Weather shocks, recall error and health*

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Abstract

A growing body of literature indicates that heat stress and precipitation deficiencies can pose a critical threat to human health, particularly in less developed countries with low coping capacities and high exposure. The aims of this study are twofold. First, we shed light on the recall of drought events in rural Thailand by linking longitudinal survey data with objective meteorological data. Here, an anomaly in the survey design serves as a natural experiment. We find that a shorter time interval between surveys has a large positive effect on households correctly reporting a drought event. Second, we shed light on the health effects of droughts. In our panel over seven waves, we find a strong effect on diseases reported by the households, which emphasizes the importance of strategies to cope with extreme weather events.

JEL-classification: Q54, I15, C83

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1 Introduction

Climate models predict rises in temperature and alterations in the rainfall patterns that will increase the frequency and intensity of droughts (IPCC, 2018), which have prolonged socioeconomic effects. (UNDRR, 2021). Drought periods can also impact health via different channels, such as increased vector survival, scarcity of water, food shortages or income losses (Kovats et al., 2003). In the case of sickness, an affected person not only has to bear the healthcare costs but also faces foregone working hours, which poses a double burden for the household. This harms disproportionately the most vulnerable populations (McElroy et al., 2022). Especially agriculturally-dependent communities in low-income and middle-income countries are at risk for detrimental health repercussions (Kurosaki, 2015).

An important strand of literature examines the effects of drought on socio-economic outcomes. However, several of these studies rely on subjective drought experiences as reported as part of the survey. Previous research has highlighted that self-reports can be prone to serious errors (Guiteras et al., 2015; Nguyen and Nguyen, 2020; Lobell et al., 2021). In order to correctly assess the effects of drought, it is crucial to ensure data accuracy, especially in household survey designs where questions about coping, losses and behavioral changes are typically only asked after a shock has been reported (conditional questions). For example, several studies rely on respondents reporting environmental shocks to estimate their socio-economic consequences (Arouri et al., 2015; Karim, 2018; Kirchberger, 2017). Thus, if a lack of recall capacities hinders reporting, valuable data for determining resilience are not collected. For example in some household survey modules[1], the reported shock is used as a necessary criterion for follow-up questions on coping or resilience. Failing to address correlations of recall errors with household characteristics in the analysis might introduce bias into the estimated results. Recently, efforts have been made to collect "good practices" on how to properly run surveys (Stantcheva, 2023) and survey experiments (Haaland et al., 2023). Recall error is still overlooked in these recent guides.

We use a panel survey of 2181 rural Thai households from the Thailand Vietnam Socio Economic Panel over 7 waves from 2008 to 2019 that we link with objective meteorological data (ERA5), first, to examine subjective drought recall, and second, to quantify the health effects.

We start by studying recall accuracy in the survey by exploiting an anomaly in the survey design that serves as a natural experiment with 272 households in the control and 741 households in the treatment group. The anomaly arises due to random exclusion since the interview interval in one province, our treatment group, was shorter than in the

[1] Examples include the *Thailand Vietnam Socio-Economic Panel* (TVSEP) or the *Coping with Climate shocks in Mongolia* household panel survey by DIW (2006).

other province, the control group. We shed light on whether a recall error in survey data exists in the context of droughts and show that shortening the period between the event and the interview date can improve the accuracy of the treatment status.

Surveys are an important tool to elicit agent's behavior and living conditions. However, measurement error in survey data can arise due to multiple sources: errors of the cognitive process, errors due to the desire to social conformity and survey conditions (Bound et al., 2001; Celhay et al., 2022). While all of these three error types may occur, in our setting, we focus particularly on the first type: Self-reporting error occurs when respondents fail to report about less salient shock events, which can be thought of as a decay function of time: The longer the recall period, the greater the loss of accuracy in the self-reports.

We reviewed 557 research articles in an important journal in the field of development economics *World Development*, and we documented 26 (15 in 2021, 11 in 2022) studies that use self-reported survey items in their main treatment variable. These studies potentially suffer from recall error. The recall period in some studies refers to short intervals such as the past 24 hours, for which we do not expect a large recall problem. For other studies, the recall period refers to at least one month up to a year (9 studies), for instance Vaiknoras and Larochelle 2021 (farming of specific bean variety), Mora-Rivera and Gameren 2021 (amount of remittances received), Scognamillo and Sitko 2021 (participation in public works program and agricultural training), Borga and D'Ambrosio 2021 (participation in public works program, type of support, benefits received). Some studies even have recall periods for the main treatment variable longer than a year, Lim et al. (10 years to recall adoption of adaptation practices in agriculture), Kianersi et al. (1.5 years to recall hurricane exposure), Adong et al. (3 years to recall conflict exposure). This raises the question, whether respondents correctly recall events which lie a long time ago.

Prior research suggests that the recall of events or information in surveys is typically weak, including self-reported exposure to natural disasters. Consequently, the validation of reported shocks is crucial: Guiteras et al. (2015) contrast self-reported flooding exposure to remotely sensed data on inundation in Bangladesh and find low cross-sectional correspondence among these two measures. Nguyen and Nguyen (2020) provide evidence that the relationship between self-reported exposure to tropical cyclone, heatwave and excessive rainfall with measured weather shocks from ground stations is weak. Karim (2018) uses two measures of exposure: a self-reported flood hazard and a rainfall-based flood measure. They find the effects of the self-reported flood hazard on economic development to be considerably stronger compared to the rainfall-based flood measure. The studies by Kirchberger (2017) and Nguyen and Nguyen (2020) use recorded measures of the environmental shock as instruments for the reported exposure status. However, none of the prior studies examines the accuracy of reports as a function of time between event and interview date.

The ability to remember accurately depends also on the salience of the event itself and therefore partly on its nature (Nguyen and Nguyen, 2020; Celhay et al., 2022). We account for this by using objective weather data to contrast correct- against mis-reporting of shocks. Moreover, individual characteristics might influence the recall capacity: Nguyen and Nguyen (2020) show that age, education and wealth play a role in shaping the tendency to report such events. Our analysis confirms these and goes further by showing that shortening the time since the event improves recall accuracy.

After the validation of recall accuracy over different time intervals, we turn toward the implications for the estimation of the impact of drought on health outcomes. We contribute towards prior studies on the weather-health relationship (Maccini and Yang, 2009; Cooper et al., 2019; Lohmann and Lechtenfeld, 2015; Dimitrova, 2021) first, by assessing the short-run effect of droughts on health with objective meteorological data and, second, by opposing it to self-reported data to determine the size and direction of the self-reporting bias. Our identification strategy relies on comparing health outcomes within the same household over time, while also controlling for confounding household characteristics, as well as for the interview month and for overall time dynamics in the health conditions.

A series of previous studies focuses on drought impact on child health outcomes: McElroy et al. (2022), who show detrimental effects on birth outcomes for children who were exposed to dry conditions during the gestational period. Other studies shed light on the consequences for children that were exposed to prolonged drought on body height when facing heat up to the age of 5 years (Cooper et al., 2019; Dimitrova and Muttarak, 2020). Flückiger and Ludwig (2022) examine the effect of quasi-random heat spells around the survey date on diarrhoea risk among African children. Their results show that risks are increased significant for extreme heat 15 days before the survey date. The effects are particularly strong beyond 30°C. Other studies examine the effect of dry conditions on mortality and morbidity among the elderly (Deschênes and Moretti, 2009; Deschenes, 2014; Barreca et al., 2015; Burgess et al., 2017). Our study examines the drought impact on health jointly for all inhabitants in a household, providing a broader picture.

Prior work heavily relies on repeated cross-sectional surveys, especially the Demographic Health Survey (Cooper et al., 2019; Dimitrova and Muttarak, 2020; Flückiger and Ludwig, 2022). If people migrated, for example due to a drought, the local population composition changes. One strength of our study is that we build on a longitudinal panel in which the same households are interviewed over multiple waves. This allows to more robustly identify the causal impact of changing environmental conditions over time holding constant household-specific characteristics. Consequently, we rely on those households who did not relocate as a reaction to drought incidents.

The natural experiment reveals that households that were asked to recall drought events during the last year reported 0.4 percentage points (more than one standard deviation or 57% of the mean) more droughts correctly as compared to households that were interviewed two years later about the same time period. Under-reporting in the province with a long interview interval largely drives this effect. Second, we find a consistently negative impact of dry conditions, both based on the subjective and the objective drought measure. Experiencing tense drought conditions leads, on average, to 0.13 more sick household members, which translates to +15% of the mean. Individuals who report in the survey that they experienced a drought, have only 0.07 more sick households members. This implies that due to the severe under-reporting, a big share of the health impact goes unnoticed.

The paper proceeds as follows: Section 2 introduces the data. We then examine recall error in Section 3 and analyze the implications for the health effects in Section 4. Finally, Section 5 summarizes our conclusion and gives an outlook.

2 Empirical approach and data

2.1 Data

We use detailed household-level survey data for three rural provinces in Thailand and link these to retrospective meteorological data.

2.1.1 The Thailand Vietnam Socio Economic Panel (TVSEP)

The survey data were collected as part of the Thailand Vietnam Socio Economic Panel (TVSEP) over a period of seven waves between 2008 and 2019. The survey covers approximately 2,200 households in 220 villages in the provinces of Ubon Ratchathani, Buri Ram and Nakhon Phanom (see Figure A1) and is representative for the Thai rural population (Hardeweg et al., 2016). The same households were interviewed in multiple waves, which allows us to control for time-invariant household-specific characteristics that are otherwise unobservable. There is one important exception in the survey schedule that we exploit in the analysis: In 2011, only one of the three provinces, Ubon Ratchathani, was surveyed. Note that the decision to exclude the other two provinces was taken due to financial constraints on the side of the survey administrators and was virtually at random with regard to our outcomes of interest, i.e., independent of the meteorological conditions or the residents' health situation. The additional survey works as a quasi-experiment for our analysis.

The interviews typically take place in the first half of the rice growing season, the region's main crop: The growing season starts in April and lasts until November. Most interviews took place in May for the earlier waves (2008, 2010, 2011 and 2013), or in July

Table (1) Survey reference periods

Wave	**Drought Events** (m/y)	**Health conditions** (m/y)	**De facto survey month**
2008	05/07 - 04/08 : 12 months	05/07 - 04/08 : 12 months	4, <u>5</u>, 6
2010	05/08 - 04/10 : 24 months	05/09 - 04/10 : 12 months	1, 2, 3, 4, <u>5</u>, 6
2011	05/10 - 04/11 : 12 months	05/10 - 04/11 : 12 months	4, <u>5</u>
2013	05/10 - 04/13 : 36 months	05/12 - 04/13 : 12 months	1, 2, 3, 4, <u>5</u>
2016	05/13 - 04/16 : 36 months	05/15 - 04/16 : 12 months	<u>7</u>, 8
2017	05/16 - 04/17 : 12 months	05/16 - 04/17 : 12 months	6, <u>7</u>
2019	05/17 - 04/19 : 24 months	05/18 - 04/19 : 12 months	<u>7</u>, 8

Notes: Wave 2011 (in red) was only conducted in one region. Wave 2013 (in blue) allows to back out the reporting for the same reference period 24 months later. Column 2: The survey question reads "Was your household affected by any of the following events between [m/y] and [m/y]? Drought." Column 3: The survey question is "What was the major impairment of [NAME]'s health between [m/y] - [m/y]?" Column 4 shows the de facto survey month, the most frequent month is underlined.

for the later waves (2016, 2017, and 2019), as displayed in the last column of Table 1. The household head answers all questions, including some on behalf of the other household members, such as the members' health status. The reported weather shocks are based on the survey question:

"*Was your household affected by any of the following events between [m/y] and [m/y]?*",

where one option is "Drought" and the time period depends on the previous survey date. If the respondent indicated being affected by a drought, the household head was asked to indicate the month and year of the shock. It was possible to indicate up to three droughts during a given reference period. Note that the length of the reference period differs across waves to reflect the different time gaps between waves. As shown in column 2 of Table 1, the reference period was 12 months for the waves 2008, 2011 and 2017, while it was 24 months for the waves 2010 and 2019. In 2016, the reference period was 36 months. 2011 and 2013 differ across the three provinces.

Importantly for our analysis, the survey conducted in Ubon Ratchathani in 2011 covers the reference period from May 2010 to April 2011. Households in the other two provinces (Nakhom Phanom and Buriram) were only interviewed during the next wave (as was Ubon Ratchathani) in 2013, yet, about the entire reference period May 2010 to April 2013. From that 36-months period, we "back out" the shock events for the reference period May 2010 to April 2011.

In order to make the subjective reported drought measure comparable to the physical meteorological indicator, we allocate the reported drought events into the shortest common interval, which is a 12-months window. In order to fill in the missing covariates for the yearly intervals, we utilize the characteristics from the subsequent wave, e.g., the number of households members from 2013 is used for the years 2011 and 2012 in the control province (the age of the household members is derived by subtracting the respective number of years).

2.1.2 Meteorological data

The survey also delivers geolocations for each village which allows us to link them to high-resolution meteorological information. Specifically, each village is assigned the monthly weather realizations of the grid cell in which the village is located. Monthly temperature, evaporation and precipitation data are obtained from the ERA5 reanalysis data set provided by the European Center for Medium Range Weather Forecast (ECMWF, 2022). These data are available globally since 1950 and are at a spatial resolution of $0.1° \times 0.1°$, which corresponds to an East-West distance of 10km in the study region. Using reanalysis data is advantageous compared to station data only, since it additionally utilizes a multitude of further meteorological sources such as measurements from satellites, as well as from ocean buoys and from aircrafts. The data have been shown to correlate strongest with ground station data as compared to other precipitation data (Beck et al., 2019) and have been employed in previous work (Kotz et al., 2022; Breckner and Sunde, 2019).

Based on precipitation and temperature data, we document the month-of-year patterns for our study region in Figure A2. Based on all years from 1981 to 2019, rain falls particularly during the months May to September, while these are at the same time the warmest months of the year.

We compute the Standardized Precipitation-Evapotranspiration Index-1 (*SPEI*), a common measure for drought that combines rainfall in conjunction with evaporation (Vicente-Serrano et al., 2010)[2] and take the average over each 12-month reference period. The SPEI-1 reflects the absolute difference between precipitation and evapotranspiration over the previous month. Negative values imply absence of rainfall, thus dry conditions. For better readability, we multiplied by -1 so that positive realizations imply dry conditions. The SPEI performs better than other drought indices such as the Standardized Precipitation Index (*SPI*), because the SPEI additionally takes into account the potential evapotranspiration via high temperatures (Vicente-Serrano et al., 2010). Due to the standardization of this variable, the long-run mean is set to zero and the standard deviation to one, which makes changes comparable over space and time. While there are many possibilities of how to parameterize drought, we do not want to take an ex-ante choice, but we leave it to the data to decide for the most accurate measure in our context.

To calibrate our analysis, we proceed in two steps: First, for validation of the drought variable, we test which drought variable has the strongest effect on individuals subjective drought experience, based on the data. While we suspect that the subjective drought reports do not reveal the full picture, it may allow us to benchmark our meteorological

[2]A recent review by National Drought Mitigation Center (2022) shows that there are more than 150 published definitions of drought.

variables. As a validation exercise, we run the regression $ReportDrought_{i,vym} = \alpha + \beta \cdot SPEI_{i,vym} + \epsilon_{i,vym}$ where the outcome is the subjective drought experience of individual i in village v as reported as part of the survey in year y in month m. As treatment variable, we run through alternative specifications of drought indicators employed in the literature. All are based on the drought conditions in the grid cell where village v of individual i is interviewed in year y in month m. The results shown in Figure A3, reveal that individuals are most likely to report drought conditions in the face of changes in the *Mean*(SPEI-1) variable as opposed to other drought indices.

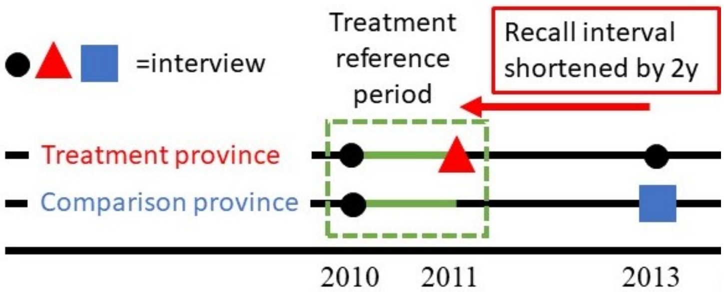
Second, we examine which level of dry conditions provokes the strongest increase in reporting likelihood. Running over a range of different thresholds of our drought variable, Figure A4 shows results from a joint regression of Drought Reporting. Against a baseline conditions with no drought, i.e. *Mean*(SPEI-1) around zero, an increase in dry conditions, i.e. the intervals (0.1 to 0.2), (0.2 to 0.3) et cetera lead to increases in reporting drought on average. This is reassuring that respondents report something sensible. Similarly, particularly wet conditions, i.e. -0.3 or lower leads to systematically less reporting. Based on this exercise, we assign a binary drought variable, taking the value of 1 if the drought indicator exceeds the value of 0.1. For robustness, we also run this exercise separately based on different recall intervals: those who reported about events 1 year back (2 years, 3 years). We find similar results, shown in Figure A5, for drought reports that lie 1 and 3 years back, although the recall after 3 years is clearly weaker.

3 Recall of drought events

3.1 Estimating the recall error

We exploit the random exclusion of provinces from the survey in 2011 as a natural experiment. The identification strategy is illustrated in Figure 1.

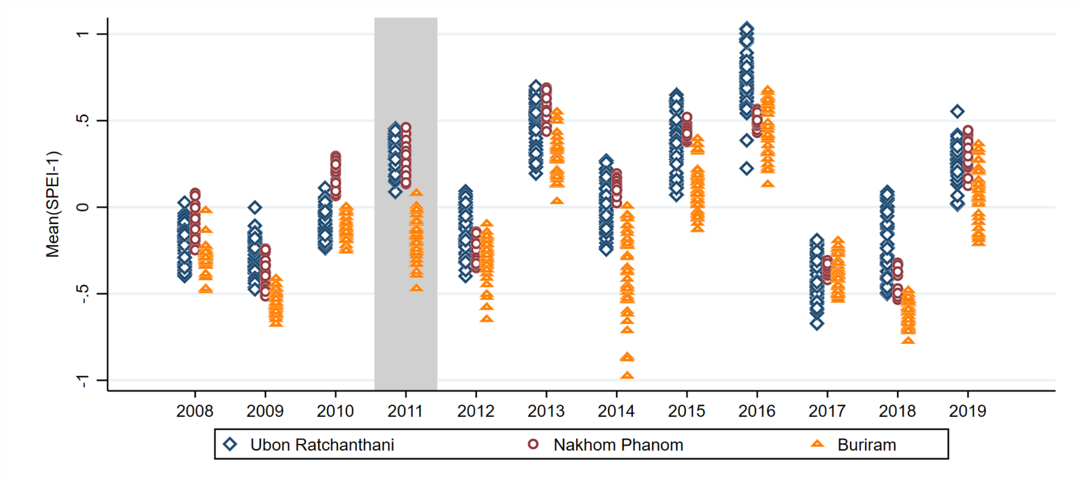
Figure (1) Illustration of the identification idea



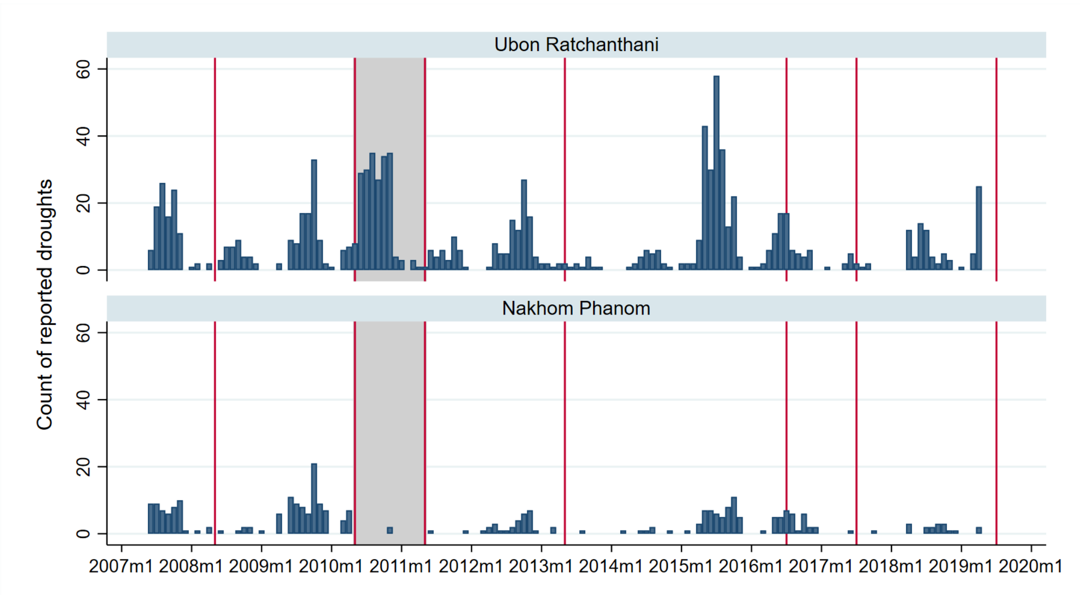
The treatment period lasts from May 2010 to April 2011. We employ a difference-in-differences setting where the treatment group consists of the household heads in Ubon Ratchathani that faced the additional survey in 2011 directly after the reference period (triangle in Figure 1). The household heads in the two other provinces were not interviewed in 2011 but instead in 2013 (square in Figure 1). The households surveyed in 2013 were surveyed about any drought events that occurred during the entire period from May 2010 to April 2013, that is, *including* the treatment reference period 2010-2011 (dashed-line box). If all households had perfect recall of drought events, the events that occurred in 2010 would be recalled equally well in both 2011 and 2013, two years after the treatment period.

Figure (2) Subjective drought reports and objective drought index

(a) Dry conditions over the survey period



(b) Count of reported droughts over the survey period



Notes: Top: The graph shows the drought index separately for the three provinces. The drought index is based on the SPEI-12 and scaled such that positive values indicate dry conditions. The solid vertical bars reflect the survey months. Bottom: The graph shows the number of reported drought events for each month between 2007 and 2019, separately by province. The solid vertical lines reflect the timing of when the households were interviewed. The survey in 2011 was only conducted in one province, Ubon Ratchathani.

The described approach provides a comparable setting to the extent that the households in the treatment versus comparison provinces are similar ex-ante and that they experience similar meteorological conditions during the same reference period. We run several plausibility checks. First, we document the meteorological conditions at the village-level. In Figure 2, panel (a) shows the drought conditions between 2008 and 2019, where higher values imply drier conditions. Overall, the swings in dry conditions in the three survey provinces are similar. Specifically for the treatment period between May 2010 to April 2011 (shaded in dark gray), the treatment province Ubon Ratchathani (blue diamonds) and Nakhon Phanom (red circles) attain a very similar values. In addition, the minimum and the maximum values are astonishingly close. However, the third province, Buri Ram (orange triangles), exhibits substantial deviations from the other two provinces during this episode. In consequence, we decided to dismiss Buri Ram from the event recall estimation since the analysis relies on similar weather conditions during the treatment period. Thus, Ubon Ratchathani serves as the treatment group, Nakhon Phanom serves as the control group. In addition, in the pre-treatment period 2010, the drought conditions are not balanced between treated and control provinces, rendering a test for parallel trends implausible. Thus, we use 2009 as the reference period. We deal with the remaining deviations by applying entropy balancing as described below and shown in Table 3.

Figure 2, panel (b), shows the number of reported drought events over time. Overall, the level of reported droughts is higher in the treatment province Ubon Ratchathani as compared to the control province Nakhon Phanom, which is very likely due to the different sample sizes: The survey comprises 818 households in Ubon Ratchathani and 397 in Nakhon Phanom. The treatment period between May 2010 and April 2011 is shaded in gray. Now we contrast, the drought incidence between the two measures in the treatment period (shaded in gray): The objective drought indicator from panel (a), is above zero in all villages - treated or control - which suggests that all individuals should have reported this period as "dry". Panel (b) shows that only few individuals reported a drought in Nakhom Phanom, while substantially more respondents reported a drought in Ubon Ratchanthani. We hypothesize that this difference arises because of the different recall interval between the provinces, which we evaluate formally in the next chapter.

In order to examine whether a reported event corresponds to an actual drought event, we benchmark the subjective reports of drought events against physical meteorological conditions. This leads to four analytical cases: 1. If a household reports a drought and that village has undergone dry conditions during that reference period, we classify it as an instance of "Correct-reporting". 2. If a household reports a drought, but the meteorological conditions were just ordinary, we classify it as "Over-reporting". 3. If the meteorological conditions indicate dryness, but the household has not reported a drought for this reference period, we assign it as "Under-reporting". The last case 4. "Correct non-reporting" applies when the meteorological conditions were ordinary and the household has not reported a drought event. Since in the treatment period all villages exhibit dry meteorological conditions, we focus on "Correct-reporting" and "Under-reporting" only.

As derived in the previous section, we assign the binary drought indicator as 1 to a village if –over the last 12 months– it has experienced average SPEI-1 conditions greater than 0.1 based on the validation exercise in the last section. Robustness of this cutoff is further examined by comparing effects over a range of cutoffs. Binary treatment indicators have been used by others including Nguyen et al. (2020).

Table (2) Summary statistics for recall classification variables

	Treatment Ubon Ratchathani (N=8,794)		**Control** Nakhon Phanom (N=3,282)		
	Mean	SD	Mean	SD	Diff
Correct reporting	0.07	0.26	0.05	0.21	0.024**
Under reporting	0.33	0.47	0.46	0.50	-0.129***

Notes: Summary statistics by province for the recall classification variables. The column "Diff" reflect the difference in means of the treatment province Ubon Ratchathani with respect to the control province Nakhon Phanom. Results from regressions including an indicator variable for the treatment province, which corresponds to a t-test of differences in means. Sample based on data from the Thailand Vietnam Socio Economic Panel, for the waves 2008, 2010, 2011, 2013, 2016, 2017, and 2019. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2 summarizes the reporting measures. Only a small fraction correctly reported a drought (7% in Ubon Ratchathani and 5% of the households in Nakhon Phanom). There is substantial under-reporting: 33% and 36%, respectively, did not report a drought although our measure indicates one. In the analysis, we will use the presented reporting classifications as binary outcome variables.

Next, we test for observable similarities across households in the treatment versus comparison province before the treatment (see Table 3). We regress a dummy variable indicating differences between the two provinces on household characteristics. Table 3 suggests that households in the treatment region experienced mildly wetter conditions prior to the treatment period. Moreover, household heads in the treatment region are older, more likely to be male, less likely to be farmer and more educated, and households have fewer members. The amount of land they possess is higher in the treatment province. These differences probably reflect the slightly poorer and more rural conditions in the control province. Due to their higher vulnerability, one would expect them to be more likely to report droughts. Yet, the opposite seems to be the case as our results show. We contrast the baseline results, where we simply control for differences in these characteristics, to weighted samples using entropy balancing techniques to increase the similarity between the treatment and the control group[3]. The last column of Table 3 shows the successfully reweighted household characteristics, which are now balanced.

Table (3) Balance check for treatment versus control province, for 2008-2010, before the treatment period.

	Treatment Ubon Ratchathani (N=2,211)		**Control** Nakhon Phanom (N=812)			
	Mean	SD	Mean	SD	Before balancing	After balancing
Mean(SPEI-1)	-0.19	0.11	-0.11	0.26	-0.07***	-0.00
Age	56.60	12.67	55.70	12.42	0.90*	-0.01
Male	0.75	0.43	0.70	0.46	0.05***	-0.00
Farmer	0.86	0.35	0.94	0.24	-0.08***	-0.00
Education	1.83	0.65	1.74	0.57	0.09***	-0.00
Household size	5.48	2.23	5.67	2.28	-0.19**	-0.00
Land area owned	5.63	5.29	4.36	3.76	1.27***	0.00

Notes: The columns *Before balancing* and *After balancing* reflect the difference in means of the treatment province Ubon Ratchathani with respect to the control province Nakhon Phanom. Results from regressions including an indicator variable for the treatment province, which corresponds to a t-test of differences in means. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Our base specification tests whether the additional interviewing of a province in 2011 has an impact on the reporting behavior. The data are collapsed at the household head level. We use a standard event-study specification[4] with an effect window running from period $\underline{j} = 2008$ to $\overline{j} = 2019$ for the treatment happening at time $t = 2011$. The estimation equation reads:

$$Reporting_{i,v,d,p,t} = \sum_{j=2008}^{2019} \beta_j b_p^j + \eta \; Drought_{v,t} + \gamma \; X'_{i,t} + \mu_i + \delta_t + \tau_m + \varepsilon_d \tag{1}$$

where *Reporting* reflects one of the two reporting statuses (correct-reporting and under-reporting) during the reference period t for household head i, residing in village v in district d, interviewed in month m. b_p^j are province-period-specific treatment indicators. Specifically, the treatment indicator is 1 for Ubon Ratchathani and 0 for the comparison province Nakhon Phanom. The coefficient for 2011 will reflect the effect of the *additional interviewing* and therefore the exogenous shortening of the recall period. The coefficients for earlier periods can be interpreted as placebo tests and reflect whether

[3]Note that this only eliminates observable differences, while unobservable characteristics may still confound the estimates. Controlling for household fixed effects helps to capture a large part of this unobserved heterogeneity.

[4]The notation is similar to Schmidheiny and Siegloch (2023).

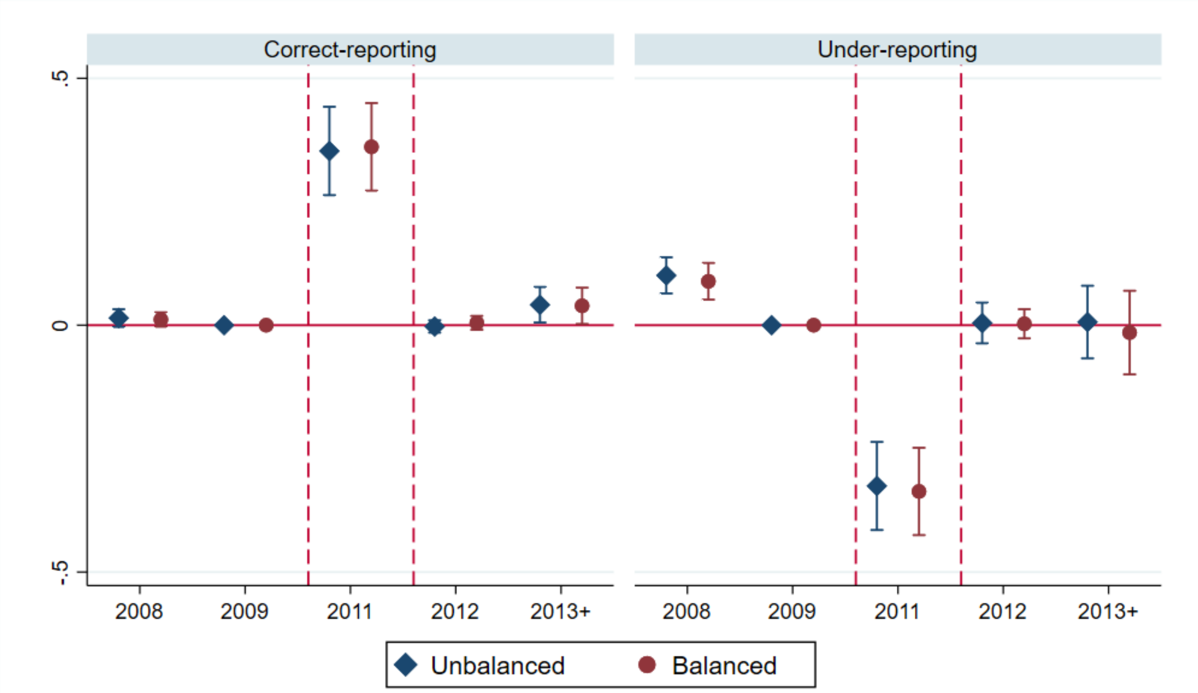
the provinces have previously undergone the same trends. Optimally, the placebos do not deviate from the pre-treatment year, which serves as the baseline in our specification. The coefficients for later periods can be interpreted as placebo or spillover effects. In general, no spillover effects are expected, as the one-time additional survey should only affect reporting behavior in the reference period and not in other waves. $Drought_{v,t}$ controls for the meteorological conditions, parameterized as the average SPEI-1 conditions over the preceding 12 months. The vector X controls for other household head characteristics, in particular age, gender (1 for male), farming as occupation (1 for farmer, 0 if not) and education, as well as household size and logarithmized land area owned by the household. Moreover, the model includes fixed effects for households μ_i, to account for time-invariant differences across households (alternatively, for villages), for periods δ_t to even out differing reporting behavior over time, and for the interview month τ_m to account for possible seasonality of reporting behavior. The errors account for correlations at the district level.

3.2 Results

First, we describe the results from our quasi-natural experiment where we examine the impact of exogenously shortening the time interval between survey and exposure on the recall accuracy.

Figure 3 presents the correct- and under-reporting behavior from 2008 to 2019 applying an event study design. We drop the pre-treatment indicator for 2009 from the regression, standardizing its coefficient $\hat{\beta}_{2010}$ to zero. The treatment indicators are binned at the endpoints. The point estimates reflect the differences in reporting behavior between households in the treated and the control province. The corresponding regression table is displayed in Table A3 in the Appendix.

To identify the treatment effect, we assume that, prior to treatment, the reporting behavior between the treatment group and the comparison group is similar. As shown in Table A3 in the Appendix, in the balanced sample, the pre-treatment indicator for correct-reporting is only weakly statistically significantly different from zero. For under-reporting it is significant at the 1 percent level. Under- and correct-reporting show a positive difference for Ubon Ratchathani compared to Nakhon Phanom during the pre-treatment period. This effect is mainly driven by the significant drought deviations during 2008. However, consistent with our expectations, the differences after the treatment are not statistically significantly different from zero for any sample or outcome in 2012, which confirms the treatment effect. Notably, in 2013^+, due to drought-related discrepancies between the treatment and control groups, the disparities in correct reporting attain statistical significance at the 5 percent level. However, upon comparing the effect sizes of all pre-treatment and post-treatment indicators in comparison to the treatment indicator, Figure (3) Comparison balanced vs. unbalanced estimates



Notes: Event study of reporting behavior of the household head. The outcome variable reflects subjective reporting benchmarked against the objectively measured drought index, both measured over the respective 12-months reference periods. Ubon Ratchathani is treated in 2011, Nakhon Phanom is the control province. Regressions control for age, gender, agricultural occupation and education of the household head; household size, ln(land area owned), as well as fixed effects for household, survey year and interview-month. The year 2009 serves as the reference period, since drought conditions in 2010 are highly unbalanced between treatment and control province (t-stat= -8.86). Standard errors are clustered at the district-level, with 95 percent confidence intervals shown. N=11,707.

it becomes evident that the effect sizes are generally modest, and the effects are largely nonsignificant at the 1 percent level.

Coming back to Figure 3, it illustrates a substantial increase in correct-reporting for the treatment period 2011 by 0.36 percentage points. The effect vanishes directly after the treatment period, indicating a return to the baseline reporting behavior. Simultaneously, a sharp decrease in under-reporting can be observed (-.33 percentage points). This suggests that a shortening of the recall period from 36 to 12 months improves the reporting accuracy significantly. Balancing the sample on pre-treatment household head characteristics corroborates these findings (in red).

As a robustness check, we run the same event study for various cutoffs to define our binary indicator of objective drought. The drought indicator can now assume a value of 1 if -in the past year- households have experienced at least one SPEI-01 value ranging around the cutoff of 0.1 SD in 0.1-intervals (from 0 to 0.3 standard deviations). Appendix Figure A6 shows that, as the drought definition gets more lenient (strict), the effect on correct-reporting gets stronger (weaker).[5] Overall, while results deviate slightly, the effect

[5]This is consistent with shifting the composition of the reporting statuses. As the drought cutoff gets more lenient by setting a lower objective drought cutoff, more drought claims will be valid. At the same

of shorter survey periods on correct-reporting remains positive and significant.

4 Implications for health impact of droughts

In the prior section, we found that recall of events can be distorted by the temporal distance of the event to the interview. This raises the question whether this finding has bearing on the quantification of drought events on health outcomes.

4.1 Estimating impact of drought on health

The health situation of the household analyzed in the second part of this study is based on the survey item "What was the major impairment of [NAME]'s health between [m/y]-[m/y]?". Household heads were able to select three out of 68 listed diseases for each member of their household. The reference period for this survey item always reflects 12 months from May of the prior year to April of the survey year. This is shown in column 3 of Table 1. We construct our two main variables of interest from this question: *Sick members* is a continuous variable that counts the sick household members, *Prob(sick members* > 0*)* is a binary variable reflecting the probability of having at least one sick household member.

In our analysis, we regress the health indicators on two drought indicators, where one is based on objective weather data and the other on the subjective reports of survey respondents and compare the magnitude of effects. The disparities between the coefficients of objective and subjective drought measures on health are shown using a chi-square test across the two models.

For the objective drought measure, we leverage the variation in weather conditions across the villages during the corresponding 12-months reference periods. We define a village to be exposed to a drought event if the SPEI-01 during the interview month (allowing dry conditions to accumulate within 12 prior months) exceeds 0.1. The unit of observation is the household. We pool observations from all three provinces. The estimation equation reads:

$$Disease_{i,v,d,m,t} = \beta \; Drought_{v,t} + \gamma \; X'_{i,t} + \mu_i + \delta_t + \tau_m + \varepsilon_d \tag{2}$$

where *Disease* is one of the sickness measures for household i residing in village v in district d interviewed in month m in wave t. $Drought_{v,m,t}$ reflects the SPEI with a 12-months scale for each village v. The vector X' comprises household characteristics[6], namely mean age of household members, share of male household members, highest

time more households will be classified as under-reporting. Vice versa, as the drought cutoff gets stricter, by setting a high objective drought cutoff, more non-reporters will be classified as correct-reporters.

[6] Here, we look at all members, not only the household head.

degree of education of any household member, household size, number of farmers in the household, and ln(owned land area). Moreover, the model includes fixed effects for households μ_i, to account for time-invariant differences across households, for years δ_t to even out differing average health conditions over time and, and for interview months τ_m to account for possible seasonality of health conditions. The errors are again allowed to be correlated at the district level.

One important point to consider is the exogeneity of the weather shocks. In dynamic settings, droughts could be anticipated, resulting in a self-selection of, for example, more educated people moving into less vulnerable areas. However, our data do not support this. The annual migration rate from one province to another is only 3.9 %. More importantly, the attrition rate in the final sample (excluding 2011 because only one province was surveyed in that year) is below 7 %. Furthermore, the low attrition is not subject to any systematic pattern as can be seen from a simple regression of the probability to leave the sample on our control variables in Appendix A8. Drought does not correlate significantly with a household leaving a sample except of in 2016. The correlation is negative, though. That is why we think that simple OLS and probit regressions with time-varying household controls and fixed effects that capture unobserved factors provide a sound basis for our analysis.

4.2 Results

Table 4 presents summary statistics of the full sample used to analyse the effects of drought on our health measures. The number of sick household members (*Sick members*) ranges from 0 to 10 and is 0.85, on average. The second variable is binary and equals one if at least one household member reports at least one disease (*Prob(Sick members* $>$ *0)*), zero else. On average, 55% of the households face at least one member with a disease.

Figure 4 illustrates the impact of variously defined drought conditions on both the number of diseases within a household and the likelihood of having at least one household member affected by a disease. Drought is defined by standard deviations ranging from 0 to 0.9, with intervals of 0.1, from a rolling 30-year average. The results show that mild droughts have no significant effect on health. However, there is a notable shift towards significant adverse health effects starting at a standard deviation of 0.6. As the severity of the drought increases, there is a corresponding increase in adverse health effects.

We now integrate the insights from Section 3 into our analysis of the relationship of drought and health. Given the sharp increase and the consistently significant health effects observed above the standard deviation of 0.6, as depicted in Figure 4, we establish the cut-off threshold at 0.6 for the comparison between meteorological and subjectively stated drought. Table 5 presents the results of the household-fixed effects regressions of drought shocks on the number of household members with at least one disease (columns

Table (4) Summary statistics for household-level variables pooling all waves across all provinces

	Mean	SD	Min	Max
Health outcomes				
Sick members	0.85	0.98	0	10
Prob(Sick members > 0)	0.55	0.50	0	1
Other household characteristics				
Average age	38.39	11.60	13	89
Share of males	0.45	0.19	0	1
Household size	5.47	2.21	1	21
Landarea owned	13.83	20.21	0	394.1
Max. education level	1.78	0.75	0	3
Farmer	1.74	1.33	0	13
Reported drought	0.28	0.45	0	1
Meteorological variables				
Objective drought	0.11	0.37	-0.67	1.03
Temperature max	29.67	1.33	26.83	32.65
Rainfall, rev. scale	0.02	0.29	-0.73	0.61
N	11,113			

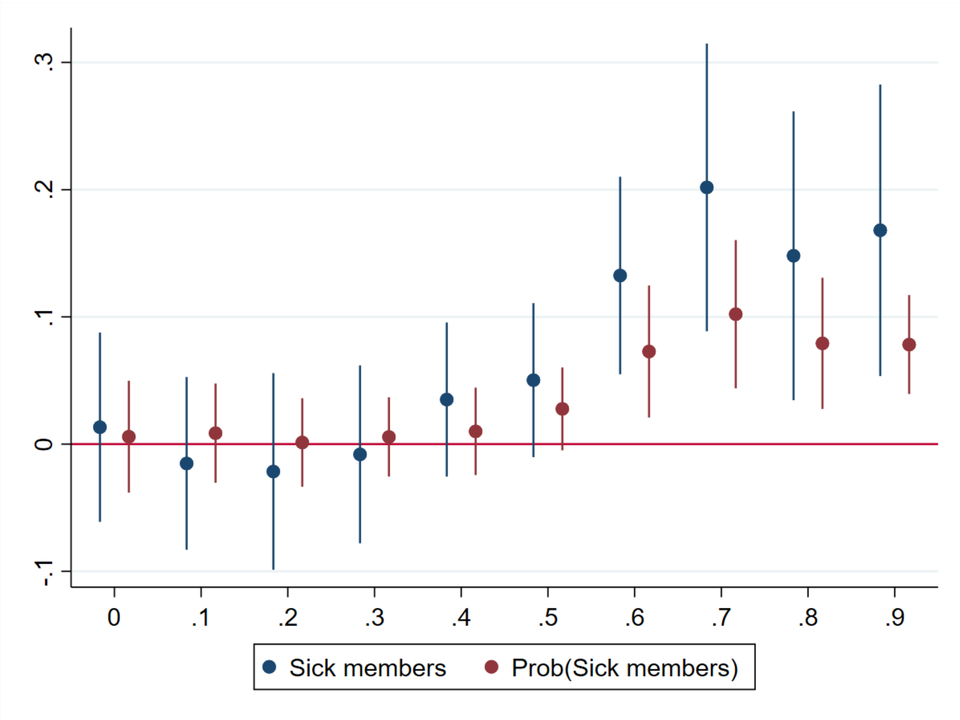
Notes: Summary statistics for the main variables of interest. *Sick members*: No. of household members sick in the last 12 months. *Prob(Sick members > 0)*: Prob(No. of hh members sick in the last 12 months > 0). Objective drought reflects the average SPEI-I over the 12-months referenceperiod. Farmer reflects the total number of farmers in the household. Sample based on data from the Thailand Vietnam Socio Economic Panel, for the waves 2008, 2010, 2011, 2013, 2016, 2017 and 2019. Sample includes data from the three survey provinces Ubon Ratchathani, Buri Ram and Nakhon Phanom.

1-2) and the probability that at least one household member reports a disease (columns 3–4). The row "Difference" presents the differences between the coefficients of objective and subjective drought on health using a chi-square test, with the associated p-values in brackets.

When comparing the subjective and the binary objective drought indicator in Table Table 5, the objective measure gives a substantially larger effect of having faced drought in the last 12 months on the number of sick members in the household than the reported measure (13 versus 7 percentage points, i.e. 15.2% versus 8.2% compared to the mean of 85%). However, the effect on the probability that at least one member is sick is very similar (5 versus 7 percentage points, i.e 9.1% versus 12,7% compared to the mean of 55%)

Given a mean incidence of 0.85 household members who are sick, having faced a

Figure (4) Impact of drought conditions on number of diseases



Notes: Each point represents results from a separate regression of health outcomes on physical drought conditions during the reference period. *Mean*(SPEI-1) above x, as displayed on the horizontal axis, in steps of 0.1. Regression includes our standard household controls: mean age of the household, share of males in the household, household size, number of farmers in the household, ln(land area owned) and maximum education in the household, as well as fixed effects for household, wave and interview-month. Sample is based on all waves. Bars reflect 95-confidence intervals based on clustered standard errors at the district-level.

drought during the last twelve months increases the number of sick household members by 0.13, on average. To put this into perspective, consider a village of 1,000 households. Under normal circumstances, 85 persons are sick; in case of a drought, 98 persons are sick. This corresponds to an increase in sick persons by 15.2%. The likelihood of having at least one sick member in the household (columns 3-4) also increases in drought periods: A drought (indicated by a binary drought indicator) increases the likelihood by 7 percentage points (or 12.7%). In summary, an increase in the drought measures considered in our study increases the incidence and the likelihood of diseases. The results are also robust to other disease measures such as the share of household members with at least one disease Table A6. Moreover, the validity of these findings is reinforced when employing a continuous health measure as opposed to the binary measures (see Appendix Table A4).

In a review article, Stanke et al. (2013) points toward five main channels of how drought may impede health: malnutrition due to less or lower quality production, water-related diseases, airborne and dust-related diseases, vector borne diseases and stress. In our analysis we do not take a specific stand on these channels, since our data is too coarse, but rather focus on the aggregate effect.

Table (5) Effects of subjective versus objective drought on health

	Sick members		Prob(Sick members > 0)	
	(1)	(2)	(3)	(4)
Subjective drought	0.07**		0.05***	
	(0.03)		(0.01)	
Objective drought		0.13***		0.07***
		(0.04)		(0.03)
Difference, χ^2	2.53		0.77	
(p-value)	(0.115)		(0.380)	
Household FE	✓	✓	✓	✓
Wave FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓
HH Controls	✓	✓	✓	✓
Adj. R-squared	0.33	0.33	0.29	0.29
N	11,113	11,113	11,113	11,113

Notes: Subjective drought is a binary variable, reflecting whether the household reported a drought in the survey. *Objective drought* is a binary variable indicating a drought when *Mean*(SPEI-1) exceeded 0.6 during the reference period prior to the survey. Household controls include mean age of the household, share of males in the household, household size, number of farmers in the household, land area owned and maximum education in the household. Sample is based on all waves. Standard errors are clustered at the district-level. *Difference* reflects the results of a χ^2-test for differences between the coefficients. Standard errors are clustered at the district-level. *** p<0.01, ** p<0.05, * p<0.1

5 Conclusion

This study provides three notable contributions. First, it leverages a unique anomaly in the design of a household panel survey conducted in Thailand, using it as a natural experiment to examine the impact of a shorter or longer recall time on the accuracy of drought reporting. Specifically, only one province (of three) was surveyed in one wave, while the other provinces were interviewed 24 months later but referring to the same reference period. We benchmark the reported droughts against objective weather data, that allows us to quantify the differences in the households' reporting behavior across provinces in an event-study design. To the best of our knowledge, this study is the first to show that shorter time intervals between survey and drought exposure can lead to more correct-reporting and less under-reporting. Since surveys are often designed with follow-up questions regarding shocks, such as the TVSEP, researchers face the risk of losing valuable data when conditioning variables are underreported. This may be for example due to less affected households with more effective coping strategies and higher resilience reporting less drought events. As a result, the most successful coping strategies are not reported and remain unobservable. However, the underreporting may also lead to lower estimates of negative health effects if affected households are captured in the control group of unaffected households. This would be due to measurement error.

Thus, we recommend that survey administrators who want to strike the balance between costs of a survey and the overall length of the panel, schedule survey dates such that regions are surveyed with equal intervals between interviews. If such a design is not possible, questions should consistently refer to equal 12-months reference intervals. Another implication for survey administrators is that survey designs should include items about coping strategies independent of the respondent's report of a shock.

Second, we examine the impact of dry conditions on health outcomes. Using meteorological data to measure exposure, the regressions show a robust increase in the number of sick household members. Furthermore, while the precise duration of the disease may be more challenging to remember, recalling whether it occurred within the last twelve months should be less prone to errors.

Linking the first and the second part, we show that, when relying on self-reported drought exposure, the correlation between health outcomes and reported droughts is smaller than when using objective meteorological measures. This implies that relying solely on self-reported drought claims leads to an underestimation of the adverse health effects of droughts.

Moreover, future studies should consider using objective weather data to validate reported extreme weather events and exercise caution when using follow-up questions based on self-reported drought claims.

References

Arouri, Mohamed, Cuong Nguyen, and Adel Ben Youssef. 2015. "Natural Disasters, Household Welfare, and Resilience: Evidence from Rural Vietnam." *World Development* 70 59–77. https://doi.org/10.1016/j.worlddev.2014.12.017.

Barreca, Alan, Karen Clay, Olivier Deschênes, Michael Greenstone, and Joseph S Shapiro. 2015. "Convergence in Adaptation to Climate Change : Evidence from." *American Economic Review: Papers & Proceedings* 105 (5): 247–251.

Beck, Hylke E., Ming Pan, Tirthankar Roy et al. 2019. "Daily evaluation of 26 precipitation datasets using Stage-IV gauge-radar data for the CONUS." *Hydrology and Earth System Sciences* 23 (1): 207–224. 10.5194/hess-23-207-2019.

Bound, John, Charles Brown, and Nancy Mathiowetz. 2001. "Measurement Error in Survey Data." In *Handbook of Econometrics*, Volume 5. 3705–3843, Rao, C.R., . 10.1016/S1573-4412(01)05012-7.

Breckner, Miriam, and Uwe Sunde. 2019. "Temperature extremes, global warming, and armed conflict: new insights from high resolution data." *World Development* 123 104624. 10.1016/j.worlddev.2019.104624.

Burgess, Robin, Olivier Deschênes, Dave Donaldson, and Michael Greenstone. 2017. "Weather, Climate Change and Death in India." *LSE Working Papers* 1–71, http://www.lse.ac.uk/economics/Assets/Documents/personal-pages/robin-burgess/weather-climate-change-and-death.pdf.

Celhay, Pablo, Bruce Meyer, and Nikolas Mittag. 2022. "What Leads to Measurement Errors? Evidence from Reports of Program Participation in Three Surveys." *NBER*. 10.2139/ssrn.4114519.

Cooper, Matthew W., Molly E. Brown, Stefan Hochrainer-Stigler, Georg Pflug, Ian McCallum, Steffen Fritz, Julie Silva, and Alexander Zvoleff. 2019. "Mapping the effects of drought on child stunting." *Proceedings of the National Academy of Sciences of the United States of America* 116 (35): 17219–17224. 10.1073/pnas.1905228116.

Dasgupta, Susmita, Golam Mustafa, Tapas Paul, and David Wheeler. 2021. "The socioeconomics of fish consumption and child health: An observational cohort study from Bangladesh." *World Development* 137 105201. https://doi.org/10.1016/j.worlddev.2020.105201.

Deschenes, Olivier. 2014. "Temperature, human health, and adaptation: A review of the empirical literature." *Energy Economics* 46 606–619. 10.1016/j.eneco.2013.10.013.

Deschênes, Olivier, and Enrico Moretti. 2009. "Extreme Weather Events, Mortality, and Migration." *Review of Economics and Statistics* 91 (4): 659–681. 10.1162/rest.91.4.659.

Dimitrova, Anna. 2021. "Seasonal droughts and the risk of childhood undernutrition in Ethiopia." *World Development* 141 105417. 10.1016/j.worlddev.2021.105417.

Dimitrova, Anna, and Raya Muttarak. 2020. "After the floods: Differential impacts of rainfall anomalies on child stunting in India." *Global Environmental Change* 64 (October 2019): 102130. 10.1016/j.gloenvcha.2020.102130.

DIW, NSO . 2006. "Coping with Climate shocks in Mongolia - household panel survey."

ECMWF. 2022. "ERA5 Re-analysis Data." `https://bit.ly/3gjtA10`.

Flückiger, Matthias, and Markus Ludwig. 2022. "Temperature and risk of diarrhoea among children in Sub-Saharan Africa." *World Development* 160 106070. https://doi.org/10.1016/j.worlddev.2022.106070.

Guiteras, Raymond, Amir Jina, and Mushfiq A. Mobarak. 2015. "Satellites, self reports, and submersion: Exposure to Floods in Bangladesh." *American Economic Review* 105 (5): 232–236. 10.1257/aer.p20151095.

Haaland, Ingar, Christopher Roth, and Johannes Wohlfart. 2023. "Designing Information Provision Experiments." *Journal of Economic Literature* 61 (1): 3–40. 10.1257/jel.20211658.

Hardeweg, Bernd, Stephan Klasen, and Hermann Waibel. 2016. "Establishing a database for vulnerability assessment." *Vulnerability to Poverty: Theory, Measurement and Determinants, with Case Studies from Thailand and Vietnam* 50–79. 10.1057/9780230306622_3.

IPCC. 2018. "Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,."

Karim, Azreen. 2018. "The Household Response to Persistent Natural Disasters: Evidence from Bangladesh." *World Development* 103 40–59. 10.1016/j.worlddev.2017.10.026.

Kirchberger, Martina. 2017. "Natural disasters and labor markets." *Journal of Development Economics* 125 (November 2016): 40–58. 10.1016/j.jdeveco.2016.11.002.

Kotz, Authors Maximilian, Anders Levermann, and Leonie Wenz. 2022. "The effect of rainfall changes on economic production." *Nature* 601 (February): . 10.1038/s41586-021-04283-8.

Kovats, R. Sari, Menno J. Bouma, Shakoor Hajat, Eve Worrall, and Andy Haines. 2003. "El Niño and health." *The Lancet* 362 (9394): 1481–1489. 10.1016/S0140-6736(03)14695-8.

Kurosaki, Takashi. 2015. "Vulnerability of household consumption to floods and droughts in developing countries: evidence from Pakistan." *Environment and Development Economics* 20 (2): 209–235. 10.1017/S1355770X14000357.

Lobell, David B., Stefania Di Tommaso, Marshall Burke, and Talip Kilic. 2021. "Twice Is Nice: The Benefits of Two Ground Measures for Evaluating the Accuracy of Satellite-Based Sustainability Estimates." *Remote Sensing* 13 (16): 3160. 10.3390/rs13163160.

Lohmann, Steffen, and Tobias Lechtenfeld. 2015. “The effect of drought on health outcomes and health expenditures in rural Vietnam.” *World Development* 72 432–448. 10.1016/j.worlddev.2015.03.003.

Maccini, Sharon, and Dean Yang. 2009. “Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall.” *The American Economic Review* 99 (3): 1006–1026. 10.1257/aer.99.3.1006.

McElroy, Sara, Sindana Ilango, Anna Dimitrova, Alexander Gershunov, and Tarik Benmarhnia. 2022. “Extreme heat, preterm birth, and stillbirth: A global analysis across 14 lower-middle income countries.” *Environment International* 158 (October 2021): 106902. 10.1016/j.envint.2021.106902.

National Drought Mitigation Center. 2022. “Types of Drought.” `https://drought.unl.edu/Education/DroughtIn-depth/TypesofDrought.aspx`.

Nguyen, and Nguyen. 2020. “Exposure to weather shocks: A comparison between self-reported record and extreme weather data.” *Economic Analysis and Policy* 65 117–138. 10.1016/j.eap.2019.11.009.

Nguyen, Thanh Tung, Trung Thanh Nguyen, and Ulrike Grote. 2020. “Multiple shocks and households’ choice of coping strategies in rural Cambodia.” *Ecological Economics* 167 (January 2020): 106442. 10.1016/j.ecolecon.2019.106442.

Schmidheiny, Kurt, and Sebastian Siegloch. 2023. “On event studies and distributed-lags in two-way fixed effects models: Identification, equivalence, and generalization.” *Journal of Applied Econometrics* 38 (5): 695–713. https://doi.org/10.1002/jae.2971.

Stanke, Carla, Marko Kerac, Christel Prudhomme, Jolyon Medlock, and Virginia Murray. 2013. “Health effects of drought: a systematic review of the evidence.” *PLoS currents* 5. 10.1371/currents.dis.7a2cee9e980f91ad7697b570bcc4b004.

Stantcheva, Stefanie. 2023. “How to Run Surveys: A Guide to Creating Your Own Identifying Variation and Revealing the Invisible.” *Annual Review of Economics* 15 (1): null. 10.1146/annurev-economics-091622-010157.

UNDRR. 2021. *Special Report on Drought 2021.* United Nations Office for Disaster Risk, 210, `https://www.undrr.org/contact-us`.

Vicente-Serrano, Sergio, Santiago Beguiria, and Juan López-Moreno. 2010. “A multi-scalar drought index sensititve to global warming: The standardized precipitation evapotranspiration index SPEI.” *Journal of Climate* 23 (7): 1–52.

A Appendix

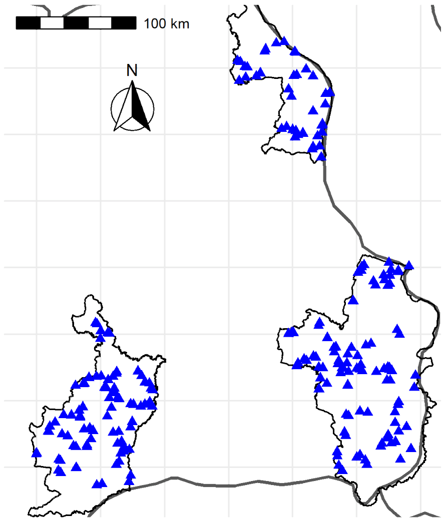
A.1 Literature review

Table (A1) Literature review: treatment based on survey report

	Treatment	Outcome	Survey
Dasgupta et al. (2021)	Children's fish consumption, during the previous 24h	Child health	DHS Bangladesh, 2008-2014
André et al.	Child labor, week before survey/ day before survey/ previous agricultural season	Production, wages	LSMS-IZA Tanzania
Asadullah et al.	Pupil's effort reported by teacher: [...] whether they have missed one day of school **in the last two weeks**.	Student performance	1988 National Education Longitudinal Study Bangladesh
Vaiknoras and Larochelle	Bean adoption during growing season 2015B (Feburary-August), reported in September	Consumption, productivity, sales	Seasonal Agricultural Survey, Rwanda
Lim et al.	Neighbors' adoption of farming practices over last 10 years	Own adaptation	CCAFS survey, 2010-2011 in 12 countries
Mora-Rivera and Gameren	Remittances, during 12 months prior to survey	Food insecurity	NEVAL Rural Households Surveys (ENCHOR) of 2013 and 2015, Mexico
Giambra and McKenzie	Self-employment over last 4 weeks	migration	7 different surveys in different countries
Ahmed and Cowan	Health shock during last quarter	Health expenditures, clinic visits	
Nuhu et al.	Soy sales during agricultural season 2011/12 (1st May- 30th April)	Welfare of household	
Grimm et al.	Income, imputed from consumtpion items over last 12 months	Remittance payment	own survey
Platteau and Ontiveros	Sickness during the insurance program 2011-2012	insurance renewal	India
Kianersi et al.	Injury or death in the household or damage to income-generation assets due to hurricane Matthew Ocotber 2016, survey in Dec 17-Feb 18. Use physical measures only to validate reports, but not in regression analysis.	Food insecurity	Haiti
Scognamillo and Sitko	Work for public works program, over last 12 months	Welfare	Integrated Household Survey, Malawi
Borga and D'Ambrosio	public program participation in last 12 months, including participation duration, type of support and the benefits received.	Welfare	Young Lives in 4 countries
Adong et al.	conflict exposure, i.e. disruption of economic activities, lived in camps, abduction or killing of household member, during the last 12 months	Food consumption	Uganda National Panel Survey data (UNPS)

A.2 Study region

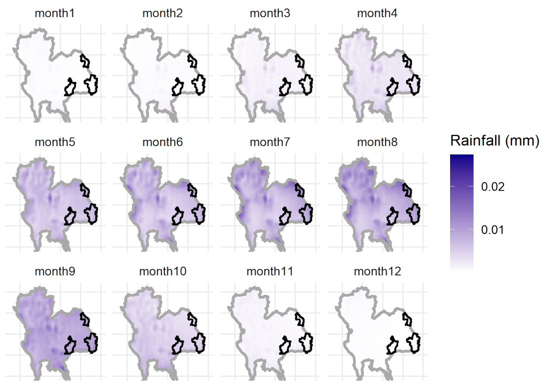
Figure (A1) Survey sites in Thailand



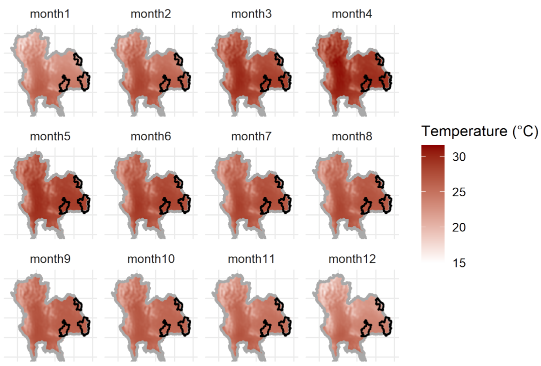
Notes: Blue triangles indicate surveyed villages. The share of surveyed households with at least one member working in the agricultural sector is 87% (Buri Ram), 89% (Nakon Phanom) and 84% (Ubon Ratchathani), resp..

Figure (A2) Long-run climatic conditions over 1981-2019 by month of the year

(a) Precipitation



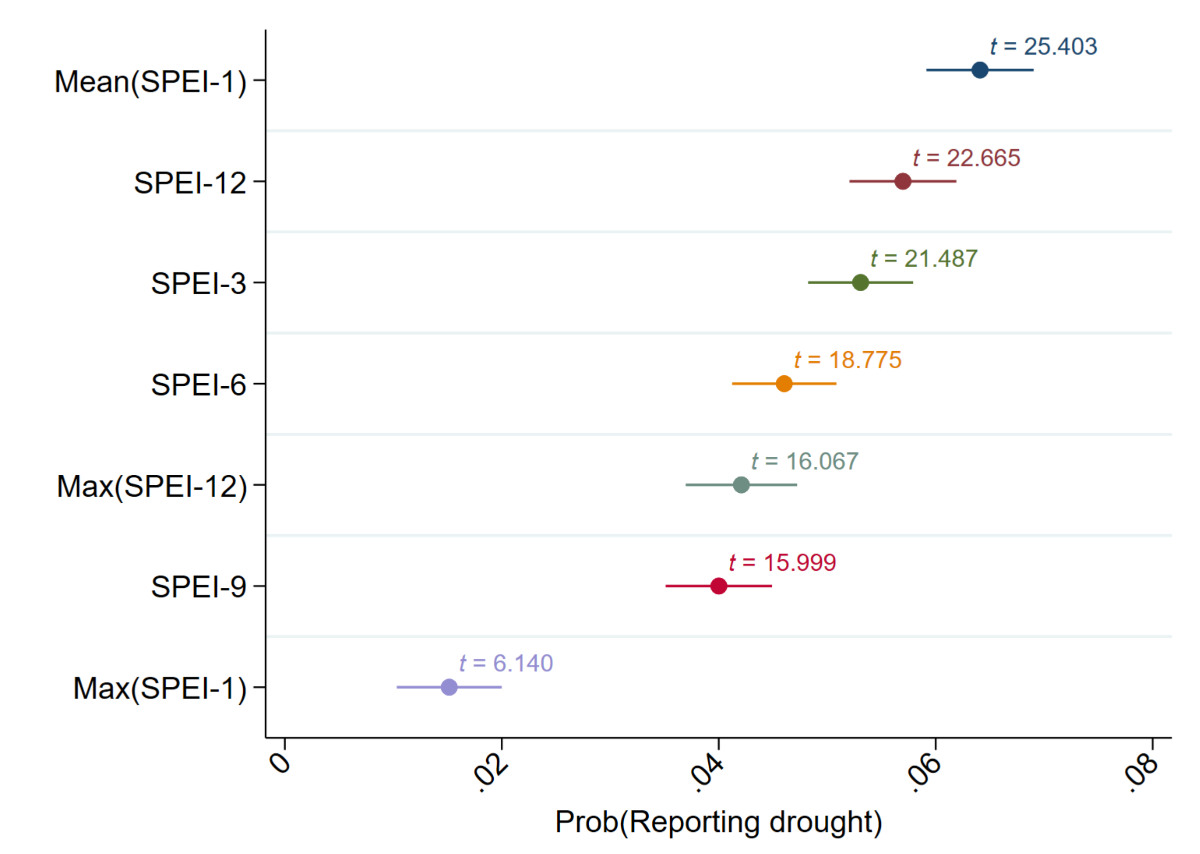
(b) Temperature



Notes: The graphs show gridded meteorological data for North-East Thailand. The survey provinces are highlighted by the black surrounding line. The color shading reflects the long-run average of precipitation (left) and temperature (right) from January to December.

A.3 Choice of drought variable

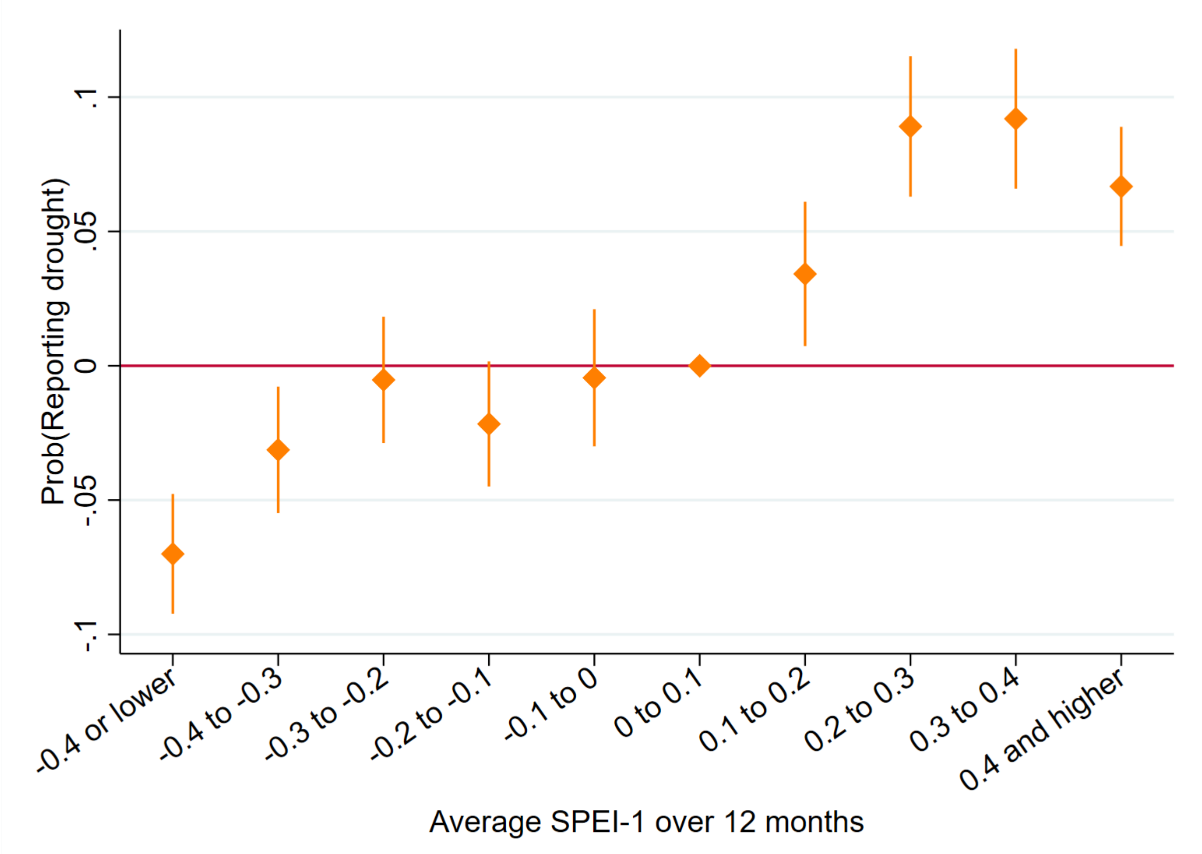
Figure (A3) Validation exercise for drought indicators



Notes: All drought variables are standardized to ensure a better comparability. Regressions of drought reporting on a range of drought variables. Horizontal bars reflect 95-percent confidence intervals. Models sorted by t-statistic. The model with the largest t-statistic is the model with the drought variable *Mean*(SPEI-1).

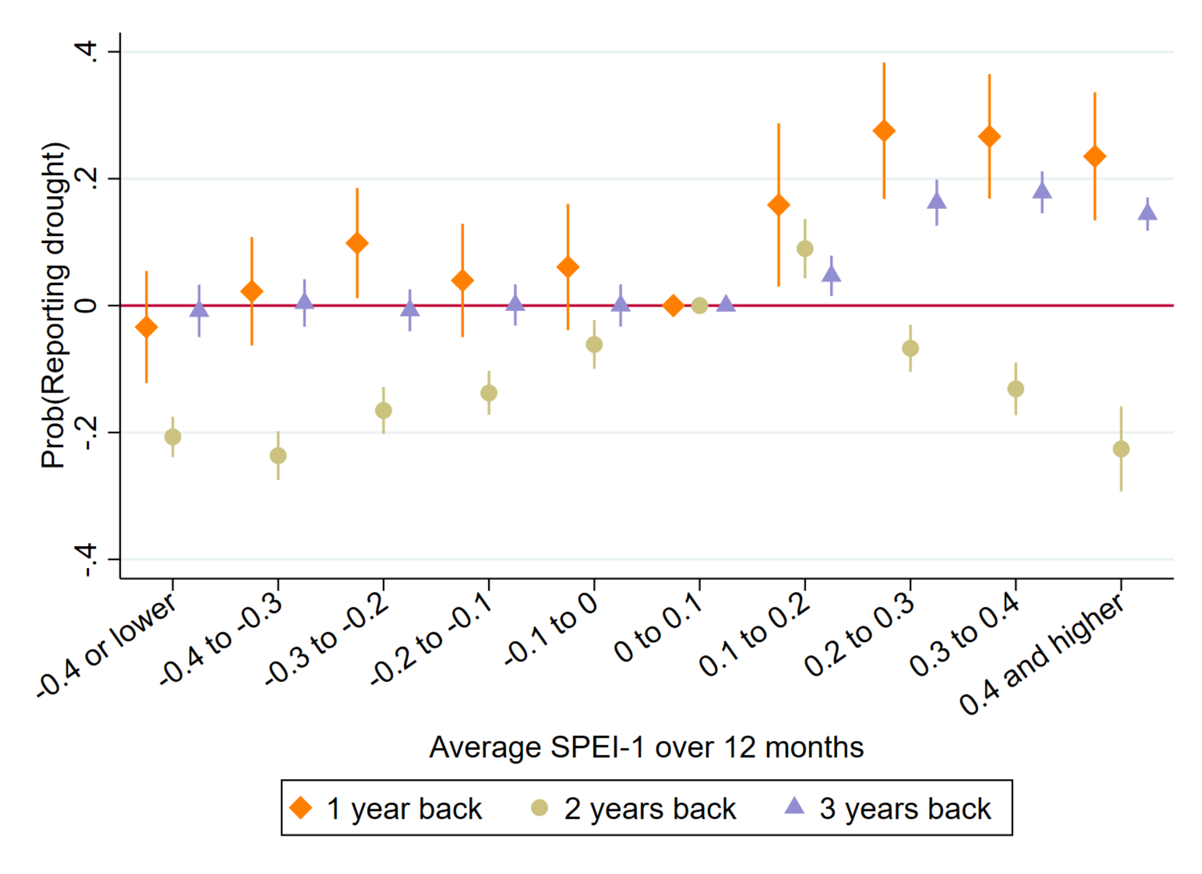
A.4 Choice of cutoff for drought variable

Figure (A4) Drought indicator cutoff selection



Notes: Results from one regression pooling observations with different recall interval (1 year, 2 years, 3 years). Main treatment variable is *Mean*(SPEI-1), split into bins of 0.1-width. Vertical bars reflect 95-percent confidence intervals.

Figure (A5) Drought indicator cutoff selection, by recall period length



Notes: Results from three different regressions according to recall intervals (1 year, 2 years, 3 years). Regressions also include fixed effects for provinces. Main treatment variable is *Mean*(SPEI-1), split into bins of 0.1-width. Vertical bars reflect 95-percent confidence intervals.

A.5 Event recall analysis

Table (A2) Recall analysis: Correlation of household head characteristics with his/her reporting behavior

	Balanced		Unbalanced	
	(1)	(2)	(3)	(4)
	Correct	Under	Correct	Under
Agegroups	-0.00	-0.00	0.00	-0.00*
	(-0.05)	(-0.55)	(1.10)	(-2.00)
Male	0.00	0.02	-0.01	0.02
	(0.33)	(1.07)	(-1.16)	(1.69)
Household size	-0.00	0.00*	-0.00	0.00
	(-0.82)	(1.86)	(-0.32)	(0.82)
Ln(Land area)	0.03***	-0.02***	0.03***	-0.02***
	(6.83)	(-4.88)	(5.48)	(-5.58)
Education	0.01	-0.01	0.01	-0.01
	(1.54)	(-1.58)	(1.63)	(-1.66)
Farmer	0.03***	-0.04***	0.04***	-0.04***
	(3.14)	(-3.42)	(4.40)	(-4.47)
Household FE	✓	✓	✓	✓
HH Controls	✓	✓	✓	✓
Wave FE	✓	✓	✓	✓
Interview Month FE	✓	✓	✓	✓
Adjusted R-squared	0.21	0.72	0.24	0.70
N	11,701	11,701	11,715	11,715

Notes: Standard errors are clustered at the district-level. *** p<0.01, ** p<0.05, * p<0.1

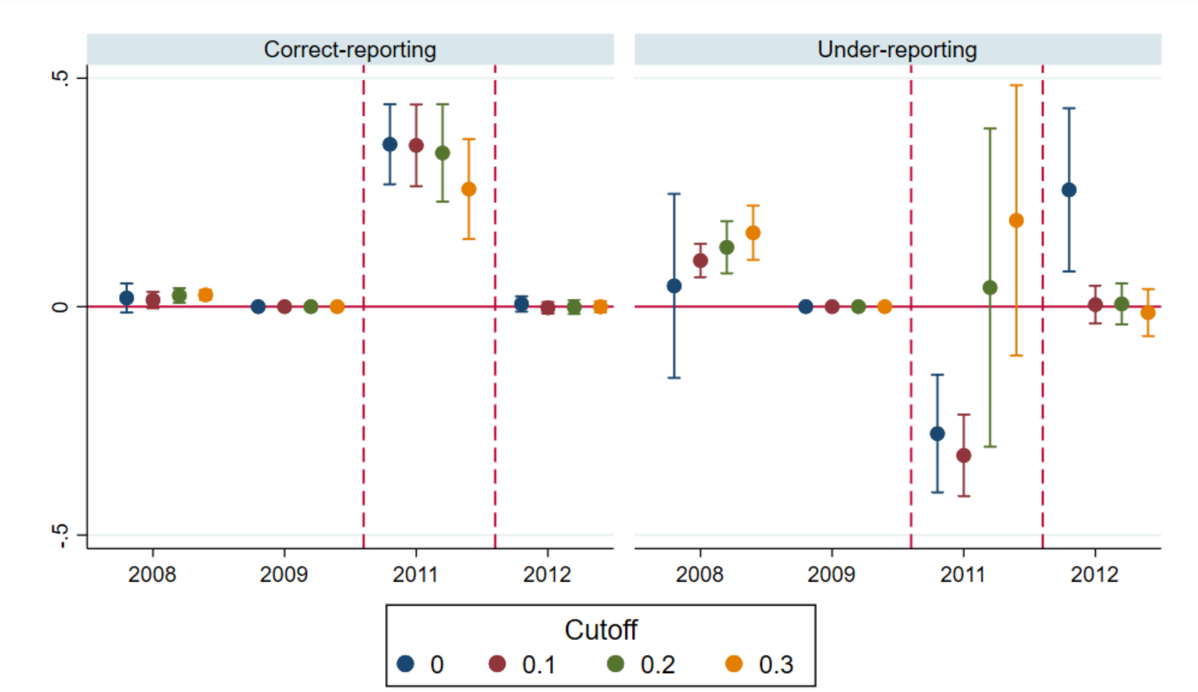
Table (A3) Recall analysis: regression version of coefficient plot - balanced

	Balanced		Unbalanced	
	(1)	(2)	(3)	(4)
	Correct	Under	Correct	Under
Treated province × 2008	0.02*	0.10***	0.01	0.09***
	(0.01)	(0.02)	(0.01)	(0.02)
Treated province × 2009	0.00	0.00	0.00	0.00
	(.)	(.)	(.)	(.)
Treated province × 2011	0.36***	-0.33***	0.36***	-0.33***
	(0.04)	(0.04)	(0.04)	(0.04)
Treated province × 2012	-0.00	0.00	0.01	0.00
	(0.01)	(0.02)	(0.01)	(0.01)
Treated province × 2013+	0.04**	0.01	0.04**	-0.01
	(0.02)	(0.04)	(0.02)	(0.04)
Household FE	✓	✓	✓	✓
HH Controls	✓	✓	✓	✓
Wave FE	✓	✓	✓	✓
Interview Month FE	✓	✓	✓	✓
Adjusted R-squared	0.25	0.75	0.27	0.72
N	11,707	11,707	11,721	11,721

Notes: Event study of reporting behavior of the household head. The outcome variable reflects subjective reporting benchmarked against the objectively measured drought index, both measured over the respective 12-months reference period. Ubon Ratchathani was surveyed in 2011 and 2013, while Nakhon Phanom, surveyed in 2013, serves as the control province. Regressions control for age, male gender, agriculture as occupation and education of the household head; household size, and ln(land area owned). Standard errors are clustered at the district-level. *** p<0.01, ** p<0.05, * p<0.1

A.6 Drought effect on health

Figure (A6) Robustness towards alternative drought cutoff



Notes: Event study of reporting behavior of the household head. The outcome variable reflects subjective reporting benchmarked against the objective drought index. The treatment group are households in Ubon Ratchathani, the treatment period is 2011. The comparison group are households in Nakhon Phanom. Regressions control for household head's age, male gender, agricultural occupation, education; as well as household's size, ln(land area owned), and include fixed effects for household, survey year and interview-month. Standard errors are clustered at the district-level.

Table (A4) Continuous SPEI-1 measure; village vs. household FE

	Sick members		Prob(Sick members>0)	
Increasing Drought	0.11**	0.11**	0.06*	0.06*
	(2.14)	(2.15)	(1.93)	(1.91)
Household FE		✓		✓
Village FE	✓		✓	
Controls	✓	✓	✓	✓
Wave FE	✓	✓	✓	✓
Interview Month FE	✓	✓	✓	✓
Adjusted R-squared	0.16	0.43	0.13	0.40
N	11,105	11,105	11,105	11,105

Notes: Drought is measured by the SPEI-1 across the 12 months prior to the survey month. Regressions control for the household-level variables mean age, share males, household size, ln(land area owned), farmers in household, as well as maximum education, and include fixed effects for household, survey year and interview-month. Standard errors are clustered at the district-level. *** p<0.01, ** p<0.05, * p<0.1

Table (A5) Continuous alternative weather measures including controls

	Sick members			Prob(Sick members>0)		
Increasing Drought	0.11**			0.06*		
	(2.15)			(1.91)		
Increasing Temperature		0.13***			0.08***	
		(2.87)			(3.12)	
Decreasing Rainfall			0.16***			0.10***
			(2.76)			(2.97)
Household FE	✓	✓	✓	✓	✓	✓
HH Controls	✓	✓	✓	✓	✓	✓
Wave FE	✓	✓	✓	✓	✓	✓
Interview Month FE	✓	✓	✓	✓	✓	✓
Adjusted R-squared	0	0	0	0	0	0
N	11,105	11,105	11,105	11,105	11,105	11,105

Notes: Meteorological variables reflect the mean anomalies of rainfall and temperature over the health reference period of 12 months prior to each interview. Standard errors are clustered at the district-level. *** p<0.01, ** p<0.05, * p<0.1

Table (A6) Health regression using alternative health outcome

	Share(Sick members>0)		
Increasing Drought	0.02*		
	(2.01)		
Increasing Temperature		0.03***	
		(2.83)	
Decreasing Rainfall			0.03**
			(2.37)
Household FE	✓	✓	✓
HH Controls	✓	✓	✓
Wave FE	✓	✓	✓
Interview Month FE	✓	✓	✓
Adjusted R-squared	0.47	0.47	0.47
N	11,105	11,105	11,105

Notes: Dependent variable: Share(Sick members >0) reflects the share of members in a household with at least one disease. Share(sick members > 0): mean=0.17 SD=0.21. Meteorological variables reflect the conditions over the health reference period of 12 months prior to each survey wave. Regressions control for age, male, household size, land area owned, and education. Standard errors are clustered at the district-level. *** p<0.01, ** p<0.05, * p<0.1

Table (A7) Effects of subjective versus objective drought on health, standardized coefficients

	Sick members		Prob(Sick members > 0)	
	(1)	(2)	(3)	(4)
Subjective drought	0.027**		0.041***	
	(0.03)		(0.01)	
Objective drought		0.038***		0.041***
		(0.04)		(0.03)
Difference				
Household FE	✓	✓	✓	✓
Wave FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓
HH Controls	✓	✓	✓	✓
Adj. R-squared	0.33	0.33	0.29	0.29
N	11,105	11,105	11,105	11,105

Notes: Subjective drought is a binary variable, reflecting whether the household reported a drought in the survey. *Objective drought* is a binary variable indicating a drought when *Mean*(SPEI-1) exceeded 0.6 during the reference period prior to the survey. Household controls include mean age of the household, share of males in the household, household size, number of farmers in the household, land area owned and maximum education in the household. Sample is based on all waves. Standard errors are clustered at the district-level. *Difference* reflects the results of a χ^2-test for differences between the coefficients. Standard errors are clustered at the district-level. *** p<0.01, ** p<0.05, * p<0.1

Table (A8) Correlation of drought and household characteristics with migration

	Moved (1)	Migrated (2)
Average age	-0.00	0.00*
	(0.00)	(0.00)
Share of males	-0.03*	-0.02
	(0.04)	(0.02)
Household size	-0.00	-0.00
	(0.00)	(0.00)
Ln(Land area)	-0.00	0.00
	(0.00)	(0.00)
Education	0.00	0.00
	(0.01)	(0.00)
Farmer	0.00*	-0.00
	(0.00)	(0.00)
SPEI-1	-0.01	-0.00
	(0.01)	(0.01)
Reported drought	-0.00	0.00
	(0.01)	(0.00)
Adjusted R-squared	0.47	0.37
N	10,287	9,063

Notes: Dependent variable "Migrated" reflects those households that migrated to another province. "Moved" reflects those households that moved to another dwelling during 2008-2019.30.08 % of the observations moved, while 3,52% of the observations migrated to another province. Standard errors are clustered at the district-level. *** p<0.01, ** p<0.05, * p<0.1