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Optimal Expectations and the Welfare Cost of Climate Variability: A Subjective Well-Being Approach[1]

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Abstract

Using panel data from rural Ethiopia, combined with a new data set containing daily atmospheric parameters, we show that increased climate variability (a proxy for future income uncertainty) reduces farmers' subjective well-being, in line with the theory of optimal expectations (Brunnermeier and Parker, 2005). The magnitude of our result indicates that a one standard deviation increase in climate variability has an equivalent effect on life satisfaction to a two standard deviation (1-2%) decrease in consumption. This effect is one of the largest determinants of life satisfaction in rural Ethiopia.
(JEL: C25, D60, I31.)

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1 Introduction

A significant proportion of the population in developing countries live in uncertain or risky conditions, especially those dependent on agriculture for their livelihood, which is highly vulnerable to changes and variability in weather and climate. Ethiopia is one of the least developed countries in Africa and is highly vulnerable to climate change and variability. Since many smallholder farmers in developing countries view weather variability as a primary source of risk (Barrett et al., 2007), it is important for policy makers to understand the welfare implications of this risk and uncertainty if policies aiming to mitigate its effects are to be effective and welfare-enhancing.

Recent evidence suggests that global climate change is likely to increase the incidence of environmental disasters, as well as the variability of rainfall, temperature, and other atmospheric parameters (IPCC, 2007, 2012), which in turn increases uncertainty in future income for this population. While some of the costs related to weather and climate are relatively easy to measure, such as impacts on agriculture, health, and labour market outcomes, other aspects are less easily measured, such as the experienced utility effects of increased risk and uncertainty associated with higher variability in weather and climate.

The motivation for this paper is two-fold. First, from a development perspective, we want to understand how uncertainty affects welfare, a question that poses a number of difficulties relating to measurement and identification. Consequently, we look at climate variability as an exogenous proxy for future income uncertainty and control for unobserved individual heterogeneity, an important determinant of SWB[2]. While this approach certainly has its own identification problems, such as the exclusion restriction, we have taken many

[2]Unobserved individual heterogeneity is a major omitted variable bias problem in research on SWB. Almost all previous studies on SWB in Africa use cross-sectional data, which makes it difficult to control for unobserved individual heterogeneity, and is likely to affect the consistency of estimated parameters. Until now the only exception is the study by Alem and Köhlin (2012), who investigate the determinants of SWB in urban Ethiopia using three rounds of panel data spanning a decade. Controlling for such unobservables is key to understanding the determinants of SWB (Argyle, 1999; Diener and Lucas, 1999; Ferrer-i-Carbonell and Frijters, 2004); Feddersen et al. 2012.

steps to disentangle the effect of future income uncertainty from other potential explanations.

Secondly, we want to better understand one of the interactions between climate and economic outcomes that, until now, has been absent from the literature on climatic influence: the role that *ex ante* beliefs about the likelihood of future climatic events plays in decision-making and determining well-being. In this respect, climate variability is likely to affect welfare predominantly through the psychological impact of risk and uncertainty (van den Bos, Hartevald & Stoop, 2009; Hare, Camerer & Rangel, 2009; Porcelli & Delgado, 2009; Doherty and Clayton, 2011). By contrast, the majority of the literature on climatic influence, which focuses on *ex post* considerations.

These studies have investigated the impact of annual or within-year (seasonal) variation in rainfall and temperature on agricultural yield and welfare (Deschênes and Greenstone, 2007, 2012; Schlenker and Roberts, 2009; Fisher, Hanemann, Schlenker, and Roberts, 2012). Skoufias et al. (2011) in rural Mexico, Rowhani et al. (2011) in Tanzania, and Guiteras (2009) and Fishman (2012), both in India, document that variation in weather affects agricultural yield and results in substantial loss of welfare for people in rain-dependent agrarian communities.

To address these questions, we investigate the impact of future income uncertainty (proxied by climate variability) on subjective well-being (SWB) – a measure of well-being that has received increased attention in the past decade – using two rounds of individual-level panel data from rural Ethiopia, allowing us to control for unobserved individual heterogeneity, combined with a new data set of village-level rainfall data. When asked whether they were satisfied with their lives, farmers in more variable climates report a lower life satisfaction than farmers in less variable climates. These results hold even after we control for a number of other individual and household-level influences, and individual fixed effects. Crucially, we are able to disentangle the effects of climate variability from weather by controlling for rainfall and temperature on the day that each household was surveyed, as well as controlling for realised weather shocks.[3]

We observe that a one standard deviation (7%) increase in climate variability has an equivalent effect on life satisfaction to a two standard deviation (1-2%) decrease in real per capita consumption. We show this to be one of the largest determinants of SWB in rural Ethiopia. In a wider context, our results are consistent with the literature, which demonstrates that SWB is correlated with stress (Diener, 2011) and weather shocks (Carroll et al., 2008). However, we show that the magnitude of this effect on the well-being of smallholder farmers in rural Ethiopia is unprecedented, and we identify a separate channel - uncertainty about future income - through which climate affects well-being.

Contrary to standard neoclassical models of expectations, we argue that this behaviour, if important, can be better explained by a model of behaviour in which beliefs about the state of the world impact utility directly (Kozegi, 2003; 2006; Caplin and Leahy, 2004; 2005; Brunnermeier and Parker, 2005; Oster, Shoulson, and Dorsey, 2013). In section 3, we present a brief model of optimal expectations, based on Brunnermeier and Parker (2005), that provides a useful framework for thinking about, and explaining, the results in our paper.

The remainder of the paper is structured in the following way: section 2 presents a brief literature review; section 3 presents the theoretical framework; section 4 presents the data and the empirical strategy; section 5 presents our main results; section 6 presents supporting evidence and robustness tests; the final section presents our conclusions.

[3] It is important to distinguish between weather, defined as atmospheric conditions over a short period of time, and climate, defined as the behaviour of the atmosphere over a longer period. By looking beyond the weather in one year, we gain a greater perspective of climate variability. By looking at the variability of rainfall over a longer period of time, more extended inter-annual patterns of climate variability are revealed that cannot be seen over one year, such as the El Niño-Southern Oscillation, which is associated with rainfall variability in East Africa, and the Quasi-biennial Oscillation, which is known to modify monsoon precipitation and affect stratospheric circulation.

2 Background

The past decade has seen rapid growth in research on, and policy interest in, SWB. In addition to 'objective' measures of welfare, most commonly GDP, subjective measures of welfare are increasingly being used to elicit measures of experienced utility (Kahneman et al., 1997; Kahneman and Krueger., 2006; Dolan and Kahneman, 2008; Frey & Stutzer, 2002), to value non-market goods (Carroll, Frijters and Shields, 2009; Feddersen, Metcalfe and Wooden, 2012; Frey, Leuchinger and Stutzer, 2007; Levinson, 2012; Metcalfe, Powdthavee, and Dolan, 2011; Rehdanz and Maddison, 2005; 2008; Welsch, 2006) and to evaluate government policy (Boarini et al., 2012; Diener et al., 2009; Dolan, Layard and Metcalfe, 2011; Gruber and Mullainathan, 2005). Well-being is a broad measure of welfare encompassing all aspects of the human experience. Researchers in this expanding field of economics use subjective measures of well-being to analyse and evaluate the impact of economic and non-economic factors on people's experienced utility.

Much of the existing evidence on the determinants of SWB come from studies undertaken in developed countries with similarities on the impact of the different correlates of SWB.[4] Several studies indicate that income has a positive effect on SWB, yet there is evidence to suggest that their relationship exhibits diminishing marginal returns, in part due to the roles that relative income and social position play, which can affect SWB negatively.[5] With its robustly documented U-shaped impact, age has been found to be one important determinant of SWB, where the lowest level of SWB experienced is in middle age (Blanchflower & Oswald, 2004; Ferrer-i-Carbonell & Gowdy, 2007) and women have been found to report a higher level of SWB than

[4]Studies on SWB conducted in developing and emerging countries include Ravallion and Lokshin (2005) on Russia; Kingdon and Knight (2006); Bookwalter and Dalenberg (2004, 2010) on South Africa; Graham and Pettinato (2001; 2002) on Peru and Russia; Appleton and Song (2008), Qian and Smyth (2008), and Knight and Gunatilaka (2010) on urban China; Knight et al. (2009) on rural China; Davis and Hinks (2008, 2010) on Malawi; and Alem & Martinsson (2011), and Alem & Köhlin (2012) in urban Ethiopia.

[5]Clark et al. (2007) undertake an extensive survey of the literature on the relationship between income and happiness.

men (Alesina, et al. 2004). Studies also document a positive impact of being in a relationship on SWB than being single, divorced or separated (e.g. Dolan et al., 2008; Frey & Stutzer, 2002; MacKerron, 2011). The levels of both physical and psychological health have also been found to be strong and positive determinants of SWB (e.g. Dolan et al. 2008).

In recent years, researchers have started to use SWB indicators to investigate the impact of a number of environmental and climatic variables. Most recently, Devoto et al. (2012) ran a randomised experiment in Tangier, Morocco, facilitating the connection of piped water to a random sample of households. While households did not experience any health benefits from a direct connection, and the water bill in newly connected households roughly doubled, households reported increased life satisfaction and other measures of well-being associated with access to clean water, indicating welfare improvements, even in the absence of health or income gains.

Using a set of cross-country and panel data from happiness surveys in combination with data on income and air pollution from European countries, Welsch (2002; 2006) investigates the relationship between pollution of the environment and SWB of citizens. The studies find that air pollution impacts SWB significantly and is one explanatory factor of observed differences in reported SWB across countries and over time. Similarly, using life satisfaction data from the German Socio-Economic Panel survey in combination with county-level pollution (sulphur dioxide) data, Luechinger (2009) documents that higher concentration levels affect SWB negatively and significantly. Ferreira and Moro (2010) document a similar negative impact of air pollution captured by the concentration of PM_{10} on reported level of happiness in Ireland.

The impact of climatic variables (amount of rainfall and temperature) on SWB has been investigated by Rehdanz and Maddison (2005), who document significant impacts on country-wide self-reported levels of happiness. More recently, Carroll et al. (2009) examine the impact of a period of drought in Australia on life satisfaction, finding a detrimental impact, equivalent to an annual reduction in income of A$18,000 (US$14,500).[6] However, many of

[6] Welsch and Kuehling (2009) and Ferreira et al. (2012) undertake comprehensive

these studies use cross-sectional data and so are unable to control for individual unobserved heterogeneity. However, the most recent paper in this literature by Feddersen, Metcalfe and Wooden (2012) examines the differential impacts of weather and climate change on SWB in Australia, controlling for unobserved individual heterogeneity. They examine the impact of short-term weather fluctuations and long-term climate on standard SWB response variables. They find that day-to-day weather variation impacts life satisfaction by a similar magnitude to acquiring a mild disability, however, the effect of long-term climate on life satisfaction disappears with the inclusion of individual fixed effects suggesting that unobserved individual-specific factors are responsible for the direct link between climate and life satisfaction in the studies focussed on average climate.

While these studies have focussed on long-run climate and weather shocks – the *ex post* realisations of weather and climate – we are unaware of any study that has looked at the effect climate variability – an *ex ante* consideration – nor the impact of future income uncertainty on well-being. Given the importance of risk and uncertainty in developing countries, and the role that climate change is likely to have on development, exploring the interaction between these issues is an important area of research.

Despite many papers examining the determinants of SWB, only a small number of studies provide causal estimates of an event or experience on SWB. This is because most SWB studies rarely have, or make use of, exogenous variation in their variable of interest. By using fixed effects to control for individual heterogeneity, controlling for potential confounding factors, and teasing out the mechanism by which we expect climate variability to be important – namely, through the impact of increased stress through uncertainty about future income – we attempt to provide supporting evidence for a causal estimate of climate variability on the SWB of smallholder farmers in rural Ethiopia.

overviews of research in the area of environmental quality and SWB.

3 The Optimal Expectations Framework

Based on the work by Brunnermeier and Parker (2005) we construct a model in which farmers care about their expectations of the future (anticipatory utility) in addition to their present consumption, that is all farmers care about current utility and expected future utility. While all forward-looking farmers who care about expected future utility will make investments to maximise future utility, such farmers will have higher current utility if they are optimistic about the future. In the context of this paper, farmers living in areas with higher climate variability will have higher subjective probabilities about the likelihood of a negative income shock being realised in the next period and so will have lower current utility. By contrast, farmers living in areas with lower climate variability, will have higher subjective probabilities that a negative income shock will not occur and so will have higher current utility.

3.1 Utility Maximization Given Beliefs

Consider a world in which uncertainty about future income can be described by a binary state $s_t \in \{0, 1\}$ where $s_t = 1$ indicates that the farmer is going to experience a negative income shock and $s_t = 0$ indicates that they will not. Let $p(s_t|\underline{s}_{t-1})$ denote the true probability that state $s_t \in \{0, 1\}$ is realised following state history $\underline{s}_{t-1} = (s_1, s_2, \ldots, s_{t-1}) \in \{0, 1\}$. We depart from the standard neoclassical model in so far as agents are endowed with subjective probabilities that may not coincide with the true state. Conditional and unconditional subjective probabilities are denoted $\hat{p}(s_t|\underline{s}_{t-1})$ and $\hat{p}(s_t)$ respectively.

At time t, the farmer receives some level of income which is consumed, c_t. For tractability we assume there is no savings and so income is equal to consumption. In addition, the farmer chooses some binary risk management action, $\alpha_t \in \{0, 1\}$ – used to mitigate income shocks – based on their beliefs about the likelihood of future income shocks to maximise utility denoted

$$\hat{\mathbb{E}}[U(c_t, \alpha_t)|\underline{s}_t] \tag{1}$$

where $U(\cdot)$ is strictly increasing and strictly quasi-concave, and $\hat{\mathbb{E}}$ is the subjective expectations operator associated with $\hat{p}$, which depends on information available at time, t.

The farmer maximises utility of consumption subject to their budget constraint

$$
\begin{aligned}
c_{t+1} &= f(c_t, \alpha_t, s_{t+1}), \qquad (2)\\
g(c_{T+1}) &\geq 0 \text{ given } c_0 \qquad (3)
\end{aligned}
$$

where $f(\cdot)$ provides the evolution of income is continuous and differentiable in c and α, and $g(\cdot)$ gives the endpoint condition. The optimal choice of action is denoted $\alpha^*(\underline{s}_t, \hat{p})$ and the induced consumption as $c^*(\underline{s}_t, \hat{p})$.

The utility of the farmer depends on expected future utility or anticipated utility, such that the subjective conditional belief has a direct impact on utility. To clarify this further, we consider time-separable utility flows with exponential discounting. In this situation, utility at time t,

$$
\hat{\mathbb{E}}[U(c_t)|\underline{s}_t] = \beta^{t-1}\left(\sum_{\tau=1}^{t-1}\beta^{\tau}u(c_{t-\tau}, \alpha_{t-\tau}) + u(c_t, \alpha_t) + \hat{\mathbb{E}}\left[\sum_{\tau}^{T-t}\beta^{\tau}u(c_{t+\tau}, \alpha_{t+\tau})|\underline{s}_t\right]\right) \qquad (4)
$$

is the sum of memory utility from past consumption, utility from current consumption, and anticipatory utility from future consumption. Empirically, we identify these factors by controlling for past weather shocks (memory utility), real per capita consumption and contemporaneous weather (current consumption), and climate variability (anticipatory utility).

3.2 Optimal beliefs

The subjective beliefs of farmers are a complete set of conditional probabilities following any history of events, $\hat{p}(s_t|\underline{s}_{t-1})$. That is, the subjective probability that a shock will occur depends on the history of shocks in the past. In this way, locations which have a more variable climate may be more likely to have a shock in the future.

Following Brunnermeier and Parker (2005), optimal expectations are the subjective probabilities that maximise the farmer's lifetime happiness and are defined as the expected time-average of the farmer's utility.

Definition 1 *Optimal expectations (OE) are a set of subjective probabilities* $\hat{p}^{OE}(s_t|\underline{s}_{t-1})$ *that maximise well-being*

$$\mathbb{W} = \mathbb{E}\left[\frac{1}{T}\sum_{t=1}^{T}\hat{\mathbb{E}}[U(c_1^*, \ldots, c_T^*, \alpha_1, \ldots, \alpha_T|\underline{s}_t)]\right] \tag{5}$$

One of the benefits of this model is that if farmers have rational expectations (i.e. $\alpha = s$) then the well-being and utility derived from the actions that farmer's will coincide. In this case utility in time t only depends on present actions, i.e. memory utility and anticipatory utility does not enter into the utility function. This could be the case, for example, if an exact weather forecast or insurance is available. However, if subjective probabilities differ from the true probability that a shock will occur then there will be a wedge between well-being and the farmer's utility, in this case memory utility and anticipatory utility enter into the utility function as in equation 4.

4 Data and Empirical Strategy

4.1 Data

The analysis conducted in this paper uses two rounds of a panel data set – the Ethiopian Rural Household Survey (ERHS) – covering households from 15 villages in rural Ethiopia[7]. The ERHS was conducted by Addis Ababa University in collaboration with the Center for the Study of African Economies (CSAE) at the University of Oxford and the International Food Policy Research Institute (IFPRI) in seven rounds between 1994 and 2009. The sampling was constructed carefully to represent the major agro-ecological zones of Ethiopia.

[7]See figure 3 in appendix A for the location of these villages

Households from six villages that were affected by drought in central and southern Ethiopia were surveyed for the first time in 1989. In 1994, the sample was expanded to cover 15 peasant associations[8] across the major regions of Ethiopia (Tigray, Amhara, Oromia, and Southern Nations Nationalities and people's region), representing 1477 households. Further rounds were completed in 1995, 1997, 1999, 2004 and 2009. The additional villages incorporated in the sampling were chosen to account for the diversity in the farming systems throughout the country. Stratified random sampling was used within each village based on the gender of household heads.

This paper makes use of the final two rounds, 2004 and 2009, as only these years contain questions on SWB, though this is sufficient to control for unobserved heterogeneity. Attrition of the panel has been low at 1-2 percent of households per year (Dercon & Hoddinott, 2009). In addition to a specific module on SWB, the data set contains detailed information on individual and household characteristics, assets, expenditures, consumption, health, agricultural production, and information related to input use.

In addition to the household survey data, daily, seasonal, and annual rainfall data has been constructed from 6-hourly precipitation reanalysis data at the village level from the ERA-Interim data archive supplied by the European Centre for Medium-Term Weather Forecasting (ECMWF).[9] Previous studies have relied on the use of meteorological data provided by the Ethiopian meteorological service and the number of missing observations is a concern. This is exacerbated by the serious decline in the past few decades in the number of weather stations around the world that are reporting. Lorenz and Kuntsman (Journal of Hydrometeorology, 2012) show that since 1990 the number of reporting weather stations in Africa has fallen from around 3,500 to around 500. With 54 countries in the continent, this results in an average of fewer than 10 weather stations per country. Looking at publicly available data, the number of stations in Ethiopia included by the National Oceanic and Atmospheric

[8]A peasant association is the lowest administrative unit in Ethiopia and normally consists of several villages.

[9]See Dee et al. 2011 for a detailed discussion of the ERA-Interim data.

Administration's (NOAA) National Climatic Data Centre (NCDC) is 18; however, if we were to apply a selection rule that required observations for 365 days this would yield a database with zero observations. For the two years for which we have economic data (2004 and 2009), weather station data is available for 50 days in Addis Ababa in 2004 and is available for all 18 stations for an average of 200 days (minimum of 67 days, maximum of 276 days) in 2009. This is likely to result in a huge increase in measurement error when this data is used to interpolate across the 63 zones and 529 woredas (districts) reported in 2008. If this measurement error is classical, i.e. uncorrelated with the actual level of rainfall measured, then our estimates of the effect of these variables will be biased towards zero. However, given the sparse density of stations across ethiopia (an average of 0.03 stations per woreda), the placement of stations is likely to be correlated with agricultural output, i.e. weather stations are placed in more agriculturally productive areas, where the need for weather information is higher. As a result, we might expect that estimates using weather stations are systematically upward biased. For these reasons, the use of remote-sensing data on a uniform grid has great value in areas with low station density.

The ERA-Interim reanalysis data archive provides 6-hourly measurements of precipitation, temperature (min., max., and mean), wind speed and wind direction, relative humidity, cloud cover (a proxy for solar reflectance), and many other atmospheric parameters, from January 1 1979 until the present day on a global grid of quadrilateral cells defined by parallels and meridians at a resolution of 0.75 x 0.75 degrees (equivalent to 83km x 83km at the equator).[10] Reanalysis data is constructed through a process by which climate scientists use available observations as inputs into climate models to produce a physically consistent record of atmospheric parameters over time (Auffhammer et al., 2013). This results in an estimate of the climate system that is separated uniformly across a grid, making it more uniform in quality and realism than observations alone, and one that is closer to the state of existence than any

[10]To convert degrees to km, multiply 83 by the cosine of the latitude, e.g at 40 degrees latitude 0.75 x 0.75 cells are 83 x cos(40) = 63.5 km x 63.5 km.

model would provide alone. This provides a consistent measure of atmospheric parameters over time and space. This type of data is increasingly being used by economists (see Guiteras, 2009; Schlenker & Lobell, 2010; Hsiang et al. 2011; Burgess et al., 2011; Kudumatsu, 2011), filling the gap in developing countries where the collection of consistent weather data is lower down the priority list in governmental budgets.

By combining the ERHS data set with the ERA-interim data, we create a unique panel allowing for microeconomic analysis of weather and climate in Ethiopia.

The outcome variable of interest from the economic data is a measure of overall life satisfaction asked to the head and spouse of the household. It is constructed using responses to a single question scored on a seven-point scale ranging from one to seven. The variable is constructed using responses related to the level of agreement with the following statement as the dependent variable: "I am satisfied with my life." A score of one is described as 'Very Dissatisfied' and a score of seven is described as 'Very Satisfied'. This is very similar to the standard questions used in cross-country surveys, such as the World Values Survey and the Eurobaromoter Survey. Later in the paper, we demonstrate the robustness of our results to alternative measures of SWB.

4.2 Variables and Descriptive Statistics

Table 1 presents descriptive statistics of the key dependent variable – the reported level of life satisfaction – for the analysed period. Average reported level of life satisfaction in rural Ethiopia was 2.93 in 2004 but increased to 3.09 in 2009. In the sample, about 40 percent of the respondents reported to be dissatisfied in 2004, but the figure declined to 34 percent in 2009. The proportion of respondents that were very satisfied was around 2 percent in 2004, but the figure increased to just over 6 percent in 2009. Overall, one can notice that there has been a considerable rise in the average reported level of life satisfaction in rural Ethiopia during the period in which the country experienced rapid economic growth.

Table 1: Life Satisfaction Responses from Full Sample

	2004	2009	(2004-2009)
Mean Satisfaction	3.82	4.09%	3.97
Very Dissatisfied	6.81%	7.32%	7.08%
Dissatisfied	24.37%	20.79%	22.47%
Slightly Dissatisfied	16.25%	13.14%	14.59%
Neither	7.08%	7.32%	7.21%
Slightly Satisfied	24.92%	22.54%	23.66%
Satisfied	18.33%	22.69%	20.64%
Very Satisfied	2.25%	6.20%	4.35
Total	100%	100%	100%
Observations	1815	2062	3877

We categorize our explanatory variables into climatic, individual (respondent) and household variables.

Rainfall at each village is calculated by taking all data points within 100km of the village, which is then interpolated through a process of inverse distance weighting. Taking the annual measure of rainfall at each village we calculate the coefficient of variation for rainfall (CV), measured as the standard deviation divided by the mean for the respective periods 2000–2004 and 2005–2009. One of the major advantages of the CV is that it is scale invariant, providing a comparable measure of variation for households that may have very different income levels.

We argue that climate variability, proxied by the CV, is a major determinant of welfare in rural areas as a result of the dependence on agriculture for subsistence consumption and livelihoods. This consideration is distinct from the literature, which examines the effects of weather shocks on welfare using the level of rainfall or deviation from its mean. Weather shocks are clearly important for welfare – as a large literature has already shown – however, the focus of this paper is on climate variability, as a proxy for future income uncertainty. While the level of rainfall or rainfall shocks tend to be used as instrumental variables or proxy variables for income or covariate income shocks, there are limitations to this (Rosenzweig and Wolpin, 2000), including identification issues. For example, more rainfall is usually defined as good, i.e. the coefficient is positive; however, even controlling for a quadratic rainfall term – expected to have a negative coefficient, indicating diminishing returns to rainfall – may not be sufficient identification. If farmers form expectations about the climatic conditions of their area, we might expect that they plant crops that are suited to that area. Any deviation from the conditions on which this optimal cropping decision is based, such as more or less rainfall, may not be welfare-improving. The formation of these expectations is key for production. For this reason, we focus on climate variability, which, we argue, generates uncertainty about the likelihood of future weather shocks. It is important to control for recent rainfall shocks as this is likely to be correlated with the CV. We include a dummy variable equal to one if the village has experienced a negative rainfall shock one standard deviation below the long-run mean in the previous 5 years. While this measure allows us to observe the realisation of rainfall shocks over the 5 year period, it is likely that a shock in the previous year would have the greatest impact on SWB. Our results are also robust to contemporaneous rainfall shocks in the most recent agricultural year.[11]

Questions relating to the respondents' personal characteristics have been selected based on earlier studies on happiness, comprising the respondent's age, gender, unemployment status, marital status, education, religion and health status.

The household-level variables we control for include the relative position of the household within the community, an indicator variable to a perceived change in living standard over the past three years, social capital proxied by an increase or decrease in the number of persons available to help the household in a time of need, household size, and measures of economic status captured by the stock of livestock and real consumption expenditure per capita. The relative position variable has been constructed from the responses given to the question "Compared to other households in the village, would you describe your household as: The richest in the village; Richer than most households; About average; A little poorer than most households; The poorest in the

[11] The results controlling for the impact of contemporaneous rainfall shocks are reported in table 5 of appendix C. The results remain robust to this specification.

Table 2: Summary statistics

Variable	Mean	Std. Dev.	N
Climate Variables			
Climate Variability	22.98	7.71	3877
Rainfall Shock (Past 5 years)	0.712	0.45245	3877
Rainfall (mm) (Day of Survey)	3.42	4.65	3877
Temperature (Day of Survey)	26.65	0.829	3877
Respondent variables			
Age	46.612	15.203	3774
Female	0.41	0.49	3877
Unemployed	0.016	0.126	3877
Married*	0.764	0.425	3773
Single	0.045	0.208	3773
Divorced	0.045	0.207	3773
Widowed	0.146	0.353	3773
No Schooling	0.563	0.496	3877
Grades 1-7	0.207	0.405	3877
Grades 8 plus	0.049	0.216	3877
Household variables			
Log Real Consumption per capita	3.973	0.776	3873
Log Household Size	1.676	0.507	3873
Richest	0.011	0.104	3869
Richer than Most	0.123	0.3288	3869
Average*	0.516	0.49	3869
Poorer than Most	0.456	0.384	3869
Poorest	0.053	0.225	3869

* denotes reference group.

village?".

The stock of livestock the household owns is measured in livestock-equivalent units, and real consumption per capita is adjusted for adult-equivalent units. The consumption measure was calculated using the approach used by Dercon and Krishnan (1996), which aggregates consumption on both food and non-food expenditures. Nominal consumption expenditures reported by households have been converted into real consumption expenditures using carefully constructed price indices from the survey. The consumption variable has been adjusted for both spatial and temporal price differences.

Table 2 presents the key descriptive statistics of variables for the period analysed (the full table is available in Appendix A) and table 3 below presents

Table 3: Annual Rainfall (mm) by Peasant Authority and Year

Peasant Association	2004	2009	mean	std. dev.	CV
Haresaw	395	470	476	155	33.12
Geblen	226	261	278	95	34.24
Dinki	810	865	853	162	18.61
Yetmen	667	713	740	149	20.00
Shumsheha	535	627	645	150	23.34
Sirbana Godeti	1150	1218	1086	172	15.61
Adele Keke	1175	1169	1008	177	17.19
Korodegaga	1478	1589	1364	218	15.60
Turfe Kechemane	1170	1177	1024	197	18.86
Imbidir	1051	1062	936	158	16.68
Aze Deboa	1232	1253	1073	210	19.08
Addado	1258	1399	1188	305	25.29
Gara Godo	1546	1520	1318	271	20.16
Doma	1134	1270	1070	257	23.71
Debre Berhan Villages	838	893	855	154	17.53

The mean, std. dev. and CV are calculated for the period 1980-2009.

the distribution of annual rainfall by village.

As discussed, rainfall in Ethiopia is low and erratic. From table 3 we observe that there is considerable inter-annual variability, as well as variability across the villages of study. The average rainfall across all the villages for the period 1995-2008 is just under 1000mm per annum, though there is considerable heterogeneity. For example, Haresaw and Geblen, villages from the Tigray region in Northern Ethiopia, experienced an average of around 400mm per annum between 1979 and 2009. Some villages also experience significant inter-annual variation. Figure 1 in the appendix provides a visualisation of the inter-annual heterogeneity in rainfall, as well as a demonstration of the degree to which the villages in the sample represent the average climate of Ethiopia. Figure 2 in the appendix shows density plots for the coefficient of variation over the two periods for which we have economic data, demonstrating the temporal variation we observe. Figures 4–6 in the appendix provide a visualisation of the spatial heterogeneity.

4.3 Empirical Strategy

We examine the effect of climate variability on SWB using the variables defined in the previous section. The model we present is estimated using a difference-in-means estimation approach (i.e., fixed-effects or "within" regression) with cluster-robust Huber-White standard errors at the village level to account for serial correlation within villages. This allows us to address the issue of time-invariant unobserved individual heterogeneity, which has been shown to be important in studies examining the determinants of SWB.[12] In addition to individual fixed effects we control for year fixed effects to control for aggregate shocks, economic development and macroeconomic policies. We also include month fixed effects to control for seasonal variation in the timing of the survey.

The model is estimated using the following specification:

$$\mathrm{W}_{it} = \alpha_i + \beta_1 \mathrm{CV}_{vt} + \beta_2 \mathrm{SHOCK}_{vt} + \beta_3 \mathrm{X}_{it} + \beta_4 \mathrm{X}_{ht} + \alpha_m + \alpha_t + \epsilon_{it}$$

where subscripts index individual, i, household, h, village, v, month, m and year, t. W_{it} is the level of life satisfaction reported by an individual i at time t. CV_{vt} corresponds to the coefficient of variation at the village level, which captures anticipatory utility. We also, include SHOCK_{vt}, a dummy variable equal to one if the village has experienced a negative rainfall shock in the past 5 years greater than or equal to a one-standard deviation deficiency below the long-run mean, which captures memory utility. In addition to these core variables, we include a set of controls and characteristics, X, measured at the individual and household level, that are determinants of current utility. α_i corresponds to the individual fixed effect, α_t to the year fixed effect, and α_m to the month fixed effect. ϵ_{ivt} is a time-varying random shock. Given that climate variability is random, and assuming that in the absence of changes in variability W_{it} would have remained the same, the parameter β_1 will represent the causal effect of climate variability on the life satisfaction of smallholder

[12] Table 4 of appendix C replicates shows the results from table 4, using village fixed effects as an alternative to individual fixed effects. The results are robust to this specification.

farmers in rural Ethiopia. More formally, in the absence of any change in climate variability, β_1 would not be statistically different from zero. Given that we control for time-invariant unobserved heterogeneity using individual fixed effects and attempt to control for other confounding variables, which may be correlated with our measure of climate variability (e.g. whether there was a negative rainfall shock in the same measurement period, the rainfall and temperature on the day of the survey to capture potential weather bias etc.) we believe that the results presented below, along with the additional evidence provided by the robustness checks, support a causal interpretation.

As a robustness check, we can extend this approach by applying an ordered probit with random effects to (1) to account for an ordinal measure of life satisfaction rather than a cardinal measure. The use of linear regression models implies that the spacing between different outcomes, e.g. "Very Satisfied" and "Dissatisfied", or "Satisfied" and "Very Satisfied" are uniform. The use of an ordered probit model assumes that the respondent's well-being W, is an unobserved latent outcome conventionally proxied by a self-reported life satisfaction response, W*, on an ordinal scale. However, since it is not possible to formulate a fixed effects ordered probit model as the fixed effects are not conditioned out of the likelihood, we have to use random effects.

However, one issue regarding the random-effects ordered probit model, indeed any random-effects model, is the strong and often unrealistic assumption that the unobserved individual heterogeneity term α_i is independent of the observable regressors X_{it}, i.e., $\mathbb{E}(\epsilon_{it}|\alpha_i, \mathrm{X}_{it}) = 0$. Because of this strong assumption, random-effects models tend to be avoided by economists and other social scientists due to issues of bias and uncertainty (Hausmann and Taylor, 1981). As unmeasurable individual heterogeneity has been shown to be an important determinant of life satisfaction (Argyle, 1999; Diener and Lucas, 1999; Ferrer-i-Carbonell and Frijters, 2004), we report results from both linear and non-linear models with fixed and random effects to test the consistency of our results across models.

5 Results

Table 4 presents results from generalised least squares with random effects (RE), ordinary least squares with fixed effects (FE), and an ordered probit model with RE to account for differences in whether one assumes cardinality or ordinality in life satisfaction data, exploring whether climate variability affects the life satisfaction of farmers surveyed in the ERHS. Table 1 in appendix B presents these results with the full set of variables. Table 2 in appendix A provides the marginal effects for the ordered probit model.

We can see that the coefficient for climate variability is negative and statistically significant at the 5% level in the most robust specification, controlling for fixed effects, an indication that anticipatory utility does enter into the utility function of farmers in line with the theory of optimal expectations. The signs and qualitative trade-off between the coefficients are relatively similar, suggesting that there is little difference in the interpretation of the results whether one assumes cardinality or ordinality in the life satisfaction data (Ferrer-i-Carbonell and Frijters, 2004). These results provide point estimates of the effect of climate variability on life satisfaction between -0.047 and -0.077 for a one unit increase in the coefficient of variation. This corresponds to approximately 2.67–4.37% of the standard deviation in the life satisfaction responses. Following a one standard deviation increase in climate variability, we would expect a decline in life satisfaction equivalent to between 20.5–33.68% of a one standard deviation in life satisfaction responses. To emphasise the potential welfare impact of climate variability, we note that this is equivalent to around a two standard deviation (1-2%) decrease in real household consumption per capita. The magnitude of this effect is considerable. Indeed, compared to the other determinants of life satisfaction examined in this paper, climate variability is shown to be one of the largest determinants.

Table 4: Climate Variability and SWB: Results from Alternative Models.

Dependent Variable: Life Satisfaction	OPROBIT- RE	RE	FE
Climate Variability	-0.047***	-0.077**	-0.070**
	(0.013)	(0.031)	(0.030)
Negative Rainfall Shock (past 5 years)	-0.115	-0.140	-0.272
	(0.081)	(0.295)	(0.307)
Average Temperature (Day of Survey)	0.030	0.091	0.313
	(0.070)	(0.165)	(0.208)
Rainfall (mm) (Day of Survey)	-0.001	-0.003	-0.014
	(0.002)	(0.006)	(0.009)
Log Real Consumption per capita	0.220***	0.300***	0.373***
	(0.031)	(0.059)	(0.109)
Month dummies	Y	Y	Y
Year dummies	Y	Y	Y
Village dummies	Y	Y	-
Individual fixed effects	N	N	Y
N	3517	3517	3517
Log-likelihood	-5710.6275	-	-
Adjusted R^2	-	0.155	0.169

[a] OPROBIT-RE, ordered probit with random effects; RE, generalised least squares with random effects; FE, ordinary least squares with fixed effects. Life Satisfaction takes a value of 1 = Very Dissatisfied, 7 = Very Satisfied. Control variables include gender, age, age-squared, log of real household consumption per capita, log of livestock owned (tropical livestock units), number of household members, dummies for marital status, unemployment, education, illness experienced in the previous 4 weeks, social network changes, relative income, household standing relative to 3 years ago. Estimates of the control variables are reported in the Appendix. Cluster-robust standard errors at the village level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Importantly, our results also reveal that present income (proxied by real consumption expenditure per capita), has a positive impact on life satisfaction. While there are clear endogeneity issues it is important to control for income to ensure that our measure of climate variability is not capturing any indirect impact on well-being through present consumption.

6 Supporting Evidence

As well as showing the robustness of our results to different linear and non-linear models, we consider a number of additional extensions and robustness checks to try and disentangle the channel observed in the reduced form results. This analysis in this section uses the most robust specification from the main analysis (the FE model).

First, we attempt to test our identifying assumption that climate variability impacts well-being through future income uncertainty and not other channels by examining the impact of CV on real consumption per capita to examine indirect effects through income.

Second, we attempt to close out the channel that increased climate variability reduces social networks through the impact that covariate risk management might have on self-insurance groups. As argued, actions to reduce exposure to covariate risk may have detrimental effects on informal insurance groups. If climate variability impacts life satisfaction only through increased stress about future income uncertainty then we should find no effect on consumption, nor social networks or self-insurance.

Third, we test our results through the use of placebo effects by looking at seasonal climate variability. We should observe that only variability during the rainy season matters, particularly the Belg season, as this is when decision-making occurs (Bezabih and Sarr, 2012). Generally, farmers in Ethiopia plant slow-maturing but high-yielding 'long-cycle' crops that grow across both the Belg and Kiremt seasons. We argue that while the Kiremt season rainfall is important for the final yield, the Belg rains are most important as a determinant of crop failure. If there is not sufficient rainfall during the Belg season for seeds to germinate, then Kiremt season rainfall is less important.

Fourth, we investigate whether climate variability affects SWB of urban Ethiopian households who do not directly depend on the rains for their livelihood.

Finally, we examine the impact of climate variability on alternative measures of SWB. We compare our results using the standard life satisfaction measure to the Cantril ladder measure and a measure of happiness. While these measures should display similar results, we exploit what we argue is an implicit time dimension in the way that these questions are interpreted. When being asked whether you are satisfied in your life or where on the Cantril ladder (an alternative measure of life satisfaction) individuals consider their lives as a whole. By contrast, when asked if an individual is happy, this is more likely to capture contemporaneous “happiness”. We argue that if climate variability is capturing the impact of future income uncertainty then we should find no effect on “happiness”. By contrast, weather effects such as rainfall and temperature on the day of the survey, if important, should matter for ‘happiness”.

Appendix B also includes a number of additional robustness tests to check the validity of our results to alternative specifications and outliers. These include: changing the period of time over which we define the coefficient of variation; alternative definitions of climate variability; more mechanical robustness tests.

6.1 The Impact of Climate Variability on Consumption and Social Networks

Table 5 provides support to our hypothesis that climate variability reduces life satisfaction through future income uncertainty. We observe that there is no effect of climate variability on real consumption per capita and no effect of climate variability on potential risk management channels. As further evidence that we are identifying *ex ante* components of climate, separate from *ex post* impacts, we observe that negative rainfall shocks reduce real consumption expenditure per capita.

Table 5: Climate Variability - Shutting Out Potentially Confounding Channels.

Dependent Variable:	Consumption	Decrease in Networks	Able to Borrow Money
	FE	FE	FE
Climate Variability	-0.008	-0.003	0.006
	(0.019)	(0.004)	(0.009)
Shock Negative Rainfall	-0.426**	-0.125**	-0.045
(past 5 years)	(0.172)	(0.054)	(0.070)
Fixed Effects	Y	Y	Y
N	3,872	3,795	3,866
Adjusted R^2	0.2076	0.045	0.058

Consumption = log real consumption per capita; Decrease in Networks = There are less people to rely on than 5 years ago, No=0, Yes=1; Able to Borrow Money = If the household needed 100 Birr for an emergency could the household obtain it within a week? Yes = 1, No=2. Cluster-robust standard errors at the village level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.2 Seasonal Variability

Table 6 shows the results from the various seasonal measures of climate variability. We observe that Belg season variability is important while Kiremt season and Bega (Dry) season variability is not. This supports our hypothesis that climate variability affects life satisfaction through stress resulting from future income uncertainty, as critical decision-making occurs in the Belg season. As stated above, Belg rainfall may be critical for agricultural output in Ethiopia, even more so than the main Kiremt rainy season, as there needs to be sufficient rainfall for seeds to germinate. A lack of rainfall in the Belg season may result in complete crop failure, whereas reductions in rainfall in the Kiremt season is likely to only reduce yields. Bezabih and Marr (2012) provide supporting evidence for this hypothesis by demonstrating that increased Belg season climate variability has a positive effect on the extensive margin of crop diversification, a risk management strategy.

Table 6: Seasonal Climate Variability and Life Satisfaction

	(1) FE	(2) FE	(3) FE	(4) FE
Climate Variability$_{Belg}$	-0.0234***			-0.0461**
	(0.00628)			(0.0175)
Climate Variability$_{Kiremt}$		-0.0171		0.0217
		(0.00981)		(0.0218)
Climate Variability$_{Bega}$			-0.0186	-0.0322
			(0.0268)	(0.0253)
Fixed Effects	Y	Y	Y	Y
Observations	3,610	3,610	3,610	3,610
Adjusted R^2	0.169	0.163	0.159	0.174

FE, ordinary least squares with fixed effects. Life Satisfaction takes a value of 1 = Very Dissatisfied, 7 = Very Satisfied. Control variables included as in table 4. Cluster-robust standard errors at the village level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.3 Rural vs. Urban Differences in the Impact of Climate Variability on SWB

Table 7 examines the impact of climate variability on SWB in Urban Ethiopia. If we expect that climate variability affects SWB through future income uncertainty, then we should expect to see no effect of climate variability on SWB in urban areas where livelihood does not directly depend on rain.[13]

We use three rounds of panel data from the Ethiopian Urban Socio-economic Survey (EUSS) in 2000, 2004, and 2009. This data consists of four cities selected to represent the major urban areas of Ethiopia: Addis Ababa, Awassa, Dessie, and Mekelle.[14]

Unlike our rural data, we are only able to control for household fixed effects, not individual fixed effects; however, we try and match the specification as closely as possible to the model used in the main results to increase the

[13]We acknowledge the caveat that climate variability could be argued to impact urban areas through general equilibrium effects on food prices, however, this is more likely to result from the realisation of shocks than climatic variability.

[14]See Alem and Söderbom (2012) for more detail on this data set.

credibility of our findings.

The results from table 7 demonstrate that SWB in urban areas is unaffected by climate variability or climate shocks in the previous 5 years. While there are limitations to this data in terms of the amount of spatial variation we can capture, we argue that the magnitude of the coefficients is small enough to support our claim, even in the event of type I error.

Table 7: Impact of Climate Variability on Life Satisfaction in Urban Ethiopia

Dependent Variable: Life Satisfaction	(1) OPROBIT RE	(2) RE	(3) FE
Climate Variability	-0.00289	-0.00128	0.00233
	(0.00577)	(0.0103)	(0.00968)
Negative Rainfall Shock (past 5 years)	0.0423	0.0392	0.192
	(0.124)	(0.242)	(0.265)
Year Dummies	Y	Y	Y
City Dummies	Y	Y	-
Household Fixed Effects	N	N	Y
Observations	2931	2931	2931
Adjusted R^2		0.241	0.248

FE, ordinary least squares with fixed effects. Life Satisfaction takes a value of 1 = Very Dissatisfied, 4 = Very Satisfied. Control variables included as in table 4. Cluster-robust standard errors at the city level are in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.4 Alternative Measures of SWB

In addition to alternative definitions of the explanatory variable, we also consider alternative dependent variables. Within the SWB literature it is generally considered that questions based on the life satisfaction scale and the Cantril ladder scale are more evaluative measures, whereas questions related to happiness are a better measure of present affect (Benjamin et al., 2013).[15]

[15] The Cantril ladder scale is measured based on the following question: "Suppose we say that the top of a ladder represents the best possible life for you and the bottom represents the worst possible life for you. Where on the ladder do you feel you personally stand at the present time?". The Happiness question, "Taken all together, how would you say things are for you these days? Would you say you are:" is measured on a 3-step likert scale with the responses: Not too happy; Pretty happy; Very happy.

Given the proposed channel through which we would expect climate variability to effect SWB, we should find similar results using the Cantril ladder scale. We do not expect that climate variability is likely to have an effect on present happiness, however, since we expect that the impact on well-being is based on uncertainty about future income.

Consistent with this hypothesis we observe in table 7 that climate variability measured annually and for the Belg season, has a negative and statistically significant effect on both life satisfaction and responses to the Cantril ladder scale; however, we observe no effect on happiness, even though all the measures are positively correlated. This indicates that the happiness responses may provide a measure of subjective well-being based on present mood, while life satisfaction and the Cantril ladder scale provide more evaluative measures of subjective well-being. This conjecture is further supported by the evidence in table 7 that average temperature on the day of the survey has a positive impact on happiness, while having no impact on the more evaluative measures. This demonstrates the importance of considering the time dimension implicit within questions on SWB when drawing policy implications from results.

Table 8: Alternative measures of subjective well-being.

	Life Satisfaction FE	Life Satisfaction FE	Ladder FE	Ladder FE	Happiness FE	Happiness FE
Annual CV	-0.070**		-0.163***		-0.016	
	(0.029)		(0.024)		(0.010)	
Belg CV		-0.023***		-0.039***		-0.003
		(0.020)		(0.007)		(0.001)
Negative Rainfall	-0.282	0.069	0.067	0.547	0.005	0.036
Shock (past 5 years)	(0.304)	(0.320)	(0.053)	(0.310)	(0.096)	(0.102)
Average Temperature	0.321	0.289	0.313	0.158	0.128**	0.119*
(Day of Survey)	(0.205)	(0.201)	(0.208)	(0.231)	(0.058)	(0.063)
Rainfall (mm)	-0.014	-0.014	-0.019*	-0.021**	-0.001	-0.001
(Day of Survey)	(0.009)	(0.009)	(0.009)	(0.008)	(0.000)	(0.001)
Fixed Effects	Y	Y	Y	Y	Y	Y
N	3517	3517	3517	3517	3517	3517
Adjusted R^2	0.169	0.173	0.271	0.265	0.146	0.145

FE, ordinary least squares with fixed effects. Life Satisfaction takes a value of 1 = Very Dissatisfied, 7 = Very Satisfied. Control variables included as in table 4. Cluster-robust standard errors at the village level are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Given the robustness of our results to the various extensions and robustness tests shown here, and in appendix C, we argue that the impact that climate variability has on farmers' SWB in rural Ethiopia is plausibly explained by the experienced utility effect of future income uncertainty. Given the lack of access to well-functioning formal insurance markets to deal with rainfall variability and the associated risk, it is not surprising that increased climate variability, capturing future income uncertainty, has a significant impact on reported subjective well-being.

7 Conclusions

In this paper we investigated the impact of future income uncertainty, proxied by climate variability, on the subjective well-being of rain-dependent farmers in Ethiopia by matching two rounds of household-level panel data with a long series of atmospheric data supplied by the European Centre for Medium-Term

Weather Forecasting (ECMWF). We implemented a series of linear and non-linear panel data models that take care of time-invariant unobserved heterogeneity and performed a number of robustness tests, which provided us with more confidence in our key results. Of particular importance is our ability to control for the level of rainfall and temperature on the day that each respondent was surveyed and disentangle the effects of climate variability from that of weather. Based on our parameter estimates we computed the welfare cost of climate variability in terms of equivalent economic loss.

Fixed-effects regression results suggest that climate variability has a significant adverse impact on the SWB of farm households in rural Ethiopia. A one standard deviation increase in climate variability is associated with a decrease in life satisfaction equivalent to a 2% decrease in real consumption per capita. We show this to be one of the largest determinants of life satisfaction in rural Ethiopia. This result indicates that anticipatory utility is an important determinant of well-being in rural Ethiopia, in line with the theory of optimal expectations (Brunnermeier and Parker, 2005). We rule out indirect channels related to effects on consumption and social network changes and demonstrate that climate variability outside the Belg season is not important for life satisfaction. Removing these channels is important as they emphasise the channel that, we argue, underpins our results, namely, that stress resulting from future income uncertainty has a negative impact on well-being. Belg season variability is arguably the most important determinant for future income uncertainty as this is the period in which production decisions occur. Furthermore, there needs to be sufficient rainfall for seeds to germinate. A lack of rainfall in the Belg season may result in complete crop failure, whereas reductions in rainfall in the Kiremt season are likely only to reduce yields. Interestingly, we show that climate variability does not have any statistically significant impact on SWB of respondents in urban Ethiopia, whose livelihoods do not directly depend on rain.

Results also confirm the importance of other conventional correlates of SWB that were found to be important in studies in other developed and developing countries, indicating the consistency of these relationships.

We argue that investigating the impact of climate variability on SWB in rural Ethiopia provides useful insights on the welfare costs of climate variability. The fact that climate variability affects utility or the welfare of farmers reinforces the findings from earlier studies on the adverse impact of a changing climate on objective indicators such as agricultural yield and income. Furthermore, we observe that the main impact of climate variability on well-being arises because of uncertainty about future income in concordance with the theory of optimal expectations. As a result, increased access to *ex post* coping mechanisms, such as insurance, and *ex ante* risk management strategies, as well as increased information helping farmers to form better subjective probabilities about the likelihood of future shocks are likely to reduce the importance of anticipatory utility, increasing welfare.

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Appendices - For Online Publication

The Following Appendices are displayed in three parts. Appendix A presents a series of Maps and Charts references in the Main text. Appendix B presents the full regression tables referred to in the main results table. Appendix C presents a series of mechanical robustness tests that demonstrate the validity of our results to alternative specifications and outliers.

Appendix A - Maps, and Graphs

Appendix A presents a series of graphs and maps that have been referenced to in section 2 of the main text. It also provides the complete table of descriptive statistics referred to in the data description.

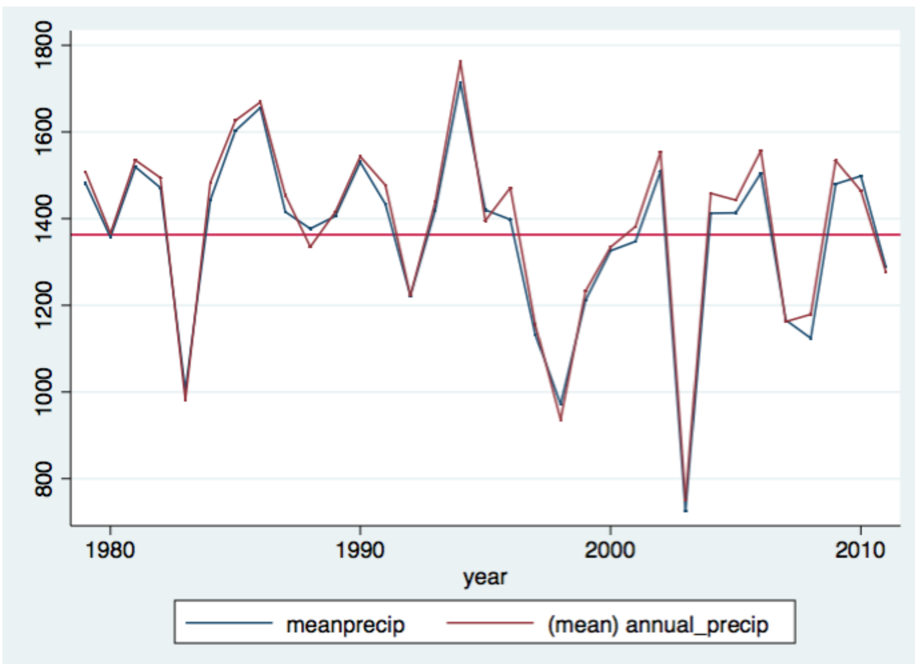

Figure 1: Differences in the average annual rainfall of the villages and Ethiopia as a whole.

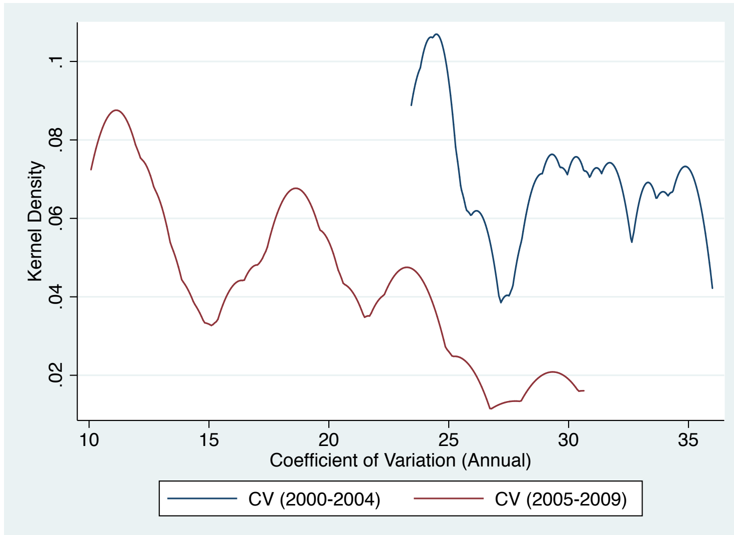

Figure 2: Differences in the Coefficient of Variation across villages between the two time periods.

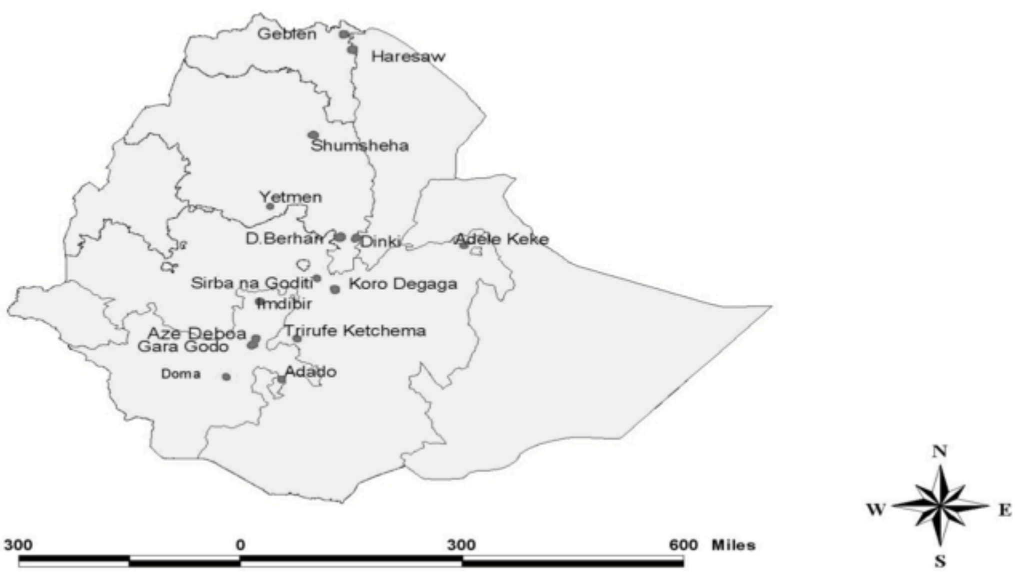

Figure 3: The ERHS Villages (Dercon & Hoddinott, 2009)

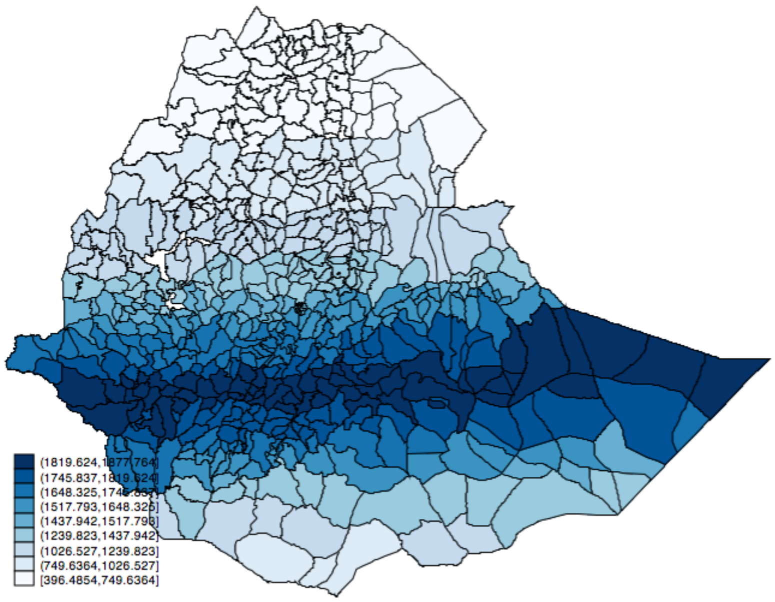

Figure 4: Average Annual Rainfall (1979-2011)

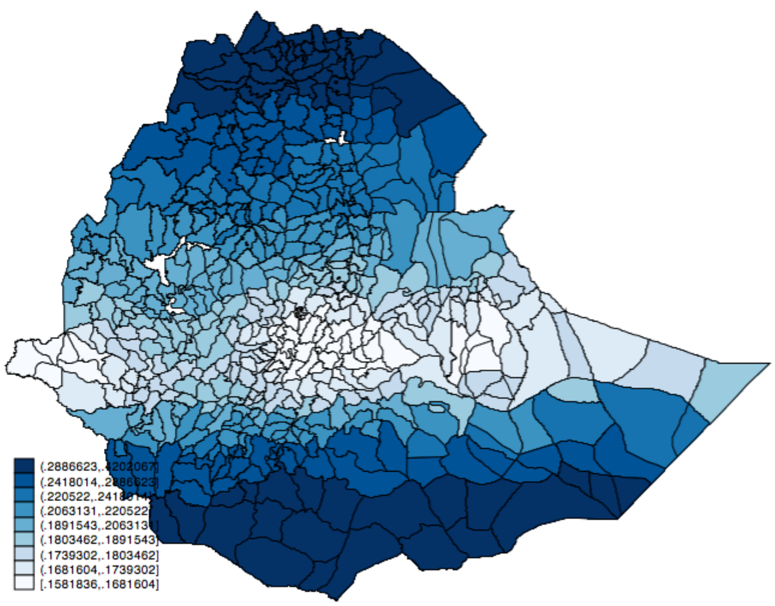

Figure 5: The Coefficient of Variation (1979-2011)

Table A1: Summary statistics - Ethiopian Rural Household Survey

Variable	Mean	Std. Dev.	N	Mean	Std. Dev.	N	
Dependent Variables				Muslim	0.24	0.427	3781
Reported Life Satisfaction	3.97	1.70	3877	Other	0.016	0.125	3781
Cantril Ladder	4.47	1.81	3866	No Schooling	0.563	0.496	3877
Reported Happiness	1.86	0.645	3869	Grades 1-7	0.207	0.405	3877
Climate Variables				Grades 8 plus	0.049	0.216	3877
Climate Variability (Annual)	22.98	7.71	3877	Illness	0.249	0.432	3796
Climate Variability (Belg)	36.29	11.78	3877	*Household variables*			
Climate Variability (Kiremt)	23.17	10.34	3877	Richest	0.011	0.104	3869
Rainfall Shock (Past 5 years)	0.712	0.45245	3877	Richer than Most	0.123	0.3288	3869
Log Annual Std. Dev. Rainfall (mm)	5.90	0.479	3877	Average*	0.516	0.49	3869
Rainfall (mm) (Day of Survey)	3.42	4.65	3877	Poorer than Most	0.456	0.384	3869
Average Daily Temperature (Day of Survey)	26.65	0.829	3877	Poorest	0.053	0.225	3869
Respondent variables				Richer than three years ago	0.469	0.499	3849
Age	46.612	15.203	3774	Poorer than three years ago	0.236	0.425	3849
Female	0.41	0.49	3877	No change in income compared to three years ago*	0.293	0.455	3849
Unemployed	0.016	0.126	3877	Larger social network	0.271	0.444	3795
Married*	0.764	0.425	3773	Smaller social network	0.277	0.447	3795
Single	0.045	0.208	3773	Smaller social network	0.277	0.447	3795
Divorced	0.045	0.207	3773	No change in social network*	0.451	0.497	3795
Widowed	0.146	0.353	3773	Livestock	2.844	3.079	3854
Not Religious*	0.002	0.043	3781	Log Real Consumption per capita	3.973	0.776	3873
Christian	0.742	0.437	3781	Log Household Size	1.676	0.507	3873

* denotes reference group.

Appendix B - Main Results

Appendix B provides the complete regression tables for the main analysis referred to in section 3. Table 1 provides the main results. Table 2 provides the marginal effects for the ordered probit specification.

Table A1: Life Satisfaction Regressions: Main Results

	(1)	(2)	(3)
Dependent Variable: Life Satisfaction	OPROBIT-RE	RE	FE
Core variable			
CV	-0.047***	-0.077**	-0.070**
	(0.013)	(0.031)	(0.030)
Negative Rainfall Shock (past 5 years)	-0.115	-0.140	-0.272
	(0.081)	(0.295)	(0.307)
Average Temperature (Day of Survey)	0.030	0.091	0.313
	(0.070)	(0.165)	(0.208)
Rainfall (mm) (Day of Survey)	-0.001	-0.003	-0.014
	(0.002)	(0.006)	(0.009)
Individual Characteristics			
Age	-0.026***	-0.033***	-0.046**
	(0.007)	(0.012)	(0.020)
Age squared	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Female	0.004	0.013	-
	(0.040)	(0.063)	-
Unemployed	-0.310**	-0.414**	-0.804*
	(0.154)	(0.185)	(0.407)
Single	-0.237**	-0.338***	-0.553*
	(0.098)	(0.122)	(0.277)
Divorced	0.050	0.109	-0.060

Continued on next page

Table A1 – continued from previous page

	(1) OPROBIT-RE	(2) RE	(3) FE
	(0.095)	(0.120)	(0.350)
Widowed	- 0.009	0.014	0.066
	(0.059)	(0.104)	(0.199)
Christian	1.221**	1.339***	-
	(0.496)	(0.233)	-
Muslim	1.106**	1.179***	-
	(0.500)	(0.260)	-
Other	1.502***	1.784***	-
	(0.514)	(0.356)	-
Grades 1-7	-0.071	-0.111**	-0.042
	(0.049)	(0.051)	(0.157)
Grades 8 plus	-0.310***	-0.498***	-0.537
	(0.090)	(0.151)	(0.303)
Illness	-0.048	-0.056	-0.032
	(0.043)	(0.090)	(0.099)
Household Characteristics			
Richest	0.295*	0.233	0.111
	(0.173)	(0.399)	(0.705)
Richer than most	0.377***	0.540***	0.315**
	(0.059)	(0.098)	(0.147)
Poorer than Most	-0.567***	-0.871***	-0.792***
	(0.046)	(0.086)	(0.147)
Poorest	-1.062***	-1.452***	-1.430***
	(0.095)	(0.101)	(0.208)
Richer than 3 years ago	0.097**	0.139	-0.003
	(0.043)	(0.103)	(0.156)
Poorer than 3 years ago	-0.213***	-0.336***	-0.410**

Continued on next page

Table A1 – continued from previous page

	(1) OPROBIT-RE	(2) RE	(3) FE
	(0.052)	(0.094)	(0.142)
Increased Social Network	0.052	0.058	0.018
	(0.044)	(0.097)	0.156
Decreased Social Network	-0.082*	-0.117	-0.364***
	(0.045)	(0.074)	(0.142)
Livestock	0.015***	0.017	0.020
	(0.005)	(0.059)	(0.017)
Log Real Consumption per capita	0.220***	0.300***	0.373***
	(0.031)	(0.059)	(0.109)
Log Household Size	0.090*	0.114	0.114
	(0.048)	(0.112)	(0.215)
Year Dummies	YES	YES	YES
Month Dummies	YES	YES	YES
Village Dummies	YES	YES	-
Individual Fixed-Effects	NO	NO	YES
Observations	3,517	3,517	3,517
Log-likelihood	-5710.6275	-	-
R^2	-	0.155	0.169

[a] OPROBIT-RE, ordered probit with random effects; RE, generalised least squares with random effects; FE, ordinary least squares with fixed effects. Life Satisfaction takes a value of 1 = Very Dissatisfied, 7 = Very Satisfied.

[b] Cluster-robust standard errors at the village level are in parentheses.

[c] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Marginal Effects: Computed from Table A2, Column 1

	(1) VD	(2) D	(3) SD	(4) Neither	(5) S	(6) SS	(7) VS
Core variable							
CV	0.060***	0.091***	0.025***	0.003***	-0.034***	-0.102***	-0.043***
Individual Characteristics							
Age	0.002***	0.004***	0.001***	0.000**	-0.001***	-0.004***	-0.001***
Age squared	0.000***	0.000***	-0.0000***	-0.000***	-0.000***	0.000***	0.000***
Female*	-0.002	-0.003	-0.000	-0.000	0.001	0.003	0.001
Unemployed*	0.032**	0.050**	0.013**	0.001*	-0.019**	-0.055**	-0.023**
Single*	0.024**	0.038**	0.010**	0.001**	-0.014**	-0.042**	-0.004
Divorced*	-0.004	-0.007	-0.001	- 0.000	0.002	0.007	0.003
Widowed*	0.000	0.001	0.000	0.000	-0.000	-0.001	-0.000
Christian*	-0.132**	-0.204**	-0.056**	-0.007**	0.079**	0.225**	0.095**
Muslim*	-0.129**	-0.185**	-0.050**	-0.006**	0.072**	0.205**	0.086**
Other*	-0.164***	-0.253***	-0.069***	-0.008**	0.099***	0.280***	0.117***
Grades 1-7*	0.006	0.010	0.002	0.000	-0.004	-0.011	-0.004
Grades 8 plus*	0.032***	0.050***	0.013***	0.001***	-0.019***	-0.055***	-0.023***
Illness*	0.004	0.006	0.001	0.000	-0.002	-0.007	-0.002
Household Characteristics							

Continued on next page

Table A2 – continued from previous page

	(1) VD	(2) D	(3) SD	(4) Neither	(5) S	(6) SS	(7) VS
Richest*	-0.031*	-0.048*	-0.013*	-0.001	0.018*	0.053*	0.022*
Richer than Most*	-0.041***	-0.063***	-0.002***	-0.0021***	0.024***	0.069***	0.029***
Poorer than Most*	0.061***	0.094***	0.025***	0.003***	-0.036***	-0.103***	-0.043***
Poorest*	0.116***	0.179***	0.049***	0.006***	-0.069**	-0.197***	-0.083***
Richer than 3 years ago*	-0.010**	-0.016**	-0.004**	-0.000**	0.006**	0.017**	0.007**
Poorer than 3 years ago*	0.023***	0.021***	0.009***	0.001***	-0.014***	-0.039***	-0.016***
Increased Social Network*	-0.004	-0.006	-0.001	-0.000	0.002	0.007	0.003
Decreased Social Network*	0.009**	0.014**	0.004**	0.000*	-0.005**	-0.016**	-0.006**
Livestock	-0.001	-0.002***	-0.000***	-0.000***	0.001***	0.003***	0.001***
Log Real Consumption per capita	-0.020***	-0.031***	-0.008***	-0.001***	0.012***	0.034***	0.014***
Log Household Size	-0.008	-0.012	-0.003	-0.000	0.004	0.013	0.005

*** p<0.01, ** p<0.05, * p<0.1

Appendix C - Robustness tests

Appendix C presents additional robustness tests referred to in section 4.

Table A1: Changes to the Temporal Measurement of Climate Variability

	(1) Annual	(2) Belg	(3) Kiremt
Climate Variability (10 years)	-0.0642	-0.0293***	-0.0205
	(0.0521)	(0.0062)	(0.0222)
Climate Variability (9 years)	-0.0550	-0.0208***	-0.0352
	(0.0419)	(0.0068)	(0.0228)
Climate Variability (8 years)	-0.615**	-0.0222***	-0.0398**
	(0.0274)	(0.0059)	(0.0134)
Climate Variability (7 years)	-0.0580	-0.0230***	-0.0278**
	(0.0247)	(0.0047)	(0.0176)
Climate Variability (6 years)	-0.0580	-0.0230***	-0.0278**
	(0.0366)	(0.0065)	(0.0127)
Climate Variability (5 years)	-0.0700**	-0.0234***	-0.0171
	(0.0297)	(0.0063)	(0.0098)
Climate Variability (4 years)	-0.0481**	-0.0149*	-0.0182*
	(0.0217)	(0.0080)	(0.0098)
Climate Variability (3 years)	-0.0166	0.0195*	-0.0087*
	(0.0144)	(0.0095)	(0.0047)
Climate Variability (2 years)	-0.0087	0.0144	-0.0058*
	(0.0108)	(0.0125)	(0.0031)
Month Dummies	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes
Observations	3,610	3,610	3,610
Adjusted R^2	[0.153 - 0.166]	[0.162 - 0.173]	[0.153 - 0.166]

[a] FE, ordinary least squares with fixed effects. Life Satisfaction takes a value of 1 = Very Dissatisfied, 7 = Very Satisfied. Control variables included as in table 4.
[b] Cluster-robust standard errors at the village level are in parentheses.
[c] For each different measure we control for whether a rainfall shock was experienced over the same period. After 5 years, all villages had experienced a shock and so we controlled for whether a shock was experienced in the previous 5 years.
[d] The range of the Adjusted R^2 is reported.
[e] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A1 demonstrates the robustness of our results to alternative time periods over which we measure the coefficient of variation. Most importantly, we observe that our measure of Climate Variability over the Belg season is significant over most alternative time periods. Given the small number of villages and rounds of data, one of the major limitations of this study is the amount of spatial and temporal variation we are able to identify an effect from. As we extend the number of time periods over which we measure the coefficient of variation, this is likely to reduce the variation through time as well, reducing the signal that we are able to capture. Similarly, as we reduce the number of years over which we measure the coefficient of variation, we are less likely to distinguish between climate and weather. In addition to the controls displayed in the table, we control for whether the village experienced a weather shock in the previous x years, in which x is equal to the time scale over which we measure the coefficient of variation, ranging from 2 years up to 10 years. Unfortunately, each village in our sample had experienced at least one shock after 5 years and so we held the variable fixed at 5 years for time scales above 5 years.

Table A2: Climate Variability and Life Satisfaction - Removal of Outliers.

Dependent Variable: Life Satisfaction	*Geblen Removed*	*Korodegaga Removed*	*Both Removed*
Belg Climate	-0.017**	-0.023***	-0.015*
Variability	(0.007)	(0.006)	(0.007)
Negative Rainfall Shock	0.075	0.232	0.238
(past 5 years)	(0.325)	(0.312)	(0.312)
Average Temperature	0.280	0.390*	0.407**
(Day of Survey)	(0.193)	(0.187)	(0.164)
Rainfall (mm)	-0.006	-0.007	-0.006
(Day of Survey)	(0.004)	(0.004)	(0.004)
Month dummies	Y	Y	Y
Year dummies	Y	Y	Y
Individual fixed effects	Y	Y	Y
N	3,351	3,288	3,122
Adjusted R^2	0.169	0.179	0.170

[a] FE, ordinary least squares with fixed effects. Life Satisfaction takes a value of 1 = Very Dissatisfied, 7 = Very Satisfied. Control variables included as in table 3.
[b] Cluster-robust standard errors at the village level are in parentheses.
[c] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2 demonstrates the robustness of our results to the removal of outliers in the explanatory variable. We begin by dropping the village with the highest climate variability, Geblen. In the next test, we drop the village with the lowest climate variability, Korodegaga. In the final test, we drop both villages. The fact that these results remain significant once we have removed so much of the variation emphasises the importance and magnitude of the effect.

Table A3 shows how our results are robust to an alternative specification of our explanatory variable, which we define as the standard deviation of rainfall over each period: 2000–2004, and 2005–2009.

Table A3: Climate Variability and Life Satisfaction - Alternative Explanatory Variable.

Dependent Variable: Life Satisfaction	FE	FE
Annual Climate Variability (log of std. dev)	-1.222**	
	(0.517)	
Belg Climate Variability (log of std. dev)		-0.934***
		(0.031)
Negative Rainfall Shock (past 5 years)	-0.326	0.131
	(0.282)	(0.295)
Average Temperature (Day of Survey)	0.496**	0.309
	(0.214)	(0.196)
Rainfall (mm) (Day of Survey)	-0.006	-0.006
	(0.004)	(0.004)
Month dummies	Y	Y
Year dummies	Y	Y
Individual fixed effects	Y	Y
N	3,610	3,610
Adjusted R^2	0.175	0.178

[a] FE, ordinary least squares with fixed effects. Life Satisfaction takes a value of 1 = Very Dissatisfied, 7 = Very Satisfied. Control variables include gender, age, age-squared, log of real household consumption per capita, log of livestock owned (tropical livestock units), number of household members, dummies for marital status, unemployment, education, illness experienced in the previous 4 weeks, social network changes, relative income, household standing relative to 3 years ago.
[b] Cluster-robust standard errors at the village level are in parentheses.
[c] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We observe surprisingly similar effects in terms of magnitude to our original measure of climate variability. As with our standard measure of climate variability, the coefficient of variation, a one standard deviation increase in the standard deviation of rainfall (0.479) results in a decrease in life satisfaction equivalent to a two percent decline in real consumption per capita.

Table A4: Climate Variability and SWB: Results from Alternative Models with Village Fixed Effects.

Dependent Variable: Life Satisfaction	OPROBIT- RE	RE	FE
Climate Variability	-0.050***	-0.059***	-0.079**
	(0.006)	(0.011)	(0.030)
Negative Rainfall Shock (past 5 years)	-0.040	0.209	-0.139
	(0.062)	(0.207)	(0.291)
Average Temperature (Day of Survey)	-0.069*	-0.171*	0.088
	(0.037)	(0.089)	(0.158)
Rainfall (mm) (Day of Survey)	-0.003	-0.003	-0.004
	(0.004)	(0.006)	(0.006)
Month dummies	Y	Y	Y
Year dummies	Y	Y	Y
Village Fixed Effects	N	N	Y
N	3,461	3,461	3,461
Log-likelihood	-5,649.0032	-	-
Adjusted R^2	-	0.213	0.219

[a] OPROBIT-RE, ordered probit with random effects; RE, generalised least squares with random effects; FE, ordinary least squares with fixed effects. Life Satisfaction takes a value of 1 = Very Dissatisfied, 7 = Very Satisfied. Control variables include gender, age, age-squared, log of real household consumption per capita, log of livestock owned (tropical livestock units), number of household members, dummies for marital status, unemployment, education, illness experienced in the previous 4 weeks, social network changes, relative income, household standing relative to 3 years ago.

[b] Cluster-robust standard errors at the village level are in parentheses.

[c] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4 demonstrates the robustness of our results to village fixed effects. As we observe there is very little change in the magnitude of the coefficients when we control for these factors.

Table A5: Climate Variability and SWB: Results from Alternative Models with Contemporaneous Weather Shock Controls.

Dependent Variable: Life Satisfaction	OPROBIT- RE	RE	FE
Climate	-0.049***	-0.079***	-0.073**
Variability	(0.012)	(0.030)	(0.003)
Negative Rainfall Shock	-0.135*	-0.160	-0.276
(Last Agricultural Year)	(0.062)	(0.298)	(0.302)
Average Temperature	0.025	0.083	0.315
(Day of Survey)	(0.071)	(0.006)	(0.224)
Rainfall (mm)	-0.003	-0.003	-0.016
(Day of Survey)	(0.004)	(0.006)	(0.009)
Month dummies	Y	Y	Y
Year dummies	Y	Y	Y
Village Dummies	Y	Y	-
Individual Fixed Effects	N	N	Y
N	3,461	3,461	3,461
Log-likelihood	-5,623.6164	-	-
Adjusted R^2	-	0.153	0.169

[a] OPROBIT-RE, ordered probit with random effects; RE, generalised least squares with random effects; FE, ordinary least squares with fixed effects. Life Satisfaction takes a value of 1 = Very Dissatisfied, 7 = Very Satisfied. Control variables include gender, age, age-squared, log of real household consumption per capita, log of livestock owned (tropical livestock units), number of household members, dummies for marital status, unemployment, education, illness experienced in the previous 4 weeks, social network changes, relative income, household standing relative to 3 years ago.
[b] Cluster-robust standard errors at the village level are in parentheses.
[c] * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5 shows that controlling for the negative rainfall shocks in the most recent agricultural has no qualitative effect, and only a minor quantitative impact on our results.