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Consumption Smoothing and the Welfare Cost of Uncertainty*

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Abstract

When agents are unable to smooth consumption and have distorted beliefs about the likelihood of future income realisations, uncertainty about future states of the world has a direct effect on individual welfare. However, separating the effects of uncertainty from realised events and identifying the welfare effects of uncertainty both present a number of empirical challenges. Combining individual-level panel data from rural and urban Ethiopia with high-resolution meteorological data, we estimate the empirical relevance of uncertainty on objective consumption and subjective well-being. While negative income shocks affect both objective consumption measures and subjective well-being, greater income uncertainty only has an affect on subjective well-being. A one standard deviation change in income uncertainty is equivalent to a one standard deviation change in realised consumption. These results indicate that the welfare gains from further consumption smoothing are substantially greater than estimates based solely on consumption fluctuations.

JEL: D8, O12, I3.

Keywords: Uncertainty, Consumption Smoothing, Subjective Well-Being

1 Introduction

Economists have long recognised that an individual's sense of well-being depends not only on their average income or expenditures, but on the risk they face as well.

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While a number of studies have attempted to isolate the effects of uncertainty on macroeconomic outcomes in both developed and developing countries (Koren and Tenreyro, 2007; Baker and Bloom, 2013; Bloom, 2009, 2014), efforts to identify the effects of uncertainty at the microeconomic level have so far been limited. In many developing countries, where insurance and credit market failures are common place, the consequences of uncertainty on individual welfare are likely to be exacerbated, providing a context within which it is possible to identify the effects of uncertainty on individual behaviour and welfare.

A significant body of research in development economics has focussed on estimating the response of household consumption to income fluctuations (Townsend, 1994; Udry, 1994; Morduch, 1995; Fafchamps and Lund, 2003; Suri, 2011; Kinnan, 2014). In the presence of insurance and credit market failures, households are exposed to consumption risk and must rely on imperfect risk sharing mechanisms. Given the nature of partial insurance, welfare gains exist from further consumption smoothing. However, these gains are likely underestimated when focussing solely on the *ex post* consequences of income shocks. A separate literature has consistently documented individuals performing poorly in assessing probabilities and overestimating the the likelihood of success as a result of distorted beliefs (Weinstein, 1980; Alpert and Raiffa, 1982; Buehler et al., 1994; Rabin and Schrag, 1999; Brunnermeier and Parker, 2005; Brunnermeier et al., 2013). In the presence of partial insurance this implies that uncertainty surrounding the likelihood of future shocks has an additional direct impact on welfare beyond the *ex post* realisation of income shocks.

This paper aims to understand the empirical relevance of uncertainty on individual welfare. If households are able to effectively smooth consumption then uncertainty about future income flows should have little effect. However, if households are exposed to consumption risk, then uncertainty about future income realisations may have a direct effect on individual welfare. In this case the returns to consumption smoothing will be greater than observed differences in consumption fluctuations.

In section 3, we present a simple theoretical framework in the spirit of Brunnermeier and Parker (2005), which introduces forecasting error in farmers' appraisal of future rainfall realisations arising from optimism about the future. This forecasting error creates a wedge between an individual's subjective probability and the objective probability of an income shock being realised, such that individuals underestimate the likelihood of a bad outcome. In this model, forward-looking farmers who care about expected future utility will make investments to maximise future utility; however, these same farmers will also have higher contemporaneous utility if they are optimistic about the future (anticipatory utility), introducing a trade-off between risk management investments and the benefits of optimism. In areas with greater rainfall variability there is greater uncertainty about a negative income shock being realised, so farmers are less optimistic about the future than farmers living in areas with lower variability. Consequently, the model predicts that farmers living in areas with greater income uncertainty will have lower well-being than comparable farmers living in areas with less variable climates. An attractive feature of this framework is that it tends towards a model of rational expectations as an individual's subjective probability tends towards the objective probability. In this instance, expectations about the future no longer enter into current utility. This highlights the potential welfare gains that increased access to information can provide (Rosenzweig and Udry, 2013, 2014).

Using panel data from two separate household surveys in rural and urban areas combined with high-resolution meteorological data we exploit plausibly exogenous variation in rainfall variability, the second moment of the rainfall distribution, – after controlling for contemporaneous and historical rainfall shocks, the first moment – to examine the effects of income uncertainty on objective consumption and subjective well-being in rural and urban Ethiopia –, one of the least developed countries in Africa, which is characterised by its high vulnerability to inclement weather.

Consistent with a large literature, we observe that the realisation of inclement weather has a negative effect on consumption in rural areas, falsifying the hypothesis that there is pareto efficient risk sharing in the face of aggregate shocks. The realisation of such consumption effects are also shown to negatively affect subjective well-being above and beyond the impact on consumption, suggesting the presence of direct psychic costs.[1] In addition, we observe that an increase in inter-annual rainfall variability, – a proxy for income uncertainty after controlling for contemporaneous and historical income shocks – has a negative effect on subjective well-being in rural areas, but has no effect on objective consumption or on either outcome in urban areas.[2]

[1]The estimated elasticities for each result are net of all risk management and insurance practices being used (both informal and formal, where present). In the presence of full insurance these coefficients should be zero.

[2]The lack of impact on consumption outcomes help to support the identification assumption

Our results indicate that the welfare gains from further consumption smoothing in rural areas of developing countries are likely to be substantially greater than estimates based solely on consumption fluctuations. Indeed, income uncertainty is shown to be one of the largest determinants of subjective well-being in rural Ethiopia. If a household were to move from the most variable climate to the least variable climate, life satisfaction would increase by 2 standard deviations, comparable to the effect of a household moving from being the poorest to the richest household. By incorporating the welfare costs of uncertainty, our findings help to provide a more complete understanding of the welfare gains from further consumption smoothing and risk management.

The remainder of the paper is structured as follows: section 2 presents the context of the study and provides a brief review of the literature; section 3 presents the theoretical framework that provides the structure for our empirical analysis; section 4 introduces the data and presents the identification strategy and main empirical specification; section 5 discusses our main results; section 6 presents supporting evidence and robustness tests exploiting differences between rural and urban areas as well as variation in the timing of the agricultural season; the final section summarises the implications of these results and concludes.

2 Background

Uncertainty is a nebulous concept. Knight (1921) created the modern definition of *uncertainty*. He began by defining the related concept of *risk*, which, he argued, covers a known probability distribution over a set of events. By contrast, *uncertainty* captures people's inability to forecast the likelihood of events happening when an individual's prior is infinitely diffuse. Bayesian uncertainty, a related concept, captures how diffuse an individual's prior is. For farmers in rain-dependent agrarian communities, an increase in rainfall variability makes forming expectations about rainfall realisations more difficult, affecting decisions about which crops to plant and which inputs, and how much of each input, to use in the production process. The concepts of risk and uncertainty are strongly related and, in many cases, the term risk may be applied in the context of uncertainty when outcomes involve a loss. Empirically, the

that rainfall variability affects well-being through *ex ante* uncertainty, rather than being driven by realised events.

measurement of uncertainty is challenging because it is not directly observed.

Interest in the economic consequences of uncertainty has seen a resurgence in recent years (Bloom, 2014). This has been driven in part by policy attention following the role that uncertainty played in shaping the Great Recession, alongside an increase in the availability of measures of uncertainty through more readily available proxies and increased computing power.

Given the difficulties associated with measuring uncertainty, it should be clear that there is no perfect measure but there is a broad range of proxies – such as the volatility of the stock market or GDP – because when a data series becomes more volatile it is harder to forecast (Ramey and Ramey, 1995; Koren and Tenreyro, 2007; Bloom, 2009; Carriere-Swallow and Céspedes, 2013; Bloom, 2014). Given these measures, much of the literature has focussed on macroeconomic outcomes in developed countries. However, risk and uncertainty is pervasive in developing countries and affects decision-making and welfare at the individual level as well as the macroeconomic level. As such, we introduce a new proxy for uncertainty – rainfall volatility – that is suited to understanding the consequences of uncertainty on individual welfare in developing countries.

A central challenge in this literature is identifying the effects of uncertainty; specifically, the challenge relates to distinguishing the impact of uncertainty from the impact of realised events. We argue that by controlling for contemporaneous and historical rainfall shocks, any residual variation in rainfall variability acts as a suitable proxy for the effects of income uncertainty on smallholder farmers. Similar to the reasoning behind the use of stock market and GDP volatility, increased volatility in rainfall patterns makes it harder to forecast, increasing uncertainty. By stripping out variation associated with realised income effects, namely the level of rainfall, the volatility parameter plausibly distinguishes the effects of uncertainty from realised events.

An additional challenge that arises when moving from the macroeconomic level to the microeconomic level is how to calculate the effects of uncertainty on individual welfare. The past decade has seen rapid growth in research on, and policy interest in, subjective well-being. In addition to "objective" measures of welfare, such as income and consumption, subjective measures of welfare are increasingly being used to elicit measures of experienced utility (Kahneman et al., 1997; Frey and Stutzer, 2002; Layard, 2005; Kahneman and Krueger, 2006; Dolan and Kahneman, 2008; Benjamin et al., 2012; Aghion et al., 2015; De Neve et al., 2015) to value non-market goods

(Welsch, 2002, 2006; Rehdanz and Maddison, 2011; Carroll et al., 2009; Frey et al., 2010; Levinson, 2012; Feddersen et al., 2015) and to evaluate government policy (Gruber and Mullainathan, 2005; Diener et al., 2009; Dolan et al., 2011; Levinson, 2013). Well-being is a broad measure of welfare that encompasses 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.

Whether uncertainty about the future has a direct effect on well-being is ambiguous. The degree to which it does relates to the concept of anticipatory utility. Anticipatory utility has been a widely debated subject in academic and policy circles dating back to the time of Hume (1711–1776), Bentham (1789), Marshall (1891) and Jevons (1905). In "Principles of Economics", Marshall writes,

> *"...when calculating the rate at which a future benefit is discounted, we must be careful to make allowance for the pleasures of expectation."* (Marshall, 1981, p.178).

The other side of the coin is that future costs are also incorporated into utility. More recently, work in behavioural economics has explored the importance of anticipatory utility on decision-making (Lowenstein, 1987; Geanakoplos et al., 1989; Caplin and Leahy, 2001; Yariv, 2001; Brunnermeier and Parker, 2005; Brunnermeier et al., 2013). The next section introduces a model, based on Brunnermeier and Parker (2005), that formalises this concept providing some structure to the empirical analysis conducted in the proceeding sections.

3 Theoretical Motivation: Subjective Probabilities and Subjective Well-Being

In this section we present a model, based on the optimal expectations framework by Brunnermeier and Parker (2005), in which beliefs about future states of the world can enter directly into the current utility function; that is, agents care about both current utility and expected future utility. While all forward-looking agents who care about expected future utility will make investments to maximise future utility, if an agent's subjective probability about a future utility shock differs from the true probability, then their beliefs about the future will affect utility today. For example, agents will have higher current utility if they are optimistic about the future; i.e., their subjective probability is lower than the true probability. In the context of this paper, farmers living in areas with lower climate variability may have lower subjective probabilities regarding the likelihood of a negative income shock being realised in the next period and so may have higher current utility. The framework presented provides a theoretical mapping between utility and life satisfaction, and motivates our empirical strategy.

3.1 Utility Maximization Given Beliefs

Consider a world in which uncertainty about future income can be described as 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 he 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. These subjective probabilities are relevant for the decision making of the agent. 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 are no savings, so income is equal to consumption in each period,

$$\hat{\mathbb{E}}[U(c_1, c_2, \ldots, c_T|\underline{s}_t] \tag{1}$$

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 the information available to farmer i at time t.

The farmer maximises utility of consumption subject to his budget constraint:

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

where $f(\cdot)$ provides the evolution of income, which is continuous and differentiable in c, $g(\cdot)$ gives the endpoint condition, and c_0 is the initial level of consumption. The optimal consumption is denoted $c^*(\underline{\mathrm{s}}_t, \hat{p})$.

When the subjective probability of an income shock does not coincide with the true probability, the utility of the farmer, $\hat{\mathbb{E}}[U(\cdot)|\underline{\mathrm{s}}_t]$, depends on expected future utility or anticipated utility, such that the subjective conditional belief has a direct impact on utility. To clarify this further, consider the standard model with time-separable utility flows and exponential discounting. In this case, utility at time t,

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

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 realizations (memory utility), contemporaneous weather (current consumption), and climate variability (anticipatory utility).

3.2 Optimal Beliefs and Life Satisfaction

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

Assumption 1 *Subjective probabilities are restricted in the following ways:*

i $\sum_{s_t \in S} \hat{p}(s_t|\underline{s}_{t-1}) = 1$

ii $\hat{p}(s_t|\underline{s}_{t-1}) \geq 0$

iii $\hat{p}(s'_t) = \hat{p}(s'_t|s'_{t-1})\hat{p}(s'_{t-1}|s'_{t-2})\ldots\hat{p}(s'_1)$

iv $\hat{p}(s'_t|s'_{t-1}) = 0$ *if* $\hat{p}(s'_t|s'_{t-1}) = 0$

Assumption 1(i) states simply that subjective probability must add up to one; assumptions 1(i) - (iii) state that the law of iterated expectations holds for subjective probabilities; and assumption 1(iv) states that in order to believe something is possible, it must be possible.

The optimal beliefs for the farmer are the subjective probabilities that maximise the farmer's lifetime well-being 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 lifetime well-being*

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

If farmers have rational expectations, (i.e, $\hat{p}(s_t|\underline{\mathrm{s}}_{t-1}) = p(s_t|\underline{\mathrm{s}}_{t-1})$) then the well-being and utility derived from the actions that farmers take will coincide. In this case, utility at time t only depends on present consumption (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 actuarially fair insurance is both available and effective. 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 will enter into the utility function as in equation 4 and 5.

4 Data and Empirical Strategy

4.1 Data

The analysis conducted in this paper uses household survey data from rural and urban Ethiopia. For the rural analysis, two rounds of a panel data set – the Ethiopian Rural Household Survey (ERHS) – that covers households from 15 villages in rural Ethiopia is used. The ERHS was conducted by Addis Ababa University in collaboration with the Centre for the Study of African Economies (CSAE) at the University of Oxford and the International Food Policy Research Institute (IFPRI) in seven rounds between 1989 and 2009. The sampling was constructed carefully to represent the major agro-ecological zones of Ethiopia. Households from six villages 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 villages across the major regions of Ethiopia (Tigray, Amhara, Oromia, and Southern Nations Nationalities and People's Region), representing 1,477 households. Further rounds were completed in 1995, 1997, 1999, 2004, and 2009. The additional villages incorporated in the sample were chosen to account for the diversity in 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 subjective well-being. One of the surprising features of the data set is the limited attrition compared to other household surveys in developing countries. Attrition of the panel has been low at 1-2 percent of households per round since the survey first began, indicating substantial persistence in the social structure of villages in rural Ethiopia (Dercon and Hoddinott (2009)). In addition to a specific module on subjective well-being, the data set contains detailed information on individual and household characteristics, assets, expenditures, consumption, health, agricultural production, and information related to input use.

For the urban analysis we use three rounds of panel data from the Ethiopian Urban Socio-economic Survey (EUSS). The EUSS was conducted by Addis Ababa University in collaboration with the University of Gothenburg in five rounds between 1994 and 2009. The data covers 1,500 households from four cities selected to represent the major urban areas of Ethiopia: Addis Ababa, Awassa, Dessie, and Mekelle.[3] As with the ERHS, we only select the rounds with questions on subjective well-being (2000, 2004, and 2009). Unlike our rural data, we are only able to control for household fixed effects, not individual fixed effects, because the respondent may have changed across rounds.

In addition to the household survey data, rainfall and temperature 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).[4] 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 has been exacerbated by the serious decline in the past few decades in the number of weather stations around the world that are reporting. Lorenz and Kuntsmann (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

[3]See Alem and Söderbom (2012) for more detail on this data set.
[4]See Dee et al. (2011) for a detailed discussion of the ERA-Interim data.

10 weather stations per country. Looking at publicly available data, the number of stations in Ethiopia included by the National Oceanic and Atmospheric 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 sparsity of stations across Ethiopia (an average of 0.03 stations per woreda), the placement of stations is likely to be correlated with agricultural output; that is, 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 biased upwards. 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 for a very rich set of atmospheric parameters, from 1st January, 1979 until the present day, on a global grid of quadrilateral cells defined by parallels and meridians at a resolution of 0.25 x 0.25 degrees (equivalent to 28km x 28km at the equator).[5] Reanalysis data is constructed through a process whereby 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 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 and Lobell (2010); Burgess et al. (2014); Kudamatsu et al. (2014); Colmer (2015a,b)), since it fills in the data gap apparent in developing countries, where the collection of consistent weather data

[5]To convert degrees to km, multiply 28 by the cosine of the latitude, e.g, at 40 degrees latitude 0.25 x 0.25 degree cells are 28 x cos(40) = 21.4 km x 21.4 km.

is lower down the priority list in governmental budgets.

By combining the household data set with the ERA-interim data, we create a unique panel that allows for microeconomic analysis of weather and climate in rural and urban Ethiopia.[6]

The outcome variables of interest from the economic data are objective real per capita consumption in adult equivalent units, c_{it}, and subjective life satisfaction, $\mathcal{W}_{it} = \hat{\mathbb{E}}[U(\cdot)|\underline{\mathrm{s}}_t]$, asked of the head and spouse of the household.

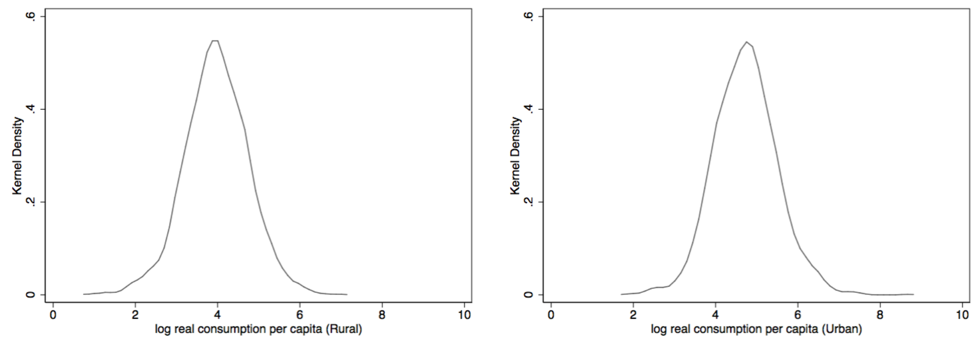
Real per capita consumption is constructed in the following way. First, all food consumption in the past 7 days is valued and scaled up to a month. In addition, expenditures on items purchased by the household in a typical month are added. On top of this, the value of own production is imputed by multiplying the quantity produced by the median price paid by other households in the same district. Finally, consumption expenditures are spatially deflated to ensure comparability over time and space. This is very important given the significant inflation observed between 2004 and 2009 due to rapid increases in world grain prices and internal monetary policy (Durevall et al., 2013), with average inflation peaking at 55.2% and food price inflation at 92% (Central Statistics Agency, 2009).

Figure 1 plots the distribution of log real consumption per capita for rural areas and urban areas. To estimate the degree of consumption dispersion, we calculate the unconditional log difference between the 99th and 1st percentile household. From this calculation we estimate that per capita consumption in the 99th percentile household is approximately 50 times greater than in the 1st percentile household, indicating substantial consumption inequality in rural Ethiopia.[7] In urban Ethiopia consumption dispersion is slightly lower: consumption per capita in the 99th percentile household is approximately 40 times greater than in the 1st percentile household.

[6] In order to test the robustness of our results we replicate the results using data from the University of Delaware Air Temperature and Precipitation Database (Willmott and Matsuura, 2012) and the TARCAT satellite rainfall data (Maidment et al., 2014) as well as instrumenting for these datasets using the ERA-interim data to account for any classical measurement error across data sets (available in the online appendix).

[7] $\exp(3.88) = 48.42$.

Figure 1: The Distribution of Consumption in Rural and Urban Ethiopia



In both rural and urban areas, average real consumption decreased between 2004 and 2009: from 86 to 58 birr per capita in rural areas and from 160 to 151 birr per capita in urban areas. This is consistent with the rapid increase in inflation during this period.

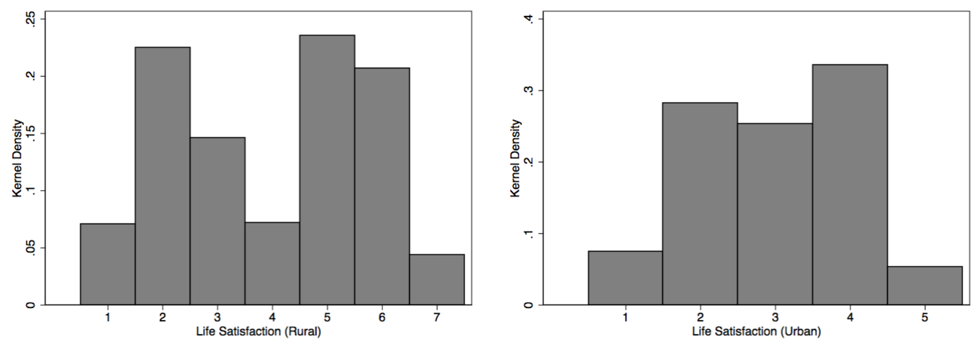
Our measure of subjective well-being in rural Ethiopia is constructed using responses to a single question scored on a seven-point scale ranging from one to seven. The variable is constructed using responses related to the level of agreement with the following statement as the dependent variable: "I am satisfied with my life." A score of one is described as "Very Dissatisfied" and a score of seven is described as "Very Satisfied". In urban areas the question is unfortunately phrased in a slightly different way and the results are reported on a scale from one to five, reducing the comparability between rural and urban areas; however, this is not the focus of the empirical exercise, thus any concerns are mitigated.[8] These questions are similar to the standard questions used in cross-country surveys such as the World Values Survey and the Eurobaromoter Survey. We also demonstrate the robustness of our results to alternative measures of subjective well-being.

Figure 2 plots the distribution of responses for rural and urban areas. The distribution of life satisfaction in rural Ethiopia is bimodal, whereas in urban Ethiopia the distribution follows a similar pattern to the responses observed in developed countries. However, in both rural and urban Ethiopia, the average level of life satisfaction is substantially lower than the average levels reported in developed countries, where responses are shown to be skewed to the right with a long left tail. The average

[8] The Life Satisfaction question in the urban survey was, "Taking everything into account, how satisfied are you with the way you live these days?"

response in both rural and urban areas is the middle group: "neither satisfied nor dissatisfied". In rural areas, life satisfaction increased between 2004 and 2009 from an average response of 3.82, to 4.09. This is particularly interesting given that real consumption fell during this period. In urban areas life satisfaction increased between 2000 and 2004 from an average response of 2.83 to 3.23. Between 2004 and 2009 life satisfaction dipped slightly again to an average response of 2.94; however, this is still in excess of the the average level of life satisfaction reported in 2000.

Figure 2: The Distribution of Life Satisfaction in Rural and Urban Ethiopia



Our treatment variables are motivated by the theoretical model in section 2. We calculate measures of memory utility, contemporaneous utility, and a proxy for uncertainty, which aims to isolate the effects of anticipatory utility.

Rainfall and temperature measures for each village are estimated by taking all data points within 100km of the village or city centroid and then interpolating through a process of inverse distance weighting. The weight attributed to each grid point decreases quadratically with distance.

The main variable of interest is our proxy for uncertainty – rainfall variability. Starting from a measure of total annual rainfall for each village, we calculate the coefficient of variation for rainfall (CV), measured as the standard deviation divided by the mean for the previous ten years. The selection of a 10-year period is based on a decision-rule in which we loop a regression of life satisfaction on the coefficient of variation – defined for all periods between 2 and 20 years – and select the specification that minimises the root-mean-square error. The results are robust to alternative time periods and to using simply the standard deviation of rainfall rather than the coefficient of variation (presented in the online appendix). However, 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.

The use of rainfall variability as a proxy for uncertainty is driven by the importance of agriculture for subsistence consumption and livelihoods in rural parts of Sub-Saharan Africa, where access to irrigation is sparse. The consideration of uncertainty as a determinant of welfare is distinct from the literature, which examines the effects of weather shocks on welfare. 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 use rainfall variability, which, we argue, affects the farmers' ability to forecast the likelihood of future rainfall realisations, increasing uncertainty.

Table 1 presents the descriptive statistics of the variables of interest for the period analysed.

Table 1: SUMMARY STATISTICS - RURAL AND URBAN AREAS

	RURAL				URBAN			
	MEAN	STD. DEV. (Within)	STD. DEV. (Between)	OBS.	MEAN	STD. DEV. (Within)	STD. DEV. (Between)	OBS.
Outcome Measures								
LIFE SATISFACTION (score/max)	0.567	0.137	0.223	3,869	0.603	0.124	0.184	2,887
LOG REAL CONSUMPTION PER CAPITA	3.970	0.392	0.695	3,869	4.735	0.377	0.699	2,887
Uncertainty Measures								
RAINFALL VARIABILITY (σ/μ)	21.577	3.171	7.077	3,869	29.38	4.13	5.39	2,887
RAINFALL VARIABILITY (σ, mm)	299.849	46.592	82.833	3,869	457.80	63.94	87.87	2,887
Contemporaneous Measures								
TOTAL RAINFALL (mm)	1,424.25	197.930	456.294	3,869	1,423.421	141.142	199.207	2,887
RAINFALL SHOCK (0/1)	0.055	0.137	0.195	3,869	0.033	0.125	0.141	2,887
Historical Measures (Previous 10 years)								
AVERAGE TOTAL RAINFALL (mm)	1,435.39	66.762	315.435	3,869	1,578.956	83.071	165.344	2,887
RAINFALL SHOCK (0/1)	0.504	0.235	0.455	3,869	0.404	0.404	0.353	2,887

4.2 Empirical Strategy

We examine the effects of uncertainty – proxied by rainfall variability – on objective consumption and subjective well-being.

$$\mathcal{W}_{it} = \beta_1 CV_{v\underline{t}} + \beta_2 f(\mathrm{w}_{vt}) + \beta_3 f(\mathrm{w}_{v\underline{t-\tau}}) + \alpha_i + \alpha_m + \alpha_t + \epsilon_{ivt} \tag{6}$$

$\mathcal{W}_{ivt}$ is our measure of subjective well-being – life satisfaction.[9] The explanatory variables of interest are the coefficient of variation for rainfall over the previous 10 years (our proxy for uncertainty), a function of contemporaneous weather variables, and a function of historical weather variables.[10]

Individual fixed effects, α_i, allow us to address any issues associated with time-invariant unobserved individual heterogeneity, which has been shown to be an important determinant of subjective well-being (Argyle, 1999; Diener and Lucas, 1999; Ferrer-i Carbonell and Frijters, 2004).[11] 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.

In analysing the effects on consumption we follow the approach of Deaton (1990), Deaton (1992), and Deaton (1997) by controlling for village fixed effects.[12]

$$\log C_{it} = \beta_1 CV_{v\underline{t}} + \beta_2 f(\mathrm{w}_{vt}) + \beta_3 f(\mathrm{w}_{v\underline{t-\tau}}) + \alpha_v + \alpha_m + \alpha_t + \epsilon_{ivt} \tag{7}$$

In controlling for the village fixed effects we control for aggregate village consumption. If households are fully insured within-village, then income shocks should have

[9] Results (available upon request) are robust to using an ordered probit model with random effects to account for an ordinal measurement of life satisfaction rather than the cardinal measurement implied by the linear regression model. 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, $\mathcal{W}_{ivt}$, is an unobserved latent outcome conventionally proxied by a self-reported life satisfaction response, $\mathcal{W}^*_{ivt}$, on an ordinal scale. However, because it is not possible to formulate a fixed effects ordered probit model since the fixed effects are not conditioned out of the likelihood, we must use random effects.

[10] The selection of a 10-year period is based on a decision-rule in which we loop a regression of life satisfaction on the coefficient of variation – defined for all periods between 2 and 20 years – and select the specification that minimises the root-mean-square error.

[11] Results (available upon request) are also robust using household or village fixed effects. The results are consistent in sign and magnitude across models.

[12] This is comparable to the within-village specification in Suri (2011).

no effect in determining consumption.

The last term in equations (6) and (7) is the stochastic error term, ϵ_{ivt}. We follow the approach of Hsiang (2010) by assuming that the error term may be heteroskedastic and spatially correlated across contemporaneous districts (Conley, 1999). For each outcome of interest we loop over all possible distances between 10km and 1000km selecting the parameter value that provides the most conservative standard errors.

As discussed above, the coefficient of variation for rainfall is defined as the standard deviation of rainfall for the previous 10 years divided by the average annual rainfall for the previous 10 years, where annual rainfall is defined based on the Ethiopian agricultural calendar, starting with rainy season (Kiremt) in June. The focus of our empirical exercise is to identify the effects of uncertainty on individual welfare. In section 3 we provided a theoretical mapping for our empirical exercise in the form of equation (4). In terms of our empirical analysis we assume that there exists a mapping between rainfall and consumption in agrarian societies such that,

$$U(rain_{it}) = \underbrace{\sum_{\tau=1}^{t-1} \beta^{\tau} u(rain_{it-\tau})}_{\text{historical shocks}} + \underbrace{\beta^{t} u(rain_{it})}_{\text{contemporaneous shocks}} + \underbrace{\hat{\mathbb{E}}\left[\sum_{\tau=t+1} \beta^{\tau} u(rain_{it+\tau|\underline{s}_t})\right]}_{\mathbb{E}(\text{future shocks})} \quad (8)$$

We argue that once historical and contemporaneous effects have been controlled for any residual variation in rainfall likely captures the expectation of future effects, i.e. the effect of uncertainty through anticipation utility.

In any analysis of uncertainty, measurement and identification is highly challenging. The main issue we face is disentangling the effects of uncertainty from the realisation of rainfall shocks. As the first moment and second moment of the rainfall distribution are correlated ($\rho = 0.28$) it is important to control for first-moment effects to isolate the effects of uncertainty, to the degree that they are empirically relevant, from income effects. We do this by controlling for historical and contemporaneous rainfall.

A second concern may be that non-linearities in the relationship between rainfall and income imply that accounting for the first moment isn't sufficient to remove all the residual variation associated with income from the error term. As a consequence, our measure of uncertainty may be driven by realised income shock effects. We account for this by defining an alternative measure of a rainfall shock that is beyond the level of rainfall that has been experienced. We define a shock to be the case in which rainfall was one standard deviation below the long-run village average.[13] Our main analysis focusses on the level effect, with support from the shock variable, defined above, to account for non-linearities.

A further concern is the high degree of correlation between atmospheric parameters. As temperature may also be an important factor in explaining variation in income – and is highly correlated with rainfall – we also account for contemporaneous and historical temperature effects to further strip away as much residual variation in income as possible. We can never be certain that our measure of uncertainty is free from any residual variation associated with income; however, one might argue that accounting for the above considerations should allay any first-order concerns.

5 Results

5.1 Uncertainty and Rural Households

We begin by examining the effects of rainfall variability and rainfall shocks on objective consumption and life satisfaction in rural areas. Our theory predicts that when there is partial insurance and the subjective probability of an income shock does not coincide with the true probability, the utility of the farmer depends on anticipatory utility, such that the subjective conditional belief has a direct effect on utility. Given the importance of rainfall as a driver of income in agrarian societies, an increase in rainfall variability increases uncertainty about future income flows. By controlling for contemporaneous and historical rainfall, any residual variation in rainfall variability captures the direct effects of income uncertainty on individual well-being. Table 2 presents our main results, examining the effects of uncertainty on life satisfaction (columns 1–5) and the logarithm of real consumption per capita (columns 6–8).

Column (1) of Table 2 presents the results of regressing life satisfaction against our measure of uncertainty – the coefficient of variation for rainfall. The relationship between uncertainty and life satisfaction is negative and highly significant. However, this specification does not control for any contemporaneous or historical weather effects and so if these factors are correlated with our measure of uncertainty, this will inflate our measure of uncertainty. Column (2) demonstrates the relevance of this

[13] Results are robust to alternative definitions of the shock variable available upon request.

omitted variable bias. When we control for contemporaneous and historical shocks (following the main empirical specification in equation 6) the coefficient on rainfall variability declines from -0.081 to -0.0562. When we account for weather shocks as opposed to using the first moment of weather – column (3) –, our estimate further decreases in magnitude to -0.0427. Columns (4) and (5) further test our specification by controlling directly for the logarithm of real consumption per capita – our other outcome variable of interest. This is a bad control, introducing selection bias into our empirical estimates (Angrist and Pischke, 2009). Consequently, these specifications are not the focus of interest. We observe, however, that the inclusion has little effect on our coefficient estimates of uncertainty, which is encouraging because it indicates that consumption variation has largely been accounted for. This is further supported by a reduction in the size of the coefficients for contemporaneous weather. These results indicate that even after accounting for the variation in life satisfaction associated with contemporaneous and historical weather effects, there is still substantial residual variation captured by our proxy for uncertainty – rainfall variability. A one standard deviation increase in rainfall variability (3.17 percentage points) is associated with a 0.141–0.176 point decrease in life satisfaction. Interestingly, even after controlling for consumption, there still exists substantial residual variation in the contemporaneous weather effects, indicating that rainfall shocks may have a direct effect on well-being beyond the income channel. This is not surprising given the wide literature exploring the psychic costs of income shocks and poverty (van den Bos et al., 2009; Hare et al., 2009; Delgado and Porcellie, 2009; Doherty and Clayton, 2011). However, the presence of multiple channels reduces our ability to provide an interpretation for these estimates, since they constitute a net effect.[14] Consequently, the focus of our analysis is on the identification of uncertainty, net of these remaining channels.

Columns (6)–(8) present the results of our analysis on objective consumption, providing further support for our identification of uncertainty, in addition to being a direct outcome of interest. The effect of uncertainty on contemporaneous consumption is theoretically ambiguous: consumption expenditures may increase if farmers increase their spending on inputs that mitigate the economic consequences of future rainfall shocks (to the degree that such investments are available); consumption may decrease if farmers exhibit decreasing absolute risk aversion and engage in precaution-

[14]See Colmer (2015a) for a discussion of the measurement and identification issues associated with the use of weather data in empirical research.

ary saving (to the degree that saving is possible); or uncertainty about future income may have no effect on present consumption if farmers are limited in their ability to smooth consumption over time. In column (6), the relationship between uncertainty and real consumption is negative and significant at conventional levels. However, as with the estimate in column (1), this specification is subject to omitted variable bias if contemporaneous and historical weather is correlated with our measure of uncertainty. The relevance of this omitted variable bias is demonstrated once again in columns (7) and (8). Once the variation in consumption associated with contemporaneous and historical weather has been stripped out, the relationship between uncertainty and consumption is precisely estimated to be statistically insignificant from zero. By contrast, both contemporaneous and historical weather effects are significantly associated with consumption. An increase (decrease) in both contemporaneous and historical rainfall (temperature) is associated with a highly significant increase (decrease) in real consumption per capita. A one standard deviation (197mm) increase in total rainfall during the most recent agricultural year is associated with a 39% increase in consumption. A one standard deviation (66mm) increase in the average rainfall for the previous ten years is associated with a 11.3% increase in consumption. In column (8) we examine the effects of contemporaneous and historical weather shocks. In this specification, a negative rainfall shock is shown to have a negative effect on consumption, indicating multicollinearity as a possible factor in driving the significant results when using the first moments of weather.[15]

It is clear in both specifications that consumption in rural Ethiopia is highly responsive to contemporaneous rainfall, indicating that households are unable to smooth consumption in response to such aggregate shocks. This implies that households are not fully insured against weather-related risk, a necessary condition for uncertainty to have a direct effect on welfare beyond the realisation of income shocks. Consequently, there appear to be significant welfare gains from further consumption smoothing; however, these gains are substantially greater than the estimates based solely on consumption fluctuations because of the direct effect that uncertainty has on well-being. The magnitude of this uncertainty effect is quite surprising. If house-

[15]The unconditional correlation between contemporaneous rainfall and the historical average level of rainfall for the previous ten years is 0.68. The correlation between contemporaneous average temperature and historical average temperature for the previous ten years is even higher at 0.97. By contrast, the same correlation coefficients between contemporaneous and historical rainfall and temperature shocks are -0.24 and 0.30 respectively.

holds in the most variable climate were to move to the least variable climate (within the empirical reality of our dataset) life satisfaction would increase by 1.769 – 2.211 standard deviations. By contrast, if the poorest household were to move to the consumption level of the richest household in our dataset, life satisfaction would increase by 2.054 – 2.335 standard deviations. These results suggest that the gains to further consumption smoothing are substantially greater than estimates based solely on consumption fluctuations.

5.2 Uncertainty and Urban Households

Table 3 presents the results of our analysis in urban Ethiopia. Unlike rural Ethiopia, where livelihoods are dependent on the weather, incomes in urban Ethiopia are much more dependent on the services and manufacturing sectors. Consequently, uncertainty about future incomes is unlikely to be driven by rainfall variability. However, if urban areas are dependent on rural areas for agricultural products, then (rural) production and (urban) consumption is inextricably linked. However, if agricultural goods are tradable across space, then production and consumption are separable. Even if food is traded across space, mitigating the consequences of localized productivity shocks on food prices, a reduction in rural income may affect demand for non-tradable services provided by urban areas, and consequently incomes in urban areas (Rijkers and Söderbom, 2013). Rural and urban areas may also be linked through local labour markets and seasonal migration responses to agricultural productivity shocks (Colmer, 2015a). If there is sufficient rural–urban migration, this may have a disutility effect on urban residents. These effects are less likely to be a concern if weather shocks are smaller in magnitude and if shocks in rural and urban areas are less correlated across space – a strong assumption in a small county like Ethiopia, which is characterised by its high vulnerability to inclement weather. Locally, weather in urban areas may have a direct effect on well-being through its value as an amenity. The multitude of potential channels highlights the difficulties faced when interpreting the first-moment effects of weather in urban areas. However, once the first-moment effects of weather have been controlled for rainfall variability – our proxy for uncertainty – should have little effect on life satisfaction or consumption in urban areas.

From columns 1–5 of table 3, we estimate that rainfall variability has no effect on life satisfaction in urban areas once we control for contemporaneous and historical weather effects. This is also the case when regressing consumption on rainfall variability, presented in columns 6–8. These results provide further support for the use of rainfall variability as a proxy for uncertainty – after controlling for contemporaneous and historical weather effects – when conducting analysis of uncertainty in rural areas of developing economies.

However, we do observe that the level of rainfall has a small effect on consumption in urban areas (a one standard deviation increase in rainfall (141mm) is associated with a 4% increase in consumption), indicating that there may be a link between rural and urban outcomes in Ethiopia; however, this is substantially smaller than the effect observed in rural areas where a one standard deviation increase in rainfall (197mm) is associated with a 43% increase in consumption. As discussed, it is difficult to interpret such an effect in urban areas given the multitude of potential explanations, but given the magnitude of the rainfall shock effects in rural areas it is possible that shocks in rural areas feed into higher food prices in urban areas, reducing real consumption, or a reduction in demand for non-tradable services provided by urban areas, affecting the incomes and consequently the consumption base of urban residents reliant on demand from rural areas. It seems unlikely that rainfall shocks in urban areas have a direct effect on urban consumption so these effects are likely driven by rainfall in surrounding rural areas, which is likely correlated with the realisation of rainfall in urban areas.

5.3 Seasonality and Uncertainty

The premise underlying our interpretation of the results is that the livelihoods of smallholder farmers in rural Ethiopia is dependent on agriculture. To further support this premise we decompose our results into three seasons – the Meher, the Belg, and the Baga – to examine the effects of uncertainty on individual well-being over the agricultural calendar. The Meher season between June and November is the major agricultural season in Ethiopia, accounting for over 90% of total crop production. In addition, a second, shorter rainy season – the Belg season –, which starts in February and ends in May, is important for smallholder farmers. The Baga period falls between the Meher and Belg seasons and is characterized by hot, dry weather.

Table 4 presents the results of this seasonal decomposition. Panel A presents the results for the Meher season, panel B the Belg season, and panel C the Baga season.

Consistent with our premise, we observe that rainfall variability during the Meher season and the Belg season is the main driver behind changes in life satisfaction. A one standard deviation increase in rainfall variability during the Meher season (2.959 percentage points) is associated with a 0.143–0.170 point decrease in life satisfaction. A one standard deviation increase in rainfall variability during the Belg season (12.751 percentage points) is associated with a 0.154–0.179 point decrease in life satisfaction. By contrast, rainfall variability during the Baga season is insignificant at conventional levels. Even if the coefficients during the Baga season were taken at face value, the magnitude of the effect during the period is substantially smaller than the estimated effects during the agricultural season (a 0.036 – 0.109 point decrease in life satisfaction).

Collectively, these results provide robustness to our initial results and provide further support to our premise that rain-fed agriculture plays an important role in the livelihoods of the survey participants.

5.4 Uncertainty and Happiness

Within the subjective well-being literature, it is generally considered that questions based on the life satisfaction scale are more evaluative measures, whereas questions related to happiness are a better measure of present affect (Benjamin et al., 2013; Levinson, 2013).[16] While both measures of subjective well-being are highly correlated ($\rho = 0.426$) we might expect that rainfall variability has a smaller effect on happiness than life satisfaction if it is a reasonable proxy for uncertainty.

Table 5 presents the results from this analysis. We estimate that rainfall variability has a smaller effect on happiness than life satisfaction, consistent with our predictions. A one standard deviation increase in rainfall variability (3.17 percentage points) is associated with a 0.051–0.140 standard deviation decrease in happiness and is insignificant in the shock specification.[17] By contrast, a one standard deviation increase in rainfall variability is associated with a 0.146–0.182 standard deviation decrease in life satisfaction and is significant across all specifications.

[16] The happiness question is, "Taken all together, how would you say things are for you these days? Would you say you are: Not too happy; Pretty happy; Very happy?"

[17] $\frac{3.17 \times 0.0058}{0.349} = 0.051$. $\frac{3.17 \times 0.0156}{0.349} = 0.140$

6 Conclusion

The ability to manage consumption risk is a significant determinant of individual and household welfare in developing countries, where households live in an uncertain environment with limited access to formal financial markets. While the realised effects of income shocks are well understood, this paper has explored the empirical relevance of income uncertainty on the welfare of smallholder farmers in rural Ethiopia. We present a simple model in the spirit of Brunnermeier and Parker (2005), in which forecasting error creates a wedge between a farmers' subjective and objective probability of an income shock being realised in the future, such that they underestimate the likelihood of a bad outcome. In this model, forward-looking farmers who care about expected future utility will make investments to maximise future utility; however, these same farmers will also have higher contemporaneous utility if they are optimistic about the future, introducing a trade-off between risk management investments and the benefits of optimism. Consequently, the utility of the farmer depends on expected future utility or anticipated utility such that the subjective conditional belief of future income shocks has a direct contemporaneous effect on utility. An increase in uncertainty reduces optimism about the future, reducing contemporaneous utility levels.

The central challenge in this exercise – as in the literature as a whole – is in measuring and identifying the effects of uncertainty. Using panel data from two household surveys combined with high-resolution atmospheric data, we exploit plausibly exogenous variation in inter-annual rainfall variability – a proxy for income uncertainty after controlling for contemporaneous and historical rainfall shocks – to examine the effects of income uncertainty on objective consumption and subjective well-being.

Consistent with a large literature, we observe that the realisation of inclement weather has a negative effect on consumption in rural areas (falsifying the hypothesis of within-village pareto efficient risk sharing in the face of aggregate shocks), and subjective well-being. However, the main contribution of our paper is to estimate the effect of income uncertainty on individual welfare in a rural development context. We observe that a one standard deviation increase in inter-annual rainfall variability is associated with a 0.146–0.182 standard deviation reduction in life satisfaction in rural areas – comparable to the effect of a one standard deviation change in realised consumption –, but has no additional effect on objective consumption. Our results suggest that, by failing to account for the welfare costs of uncertainty, we are substantially underestimating the welfare gains from further consumption smoothing in rural areas of developing countries, where credit constraints and insurance market failures limit the households ability to manage aggregate consumption risk.

Our results are further supported by evidence suggesting that: rainfall variability has little effect on subjective well-being or objective consumption in urban areas, where income uncertainty is less likely to be driven by the weather; income uncertainty in rural areas is driven by the rainy season; income uncertainty has less of an effect on measures of subjective well-being associated with contemporaneous affect.

The consistency of these results highlights the costs associated with weather-related consumption risk in developing countries. By moving from the most variable climate to the least variable climate, ceteris paribus, individuals would receive a 1.833–2.291 standard deviation increase in life satisfaction. By comparison, a movement in position from living in "the poorest" to "the richest" household, ceteris paribus, would be associated with a 2.054–2.335 standard deviation increase in life satisfaction. This suggests that the returns to consumption smoothing are substantially larger than estimates based solely on consumption fluctuations. The inclusion of subjective welfare measures alongside objective measures will better allow researchers and policy makers to understand the overall welfare effects of policy interventions that mitigate risk and uncertainty and in the process, mitigate omitted variable bias in cost–benefit analyses.

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Table 2: The Welfare Cost of Uncertainty in Rural Ethiopia

	Life Satisfaction					Log Consumption		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall Variability (σ/μ)	-0.0810***	-0.0533***	-0.0523***	-0.0424**	-0.0439**	-0.0224**	0.000364	0.00966
	(0.00855)	(0.0122)	(0.0115)	(0.0195)	(0.0178)	(0.00956)	(0.00499)	(0.0116)
Annual Rainfall (100mm)		0.177***	-0.995***	0.114***	-0.735**		0.219***	-0.823***
		(0.0445)	(0.372)	(0.0384)	(0.353)		(0.0265)	(0.215)
Historical Rainfall (100mm)		0.148*	-0.00859	0.0957	0.0219		0.190***	-0.126
		(0.0820)	(0.161)	(0.0746)	(0.131)		(0.0473)	(0.102)
Log Consumption				0.322***	0.367***			
				(0.0331)	(0.0523)			
Fixed Effects	Individual, Year, Month					Village, Year, Month		
Temperature Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes
Shock Specification	No	No	Yes	No	Yes	No	No	Yes
Observations	3,869	3869	3869	3865	3865	3,865	3,865	3,865
Adjusted R^2	0.869	0.870	0.868	0.873	0.871	0.973	0.974	0.974

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Our proxy for uncertainty is the coefficient of variation for rainfall over the previous 10 years. The number of years is selected by estimating the model for all possible time periods between 2 and 20 years and selecting the model which minimises the root-mean-square errror. Historical measures of atmospheric parameters correspond to this period. Individual, year, and month fixed effects are included for life satisfaction estimates. Village, year, and month fixed effects are included for consumption estimates. Contemporaneous and historical rainfall is measured in hundreds of mm, except for the shock specification – a binary variable equal to 1 if rainfall is 1 standard deviation below the village long run average rainfall. Contemporaneous and historical temperature is measured in °C, except for the shock specification – a binary variable equal to 1 if temperature is 1 standard deviation above the village long run average temperature. Standard errors are adjusted to reflect spatial dependence, as modelled in Conley (1999). Spatial autocorrelation is assumed to linearly decrease in distance up to a cut-off of 220 km for Life Satisfaction regression results and 160 km for Consumption regression results. The distance is selected following a decision rule in which we choose the distance that provides the most conservative standard errors, looped over all distances between 10 and 1000km.

Table 3: The Welfare Cost of Uncertainty in Urban Ethiopia

	Life Satisfaction					Log Consumption		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall Variability (σ/μ)	-0.0188***	0.00954	-0.0398	0.00714	-0.0385	0.00108	-0.00176	-0.00313
	(0.008)	(0.012)	(0.0147)	(0.011)	(0.0147)	(0.00462)	(0.0116)	(0.00359)
Annual Rainfall (100mm)		-0.0228	0.420	-0.0353	0.462		0.0287**	-0.100**
		(0.0301)	(0.353)	(0.0331)	(0.330)		(0.0126)	(0.0429)
Historical Rainfall (100mm)		0.120***	-0.0412	0.127***	-0.0971		-0.0349**	0.177***
		(0.0346)	(0.212)	(0.0383)	(0.204)		(0.0172)	(0.210)
Log Consumption				0.256***	0.269***			
				(0.0306)	(0.0314)			
Fixed Effects			Household, Year, Month				City, Year, Month	
Shock Specification	No	No	Yes	No	Yes	No	No	Yes
Temperature Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes
Observations	2,880	2,880	2,880	2,880	2,880	2,880	2,880	2,880
Adjusted R^2	0.923	0.923	0.923	0.925	0.925	0.987	0.987	0.987

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Our proxy for uncertainty is the coefficient of variation for rainfall over the previous 10 years. The number of years is selected by estimating the model for all possible time periods between 2 and 20 years and selecting the model which minimises the root-mean-square errror. Historical measures of atmospheric parameters correspond to this period. Individual, year, and month fixed effects are included for life satisfaction estimates. Village, year, and month fixed effects are included for consumption estimates. Contemporaneous and historical rainfall is measured in hundreds of mm, except for the shock specification – a binary variable equal to 1 if rainfall is 1 standard deviation below the village long run average rainfall. Contemporaneous and historical temperature is measured in $^\circ$C, except for the shock specification – a binary variable equal to 1 if temperature is 1 standard deviation above the village long run average temperature. Standard errors are adjusted to reflect spatial dependence, as modelled in Conley (1999). Spatial autocorrelation is assumed to linearly decrease in distance up to a cut-off of 460km for Life Satisfaction regression results and 360 km for Consumption regression results. The distance is selected following a decision rule in which we choose the distance that provides the most conservative standard errors, looped over all distances between 10 and 1000km.

Table 4: Seasonal Uncertainty in Rural Ethiopia

	Life Satisfaction				
	(1)	(2)	(3)	(4)	(5)
Panel A: *Meher Season*					
Rainfall Variability (σ/μ)	-0.0685***	-0.0484***	-0.0423***	-0.0574***	-0.0539***
	(0.0154)	(0.00845)	(0.00881)	(0.0141)	(0.00976)
Panel B: *Belg Season*					
Rainfall Variability (σ/μ)	-0.0112***	-0.0141***	-0.0122***	-0.0121***	-0.0106***
	(0.00129)	(0.00230)	(0.00156)	(0.00130)	(0.00130)
Panel C: *Baga Season*					
Rainfall Variability (σ/μ)	-0.00437*	-0.00523	-0.00749	-0.00175	-0.00257*
	(0.00239)	(0.00564)	(0.00500)	(0.00175)	(0.00145)
Observations	3869	3869	3869	3869	3869
Fixed Effects	Individual, Year, Month				
Shock Specification	No	No	No	Yes	Yes
Contemporaneous and Historical Weather Controls	No	Yes	Yes	Yes	Yes
Consumption Control	No	No	Yes	No	Yes

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Our proxy for uncertainty is the coefficient of variation for rainfall over the previous 10 years. The number of years is selected by estimating the model for all possible time periods between 2 and 20 years and selecting the model which minimises the root-mean-square errror. Historical measures of atmospheric parameters correspond to this period. Individual, year, and month fixed effects are included for life satisfaction estimates. Village, year, and month fixed effects are included for consumption estimates. Standard errors are adjusted to reflect spatial dependence, as modelled in Conley (1999). Spatial autocorrelation is assumed to linearly decrease in distance up to a cut-off of 170km for the Meher season, 220km for the Belg season, and 80km for the Baga season. The distance is selected following a decision rule in which we choose the distance that provides the most conservative standard errors, looped over all distances between 10 and 1000km.

Table 5: Uncertainty and Happiness in Rural Ethiopia

	Happiness				
	(1)	(2)	(3)		
Rainfall Variability (σ/μ)	-0.0129***	-0.0121***	-0.0119***	-0.00918	-0.00945
	(0.00367)	(0.00432)	(0.00409)	(0.00737)	(0.00723)
Annual Rainfall (100mm)		0.00214	-0.0124	-0.0643	-0.0231
		(0.0154)	(0.0169)	(0.113)	(0.121)
Historical Rainfall (100mm)		0.0364*	0.0242	-0.120***	-0.117***
		(0.0212)	(0.0225)	(0.0448)	(0.0416)
Log Consumption			0.0751***		0.0586***
			(0.0130)		(0.0159)
Fixed Effects	Individual, Year, Month				
Shock Specification	No	No	No	Yes	Yes
Temperature Controls	No	Yes	Yes	Yes	Yes
Observations	3,861	3861	3861	3861	3861
Adjusted R^2	0.915	0.916	0.916		

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Our proxy for uncertainty is the coefficient of variation for rainfall over the previous 10 years. The number of years is selected by estimating the model for all possible time periods between 2 and 20 years and selecting the model which minimises the root-mean-square errror. Contemporaneous and historical rainfall is measured in hundreds of mm, except for the shock specification – a binary variable equal to 1 if rainfall is 1 standard deviation below the village long run average rainfall. Contemporaneous and historical temperature is measured in °C, except for the shock specification – a binary variable equal to 1 if temperature is 1 standard deviation above the village long run average temperature. Standard errors are adjusted to reflect spatial dependence, as modelled in Conley (1999). Spatial autocorrelation is assumed to linearly decrease in distance up to a cut-off of 220 km. The distance is selected following a decision rule in which we choose the distance that provides the most conservative standard errors, looped over all distances between 10 and 1000km.

Appendix - For Online Publication

Data

Table A1: Summary statistics – Rural Areas (Additional Variables)

	Mean	Std. Dev. (Within)	Std. Dev. (Between)	Obs.
Outcome Measures				
Life Satisfaction (score/max)	0.567	0.137	0.223	3,869
Happiness (score/max)	0.621	0.349	0.572	3,869
Meher Season Measures				
Meher Rainfall Variability (σ/μ)	22.449	2.959	9.161	3,869
Meher Rainfall Variability (σ, mm)	209.400	33.631	88.592	3,869
Meher Rainfall (mm)	1,088.986	132.803	365.255	3,869
Belg Season Measures				=
Belg Rainfall Variability (σ/μ)	46.674	12.751	26.687	3,869
Belg Rainfall Variability (σ, mm)	145.729	34.753	56.981	3,869
Belg Rainfall (mm)	268.805	73.261	191.85	3,869
Baga Season Measures				
Baga Rainfall Variability (σ/μ)	116.046	21.047	36.333	3,869
Belg Rainfall Variability (σ, mm)	118.876	57.400	79.909	3,869
Belg Rainfall (mm)	66.458	28.656	39.682	3,869

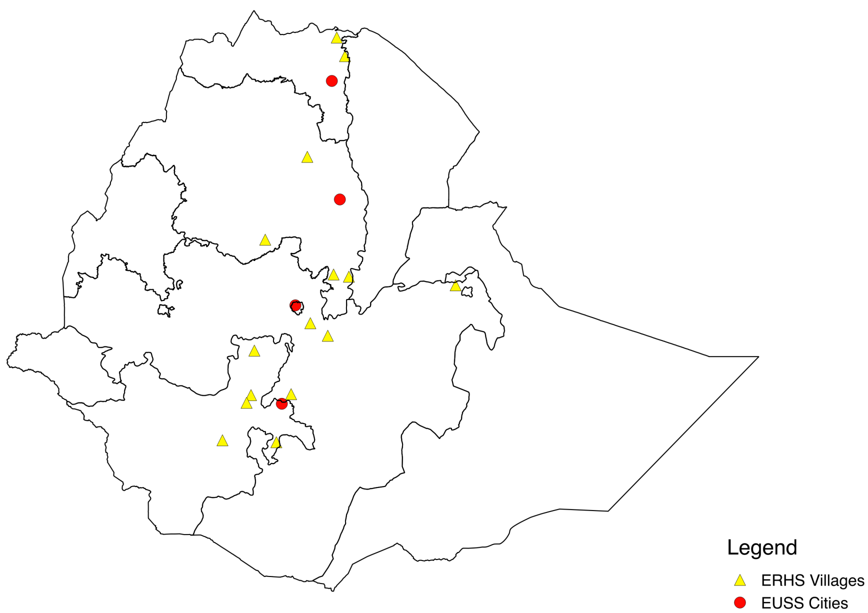

Figure 3: Survey Locations for Rural and Urban areas

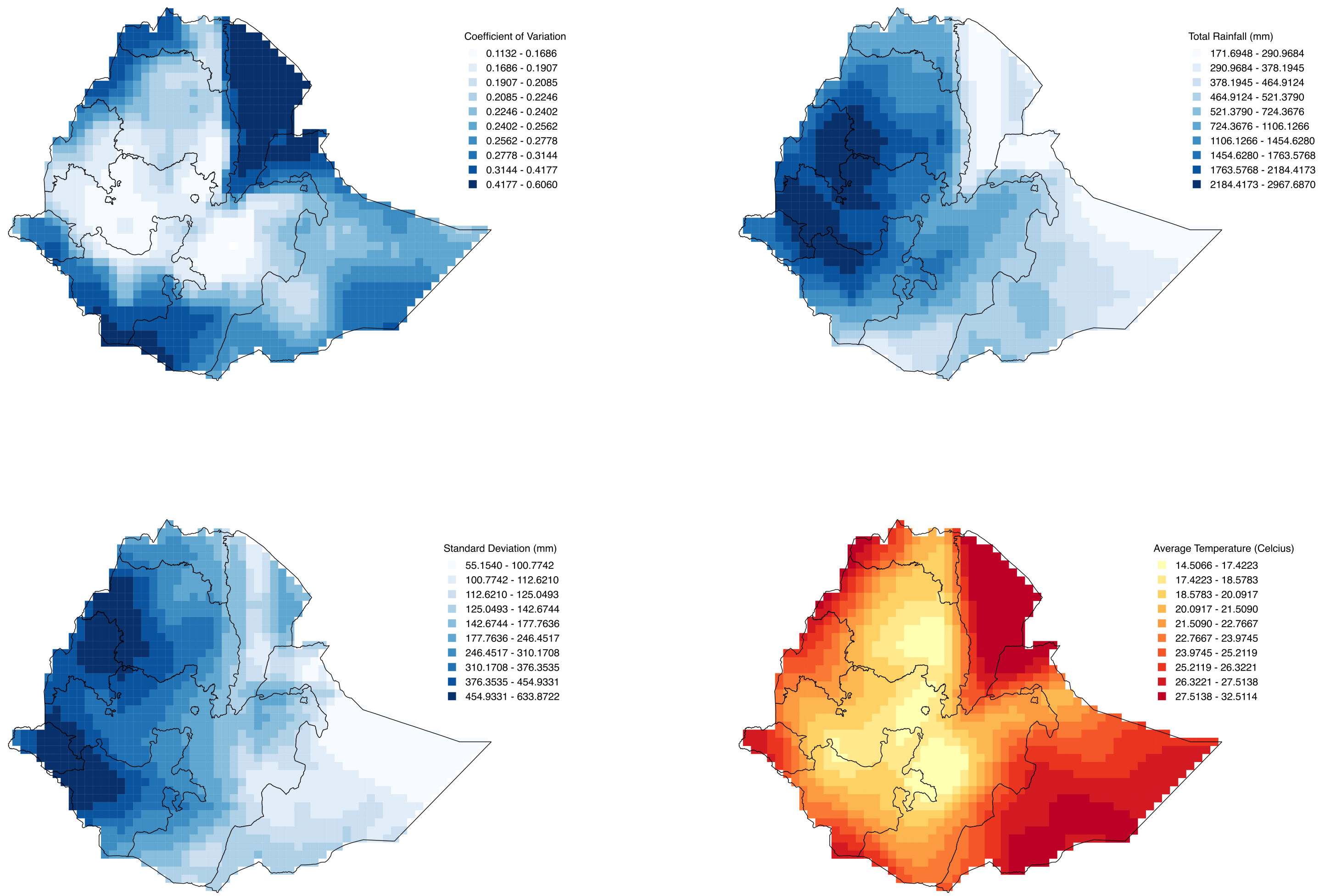

Figure 4: Spatial Variation in Rainfall and Temperature (1979–2012). Top Left = Coefficient of Variation; Top Right = Total Rainfall (mm); Bottom Left = Std Dev. Rainfall (mm); Bottom Right = Average Temperature (°C)

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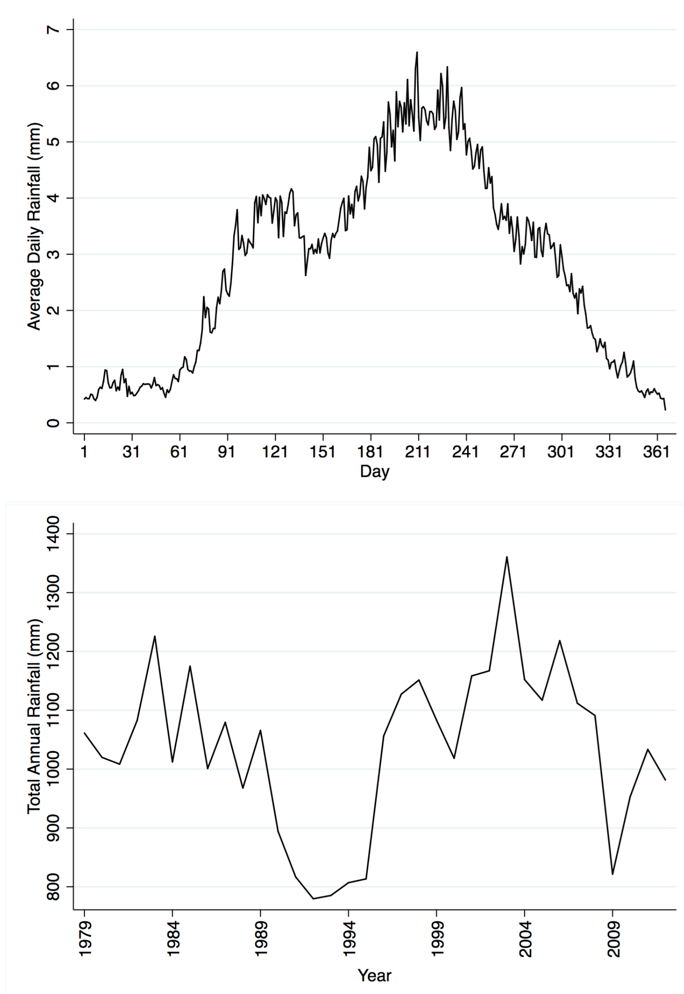

Figure 5: Temporal Variation in Rainfall (1979–2013). Top = Within-year Distribution (1979-2012 average). Bottom = Between-year Distribution

.

Additional Results

Table A2: Time Period Estimation

	(1) Coefficient Estimate	(2) Std. Dev. (Within)	(3) RMSE
Rainfall Variability (σ/μ) (2 Years)	-0.0176***	10.671	0.939
	(0.00337)		
Rainfall Variability (σ/μ) (3 Years)	-0.0309***	6.212	0.937
	(0.00398)		
Rainfall Variability (σ/μ) (4 Years)	-0.04390	5.128	0.931
	(0.00317)		
Rainfall Variability (σ/μ) (5 Years)	-0.0330***	5.870	0.940
	(0.00746)		
Rainfall Variability (σ/μ) (6 Years)	-0.0386***	5.334	0.938
	(0.00648)		
Rainfall Variability (σ/μ) (7 Years)	-0.0466***	4.565	0.935
	(0.00735)		
Rainfall Variability (σ/μ) (8 Years)	-0.0545***	3.768	0.938
	(0.0111)		
Rainfall Variability (σ/μ) (9 Years)	-0.0531***	3.931	0.939
	(0.0102)		
Rainfall Variability (σ/μ) (10 Years)	-0.0810***	3.171	**0.934**
	(0.00855)		
Rainfall Variability (σ/μ) (11 Years)	-0.0675***	2.745	0.942
	(0.0155)		
Rainfall Variability (σ/μ) (12 Years)	-0.0692***	3.030	0.941
	(0.0153)		
Rainfall Variability (σ/μ) (13 Years)	-0.0579***	3.644	0.943
	(0.0188)		
Rainfall Variability (σ/μ) (14 Years)	-0.0654**	3.263	0.945
	(0.0262)		
Rainfall Variability (σ/μ) (15 Years)	-0.0703***	2.908	0.944
	(0.0249)		
Rainfall Variability (σ/μ) (16 Years)	-0.0826***	2.392	0.944
	(0.0317)		
Rainfall Variability (σ/μ) (17 Years)	-0.124***	1.832	0.942
	(0.0302)		
Rainfall Variability (σ/μ) (18 Years)	-0.138***	1.383	0.942
	(0.0132)		
Rainfall Variability (σ/μ) (19 Years)	-0.118***	1.532	0.940
	(0.0140)		
Rainfall Variability (σ/μ) (20 Years)	-0.148***	1.260	0.939
	(0.0126)		

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Dependent Variable = Life Satisfaction.

Table A3: Alternative Meteorological Data

	(1) (UDEL - OLS)	(2) (UDEL - IV)	(3) (TARCAT - OLS)	(4) (TARCAT - IV)
Panel A: Life Satisfaction				
Rainfall Variability (σ/μ)	-0.557***	-1.623***	-0.0262***	-0.0999**
	(0.0890)	(0.310)	(0.00732)	(0.0484)
Panel B: Log Consumption				
Rainfall Variability (σ/μ)	-0.0445***	-0.151	0.00259	-0.0143
	(0.0518)	(0.235)	(0.00217)	(0.00918)
Fixed Effects	Yes	Yes	Yes	Yes
Contemporaneous and Historical Weather Controls	Yes	Yes	Yes	Yes

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Regressions are run using the rural household survey data. Our proxy for uncertainty is the coefficient of variation for rainfall over the previous 10 years. The number of years is selected by estimating the model for all possible time periods between 2 and 20 years and selecting the model which minimises the root-mean-square errror. Historical measures of atmospheric parameters correspond to this period. Individual, year, and month fixed effects are included for life satisfaction estimates. Village, year, and month fixed effects are included for consumption estimates. Standard errors are adjusted to reflect spatial dependence, as modelled in Conley (1999). Spatial autocorrelation is assumed to linearly decrease in distance up to a cut-off of 220 km for Life Satisfaction regression results and 160 km for Consumption regression results. The distance is selected following a decision rule in which we choose the distance that provides the most conservative standard errors, looped over all distances between 10 and 1000km.

Table A4: The Welfare Cost of Uncertainty in Rural Ethiopia – Log Standard Deviation

	Life Satisfaction					Log Consumption		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log Rainfall Variability (σ)	-1.490***	-1.081***	-0.824**	-1.059***	-0.794***	-0.422**	-0.0170	-0.0494
	(0.352)	(0.279)	(0.355)	(0.249)	(0.291)	(0.210)	(0.112)	(0.211)
Annual Rainfall (100mm)		0.228***	-1.170***	0.165***	-0.954***		0.218***	-0.655***
		(0.0461)	(0.255)	(0.0397)	(0.214)		(0.0232)	(0.167)
Historical Rainfall (100mm)		0.302***	-0.0865	0.247***	-0.0579		0.190***	-0.111
		(0.0554)	(0.166)	(0.0471)	(0.136)		(0.0382)	(0.110)
Fixed Effects	Individual, Year, Month					Village, Year, Month		
Temperature Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes
Shock Specification	No	No	Yes	No	Yes	No	No	Yes
Observations	3,869	3869	3869	3865	3865	3,865	3,865	3,865
Adjusted R^2	0.868	0.872	0.871	0.874	0.873	0.973	0.974	0.974

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Our proxy for uncertainty is the inter-annual standard deviation for rainfall over the previous 10 years. The number of years is selected by estimating the model for all possible time periods between 2 and 20 years and selecting the model which minimises the root-mean-square errror. Historical measures of atmospheric parameters correspond to this period. Individual, year, and month fixed effects are included for life satisfaction estimates. Village, year, and month fixed effects are included for consumption estimates. Contemporaneous and historical rainfall is measured in hundreds of mm, except for the shock specification – a binary variable equal to 1 if rainfall is 1 standard deviation below the village long run average rainfall. Contemporaneous and historical temperature is measured in $^\circ$C, except for the shock specification – a binary variable equal to 1 if temperature is 1 standard deviation above the village long run average temperature. Standard errors are adjusted to reflect spatial dependence, as modelled in Conley (1999). Spatial autocorrelation is assumed to linearly decrease in distance up to a cut-off of 220 km for Life Satisfaction regression results and 160 km for Consumption regression results. The distance is selected following a decision rule in which we choose the distance that provides the most conservative standard errors, looped over all distances between 10 and 1000km.

Table A5: The Welfare Cost of Uncertainty in Urban Ethiopia – Log Standard Deviation

	Life Satisfaction					Log Consumption		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log Rainfall Variability (σ)	-0.0946**	-0.00498	-0.0888	-0.0281	-0.0872	0.00393	0.0181	-0.0120
	(0.0405)	(0.159)	(0.131)	(0.176)	(0.123)	(0.0236)	(0.0757)	(0.0138)
Annual Rainfall (100mm)		-0.0239	0.155	-0.0358	0.208		0.0288**	-0.113***
		(0.0299)	(0.278)	(0.0330)	(0.258)		(0.0377)	(0.0300)
Historical Rainfall (100mm)		0.125**	-0.162	0.137**	-0.213		-0.0409	0.172***
		(0.0573)	(0.185)	(0.0629)	(0.178)		(0.0283)	(0.0178)
Fixed Effects	Household, Year, Month					City, Year, Month		
Temperature Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes
Shock Specification	No	No	Yes	No	Yes	No	No	Yes
Observations	3,869	3869	3869	3865	3865	3,865	3,865	3,865
Adjusted R^2	0.868	0.872	0.871	0.874	0.873	0.973	0.974	0.974

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Our proxy for uncertainty is the inter-annual standard deviation for rainfall over the previous 10 years. The number of years is selected by estimating the model for all possible time periods between 2 and 20 years and selecting the model which minimises the root-mean-square errror. Historical measures of atmospheric parameters correspond to this period. Individual, year, and month fixed effects are included for life satisfaction estimates. Village, year, and month fixed effects are included for consumption estimates. Contemporaneous and historical rainfall is measured in hundreds of mm, except for the shock specification – a binary variable equal to 1 if rainfall is 1 standard deviation below the village long run average rainfall. Contemporaneous and historical temperature is measured in °C, except for the shock specification – a binary variable equal to 1 if temperature is 1 standard deviation above the village long run average temperature. Standard errors are adjusted to reflect spatial dependence, as modelled in Conley (1999). Spatial autocorrelation is assumed to linearly decrease in distance up to a cut-off of 460km for Life Satisfaction regression results and 360 km for Consumption regression results. The distance is selected following a decision rule in which we choose the distance that provides the most conservative standard errors, looped over all distances between 10 and 1000km.