence from Zambia

Yoko Kusunose, Solomon Tembo, Nicole M. Mason[1]

PRELIMINARY DRAFT: PLEASE DO NOT CITE.

Selected Paper prepared for presentation at the 2015 Agricultural & Applied Economics Association and Western Agricultural Economics Association Annual Meeting, San Francisco, CA, July 26-28

[1] Yoko Kusunose: Dept. of Agricultural Economics, University of Kentucky, Kentucky (yoko.kusunose@uky.edu); Solomon Tembo: Indaba Agricultural Policy Research Institute, Lusaka, Zambia (solomon.tembo@iapri.org.zm); Nicole M. Mason: Dept. of Agricultural Food and Resource Economics, Michigan State University, Michigan (masonn@msu.edu).

1. Introduction

In the wake of an income shock, a household will reallocate and transact its many types of assets—including livestock, land, labor, and cash—with the dual objectives of maintaining a minimum level of current consumption and protecting its prospects for future consumption. 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. Poorer households, it appears, are not able to perfectly smooth present consumption; nor are they able to fully protect future consumption. For these households, the effects of 'bad' seasons may be transmitted into the future via depleted assets and the diversion of resources from the most remunerative activities.

The persistence of negative effects from past agricultural and weather shocks on consumption has been well documented (e.g. Dercon et al. 2005, Dercon 2004). 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 et al. 1998) and to draw down productive assets below critical levels. Studies linking shocks to year-to-year own-farm investment 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 (page 16)." For these households, how much cash and labor to invest in production is potentially the most important financial decisions 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.

Theory suggests that differences in liquidity and/or credit access will give rise to qualitatively different investment responses to shocks. That is, following negative shocks, cash-constrained households may have to reduce own-farm investments, exacerbating future-season cash constraints. At the same time, cash-unconstrained households may invest as usual, or even increase investments if input prices (for example, labor costs) fall as a result. The troubling implication of such a mechanism is that periodic shocks may perpetuate poverty for one class of households, while another class is able to survive unscathed, or even thrive, following harvest shocks, thus widening the income gap between cash-constrained and unconstrained households.

Using household-level panel data from rural Zambia, we test for differential effects--by household liquidity level--of negative crop income shocks on 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 the area of the largest maize field, hybrid seed use, mineral fertilizer use, and the number of weedings. In rural Zambia, maize is a staple food crop that is grown by the vast majority of households and 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. In the context of rural Zambia, some households may respond 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, in turn, lead to reductions in future household income, consumption, and savings (Smale and Mason 2014). Still other households may be able to cover cash deficits via savings and/or credit, leaving investment in maize production unaffected. In other words, we hypothesize that liquidity will shield household investments and future productivity from negative income shocks.

In this study, we use two consecutive years of data (2010/2011 and 2011/2012) from a nationally-representative study of rural livelihoods in Zambia and test for the effect of household liquidity—interacted with rainfall shocks—on season-to-season changes in inputs to maize production. Because liquidity can come from various sources, we use three liquidity measures: livestock (excluding cattle), regular off-farm wage employment, and access to lending agencies. Our covariates include access to input subsidies. Liquidity measures and subsidy measures may be endogenous to the input decision; we therefore use two-stage least squares estimation and three-stage least squares estimation. Our instruments include village-level medians of distance variables (the closest livestock marketing area and the closest basic school), village-level means (land holdings and number of credit sources available to households), the educational attainment of households, district-level past allocations of inputs from the subsidy program, and district-level past presidential election outcomes.

Our results lend weak support for our hypothesis. Sources of regular off-farm wages reduce downward fluctuations in the area planted, although we are not able to conclude the same for mineral fertilizer and hybrid maize seed. And as expected, past receipt of hybrid maize seed subsidies also buffers hybrid maize seed use from negative income shocks. Finally, changes in area, hybrid seed, and fertilizer are positively correlated, lending support to our assumptions that the inputs decisions are inter-dependent and that there is little substitutability between the inputs.

One exception is the number of weedings--this is negatively correlated with hybrid seed use and fertilizer use, suggesting that households may compensate for lack of cash by increasing on-farm labor effort. However, given our data limitations, we do not interpret the weakness of our results as a rejection of our model of liquidity and coping, but rather as an illustration of the need to test the hypothesis with longer panels of data and the stronger empirical methods that such data would permit.

2. Conceptual approach and empirical context

This study lies at the intersection of four major areas of inquiry: poverty traps, asset dynamics, credit constraints and input demand. Underlying the first three branches of literature is typically a model of intertemporal utility maximization (e.g. Deaton 1991), where utility comes from consumption in each period. Generally speaking, this literature asks about the behavior of households following income shocks, where the household's choice variables are consumption, investment, and savings.

The literature on asset dynamics and resultant poverty traps has been most commonly motivated and illustrated using the example of livestock acquisition and liquidation. Models suggest the existence of critical asset thresholds above and below which household response behavior bifurcates; the existence of such a threshold is motivated by technological economies of scale (e.g. Carter and Barrett 2006), lack of access to credit and insurance, and greater risk aversion on the part of low-asset households (e.g. Lybbert and McPeak 2012). Empirical studies based on pastoral communities in Zimbabwe (Hoddinott, 2006), Northern Kenya (Lybbert and McPeak 2012), and Burkina Faso (Carter and Lybbert, 2012) suggest that the coping behavior of households nearing critical minimum asset levels does indeed differ from those safely above it.

Adato, Carter, and May (2006) define assets more generally, and test for a critical threshold in the South African context. By estimating the marginal expenditure contribution of various income sources and forms of physical and human capital, the authors are able to identify a critical asset index level, below which households are trapped in low-expenditure equilibrium.

Clearly, assets can help predict the welfare trajectories of households. In this study, we propose and test a specific mechanism through which assets may translate into vulnerability for Zambian smallholders. 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. Following Kusunose and Lybbert (2014), we focus on land, household labor, and cash as the primary assets. Livestock, while important for many--but far from all--households, is treated as a form of fungible savings. Land is only rarely bought or sold, and household labor may be allocated, on a season-by-season basis, to own-farm production or off-farm work. Hence asset responses to shocks will primarily manifest themselves in the allocation of household labor and cash between immediate consumption and investment in own-farm production.

As in the classic asset dynamics model, there may exist critical thresholds at which investment behavior bifurcates. Kusunose and Lybbert (2014) show that the response behavior of a household can depend on its cash reserves and/or access to credit. If a household's reserve of cash (or any fungible asset) is so low that an income shock makes it cash constrained, 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 their model, this outcome is driven by: (i) limited substitutability of cash, land, and labor in agricultural production; (ii) the interaction of cash-constrained and cash-unconstrained households through endogenous input prices; and (iii) production risk. Intuitively, if a household finds that its cash resources (or access to credit) are insufficient to support a certainty equivalent minimum efficient production level, it will re-allocate its cash toward immediate consumption, and its labor toward activities with immediate (and/or less risky) returns.

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. Thus, in such a model, a household's response to income shocks may be predicted by whether a negative shock causes its cash constraint to bind.

The model above predicts that liquidity-constrained households will be more likely to respond to negative income shocks by seeking off-farm work and, simultaneously, divesting from own-farm production. The former response to distress has received far more attention than the latter: Kochar (1999) demonstrates the importance of off-farm work as a coping strategy in response to weather shocks based on observations from the ICRISAT villages in India. In Zambia, too, temporary off-farm income opportunities exist and agricultural households periodically rely on these. A field experiment conducted by Fink et al. (2014) in select rural villages shows that easing credit constraints reduces households' participation in off-farm work during the 'hungry season.' While neither study addresses the effect of this labor-market participation on other on-farm investments, the observation of workers leaving farms during critical agricultural periods, combined with the assumption of limited substitutability between labor and other inputs, suggests a general divestment from own agricultural production.

Divestment from own production as a coping response *per se* has received relatively little attention, despite the high degree of exposure to production risk that many rural households in Africa still face, and in spite of the perennial emphasis placed on increasing agricultural productivity in the development policies of many African countries. Moreover, given periodic 'bad seasons,' the mechanism described above can ensnare cash-constrained households in a poverty trap: reduced investment in maize production is likely to lead to reductions in future household income, consumption, and savings (Smale and Mason 2014). This, in turn, makes it more likely that a household is cash constrained in future periods.

Empirical work by Dercon et al. (2005) in a relatively similar context--regions of Ethiopia that practice sedentary agriculture--suggests that drought and other negative agricultural income shocks can negatively affect consumption several seasons into the future. Additionally, the authors find that these lasting negative effects are stronger for households with smaller land holdings. Their findings are consistent with our hypothesis that the cash-constrained are more likely than the cash-unconstrained to compromise their own agricultural production in subsequent seasons in response to a negative shock.

Our study uses observational data and instrumental variables regressions to approximate an experiment in which a cross-section of households is 'treated' with income reductions of varying degrees; hence the cash constraints for a portion of households are made to bind. For obvious reasons, such an experiment has and never will be undertaken. However, conceptually similar 'reverse' experiments--those in which households are randomly awarded input vouchers, subsidies, and/or opportunities to access credit--have their own extensive literature. Of greatest relevance to this study are those that examine the effect of easing credit constraints on cash inputs to agricultural production, namely higher-yielding variety (HYV) seeds and mineral fertilizer. Empirical evidence suggests that the use (or non-use) of such purchased inputs is the result of many factors in addition to having insufficient liquidity. A randomized control trial study in Mozambique by Carter et al. (2014) suggests that subsidies increase fertilizer use primarily through learning/experimentation, rather than by relaxing liquidity constraints. But in other contexts--for example, where farmers are already adequately familiar with and desire such inputs, including in Zambia--lack of liquidity may still pose a hurdle to optimal fertilizer use. Duflo et al. (2011) show through a randomized control trial in Western Kenya that even farmers who fully intend to apply (and who have past experience in applying) fertilizer to their maize crops can fail to do so if they overestimate their ability to set aside the requisite cash until the window for dressing their crops. Mathenge et al. (2015) estimate the effect of off-farm earnings on input intensification by maize-growing smallholders in Kenya; their work suggests a complex relationship between the type of off-farm work (farm v. non-farm), the productivity potential of the farm, and the labor costs of the inputs. Their work underscores the importance of considering household labor constraints in addition to liquidity constraints, and how the two constraints are inter-dependent.

3. Methods

We hypothesize that negative income shocks in one season differentially affect households' investments in the following season's maize crop, to the extent that such shocks can suddenly cause cash constraints to bind for some households, but not others. According to our model, these newly cash-constrained households will cut back on all maize inputs, but cash-unconstrained households will maintain or may even increase all maize inputs in response to negative shocks. Therefore, we require a specification that can test whether poorer households—

specifically those most likely to be nudged by a negative income shock from ‘unconstrained’ to ‘constrained’—respond differently to income shocks compared to richer households.

In rural Zambia, common causes of income shocks include HIV-related mortality and morbidity, pest infestations (e.g., army worms) and, of course, insufficient or ill-timed rainfall (e.g. Chapoto et al. 2011, Mason et al. 2010). Here, we use regional rainfall shocks as a proxy for household-level income shocks. Rainfall is an attractive proxy in that it is an important determinant of household income while being exogenous to the household and thus uncorrelated with unobserved household-level characteristics that may also influence investment behavior (Dell et al. 2014). Following Chapoto et al. (2011), we measure rainfall shocks as the number of 20-day periods during the growing season that experienced less than 40 mm of cumulative rainfall.

Representing the change in maize investment of household *i* from one year to the next as ΔI_i, regional rainfall shocks as R_v, household liquidity as L_i, and other covariates as $\boldsymbol{X_i}$ and $\boldsymbol{x_i}$, we propose the following general model:

$$\Delta I_i = \beta_R R_v + \beta_{RL} R_v L_i + \beta_L L_i + \boldsymbol{\beta_{RX}}' R_v \boldsymbol{X_i} + \boldsymbol{\beta_x}' \boldsymbol{x_i} + \epsilon_i \qquad (1)$$

Ceteris paribus, we expect rainfall deficits to induce reductions in maize investments.[2] However, we predict that this response will be muted for households with 'sufficient' liquidity, suggesting a positive β_{RL} (Equation 2).

$$\frac{\partial \Delta I_i}{\partial R_v} = \beta_R + \beta_{RL} L_i + \boldsymbol{\beta_{RX}}' X_i \quad (2)$$

[2] One exception is the number of weedings. If rainfall deficits in season *t-1* induce the cash-constrained households to seek agricultural work in lieu of tending their own fields in time *t*, the wage for agricultural labor could fall, causing non-cash-constrained households to increase their weeding efforts via (now cheaper) hired labor. It is possible that this could induce increases in the use of other inputs by these non-constrained households (via the income effect), but we predict that this secondary effect would be small.

The covariate vector $\boldsymbol{X}$ includes the dummy variables indicating the agro-ecological zone, the farm-gate price of maize grain, the price of hybrid maize seed, the price of mineral fertilizer, and the local wage for agricultural labor. These input and output prices are from the 2010/11 marketing year, one year prior to the rainfall shocks. Higher input prices may make households more sensitive (and responsive) to negative income shocks; we therefore expect the coefficients on input prices interacted with rainfall shocks to be negative. The effect of higher maize grain prices cannot be clearly predicted. For net maize selling households, we expect higher maize grain prices, when interacted with rainfall shocks, to have a positive effect. However, the majority of smallholders in Zambia are autarkic or net buyers of maize. For example in 2007/08, an average-to-slightly-above-average maize production year, 49% were net buyers, 23% neither bought nor sold maize (i.e., were autarkic), and 28% were net sellers (CSO/MACO/FSRP 2008). In 2011/12, a bumper maize harvest year, 28% were net buyers, 30% were autarkic, and 42% were net sellers (CSO/MAL/IAPRI 2012). Finally, the vector $\boldsymbol{x}$ includes agro-ecological zone dummies. This vector is not interacted with rainfall to allow for the possibility of unobservable zone-specific factors to cause households to change their input use.

3.1 Data

The data are drawn mainly from the 2012 Rural Agricultural Livelihoods Survey (RALS), a nationally representative survey of smallholder farm households in Zambia.[3] RALS was conducted in June/July 2012 by the Indaba Agricultural Policy Research Institute in collaboration with the Central Statistical Office and the Ministry of Agriculture and Livestock. A total of 8,839 households from 442 standard enumeration areas (SEAs) were interviewed for

[3] In Zambia, smallholder households are defined as those cultivating less than 20 hectares of land.

RALS.[4] (See IAPRI (2012) for further details on the RALS sample design and survey instrument.) The main RALS questionnaire collected detailed information on households' farm and off-farm activities during the 2010/11 agricultural year.[5] In addition, 1,684 of the RALS households (approximately four maize-growing households per SEA) were randomly selected and administered a supplemental "largest maize field survey" to collect information about input use and management practices on their largest maize field during the 2011/12 agricultural year. Similar information was collected for all 8,839 RALS households for the 2010/11 agricultural year for all cropped fields. We use in the analysis data on the largest maize field cultivated in the 2010/11 and 2011/12 agricultural seasons from the 1,684 randomly selected households that were administered both the main RALS instrument and the largest maize field survey. In this sense, we have panel data and are able to construct the dependent variable dependent variable ΔI. But because ΔI is observed just once for all households, and because the explanatory variables are available for only 2010/2011, we are not able to use panel data methods to control for time-invariant unobserved heterogeneity.

In addition, we use dekadal (10-day period), geo-referenced rainfall data from Tropical Applications of Meteorology using SATellite data (TAMSAT) (Tarnavsky et al. 2013; Maidment et al. 2013; Grimes, Pardo-Igúzquiza, and Bonifacio 1999; Milford and Dugdale 1990). While the analysis itself relies only on rainfall data over the 2010/11 growing season, we take advantage of the fact that these data extend as far back as 1983 to verify that the 40 mm threshold described above does indeed indicate an anomalously dry period. Finally, the resolution of these data is 4km^2 corresponding to SEAs, generating sufficient variation across observations.

---

[4] An SEA is the most disaggregated geographic unit in the dataset and typically contains 150-200 households or 2-4 villages.
[5] In Zambia, the agricultural year runs from October through September.

3.2 Variables

Inputs

Four types of inputs are considered for the dependent variable: (i) land--specifically, the largest contiguous area planted in maize (i.e. the size of the largest maize field); (ii) the total quantity of hybrid maize seed sown on the largest maize field; (iii) the total (mineral) nutrient nitrogen applied on this field;[6] and (iv) the number of weedings completed on the field. For each input, the change in investment (ΔI_i) is the difference in input levels between the 2011/12 and 2010/11 agricultural seasons. In other words, we generate our dependent variables by comparing input levels on households' largest maize fields for the two agricultural seasons. Households generally use the same field across the two years, precluding concerns about changing field characteristics. As expected, many households do not change their input levels across the two years. However, as we show in the summary statistics in table 1, there is sufficient fluctuation in input levels to warrant this investigation.

Rainfall shocks

Given that we proxy negative income shocks with rainfall deficits, it is crucial that there be a strong correlation between household income and the rainfall measure. Given our data, we are not able to directly verify this correlation. However, using a correlated random effects model on a nationally-representative panel (2001-2008) of Zambian households, Chapoto et al. (2011) find a significantly negative effect of rainfall deficits on household income.[7] As mentioned above, we use here the same rainfall shock variable as Chapoto et al.: the number of 20-day periods

---

[6] We are able to aggregate across various mineral fertilizer products by converting to total nutrient nitrogen.
[7] Households were interviewed in 2001, 2004, and 2008 over the seven-year period.

between November and March in which cumulative rainfall is less than 40mm.[8] This measure partially captures the timing of rainfall throughout the season, as well as amounts. For example, as table 1 shows, many households experience one 20-day period in which rainfall totals less than 40mm--this is typically in November, the beginning of the rainy season when rainfall is generally not as heavy. 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 the number of deficit periods, the more likely it is that a household's crops are compromised.

Liquidity

Though equation 1 above represents household liquidity with just one variable, in our empirical specifications we simultaneously test the effects of multiple liquidity measures: (i) livestock owned, (ii) the number of household members with regular, salaried jobs, and (iii) the household's own perception of its access to credit sources. We include all three measures because rural Zambian households differ widely in their livelihood activities--and therefore in their sources of wealth and liquidity--and because each of the sources is distinct in how it generates cash.

The livestock variable is measured in tropical livestock units (TLU) and includes the number of sheep, goats, and pigs owned by the household in April of 2011. Cattle are excluded; though cattle represent wealth, they are not a good measure of liquidity *per se* because they are comparatively less fungible. A household's livestock, thus defined, captures a commonly used form of savings and liquidity. Sixty percent of households owned at least one sheep, goat, or pig, although the summary statistics in table 2 show only the average TLUs for each agro-ecological

[8] These periods 'overlap' in that each 20-day interval starts every ten days, or dekad, throughout the growing season. Thus this rainfall deficit measure could conceivably be as high as fifteen, although this would be highly improbable.

zone. We include a household's number of regular off-farm, non-agricultural income sources because this represents access to a regular stream of cash. For this variable, we count the number of household members holding a non-agricultural, salaried job at any point between May and October of 2011, the period between the 2010/11 harvest and before the land preparation and planting of the 2011/12 season (16.1% of households have at least one such member.) In contrast to these above two measures, our third measure--a household's credit access--is a qualitatively distinct liquidity measure in that using credit entails risk of default. As Karlan et al. (2014) note, this risk component may make credit a more costly source of liquidity. We measure a household's credit access as the number of credit sources from which the household believes it could borrow money (36% of households report at least one source).[9]

The Farmer Input Support Program

An important explanatory variable is household participation in the Farmer Input Support Program (FISP), a government subsidy program for fertilizer and hybrid maize seed. Included in our specifications is a dummy variable indicating whether the household acquired fertilizer and/or seed in 2010 through the FISP. This FISP "participation" variable is treated in the same manner as the liquidity variables above. See Mason et al. (2013) for detailed information on FISP.

3.3 Specification Issues and Estimation

Two-stage least squares and two-stage Generalized Method of Moments estimation

The liquidity measures and FISP variables may be correlated with unobserved household traits affecting its season-to-season input decisions. We therefore test the effect of liquidity on the

[9] The question was asked of the survey respondent and was worded as, "Between October 2010 and now, would any member of this HH be given a loan/credit from *XYZ* if they applied for it?", where enumerators listed various local lending agencies for 'XYZ.'

sensitivity of investments to rainfall shocks using two-stage least squares regression and Generalized Method of Moments (GMM) estimation. For livestock owned, we use the community-level mean of landholdings (where the household itself is excluded), distance to the closest livestock marketing point and distance to the closest dip tank; for the number of household members with regular, salaried jobs, we use the household's distance to the closest primary school, its distance to the electrical grid, and the educational attainment of the household head; and for the household's level of perceived credit access, we use the community-level mean of households' potential sources of credit (again, where the household itself is excluded). Access to FISP subsidies may also be endogenous; we therefore follow Mason and Ricker-Gilbert (2013) and use as instruments the district-level administrative allocation of FISP fertilizer and maize seed, and past election outcomes in the household's constituency. Note, however, that the mechanics of two-stage least squares regression are such that all endogenous variables are effectively regressed onto all of the exogenous variables, including the instruments. We cluster errors by SEA. Table 2 below shows the full list of variables and provides a description for each.

Three-stage least squares estimation

Another prediction of Kusunose and Lybbert's (2014) model is that land, hybrid seed, mineral fertilizer, and weeding effort are complements; that is, it predicts that 'divesting' households will reduce all four inputs, while 'investing' households will maintain or even increase all four. To address this hypothesis, we use three-stage least squares regression and treat the four input decisions as a system of decisions made simultaneously. Estimation via three-stage least squares is useful in two ways: it increases the efficiency of our estimates (if all individual equations are correctly specified), and it allows for correlation between the four input decisions. The first two stages--effectively the equation-by-equation two-stage least squares above--address the endogeneity issue, while the third stage comprises feasible generalized least squares (FGLS) regression using residuals from the previous stage to increase the efficiency of the parameter estimates. Importantly, we are able to use the contemporaneous correlation matrix from the third stage FGLS step to 'test' whether the inputs are correlated.[10] Because the k,j^{th} element in this matrix is the mean of the residuals from each household's input k equation multiplied with the residuals from its input j equation, it captures the correlation of the input decisions induced by unobservable factors. Here, unobserved factors could include income shocks not captured by the rainfall deficit variable. Given the context of this study, we assume that these pair-wise correlations primarily reflect the inter-dependent nature of the input decisions to income shocks, both observed and unobserved.

4. Results

Endogeneity of liquidity and FISP variables

For each input equation, we test the endogeneity of the liquidity and FISP variables. The test statistic is the difference in Hansen-Sargan statistics between a specification in which the suspectedly endogenous variables are treated as exogenous and one in which they are treated as endogenous.[11] It is akin to a Hausman test adjusted for heteroskedasticity. For the (change in) area equation, this statistic is 8.700 (p=0.3682; for the fertilizer equation, it is 11.384 (p=0.1809); for the hybrid maize seed equation, it is 4.424 (p=0.8170); and for the weeding equation, it is 7.822 (p=0.4511). Based on these statistics, we fail to reject the null hypotheses that the liquidity and FISP variables are exogenous. It is not surprising that the exogeneity of the liquidity and

[10] We are not able to *formally* test the significance of the elements, hence the quotation marks.
[11] For a more complete description of this and other test statistics, we refer the reader to the help file for the user-written stata command ivreg2.

FISP variables cannot be ruled out, given that the dependent variables are *changes* in inputs, rather than *levels* of inputs. However, as table 5 shows, our parameter estimates from the instrumental-variables specifications differ dramatically from those produced using ordinary least squares (OLS), possibly indicating endogenous variables, weak instruments or both.

Validity of instruments

We gauge the validity of our instrumental variables using first-stage regression results as well as tests of overidentifying restrictions. Table 3 summarizes first-stage regression results for each of the eight endogenous terms in each equation. These include the partial R-squared, the Angrist-Pischke R-squared, the F statistic from a joint significance test of the excluded instruments, the Sanderson-Windmeijer (SW) F statistic, and the Angrist-Pischke (AP) F statistic. For all eight endogenous variables, the R-squared values are low. Based on the (univariate) F-test of excluded instruments, we are able to reject the null hypothesis that the coefficients on the excluded coefficients are jointly zero. However, the SW and AP *multivariate* F tests indicate that the variables *livestock*, *FISP* and *shock x FISP* likely suffer from weak instruments. Though Stock and Yogo's (2005) critical F values are for the case of homoskedastic errors, they provide an approximate benchmark. For example, the critical values (for the case of a single endogenous regressor) for 5% and 10% maximal bias are 21.40 and 11.42, respectively. For the abovementioned three variables, the Angrist-Pischke F statistics are approximately one order of magnitude smaller than these benchmark values, suggesting weak instruments.

Table 4 shows statistics from our tests of overidentifying restrictions. The null hypothesis in Hansen’s J test is that the instruments are uncorrelated with the error term. In the case of Anderson-Rubin test, the null hypothesis is that the coefficients on the endogenous regressors are jointly zero in the structural equation—i.e. that the variation of the endogenous regressors is fully represented by the exogenous variables. Based on these tests, we fail to reject the overidentifying restrictions. One exception, however, is the restriction for the *weedings* equation, based on the Anderson-Rubin test (p=0.0041). Taken together, we conclude that our instruments are weak in the case of three variables: *livestock*, *FISP* and *shock x FISP*.

Two-stage least squares, two-stage GMM, and three-stage least squares results

Table 5 shows, for all four input equations, the two-stage least squares (2SLS), two-stage GMM, and three-stage least squares (3SLS) results, as well as those from OLS, which are included for comparison. As mentioned above, the OLS results differ dramatically from the 2SLS and two-stage GMM results, most likely reflecting a combination of endogenous regressors and weak instruments. We restrict our attention to the instrumental variables estimation results. The 2SLS, two-stage GMM, and 3SLS parameter estimates are similar, though the standard errors cannot be compared between the 2SLS and GMM methods and the 3SLS method, as errors were not clustered in the latter. Given the hypothesis that sources of liquidity and access to the FISP program will buffer production input decisions from negative shocks, we expect positive coefficients on the interaction terms *shock x credit*, *shock x TLUs*, *shock x wages*, and *shock x FISP*. We also expect that higher input prices will make households more responsive to negative shocks (input prices interacted with shocks will have a negative effect.

The estimated effects for all four equations are generally weak. A few results, however, stand out. The coefficients on *shock x TLUs* are significantly positive in two of the area specifications (2SLS and GMM), suggesting that livestock can indeed crop production after bad harvests. Surprisingly, however, this same relationship is not borne out for hybrid seed and fertilizer, precisely the two inputs that require cash. In the *weeding* equations, the coefficients on *shock x credit* are significantly negative. As we discuss below, the effect of liquidity constraints on weeding effort is likely to be more complicated than that on, say, fertilizer, since weeding does not necessarily require cash and may even serve as a substitute for cash inputs.

Having more regular earners of non-agricultural income in the household--irrespective of rainfall shocks--appears to induce increases in fertilizer use. Surprisingly, having participated in the FISP program makes households more likely to reduce fertilizer use, regardless of rainfall shocks. Interpretation of these findings is complicated by the fact that all of the variation in these variables comes from the cross-section, rather than over time. Finally, FISP participation--through subsidized maize seed and/or fertilizer has--no discernible effect on the sensitivity of hybrid seed use and fertilizer use to income shocks. This last result must be interpreted with caution, however, given that the variable *shock x FISP* suffered from weak instruments.

Inter-dependence of input decisions

If the rainfall shocks cause cash constraints to bind for poor households, then our model predicts that this subset of the sample will reduce all four inputs, as households in this group will allocate more of their cash to consumption and more of their labor to off-farm work. On the other hand, households with 'sufficient' liquidity may increase some or all inputs. Even if these households increase the number of weedings (if, for example, labor becomes cheaper due to the newly available labor), our assumption of limited substitutability between inputs implies that other input levels will not decrease as a result. Hence regardless of whether households are cash-constrained we expect positive pair-wise correlation between all four inputs, or positive signs on the off-diagonal elements of the contemporaneous correlation matrix used in the 3SLS estimation (table 6). As expected, cultivated area, hybrid maize seed, and mineral fertilizer show such a relationship. Weeding effort, however, appears to be a substitute for area, hybrid maize seed, and fertilizer. This may be capturing a scenario in which some household members--such as those who are unable to sell their labor off-farm--simply work harder on-farm to compensate for the decrease in cash inputs.

5. Conclusions

This study uses a nationally-representative panel of data on rural Zambian households to test the hypothesis, developed in Kusunose and Lybbert (2014), that liquidity-constrained households will respond to income shortfalls in a qualitatively distinct manner from households with sufficient liquidity. Specifically, it posits that, for some households, a negative income shock will cause cash constraints to bind, forcing the sale of labor off-farm (away from on-farm production) and reductions in cash inputs to production. Households with 'sufficient' liquidity, on the other hand, would not show such a response. Given that the poorest rural households in Zambia rely heavily on on-farm production, such a 'divestment' response--while completely rational--could constitute one specific mechanism that keeps poor households poor.

Testing this hypothesis is complicated by the fact that sources of liquidity take may forms, that liquidity may be endogenous to the input decision, and that we are not able to distinguish, *a priori*, 'liquidity-constrained' from 'liquidity-unconstrained' households. However, if true, we would expect that, on average, having more sources of liquidity would buffer investment decisions from negative income shocks. We therefore estimate season-to-season changes in levels of maize inputs--land, hybrid seed, mineral fertilizer, and weeding effort--as functions of rainfall deficits and liquidity, where liquidity is instrumented. We find limited support of our hypothesis. For example, households with more livestock are less likely to reduce their maize plot sizes in response to a bad prior season. Interestingly, however, this buffering effect is not observed for hybrid seed and fertilizer, precisely the two inputs that require cash. The contemporaneous correlation matrix used in three-stage least squares estimation supports the hypothesis of limited substitutability between inputs. With the exception of weeding effort, the correlation between all four inputs is positive. The negative correlation of weeding effort with the three other inputs could indicate poorer households allocating more hours on-farm to compensate for reductions in the cash inputs.

In general, our estimated effects are weak. This is likely due, in part, to the short panel, which forced us to rely on cross-sectional variation in rainfall shocks and liquidity and precluded us from using panel-data methods to better control for unobserved sources of variation. Moreover, our study year was a favorable rainfall year, generating less rainfall variation than other years. It is therefore difficult to judge whether these results constitute a rejection of our hypothesis. Nonetheless, this study draws attention to an alternative but potentially important mechanism driving poverty traps: the effect of shocks on on-farm investments. How much to invest in the next season’s crop is a decision faced by households across the entire wealth spectrum. For the poorest households, it may be the most important decision it makes each season. This study contributes to a small but vital literature that seeks to understand this decision.

References

Adato, M., M. Carter and J. May (2006). Exploring poverty traps and social exclusion in South Africa using qualitative and quantitative data, *Journal of Development Studies* 42 (2), 226–247.

Carter, M. and C. Barrett (2006). The economics of poverty traps and persistent poverty: an asset-based approach. *Journal of Development Studies* 42(2):178-199.

Carter, M. and T. Lybbert (2012). Consumption versus asset smoothing: Testing the implication of poverty trap theory in Burkina Faso. *Journal of Development Economics,* 99(2): 255-264.

Chapoto, A., D. Banda, S. Haggblade, and P. Hamkwala (2011). Factors Affecting Poverty Dynamics in Rural Zambia. Working Paper No. 55, Food Security Research Project, Lusaka, Zambia. http://www.aec.msu.edu/agecon/fs2/zambia/index.htm

Central Statistical Office, Ministry of Agriculture and Cooperatives and Food Security Research Project (CSO/MACO/FSRP). 2008. Third Supplemental Survey to the 1999/2000 Post-Harvest Survey Data. Lusaka, Zambia: FSRP.

Central Statistical Office, Ministry of Agriculture and Livestock and Indaba Agricultural Policy Research Institute (CSO/MAL/IAPRI). 2012. Rural Agricultural Livelihoods Survey Data. Lusaka, Zambia: IAPRI.

Deaton, A. (1991). Saving and liquidity constraints. *Econometrica*, 59(5):1221–1248.

Dercon, S. (2004). Growth and shocks: evidence from rural Ethiopia. *Journal of Development Economics,* 74(2):309-329.

Dell, M., B. Jones, and B. Olken (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature*, 52(3):740-798.

Dercon, S., J. Hoddinott, and T. Woldehanna (2005). Shocks and consumption in 15 Ethiopian Villages, 1999-2004. *Journal of African Economies*, 14(4)559-585.

Duflo, E., M. Kremer, and J. Robinson (2011). Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya. *American Economic Review*, 101:2350-2390.

Fink, G., B.K. Jack, & F. Masiye (2014). Seasonal credit constraints and agricultural labor supply: evidence from Zambia (Working Paper No. 20218). National Bureau of Economic Research.

Grimes, D.I.F., E. Pardo-Igúzquiza, and R. Bonifacio. 1999. Optimal Areal Rainfall Estimation Using Rain Gauges and Satellite Data. *Journal of Hydrology* 222: 93-108.

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

Indaba Agricultural Policy Research Institute (IAPRI). (2012). *The 2012 Rural Agricultural Livelihoods Survey: Interviewer's instruction manual*. Lusaka, Zambia: IAPRI.

Karlan, D., I. Osei-Akoto, R. Osei, and C. Udry (2013). Agricultural decisions after relaxing credit and risk constraints. *Quarterly Journal of Economics*, 129(2): 597-652.

Kinsey, B., Burger, K., and Gunning, J. W. (1998). Coping with drought in Zimbabwe: Survey evidence on responses of rural households to risk. *World Development.* 26(1):89– 110.

Kochar, A. (1999). Smoothing consumption by smoothing income: hours-of-work responses to idiosyncratic agricultural shocks in rural India. *Review of Economics and Statistics.* 81:50–61.

Kusunose, Y., and T. Lybbert (2014). Coping with drought by adjusting land tenancy contracts: a model and evidence from rural Morocco. *World Development.* 61:114-126.

Lybbert, T., and J. McPeak (2012). Risk and intertemporal substitution: Livestock portfolios and off-take among Kenyan pastoralists. *Journal of Development Economics*, 97:415-426.

Maidment, R., D. Grimes, R.P. Allan, E. Tarnavsky, M. Stringer, T. Hewison, R. Roebeling and E. Black. 2014. The 30 Year TAMSAT African Rainfall Climatology and Time Series (TARCAT) Data Set. *Journal of Geophysical Research: Atmospheres* 119: 10619-10644.

Mason, N. M., T. S. Jayne, and R. Mofya-Mukuka (2013). Zambia's input subsidy programs. *Agricultural Economics* 44(6): 613-628.

Mason, N.M. and J. Ricker-Gilbert (2013). Disrupting demand for commercial seed: Input subsidies in Malawi and Zambia. *World Development*. 45:75–91.

Mason, N. M., T. S. Jayne, A. Chapoto, and R. Myers (2010). A test of the new variant famine hypothesis: Panel survey evidence from Zambia. *World Development* 38(3):356-368.

Mathenge, M. K., M. Smale, and D. Tschirley (2015). Off-farm Employment and Input Intensification among Smallholder Maize Farmers in Kenya. *Journal of Agricultural Economics*

Milford, J.R. and G. Dugdale. 1990. Estimation of Rainfall Using Geostationary Satellite Data. In *Applications of Remote Sensing in Agriculture*, ed. M.D. Steven and J.A. Clark. London: Butterworth-Heinemann.

Smale, M. and N. Mason (2014). Hybrid seed and the economic well-being of small-holder maize farmers in Zambia. *The Journal of Development Studies,* 50(5):680-695.

Stock, J.H. and Yogo, M. 2005. Testing for Weak Instruments in Linear IV Regression. In D.W.K. Andrews and J.H. Stock, eds. Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg. Cambridge: Cambridge University Press, 2005, pp. 80–108. Working paper version: NBER Technical Working Paper 284. http://www.nber.org/papers/T0284.

Tarnavsky, E., D. Grimes, R. Maidment, E. Black, R. Allan, M. Stringer, R. Chadwick, and F. Kayitakire. 2014. Extension of the TAMSAT Satellite-Based Rainfall Monitoring over Africa and from 1983 to Present. *Journal of Applied Meteorology and Climatology* 53: 2805-2822.

Table 1. Summary statistics: input changes and rainfall shocks

		Zone 1: Western Semi-Arid Plains	Zone 2: Luangwa-Zambezi Rift Valleys	Zone 3: Central, Southern and Eastern Plains	Zone 4: Northern High Rainfall Zone
	obs.	120	140	733	690
area	*decreased*	0.267	0.371	0.572	0.336
	no change	0.492	0.364	0.144	0.343
	increased	0.242	0.264	0.284	0.302
fertilizer	*decreased*	0.033	0.143	0.288	0.271
	no change	0.850	0.693	0.471	0.422
	increased	0.117	0.164	0.241	0.307
hybrid maize seed	*decreased*	0.125	0.179	0.263	0.222
	no change	0.717	0.571	0.511	0.452
	increased	0.158	0.250	0.226	0.326
weedings	*decreased*	0.167	0.171	0.129	0.142
	no change	0.667	0.721	0.729	0.632
	increased	0.167	0.107	0.143	0.226
rainfall deficit periods	**0**	76.67	37.14	20.91	63.62
(number of 2-dekad	**1**	23.33	42.86	53.88	23.48
intervals with less	**2**	0	14.29	23.55	12.90
than 40mm of rainfall)	**3**	0	0	1.66	0
	4	0	5.71	0	0

Table 2. Summary statistics: explanatory variables

	Zone 1: Western Semi-Arid Plains	Zone 2: Luangwa-Zambezi Rift Valleys	Zone 3: Central, Southern and Eastern Plains	Zone 4: Northern High Rainfall Zone
ENDOGENOUS VARIABLES				
credit (binary)	0.115	0.401	0.487	0.250
access to at least one credit source	(0.320)	(0.492)	(0.500)	(0.433)
livestock (TLU)	0.049	0.641	0.767	0.309
pigs, goats, and sheep in April 2011	(0.236)	(1.285)	(1.337)	(0.794)
earners	0.042	0.129	0.148	0.207
no. of members with non-ag. wages	(0.201)	(0.357)	(0.423)	(0.443)
FISP (binary)	0.108	0.221	0.449	0.509
rec'd FISP maize seed and/or fertilizer in 2(	(0.312)	(0.417)	(0.498)	(0.500)
CONTROL VARIABLES				
price maize (ZMK/kg)	1144.667	1213.143	1231.884	1230.275
farm-gate FRA maize price in 2011	(86.568)	(43.234)	(26.967)	(30.907)
price maize seed (ZMK/kg)	7068.966	9495.074	9383.776	7806.097
village-leve hybrid maize seed price	(848.193)	(2372.700)	(1594.404)	(1418.018)
price basal fertilizer (ZMK/kg)	3733.333	3705.185	3840.702	4197.574
farm-gate	(1365.040)	(778.452)	(670.371)	(855.522)
price top dress fertilizer (ZMK/kg)	3733.333	3780.714	3773.414	3970.286
farm-gate	(1365.040)	(793.706)	(631.961)	(932.975)
weeding wage (ZMK)	7.5e+04	6.0e+04	6.0e+04	5.3e+04
hired labor wage per .25 ha maize	(1.7e+04)	(3.1e+04)	(2.7e+04)	(1.9e+04)
INSTUMENTAL VARIABLES				
credit sources	0.230	0.788	1.269	0.516
village mean, excludes household	(0.455)	(0.770)	(1.200)	(0.850)
landholdings (ha)	2.712	3.045	3.346	2.991
village mean, excludes household	(1.616)	(1.920)	(2.035)	(2.271)
dist. to livestock mkting area (km)	41.421	41.936	26.223	27.669
	(42.123)	(40.151)	(31.189)	(43.916)
dist. to diptank (km)	31.546	13.964	16.888	34.410
	(31.161)	(16.590)	(28.801)	(42.027)
distance to basic school (km)	4.433	3.179	3.687	3.328
	(4.650)	(3.052)	(5.962)	(4.445)
educ. attainment of head (years)	5.975	5.971	6.152	7.000
	(3.738)	(3.564)	(3.970)	(4.085)
dist. to electricity (km)	30.908	12.150	16.886	26.759
	(31.651)	(22.898)	(20.256)	(41.723)
FISP maize seed allocation (mt)	38.940	100.440	257.862	116.040
district-level, 2010/2011	(55.627)	(110.283)	(101.290)	(65.453)
FISP fertilizer allocation (mt)	800.800	2012.229	5158.232	2324.330
district-level, 2010/2011	(1101.093)	(2202.900)	(2023.841)	(1308.159)
presidential election outcome	1.000	0.400	0.780	0.426
(=1 if MMD won the constituency)	(0.000)	(0.492)	(0.415)	(0.495)

Table 3. Validity of instruments: first stage regression results

	Endogenous variables							
	shock x credit	*shock x TLUs*	*shock x earners*	*shock x FISP*	*credit*	*TLUs*	*earners*	*FISP*
Partial R-sq	0.049	0.020	0.138	0.041	0.049	0.017	0.165	0.037
Angrist-Pischke R-sq	0.017	0.012	0.025	0.007	0.019	0.006	0.041	0.007
F test of excluded instruments								
F(22, 418)	3.029	2.139	5.333	1.768	3.932	1.925	8.828	2.662
p-value	0.000	0.002	0.000	0.018	0.000	0.008	0.000	0.000
Sanderson-Windmeijer multivariate F test of excluded instruments								
F(15, 418)	1.986	2.238	0.870	1.005	2.247	0.664	1.159	0.966
p-value	0.015	0.005	0.598	0.449	0.005	0.820	0.301	0.491
Angrist-Pischke multivariate F test of excluded instruments								
F(15,418)	3.912	3.351	6.334	0.949	1.786	0.723	4.407	0.709
p-value	0.000	0.000	0.000	0.509	0.034	0.762	0.000	0.776

Table 4. Validity of instruments: tests o overidentifying restrictions

	area	*nitrogen*	*hybrid seed*	*weedings*
Hansen J test				
Chi-sq (12)	13.502	7.982	13.729	11.275
p-value	.4875	0.8903	0.4701	0.6643
Anderson-Rubin Wald test				
F(22,418)	1.15	.97	1.33	2.03
p-value	0.2943	0.5040	0.1442	0.0041

Table 5. Comparison of OLS, generalized method of moments, two-stage least squares, and three-stage least squares results

	Change in area (ha)				**Change in total nutrient nitrogen (kg)**			
	OLS	**2SLS**	**GMM**	**3SLS**	**OLS**	**2SLS**	**GMM**	**3SLS**
rainfall shock	0.673	0.846	1.275	0.533	-52.898	-192.322	-187.976	-213.079
	(0.864)	(1.500)	(1.370)	(1.725)	(57.384)	(124.196)	(116.454)	(141.155)
liquidity variables								
shock X credit	-0.197 ***	-0.108	-0.225	-0.125	-6.121	34.428	26.342	36.925
	(0.065)	(0.330)	(0.304)	(0.422)	(4.117)	(29.449)	(27.289)	(34.496)
shock X TLUs	0.005	0.385 *	0.362 *	0.354	4.027	13.036	10.096	12.294
	(0.042)	(0.214)	(0.190)	(0.233)	(2.866)	(16.853)	(15.762)	(19.096)
shock X earners	0.073	0.379	0.174	0.462	4.639	-1.656	-19.762	0.479
	(0.061)	(0.461)	(0.377)	(0.480)	(5.149)	(32.734)	(28.986)	(39.314)
shock X FISP	-0.110 *	-0.529	-0.308	-0.585	-5.723	-0.580	18.138	-0.739
	(0.064)	(0.488)	(0.437)	(0.599)	(5.277)	(40.704)	(37.023)	(49.007)
credit	0.210 ***	-0.042	-0.016	-0.023	4.191	-59.583 *	-37.122	-58.362
	(0.067)	(0.336)	(0.305)	(0.443)	(5.327)	(36.263)	(33.514)	(36.219)
livestock	-0.055	-0.447	-0.368	-0.463	-2.144	-15.148	-10.066	-12.791
	(0.043)	(0.286)	(0.257)	(0.325)	(2.810)	(23.764)	(22.878)	(26.557)
earners	-0.032	0.078	0.198	0.099	-2.962	51.372 *	55.090 **	55.795 *
	(0.057)	(0.302)	(0.252)	(0.385)	(5.433)	(27.464)	(25.250)	(31.466)
FISP	-0.039	0.169	-0.137	0.158	-11.127 *	-83.029	-94.040 *	-94.760
	(0.074)	(0.576)	(0.509)	(0.713)	(6.339)	(56.944)	(53.676)	(58.362)
control variables								
shock X	-0.000	-0.000	-0.000	-0.000	-0.001	-0.002	-0.001	-0.002
maize seed price	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
shock X	-0.000	-0.001	-0.001	-0.000	0.044	0.152	0.149	0.165
maize grain price	(0.001)	(0.001)	(0.001)	(0.001)	(0.048)	(0.102)	(0.096)	(0.115)
shock X	0.000	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000
weeding wage	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
shock X	0.000	-0.000	-0.000	-0.000	0.006	0.001	0.005	-0.001
basal fert. price	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.008)	(0.008)	(0.010)
shock X top dress	0.000	0.000	0.000	0.000	-0.006	0.001	-0.004	0.005
fert. price	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.010)	(0.010)	(0.013)
clustered S.E.s	yes	yes	yes	no	yes	yes	yes	no

* p<.10; ** p<.05; *** p<.01

Coefficients on agro-ecological zones and agro-ecological zones x shock omitted from output.

Table 5, continued

	Change in total hybrid maize seed (kg)				Change in number of weedings			
	OLS	2SLS	GMM	3SLS	OLS	2SLS	GMM	3SLS
rainfall shock	19.092	39.072	-67.761	35.709	-0.134	1.438	1.176	1.411
	(42.623)	(82.941)	(57.661)	(72.990)	(0.668)	(1.115)	(1.052)	(1.139)
liquidity variables								
shock X credit	-0.632	3.038	-12.946	2.065	0.025	-0.662 **	-0.581 *	-0.693 **
	(1.620)	(19.335)	(13.285)	(17.838)	(0.051)	(0.328)	(0.306)	(0.278)
shock X TLUs	0.341	15.254	-3.036	14.678	0.018	-0.073	-0.019	-0.100
	(1.279)	(11.988)	(7.579)	(9.874)	(0.027)	(0.140)	(0.132)	(0.154)
shock X earners	3.472	14.742	0.056	15.611	0.015	0.059	0.154	0.044
	(2.252)	(22.945)	(16.251)	(20.329)	(0.065)	(0.328)	(0.316)	(0.317)
shock X FISP	-2.383	-28.669	-14.392	-26.867	-0.003	0.455	0.279	0.493
	(2.391)	(22.924)	(20.402)	(25.341)	(0.047)	(0.372)	(0.345)	(0.396)
credit	2.309	8.633	12.468	11.746	-0.050	0.421	0.481	0.455
	(1.796)	(19.273)	(16.425)	(18.728)	(0.058)	(0.317)	(0.298)	(0.292)
livestock	-0.164	-22.935	-8.438	-24.344 *	0.011	0.105	0.093	0.115
	(1.100)	(17.009)	(10.918)	(13.732)	(0.028)	(0.185)	(0.173)	(0.214)
earners	-1.488	-21.479	6.235	-21.144	0.032	-0.223	-0.238	-0.224
	(1.477)	(19.083)	(13.712)	(16.271)	(0.050)	(0.225)	(0.220)	(0.254)
FISP	-1.049	49.006	-2.936	47.811	0.043	-0.180	-0.135	-0.211
	(2.133)	(41.731)	(28.551)	(30.179)	(0.053)	(0.402)	(0.375)	(0.471)
control variables								
shock X	-0.000	-0.001	-0.001 **	-0.001	-0.000	-0.000	0.000	-0.000
maize seed price	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
shock X	-0.032	-0.050	0.056	-0.047	-0.000	-0.001	-0.001	-0.001
maize grain price	(0.041)	(0.073)	(0.048)	(0.060)	(0.001)	(0.001)	(0.001)	(0.001)
shock X	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
weeding wage	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
shock X	0.002	0.003	-0.001	0.003	0.000	0.000	-0.000	0.000
basal fert. price	(0.003)	(0.007)	(0.004)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
shock X top dress	0.003	0.002	0.003	0.001	0.000	-0.000	0.000	-0.000
fert. price	(0.005)	(0.010)	(0.005)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)
clustered S.E.s	yes	yes	yes	no	yes	yes	yes	no

* p<.10; ** p<.05; *** p<.01

Coefficients on agro-ecological zones and agro-ecological zones x shock omitted from output.

Table 6. Contemporaneous correlation matrix used in three-stage least squares estimation

	area	*fertilizer*	*hybrid seed*	*weedings*
area	1.20			
fertilizer	43.21	8022.90		
hybrid seed	17.37	319.45	2145.17	
weedings	-0.02	-7.37	-0.51	0.52