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Does Weather Risk Explain Low Uptake of Agricultural Credit?

Evidence from Ethiopia

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ABSTRACT

Credit markets are key instruments by which liquidity constrained smallholder farmers may finance productivity investments. However, the documented low demand and uptake of agricultural credit by smallholder farmers in sub-Saharan Africa poses challenges for energizing rural transformation in the region. In this paper we investigate the impact of rainfall uncertainty (and risk more generally) on the expressed demand for credit among rural households in Ethiopia. We explore potential mechanisms through which weather risk may explain the low demand for credit. We also examine the consequences of uninsured rainfall uncertainty on productivity-enhancing and loss-reducing agricultural investments. We provide evidence that rainfall uncertainty dampens households' demand for agricultural credit. Rainfall uncertainty is associated with credit risk-rationing, which underlies the low demand for agricultural credit in Ethiopia. We also show that rainfall uncertainty helps to explain the low uptake of productivity-enhancing agricultural technologies, such as fertilizers. On the other hand, rainfall uncertainty encourages investments in defensive agricultural inputs, such as pesticides, herbicides, and fungicides. Our results highlight the impacts of uninsured production risk on agricultural investments made by African smallholders.

Keywords: agricultural credit, production risk, credit constraint, credit rationing, agricultural investment.

1. INTRODUCTION

Access to credit is widely acknowledged as a key means of transforming the livelihoods of poor rural households in developing countries. Previous empirical studies have shown that microcredit can stimulate agricultural investments, including use of modern agricultural inputs (Giné and Yang 2009; Zerfu and Larson 2010; Abate et al. 2016), facilitates the start-up of new enterprises (de Mel et al. 2008) and, at least in some cases, reduces poverty (Berhane and Gardebroek 2011).[1] Such evidence has generally encouraged the expansion of microfinance institutions in many developing countries over the last few decades. The outcomes that microcredit is presumed to engender are conceptually well-founded: where the marginal returns to capital investments exceed the costs of accessing credit markets, after adjusting for risk-preferences and the stochastic nature of agricultural investment outcomes, we would expect farmers to be net demanders of agricultural credit markets where they are available (de Mel et al. 2008; Fafchamps et al. 2011; Duflo et al. 2008). The fact that the significant expansion of microfinance institutions (MFI) and credit services in much of sub-Saharan Africa has generally *not* been accompanied by high rates of credit uptake suggests that the costs and risks of credit market participation by African smallholders deserve more scrutiny (Karlan and Morduch 2009; Karlan et al. 2010). The contribution of this paper is to provide such scrutiny, focusing on the role of risk in conditioning the demand for credit, and using Ethiopia as an empirical case study.

Rural financial markets in Ethiopia remain in their infancy and are mostly dominated by informal financing schemes. Despite significant expansion of microcredit schemes in recent years, the majority of rural households in Ethiopia remain underserved (Amha and Peck 2010). A recent World Bank global financial inclusion study shows that only 22 percent of adults in Ethiopia have access to financial services,

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[1] Empirical evidence on the welfare impacts of microcredit remains mixed. Rooyen et al. (2012) provide a thorough review of the impact of microfinance in sub-Saharan Africa. Despite several studies showing positive welfare impacts of microcredit (e.g., de Mel et al. 2008; Giné and Yang 2009; Zerfu and Larson 2010; Berhane and Gardebroek 2011; Abate et al. 2016), other studies find negligible impacts. For instance, Duflo et al. (2013) find no effect on consumption expenditures and related outcomes. For the case of Ethiopia, Tarozzi et al. (2015) find that microcredit has little or negligible impact on most outcomes. These mixed pieces of evidence highlight that we still do not know why and when microcredit can improve the livelihoods of poor rural households (Banerjee 2013). Banerjee (2013) notes that despite some evolving evidence on the potential of microcredit ‘‘We still do not know why microcredit does not do more to transform the lives of its participants.’’

with corresponding figures for sub-Saharan Africa and the globe amounting 29 and 62 percent, respectively (Demirguc-Kunt et al. 2015). Wiedmaier-Pfister et al. (2008) estimate that about 80 percent of the potential demand for financial services in Ethiopia remains unmet. Recent nationally representative surveys from the Central Statistics Agency (CSA) of Ethiopia show that only about 10 percent of smallholders in Ethiopia have access to formal credit from formal financial institutions. Moreover, credit market participation of rural households in Ethiopia is characterized as irregular and sporadic, with significant default rates.

Despite the improved coverage of MFIs and financial cooperatives in recent years, the number of farmers using credit remains very low: less than 10 percent of rural households report having taken loans from formal financial institutions (Berhane and Abay 2018; Abay et al. 2018a). This is particularly intriguing in the Ethiopian context where credit constraints and uninsured agricultural production risks are perceived to be key factors that keep smallholder farmers trapped in poverty (Dercon and Christiaensen 2011). The majority of households who do not use credit appear to do so not because credit markets are not locally accessible, but rather because the terms of credit are not perceived as favorable (Berhane and Abay 2018). Reasons for not using credit include the unsuitability of existing microcredit products and contract designs that introduce an additional layer of risks (ibid.).

Given the expansion of rural financial services in recent years (mainly through MFIs and rural financial cooperatives), a central question facing policy makers in Ethiopia and beyond is why the uptake of microcredit services remain low. This question is broadly related to the global debate on why the expansion of rural microfinance has not had larger apparent impacts on rural livelihoods (Karlan and Morduch 2009; Banerjee 2013). At the center of this debate are questions related to whether it is the nature of borrowers or the nature of credit products that is inducing such low demand for microcredit products. There is some empirical evidence for both demand- and supply-related constraints to credit market participation. For instance, from the supply side, Karlan and Mullainathan (2007) argue that onerous qualification requirements and the one-size-fits-all nature of typical microfinance packages might be one reason why they fail to satisfy the financial needs of the poor in developing countries.[2] Other studies suggest that demand-related attributes of rural households contribute to low demand and uptake of credit products. Banerjee (2013) argues that microcredit borrowers in developing countries often lack human capital which, in turn, leads to poor financial judgement and risk-taking behavior. This suggests higher rates of default than would otherwise be the case, which may dampen demand by other would-be credit users who observe such outcomes. Other studies, such as Karlan and Valdivia (2011) and Giné and Mansuri (2011) suggest that microcredit borrowers often lack consumer know-how regarding how to exploit credit markets, which reduces demand. Amha and Peck (2010) argue that such skill gaps in rural households contribute to the low demand for financial services in Ethiopia.

In this paper we explore an alternative explanation for the existing low demand for microcredit. We argue that smallholders in Ethiopia operate in fundamentally risky contexts where agriculture is predominantly rainfed and, hence, production is subject to the vagaries of nature. Theoretically, the presence of uninsured production and consumption risk can contribute to credit market imperfections that may lead to credit rationing in rural economies. In the context of Ethiopia, lenders usually require collateral, which smallholder farmers lack, or rely on other lending schemes, e.g., group lending, to alleviate, among others, asymmetric information problems. In the absence of well-functioning insurance markets to deal with covariant production risk, lenders' requirement for collateral or the additional layer of risk of having to bail out fellow group members in the group lending scheme effectively interacts with the production risk rural farmers face and, hence, introduces an additional source of credit-rationing. The

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[2] In the context of Ethiopia, lack of flexibility in product designs – limited loan term and inflexibility to negotiate defaults when real challenges are faced by the borrower, such as, for example, during droughts – is another important constraint of microcredit programs.

specific type of credit-rationing associated with production risk and associated risk of default is commonly referred to as *risk rationing* (Guirkinger and Boucher 2008; Boucher et al. 2008; Boucher et al. 2009). In the context of Ethiopia, nationally representative datasets show that more than half of households are not borrowing due to the risk of default, i.e., fear of being in debt or distress of losing assets in the case of default (Mukasa et al. 2017; Berhane and Abay 2018). Thus, we investigate the impact of weather risk – measured by rainfall uncertainty – on demand for credit by rural households in Ethiopia. In addition to its impacts on credit usage, we also examine the direct impacts of weather risk on productivity-enhancing and loss-reducing agricultural investments.

We employ three waves of the Living Standard Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) for Ethiopia: 2011/12, 2013/14, and 2015/16. These nationally representative datasets cover a large sample of rural households throughout the country and, hence, provide substantial variation in demand for credit. The LSMS data provides GPS coordinates of households' residences, enabling us to merge these longitudinal data with time series rainfall data. We define several measures of rainfall variability, including the coefficient of variation and the standard deviation of rainfall, over a reasonably long-run period of 10 years.

We find that inter-annual rainfall variability strongly and negatively affects demand for credit. This result holds under alternative measures of rainfall uncertainty and remains robust to a battery of robustness checks. As expected, we find that these effects are only significant in rural areas where livelihoods are heavily reliant on rainfed agriculture. We provide suggestive evidence showing that the effect works through increasing farmers' credit risk aversion and, hence, by introducing risk rationing. We also show that rainfall variability negatively affects productivity-enhancing agricultural investments, including fertilizer application decisions, while encouraging defensive agricultural investments, such as herbicide use. These results are noteworthy in terms of understanding the implications of weather risk on rural households' demand for credit and associated agricultural technologies as well as in view of identifying rural farmers' adaptive strategies to climate change. These results speak to the empirical puzzle of low uptake of credit and underinvestment in agricultural technologies documented in many African countries. Our findings highlight the importance of interventions aimed at both relaxing smallholders' credit rationing while also reducing their production risk.

2. DEMAND FOR AGRICULTURAL CREDIT: CONTEXT AND CONCEPTS

2.1. Agricultural Credit in Ethiopia

Given the role agriculture plays in Ethiopia's economy -- contributing ~40 percent of national GDP and employing ~80 percent of the workforce – agricultural microcredit has a large potential role to play in the transformation of smallholder livelihoods. However, despite the recent expansion of rural financial services, the sector receives less than 10 percent of overall lending from these formal sources (Mukasa et al. 2017). In the quest to explain this, most of the theoretical and empirical literature on rural credit has focused on the supply side constraints, with little attempt to explore households' demand for services (Mpuga 2010; Karlan et al 2010).

Besides supply-related constraints, the existing low demand for agricultural credit in Ethiopia may be partially attributed to borrower attributes or to the environment under which smallholder borrowers operate. Previous studies have shown that consumer knowledge gaps on how to exploit existing financial products can contribute to limited uptake of financial services (Amha and Peck 2010; Karlan and Valdivia 2011; Giné and Mansuri 2011). In Ethiopia, Berhane and Abay (2018) compile several datasets to show low uptake of agricultural credit. They document that more than half of survey households fail to participate in rural credit markets because of fear of being in debt or loss of assets in case of defaults associated with frequent droughts. This fear is exacerbated by the additional risk assumed when loans are given in groups –

that is the fear of having to repay for a partner when the group is hit by covariate shocks. In another study of rural credit use in Ethiopia, Mukasa et al. (2017) report similar findings. These studies suggest the problem of credit risk rationing related to the design of the credit product itself might be common among rural borrowers in Ethiopia, preventing them from making credit-financed investments. However, we are not aware of previous empirical studies quantifying the impact and implication of smallholders' production risk on their demand for credit. This study aims to fill that gap by examining the impact of weather risk in explaining the existing low demand for agricultural credit in Ethiopia.

2.2. Conceptual Framework

There exist several theoretical models that can help understand the linkage between weather risk, demand for credit, and ultimate investment decisions. For simplicity, we adapt a simple model of technology adoption under credit constraints and uncertainties by Magruder (2018), which is an extension of Karlan et al.'s (2014) model. In this model, farm households face uncertainty about the state of the world ($s \in S$), which includes rainfall uncertainties and other risks which affect production and consumption outcomes. Given these uncertainties, a farmer's expectations for choice of inputs x is $E_s[f_s(x)]$. Within a simple two-period framework, a farmer maximizes utility:

$$u(c^0) + \beta \sum_{s \in S} \pi_s u(c_s^1)$$

where $u(c^0)$ is the expected consumption in period 0; $u(c_s^1)$ is expected consumption in period 1, conditional on s; π is the set of beliefs the farmer has about the likelihood of outcomes s; and β is a discount factor. In addition to choosing inputs x, a farmer can choose to invest in an asset a, which has a return of R in the next period. There are four constraints arising from this maximization problem:

$$c^0 = Y - x - a$$

$$c_s^1 = f_s(x) + Ra$$

$$x \geq 0$$

$$a \geq \tilde{a}$$

The last of these constraints is a constraint on borrowing: when a takes negative values, it represents credit (and R is then the corresponding interest rate). Production risk (rainfall uncertainty) enters through s. If we assume that greater values of s correspond with greater productivity states of the world, that $f_s(x)$ and $f_s'(x)$ are increasing in s, and that the Inada conditions hold for $f_s(x)$, a farmer will have the following first order conditions:

$$u'(c^0) = \beta \sum_{s \in S} \pi_s f'(x) u'(c_s^1)$$

$$u'(c^0) = \beta R E[u'(c_s^1)] + \lambda_a$$

Taking the derivative of these with respect to the credit constraint $\tilde{a}$, we see that $\frac{dx^*}{d\tilde{a}} < 0$, i.e. if credit constraints are binding, then the optimal input use x^* is increasing in the amount of credit available. When farmers are not credit-constrained, $cov\left(f'(x), u'(c_s^1)\right) < 0$ and $\lambda_a = 0$. This has two important implications: first, the presence of risk reduces inputs x; second, production risk reduces the demand for credit. We see the latter by noting that in the case of no credit constraints, input use is lower in the second period and so is the marginal utility of consumption for any level of borrowing a. The implication of this is that exposure to uninsured risk will reduce the demand for credit by risk-averse farmers.

2.3. Estimation and Identification Strategy

To empirically test the hypothesis that exogenous weather-related risk exposure significantly affects credit uptake, we estimate the following credit demand equation:

$$C_{ht} = \beta_1 \text{Rainfall Variability}_{vt-1} + \beta_2 \text{Rainfall}_{vt-1} + \beta_3 Household_{ht} + \alpha_t + \alpha_h + \varepsilon_{ht} \qquad (1)$$

where C_{ht} is households' uptake of credit from formal sources. Rainfall variability is our key variable of interest, measured by the coefficient of variation or standard deviation in rainfall over the previous ten years. Given the exogenous nature of rainfall and, hence, rainfall variability, β_1 quantifies the impact of rainfall variability, while β_2 captures the impact of the most recent season's rainfall. Due to the framing of our credit uptake questions, which goes 12 months back, the relevant and most recent rainfall spell is pushed back accordingly. For instance, the recent rainfall spell for the 2011/12 round of our data is the precipitation for the year 2010. Our measures of rainfall variability are computed up until these most recent rainfall periods. β_3 captures the effect of additional household characteristics, while α_t and α_h represents year and household fixed effects, respectively. These year fixed effects can capture aggregate shocks and macroeconomic conditions that may affect demand for credit. The household fixed effects allow us to control for time-invariant unobserved heterogeneity that may affect demand for agricultural credit. The last term in equation (1) is a stochastic error term that captures remaining sources of variation in demand for credit.

We initially estimate equation (1) without additional controls and later extend the specification through a step-wise inclusion of relevant covariates in order to understand alternative mechanisms through which rainfall uncertainty may affect demand for credit. For instance, without controlling for contemporaneous or recent rainfall spells, β_1 captures both the effect of weather uncertainty as well as the effect of recent rainfall spells, which, in turn, can have negative or positive impact on households' demand for credit. In extending the specification in equation (1), we consider and employ detailed household and community-level characteristics that may explain either the demand or supply side of credit. Credit market participation is a result of the interaction between the demand and supply sides of the credit market. Thus, we control both for demand and supply side attributes of rural credit markets. From a supply point of view, we control for households' access to microfinance and related indicators of these amenities.

Our measures of inter-annual rainfall variability (coefficient of variation or standard deviation of rainfall over the previous ten years of each survey year) are expected to show little dynamism across two-year panel waves. Thus, including household fixed effects in such estimations can be expected to attenuate the true effect of rainfall uncertainty and, hence, can be viewed as a conservative approach. Furthermore, rainfall variability is reasonably taken as exogenous and, hence, estimates can be expected to be robust to inclusion of these household characteristics and household fixed effects. In estimating equation (1), we have two sources of correlation in error terms (unobserved effects), arising from spatial and temporal dimensions. We have a panel structure in our surveys through which we follow households across years. Similarly, our key variable of interest (coefficient of variation) varies at the enumeration area level, where households living in the same enumeration area share similar unobserved effects. Thus, we report results with standard errors clustered at the enumeration area level.[3] Because of the clustering challenges in binary outcome models, we estimate linear probability models, even though our key outcome variables are measured as binary indicators.

We test the robustness of our results in several ways: (i) We estimate our empirical models using two alternative measures of rainfall: the coefficient of variation (CV) and standard deviation in annual

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[3] Other types of clustering, including household and village-round level clustering result in similar inferences.

rainfall over the last ten years; (ii) We test alternative measures of CV and standard deviations computed over five years instead of ten years; (iii) We split and construct our rainfall variability measures for each of highland Ethiopia's two main growing seasons: *meher* (long rainy season) and *belg* (short rainy season).[4] Finally, to confirm our expectation that the effect of rainfall uncertainty is more pronounced in contexts where livelihoods depend on rainfed agriculture, we also estimate the effect of rainfall risk using the urban sample.

3. DATA AND DESCRIPTIVE STATISTICS

3.1. Data

The primary source of data for this study is the Living Standards Measurement Study Integrated Surveys on Agriculture (LSMS-ISA) for Ethiopia, a collaborative project between the Central Statistics Agency of Ethiopia (CSA) and the World Bank (CSA and World Bank 2017).The Ethiopian LSMS-ISA data are longitudinal datasets collected every two years, covering a wide range of topics related to agricultural production decisions, including a detailed module on agricultural credit use and reasons for borrowing (or not).

The first round of the LSMS-ISA data for Ethiopia was collected in 2011/12. This round covers only rural and small towns and, hence, is only representative of the rural population in Ethiopia.[5] The first wave reached 3,776 households from 333 enumeration area across all regional states. The second and third rounds, collected in 2013/14 and 2015/16, respectively, include urban areas and are designed to be nationally representative. For example, the third round covers 433 enumeration areas of the same regions (including major towns and cities), reaching 5,262 rural and urban households. In the interest of constructing nationally representative longitudinal data and given our subject of agricultural credit, we focus on the rural sample and, hence, exclude major towns and cities. Our final sample therefore is only representative of the Ethiopian rural population.

The LSMS-ISA households are georeferenced, allowing us to merge them with other geospatial datasets. [6] We use spatial time-series rainfall data from the National Aeronautics and Space Administration (NASA).[7] Using the geographic information on households' residence, we are able to construct enumeration area-level daily rainfall data for the last 29 years, from which we construct measures of weather risk.[8] Our key measure of rainfall uncertainty, coefficient of variation of rainfall, is constructed for the ten years prior to each enumeration (survey period). Intuitively, it may be difficult for farmers to recall rainfall spells of the distant past, arguably, going beyond ten years. However, as a robustness check, we also evaluated the sensitivity of results using measures based on longer and shorter time spans.

3.2. Descriptive Statistics

The LSMS surveys for Ethiopia elicit households' credit uptake over the 12 months prior to enumeration, both from formal and informal sources. All credit related outcomes in all rounds of the Ethiopian LSMS data

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[4] *Meher* is the main rainy and production season which normally runs from June to September. *Belg* is also a rainy and production season in some parts of the country and often covers the period from February to May.

[5] The CSA defines small towns based on population estimates from the 2007 Population Census; a town with the population of less than 10,000 is a small town.

[6] To protect respondent anonymity, a small random offset is introduced into the household geographic coordinates: 0 to 5 km for 99 percent of rural enumeration areas, with 1 percent of enumeration areas given a random offset of 0 to 10 km (CSA and World Bank 2017). Given the spatial scale of rainfall patterns, however, this offset should not affect our analysis.

[7] NASA has long supported and provided satellite-based datasets for research purposes, including precipitation and temperature data. See at https://power.larc.nasa.gov/common/php/POWER_AboutAgroclimatology.php

[8] We used longitude and latitude location from the enumeration area of the household to precisely locate and download the daily precipitation data.

were collected at similar times of the year (January to April). Thus, the 12-month recall period covers the most recent main (*Meher*) production season, which ends in December in most areas. We expect that a good share of the credit taken over the 12 months prior to enumeration would be spent on inputs for the most recent production season. We confirm this in our analysis. For reducing some heterogeneity in credit sources, we focus on formal credit, meaning credit from commercial banks, rural microfinance organizations, and rural savings and cooperatives.

In Table 3.1, we report household credit market participation for the three waves. This shows that rural credit participation is low, with less than 10 percent rural households taking credit. These participation rates are consistent with those reported in Berhane and Abay (2018), which come from different data sources. A more exhaustive list of household characteristics and summary statistics of our analytical sample are given in Table A1 in the Appendix.

Table 3.1. Households' uptake of formal credit

Survey year (round)	**2011/12**	**2013/14**	**2015/16**	**All**
Households who took credit, %	7.8	9.5	7.0	8.1
Observations	3,589	3,503	3,454	10,647

Source: Authors' computation from LSMS-ISA data.

Rural households' credit market participation rates are the results of an interaction of demand- and supply-side attributes of rural credit markets. The supply-side attributes can be measured by availability of credit in each village, in the form of availability and accessibility of financial institutions. In the context of Ethiopia, despite the need for further progress, several microfinance institutions and cooperatives have been established to improve household access to financial services. Berhane and Abay (2018) show that many rural villages have at least one microfinance or credit and saving association.

In terms of identifying the impact of rainfall uncertainty on demand for agricultural credit, the distribution of these rural microfinance institutions and their relationship with weather risk have important implications. For instance, if microfinance institutions are targeting high agricultural potential areas or those areas less susceptible to rainfall failure, we are more likely to overestimate the impact of rainfall uncertainty on demand for agricultural credit. In the context of Ethiopia, where regional and federal governments have heavy hands over and stakes in most microfinance institutions, distribution of microfinance institutions and services in a systematic manner related to the credit market potential of villages and enumeration areas is less likely to prevail.[9] To empirically confirm that our measure of weather risk is uncorrelated with access to microfinance, we run simple regressions characterizing farmers' access to microfinance as a function of rainfall uncertainty. These regressions are given in Table A2 in the Appendix. These results clearly show that access to microfinance and, hence, the distribution of microfinance services is not significantly related to our measure of production risk, rainfall uncertainty.

Table 3.2 summarizes households' major reasons and purposes for obtaining loans from formal sources. More than half of the credit taken from formal sources is targeted for agricultural investments, i.e., the purchase of inputs. This is consistent with the Ethiopian government's agenda of expanding access to credit for smallholders geared towards boosting agricultural investments. An important proportion of credit taken over the prior 12 months was used for agricultural investments in the season. The next important reason appears to be starting up or expanding businesses. The purposes for which credit is used remains comparable across years.

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[9] Potentially attributable to this significant government support, Ethiopia is now home to two of the largest MFIs in Africa, ACSI (Amhara Credit and Savings Institution) and DECSI (Dedebit Credit and Savings Institution).

Table 3.2. Purpose of credit from financial institution, percent of households receiving credit

Survey year	2011/12	2013/14	2015/16	All
Purchase agricultural inputs	59	56	53	56
Business startup/expanding business	19	15	20	17
Purchase house/lease land	2	2	3	2
Purchase nonfarm inputs	1	3	4	3
Other purposes	18	23	19	21
Observations	284	328	242	854

Source: Authors' computation from the LSMS-ISA data. Values stand for percentage of households reporting the main use of credit falling in each category.

In Table 3.3 we report households' reasons for not participating in rural credit markets, with responses grouped into four categories, following the literature on eliciting credit constraints and types of credit rationing (Guirkinger and Boucher 2008; Boucher et al. 2008; Boucher et al. 2009). We classify households to be "unconstrained" if they do not need credit or have enough resource for their business. Those households who are not borrowing either due to fear of being in debt or fear of losing their collateral in case of default are categorized as "risk rationed". Those households for whom credit market participation is sufficiently expensive due to high interest rates or the potential costs of accessing, processing, screening, and monitoring loans are classified as "transaction cost or price rationed". We then have an additional category for those mentioning "other reasons", including personal and religious reasons. As also shown from other data sources for Ethiopia, the most important constraint limiting rural households' credit uptake is risk rationing. About half the households are categorized as "risk rationed", so are not taking credit for reasons related to the production risk they face, which may involve fear of loss of assets or additional risk of having to bail out fellow group members in the case of group lending.

Table 3.3. Reasons for not taking credit from financial institution, percent of households not taking credit

Survey year	2011/12	2013/14	2015/16	All
Unconstrained	6	12	13	10
Risk rationed	52	44	50	49
Transaction cost and price rationed	20	14	14	16
Other reasons	22	29	23	25
Observations	3,389	3,181	3,211	9,781

Source: Authors' computation from LSMS-ISA data. Values represent percentage of non-borrowing households falling in each category.

4. ECONOMETRIC ESTIMATION RESULTS AND DISCUSSION

4.1. The Effect of Rainfall Uncertainty on Credit Uptake

In Table 4.1 we provide benchmark estimates of our main model of interest (equation 1 in Section 2.3), based on coefficient of variation as the measure of rainfall uncertainty. In column 1 of Table 4.1 we regress credit uptake as a function of only inter-annual rainfall variability. In column 2 we additionally control for last year's rainfall to account for income or related effects of recent rainfall. The coefficient of variation of rainfall is aggregated over the last ten years and, hence, is correlated with recent rainfall. Then, in the third and fourth columns we extend the empirical specification by adding household and community-level characteristics that may explain demand for agricultural credit. The estimates associated with rainfall variability in columns 2 to 4 remain stable, suggesting that rainfall uncertainty is almost uncorrelated with these household and community-level characteristics. Finally, in column 5 we provide estimates controlling for household fixed effects. Given that our measure of rainfall variability may not be sufficiently dynamic across time, these household fixed effects are expected to be conservative estimates (for comparison, model results with rainfall variability computed over five years are shown in Tables A3 and A4 in the Appendix).

Table 4.1. Impact of rainfall uncertainty, measured by coefficient of variation, on credit uptake

Explanatory variables	(1)	(2)	(3)	(4)	(5)
Coefficient of variation for annual rainfall for the last 10 years	-0.551***	-0.694***	-0.687***	-0.722***	-0.395**
	(0.135)	(0.160)	(0.164)	(0.159)	(0.171)
Log (last year rainfall in mm)		-0.044**	-0.045**	-0.048**	-0.018
		(0.019)	(0.020)	(0.020)	(0.033)
Log (age of household head)			0.018	0.017	-0.027
			(0.013)	(0.013)	(0.022)
Log (household average age)			-0.029**	-0.033**	-0.025
			(0.013)	(0.013)	(0.016)
Sex of household head (1=male)			0.032***	0.026***	0.036**
			(0.008)	(0.007)	(0.014)
Mother education (1=literate)			-0.050***	-0.047***	-0.054***
			(0.015)	(0.016)	(0.017)
Father education (1=literate)			0.020*	0.017	0.022*
			(0.012)	(0.012)	(0.012)
Household size			0.002	0.000	-0.002
			(0.002)	(0.002)	(0.003)
Log (tropical livestock unit)			0.005	-0.007	0.010
			(0.005)	(0.005)	(0.006)
Log (area measured in ha)				0.047***	-0.000
				(0.010)	(0.012)
Log (distance to the nearest market)				-0.015**	-0.019
				(0.007)	(0.016)
Access to microfinance (1=yes)				0.013	-0.004
				(0.012)	(0.013)
Household fixed effects	No	No	No	No	Yes
R-squared	0.005	0.007	0.014	0.022	0.525
Observations	10,623	10,623	10,543	10,519	10,408

Notes: Standard errors are clustered at enumeration area level and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 4.2 we repeat these empirical exercises, now using standard deviation of rainfall as an alternative measure of weather risk. We follow similar empirical specifications as in Table 4.1. The estimates in Tables 4 .1 and 4.2 show that rainfall uncertainty negatively and significantly affects uptake of agricultural credit. These effects are large and consistent across both measures of weather risk. The sizes of the effects are broadly stable and comparable across all specifications. The sizes of the effects in Tables 4.1 and 4.2 suggest that agricultural credit uptake is non-trivially responsive to rainfall variability. For instance, the estimates in Table 4.2 show that a 1 percent increase in the variability of rainfall (measured by standard deviation of rainfall) decreases uptake of (that is, demand for) agricultural credit by between 5 and 10 percentage points.

Besides the estimates on rainfall variability, Tables 4.1 and 4.2 provide additional estimates on the impact of recent rainfall spells. Theoretically, the effect of recent, e.g., last year's, rainfall on uptake of agricultural credit is ambiguous and depends on the purpose of taking the credit. If the purpose of the credit is mainly for purchase of agricultural inputs, e.g., fertilizer and improved seed, as seems the case for Ethiopian households (see Table 3.2), favorable rainfall spells may lead to increased productivity, which can be used to purchase agricultural inputs and, hence, reduce demand for credit. Similarly, in situations where credit is mainly used for consumption smoothing purposes, then positive rainfall shocks can reduce demand for consumption credit, while negative rainfall shocks may boost demand for credit. In our context, the most dominant purpose of credit seems to be the purchase of agricultural inputs (see Table 3.2). Consistent with this, the estimates in Table 4.1 show that the level of recent rainfall has a negative impact on demand for credit.

Table 4.2. Impact of rainfall uncertainty, measured by standard deviation, on demand for credit

Explanatory variables	(1)	(2)	(3)	(4)	(5)
Log (standard deviation for annual rainfall for the last 10 years)	-0.089***	-0.097***	-0.099***	-0.103***	-0.054**
	(0.019)	(0.020)	(0.021)	(0.020)	(0.025)
Log (last year rainfall in mm)		0.026	0.025	0.027	-0.016
		(0.017)	(0.017)	(0.018)	(0.032)
Log (age of household head)			0.019	0.019	-0.028
			(0.013)	(0.013)	(0.023)
Log (household average age)			-0.031**	-0.036***	-0.025
			(0.013)	(0.013)	(0.016)
Sex of household head (1=male)			0.032***	0.026***	0.036**
			(0.008)	(0.007)	(0.014)
Mother education (1=literate)			-0.050***	-0.047***	-0.055***
			(0.016)	(0.016)	(0.017)
Father education (1=literate)			0.021*	0.018	0.022*
			(0.012)	(0.012)	(0.012)
Household size			0.002	0.000	-0.002
			(0.002)	(0.002)	(0.003)
Log (tropical livestock unit)			0.005	-0.007	0.010
			(0.005)	(0.005)	(0.006)
Log (area measured in ha)				0.045***	-0.000
				(0.010)	(0.012)
Log (distance to the nearest market)				-0.017**	-0.018
				(0.007)	(0.016)
Access to microfinance (1=yes)				0.013	-0.005
				(0.012)	(0.013)
Household fixed effects	No	No	No	No	Yes
R-squared	0.009	0.010	0.018	0.026	0.525
Observations	10,623	10,623	10,543	10,519	10,408

Notes: Standard errors are clustered at enumeration area level and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 4.3 we consider inter-season rainfall variability, instead of inter-annual rainfall variability. This involves computing rainfall variability across seasons rather than across years. Panel A of Table 4.3 provides results based on inter-season variability for *meher* season, while Panel B provides corresponding results for *belg* season. Consistent with the estimates associated with inter-annual rainfall variability, the estimates in Table 4.3 show that inter-season rainfall variability negatively affects demand for agricultural credit. The effects are consistent across both seasons and the magnitude of the effect is broadly comparable across both seasons. However, rainfall variability in the *belg* season appears to have a more pronounced effect. This is plausible in the context of Ethiopia where most credit is used for input use in the main production (*meher*) season that immediately follows the *belg* season. Rainfall uncertainty during the *belg* season can give an important signal as to the favorability of the forthcoming production season. Farmer may rely on this signal in deciding on their *meher* input use and associated demand for credit.

Table 4.3. The impact of rainfall uncertainty, measured by inter-seasonal coefficient of variation, on demand for credit

	(1)	(2)	(3)	(4)	(5)
Panel A: Inter-season rainfall variability for *meher* season					
Coefficient of variation for the last 10 years	-0.278**	-0.309**	-0.316**	-0.304**	-0.308
	(0.122)	(0.131)	(0.133)	(0.129)	(0.219)
Recent rainfall spell	No	Yes	Yes	Yes	Yes
Household characteristics	No	No	Yes	Yes	Yes
Household fixed effects	No	No	No	No	Yes
R-squared	0.005	0.007	0.014	0.022	0.525
No. observations	10,623	10,623	10,543	10,519	10,408
Panel B: Inter-season rainfall variability for *belg* season					
Coefficient of variation for the last 10 years	-0.178***	-0.378***	-0.361***	-0.399***	-0.271**
	(0.067)	(0.105)	(0.105)	(0.099)	(0.134)
Recent rainfall spell	No	Yes	Yes	Yes	Yes
Household characteristics	No	No	Yes	Yes	Yes
Household fixed effects	No	No	No	No	Yes
R-squared	0.005	0.007	0.014	0.022	0.525
No. observations	10,623	10,623	10,543	10,519	10,408
Coefficient of variation for the last 10 years	-0.551***	-0.694***	-0.687***	-0.722***	-0.395**

Notes: Standard errors are clustered at enumeration area level and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Despite our focus on the rural sample of households, our data have an additional relatively ‘’urban’’ sample, those households living in enumeration areas defined as medium and major towns by the CSA of Ethiopia. Thus, we can employ these data to probe the robustness of our results and, hence, as a falsification test. A priori, we would expect the demand for credit to be more risk-elastic in the rural sample where production and livelihoods rely on rainfed agriculture. To confirm this, we estimate similar empirical models focusing on the urban sample. These results are given in Table A5 in the Appendix. These results confirm that the effect of rainfall uncertainty is statistically insignificant in the urban sample, implying that their demand for credit is unaffected by the weather risk in their environment.

4.2. Rainfall Uncertainty and Credit Rationing

A large literature attributes rural financial market failure to an imperfect information problem, which arises due to lenders’ lack of critical information needed to screen and monitor the credit-worthiness of potential borrowers (Stiglitz and Weiss 1981; Hoff and Stiglitz 1990). This type of information asymmetry leads to two fundamental problems in rural credit market: (i) adverse selection, a situation where lenders cannot identify creditworthy borrowers and discriminate against bad borrowers due to lack of information; and (ii) moral hazard, where lenders cannot observe and monitor the efforts and actions of borrowers once a loan is dispersed. Besides these costs driven by scarcity of information, working with poor rural communities that are dispersed over a large geographic area involves high transaction costs, making lending costly (Adams and Nehman 1979; Armedariz and Morduch 2010). In response to these information and cost problems, lenders resort to requiring collateral or group lending schemes that can provide borrowers the incentives to reduce the risk of failure to repay. The coexistence of these two hurdles in rural financial markets – the information asymmetry among lenders and borrowers, and the poor’s lack of collateral to pledge – leads to credit rationing (Conning and Udry 2007; Guirkinger and Boucher 2008; Boucher et al. 2008; Boucher et al. 2009; Armedariz and Morduch 2010).

Previous studies have employed direct elicitation methods to understand and quantify the prevalence and types of credit rationing. More specifically, households not participating in credit markets mention that they face one or more of the following types of credit rationing: quantity rationed, transaction cost rationed, and risk rationed (Guirkinger and Boucher 2008; Boucher et al. 2008; Boucher et al. 2009). Quantity rationing involves a situation where households' effective demand exceeds existing supply due to lack of collateral to access supplied loans or due to credit limits put forth by the lender. Thus, quantity rationing is mostly driven by supply-driven constraints. Transaction cost (or price) rationed households are those for whom credit market participation is sufficiently expensive due to high interest rates or the potential cost of processing, screening, and monitoring loans. Risk-rationing is demand-driven and involves voluntary exclusion from the credit market for reasons associated with the risks involved in credit participation, including the risk of indebtedness or potential loss of collateral in case of default.

In the context of Ethiopia, Mukasa et al. (2017) and Berhane and Abay (2018) show that risk-rationing is the most pervasive form and type of credit rationing. Table 3.3 shows this also to be true of our sample, with about half of households not borrowing either due to fear of being in debt or distress of losing assets in case of default. This implies that in situations where borrowers either lack the collateral required by lenders or operate in rainfed agriculture involving covariance production risk that may endanger their collateral, lenders' resort to requiring collateral or group lending schemes to address adverse selection and moral hazard problems. These requirements can drive potentially creditworthy borrowers from the market. When insurance markets to deal with covariance production risk are missing, these attributes of rural credit market introduce risk rationing problems that effectively limit household participation in rural credit markets.

In this section, we aim to empirically investigate the implication of rainfall uncertainty in explaining credit risk rationing. Given the share of households reporting to be risk-rationed, we particularly aim to explore the impact of rainfall uncertainty on farmers' risk aversion and associated risk-rationing in their demand for agricultural credit. We hypothesize that the environment in which rural households in Ethiopia operate and the associated production risks can contribute to risk-rationing in the credit market. We directly test this hypothesis by categorizing our sample by whether the household is participating in credit markets. Following the direct elicitation method commonly employed in the literature, we classify households by their reasons for not participating in the credit market (see Table 3.2). We then run simple multinomial logit regressions characterizing households' credit participation and credit rationing.

The marginal effects shown in Table 4.4 indicate that rainfall uncertainty significantly and positively predicts risk-rationing. Those households exposed to substantial rainfall variability are more likely to be risk-rationed in their quest for credit market participation. This confirms our hypothesis that production risk may lead to a specific type of credit rationing, which forces households out of credit markets and, hence, potentially into engaging in low-risk, but low-return, agricultural investments. Intuitively, these results corroborate our main estimates characterizing households' demand for credit by highlighting potential mechanisms for the low demand for credit. That is, given rural households' aversion to borrowing, rainfall uncertainty discourages demand for agricultural credit. These results corroborate recent attempts and interventions that relax rural households' credit constraints while also addressing production risks rural households face (e.g., Giné and Yang 2009).

Table 4.4. Marginal effects from a multinomial logit model characterizing credit participation and credit rationing

Explanatory variables	(1) Unconstrained or with credit access	(2) Risk-rationed	(3) Transaction-cost-price rationed	(4) Other reasons (e.g., personal issue)
Coefficient of variation for annual rainfall for the last 10 years	-0.988***	0.500***	0.512***	-0.024
	(0.124)	(0.151)	(0.103)	(0.128)
Log (last year rainfall in mm)	-0.000***	0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Log (age of household head)	-0.000	0.002***	-0.001**	-0.001
	(0.000)	(0.001)	(0.000)	(0.000)
Log (household average age)	-0.001	0.001	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.001)
Sex of household head (1=male)	0.039***	-0.036***	-0.003	0.000
	(0.010)	(0.012)	(0.009)	(0.010)
Household size	0.025***	-0.025**	-0.022***	0.021**
	(0.008)	(0.011)	(0.008)	(0.009)
Log (tropical livestock unit)	0.001***	0.002**	-0.001	-0.002*
	(0.000)	(0.001)	(0.001)	(0.001)
Log (area measured in ha)	0.004***	-0.007***	0.003***	0.000
	(0.001)	(0.003)	(0.001)	(0.002)
Log (distance to nearest market)	-0.000***	0.000***	0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Access to microfinance (1=yes)	0.010	0.031***	-0.021***	-0.020**
	(0.008)	(0.011)	(0.008)	(0.009)

Notes: Standard errors are given in parentheses. * p<0.10, **p<0.05, ***p<0.01.
Observations: 10,519.

4.3. Rainfall Uncertainty and Agricultural Investments

Finally, we investigate the direct effects of weather-related production risk on agricultural investments, distinguishing between productivity-enhancing agricultural investments, such as fertilizer, and defensive or loss-reducing investments, such as pesticides, herbicides, and fungicides. Intuitively, rainfall uncertainty may have divergent impacts on different types of agricultural inputs. In particular, following Karlan et al. (2011), let us consider two types of technologies: (i) defensive inputs (or hedging inputs), which have higher marginal products in less productive states of the world, and (ii) riskier productive inputs, like mineral fertilizer, which have higher marginal products in more productive states of the world. If we take rainfall uncertainty to represent an increased likelihood of lower productive states of the world, then we would expect to see, *ceteris paribus*, greater adoption of defensive investments in areas with greater rainfall uncertainty.

Table 4.5 shows that rainfall uncertainty negatively affects the propensity to adopt productivity-enhancing agricultural technologies, mainly chemical fertilizers. This is consistent with some previous studies showing negative impacts of weather risk on agricultural investments (Lamb 2003; Alem et al. 2010; Dercon and Christiaensen 2011). Our results also provide some evidence that part of this impact comes through deterred demand for agricultural credit. This evidence can be deduced from the shrinkage of the effect of rainfall variability when we control for credit take-up. Once we control for credit take-up, the effect of rainfall variability on the probability of investment declines substantially. These results highlight that smallholder exposure to production risk is an important constraint on the adoption of profitable agricultural technologies, and one which is likely to interact with other internal and external constraints, such as access to credit.[10]

Table 4.5. Impact of rainfall uncertainty on adoption of productivity-enhancing agricultural inputs

Explanatory variables	(1) Fertilizer use	(2) Fertilizer use	(3) Fertilizer use
Coefficient of variation for annual rainfall for the last 10 years	-1.774***	-1.658***	-1.136***
	(0.136)	(0.136)	(0.135)
Access to formal credit (1=yes)		0.208***	0.137***
		(0.017)	(0.016)
Log (last year rainfall in mm)			0.181***
			(0.017)
Log (age of household head)			0.171***
			(0.020)
Log (household average age)			-0.123***
			(0.018)
Sex of household head (1=male)			0.049***
			(0.011)
Mother education (1=literate)			-0.099***
			(0.025)
Father education (1=literate)			0.030*
			(0.017)
Household size			-0.003
			(0.002)
Log (tropical livestock unit)			0.088***
			(0.006)
Log (area measured in ha)			0.259***
			(0.010)
Log (distance to the nearest market)			-0.028***
			(0.005)
Access to microfinance (1=yes)			-0.000
			(0.010)
Constant	0.775***	0.746***	-0.932***
	(0.016)	(0.016)	(0.135)
R-squared	0.016	0.029	0.235
Observations	10,620	10,620	10,516

Notes: Standard errors are clustered at enumeration area level and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table 4.6 we provide evidence on the impact of rainfall uncertainty on defensive, or loss-reducing, agricultural inputs, including herbicides, fungicides, and other pesticides. Most commonly these defensive agricultural inputs are applied to reduce the loss associated with crop failure due to rainfall shocks, pests, and related crop diseases. Negative rainfall or temperature shocks are associated with the incidence of pests and crop diseases (e.g., Rosenzweig et al. 2001). In response to these dynamics in precipitation and temperature, farmers are expected to respond using various mechanisms and investments. These adaptive responses ranges from asset ownership to production decisions and orientations. For instance, Rosenzweig and Binswanger (1993) show that poor farmers exposed to substantial rainfall uncertainty tend to build and invest in assets less affected by rainfall.[11] More recently,

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[10] Several studies indicate that credit constraints are central limiting factors for the adoption of agricultural technologies in Africa (Croppenstedt et al. 2003; Moser and Barrett 2006; Giné and Klonner 2007; Zerfu and Larsen 2010; Abate et al. 2016). Other studies identify and highlight the role of farmers' internal constraints (Duflo et al. 2011; Abay et al. 2017).

[11] Similarly, several other studies show that farmers' crop choice and, hence, production decisions are affected by weather variability and rainfall shocks (e.g., Dercon et al. 1996; Amare et al. 2018).

Jagnani and Barrett (2018) show that maize farmers in Kenya increase their investment in defensive agricultural inputs (pesticides, herbicides and fungicides) in response to warmer temperatures. This implies that farmers adapt to warmer temperatures by investing in loss-reducing agro-chemical inputs. They also show potential trade-off between farmers' investment in productivity-enhancing agricultural inputs and defensive agricultural inputs.

Table 4.6. Impact of rainfall uncertainty on adoption of defensive agricultural inputs

Explanatory variables	(1) Agro-chemical use	(2) Agro-chemical use	(3) Agro-chemical use
Coefficient of variation for annual rainfall for the last 10 years	0.231**	0.313***	1.080***
	(0.109)	(0.109)	(0.112)
Access to formal credit (1=yes)		0.149***	0.112***
		(0.014)	(0.013)
Log (last year rainfall in mm)			0.202***
			(0.014)
Log (age of household head)			-0.009
			(0.017)
Log (household average age)			-0.021
			(0.015)
Sex of household head (1=male)			-0.027***
			(0.009)
Mother education (1=literate)			0.018
			(0.021)
Father education (1=literate)			0.022
			(0.014)
Household size			-0.003*
			(0.002)
Log (tropical livestock unit)			0.043***
			(0.005)
Log (area measured in ha)			0.235***
			(0.008)
Log (distance to the nearest market)			0.005
			(0.004)
Access to microfinance (1=yes)			-0.006
			(0.008)
Constant	0.164***	0.143***	-1.357***
	(0.013)	(0.013)	(0.112)
R-squared	0.000	0.011	0.169
Observations	10,623	10,623	10,519

Standard errors are clustered at enumeration area level and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results in Table 4.6 confirm the above hypotheses and evidence. Those households exposed to more variable rainfall are more likely to invest in defensive agricultural inputs, including herbicides, fungicides, and pesticides. Tables A6 to A8 in the Appendix provide separate estimates for each agro-chemical input. These estimates show that much of the overall story in Table 4.6 is driven by herbicide use, which is the most common agro-chemical applied in Ethiopia (see Table A1 in our data; also Tamru et al. 2017). This is intuitive in view of the adverse consequences of rainfall shocks and the role of these chemicals in reducing the chance of crop failure. These results are consistent with the broader adaptive strategies that farmers employ to cope with the consequences of climate change (e.g., Burke and Emerick 2016). Combining the insights from Tables 4.5 and 4.6, we see that rainfall uncertainty is driving the allocation of investment resources from productive-enhancing agricultural investments to defensive agricultural investments. As discussed in Jagnani and Barrett (2018), this trade-off between these types of agricultural investments may arise due to the production risk associated with uncertain rainfall or the financial constraints poor farmers in developing countries face. Overall, these results highlight the potential impact of uninsured weather variability in terms of conditioning the kinds of agricultural investments that smallholders make in different areas.

5. CONCLUDING REMARKS

Despite considerable theoretical discussion on the role of production risk in deterring demand for agricultural credit and discouraging investments with positive expected net returns, there exists limited empirical evidence for these linkages. In this paper, we have shown that rainfall variability dampens households' demand for agricultural credit. To uncover potential mechanisms, we show that rainfall variability is associated with credit risk-rationing and, hence, is a key determinant of the observed low uptake of agricultural credit in Ethiopia. We have also shown that rainfall variability is negatively associated with adoption of productivity-enhancing agricultural investments, such as fertilizers. In contrast, we find that rainfall variability encourages investments in defensive agricultural inputs, such as herbicides. These results imply that exposure to rainfall uncertainty may induce a shift in investments from higher-risk, but higher-return agricultural investments, such as fertilizer, to more defensively-oriented agricultural investments.

The evidence in this paper speaks to the literatures both on agricultural credit and on the uptake of profitable agricultural technologies in sub-Saharan Africa (Morris et al. 2007; Alem et al. 2010; Rashid et al. 2013; Sheahan and Barrett 2017; Abay et al. 2018b). Our results suggest that rainfall variability, a key source of risk in rainfed production systems, is an important factor in the low uptake of credit products and profitable agricultural technologies in the region. Our results support the credit literature's general assertion that smallholders' production risks, coupled with the absence of well-functioning insurance markets, stifles demand for credit by introducing risk rationing. Given the covariance of production risk in rainfed agriculture, this type of credit rationing mainly arises due to lenders' requirement for collateral or the additional risk to bail out fellow group members in most of the group lending schemes that most MFIs rely on. At the same, the inherent riskiness of rainfed agriculture poses a serious challenge to the sustainability and, hence, an existential threat to MFIs often mandated to serve the rural poor.

Our finding that rainfall uncertainty decreases fertilizer use, but increases defensive agricultural investments contributes to the evolving evidence on how rural farmers adapt and cope with the consequences of climate change (e.g., Burke and Emerick 2016; Jagnani and Barrett 2017). Beyond establishing and quantifying the impact of rainfall uncertainty on alternative types of agricultural investments, we also provide suggestive evidence on the potential mechanism for such strong effects. We show that part of the deterring effect of rainfall uncertainty on productivity-enhancing agricultural investments works by introducing credit risk rationing and, hence, stifling demand for credit. Overall, these results highlight the potential impact of uninsured weather risk in terms of deterring and allocating agricultural investments.

Intuitively, combining the implication of weather risk on demand for credit and the latter's implication on agricultural investment suggests that weather risk may induce poverty traps (see also Zimmerman and Carter 2003; Dercon and Christiaensen 2011). Those households with pervasive investment constraints coupled with production risk are less likely to make profitable investments and more likely to remain poor. For instance, Dercon (1996) shows that rural households in Tanzania are willing to forgo up to 20 percent of their income to avoid the production risk associated with some crops. Our study suggests the importance of complementary interventions that relax rural farmers' credit constraints while also addressing the production risks they face. Such complementary interventions are more challenging to design and implement, but the available evidence suggests that their payoffs may be particularly high in areas of erratic rainfall. Efforts to catalyze a rural transformation in sub-Saharan Africa's primarily rainfed smallholder production systems should incorporate these insights into the design and targeting of complementary investments in agricultural technologies, credit, and insurance markets.

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APPENDIX

Table A1. Descriptive statistics of analytical variables

Variables	Mean	Standard deviation
Household characteristics and resource		
Credit uptake from formal source, %	8.12	27.3
Age of household head, years	45.6	15.5
Household average age, years	25.9	12.6
Household gender, 0/1	0.74	0.43
Household head education (1=literate)	0.48	0.50
Household size, number	5.4	2.5
Tropical Livestock Unit (TLU)	4.0	10.19
Land area, ha	1.14	4.68
Distance to nearest market, km	67.88	48.9
Access to microfinance, 0/1	0.29	0.45
Agricultural Input uses		
Fertilizer (DAP or urea) use, 0/1	0.57	0.49
DAP, 0/1	0.37	0.48
Urea, 0/1	0.33	0.46
Agro-chemicals (herbicides, fungicide, or other pesticides), 0/1	0.22	0.42
Herbicides, 0/1	0.20	0.4
Other pesticides, 0/1	0.07	0.26
Fungicides	0.02	0.15
Rainfall and rainfall uncertainty measures		
Recent annual (last year’s) rainfall, mm	812	194
Average rainfall for the last 10 years, mm	833	194
Rainfall variability (CV), %	11.17	3.4
Standard deviation, mm	90.82	28.33
Observations across the three rounds	10,647	

Source: Authors computation from LSMS survey of 2011, 2013 and 2015. SD stands for standard deviation.

Table A2. Access to microfinance and rainfall uncertainty

Explanatory variables	(1)	(2)	(3)
Coefficient of variation for annual rainfall for the last 10 years	-0.310	-0.152	-0.208
	(0.446)	(0.519)	(0.529)
Log (last year rainfall in mm)			-0.110
			(0.095)
Log (distance to the nearest market)			0.040
			(0.025)
Constant	0.314***	0.184	0.743
	(0.085)	(0.166)	(0.667)
Region dummies	Yes	Yes	No
Zone dummies	No	No	Yes
Observations	10,611	10,611	10,566

Notes: The dependent variable in these regressions is an indicator variable for access to microfinance institutions. Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3. Impact of rainfall variability, based on coefficient of variation computed over five years, on demand for credit

Explanatory variables	(1)	(2)	(3)	(4)
Coefficient of variation for annual rainfall for the last 5 years	-0.427***	-0.579***	-0.569***	-0.580***
	(0.135)	(0.171)	(0.175)	(0.178)
Log (last year rainfall in mm)		-0.041**	-0.041*	-0.043*
		(0.021)	(0.021)	(0.022)
Log (age of household head)			0.016	0.016
			(0.013)	(0.013)
Log (household average age)			-0.027**	-0.031**
			(0.013)	(0.013)
Sex of household head (1=male)			0.034***	0.028***
			(0.008)	(0.007)
Mother education (1=literate)			-0.044***	-0.041**
			(0.016)	(0.016)
Father education (1=literate)			0.017	0.015
			(0.012)	(0.012)
Household size			0.001	-0.000
			(0.002)	(0.002)
Log (tropical Livestock unit)			0.006	-0.004
			(0.005)	(0.005)
Log (area measured in ha)				0.043***
				(0.010)
Log (distance to the nearest market)				-0.014*
				(0.007)
Access to microfinance (1=yes)				0.018
				(0.012)
Household fixed effects	No	No	No	No
R-squared	0.003	0.004	0.012	0.019
Observations	10,623	10,623	10,544	10,520

Notes: In this table, rainfall variability is measured using the coefficient of variation computed over the last five years. Standard errors are clustered at enumeration area level and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4. Impact of rainfall variability, based on standard deviation computed over five years, on demand for credit

Explanatory variables	(1)	(2)	(3)	(4)
Log (standard deviation for annual rainfall for the last 5 years)	-0.044***	-0.045***	-0.044***	-0.046***
	(0.016)	(0.016)	(0.016)	(0.016)
Log (last year rainfall in mm)		0.004	0.004	0.002
		(0.017)	(0.017)	(0.019)
Log (age of household head)			0.019	0.019
			(0.013)	(0.013)
Log (household average age)			-0.030**	-0.034***
			(0.013)	(0.013)
Sex of household head (1=male)			0.034***	0.028***
			(0.008)	(0.007)
Mother education (1=literate)			-0.044***	-0.041**
			(0.016)	(0.016)
Father education (1=literate)			0.019	0.017
			(0.012)	(0.012)
Household size			0.001	-0.000
			(0.002)	(0.002)
Log (tropical Livestock unit)			0.005	-0.005
			(0.005)	(0.005)
Log (area measured in ha)				0.044***
				(0.010)
Log (distance to the nearest market)				-0.014*
				(0.007)
Access to microfinance (1=yes)				0.018
				(0.012)
Household fixed effects	No	No	No	Yes
R-squared	0.003	0.004	0.011	0.019
Observations	10,623	10,623	10,544	10,520

Notes: in this table rainfall variability is measured using the coefficient of variation, computed over the last five years. Standard errors are clustered at enumeration area level and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5. Impact of rainfall uncertainty on demand for credit for the urban sample

Explanatory variables	(1)	(2)	(3)	(4)	(5)
Coefficient of variation for annual rainfall for the last 10 years	0.728	0.627	0.576	0.415	0.143
	(0.707)	(0.666)	(0.599)	(0.426)	(0.404)
Log (last year rainfall in mm)		-0.034	-0.038	-0.046	0.122
		(0.038)	(0.037)	(0.036)	(0.074)
Log (age of household head)			0.050**	0.045*	-0.022
			(0.024)	(0.023)	(0.033)
Log (household average age)			-0.021	-0.015	0.053
			(0.019)	(0.019)	(0.044)
Sex of household head (1=male)			-0.001	-0.003	-0.017
			(0.011)	(0.012)	(0.030)
Mother education (1=literate)			-0.023	-0.020	-0.008
			(0.014)	(0.015)	(0.020)
Father education (1=literate)			0.022*	0.021	-0.007
			(0.013)	(0.013)	(0.017)
Household size			0.005*	0.005*	0.011
			(0.003)	(0.003)	(0.010)
Log (Tropical Livestock Unit)			0.103**	0.066	0.029
			(0.043)	(0.041)	(0.034)
Log (area measured in ha)				0.184**	-0.055***
				(0.074)	(0.021)
Log (distance to the nearest market)				0.005	-0.007
				(0.006)	(0.014)
Access to microfinance (1=yes)				0.006	-0.006
				(0.018)	(0.011)
Household fixed effects	No	No	No	No	Yes
R-squared	0.011	0.012	0.049	0.067	0.673
Observations	2,369	2,369	2,368	2,343	2,148

Notes: In this table, our sample consists of urban households, i.e., those living in major towns and cities. Standard errors are clustered at enumeration area level and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6. Effect of rainfall variability on herbicide use

Explanatory variables	(1) Herbicide use	(2) Herbicide use	(3) Herbicide use
Coefficient of variation for annual rainfall for the last 10 years	0.264**	0.350***	1.212***
	(0.117)	(0.117)	(0.122)
Access to formal credit (1=yes)		0.153***	0.123***
		(0.015)	(0.014)
Log (last year rainfall in mm)			0.232***
			(0.015)
Log (age of household head)			-0.014
			(0.019)
Log (household average age)			-0.015
			(0.016)
Sex of household head (1=male)			-0.036***
			(0.010)
Mother education (1=literate)			0.019
			(0.023)
Father education (1=literate)			0.022
			(0.015)
Household size			-0.004
			(0.002)
Log (tropical livestock unit)			0.043***
			(0.005)
Log (area measured in ha)			0.228***
			(0.009)
Log (distance to the nearest market)			0.005
			(0.005)
Access to microfinance (1=yes)			-0.000
			(0.009)
Constant	0.174***	0.151***	-1.566***
	(0.014)	(0.014)	(0.122)
R-squared	0.001	0.012	0.154
Observations	9,543	9,543	9,485

Notes: the outcome variable in the above regressions is an indicator variable for those households using herbicides. Standard errors are clustered at enumeration area level and given in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A7. Effect of rainfall variability on fungicide use

Explanatory variables	(1) Fungicide use	(2) Fungicide use	(3) Fungicide use
Coefficient of variation for annual rainfall for the last 10 years	0.039	0.043	0.065
	(0.046)	(0.046)	(0.052)
Access to formal credit (1=yes)		0.007	0.003
		(0.006)	(0.006)
Log (last year rainfall in mm)			0.006
			(0.007)
Log (age of household head)			-0.006
			(0.008)
Log (household average age)			-0.002
			(0.007)
Sex of household head (1=male)			0.001
			(0.004)
Mother education (1=literate)			0.011
			(0.010)
Father education (1=literate)			0.001
			(0.006)
Household size			0.002*
			(0.001)
Log (tropical livestock unit)			0.000
			(0.002)
Log (area measured in ha)			0.021***
			(0.004)
Log (distance to the nearest market)			0.001
			(0.002)
Access to microfinance (1=yes)			-0.008**
			(0.004)
Constant	0.022***	0.020***	-0.016
	(0.005)	(0.005)	(0.052)
R-squared	0.000	0.000	0.008
Observations	9,543	9,543	9,485

Notes: the outcome variable in the above regressions is an indicator variable for those households applying fungicides. Standard errors are clustered at enumeration area level and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8. Effect of rainfall variability on use of other types of pesticides

Explanatory variables	(1) Other types of pesticides use	(2) Other types of pesticides use	(3) Other types of pesticides use
Coefficient of variation for annual rainfall for the last 10 years	-0.125*	-0.117	-0.409***
	(0.075)	(0.075)	(0.084)
Access to formal credit (1=yes)		0.015	-0.000
		(0.010)	(0.009)
Log (last year rainfall in mm)			-0.024**
			(0.011)
Log (age of household head)			-0.010
			(0.013)
Log (household average age)			-0.005
			(0.011)
Sex of household head (1=male)			0.018***
			(0.007)
Mother education (1=literate)			0.001
			(0.016)
Father education (1=literate)			0.000
			(0.010)
Household size			0.003**
			(0.001)
Log (tropical livestock unit)			0.005
			(0.004)
Log (area measured in ha)			0.025***
			(0.006)
Log (distance to the nearest market)			-0.035***
			(0.003)
Access to microfinance (1=yes)			-0.016***
			(0.006)
Constant	0.086***	0.084***	0.420***
	(0.009)	(0.009)	(0.084)
R-squared	0.000	0.001	0.026
Observations	9,543	9,543	9,485

Notes: The outcome variable in the above regressions is an indicator variable for those households using other types of pesticides. Standard errors are clustered at enumeration area level and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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