Risk aversion and gender gaps in technology adoption by smallholder farmers:

Evidence from Ethiopia*

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Abstract

Adoption of chemical fertilizers is a high-risk and high-return investment option for smallholder agricultural households that heavily rely on rainfall. I document a persistent gap of above 10% in adoption of chemical fertilizer between male- and female-headed smallholder farmers in Ethiopia. This gender gap remains after accounting for household characteristics, access to complementary farm inputs, access to credit, soil quality, and crop selection. Using historical variability of rainfall at district level as a measure of a district's risk of crop failure, I find strong evidence that the gender gap in fertilizer adoption increases with the level of risk in the district. I explore the role of two competing hypotheses to explain this observation: gender difference in risk aversion and differential access to consumption smoothing/liquidity constraints by male- and female-headed households. I find strong evidence that gender differences in access to consumption smoothing/liquidity constraints play minimal role, implying that gender difference in risk aversion plays the dominant role. This is consistent with a bulk of lab and field experimental studies that find evidences that women tend to be more risk averse than men.

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1 Introduction

Why do male- and female-headed agricultural households take-up welfare-enhancing technologies, such as high-yield varieties, at different rates?[1] In particular, what explains the persistent gender gap in adoption of chemical fertilizers? In view of the fact that female-headed households are also more food insecure (Kassie et al., 2014), understanding why female-headed households are less likely, compared to their male-headed counterparts, to take-up agricultural technologies that significantly improve yield, such as chemical fertilizers,[2] is crucial. The literature suggests a number of factors that effect adoption of improved inputs in general, such as availability, knowledge and education, risk preference, access to credit, wealth, etc., (see for instance Dercon and Christiaensen, 2011; Duflo et al., 2011; Foster and Rosenzweig, 1995 among others). However, literature on the gender gap in take-up of this technology is very limited (Doss and Morris, 2001) and it is not straight forward to conclude which of the above mentioned factors affecting take-up are responsible for the gender gap.

In this paper, I document a persistent gender gap in adoption of chemical fertilizer among smallholder farmers in Ethiopia, and investigate what drives this gap. In particular, I investigate the role of rainfall risk in driving the gender gap. I explore two mechanisms through which risky environment might lead to the gender gap: (1) gender difference in risk preference, and (2) male- and female-headed households' differential access to technologies that help smooth consumption and liquidity constraints.

My setup is well suited to identify gender difference in risk preference, and its role in explaining gender gap in chemical fertilizer adoption. I exploit variation of risk across two dimensions: (1) across investment options with different level of risk and return (chemical fertilizers vs. manure)[3], and (2) across different level of risk environments (districts with different rainfall variability). I use historical rainfall variability in districts as a measure of the districts' rainfall risk. In rural Ethiopia, over 94% of farming is rain-fed.[4] Hence, rainfall variability is considered to be the most important source of risk. I use the significant variation in rainfall risk across districts and explore how male- and female-headed households respond to different levels of rainfall risk in adopting chemical fertilizers vs. manure. Also, using information on households' access to credit and ownership of liquid assets, I investigate the role of male- and female-headed households' differential access to *ex-post* consumption smoothing options and ex-ante liquidity constraints in driving the gender gap.

I use very rich datasets: the Agricultural Sample Survey (AgSS) dataset and Ethiopian Socioeconomic Survey (ESS). The richness of these datasets enables me to overcome a number challenges in identifying gender gap in technology adoption from other factors that are potentially correlated with gender of the household head, such as education. I observe several household characteristics such as sex and education of the head, demographic characteristics of the household (age and gender composition), ownership of different agricultural inputs and assets, access to credit, and participation in agricultural extension program, among others. This enables me to investigate to what extent the gender gap is attributed to differences in wealth, access to complementary inputs (male labor, female labor, ploughing animals, pack animals), credit access, and information access across male- and female-headed households. Moreover, I observe whether the farmers have used different kinds of fertilizers (both organic and chemical) at a plot level, and characteristics of the plots such as area, irrigation facility, the crop planted, soil quality, and slope. This enables me to address concerns that the gender gap might be attributed to unobserved characteristics of plots farmed by male-headed and female-headed households, and that male- and female-headed households might endogenously select different crops that require different intensities of fertilizer use (Doss (2002)).

I find a large gender gap of about 14% in adoption of chemical fertilizers. Accounting for observed household and village characteristics reduces this estimate to about 4%. I show that this estimate is robust to alternative estimation strategies such as Propensity Score Matching (PSM), where female-headed households are compared to male-headed households who have similar observed household and village characteristics. I also explore sensitivity of the result to unobserved factors that may bias the gender gap estimate using Rosenbaum's bound analysis.

Next, I find that the gender gap in chemical fertilizer adoption is strongly related to the rainfall risk, as measured by the log standard deviation of district historical rainfall. Moving from a district at 10th percentile of rainfall risk to a district at 90th percentile leads to doubling of the gender gap estimate from 4% to 9%. By comparing male- and female-headed households' behavior in adopting chemical fertilizers vs. *manure*, a low-risk low-return alternative to chemical fertilizers, across districts with different rainfall risk, I conclude that most of the gender gap in chemical fertilizer adoption can be attributed to gender difference in risk aversion. The remaining is attributed to male- and female-headed households' *ex-ante* liquidity constraint and differential access to *ex-post* consumption smoothing options, in the event of harvest failure.

A number of recent studies find that adverse rainfall shocks have less severe effect on consumption in districts that have road connectivity to neighboring districts, compared to remote districts that lack connectivity (see, for instance, Nakamura et al., 2019). I investigate whether the effect of rainfall risk on gender gap in fertilizer adoption is muted when households have better access to market centers or roads, using Ethiopia's massive rural road expansion project between 2011 and 2015 as a source variation. I find no evidence that access to markets or roads mitigate the role of risk in chemical fertilizer adoption, and the gender gap.

A bulk of lab and field experimental studies find that women tend to be more risk averse than men (Powell and Ansic, 1997; Holt and Laury, 2002; Charness and Gneezy, 2012; Faccio et al., 2016; Filippin, 2016; Nelson, 2016; and Huang and Kisgen, 2013). Others contest these evidence and suggest that women are less risk averse in abstract gambling but not in contextual decisions (see for instance, Schubert et al., 1999).[5]. Studies also suggest that the gender differences in risk aversion is pronounced in a more risky environment than less risky ones (Pawlowski et al., 2008). This paper is directly related to observational studies on gender difference in risk aversion (Faccio et al., 2016; Huang and Kisgen, 2013; Harris and Jenkins, 2006; Barber and Odean, 2001; and Gong and Yang, 2012). In particular, the first two papers compare the performance and risk taking behavior of firms that are run by male CEOs vs. female CEOs, and document that firms run by male CEOs take significantly more risk than those run by female CEOs. The current paper extends this literature to a developing country setting and the agricultural sector. Moreover, the setup in the current paper is more suitable to address a number of identification challenges faced by other observational studies because male- and female-headed households are compared under exogenously different risk environments (districts with different rainfall variability).This closely mimics lab experiments on gender gap in risk preferences that vary the probabilities of "success" and "failure" across lotteries (see for instance Holt and Laury, 2002).

Few papers document the gender gap in technology adoption (Doss and Morris, 2001; Doss, 2002; Diiro et al., 2015; Muriithi et al., 2018; and Teklewold et al., 2020). Due to data limitation, most of these papers face identification challenges in measuring the gender gap in adoption of technology. I contribute to this literature by identifying gender gap from confounding factors correlated to the gender of household head such as education, access to complementary agricultural inputs such as labor and animals, and soil quality. I also contribute to this literature by identifying gender differences in risk aversion and consumption smoothing options as the drivers of gender gap in chemical fertilizer adoption.

Finally, this paper is related to a broad literature on adoption of modern input by farm households. In their seminal paper, Foster and Rosenzweig (1995) study how learning from own and from neighbors' experiences improves adoption of high-yield seed varieties in rural India. Dercon and Christiaensen (2011) study the role of downside consumption risks in adoption of chemical fertilizer in Ethiopia. Duflo et al. (2011) use field experiments to study the role of fixed costs in learning to use (experimental cost) or buying (transport cost) fertilizer. Aggarwal et al. (2018) study the role of transport costs and market access in adoption of chemical fertilizer in rural Kilimanjaro. Unlike these studies, I investigate whether a decrease in trade cost via new road constructions improves adoption of inputs, and in particular whether it closes the gender gap.

The rest of this paper is organized as follows. Section 2 describes the data. Section 3 explains the empirical strategy. Section 4 presents the main results while Section 5 provides robustness checks. Section 6 concludes the paper.

2 Data and Background

2.1 Data sources

I use two main datasets in this study. The main dataset is the Agricultural Sample Survey (AgSS) collected by the Ethiopian Central Statistical Authority (CSA). This dataset is the largest annual survey of agricultural households that collects information from about 40,000 nationally representative farmers. After 2010 CSA kept the same sample of about 2000 Enumeration Areas (EAs), which are sub-villages, but randomly drawn about 20 farm households from each EA every year. Besides its massive coverage, this dataset is also particularly well suited to study the farmers' technology adoption, in general, and the gender gap, in particular. The dataset includes information about fertilizer use at plot level, the crops planted on each plot, area of the plot, and whether the plot is under agricultural extension coverage. The data also includes a number of characteristics about the household such as credit access, family size, and age, gender and education of the holder (and the household head).

However, there are some key shortcomings of this dataset to study gender gap: the dataset does not include the soil quality of the plot and household detailed demographic characteristics such as number of active-age male and female household members. As stated in the introduction, accounting for these factors is crucial to address the concern that female-headed households might farm less quality plots or have less of complementary inputs such as labor and oxen. To address these concerns, I exploit the exceptional richness of the Ethiopian Socioeconomic Survey (ESS) collected by the World Bank in collaboration with CSA. ESS includes information on each plot's soil quality (ranked as poor, fair and good by well trained agricultural staff), the household demographic characteristics (age, gender, education, etc. of each household member), and household livestock ownership and the purpose for which each of the livestock is being utilized (eg., farming, transport, milk, sale, etc.). The downside of ESS data is the small sample size – it includes a panel of only 4000 rural households observed in three rounds. Thus, I use this dataset only to address the concern that gender gap in fertilizer adoption could be driven by: (1) unobserved (soil) characteristics of plots farmed by female and male holders, and (2) potential gap in female and male holders' ownership of complementary farm inputs such as male labor and female labor.

The rainfall data comes from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), which provides quasi-global rainfall dataset starting in 1981 to near-present. CHIRPS incorporates 0.05° resolution satellite imagery with in-situ station data to create gridded rainfall time series for trend analysis and seasonal drought monitoring. It is widely used to monitor drought in East Africa (see Funk et al. (2015)). I use this data to construct several measures of district level rainfall variability based on district level time series data covering the years 1990-2010. My preferred measures for rainfall variability are district-level log standard deviation and log of the difference between the 80th and 20th percentiles.[6]

2.2 Background: male vs. female-headed households

A household head is a person responsible for the household's socioeconomic decisions. In my AgSS data, 20% of rural households report female-headship. This is comparable to the average female-headship of 22% in sub-Saharan Africa reported in Bongaarts (2001) and more recently in Milazzo and van de Walle (2015). I refer interested readers to Buvinic and Gupta (1997) and Milazzo and van de Walle (2015) for issues regarding the definition, general trends, and detailed socioeconomic comparison of female vs. male-headed households in developing countries.

ESS data collects information on who in the household makes decisions in the selling of crops and livestock, and the utilization of the revenues. Almost all households report the household heads as the principal decision maker. In many households, other household members (e.g., the wives in the male-headed households) are reported as the co-decision makers. This suggests that household heads are the ones who make decision on whether to apply fertilizer.

Table 1 gives summary statistics of key variables disaggregated by gender of the household head. Clearly, male-headed households tend to be better off in terms of access to credit, number of oxen owned, land size, and use of chemical and natural fertilizers.

3 Empirical Strategy

3.1 The ideal variation to identify risk preference

Studies that use lab experiments to identify risk preference serve as a useful benchmark as to what kind of variation is ideal to credibly estimate gender difference in risk aversion. To emphasize the pros and cons of the identification strategy utilized in this paper, I compare it with the seminal lab experiment by Holt and Laury (2002). Table 1 in Holt and Laury (2002) is reproduced here (table D1) to facilitate comparison with the setup in the current paper. In Holt and Laury (2002), subjects are offered paired lottery. One of the lottery pairs is "safe" option (meaning the payoffs are less variable, i.e., $2 if success or $1.6 if failure) and the other is "risky" option (the payoffs are more variable $3.85 if success or $0.1 if failure). The probabilities of "success" and "failure" are changed to create ten paired lottery. Subjects are given the ten paired lotteries shown in table D1.

The setup in this paper can be related to table D1:

1. Districts with different probability of rainfall failure can be compared to the rows in table D1 (say districts in the top rows are those with lower probability of rainfall failure).

2. The risky option is "using fertilizer", because the variance of the farmer's net income is higher if the farmer uses fertilizer (net income will be higher if rainfall is good and lower or even negative if the rain fails). The safe option is "not using fertilizer" because the variance in net income is lower if the farmer doesn't use fertilizer. As a robustness check, I also consider "using manure" as safe option – manure is financially less costly but preparation is labor intensive, hence net income is less variable if the household uses manure as opposed to chemical fertilizer.

The difference between the Holt and Laury (2002) experiment and the current setup is that in Holt and Laury (2002) experiment each subject makes decision on each of the ten paired lottery, and the degree of risk aversion is identified from how late a subject switches choice from column A to column B as we move down in table D1 (more risk averse subjects switch later than less risk averse subjects). Since households' location is fixed in the current paper, we only observe each household's decision on one lottery pair, instead of ten, but households in different districts are given different lottery pairs. Identification in the current setup comes from comparison of male- and female-headed households in a given district while exogenously varying the probability of rainfall failure across districts.

3.2 Gender gap in adoption of chemical fertilizers

First, I explore a household's decision to adopt fertilizer on any of its plots. My basic estimation equation is the following:

$$\text{Fertilizer}_{hdt} = \beta_0 + \beta_1 \text{Female}_h + \sum_k \beta_k X^k_{hdt} + \gamma_d + \gamma_t + \varepsilon_{hdt} \tag{1}$$

where $Fertilizer$ is whether household h in district d has used chemical fertilizer on any of its farm plots in year t. While most of my discussions are based on *chemical* fertilizer in general, I report disaggregated results based on the type of chemical fertilizers (Urea vs. DAP, the two mainly used chemical fertilizers in Ethiopia). I also report result for *organic* fertilizer use (Manure) for comparison, as it has some crucial implications for the analysis below.

$Female$ represents whether the household head is female ($Female = 1, Male = 0$). X is a vector of household and village characteristics. The household characteristics includes: age and education of the household head, access to credit and agricultural advisory services, ownership of oxen, and land size. The village characteristics includes: rainfall in the previous season, several measures of proximity to road and markets, and average slope and altitude of the village. I use the AgSS data for the years 2011-2016 for my main analysis.

It is also possible that male and female headed households have differential access to complementary farm inputs such male labor, female labor, ploughing animals and pack animals. To account for these factors, I run equation (1) using the ESS data which includes information on these complementary inputs.

Propensity Score Matching (PSM) estimation: One can imagine that PSM estimation strategy is a better way of accounting for the the heterogeneity between male- and female-headed households, compared to controlling for the observed household and village characteristics in OLS estimation of equation (1). To see whether the OLS results are robust, I also use PSM estimation where I match female-headed households to male-headed households based on propensity score estimated using the following variables: household size, age of the head, education of the head, land size, ownership of oxen, access to credit, access to agricultural advisory service, village rainfall, village distance to nearest town, and village distance to nearest all-weather road. These variables are important predictors of adoption of chemical fertilized in OLS estimation, and it is essential to do the matching based on both household and village characteristics.[7] I also conduct the Rosenbaum bounds analysis (Becker and Caliendo, 2007; DiPrete and Gangl, 2004) to explore the sensitivity of the estimated gender gaps to unobserved differences between male- and female-headed households.

3.3 The role of risk aversion in the gender gap

Districts face different risks of rainfall failure due to difference in their agro-climatic features. Rainfall in Ethiopia is determined by a complex interaction of the temperature, wind circulation, and several other climatic conditions on Central Pacific and Indian Oceans. Ethiopian districts are differently exposed to these regional and global climatic forces due to altitude variations and geographic locations, and as a result, have different levels of rainfall amount and variability. For instance, southern and southeastern parts of Ethiopia are frequently hit by the El Niño effect while the El Niño effect on the western and northwestern part of Ethiopia is less significant.[8] I use district level rainfall data from 1990-2010 to construct district level rainfall variability measures and use these as a measure of district's crop failure risk, which I refer to as *risk* for short.

In order to formally test whether male- and female-headed households respond differently to rainfall risk, I run the following regression:

$$\text{Fertilizer}_{hdt} = \beta_0 + \beta_1 \text{Female}_h + \beta_2(\text{Female}_h \times \text{Risk}_d) + \sum_k \beta_k X^k_{hdt} + \gamma_d + \gamma_t + \varepsilon_{hdt} \tag{2}$$

where β_2 captures how male- and female-headed households' respond deferentially to rainfall risk in their investment decision on chemical fertilizers. A negative β_2 can be used as evidence that the gender gap in fertilizer adoption is stronger in risky environments. However, this alone does not necessarily imply that female-headed households are more risk averse because it could also be the case that female- and male-headed households do not have equal access to consumption smoothing means during adverse rainfall shocks. That is, if female-headed households, compared to male-headed households, have less access to consumption smoothing technologies overall, they would likely be more reluctant to invest in fertilizer, particularly in districts with higher rainfall risks.

3.4 Risk aversion and access to consumption smoothing and/or liquidity

At the core of decision to adopt chemical fertilizer is downside consumption risk in case of harvest failure and ex-ante liquidity problem. Households with different levels of asset holding and or access to credit are likely to have different levels of risk tolerance. If harvest fails, households need liquid assets (such as cattle) not only to buy food but also to repay their fertilizer debt. Similarly, in the situations where households have access to credit, the downside consumption risk is loosened because households can use the loan to either repay their debt and use their liquid asset to smooth out consumption or vice versa.

Moreover, it also important to note that access to credit and ownership of liquid assets may affect the households' adoption of fertilizers via affecting the households' ex-ante liquidity constraint. Thus, we need to interpret the effect of access to credit and ownership of liquid assets as combination of ex-post consumption smoothing and ex-ante liquidity constraints.

In order to isolate gender difference in risk aversion from differential access to consumption smoothing (or ex-ante liquidity constraint), we need to compare the effect of risk on gender gap across households with and without access to credit and ownership of oxen. The following triple-differences regressions do that using access to credit and ownership of oxen (liquid asset):

$$\begin{aligned}\text{Fertilizer}_{hdt} = \beta_0 + \beta_1\text{Female}_h + \beta_2(\text{Female}_h \times \text{Risk}_d) + \beta_3(\text{Female}_h \times \text{Risk}_d \times \text{Credit}_{ht}) \\ + \beta_4\text{Credit}_{ht} + \sum_k \beta_k X^k_{hdt} + \gamma_d + \gamma_t + \varepsilon_{hdt} \qquad (3)\end{aligned}$$

and

$$\begin{aligned}\text{Fertilizer}_{hdt} = \beta_0 + \beta_1\text{Female}_h + \beta_2(\text{Female}_h \times \text{Risk}_d) + \beta_3(\text{Female}_h \times \text{Risk}_d \times \text{Oxen}_{ht}) \\ + \beta_4\text{Oxen}_{ht} + \sum_k \beta_k X^k_{hd} + \gamma_d + \gamma_t + \varepsilon_{hdt} \qquad (4)\end{aligned}$$

where $credit = 1$ if the household has access to credit[9]. $Oxen$, is whether household owns oxen in the survey year.[10] The ideal measure of a household's liquid asset is ownership of every kind of cattle weighted by their prices, and households' cash holdings at hand or in bank account. Unfortunately such data is not available for Ethiopia. However, because oxen are both liquid assets that can be converted to cash, and productive assets that are used for ploughing and harvesting/threshing of crops, ownership of oxen is very crucial for farm households. As a result, number of oxen owned is arguably a good predictor of household's ownership of liquid assets.

In both the above regressions, a positive β_3 is evidence for the role of availability of consumption smoothing options or ex-ante liquidity constraints in determining household's willingness to take risk. Once these equations are estimated, the role of risk on gender gap can be decomposed into: (1) gender difference in risk aversion and (2) differential access to consumption smoothing or liquidity. For instance, in equation (3) the effect of risk on gender gap is given by $\beta_2 + \beta_3\text{Credit}$. For households with access to credit, the effect of risk on gender gap is given by $\beta_2 + \beta_3$ whereas for those without access to credit it is given by β_2. Comparison of these two tells us how much of the effect of risk can be attributed to gender difference in risk aversion and how much of it is attributed to gender differences in access to consumption smoothing. Similar logic applies in the regression using ownership of oxen.

3.5 Using observed choice between chemical fertilizers and manure to identify risk aversion

So far, we have used the choice between *chemical fertilizer* (risky option) vs. *no chemical fertilizer* (the safe option) to analyse gender gap and the role of gender difference in risk aversion. An alternative approach is to use observed choices between *chemical fertilizer* (risky option) and *manure* (less risky option). There are few distinctions between manure and chemical fertilizers that could explain this difference. First, chemical fertilizer is a high-risk and high-yield investment compared to manure, in the sense that the former is both significantly more expensive and more productive than the latter. Second, because manure is home-made, there is no financial cost involved[11] – hence unlike the case of chemical fertilizers, in the event of harvest failure, farmers do not have to sell their productive and liquid assets to repay the costs. Instead, they can use these liquid assets to smooth out their consumption. However, one needs to keep in mind that investment in manure is more risky than *not using any fertilizer* because of the significant labor involved in the preparation and implementation.

We redo the analysis in the previous subsection using the choice between chemical fertilizer vs. manure. First, we investigate whether the gender gap in choice of chemical fertilizer over manure is increasing with the rainfall risk. Next, we decompose the role of risk into gender difference in risk aversion and gender difference in consumption smoothing or liquidity constraint by using similar triple-differences regression as above. Consider the following two regressions:

$$\begin{aligned}\text{ChemFertilizer}_{hdt} = \beta_0 + \beta_1\text{Female}_h + \beta_2(\text{Female}_h \times \text{Risk}_d) \\ + \sum_k \beta_k X^k_{hdt} + \gamma_d + \gamma_t + \lambda^1_h + \varepsilon^1_{hdt}\end{aligned} \tag{5}$$

and

$$\begin{aligned}\text{Manure}_{hdt} = \alpha_0 + \alpha_1\text{Female}_h + \alpha_2(\text{Female}_h \times \text{Risk}_d) \\ + \sum_k \alpha_k X^k_{hdt} + \gamma_d + \gamma_t + \lambda^2_h + \varepsilon^2_{hdt}\end{aligned} \tag{6}$$

where λ^1_h and λ^2_h are unobserved household characteristics that affect adoption of chemical fertilizer and manure, respectively. Taking the difference of the above equations:

$$\begin{aligned}\text{ChemFertilizer-Manure}_{hdt} = \theta_0 + \theta_1\text{Female}_h + \theta_2(\text{Female}_h \times \text{Risk}_d) \\ + \sum_k \theta_k X^k_{hdt} + \gamma_d + \gamma_t + \Delta\lambda_h + \Delta\varepsilon_{hdt}\end{aligned} \tag{7}$$

where $\Delta\lambda_h = \lambda^1_h - \lambda^2_h$ is the difference in household unobserved characteristics in the two regressions, and $\Delta\varepsilon_{hd} = \varepsilon^1_{hd} - \varepsilon^2_{hd}$ is the difference in the two error terms. Under the assumption that $\lambda^1_h = \lambda^2_h$ or that $\Delta\lambda_h$ is uncorrelated to the gender of the household head and the rainfall risk of the district, θ_2 can be interpreted as gender difference in risk attitude. Roughly, comparison of the regressions in (5) and (6) with (7) can be used to see if these assumptions are reasonable. If $\theta_2 \approx \beta_2 - \alpha_2$, then the assumptions are reasonable and θ_2 can be used as evidence of gender difference in risk attitude.

To decompose the role of risk into gender difference in risk aversion and gender difference in consumption smoothing or liquidity constraint, I run similar specifications as equations (3) and (4) by changing just the dependent variable to ChemFertilizer-Manure$_{hd}$.

4 Results

4.1 The gender gap

Before reporting estimation results, I present the summary statistics in figure 1. This figure shows the fraction of male- and female-headed households adopting chemical fertilizer (panel (a)) and manure (panel (b)) together with the gender gap for districts in five different rainfall risk category. The figure shows three important results: (1) the fraction of households adopting chemical fertilizer decreases while the fraction of households adopting manure slightly increases as the rainfall risk increases; (2) there is significant gender gap in adoption of chemical fertilizer but not for manure; and (3) the gender gap in adoption of chemical fertilizer increases with the level of rainfall risk while there is no such trend for manure.

I estimate equation (1) pooling the data for years 2011-2016 together. Table 2 shows the estimation results for gender gap. In the first column, I include only gender of the household head and rainfall measure during the previous year to obtain the estimate for unconditional gender gap. There is a 14.4% gender gap in adoption of chemical fertilizer. In the second column, I include a vector of household controls (household size, age of the head, education of the head, credit access, number of oxen, land holding (in hectares)); and village controls (rainfall, distance to nearest town, distance to nearest road, market access, average slope, and population density). The result is a significant drop in gender gap to about 4%. Large household size, access to credit service, access to advisory service from development associates (DAs), ownership of oxen, size of land owned are all positively correlated with adoption of chemical fertilizer while older households tend to adopt fertilizer less often. The fact that the gender gap estimate drops significantly once these controls are included implies that most of the gender gap in adoption of chemical fertilizer is driven by female- and male-headed households' differential access to complementary services such as credit and advisory services and differences in ownership of fixed assets (land) and liquid/productive assets (oxen).

In columns 3 and 4, I report estimation results from the Propensity Score Matching (PSM). I use the following household and village characteristics to estimate propensity score: household size, age of the head, education of the head, credit access, number of oxen, land holding (in hectares), advisory service, rainfall, distance to nearest town and distance to nearest road. I then match each female-headed household to male-headed household(s) that have similar observed characteristics in these variables. Column 3 includes all observations while column 4 restricts the estimation to region of common support. The results in two columns are almost identical because only 4 observations fall outside region of common support. The estimated results again confirm that there is about 3% gender gap in adoption of chemical fertilizer, even after we compare female-headed households with male-headed households with the similar observed characteristics. However, PSM estimation cannot address the role of unobserved characteristics that could differ across male- and female-headed households. To shed some light on how much such unobserved characteristics might bias the estimated gender gap, I undertake the so-called Rosenbaum bound analysis (see DiPrete and Gangl, 2004; Becker and Caliendo, 2007). The result is reported in table B1. The results in this table clearly indicate that our estimated gender gap is not sensitive to on observed characteristics of male- and female-headed households. This is the case regardless of the chosen level of Γ (odds of differential assignment due to unobserved factors) – the test statistics for upward or downward bias imply rejection of the null hypotheses of upward or downward bias.

Columns 5 and 6, I go back to OLS estimation but disaggregate fertilizer into DAP and UREA, the two most commonly used chemical fertilizer types. Both columns show nearly the same estimate for gender gap as column 2. In the last column, I look at households' adoption of *manure*, a much cheaper and much less productive alternative to chemical fertilizer. We see that there is a gender gap in adoption of manure, but the estimated gender gap is about one-sixth that of chemical fertilizer. One reason for observing gender gap in manure adoption could be due to its high labor intensity to prepare and transport it to the field.

4.2 The role of rainfall risks

I now turn to the role of rainfall risks. The results for estimation of equation (2) are reported in table 3. Two measure of rainfall risks are generated from a district's annual rainfall distribution between 1990 and 2010. In the first four columns of table 3, I use log of the standard deviation of the distribution. In the last four columns, I use the log of the difference between the 80th percentile and the 20th percentile of the distribution. This measure is less susceptible to a one-time extreme shock, but does not account for all variations.

Overall, the results in table 3 show that the gender gap in chemical fertilizer adoption significantly increases with the district's rainfall risk, regardless of the measure of rainfall risk used. Figure 2 shows the relationship between the gender gap and the rainfall risk of districts. In districts with reliable rainfall, i.e., those with the lowest end of rainfall risk, the gender gap in adoption of chemical fertilizers is statistically insignificant. On the other hand, for districts with above 20th percentile of rainfall risk, the gender gap estimate is statistically highly significant. As we move from a district at the 10th percentile of rainfall risk to a district at the 90th percentile of rainfall risk, the gender gap estimate more than doubles from about 4% to 9%.

The column 4 and 8 of table 3 shows that there is no similar trend for manure. Interacting the gender dummy with the district rainfall risk makes both the gender and the interaction terms statistically insignificant. This implies that the gender gap in manure adoption was probably driven by other factors than the riskiness of the environment.

One may argue that high and low rainfall events do not imply the same level of risk to crop production. That is, drought is more serious risk for crop production than too much rainfall. But our measures of rainfall risk so far measure the dispersion in rainfall over years in a district, which captures both extremely high and low rainfall events. Thus, I construct a new measure of rainfall risk, which I call drought risk . The drought risk in a district is measured as the number of years (over a period 1990-2010) for which rainfall in the district falls less than one standard deviation below the average rainfall in the district over the same period (i.e., number of years for which $\text{rainfall}_{district} < \text{average rainfall}_{district} - sd_{district}$ over 1990-2010). The median district has 3 years of drought while 15% of the districts had five or six years of drought over the same period.

Table A2 reports the result using this measure. I run similar specification to table 2 except that the measure of rainfall risk is drought risk. The results in the first three columns clearly show that gender gap in adoption of chemical fertilizer is higher in districts with higher drought risk. The last column shows that this is not the case for adoption of manure. Thus, we reach on the same conclusion as in table 2 using our new measure of risk.

4.3 The role of liquidity, consumption smoothing, and risk aversion

Next, I turn to exploring what explains the increase in gender gap with the level of rainfall risk. Three potential explanations have been suggested in the previous sections: gender difference in access to consumption smoothing, gender differences in liquidity, and gender difference in risk aversion. The first two are difficult to disentangle empirically because factors that help households to smooth consumption ex-post also improve the household's liquidity constraints ex-ante. Thus, I will not try to distinguish between the two here. However, any gender gap that is not accounted for by variation in liquidity constraint or consumption smoothing options across male- and female-headed households is likely to be caused by gender difference in risk aversion.

The results are presented in table 4 and figure 3. Panel A of table 4 use the log standard deviation of rainfall as a measure of risk. The first two columns interact access to credit with gender dummy and rainfall risk and show that the interaction term is positive and statistically significant in both columns 1 and 2. However, this interaction term is quantitatively small. From columns 1 and 2, the effect of risk on gender gap is 0.055-0.065 for households without access to credit and 0.045-0.055 for households with access to credit. This suggests that differential access to credit explains just a tiny fraction of (less than one-fifth) of the effect of risk on gender gap in fertilizer adoption. This suggests that gender difference in liquidity constraint or ex post consumption smoothing option play very minimal role in explaining why the gender gap increases with rainfall risk. Hence, this suggests that gender difference in risk aversion is perhaps the main driving factor behind the increase in gender gap with riskiness of the environment.

We arrive at similar conclusions using ownership of oxen as proxy for consumption smoothing or ex-ante liquidity constraint. Columns 3 and 4 show that the effect of risk on gender gap is 0.057-0.071 for households that do not own oxen and 0.047-0.068 for households that own oxen, again suggesting that ownership of oxen plays statistically significant but small role in explaining the effect of risk on gender gap.

Panel B replicates the results in panel A using the log of the difference between 80th and 20th percentiles as a measure of rainfall risk. The results are almost identical to those in Panel A.

The results in table 4 clearly show that availability of ex-post consumption smoothing means or ex ante liquidity constraints explain only a small fraction of the effect of risk on gender gap. Both access to credit and number of oxen owned tend to mute the effect of risk on gender gap, but only slightly. To see this even more clearly, I plot the marginal effects of rainfall risk on the gender gap estimates for households with and without credit access and oxen in figures 3 and 4. In figure 3, the marginal effects of rainfall risk on the gender gap in chemical fertilizer adoption is plotted for households with and without credit access and oxen separately (these results plot the first and third columns in panel A of table 4).[12] Panel A of this figure plots separate marginal effects for households with and without access to credit, while panel B plots separate marginal effects for households with and without ownership of oxen. Both panels clearly show the importance of access to credit and ownership of oxen, as the estimated gender gaps in adoption of fertilizer are slightly different across households with and without access to credit and ownership of oxen. However, the figures also show that gender gap in adoption of fertilizers increases with the rainfall risk regardless of the households' access to credit or ownership of oxen. Figure 4 replicates figure 3 based on the columns 2 and 4 of panel A of table 4, and leads to the same conclusion as figure 3.

To conclude this section, the effect of risk on gender gap in fertilizer adoption is not mainly driven by differential access to credit or ownership of liquid assets such as oxen. Rather, the main driving factor for the increase in gender gap with the rainfall risk is likely to be gender difference in risk preference.

4.4 Estimation based on manure and chemical fertilizers

Table 5 gives the results for estimation of equation (7). The first three columns use the log of standard deviation of rainfall distribution as a measure of risk. In these columns, I look at households' decision to adopt chemical fertilizer relative to manure, DAP relative to manure, and UREA relative to manure. In all the regressions, the interaction of gender dummy and risk measure are statistically significant and roughly of the same magnitude as our results in table 3. The last three columns of table 5 replicate the first three columns using the log of the difference between the 80th percentile and the 20th percentile of the rainfall distribution as a measure of risk.

Also note that the estimates in table 5 are almost identical to the difference between the separately estimated coefficients for chemical fertilizer and manure, DAP and manure, and UREA and manure in table 3. This suggests that our identifying assumptions for equation (7) are reasonable. Overall, the result in table 5 complement those in table 3. The second panel of figure 2 plots these results, which shows that the gender gap is statistically significant for districts with above the 20th percentile in rainfall risk, and that the gender gap increases significantly as we move from districts with lower rainfall risk to those with higher rainfall risk.

4.5 Does proximity to markets mute the role of risk?

Exposure to market may affect not only the level of risks households face (see, for instance, Burgess and Donaldson, 2010 and Burgess and Donaldson, 2014 who provide evidence that access to road infrastructure or improved market access significantly reduces the damages from adverse climate shocks such as famine and mortality), but may also influence household's attitude towards risks, i.e their risk preferences (see, for instance, Melesse and Cecchi (2017) who find that greater market experience improves risk tolerance for landed farm households by reducing the relative weighing of potential losses over gains).[13] In this section, I explore whether access to market mutes the role of risk in adopting chemical fertilizers.[14]

I use a number of proxies for access to market including: (i) whether the village has an all-weather road, (ii) distance of the village from the nearest all-weather road, (iii) distance of the village from the nearest urban area of at least 20,000, and (iv) market access measure derived from general equilibrium trade models and constructed from the entire road network of the country and spatial distribution of population (see Donaldson and Hornbeck (2016)). Three of these measures, (i), (ii) and (iv), vary over time due to large-scale rural road expansion in Ethiopia between 2011 and 2016. If proximity to markets reduces the likelihood of severe famine during harvest failures, perhaps by facilitating flow of crops from drought non-affected regions to drought affected regions, then rainfall risk would have a lesser effect on decision to adopt chemical fertilizers. I run the following generalized triple-differences regression to test this:

$$\begin{aligned}\text{Fertilizer}_{hvdt} &= \beta_0 + \beta_1 \text{Female}_h + \beta_2(\text{Female}_h \times \text{Risk}_d) \\ &\quad + \beta_3(\text{Female}_h \times \mathit{Risk}_d \times \text{Proximity}_{vt}) + \sum_k \beta_k X^k_{hdt} + \sum_l \beta_l W^l_{vdt} + \gamma_d + \lambda_t + \varepsilon_{hvt}\end{aligned} \tag{8}$$

where $Proximity_{vt}$ is represents one of the above proxies of access to markets. γ_d is district fixed effect. β_3 captures the effect of road construction on the gender gap in risk aversion in adoption of chemical fertilizer.

Table 6 reports the results for the role of access to markets. Columns 1-4 report the estimation result using each of the above mentioned proxies for access to market. Panel A uses log standard deviation of rainfall as a measure of risk while the Panel B uses log of the difference between the 80th and 20th percentiles. Across all the four columns, we see that the triple-interaction terms involving proxies for access to market are statistically insignificant. This is true regardless of the measure of district rainfall risk used. In conclusion, there is no evidence that access to markets mitigates the effect of risk on the gender gap in chemical fertilizer adoption.

5 Robustness

5.1 Plot level analysis

The household level analysis is subject to concerns that female- and male-headed households might: (1) own plots of different soil quality and (2) endogenously choose to plant different crops which require different intensities of fertilizer application. We need a plot level analysis to address these concerns and I rely on the ESS dataset that includes this information. I estimate the following regression:

$$\text{Fertilizer}_{ihdt} = \alpha_0 + \alpha_1 \text{Female}_h + \sum_n \alpha_n Z^n_{ihdt} + \sum_l \alpha_l X^l_{hdt} + \gamma_d + \kappa_k + \lambda_t + \varepsilon_{ihdt} \tag{9}$$

where i indexes plots farmed by the household, Z is a vector of plot characteristics including whether the plot is under extension coverage, X is a vector of household characteristics and the complementary inputs such as labor, pack animals and ploughing animals, γ_d is district fixed effect, κ_k is crop fixed effect.

It is crucial to note the relationship between equations (1) and (9). The α_1 in equation (9) gives per-plot gender gap in fertilizer adoption conditional on plot and household characteristics while equation (1) gives household level estimate of gender gap conditional on household characteristics (but not plot characteristics). To obtain household level measure of gender gap from equation (9), we need to sum the equation across plots farmed by the household. Assuming α_1 is constant across plots (conditional on plot characteristics) and across households as assumed in the regression, the household level measure of gender gap is simply given by $\alpha_1 \times \bar{N}$ where $\bar{N}$ is the average number of plots farmed by a household.

Table A1 in the appendix reports the result for plot-level regression that accounts for soil quality, plot area, and potentially endogenous selection of crops. The result shows that gender gap still exists. Moreover, the size of the gender gap is roughly the same as what we obtained above for the household level analysis, which can be verified by multiplying the per-plot gender gap estimate obtained in table A1 by the average number of plots farmed by a household, which is 9. This implies the plot level analysis in fact implies slightly higher gender gap estimate than the household level analysis.

Thus, the gender gap cannot be attributed to soil quality, plot area, and endogenous crop selection. In fact, taking these factors into account implies a higher gender gap estimate of close to 10% conditional on household ownership of complementary agricultural inputs and access to complementary services.

5.2 Using irrigated vs. non-irrigated plots

Rainfall risk affects decision to use fertilizers on non-irrigated plots only. Thus any differential effect of gender on fertilizer adoption across irrigated vs. non-irrigated plots can be used as evidence for the gender difference in risk aversion. That is, if female-headed households are equally likely to adopt fertilizer on their irrigated plots but are less likely to adopt fertilizer on their non-irrigated plots, compared to their male counter parts, then this can be used to support the above evidence on gender difference in risk preferences. I run the following specification:

$$\begin{aligned}\text{Fertilizer}_{ihdt} = \alpha_0 + \alpha_1\text{Female}_{ht} + \alpha_2\text{Irrigated}_{ihdt} + \alpha_3(\text{Female}_{ht} \times \text{Irrigated}_{ihdt}) \\ + \sum_n \alpha_n Z^n_{ihdt} + \sum_l \alpha_l X^l_{hdt} + \gamma_d + \kappa_k + \lambda_t + \varepsilon_{ihdt}\end{aligned} \tag{10}$$

A positive and statistically significant α_3 is thus an evidence in support of the gender difference in risk aversion. Some caveats in this analysis are that: (1) irrigated land is a tiny (6%) of the plots farmed, and (2) most of the irrigated plots are used to grow cash crops (mainly vegetables) while fertilizer is mostly used for production of cereals in Ethiopia – that is, less fertilizer is used on irrigated plots on average.

Table C1 gives the estimation result. The first three columns pool all plots owned by all households. In the last three columns, I keep only households that have both irrigated and non-irrigated plots. Overall, these results give a strong support to our main results. The interaction of female dummy with irrigation dummy is positive and statistically significant across all the columns, implying that female headed households are less risk averse on irrigated plots, compared to non-irrigated plots.

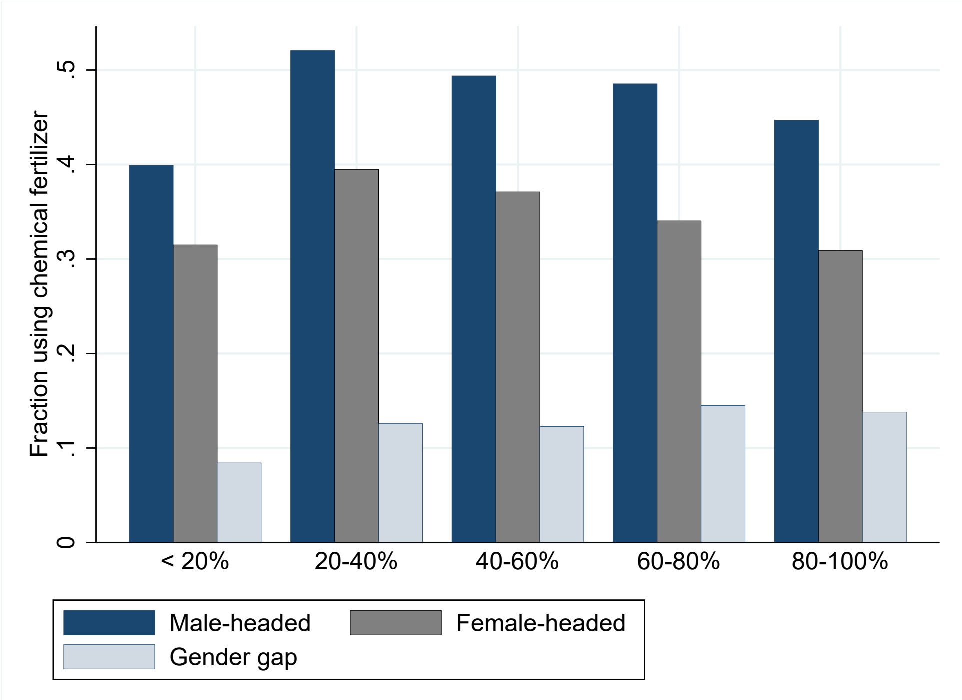
6 Conclusions

In this paper, I document significant gender gap in adoption of chemical fertilizer among smallholder farmers in Ethiopia, accounting for several confounding factors that might be correlated with the gender of the household head. I find that this gender gap is strongly related to the rainfall risk across districts. I explore the role of two competing hypotheses to explain this observation: gender difference in risk aversion, and gender differences in liquidity constraints or in access to *ex-post* consumption smoothing. I find that both factors play a role, but gender difference in risk aversion seems to be the dominant factor.

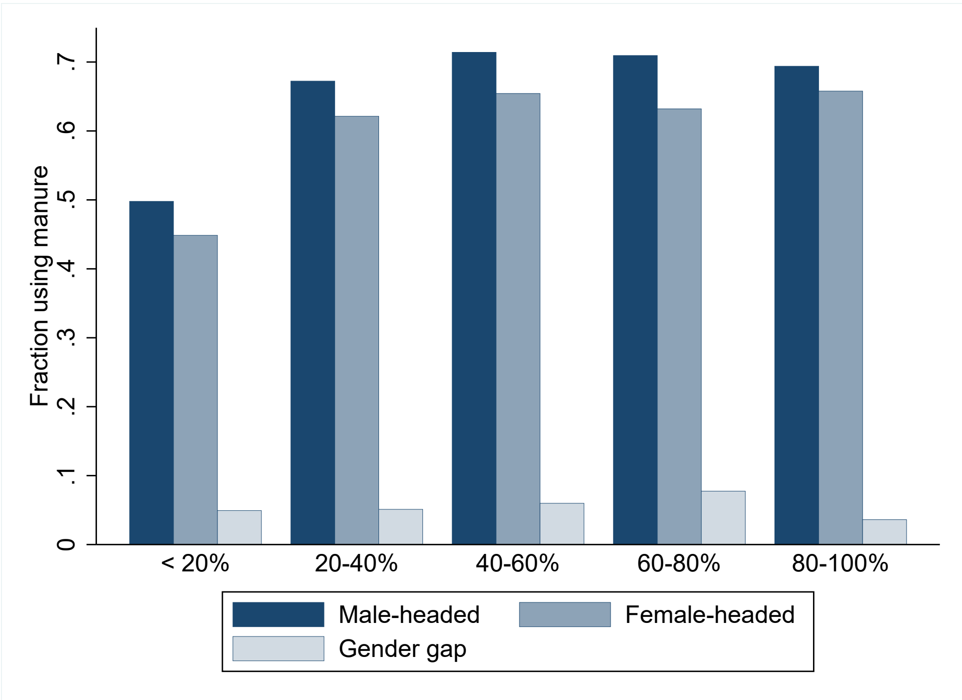
In view of the fact that female-headed households tend to be significantly more food insecure than male-headed households, improving adoption of fertilizer by female-headed households would have significant welfare effect. Government agencies may achieve this by targeting agricultural extension services or credit services towards female-headed households. In particular, this paper finds that access to credit significantly improves adoption of chemical fertilizer and the gender gap in adoption. Moreover, future research should explore policy options that may improve risk tolerance among households, particularly female-headed households.

Figure 1: Rain fall risk and gender gap in fertilizer adoption

(a)



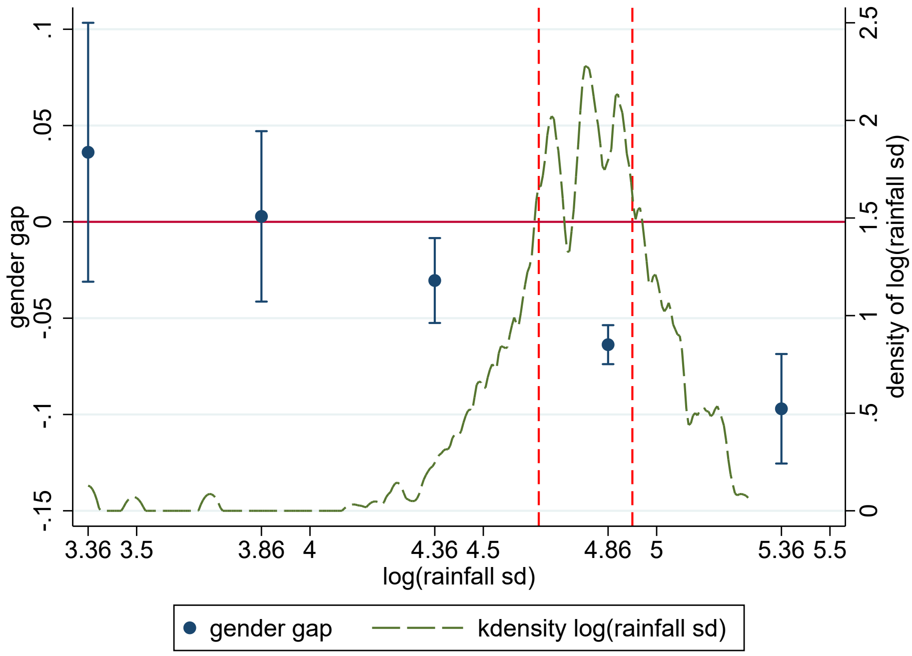
(b)



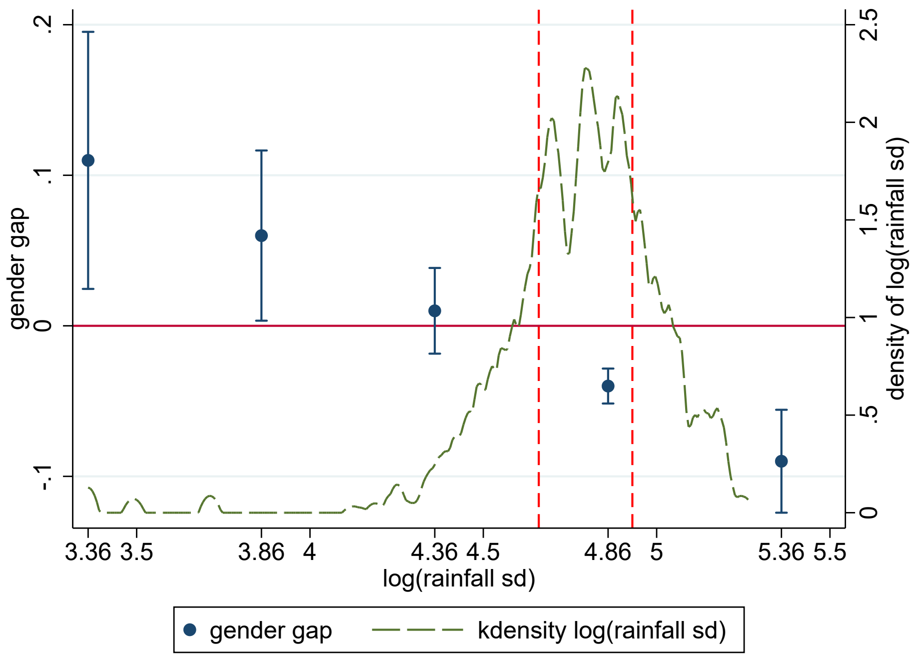
Notes: This figure plots the fraction of male-headed and female-headed households adopting chemical fertilizer and manure by district rainfall risks (573 districts). The figure also reports the corresponding gender gap in adoption of chemical fertilizer and manure.

Figure 2: The effect of rainfall risk on gender gap estimate

(a)



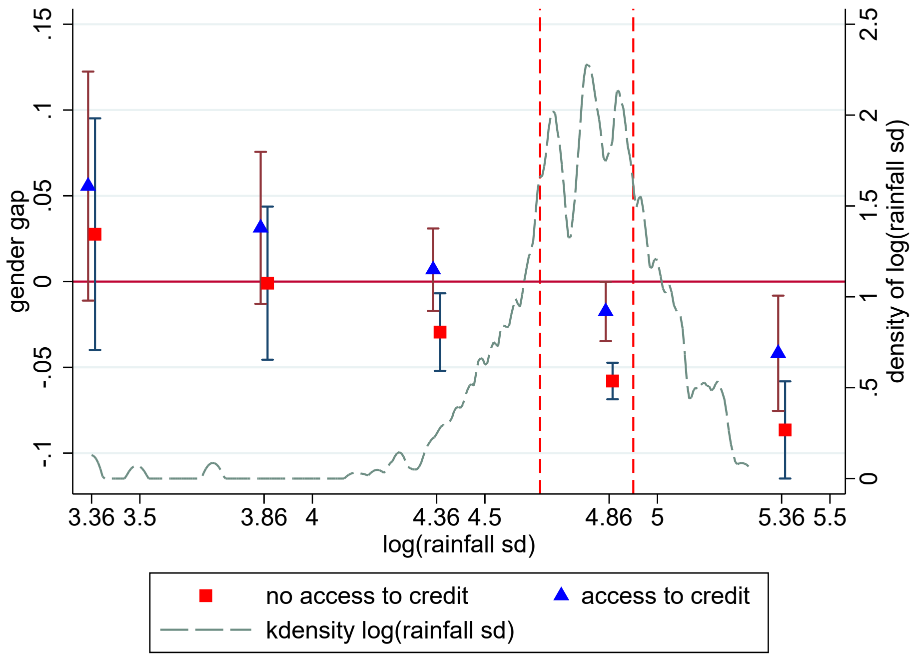
(b)



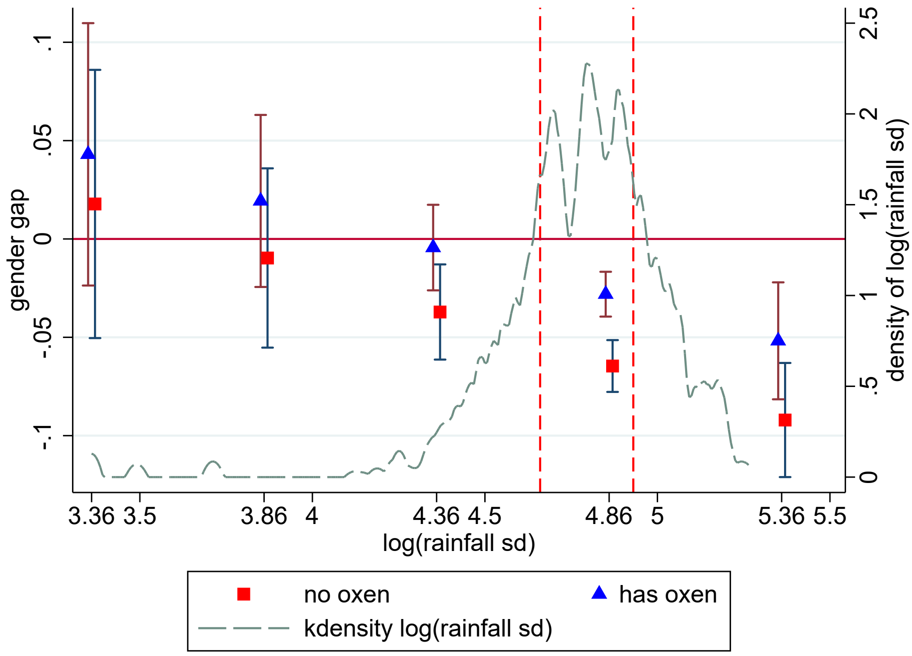
Notes: This figure plots the marginal effect of rainfall risk on gender gap in chemical fertilizer adoption (panel (a)) and the marginal effect of rainfall risk on gender gap in Chemical-Manure (panel (b)). Panel (a) is based on the regression result in table 2 column 1, while panel (b) is based on the first column of table 3. The two vertical dropped lines indicate the 25th and 75th percentiles of the log(rainfall standard deviation) across districts.

Figure 3: The role of access to consumption smoothing options on adoption of chemical fertilizer

(a)



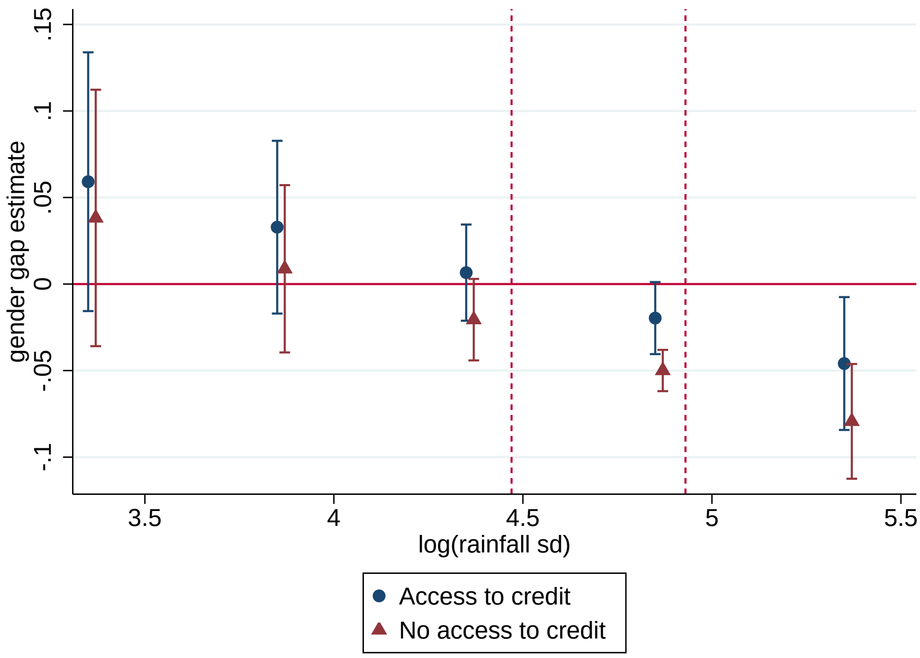
(b)



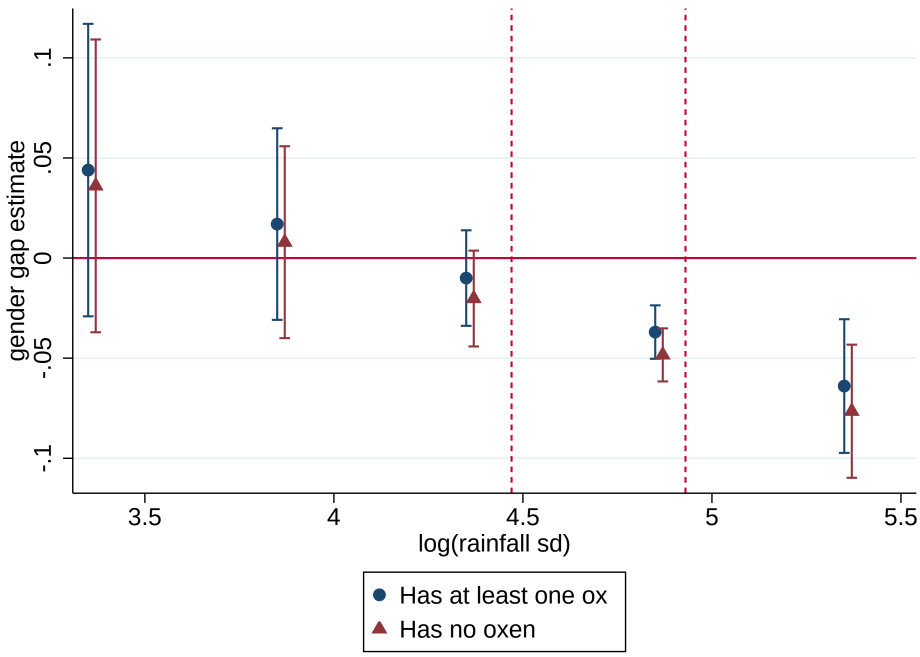
Notes: This figure plots the marginal effect of rainfall risk on gender gap in chemical fertilizer adoption for households with and without consumption smoothing options. Panel (a) plots the marginal effect of risk on gender gap estimate for households with and without access to credit. Panel (b) plots the marginal effect of risk on gender gap for households who own at least one oxen, and for households with no oxen. The two vertical dropped lines indicate the 25th and 75th percentiles of the log(rainfall standard deviation) across districts.

Figure 4: The role of access to consumption smoothing options on choosing chemical fertilizer vs. manure

(a)



(b)



Notes: This figure plots the marginal effect of rainfall risk on gender gap in chemical fertilizer adoption *relative to manure* from the triple differences estimate, for households with and without consumption smoothing options. Panel (a) plots the marginal effect of risk on gender gap estimate for households with and without access to credit. Panel (b) plots the marginal effect of risk on gender gap for households who own at least one oxen, and for households with no oxen. The two vertical dropped lines indicate the 25th and 75th percentiles of the log(rainfall standard deviation) across districts.

Table 1: Summary statistics of key variables by gender of household head

Variable	Male-headed	Female-headed	Difference	P-value
Used chemical fertilizer	0.49	0.37	0.12	0.00
Used manure	0.61	0.54	0.08	0.00
Age	43.00	47.29	-4.29	0.00
Education (Highest Grade)	3.92	2.62	1.30	0.00
Household Size	5.54	3.92	1.62	0.00
Credit	0.22	0.15	0.07	0.00
Oxen	1.10	0.56	0.54	0.00
Advisory	0.66	0.53	0.13	0.00
Land	1.21	0.68	0.53	0.00
Market access	9.59	9.64	-0.05	0.00
Log distance to nearest town	9.16	9.13	0.03	0.00
Log distance to nearest road	7.85	7.75	0.10	0.00
Average village slope	10.41	10.10	0.31	0.00
Average village altitude	18.33	18.47	-0.14	0.00
Population density	1.71	1.79	-0.07	0.00

Statistics is based on pooled data from AgSS for the years 2011-2016.

Table 2: Gender gap in chemical fertilizer adoption

	Chemical Fertilizer				Dap	Urea	Manure
	OLS		PS matching			OLS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female Head	-0.144***	-0.041***	-0.03***	-0.03***	-0.046***	-0.043***	-0.007**
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Household Size		0.006***			0.004***	0.003***	0.013***
		(0.001)			(0.001)	(0.001)	(0.001)
Head Education		0.000			-0.004***	-0.004***	-0.001***
		(0.000)			(0.000)	(0.000)	(0.000)
Head Age		-0.001***			-0.001***	-0.001***	0.001***
		(0.000)			(0.000)	(0.000)	(0.000)
Credit Access		0.125***			0.113***	0.112***	0.024***
		(0.006)			(0.006)	(0.006)	(0.004)
Owns Oxen		0.123***			0.116***	0.092***	0.068***
		(0.005)			(0.005)	(0.005)	(0.005)
Land size (hec)		0.047***			0.052***	0.043***	0.022***
		(0.003)			(0.003)	(0.003)	(0.002)
Adivisory Serv		0.151***			0.125***	0.099***	0.049***
		(0.007)			(0.007)	(0.006)	(0.005)
Rainfall	-0.023	-0.040**			-0.050*	0.033	0.077***
	(0.019)	(0.019)			(0.029)	(0.025)	(0.021)
N	237679	231866	231,857	231,853	231866	231866	231866
R^2	0.332	0.407	.	.	0.359	0.358	0.251

Standard errors are clustered at district level (573 districts). Observations are weighted by the household sampling weight. All regressions include district fixed effects and year fixed effect. Columns 2, 5, 6 and 7 also include the following household controls (household size, age of the head, education of the head, credit access, number of oxen, land holding (in hectares)); and village controls (rainfall, distance to nearest town, distance to nearest road, market access, average slope, and population density). Columns 3 reports the result from Propensity Score Matching estimator where female-headed households are compared with male headed households that similar based on the following observed characteristics: (household size, age of the head, education of the head, credit access, number of oxen, land holding (in hectares), received advisory service, rainfall, distance to nearest town and distance to nearest road. Column 4 restricts estimation in column 3 to region of common support.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Risk aversion and gender gap in chemical fertilizer adoption

	Risk1=log(Standard Deviation)				Risk2=log(80th perc-20th perc)			
	Chemical	Dap	Urea	Manure	Chemical	Dap	Urea	Manure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.261***	0.179**	0.087	-0.044	0.244***	0.205***	0.197***	-0.012
	(0.090)	(0.084)	(0.079)	(0.087)	(0.083)	(0.074)	(0.070)	(0.078)
Female X Risk1	-0.065***	-0.049***	-0.029*	0.007				
	(0.019)	(0.018)	(0.017)	(0.018)				
Female X Risk2					-0.056***	-0.049***	-0.047***	-0.001
					(0.016)	(0.014)	(0.013)	(0.015)
N	231880	231880	231880	231880	231880	231880	231880	213120
R^2	0.392	0.349	0.351	0.249	0.392	0.349	0.351	0.245

Standard errors are clustered at district level (573 districts). Observations are weighted by the household sampling weight. All regressions include district fixed effects, year fixed effect and the following household controls (household size, age of the head, education of the head, credit access, number of oxen, land holding (in hectares)); and village controls (rainfall, distance to nearest town, distance to nearest road, market access, average slope, and population density).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Access to consumption smoothing and gender gap

	Access to Credit		Number of Oxen	
	Chemical	Chemical-Manure	Chemical	Chemical-Manure
	(1)	(2)	(3)	(4)
	Panel A: Risk1= log(Rainfall SD)			
Female	0.182*	0.256**	0.195**	0.288**
	(0.100)	(0.125)	(0.094)	(0.127)
Female X Risk1	-0.055***	-0.065**	-0.057***	-0.071***
	(0.021)	(0.026)	(0.020)	(0.026)
Female X Risk1 X Credit	0.010***	0.008***		
	(0.002)	(0.002)		
Female X Risk1 X Owns Oxen			0.010***	0.003
			(0.001)	(0.002)
N	231880	231880	231922	231922
R^2	0.381	0.229	0.380	0.225
	Panel B: Risk2= log(80th percentiles-20th percentiles)			
Female	0.220**	0.232**	0.208**	0.242**
	(0.093)	(0.110)	(0.088)	(0.109)
Female X Risk2	-0.057***	-0.055***	-0.054***	-0.056***
	(0.018)	(0.021)	(0.017)	(0.021)
Female X Risk2 X Credit	0.009***	0.007***		
	(0.001)	(0.002)		
Female X Risk2 X Owns Oxen			0.009***	0.003*
			(0.001)	(0.002)
N	231880	231880	231922	231922
R^2	0.381	0.229	0.380	0.225

Standard errors are clustered at district level (573 districts). Observations are weighted by the household sampling weight. All regressions include district fixed effects, year fixed effect and the following household controls (household size, age of the head, education of the head, credit access, number of oxen, land holding (in hectares)); and village controls (rainfall, distance to nearest town, distance to nearest road, market access, average slope, and population density).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Rainfall risk and gender gap in fertilizer adoption: chemical vs. manure decision

	Risk1=log(standard deviation)			Risk2=log(80th perc-20th perc)		
	Chem-Manure	Dap-Manure	Urea-Manure	Chem-Manure	Dap-Manure	Urea-Manure
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.305**	0.224*	0.131	0.249**	0.210**	0.202**
	(0.124)	(0.123)	(0.113)	(0.107)	(0.105)	(0.100)
Female X Risk1	-0.072***	-0.056**	-0.036			
	(0.026)	(0.026)	(0.024)			
Female X Risk2				-0.055***	-0.048**	-0.046**
				(0.020)	(0.020)	(0.019)
N	231880	231880	231880	231880	231880	231880
R^2	0.230	0.211	0.239	0.230	0.211	0.239

Standard errors are clustered at district level (573 districts). Observations are weighted by the household sampling weight. All regressions include district fixed effects, year fixed effect and the following household controls (household size, age of the head, education of the head, credit access, number of oxen, land holding (in hectares)); and village controls (rainfall, distance to nearest town, distance to nearest road, market access, average slope, and population density).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Roads, risks, and the gender gap: The dependent Variable is whether the household has used chemical fertilizer

	(1)	(2)	(3)	(4)
	Panel A: Risk1= log(Sd)			
Female	0.2238**	0.2164**	0.2188**	0.2244**
	(0.1027)	(0.1013)	(0.1025)	(0.1012)
Female X Risk1	-0.0638***	-0.0665***	-0.0680***	-0.0649***
	(0.0216)	(0.0220)	(0.0241)	(0.0222)
Female X Risk1 X Road Access	-0.0005			
	(0.0016)			
Female X Risk1 X Distance from road		0.0005		
		(0.0006)		
Female X Risk1 X Distance from town			0.0006	
			(0.0012)	
Female X Risk1 X Market access				0.0001
				(0.0011)
N	231922	231922	231922	231922
R^2	0.367	0.370	0.367	0.367
	Panel B: Risk2= log(80th percentiles-20th percentiles)			
Female	0.2407**	0.2382**	0.2380**	0.2422**
	(0.0970)	(0.0956)	(0.0966)	(0.0961)
Female X Risk2	-0.0610***	-0.0639***	-0.0649***	-0.0626***
	(0.0185)	(0.0190)	(0.0213)	(0.0194)
Female X Risk2 X Road Access	-0.0004			
	(0.0015)			
Female X Risk2 X Distance from road		0.0004		
		(0.0005)		
Female X Risk2 X Distance from town			0.0005	
			(0.0011)	
Female X Risk2 X Market access				0.0001
				(0.0010)
N	231922	231922	231922	231922
R^2	0.367	0.370	0.367	0.367

Standard errors are clustered at district level (573 districts). All regressions include district fixed effects, year fixed effect. Observations are weighted by the household sampling weight. All regressions include district fixed effects, year fixed effect and the following household controls (household size, age of the head, education of the head, credit access, number of oxen, land holding (in hectares)); and village controls (rainfall, distance to nearest town, distance to nearest road, market access, average slope, and population density).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix A Plot level analysis

Table A1: Gender gap in chemical fertilizer adoption: plot level analysis

	Chemical Fertilizer	Urea	DAP	Manure
	(1)	(2)	(3)	(4)
Female	-0.011**	-0.010**	-0.006	0.018***
	(0.005)	(0.005)	(0.005)	(0.006)
Extension	0.441***	0.352***	0.373***	-0.040***
	(0.008)	(0.008)	(0.008)	(0.008)
Holder Age	-0.001***	-0.001***	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Holder Years of Schooling	-0.001*	-0.002**	-0.000	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Area of plot	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Household Size	0.000	-0.000	0.001	0.008***
	(0.001)	(0.001)	(0.001)	(0.002)
# of active age men	0.002	0.001	0.007***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.003)
# of active age women	0.002	0.001	-0.003	0.009***
	(0.003)	(0.002)	(0.003)	(0.004)
# of ploughing animals	0.003*	0.003**	0.000	-0.004**
	(0.002)	(0.002)	(0.001)	(0.002)
# of pack animals	0.002	0.005*	-0.002	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Soil quality	0.005	0.004	0.004	-0.043***
	(0.003)	(0.003)	(0.003)	(0.004)
N	52383	52364	52354	52301
R^2	0.502	0.419	0.455	0.304

Robust standard errors in parenthesis. Observations are weighted by the household sampling weight. All regressions include district, crop, and year fixed effects. Soil quality is measured as Good=1, Fair=2, and Poor=3.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Gender gap in chemical fertilizer adoption: drought frequency

	Chemical Fertilizer	Urea	DAP	Manure
	(1)	(2)	(3)	(4)
Female	-0.002	-0.025***	0.008	0.006
	(0.010)	(0.009)	(0.009)	(0.010)
Female X Frequency of Drought	-0.011***	-0.006**	-0.015***	-0.004
	(0.003)	(0.003)	(0.002)	(0.003)
N	231866	231866	231866	231866
R^2	0.407	0.359	0.358	0.251

Robust standard errors in parenthesis. Observations are weighted by the household sampling weight. All regressions include district and year fixed effects, and all the control variables included in column 2 of table 2. Drought frequency in a district is defined as the number of years between 1990 and 2010 a district has a rainfall measure below one standard deviation less than the mean rainfall in the district over the same period.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B Rosenbaum bounds on the matching estimator

Table B1: Mantel-Haenszel (1959) bounds for adoption of chemical fertilizer

Γ	Q_mh+	Q_mh-	p_mh+	p_mh-
1	14.4108	14.4108	0	0
1.1	20.9371	7.89421	0	1.4e-15
1.2	26.9074	1.94961	0	.025611
1.3	32.4131	3.50322	0	.00023
1.4	37.5246	8.56668	0	0
1.5	42.2976	13.2836	0	0
1.6	46.7767	17.6999	0	0
1.7	50.9983	21.8531	0	0
1.8	54.9923	25.7738	0	0
1.9	58.7837	29.4878	0	0
2	62.3937	33.0168	0	0
2.1	65.8402	36.3789	0	0
2.2	69.1386	39.5901	0	0
2.3	72.3023	42.664	0	0
2.4	75.3428	45.6123	0	0
2.5	78.2704	48.4455	0	0
2.6	81.0939	51.1726	0	0
2.7	83.8214	53.8018	0	0
2.8	86.4597	56.3401	0	0
2.9	89.0153	58.7941	0	0
3	91.4938	61.1694	0	0
3.1	93.9003	63.4713	0	0
3.2	96.2393	65.7044	0	0
3.3	98.5151	67.8729	0	0
3.4	100.731	69.9808	0	0
3.5	102.892	72.0315	0	0
3.6	104.999	74.0282	0	0
3.7	107.057	75.9739	0	0
3.8	109.067	77.8713	0	0
3.9	111.032	79.7229	0	0
4	112.955	81.5311	0	0

This table reports Rosenbaum bounds on the matching estimator in reported in column3 of table 2.
Γ: odds of differential assignment due to unobserved factors
$Q_m h+$: Mantel-Haenszel statistic (assumption: overestimation of treatment effect)
$Q_m h-$: Mantel-Haenszel statistic (assumption: underestimation of treatment effect)
$p_m h+$: significance level (assumption: overestimation of treatment effect)
$p_m h-$: significance level (assumption: underestimation of treatment effect)

Appendix C Using irrigated vs. non-irrigated

Table C1: Gender gap: irrigated vs. non-irrigated plots

	All Sample			HHs with both irrigated and non-irrigated plots		
	Chemical	Urea	Dap	Chemical	Urea	Dap
Female	-0.013**	-0.011**	-0.007	0.023	0.062***	0.010
	(0.005)	(0.005)	(0.005)	(0.021)	(0.022)	(0.021)
Irrigated	-0.084**	-0.091***	-0.042	-0.152***	-0.144***	-0.088**
	(0.033)	(0.030)	(0.031)	(0.039)	(0.039)	(0.038)
Female X Irrigated	0.056**	0.049**	0.048*	0.082***	0.065**	0.055*
	(0.026)	(0.023)	(0.025)	(0.030)	(0.031)	(0.030)
N	52338	52320	52309	5840	5837	5836
R^2	0.502	0.419	0.455	0.618	0.530	0.574

Robust standard errors in parenthesis. Observations are weighted by the household sampling weight. All the control variables in Table A1 are included in all the regressions. All regressions include district, crop, and year fixed effects. Soil quality is measured as Good=1, Fair=2, and Poor=3.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix D Other tables

Table D1: The Ten Paired Lottery-Choice Decisions with Low Payoffs (from Holt and Laury (2002))

Option A (Safe Option)		Option B (Risky Option)		Expected payoff difference
1/10 of \$2,	9/10 of \$1.6	1/10 of \$3.85,	9/10 of \$0.1	\$1.17
2/10 of \$2,	8/10 of \$1.6	2/10 of \$3.85,	8/10 of \$0.1	\$0.83
3/10 of \$2,	7/10 of \$1.6	3/10 of \$3.85,	7/10 of \$0.1	\$0.50
4/10 of \$2,	6/10 of \$1.6	4/10 of \$3.85,	6/10 of \$0.1	\$0.16
5/10 of \$2,	5/10 of \$1.6	5/10 of \$3.85,	5/10 of \$0.1	-\$0.18
6/10 of \$2,	4/10 of \$1.6	6/10 of \$3.85,	4/10 of \$0.1	-\$0.51
7/10 of \$2,	3/10 of \$1.6	7/10 of \$3.85,	3/10 of \$0.1	-\$0.85
8/10 of \$2,	2/10 of \$1.6	8/10 of \$3.85,	2/10 of \$0.1	-\$1.18
9/10 of \$2,	1/10 of \$1.6	9/10 of \$3.85,	1/10 of \$0.1	-\$1.52
10/10 of \$2,	0/10 of \$1.6	10/10 of \$3.85,	0/10 of \$0.1	-\$1.85

Notes

1. See Doss and Morris (2001), for instance.

2. See Duflo et al., 2008 for instance.

3. I also consider households' choice between chemical fertilizer and no chemical fertilizer.

4. Based on Ethiopian Socioeconomic Survey (2011-2015), only 6% of the plots farmed were irrigated.

5. There are also studies that document that attitudes towards risk could change significantly, particularly when individuals are exposed to extreme shocks. See for instance Voors et al., 2012; and Cassar et al., 2017

6. However, the result is robust to using alternative measures such as the the log of differences between (i) maximum and minimum, (ii) 90th and 10th percentiles, and (iii) 70th and 30th percentiles.

7. While the OLS includes more village level control variables, I limit the variable list to only the above list due to problem in convergence of the matching estimation (the village characteristics that are left out are highly correlated with the ones included).

8. See Korecha and Barnston (2007) for a detailed discussion on predictability of rainfall and other climatic conditions in Ethiopia.

9. The survey asks if the household has access to credit service, and if the household doesn't have access, the main reason for not having access.

10. I also use the number of oxen owned as an alternative. Results are quite similar.

11. However, there is significant labor and time investment required to produce manure and transport to the farm field.

12. The minor differences of point estimates from the corresponding tables are because I use zone fixed effects instead of district fixed effects to produce these figures. This was dictated because district fixed effects would subsume the marginal effects.

13. Related strands of literature suggest alternative mechanisms through which market exposure affect households' risk preferences. For instance, List (2003) argues that market exposure eliminates behavioural anomalies such as endowment effects. Several related studies argue that market exposure improves rational decision making (List and Millimet 2008; and Cecchi and Bulte 2013

14. I am not attempting to identify the detailed mechanisms through which improved market access mute the role of risks, as doing so is difficult with observational data.

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