Climate risk, risk preference and agricultural input demand in Ethiopia: Does input type matter?

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Abstract

In this paper, we investigate the effects of climate risk and risk preference on agricultural input demand. For the empirical analysis, we used rural household survey data, which was matched with climate risk data and experimentally generated measures of risk aversion. Using instrumental variable (IV) Tobit and Censored Least Absolute Deviation (CLAD) estimators, we show that both climate risk and risk-aversion raise demand for manure, but attenuate that of chemical fertilizer. These results imply that manure use is widely adopted in areas characterized by climate risk and missing insurance markets, where risk-averse farmers cannot pass risk onto a third party. The converse is true for fertilizer demand. Thus, whereas weather index-based insurance market interventions and public programs such as irrigation schemes can spur the demand for fertilizer, they are likely to deter adoption of sustainable land management practices in terms of manure application. Moreover, poverty reduction through reducing risk aversion, leads to the same outcome.

Key words: climate risk, risk preferences, inorganic fertilizer, manure

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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 (Dixson and Sergerson 1999, Salinger *et al.* 1997, 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 its impact on the length and quality of growing seasons. Not only are the mean values and any changes in those values important, but also the range in variability and predictability in these climatological variables (Block *et al.* 2008). 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 and Alem et al. 2010). In adapting to more complex and prolonged changes in climate, farmers will have to rely on the efficacy of the interaction among a list of farm-level input[1] decisions. These input decisions include, inter alia, the increased use of irrigation, the shift to early-maturing crop varieties, the use of pesticides, chemical and/or organic fertilizers, a diversification of crop portfolio, and the allocation of the land under production for each crop (Hassan and Nhemachena 2007, Kurukulasuriya and Mendelssohn 2007, Deressa *et al.* 2008). In short, farmers' adaptation to climate change manifests itself mainly through a shift in the demand for, and use of, inputs such as

[1] We are using inputs and innovations interchangeably.

fertilisers, specific crop varieties, pesticides, irrigation water, arable land and labour use and allocation to specific crops. It is worth noting, though, that each of these inputs has a direct and meaningful interaction with the magnitude of climatic-induced crop production variability. Inputs are either risk increasing or 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 plants' roots, 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 and hence affects the distribution of the yield.

For the most part, micro-level studies on the linkage between agriculture and climate in Africa have focused on determinants of adaptation to climate change (Hassan and Nhemachena 2007, Kurukulasuriya and Mendelssohn 2007, Deressa et al. 2008, Block et al. 2008), the impact of climate change on household's farm income (Deressa and Hassan, 2009), the impact of adaptation to climate change on food security (Di Falco et al. 2011), 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 et al. 2013) and climate uncertainty and demand for chemical fertilizer (Alem et al. 2011). Although these studies have contributed to our knowledge and understanding of this modern day phenomenon, evidence on whether behavioural response, in terms of demands for agricultural inputs, to climate change varies with the input's risk-profile i.e. risk-increasing, risk-decreasing, and risk-neutral properties, structure of market within which inputs are demanded (missing or otherwise) is largely missing. Particularly, although Alem et al. (2011) confirmed that climate variability as measured by rainfall coefficient of variation reduces demand for chemical fertilizer, the question remains whether the same relation holds for alternative input demand such as that for organic manure. Moreover, the aforementioned did not control for risk preference in its empirical specification.

In the present study, we extend Alem et al. (2011) in two ways. First, we account for individual risk preferences in the demand decision for agricultural inputs while controlling for climate risk in the form of rainfall variability. Second, in investigating this relationship, we account for the typology of the inputs. We hypothesise that the impact of climatic risk and risk preference are input-type differentiated for the following reasons. First, although both manure and fertilizer are used to improve soil fertility and bolster crop production, they have differential interaction with extreme weathers; fertilizer is likely to burn soil upon rain failure than manure will and hence results in varied distributions of crop yield, all other things remaining constant. Second, alternative inputs have different farm income distributions intertemporally. Particularly, current fertilizer use bolsters crop yield in the short run, but gradually pose detrimental effect on soil fertility (through soil mining) and hence reduces crop yield in the long run. However, current manure application has opposite implications for intertemporal farm income distribution. Third, whereas fertilizer is a tradable input, manure is non-tradable due to the missing market. This factor that may have implications for how input demand responds to climate risk and risk preference. Accounting for input typology in terms of their demand's response to climate risk and risk preference would enable us to draw varying policy implications on managing risk and poverty reduction measures.

We first develop a theoretical model that formalizes farmers' input demand response to changing climate (climatic risk). We account for farmers' risk preferences and the risk property of agricultural inputs by drawing on the standard framework of choice under uncertainty (Pratt 1964). As is common in extant literature, we assume that this assumption is also supported by empirical literature (Bezabih and Sarr 2012, Yesuf and Buffstone 2009, Wik et al. 2004, Yesuf 2002 and Hansen and Singleton 1983). As a related stylized fact to this outcome, Ellis (1988) established that risk aversion results in sub-optimal resource allocation, and 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 as insurance and credit markets are often malfunctioning, poorly developed or absent altogether in the developing countries where the great majority of peasants live and farm. This is of particular importance when it comes to climatic uncertainty which is covariate in nature. The second stylized fact is the 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 (Just and Pope 1978, Quiggin et al. 1991, Grepperud 2000).

Unlike related literature in developing countries, we develop a theoretical model within this context to inform our empirical specifications.

2. Theoretical frameworks

In this section, we implement a comparative static analysis for risk-averse peasant farmers using the Just and Pope (1978) production function and a linear mean-variance utility function. For ease of exposition, we assume Constant Absolute Risk-Aversion (CARA) of farmers' attitudes to risk, as opposed to Decreasing Absolute Risk-Aversion

(DARA) or Increasing Absolute Risk-Aversion (IARA). We draw on Silberberg's (1994) seminal work of primal-dual approach of comparative static analysis. It should be noted that Coyle (1992) produced a precursor of our model to derive comparative static results of input demand and supply response to change in expected output price under uncertainty. We here extend this model by introducing production uncertainty which is germane for the analysis of climate change impact in the context of farming behaviour.

To develop this model, we first present a review of the Just and Pope (1978) production function and the optimisation problem of a risk-averse peasant farmer. This is followed by a derivation of the comparative static results and its discussion. The last section concludes the paper. Here we develop a static model for a utility maximizing peasant farming household in an environment characterized by production risk. We assume that the production function is given by Just and Pope's (1978) specification, namely $q = f(x) + h(x)\theta$ where $x \in X^N$ is a vector of N variable inputs. We specify the stochastic variable as $\theta = \varpi + \varepsilon$, $\varepsilon \sim (0,\ \sigma_\varepsilon{}^2)$ where ϖ is the mean of, for example, annual rainfall and ε is white noise around the average value of the stochastic variable.

The Just and Pope production function consists of two components, namely the deterministic components 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. Just and Pope assume that: $f_x + h_x\varpi \succ 0,\ f_{xx} + h_{xx}\varpi \prec 0$

$h_x \succ 0,\ h_x = 0,\ h_x \prec 0$ for risk increasing, risk neutral and risk decreasing inputs respectively. Risk increasing inputs are those inputs that increase both the mean and the variance of the crop yield. For example, as stated earlier, the application of chemical fertilisers increases the probability of very high yield when rainfall is adequate, but also increase the probability of low yield when rainfall is inadequate and chemical burning occurs (Just and Pope 1978). On the other hand, inputs such as early maturing variety seeds, 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 yield distribution the use of manure increases the mean yield and reduce 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 reduces risk by eliminating the lower tail of yield. We also assume that a peasant farmer household seeks to maximize utility from income, π, and leisure time, l, specified as: $Max_{\pi l}\, Z(\pi, l)$. Furthermore, this composite utility function is weakly separable in its arguments and can be decomposed into the utility from income, or also the total consumption of goods and services, and the utility from leisure consumption. Here we focus on utility from income rather than that from leisure. We also postulate that household utility of income is represented by a mean-variance utility function, which is linear with expected income and income variance given as:

$$\text{Max}\, U(\pi) = E(\pi) - \frac{1}{2} r \sigma^2{}_{\pi} \qquad (1)$$

Where $E(\pi) = pq(x) + ph(x)\varpi - wx$, $\sigma_{\pi}{}^2 = p^2 h^2(x) \sigma^2{}_{\theta}$, $\theta \sim$ normal $(\varpi, \sigma^2{}_{\theta})$ stands for stochastic variable representing uncertainty at each point in time and r stands for coefficient of risk aversion.

The first order condition of optimisation yields:

$$\frac{\partial U}{\partial x} = pq_x + ph_x\varpi - w - rp^2 hh_x \sigma^2{}_\theta = 0 \qquad (2)$$

From (2), we can see that the intensity of input use will depend on its risk property i.e. whether the term h_x is positive, zero or negative. Keeping all other things constant, the demand for risk reducing inputs is larger than that of risk neutral and risk increasing inputs.

Proposition 1 *An exogenous increase of production uncertainty due to climate change, holding mean yield constant, increases the demand of risk reducing inputs, but decreases that of risk increasing ones.*

Proof: Taking the last diagonal term of equation (14) in the appendix, the risk reducing profile of an input implies that the term $-rp^2hh_x \succ 0$. It thus follows from non-negativity of the diagonal term that $\frac{\partial x}{\partial \sigma_\theta{}^2} \succ 0$. For the risk increasing inputs, however, the term becomes $-rp^2hh_x \prec 0$. From non-negativity of the diagonal term, it follows that $\frac{\partial x}{\partial \sigma_\theta{}^2} \prec 0$. These results are also consistent with Leather and Quiggin's (1991) comparative static results under the assumption of Constant Absolute Risk Aversion (CARA). Important policy implications can emerge from these results. First, introduction of drought-tolerant crop varieties and methods of improved cultivation to reduce moisture risk (e.g. mulching, *ceteris paribus*) without affecting the mean of the distribution encourages the use of inputs such as fertilizers and hence increases production and productivities in lieu of climate change. However, the converse is true with demand for water, pesticide[2] etc. It implies that such inputs (innovations) are substitutes for water.

Proposition 2. *An exogenous increase in mean* rainfall*, keeping yield variance constant, increases the risk-increasing input demand, but decrease the demand of risk-reducing ones.*

Proof: The proof follows directly from the non-negativity of the diagonal terms of the matrix and the sign of h_x. Should h_x have a positive sign and non-negativity conditions prevail, it must be the case that $\frac{\partial x}{\partial \varpi} \succ 0$. The opposite holds if h_x bears a negative sign. Again these results confirm that of Leather and Quiggin's (1991) comparative static results for CARA and Decreasing Absolute Risk Aversion (DARA) producers. Introduction of new crop varieties and new cultivation methods that increase mean yield of crops without affecting the variance of the distribution, are likely to decrease the demand for water and pesticide but increase that for fertilizer. This calls into the belief that crop breeding and new cultivation methods research with lesser impacts on yield distribution can be used to increase the adoption of external inputs such as fertilizers (intensification of production system) even in the changing climate scenario.

3. Econometric Framework

By virtue of being observational than experimental, our dataset poses several econometric challenges; first, from production economics, we expect that fertilizer and manure are

[2] Pest outbreak could be associated with climate change and hence the variability of outbreak could be linked to variability of rainfall.

substitute inputs of production, with the econometric implication of endogeneity bias arising from reverse causality.

Second, one stylized fact in Sub-Saharan Africa is that many farmers do not use fertilizer or manure or both (Gilbert et al. 2011). Such outcomes arise because many farmers choose not to use fertilizer owing to market and agronomic conditions. Not to use fertilizer, in fact, signifies 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. Unlike fertilizer, we do not have clear evidence as to why farmers choose zero quantity of manure. We therefore, assume that zero observation for manure use results from incidental truncation, i.e. there is some latent variables the threshold of which drives the decision of whether a farmers use positive or zero quantity of manure. If that latent variable is related with manure demand, parameter estimation for manure demand equation thus, suffers from endogeneity bias due to sample selection (Heckman, 1979). Third, the assumption of normality distribution of the data generating process (DGP) for both manure and fertilizer, as followed by early literature, may not be warranted. We address these econometric challenges as follows; first, we choose a corner solution model as being appropriate to model fertilizer demand. Let the system of demand equations, be given by

$$M_i = \max(0, \alpha F_i + X_i\beta + \varepsilon_i) \qquad (1)$$

$$F_i = \alpha M_i + X_i\beta + v_i \quad \text{if } F^* > 0 \qquad (2)$$

$$F_i = 0 \qquad \text{otherwise}$$

Equations (1) and (2) are a system of Tobit models proposed by Tobin (1958) to model farmer's manure demand and fertilizer demand respectively, where M_i is manure quantity, F_i is fertilizer quantity, F^* is the latent variable that determines the manure application decision, X_i is the matrix of the rest of the covariates and ε_i is the error term. Endogeneity implies that $F_i \perp \varepsilon_i$ and $M_i \perp v_i$ do not hold. To control for the endogeneity bias arising from correlation between the error term of the fertilizer demand decision and the error term of manure demand, we employed both instrumental variable (IV) and control function (CF) methods. In both specifications, we used fertilizer as the endogenous variable and specified the first stage Tobit model of fertilizer demand. We used total expenditure on variable inputs as the excluded variable. This variable reflects liquidity constraint of farmers, which impact on the demand for tradable inputs like fertilizer. However, manure is non-tradable; liquidity constraint has no direct effect on its use other than through impacting on the demand for substitute or complement tradable inputs. To control for sample-selection bias, we implemented the Heckman two-step selection estimators.

To implement the CF model following Gilbert et al. (2011), residuals from a fertilizer Tobit demand equation were taken and included as a covariate in the structural model of the manure demand equation. Statistical significance of the coefficient on the residual both confirms endogeneity of the fertilizer variable and controls for correlation between it and the error term of the manure equation (Lewbel 2004; Papke and Wooldridge 2008). Finally, to relax distributional assumptions and check robustness, we implemented the Censored Least Absolute Deviations (CLAD) estimator in both equations.

4. Data

Our analysis employed data collected by the Sustainable Land Management Survey project carried out by the Environmental Economics Policy Forum for Ethiopia and Department of Economics, Addis Ababa University. The survey was conducted in two zones of Amhara Nat included variables such as household characteristics, farm physical characteristics, and risk preferences; Table 1 presents the summary statistics of variables used for the analysis.

Risk preferences data was generated from a framed field experiment. The experiment involved offering farmers a choice between six pairs of farming systems, wherein each choice consists of a pair of good and bad outcomes, each outcome occurring with a probability of 50% ((Bezabih and Sarr, 2012). On the basis of the choice made by farmers, Bezabih and Sarr (2012) classified farmers into risk-aversion classes following Binswanger (1980). In this classification, the extreme risk-aversion category has households who are 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)[3].

Climate risk 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 rainy season on account those agricultural productions are season and the effective climate risk applies only over these seasons (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

[3] For detailed exposition see Bezabih and Sarr (2012) as they used the same data and offered fairly good account of description of this variable.

minor rainy season which ranges from February to May; and the Meher (summer) or major rainy season which runs from June to September (Bezabih and Sarr 2012, Alem et al. 2011).

In addition to climatic risk and risk preferences, we also controlled for a range of household and farm characteristics. These include household head's age and sex, asset holding, farm size, livestock holding, male labor endowment, the ability to cope with risk - proxied by the interaction of rainfall variability and livestock holding, liquidity measure, total expenditure on variable inputs, physical characteristics, number of fertile plots and number of flat-slopped plots.

5. Result and discussion

In this section we discuss the results of the empirical investigation of the role of climatic risk and risk preference on manure and fertilizer demands in rural Ethiopia. The results are presented in Table 2. In the interest of relaxing the distributional assumption, we prefer to present the results from the CLAD model. Starting with the model specification test, we find that the coefficients on residuals and the Mills ratio are statistically significant suggesting endogeneity biases that would have arisen respectively due to simultaneity of manure and fertilizer and sample selection in the decision of manure application. The coefficient of fertilizer in the manure equation is negative and statistically significant supporting our prior hypothesis that fertilizer is a substitute input for manure.

The results also show that the coefficient of rainfall variability is positive and statistically significant in the manure application equation. However, it turns out to be negative and statistically significant in the fertilizer application equation. The results show that rainfall variability engenders more of manure application, but attenuates fertilizer use intensity -- supporting the hypothesis derived from the theoretical model. The finding of the inverse relationship between rainfall variability and fertilizer use intensity is also consistent with Alem et al. (2011). Moreover, the coefficients of risk-preference variables (risk-aversion and risk-neutral preferences) are positive and statistically significant in the manure equation, but turns out to be negative and statistically significant in the fertilizer equation. The positive relationship between risk-aversion and rainfall variability, on the one hand, and manure use, on the other hand, suggests that the latter is a risk-reducing input. In that case, we can claim that in view of smoothing income, risk-averse farmers self-insure by applying more manure (the risk-reducing input) but less of, or no, risk-increasing inputs in the face of missing or imperfect insurance markets. On the contrary, the negative association between rainfall variability and risk-aversion, on the one hand, and the demand for fertilizer suggest that fertilizer is a risk-increasing input lending support to our prior expectations.

The results also show that previous year's rainfall levels negatively affect manure demand, but are positively associated with fertilizer demand, the latter of which is in line with Alem et al. (2011).

In addition to risk-aversion and rainfall variability, which are our key variables of interest, we found that education of the household head has a positive and statistically significant coefficient in the manure equation, but a negative and statistically significant coefficient in the fertilizer equation. This is not surprising as less educated farmers are slow in technology uptake of externally introduced inputs such as fertilizer, but are more likely to use locally available inputs including manure. The result signifies the importance of training in use of external inputs. Moreover, the size of land holding is negatively associated with use of manure suggesting the intensification and extensification trade-off, that large landholders can increase production by using more land compared to smallholders. The latter can only increase production through applying more inputs as the land shortages constrain them from increasing production through bringing more land into production.

We find also that age of the household head is positively related to manure demand suggesting older farmers are likely to have accumulated knowledge on *pros* and *cons* of manure use from various sources and thus, are likely to use this input. However, increased age decreased fertilizer demand, partly because, older farmers accumulated discouraging experiences (repeated observation) on the risk the interaction of fertilizer with down-side risk of rainfall failure than youth. Alternative explanation is that the youth are targeted more by government extension package as they seem to pick information quickly than their elderly counterparts.

The zone variable has a statistically significant coefficient suggesting that the demand for either input is location specific. Measure of liquidity constraint (total expenditure on variable inputs) variable is significantly and positively associated with fertilizer use intensity. The result implies that fertilizer 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 holding and the rainfall coefficient of variation, is positive supporting prior expectation. It shows that livestock holding cushions against the downside risk in which case farmers with larger livestock holdings are willing to use more fertilizer *ceteris paribus.*

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

6. Conclusion

In this study we investigated the link between manure and fertilizer demands, on the one hand, and climatic risk (measured as rainfall variability) and risk-preference, on the other hand. To formalize these linkages, we modelled the behaviour of risk-averse peasant farmers using the assumptions of the Just and Pope (1978) production function and linear mean-variance utility function. Primal-dual comparative analysis results based on this model enabled us to hypothesize that, an increase in climate risk - the variability of rainfall, *ceteris paribus* - increases the use of risk-reducing inputs such as manure, early maturing crop varieties, pesticide and irrigation, but reduce the use of risk-increasing inputs including chemical fertilizers. Via implementing IV Tobit and CLAD models, we tested these hypotheses by analysing the linkages between manure and fertilizer, on the one hand, and rainfall variability, on the other hand, for risk-averse peasant farmers in Ethiopia. Empirical results obtained strongly support the prediction of our theoretical model. Specifically, controlling for risk preferences, we found that climate risk (rainfall variability) spurs demand for manure, but attenuates that of fertilizer among risk-averse peasant farmers.

Several policy implications emerge from these finding. First, mitigation of climatic risk, through for example, irrigation interventions and weather-based crop insurance, have varying implications for the demand of the two inputs considered. Whereas reduction of climatic risk deters manure demand and hence undermines sustainable land management, the demand for fertilizer will be bolstered by measures aimed at reducing climatic risk. Overall, the finding underscores that such measures pose trade-offs between intensifying short-term crop production through increased fertilizer use and compromising sustainability of land use resulting from lessened or deterred manure use. Moreover, policies that reduce poverty (rise in wealth and income) of farmers seem to bolster fertilizer use and hence crop production, but relegate manure demand via reducing risk-aversion, the latter of which was confirmed by Yesuf and Bluffstone (2009).

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Appendix I: Primal-dual comparative proofs of propositions

The primal-dual function corresponding to equation (1) is specified as:

$$Max_{\alpha}\ D(x, p, w, \varpi, \sigma_{\theta}{}^{2}) = pq(x) + ph(x)\varpi - wx - \frac{1}{2} rp^{2} h^{2} \sigma^{2}{}_{\theta} - V(p, w, \varpi, \sigma_{\theta}{}^{2}) \quad (3)$$

where V stands for indirect utility function. The maximization of D with respect to a vector of parameters α where $\alpha \in \lfloor p, w, \varpi, \sigma_{\theta}{}^{2} \rfloor$ yields the following envelope relations:

$$D_{p} = q(x) + h(x)\varpi - \frac{1}{2} rp\ h^{2}(x)\sigma_{\theta}{}^{2} - V_{p} = 0 \qquad (4)$$

$$D_{w} = -x - V_{w} = 0 \qquad (5)$$

$$D_{\varpi} = ph(x)\varpi - V_{\varpi} = \bar{q}(x) - V_{\varpi} = 0 \qquad (6)$$

$$D_{\sigma_{\theta}{}^{2}} = -\frac{1}{2} rp^{2} h^{2}(x) - V_{\sigma_{\theta}{}^{2}} = 0 \qquad (7)$$

where $p, w, \varpi, \sigma_\theta{}^2$ stands for output price, input price, mean of random (stochastic)[4] variable, and the variance of the random (stochastic) variable. The second order condition is:

$$u^{'} D_{\alpha\alpha} u = u^{'} \left[F_{\alpha\alpha} - V_{\alpha\alpha}\right] u \leq 0 \ , \forall u \in R^{n+1} \qquad (8)$$

This means that the matrix $D_{\alpha\alpha}$ and its equivalent $F_{\alpha\alpha} - V_{\alpha\alpha}$ are symmetric negative semi-definite with the assumption that D is concave with its arguments. This is simply a Hessian matrix of the primal-dual objective function, D, with respect to $\alpha \in \left[p, w, \varpi, \sigma_\theta{}^2\right]$ denoted as:

$$D_{\alpha\alpha} =$$

$$\begin{bmatrix} D_{pp} & D_{pw} & D_{p\varpi\,\varpi} & D_{p\sigma_\theta{}^2} \\ D_{wp}, & D_{ww} & D_{w\varpi} & D_{w\sigma_\theta{}^2} \\ D_{\varpi p} & D_{\varpi w} & D_{\varpi\varpi} & D_{\varpi\sigma_\theta{}^2} \\ D_{\sigma^2 p} & D_{\sigma_\theta{}^2} & D_{\theta^2\,\varpi} & D_{\theta^2\,\sigma_\theta{}^2} \end{bmatrix} = \begin{bmatrix} -0.5rh^2\sigma_\theta{}^2 - V_{pp} & 0 - V_{ww} & \bar{q} - V_{p\varpi\quad\varpi} & -0.5rp^2h^2 - V_{p\sigma_\theta{}^2} \\ 0 - V_{wp}, & 0 - V_{ww} & 0 - V_{w\varpi} & 0 - V_{w\sigma_\theta{}^2} \\ h - V_{\varpi p} & 0 - V_{\varpi w} & 0 - V_{\varpi\varpi} & 0 - V_{\varpi\sigma_\theta{}^2} \\ -0.5rp^2h^2 - V_{\sigma^2 p} & 0 - V_{\sigma_\theta{}^2} & 0 - V_{\theta^2\,\varpi} & 0 - V_{\theta^2\,\sigma_\theta{}^2} \end{bmatrix}$$

(9)

To derive the comparative static results, we differentiate the envelope relation 3 through 6 after transforming them into the required forms, namely:

$$D_p = q(x(\alpha) + h(x(\alpha))\varpi - rp\ h^2(x(\alpha))\sigma_\theta{}^2 - V_p = 0 \qquad (10)$$

$$D_w = -x(\alpha) - V_w = 0 \qquad (11)$$

$$D_\varpi = ph(x(\alpha)) - V_\varpi = 0 \qquad (12)$$

$$D_{\sigma_\theta{}^2} = -\frac{1}{2} rp^2 h^2(x(\alpha)) - V_{\sigma_\theta{}^2} = 0 \qquad (13)$$

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[4] This variable is the source of yield variability for a given level of in put use. For example it represents rainfall, pest outbreak, etc.

Differentiation of 10 through 13 and solving for $V_{\alpha\alpha}$, substituting the result into 9, cancelling common terms and then multiplying by -1 yields the required result: which is a symmetric positive semi-definite matrix of non-negative diagonal elements. Comparative static results are implied from such non-negativity of the diagonal elements and standard reciprocity relations of (14).

$$D^*{}_{\alpha\alpha} = \begin{bmatrix} (\overline{q_x} - 2rphh_x\sigma_\theta{}^2)\dfrac{\partial x}{\partial p} & (q_x - 2rphh_x)\dfrac{\partial x}{\partial w} & (q_x - 2rphh_x)\dfrac{\partial x}{\partial \varpi} & (q_x - 2rphh_x)\dfrac{\partial x}{\partial \sigma_\theta{}^2} \\ -\dfrac{\partial x}{\partial p} & -\dfrac{\partial x}{\partial w} & -\dfrac{\partial x}{\partial \varpi} & -\dfrac{\partial x}{\partial \sigma_\theta{}^2} \\ ph_x\,\dfrac{\partial x}{\partial p}{}_{\varpi p} & ph_x\,\dfrac{\partial x}{\partial w} & ph_x\,\dfrac{\partial x}{\partial \varpi} & ph_x\,\dfrac{\partial x}{\partial \sigma_\theta{}^2} \\ -rp^2hh_x\,\dfrac{\partial x}{\partial p} & -rp^2hh_x\,\dfrac{\partial x}{\partial w} & -rp^2hh'\,\dfrac{\partial x}{\partial \varpi} & -rp^2hh_x\,\dfrac{\partial x}{\partial \sigma_\theta{}^2} \end{bmatrix} \geq 0 \qquad (14)$$

Table.2 CLAD and Tobit estimates of determinants of manure and fertilizer demands

VARIABLES	Manure		Fertilizer	
	CLAD	Tobit	CLAD	Tobit
fertilizer	-0.310*	-16.97***		
	(0.169)	(6.297)		
residuals	-1.715***	12.73**		
	(0.149)	(6.186)		
mills	12.98***	151.5***		
	(1.498)	(53.92)		
rf	-0.00173***	0.0180	0.000118***	0.000752***
	(0.000228)	(0.0110)	(1.69e-05)	(0.000187)
uncertainty	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)
maleadult	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)
flatslop	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

Variable	Description	Mean	Standard deviation
Dependent variables			
Fertlz	Fertilizer application per hectare, in kilograms	56.102	803.67
Manur	Manure application per hectare, in kilograms	128.91	957.12
Risk preference			
Neutral risk aversion	Household classified as neutral in risk aversion (dummy)	.492	.500
Slight risk aversion	Household classified as slightly risk averse (dummy)	.2456	.4306
Intermediate risk aversion	Household classified as intermediately risk averse (dummy)	.1637	.3702
Moderate risk aversion	Household classified as moderately risk averse (dummy)	.0927	.2902
Severe risk aversion	Household classified as severely risk averse (dummy)	.0179	.1326
Extreme risk aversion	Household classified as severely risk averse (dummy)	.0108	.1037
Rainfall variables			
Annual mean rainfall	Average annual rainfall for the production year. It is measured for the year prior to the observed planting season	1008.312	223.7697
Rainfall variability	Coefficient of variation of the annual rainfall observations. It is measured for the year prior to the observed planting season	.356	.0661
Summer mean rainfall	Average seasonal rainfall for summer season. It is measured for the year prior to the observed planting season	192.2015	26.115
Summer rainfall variability	Coefficient of variation of the summer rainfall observations. It is measured for the year prior to the observed planting season	.4900	.05976
Spring mean rainfall	Average seasonal rainfall for spring season. It is measured for the year prior to the observed planting season	93.044	9.786
Spring rainfall variability	Coefficient of variation of the spring rainfall observations. It is measured for the year prior to the observed planting season	.4900	.0597684
Household characteristics		49.625	16.757
Age	Household head's age(years)		
Sex	A dummy variable representing the gender of the household head (1=female; 0=male)	.1625	.3690
Adult male labor	The number of male working-age family members of the household	2.0153	1.249
Input expenditure	Total expenditure on variable inputs during the year.	131.548	292.20
Farm size Total farm size (ha)	Size of the farm, in hectares	.1826	.2979
Livestock holding	Total number of livestock	4.35	3.4641
Ability	Measure of ability to cushion risk. It is interaction of rainfall variability with livestock holding	1.546	1.2611
Farm characteristics			
Fertile plots	number of fertile plots	2.431	2.535
Flat plots	number of flat slopped plots	3.705	2.7359