Climatic Variability, Risk Diversification, and Vulnerability: Cases from Rural Ethiopia

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Contents

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1 Introduction

Households in poor or remote areas live under inherently uncertain conditions. Climate change and the destabilisation of weather patterns can directly threaten the well-being and long-term development prospects of households in poverty.

Traditionally, much focus has been on quantifying the negative impacts of variability in climate on agricultural production using quantitative crop simulation modelling or statistical time series. However, it remains difficult to rely on direct quantitative estimates due to the historically poor agricultural data for Africa (Lobell, Burke, Tebaldi, Mastrandrea, Falcon & Naylor 2008). Instead, this paper assumes a micro-level perspective by investigating the behavioural responses of households to shifts in climate and the uncertainty which arises.

There exists only a rigid understanding of the dynamics and motivations at work when households respond to climate risk. The purpose of this paper is two-fold. First, to shed light on the strategies agriculturally-dependent households are taking to diversify risk and cope with climatic variability. Second, if certain strategies seem more appealing than others, to analyse the direct consequences of such responses on the long-term resilience of households to climate change.

GIS software is used to calculate the coefficient of variation of precipitation, which emulates income uncertainty, for various districts (*woredas*) in Ethiopia. Greater climate variability is found to be significant in explaining increases in livestock units owned by households and decreases in early-stage expenditure on fertilisers.

2 Background

Sub-Saharan Africa (SSA) remains largely dependent on rain-fed agriculture, comprising approximately 40% of GNP and serving as the main source of income for 70% of workers (Fields 2005). Coupled with limited opportunities for livelihood diversification and capital constraints, this dependence makes many households vulnerable to a more variable and extreme climate (Eriksen, Brown & Kelly 2005).

The impact of climate change will vary across agroecological regions in Africa (IPCC 2014). Areas which currently receive significant rainfall, such as equatorial rain belts, will experience increases in precipitation, while subtropical dry zones will receive even less (IPCC 2013, Schlenker & Lobell 2010). Furthermore, the intensity and frequency of extreme temperature and precipitation events is expected to increase across all regions (IPCC 2013).

Shifting precipitation patterns — more floods and, almost paradoxically, more droughts — will place enormous stress on households in this region. Longer and more frequent dry spells expected in semi-arid conditions during growing seasons decrease crop yields significantly (Barrios, Bertinelli & Strobl 2010, Barron, Rockstrom, Gichuki & Hatibu 2003, Semenov & Porter 1995). Higher temperatures lead to higher rates of evapotranspiration[2], which can dramatically reduce soil moisture needed for crop growth (Assan, Caminade & Obeng 2009). Overall, both inter and intraseasonal variations in temperatures and precipitation stand to have a considerable negative impact on cereal yields in East Africa (Rowhani, Lobell, Linderman & Ramankutty 2011).

On the ground, uncertainty over future weather conditions has been shown to lower the *ex ante* subjective well-being of farmers in Ethiopia (Alem & Colmer 2013). Intuitively, farmers must make decisions many months in advance; uncertainty over the arrival of rainfall seasons complicates farm-level

[2]Evapotranspiration is the sum of surface evaporation and plant transpiration; a central component of the Earth's water cycle.

decisions (Assan et al. 2009, Rowhani et al. 2011). Leaving insufficient time for land preparation, or planting too early or too late, can have disastrous consequences for crop yields. A volatile climate can make cross-seasonal decisions — how long to fallow fields for, which crops to grow, how many acres to plant — considerably more complex (Schlenker & Lobell 2010, Paavola 2008).

How households view and cope with this risk and uncertainty is central to the literature and to the analysis. Games which include only a remote possibility of minor losses result in extremely risk averse behaviour among poor farmers (Yesuf & Bluffstone 2009). This may prevent households from undertaking investments which are profitable over time but may not yield immediate rewards (Rosenzeig & Binswanger 1993). For instance, diversifying into plots of land with different risk attributes or growing cash crops alongside staple crops can help farmers avoid financial risks associated with rain-fed agriculture (McCloskey 1976), but may not generate the immediate rewards needed to incentivise adoption. This is exacerbated under the presence of missing or imperfect markets, which constrain the ability to mitigate downside risk (Yesuf & Bluffstone 2009). Examples include poor opportunities for credit, the lack of affordable — or altogether non-existent — insurance schemes, and very rigid or thin labour markets. A further example is the low adoption rate in SSA of proven intensification methods such as fertiliser application. Despite requiring little upfront investment, rates of fertiliser use are still low. This may be due to doubts over its efficacy or in the inability (or unwillingness) of farmers to put away small sums of money to save and invest into fertiliser (Duflo, Kremer & Robinson 2011).

Several other mechanisms for farmers to cope with climate uncertainty exist. Diversifying sources of income can help farmers spread the risk of climate change, smooth consumption, and at least partially insure against shocks (Dercon 2005). Livestock, where suitable, can serve as potential buffers for shocks to agricultural production (Herrero, Grace, Njuki, Johnson, Enahoro, Silvestri & Rufino 2013, Hahn, Riederer & Foster 2009). However, expansions in livestock size are often limited due to the scarcity of suitable grazing lands.

There is a growing tendency for farmers to diversify into off-farm activities to supplement farm-based incomes. For many, petty trade, especially among women, is the predominant form of livelihood diversification, with weaving and the sale of cooked foods being the most common items sold (Assan et al. 2009). Households in poverty often do not specialise and actively undertake multiple on- and off-farm occupations, such as livestock rearing, the sale of goods, and employed labour, on top of growing crops for subsistence (Banerjee & Duflo 2007). Additionally, environmentally-induced migration, such as a household member moving to urban areas in search of more reliable sources of income, can introduce remittances into income profiles of households and rural economies (van der Geest 2004). With the advent and rising popularity of mobile banking in Africa, such coping strategies are becoming more and more viable.

3 Data

Data from 15 villages across Ethiopia, representing a variety of agroecological zones, have been drawn from the Ethiopia Rural Household Survey (ERHS)[3]. The survey covers seven rounds between 1994-2009. Within villages, stratified random sampling was used based on the gender of household heads (IFPRI 2011). This paper uses only the most recent iterations (2004-2009) due to completeness of relevant data, creating a two-period panel dataset. This is still, however, sufficient to control for individual heterogeneity. Importantly, the attrition rate is low: approximately 1.3% per annum. Included within

[3]For a map of survey zones, regions, and other descriptive characteristics of Ethiopia, see Appendix A.

Table 1: Average annual precipitation across *woredas* (districts)

District (*woreda*)	Mean (mm)	SD	CV
Adaa	950.8	116.9	98.63
Ankober	1163.8	140.5	97.63
Bako Tibe	1630.9	218.1	91.69
Basona Worena	665.9	85.34	101.7
Boloso Sore	1166.2	146.4	63.25
Bugna	992.8	174.8	125.0
Bule	668.7	93.57	106.3
Cheha	1158.7	139.7	87.65
Daramalo	1076.5	209.5	63.18
Dodota	909.4	103.9	104.8
Enemay	1357.1	128.1	102.1
Jimma Somodo	1532.2	187.0	74.70
Kedida Gamela	1144.9	127.1	77.68
Kersa	562.7	96.30	94.29
Saesi Tsaedamba	451.7	99.19	145.2
Shashemene Zuria	1115.9	138.5	72.44
Tiyo	969.9	122.8	95.06

the survey is data on agricultural inputs and outputs, household characteristics (education, health, demographics), assets and consumption expenditures, and engagement in other economic activities.

Monthly precipitation and temperature data since 1989 has been calculated at the village-level using 0.5×0.5 resolution gridded weather data ($\approx$55.6km $\times$ 55.6km grids at the equator) from the Climatic Research Unit (CRU) at the University of East Anglia (Harris, Jones, Osborn & Lister 2014). Using GIS software, the data has been merged and interpolated onto a map of the various *woredas* (districts) in Ethiopia to match the locations where household surveys have taken place.

4 Empirical Specification and Methodology

This paper aims to isolate the impact of climatic variability on household investment decisions and on choices concerning economic activity. Climatic variability generates uncertainty over future weather conditions and shocks. The heavy dependence on rain-fed agriculture for subsistence directly links this variability to household income uncertainty. Thus, I explore the significance of climatic variability in explaining changes in the following behaviours and investments of a household: (i) livestock units owned[4], (ii) total farming area (in hectares), (iii) fertiliser and improved seed expenditure (agricultural intensification) , (iv) propensity to engage in trading or selling of goods (non-farm economic activities), and (v) on the likelihood that a household receives remittances from outside the village (migration of a family member). In the discussion, I analyse how these responses might influence the long-term susceptibility of households to climate change. Without loss of generality, I focus on the responses of the

[4]For comparison across different species, livestock numbers are calculated in tropical livestock units (TLU). This compares the ratio of metabolic weights across different species. The basal metabolic rate captures energy expenditure per unit body weight per unit time (kcal/weight/day), and is approximated by $kg^{0.75}$ (Kleiber 1947), where kg is the weight in kilograms of the animal. I standardise 1 TLU as one cattle with a body weight of 250kg. One chicken $\approx$ 1.5kg $\Rightarrow$ 1.35kg metabolic weight $\approx$ 0.025 TLU.

Table 2: Summary statistics

Variable	Mean	SD	Observations
Climate variables			
Climatic variability	97.50	22.15	2178
Temperature (C) (Month of survey)	20.58	4.429	2178
Precipitation (mm) (Month of survey)	113.8	77.80	2178
Rainfall shock	0.0803	0.2719	2178
Household variables			
Highest completed education			
No formal schooling	0.3770	0.4847	2594
Primary school education	0.3161	0.4650	2594
Secondary school education	0.1981	0.3987	2594
High school & above	0.1087	0.3113	2594
Economic status and activity			
Log consumption expenditure	0.5054	1.395	2168
Total livestock units	2.058	2.862	2178
Total farming area (hectares)	2.862	2.451	2030
Engage in selling of goods	0.2043	0.4033	2178
Engage in trading of goods	0.2001	0.4002	2178
Purchase fertiliser	0.3338	0.4717	2178
Proportion receiving remittances	0.4441	0.4970	2175
Subjective circumstances			
Richest in village	0.0624	0.2420	2163
Richer than most	0.0758	0.2648	2163
About average	0.5261	0.4994	2163
Poorer than most	0.1752	0.3802	2163
Poorest in village	0.1604	0.3671	2163

head of each household surveyed, as they are the most likely to make key investment decisions. The work of Colmer (2013) and Alem & Colmer (2013), who investigate similar data on different variables, has been widely consulted in the construction of the empirical specification and methodology of this paper.

Climate variability is proxied by the coefficient of variation (CV) of precipitation. The CV has been calculated over a 20-year period for both rounds of the survey data used. The CV is simply the standard deviation divided by the mean of the series. Importantly, it is scale invariant, which allows comparisons to be made across regions with differing climates, which likely influences household incomes.

Many factors may influence an increase in total livestock units, an extensification of agricultural production or a shift into non-farm economic activities. These factors are diverse and often household or community specific. Considerable care must be taken in establishing adequate controls to ensure results are absent of omitted variable biases.

First, precipitation and temperature measurements for the month and year in which the household survey took place are included to capture current climate conditions. A rainfall shock dummy is created to appear in instances where precipitation is at least one standard deviation below the long-run mean. Recent shocks must be controlled for as they are likely to be correlated with our calculated coefficient of variation.

Secondly, other household and production-related shocks in the past 5 years have been controlled for. Dummies for crop damage resulting from high winds, frost, floods, or disease have been included. Other shocks which may directly influence the asset portfolio or economic activity of a household — illness, a death in the family, pests, food price spikes, or theft — have also been accounted for.

Thirdly, dummies covering the subjective circumstances of a household (in comparison to other households in the village) are included, as they may be correlated with growth in economic indicators such as livestock units or agricultural output[5]. Other societal factors such as trust, how honest other members of the village are, and whether individuals believe they have the power to determine their outcome in life are included in the model. All these factors may reflect the willingness of households to make investments into certain assets or engage in other forms of economic activity due their perceived risk-reward trade-off. Religious or spiritual beliefs concerning fate may prevent or delay efforts to adapt and cope with climate uncertainty, while low levels of trust in a village may disincentivise the selling or trading of goods.

Lastly, a household's access to social capital and informal sources of insurance, proxied by the network size of individuals a household can rely upon in times of need[6], and whether a household has been successful in obtaining a loan in the past year are also included. This controls for differing credit constraints across villages and households, which might prevent the uptake of more advanced production technologies or the start of microenterprises. A full list of controls and summary statistics can be found in Appendix B.

Using the above variables, a series of fixed-effect regressions are run on the various dependent variables highlighted at the start of this section. Huber-White cluster-robust standard errors at the village level are used to account for potential serial correlation within villages. As circumstances are household and village-specific, this fixed-effects approach is necessary to account for any time-invariant unobserved individual heterogeneity (α_i). The model can be specified as follows:

$$y_{it} = \beta_1 \mathrm{CV}_{vt} + \beta_2 \xi_{vt} + \delta_1 X_{it} + \alpha_i + \gamma_m + \gamma_t + \varepsilon_{it}$$

where index i represents individual households[7], v village, m month and t year. Year and month fixed effects (γ_m and γ_t) are included to control for outside factors which may influence the observed data: economic development, shifts in macroeconomic policy, or any other related market shocks. Monthly fixed effects capture seasonal variation. In the above specification, CV is the village-level coefficient of variation of precipitation and ξ represents a dummy for whether the village has experienced a recent rainfall shock. X represents household controls, which have been given above. ε represents any time-varying random shock experienced by a household over time.

A non-linear maximum-likelihood approach is used to analyse the marginal effect of variability on the propensity of households to engage in non-farm economic activities and on the likelihood that they receive remittances. Household-specific effects cannot easily be swept out using a Probit model, due

[5]An emerging literature analyses the reliability of subjective measures concerning status, wealth, or well-being due to 'priming'. For more, see Sgroi, Proto, Oswald & Dobson (2010). These indicators remain robust enough to be used as broad controls.

[6]Motivated by the work done by Alem & Colmer (2013).

[7]NB: To avoid any confusion, individuals and households are used inter-changeably throughout, as all data has been aggregated to create sets of 'individual households'.

to the ‘incidental parameters problem’ (Neyman & Scott 1948, Hsiao 2003)[8]. For a random-effects (Probit) model to be appropriate, there must be independence between unobserved individual heterogeneity α_i and our independent regressors X — a very strong assumption, which is unlikely to hold. Therefore, a conditional fixed-effects Logit model, which operates in a way similar to a within transformation (Chamberlain 1980), is used[9]. Ideally, a panel Tobit model would have been used to account for left-censoring in variables such as fertiliser expenditure or non-farm earnings. Unfortunately, the heavy assumptions of random effects (independence between unobserved effects and our covariates) and normally distributed homoskedastic errors needed for consistent estimation under such a model proved ill-suited for this analysis.

It must be noted that the gridded weather data used is observational and based on reported results from weather stations in Ethiopia. The number of stations in Ethiopia is very limited and not evenly distributed. Recent advances in reconstructed gridded weather data using global climate models have helped overcome limitations from poor observational data (Auffhammer, Hsiang, Schlenker & Sobel 2013); unfortunately, the high fixed cost and technical detail associated with transforming such data did not make it amenable to this particular study. Thus, the placement of weather stations may be correlated with agricultural output, as stations tend to be placed in more agriculturally productive areas. Therefore, it is very likely that relying on observational data creates systematically upward biased results. This caveat must be kept in mind when judging the following presented results.

5 Results and Discussion

5.1 Livestock

Livestock can buffer against adverse whether shocks and can serve as a source of emergency income. 32.3% of households cite the sale of animals as their main source of funding in times of need[10]. If there is growing uncertainty about future crop yields and weather conditions, it might be plausible to expect a transition into households owning more livestock units as they are less sensitive to climate fluctuations and can act as insurance in incidences of crop failure. Table 3 shows a one standard deviation increase in climate variability corresponds to an increase of ≈ 0.6596 tropical livestock units, or roughly a 32% increase in the portfolio of livestock units owned on average per household. Seo (2010) uses household surveys across 11 African countries to simulate changes due to climate change, likewise finding a greater proportion of land being utilised for livestock as animal numbers increase in this area.

Prima facie this has considerable implications for long-term environmental conditions. Small average land sizes and sparse opportunities to expand grazing areas can quickly lead to overgrazing and land degradation. 45% of households surveyed cited a lack of adequate grazing land. Biodiversity loss and the irreversible loss of topsoil from induced desertification pose serious concerns for households whose incomes are dependent on the land (Adhikari 2013, Jacobs, Wilson & Morrison 2000). However, households with more livestock are more likely to be engaging in soil conservation efforts[11], which may partially counter-act these long-term negative consequences. Disentangling whether this is a preventative *ex ante* or adaptive *ex post* response shows that conservation efforts tend to begin only *after* land quality

[8]Under limited dependent variable models, fixed effects cannot be treated as incidental parameters without biasing our coefficients.

[9]A Hausman test indicates that individual-specific effects exist. Therefore, using a standard unconditional Logit model would yield inconsistent estimates.

[10]Table C.1 in Appendix C.

[11]Table C.2 in Appendix C.

Table 3: Regression results on TLU

Dependent variable: **Tropical Livestock Units**	FE (1)	FE (2)
Climate Variability	0.0286	0.0297^{**}
	(0.0270)	(0.0138)
Rainfall Shock	0.0627	-0.1403
	(0.1621)	(0.2158)
Average Temperature (Month of survey)	-0.0007	-0.0027
	(0.0078)	(0.0112)
Average Rainfall (Month of survey)	-0.0002^{*}	-0.0002^{*}
	(0.0001)	(0.0001)
Log Consumption Expenditure	0.0623	0.0274
	(0.0352)	(0.0325)
Total Livestock Units (1 year ago)	0.5006^{***}	0.4367^{***}
	(0.0875)	(0.0981)
Livestock Units Bought (Past year)	0.7182^{***}	0.7826^{***}
	(0.2127)	(0.1932)
Time dummies	Yes	Yes
Village dummies	-	-
Individual fixed effects	**Yes**	**Yes**
Household controls	No	**Yes**
N	2041	1827
Adjusted R^2	0.2568	0.4469

Huber-White cluster-robust standard errors at the village-level reported in parentheses. Significance levels given by: $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

deteriorates, for both grazing and cultivated land[12]. Therefore, land degradation concerns still remain and are likely to intensify with more livestock.

A closer investigation into variability impacts on grazing vs. non-grazing animal numbers may be more suitable. Table 4 lists animal-specific regression results. Interestingly, climate variability is not significant in explaining changes in the number of large grazing animals (dairy cattle and draft animals). Purchasing larger animals requires much more capital relative to the total assets owned by a household than purchasing smaller animals. Given that households tend to be highly risk averse, it is not surprising that large animal numbers might remain relatively stable over time in an uncertain environment[13]. Potential credit constraints aside, the upfront risk of making a large investment into cattle or draft animals may outweigh the possible rewards (sustained milk production for consumption or sale; use of animals for transport of harvest or ploughing of fields). The high prevalence of the tsetse fly disease *Gendi* amongst cattle in Ethiopia (internationally known as *Trypanosomiasis*) may be a factor contributing to the reluctance of households to make such large investments when responding to climate uncertainty (Morrison, Murray & McIntyre 1981, Denu, Asfaw & Tolossa 2012). 42% of households indicated their livestock suffered from some disease in the past year, of which *Gendi* contributed to 44% of cases. Alternatively, large livestock may be viewed as 'safe assets', which can lead to hoarding behaviour. If

[12] Table C.2 in Appendix C.

[13] Time controls are very insignificant, indicating little or no trend over time. Coupled with very similar means across periods, this supports the claim of relatively constant large animal numbers.

Table 4: Animal-specific regression results

Dependent variable:	**Chickens**	**Dairy**	**Goats & Sheep**	**Draft**
	(1)	(2)	(3)	(4)
Climate Variability	-0.0067^{***}	0.0013	0.0258^{**}	0.0081
	(0.0015)	(0.0108)	(0.0115)	(0.0092)
Rainfall Shock	0.0045	0.1961	-0.2776^{*}	-0.0038
	(0.0217)	(0.1500)	(0.1480)	(0.1472)
Average Temperature (Month of survey)	-0.0002	-0.0245^{***}	0.0191^{**}	0.0038
	(0.0012)	(0.0092)	(0.0079)	(0.0056)
Average Rainfall (Month of survey)	0.0000	-0.0001	-0.0001^{*}	0.0001^{*}
	(0.00001)	(0.1500)	(0.0001)	(0.0001)
Log Consumption Expenditure	0.0030	-0.0146	0.0109	0.0327^{**}
	(0.0028)	(0.0163)	(0.0215)	(0.0142)
Total Livestock Units (1 year ago)	0.0040	0.1364^{***}	0.1622^{***}	0.0838^{***}
	(0.0028)	(0.0414)	(0.0510)	(0.0209)
Livestock Units Bought (Past year)	0.0121	0.3048^{**}	0.2626^{**}	0.1864^{***}
	(0.0126)	(0.1221)	(0.1200)	(0.0702)
Time dummies	Yes	Yes	Yes	Yes
Village dummies	-	-	-	-
Individual fixed effects	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes
N	1825	1825	1824	1824
Adjusted R^2	0.1379	0.1970	0.2527	0.1917

Fixed-effect ordinary least squares with cluster-robust standard errors reported in parentheses. Dairy animals include various breeds of cattle; draft animals include donkeys, horses, and camels.

households become unwilling to sell or trade cattle or draft animals, few opportunities for an expansion in units owned beyond the natural reproductive rate may exist.

Smaller animals are much more liquid assets. They can more readily be consumed, bought, or sold in response to climate shocks or uncertainties. Climate variability has a significant impact on the number of chickens, goats, and sheep (Table 4: (1) and (3)). The negative coefficient on chicken numbers may suggest they are being sold or traded to make investments into other assets or livestock (or eaten). A one standard deviation increase in climate variability increases goat and sheep numbers by an estimated 44% (an increase of approximately three goats or sheep above a household average of five to seven units owned). This difference between large and small animals highlights a key empirical difficulty of the paper: disentangling short and long-term responses to climate variability. While investing in cattle might provide better protection over a long time frame (a relatively stable and continual source of nourishment or income), owning more goats or sheep could act as a better short-term insurance mechanism against shocks as they more liquid. Short-term responses are likely to dominate (and might help explain differences in reported significance) as households in poverty often exhibit high levels of risk aversion and myopia in decision making. When asked how much households must be given (in birr) to wait a set period of months instead of receiving 100 birr today, a simple calibration[14] yields an average

[14] NB: Questions on time discounting were only introduced in the most recent iteration of the household survey, 2009. These values should not be interpreted literally, but should serve as rough indicators of temporal preferences. The simple model $U_t = u(\pi_t) + \beta\left[\delta\, u(\pi_{t+1}) + \delta^2\, u(\pi_{t+2})\right]$ was used, where t is months and π is the required subjective payoff. Mean values given by: $\bar{\pi}_{t+1} \approx 457.97$ and $\bar{\pi}_{t+2} \approx 596.16$.

short-term discount factor of $\beta \approx 0.2824$ and long-term discount factor of $\delta \approx 0.7682$. A cautionary note: surveys took place during the dry season, and it is likely that time impatience is overstated due to circumstantial difficulties associated with the dry season. Regardless, this indicates strong present-biased preferences among households and therefore adds weight to the argument that households are responding to climate uncertainty first based on short-term incentives.

One last concern is the relative feed intensity of smaller animals compared to their larger counterparts. The basal metabolic rate of smaller animals is considerably higher in proportion to overall body weight than large animals. The availability of feed is already an enormous issue in rural areas, with dummies for price shocks having a significant negative impact on units owned[15]. Greater variability in climate may cause more volatility in feed prices, and may bring into question the viability of an expansion in livestock size as a long-term strategy to deal with climate uncertainty. Well-connected households can use forms of social capital (borrowing crop residues from a trusted neighbour to substitute as feed) to smooth out price shocks. However, such an informal insurance mechanism is unlikely to be robust, as availability of even the cheapest forms of feed such as crop residues are themselves dependent on weather conditions.

5.2 Land area

A larger land area can accommodate more livestock and can increase total potential agricultural output. Likewise, diversifying into planting more crops with varying sensitivities to climate (for instance, less water intensive crops) or by growing cash crops to boost household income are possible strategies to cope with climate uncertainty. In reality, however, this may be very difficult. Competition over land is fierce and often based on paternal or hierarchical ties. With little formal titling, acquiring land to expand growing or grazing areas becomes tremendously complicated. Instead, increases in cultivated or grazed land may result through deforestation or other alterations to natural vegetation. This leads to similar risks associated with land degradation stated earlier. Table 5 indicates that variability in climate does not significantly explain variations in total farming area across time, although our model explains only a small portion of overall variation. This is likely attributed to the fact that a vast majority of households have not experienced a positive or negative change in land size: approximately 70% of households state that their current land size is the same as five years ago. Of those that witnessed a change, 23% cited this was due to land inheritance or transfer to/from a relative, while almost 60% indicated this was due to a sharecropping agreement with a neighbour[16]. Such agreements may represent the only viable form of land expansion available to a household. Lack of formal titling and the strong reluctance of a household to sell a portion of its land — its predominant source of income generation, both now and in the future — makes it very scarce, resulting in no market being present for the formal acquisition of land.

Instead, farmers may be willing to sacrifice the long-term benefits of forests to expand cultivated or grazing land area as a means of short-term insurance. Trees play a key role in preventing soil erosion and slowing the decline of soil fertility. One caveat of this analysis is that it is difficult to draw direct conclusions on the prevalence of deforestation, and hence the implications for long-term vulnerability to climate change. It is plausible that, as soil fertility diminishes, farmers shift to planting crops on areas of newly cleared forest, which have higher nutrient levels. Likewise, if grazing lands become depleted, forests may be cleared to generate more room for livestock. Plots of land can therefore go in and out of use without resulting in a net change in current land area being utilised, despite coming at the cost

[15] See Full Regression Results, Appendix D.

[16] Sharecropping is renting out a plot of land to an individual in exchange for rents or a proportion of harvested crops.

Table 5: Climate variability on total farming area (hectares)

Dependent variable: **Total Farming Area**	FE (1)	FE (2)	**(Cash crops only)** FE (3)
Climate Variability	0.0060	−0.0137	0.0010
	(0.0172)	(0.0255)	(0.0067)
Rainfall Shock	−0.4888**	0.1144	−0.0211
	(0.2455)	(0.3174)	(0.0784)
Average Temperature (Month of survey)	0.0040	−0.0151	−0.0012
	(0.0082)	(0.0212)	(0.0063)
Average Rainfall (Month of survey)	−0.0001*	−0.0002	0.0000
	(0.0001)	(0.0002)	(0.0000)
Log Consumption Expenditure	0.0597*	0.0456	−0.0037
	(0.0360)	(0.0388)	(0.0159)
Land Size (5 years ago)	0.1085	0.1092	−0.0461**
	(0.1038)	(0.0831)	(0.0186)
Total Livestock Units	0.0587	0.1017**	0.0052
	(0.0391)	(0.0444)	(0.0067)
Time dummies	Yes	Yes	Yes
Village dummies	-	-	-
Individual fixed effects	Yes	Yes	Yes
Household controls	No	**Yes**	**Yes**
N	1875	1680	1776
Adjusted R^2	0.0524	0.1142	0.0270

Total hectares planted by household. Land size is a categorical variable comparing land size to 5 years ago: smaller, same size, or larger. Traditional cash crops represented by coffee and khat trees grown by the household.

of greater long-term vulnerability. Deforestation may therefore be 'nested' within survey data over total land area used for farming or grazing, and conclusions cannot be drawn.

5.3 Intensification measures

Alternatively, farmers may make investments into boosting the productive potential of their fixed land area. Advances in best management practices[17], seed technology and fertiliser application can help protect households against erratic and unpredictable rainfall patterns and improve crop yields. Table 6 shows no initial significant impact of climate variability on fertiliser expenditure. However, it is not appropriate to view investments into agricultural intensification on a year-round basis. The most important decisions are made just prior to the start of the growing season. Farmers must take into account conditions many months in advance when making decisions on which seeds to purchase, the types of crops to grow, whether it is worthwhile to invest in fertiliser, and which land preparation methods to undertake. In Ethiopia, the majority of farm-based decisions are made during the light rainy season *Belg* prior to the heavy rainy and growing season *Meher*. Therefore, if climate variability impacts decisions over intensification measures, it would be during the light rainy season *Belg*. Isolating the

[17] Best management practices are farming methods aimed at ensuring optimal crop growth while minimising negative environmental effects. These cover a wide variety of methods: appropriate surface application of nitrogen and phosphorus to fields, controlling soil erosion, managing water flow, use of manure as a nutrient source, et cetera.

Table 6: Climate variability of fertiliser expenditure

Dependent variable: **Fertiliser Expenditure**	All seasons	*Belg*	*Meher*
	(1)	(2)	(3)
Climate Variability	3.347	-9.164^{***}	12.51
	(9.875)	(2.285)	(8.789)
Rainfall Shock	433.2^{**}	26.92	406.3^{**}
	(200.0)	(24.40)	(196.6)
Average Temperature (Month of survey)	0.8390	−1.305	2.144
	(5.884)	(0.9890)	(5.583)
Average Rainfall (Month of survey)	0.0653	−0.0156	0.0808
	(0.0670)	(0.0125)	(0.0671)
Log Consumption Expenditure	21.36	5.215	16.15
	(15.82)	(4.087)	(13.34)
Total Farming Area	37.60^{***}	7.032^{***}	30.57^{***}
	(11.85)	(2.718)	(11.70)
Loan Received	−35.65	0.2168	−35.86
	(26.31)	(6.448)	(23.58)
Fertiliser Used in Past 5 Years	133.5^{***}	8.782	124.7^{***}
	(34.66)	(7.961)	(34.66)
Time dummies	Yes	Yes	Yes
Village dummies	-	-	-
Individual fixed effects	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
N	1648	1648	1648
Adjusted R^2	0.5936	0.3147	0.5821

Fixed-effects ordinary least squares. Cluster-robust standard errors in parentheses. *Belg* is the initial 'light' rainy period before the heavy rainy & growing season *Meher*.

effect of climate variability based on season, a very significant negative coefficient for climate variability is found on fertiliser expenditure (Table 6: (2)).

Fertiliser is typically applied twice per harvest cycle: once prior — or immediately after — the planting of seeds to provide essential nutrients, and once more mid-way through the growth stage. The dosage and frequency or timing varies depending on crop type, but follows roughly the same pattern. Only 2% of surveyed households who purchased fertiliser used it only during the *Belg* season; the vast majority apply fertiliser in both periods, as would be expected. Therefore, the negative coefficient on fertiliser expenditure suggests that a more variable climate disincentivises early first-stage application of fertiliser, quite considerably. During the period when field-level decisions must be made, it remains unclear when the rainy season will arrive and whether rains will be sufficient. 55% of households said rains began or stopped either too early or too late. The results indicate that greater climate uncertainty might postpone initial investments into fertiliser until weather conditions are realised. This compliments the results of Dercon & Christiaensen (2011) who show that concerns over *ex post* harvests reduce *ex ante* fertiliser use in Ethiopia. Such a reduction in fertiliser application at the crucial early growth stage can significantly harm crop development and, ultimately, lower the overall expected harvest. This places households under continued food stress and hence greater vulnerability to expected future changes in climate.

Table 7: Non-farm economic activities

Dependent variable:	Logit (FE)	
Engage in selling or trading	Coefficient	Odds Ratio
Climate Variability	-0.1527	0.8583
	(0.0968)	(0.0831)
Rainfall Shock	2.953^{***}	19.17^{***}
	(1.084)	(20.78)
Average Temperature (Month of survey)	-0.0255	0.9749
	(0.0652)	(0.0636)
Average Rainfall (Month of survey)	0.0012^{*}	1.001^{*}
	(0.0001)	(0.0007)
Log Consumption Expenditure	0.2605^{**}	1.298^{**}
	(0.1255)	(0.1629)
Time dummies	Yes	
Village dummies	-	
Individual fixed effects	Yes	
Household controls	Yes	
N	330	
Log-likelihood	-81.22	

One limitation is the absence of data on expenditure on enhanced seeds. These seeds may be higher yielding, more drought-tolerant, or pest resistant. A regression on total seed expenditure (including normal and enhanced seeds) presents a highly significant negative coefficient of climate variability, relatively robust across all seasons[18]. If households have sufficient capital at their disposal, this might represent a transition away from purchasing enhanced seeds if there is uncertainty over their future return. Alternatively, this negative coefficient may represent a broader shift away from engaging in — or, perhaps, relying on — solely agriculture for the majority of household income as weather patterns become less predictable. Likewise, seeds may be stored for future use if farmers are concerned that rainfall will be insufficient in the coming season, which could reduce current expenditure levels. Data limitations make it difficult to draw more direct conclusions.

5.4 Off-farm economic activities

Diversifying away from farm-based sources of income can reduce dependency on weather. However, climate variability does not significantly explain the propensity for households to engage in the selling or trading of basic goods (Table 7). It must be noted that a conditional fixed-effects Logit model requires variation in observations across periods to determine within-household variability; this considerably limits our sample size and power of hypothesis testing as considerable observations are lost. Rainfall shocks are very prevalent in explaining the likelihood that a household engages in such business activities. This indicates that engaging in non-farm activities may be an *ex post* response to when harvests or other farm-based sources of income are insufficient. Across time, households are considerably more likely to be engaging in these non-farm activities (exhibited by high significance of our time controls). Therefore, other factors are likely to be at play, such as village-level development, better infrastructure or greater

[18]Table D.1 in Appendix D.

market access increasing the rewards of starting up microenterprises. This cannot be attributed to the role of climate variability. This is further confirmed when restricting the sample to households who are already engaging in non-farm economic activities and analysing their earnings and duration spent in these activities[19]. A large concern is that an increasing trend in engaging in non-farm work and in migration may saturate markets — there are only so many vendors needed in a financially-constrained market with limited demand — and cause greater food stress as households shift away from agriculture, making them vulnerable to higher and more volatile food prices.

Surprisingly, a very small proportion of remittances received came from family-based sources, peaking during the dry season and light rainy season[20]. Of those receiving some form of remittance (cash or in-kind), only 29% came from relatives, family or non-present household members. In total, this represents a mere 13% of the sample, and on average concerns less than 15% of households in each village. Therefore, it is ill-suited for regression analysis as it is not widely representative of the observed data. This small proportion may indicate that few immediate opportunities for employment outside of local areas exist, perhaps due to poor infrastructure, lack of access, or an inherent skill mismatch. Alternatively, high transaction costs associated with transferring money might be present. This brings into question its role as an immediate strategy used by households to cope with uncertainty, though direct conclusions cannot be drawn.

6 Conclusion

The coefficient of variation of precipitation is used as a proxy for income uncertainty. Climate variability significantly explains variations in the numbers of small livestock owned and on early-stage agricultural intensification measures. Households own more goats and sheep if they are faced with more variability in climate, indicating the role such animals play as a form of short-term insurance. Greater uncertainty over the arrival and level of precipitation during the growing season causes farmers to become more hesitant in investing in fertiliser or spending on seeds when crucial decisions must be made. These behaviours, coupled with land scarcity and a tendency to shift into non-farm economic activities over time, puts many households at increased risk of food insecurity. The short-term nature of responses to climate variability may result in deforestation or land degradation, and are unsuitable to reduce the long-term vulnerability faced by households. While decreasing dependency on farm and rain-fed-based incomes may lower direct exposure to changes in climate, it is likely indirect impacts such as higher and more volatile food or feed prices will adversely affect households.

Policies aimed at incentivising a more sustainable response to climate uncertainty can improve the resilience of households over time. Ensuring the presence of functioning savings and credit markets can promote the adoption of fertiliser or enhanced seeds, even in uncertain conditions. Promoting better land management practices, water harvesting, mixed cropping, and land conservation measures can improve long-run soil fertility and widen natural grazing opportunities in an environmentally-friendly manner.

Further studies can gain from investigating in more detail the dynamics and behaviour of households on specific coping strategies and using more frequent (daily) climate data, as monthly data only crudely captures variation in climate and may be too infrequent of a measure to accurately capture household-level decisions and behavior.

[19]Table D.2 in Appendix D.
[20]Figure C.1 in Appendix C.

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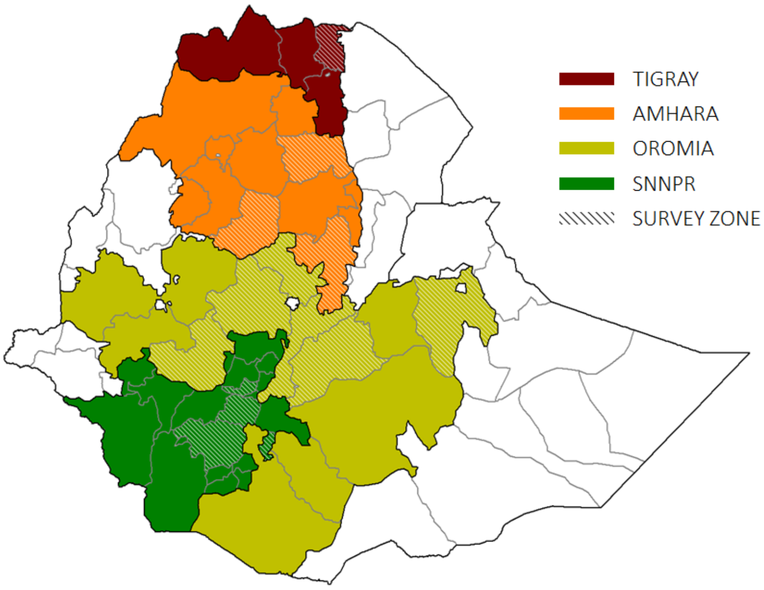
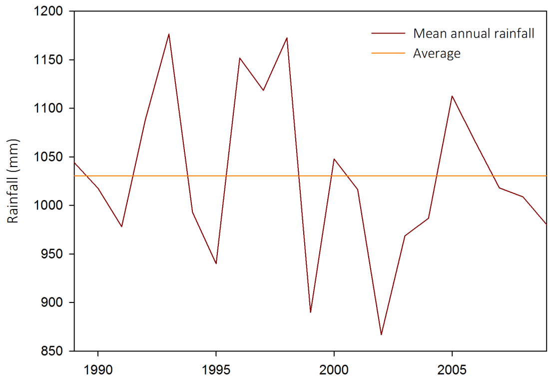
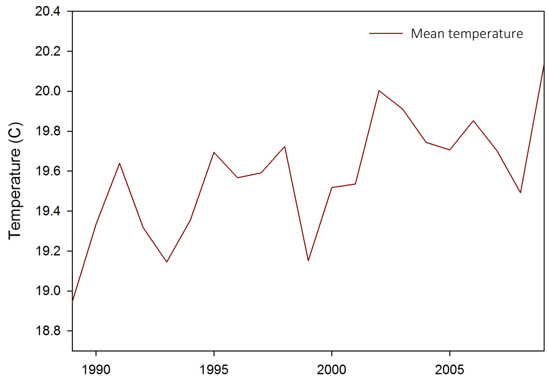
A Maps and Graphs: Descriptive characteristics of Ethiopia

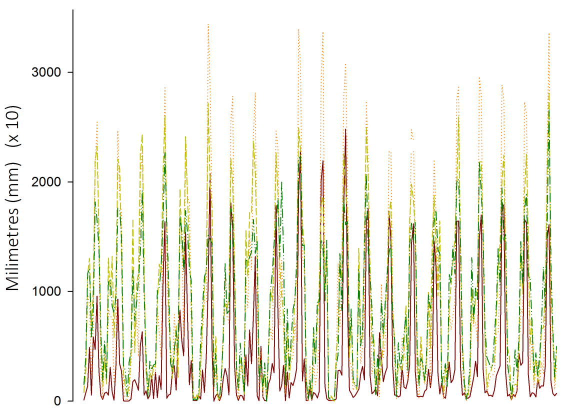


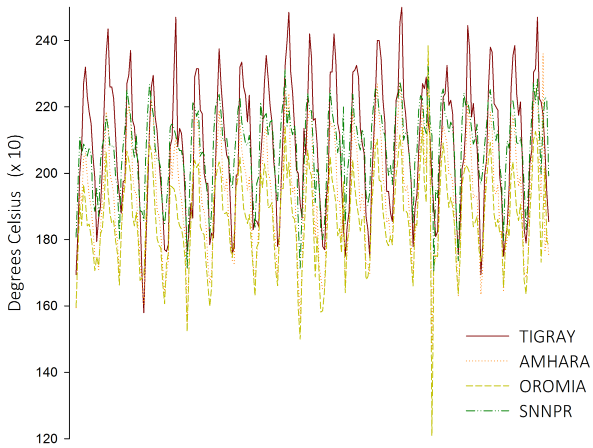
Country-wide precipitation (left) and temperature (right) trends (1989-2009):



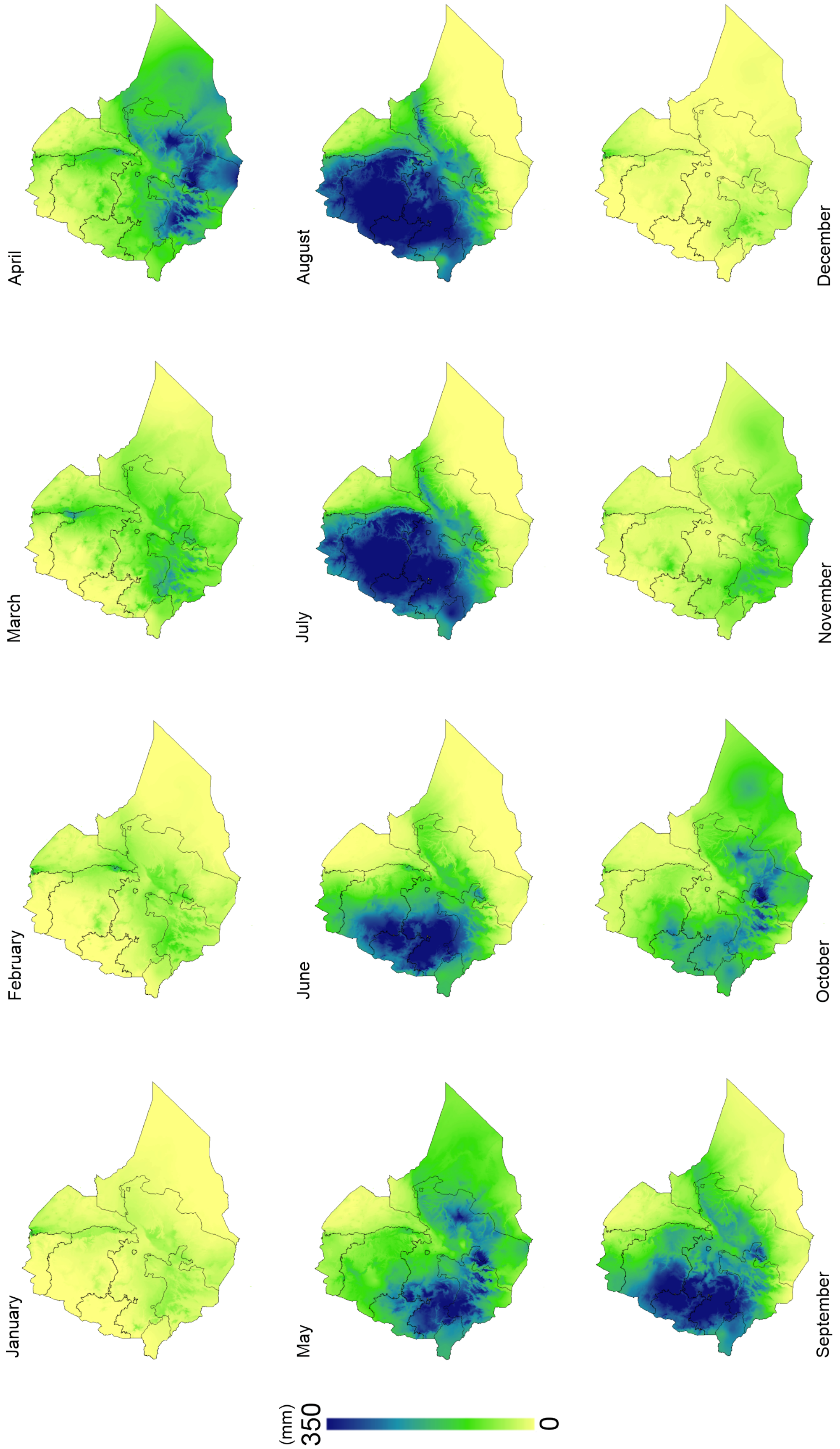


Regional precipitation (left) and temperature (right) trends (1989-2009):





Ethiopia: Average Monthly Precipitation 1950 - 2000



B Further summary statistics and controls

Variable	Mean	SD	Observations
Shocks			
Crop damages			
Low temperature	0.1603	0.3670	2152
Wind damage	0.1870	0.3900	2155
Flood damage	0.1676	0.3736	2154
Plant disease	0.2219	0.4156	2154
Household responses			
Death in family	0.1166	0.3210	2178
Climate	0.3572	0.4793	2178
Illness in family	0.0863	0.2809	2178
Price shock	0.1736	0.2791	2178
Pests or insects	0.1336	0.3403	2178
Theft	0.0422	0.2012	2178
Societal			
Most people can be trusted			
Strongly agree	0.0648	0.2462	1760
Agree	0.4591	0.4985	1760
Neither agree nor disagree*	0.0864	0.2810	1760
Disagree	0.3148	0.4646	1760
Strongly disagree	0.0750	0.2635	1760
Most people are honest			
Strongly agree	0.0664	0.2491	1761
Agree	0.4696	0.4992	1761
Neither agree nor disagree*	0.0971	0.2962	1761
Disagree	0.2890	0.4534	1761
Strongly disagree	0.0778	0.2679	1761
My life is determined by my own actions			
Strongly agree	0.1098	0.3127	1758
Agree	0.5842	0.4930	1758
Neither agree nor disagree*	0.1035	0.3047	1758
Disagree	0.1906	0.3929	1758
Strongly disagree	0.0119	0.1087	1758
Social network			
Larger network	0.2779	0.4480	2127
Same size*	0.4542	0.4980	2127
Smaller network	0.2680	0.4430	2127

* indicates default specification.

C Other sample statistics

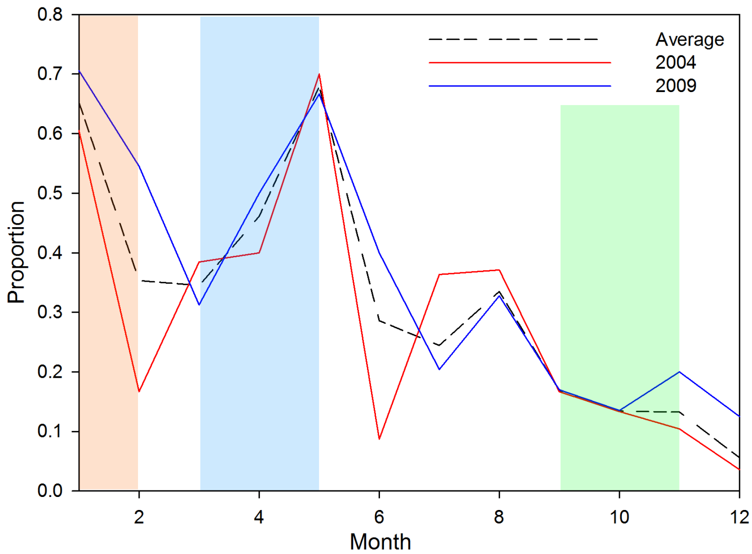
Table C.1: Household sources of emergency funding:

Source	Mean	SD	Frequency
Sale of animals	0.3227	0.4677	539
Sale of farm/business assets	0.0766	0.2661	128
Sale of household assets	0.0126	0.1115	21
Own cash	0.1138	0.3176	190
Savings association	0.0389	0.1935	65
Loan	0.3174	0.4656	530
Sale of crops	0.1174	0.3220	196

Table C.2: Summary statistics for households engaging in soil conservation measures:

Variable	Practices soil conservation	No soil conservation	Observations
(Values in means)	(49.81%)	(50.19%)	
Livestock owned (TLU)	2.576	1.554	2162
Hectares planted (TFA)	3.151	2.579	2016
Land quality			
Grazing only	$\rho = -0.3015$		
Good *(Lem)*	0.2885	0.5344	235
Reasonable *(Lem-Teuf)*	0.3365	0.3282	235
Bad *(Teuf)*	0.3750	0.1374	235
Cultivated land	$\rho = -0.2201$		
Good *(Lem)*	0.4964	0.7012	1937
Reasonable *(Lem-Teuf)*	0.3597	0.2448	1937
Bad *(Teuf)*	0.1439	0.0539	1937

Figure C.1: Proportion of remittances received from family-based sources:



Dry season (*red shaded*), light rainy season (*blue shaded*), and harvest season (*green shaded*).

D Regression results

Table D.1: Results on household expenditures on seeds:

Dependent variable: **Seed Expenditure**	All seasons (1)	*Belg* (2)	*Meher* (3)
Climate Variability	-9.318^{***}	-1.757^{*}	-7.561^{***}
	(2.105)	(0.9698)	(1.993)
Rainfall Shock	101.9^{**}	9.222	92.66^{*}
	(49.47)	(11.05)	(48.89)
Average Temperature (Month of survey)	-3.680^{***}	-1.348^{*}	-2.332^{**}
	(1.344)	(0.7689)	(1.134)
Average Rainfall (Month of survey)	-0.0142	-0.0094	-0.0048
	(0.0197)	(0.0066)	(0.0195)
Log Consumption Expenditure	-3.421	-1.610	-1.812
	(4.532)	(1.729)	(4.396)
Total Farming Area	10.08^{***}	3.517	6.559^{**}
	(3.678)	(2.273)	(2.825)
Loan Received	-32.00^{*}	-3.211	-28.79^{*}
	(18.10)	(7.664)	(15.41)
Currently Use Fertiliser	54.69^{***}	5.127	49.56^{***}
	(17.16)	(5.811)	(15.64)
Time dummies	Yes	Yes	Yes
Village dummies	-	-	-
Individual fixed effects	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
N	1692	1692	1648
Adjusted R^2	0.3000	0.1246	0.2774

Fixed-effects ordinary least squares. Cluster-robust standard errors in parentheses. *Belg* is the initial 'light' rainy period before the heavy rainy & growing season *Meher*.

Table D.2: Results on household duration & earnings in non-farm work:

Dependent variable:	**Non-farm Earnings**	**Duration in Non-farm Work**
	FE (1)	FE (2)
Climate Variability	11.28	-0.2913
	(45.78)	(0.2823)
Rainfall Shock	82.07	-0.3716
	(363.4)	(2.124)
Average Temperature (Month of survey)	10.12	-0.1473
	(18.72)	(0.1223)
Average Rainfall (Month of survey)	-0.1160	0.0018^{*}
	(0.1606)	(0.0010)
Log Consumption Expenditure	25.08	-0.2191
	(45.65)	(0.2224)
Loan Received	122.2	1.406^{*}
	(93.55)	(0.7940)
Time dummies	Yes	Yes
Village dummies	-	-
Individual fixed effects	Yes	Yes
Household controls	Yes	Yes
N	548	524
Adjusted R^2	0.4167	0.3822

Fixed-effects regression with cluster-robust standard errors. Non-farm activities include: weaving/spinning, milling, handicrafts, religious teaching, selling of firewood, trading of livestock.

Full Regression Results: Livestock

Dependent variable:	**TLU**	**Chickens**	**Dairy**	**Goats & Sheep**	**Draft**
	(1)	(2)	(3)	(4)	(5)
Climate Variability	0.0348**	−0.0067***	0.0013	0.0258**	0.0081
Rainfall Shock	-0.1969	0.0045	0.1961	−0.2776*	-0.0038
Avg Temperature (Month of survey)	-0.0038	-0.0002	−0.0245***	0.0191**	0.0038
Avg Rainfall (Month of survey)	−0.0002*	0.0000	-0.0001	−0.0001*	0.0001*
Log Consumption Expenditure	0.0233	0.0030	-0.0146	0.0109	0.0327**
Total Livestock Units (1 year ago)	0.4430***	0.0040	0.1364***	0.1622***	0.0838***
Livestock Bought (Past year)	0.8224***	0.0121	0.3048**	0.2626**	0.1864***
Time controls					
2009	-0.3246	0.0520**	0.0492	−0.3033*	-0.0371
August	0.1399	-0.0530	0.3836	-0.1095	-0.1788
September	-0.1369	-0.0251	0.2176	-0.2588	-0.1060
October	-0.0944	-0.0145	-0.1140	0.1092	-0.1259
Crop shocks					
Low temperature	0.0569	-0.0042	0.0015	0.1198*	-0.0415
Wind	-0.0585	0.0082	−0.1243**	-0.0548	0.1288***
Flood	-0.0241	-0.0158	0.0692	−0.1827**	0.0125
Disease	−0.1428*	0.0060	-0.0496	-0.0291	-0.0451
Livestock trampled	-0.0439	-0.0082	0.1015	-0.1512	0.0196
Household shocks					
Death in family	-0.1082	0.0246*	-0.1606	0.0744	0.0248
Climate shock	0.2797**	0.0070	0.0971	0.1903	0.0174
Illness in family	-0.1566	-0.0030	0.0545	-0.1363	-0.1374
Price shock	0.0125	0.0053	-0.0053	-0.0232	0.1030
Pests	0.3686	-0.0271	0.0541	0.2390	0.1326*
Food price shock	−1.602**	-0.0145	-0.0080	−1.694***	0.1204*
Theft	-0.2932	-0.0103	-0.1160	0.0301	-0.2224
Household circumstances					
Richest	0.2456	0.0178	0.1277	0.0046	0.1790
Richer	0.1028	-0.0131	0.0641	0.1158	-0.0038
Poorer	-0.0418	-0.0040	-0.0051	0.0481	-0.0589
Poorest	-0.1481	-0.0133	-0.0314	-0.0705	-0.0213
Social capital					
Larger network size	-0.0632	-0.0109	-0.0094	-0.0117	-0.0411
Smaller network size	-0.0078	0.0034	-0.0004	0.0010	-0.0233
Societal					
People can be trusted	0.0827**	0.0093*	0.0567**	0.0206	0.0087
People are honest	−0.0820*	−0.0097**	-0.0453	-0.0357	0.0004
Determine life's outcome	-0.0181	0.0000	-0.0248	0.0117	0-0.0049

Full Regression Results: Total Farming Area

Dependent variable:	**TFA**	**TFA - Cash Crops**
	(1)	(2)
Climate Variability	-0.0137	0.0010
Rainfall Shock	0.1144	-0.0211
Avg Temperature (Month of survey)	-0.0151	-0.0012
Avg Rainfall (Month of survey)	-0.0002	0.0000
Log Consumption Expenditure	0.0456	-0.0037
Landsize (5 years ago)	0.1092	-0.0461^{**}
Total Livestock Units	0.1017^{**}	0.0052
Time controls		
2009	-0.1177	-0.1146
August	1.083	0.0357
September	1.004^{*}	0.0263
October	0.9515^{***}	0.0631
Crop shocks		
Low temperature	-0.0447	-0.0278
Wind	-0.0522	0.0284
Flood	0.1993	0.0065
Disease	-0.2563^{**}	-0.0105
Livestock trampled	-0.3103^{*}	0.0341
Household shocks		
Death in family	0.1853	-0.0377
Climate shock	-0.0582	0.0390
Illness in family	-0.2742	-0.0846
Price shock	0.4146^{**}	-0.0205
Pests	0.3804	-0.2875^{**}
Food price shock	-0.2540	-0.0118
Theft	-0.4325	-0.0370
Household circumstances		
Richest	0.5845^{***}	0.0549
Richer	0.3846^{*}	-0.0396
Poorer	-0.1373	0.0239
Poorest	-0.2009	-0.0393
Social capital		
Larger network size	0.1745	0.0400
Smaller network size	0.0762	0.0029
Societal		
People can be trusted	0.0163	0.0089
People are honest	-0.0166	-0.0103
Determine life's outcome	-0.0624^{*}	0.0219

Full Regression Results: Fertiliser Expenditure

Dependent variable: **Fertiliser Expenditure**	**All seasons** (1)	*Belg* (2)	*Meher* (3)
Climate Variability	3.347	-9.1646^{***}	12.51
Rainfall Shock	433.2^{*}	26.92	406.3^{**}
Avg Temperature (Month of survey)	0.8390	-1.305	2.144
Avg Rainfall (Month of survey)	0.0653	-0.0156	0.0808
Log Consumption Expenditure	21.36	5.215	16.15
Total Farming Area	37.60^{***}	7.032^{***}	30.57^{***}
Loan Received	-35.65	0.2168	-35.86
Fertiliser Used Previously	133.5^{*}	8.782	124.7^{***}
Time controls			
2009	55.72	20.18	35.53
August	-272.5	34.57	-307.1
September	-382.3^{**}	16.58	-398.9^{**}
October	-445.7^{***}	21.07	-466.7^{***}
Crop shocks			
Low temperature	40.32	0.4335	39.89
Wind	0.4271	3.890	-3.463
Flood	-20.21	16.68	-36.89
Disease	16.81	2.821	13.99
Livestock trampled	46.97	-0.3652	47.33
Household shocks			
Death in family	-28.83	0.6224	-29.46
Climate shock	34.14	-17.91	52.05
Illness in family	-94.04	-26.98	-67.06
Price shock	-60.25	8.095	-68.35
Pests	-76.96	25.86	-102.8^{**}
Food price shock	-79.69	28.88	-108.6
Theft	106.6	-96.53	203.1^{**}
Household circumstances			
Richest	272.0^{**}	44.56^{*}	227.5^{**}
Richer	-92.65	-13.98	-78.67
Poorer	-22.07	-12.02	-10.06
Poorest	35.39	13.81	21.58
Social capital			
Larger network size	-44.87	7.665	-52.53^{*}
Smaller network size	-8.798	-0.8071	-7.991
Societal			
People can be trusted	6.491	1.310	5.181
People are honest	-7.599	-0.8054	-6.793
Determine life's outcome	-6.853	-3.922	-2.931

Full Regression Results: Non-farm Economic Activities

Dependent variable:	**Likelihood**		**Earnings**	**Duration**
Non-farm Work	Coefficient (1)	Odds Ratio (2)	FE (3)	FE (4)
Climate Variability	-0.1527	0.8583	11.28	-0.2913
Rainfall Shock	−2.953***	19.17***	82.07	-0.3716
Avg Temperature (Month of survey)	-0.0255	0.9749	10.12	-0.1473
Avg Rainfall (Month of survey)	0.0012*	1.001*	-0.1160	0.0018*
Log Consumption Expenditure	0.2605**	1.298**	25.08	-0.2191
Loan Received	0.0322	1.033	122.2	1.406*
Time controls				
2009	2.732***	15.36***	-232.4	3.147
August	-1.027	0.3580	52.41	3.154
September	-1.374	0.2532	-5.240	3.533
October	−1.528*	0.2170*	104.1	1.671*
Crop shocks				
Low temperature	-0.0158	0.9844	272.0	2.640
Wind	0.0592	1.061	33.00	1.582
Flood	-0.2942	0.7451	108.8	-0.9955
Disease	0.3022	1.353	-0.7423	−1.211**
Livestock trampled	-0.2664	0.7661	-79.93	−2.039*
Household shocks				
Death in family	-0.6446	0.5249	-213.8	−4.222***
Climate shock	0.4111	1.508	227.6	1.539
Illness in family	-1.175	0.3088	-147.7	-0.2386
Price shock	-0.7111	0.4911	152.7	-0.3813
Pests	-1.180	0.3072	-461.2	0.7808
Theft	1.503	4.497	9.737	−4.106*
Household circumstances				
Richest	-0.3714	0.6897	138.2	-0.1645
Richer	-0.8022	0.4483	374.5**	2.000*
Poorer	-0.1742	0.8401	-122.5	0.5166
Poorest	−1.256*	0.2847*	-60.00	0.3709
Social capital				
Larger network size	0.0642	1.066	97.22	0.0656
Smaller network size	0.0053	1.005	197.1**	1.786*
Societal				
People can be trusted	0.1777	1.194	0.9829	−0.9917***
People are honest	-0.1288	0.8792	-8.929	0.4561**
Determine life's outcome	0.0039	1.004	−70.75**	0.3711