Risk-related effects of cash transfers on modern inputs demand

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<u>THIS VERSION:</u>

Abstract

Risk avoidance in the face of incomplete insurance and credit markets pushes households, especially poorer ones, to opt for less risky technologies, giving up at the same time the possibility for higher returns and trapping themselves in persistent poverty. This paper focuses on the role of Unconditional Cash Transfer in helping smallholder overcome risk-induced poverty traps by reducing their degree of risk aversion and inducing greater investments in yield increasing modern inputs. We use data from a Randomized Controlled Trial collected for the evaluation of the Child Grant Program (CGP) - Zambia's flagship social protection cash transfer program. We employ a moments-based method to estimate farmers' risk attitudes from revealed preferences through production decisions. We also estimate the impact of cash transfers on modern input demand by simultaneous equations methods. We find that the program significantly contributes to helping farmers breaking the poverty cycle by tapering risk aversion and pushing towards higher-risk higher-returns production choices.

Keywords: cash transfers, risk attitudes, output risk, input demand, SEMs, 3SLS

JEL Classification:

1. Introduction and motivation

Strategic objectives such as increasing food security and reducing poverty, which top the policy agenda of most governments across Africa, hinge on increasing farm output and productivity. The primary pathway to increased agricultural productivity passes through the adoption of new production techniques, especially new seeds varieties and chemical fertilizers. However, a common finding in agriculture is that small-scale farmers in developing countries often use less fertilizer and other modern inputs than they would if they maximized expected profits (Duflo et al., 2011). A major obstacle to the adoption of modern inputs and of new technologies in general is famers' risk aversion (Binswanger, 1981; Feder et al., 1985; Antle, 1987; Lamb 2003). Since formal insurance schemes are virtually absent in most of rural areas in Sub Saharan Africa, investing in new production techniques exposes the farmers to the consequences of output risks, such as weather shocks, which may cause permanent damage with irreversible consequences, or may even throw farmers below a critical asset threshold from which recovery is not possible. In anticipation of such outcomes, households, especially poorer ones, may opt for less risky technologies and portfolios in order to avoid permanent damage. Yet, these often also generate lower returns on average trapping farmers in persistent poverty (Rosenzweig and Binswanger, 1993). In this paper we investigate the potential of unconditional cash transfers to help poor farmers break these poverty traps by inducing riskier production decisions through higher demand for modern inputs.[1]

Economic theory suggests that if the markets for credit and insurance are fully functioning, farm households should make income-earning choices that produce the highest expected value, and, after shocks occur, use market instruments to achieve consumption smoothing and insulate consumption patterns from income variability. In this scenario, farm households smooth consumption by borrowing and saving and by employing formal and informal insurance instruments. Thus, when perfect consumption smoothing is possible production and consumption decisions are separable, and production choices are made to maximize profits without concern for risk. When markets for consumption smoothing are missing or incomplete, households anticipate being unable to borrow or insure and the effects of risk aversion on production can be large. In this case, farmers engage in income smoothing, i.e. they tend to

[1] Here by modern inputs we mean commercial seeds and fertilizers. We observe households that purchased commercial seeds in the given main season. Commercially purchased seeds are not necessarily equivalent to improved seed varieties since households may choose to purchase traditional variety seeds instead or may plant saved improved varieties instead of newly purchased ones. This circumstance likely under-estimates total improved seed variety use, particularly for crops where improved seeds are saved for use in later years.

reduce income variability before income shocks materialize by making conservative input and output choices. This, in turn, implies sacrificing high return for low risk activities and underinvesting, and over time by showing reluctance to adopt new technologies or to exploit new economic opportunities (Morduch, 1995). Poor farmers are blocked in risk-induced poverty traps, whereby in order to avoid further destitution they are forced to forgo profitable but risky opportunities, and with it the opportunity to move out of poverty (Mendola, 2007). For example, farmers may use inputs less intensively in order to reduce exposure in a risky investment and reduce losses in case things go bad. Morduch (1995) finds that fertilizer is a highly productive input in wheat cultivation among farmers in India, but the marginal product of fertilizer remains 3.5 times its price. Farmers could substantially raise expected profits by increasing applications of fertilizer. Risk avoidance in the face of incomplete insurance may therefore be key in understanding limited spread of modern inputs (Feder et al., 1985). To the extent that farmers choose traditional inputs over modern inputs in order to lower risk ex-ante, any mechanism that allows farmers to smooth consumption ex-post will raise the use of modern inputs. Moreover, since poorer farmers are likely more risk averse than wealthy farmers, their choice will be affected more by increased opportunities for ex-post consumption smoothing. One such mechanism that eases credit and insurance markets constraints allowing farm households to smooth consumption and avoid income smoothing is income support through unconditional cash transfers (Lamb, 2003; Fiszbein and Schady, 2009).

Hennessy (1998) developed a comprehensive neo-classical framework to analyze the production impacts of income support policies under uncertainty in the agricultural sector. Hennessy identifies a *wealth effect* that arises when farmers are risk averse and face production risk.[2] The government payment changes the total wealth of the farmer and this increase in wealth can affect the farmers' risk aversion. Assuming that the risk aversion decreases with the level of wealth (Decreasing Absolute Risk Aversion), Hennessy shows that income support, by increasing a farmer's wealth, will induce them to make riskier investments therefore increasing the quantity or the quality of inputs used. The drop in risk aversion is going to be greater for poorer farmers compared to what will happen to their "richer" counterparts since the government transfer increases the wealth of the former more in relative terms. An extensive

[2] A second effect introduced by Hennessy is the insurance effect. The government scheme may affect the degree of risk faced by the farmer. This would be true whenever the payment also depends on the source of uncertainty, say, weather or price. For example, a government scheme that increases payments when prices fall and reduces payments when prices rise will increase production if there is partial income compensation for the price movements. Since cash transfers are unconditional, their risk-induced effects on production work completely through the wealth effect.

literature has shown that lump sum payments can affect economic agents' risk attitudes by altering farm household wealth (Sandmo, 1971; Bar-Shira et al., 1997; Hennessy, 1998; Serra et al., 2006).

However, the conclusion that unconditional income support will yield an increase in input use does not account for the effects that inputs can have on farm production variability. As Just and Pope (1978) explained, agricultural inputs can increase or decrease output risk by influencing production variability. Serra et al. (2006) and Serra et al. (2011) dig one layer deeper into the relationship between risk aversion and input use and establish that a farmer will increase the use of a certain input, only in so far as the input increases output variability and the chances of getting a higher net return (*risk increasing input*). However, if the input has the effect of reducing output variance, farmers will use less of it. In their empirical analysis Serra et al. (2006) find that unconditional government transfers to farmers in the USA (*decoupled payments*) motivate an increase in input use (pesticides and fertilizers), although elasticity values are very small. The literature on the risk-related productive impacts of income support policies is very scant and has mainly focused on developed countries (Sckokai and Anton 2005; Sckokai and Moro, 2006; Serra et al. 2006; Goodwin and Mishra, 2006; Lin and Dismukes, 2007; McIntosh et al., 2007; Serra et al., 2007; Femenia et al., 2010; Serra et al. 2011; Just, 2011). To the best of our knowledge, no previous study has analyzed the risk-related effect of unconditional government transfers on modern input use in the context of developing countries. In this paper we show that unconditional cash transfers reduce farmers' risk aversion pushing them to invest more in modern inputs, namely, chemical fertilizer and commercially purchased seeds. A partly related strand of literature is the one on the effects of risk on new technology adoption (Smale and Heisey, 1993; Nkonya et al., 1997; Roosen and Hennessy, 2003; Knight et al., 2003). The bulk of the evidence suggests that risk aversion slows the adoption of improved seed varieties, depresses the use of fertilizer, and results in farmers choosing production activities that lead to lower, though less variable, returns.

For the purposes of this study, we use data from the household survey originally conducted for the impact evaluation of the Child Grant Program – the flagship social protection program in Zambia – consisting of an unconditional social cash transfer targeted to poor and vulnerable households. For seeds we find that beneficiary farmers engage in riskier behavior by increasing demand, arguably, as a result of the cash-transfer-induced reduction in risk aversion. The surge in seeds purchases results in an increase in output variability. While in the case of fertilizers we find weak evidence of increased use caused by the program in line with the finding that fertilizer use does not increase output risk significantly.

The rest of the paper is organized as follows. In section 2 we describe the CGP program and provide some descriptive statistics. In section 3 the theoretical framework is illustrated. Section 4 explains the estimation approach for the empirical part. Section 5 illustrates the findings and section 6 provides some conclusions and discusses the possible policy implications.

2. Data and summary statistics

In 2010, the Zambia's Ministry of Community Development and Social Services (MCDSS) started to implement the Child Grant Programme (CGP). The stated goal of the programme is to alleviate poverty among the poorest households and block its intergenerational transmission by stimulating progress in a number of intermediate objectives: supplementing and not replacing household income; increase in the number of children enrolled in and attending primary school; reduction of the rate of mortality and morbidity among children under 5 years old; reduction in stunting and wasting among children under 5 years old; increase in the number of households owning assets such as livestock; and increase in the number of households that have a second meal a day.

The pilot evaluation of the CGP was implemented in three districts that had never received any CTs and with highest rates of mortality, morbidity and stunting among children under 5 years of age. The three districts are located in very isolated and remote areas. They include Kaputa, located in Northern Province and Shongombo and Kalabo, located in Western Province. The CGP was based on a categorical targeting mechanism, reaching any household with a child under 5 years old. Only households with children under three years old were enrolled in the programme to ensure that every recipient household receives the transfers for at least two years after the programme is introduced to that area. A continuous enrolment system was implemented in which households were immediately enrolled after having a newborn baby. Beneficiary households received 60000 kwacha (ZMK) a month[3]. The planned transfer

[3] On January 1, 2013 the new Zambian kwacha was introduced at a rate of 1000 old kwacha = 1 new kwacha, a move that was aimed at strengthening the local currency against major convertible currencies. In our data, variables are denominated in the old base.

size is constant regardless of household size and amounts on average to about 25 percent of a household's monthly consumption expenditure. Payments are unconditional of income, wealth or labour market status leaving households entirely free in how to spend the money. The designated recipient of the cash is the female head of household, who could be a mother or a grandmother. CGP recipient households did not face significant costs in accessing the cash; less than 10 percent of recipients report ever having to make multiple trips to receive a single payment. During the 2-year period, payments were made on time for all three districts, following a bimonthly schedule.

CGP's impact evaluation was designed as a longitudinal randomized controlled trial (RCT) with random assignment at the community level. There were two levels of random selection of participants, at the Community Welfare Assistance Committees (CWACs) and household level. The first stage of the randomization process was carried out by the Ministry by selecting and ordering 30 CWACs within each of the three districts (out of roughly 100 CWACs in each district) through a lottery. After the 90 CWACs were randomly selected for the study, the Ministry identified all eligible households with at least one child under 3 years old. In the second stage 28 households were then randomly sampled from each CWAC for inclusion in the study. Random assignment of the communities to treated and control groups occurred only after baseline data were collected, thus avoiding anticipation effects in the baseline data, as neither the respondent nor the enumerator knew their future treatment status. The final assignment to treatment and control groups was implemented by flipping a coin to determine whether the first half of the list of randomly selected CWACs would be treated or not. The final sample has 2515 households which amounts to 14,565 people. Due to the targeting criteria, the CGP final sample is significantly different from the rest of Zambian households. CGP sample households are significantly poorer and more food insecure compared to the average Zambian rural household or even to rest of the households in the three districts (American Institute for Research, 2011).[4]

Baseline data were collected during the lean season that spans from September through February, during which people have little food left from the previous harvest and hunger is most felt. The 24-month follow-up data collection occurred in September and October 2012 exactly 24 months from the baseline study, ensuring that households are being compared in the same season as at the baseline, avoiding seasonal effects.

[4] A detailed description of the evaluation design can be found in American Institutes for Research (2011).

In this paper we are interested in estimating the effects of the CGP program on input use, while isolating the role of risk in channeling these effects. Identification of the effects relies on the comparison of average outcomes between the treated and the control group at follow-up. We use only the follow-up wave because some of the variables included in the analysis have a considerable proportion of missing data at baseline, which would lead to a reduction in sample size. Baseline data become valuable in non-experimental contexts as they allow one to control for baseline differences across individuals that might otherwise confound the effects of the program. However, the binary randomization mechanism of the RCT design should ensure perfect comparability at baseline along every observed and unobserved dimension between the treated and the controls. This allows attribution to the intervention of any observed post-treatment differences resulting from the binary comparison of the average outcome between the treatment and control groups. Moreover, the single-difference estimator at follow-up produces the same impact estimates as a double-difference provided that, on average, there are no statistically significant differences at baseline in the outcome of interest. We performed a mean comparison test at baseline on our three main outcomes, namely, expenditures for seeds, expenditures for fertilizers and the farm output value. The null hypothesis of equal means could not be rejected in any of the cases. The official Baseline Report uses the full set of observed characteristics providing evidence of success of the binary randomization process that foreran the implementation of the CGP programme (Seidenfeld et al., 2011). The report establishes that treated and controls are observationally equivalent in terms of observed characteristics.

Table 1 shows descriptive statistics for our estimation sample at follow-up. We estimate the sample means for all covariates used in estimation and for the outcome variables. The average household size is high (5.7 members) due to the targeting mechanism of the program that was aimed at households with children under 5. Farm size is generally small with an average area of operated land below one hectare. Almost half of the communities suffered some negative shock related to draughts while ten percent were subject to crop diseases in the last season. To reduce the variance in the residuals and increase the statistical precision of the estimates we include these covariates in all our regressions. To build a measure of the monetary value of farm output we sum the values of all major crops. The latter are computed by multiplying the physical quantity of harvest for the crop by the corresponding market price at the community level. To construct the price of each crop at the community we first back out the selling price obtained by each farmer who actually sold the crop, as the ratio of the revenue to the quantity sold and then take the median of the resulting distribution. The value of expenditures for seeds and fertilizer incurred by farmers is taken directly from the questionnaire. The price of seeds and fertilizer are registered at the community level. We have aggregated the harvested quantities of all crops into the value of output in order to use it in a single-output production function. Similarly, we need to club the prices of all crops together to get some aggregate price index that refers to the whole output. It is not appropriate to take the simple average of the prices since the selling price for the farmer is already an average figure. We follow Kumar (2007) to compute the output price at the community level. He suggests using the following quantity-weighted average $P_j = \frac{\sum P_{ij}Q_{ij}}{\sum Q_{ij}}$ where i is the crop index and j is the household index. The price index for the j-th household is obtained by multiplying the j-th farmer's price obtained for each crop by the quantity sold of each crop and dividing the sum of all crops by the sum of quantities sold for all crops. We then take the median of the resulting price distribution at the community level.

3. Theoretical framework

The theoretical framework adopted in this paper follows along the lines of Serra et al. (2006). We explicitly take into consideration production risk, which consists in output variability due to random weather conditions, technological innovations or government policies related to input use. Moreover, when choices are made under uncertainty, farmers' risk preferences play a key role in shaping production decisions on input use. Hennessy (1998) shows that farmers with decreasing absolute risk aversion – those who tend to assume more risks as their wealth increases – will react to a government transfer that boosts their wealth by taking more risk and increasing input use. However, this conclusion ignores the effects that a certain agricultural input can have on production risk. In fact, inputs may increase (*risk increasing*) or decrease (*risk decreasing*) output variability (Just and Pope, 1978). In the current framework it is established that farmers will increase input use following a CT-induced reduction in risk aversion only if an input is risk increasing.

Let y be the output produced by a single-output farm. Following Just and Pope (1978) the stochastic production function is given by

$$y = f(x_1, x_2, \boldsymbol{Z}, \boldsymbol{\alpha}) + h(x_1, x_2, \boldsymbol{Z}, \boldsymbol{\beta})\varepsilon \qquad (1)$$

where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are parameter vectors, $x_1$and x_2 are two variable inputs of interest, seeds and fertilizer in our case, $\boldsymbol{Z}$ includes other factors that influence farm output supply, $f(x_1, x_2, \boldsymbol{Z}, \boldsymbol{\alpha})$ is the deterministic component of production and $h(x_1, x_2, \boldsymbol{Z}, \boldsymbol{\beta})$ is a function that captures the relationship between inputs and output variability since $V(y) = E(y - \bar{y})^2 = h^2(x_1, x_2, \boldsymbol{Z}, \boldsymbol{\beta})$. Finally, ε is a random shock such that $E(\varepsilon) = 0$ and $E(\varepsilon^2) = 1$. The function $h(.)$ models the interaction of input levels with random fluctuations in production (ε). The stochastic shocks in the model are the result of variability in weather conditions, in pest and disease infestations, the use of proxy variables that have not accounted fully for the effects of underlying physical processes, and the influence of other factors that are uncontrolled for in the analysis (e.g., soil quality, managerial experience). The magnitude of this random disturbance is mediated by the vector of inputs. Examples of studies that have used the Just and Pope function are Love and Buccola (1991) and Kumbhakar (1993). This framework allows for the development of a significantly more flexible statistical model that accommodates both risk-increasing and risk-decreasing factors of production. An input will cause production risk to increase if $\frac{\partial V(y)}{\partial x} > 0$ while the input is risk-decreasing if $\frac{\partial V(y)}{\partial x} < 0$. The impacts of the main inputs on output variability have been widely analyzed in the literature with no clear-cut conclusions. While evidence on the risk impact of seeds is scant, fertilizers have been found to be risk-decreasing by some studies, while many others find that these inputs increase output risk (Just and Pope, 1978; Just and Zilberman, 1983; Horowitz and Lichtenberg, 1994).

In a non-deterministic world, farmers take their decisions with the objective to maximize the expected utility of wealth, $\max_{x_1, x_2} E[u(W)] = \max_{x_1, x_2} E[u(W_0 + py - w_1 x_1 - w_2 x_2 + G)]$ where W is the farmer's total wealth, W_0 is initial wealth and is a known quantity, p is the market price of the output, w_1 and w_2 are the prices of the variable inputs and G represents the amount of the government transfer. In this model, only one of the two main sources of risk is modelled, namely output risk, while we ignore price uncertainty and assume that output and input prices are known variables. The argument of the utility function is the sum of initial wealth plus net farm income (ignoring livestock activities). Antle (1987) points out that the net income distribution is equivalent to a revenue or output distribution if input and output prices are non-stochastic as in our case.

The first order conditions for the maximization of the expected utility can be cast as: $\partial E[u(W)]/\partial x_i = E[u_w(p y_{x_i} - w_i)]$ where subscripts denote partial derivatives. Since no functional form assumptions were made for the utility function, the first derivative of utility with respect to wealth (u_w) is unknown. In order to made the FOC-s operational, a first-order Taylor expansion around the expected wealth is applied so that $u_w = \bar{u}_w + \bar{u}_{ww}(w - \bar{w}) = \bar{u}_w + \bar{u}_{ww}p(y - \bar{y})$, where to $\bar{u}_w$and $\bar{u}_{ww}$ are the first and second-order derivatives of the utility function evaluated at the expected wealth ($\bar{w}$) and $\bar{y}$ is expected output. Substituting the series expansion into the FOC-s we obtain $pE[y]_{x_i} + \frac{\bar{u}_{ww}}{\bar{u}_w} p^2 E[(y - \bar{y})y_{x_i}] = w_i$. Transforming the FOC-s further we are able to highlight the role of the two major risk channels analyzed in this study. First, the ratio of the second to the first derivative of the utility function is the Arrow-Prat coefficient of absolute risk aversion, which is a standard measure of individual risk attitudes, defined as $R(W) = -\frac{\bar{u}_{ww}}{\bar{u}_w}$. A negative (positive, null) coefficient of absolute risk aversion implies that the farmer is risk averse (seeking, neutral). Depending on how R reacts to changes in wealth, a farmer has Decreasing (Increasing, Constant) Absolute Risk Aversion if $\frac{dR(W)}{dW}$<0 (>0, =0). Secondly, $E[(y - \bar{y})y_{x_i}]$ is equal to half of the derivative of the output variance with respect to the variable input, i.e. $0.5 * V[y]_{x_i}$. Substituting these expressions we obtain the standard form of the FOC-s when output risk and individual risk preferences are explicitly considered in the model.

$$pE[y]_{x_i} - w_i - 0.5 * Rp^2 V[y]_{x_i} = 0 \qquad i = \{1,2\} \tag{2}$$

The first two terms on the left hand side of equation (2) represent the expected marginal income given by the difference between the value of expected marginal product and the marginal cost of the input as given by its price, $E[MI_i] = pE[y]_{x_i} - w_i$. The last term is a notorious second-order Taylor approximation of the risk premium, $RP_i = 0.5 * Rp^2 V[y]_{x_i}$. Before proceeding with the analysis it must be observed that theoretical production functions explain quantities of output trough quantities of inputs. However, in empirical applications quantities of output and inputs are replaced with values. The main reason for doing so is to aggregate quantities of heterogeneous crops and express all the variables in the same unit (Zhang and Xue, 2005). To make this explicit in the remaining exposition we use $Y = py$. From the last equality we have that $E[Y]_{x_i} = pE[y]_{x_i}$and $V[Y]_{x_i}$=$p^2 V[y]_{x_i}$. Substituting into equation (2) we obtain the FOC-s in terms of monetary values,

$$E[Y]_{x_i} - w_i - 0.5 * RV[Y]_{x_i} = 0 \qquad i = \{1,2\} \tag{2a}$$

In a world without uncertainty, or with risk-neutral farmers, the FOC-s consists typically of equating the value of marginal output to the input price, i.e. $E[MI] = 0$. Equation

(2a) shows that, when farmers take decisions under uncertainty and they are risk-averse, their behavior deviates from the one described by neoclassical theory and depends on the size and the sign of the risk premium associated with inputs (Antle, 1989). The risk premium depends in turn on the degree of risk aversion, measured by R, and the effects inputs have on the variance of output, measured by $V[Y]_{x_i}$.

Applying the chain rule for implicit functions we can obtain the total differential of the FOC-s with respect to G, which represents the effect of the government transfer on input use (Serra et al., 2005b).

$$\frac{dx_i}{dG} = \frac{1}{2E[U(W)]_{x_i x_i}} * R_G V[Y]_{x_i} \qquad i = \{1,2\} \tag{3}$$

where $E[U(W)]_{x_i x_i}$is the first derivative of the FOC with respect to x_i or, equivalently, the second derivative of expected utility with respect to *x*. Furthermore, $R_G = \frac{dR}{dG}$ represents the change in a farmer's risk aversion due to a wealth increase from the government transfer. We maintain the assumption that farmers are characterized by decreasing absolute risk aversion (DARA). Given this assumption of risk aversion we have that $E[U(W)]_{x_i x_i} < 0$ and from DARA it follows immediately that $R_G < 0$. As a result, the sign of equation (3) depends on the sign of $V[Y]_{x_i}$. If $V[Y]_{x_i}$> (=) [<] 0 then $\frac{dx_i}{dG}$ > (=) [<] 0. An increase in government transfers will result in an increase in the household's wealth, which will induce a reduction in the farmer's degree of risk reduction. Given this change in risk attitudes farmers will increase the use of a certain input if it is risk-increasing ($V[Y]_{x_i}$>0) and will use less of the input if it is risk-decreasing ($V[Y]_{x_i}$<0). Given inputs that affect variance and the risk preferences of producers, these conditions demonstrate the importance of the risk channel in influencing input choice.

4. Empirical strategy

The aim of the empirical application is to estimate the impact of a cash transfer on input demand while assessing the role of output risk and risk preferences in mediating the farmers' response to the government transfer. The estimation strategy has three parts, each corresponding to one of the derivatives in equation (3). In the first part, we use the stochastic production function in (1) to estimate the marginal contribution of the two variable inputs – seeds and fertilizers – to average output ($E[Y]_{x_i}$) and, most importantly, to output variability

($V[Y]_{x_i}$). The results of the first part are the building blocks of the second part. We substitute into the FOC-s the marginal effects of the inputs on the mean and the variance of output and estimate R_G from the resulting system of equations. In the third part we use the first order conditions in (2) to estimate the impact of the government transfer on input use ($\frac{dx_i}{dG}$).

In order to estimate the partial effect of the variable inputs on the first and the second moment of the output distribution we need to specify functional forms for the mean ($f(.)$) and the variance ($h(.)$) functions of the stochastic production function in equation (1). Following previous literature we use a quadratic form in the inputs for both functions (Antle, 1983; Groom et al., 2003; Vollenveider et al., 2011; Serra et al., 2011). One major drawback of this particular functional form is that the number of parameters grows quickly with the number of variables leading to multicollinearity issues especially for the interaction terms. To avoid this we omit the interactions in the two functions and include only the linear and quadratic terms. This allows to determine the magnitude of the marginal impact of each input and whether that particular input has decreasing or increasing marginal productivity, but rules out the possibility to investigate the complementarity and substitutability among inputs. The mean output is approximated through the following quadratic function $f(x_1, x_2, \boldsymbol{Z}, \boldsymbol{\alpha}) = \alpha_0 + \alpha_Z \boldsymbol{Z} + \sum_{i=1}^{2} \alpha_i x_i + \sum_{i=1}^{2} \alpha_{ii} x_i^2$ and the variance function is approximated by $h(x_1, x_2, \boldsymbol{Z}, \boldsymbol{\beta}) = \beta_0 + \beta_Z \boldsymbol{Z} + \sum_{i=1}^{2} \beta_i x_i + \sum_{i=1}^{2} \beta_{ii} x_i^2$. The other factors in $\mathbf{Z}$ which we control for in the estimation of the production function include the area of operated land in hectares and household size. The area of land controls for the amount of fixed capital that contributed to the production of farm output and is a proxy for household wealth. Household size directly determines the amount of labor supply that can be employed on the farm.

Unbiased OLS estimates of the parameter vector $\boldsymbol{\alpha}$ can be obtained by regressing the value of farm production on input expenditure, their squares and the controls for operated land and household size as shown the following equation, where to avoid confusion we have omitted the household subscript.

$$Y = \alpha_0 + \alpha_Z \boldsymbol{Z} + \sum_{i=1}^{2} \alpha_i X_i + \sum_{i=1}^{2} \alpha_{ii} X_i^2 + u \qquad (4)$$

where Y is the value of farm output, $X_i = w_i x_i$ represents expenditure for input i and $u = h(X_1, X_2, \boldsymbol{Z}, \boldsymbol{\beta})\varepsilon$. The residuals from this stage ($\hat{u}$) are a consistent estimate of the true error distribution (u) and are therefore used to compute the variance of the output distribution. In fact, we have that $\mathrm{E}[u^2] = h^2(X_1, X_2, \boldsymbol{Z}, \boldsymbol{\beta})$ since $\mathrm{E}[\varepsilon^2] = 1$ and ε is an independent shock. At this point, in order to obtain an unbiased estimate of the parameter vector $\boldsymbol{\beta}$ of the variance function we follow Antle (1983) and regress the square of the estimated residuals from (4) on the same set of covariates included in the estimation of the mean effect, namely

$$\hat{u}^2 = \beta_0 + \beta_Z \boldsymbol{Z} + \sum_{i=1}^{2} \beta_i X + \sum_{i=1}^{2} \beta_{ii} X_i^2 + v \tag{5}$$

where $E[v] = 0$. One last issue in this first part of the estimation concerns heteroschedasticity. Although the OLS estimates of $\boldsymbol{\alpha}$ are unbiased and consistent they are not efficient since the variance of the model in (4) is clearly not constant across observations and depends on the regressors. This causes heteroskedastic errors and results in estimated standard errors that are biased. The correction for this problem leads to an estimation of the parameter $\boldsymbol{\alpha}$ that is both consisten and efficient. To correct for heteroschedasticity, a feasible generalized least squares (FGLS) estimator is used (Antle 1987; Hurd 1994). Therefore, the estimates of $\boldsymbol{\beta}$ are used to construct the predicted values of the output variance. In a final step, we re-estimate equation (4) by weighted least squares where the weights are given by the reciprocal of the output standard deviation. This method, first introduced by Just and Pope (1978) and later generalized by Antle (1983, 1987, 1989), allows estimating in a flexible way the interaction between the set of inputs and the different moments of the output distribution without imposing any cross-moment restriction on the sign of the effects.

In the second part of the estimation strategy we want to estimate how farmers' risk attitudes measured by the coefficient of absolute risk aversion (R) change in the population of the beneficiaries relative to the control group as a result of the cash transfer program. The econometric estimation of risk attitudes based on production decisions has produced a significant literature (Antle, 1987; Love and Buccola, 1991; Saha, 1997; Groom et al., 2008; Serra et al., 2011). Here we follow a non-structural approach proposed by Antle (1987, 1989) which has fewer data requirements and avoids making assumption on the form of the utility function, of the coefficient of absolute risk aversion or on the distribution of the random shock ε. The fundamental idea is that the farmer engages in a trade-off between marginal increases in mean output and marginal increases in the output variance while choosing his input. This is expressed formally by the FOC-s in equation (2) where the average marginal change in income ($E[MI_i]$) due to a marginal change in input *i* is compensated by a change in the variance of the output value ($V[Y]_{x_i}$) induced by the same change in input *i*. The mean-variance trade-off is mediated by the coefficient of risk aversion R so that the impact of each input mix on each farmer's income and risk, helps trace his risk profile. Risk averse farmers tend to select input combinations that decrease the variance of income at the cost of a lower expected income by adopting diversification strategies at the cost of economy of scale or by adopting too few new technologies. In terms of farm production, this translates in less efficient use of labor, smaller production scale and off-farm jobs to diversify the sources of income (Vollenweider et al., 2011). The implicit assumption in this model is that income smoothing takes place as there are no insurance or credit mechanisms at all (Antle, 1987; 1989). In that case, income translates directly to consumption, and production choice will fully reflect the tradeoff between risk aversion and expected profit maximization. Since profit maximization implies that the marginal products of inputs will equal their prices, measures of risk aversion can be quantified by estimating the degree to which marginal products and prices depart. In our context, the cash transfer is the only means that introduces a consumption smoothing differential between the treated and the controls. The assumption of no consumption smoothing is, of course, a strong one, and its tenability is questionable. Even in a rural context with rudimental financial markets, households will be able to achieve some level of consumption smoothing by accumulating and depleting assets or using informal mechanisms. Given some consumption smoothing, measures of risk aversion taken from this methodology will be understated. As for the difference in risk aversion between the treated and controls, it should be unbiased as access to consumption smoothing means other than the cash transfer should be equal for both groups due to randomization.

Estimation proceeds with the assembling of the system of FOC-s in (2).[5] To do so we need to construct first estimates of $E[y]_{x_i}$and $V[y]_{x_i}$. We use the estimates of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ obtained in the first part and the functional form for $f(.)$ and $h(.)$ to construct the marginal effects of the inputs on the first and the second moment of the output distribution. Since we used the value of output instead of physical quantities we obtain directly the input's *i* marginal product as $\hat{E}[Y]_{x_i} = p\hat{E}[y]_{x_i}$= $\widehat{\alpha_\iota} + 2\widehat{\alpha_{\iota\iota}}X_i$ so that the expected marginal income is $\hat{E}[MI_i] = \hat{E}[Y]_{x_i} - w_i$. Furthermore, the marginal contribution of each input to the variance of output value is given by $\hat{V}[Y]_{x_i}$=$p^2\hat{V}[y]_{x_i} = \widehat{\beta_\iota} + 2\widehat{\beta_{\iota\iota}}x_i$. The system of linear equations is then

[5] Many of the previous studies of decisions on seed-fertilizer adoption analysed them separately in a single equation model. From an econometric point of view, a single equation estimation approach could cause biased parameter estimates if decisions were truly simultaneous and/or unobserved heterogeneities were correlated for these decisions.

$$\begin{cases} \hat{E}[MI_1] = \gamma_0 + \gamma_1 \hat{V}[Y]_{x_1} + \gamma_2 G + \gamma_3 \hat{V}[Y]_{x_1} G + e_1 \\ \hat{E}[MI_2] = \delta_0 + \delta_1 \hat{V}[Y]_{x_2} + \delta_2 G + \delta_3 \hat{V}[Y]_{x_2} G + e_2 \end{cases} \tag{6}$$

where $e_1$and $e_2$are correlated error terms. The coefficient of absolute risk aversion R can be recovered from system (4) as $\frac{\partial \hat{E}[MI_i]}{\partial \hat{V}[Y]_{x_i}}$=$\gamma_1 = \delta_1 = 0.5R$, so that $R = 2\gamma_1 = 2\delta_1$. We follow previous literature and impose the cross-equation constraint that farmers exhibit the same level of risk aversion for the whole range of input choices, i.e. $\gamma_1 = \delta_1$ (Groom et al., 2008; Vollenweider et al., 2011; Koundouri et al., 2005). Although each input can affect the moments of output distribution in different ways, the risk coefficient is not associated with specific inputs as it expresses the farmer's preferences in the mean-variance trade-off. A positive coefficient of absolute risk aversion indicates that the farmer is risk averse. Furthermore, we obtain the change in risk aversion at the population level as a result of the cash transfer program by comparing the risk attitude of the treated to that of controls after the program. Formally, we estimate $R_G = \frac{\partial R}{\partial G} = 2\frac{\partial \hat{E}[MI_i]}{\partial \hat{V}[Y]_{x_i} \partial G} = 2\gamma_3 = 2\delta_3$. We expect a reduction in the risk aversion coefficient in the treated group ($\gamma_3, \delta_3 < 0$) as a result of the increase in exogenous income induced by the cash transfer (*wealth effect*). Estimation of the system of linear equations is carried out by three stage least squares (3SLS) in order to correct for the possible endogeneity of output variance. In fact, the residuals e_i partly reflect differences in risk attitudes that are likely to affect the moments of the output value distribution. There are three exogenous variables used in the estimation as instrumental variables. The dummy for program participation acts as its own instrument. Two excluded instruments consist of the amount of cash transfer received by the household during the twelve months preceding follow-up data collection and a shock dummy that registers the occurrence of a pest or a crop disease outbreak at the community level (Kim T-H, 2008). The latter two instruments are likely to affect mean output and its variability but can be reasonably expected to be independent from a farmer's risk preferences. The same set of instruments is used for both equations. Besides being the system equivalent of the single equation two-stage least square estimator (2SLS), thus allowing to correct for endogenous right-hand side variables in a multi- equation setup, the 3SLS procedure recognizes the potential for inter-equations correlation of the errors, since decisions on the two inputs analyzed (seeds and fertilizers) are taken jointly.

The third and last part of the empirical strategy is concerned with the estimation of the cash transfer program's impact on input demand. The FOC-s equations (2a) from the economic framework presented in the previous section implicitly define the structural relationship between input use and other variables. We may define the input demand functions as $X_1 = g_1(X_2, Y(X_1, X_2, \boldsymbol{Z}), w_1, G)$ and $X_2 = g_2(X_1, Y(X_1, X_2, \boldsymbol{Z}), w_2, G)$. These provide the structural form equations for a system that, in general, can be solved simultaneously for optimal input use. However, this requires the analyst to impose more structure by making assumptions on the functional form of the utility function and of the absolute risk aversion coefficient. This results in complicated estimation procedures of a system of non-linear equations whose solutions strongly depend on the functional form assumptions. Here, instead, we assume a linear relationship between the input demand and the arguments of the demand function $g_i(.)$ and form a system of linear simultaneous equation (SEM),

$$\begin{cases} X_1 = \pi_0 + \pi_1 X_2 + \pi_2 Y + \pi_3 \boldsymbol{Z} + \pi_4 w_1 + \pi_5 G + \zeta_1 \\ X_2 = \varphi_0 + \varphi_1 X_1 + \varphi_2 Y + \varphi_3 \boldsymbol{Z} + \varphi_4 w_2 + \varphi_5 G + \zeta_2 \end{cases} \tag{7}$$

where the two errors, ζ_1 and ζ_2, are potentially correlated according to some covariance matrix Σ, since the decisions on both inputs are jointly determined. In fact, the defining feature of the linear simultaneous equation model in (7) is that the dependent variable in the first equation appears on the right-hand side of the second equation and, vice versa, X_2 is among the determinants of X_1. Moreover, the value of output (Y) in both equations is potentially endogenous since it is correlated with the unobserved determinants of input choice. These circumstances cause the system OLS estimator to be plagued by simultaneity and endogeneity bias. A popular solution to the endogeneity problem is using an instrumental variable approach. This motivates our choice to estimate the parameters of system (7) by two stage least squares and by three stage least squares. The 2SLS is a limited information method since it consists in applying instrumental variable estimation to one equation at time ignoring the cross-equation correlation in the errors and the information contained in other equations. In other terms, while 2SLS is consistent, it is also inefficient. Therefore, we also apply a full information estimator, the 3SLS, that corrects the endogeneity while properly accounting for the fact that system (7) has a non-constant variance covariance matrix correlation and for the deriving cross-equation correlation. The 3SLS offers a solution to both the endogeneity and simultaneity issues since is consists of a combination of instrumental variables estimation and the generalized least squares. The relationship between this 3SLS estimator and the 2SLS estimator for the entire system is essentially the same as the relationship between the feasible GLS estimator and the OLS estimator for a system of seemingly unrelated regressions (SUR) (Davidson and McKinnon, 2004).

The first two stages of the 3SLS estimation method coincide with the 2SLS. The first stage solves for all endogenous variables in the system by rewriting the endogenous variables as a function of the exogenous variables. The fitted values of each endogenous variable from the system OLS estimation of the reduced form equations are used as instruments in the structural equations. The second stage involves estimating the structural equations separately using the first stage fitted values. In the final stage, 3SLS, unlike 2SLS, makes use of the covariance matrix computed from the two disturbance terms that result from the second stage. In particular, this involves using the covariance matrix as a weighting matrix as well as the instruments derived in the first stage to jointly estimate the equations in the structural model. Using instruments to estimate endogenous variables ensures consistency, while joint estimation ensures asymptotic efficiency (Wacziarg, 2001).

We also note that in the case where Σ is a diagonal matrix, 3SLS estimation is identical to 2SLS estimation on each equation. This is also the case if every equation is exactly identified. The reason is that in these cases there is no informational gain in considering all the equations together. In these situations the coefficients on 2SLS and 3SLS will be identical. However, the standard errors will be different. In our case, though, we have more instruments than there are endogenous variables, so we expect coefficients and standard errors to differ between 2SLS and 3SLS. The reason we use both limited information and full information estimators is that they present both advantages and disadvantages. Although the systems methods are asymptotically more efficient, they are more prone to misspecifications. Any specification error in the structure of the model will be propagated throughout the system by the 3SLS. The limited information 2SLS will, by and large, confine a problem to the particular equation in which it appears (Greene, 2008). If we assume that all equations are correctly specified, 3SLS is asymptotically more efficient than the 2SLS procedure, but 2SLS is more robust. Assuming that our instruments are exogenous, the 2SLS estimates can be considered consistent. Instead of making assumptions about whether the equations in our system are correctly specified, we just present 3SLS estimates and compare them to the 2SLS estimates.

The parameters of the system are estimable provided some assumptions are verified. In other terms, identification of system (7) hinges on two conditions, an order condition and a rank condition. We use the same set of instruments for both equations. We start by describing the natural exclusion restrictions that help identify the system. These are variables that exogenously shift demand for one input but not for the other. The price of seeds is included in the first equation but can be excluded from the second. The assumption here is that the seeds price can serve as a demand shifter for fertilizers through its influence on seeds expenditure.

Similarly, the price of fertilizer is excluded in the first equation so that it shifts seeds demand only through its impacts on fertilizer use. The rest of the exogenous variables used for the estimation of system (7) include the price of the output, a shock dummy that registers the occurrence of a pest or a crop disease outbreak at the community level and a shock dummy for the occurrence of draughts at the community level. This brings the number of excluded exogenous variables to four in each equation. The program dummy, the household size and the area of operated land serve as their own instruments. The necessary order condition for identification of a SEM is trivially satisfied in our case since the number of excluded exogenous variables (four) is higher than the number of endogenous variables (two) in each equation. The rank condition is a necessary and sufficient condition for identification. In a model with M equations and M endogenous, an equation is identified if at least one nonzero determinant of order (M-1)(M-1) can be composed from the coefficients of variables excluded from that equation but included in other equations in the model. In a two-equation simultaneous equations model, the first equation is identified if and only if the second equation contains at least one exogenous variable (with nonzero coefficient) that is excluded from the first equation A similar case can be made for the second equation (Wooldridge, 2002). The rank condition is in many cases assumed to be satisfied unless there is a failure of the order condition. The rank condition in our model is indeed satisfied.[6]

5. Results

This paper investigates the theoretical hypothesis that a cash transfer program' impacts on input use depend on the CT-induced wealth effects on the famers' risk attitudes and on the input's contribution to output variability. In section 3 we made the claim that an increase in government transfers will result in an increase in the household's wealth, which will induce a reduction in the farmer's degree of risk reduction. Given this change in risk attitudes famers will increase the use of a certain input if it is risk-increasing ($V[Y]_{x_i}$>0) and will use less of the input if it is risk-decreasing ($V[Y]_{x_i}$<0).

In order to capture the impact of the variable inputs, namely seeds and fertilizers, on the output variability, we estimate a Just-Pope type of stochastic function. The choice of the functional was influenced both by previous literature and by limitations imposed by our data. First among these limitations was mass of zeros in the variables measuring expenditure on

[6] We use Stata's command checkreg3 to verify the validity of the rank condition in our sample.

seeds and fertilizers due to the fact that many farmers do not buy fertilizers and use seeds homemade seeds or borrow these inputs. This limitation greatly influenced the choice of a linear/quadratic specification by ruling out logarithmic transformations of the dependent variables. The quadratic specification allowed the model to reflect diminishing returns for many of the modeled inputs. Besides the variable inputs, the factors hypothesized to affect output and output variability included other factors that are fixed in the given time period or exogenous to the producer, such as household size and area of operated land.

Estimation results from the econometric analysis of the stochastic production function are presented in Table 2. The first and second columns show results from the OLS and FGLS estimation, respectively, of equation (4), while the third column reports the impact of each input on output variability as specified in equation (5). These parameter estimates and associated t-statistics indicate the magnitude and strength of the relationships among various inputs, and the expected value and variance of output. Parameter estimates for the mean output have the expected signs and linear and quadratic terms are, with few exceptions, statistically significant. Both seeds and fertilizers have a positive impact and the coefficients on the quadratic terms are negative and statistically significant, indicating that both variables inputs increase output at a decreasing rate.[7] An increase in the use of seeds is associated with a statistically significant increase in output variability. The literature has often considered fertilizers as an example of inputs that increase output variability (Just and Pope, 1979; Serra et al., 2006). In fact, we find fertilizer use also increases output variability but the effect is imprecisely estimated. The area of operated land performs according to expectations with the linear and quadratic coefficients being positive and negative, respectively, indicating diminishing marginal productivity of land. The impact of household size on mean output is negative and diminishes at an increasing rate. This may be the result of the eligibility criteria that target families with children under five. Therefore, a larger household size may not be indicative of greater labor potential, but of a larger number of children. Child care may take time from the adults that could be alternatively used on the farm. Our findings for the stochastic production function estimates are in line with some of the previous research that has explored the risk natures of different inputs. Roll et al. (2006) show that land and fertilizers have a risk-increasing effect based on a cross-section of subsistence farmers in Tanzania. Yusef et al.

[7] The estimation sample for FGLS is smaller as some observations corresponding to negative weights are lost. This is due to the fact that the linear regression used in the second step is not guaranteed to predict positive values of the variance.

(2009) show that fertilizers increase downside risk in production based on cross-section of farmers in the Ethiopian highlands. Ligeon et al. (2013) find that the quantity of seeds used increases the output variability among peanut farmers in Bulgaria. Kohansal and Aliabadi (2014) show that Potash fertilizer and land have positive and significant impact on wheat production risk. However, the extent to which an input is risk increasing or decreasing also depends on the nature of the crop and the soil fertility on which the crop is cultivated.

To express the estimation results more clearly, the estimates of elasticities associated with each input are shown in Table 3. The elasticity measures were calculated at the mean values for output and inputs, and indicate the percentage changes for the mean and variance of output from a percentage change in the level of the input. For example, from column 1, doubling the expenses on seeds leads to an increase of 17.4% in the value of production and to a 31,8% increase in output risk, while the same increase in fertilizers raises output by 15.8% on average. Considering the effect of the latter input on the variability of output, no support was found in this study for the view of fertilizers as a risk-increasing input, as has been suggested by previous theoretical research (Just and Pope, 1979; Pope and Kramer, 1979; Paulson and Babcock, 2010). In fact, the marginal impact on output variability associated with fertilizer is positive but statistically insignificant. This may be due to the fact that only 5% of the sample buy any fertilizers at all compared to 37% of those who buy seeds. Household size has a positive and sizable impact on output risk but the computed elasticity does not achieve statistical significance. The area of operated land is, by and large, the most influencing factor of production. Doubling the area of planted land would lead to a 63.7% increase in mean output and to a more than twofold jump in output variability.

Table 4 presents results for the estimation of the Arrow-Pratt coefficient of risk aversion from the system of FOCs in equation (6). The system of the two linear equations, one for each input, is estimated by three stage least squares. The Arrow-Pratt coefficient of absolute risk aversion is constrained to be equal for both inputs as it expresses the risk aversion of the farmer and is equal to twice the coefficient on the variance of the output value. Zambian farmers in our sample exhibit risk aversion with an average Arrow-Pratt absolute coefficient of 0.007. This estimate of the coefficient of absolute risk aversion is in the lower bound of the literature. Previous studies like Love and Buccola (1991) find an Arrow-Pratt coefficient of absolute risk aversion equal to 0.016 for US farmers, Groom et al. (2008) estimate a coefficient of 0.0726 for Cypriot farmers, Korir (2011) finds a coefficient of 9.1e-06 in Kenya, while Arcand and Mbaye (2013) find coefficients very close to zero in Senegal. There are no formal criteria, however, for how close to zero the coefficient should be for the individuals to be considered risk neutral. Since our estimated coefficient is small but statistically different from zero we interpret the finding as an indication of a low degree of risk aversion.

The findings of low risk aversion or almost risk neutrality may conceal the possible failure of the no consumption smoothing assumption in Antle's model. As we mentioned in the previous section, given some consumption smoothing, measures of risk aversion will be understated. Parameters of low risk aversion may indicate that the households have good consumption smoothing possibilities rather than no fundamental concern about risk. However, here we are interested in the difference in risk aversion between the treated and controls. This should be unbiased as access to consumption smoothing means other than the cash transfer should be equal for both groups due to randomization. The regression coefficient of the interaction between the output variance and the program dummy points to a reduction of the degree of risk aversion in the treated group pushing this group even closer to risk-neutrality. This is consistent with our expectations since the average amount of the transfer is considerable even relative to the value of production (Table 1) and constitutes a significant increase in the household's wealth. As a result, the treated group may be expected to engage in riskier behavior in terms of production decisions and input mix choices. Incidentally, the latter result also suggests that farmers' choices were consistent with decreasing absolute risk aversion (DARA). We now focus on the estimates of the intercept in each input equation. A constant term close to zero indicates that, given the marginal cost, the input is efficiently used. This is because the estimated system of equations (2) is derived from the first order condition for expected profit maximization. If there are no systematic deviations from expected utility maximization and no specification errors the intercepts for each input shall be equal to zero (Antle, 1987; Buzzola, 2014). Estimates of the intercepts that are different from zero can be interpreted as deviations from profit maximizing choice of the particular input (Groom et al., 2008; Buzzola, 2014). We find large negative and statistically significant intercepts for both equations which, as expected, points at the severe underutilization of bought seeds and fertilizers.

We now analyze results from the estimation of the system of input demand equations (7). Table 5 and Table 6 show the findings from the application of the 2SLS and 3SLS estimators, respectively. The 2SLS estimate of the program impacts indicates that farmers in the treated group increased demand for seeds by 10675 ZMK as a result of the cash transfer. The impact of the cash transfer on fertilizer use is positive but statistically insignificant. Since we found fertilizers not to be risk-increasing, this finding would seem to lend support to the theoretical hypothesis that, given a reduction in risk aversion induced by the extra cash, demand for an input will increase only if the input increases output variability. However, as mentioned in the previous section, the system 2SLS is not the most efficient estimator which may also cause the program impact on fertilizer demand to be insignificant. In fact, the 3SLS produces a program impact for fertilizer demand that is higher in magnitude (5618) and barely significant. For seeds demand the 3SLS estimates confirm a strong and significant increase in seeds demand as a result of the cash transfers that amounts to 11074 ZMK. In terms of elasticities these coefficients amounts to an increase in seeds and fertilizer demand of 87.3% and 49.2%, respectively. As to the rest of the variables we note that own price elasticity is positive for both inputs although the 3SLS estimates are imprecise. Household size and land area are positively associate with seeds use both in the 2SLS and in the 3SLS estimator but their influence is statistically insignificant. On the other hand, an increase in farm size significantly decreases the quantity of fertilizer demanded. These findings are consistent with those found in India (Dholakia and Majumdar, 1995), in Bangladesh (Mahmood et al., 1995) on paddy rice and in Malawi (Likoya and Minagisoni, 2012). The reason for the negative relationship may lie in the need for smaller farmers to intensify production through the increased use of fertilizer on smaller pieces of land.

To gauge the validity of the rank condition and the presence of weak instruments we show the common first stage regressions for both the 2SLS and 3SLS estimators. Table 7 presents F-test for the first stage of the 2SLS/3SLS estimators. They test the joint significance of the instruments in the system regressions of the endogenous variables on all exogenous variables. The F-tests for first stages corresponding to our three endogenous variables show that the instruments are strong determinants of the variables they are instrumenting for, thus limiting the potential for weak instruments. F tests reject at greater than the 99% level the null hypothesis that excluded instruments do not have explanatory power. The impact of inconsistency arising from a possible correlation of instruments with errors can be reduced by a strong correlation between the instruments and the endogenous variables (Bound, Jaeger, and Baker, 1995).

Thus, from the empirical results above we conclude that, for our sample of Zambian farmers, the cash transfer consisting of a substantial increase in the household’s exogenous income and wealth, may have the effect of boosting output variance and mean by increasing the use of risk-increasing inputs. Our result seem to strongly support this interpretation.

For seeds we find that beneficiary farmers engage in riskier behavior by increasing demand, arguably, as a result of the cash-transfer-induced reduction in risk aversion. The surge in seeds purchases results in an increase in output variability. While in the case of fertilizers we find weak evidence of increased use caused by the program in line with the finding that fertilizer use does not increase output risk significantly.

6. Conclusions

In this paper we study the role of unconditional government transfers in Zambia in helping poor farmers break out of risk-induced poverty traps. Lack of access to credit and insurance mechanisms precludes the possibility of smoothing consumption once post-production decisions risks materialize. In order to avoid permanent damage, households, especially poorer ones, may opt for less risky technologies, giving up at the same time the possibility for higher returns. The absence of insurance can be very costly to rural households, leading them to forego economic opportunities that offer the prospect of significant income improvement. To reduce their income risk, poor households may enter low-risk, low return activities. In this way, risk avoidance in the face of incomplete insurance and credit markets contributes to continuing low agricultural productivity and persistent poverty. Thus, if we are to understand the dynamics of poverty, we need to understand attitudes to risk and what policies have a bearing on these attitudes.

We use data from the household survey for the evaluation of the Child Grant Program in Zambia to study the effects of unconditional cash transfers on farmers' risk aversion and input demand. In our analysis we also account for the potentially different impact of a certain input on average output and on output variability, which in turn mediates the influence of the *wealth effect* on input demand. We find that seeds are risk increasing while the influence of chemical fertilizers on output risk is positive but insignificant. Cash transfers cause a reduction in risk aversion among the treated, which translates in greater demand of commercial seeds. The impact of cash transfers on chemical fertilizer demand is positive but statistically insignificant.

Until the underlying causes of failures in credit and insurance markets can be corrected, unconditional cash transfers can be a useful in pushing farmers out of the poverty trap as they offer a stable source of liquidity that allows consumption smoothing and increases their wealth thus reducing risk aversion and inducing higher-risk higher-return production choices.

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Appendix

Table 1: Descriptive statistics

	Mean	SE
HH size	5.765***	[0.044]
Operated land	0.735***	[0.018]
Value of transfer	613625	[211546]
Price of seeds	7499***	[0.038]
Price of fertilizer	4891***	[0.009]
Price of output	1242***	[0.008]
Expenses for seeds	12679***	[0.776]
Expenses for fertilizers	8661***	[1.042]
Value of production	589380***	[18.838]
Shock: drought	0.470***	[0.010]
Shock: crop disease/pest	0.106***	[0.006]
N	2298	

Table 2: Stochastic production function coefficients estimates

	Mean (OLS)		Mean (FGLS)		Variance	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Exp. for seeds	5.320***	[4.305]	6.962	[1.599]	1.36e+07**	[2.042]
Exp. for fertilizers	5.557***	[4.760]	6.858***	[3.385]	1.00e+06	[0.384]
HH size	-1.91e+05***	[-2.725]	-3.83e+05***	[-3.781]	-4.30e+10	[-0.323]
Operated land	4.55e+05***	[4.503]	5.08e+05**	[2.282]	7.49e+11**	[2.476]
E. seeds squared	-0.000**	[-2.008]	-0.000	[-0.690]	-28.576	[-1.492]
E. fertilizers squared	-0.000***	[-4.540]	-0.000***	[-2.725]	0.710	[0.198]
HH size squared	17715.972***	[3.062]	32743.168***	[5.101]	6.10e+09	[0.528]
Op. land squared	-1.20E+04	[-0.651]	-2.58e+04	[-0.964]	3.20e+10	[0.738]
Constant	6.13e+05***	[3.055]	1.00e+06**	[2.403]	-1.85e+11	[-0.418]
Observations	2298		1688		2298	

Table 3: Stochastic production function elasticities estimates

	Mean (FGLS)		Variance	
	Elasticity	t-stat	Elasticity	t-stat
Expenses for seeds	0.174**	[2.296]	0.318***	[2.649]
Expenses for fertilizers	0.158***	[2.757]	0.017	[0.375]
HH size	0.338*	[1.835]	0.306	[1.356]
Operated land	0.637***	[5.170]	1.139***	[7.288]
Observations	1688		2298	

Table 4: Arrow-Pratt coefficient estimates

	Seeds		Fertilizers	
	Coefficient	t-stat	Coefficient	t-stat
(1/2)V[y]	3.59e-03**	[2.314]	3.59e-03**	[2.314]
(1/2)V[y]*T	-4.41e-03*	[-1.758]	-4.41e-03*	[-1.758]
T	2.83e+04*	[1.750]	2.06e+03	[1.618]
Constant	-3.09e+04***	[-3.024]	-6.61e+03***	[-8.433]
Observations	2298		2298	

Table 5: Two-stage least squares (2SLS) estimates for input demand

	Seeds		Fertilizers	
	Coefficient	t-stat	Coefficient	t-stat
Expenses for fertilizers	-0.369	[-0.793]		
Price of seeds	2.227*	[1.640]		
Treatment	10675.847***	[3.837]	2025.102	[0.624]
HH size	1576.764	[1.613]	-255.080	[-0.353]
Operated land	6056.522	[1.392]	-1.34e+04**	[-3.104]
Value of production	-0.001	[-0.068]	0.037***	[3.959]
Expenses for seeds			0.082	[0.300]
Price of fertilizers			8.089*	[2.498]
Constant	-1.94e+04	[-1.404]	-4.37e+04**	[-2.906]
Observations	2298		2298	

Table 6: Three-stage least squares (3SLS) estimates for input demand

	Seeds		Fertilizers	
	Coefficient	t-stat	Coefficient	t-stat
Expenses for fertilizers	-0.432	[-0.977]		
Price of seeds	1.681	[1.322]		
Treatment	11074.994***	[4.085]	5618.530*	[1.801]
HH size	1412.007	[1.502]	-30.278	[-0.042]
Operated land	3475.262	[0.826]	-1.32e+04***	[-3.097]
Value of production	0.005	[0.620]	0.040***	[4.300]
Expenses for seeds			-0.294	[-1.151]
Price of fertilizers			7.743*	[2.494]
Constant	-1.55e+04	[-1.194]	-4.19e+04**	[-2.900]
Observations	2298		2298	

Table 7: First stage estimates 2SLS and 3SLS

	Seeds		Fertilizers		Value of production	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Price of seeds	1.107	[1.376]	2.774*	[1.938]	51.282**	[2.214]
Price of fertile.	1.158	[0.534]	1.234	[0.268]	-183.149*	[-1.912]
Price of output	7.194***	[2.645]	-4.153	[-1.415]	-28.577	[-0.390]
Treatment	9148.018***	[4.376]	3994.739	[1.133]	43650.992	[0.593]
HH size	738.638*	[1.852]	1893.062***	[2.879]	56290.805***	[4.566]
Operated land	3998.272***	[2.859]	5246.730**	[2.423]	4.89e+05***	[5.853]
Drought	-2140.201	[-0.970]	-3313.654	[-1.154]	-1.41e+05***	[-3.052]
Crop dis./pest	4854.082	[1.364]	1231.824	[0.404]	-1.13e+05**	[-2.149]
Constant	-2.15e+04*	[-1.689]	-2.84e+04	[-1.148]	5.09e+05	[0.945]
F stat (p value)	6.91 (0.00)		2.75 (0.009)		8.13 (0.00)	
Observations	2298		2298		2298	