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Consumption risk, technology adoption and poverty traps: evidence from Ethiopia

Stefan Dercon and Luc Christiaensen[1]

Abstract

Much has been written on the determinants of input and technology adoption in agriculture, with issues such as input availability, knowledge and education, risk preferences, profitability, and credit constraints receiving much attention. This paper focuses on a factor that has been less well documented: the differential ability of households to take on risky production technologies for fear of the welfare consequences if shocks result in poor harvests. Building on an explicit model, this is explored in panel data for Ethiopia. Historical rainfall distributions are used to identify the counterfactual consumption risk. Controlling for unobserved household and time-varying village characteristics, it emerges that not just ex-ante credit constraints, but also the possibly low consumption outcomes when harvests fail, discourage the application of fertiliser. The lack of insurance causes inefficiency in production choices.

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[1] Stefan Dercon, Professor, Oxford University, CEPR and EUDN, stefan.dercon@economics.ox.ac.uk, and Luc Christiaensen, Senior Economist, World Bank, lchristiaensen@worldbank.org. Financial support from the Norwegian-Finnish Environmentally and Socially Sustainable Development Trust Fund. and the Economic and Social Research Council, as part of the World Economy and Finance programme (RES 156-25-0034) is gratefully acknowledged. The authors would also like to thank Harold Alderman for valuable feedback.

1 Introduction

Households in poor developing countries are typically ill-equipped to cope with large shocks. Formal insurance schemes are mostly absent and informal risk-sharing arrangements and savings offer only partial consumption smoothing (Morduch, 1995; Townsend, 1995, Dercon 2002). Especially the consequences of covariate shocks, such as droughts, are most often hard felt, often affecting people's welfare many years after the shock (Dercon, 2004). 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 (Just and Pope, 1979; Rosenzweig and Binswanger, 1993).

This suggests the potential existence of risk induced poverty traps, whereby those who can insure their consumption against income shocks can take advantage of the more profitable opportunities and possibly grow out of poverty, while others are stuck with low return, low risk activities, trapping them into poverty, even though their inherent risk preferences may fundamentally be the same. Zimmerman and Carter (2003) simulate for example that, even when assets are divisible and agents fully rational, optimal portfolio strategies bifurcate in resource-poor, risky environments with subsistence constraints and imperfect credit and insurance markets. Initially wealthier agents obtain higher yielding, higher risk portfolios, while smoothing their consumption. Initially poorer agents revert to lower yielding and lower risk portfolios, often absorbing the shock by reducing their consumption to maintain their asset levels.

While theoretically sound[2] and supported by anecdotal evidence (Narayan et al. 2000), whether households actually engage in risk avoidance in the face of subsistence constraints, ineffective self-insurance strategies and incomplete credit and insurance markets, and whether such behaviour is quantitatively important in explaining persistent poverty in

[2] Sandmo (1971), Eswaran and Kotwal (1990), Kurosaki and Fafchamps (2002).

poor, risky, agrarian settings is hard to investigate empirically. The limited available evidence suggests nonetheless that the income and welfare losses associated with risk avoidance can be significant, especially in drought prone areas.

Rosenzweig and Binswanger (1993) for example find that a one standard deviation decrease in weather risk would raise average profits by up to 35 per cent among the lowest wealth quintile of their sample in semi-arid India. Similarly, farmers in Shinyanga, a semi-arid district in western Tanzania, with limited options to smooth consumption ex post, were found to grow more lower return, but safer crops (in this case sweet potatoes) foregoing up to 20 per cent of their income as implicit insurance premium (Dercon, 1996). Adaptation of the crop portfolio (substituting fodder for Basmati rice production largely in response to covariant fodder price risk) was also observed in Punjab Pakistan (Kurosaki and Fafchamps, 2002), despite well developed input and product markets, though income and welfare losses were smaller (2 and 9.4 percent respectively).

Risk avoidance in the face of incomplete insurance may also be key in understanding limited fertiliser use (Lamb, 2003). Modern input use, including fertiliser, is an important determinant of agricultural productivity, and continuing low agricultural productivity is an important contributor to poverty persistence especially in agriculture based countries such as in Sub Saharan Africa (Christiaensen and Demery, 2007; Morris et al., 2007). If so, there would be substantial synergies in complementing interventions that foster access to credit with interventions that help households cope with shocks (e.g. insurance), a critical insight for the design of effective poverty reducing strategies.

This paper explores the empirical importance of risk avoidance in fertiliser adoption in Ethiopia, using a four round panel data set of about 1500 rural households. Fertiliser use in Ethiopia has remained limited despite concerted efforts by the government to promote its adoption through improved extension services and access to credit. A host of demand and supply side factors have been invoked to explain the limited adoption of fertiliser in Ethiopia[3] including limited knowledge and education (Asfaw and Admassie, 2004), risk preferences, credit constraints (Croppenstedt, Demeke and Meschi, 2003), limited profitability of fertiliser use (Dadi, Burton, and Ozanne, 2004; World Bank, 2006b), lack of market access (Abrar, Morrissey, and Rayner, 2004) as well as limited or untimely availability of the inputs themselves. Carlsson, et al. (2005), the World Bank (2006a) and anecdotal evidence[4] have recently also highlighted the importance of the households' limited ex-post consumption coping capacity.

The paper proceeds by introducing a model of risky input choice in section 2. In this model, the possible impact of *seasonal* credit constraints on input adoption is distinguished[5] from intertemporal constraints related to risk and consumption outcomes, a key contribution of the paper. An empirical model to test these propositions is presented in section 3. Section 4 describes the data with a particular emphasis on the effect of fertiliser use on profit variability. The econometric results are discussed in section 5 and section 6 concludes.

2 A theoretical model of risky input choice

Households derive income from agricultural production, which involves determining the level of risky inputs (such as high yielding varieties and fertiliser) that increase both the mean and the variance of the net returns to production. The level of input use has to be decided before the rains have come and the harvest is known, i.e. before uncertainty has been resolved, and often in the face of imperfect credit and insurance markets.

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[3] Morris et al. (2007) provide a comprehensive review of the factors affecting fertiliser use in Africa. Feder et al. (1985) review the international evidence.

[4] Bonger et al. (2004). Largely uncorroborated but insistent reports exist that strict enforcement of repayment of loans that are granted without insurance in case of crop failure may well have discouraged farmers to continue fertiliser use after local or widespread droughts such as in 2002.

[5] Duflo et al. (2006), in an innovative field experiment in rural Kenya, identified access to finance at the right time as the critical constraint to fertiliser adoption. While they specifically focused on the inability to save over the agricultural cycle to have sufficient funds when fertiliser needs to be applied, widespread access to credit to finance fertiliser adoption, as in Ethiopia, is another way of alleviating this constraint.

This decision making process, common in many rural settings, is modelled building on Evans and Jovanovic (1989), Eswaran and Kotwal (1990), Morduch (1990), and Deaton (1992). We explore in particular the implications of a household's capacity to protect its consumption from falling in case of a shock for its ex ante risk-taking in agriculture (i.e. assuming income endogenous), beyond the effects from working-capital related credit constraints. This means taking into account both limitations on using insurance, credit or savings *ex-post*, i.e. after uncertainty has been resolved, as well as credit constraints *ex-ante,* when input decisions have to be taken, i.e. before uncertainty has been resolved.

To highlight the differential impact of input credit market imperfections, and risk and coping capacity, the adoption of risky inputs is first modelled in a world without uncertainty but with imperfect credit markets, and then in a world with uncertainty. The level of risky inputs determines riskiness in production. This suffices to capture the core insights regarding the dynamic interaction between limited ex-post consumption smoothing capacity and ex-ante production choices. Abstraction is made from other income risk reducing mechanisms (such as land and labour allocations to diversify the crop and income portfolio).

Denote gross returns at the end of period t as $g(x_t)$, with x_t the quantity of inputs used, to be decided at the beginning of the period, and $g(.)$ increasing at a decreasing rate in x_t. For now, there is no risk. Input prices are p_x and inputs have to be paid before the harvest is known, although we will allow for credit. Purchased inputs, such as fertiliser, are divisible and can be used in small quantities, with limited start-up costs in production. Still, transactions costs in contacting and travelling to suppliers, and learning, may imply some sunk costs[6]. Net returns from agricultural production can be defined as $y_t = g(x_t) - p_x x_t$ - $I(x_t).m$, with m defined as sunk costs incurred from using fertiliser ($m \geq 0$) and $I(x_t)$ is the indicator function taking on the value one if fertiliser is used, and zero otherwise.

[6] World Bank (2006b) reports that most fertiliser in Ethiopia is sold in bags of 25 kilograms.

Assume that households optimize intertemporal welfare defined in consumption. Suppose they have an intertemporally additive utility function u defined over lifetime T as:

$$u_t = \sum_{\tau=t}^{T} (1+\delta)^{t-\tau} v(c_\tau) \tag{1}$$

with $v(.)$ instantaneous utility derived from consumption c_τ (≥ 0) and δ the rate of time preference, $(v'(.)>0, v''(.)<0)$. Define r as the rate of returns of savings between periods and A_{t+1} as assets at the beginning of period $t+1$. Assets evolve from one period to the next according to:

$$A_{t+1} = (1+r)(A_t + g(x_t) - p_x x_t - I(x_t).m - c_t) \tag{2}$$

We assume for simplicity that assets can be liquidated at any point in time. Consumption prices are used as the numéraire. Consumption decisions are made after income has been generated from production, while inputs have to be paid beforehand unless credit is available.

Even though (formal) consumption credit is rarely available, input credit is common, an important distinction to be taken into account. In Ethiopia, inputs such as fertiliser are provided under regional government guarantees usually offering seasonal credit without collateral. Repayment is strictly enforced, and default rates are low, albeit non-zero.[7] Following Evans and Jovanovic (1989), suppose that that enforcement is not perfect, but that those caught are punished by losing the equivalent of a proportion of their assets, and that the net return on their assets and production for those not repaying $p_x x_t$ will only be $g(x_t) - \theta A_t - I(x_t).m$, with $\theta(>0)$ determined by factors such as the probability of getting caught and the share of assets impounded when caught. However, lenders will only offer

[7] Bonger et al. (2004) for example found that 20 percent of the farmers in their sample did not fully repay the fertiliser credit, largely due to harvest failure. Those farmers faced severe penalties such as imprisonment, or had to sell livestock and other property or sell their food items.

credit if there are incentives to repay loans, or if net returns when repaying outweigh returns when cheating, i.e.[8]:

$$\theta A_t - p_x x_t \geq 0 \tag{3}$$

This equation is then the seasonal credit constraint, whereby credit is an increasing function of initial assets levels. When assets are fully liquid, values $\theta < 1$ won't hold since the household can use cash purchases up to the value of its assets. If $\theta = 1$, a household's purchases of inputs must be fully collateralised. They are indifferent between borrowing for the purchase of inputs (to repay later) and selling the assets now to purchase the inputs. Higher values imply access to not-fully collateralised credit, such as borrowing against future harvests. Reflecting the Ethiopian reality—seasonal loans without collateral but with harsh enforcement—we assume $\theta \geq 1$, nesting the more conventional case of credit constraints ($A_t - p_x x_t \geq 0$).

Consumption is decided after income has been generated from production and after seasonal credit has been repaid. Borrowing against future income is not possible[9] and consumption is limited to the sum of the realized income and the value of assets A_t at the end of t, or formally:

$$A_{t+1} = A_t + g(x_t) - p_x x_t - I(x_t)m - c_t \geq 0 \tag{4}$$

This is the "consumption credit constraint" 'ex-post', which together with the ('ex-ante') seasonal credit constraint (3) and the transversality condition $A_{T+1}=0$, i.e. there is no savings beyond the last period T, and $c_t \geq 0$, form the constraints of the optimization problem. The value function, defined in initial asset levels, can be written as:

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[8] It is assumed that no interest rate is charged on seasonal credit, but this could be easily introduced, without affecting the general thrust of the results.

[9] Given that informal insurance is only partially effective at best in insuring households against idiosyncratic shocks and ineffective in insuring them against covariant shocks (Townsend (1995), Morduch (1995)), we abstract from effects of informal insurance on consumption smoothing. Lamb (2003) highlights the potential for ex post consumption smoothing in semi-arid India through the labor market. In Ethiopia, opportunities for both off-farm employment and seasonal migration are very limited.

$$V_t(A_t) = \max_{c_t, x_t} v(c_t) + \frac{1}{1+\delta} V_{t+1}((1+r).(A_t + g(x_t) - c_t - p_x x_t - I(x_t)m))$$
$$+ \lambda_t (A_t - \frac{p_x x_t}{\theta}) + \gamma_t (A_t + g(x_t) - p_x x_t - I(x_t)m - c_t) \tag{5}$$

Solving this problem backwardly implies that we get the solution for optimal consumption in each period and then derive the optimal input decision, given the optimal rule for deciding on consumption. The optimal consumption rule satisfies:

$$\frac{\partial V_t}{\partial c_t} = v'(c_t) - \frac{(1+r)}{(1+\delta)}.V_{t+1}'(A_{t+1}) - \gamma_t = 0 \tag{6}$$

Given (6), when the input decision is being taken (and given that the seasonal credit constraint has built-in incentives for credit repayment to be the optimal decision ex-post), the subsequent intertemporal (or 'ex-post') budget constraint is not relevant and only the seasonal credit constraint matters. The optimal level of input use (for non-zero input use) can be obtained from (5) as:

$$\frac{\partial V_t}{\partial x_t} = \left[\frac{(1+r)}{(1+\delta)}.V_{t+1}'(A_{t+1}) + \gamma_t\right]\frac{\partial y_t}{\partial x_t} - \frac{\lambda_t p_x}{\theta} = 0 \tag{7}$$

Substituting (6) into (7) gives the optimal decision rule for the adoption of x_t:

$$\frac{\partial V_t}{\partial x_t} = v'(c_t)\frac{\partial y_t}{\partial x_t} - \frac{\lambda_t p_x}{\theta} = 0 \tag{8}$$

Equation (6) is the standard rule for intertemporal consumption with (consumption) credit constraints: if binding, then the marginal utility of current consumption is higher than the marginal value of future (appropriately discounted) consumption, or consumption now is lower than optimal. Equation (8) shows how the seasonal credit constraint may result in inefficiency: if seasonal budget constraints do not bind ($\lambda_t=0$), an efficient allocation in production is obtained when the marginal value product equals the input price, i.e. when the marginal net return equals zero. Otherwise, the seasonal credit constraint and decreasing marginal returns imply that sub-optimal and lower input levels are obtained, with positive marginal net returns. Note furthermore that, given positive marginal returns, the larger is the input use, the larger is the household's income and the less likely it is that γ_t binds. In the deterministic case, it is thus optimal to choose the input level that maximizes income, as this also minimizes the risk that the intertemporal liquidity constraint binds.[10]

To introduce risk in the income process, consider gross returns being governed by $g(x_t, \varepsilon_t)$, whereby ε_t is a random, serially uncorrelated shock, realised after input decisions have been made. It is assumed that $min[g(x_t, \varepsilon_t)] = a \geq 0$, i.e. the lowest gross returns are nonnegative. Define $y_t = g(x_t, \varepsilon_t) - p_x x_t - I(x_t)m$ as the net returns to production and $\partial E_t(y_t)/\partial x_t > 0$ (with E_t the expectation at the beginning of t before y_t is known), so that expected returns with risky inputs are always higher than without inputs, albeit at a decreasing rate, $\partial^2 E_t(y_t)/\partial x_t^2 < 0$. It is further assumed that $\partial y_t/\partial \varepsilon_t > 0$, that $\partial y_t/\partial x_t > 0$ if $\varepsilon_t > 0$ and that $\partial y_t/\partial x_t < 0$ if $\varepsilon_t < 0$. In good times, choosing more risk increases net returns, while in bad times, choosing more risk results in losses, or the dispersion of net returns increases as inputs increase.[11] If the household were maximising expected income (i.e. risk-neutrality), it would choose x_t such that $E_t \frac{\partial y_t}{\partial x_t} = 0$, or $E_t \frac{\partial g(x_t, \varepsilon_t)}{\partial x_t} = p_x$, and some inputs would always be used given the assumptions (including that input use is profitable in expectation).

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10 The sunk costs m do not play a role in deciding the level of input use here, since these decision rules are derived for non-zero input use. Non-zero input use will only apply if it is profitable to do so, i.e. it yields positive net returns y_t. The sunk costs imply that there is a threshold level of fertiliser below which marginal return to using more fertiliser is positive but levels used are zero since it would result in negative overall profits (net returns). Introducing risk does not affect this. Formally, this is equivalent to introducing the condition $g(x_t) - p_x x_t - I(x_t)m \geq 0$ into the optimization problem.

11 We remain agnostic about whether the increased riskiness stems from higher risk in yields or (given the non-zero costs of inputs) higher risk in returns, even if yields are not 'more risky'. Inputs could also be *perceived* to be more risky given limited knowledge of the new production technique inducing a degree of subjective uncertainty which typically declines as producers become more familiar with the technique (Hiebert, 1974). In the empirical analysis, we do not find evidence that fertiliser results in more risky yields, but the non-zero costs result in higher, but more risky returns as assumed in the model.

Assume that the household maximises the expected flow of utility from consumption, $u_t = \sum_{\tau=t}^{T} (1+\delta)^{t-\tau} E_{t-\tau} v(c_\tau)$. All assumptions made before regarding risk aversion are maintained. The period t value function for the household can now be written as:

$$V_t(A_t) = \max_{c_t, x_t} E_t \left[\begin{array}{c} v(c_t) + \frac{1}{1+\delta} V_{t+1}((1+r).(A_t + g(x_t, \varepsilon_t) - c_t - p_x x_t - I(x_t)m) \\ + \gamma_t (A_t + g(x_t, \varepsilon_t) - p_x x_t - I(x_t)m - c_t) \end{array} \right] + \lambda_t (A_t - \tfrac{p_x x_t}{\theta}) \quad (9)$$

with λ_t and γ_t defined as before. Backwardly solving this problem, we first derive the optimal consumption rule (after uncertainty over income has been resolved):

$$\frac{\partial V_t}{\partial c_t} = v'(c_t) - E_t \left[\frac{(1+r)}{(1+\delta)} .V_{t+1}'(A_{t+1}) + \gamma_t \right] = 0 \quad (10)$$

Given (10), we subsequently take the derivative of (9) with respect to x_t at the beginning of t, i.e. before uncertainty has been resolved and obtain the optimal decision rule for x_t (for non-zero input allocations) as:

$$\frac{\partial V_t}{\partial x_t} = E_t \left[\left(\frac{(1+r)}{(1+\delta)} V_{t+1}'(A_{t+1}) + \gamma_t \right) \frac{\partial y_t}{\partial x_t} \right] - \frac{\lambda_t p_x}{\theta} = 0 \quad (11)$$

Expanding equation (11) yields:

$$\frac{\partial V_t}{\partial x_t} = E_t \left(\frac{(1+r)}{(1+\delta)} V_{t+1}'(A_{t+1}) + \gamma_t \right) E_t \left(\frac{\partial y_t}{\partial x_t} \right) + \operatorname{cov} \left(\left(\frac{(1+r)}{(1+\delta)} V_{t+1}'(A_{t+1}) + \gamma_t \right), \frac{\partial y_t}{\partial x_t} \right) - \frac{\lambda_t p_x}{\theta} = 0 \quad (12)$$

Since ε_t and ε_{t+1} are uncorrelated and given (10):

$$\operatorname{cov} \left(\left(\frac{(1+r)}{(1+\delta)} V_{t+1}'(A_{t+1}) + \gamma_t \right), \frac{\partial y_t}{\partial x_t} \right) = \operatorname{cov} \left(\left(E_t \left(\frac{(1+r)}{(1+\delta)} V_{t+1}'(A_{t+1}) \right) + \gamma_t \right), \frac{\partial y_t}{\partial x_t} \right) = \operatorname{cov} \left(v'(c_t), \frac{\partial y_t}{\partial x_t} \right)$$

From (10) it can furthermore be seen that $E_t(v'(c_t)) = E_t \left[\frac{(1+r)}{(1+\delta)} .V_{t+1}'(A_{t+1}) + \gamma_t \right]$ at the beginning of t. Using these insights, (12) can be rewritten as

$$\frac{\partial V_t}{\partial x_t} = E_t[v'(c_t)].E_t\left[\frac{\partial y_t}{\partial x_t}\right] + Cov\left[v'(c_t), \frac{\partial y_t}{\partial x_t}\right] - \frac{\lambda_t p_x}{\theta} = 0 \qquad (13)$$

which is equivalent to:

$$\frac{\partial V_t}{\partial x_t} = E_t\left[v'(c_t)\frac{\partial y_t}{\partial x_t}\right] - \frac{\lambda_t p_x}{\theta} = 0 \qquad (14)$$

While there is obviously much similarity between (14) and (8), uncertainty and risk aversion make it no longer optimal to maximize income by maximizing the amount of inputs used. Given risk aversion, low levels of consumption (i.e. higher marginal utility) will have a higher weight in the expected value in (14), so that incentives exist to allocate inputs at lower levels (i.e. higher marginal returns) than without risk. In other words, risk may result in lower risky inputs in production.[12]

These insights follow readily from equation (13). To see this, note that the covariance in (13) is non-positive. In moving from a good to a bad state of the world, the marginal return to input use turns negative, or income is lower for higher levels of input use in a bad state of the world. If as a result, the consumption credit constraint (γ_t) binds and current consumption has to be reduced, the marginal utility of consumption will increase—the marginal return to risky inputs and the marginal utility of consumption move in the opposite direction. In other words, if at least in some states of the world the consumption constraint (γ_t) is likely to bind, the covariance is negative. As a result, the expected marginal return to input use increases, making it optimal to reduce the use of risky inputs. If liquidity constraints never bind, the covariance will be zero.

[12]This may seem a trivial result, and could be obtained from a static model with income risk and risk aversion. However, this result is dependent on consumption being lower when poor harvests occur, and in an intertemporal model this means that intertemporal constraints have to be taken into account. To see this, note from (10) that the presence of credit constraints in particular states of the world at t ($\gamma_t>0$) implies that current marginal utility will be higher (and thus consumption lower).

More broadly, the insights related to equations (13) and (10) can help us to identify whether the choice of risky inputs is determined just by seasonal 'ex-ante' credit constraints (λ_t) or whether possible risk-related intertemporal 'ex-post' credit constraints (γ_t) are relevant as well. Consider the following scenarios. If consumption can be kept smooth over time ($\forall \varepsilon_t$: γ_t=0 and $\lambda_t \geq 0$), then the covariance between marginal returns in different states of the world and marginal utility is zero. The only cause for a deviation from a risk-neutral allocation based on expected marginal returns to inputs equal to zero would be seasonal credit constraints (λ_t>0) – effectively similar to (8). These seasonal credit constraints would be determined by the levels of assets available and the nature of the credit market constraints at the time of the input decision.

However, whenever ex post consumption credit constraints are more likely to bind due to limited ex post coping capacity (γ_t>0 for some ε_t and $\lambda_t \geq 0$), the choice of risky inputs is likely affected as it affects the likelihood of ex post credit constraints to bind. In particular, poorer households (with limited assets A_t) are more likely to forego risky inputs (such as fertiliser), not just because they have less access to credit ($\lambda_t \geq 0$) but also because they are less able to avoid consumption shortfalls (γ_t>0). Note furthermore, at low levels of consumption, instantaneous utility is likely to be steep and highly concave as the household is concerned about very low levels of consumption. As a result, small reductions in income will result in large increases in marginal utility and consumption credit constraints will be much more likely to bind.

In sum, factors contributing to more likely binding consumption credit constraints—including more risky production patterns and less smoothing possibilities—reduce people's willingness to take risk. This effect goes beyond just risk averse preferences: risk averse households with appropriate means for risk-sharing and consumption smoothing, so that their marginal utilities ex-post are not affected by particular outcomes, could take decisions on production as if they were risk-neutral. Lower risk taking results in lower returns on average, and perpetuates poverty.

3 Empirical Approach

To test the key prediction from our model— fewer risky inputs will be used, *ceteris paribus,* when households face higher ex-post downside consumption risk—a credible identification of each household's downside consumption risk is needed. This information is subsequently used to explore whether households' expectations about ex post consumption downfalls (γ_t) affect their ex ante decisions on modern input use, in addition to seasonal credit constraints (related to the need for working capital). If the likelihood of consumption downfall is properly controlled for, then measures of current liquidity positions (A_t) and any required down payments for inputs would allow one to distinguish (*ex-ante*) working capital constraints (λ_t) from (*ex-post*) consumption smoothing constraints (γ_t).

Equation (14) shows that input decisions are based on ex-post consumption outcomes in expectation. Obviously, using information on actual consumption ex-post to proxy this is endogenous as it is itself a function of actual adoption of the inputs. Initial assets could be used as instruments (Morduch, 1990), though they would not allow us to distinguish seasonal credit constraints from ex-post consumption risk. Instead, a parametrised version of the ex-post consumption model is first estimated including explicit information on shocks, and the ex-ante consumption risk faced by the household is then simulated using historical data on rainfall shocks and conditioned on other current household and community characteristics.[13]

By applying the envelope theorem to equation (6) and assuming that households can perfectly smooth consumption, the optimal consumption path is defined by:

13 This means that we assume rational expectations, i.e. households know the underlying consumption model including the ex-ante distribution of the stochastic variables and the effect of these shocks on consumption. This procedure is similar to Kazianga and Udry (2006) in their test for precautionary savings in Burkina Faso.

$$v'(c_t) = \frac{(1+r)}{(1+\delta)} v'(c_{t+1}) \quad (15)$$

Assuming constant relative risk aversion with direct marginal utility defined at t as $\mathrm{c}_{\mathrm{t}}^{-\rho}\mathrm{e}^{\varphi_{\mathrm{t}}}$, with ρ defined as the coefficient of relative risk aversion and φ_t a general taste shifter, taking logs, and introducing subscript i to denote households, an empirical specification can be obtained from (15) as[14]:

$$\ln \frac{c_{it+1}}{c_{it}} = \frac{1}{\rho}\left(\ln(1+r) - \ln(1+\delta) + (\varphi_{it+1} - \varphi_{it})\right) \quad (16)$$

Equation (16) suggests that the path of consumption over time is only affected by taste and preference shifters, as long as there are no binding liquidity constraints over time and provided the underlying factors determining wealth (or permanent income) are not changing. Overidentifying this equation to reflect shocks (ΔS_{it+1}) to income and possible heterogeneity in households' capacity to cope with these shocks[15], this leads to the following linear specification:

$$\ln \frac{c_{it+1}}{c_{it}} = \alpha_0 + \alpha_1 Z_{it+1} + \alpha_2 \Delta S_{it+1} \otimes B_{it} + e_{it+1}` \quad (17)$$

with Z_{it+1} taste and other preference shifters (such as, changes in household composition, price changes, or seasonality shifters), ΔS_{it+1}, shocks linked to idiosyncratic and common risk and e_{it+1} an error term. If consumption credit constraints do not bind, then α_2 is zero.

The first regression to be estimated is based on (17), though expressed as a household fixed effects levels model, rather than a difference model. Define X_{it} as a set of (exogenous) household characteristics affecting preferences and 'permanent' income (such as changes in

[14] In (16), r and δ are assumed constant across households. It is less straightforward to defend that ρ is assumed constant, i.e. constant relative risk aversion with the same coefficient across households. Given fixed effects, some of the heterogeneity in risk preferences will nevertheless be controlled for in this regression, as well as in the adoption regression discussed below.

household composition) and S_{it} are variables that describe different sources of risk (such as weather, pests, and general health conditions). To capture households' differential ability to cope with changes in income, S_{it} is interacted with liquid asset levels B_{it}, proxied by livestock at t-1 to avoid endogeneity. Livestock is the most important liquid asset in rural Ethiopia. The indicator variable G_{it} is introduced to reflect the fact that it may be easier to protect consumption from positive (e.g. good harvests) than from negative shocks. Unobserved household fixed effects are represented by v_i and ε_{it} is a white noise error term.

$$\ln c_{it} = \delta_o + \delta_1 X_{it} + \delta_2 S_{it}.B_{it}.G_{it} + \delta_3 B_{it} + v_i + \varepsilon_{it} \tag{18}$$

From equation (18) consumption expectations for different possible values of the shock variables can be obtained to investigate whether expected values in 'bad' years matter for input adoption.

Equation (14) implied that the demand for risky inputs will be influenced by factors influencing the marginal utility and the value of the marginal productivity of these inputs. These include: L_{it} fixed inputs (such as land endowments) and other household specific characteristics, some of which are fixed, such as land quality or risk preferences; V_{it}, input and output prices and other community[16] and agro-ecological characteristics; $A_{it,}$ asset variables capturing (ex-ante) working capital-related credit constraints at the time of making the input use decisions; and $g(c_{it})$, expectations about (ex-post) consumption outcomes, weighted towards the anticipated downside risk in consumption; ν_{it} reflecting unobserved community characteristics; and ω_i reflecting unobserved time invariant household characteristics. u_{it} is a white noise error term. In a linear specification, this could be written as:

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[15] Datt and Hoogeveen (2003) and Christiaensen and Subbarao (2005) provide empirical evidence of the differential ability of households to smooth consumption in the face of shocks in the Philippines and Kenya respectively.

[16] V_{it} may also capture changing availability of fertiliser, the changing presence of extension officers offering information on fertiliser use, and more general learning and increased familiarity with fertiliser use.

$$x_{it} = \mu_0 + \mu_1 L_{it} + \mu_2 V_{it} + \mu_3 A_{it} + \mu_4 g(c_{it}) + \nu_{it} + \omega_i + u_{it} \tag{19}$$

Identification of $g(c_{it})$ is achieved by using counterfactual values based on possible (not actual) realisations of the shock variables. From equation (18), different households have a differential ability to bear risk over time. When combined with the historical rainfall distribution data for each cluster, time variant and household specific ex ante (counterfactual) consumption distributions can be generated to construct the potential downside risk variable at the time of the fertiliser use decision $g(c_{it})$.

This leaves the choice of the relevant counterfactual. If fertiliser adoption results in changing the distribution of consumption outcomes (higher mean but higher variance), then estimating (18) without controlling for fertiliser use effectively ignores the differential consumption risk distribution for users versus non-users. Inclusion of fertiliser use in model (18) would introduce an endogenous variable–the theory clearly showed non-separability of consumption and production decisions if risk is not fully insured. Instead, the reduced form specification as in (18) is used, in effect ignoring fertiliser as a variable shifting the distribution of consumption, to avoid introducing endogeneity. It will be shown below that fertiliser use results in larger downside income risk, and that households have in general a limited ability to smooth consumption. The reduced form approach thus offers a lower bound on the risk faced by households.

4 Fertiliser use, agricultural production and households in rural Ethiopia

Our data are taken from the Ethiopia Rural Household Survey (ERHS), which comprises 1477 households in 15 Peasant Associations across the four major regions in Ethiopia. Households were surveyed 4 times between 1994 and 1999. The sample is broadly representative for the main farming systems in the country, including the ox-plough cereal producing areas in the northern and central areas (about 63 percent of the sample), the enset[17] dominated areas which are typically also suitable for coffee and chat (about 30 percent) and the much smaller hoe-based cereal areas (about 7 percent).[18] Attrition is low. For about 88 percent of the sample, we have observations in each year, but many households were recovered within the sample during the five year period and in 1999 there is information for 94 percent of the households interviewed in 1994. Estimations are done on the unbalanced panel.

Cereal yields in Ethiopia are currently only about 1,250 kg per hectare, compared with 2,500 and 4,500 kg per hectare in South and East Asia respectively.[19] Yields increased only marginally over the past decade (by 0.3 percent per year between 1991/92 and 2003/4), most of it accounted for by increased maize yields and an expansion of the fertilized area (about 43 percent of the area under cereals fertilized in 2002/3, up from 32.5 percent in 1994/5). Intensity remained constant at about 100kg per hectare and the number of users remained at less than a quarter of all farmers.[20]

Consistent with national trends both adoption rates and intensity of fertiliser use in the sample are low with an overall expansion in the main cereal areas and a decline in the enset and other permanent crop areas (Table 1). Only 22 percent of all households used fertiliser in each period and many households switch in and out of fertiliser from year to year. In 1999,

[17] A permanent food crop, commonly known as false banana.
[18] See Dercon, Hoddinott, and Woldehanna (2005) for more details on the sample.
[19] Average yields during 2003-2005 (World Bank, 2007).
[20] See World Bank (2006b) for a comprehensive review of the performance of the agricultural sector in Ethiopia

14 percent of households did not use fertiliser, despite having used it in one of the three earlier rounds and 3 percent stopped using fertiliser after having used it every round before. Three quarters of all purchased quantities are multiples of 25 kilogrammes (a small bag), suggesting the existence of a small threshold due to fixed costs or other indivisibilities.

Table 1: Fertiliser use in ERHS, 1994-1999

	Incidence of farmers using fertiliser (%)			*Application rate per hectare[1)] (kg)*		
	Main cereal areas	Enset and other permanent crop areas	*Total*	Main cereal areas	Enset and other permanent crop areas	*Total*
1994	43.0	44.5	43.5	35.0	33.9	34.6
1995	41.6	28.0	37.0	31.1	13.2	25.1
1997	49.9	41.8	47.3	32.1	25.0	29.8
1999	50.0	36.4	45.5	39.0	18.1	32.2

[1)] Average across users and non-users.

Source: Data from the ERHS 1994-99

In 1994, about half the farmers quoted costs as the main reason for not using modern inputs (including fertiliser), increasing to about 60 percent in 1999 (Table 2).[21] Only 15 percent mentioned limited availability as a constraint.[22] The percentage of farmers indicating non-suitability of the agro-climatic conditions as reasons for nonadoption, declined from 19 percent in 1994 to only 8 percent in 1999. This coincided with the declining importance of knowledge and skills in adopting modern inputs and suggests better understanding of how fertiliser works over time. Only 3 percent reported not to have the relevant skills in 1999.

over the past 25 years (including the functioning of the fertiliser market).

[21] In 1994, the question distinguished profitability from costs and lack of cash, and very few farmers (2 percent) suggested that the profitability of fertiliser itself was the problem, settling for cost reasons, suggestive of credit constraints. In 1999, this distinction was not made and the two groups are reported together in table 2, even though profitability had likely declined following the fertiliser price increase since 1997.

[22] In 1994, lack of availability was concentrated in two enset growing villages. In 1999, this response was concentrated in one coffee producing village (Adado, near Dilla in SNNPR), and most likely referred to pesticides for coffee disease.

Table 2: Main two reasons for not using modern inputs (% of farmers reporting)

	1994	1999
Too expensive/low profitability/lack of cash	49	60
Fertiliser not available in area	15	15
Soil/crops/climate not suitable	19	8
Don't have skills	10	3
Other	7	15

Source: ERHS

Consistent with the observation that input use is expensive, real fertiliser prices in the areas under study at the time of planting increased by 28 percent between 1993/4 and 1998/99 (see Table 3). This follows the gradual removal of panterritorial price fixing, completed by 1997/98. However, cereal prices did not follow this increase and the relative output-fertiliser price decreased considerably during the latter years of the survey.

Table 3 : Evolution of fertiliser and cereal prices during 1994-1999.

	Average Fertiliser Price per Quintal (per 100 kg in 1993 prices)	Average cereal price (Ethiopian birr) per 100 kg in 1993 prices	Average cereal/fertiliser price ratio
1993/94	141	227	1.61
1994/95	129	242	1.88
1996/97	176	212	1.20
1998/99	180	221	1.23

Fertiliser prices are the average of DAP and UREA prices around the time of planting for the main season (June). DAP and UREA are the two main types of fertiliser used. Cereal prices are averages based on village-specific prices derived from price surveys in the Ethiopian Rural Household Survey at the time of the harvest given that loans must repaid upon harvesting. All prices are deflated using the consumer price index.

Source: Development Studies Associates (2001), IMF, International Financial Statistics, and own calculations using ERHS.

The cost of credit adds to the cost of fertiliser. In 1999, 71 percent of those purchasing fertiliser used seasonal credit and the implicit median interest rate is calculated at 57 percent per year.[23] While the data on the terms of loans are noisy, incurring credit appears

[23] A down payment of about 0.65 birr per kg or about 30 percent of the purchase price is required. Interest payments and other costs related to the loan have a median of about 0.34 birr per kg, though the data on the terms of loans in the survey are noisy and there is a lot of variation around this. Given a median repayment period of about 7 months, this suggests an interest rate of about 30 percent for the median loan duration (or 57 percent per year). In an economy with consistently very low inflation (in this period, about 4 percent per annum on average) this is substantial.

costly. Most of those using cash to purchase fertiliser mention the perceived high interest rates (and not lack of fertiliser availability) as main reason for using cash. The latter is not an important reason for not using fertiliser either.

Understanding the profitability of fertiliser use under uncertainty is critical for our analysis. However, data on input application and outputs by crop and plot were only collected in 1999. In other years, the data were collected at the farm-level, so crops that use modern inputs cannot be identified. Given the high variability in climatic and other conditions, it is thus difficult to establish the distribution of returns for crops in different areas, with and without fertiliser application.[24] Nonetheless, comparing the (counterfactual) yields across plots with and without fertiliser based on (cross-sectional) production function analysis, is still suggestive. About 28 percent of all cereal plots in the sample are fertilized.[25]

A standard Cobb-Douglas production function is estimated linking plot-level cereal yields to plot size, livestock, the input of different types of labour (male, female and children), fertiliser input, herbicide, fungicide, insecticide, controls for land quality and slope, controls for the particular crop grown as well as a series of village-level (e.g. rainfall) and idiosyncratic (e.g. pests) shock variables. A set of interaction terms of the rainfall variables and fertiliser use are introduced to account for different sensitivity of yields to fertiliser across the rainfall distribution. Yields are significantly affected by fertiliser use, by rainfall and other shock variables, as well as their interactions. The full estimation results and robustness tests using household fixed effects are reported in Appendix 1.

This regression is used to construct (counterfactual) yield and return distributions for an otherwise average farmer for 1999, by simulating through the rainfall distribution from the nearest rainfall station to each survey site[26] and the distribution of a self-reported quality of

[24] Lack of agricultural labour input data in the other rounds and inconsistencies in the questionnaire design of the crop production modules across rounds made production analysis at the household level inappropriate.
[25] Fertiliser is mainly used on plots with cereals but most farmers using fertiliser do not use it on all their plots.
[26] For each station, rainfall levels over the past 20 years or more are available. In simulating the counterfactual

rainfall index derived from the different survey rounds. For each crop, average fertilizer application rates among those using fertilizer are used.

Across the rainfall distribution, cereal yields on fertilized plots dominate yields on non-fertilized plots, despite being more risky (Figure 1). Gains can be up to 24 percent (given average fertiliser use)[27], declining as we move away from the median rainfall and virtually disappearing in periods of extreme droughts and floods (below the 20th and above the 80th percentile).[28] At the 1994-5 prices, fertiliser use is also profitable over a wide range of rainfalls, though not at the extremes. At median rainfall levels, returns were 11 percent higher when using fertiliser in 1994-95; beyond the 30-60th percentile rainfall range, they were lower.

While the estimates are approximate at best, these results give credence to our contention that fertiliser use is a high return, but high risk technology. Given the sharp increase in fertiliser price across the survey rounds, returns to using fertiliser were lower in the last few years of our sample, and turning negative more rapidly when moving away from the median.[29] In conclusion, our sample encompasses a period where cereal production under fertiliser yields is more profitable on average, but more risky, facilitating the identification of the effect of limited ex post coping capacity on fertiliser adoption. The findings further highlight the critical need to control for changing price ratios and other factors in analyzing fertiliser use.

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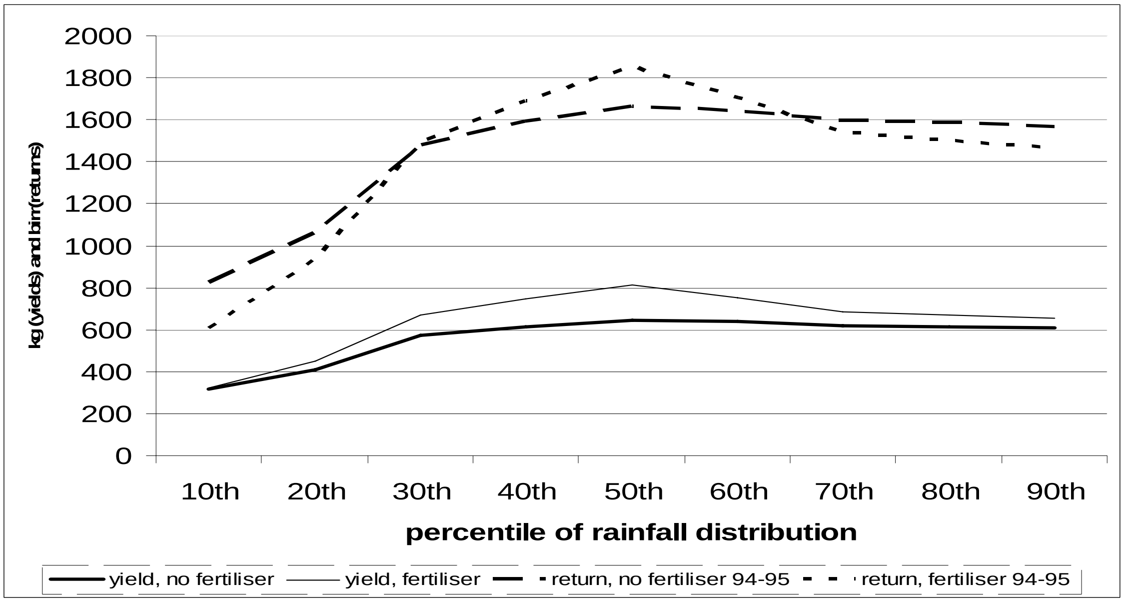
cereal yield distribution, the 10th percentile rainfall is equivalent to the 10th percentile of the rainfall distribution, and so on.

[27] Detailed results can be found in Appendix 1.

[28] As 87 percent of the sample had rainfall levels between the 21st and 80th percentile, caution is warranted in interpreting the counterfactual results for very low and very high rainfall.

[29] The profitability of fertiliser use is sensitive to the cereal-fertiliser price ratio and at average 1997-99 prices, cereal cultivation with fertiliser use may on average no longer be more profitable than cereal cultivation without fertiliser use. Indeed, most recently, two World Bank studies (2006b; Morris, et al., 2007) have highlighted the lack of profitability as an important factor in explaining limited fertiliser use in Ethiopia in particular, and Sub-Saharan Africa more widely. Yet, they also emphasize that fertiliser use is the outcome of many other demand and supply factors, including agronomic practices that strongly affect the physical (and thus also the economic) returns to fertiliser use.

Figure 1: Distribution of yields and returns for cereals in 1994-1995



Note: Simulations based on the estimates reported in table A.1, column (3). Yields based on estimated output per hectare for an average plot (i.e. with mean characteristics for plot, farmer and village), among 2294 plots, and the mean application rate for fertiliser users for each crop. For example, the 10th percentile reflects cereal yields when the rainfall was equivalent to the 10^{th} percentile of the rainfall distribution, i.e. very poor rains. Returns are the gross returns (yield times output price, evaluated at the mean output price in 1994-5) minus the cost of the fertiliser (using the mean fertiliser price of at the time of planting in 1994-5). Prices are expressed in 1999 prices.

Source: Own calculations using EHRS.

5 Empirical results

Equation (18) is first estimated using a household fixed effects regression applied to the 1994, 1995, 1997 and 1999 ERHS data. "Permanent" income terms are thus tied up in the fixed household effects. To investigate the sensitivity of consumption to shocks, (village-level) rainfall[30], and a set of variables describing idiosyncratic shocks are included. As downside risk may be harder to handle—"good" shocks could presumably be saved—the rainfall variable is interacted with a dummy with value one when rainfall is below the median level of the last twenty years. The idiosyncratic shock variables include an index based on (self-reported) descriptions of the quality of 'rainfall' (one if the rainfall distribution was

[30] Not only do we have four time periods, but there is substantial between and within-village variation in this period in the village-level rainfall data. First, 24 percent of the variation is within-village variation, i.e. not explained by village fixed-effects and time dummies. Only 6 percent is explained by the time dummies, i.e.

satisfactory in all respect, zero if unsatisfactory in all respects—see appendix), an index of 'non-rain' crop shocks, such as weed damage, plant diseases and insect damage, which is one if there is no problem, and illness shocks (the number of adults ill in the month before the survey).

To capture differential risk bearing capacity, all shocks are interacted with the (natural logarithm) of livestock holdings per adult (measured at t-1). Livestock values were scaled by the median value of livestock in the village to control for the different role livestock may play across farming systems.[31] Despite considerable persistency, livestock possessions vary over time—about 25 percent of variation remains in the livestock holdings data after controlling for household fixed effects and time trends. Through the interaction terms, this variation allows us to identify the time-varying consumption risk at the household level.

Livestock holdings at t-1 are also included separately in the regression to control for time-varying changes in wealth.[32] Finally, in addition to basic time-varying household characteristics, such as household demographics, which may reflect taste shifters[33], a post harvest period dummy is included, to control for seasonal variation in food prices and consumption.

The effect of village-level rainfall shocks on consumption is substantial, but smaller for those with relatively high livestock holdings (column (1), Table 4). For example, a 10 percent drop in rainfall reduces consumption by 1.5 percent in a household with 2.7 times more livestock than the village median, compared to 2 percent for someone with median livestock holdings.[34] Idiosyncratic shocks have no significant impact.[35]

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common patterns over time between the villages, and the rest, 70 percent, is between village-variation.

[31] The findings are only marginally affected by this scaling, but offer advantages in terms of interpretation.

[32] Initially, land was included as well but it was systematically insignificant, possibly because of multicollinearity (Pearson correlation coefficient between land and livestock possessions is 0.75). As it was only included as an alternative proxy for wealth, it was dropped.

[33] Demographic variables also act as an implicit control for incorrect equivalence scales and the lack of allowing for economies of scale in the nutritional adult equivalent corrections used in the construction of the left hand side variable, consumption per adult equivalent.

[34] Note that given our definition, the interaction term is zero for someone with median livestock holdings. The

Those with higher levels of livestock (above the median) are less sensitive to poor rainfall outcomes than to rainfall outcomes above the long term median (column 2). In other words, 'positive' rainfall shocks are not fully saved, but reflected in consumption; a result consistent with other studies on Ethiopia (Dercon, 2004).[36] For simulating counterfactual consumption distributions for our sampled households, the insignificant rainfall variable interacted with below the median rainfall dummy is dropped (column (3)).

The two key conclusions for the purposes of this paper are, first, that covariate rainfall shocks are the most important source of uninsured risk in these communities and second, that households clearly differ in their ability to cope with shocks depending on their livestock wealth.

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specification controls for village specific rainfall averages through the fixed effects. Finally, the result does not necessarily imply that livestock is being used to smooth consumption, but rather, that better smoothing is correlated with having more assets. Wealthier households may have better access to village level risk-sharing or to other coping mechanisms, such as off-farm employment or migration opportunities when required.

[35] The lack of significance of the idiosyncratic shocks may follow from errors in measuring (self-reported) idiosyncratic shocks. As yields are highly sensitive to some of these shocks (appendix 1), it is also plausible that households actually manage to insure themselves against idiosyncratic risk..

[36] This may reflect choices by households—a preference for feasting when good rains occur—rather than their inability to smooth consumption. This provides support for focusing on the downside risk in consumption in assessing its relevance for production decisions, as pursued below.

Table 4 : Determinants of real consumption per adult. Household fixed effects regression.

Dependent variable: ln of real consumption per adult equivalent	(1)	(2)	(3)
ln livestock holdings in t-1 (per adult, relative to village median)	0.445	0.554	0.547
	[2.57]**	[3.07]***	[3.03]***
ln annual level of rainfall	0.200	0.218	0.190
	[4.30]***	[4.03]***	[4.07]***
ln rainfall * ln livestock holdings at t-1 (relative to median)	-0.049	-0.062	-0.061
	[1.96]*	[2.41]**	[2.37]**
quality of rain index (1 is best, 0 is worst)	-0.091	-0.094	-0.086
	[0.74]	[0.77]	[0.70]
quality of rain * ln livestock holdings	-0.027	-0.017	-0.018
	[0.38]	[0.24]	[0.25]
quality of rain squared	0.065	0.065	0.059
	[0.59]	[0.59]	[0.53]
quality of rain squared * ln livestock holdings	0.013	0.009	0.008
	[0.21]	[0.14]	[0.14]
Index of pests, trampling, frost, flooding (1 is best, 0 is worst)	-0.003	-0.015	-0.019
	[0.02]	[0.09]	[0.12]
Index of pests etc * ln livestock holdings in t-1	-0.114	-0.111	-0.111
	[1.40]	[1.35]	[1.35]
index of pests squared	0.253	0.252	0.247
	[1.02]	[1.02]	[0.99]
index of pests squared*ln livestock holdings in t-1	-0.226	-0.234	-0.23
	[1.63]	[1.68]*	[1.66]*
Number of adults ill in last 4 weeks	0.021	0.022	0.023
	[1.08]	[1.15]	[1.21]
adults ill * ln livestock holdings in t-1	-0.001	-0.002	-0.001
	[0.07]	[0.17]	[0.15]
ln rainfall * rainfall below median dummy		0.005	
		[1.00]	
ln rainfall * ln livestock * below median		-0.005	-0.006
		[1.93]*	[2.02]**
Constant	3.532	3.417	3.614
	[10.77]***	[8.88]***	[10.94]***
Observations	4336	4336	4336
R-squared	0.13	0.13	0.13

Absolute value of t statistics in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.
Note: The regression includes further controls for whether consumption is measured in post harvest period, and variables controlling for changes in demographic composition (male adults, female adults, children 0-5, children 5-15, all by gender) and sex of the head. All values in 1994 prices, adult equivalent corrections based on nutritional scales, see Dercon and Krishnan (2000).

In estimating (19), we control for household labour characteristics (adults and children above 15, and sex of the head) as well as land holdings (and a square), given relatively poorly functioning labour markets and missing land markets.[37] Livestock holdings at t-1 are included to capture seasonal (working capital) credit constraints.

To test whether the risk of low consumption outcomes affects fertiliser use, we include the predicted counterfactual level of consumption, simulated based on column (3), table 4 and using historical rainfall data from the nearest rainfall station near each survey site. Three alternatives to represent the presence of downside risk are explored. First, the level of consumption if the 20th percentile of the rainfall distribution were realised, is used. Subsequently, the probability-weighted mean value of the natural logarithm of consumption across the entire rainfall distribution has been taken—which is equivalent to using expected utility given constant relative risk aversion with a coefficient of one. Finally, to focus more on the downside risk in consumption, the previous measure is truncated at the median level of rainfall. It is noted again that in calibrating the downside risk on the historical rainfall distribution, reliance on within-sample variables to supply instruments is avoided, and the fundamental identification problem in assessing the impact of consumption risk on production decisions is circumvented.

Since fertiliser use is far from general, limited dependent variable models are appropriate. But fixed effects in limited dependent variable models based on the normal distribution (such as the probit and tobit) yield inconsistent estimates, as fixed effects cannot be treated as incidental parameters without biasing the other model coefficients (as long as N > T) (Hsiao, 1986). To get around this, we use the conditional fixed effects logit model to explore adoption of fertiliser (not the amount used) and the Honoré semiparametric fixed effect tobit estimator (Honoré, 1992) to look at the effect of consumption risk on fertiliser application rates.[38]

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[37] All land is state-owned and allocated by the local government for farmers to cultivate.

[38] This estimator is consistent, even if N is increasing relative to T. We used an adapted version of Honoré's Pantob programme, using Gauss 6.0. We tried a number of alternative versions. We report the results from a simple quadratic loss function with zero bandwith, but all models estimated offered very similar estimates for

In addition to household fixed effects that allow us to capture all time-invariant household characteristics, such as risk preferences, skill and education levels or permanent income, both approaches also control for time varying village level effects. This allows us to control for *all* community wide influences on fertilizer adoption and use, including prices, availability, general economic trends, increased extension service availability, broad changes in the delivery systems and general village-wide learning over time. They also force all identification of variables of interest to be based on within village variation in each period, making any significant results rather remarkable and robust.

From column (1), table 5, it is clear that the possibility of low consumption ex post following low rainfall and low harvests reduces a household's likelihood of adopting fertiliser ex ante (column (1), table 5). This finding is quite striking given that it is identified from farm households switching in and out of fertilizer, substantially reducing the sample size (to 417 households), and after controlling for all household time invariant and community time varying effects. Though positively correlated, the effect of livestock, our other variable of interest as the main measure of liquid wealth, is not statistically significant. Households with more labor (male and female adults) are more likely to adopt fertiliser. The same holds for male headed households.[39] The village-time dummies are mostly significant.

The second column shows the estimated coefficients of the determinants of the intensity of fertiliser use based on the Honoré household fixed effects tobit. As before, there is a strongly significant positive effect from the counterfactual level of consumption if rains were to be relatively poor.

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the coefficients of the variables of interest.

[39] We have to be cautious with this effect, as it is identified from households with a change in the head of the household, mainly involving a change from male to female head, due to the death of the head of the household. About 11 percent of households experienced a change in the sex of the head of the household, more than 75

Table 5: Explaining fertilizer adoption and aplication Rates (log kg per hectare):

	(1) Conditional fixed effects logit model (n=1540, 417 groups)			(2) Honoré Fixed Effects Tobit Model (n=4397)			(3) Standard Tobit Model (n=4397)		
	Whether using fertiliser (yes=1)			Ln fertiliser in kg per ha			Ln fertiliser in kg per ha		
	Coeff.	z-value		Coeff.	z-value		Coeff.	z-value	
Male child <15	0.069	0.59		-0.105	2.01	**	0.037	0.78	
Male adults	0.354	3.01	***	-0.071	1.51		0.135	2.96	***
Female child <15	-0.032	0.26		-0.118	2.28	**	0.029	0.59	
Female adults	0.269	2.51	**	0.055	1.25		0.220	4.75	***
Sex head (male=1)	0.779	2.13	**	0.443	2.35	**	0.500	4.05	***
Ln Livestock/1000 (birr) at t-1	0.160	1.45		0.068	1.17		0.693	13.55	***
Ln Land per adult	0.114	0.73		-0.936	6.44	***	-0.001	0.01	
Ln consumption at 20th percentile for rain	0.236	2.02	**	0.165	2.69	***	0.431	5.87	***
Time (round) dummies, and interaction between village and time dummies included but not reported	YES			YES			YES		
Joint-significance tests Wald chi2				2650.11***			766.2***		

Notes: Natural logarithm of fertiliser in kg plus 1 per hectare. One is added to allow zero values to be transformed in logarithms. Land per adult and livestock per adult (in '000) is adjusted by 0.01 to allow logarithms. * significant at 10%; ** significant at 5%; *** significant at 1%.

The coefficients for livestock, land and downside consumption risk are lower in the household fixed effects specification than in the standard tobit, presented in column (3) for comparison Indeed, the level of consumption in 'bad years' as well as current livestock wealth and land holdings (at t-1) are likely correlated with fixed characteristics of the household, such as higher permanent income, that in turn positively affects fertiliser use.

More striking is that the consumption outcome in a bad year remains relevant, even in the fixed effects regression, while the effect of livestock wealth around the time of the fertiliser decision disappears—the household's position at the time of the fertiliser decision matters largely to extent that it may cause hardship in bad years. This supports our interpretation that potential ex-post credit constraints when harvests fail matter in a distinct manner from the seasonal credit constraint. Furthermore, households with higher land-labor ratios are found to use less fertilisers (even though their adoption of fertiliser is unaffected).

percent from male to female headed.

This is consistent with their comparative advantage, and only emerged when the household's total (liquid and illiquid) wealth was properly controlled (through the household fixed effects).

These results are robust to the use of alternative definitions of the downside risk variable. When the downside risk variable is defined as the expected value of the logarithm of consumption for rainfall levels up to the median (column (1), table 6), the results are virtually identical as in table 5, column (2). Very similar results were obtained when using the expected value of the logarithm of consumption (not truncated), giving a higher weight to downside consumption risk than upside risk.[40]

[40] These and all other robustness checks also hold in the fixed effects conditional logit model (not reported here).

Table 6: Robustness checks

	(1) Honoré Fixed Effects Tobit Model (n=4397)			(2) Honoré Fixed Effects Tobit Model (n=4397)			(3) Honoré Fixed Effects Tobit Model (n=4397)			(4) Conditional fixed effects logit model (n=1540, 417 groups)			(5) Honoré Fixed Effects Tobit Model (n=3260)		
Dependent Variable	Ln fertiliser in kg per ha			Ln fertiliser in kg per ha			Ln fertiliser in kg per ha			Whether using fertiliser (yes=1)			Ln fertiliser in kg per ha		
	coeff	z-value		coeff	z-value		coeff	z-value		Coeff	z-value		Coeff	z-value	
Male child <15	-0.105	2.01	**	-0.087	1.34		-0.103	1.97	**	0.071	0.61		-0.064	0.97	
Male adults	-0.072	1.51		-0.041	0.72		-0.073	1.54		0.356	3.03	***	-0.039	0.63	
Female child <15	-0.118	2.28	**	-0.107	1.66	*	-0.118	2.28	**	-0.029	0.24		-0.113	1.93	*
Female adults	0.055	1.26		0.105	2.01	**	0.056	1.27		0.267	2.49	**	0.076	1.32	
Sex head (male=1)	0.443	2.35	**	0.536	2.76	***	0.446	2.36	**	0.776	2.12	**	0.731	3.31	***
Ln Livestock at t-1	0.067	1.16		0.035	0.51		0.113	1.49		0.264	1.06		0.132	1.96	**
Ln Land per adult	-0.936	6.44	***	-0.979	6.48	***	-0.936	6.45	***	0.117	0.75		-0.771	4.40	***
Ln consumption 20th perc							0.166	2.70	***	0.237	2.03	**	0.221	2.49	**
Expected ln consumption Below median rainfall	0.165	2.69	***												
Ln consumption 20th perc based on predicted cons				0.478	1.64	*									
Ln Livestock at t-1 interacted with down payment fertiliser loan							0.105	0.88		0.207	0.47				
Ln consumption at t-1													-0.034	0.35	
Time (round) dummies, and interaction between village and time dummies included but not reported	YES			YES			YES			YES			YES		

* significant at 10%; ** significant at 5%; *** significant at 1%.

So far, the counterfactual distribution of consumption for different levels of rainfall was calculated starting from actual consumption, and then using the estimated coefficients from table 4. The counterfactual consumption levels in column (2), table 6, start from predicted values of consumption based on table 4. If actual consumption is measured with substantial measurement error, then the estimates in column (2) will be superior; however, predicted consumption ignores any factors causing consumption differences between households known to the household but not observed by the researcher. The results reported so far are maintained: insignificant effects from livestock holdings at t-1, but counterfactual consumption if the harvest were to be poor, is still significant. The coefficient on the latter is higher than in column (2), table 5, consistent with attenuation bias when using our original estimate for counterfactual consumption.

The next two columns investigate further whether seasonal credit constraints matter at all, and whether our interpretation is robust. It could be argued that simply using asset holdings at t-1 is a poor proxy of the true cost ex-ante of fertiliser. Even though credit is available, a down payment is required. As discussed in section 4, a payment of about 30 percent of the purchase price is required, but there is considerable variation across areas. This variation is exploited to explore the impact of seasonal credit constraints further (columns (3) and (4)). In particular, even though the village time-varying fixed effects contain this variation in down payment, it could be expected that in areas with higher downpayment, the same asset holdings would result in lower fertiliser application rates – in other words, an interaction effect of asset holdings and downpayments should be negative if seasonal constraints matter. The results do not confirm this: this variable, just as the asset levels at t-1, is insignificant.

Finally, in column (5), a further robustness test is shown, focusing on the interpretation of our counterfactual consumption term. It could be argued that as consumption levels move only slowly, and as our prediction model is based on the evolution of actual consumption, our counterfactual consumption level is likely to be highly correlated with consumption and welfare levels at t-1. In fact, our measure may then be more a reflection of current conditions, not really capturing a counterfactual outcome. Similarly, it could be argued that livestock holdings are a poor proxy of current conditions, and our predicted consumption levels are in fact a better measure of current circumstances. One way of examining the robustness of our interpretation is by including a stronger measure of living conditions ex-ante, via consumption levels at t-1, before the fertiliser decision, as well as our counterfactual prediction. Even though we lose a round of data now[41], the results regarding the relevance of counterfactual consumption for fertiliser application are confirmed, while the consumption level at t-1 is simply insignificant. Taken together, these results highlight the impact of possibly low consumption outcomes ex-post on fertiliser use, controlling for the level of assets at the time of fertiliser purchase, and household fixed characteristics and time-varying village level conditions.

[41] Contrary to livestock levels, which were easily collected at t-1 via a set of simple recall questions, this is not possible for consumption.

6 Conclusions

This paper has investigated the impact of the risk of poor consumption outcomes on the adoption and use of fertiliser in Ethiopia. Fertiliser results in higher yields and substantial returns on average. However, as a costly input, when harvests are poor, for example due to poor weather conditions, returns tend to be low given the sunk cost of fertiliser, making it a high risk activity with moderately higher returns compared to not using fertiliser. We developed a simple framework to assess whether the possibility of poor consumption outcomes affects modern input use, controlling for a simple asset effect, that could also be a reflection of seasonal working capital constraints.

Using data from Ethiopia, we find evidence that after controlling for these seasonal working capital constraints, as well as household fixed effects (including factors such as risk preferences and permanent income) and time-varying community fixed effects (including factors such as input output price ratios and extension programs) fertiliser application rates are significantly lower due to downside risk in consumption. Consequently, measures to remove the downside risk of agricultural innovations via insurance systems would have beneficial impacts on stimulating their spread.

The presence of a link between downside consumption risk and modern input adoption also suggests that risk is a cause of perpetuating poverty: those (poorer) households unable to protect themselves against downside risk are forced to avoid some downside risk by reducing their use of profitable modern inputs. As such, risk induces the persistence of poverty for some, as if trapped in low return, lower risk agriculture.

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Appendix 1: The distribution of cereal yields and returns

Table A.1 explores the determinants of output per hectare using plot-level data from 1999. Yields are regressed on plot level inputs including the plot size in hectares, hours worked by male and female adults, and children (up to the age of 15 years), and purchased inputs, such as fertiliser, herbicides, fungicides, insecticides, and other pest controls (in kg). All variables are expressed in natural logarithms (plus 0.01 to allow for zero values to be defined when taking logarithms). Table A.1 adds controls for the different crops (whereby white teff is the basegroup), whether the plot is intercropped, local standard descriptions for land quality (lem, lemteuf, teuf, with lem the best and teuf the base group) and the slope of the plot (flat, sloping and 'geddel', the base group, meaning a steep slope). The regression also controls at the household level for the number of livestock in tropical livestock units (as a proxy for both wealth and for access to oxen for ploughing).

Plot-specific, self-reported 'shocks' related to flooding, weed damage, animals damaging crops, etc. are introduced as dummies with one suggesting a 'bad' event. A number of variables describing the rainfall distribution and experience in this particular year are further introduced. First, we have access to historical rainfall data in most locations going back for about 20 years, based on rainfall in the nearest station. We use village level variables to describe whether the rainfall in the 1999 season was in a particular quintile of the historical distribution (from 0-19, 20-39, etc.) To reflect differences in 'normal' conditions, we control for the median level of rainfall in each area. We also use a self-reported index of how good the rain distribution was in this particular year, based on plot-level data from the 1999 survey: was the rain on time, did it rain too long, into the harvest period, was there enough at critical points, etc. The answers to these questions were added into a simple score, normalised to one if the rain was as good as it could get, and zero if it was bad on all counts. The squared value of this index was used.

Finally, market access was proxied by a variable for 'road access and quality' based on community level surveys. It is an index on a scale of six, with the value one a road with access for all possible vehicles in all seasons, and six only a track not accessible in the rainy season. The value of three is for example a road accessible to trucks most of the time.

Application of OLS shows that here are clear signs of lower yields on larger plots, with returns to male labour, fertiliser and insecticide strongly significant (column (1), table A1). Livestock and good land quality appears to matter as well. Most of the idiosyncratic shocks (with the exception of frost damage, a rare event in the data) have the expected signs and several cause substantial and significant yield losses. Areas with good roads appear to have higher yields on average, consistent with increased incentives for producing crops. The effect is large, though dropping this variable did not affect the signs or size of the rainfall variables.

Unsurprisingly, rainfall matters significantly, with median levels increasing yields (but only marginally in magnitude). The realised quintile of the rainfall in 1999 based on the historical distribution also displays the expected signs and magnitude. As there were no observations in the 1999 data of the highest quintile, the lowest quintile is the basegroup, and all other three quintiles showed significantly higher yields (by at least 20 percent). Having rainfall around the 40 to 60 percentile compared to historical distribution (ie around the median) had the highest yield gain. Finally, the self-reported 'quality' of rainfall index showed higher yields with a better index but at a decreasing rate.
Table A.1 Plot-Level Production Function (ln output in kg per hectare) 1999

	(1)	(2)	(3)
	Ln yield	Ln yield	Ln yield
Ln Plot size (in hectares)	-0.618	-0.582	-0.616
	[25.42]***	[18.11]***	[25.22]***
Ln Hours Male Labour	0.267	0.409	0.274
	[11.40]***	[11.31]***	[11.55]***
Ln Hours Female Labour	0.014	0.065	0.017
	[0.96]	[2.51]**	[1.12]
Ln Hours Child Labour (<15 years)	-0.003	0.056	-0.003
	[0.25]	[1.84]*	[0.23]
Ln Fertiliser in kg	0.034	0.028	0.003
	[8.34]***	[5.39]***	[0.10]
Ln Herbicide in kg	0.205	0.261	0.175
	[1.80]*	[1.46]	[1.52]
Ln Fungicide in kg	-0.015	-0.913	0.011
	[0.05]	[1.16]	[0.04]
Ln Insecticide in kg	0.144	0.191	0.138
	[2.06]**	[2.00]**	[1.98]**
Ln Other Pest Control in kg	0.224	-0.18	0.213
	[0.85]	[0.36]	[0.81]
Ln Livestock (livestock units)	0.072		0.072
	[5.33]***		[5.37]***
Is the plot intercropped?	0.12	0.072	0.119
	[2.41]**	[1.07]	[2.41]**
Black Teff	-0.143	0.114	-0.162
	[2.61]***	[2.14]**	[2.96]***
Barley	0.33	0.565	0.345
	[6.35]***	[10.36]***	[6.59]***
Wheat	0.267	0.407	0.272
	[5.53]***	[8.45]***	[5.60]***
Maize	0.461	0.581	0.474
	[9.69]***	[12.35]***	[9.97]***
Sorghum	0.416	0.434	0.409
	[6.73]***	[6.83]***	[6.60]***
Land quality: very good (lem)	0.101	0.192	0.095
	[2.24]**	[3.38]***	[2.11]**
Land quality: OK (lemteuf)	0.037	0.077	0.037
	[0.83]	[1.34]	[0.81]
Land Slope: flat (Medda)	0.011	-0.089	0.017
	[0.11]	[0.60]	[0.16]
Land Slope: sloping (Dagathama)	0.037	-0.171	0.036
	[0.35]	[1.10]	[0.34]
Wind damage?	-0.07	-0.017	-0.074
	[1.42]	[0.14]	[1.51]
Hail damage?	-0.029	-0.139	-0.05
	[0.46]	[1.06]	[0.79]
Frost damage?	0.145	0.047	0.152
	[3.43]***	[0.56]	[3.60]***
Flood damage?	-0.151	0.139	-0.146
	[3.09]***	[1.58]	[2.99]***
Plant disease damage?	-0.094	-0.182	-0.108
	[1.02]	[1.05]	[1.17]
Insect damage?	0.066	0.08	0.058

	(1)	(2)	(3)
	Ln yield	Ln yield	Ln yield
	[0.98]	[0.89]	[0.87]
Weed damage?	-0.218	-0.145	-0.225
	[2.79]***	[1.35]	[2.88]***
Bird damage?	-0.207	-0.209	-0.21
	[2.13]**	[1.44]	[2.17]**
Wild animals damage?	-0.049	0.066	-0.052
	[0.76]	[0.62]	[0.81]
Livestock trampling damage?	-0.025	-0.069	-0.012
	[0.18]	[0.32]	[0.09]
Road quality index	-0.081		-0.081
(1=best, 6=worst)	[7.94]***		[7.91]***
Median rainfall in area	0.001		0.001
	[2.52]**		[2.72]***
Is rainfall 20-40 percentile?	0.284		0.472
	[2.37]**		[2.93]***
Is rainfall 40-60 percentile?	0.38		0.475
	[3.00]***		[2.76]***
Is rainfall 60-80 percentile?	0.218		0.403
	[1.87]*		[2.54]**
Rainfall distribution index	0.752		0.749
(1=best, 0=worst)	[4.18]***		[4.16]***
Rainfall distribution index squared	-0.501		-0.503
	[2.75]***		[2.77]***
Rainfall index*ln fertiliser			-0.042
			[3.33]***
20-40% * ln fertiliser			0.049
			[1.49]
40-60% * ln fertiliser			0.084
			[2.30]**
60-80% * ln fertiliser			0.057
			[1.74]*
Constant	4.04	4.005	3.816
	[20.11]***	[19.67]***	[16.69]***
Observations	2502	2502	2502
R-squared	0.4	0.31	0.41
Absolute value of t statistics in brackets			
* significant at 10%; ** significant at 5%; *** significant at 1%			

Column (2) looks at the robustness of the results by showing the household fixed effects regression results. By definition, all the household and community level variables are absorbed in the fixed effects, so that no results on rainfall can be reported. Importantly, the coefficient on fertiliser retains its significance, and is similar in value. While there are some signs of correlations of some of the plot-level variables with the household fixed effect (i.e. bias in column (1)), it may not affect our inference on the impact of fertiliser on yields. This is a striking result, as identification of the impact has to be done across the plots of each household, who usually farm about 2-3 plots each. As there is relatively little variation in terms of most of the idiosyncratic shocks, it should not come as a surprise that the impacts of most shocks are measured with considerable error.

Finally, to test whether the returns to fertiliser are rainfall dependent, interaction terms of the level of fertiliser use and the various rainfall variables are introduced in column (3). These interactions are generally significant. However, the impact of fertiliser without interaction is now no longer different from zero. This term is now the basegroup for the interaction terms giving the impact of fertiliser when the rains are really poor (the base group is the 0 to 20th percentile of the rainfall distribution). Or, during drought fertiliser has no impact. Simulations are undertaken to obtain clearer inference on the impact of fertiliser on yields across the rainfall distribution.

For the village-level rainfall distribution, the historical data are used to show the distribution of yields for different levels of rainfall, by comparing otherwise similar plots with 'mean' characteristics in terms of fertiliser use and non-use. For the self-reported rainfall distribution index we rely on the distribution implied across all four rounds of the household-level self-reported shocks. The frequency distribution of all possible outcomes between 1994-1999 is used in the simulations. As was shown in Dercon and Krishnan (2000), this index is largely (although not perfectly) covariate by village; the simulations assume perfect covariance, although some sensitivity analysis showed that less than perfect covariance hardly affected the results reported in the main text.

The equations above use pooled data for all crops. We experimented with specifications by crop, but the sample sizes become much smaller, especially to identify the impact of rainfall across the distribution as most villages do not grow all different possible crops in this year. Broadly speaking, the coefficients are comparable though estimated with less accuracy. Restricting the crop-specific effects to multiplicative shifters of yields appears to capture the diversity of yields reasonably well in the data.

The regressions are used to construct counterfactual yield distribution for different levels of rainfall, based on the historical rainfall distribution, and assuming here that the household specific quality of rainfall index is covariate with village rainfall. As the results are in size dominated by the village rainfall index, alternative assumptions on the quality of rainfall did not make much difference. The results suggest considerably higher yields for fertilised plots compared to non-fertilised plots (Table A2). Across cereals, median rainfall conditions offer about 24 percent higher yields when using the average amount of fertiliser. While yields on fertilised plots dominate those on non-fertilised plots across the rainfall distribution, the relative benefit systematically declines the further rainfall levels are from the median.

Table A.3 shows calculations of the implied returns per hectare for these different yield levels. These returns are simply defined as the mean gross return (yields times output prices) minus (for the simulations for fertilised plots) the cost of the fertiliser, i.e. mean application rates times the fertiliser price, assuming a cash purchase. To get a sense of the distribution of returns by fertilised and non-fertilised plots during the survey period, we use the mean output and fertiliser price for the period 1994-99. In the main text, we offer in figure 1 the distribution for all cereals using average 1994-95 prices and compare it to 1997-99 prices to reflect changing profitability.

For all crops, using fertiliser is profitable as long as the rainfall is not deviating too much from the usual patterns of rainfall. With median rainfall, the returns on fertilised plots are about 10 percent higher than for non-fertilised plots. Given that using fertiliser offers little yield gain at low rainfall levels, non-fertilised plots have higher returns per hectare in these circumstances. The data suggest that with abundant rain, returns are also better for non-fertilised crops.

Table A.2 Fertiliser use and the distribution of yields

Yields in kg per ha across the rainfall distribution	All cereals		Teff		Barley		Wheat		Maize		Sorghum	
	No fert	fert	No fert	fert	No fert	fert	No fert	fert	No fert	Fert	No fert	fert
10th percentile	440	443	319	321	394	397	424	427	574	578	584	588
20th percentile	568	618	412	450	508	555	547	597	741	803	754	806
30th percentile	790	912	573	668	707	822	761	885	1030	1184	1049	1175
40th percentile	850	1018	616	748	761	920	819	990	1108	1320	1129	1301
50th percentile	889	1106	644	815	796	1002	856	1079	1159	1434	1180	1403
60th percentile	879	1027	637	753	787	927	846	998	1146	1334	1167	1320
70th percentile	853	939	618	686	764	845	821	909	1112	1221	1133	1222
80th percentile	847	917	614	669	758	824	815	887	1104	1193	1124	1197
90th percentile	838	899	607	655	750	808	807	869	1092	1170	1112	1176

Note: Simulations based on the estimates reported in table A.1, column (3). Yields based on estimated output per hectare in 1999 for an average plot (i.e. with mean characteristics for plot, farmer and village), among 2294 plots. Yields on fertilised plots based on approximately the mean application rate for fertiliser users for each crop. The table offers the counterfactual yield distribution for different cereals across the rainfall distribution. For example, the 10th percentile gives yields when the rainfall was equivalent to the 10th percentile of the rainfall distribution, i.e. very poor rains, the 50th percentile when rains were to be at the median level of rainfall in all villages, and the 90th percentile is very abundant rainfall, i.e. rain at the 90th percentile of the historical distribution. The crop-specific yield estimates are based on calculating counterfactual yields only for those plots currently growing the crop.

Table A.3 Fertiliser use and the distribution of returns 1994-99

Returns per hectare across the rainfall distribution	All cereals		Teff		Barley		Wheat		Maize		Sorghum	
	No fert	fert	No fert	fert	No fert	fert	No fert	fert	No fert	Fert	No fert	fert
10th percentile	793	544	688	478	772	535	867	622	742	459	1180	861
20th percentile	1023	858	888	757	997	846	1119	970	957	751	1523	1301
30th percentile	1423	1388	1235	1226	1387	1369	1556	1559	1332	1243	2119	2046
40th percentile	1531	1579	1329	1398	1492	1560	1675	1773	1433	1419	2280	2301
50th percentile	1601	1740	1389	1543	1560	1721	1751	1955	1499	1567	2384	2507
60th percentile	1582	1596	1373	1410	1542	1575	1731	1790	1481	1437	2356	2339
70th percentile	1536	1437	1333	1264	1497	1413	1680	1608	1438	1291	2287	2141
80th percentile	1525	1397	1323	1227	1486	1373	1668	1563	1427	1255	2270	2092
90th percentile	1509	1365	1309	1198	1470	1341	1650	1527	1412	1225	2246	2050

Note: Simulations based on the estimates reported in table A.1, column (3).. Returns are the gross returns (yield times output price, evaluated at the mean output price in 1994-99) minus the cost of the fertiliser (using the mean fertiliser price at the time of planting in 1994-99).