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ABSTRACT

This paper investigates the effects of rainfall variability on agricultural input demand while controlling for risk preference and other covariates. For the empirical analysis, rural household survey data, which was matched with rainfall variability data and experimentally generated measures of risk preference, was used. The results show that increased rainfall variability prompts households to reduce the application of productivity-enhancing inputs, such as fertiliser, but bolsters the application of low-risk inputs such as manure. These results are robust to alternative specifications and support the theoretical predictions developed. The findings suggest the following policy implications for chemical fertiliser use among risk-averse smallholder farmers in areas characterized by rainfall variability. First, developing more weather-resilient crop varieties and irrigation could stimulate higher use of chemical fertiliser by producing more stable yields. Secondly, weather index insurance (WII) could incentivize higher chemical fertiliser use by reducing income risk and easing liquidity constraints. Thirdly, social protection such as cash transfer programmes could lead to a higher use of chemical fertiliser by serving as insurance against income risks (i.e., through providing regular and predictable financial resources).

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Rainfall variability; risk preferences; inorganic fertiliser; manure

1. Introduction

Internationally, there is a vast and fast-growing body of literature concerning the economic impacts of climate change. One main focus area is the potential impact of climate change on agriculture (Salinger et al. 1997; Dixson and Sergerson 1999; Blignaut et al. 2009). Unlike other sectors such as trade and industry, agriculture is directly impacted by climatological variables such as temperature and precipitation, and their impact on the length and quality of growing seasons. Not only are the mean values important, as well as any changes in those values; so are the range in variability and predictability of these climatological variables. Climate change, defined as the long-run change in the mean and variability of climatological variables (Hassan and Nhemachena 2007), prompts a change in the choice of agricultural inputs, production, and methods of production in agricultural systems (Kane and Shogren 2000).

It has been shown that farmers adapt readily to rainfall variability (Hassan and Nhemachena 2007; Alem et al. 2010). In adapting to more complex and prolonged changes in climate, farmers have to rely on the efficacy of the interaction between a list of farm-level input decisions.[1] *Inter alia*, these input decisions include the increased use of irrigation, the shift to early-maturing crop varieties, the use of pesticides, chemical and/or organic fertilisers, diversification of crop portfolio, and the allocation of the land under production for each crop (Hassan and Nhemachena 2007; Kurukulasuriya and

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Mendelssohn 2007; Deressa et al. 2009). In short, farmers' adaptation to climate change manifests itself mainly through a shift in the demand for and the use of inputs such as fertilisers, specific crop varieties, pesticides, irrigation water, and arable land and labour use and allocation to specific crops. It is worth noting that each of these inputs has a direct and meaningful interaction with the magnitude of variable climate. Inputs are either risk-increasing, risk decreasing, or risk-neutral (Just and Pope 1978). The use of chemical fertilisers, for example, reduces yield when rain fails, since they "burn" the roots of plants, but it increases yield during a normal or better-than-average-rain year. Thus, the use of fertilisers increases both the first (mean) and the second (variance) moments of yield determination, affecting the yield distribution. However, apart from maintaining soil fertility, the use of manure helps conserve water in the soil (Sesmero et al. 2018) and hence reduces yield variance.

For the most part, micro-level studies on the link between agriculture and climate in Africa have focused on the determinants of adaptation to climate change (Hassan and Nhemachena 2007; Kurukulasuriya and Mendelssohn 2007; Deressa et al. 2009), the impact of climate change on a household's farm income (Deressa et al., 2009), the impact of adaptation to climate change on food security, the impact of rainfall variability on crop diversification (Bezabih and Sarr 2012), the impact of climate change adaptation on farm households' downside risk exposure (Di Falco and Veronesi 2013) and climate uncertainty and demand for chemical fertiliser (Alem et al. 2010). Although these studies have contributed to the knowledge and understanding of this modern-day phenomenon, evidence on whether the behavioural response to climate change (in terms of demand for agricultural inputs) varies with an input's risk profile, i.e. its risk-increasing, risk-decreasing, and risk-neutral properties. Particularly, although Alem et al. (2010) confirmed that rainfall variability as measured by rainfall coefficient of variation reduces demand for chemical fertiliser, the question remains whether the same relation holds for an alternative input demand, such as that for organic manure. Moreover, the study referenced did not control for risk preference in its empirical specification.

This study extends Alem et al. (2010) in two ways. First, it accounts for individual risk preferences in the demand decision for agricultural inputs, while controlling for climate risk in the form of rainfall variability. Secondly, in investigating this relationship it account for the typology of the inputs owing to the implication of their use for yield variability. The key hypothesis of this study is that the impacts of rainfall variability (yield risk) are input-type-differentiated, for the following reasons. First, although both manure and fertiliser are used to improve soil fertility and bolster crop production, they have differential interaction with extreme weathers conditions; if the rains fail, fertiliser is more likely to burn soil than manure is and hence will result in varied distributions of crop yield, all other variables remaining constant. Secondly, alternative inputs have different intertemporal farm-income distributions. In particular, current fertiliser use bolsters crop yield in the short run, but gradually imposes a detrimental effect on soil fertility (through soil mining) and hence reduces crop yield in the long run. Current manure application, on the other hand, has the opposite implications for intertemporal farm-income distribution. Thirdly, whereas fertiliser is a tradable input, manure is non-tradable, due to the missing market. This may have implications for how input demand responds to rainfall variability and risk preference. Accounting for input typology in terms of its demand's response to rainfall risk would enable us to extract specific policy implications for managing risk and poverty-reduction measures.

In the interest of deriving and testing these implications, this study first developed a theoretical model that formalizes farmers' input-demand responses to rainfall variability (yield risk) thereby informing empirical specifications. The model accounts for farmers' risk preferences and the risk properties of agricultural inputs by drawing on the standard framework of choice under uncertainty (Pratt 1964).[2] As a related stylized fact to this outcome, Ellis (1998) established that risk aversion results in sub-optimal resource allocation, and that the extent of this outcome increases with the degree of risk. This is mainly because peasant households cannot transfer risks partly or wholly to other parties; in the developing countries where the great majority of peasants live and farm, insurance and credit markets are often malfunctioning, poorly developed, or absent altogether. This is of particular importance when it comes to rainfall uncertainty, which is a covariate in nature. A second stylized fact is an evidence that risk-averse peasant farmers' resource allocation is also affected by the interaction of these resources with risks, i.e., whether they are risk-increasing, risk-decreasing, or risk-neutral (Grepperud 2000).

2. Theoretical frameworks

In this section, a comparative static analysis of input demand for risk-averse peasant farmers using the Just and Pope (1978) production function and a linear mean-variance utility function was derived. For ease of exposition, Constant Absolute Risk Aversion (CARA) of farmers' attitudes to risk, as opposed to Decreasing Absolute Risk Aversion (DARA) or Increasing Absolute Risk Aversion (IARA) was assumed. The comparative statics were derived from the extended Coyle (1992) model that introduces production uncertainty, which is germane for the analysis of climate change impact in the context of farming behaviour.

In what follows, in the interest of exposition, a review of the Just and Pope (1978) production function and the optimisation problem of a risk-averse peasant farmer was presented. This is followed by a derivation of the comparative static results from a static model of a utility-maximizing peasant farming household in an environment characterized by production risk. To start with, the production function is given by the Just and Pope's (1978) specification:

$$y = q(x) + h(x)\theta \tag{1}$$

where x is a vector of n variable inputs. Note also that the stochastic variable θ is defined as $\theta = \varpi + \varepsilon,\ \varepsilon \sim (0, \sigma_\varepsilon^2)$, where ϖ is the average annual or seasonal rainfall and ε is a shock around this average value. The Just and Pope production function consists of two components; namely the deterministic component represented by the first term, and the stochastic component represented by the second term. The arguments of both components are assumed to remain the same. By assumption, more input use increases average product at decreasing rate; $f_x + h_x > 0$, $f_{xx} + h_{xx} < 0$ where $h_x > 0$, $h_x = 0$ and $h_x < 0$ for risk-increasing, risk-neutral and risk-decreasing inputs, respectively. Risk-increasing inputs are those that increase both the mean and the variance of the crop yield. For example, as stated earlier, the application of chemical fertilisers increases yield when rainfall is adequate, but also decreases yield when rainfall is inadequate and chemical burning occurs (Just and Pope 1979).

On the other hand, inputs such as early maturing crop varieties, manure, and irrigation water are risk-reducing variables. The use of manure, for example, increases yield when rain failure occurs but does not affect yield when a good rain year occurs. Thus, by eliminating the lower tail of the yield distribution, the use of manure increases the mean yield and reduces the variance of the yield, and hence is a risk-reducing input. In the same way, irrigation increases yield when the rain fails but does not affect yield when the rain is adequate, and hence also reduces risk, by eliminating the lower tail of the yield distribution. A peasant farmer's household chooses x to maximise the expected utility of income;

$$Max_x EU(\pi(x)) \tag{2}$$

where U is a continuously differentiable utility function defined on crop production income π. The solution to the optimisation problem in (1) is equivalent to a solution to the following mean-variance utility function in the sense of Leathers and Quiggin (1991);

$$Max_x V(\mu, \ \sigma) \tag{3}$$

Where $\mu = pq(x) + ph(x)\varpi - wx$ and $\sigma = ph(x)\sigma_\varepsilon$, $V_\mu > 0,\ V_{\mu\mu} < 0,\ V_\sigma < 0$ and $V_{\sigma\sigma} < 0$. The first-order condition of optimisation of (3) yields:

$$\frac{\partial V}{\partial x} = V_\mu \mu_x + V_\sigma \sigma_x = V_\mu(pq' + ph'\varpi - w) + V_\sigma(ph'\sigma_\theta) = 0 \tag{4}$$

Note that one can re-arrange (4) as;

$$\psi = pq' + ph'\varpi - w - \Lambda(\mu, \ \sigma)ph'\sigma_\varepsilon = 0 \tag{5}$$

where $\Lambda = V_\sigma / V_\mu$.[3] Note also that $\Lambda_\mu > 0$, $\Lambda_\mu = 0$, and $\Lambda_\mu = 0$ respectively for DARA, CARA, and IARA whereas $\Lambda_\sigma > 0$ for DARA or CARA.

In what follows, implicit function differentiation was applied to (5) to derive comparative static results.

Proposition 1 An exogenous increase of production risk in terms of rainfall variability, holding mean yield constant, increases the demand of risk-reducing inputs, but decreases the demand for risk-increasing inputs.

Proof: The parameter of interest is σ_ε. Differentiation of the implicit function ψ with respect to σ_ε is given by

$$\frac{\partial x}{\partial \sigma_\theta} = -\frac{\partial \psi}{\partial \sigma_\theta} / \frac{\partial \psi}{\partial x} \tag{6}$$

Concavity of V i.e., $V_{\mu\mu} < 0$ implies that $\partial\psi/\partial x < 0$ for interior solution of x. It then follows that the sign of $\partial x/\partial\sigma_\varepsilon$ is the same as the sign of $\partial\psi/\partial\sigma_\varepsilon = -\Lambda ph' - \Lambda_\sigma ph{*}ph'\partial\sigma_\varepsilon = -ph'(\Lambda + \Lambda_\sigma ph\sigma_\varepsilon)$, which in turn depends on the sign of ph'. For risk-reducing inputs; $\partial\psi/\partial\sigma_\varepsilon > 0$ as $ph' < 0$ and for risk-increasing input; $\partial\psi/\partial\sigma_\varepsilon < 0$ as $ph' > 0$ ■

3. Econometric framework

By virtue of being observational rather than experimental, our dataset poses several econometric challenges; first, from production economics, that fertiliser and manure are substitute inputs of production, with the econometric implication of endogeneity bias arising from reverse causality.

Secondly, one stylised fact in Sub-Saharan Africa is that many farmers use fertiliser rather than manure, or manure rather than fertiliser, or neither (Gilbert et al. 2011). Many farmers choose not to use fertiliser owing to market and agronomic conditions. Not using fertiliser, in fact, signifies a farmers' optimal choice (corner solution) rather than representing a missing value. However, mass zero observation has implications for the selection of the functional form of the econometric model. However, unlike with fertiliser, there is no clear evidence as to why farmers choose not to use manure. Following Beckman and Livingston (2012) this study, therefore, assumes that missing observation for manure use results from incidental truncation, i.e., there is at least one latent variable the threshold of which drives the decision as to whether a farmer uses a positive or zero quantity of manure. If the latent variable is related to manure demand, parameter estimation for the manure demand equation thus suffers from sample selection bias (Heckman 1979).

Thirdly, the assumption of the normality distribution of the data-generating process (DGP) for both manure and fertiliser, as suggested by the early literature, may not be warranted. These econometric challenges were addressed as follows: first, a corner-solution model as being appropriate to model fertiliser demand was chosen. Let the system of demand equations be given by:

$$\begin{aligned} F_i &= \alpha M_i + X_i\beta + \varepsilon_i \ \text{ if } \ F_i > 0 \\ &= 0 \, \text{otherwise} \end{aligned} \tag{7}$$

$$\begin{aligned} M_i &= \alpha F_i + X_i\beta + v_i \ \text{ if } \ M^* > 0 \\ M_i & \text{ not observed otherwise} \end{aligned} \tag{8}$$

Equations (4) is a Tobit model proposed by Tobin (1958); Equation (5) is a sample-selection model of Heckman (1979). These equations were used to model farmers' fertiliser and manure demands, respectively, where M_i is manure quantity, F_i is fertiliser quantity, M^* is the latent variable that determines the manure application decision, X_i is the matrix of the covariates, and ε_i is the error term. Endogeneity implies that $M_i \perp \varepsilon_i$ and $F_i \perp v_i$ do not hold. To control for the endogeneity bias arising from the correlation between ε_i and v_i, the Control function (CF) method was employed. To implement the CF model, residual from a fertiliser Tobit of fertiliser demand function in (1) and using it as one covariates in the structural model of the manure demand equation in (2) was derived. Statistical significance of the coefficient on the residual confirms both endogeneity of the fertiliser variable, and controls for correlation between it and the error term of the manure equation (Papke and Wooldridge 2008).

The CF approach requires an instrumental variable (IV) to be used in the reduced form model that is not in the structural model of manure demand. Fertiliser was considered as the endogenous variable and its demand equation was specified as the first-stage Tobit model.

Total expenditure on variable inputs was used as the excluded variable. This variable reflects the liquidity constraint that farmers have, which impacts the demand for tradable inputs such as fertiliser. However, manure is non-tradable; the liquidity constraint has no direct effect on its use other than through affecting the demand for substitute or complementary tradable inputs; leftover endogeneity, if any, after using the CF approach was expected to be uncorrelated with the other covariates in the structural model.

To control for sample selection bias in manure demand in equation (2), the Heckman two-step selection estimator was implemented. Finally, to relax distributional assumptions and check robustness, the Censored Least Absolute Deviations (CLAD) estimator in both manure and fertiliser demand equations was implemented.

4. Data

The data collected by the Sustainable Land Management Survey project carried out by the Environmental Economics Policy Forum for Ethiopia and the Department of Economics, Addis Ababa University was employed for the analysis in this study.

The survey was conducted in 14 villages selected from two zones of the Amhara National Regional State of Ethiopia; East Gojjam Zone and South Wollo Zone. [4] The survey selected 120 households from each of these villages using a stratified sampling technique. East is located on a relatively high production-potential plateau; Gojjam zone receives bountiful rainfall whereas South Wollo only receives erratic and insufficient rainfall (Alem et al. 2010). Although the survey was conducted in 2002, 2005, and 2007 as part of a longitudinal study, we only used the data from the 2005 wave. The dataset included variables such as household characteristics, farm physical characteristics, and risk preferences.

Risk-preference data was generated from a framed field experiment. The experiment involved offering farmers a choice of six pairs of farming systems, wherein each choice consists of a pair of outcomes, one good and one bad, each outcome occurring with a probability of 50% (Bezabih and Sarr 2012). Based on the choices made by the farmers, Bezabih and Sarr (2012) classified farmers into risk-aversion classes, following Binswanger (1980). In this classification, the extreme risk-aversion category includes households willing to take the smallest spread in gains and losses followed by severe, moderate, intermediate, and slight risk-aversion categories; while the neutral risk-aversion category corresponds to respondents willing to take the biggest spread in gains and losses (*ibid*).[5]

Rainfall variability is represented by the coefficient of variation of rainfall, which was calculated as the ratio of the standard deviation to the mean of monthly rainfall in a given season, and/or annual average. This variable pertains only to the rainy season because the agricultural production in question is seasonal, and the effective rainfall variability applies only over the rainy season (Bezabih and Sarr 2012). In the Ethiopian context, particularly in regions where this survey was carried out, farmers experience two rainy seasons: the Belg (spring) or minor rainy season, which lasts from February to

May; and the Meher (summer) or major rainy season which runs from June to September (Alem et al. 2010; Bezabih and Sarr 2012).

Table 1 presents the descriptive statistics of variables used for the analysis. Average fertiliser and manure use rates are 70 kg/ha and 128.9/ha, respectively, among the sample farmers.

Average annual rainfall for the production year 1008.312 and its coefficient of variation is 0.356. In practice, these statistics vary across seasons: summer and winter.

In addition to rainfall variability and risk preferences, a range of household and farm characteristics were controlled for. These include the household head's age and sex, asset holdings, farm size, livestock holdings, male labour endowment, and the ability to cope with risk proxied by the interaction of rainfall variability and livestock holdings, a liquidity measure, total expenditure on variable inputs, physical characteristics, number of fertile plots and number of flat plots. Average household has a labour force of 2.0153 adult male members and 2.013 female adult members, respectively. Regarding households measure of wealth, the average household has 1.73 oxen, 0.555 ha of land per adult member and 4.35 livestock excluding oxen.

Table 1. Descriptive statistics of variables used in the analysis.

Dependent variables	Description	Expected sign	Mean	St.Dev
Fertilize	Fertiliser application per hectare, in kilograms		56.102	803.67
Manor	Manure application per hectare, in kilograms		128.91	957.12
Risk preference				
Neutral risk aversion	Household classified as neutral in risk aversion (dummy)	?	0.492	0.500
Slight risk aversion	Household classified as slightly risk-averse (dummy)	?	0.2456	0.4306
Intermediate risk aversion	Household classified as intermediately risk-averse (dummy)		0.1637	0.3702
Moderate risk aversion	Household classified as moderate risk-averse (dummy)	+/-	0.0927	0.2902
Severe risk aversion	Household classified as severely risk-averse (dummy)	+/-	0.0179	0.1326
Extreme risk aversion	Household classified as severely risk-averse (dummy)	+/-	0.0108	0.1037
Rainfall variables				
Annual mean rainfall	Average annual rainfall for the production year.	+/+	1008.312	223.7697
Rainfall variability	Coefficient of variation of the annual rainfall observations.	+/-	0.356	0.0661
Summer means rainfall	Average seasonal rainfall for the summer season. It is measured for the year before the observed planting season	+/+	192.2015	26.115
Summer rainfall variability	Coefficient of variation of the summer rainfall	+/- +/ -	0.4900	0.05976
Spring means rainfall	Average seasonal rainfall for the spring season.	+/+	93.044	9.786
Spring rainfall variability	Coefficient of variation of the spring rainfall observations.	-	.4900	.059768
Household characteristics			49.625	16.757
Age	Household head's age(years)			
Gender	A dummy variable representing the gender of the household head (1 = female; 0 = male)		0.1625	0.369
Adult male labour	The number of male working-age members of the household		2.0153	1.249
Adult female labour	The number of female working-age members of the household		2.013	1.097
Input expenditure	Total expenditure on variable inputs during the year.	+	131.548	292.20
Livestock holding	Total number of livestock (excluding oxen)		4.35	3.4641
Landarea_10	Land holding per adult	_-	0.555	0.679
Oxen	Number of oxen owned and used by the household	+	1.73	1.41
Ability	Measure of ability to cushion risk. It is the interaction of rainfall variability with livestock holding	+	1.546	1.2611
Zone	South Wollo = 1, East Gojjam = 0,	?	0.431	0.495
Illiteracy			0.548	0.497
Farm characteristics				
Fertile plots	number of fertile plots	_-	2.431	2.535
Flat plots	number of flat slopped plots	+/-	3.705	2.7359

5. Results and discussion

This section presents the results of the empirical investigation into the role of climate risk and risk preference on manure and fertiliser demands in rural Ethiopia (see Table 2).

In the interest of relaxing the distributional assumption, the results from the CLAD model were preferred to those from theTobit model. Starting with the model specification test, the coefficients on residuals and the inverse Mills ratio were found to be statistically significant, suggesting that, respectively, biases due to simultaneity between manure and fertiliser demand equations, and sample selection in the decision of manure demand exist. The coefficient of fertiliser in the manure demand equation is negative and statistically significant supporting our prior hypothesis that fertiliser is a substitute input for manure.

The results also show that the coefficient of rainfall variability is positive and statistically significant in the manure demand equation. However, this coefficient turns out to be negative and statistically significant in the fertiliser demand equation. These results show that rainfall variability increased manure demand, but attenuated that of fertiliser on intensive margins supporting our theoretical prediction in proposition 1. The finding of the inverse relationship between rainfall variability and fertiliser demand lends support to Alem et al. (2010), and Sesmero et al. (2018). Moreover, the coefficients of the risk-preference variables (risk-aversion and risk-neutral preferences) are positive and statistically significant in the manure equation, but turn out to be negative fertiliser and statistically significant in the fertiliser equation.

The positive relationship between risk-aversion and rainfall variability on the one hand and manure use on the other, suggests that the latter is a risk-reducing input. If this is the case, one can claim that in the interests of smoothing income, risk-averse farmers self-insure by applying more manure (the risk-reducing input), but less, (or none) of the risk-increasing inputs, given the missing crop insurance markets. Conversely, the negative association between rainfall variability and risk aversion, on the one hand, and the demand for fertiliser on the other, suggests that fertiliser is a risk-increasing input, lending support to our prior expectations. The results also show that the previous year's rainfall levels negatively affect manure demand, but are positively associated with fertiliser demand with the latter result being in line with Alem et al. (2010).

In addition to risk-aversion and rainfall variability, which are our key variables of interest, it was found that the illiteracy of the household head has negative and statistically significant coefficient in both manure equation and fertiliser demand. Moreover, the land holding is negatively associated with manure use suggesting the intensification and extensification trade-off: large landholders can increase production by using more land, compared to small landholders. The latter can only increase production through applying more inputs; shortages of land constrain them from increasing production through bringing more land into production.

The age of the household head is positively related to manure demand, suggesting that older farmers are likely to have accumulated knowledge on the pros and cons of manure use from various sources, and thus are likely to use this input. However, increased age decreased fertiliser demand, partly because older farmers have accumulated discouraging experiences (repeated observation) on the risk of the interaction of fertiliser with the downside risk of rainfall failure – unlike young farmers. The alternative explanation is that the youth are targeted more by the government offering extension packages, as they seem to pick up information more quickly than their elderly counterparts.

The zone variable has a statistically significant coefficient, suggesting that the demand for either input is location-specific. The measure of the liquidity constraint (total expenditure on variable inputs) variable is significantly and positively associated with fertiliser demand. This result implies that fertiliser is a tradable input. Moreover, the coefficient on the measure of farmers' ability to cope with downside risk (shocks) as measured by the interaction between livestock holdings and the rainfall coefficient of variation is positive, supporting our prior expectation. It shows that livestock holdings have cushion against the downside risk, meaning that farmers with larger livestock holdings are willing to use more fertiliser *ceteris paribus*.

Table 2. CLAD and Tobit estimates of determinants of manure and fertiliser demands.s

VARIABLES	Manure CLAD	Manure Tobit	Fertiliser CLAD	Fertilizer Tobit
fertiliser	−0.310*	−16.97***		
	(0.169)	(6.297)		
residuals	−1.715***	12.73**		
	(0.149)	(6.186)		
inverse Mills ratio	12.98***			
	(1.498)			
Rainfall	−0.00173***	0.0180	0.000118***	0.000752***
	(0.000228)	(0.0110)	(1.69e-05)	(0.000187)
Rainfall variability	5.220***	6.787	−0.382***	−3.159***
	(0.672)	(31.99)	(0.0566)	(0.598)
input_exp			0.00102***	0.00100***
			(8.62e-06)	(9.17e-05)
extreme	1.041***	−11.05	−0.107***	−0.0438
	(0.268)	(17.51)	(0.0224)	(0.263)
severe	1.041***	−2.561	0.138***	−0.201
	(0.268)	(13.31)	(0.0156)	(0.239)
intermediate	0.729**	42.78***	−0.0672***	0.155
	(0.285)	(12.27)	(0.0190)	(0.233)
moderate	0.00683	49.10***	−0.0324*	0.311
	(0.282)	(12.60)	(0.0194)	(0.238)
slight	0.452*	40.10***	−0.0883***	0.0648
	(0.271)	(11.73)	(0.0189)	(0.229)
neutral	0.274	42.10***	−0.0622***	0.0766
	(0.271)	(11.61)	(0.0186)	(0.227)
illiterate	−0.456***	4.289	−0.0222***	0.0863
	(0.0936)	(4.382)	(0.00543)	(0.0631)
Male adult	0.0340	0.730	−0.0230***	−0.00356
	(0.0319)	(1.521)	(0.00237)	(0.0269)
landarea_10	−5.411***	−4.673	−0.0505***	−0.143
	(0.486)	(5.577)	(0.00529)	(0.131)
zone	−1.055***	−3.087	0.0638***	0.590***
	(0.119)	(5.115)	(0.00576)	(0.0661)
age	0.0268***	−0.132	−0.000368**	−0.00751***
	(0.00273)	(0.119)	(0.000161)	(0.00198)
sex	0.826***	−1.360	−0.0252***	−0.218**
	(0.112)	(5.054)	(0.00873)	(0.0934)
livestock	−0.0849***			
	(0.0179)			
oxen			0.00494*	−0.0707**
			(0.00269)	(0.0320)
ability			0.0372***	0.227***
			(0.00309)	(0.0361)
fertile	0.0554***	−0.333	0.00609***	−0.0211
	(0.0149)	(0.826)	(0.00116)	(0.0132)
Flat slip	0.107***	−1.015	−0.00174*	0.0501***
	(0.0160)	(0.768)	(0.000973)	(0.0113)
Constant	0.945*	−91.29***	0.0501	−0.536
	(0.498)	(22.87)	(0.0352)	(0.413)
Observations	1,101	1,511	730	1,511

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In terms of farm characteristics, the proportion of fertile plots was found to be positively associated with manure demand, but this relationship turns out to be negative for fertiliser demand. From the correlation coefficient between the error terms of the two equations, which is negative and statistically significant, it can be inferred that manure and fertiliser are substitute inputs for the sampled households.

6. Conclusion

In this study, the link between manure and fertiliser demand and climate risk (measured as rainfall variability) was investigated. To formalise these linkages, the behaviour of risk-averse smallholder farmers was modelled, using the assumptions of the Just and Pope (1979) production function and the linear mean-variance utility function. The comparative static analysis results based on this model enabled us to hypothesise that an increase in rainfall risk – the variability of rainfall, *ceteris paribus* – increases the use of risk-reducing inputs such as manure, but reduces the use of risk-increasing inputs, including chemical fertilisers. Through the implementation of control function (CF) Tobit and CLAD models, we tested these hypotheses for risk-averse peasant farmers in Ethiopia. Empirical results obtained strongly support the prediction of our theoretical model. Specifically, after controlling for risk preferences, we found that among risk-averse peasant farmers, rainfall variability spurs demand for manure, but attenuates demand for fertiliser.

It follows that in areas where rainfall is less erratic, demand for manure falls, but the use of fertiliser increases among smallholder farmers.

Several policy implications emerge from these findings. First, a subsidy on fertiliser use will not cause all risk-averse farmers to increase fertiliser use or expected output in areas characterised by rainfall variability coupled with a common phenomenon of crop insurance non-existence. Secondly, developing drought-tolerant crop varieties and irrigation, subsidising the adoption of improved methods of cultivation to reduce soil moisture loss, and promoting smallholder livelihood diversification strategies, *ceterus parbus* encourages the application of chemical fertiliser and hence increase production and productivities in areas characterised by rainfall variability. Secondly, weather index insurance (WII) could incentivize higher chemical fertiliser use by reducing income risk and easing liquidity constraints. Thirdly, social protection such as cash transfer programmes could lead to a higher use of chemical fertiliser by serving as insurance against income risks (i.e., through providing regular and predictable financial resources).[6]

However, these instruments (production risk – reducing measures) discourage manure use and hence undermine sustainable land management. This means that such measures pose trade-offs between intensifying short-term crop production through increased chemical fertiliser use, and compromising the sustainability of land through reduced manure use.

Notes

1. The terms “input” and “innovation are used” interchangeably.
2. Many empirical studies have been based on the risk preference assumptions of Pratt (1964) model. (See for example, Hansen and Singleton 1983; Yesuf and Buffstone 2009; Bezabih and Sarr 2012).
3. Note that Λ is considered as reservation price (willingness to pay) often referred to as risk-premium eliminate risk (crop income risk arising from rainfall variability). It forms the basis of a household’s demand for crop insurance.
4. Zone is a 1st level subdivision of state (province) in Ethiopia.
5. For a detailed exposition, see Bezabih and Sarr (2012), as they used the same data and offer a fairly good description of this variable.
6. Apart from insurance channel, cash transfers may promote higher use of chemical fertiliser through its effect on farmers’ risk preferences. To be specific, by altering/increasing total farm household wealth, it reduces farmers’ risk-aversion (increased willingness to assume more risk), which in turn may lead to an increase in fertiliser use under income risk (Serra et al. 2006; Daidone et al., 2019).

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