Rainfall Variability, Child Labor, and Human Capital Accumulation in Rural Ethiopia

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How does income uncertainty affect human capital investments in agrarian economies? Using child-level panel data, I exploit a medium-run change in mean-preserving rainfall variability to identify the effects of income uncertainty on the child labor decisions and human capital investments of smallholder farmers in rural Ethiopia. I estimate that increased rainfall variability is associated with less child labor and more schooling, consistent with a diversification mechanism. These findings highlight the empirical relevance of income uncertainty for decision making and household investment in rural economies. I find no evidence that rainfall variability is associated with past, present, or future rainfall, nor with income, wealth, and agricultural outcomes. As such, residual variation in realized income shocks—the main confounding interpretation—does not appear to explain the results.

Key words: Child labor, human capital, income uncertainty, rainfall variability.

JEL codes: D81, D13, I25, O13, Q12.

Income uncertainty is a ubiquitous feature of life for those living in poverty. This is especially true for those living in rural parts of developing countries, most of whom depend on risky rain-fed agriculture for their livelihoods. The dominant risk in these settings is unpredictable rainfall, resulting in production, income, and price risk (Townsend 1994; Jayachandran 2006; Giné, Townsend, and Vickery 2007; Bellemare, Barrett, and Just 2013; Allen and Atkin 2016).

Understanding income uncertainty is also important because its consequences for economic behavior are theoretically ambiguous. On the one hand, greater economic uncertainty may lead households to accumulate precautionary savings, reducing investments, to smooth consumption against future risk (Kimball 1991; Paxson 1992; Carroll 1997; Blundell and Preston 1998; Hahm and Steigerwald 1999; Carroll and Kimball 2001; Chou, Liu, and Hammitt 2003). On the other hand, if households believe that greater spending and investment would allow them to diversify away from risky farming activities they may increase investments—a portfolio mechanism (Dercon and Krishnan 1996; Dercon 2002; Fafchamps 2003).

Despite its practical and theoretical relevance, relatively little research has been devoted to understanding the economic consequences of income uncertainty. Instead, much of the empirical work exploring agrarian life in developing economies has focused on the consequences of realized income shocks.

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I thank Marc Bellemare and anonymous referees for their helpful thoughts, comments, and guidance. I also thank Yonas Alem, Robin Burgess, Gharad Bryan, Naomi Colmer, Antoine Dechezleprêtre, Jon de Quidt, Dave Donaldson, Greg Fisher, Maitreesh Ghatak, Vernon Henderson, Solomon Hsiang, Rob Jensen, Amir Jina, Supreet Kaur, Isaac Mbiti, Kyle Meng, Anthony Millner, Eric Neumayer, Jay Shimshack, Munir Squires, Sandip Sukhtankar, and John Van Reenen. I am also grateful to seminar participants at the London School of Economics, EAERE, AERE, CSAE, and the European Economic Association for their comments and suggestions. This work was supported by the ESRC Centre for Climate Change Economics and Policy and the Grantham Foundation. All errors and omissions are my own.
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Amer. J. Agr. Econ. 103(3): 858–877; doi:10.1111/ajae.12128
Published online August 24, 2020

This article highlights the empirical relevance of income uncertainty for household decision making in agrarian economies. Using panel data on the children of smallholder farmers in rural Ethiopia combined with high-resolution meteorological data, I measure and identify the effects of income uncertainty on child labor and human capital accumulation. To identify the effects of income uncertainty, I exploit within-village variation in a five-year moving average of the coefficient of variation of rainfall, controlling for rainfall and temperature realizations over the same period.[1] I estimate that an increase in rainfall variability is associated with a reallocation of time away from labor on the farm toward time spent on educational activities. I also find that an increase in rainfall variability is associated with an increase in the likelihood that children attend school and the number of grades attained. A one standard deviation increase in rainfall variability is associated with an additional two weeks of schooling.[2] These findings have two key implications. Informing theory, they are most consistent with the portfolio mechanism being dominant in this context. Informing practice, a back-of-the-envelope calculation suggests that the increase in schooling could be associated with a 0.83%–1.67% increase in later life earnings.

The main empirical challenge is separately identifying the effects of income uncertainty from realized income shocks. As such, there are two possible ways to interpret changes in rainfall variability. One is that increases in rainfall variability capture an increase in income uncertainty. Alternatively, it is possible that residual variation in realized income shocks could be driving the effects. I present direct evidence that this is unlikely to be a first-order explanation in this context.

Rainfall variability is uncorrelated with historical, contemporaneous, and future rainfall realizations. This implies that rainfall variability is not systematically correlated with more or less rainfall, attenuating the possibility of a direct income effect. In further support of an income uncertainty interpretation I show that rainfall variability has no effect on a broad range of income, wealth, and agricultural production outcomes. Collectively, these findings support the premise that rainfall variability is not having an effect through agricultural markets or income. It stands to reason that if increased rainfall variability was picking up residual income shocks then these shocks should have an effect on income and agricultural outcomes. The results also suggest that adults may be limited in their ability to diversify their own income in response to increased income uncertainty.

My results make three contributions to the existing literature. First, I contribute to the literature exploring the effects of income uncertainty and realized income shocks on child labor and human capital investments (Jalan and Ravallion 2001; Bhalotra and Heady 2003; Dehejia and Gatti 2005; Beegle, Dehejia, and Gatti 2006; Edmonds 2006; Fitzsimons 2007; Kruger 2007; Edmonds and Schady 2012; Kazianga 2012; Edmonds and Shrestha 2014; Akresh et al. 2017; Shah and Steinberg 2017). To date, much of the empirical work on child labor has focused on extensive margin measures of participation. However, examining how the re-allocation of time between activities changes is an interesting, important, and under-studied margin of adjustment.

Second, I contribute to the literature seeking to understand the economic consequences of income and price uncertainty in developing countries (Jensen 2000; Jalan and Ravallion 2001; Fitzsimons 2007; Yesuf and Bluffstone 2009; Alem et al. 2010; Kazianga 2012; Bellemare, Barrett, and Just 2013; Kala 2017; Alem and Colmer 2020; Foster and Gehrke 2020). I provide support for the premise that rainfall variability is capturing income uncertainty rather than income shocks. In light of the insight that rainfall variability is mean preserving and unlikely to be capturing residual variation in realized weather shocks, I argue that the results presented here highlight the empirical relevance of income uncertainty on household decision making and investments. My results do not say anything about the welfare effects of income uncertainty. Instead my results highlight a behavioral response through which households respond to, and try to manage the economic consequences of, increased income uncertainty in a context with limited access to consumption smoothing technologies.

Third, I build on this literature by employing a different methodological approach. The existing literature has either exploited cross-sectional variation in income uncertainty or

[1] The choice of a 5-year moving average is made based on the time between survey round. Results are robust to alternative measures.

[2] $0.044 \times 365 = 16.1$ days, or roughly two more weeks of schooling.

exploits within-village variation by interacting a cross-sectional proxy of income uncertainty with household characteristics, such as the area of cultivated land. A concern associated with exploiting such variation is that there could be fundamental differences across villages (unobservable to the econometrician) that are correlated with proxies for income uncertainty, such as suitability for agriculture or risk preferences and attitudes. By exploiting medium-run changes in rainfall variability within village, I am able to control for these time-invariant considerations using fixed effects.

Conceptual Framework

In this section I present a simple two-period model of human capital investment, based on Fitzsimons (2007) and Shah and Steinberg (2017). The purpose of the model is to motivate the empirical work and highlight the theoretical implications of income uncertainty on human capital accumulation. I do not make a theoretical contribution.

Parents invest in the human capital of their children in the first period and receive a payoff from the child's accumulated human capital in the second period, upon reaching adulthood. I assume that there is one child and one parent without any loss of generality, and that the parent maximizes the total utility of the household.

The parent works and earns an exogenous income $w_t^p h^p$, where w_t^p is the market wage per unit of parental human capital, h^p. I assume that the parent's human capital does not change.[3] By contrast, the child's time is allocated between school and child labor. This decision is made by the parent, jointly with the decision over consumption. Consequently, during the first period, household income is equal to the earnings of the parent, $w_1^p h^p$, plus the returns to child labor, $(1-s_1)w_1^k$, where $s_1 \in [0,1]$ denotes the share of time that children spend in school accumulating human capital. I assume that child labor income in period 1 is not a function of human capital (Rosenzweig 1980; Jacoby and Skoufias 1997; Fitzsimons 2007).

The amount of time spent in school, s_1, increases the child's stock of human capital $h_2 = f(s_1)$. I assume that $\frac{\partial f}{\partial s_1} \geq 0$, and $\frac{\partial^2 f}{\partial s_1^2} \leq 0$, implying that schooling results in weakly more human capital and that there are diminishing marginal returns to schooling. During the second period the child earns $w_2^k h_2$. Following Cunha and Heckman (2007), I assume that the income received by the child in period 2 is a function of their initial human capital in period 1, normalized to zero, plus any human capital investments made in period 1, $h_2 = f(s_1)$. Theoretical ambiguity in the effects of increased uncertainty on human capital investments arises if there is the possibility that the parent benefits from investment in their child's education through intrahousehold transfers, a common practice in developing countries where support for elderly relatives is largely provided by their children. Denoting the share of earnings that the child transfers to their parent as δ, where $0<\delta<1$, the parent receives $\delta w_2^k h_2$. Such transfers provide a pecuniary benefit to the parent in the second period, reducing the net cost of human capital investments.

The parent chooses household consumption and schooling at the beginning of period 1, without knowing income in period 2, $w_2^p h^p$. The parent's problem is written,

$$\text{(1)} \quad \max_{c_1^{hh}, s_1} u\left(c_1^{hh}\right) + \beta(1+\lambda\delta)\mathbb{E}\left[u\left(c_2^p\right)\right] + \beta\delta u\left(c_2^k\right)$$

subject to

$$c_1^{hh} = w_1^p h^p + (1-s_1)w_1^k$$
$$c_2^p = w_2^p h^p + \delta w_2^k h_2$$

Here c_t^i denotes consumption in period t, by the household, hh, the parent, p, and the child, c. For simplicity, I assume that there is no borrowing or saving, such that income is equal to consumption in each period. As defined above, s_1 is the fraction of time spent in school. β is the parental discount rate; λ is the weight that the parent places on their child's utility in period 2, where $0<\lambda<1$; and δ the weight that the child puts on their parent's utility in period 2, where $0<\delta<1$. The expectations operator reflects that there is uncertainty in period 1 about period 2 parental income. Since the focus of the article is on parental income uncertainty, I abstract from introducing uncertainty into the child's second period income. This captures the idea that educational

[3] In practice, parental labor may itself respond to changes in income uncertainty. This is explored in the empirical analysis.

investments could constitute a diversification of household income by opening up opportunities for children to work in less risky activities.

For an interior optimum, the household equalizes the utility-weighted marginal cost of investments in human capital, that is, foregone consumption, with the utility-weighted marginal benefit of human capital in later periods, such that,

$$(2)\quad (1+\lambda\delta)\left[w_1^k - w_2^2 f'(s_1)\right]\mathbb{E}\left[u\left(c_2^p\right)\right] = \lambda\left[u'\left(c_2^k\right)f'(s_1)\right]$$

The focus of this section is to consider how parental income uncertainty affects the optimal level of schooling; that is, as income uncertainty increases, do parents invest more or less in schooling and, consequently, do overall levels of human capital increase or decrease?

The Effect of Parental Income Uncertainty on Human Capital

To isolate the effects of income uncertainty on human capital investment, I explore the effects of an increase in income dispersion, defined as a combination of additive and multiplicative shifts in the distribution of parental income (Sandmo 1970; Fitzsimons 2007; Fafchamps 2010).

I rewrite period 2 parental income as, $\gamma\left(w_2^p h^p\right)+\theta$, the expected value of which is $\mathbb{E}\left[\gamma\left(w_2^p h^p\right)+\theta\right]$. The multiplicative shift parameter, $\gamma > 1$, stretches the distribution, and the additive shift parameter, θ, increases the mean while holding all other moments constant. Under the assumption of non-negative income, a multiplicative shift around zero will increase the mean. Consequently, for there to be a mean-preserving increase in risk, this must be counteracted by a negative shift in the additive parameter, holding the expected value constant. This requires that the differential of the expected value of future income is 0; that is, $\mathbb{E}[(w_2 h^p)\mathrm{d}\gamma + \mathrm{d}\theta] = 0$. This implies that $\mathrm{d}\,\theta/\mathrm{d}\gamma = -\mathbb{E}[w_2 h^p] = -\xi$.

With this I examine the effect of a mean-preserving increase in income dispersion, γ, on the optimal choice of schooling, s_1^*, and the resulting level of human capital, h_2^*,

$$(3)\quad \left.\frac{\partial s_1^*}{\partial \gamma}\right|_{\frac{\mathrm{d}\theta}{\mathrm{d}\gamma}=-\xi} \propto \frac{\beta(1+\lambda\delta)\left[w_1^k - w_2^k f'(s_1)\right]\cdot u''\left(c_1^{hh}\right)\mathbb{E}[u''\left(c_2^p\right)\left(w_2^p h^p - \xi\right)}{|\mathrm{H}|}$$

where |H| is the determinant of the Hessian matrix, known to be positive based on the second-order conditions.

Following Sandmo (1970), it is straightforward to show that decreasing absolute risk aversion is a sufficient condition for the component $u''\left(c_1^{hh}\right)\mathbb{E}\left[u''\left(c_2^p\right)\left(w_2^p h^p - \xi\right)\right]$ to be negative, such that increased uncertainty about future income decreases investments in human capital. However, the sign of the term $\left[w_1^k - w_2^k f\left(s_1^*\right)\right]$ is ambiguous. If the returns to schooling are high enough, then this may offset the adverse effects of uncertainty on human capital investments. Consequently, whether increased uncertainty increases or decreases investments in human capital is theoretically ambiguous.

The empirical analysis investigates which of these mechanisms are dominant, exploiting plausibly exogenous changes in rainfall variability. In the following sections, I show that rainfall variability has no effect on past, contemporaneous, or future rainfall realizations. Rainfall variability also has no direct effect on a broad range of income, wealth, and agricultural outcomes. These results provide support for the necessary condition that the differential of the expected value of future income is zero. I therefore argue that the estimates capture the effect of an increase in income dispersion rather than the effects of changes in historical, contemporaneous, or expected future income.

Data

The main analysis uses data from the Ethiopian Rural Household Survey collected by the University of Addis Ababa, the Centre for the Study of African Economics (CSAE) at the University of Oxford, and the International Food Policy Research Institute (IFPRI).[4] The data cover fifteen village communities in rural Ethiopia. These villages represent the diversity of farming systems throughout Ethiopia and capture climate differences across the country, providing significant spatial variability in atmospheric conditions. The survey consists of seven rounds between 1989 and 2009. In 1989, households from six villages in central and southern Ethiopia were interviewed. In 1994, however, the sample was expanded to cover fifteen villages across the country, representing 1,477 households. Further rounds were completed in 1995, 1997, 1999, 2004, and 2009. I use the latest two rounds of this panel, 2004 and 2009. All surveys were completed within three months and at roughly the same time each round. These years are the focus of the child level analysis as they contain consistent survey questions across rounds, as well as child identifiers.[5]

Data Collection

The data were collected to account for diversity in the agricultural systems across the country. The villages are widely dispersed, some being more than 1,000 km apart. The sampling frame for the villages was strictly stratified across the main agro-ecological zones and subzones, with one to three villages selected per strata.

A list of households within each village was constructed in 1994. From this sampling frame, random sampling was used, stratified by female-headed and male-headed households, with sample sizes chosen to represent the population of each main farming system. Consequently, the data are not nationally representative but can be considered representative of households in non-pastoralist farming systems. Attrition in the sample has also been very low. The attrition rate between 1994 and 2004 was 13.2% or 1.3% per year (Dercon and Hoddinott 2011).

[4]The data used can be obtained from the Harvard Dataverse (Hoddinott, John; Yohannes, Yisehac, 2011, "Ethiopian Rural Household Surveys (ERHS), 1989–2009" https://hdl.handle.net/1902.1/15646

[5]Earlier rounds either do not contain data on time use.

Sample Construction

In the raw data, the age distribution for individuals reporting child labor and educational activities ranges from 0 to 58, indicating measurement error in the reporting of age—a common issue in household surveys from developing countries. I trim the data to exclude children that are over the age of twenty-one, a decision rule based on excluding ages that account for less than 1% of the data. As an illustration, "children" that are reported to be age twenty-one account for 1.74% of the data and so are retained in the sample. By contrast, the combined contribution of all ages greater than twenty-one account for 0.32% of the data and so are dropped. At the bottom end of the age distribution I restrict the sample to children aged four and above, following the same decision rule. The results presented are robust to using the full sample, and to restricting the maximum age of children to be eighteen or sixteen. The average age of children in the benchmark analysis sample (ages 4–21) is twelve.

In addition to imposing sample restrictions based on the age of the children, I also impose restrictions based on the consistency of individual characteristics. Specifically, I drop individuals that are reported to be older in 2004 than they are in 2009, and also drop individuals that are reported to be a different sex across rounds. Results are robust to retaining these individuals. These restrictions are imposed to address concerns that individual identifiers may be misattributed, which could bias results when imposing individual fixed effects.[6]

Time Allocation Data

When analyzing the time allocation of children, the outcomes of interest are defined as the total number of hours spent on an activity per week. In terms of the activities that children engage in, economic activities generally consist of farming activities, including land preparation, tending crops, processing crops, and looking after livestock. I also look at domestic chores, for two reasons: first, child

[6]Results are also robust to conducting the analysis using household fixed effects rather than individual fixed effects, which avoids the problem of intrapersonal comparisons in cases where different people are assigned the same identifier. Results are also robust to using village fixed effects and age fixed effects, comparing children of the same age from the same village across different periods.

labor is not restricted to economic activities, and so it is interesting to consider the substitution of time among activities in response to an increase in uncertainty; second, in rural areas it may be difficult to distinguish between time spent on household chore activities and time spent on chores relating to farming activities. Finally, I also look at the amount of time spent on wage labor; however, on average, very few hours are reported to be spent on this activity.

In addition to the time spent on child labor activities, I examine the time spent on human capital accumulation. Unfortunately, it is not possible to directly observe time spent studying in school. However, conditional on attending school, children attend for half of the day (four hours), and a measure of time spent in school can be constructed using data on attendance and this assumption. This measure assumes that there is no intensive margin response conditional on attending school; that is, all of the variation comes from the extensive margin of whether the child attends school. To some degree, this is a reasonable assumption, given that school is only in session for a half day. However, it should be clear that in the main analysis this measure provides no additional information above and beyond the extensive margin analysis on whether there is an increase in the likelihood that the child attends school.

Despite a lack of information on the time spent in school, data are available on the number of hours that children spend studying at home, providing at least some insight into intensive margin responses to time spent on educational activities.

Although the constructed measure of time spent in school provides no insights into the intensive margin of school attendance, it does help in the construction of the final time allocation, defined loosely as leisure. Leisure is defined as the sum of all time spent on activities that are not work or study related. It is constructed to be the total number of hours in the week minus the amount of time spent on work and study—a residual measure. This measure captures time spent eating, sleeping, and playing, as well as any other work activities that have been misreported. When combined with the number of hours spent working or studying, "leisure" provides a full account of time use for each child.

Unsurprisingly, children spend the majority of their time on these other activities, accounting for 120 hours per week on average. Being close to the equator, where there are roughly twelve hours of daylight each day throughout the year, sleep and night time activities may account for eighty-four hours (70%) of this residual with the remaining thirty-six hours (30%) being allocated among leisure activities.

Although it is commonly believed that an increase in time spent on child labor activities will translate into a reduction in educational investments, this may not be the case. In many studies—this study included—we observe that children are capable of both working and attending school.[7] Ravallion and Wodon (2000) argue that poor families can protect the educational investments of working children because there are other things that children do besides school and work.

One cannot assume that the time these children spend working must come at the expense of formal time at school, although there may be displacement of informal (after-school) tutorials or homework.[8]

In the context of Ethiopia, where children only attend school for half of the day, the degree to which child labor could crowd out formal schooling may be further mitigated. As a result, it is unclear whether changes in time allocation will necessarily translate into changes in educational investment, and vice versa. Consequently, it is important to directly assess the full time-use of children to better understand the reallocation of time across activities in response to changes in economic conditions, rather than focusing solely on whether children engage in education and child labor. By using data on the time allocation of children, this article is able to provide insights into both intensive-margin and extensive-margin responses to income uncertainty.

In Table 1 we observe that farming activities account for 8% of time each week, with an additional 8% of time being spent on domestic

[7]57% of the sample attend school. Conditional on attending school, 97% of the sample also work, either on the farm, in the home, or for wages. 65% attend school and work on the farm. 77% attend school and work in the home. 2.2% of children attend school and engage in wage labor.

[8]Jayachandran (2014) demonstrates that the displacement of informal schooling may have significant welfare effects of its own. If schools offer for-profit tutoring to their own students, this gives teachers a perverse incentive to teach less during school to increase demand for tutoring. Consequently, those who do not participate in out-of-school human capital investments could be adversely affected. It is not possible to test this implication due to the absence of test scores. However, intensive margin adjustments capturing home study provide some insight into out-of-school educational investments.

Table 1. Descriptive Statistics: Children's Activities

	MEAN	STD. DEV. (within)	STD. DEV. (between)	OBS.
Panel A: *weather data* (village level):				
RAINFALL VARIABILITY (σ/μ)	18.590	7.200	10.908	30
TOTAL RAINFALL (mm)	1,452.574	243.248	471.184	30
AVERAGE TEMPERATURE (°C)	19.187	0.329	1.873	30
Panel B: *children's characteristics*				
AGE	11.876	1.792	4.638	7,142
MALE	0.527	0	0.499	5,656
PRIMARY ACTIVITY (Farming)	0.163	0.182	0.341	7,142
PRIMARY ACTIVITY (School)	0.549	0.256	0.450	7,142
PRIMARY ACTIVITY (Domestic)	0.148	0.154	0.343	7,142
PRIMARY ACTIVITY (Other)	0.138	0.178	0.320	7,142
Panel C: *time allocation (share of time, %)*				
CHILD LABOR (farming)	8.005	4.376	8.864	7,142
CHILD LABOR (domestic chores)	7.787	3.685	7.692	7,142
CHILD LABOR (wage)	0.514	1.702	3.160	7,142
SCHOOL	6.330	3.055	5.373	7,142
HOME STUDY	4.437	2.967	5.763	7,142
LEISURE	72.924	7.733	14.459	7,142
Panel D: *participation (0/1)*				
CHILD LABOR (FARMING)	0.590	0.236	0.451	7,142
CHILD LABOR (DOMESTIC CHORES)	0.694	0.224	0.422	7,142
CHILD LABOR (QAGE)	0.033	0.088	0.167	7,142
HOME STUDY	0.531	0.254	0.452	7,142
Panel E: *education*				
ATTENDING SCHOOl (%)	0.531	0.256	0.451	7,142
HIGHEST GRADE ATTAINED	3.683	1.229	2.500	4,690

Note: Calculated from the 2004 and 2009 rounds of the Ethiopian Rural Household Survey (ERHS). The time allocated to each activity is defined as the number of hours spent per week on each activity. The time allocated to school is constructed as the length of the school day (four hours per day) if in attendance, zero otherwise. Leisure is defined as the residual number of hours after accounting for the time allocated to child labor, schooling, and home study. This residual accounts for the amount of time children spent eating, sleeping, and playing. Highest grade attained is the number of grades that have been completed at the time of the survey ranging from 0 grades to 12 grades in total.

chores. As mentioned, very little time is spent on wage labor, accounting for an average of 0.5% of time each week. Aggregating these activities, we observe that the share of time spent on all labor activities is 16.5%. By contrast, educational activities account for 11.5% of time. This is a non-trivial amount of time and could result in a trade-off with time spent on educational activities. The residual time spent on leisure accounts for 72% of activity (or inactivity) each week.

Extensive Margin Measures

In addition to the time allocated to these activities, I construct binary variable measures of whether children engage in child labor activities—the extensive margin—and more importantly for human capital accumulation, whether children attend school, and the highest grade that they have achieved. We observe that 89% of children engage in some child labor activities, either farming (60%) or domestic chores (70%), and 53% of children are reported to attend school, achieving an average of 3.6 grades. There are fewer reported observations for the highest grade achieved, resulting in a smaller sample size for this variable.

Measuring Parental Income Uncertainty

To analyze the effects of parental income uncertainty on child labor and human capital investments, I combine the survey data with meteorological data constructed at the village level from the ERA-Interim data archive supplied by the European Centre for Medium-Term Weather Forecasting (ECMWF).[9]

[9]See Dee *et al.* (2011) for a detailed discussion of the ERA-Interim data. The data can be found at the following website (https://www.ecmwf.int/en/forecasts/datasets/archive-datasets/reanalysis-datasets/era-interim)

Where previous studies have relied on the use of meteorological data provided by the Ethiopian meteorological service, the number of missing observations, or observations that are recorded as zero on days when there are no records, is of concern. Making use of data provided by the Ethiopian meteorological service, it was only possible to construct the relevant analysis measures for five villages.

By contrast, the ERA-Interim reanalysis data archive provides daily measurements of many atmospheric parameters, of which precipitation and daily average temperature are exploited for the purposes of this article. The data are available from January 1, 1979 until the present day, on a global grid of quadrilateral cells defined by parallels and meridians at a resolution of 0.25×0.25 degrees (equivalent to 28×28 km at the equator).[10] Rainfall and temperature variables for each village are calculated through a process of inverse distance weighting, taking all data points within 100 km of the village. The weight attributed to each grid point decreases quadratically with distance.

Reanalysis data are constructed through a process whereby model information and observations are combined to produce a consistent global best estimate of atmospheric parameters over a long period of time by optimally fitting a dynamic model to each period simultaneously (Auffhammer *et al.* 2013). Models propagate information from areas with more observational data for areas in which observational data are scarce. This results in an estimate of the climate system that is separated uniformly across a grid that is more uniform in its quality and realism than observations alone and that is closer to the state of existence than any single model would provide. This provides a consistent measure of atmospheric parameters over time and space. This type of data is increasingly being used by economists, especially in developing countries, where the quality and quantity of weather data is more limited (see Dell, Jones, and Olken (2014) and Carleton and Hsiang (2016) for a review of recent applications in the literature).[11]

Using this data I construct my proxy for parental income uncertainty: rainfall variability. I start with a measure of total annual rainfall for each village, then I calculate the coefficient of variation for rainfall (CV), measured as the standard deviation divided by the mean for the previous five years, the time between survey rounds. The coefficient of variation for rainfall for each village is time-varying across rounds. One of the major advantages of the CV is that it is scale invariant, providing a comparable measure of variation across villages that may face very different levels of rainfall.

In addition, I construct linear and nonlinear measures of average rainfall and temperature, measured over the same period, to control for realized income shocks. Since the first moment and second moment of the rainfall distribution are correlated, it is important to control for first-moment effects to isolate the effects of income uncertainty, to the degree that it is empirically relevant, from realized income effects. Descriptive statistics for the weather variables used are reported in Table 1.

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[10] To convert degrees to km, multiply 28 by the cosine of the latitude, e.g. at 40° latitude $0.25^{\circ} \times 0.25^{\circ}$ cells are $28 \times \cos(40) = 21.4 \times 21.4$ km.

[11] All climate data, whether reanalysis or observational data, are subject to caveats and concerns. Reanalysis data are unlikely to match observational data perfectly. It is limited to some degree by resolution, even where observational data is present. Furthermore, reanalysis data are partly computed using climate models that are imperfect and contain systematic biases. This brings up further concern to issues of accuracy. However, in areas with limited observational data such as Ethiopia, reanalysis data is known to provide estimates that are better than observational data alone could provide. In addition, there are also statistical reasons as to why reanalysis data may be preferable. Previous studies have relied on the use of meteorological data provided by the Ethiopian meteorological service and the number of missing observations is a serious concern. This availability of ground station data is exacerbated by the serious decline in the number of reporting weather stations over the past few decades. 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 fifty-four countries in the continent, this results in an average of fewer than ten 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 eighteen; 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 I have economic data (2004 and 2009), weather station data is available for fifty days from one station (Addis Ababa) in 2004 and is available for all eighteen 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 sixty-three zones and 529 Woredas (districts) reported in 2008. If this measurement error is classical, that is, uncorrelated with the actual level of rainfall measured, then the estimates of the effect of these variables will be biased toward 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, that is, weather stations are placed in more agriculturally productive areas, where the need for weather information is greater.

Empirical Strategy

To explore the empirical relevance of parental income uncertainty on human capital accumulation and child labor, I exploit within-village variation in rainfall variability measured over the previous five years and control for average rainfall and temperature realizations over the same period.

Estimating Equation

I estimate the effects of rainfall variability on time-use and educational outcomes, using the following specification,

$$(4) \quad Y_{\text{ivt}} = \beta_1 \text{Rainfall Variability}_{\text{vt},\ldots,t-4} + \gamma \text{f}(\bar{w}_{\text{vt},\ldots,t-4}) + \alpha_i + \alpha_a + \alpha_m + \alpha_t + \epsilon_{\text{ihvt}}$$

Y_{ivt} is the outcome variable of interest, defined as the share of time spent in each activity, or a binary variable, indicating participation in each activity and various education outcomes, such as attendance and the highest grade attained to date. The key explanatory variable of interest is a five-year moving average of Rainfall Variability$_{vt,\ \ldots,\ t-4}$ – a proxy for parental income uncertainty after controlling for a five-year moving average of weather realizations, $f(\bar{w}_{vt,\ldots,t-4})$. The choice of a five-year moving average is made based on the time between survey rounds. In the main specification I control for linear and quadratic measures of total rainfall and daily average temperature over this period as well as interactions between these terms,

$$f(\bar{w}_{\text{vt},\ldots,t-4}) = \gamma_1 \bar{\text{rain}}_{\text{vt},\ldots,t-4} + \gamma_2 \bar{\text{rain}}^2_{\text{vt},\ldots,t-4} + \gamma_3 \bar{\text{temp}}_{\text{vt},\ldots,t-4} + \gamma_4 \bar{\text{temp}}^2_{\text{vt},\ldots,t-4} + \gamma_5 \bar{\text{rain}} \times \bar{\text{temp}}_{\text{vt},\ldots,t-4} + \gamma_6 \bar{\text{rain}}^2 \times \bar{\text{temp}}^2_{\text{vt},\ldots,t-4}$$

Results are robust to less stringent specifications. In addition, I control for individual fixed effects (α_i), to allow comparison within child over time, year fixed effects (α_t) to control for aggregate shocks and uncertainty, month of survey fixed effects (α_m) to control for seasonal variation in the timing of the survey, and age fixed effects (α_a) to allow comparison within each age cohort.

The last term in Equation 4 is the stochastic error term, ϵ_{ihvt}. Standard errors are clustered at the village level and are robust to bootstrap adjustments put forward by Cameron, Gelbach, and Miller (2008) to account for the small number of clusters.[12] Results are also robust to following the approach of Hsiang (2010) by assuming that the error term may be heteroskedastic and serially correlated within a district over time (Newey and West 1987), and spatially correlated across contemporaneous villages (Conley 1999). However, standard errors are substantially smaller.

Identification Assumptions

One of the attractive properties of rainfall realizations are that they are exogenous. As such, there are unlikely to be other confounding factors that are correlated both with rainfall variability and household decisions, relating to time use and education. Formally, we invoke the zero conditional mean assumption, $\mathbb{E}(\epsilon_{ihvt} | \bar{rain}_{vt,\ldots,t-4}, \alpha_v, \alpha_t) = 0$. However, we are not trying to identify rainfall variability, rather we are using rainfall variability as a proxy for income uncertainty. As such, even though the exogeneity of rainfall variability means that the estimate will in all likelihood be identified, it is unclear a priori how it should be interpreted. This is true of any treatment effect that could affect outcomes through multiple channels. Randomization provides identification not interpretation.

There are two possible interpretations for an identified rainfall variability coefficient $\beta_{1:}$ (*a*) rainfall variability is capturing the effects of parental income uncertainty; and (*b*) there is no change in parental income uncertainty, and rainfall variability is simply capturing a mix of past and contemporaneous income shocks.

As highlighted in the theoretical framework, it is important that an increase in income uncertainty is mean preserving; that is, that the expected value of income remains constant. Consequently, the key assumption for identifying the effects of income uncertainty, rather than rainfall variability more broadly, is that rainfall variability is uncorrelated with past,

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[12]In Appendix A.4. I engage in a randomization inference exercise as a final exercise to address the small number of clusters, as well as any concerns that the results are driven by sampling variability. Holding the sample fixed I re-assign rainfall variability across village-years 10,000 times and use these placebo realizations of rainfall variability to estimate the original model. I then plot the distribution of each estimated coefficient and compute the share of placebo β's that are higher in absolute value than the original estimate of β, providing an exact p-value.

contemporaneous, or expected future, rainfall shocks. Weather controls, $f(\bar{w}_{vt,\ldots,t-4})$, are included to control for past and contemporaneous income shocks. However, in principle these need not be required. If rainfall variability is mean preserving, that is, rainfall variations doesn't systematically affect the sign or magnitude of deviations in rainfall from the mean, then the inclusion of these terms will have little effect on the estimated coefficient.

A second consideration is that, for the first interpretation to be true, it must be the case that there is both a change in the underlying rainfall distribution and that parents' beliefs about the underlying rainfall distribution also change. Looking at the data one observes that, on average, there is a significant reduction in five-year rainfall variability between rounds rather than a stable distribution over time (figure 1). Prior to the 2004 round, average rainfall variability was at a markedly higher level. Following this round, rainfall variability dropped and remained at a lower level for the next five years. This suggests that the underlying distribution of rainfall does change and that, consequently, there is scope for individuals to change their beliefs in response to changes in rainfall variability across rounds. Unfortunately, data limitations do not allow us to test whether beliefs also change. This is an important assumption because if beliefs donot change there should be no change in outcomes, unless driven by residual variation in income shocks. The following set of exercises provide evidence to suggest that this alternative interpretation is not a first-order concern.

Supporting evidence: The mean-preserving nature of rainfall variability

I begin by directly assessing whether rainfall variability is mean preserving. I do this by evaluating the effects of rainfall variability on past and future rainfall realizations, using the full sample of weather data described above (1979–2012). If rainfall variability is not mean preserving and affects past weather realizations, then the measure of income uncertainty used may simply capture any residual contemporaneous or persistent impacts of realized income shocks. If rainfall variability is associated with contemporaneous or past income shocks (which could have persistent effects), these could drive the main results. Furthermore,

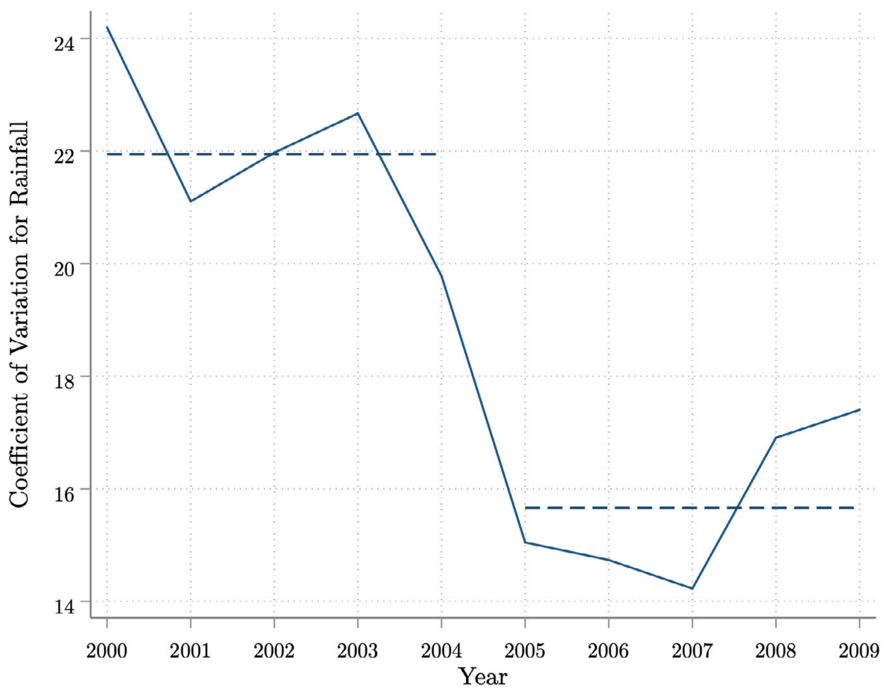

Figure 1. Changes in rainfall variability over time

Note: This figure graphically represents a five-year moving average of the coefficient of variation for rainfall for the period 2000–2009. Between 2000 and 2004 we observe that rainfall variability was, on average, systematically higher than between 2005 and 2009. The dashed lines represent the mean rainfall variability over these periods.

if rainfall variability is not mean preserving and farmers update their expectations about future rainfall realizations based on changes in rainfall variability, then increases in rainfall variability may simply capture expectations about future income. To explore these considerations, I regress rainfall, measured in mm, in period *t* on rainfall variability in the previous five years—the time between survey rounds—using the following specification,

$$\text{(5)}\quad \text{Rainfall}_{\text{vt}} = \beta_2 \text{Rainfall Variability}_{\text{vt},\ldots,t-4} + \gamma \text{f}\left(\text{w}_{\text{vt},\ldots,t-4}\right) + \alpha_v + \alpha_t + \epsilon_{\text{vt}}$$

The results of this exercise are presented in Table 2. I find no evidence that rainfall variability has a meaningful statistical or meteorological effect on past, contemporaneous, or future rainfall realizations. In terms of magnitude I estimate that a one standard deviation increase in the coefficient of variability for rainfall is associated with between an 8.8 mm reduction (t−4) and a 34 mm increase in rainfall (t + 2). A one standard deviation change in rainfall within village is 482 mm, and so these effect sizes are small. This supports the premise that rainfall variability is mean preserving and so should not have a direct income

Table 2. Disentangling Income Shocks from Income Uncertainty: The Effects of Rainfall Variability on Rainfall Realizations

	TREATMENT VARIABLE: RAINFALL VARIABILITY (σ/μ)					DEP. VAR. MEAN
OUTCOME VARIABLE	(1)	(2)	(3)	(4)	(5)	(6)
ANNUAL RAINFALL (t + 4)	2.142	2.550	2.462	3.039	2.805	1,376.497
	(1.693)	(2.031)	(1.986)	(1.931)	(1.996)	
	[0.209]	[0.240]	[0.224]	[0.129]	[0.187]	
ANNUAL RAINFALL (t + 3)	2.286	2.406	2.361	2.594*	2.760*	1,383.802
	(1.645)	(1.836)	(1.550)	(1.383)	(1.411)	
	[0.179]	[0.233]	[0.110]	[0.042]	[0.041]	
ANNUAL RAINFALL (t + 2)	2.368	2.270	3.087	3.823	4.192*	1,384.363
	(2.194)	(2.159)	(2.037)	(2.282)	(2.253)	
	[0.316]	[0.314]	[0.182]	[0.131]	[0.123]	
ANNUAL RAINFALL (t + 1)	0.622	0.139	0.970	1.169	1.925	1,376.004
	(2.226)	(2.127)	(1.594)	(1.702)	(1.687)	
	[0.793]	[0.952]	[0.539]	[0.465]	[0.253]	
ANNUAL RAINFALL (t)	3.911**	2.211	1.847	1.502	1.762	1,347.258
	(1.727)	(1.335)	(1.141)	(1.071)	(1.066)	
	[0.052]	[0.128]	[0.135]	[0.173]	[0.130]	
ANNUAL RAINFALL (t-1)	1.873	0.171	0.217	0.121	0.393	1,342.532
	(1.812)	(0.874)	(1.036)	(0.959)	(1.084)	
	[0.355]	[0.853]	[0.847]	[0.896]	[0.722]	
ANNUAL RAINFALL (t-2)	1.520	−1.253	−0.846	−0.768	−0.688	1,344.297
	(1.697)	(0.717)	(0.873)	(0.766)	(0.851)	
	[0.391]	[0.105]	[0.413]	[0.380]	[0.507]	
ANNUAL RAINFALL (t-3)	2.002	−1.143	−1.048	−0.719	−0.979	1,346.462
	(1.635)	(1.163)	(0.991)	(1.004)	(1.018)	
	[0.262]	[0.359]	[0.338]	[0.479]	[0.371]	
ANNUAL RAINFALL (t-4)	2.064	−0.484	−0.483	−0.545	−1.088	1,350.294
	(1.946)	(1.478)	(1.556)	(1.549)	(1.839)	
	[0.313]	[0.739]	[0.753]	[0.729]	[0.587]	
Observations	495	495	495	495	495	
Treatment std. dev.	9.058	8.947	8.382	8.419	8.163	
FIXED EFFECTS	VILLAGE, MONTH, AND YEAR					
WEATHER CONTROLS	NO	YES	YES	YES	YES	
QUADRATIC WEATHER CONTROLS	NO	NO	NO	YES	YES	
WEATHER INTERACTIONS	NO	NO	YES	NO	YES	

Note: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. The unit of analysis is at the village level. Each coefficient relates to an individual regression. Rainfall variability is defined as the coefficient of variation for rainfall. Historical measures of atmospheric parameters correspond to the time period, over which rainfall variability is measured. Historical rainfall is measured in hundreds of mm. historical temperature is measured in °C. Cluster robust standard errors are reported in parentheses. Wild cluster bootstrap-t p-values (null-imposed, 1,000 replications) are reported underneath in brackets, addressing concerns relating to the small number of clusters (Cameron, Gelbach, and Miller 2008).

or wealth effect, other than through behavioral responses to changes in uncertainty. Indeed, the absence of direct effects on rainfall realizations significantly attenuates the mechanism through which direct income effects might arise.

Consequently, it is unlikely that increases in rainfall variability capture contemporaneous income effects, the persistent effects of past income shocks, or expectations about future income realizations. Although we can never rule out any residual correlation between rainfall variability and realized events, these results suggest that first-order concerns should be alleviated.

Supporting evidence: The absence of rainfall variability effects on income-related outcomes. In addition, to demonstrating the mean-preserving properties of rainfall variability I also directly examine the consequences of rainfall variability on a broad set of income, wealth, and agricultural outcomes. Descriptive statistics for these outcomes are reported in Table 1.

Agricultural outcomes

Using data on each household's agricultural production, I calculate agricultural yields, defined as the cultivated production of each crop divided by its cultivated area.[13,14]

However, exploring the effects of rainfall variability on yields is not sufficient to rule out a change in income. Although yields and income are correlated, prices, wages, and consequently labor supply decisions may also be affected (Foster and Rosenzweig 2004; Jayachandran 2006; Kaur 2019; Colmer 2020). If the price that households receive for their crops changes, or wages change, then income may still be affected. Consequently, in addition to examining the effects of rainfall variability on yields, I explore the effects of rainfall variability on the share of crop sold—an evaluation of the degree to which households respond to price effects if they exist—as well as directly examining the effects of rainfall variability on price, which can be calculated for households that sell their produce.

Using this data, I estimate crop-specific effects of rainfall variability on yield, share sold, and price,

$$(6) \quad \log(\text{Yield}_{\text{chvt}}) = \beta_3 \text{Rainfall Variability}_{\text{vt},\ldots,t-4} + \gamma \text{f}(\text{w}_{\text{vt},\ldots,t-4}) + \alpha_{\text{ch}} + \alpha_m + \alpha_t + \epsilon_{\text{chvt}}$$

where Rainfall Variability$_{vt,\ \ldots,\ t-4}$ is my proxy for income uncertainty – the coefficient of variation for rainfall measured over the previous five years – and $f(\text{w}_{vt,\ \ldots,\ t-4})$ is a function of past weather variables measured over the previous five years. In the most rigorous specification, I control for average rainfall and temperature realizations in the previous five years, quadratic terms of each variable to account for possible non-linearities and the interaction between these terms.[15] α_{ch} captures crop-household fixed effects, α_t captures year fixed effects, and α_m captures month of survey fixed effects.

Labor supply, non-crop income, and wealth. In addition, I evaluate the potential for wage and labor supply effects, examining the average daily wage of hired farm labor, the number of worker days conditional on hiring labor, and whether the household hired any workers.

As well as on-farm labor decisions that affect cost, I also explore the off-farm labor decisions of parents as an alternative income-generating activity. I examine whether adults are engaged in off-farm work, whether they are engaged in work outside of the village—a proxy for migratory behavior—and the number of days that they work off farm. Finally, I explore whether household assets are likely to be affected through an examination of livestock—the most important marketable asset in Ethiopia, accounting for more than 90% of the total value of assets (Dercon 2004). I examine whether households make any changes to the number of livestock they own or whether they sell or slaughter any livestock.

[13]The crops used are maize, wheat, white teff, barley, sorghum, black teff, coffee, chat, and enset, constituting the major staple crops and cash crops of Ethiopia.

[14]In Appendix A.1 I provide an initial examination of the relationship between rainfall and yields, to underscore the importance of rainfall for the livelihoods of smallholder farmers in Ethiopia and shed some light on the potential structure of the functional form underlying the relationship within this context. Table A1 presents the results of various specifications, all demonstrating that rainfall appears to have a positive and relatively linear relationship with yields; that is, more rainfall is better.

[15]Results are also robust to controlling for linear and quadratic rainfall realizations in each of the individual years and to controlling for rainfall shocks in each of the individual years to account for more recent weather events.

Table 3. Disentangling Income Shocks from Income Uncertainty: The Effects of Rainfall Variability on Agricultural Yields, Share Sold, Prices, and Crop Choices

	(1)	(2)	(3)	(4)	(5)
	LOG YIELDS	SHARE SOLD	LOG PRICE	CROP COUNT	MAIN CROP
Rainfall Variability (σ/μ)	−0.00230	−0.00194	−0.0119	−0.00917	0.00181
	(0.00773)	(0.00137)	(0.0158)	(0.00544)	(0.00208)
	[0.764]	[0.291]	[0.528]	[0.113]	[0.491]
exp (DEP. VAR. MEAN)	1,109.769	0.230	7.352	2.402	0.458
TREATMENT STD. DEV.	1.692	1.692	0.804	2.154	2.154
OBSERVATIONS	3,812	3,812	1,546	2,072	2,072
WEATHER CONTROLS	YES	YES	YES	YES	YES
QUADRATIC WEATHER CONTROLS	YES	YES	YES	YES	YES
WEATHER INTERACTIONS	YES	YES	YES	YES	YES

Note: Significance levels are indicated as *0.10 **0.05 ***0.01. The unit of analysis in columns 1–3 is a crop within a household. For columns 1–3 I include crop × household, year, and month-of-year fixed effects. The unit of analysis in columns 4 and 5 is a household. For columns 4 and 5 I include household, year, and month-of-year fixed effects. Rainfall variability is defined as the coefficient of variation for rainfall, measured over the previous five years, the time period between each survey round. Historical measures of atmospheric parameters correspond to this period. Historical rainfall is measured in hundreds of mm. Historical temperature is measured in °C. Cluster robust standard errors are reported in parentheses. Wild cluster bootstrap-t p-values (null-imposed, 1,000 replications) are reported underneath in brackets, addressing concerns relating to the small number of clusters (Cameron, Gelbach, and Miller 2008).

These outcomes are evaluated at the household level,

$$(7)\quad \log(\text{Labor Supply}_{\text{hvt}}) = \beta_4 \text{Rainfall Variability}_{\text{vt},\ldots,t-4} + \gamma f(\text{w}_{\text{vt},\ldots,t-4}) + \alpha_h + \alpha_m + \alpha_t + \epsilon_{\text{hvt}}$$

except for livestock outcomes, which are evaluated at the livestock-type level.[16]

$$(8)\quad \log(\text{Livestock}_{\text{lhvt}}) = \beta_5 \text{Rainfall Variability}_{\text{vt},\ldots,t-4} + \gamma f(\text{w}_{\text{vt},\ldots,t-4}) + \alpha_{\text{lh}} + \alpha_m + \alpha_t + \epsilon_{\text{lhvt}}$$

Tables 3–5 present the results of these exercises. I find no effects of rainfall variability on agricultural, income, or wealth related outcomes. These results are robust to excluding or including weather controls, accounting for non-linearities in the rainfall and temperature distribution, and accounting for interactions between temperature and rainfall. The estimated effects are statistically insignificant and small in magnitude. In addition, Appendix A2 provides additional results, highlighting the robustness of these findings to alternative measures and time definitions of rainfall variability (Tables A2 – A31). Combined, these findings provide compelling support for the premise that rainfall variability has no direct effect on income. As such, it stands to reason that the estimated effects of rainfall variability on children's outcomes capture the effects of parental income uncertainty rather than residual income shocks.

[16]Thirteen types of livestock are included in the analysis: calves, bulls, oxen, heifer, cows, sheep, goats, horses, donkeys, mules, camels, young bulls, and chickens.

Main Results

As highlighted in the conceptual framework, the effect of an increase in parental income uncertainty on child labor and human capital accumulation is theoretically ambiguous. On the one hand, households may reduce investments in human capital by allocating more time to child labor on the farm to mitigate the economic consequences of realized productivity shocks—the precautionary mechanism. On the other hand, households may increase investments in human capital, adjusting the time allocation of children away from risky activities on the farm toward less risky investments—the portfolio mechanism.

First, I examine the effect of rainfall variability on the share of time children allocate to child labor, education, and leisure activities in rural Ethiopia. To date, most empirical work on child labor has focused on extensive margin measures of participation; however, understanding the reallocation of time between activities is an interesting, important, and understudied margin of adjustment. The

Table 4. Disentangling Income Shocks from Income Uncertainty: The Effects of Rainfall Variability on Hired and Parental Labor Market Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	LOG AVG.	LOG WORKER	HIRED ANY	OFF-FARM	OUT-OF-VILLAGE	LOG OFF-FARM
	WAGE	DAYS (HIRED)	WORKERS	WORK	WORK	DAYS WORKED
Rainfall Variability (σ/μ)	0.0270	−0.0314	0.00416	−0.00957	−0.00312	0.0172
	(0.0287)	(0.0268)	(0.00308)	(0.00598)	(0.00358)	(0.0979)
	[0.524]	[0.385]	[0.222]	[0.375]	[0.534]	[0.785]
exp (DEP. VAR. MEAN)	42.420	57.394	0.365	0.122	0.130	27.215
TREATMENT STD. DEV.	1.398	1.445	2.159	1.618	1.620	0.556
OBSERVATIONS	683	727	2,053	1,039	1,037	536
WEATHER CONTROLS	YES	YES	YES	YES	YES	YES
QUADRATIC WEATHER CONTROLS	YES	YES	YES	YES	YES	YES
WEATHER INTERACTIONS	YES	YES	YES	YES	YES	YES

Note: Significance levels are indicated as *0.10 **0.05 ***0.01. The unit of analysis in columns 1–3 is a household. For columns 1–3 I include household, year, and month-of-year fixed effects. The unit of analysis in columns 4–6 is an individual. For columns 4–6 I include individual, year, and month-of-year fixed effects. Rainfall variability is defined as the coefficient of variation for rainfall, measured over the previous five years, the time period between each survey round. Historical measures of atmospheric parameters correspond to this period. Historical rainfall is measured in hundreds of mm. Historical temperature is measured in °C. Cluster robust standard errors are reported in parentheses. Wild cluster bootstrap-t p-values (null-imposed, 1,000 replications) are reported underneath in brackets, addressing concerns relating to the small number of clusters (Cameron, Gelbach, and Miller 2008).

results of this exercise are presented in Table 6. We observe that an increase in rainfall variability is associated with a reduction in the share of time that children spend working on the farm and an increase in the share of time spent in school and on home study. This reallocation is consistent with the portfolio mechanism. There is no significant effect of rainfall variability on domestic chores or wage labor. Furthermore, although statistically insignificant, there also appears to be a non-trivial reduction in time spent on the residual "leisure" activities; that is, sleeping, eating, and playing. In terms of the magnitude of these effects, a one standard deviation increase in rainfall variability is associated with an

Table 5. Disentangling Income Shocks from Income Uncertainty: The Effects of Rainfall Variability on Livestock Assets

	(1)	(2)	(3)
	LIVESTOCK OWNED	LIVESTOCK SLAUGHTERED	LIVESTOCK SOLD
Rainfall variability (σ/μ)	0.00467*	−0.0000576	0.00171
	(0.00258)	(0.000751)	(0.00147)
	[0.225]	[0.952]	[0.549]
exp (DEP. VAR. MEAN)	0.865	0.081	0.145
TREATMENT STD. DEV.	2.754	2.754	2.754
OBSERVATIONS	33,286	33,286	33,286
FIXED EFFECTS	LIVESTOCK × HOUSEHOLD, MONTH, AND YEAR		
WEATHER CONTROLS	YES	YES	YES
QUADRATIC WEATHER CONTROLS	YES	YES	YES
WEATHER INTERACTIONS	YES	YES	YES

Note: Significance levels are indicated as *0.10 **0.05 ***0.01. The unit of analysis is a type of livestock within a household. Rainfall variability is defined as the coefficient of variation for rainfall, measured over the previous five years, the time period between each survey round. Historical measures of atmospheric parameters correspond to this period. Historical rainfall is measured in hundreds of mm. Historical temperature is measured in °C. Cluster robust standard errors are reported in parentheses. Wild cluster bootstrap-t p-values (null-imposed, 1,000 replications) are reported underneath in brackets, addressing concerns relating to the small number of clusters (Cameron, Gelbach, and Miller 2008).

Table 6. The Effects of Rainfall Variability on Children's Activities (Time Allocation)

	(1)	(2)	(3)	(4)	(5)	(6)
SHARE OF TIME	FARM	DOMESTIC	WAGE WORK	SCHOOL	HOME STUDY	LEISURE
Rainfall variability (σ/μ)	–0.119**	–0.0240	0.00593	0.132***	0.0896***	–0.0845
	(0.0514)	(0.0406)	(0.0183)	(0.0159)	(0.0277)	(0.0702)
Wild cluster bootstrap-t p-value	[0.097]	[0.656]	[0.838]	[0.006]	[0.036]	[0.405]
FIXED EFFECTS	INDIVIDUAL, AGE, YEAR, MONTH					
Dep. var. mean	8.005	7.787	0.514	6.330	4.437	72.924
Treatment std. dev.	2.179	2.179	2.179	2.179	2.179	2.179
Observations	7,142	7,142	7,142	7,142	7,142	7,142

Note: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. The unit of analysis is a child. Rainfall variability is defined as the coefficient of variation for rainfall, measured over the previous five years, the time period between each survey round. Historical measures of atmospheric parameters correspond to this period. Historical rainfall is measured in hundreds of mm. Historical temperature is measured in °C. All regressions include linear, quadratic, rainfall, and temperature controls, as well as interactions between rainfall and temperature measures. Cluster robust standard errors are reported in parentheses. Wild cluster bootstrap-t p-values (null-imposed, 1,000 replications) are reported underneath in brackets, addressing concerns relating to the small number of clusters (Cameron, Gelbach, and Miller 2008).

average reallocation of ≈ one hour per week toward educational activities.[17] These results suggest that households may be responding to an increase in rainfall variability by adjusting the time allocation of children away from risky farm activities toward time spent accumulating human capital, a strategy that may be used to diversify the income portfolio of the household.

In addition to exploring how rainfall variability affects children's time use, it is also important to understand whether it has any effects on the extensive margin. To explore this, I estimate the effects of rainfall variability on school attendance and grades achieved, as well as extensive margin participation in child labor activities.

The results of this exercise are presented in Table 7. We observe that an increase in rainfall variability is associated with an increase in the likelihood that children attend school, as well as an increase in the highest grade attained. These results are consistent with the portfolio mechanism, providing further support for the premise that households invest more in accumulating human capital to diversify the income portfolio of the household.

A one standard deviation increase in rainfall variability is associated with a 2.41 percentage point increase in the likelihood of attending school and an additional 0.044 grades attained.[18] Combined with estimates on the private returns to schooling in rural Ethiopia (World Bank 2005), a naive estimate associates a one standard deviation increase in rainfall variability with a 0.83%–1.67% increase in later life earnings.[19]

It is interesting to contrast these results with other studies examining the effects of various treatments on grades of schooling. Consider the findings of Duflo (2001), who estimates that an additional primary school per 1,000 children in Indonesia is associated with an additional 0.12–0.19 grades. Alternatively, consider Jensen (2010) who explores the effects of providing information on the measured returns to schooling in the Dominican Republic, finding that the provision of this information is associated with an additional 0.25–0.32 years of education over a four-year period—0.0625–0.08 years of education per year—highlighting the gap between the perceived and measured returns to education. These comparisons suggest that rainfall variability could have a meaningful effect on educational investments.

In addition to schooling outcomes, we also observe that an increase in rainfall variability is associated with extensive margin adjustments in child labor participation. We observe

[17] $2.179 \times 0.2216 = 0.482\%$. 10,080 minutes $\times 0.00482 =$ 48.58 minutes.

[18] These magnitudes are calculated from Table 7 by multiplying the treatment standard deviation with the estimated coefficient.

[19] The World Bank estimate that the return to an additional year of schooling (across all grades) in rural Ethiopia is 19% per year (Table 6.9, World Bank (2005)). This is a weighted average of the income returns to an additional year in grades 1–4, grades 5–8 and grades 9–12. They estimate that the average return to an additional year of schooling between grades 1 and 4 is 38%. Consequently, if we evaluate the effects of a one standard deviation increase in rainfall variability on the average child in the sample, who has 3.46 grades of schooling, this would be associated with a 1.67% increase in earnings.

Table 7. The Effects of Rainfall Variability on Participation in Educational and Child Labor Activities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ATTENDING SCHOOL	GRADES ATTAINED	FARM WORK	DOMESTIC WORK	WAGE WORK	HOME STUDY	FOCUS ON SCHOOL	FOCUS ON FARMING
Rainfall Variability (σ/μ)	0.0111***	0.0203**	−0.0102***	−0.00322	−0.00177**	0.0132***	0.0126***	−0.0109***
	(0.00133)	(0.00773)	(0.00187)	(0.00215)	(0.000609)	(0.00116)	(0.00136)	(0.00185)
Wild cluster bootstrap-t p-value	[0.004]	[0.153]	[0.004]	[0.319]	[0.060]	[0.001]	[0.002]	[0.018]
FIXED EFFECTS	INDIVIDUAL, AGE, YEAR, MONTH							
Dep. var. mean	0.531	3.683	0.590	0.694	0.0334	0.531	0.549	0.163
Treatment std. dev.	2.179	2.179	2.179	2.179	2.179	2.179	2.179	2.179
Observations	7,142	4,690	7,142	7,142	7,142	7,142	7,142	7,142

Note: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. The unit of analysis is a child. Rainfall variability is defined as the coefficient of variation for rainfall, measured over the previous five years, the time period between each survey round. Historical measures of atmospheric parameters correspond to this period. Historical rainfall is measured in hundreds of mm. Historical temperature is measured in °C. All regressions include linear, quadratic, rainfall, and temperature controls, as well as interactions between rainfall and temperature measures.. Cluster robust standard errors are reported in parentheses. Wild cluster bootstrap-t p-values (null-imposed, 1,000 replications) are reported underneath in brackets, addressing concerns relating to the small number of clusters (Cameron, Gelbach, and Miller 2008).

a reduction in the likelihood that children engage in child labor on the farm and an increase in the likelihood that children engage in home study. A one standard deviation increase in rainfall variability is associated with a 2.2 percentage point decrease in the likelihood that children engage in child labor on the farm, a 2.8 percentage point increase in the likelihood that children engage in home study, and a 0.38 percentage point decrease in the likelihood that children engage in wage labor.

Finally, I present results in support of the interpretations above, showing that the self-reported focus of children's activities has switched from farming to education. In response to increases in rainfall variability, parents are more likely to report that the "primary occupation" of their child is as a student and are less likely to report that the "primary occupation" of their child is working on the farm. Collectively, these findings provide support for the interpretation of the main results: that parents are actively investing in their children's education.

Appendix A3 presents a series of additional results, highlighting the robustness of these inferences to alternative empirical specifications. First, I present results demonstrating the robustness of the results to alternative timing definitions to those evaluated in the previous exercises (Tables A32–A35). Second, I demonstrate that the time-use results are robust to alternative specifications (Table A36 and A37). Third, I demonstrate that the results are robust to alternative measures of weather shocks (Table A38 and A39). Following Jayachandran (2006) and Shah and Steinberg (2017) I define low rainfall shocks as occurring if rainfall is within the bottom twentieth percentile of the long-run rainfall distribution for each village. High rainfall shocks are defined as rainfall realizations above the eightieth percentile of the long-run rainfall distribution. Comparable measures are defined for temperature. I check for robustness to these measures to address functional form concerns relating to past and contemporaneous realizations. Fourth, I present results demonstrating robustness to alternative fixed effects specifications (Tables A40–A43). The most relevant specification from a robustness perspective includes only village and age cohort fixed effects. The main specification identifies variation off changes in rainfall variability to which the child is exposed. This assumes that parents update their expectations in response to medium-run changes in rainfall variability. The specification using village and age cohort fixed effects does not rely on this assumption. Instead, I exploit variation across periods within the village, comparing outcomes for children that are in village v of age a in the first round of data to children in the same village and same age in the following round. Results are robust to this alternative specification. Fifth, I impose different sample restrictions relating to the age of the children. I show that results are robust to dropping children that are older than eighteen (Table A44 and A45); older than sixteen (Table A46 and A47); of school age in both 2004 and 2009 (Table A48 and A49).

I also explore heterogeneity in these results along the lines of age and sex. One interesting finding is that although all ages experience an increase in the share of time spent on educational activities, the activity that this time is reallocated from differs across age groups (Table A50 and A51). For children aged four through nine, the time spent on education is drawn entirely from the residual timeshare. I refer to this residual category as leisure. However, for children aged ten and above, the time is drawn entirely from time spent on the farm. This is consistent with the hypothesis that younger children may be less productive as farm hands, and so there is less time to be drawn from farming, but as they grow older and more time in total is spent on farm work, this becomes the pot that is drawn from to increase time spent in school. The largest effects on school attendance are estimated for the youngest group. There are no distinguishable differences in time-use effects between boys and girls (Table A52). The only notable difference relates to the highest grade attained (Table A53). Here we observe that the increase in grades attained associated with rainfall variability is driven predominantly by girls.

Finally, in Appendix A5 I explore the effects of early-life exposure to rainfall varability on later-life outcomes, following an approach similar to the one used by Maccini and Yang (2009). This exercise provides an opportunity to explore the empirical relevance of precautionary responses on human capital. If households engage in precautionary savings as a response to income uncertainty, this may have a persistent effect on child development, especially in the early stages of childhood. I find that in the year of birth and for the first few years of childhood -- a critical period in child development -- higher rainfall variability is associated with a reduction in the likelihood of attending school at the time of the survey and a reduction in the likelihood that children engage in farm labor (Table A54). I also present suggestive evidence that these effects are driven by reductions in food consumption during this critical stage of development (Table A55). These findings are consistent with a well-established literature that has found that even relatively mild shocks in early life can have substantial and persistent negative impacts on child development (Yamano, Alderman, and Christiansen 2005; Gilligan and Hoddinott 2007; Almond and Currie 2011; Currie and Vogl 2013; Almond, Currie, and Duque 2018).

Summary and Concluding Remarks

Although a significant body of work has sought to understand the effects of realized income shocks on economic behavior in developing economies, there is very little evidence relating to the economic consequences of income uncertainty. Exploiting exogenous variation in intra-annual rainfall variability, while controlling for average rainfall and temperature realizations, I explore the empirical relevance of income uncertainty for household decision making in rural Ethiopia. I find that a within-village increase in rainfall variability is associated with a reallocation of time away from labor on the farm toward time spent on educational activities on the intensive margin, as well as an increase in the likelihood that children attend school and the number of grades attained on the extensive margin.

I note caveats. First, it is possible that part of these estimated effects could be driven by residual variation in income shocks rather than income uncertainty. Supporting evidence suggests that this is very unlikely to be the case; however, we can never rule out the possibility. Second, these results do not say anything about the welfare effects of income uncertainty.

These findings contribute to an emerging body of evidence that highlights the empirical relevance of income uncertainty (Fitzsimons 2007; Yesuf and Bluffstone 2009; Alem *et al.* 2010; Kazianga 2012; Bellemare, Barrett, and Just 2013; Kala 2017; Alem and Colmer 2020; Foster and Gehrke 2020). My findings highlight a behavioral response through which households respond to, and try to manage the economic consequences of, increased income uncertainty in a context with limited access to consumption smoothing technologies. The results presented suggest that farmers are responsive to changes in income uncertainty and are actively making decisions to manage uncertainty by investing in the human capital of their children—a portfolio response. More work to fully understand the empirical effects of uncertainty is encouraged, providing an interesting, important, and challenging topic for future research.

Supplementary Material

Supplementary material are available at *American Journal of Agricultural Economics* online.

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