Exploring technology use under climate risk and shocks through an experimental lens

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Abstract
Increasing agricultural productivity among smallholders in developing countries remains essential to improving food security, and one potential avenue for this increase is through stimulating technology adoption. In this paper we combine rainfall data with household survey and field experimental data to assess households' use and potential demand for a risky agricultural input in Tigray, Ethiopia. More specifically, we explore how average rainfall, rainfall variability, lagged rainfall shocks and risk aversion relate to inorganic fertiliser use at the farm plot level. Further, we analyse how these variables and exogenous price variation affect the demand for inorganic fertiliser at the household level. The findings are potentially important for the design of policies to promote agricultural production in semi-arid rain-fed agricultural areas with vulnerable populations facing rainfall risk and shocks.

Key words: rainfall shocks and risk; framed field experiments; risk aversion; technology adoption; Ethiopia

1. Introduction

Increasing agricultural productivity remains a central challenge to reducing poverty and improving food security among smallholders in sub-Saharan Africa. An avenue for achieving this is through technology adoption in agriculture.[1] However, despite improvements in technology supply, adoption rates and continued usage of modern technologies remain low. Proposed explanations include credit constraints and consumption risk (Dercon & Christiaensen 2011), liquidity constraints (Holden & Lunduka 2014), imperfect insurance and input markets (Binswanger & Rosenzweig 1986; Hagos & Holden 2006; Foster & Rosenzweig 2010), labour market imperfections (Lamb 2003; Holden *et al*. 2004), behavioural biases (Duflo *et al*. 2011), limited experience (Conley & Udry 2010), and heterogeneous returns (Suri 2011). Risk and risk aversion are central to several of these factors and may affect households' investment in technologies.

Theoretical work suggests that risk and risk aversion affect farmers' input use. According to Sandmo's (1971) model, risk-averse producers produce less under output price risk than under price certainty. However, risk-averse farmers who are net buyers of food may respond differently to changes in risk and risk aversion in order to protect their consumption needs, instead increasing their production with the level of risk aversion, while the response to increasing risk is ambiguous (Finkelshtain & Chalfant 1991). In addition, the extent to which risk and risk aversion affect farmers'

[1] We use Foster and Rosenzweig's (2010) definition of technology as "the relationship between inputs and outputs".

input choice depends on the factor market access. Higher risk or risk aversion under credit constraints may reduce investments in relatively more risky technologies (Feder, 1980).

Production risk due to rainfall variability and its impact on rain-fed agriculture is central to our context, and is fundamentally related to output price risk due to covariate risk and limited market integration. We focus on one technology, inorganic fertiliser, and its adoption under rainfall risk, rainfall shocks and risk aversion among farmers in the semi-arid Tigray region in northern Ethiopia. We define rainfall risk as inter-annual rainfall variability, whereas a rainfall shock is captured as deviations in annual rainfall compared to the local average.[2] We are not the first to analyse fertiliser adoption in view of risk aversion or rainfall patterns in the Ethiopian context. For instance, risk aversion is positively correlated with fertiliser use in the Tigray region (Hagos & Holden, 2011), recent subjective drought experience and higher risk aversion reduce the probability of purchasing fertiliser in the Amhara region (McIntosh *et al*. 2013), whereas fertiliser use is concavely and convexly related to lagged annual rainfall and current intra-annual rainfall variability respectively (Alem *et al*. 2010). The novelty of our approach is that it combines these issues, assessing fertiliser use under rainfall risk and shocks for different degrees of risk aversion, in an area where the majority of farmers are net buyers of food. More specifically, we aim to answer the following questions. How does risk aversion interact with rainfall risk in their correlation with fertiliser *use* at the farm plot level? How do lagged rainfall shocks affect fertiliser use? Further, how does fertiliser *demand* respond to exogenous variation in fertiliser prices and correlate with average rainfall, rainfall risk, lagged rainfall shocks, and varying risk aversion? And finally, what are the policy implications of these findings?

We combined several methods and data sources to answer these questions. First, we assessed fertiliser *use* under varying levels of average rainfall, lagged rainfall shocks and inter-annual rainfall variability, coupling observational farm plot data with rainfall data from local meteorological stations. We placed particular emphasis on plots planted with cereal crops, given our focus on food security. This was further combined with risk aversion, which was elicited based on hypothetical crop choice scenarios. Second, we experimentally assessed households' *demand* for fertiliser under exogenous price variation and examined how demand correlates with average rainfall, inter-annual rainfall variability, lagged rainfall shocks and risk aversion. We combined fertiliser offers to our random sample of households with randomisation of the amount of cash offered as an alternative to fertiliser, allowing us to assess demand in response to exogenous price variation. This framed field experiment provided us with a wide array of prices within the same area and captured how the share of all households demanding fertiliser changed with fertiliser price. This provided a measure of potential unconstrained demand that was based on the perceived local production potential and was free of access and liquidity constraints. Our main contributions thus are (a) to assess how rainfall (average, variability and lagged shocks) and the interaction between risk aversion and rainfall risk relate to fertiliser use and (b) to assess the potential demand for the risky input at varying exogenous input prices through randomised experimental treatments and to determine whether it correlates with the rainfall variables and risk aversion. We assessed the robustness of our findings by imposing varying sets of controls.

We found that cereal crop planting and fertiliser application at the plot level, which comprise a joint decision, are statistically significantly and positively correlated with average annual rainfall and risk aversion at a given level of risk for the typical net buyers of cereals in the study areas. Further, these were negatively correlated with the interaction between rainfall risk and risk aversion when controlling for plot and household characteristics, irrigation and access to farm credit. For cereal plots, we found that rainfall variability was negatively related to fertiliser use on the extensive margin, that

[2] Our short history of rainfall data to draw upon precludes a more narrow definition of a ”shock”.

less than average rainfall in the previous season reduced fertiliser on the intensive margin, whereas average rainfall was positively correlated with fertiliser use on both margins. Our results from the framed field experiment reveal a strongly significant negative sign for the price of ,fertiliser and a positive and significant relationship with average annual rainfall. This demonstrates that basic economic theory holds and that average annual rainfall is a good indicator of expected return to fertiliser in this semi-arid area. Further, we found that rainfall variability and lagged rainfall shocks were negatively correlated with the probability of choosing fertiliser in the experiments. Farm input credit appeared not to stimulate fertiliser use in this semi-arid environment.

2. Conceptual framework

We conceptualised a model in which we assumed risk-averse farmers who produce a food crop that is viewed as a normal good and who maximise the expected utility of income and leisure.[3] Input decisions take place under uncertainty in the first period, whereas the amount of rainfall is revealed in the second period, after which output is harvested. For simplicity, we limited the inputs used to labour and fertiliser in addition to land. Farmers' net income follows from the value of the output, subtracting the value of the inputs used in production.

In line with previous work, we assumed that fertiliser is a yield-enhancing, but risky, input (Feder 1980; Dercon & Christiaensen 2011). There are several reasons why this is a realistic assumption in our context. First, Dercon and Christiaensen (2011) found negative net returns to fertiliser at very high and low levels of rainfall in Ethiopia. Second, farmers' ability to assess the net returns is most likely variable (Beaman *et al*. 2013), although previous experience may improve their input management abilities and thus reduce variability (Foster & Rosenzweig 2010). Further, we assumed that expected net returns under adoption were higher than under no adoption, also in line with Dercon and Christiaensen's (2011) findings, but that the realisation of a bad (rainfall) state results in lower net returns than under no adoption. There thus is a trade-off between risk and the expected income.

We organised the factors that affect farm households' adoption of inorganic fertiliser into five categories based on the proposed explanations for limited technology adoption: (1) rainfall risk and shocks, (2) local terms of trade and market access, (3) institutions and policies that stimulate input demand, (4) household composition (labour supply and consumption needs), and (5) preferences.[4] The first three categories are largely exogenous, although actual participation in institutions is not, whereas the latter two are internal to the farm households.[5] We discuss these factors further below.

Assuming that the marginal return to fertiliser is weather dependent, that farmers update their expectations based on past experience, and that agriculture is their main income source, then rainfall shocks and risk may affect fertiliser use, (1). First, higher rainfall risk, measured in terms of the coefficient of variation (CV) of inter-annual rainfall, increases the expected variability of output and output prices in the second period.[6] This may have less of an effect on input use among risk-neutral farmers who produce a normal good, but may influence fertiliser use among risk-averse farmers. We return to this in our discussion of risk aversion. Second, a previous rainfall shock, captured as a shortfall in lagged rainfall compared to the local average, may tighten present liquidity constraints,

[3] Here we assume a unitary model and use farmer and household interchangeably. Utility maximisation implies a trade-off between labour and leisure in the household.
[4] Unfortunately we were unable to assess the role of risk-bearing institutions, in part due to limited access to institutions such as consumption credit, and leave this for future work.
[5] We set aside the question of whether, taking a long-term perspective, a household's decision to remain in a risky environment can also be characterised as endogenous.
[6] Our approach differs from that of Alem *et al*. (2010), as we focused on inter-annual, rather than intra-annual, rainfall variability.

thus reducing fertiliser use.[7] We expected tightened liquidity constraints to affect farm households, regardless of their level of risk aversion. Lastly, we controlled for average rainfall, as higher average rainfall is expected to increase expected returns.

Further, the net return to fertiliser use depends on the relative prices between fertiliser and the output good, (2). Higher local output prices relative to the input cost increase the net return to fertiliser. Market access feeds into this calculation, as longer distances increase transaction costs and are likely to reduce households' market participation. In terms of institutions and policies that stimulate fertiliser use (3), we focused on credit access and irrigation, which are both provided through government programmes. Access to farm credit relaxes the seasonal credit constraint, whereas irrigation both mitigates the impact of rainfall variability on output and enhances land productivity. In a setting with imperfect or missing factor and output markets, fertiliser use also depends on households' characteristics, (4). For instance, household composition conditions the food demanded and the labour available. Labour markets are thin (Bezu *et al*. 2012), and thus farmers are largely reliant on their own labour as input in production. We restricted our focus to household composition, ignoring other endowments that may affect households' ability to tackle downside risk.

Lastly, the fertiliser use decision depends on farmers' preferences, (5). Preferences can refer to, among others, crop and risk preferences. The main crops in our setting are cereals (e.g. teff, wheat and barley), which all respond to fertiliser, and we therefore ignore potential crop differences hereafter. However, risk preferences may affect households' input use decisions. As discussed earlier, more risk-averse pure producers produce less than less risk-averse producers at a given level of output price risk (Sandmo 1971), thus reducing their input use. Higher risk due to higher rainfall variability may also reduce the use of and demand for a risky input. However, risk-averse net buyers of food are less likely to reduce their demand for an input that is used to produce a normal good as risk increases, as shown by Finkelshtain and Chalfant (1991). Further, these authors show that, at a given level of risk, risk aversion is positively correlated with output (and thus input demand) for net buyers as opposed to the negative relationship expected for net sellers and pure producers. Sandmo's (1971) and Finkelshtain and Chalfant's (1991) theoretical predictions are made with regard to output price risk. Our setting is complicated by two factors. First, covariate risk implies that output prices are negatively correlated with rainfall deviations from the average. Lower than usual rainfall in a larger geographical area means lower production and higher market prices for cereals due to limited output market integration. Local demand for cereals may exceed local supply in such years, while an area is more likely to produce a surplus for export in years with good rainfall (Holden & Shiferaw, 2004). Second, net buyers of food have an increased incentive to increase production, thereby enhancing their input demand, but this incentive may be dampened by the riskiness of the input used. We considered such a risky input. We assessed whether the theoretical predictions were consistent with the empirical data in a situation in which households faced covariate production risk. We also assessed how the interaction between risk aversion and rainfall risk were related to fertiliser use and demand. The majority of our households were net buyers of food, and they produced food cereals that can be defined as normal goods.[8]

Given that risk aversion affects the adoption decision, then omitting risk aversion would bias the estimates of correlated observables. Following Binswanger's (1980) seminal study in India, several studies have aimed to elicit farmers' risk aversion using experiments (Wik *et al*. 2004; Harrison *et al*.

[7] Experiencing a rainfall shock may also affect farmers' perceived risk and risk aversion *ex post*, but we were unable to address this.

[8] Overall, approximately 77% of our sample can be considered to be net buyers of cereals, as the quantity of cereals they receive in the form of food aid, through Food-for-Work and purchases, is higher than the quantity sold.

2010). Experimentally deriving risk aversion is not without its challenges,[9] but it is less likely to be confounded by omitted constraints than deriving risk preferences based on observable production behaviour (Just & Pope 2003). Combining behavioural experiments with observational data to understand technology uptake is less common (Herberich *et al*. 2009; Barrett & Carter 2010). Exceptions include Knight *et al*. (2003), who found lower adoption of modern inputs and crops among more risk-averse[10] farmers in Addis Ababa, Ethiopia, and Liu (2013), who found that Chinese farmers with higher risk and loss aversion, measured *ex post*, adopted a modern cotton type later. Further, McIntosh *et al*. (2013) found that more risk-averse[11] household heads were less likely to purchase inorganic fertiliser in the Amhara region of Ethiopia, and Hagos and Holden (2011) found a positive correlation between risk aversion and fertiliser use in Tigray. These contrasting findings from Ethiopia could relate to the larger share of farmers being net buyers in Tigray than in Amhara.[12]

As noted, several studies have assessed fertiliser use following rainfall shocks (Alem *et al*. 2010; McIntosh *et al*. 2013), whereas empirical findings on how rainfall risk affects input use are more limited. Foster and Rosenzweig (2010) attribute this lack largely to the difficulty of capturing a shift in the risk distribution, while at the same time controlling for locality-fixed effects. They argue that a second best approach is to focus on differences in households' ability to tackle risk given their endowments. Rosenzweig and Binswanger (1993) assessed the riskiness of asset portfolios based on differences in inherited wealth and weather risk, whereas Dercon and Christiaensen (2011) investigated fertiliser use under predicted consumption variability. An alternative method is to provide random access to less risky technologies or risk-mitigating mechanisms (Karlan *et al*. 2014). Regardless of the approach, ignoring farmers' risk preferences under rainfall risk may deprive us of important insights with regard to farmers' adoption decisions. Moreover, climate change may increase future rainfall risk (IPCC 2014), further affecting smallholders' scope of action, with potentially large poverty and vulnerability implications. Households may be net sellers of food in years with adequate rainfall and net buyers in years with low rainfall (Holden & Shiferaw 2004). This again has implications for households' liquidity constraints and their input demand in the following year. More research therefore is needed to assess how rainfall risk and shocks interact with risk preferences and relate to the use of and demand for yield-enhancing inputs. A related question is to what extent policies, such as input credit programmes, can stimulate input use in more marginal semi-arid areas, and whether such programmes magnify the severity of shocks for borrowers with unlucky timing in their input loans.

3. Context, data and empirical strategy

3.1 Setting

We analysed the fertiliser use decision among farmers in the semi-arid highlands of Tigray, Ethiopia. Most farmers practise an integrated crop-livestock system, where oxen serve as the main source of traction power. They have on average one hectare of land and the majority are net buyers of food (Hagos 2003). Average rainfall is lower in this region relative to the other highland regions of Ethiopia (Benin *et al*. 2004). In terms of fertiliser, adoption in Ethiopia is low compared to other East African countries, and Tigray ranks low in usage within the country (Rashid *et al*. 2013). The

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[9] Experimentally derived risk preferences may place people in a gambling mode because the experimental context is different from their real-life situations. However, incentive-compatible risk preference experiments have an advantage in that they have real consequences for respondents. See, among others, Harrison and Rutström (2008) for a discussion on experimentally derived risk preferences.
[10] Knight *et al*. (2003) categorise farmers into "risk-averse" and "not risk-averse" based on a hypothetical question in which two outcomes are compared.
[11] It is not clear how McIntosh *et al.* (2013) constructed their measure of risk aversion.
[12] Amhara has greater agricultural potential than Tigray due to higher average rainfall and a larger average farm size; further, a larger share of the households in Amhara are net sellers of food (Benin *et al*. 2004).

Ethiopian government has in recent years stimulated input demand through the provision of credit and improved seeds. DAP (basal) and urea (top dressing) are the most common fertiliser types available, and these are typically purchased in 50 kg bags (Spielman *et al*. 2011). Important policy interventions in the region include investments in irrigation, the provision of agricultural credit and the Productive Safety Net Program (PSNP). The latter programme grants members access to a seasonal employment opportunity with payment in kind or cash, and credit (Government of Ethiopia 2009). Credit programmes were first promoted in the region in the mid-1990s, and more than half of the distributed credit is typically allocated for the purchase of farm inputs (Hagos 2003).

3.2 Data

3.2.1 Sample

The survey and experiments covered a stratified random sample of 527[13] households in 17 rural communities (*tabias*) from four zones in Tigray. Communities were stratified based on geographical (agro-ecological) zones, market access, population density and access to irrigation (Hagos & Holden 2002).[14] Households were interviewed in June and July 2010 by a group of researchers, students and enumerators, and the survey is a collaboration between the Norwegian University of Life Sciences and Mekelle University. All questions were asked in the local language, Tigrinya.

3.2.2 Household and plot survey

The survey data include information on household composition, resource endowments and agricultural activities at the plot level, including rented plots. We discuss the relevant variables in more detail below, under summary statistics.

3.2.3 Framed field experiment and hypothetical choice experiment

Our experimental component consisted of a framed field experiment and a hypothetical choice experiment for eliciting risk aversion. Real payoffs were included in the framed field experiment. This was the last question in the experimental component so as to avoid the real payoff generating bias in other responses.

In the framed field experiment, the respondent, either the male head or the wife/female head, was offered the choice between 5 kg fertiliser (DAP) and cash. The cash amount varied from 10 to 60 Ethiopian Birr (ETB), depending on the die outcome (see Appendix A1 for the experimental protocol).[15] We interpreted the responses as random bounds on unconstrained shadow prices, because the fertiliser was obtained without the respondent having to mobilise additional cash, given this choice. This allowed us to identify a price band within which a varying share of the households preferred fertiliser to cash, thus capturing the distribution of shadow prices in our sample and, assuming representativeness, also for the overall population. Constrained shadow prices are typically found to be significantly lower than unconstrained shadow prices (Holden & Lunduka 2014). The latter are likely to offer a better picture of the perceived benefits, unlike constrained shadow prices, which reveal more about affordability.

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[13] We have experimental data on 465 households, whereas fertiliser use and household characteristics were captured for 434 and 517 households respectively. The issue of attrition in plot and experimental data is addressed in the analysis.

[14] Sampling took place in 1998 for the baseline survey of 16 communities (Hagos & Holden 2002). Four follow-up surveys were subsequently implemented in 2001, 2003, 2006 and 2010. Only the last survey round included experiments on fertiliser demand, and we therefore restrict our attention to these cross-sectional data. Two communities were included, and one was dropped from 2006. The present data cover communities from two districts (*woredas)* in the Western Zone, three in the Eastern Zone, three in the Central Zone, and three in the Southern Zone.

[15] In June/July 2010, 10 to 60 ETB were equivalent to 0.52 to 3.11 US$. This gives an approximate price variation of 25% to 150% of the local commercial price.

We elicited risk aversion based on a hypothetical choice experiment (see Appendix A2) that was placed in a context that the farmer can relate to easily.[16] Each respondent was asked to compare two crop varieties, where the difference lay in their outcome in good and bad years. They were informed that we assumed that a bad year occurred in one out of five years. The further the respondents moved down the list before they switched, the more risk averse they were assumed to be, as there is a trade-off between risk and expected outcome. Their preferred variety therefore gives a risk-aversion rank that varies between 1 (low) and 6 (high risk aversion). For simplicity, we did not impose any additional assumptions on their utility function by using these ranks. Both the husband/male head and the wife/female head took part in the experiment separately. We used the risk-aversion rank of the husband when present, as it is typically the household head that is responsible for the agricultural production activities, and the wife/female head otherwise.

3.2.4 Rainfall data

Our rainfall variables were constructed based on monthly rainfall data obtained from the Ethiopian National Meteorology Agency (NMA). Continuous time series for all meteorological stations are available only for recent years, viz. 2003 to 2009. Each community (*tabia*) was matched with the nearest station based on elevation and proximity. In total, we used rainfall data from 13 stations. The rainfall data were likely to provide imperfect measures of actual rainfall at our study sites due to differences in distance between the nearest station and each survey village, and differences in elevation. This introduced measurement error into our rainfall variables and created a downward bias in the coefficient estimates. However, as long as this measurement error was not systematically related to any unobservables that enter into the error term, we would still obtain consistent estimates.

We measured rainfall risk in terms of the coefficient of variation (CV) of annual rainfall across the period 2003 to 2009. We used total annual rainfall, as the rain-fed agricultural season in Tigray lasts from May to June to September to October, and thus falls within the same calendar year. A lagged rainfall shock is defined as the shortfall in annual rainfall in the year prior to the decision of interest, i.e. fertiliser use or experimental choice, relative to the seven-year average. Households were surveyed on their input use in the main production season in 2009, whereas the experiments took place in 2010. We therefore constructed annual shortfall measures for 2008 and 2009. Lastly, we constructed a measure of average rainfall over the period 2003 to 2009, which was used as a proxy for the expected profitability of fertiliser use.

3.3 Empirical strategy

3.3.1 Fertilizer *use*

We investigated the relationship between rainfall, risk aversion and fertiliser use at the extensive and intensive margins. We were primarily interested in cereal plots, but as the planting decision and whether to apply fertiliser are likely to be a joint decision, we first applied a bivariate probit when assessing the factors correlated with fertiliser use at the extensive margin. Following this, we applied a Cragg (double hurdle) model to assess the factors correlated with fertiliser use at the extensive and intensive margin on cereal plots.[17] Our dependent variables in the first and second hurdles were whether the plot received fertiliser and the amount of fertiliser (in kg per hectare) respectively. We analysed fertilizer use at the plot level rather than at the household level, because input-use decisions

[16] Hagos and Holden (2006) employ an identical setup using the same initial sample.

[17] There is no consensus on what type of model to use to analyse the fertiliser-use decision. We have compared the results of the Cragg (double hurdle) model to a censored Tobit and found the latter to be inappropriate, as different factors affected the extensive and intensive margins, unlike the findings of Alem *et al*. (2010). An alternative to these approaches may be a selection model, as the decisions on whether to participate in the fertiliser market and how much to purchase may be associated with selection bias. However, using the Heckman selection model requires an identification strategy with a valid instrument (Wooldridge 2010). Unfortunately, we do not have such a variable available.

are likely to be affected by plot-level characteristics, which again are likely to affect expected returns to fertiliser.

We were interested in the relationship between risk aversion and fertiliser use; how average rainfall, rainfall risk and shocks correlate with fertiliser use; and the extent to which credit access and irrigation stimulate fertiliser use on cereal crops in this semi-arid area with high rainfall risk. We expected different responses to rainfall risk, depending on the level of risk aversion, and therefore included an interaction of rainfall risk (the CV of annual rainfall) with risk aversion. While we expected a positive sign for the risk-aversion variable at a given level of risk, given that the majority of respondents were net buyers of cereals, the expectation for the interaction variable was ambiguous. However, we expected lagged shortfall in rainfall to reduce investments in fertiliser due to tightened liquidity constraints, regardless of risk aversion.

The bivariate probit and the Cragg models assume that unobserved plot and household heterogeneity is uncorrelated with the covariates of interest and the dependent variable. This is a strong assumption. By including plot-specific characteristics, such as slope, land quality and soil type, we hoped to minimise such bias. In addition, we controlled for gender, age (including a squared term), whether the household head had received some education,[18] the number of adults (aged 15 to 65) by gender, children (below the age of 15), older adults (above the age of 65), and walking distance (in hours) to an all-year all-weather road. Finally, we introduced access to farm credit[19] and irrigation on plot, where the latter affects households' ability to hedge against rainfall risk. We controlled for whether the wife's risk-aversion rank was used instead of the husband if his was missing, even though the household was not female headed. Zone-specific fixed effects were included throughout, and standard errors were clustered at the meteorological station level. Lastly, we addressed the noted issue of attrition in the plot data by way of inverse probability weighting.[20]

We must be very cautious about making causal inferences based on our plot level models. We can only assess whether our results are consistent or inconsistent with the theoretical models providing causal predictions. Our key variables may be correlated with other confounding factors that affect input use, thus introducing omitted variable bias. Moreover, our use of cross-sectional data inhibits us from controlling for unobservable heterogeneous plot and household characteristics that may be correlated with our variables of interest.

3.3.2 Fertiliser *demand*

Next, we explored the responses to the framed field experiment and how these related to the prices offered, the expected rainfall, rainfall risk, lagged rainfall shocks, and risk aversion. Our workhorse was a linear probability model (LPM), where the dependent variable was set equal to one if the respondent chose fertiliser (DAP) and equal to zero if the respondent chose cash. We included the cash amount indicated by the die outcome (10 to 60 ETB), the timing of the experiment,[21] and whether the wife responded in the absence of the husband, in addition to the covariates described above, which were introduced sequentially. Again, we addressed the issue of data attrition, in this case for the experimental component, by way of inverse probability weighting.

[18] Education includes elementary schooling and higher levels, religious schooling, and adult literacy programmes.

[19] Access to farm credit was captured by whether the respondent responded yes to "If you wish, are you able to obtain credit for farm inputs?"

[20] We used household characteristics to predict the probability that plot data were missing, and used the inverse as weights. Assuming that the household sample was representative, this should reduce the attrition bias.

[21] Rainfall received so far in 2010 may also have influenced the respondents' choices. Unfortunately, we did not have rainfall data for this year, nor did we have data on when fertiliser application took place, thus preventing us from controlling for whether the experiment took place pre- or post-fertiliser application. Instead, we controlled for the week in which the experiment took place in order to capture how far into the production season the households from each village were.

We expected higher average rainfall to increase the likelihood that the respondent chose fertiliser over cash, whereas higher rainfall risk (a higher CV of inter-annual rainfall) was expected to reduce fertiliser demand, as the returns to fertiliser would be more risky. Applying Finkelshtain and Chalfant's (1991) insights on output price risk to rainfall risk, we expected that, at a given level of risk, net buyers would aim to produce more food, and thus use more inputs, the more risk-averse they were. The expected sign on the interaction between risk aversion and risk was again ambiguous. Likewise, we expected a rainfall shock (lagged shortfall in rainfall) to be negatively related to fertiliser demand. However, the intuition differed somewhat for fertiliser *demand* compared to fertiliser *use*, because the alternative now is cash, and the decisions are not constrained by liquidity shortage. Although the decision itself is not affected directly by a liquidity constraint, the tougher liquidity situation that a household faces after a rainfall shock may increase the demand for cash relative to fertiliser. Further, we cannot rule out that recent shocks may affect future weather expectations.

3.4 Summary statistics

In Table 1 we present descriptive statistics at the household and plot levels. One third of the households were female-headed, and less than a third of the household heads had some form of education. Approximately 65% of the households applied inorganic fertiliser on approximately 45% of all plots. The average plot size was close to 0.3 hectares and the plots received on average 59 kg fertiliser per hectare.[22] Among the households that used fertiliser in 2009, just over half purchased fertiliser at the district market, whereas the remaining purchases were made within the village or at the local market. Approximately 40% of the households had purchased fertiliser using their own savings, whereas a similar share acquired fertiliser through credit, which primarily was formal. The average commercial price per kilogram of fertiliser (DAP) was approximately 7.6 ETB, while the prices offered in the experiments varied from 2 to 12 ETB per kg. In terms of risk aversion, approximately 30% of the respondents chose rank 3, while 26% chose rank 4.[23]

Each household received on average 6.65 decimetres of rainfall annually, but there were large variations across the communities. All of the households experienced a shortfall in rainfall in 2008 relative to the seven-year average. The majority also experienced a shortfall in rainfall in 2009, with the exception being households in two communities that received more rainfall than the average.

[22] We dropped outliers by excluding the top one percent of values of fertiliser per hectare. The recommended application rate of fertiliser per hectare in Ethiopia is 200 kg, according to McIntosh *et al*. (2013), which represents 100 kg DAP and 100 kg urea.

[23] Although we did not explicitly impose any structure on risk aversion, rank 3 implies a constant partial risk aversion coefficient (CPRA) in the range of 0.59 to 0.99, while rank 4 implies a CPRA in the range of 0.99 to 2.44. Approximately one quarter of the respondents chose a rank higher than 4, implying CPRA > 2.44, whereas just over 17% chose ranks 1 and 2, equivalent to a CPRA < 0.59. This shows that the distribution of CPRA is in line with other studies using a similar monetary experimental approach (Binswanger 1980; Wik *et al*. 2004).

Table 1: Summary statistics, plot and household level

Variables	Mean	Std. dev.	Min.	Max.	N
Plot characteristics:					
Plot planted with cereal	0.844	0.363	0	1	1775
Fertiliser (in kg) per hectare	59.450	104.937	0	800	1776
Area planted in hectares (self-reported)	0.273	0.250	0.003	2.250	1776
Irrigated plot: 1 = yes, 0 = no	0.105	0.307	0	1	1775
Soil type[24]	2.546	1.129	1	4	1770
Slope[25]	1.311	0.610	1	4	1774
Land quality: 1 = poor, 2 = medium, 3 = good	1.866	0.750	1	3	1774
Household characteristics:					
Female headed household: 1 = yes, 0 = no	0.300	0.459	0	1	517
Age of household head	54.679	14.825	15	100	517
HH head has some education: 1 = yes, 0 = no	0.268	0.443	0	1	515
Number of female adults aged 15–65	1.356	0.896	0	5	517
Number of male adults aged 15–65	1.288	1.160	0	6	517
Number of children aged 0–14	1.697	1.697	0	7	517
Number of HH members above age 65	0.298	0.529	0	2	517
Can access credit for farm inputs: 1 = yes, 0 = no	0.338	0.473	0	1	509
Applied fertiliser in 2009: 1 = yes, 0 = no	0.652	0.477	0	1	434
Distance to all-year all-weather road (hours walking)	0.789	0.770	0	7	510
Risk aversion:					
Husband's (wife/female head if no husband available) risk-aversion rank	3.592	3.592	1	6	515
Framed field experiment:					
Real choice experiment: 1 = fertiliser, 0 = cash	0.529	0.500	0	1	465
Cash price per kg DAP	6.585	3.368	2	12	465
Rainfall (dm) by calendar year:					
Total rainfall in 2008	5.530	1.838	2.869	10.406	527
Total rainfall in 2009	5.532	2.112	2.613	10.375	527
Average rainfall, 2003–2009	6.652	1.556	4.688	10.741	527
Shortfall in 2008 compared to seven-year average	1.122	0.661	0.288	2.675	527
Shortfall in 2009 compared to seven-year average	1.119	1.459	-2.861	3.730	527
CV of annual rainfall, 2003–2009 (%)	23.885	7.416	10.633	35.722	527

4. Results and discussion

4.1 Observational inorganic fertiliser use and cereal production at the plot level

We first assessed households' use of inorganic fertilisers at the plot level and how this related to the rainfall variables and to risk aversion in particular. The results from the bivariate probit[26] and the Cragg models are reported in Table 2. Our results from the joint decision on whether to plant cereals and apply fertiliser show that these are positively correlated with risk aversion, in line with the theory for net buyers of food. Rainfall risk was associated with a lower probability of fertiliser use, as we expected for a risky input, and rainfall risk interacted with risk aversion also was negatively signed and statistically significant (where theory was ambiguous).

[24] 1 = Cambisol (*Baekel*), 2 = Vertisol (*Walka*), 3 = sandy (*Hutsa*), and 4 = Luvisol (*Mekeyih*).
[25] 1 = flat, 2 = foothill, 3 = mid-hill and 4 = steep.
[26] The bivariate probit is appropriate because the covariance between the two error terms is statistically significantly different from zero at the 1% level.

Table 2: Cereal planting and fertiliser use

Model	(1) Bivariate probit		(2) Cragg	
	Cereal planting	Fertiliser use	Hurdle 1: Fertiliser use	Hurdle 2: Fertiliser use intensity
Husband's (wife if no husband) risk aversion rank	0.138**	0.141*	0.147	10.513
	(0.062)	(0.077)	(0.114)	(20.057)
Average annual rainfall (dm) 2003–2009	0.148**	0.251***	0.240***	38.175***
	(0.070)	(0.043)	(0.060)	(5.264)
Shortfall in rainfall (lagged) compared to seven-year average (dm)	0.230***	-0.086	-0.068	-62.596***
	(0.084)	(0.090)	(0.093)	(16.307)
CV of annual rainfall (%), 2003–2009	-0.010	-0.023**	-0.026*	4.201
	(0.013)	(0.010)	(0.015)	(3.252)
CV of rainfall (%) * Risk-aversion rank	-0.005**	-0.006**	-0.007	-1.113
	(0.002)	(0.003)	(0.005)	(0.891)
Irrigated	-1.063***	0.124	0.206	-52.970
	(0.196)	(0.170)	(0.141)	(64.548)
Can access credit for farm inputs	-0.265**	0.185	0.258	-19.566
	(0.128)	(0.212)	(0.276)	(21.930)
Athro	0.426***			
	(0.061)			
Number of observations	1 722	1 722	1 458	693
Mean of dependent variable	0.802	0.448	0.475	61.083

Note: Robust standard errors clustered at station level are in parentheses. Distance to all-year all-weather road, plot and household characteristics, whether wife's risk aversion rank is used in male-headed household, and zone fixed effects are included throughout but not reported. Hurdle 1 refers to the binary fertiliser use decision; hurdle 2 refers to fertiliser intensity on plots that receive fertiliser. Inverse probability weighting is applied to address attrition in plot data.
Source: Own results based on household survey and rainfall data. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Lagged shortfall in rainfall is associated with a higher probability of cereal planting, while cereals are less likely to be planted on irrigated land. Interestingly, we did not find that credit access was associated with a higher probability of fertiliser use.

Moving on to cereal plots only (Cragg model), we found that fertiliser use was significantly and positively associated with average rainfall at both the intensive and extensive margins, whereas rainfall variability was only negatively correlated with fertiliser use at the extensive margin. We found no statistically significant relationship between risk aversion and its interaction with rainfall variability and fertiliser use on cereal plots at the intensive and extensive margins. However, risk aversion exhibited a statistically significant relationship with fertiliser use intensity when excluding the interaction term (results available upon request), which may suggest that we do not have sufficient variation to estimate both coefficients. Lastly, we found that experiencing a shortfall in rainfall the previous year relative to the seven-year average was negatively correlated with fertiliser-use intensity. We included controls for plot and household characteristics throughout, and excluding these and access to credit and irrigation resulted in the same pattern of results reported in column (2), with the exception of the interaction term, which turned statistically significant at the 10% level in hurdle 2, maintaining its negative sign (results available upon request).

4.2 Framed field experiment: Demand for fertiliser

Next, we explored the households' responses to the real choice experiment[27] and how these varied with the amount of cash offered (the implicit fertiliser price) and the measures of expected rainfall, rainfall risk, lagged rainfall shocks and risk aversion. The results are reported in Table 3, where we

[27] 5 kg DAP fertiliser versus a randomised amount of cash offered at the farm gate.

report results from specifications without and with the interaction between the CV of rainfall and risk aversion. Controls for distance to an all-year all-weather road and household-specific characteristics are included throughout, whereas we added irrigation and credit access in columns (2) and (4).

In terms of price responsiveness, we found that the probability of choosing fertiliser instead of cash declined by approximately 9.1 to 9.5 percentage points when the fertiliser price increased by one ETB per kg. Further, households that resided in areas that received on average more rainfall were more likely to choose fertiliser, showing that expected rainfall affected the expected profitability of fertiliser use. A 100 mm increase in average expected rainfall increased the probability of choosing fertilizer by 5.4 to 5.5 percentage points when introducing the full set of controls. We cannot rule out that average rainfall also correlated with other variables that affected fertiliser adoption, but average rainfall is the best proxy variable we have for expected profitability after imposing other controls. Shortfall in lagged rainfall was negatively signed and statistically significant throughout. A 100 mm increase in shortfall relative to the average reduced the probability of choosing fertiliser over cash by 8.3 to 9.4 percentage points. This may suggest that households face a binding liquidity constraint in terms of satisfying other needs and/or are adjusting their expectations for rainfall and fertiliser profitability in the following year. Similarly, households that experienced more rainfall variability across the seven-year period were less likely to choose fertiliser over cash. We found no statistically significant relationship between the experimental choice and the interaction between risk aversion and rainfall risk, risk aversion by itself, or rainfall risk after including the interaction term.

Table 3: Real choice experiment: Choice of 5 kg fertiliser (= 1) versus cash (= 0), LPM

Variables	**(1)**	**(2)**	**(3)**	**(4)**
Cash price per kg DAP	-0.095***	-0.091***	-0.095***	-0.091***
	(0.004)	(0.004)	(0.007)	(0.008)
Husband's (wife if no husband) risk-aversion rank	-0.0002	-0.002	0.028	0.037
	(0.015)	(0.018)	(0.064)	(0.066)
Average annual rainfall, 2003-2009 (dm)	0.029*	0.055***	0.028*	0.054***
	(0.016)	(0.015)	(0.015)	(0.015)
Shortfall in rainfall (lagged) compared to seven-year average (dm)	-0.083***	-0.093***	-0.084***	-0.094***
	(0.016)	(0.026)	(0.016)	(0.026)
CV of annual rainfall (%), 2003–2009	-0.014***	-0.010**	-0.011	-0.006
	(0.004)	(0.004)	(0.007)	(0.007)
CV of rainfall (%) * Risk-aversion rank			-0.001	-0.001
			(0.002)	(0.002)
Distance to all-year all-weather road	Yes	Yes	Yes	Yes
Household-specific characteristics	Yes	Yes	Yes	Yes
Credit access and irrigation	No	Yes	No	Yes
Number of observations	456	385	456	385
Mean of dependent variable	0.52	0.55	0.52	0.55

LPM = Linear probability model. Robust standard errors clustered at station level are in parentheses. Week of experiment, enumerator dummies, whether wife's risk-aversion rank is used in male-headed household, and zone fixed effects are included throughout but are not reported. Inverse probability weighting is applied to address attrition in experimental data.

Source: Own results based on household survey and rainfall data. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5. Conclusion

We have explored how risk aversion, average rainfall, rainfall risk and rainfall shocks correlate with households' use and demand for inorganic fertiliser in the semi-arid highlands of Tigray, northern Ethiopia. We found that fertiliser use and demand were positively associated with average annual rainfall. Lagged rainfall shocks were associated with lower fertiliser-use intensity at the plot level and lower demand for fertiliser, as would be expected. Rainfall risk was negatively related to fertiliser use at the plot level, as well as to the experimentally derived fertiliser demand. However, at a given level of rainfall risk, the risk aversion rank was positively correlated with fertiliser use on plots planted with cereals and non-cereals, when imposing a set of controls, whereas the interaction with rainfall risk was negatively associated with fertiliser use. The former result is consistent with Finkelshtain and Chalfant's (1991) theory for net buyers regarding their response to output price risk. We did not find a similar relationship for risk aversion in terms of the demand for fertiliser captured through the framed field experiment, or in terms of fertiliser use on cereal plots only. We also found that, for our sample, which comprised mainly buyers of cereals, lagged shortfall in rainfall and risk aversion were positively associated with the planting of cereals. Responses to shocks by vulnerable households therefore sometimes can be the opposite of what may be expected from pure producers. Our framed field experiment also allowed us to investigate the price responsiveness of fertiliser. Approximately 40% of the households preferred fertiliser to cash at the going fertiliser price (7.6 ETB/kg) at the time of the survey, and a one ETB increase in the price per kg of DAP fertiliser reduced the share of households demanding fertiliser over cash by 9.1 to 9.5 percentage points.

Our findings have important policy implications. Rainfall is a key constraint to cereal food production in semi-arid rain-fed agriculture. Although we were unable to find any clear relationship between irrigation and fertiliser use, the expansion of irrigation in such areas can be an important measure for reducing the vulnerability to rainfall shocks, provided that irrigation water is available when droughts occur. The provision of credit for rain-fed cereal production has its limitations in stimulating fertiliser use in such areas, as taking credit for input use prior to a rainfall shock may magnify the negative impact of such a shock on vulnerable households. This may explain why we found no significant positive effect from access to farm input credit on fertiliser use in our study. This does not mean that liquidity constraints are not important, as the responses to lagged shortfalls of rainfall may indicate, but instead may point in the direction of safety nets (Food-for-Work, or Work-for-Inputs) as a better option than farm credit for stimulating agricultural production.

Acknowledgements

The authors gratefully acknowledge funding for the fieldwork from NORAD under the NOMA programme, the efforts during the fieldwork by students and enumerators, Hosaena Ghebru, Bethelhem Legesse Debela and staff at the Department of Economics, Mekelle University, the provision of rainfall data by the Ethiopian National Meteorology Agency (NMA), and comments from Erwin Bulte, Maarten Voors and an anonymous reviewer.

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Appendix 1. Survey instrument for real experiment

<table>
<tr><td colspan="2">Experimental component: Extract
The decision should be what the household (head) would prefer to do today (day of interview), given the current resource situation of the household and information that the household has. The household head/representative will throw a die once for the experiment below:</td></tr>
<tr><td>E1</td><td>Choice experiment 1 (Real). Compensation experiment for your time spent on all the interviews: You have the choice between receiving 5 kg basal (DAP) fertiliser and an amount of money that is determined by you throwing the die: The amount of money that you can choose instead of the fertiliser (if you prefer so) is as follows:
Die outcome in Ethiopian Birr (ETB): 1 = 10, 2 = 20, 3 = 30, 4 = 40, 5 = 50, 6 = 60
Choice: 1. Choose the fertiliser, 2. Choose the money</td></tr>
</table>

Appendix 2. Hypothetical choice experiment: Risk-aversion rank

Each respondent is asked the following question, to which choosing Crop 2 results in a re-framing of the question based on the next pair of outcomes: "If you have the choice between a crop that gives 20 quintal[28] in a good year but no yield in a bad year, and a crop that gives 19.5 quintal in a good year and 2 quintal in a bad year, which crop would you prefer to plant? We assume a bad year occurs one out of five years (two out of 10 years are bad)."

	Good year	**Bad year**	**Choice**	**Expected outcome**	**Risk-aversion rank**
Crop 1	20	0	1	16	1
Crop 2	19,5	2	2	16	
If choice 2, cont.					
Crop 2	19,5	2	1	16	2
Crop 3	18	4	2	15,2	
If choice 2, cont.					
Crop 3	18	4	1	15,2	3
Crop 4	16	6	2	14	
If choice 2, cont.					
Crop 4	16	6	1	14	4
Crop 5	13	8	2	12	
If choice 2, cont.					
Crop 5	13	8	1	12	5
Crop 6	9	9	2	9	6

[28] 1 quintal = 100 kg