Observing traumatic events:
Indirect effects of flood shocks on well-being and preferences*

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Abstract

This paper investigates how witnessing adverse weather events affects individuals' perceptions and consequently their personal well-being. To identify potential exposure to a weather shock, we link satellite-based data on flooding to an extensive household panel survey from rural Southeast Asia. We find that mere proximity to a potentially adverse shock, even without reporting any actual experience of the shock, can be sufficient to reduce individual well-being levels. This effect is not only restricted to the present but can also impinge on expected future well-being dynamics. Such a persistent distortionary effect from witnessing a weather shock may also have politico-economic repercussions by, for instance, altering support for redistributive policies.

Keywords: Environmental shocks; Perception; Subjective well-being; GIS data; MODIS flood mapping

JEL: I31; Q51; R23

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1 Introduction

Extreme weather events, such as floods and heavy rain, not only severely affect a person's economic well-being but can also have repercussions on a person's subjective well-being.[1] Recent studies address the impact of directly experienced shock events on individual subjective well-being (SWB) and demonstrate that adverse shock events can lower SWB levels (e.g., Maddison and Rehdanz, 2011; von Möllendorff and Hirschfeld, 2016; Sekulova and Van den Bergh, 2016). However, until now, there has been little evidence on how shock events that are witnessed but not directly experienced affect individual SWB. Psychological and medical research, in contrast, has long discussed the impacts of traumatic events on the mental well-being of individuals who observe such events or hear about them from others (e.g., Figley, 1995; Potter et al., 2010; Cocker and Joss, 2016). These studies show that witnessing traumatic events can cause severe stress, consequently resulting in a decrease in quality of life. However, the topic has received little attention in the literature on SWB dynamics or in the economics literature in general. Thus, the potential ramifications of these experiences for economic decision-making are neither known nor incorporated into economic analyses.

We investigate this phenomenon from an economics viewpoint and ask the following question: What are the repercussions of witnessing nearby shock events on the SWB of individuals who did not experience any direct shock exposure? We call such events *tangential shock events (TSEs)* and argue that a recorded decline in well-being may not exclusively reflect shock-related economic losses but may also entail a transitory shift in perceptions.

The scenario we study to demonstrate the impact of TSEs on subjective well-being is flooding in rural villages in Thailand and Vietnam. Floods pose a severe threat to livelihoods, in particular to rural agricultural communities. Their frequency and severity have increased in many regions and will likely become even more prominent in the future (IPCC, 2014). This also suggests an increase in the relevance of TSEs in the future.

To study the influence of witnessing shock events, we use data from an extensive household panel survey in Southeast Asia, as well as high-resolution satellite-based flood data. Within our analysis, we apply a multinomial logit model, which allows us to identify whether TSEs (and other factors) exert a differential effect on positive and negative well-being dynamics. This approach is related to prospect theory (Kahnemann and Tversky, 1979) and accounts for different evaluations of SWB above and below a reference point.[2] Ultimately, we find that the mere presence of a flood event can indeed lower individual subjective well-being levels, even if individuals were not affected by the flood itself. Individual behavioural reactions might thus be triggered not only by directly experienced events but also by tangential shocks.

In our sensitivity analysis, we demonstrate that this effect is a robust phenomenon: it is seen even when controlling for potential village network effects, the emergence of coping strategies, unobserved household characteristics, agricultural dependency or indirect psychological effects.

Having established a robust relation between TSEs and subjective well-being, we further investigate whether this is merely a temporary phenomenon or has lasting consequences. Ultimately,

[1] Subjective well-being can be defined as a function of an individual's personality and his/her reactions to different life events (Stevenson and Wolfers, 2008), or as Diener (2006, p. 400) puts it: "Subjective well-being is an umbrella term for the different valuations people make regarding their lives, the events happening to them, their bodies and minds, and the circumstances in which they live".

[2] A \$1,000 increase in income might raise SWB to a lesser extent than a \$1,000 decrease would lower SWB. Within our research, the presence of a shock could result in negative SWB dynamics, yet its absence would not necessarily translate into positive SWB dynamics.

such potentially persistent effects may influence decision-making processes or preferences. Related to our focus on the perception of weather shocks in developing countries, we thus investigate the emergence of shifting preferences related to redistributional policies. Such local changes in redistributional preferences, in turn, could be an important aspect to consider when designing disaster relief policies.

Our research adds to the literature on the determinants of SWB, particularly to a better understanding of the impact of severe weather events. These events will become more prominent in the future due to the effects of climate change. This is especially true for vulnerable households living in rural developing areas of the world. We therefore demonstrate that flood shocks not only have the potential to destroy a person's economic well-being but also may have severe indirect effects on the individuals witnessing these shock events by lowering their subjective well-being.

The phenomenon we describe not only results in current evaluations of SWB being altered but it impacts the formation of expected future SWB dynamics. This is an important finding since we demonstrate that expected SWB dynamics shape support for redistributional policies. Ultimately, a seemingly innocuous event such as observing an environmental shock (without being directly affected) may alter policy preferences within the population.

The paper is organised as follows: We first present a short literature overview (Section 2). In Section 3, we explain our empirical approach and the derivation of our tangential shock indicators. This is followed by our empirical analysis (Section 4), including a detailed sensitivity analysis. We end with a discussion of our results in Section 5.

2 Related Literature

For our research on the impact of tangential shock events, we built upon the literature on the determinants of subjective well-being, such as sociodemographic and socioeconomic factors. In addition, our research also draws upon the literature on shock events, both from an economic and psychological perspective. To subsequently showcase our contribution, i.e., establishing the relevance of TSEs, we briefly sketch the main lines of thought in the relevant strands of literature.

Sociodemographic factors Sociodemographic determinants of SWB have been reviewed extensively (e.g., Myers and Diener, 1995; Easterlin, 2003; Helliwell, 2006; Reyes-García et al., 2016). Factors such as age, education, gender, health, and personality explain a substantial degree of the variation in SWB levels (Diener, 1994; van Praag et al., 2003; González et al., 2005). Moreover, close relationships (mostly measured through marital status) and strong religious beliefs have a positive effect on SWB. Poor health, in contrast, is mostly associated with lower levels of SWB (González et al., 2005; Dolan et al., 2008).[3] Many studies address the relationship between SWB and personal life events, such as unemployment, marriage/divorce, educational achievements, or the death of a family member (Clark and Oswald, 1994; Luhmann et al., 2012; Pedersen and Schmidt, 2014). Most of the authors argue that the impacts of such events only prevail in the short run (Diener, 1996; Luhmann et al., 2012).[4]

[3] Although most studies on sociodemographic traits focus on high-income countries, it is worth noting that different studies find a sort of "unique happiness equation" (Veenhoven, 2010; Sarracino et al., 2013; Reyes-García et al., 2016; Markussen et al., 2018). Ultimately, the most essential findings on SWB not only hold in high-income countries but also hold in lower and middle-income countries.

[4] Recent work on panel data has revealed mixed results, showing that the effects of life events are heterogeneous and can have long-lasting repercussions on SWB (Lucas et al., 2003; Lucas, 2005).

Socioeconomic factors Another intensively investigated group of determinants are material circumstances, i.e., income or assets. In general, these studies find a positive relationship between income levels and SWB (Easterlin, 2008). Currently, there is some level of consensus that income has positive but diminishing returns (Dolan et al., 2008). In lower-income countries, income plays a more prominent role in individuals' happiness than in wealthier nations (Diener and Biswas-Diener, 2002; Reyes-García et al., 2016). Evidence also suggests that relative income matters for SWB (Luttmer, 2005; Clark et al., 2008; Dolan et al., 2008). In the context of our research (with Thailand and Vietnam being the countries of interest), income plays a significant role in the determination of personal well-being. These economic factors are of particular relevance for our research since they are almost surely affected by flood shocks and are thus correlated with our variables of interest. We therefore include controls for a person's sociodemographic and socioeconomic situation in the analysis.

Environmental shocks Other recent studies assess the direct impact of severe weather events on SWB levels and have demonstrated that the adverse effects on SWB may also result from unfavourable climate conditions or environmental shocks (Maddison and Rehdanz, 2011). Flooding has an especially persistent and strong negative effect on SWB (Luechinger and Raschky, 2009; Sekulova and Van den Bergh, 2016; von Möllendorff and Hirschfeld, 2016). Sekulova and Van den Bergh (2016) compare data from individuals living in flood-prone regions in Bulgaria to data from those who live in areas without flood occurrence. While they find a strong negative impact of flooding on SWB, they also point out that intangible factors, e.g., psychological damage, explain a large part of the negative effects on SWB levels. They stress that "expecting a flood can be equally traumatic as experiencing the disaster itself" (Sekulova and Van den Bergh, 2016, p.56). We follow this idea of indirect psychological consequences from (flood) shocks and shift the attention from *expecting* to *observing* an environmental shock *without being hit* by it.

Observing traumatic events Our research therefore also relates to psychological and medical studies on the effects of witnessing traumatic events (Figley, 1995; Abendroth and Flannery, 2006; Sabo, 2006; Frančišković et al., 2007; Potter et al., 2010; Patki et al., 2014, 2015; Cocker and Joss, 2016) and the literature on the externalities associated with terrorist attacks (Bozzoli and Müller, 2011; Finseraas and Listhaug, 2013). Psychological studies have revealed, for instance, that caring for traumatized individuals can cause severe mental trauma for the caregiver, such as nurses or social workers, as well as the wives of veterans. Experimental studies have shown that even rats are affected by tangential shocks, i.e., observing other rats being socially defeated by a predator (Patki et al., 2014). Overall, observing traumatic events may increase the risk of developing post-traumatic stress disorder or may raise levels of anxiety, even without direct exposure to the threatening event. Both outcomes are ultimately related to a decrease in quality of life and well-being.

3 Study Design

3.1 Data

In this paper, we use two types of data. First, we draw upon micro data originating from an extensive household survey in rural Thailand and Vietnam, called the Thailand Vietnam Socio Economic

Panel (TVSEP) (Klasen and Waibel, 2013).[5] We link these household data with high-resolution satellite-based flood data to investigate the differential responses of individuals to precisely localised flood shock events.

3.1.1 Household data

The TVSEP data have been collected since 2007 in Thailand and Vietnam. For the purposes of this research, we use the data obtained from the six waves between 2007 and 2016.[6] The survey is conducted in six rural provinces, three in each country (cf. Figure A.1). When the survey started in 2007, 4,381 households in 440 villages were interviewed.[7] The same households have been interviewed in each wave.[8] Across the different waves, the respondents within the households have varied in a number of cases. We thus treat the data set as linked cross-sectional observations of individuals in our main analysis and use the full household panel structure in our sensitivity analysis.[9]

Respondents in our sample typically originate from rural, multigenerational households. They are on average 50 years old, and the majority are married (84%) and engaged in subsistence farming (70%). The sample is balanced in terms of gender, and education levels are relatively low-76% have completed primary schooling at best. The information on individual health dynamics is mixed; approximately 30% (11%) of the respondents stated that their health status is worse (better) than one year before. A detailed overview of all variables used in the analysis can be found in Table A.1 in the appendix. For our analysis, we use a pooled sample that includes respondents at least 15 years of age who lived in households that did not move between 2007 and 2016 and for whom the interview date could be identified reliably.[10]

In addition to information on sociodemographic characteristics, the survey's household questionnaire elicits detailed information on agricultural production, income sources and assets, and individual or household well-being. We enrich the basic household dataset with information on household location, which is available from 2016 onward. Household locations are recorded using GPS devices, which provides us with coordinates for most households in the sample. Since the TVSEP survey has a particular focus on the effects of shocks on vulnerable households in Southeast Asia, respondents also answer detailed questions about their own and their household's shock experience since the last survey. We use this information as our measure of direct flood shock experience. 10% of respondents stated that their household was hit by a flood or heavy rain shock, and more than half of these households were affected by a severe shock event.

Our outcome variable is self-reported subjective well-being.[11] The relevant survey item is formulated such that respondents identify their level of well-being in relation to one year ago.

[5] More information and data access can be obtained via the project webpage: https://www.tvsep.de/overview-tvsep.html

[6] The waves took place in 2007, 2008, 2010, 2011, 2013, and 2016.

[7] To identify a group that is representative for the rural population, approximately 2,000 households in each country were selected through a three-stage cluster sampling strategy (cf. Hardeweg et al. (2013)).

[8] In 2011 only one province in each country was surveyed.

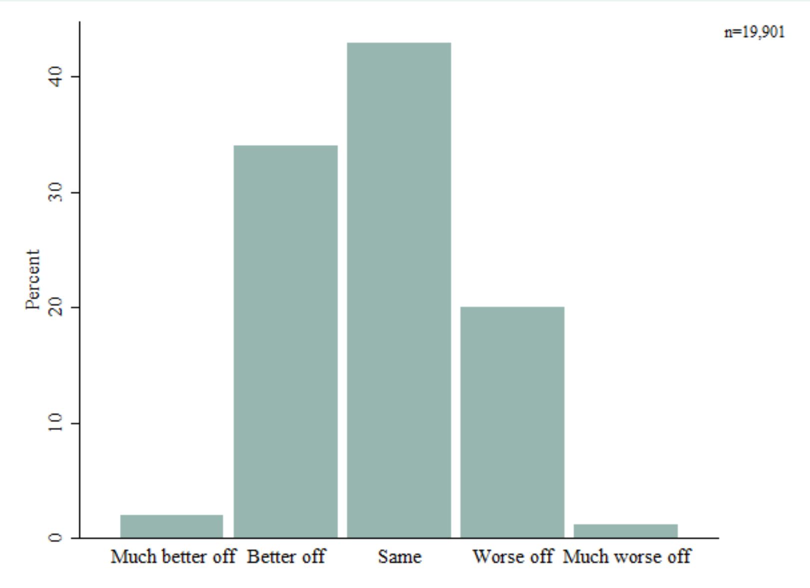
[9] We follow the idea of Ferrer-i Carbonell and Frijters (2004), pointing out the relevance of unobserved, time-invariant factors correlated with likely determinants of subjective well-being. Therefore, we also present random- and fixed-effects specifications (Table A.9).

[10] Sometimes the interview date could not be determined. The household was then excluded from the analysis since we need a precise interview date to link the data with the respective shock events.

[11] We focus on individual subjective well-being levels because the respondents' assessment of well-being at the household level would still be the outcome of a cognitive process on the individual level, and thus susceptible to the influence of individual traits and perceptions. Our data also show that reported well-being dynamics at the household and the individual level are highly correlated.

The question posed to the respondent reads: *"Do you think you in person are better off than last year?"*. Each respondent can choose between five answers, namely, *(1) Much better off, (2) Better off, (3) Same, (4) Worse off, and (5) Much worse off.* Only a few respondents chose categories (1) or (5) (see Figure 1). We therefore regroup the categories, such that answer options (1) and (2) are summed up in one category and options (4) and (5) form another category, yielding three categories of well-being dynamics: "better off" (ΔSWB^{+}), "same", and "worse off" (ΔSWB^{-}).

Figure 1: Distribution of subjective well-being on the individual level (5-point scale)



Note: The figure displays the relative frequency of individually reported subjective well-being dynamics. The number of individual-year observations refers to the unrestricted base sample and includes respondents from all waves from 2007 to 2016.

We also conduct a balance test to evaluate the ex-ante comparability of respondents across a range of sociodemographic variables with respect to both their direct experience of flood shocks and their exposure to tangential shocks (cf. Table A.2). Only in the case of Vietnamese respondents did we observe some differences between those who experienced a direct shock and those lacking such an experience. To address this, we include the respective sociodemographic variables (income measures, age, marital status, health dynamics, educational attainment and occupation) as control variables in all our models, as well as a country dummy.

3.1.2 Spatial data on flood events

In addition to the household data, we use derivatives of the NASA/DFO MODIS[12] near-real-time global flood mapping product (Nigro et al., 2014) to identify tangential flood shock events (see Section 3.2 for a detailed definition and explanation of our identification approach). Based on the satellite data, the flood mapping algorithm provides information on flood water (FW) events with a relatively high degree of spatiotemporal precision. Flood events are identified if the algorithm detects water-like electromagnetic emissions outside reference water areas, i.e., the sea, lakes or

[12] The measuring instrument on board the satellites is called Moderate Resolution Imaging Spectrodiameter, hence the acronym MODIS.

rivers. The information on flood water events is provided at a spatial resolution of approximately 250x250 meters: for each of these tiles (or pixels), the number of flood water days within the observation interval is recorded.[13] Based on the derivation algorithm (Nigro et al., 2014), the day count for flood water can be interpreted as a lower bound.

3.2 Definition and identification of shock events

In our research, we want to distinguish between the impact of directly experienced shocks and tangential shock events. We define the latter as follows:

> *A tangential shock event (TSE) is an event of potential shock exposure, i.e., a shock event occurring in the local or social vicinity (sphere of interest) of an individual or household. Such an event may be merely observed by an individual without any immediate consequence for the observer's economic well-being or health.*

This implies that tangential shocks should only be *observed*, i.e., their occurrence *could* have been noticed, but actual shocks were not *directly experienced* or reported as an adverse event hitting a household or individual. Relevant direct shock events are those with the potential to reduce levels of well-being in general and in an economic sense, i.e., by causing income or productive factor losses, unforeseen expenditures, or the loss of assets. Ultimately, this *relevance criterion* implies that an individual or household is vulnerable to such a shock, or otherwise well-being should not be affected directly. The *relevance criterion* is met by the households in the TVSEP. Households in the sample are mainly dependent on agricultural or livestock production and thus can be considered vulnerable to shocks (cf. Klasen and Waibel, 2013). Additionally, these data feature detailed information on a wide range of actual shock experiences.

In the context of these vulnerable households, flood shocks are especially harmful because they can diminish crop yields and livestock production, with the potential to be life-threatening. Furthermore, flood and heavy rain shocks have the potential to destroy nonproductive factor assets, such as homesteads.[14] Another characteristic of these shocks is their high degree of visibility: Flooded fields or drowned livestock can be visually detected by respondents. Such a severe event can be recalled easily and reliably at the interview.

In the analysis, we want to contrast these direct flood shock experiences (as reported in the TVSEP) with tangential flood shock exposure. Therefore, we need to differentiate between the two types of shocks. Whereas direct shock experience can be identified based on the self-reported shock measure from the survey, the identification of tangential shock events is more challenging. Due to their subliminal nature, i.e., they only had to be potentially observable, reliable information retrieval in a survey is infeasible. To quantify tangential shock exposure, we therefore need an

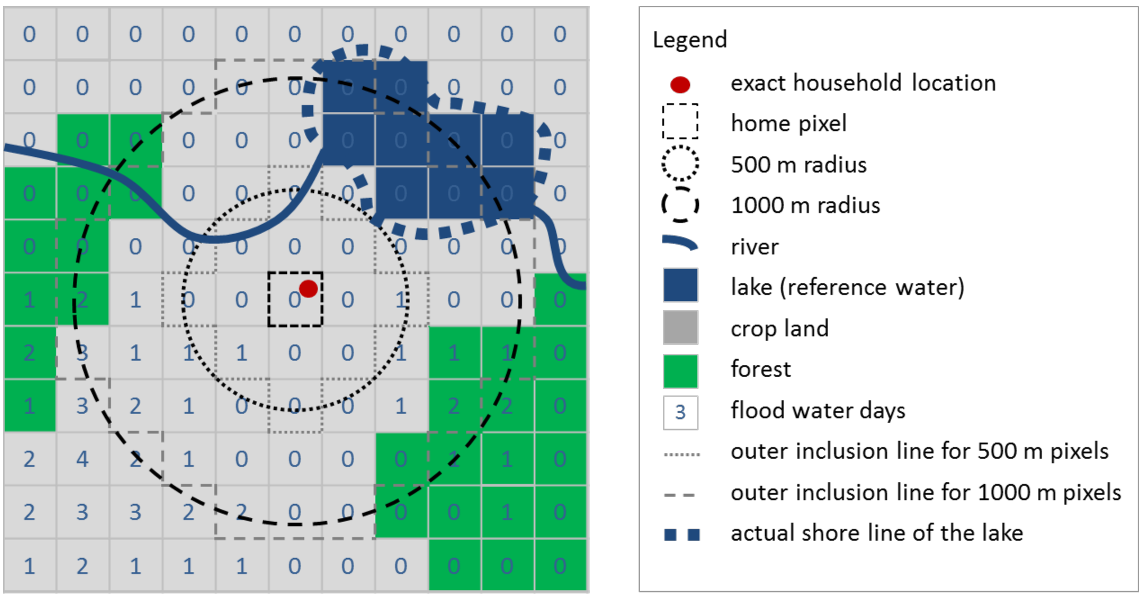
[13] Since the detection algorithm relies on surface reflections, cloud coverage imposes a severe limitation. To overcome this issue, we use the 14-day composite product. Each daily observation in this interval is included as non-missing if three cloud-free observations originating from the respective reference day or the two previous days are available. In addition, a flood water day is only recorded if water has been detected at least three times among the six satellite transits within this 3-day interval. The corresponding data for Thailand and Vietnam (covering 2004 to 2016) have been kindly provided by NASA on special request. We are grateful for their support. A further merit of flood identification based on multiple water detections is a substantially reduced likelihood of false positives, which can be caused by cloud or terrain shadows, both generating emissions in a wavelength similar to water. Ultimately, recorded flood water days for each tile and each of the 26 yearly observation intervals range from 0 to 14 days (15 or 16 in the case of a year's last interval).

[14] The incorporation of heavy rain shocks is justifiable for two reasons: first, heavy rain may directly cause spontaneous flooding on a localised scale, hence, cause damage to agricultural production. Second, these events tend to coincide, therefore making it hard to discern them when interviewed several months after such an event.

external measure of shock occurrences. To precisely evaluate whether any individual could have observed a shock event, i.e., whether such an event happened near the individual's homestead, these data have to be of sufficient spatiotemporal resolution.

The MODIS near-real-time flood mapping product satisfies the criterion of *external measurability* for tangential flood shocks. We therefore use the MODIS data to construct an indicator for tangential shock exposure. Based on households' homestead coordinates from the TVSEP, the closest 250x250 meter tile in the MODIS flood data is identified as the 'home pixel'. In the next step, all relevant tiles within varying radii up to five kilometer are identified. We call this area around a household's homestead the individual's sphere of interest. This five kilometer threshold was chosen because it comprises 95% of a household's cultivation areas and hence comprises the land most relevant for the livelihood of households that are dependent on agricultural production. Figure 2 is a stylised representation of the MODIS flood water data for a fictitious household. In addition to the home pixel, it also depicts the relevant pixels in the 500 and 1,000 meter radii.

Figure 2: Stylised MODIS flood water data



The TSE indicator captures the highest number of flood days that affected any tile within a certain radius of the home pixel. Such a maximum day count provides an indicator for the maximum local severity of flooding: the longer it lasts or the more events that occur within a given time horizon, the more likely agricultural production will suffer. Maximum local flood severity, i.e., the maximum number of flood days in a pixel, mirrors potentially threatening events in a precise manner.

Conditioning on the exact interview date, we further construct time horizon-specific TSE indicators. Evaluating TSE exposure over the last one-month, three-months or 12-months horizon allows us to test whether any potentially observed tangential shock effects are transitory or more permanent. Table A.3 provides a descriptive overview of the TSE indicator for all three time horizons.

3.3 Econometric specification

The premise of our research is to analyse the effects of tangential shock events on individual subjective well-being. The relationship between individual i's subjective well-being (SWB_i), individual characteristics x_i and shocks s_i can be represented by the linear model

$$\Delta SWB_i = x_i\beta + s_i'\gamma_1 + s_i^{TSE}\gamma_2 + s_i s_i^{TSE}\theta \tag{1}$$

To isolate the effect of TSEs from well-being dynamics induced by direct shock experience and potentially correlated changes in individual circumstances, the vector x_i comprises the set of sociodemographic and socioeconomic SWB determinants known from the literature: age, age squared, health status, marital status, educational attainment, religious beliefs, and occupational status.[15] Economic determinants, i.e., a measure of household income per capita and income dynamics, are represented in x_i as well.

In line with the literature on environmental shocks, experienced adverse shocks (s_i) may not only have an indirect effect, e.g., by lowering income, but may also have an immediate impact on subjective well-being. Being hit by a shock translates into diminished levels of subjective well-being by, for instance, reducing quality of life or deteriorating expectations for the future. The vector s_i includes a binary indicator. This binary indicator reflects whether an individual experienced a flood shock event.

In our data, subjective well-being is measured as a change over the preceding 12 months. This yields a difference interpretation for reported subjective well-being in year t, i.e., a well-being dynamic. Our dependent variable (ΔSWB) has three categories: Subjective well-being may have increased, decreased or stayed the same–the final option being a natural reference point. A valid modelling approach to estimate such a categorical dependent variable (with a natural reference point) is to fit a multinomial logit model (cf. Greene, 2012, p.763), given by

$$P(\Delta SWB_{i,t} = j | x_{i,t}, s_{i,t}, s_{i,t}^{TSE}) = \frac{\exp(x_{i,j,t}\beta_j + s_{i,j,t}'\gamma_{1,j} + s_{i,j,t}^{TSE}\gamma_{2,j} + s_{i,j,t}s_{i,j,t}^{TSE}\theta_j)}{1 + \sum_{k=1}^{2}\exp(x_{i,k,t}\beta_k + s_{i,k,t}'\gamma_{1,k} + s_{i,k,t}^{TSE}\gamma_{2,k} + s_{i,k,t}s_{i,k,t}^{TSE}\theta_k)} \tag{2}$$

For each of the two nonreference response categories (worse off and better off), we obtain a distinct set of parameter estimates. This approach is more flexible than other estimation approaches for categorical variables, e.g., an ordered logit model: it allows for modelling asymmetric effects of the explanatory variables across the response categories.

In contrast to other studies that analyse the impacts of directly experienced flood shocks on well-being, our research is guided by the hypothesis that tangential shocks may also sway perceptions of well-being.[16] Thus, tangential shocks may be interpreted as important externalities. The impact of observing such a local tangential shock s^{TSE} is modelled by an interaction with the reported shock experience (s_i). The respective interaction coefficient θ allows us to retrieve the influence of tangential shocks as the relative SWB difference between individuals from households not reporting any actual shock experience and those having suffered a relevant shock. Tangential shocks play a

[15] Individual educational attainment may also be correlated with (individual or household) income. This supports its inclusion into a model of individual well-being.

[16] Our research relates to Guiteras et al. (2015) pointing out the limitation of focusing solely on self-reported shock measures.

role if we observe $\theta \neq 0$.

With respect to our analysis, we expect that the overall effect will differ between those with and those without a direct shock experience. Referring to the multinomial logit specification in equation (2) with the two categories "better off" (b) and "worse off" (w), we anticipate $\theta^b < 0$ and $\theta^w > 0$. The presence of a tangential shock will reduce (increase) the probability someone without direct shock experience will be better (worse) off. This is then evidence in favour of a divergence in subjective and economic well-being induced by the mere perception of shocks.

Apart from our main analysis in Section 4.1, we present a sensitivity analysis in which we run several modifications of our model to test the robustness of our results. The results are presented in Section 4.2.

After we establish a robust relation between tangential shocks and SWB dynamics, we examine (i) the consequences of TSE for respondents' future subjective well-being expectations in Section 4.3, and (ii) the indirect politico-economic implications of TSE regarding respondents' distributional preferences in Section 4.4.

3.4 The distribution of well-being dynamics and flood shocks

Figure A.1 provides insight into the distribution of flood shock exposure for the year 2013. It illustrates the locations of villages in Thailand and Vietnam where at least three households have been interviewed. For each enlarged province, the left panel reports the share of villagers (in blue) who were exposed to a satellite-detected flood shock occurring in a radius of 5,000 meters around their homestead and a time horizon of 12 months. The right panel displays negative well-being dynamics, i.e., the shares of respondents in a village reporting that they are worse off (in red).

We observe that households in villages close to the Mekong River and those situated in river deltas are more likely to have witnessed a flood event. The occurrence of adverse, unconditional well-being dynamics, however, does not seem to be systematically related to satellite-detected flood shock exposure. On the one hand, villagers in these areas might witness such a shock more frequently. On the other hand, they should also be more familiar with recurring flooding and their judgement less sensitive to tangential shocks. We account for past shock exposure in our sensitivity analysis.

Table A.3 presents descriptive statistics for our tangential shock indicator for all considered time horizons and a selection of sphere-of-interest radii (1 km, 3km, and 5 km). The tangential shock indicators display a substantial degree of variation. While the mean values for smaller radii or shorter time horizons can be relatively small, extending the time horizon or the radius reveals a notable share of households that might have observed severe flood events in their vicinity. The sample average for the largest sphere of interest amounts to 4.5 days of flooding over three months and 21 days for the 12-month horizon. These values reflect a substantial likelihood that one longer or several shorter flood events occurred during the growing season. This measure also captures the fact that longer (or more frequent) events increase the likelihood that a flood event is observed by an individual and thus might impinge on subjective well-being.

In the subsequent econometric analysis, we examine whether this variation allows us to detect any robust micro-founded conditional interdependencies. This would be evidence confirming the relevance of tangential shocks in the evaluation of subjective well-being.

4 Econometric Analysis

4.1 Main Results

In this section, we analyse our main research question: Do tangential shocks shift subjective well-being? To answer this question, we estimate different versions of our multinomial logit model, as given by equation (2). Due to an unbalanced panel at the respondent level and to exploit a sufficient number of person-year observations, we use a pooled sample, as described in Section 3.1.[17] To account for systematic (measurement) error at the household level, we cluster our standard errors at the household level. Potential year- and country-specific effects are absorbed by wave and country fixed effects. We include controls for individuals' demographic and economic background in all our estimations.

The first analysis of subjective well-being determinants is presented in Table A.4 in the Appendix. The results from the baseline specification (Columns (1) and (2)) show the expected effects of our control variables on subjective well-being. Higher per-capita household income is associated with an increased likelihood of reporting a positive well-being dynamic (Δ^+), and analogously, it translates into a lower probability of reporting a negative well-being dynamic (Δ^-). Higher income fluctuations reduce (raise) the probability of being better (worse) off. In line with the literature, we document a direct effect of actual flood shock experience on subjective well-being: those without such an experience are less likely to report negative SWB dynamics.

Having established the basic determinants of subjective well-being dynamics in our sample, we now include our tangential shock indicator in the analysis. Since we are interested in differentiating the effects of TSE for those with and without an actual shock experience, we interact the binary flood experience indicator ($s_{i,t}$) and the tangential shock measure (s^{TSE}). This allows for differentiation of the likely impact of tangential shocks on those individuals who reported an actual shock experience (the reference group) and those who were merely observers. We concentrate on this interaction effect in our main analysis and run several multinomial logit regressions using the tangential shock indicator with various time horizons and radii, as described in Section 3.4. Coefficient estimates for the tangential shock interactions θ are reported in Table 1.[18]

[17] We account for household fixed effects in our sensitivity analysis. We also run alternative specifications controlling for common effects on the province level.

[18] Table A.4 in the appendix exemplifies further details on control variables and model fit using the tangential shock indicator with our baseline thresholds (i.e., 5 km radius and a 12-month time horizon). We abstain from presenting full regression outputs for all specifications for the sake of simplicity.

Table 1: TSE interaction estimates for θ (various time horizons and spheres of interest)

	1 Month		3 Months		12 Months	
SWB response category	Δ^+	Δ^-	Δ^+	Δ^-	Δ^+	Δ^-
1 km	-0.063	-0.052	-0.015	-0.010	-0.003	-0.000
	(0.067)	(0.067)	(0.024)	(0.026)	(0.005)	(0.005)
2 km	0.023	0.021	0.004	0.016	0.000	0.004
	(0.038)	(0.039)	(0.013)	(0.016)	(0.003)	(0.003)
3 km	0.034	0.034	0.009	**0.021***	0.003	**0.006****
	(0.030)	(0.029)	(0.010)	(0.012)	(0.002)	(0.003)
4 km	0.019	**0.041***	0.007	**0.021****	0.002	**0.006****
	(0.022)	(0.023)	(0.008)	(0.010)	(0.002)	(0.002)
5 km	0.018	**0.043****	0.007	**0.021*****	0.002	**0.005*****
	(0.019)	(0.019)	(0.007)	(0.008)	(0.002)	(0.002)

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

Note: All specifications include sociodemographic (age, age squared, gender, health dynamics, marital status, religion, educational attainment and occupational status) and socioeconomic (relative income, income dynamics) controls, as well as year and country FE. Standard errors (in parentheses) are clustered at the household level. All estimations are based on the identical sample comprising of 17,346 observations.

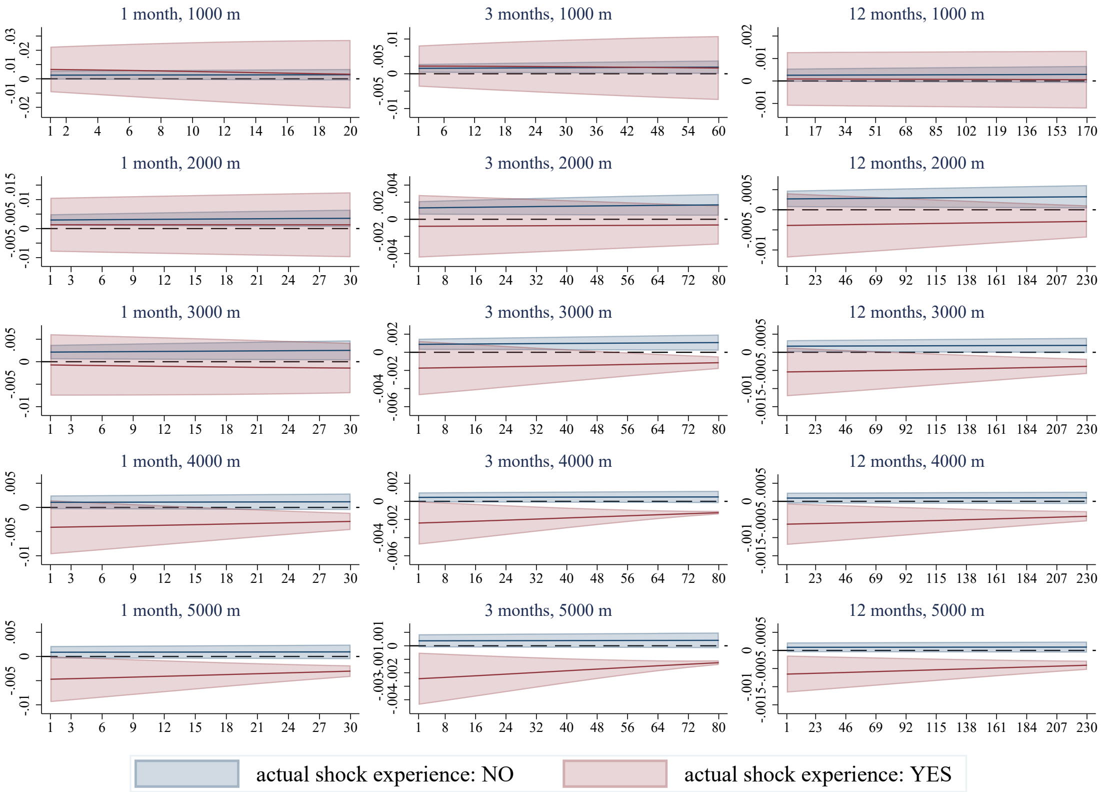
The results in Table 1 document significant interaction effects, mostly for larger radii (with a radius of at least 3 km). We also see that these findings are asymmetric, i.e., restricted to negative well-being dynamics (Δ^-). A positive interaction coefficient θ implies that the well-being dynamics of individuals without any shock experience are indeed sensitive to exposure to a tangential shock: they seem more likely to report a decline in subjective well-being than those who reported a shock experience in the last 12 months.

To provide a more refined interpretation of the results for the tangential shock indicator, we transform coefficient estimates from the nonlinear multinomial logit model, displayed in Table 1, into directly interpretable average marginal effects (AME). This allows us to investigate the overall relevance of the observed effects based on the significant coefficient estimates in Table 1. Figure 3 therefore illustrates the corresponding average marginal effects in the negative SWB domain.[19]

A first comparison of the absolute sizes of the average marginal effects reveals a more differentiated picture than the previous coefficient estimates suggested. Average marginal effects decrease with higher radii and increasing time horizons; i.e., the effect of tangential shocks is stronger for events that occur closer to a respondent's residence and in the more recent past.

[19] Figure A.2 in the Appendix provides an overview of both the positive and negative SWB dynamics. There we also account for different effects depending on the intensity of the tangential shock; AMEs are evaluated at the TSE indicator's mean, 90^{th} and 95^{th} percentile.

Figure 3: Average marginal effects for negative SWB dynamics



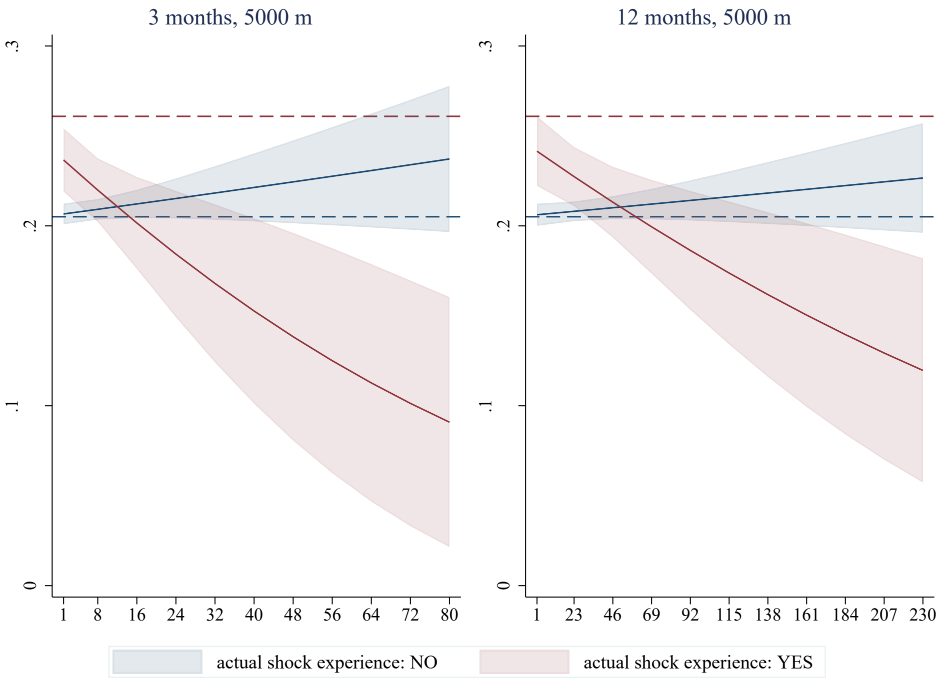
Note: All marginal effects draw upon the same sample comprising of 17,346 observations. The depicted response and shock-experience-specific average marginal effects have been evaluated over the range of the tangential shock measure, depicted on the x-axis. The shaded areas indicate the 90% confidence intervals.

With the 90% confidence band being just above zero (dashed line), the results suggest that individuals without any shock experience (blue graph) are on average more likely to report negative well-being dynamics only for smaller spheres of interest (up to 2,000 m). In the case of at least intermediate radii or time horizons, the confidence bands of the two groups (those with and without actual shock experience) do not overlap–the average marginal effects, and thus perceptions of SWB, differ notably between these groups.

The average marginal effects for those with an actual shock experience (red graph) are inverted and significantly negative for more severe tangential shock events: given an actual shock experience, prolonged tangential shock exposure does not increase the likelihood a respondent reports a negative subjective well-being dynamic. In fact, those who suffered an actual shock seem less affected by an incremental increase in tangential shock exposure since they are less likely to report a deterioration of their SWB. This could be interpreted as a form of resilience to such an adverse condition. Yet, ever-increasing TSE exposure has a dampening effect on negative SWB dynamics for individuals with actual shock experience. The positive slope of the AME curve for this group, gradually converging towards zero, indicates that more intensive tangential shocks may increase resilience only up to a certain point.

To demonstrate the size of the observed effects, Figure 4 shows the predicted probabilities of negative SWB dynamics for different levels of TSE intensities on the x-axis.

Figure 4: Predicted probabilities for negative SWB dynamics



Note: Horizontal dashed lines represent the group-specific in-sample probabilities for negative SWB dynamics. The x-axis depicts the intensity of TSE.

We see a mild increase in the probability of a negative SWB dynamic for those without actual shock experience if the intensity of the TSE increases. This reflects our initial expectation that those without any actual shock experience will still feel worse off if they are exposed to tangential shock events. For those actually suffering a shock, predicted negative SWB dynamics are substantially dampened and notably below the group-specific unconditional probability (26%, depicted as a dashed red line): exposure to a tangential shock event lasting for a cumulative month (30 days) in the last quarter reduces the expected probability of a negative SWB dynamic by almost 10 percentage points relative to the unconditional probability. A similar TSE in the last 12 months would still result in a 4 percentage-point reduction in negative SWB dynamics.

These findings have an important implication: if SWB is measured during a season with frequent TSE exposure, individuals not hit by a shock may report more negative outcomes, whereas those actually hurt by the shock may develop resilience due to the additional TSE exposure. Thus, the reporting of subjective well-being might be distorted. Interviewing individuals and asking for their subjective evaluations directly after they *observed* a shock or traumatic event may result in a misrepresentation of well-being levels.

4.2 Sensitivity analyses

This section describes various robustness tests for our main analysis, addressing concerns about control variables, attrition and unobserved heterogeneity. Output tables are presented in the Appendix.

Shock severity Our analysis builds on different intensities of TSE exposure. So far, however, we have not accounted for variation in the intensity levels of actual flood shock experiences; respondents were either affected or not. In the first sensitivity analysis, we demonstrate that our findings are upheld if we allow actual shock experience to vary in its severity. Table A.4 (Models 2 and 4) shows that both the magnitude and precision of our TSE estimate remain comparable for different specifications of the actual shock indicator variable.[20]

Exposure to other environmental shocks The households in our sample are largely involved in agricultural activities, which explains their overall responsiveness to an environmental shock such as flooding. However, other (possibly correlated) environmental shocks could also be impacting on SWB dynamics. To this end, we integrate three additional environmental shock experiences during the last 12 months: drought, storm, and snow or freezing rain. This does not impact our TSE estimate. However, all three environmental shocks are relevant predictors for negative SWB dynamics (cf. Table A.5, model 1).[21] The same robustness can be observed in the specification where we control for a full set of shocks, including falling victim to a property crime, experiencing a job loss, adverse financial shocks, the death of a household member, etc. (see Table A.5, model 2).

Network effects We also control for the potential transfer of shock-related well-being dynamics between households in the village network. This transfer may be the result of household interdependencies or communication within the village community. The network variable corresponds to the log distance-weighted share of in-sample households (in the same village) who were exposed to a tangential flood shock during the corresponding time horizon.[22] Shock exposure of neighbouring households is weighted more heavily than shock exposure of remote households. With a range between zero and one, our network variable is a proxy for the likelihood of interacting with a fellow villager exposed to a tangential shock. Table A.6 (Model 2) documents the robustness of our findings for various time horizons (3 and 12 months) and spheres of interest (3 and 5 km). Notably, our network variable is significant across specifications with a time horizon of 12 months, yet only for positive well-being dynamics: the larger the share of other households exposed to a tangential shock, the lower is the likelihood a respondent reported an improvement in well-being. Intra-village shock correlation seems to play a relevant role in the formation of subjective well-being, although it does not affect our main results.

Coping strategies Next, we account for the emergence of coping strategies. Households with frequent past exposure to flood shocks might have adapted, and their well-being could be unaffected by tangential shocks. Model 3 in Table A.6 displays the robustness of our findings to controlling for flood history. Accounting for the yearly average exposure to tangential shocks (based on the history from 2004 to the last year prior to the interview in a survey year) does not alter our findings. The same holds for an alternative measure (results not reported) where we only focus on the flood history in the two years prior to the 12-month pre-interview time horizon.

Land usage In another specification (Table A.6, Model 4), we investigate our results' robustness

[20] We show results for the 5 km- and 12-month TSE indicator.

[21] As a type of falsification test, we run a further set of estimations where we interacted all environmental shock experiences with the tangential flood shock measure (model 3). The only significant TSE interaction for negative SWB dynamics is the interaction with the actual flood shock experience.

[22] We also applied equal and linear distance weights. The results were unaffected. We selected the log-distance weights due to a specific desirable feature, i.e., partially reducing the dominance of one very close neighbour over a number of more distant neighbours.

with respect to the diverging possible relevance of events in a given sphere of interest, depending on how households make their livelihoods. In principle, we account for respondents' main occupation in our main analysis; this accounts for the fact that farming households might be more susceptible to (tangential) flood shocks in general. Next, we further account for households' land use, i.e., the overall number of cultivation plots (or the cultivation area) used or owned by the household. Eventually, this could yield a refined interpretation of our results if individuals from farming households with productive assets at stake in a sphere of interest were particularly sensitive with respect to tangential shock events. Although individuals with more farmland at stake (i.e., those that are relatively better off) display positive well-being dynamics more frequently, we still observe the familiar impact of tangential shocks on negative well-being dynamics.

Psychological factors Another important sensitivity check investigates the extent to which observed well-being dynamics are driven by psychological factors. Since our research examines the impact of potentially traumatic events on subjective well-being, these factors could be a potential source of omitted variable bias: both direct shock experience and tangential shock exposure might adversely impact mental health (e.g., Sekulova and Van den Bergh, 2016; von Möllendorff and Hirschfeld, 2016). Simultaneously, we expect worsening mental health to affect subjective well-being levels. To investigate the relevance of indirect psychological effects, we integrate measures of mental health into our analysis. Since there are no direct measures available for our sample, we resort to the self-reported prevalence of *mental issues* and *headaches* as predictors for underlying mental health conditions.[23] This specific sensitivity analysis comes with two additional caveats: first, the sample is reduced by ca. 10% due to a substantial share of missing values in the underlying health-related variable. Another issue is the low general prevalence of both conditions: only 0.3% of respondents declare mental issues, and only 1.2% report headaches.

Table A.7 illustrates that there is no strong correlation between TSE exposure and mental issues or headaches. The retrieved TSE interaction coefficient for the negative well-being domain corresponds to our earlier results. The last two columns of Table A.7 present the direct correlation structure between flood shock experience and exposure and our mental health proxies. We see a minor but significant correlation between mental issues and TSE exposure. However, this effect does not translate into a differential effect of mental issues on SWB between those with and those without direct shock experience. Overall, we do not find evidence that our previously uncovered TSE effects are driven by unobserved psychological conditions.

Sample attrition A further sensitivity analysis assesses whether sample attrition might invalidate our findings. Overall sample attrition is relatively low, with a rate of approximately 2% between each wave. We re-estimate our baseline model, including only respondents from households that are represented in all waves.[24] This approach, following Gröger and Zylberberg (2016)[25], reduces our sample by 140 households (corresponding to 537 respondent-year observations). Our main

[23] The TVSEP questionnaire does not include specific questions on a person's mental health but rather asks the respondent to report on any impairment over the past year. We chose the answer options most closely related to mental health, i.e., mental issues (including unspecified mental disease or depression) and headaches, which have been found to be a comorbidity of anxiety or psychic disorders (Baskin et al., 2006; Mercante et al., 2011; Lampl et al., 2016).

[24] The 2011 wave was run in two provinces only. For a respondent from these provinces to be included, we thus require that their household is represented in six waves in our dataset. For all other provinces, the zero attrition condition requires a household to be present in five waves.

[25] Gröger and Zylberberg (2016) use the Vietnam TVSEP data.

results in this zero-attrition sample (cf. Table A.8) are highly comparable to the overall sample.[26] We thus conclude that sample attrition does not bias our general findings.

Unobserved heterogeneity Our last robustness check assesses the reliability of our previous estimation results with respect to unobserved heterogeneity. Thus far, our estimations were based on a multinomial logit framework in a cross-sectional pooled sample where observations are linked at the household level. This allowed us to examine asymmetric relations between potentially relevant factors across the positive and negative well-being domains. These dynamics, however, are rooted in the cognitive evaluation processes of a responding household member. If certain unobserved household characteristics or respondent traits were correlated with our variables of interest and, at the same time, relevant to the formation of subjective well-being, our previously presented estimates might be biased.

We investigate the influence of such unobserved characteristics, both on the household and the respondent level, by re-estimating our benchmark models (3 km/5 km spheres of interest and 1-/3-/12-month time horizons) in a panel setting. We run fixed-effect multinomial logit models (Pforr, 2014) and panel fixed- and random-effect models. The latter corresponds to a more conventional panel setting and is based on a binary dependent variable, with negative well-being dynamics coded as one. Positive well-being dynamics and stable well-being levels are combined in the reference category. Table A.9 reports the results from our panel models on the respondent level (Panel A) and the household level (Panel B). In the respondent panel, by controlling for unobserved heterogeneity on the respondent level, significant interaction coefficients can be retrieved from the fixed-effects multinomial logit and the random-effects model when larger spheres of interest and longer time horizons are considered but not from the standard panel fixed-effects model. Controlling for unobserved heterogeneity at the household level, however, we once more establish a familiar set of TSE interaction coefficients (Table A.9, Panel B). In accordance with our earlier results, coefficient estimates are significant and of a similar size across all three types of panel estimation models. For the maximum sphere of interest and a time horizon of 3 months, for instance, we obtain an estimate of 0.0029 (corresponding to a 0.29 percentage-point change) in both the panel FE and RE specifications: in these linear models, an additional flood exposure episode of one week translates into a 2 percentage point (7×0.29) increase in the probability that a respondent without actual shock experience reports being worse off. Given their baseline response behaviour (20% stating they are worse off), this implies a 10% increase over baseline.

Ultimately, we are confident that controlling for unobserved, potentially correlated factors at the individual or household level in a panel model supports our findings in the linked cross-sectional analysis: the distortionary effects of tangential shocks impinge on the formation of subjective well-being in an asymmetric manner, e.g., by prompting negative well-being dynamics.

4.3 The propagation of TSE into future expectations

In the previous sections, we have shown that tangential shock exposure may sway current SWB dynamics such that respondents without actual shock experience are more likely to report deteriorating SWB (cf. Figure 4). This effect is more pronounced for more recent TSEs, and thus timing matters. In the next step, we are interested in the consequences of this effect. Therefore, a related question is whether this distortionary impact of TSE exposure is restricted to evaluations

[26] As in our previous findings, we do not obtain any significant shock estimates for positive SWB dynamics.

of current well-being dynamics or if it propagates into the formation of well-being expectations for the future.

To investigate a potential forward-carrying effect of TSE exposure, we first examine whether TSE exposure is associated with an update to beliefs about future flood shocks, i.e., respondents are more likely to expect flooding in the future.[27] Subsequently, we investigate whether belief updates are relevant drivers of expectations for future well-being.

Table 2 (Model 1) presents coefficient estimates from a linear probability model predicting a respondent's update to flood shock beliefs. Here, the dependent variable is one if an individual expects a flood shock to occur in the next five years.[28] Individuals without an actual flood shock experience are 51 percentage points less likely to expect a flood shock event in the future than those who experienced a flood shock. Individuals' belief updates seem to be in line with their actual experience. Insignificant TSE estimates, on the other hand, highlight that their exposure to TSEs does not impact their belief formation.

Table 2: Belief updates and future SWB expectations (maximum flood exposure, 5km, 12 months)

	(1) FW shock believe update	(2) Future SWB expectations		(3) Future SWB expectations + belief updating	
	s_F	Δ_F^+	Δ_F^-	Δ_F^+	Δ_F^-
s (no shock)	-0.5119^{***}	0.0903	0.0936	-0.0222	-0.0507
	(0.0135)	(0.0760)	(0.1185)	(0.1480)	(0.2355)
s^{TSE}	-0.0002	0.0042^{***}	-0.0061^{**}	0.0042^{***}	-0.0060^{**}
	(0.0003)	(0.0016)	(0.0030)	(0.0016)	(0.0029)
$s \times s^{TSE}$	0.0003	-0.0037^{**}	0.0063^{**}	-0.0037^{**}	0.0062^{**}
	(0.0003)	(0.0017)	(0.0031)	(0.0017)	(0.0031)
Present SWB Δ^+		1.4270^{***}	-0.0587	1.4269^{***}	-0.0587
		(0.0469)	(0.1011)	(0.0469)	(0.1011)
Present SWB Δ^-		-0.0247	1.2130^{***}	-0.0246	1.2131^{***}
		(0.0532)	(0.0714)	(0.0532)	(0.0714)
s_F				-0.1405	-0.1858
				(0.1562)	(0.2531)
$s \times s_F$				0.1339	0.1696
				(0.1652)	(0.2636)
N	13692	13692		13692	

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

Note: All specifications include sociodemographic (age, age squared, gender, health dynamics, marital status, religion, educational attainment and occupational status) and socioeconomic (relative income, income dynamics) controls, as well as year and country FE. Standard errors (in parentheses) are clustered at the household level.

Model (2) presents results for future SWB expectations, which include the full set of our standard controls.[29] We obtain a significant positive TSE interaction coefficient for expected negative SWB dynamics (Δ_F^-). Interestingly, there is also a significant negative interaction estimate for ex-

[27] The household questionnaire includes a section on expected future shocks. The question posed to respondents is: "Do you think that (event xyz) will occur in the next 5 years?" We use this question to measure a respondent's belief updates. A respondent updates his/her belief if he/she becomes more likely to expect a future flood shock in response to a past flood shock experience or TSE exposure.

[28] The full set of variables is only available for the years 2008 to 2016, hence the smaller sample.

[29] Future SWB expectations are captured through the following question: "Do you think you personally will be better off next year?"

pected positive SWB dynamics (Δ_F^+): compared to those with actual shock experience, individuals without such an experience seem to be less optimistic about their future prospects when their TSE exposure is more pronounced. Furthermore, expectations of SWB dynamics are conditional on current SWB evaluations. Individuals reporting positive SWB dynamics over the last year are also more likely to expect future SWB improvement, as signified by the positive coefficient estimate. Those displaying negative past SWB dynamics expect a further downward spiral in the future.

Turning to model (3), which accounts for belief updating in regard to the future occurrence of flood shocks (s_F), we find two interesting insights: (i) flood shock belief updates do not translate into changing SWB expectations, since all estimates related to future flood shock expectations (s_F) are insignificant, and (ii) the influence of tangential shock exposure also remains prevalent in this setting.

Future SWB expectations are hence highly sensitive to TSE exposure. Thus, TSE exposure has the potential to be carried over into the future by lowering an individual's outlook on future well-being dynamics. Most importantly, this is not a result of rationally updated beliefs based on newly acquired information of flood shock frequency or severity in one's sphere of interest. Observing a flood shock, even without being hit or updating beliefs regarding underlying flood risks, is sufficient to trigger negative expectations of future well-being.

4.4 Indirect politico-economic implications of TSE

Thus far, we have established that TSEs may sway both retrospective and prospective SWB dynamics. Since this effect is particularly strong in the short run, one may be tempted to ask why we should care about this observed phenomenon. We will present suggestive evidence that such transitory dynamics could be of interest to policy-makers, especially when designing policies in the aftermath of shock events.

In the context of (environmental) shocks, one particularly relevant practical policy measure comes to mind: the provision of short-term emergency relief and subsequent support schemes. Here, governments or aid organisations redistribute resources towards individuals who have been affected. In the case of governmental measures, public support for such a policy with inherent redistributional features may determine its intensity and duration. The underlying motives for supporting this policy may vary: some citizens may have purely altruistic motives, while others may support it in hope of an amelioration of their own situation. The latter could be expected if the respective individual perceives his or her well-being as dire or deteriorating.

Using data from the 2013 TVSEP wave, we highlight the way in which transitory SWB dynamics, triggered by TSE exposure, could alter the population's support for redistributive policies. Individual support for government redistribution is inferred based on respondents' answers regarding whether the government should redistribute income between richer and poorer households in the respective country: 62% agree, 21% disagree, and the remaining are indifferent. Overall, there seems to be strong support for governmental redistribution among rural households in Thailand and Vietnam.

Table 3 presents the results from various linear probability models where the binary dependent variable indicates support for such governmental redistribution. In this approach, we are not interested in any direct effect of TSE exposure on the outcome. Instead, we ask how potentially distorted individual SWB dynamics may change support for redistribution.

Table 3: SWB dynamics and support for government redistribution

	(1)	(2)	(3)	(3)
s (no shock)	−0.0562	−0.0536	−0.0543	−0.0409
	(0.0466)	(0.0469)	(0.0467)	(0.0502)
s^{TSE}	0.0014	0.0014	0.0014	0.0011
	(0.0013)	(0.0013)	(0.0012)	(0.0013)
$s \times s^{TSE}$	−0.0008	−0.0008	−0.0008	−0.0005
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Future SWB Δ^{+}		−0.0166	−0.0253	−0.0319
		(0.0196)	(0.0207)	(0.0222)
Future SWB Δ^{-}		0.1079***	0.1178***	0.1193***
		(0.0359)	(0.0370)	(0.0387)
Past SWB Δ^{+}			0.0196	0.0265
			(0.0209)	(0.0224)
Past SWB Δ^{-}			−0.0255	−0.0152
			(0.0274)	(0.0294)
Network exposure				0.0471**
				(0.0224)
Observations	2,963	2,963	2,963	2,560

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

Note: TSE exposure is represented by the maximum exposure measure (radius of 5 km, time horizon of 12 months). All specifications include sociodemographic (age, age squared, gender, health dynamics, marital status, religion, educational attainment and occupational status) and socioeconomic (relative income, income dynamics) controls, as well country FE. Standard errors (in parentheses) are clustered at the household level.

The results show that there is, indeed, no direct association between TSE exposure and support for government redistribution. In contrast, we find clear evidence that there is an indirect link via expected future SWB dynamics.[30] Individuals expecting deteriorating future SWB are 10.8 to 11.9 percentage points more likely to support government redistribution. This also holds when we account for flood exposure within the village network, which reflects the relevance of shared flood exposure or potential altruistic tendencies.[31]

If we turn back to Table 2, which displays the relation between TSE exposure and future SWB expectations, we can conclude the following: individuals without direct shock experience but with TSE exposure are relatively more likely to expect negative future SWB dynamics than those who were actually hit by a shock. At the same time, individuals with a negative outlook on their future SWB are also more likely to support government redistribution. Ultimately, there seems to be a relatively higher likelihood of endorsing government redistribution among those who were only exposed to a tangential shock.

[30] We run alternative specifications using the feasible set of additional control variables from our sensitivity analyses. Both findings, i.e., those regarding the lack of a direct TSE effect and the detection of an indirect TSE effect via distorted future SWB dynamics, prove to be robust.

[31] Since this network measure is bound between zero and one, a 10 percentage point increase translates into a 0.47 percentage point higher likelihood to support redistributive policies.

5 Conclusion

Employing a unique household sample from Southeast Asia, we investigate the sensitivity of subjective well-being dynamics to the observation of environmental shocks. We investigate the implications of such tangential shock event (TSE) exposure by studying flood events in rural villages in Thailand and Vietnam. Capitalising on satellite-based, near-real-time flood event data, we compare the well-being dynamics of individuals reporting an actual flood shock experience with the dynamics of those who were not directly hit but lived in close proximity to the flood event.

In the analysis, we establish three essential findings. (i) In our main analysis, we document that merely witnessing a flood event can be sufficient to trigger negative well-being dynamics. The effects of these tangential shocks are found to be heterogeneous across households and depend on the relative position of a household as well as the timing of the interview. Moreover, the analysis of marginal effects shows that individuals with direct actual flood experience are more resilient to the occurrence of more severe flood events. Once an individual is directly affected by a flood shock of any severity, more extreme flood events do not further depress the subjective well-being dynamics of that individual. For individuals who were not hit by a flood shock, on the other hand, it seems that the lack of direct self-experience translates into an overemphasis on potentially adverse, yet not experienced, consequences. (ii) Our results demonstrate that TSEs not only affect contemporary outcomes but they may also further distort the formation of expectations for the future. We find that witnessing flood shocks without actually being hit translates into less optimistic expectations with respect to the future development of SWB. Notably, we establish that this outcome is not the consequence of a rational belief update. (iii) We note the consequences of potentially distorted SWB expectations for individual preferences towards government redistribution. The results reveal a higher preference for redistribution among individuals with less optimistic future well-being expectations, which are possibly distorted by TSEs.

In conclusion, our findings show that present and future subjective well-being are determined not only by direct (shock) experiences but also by subjective perceptions related to the observation of tangential shock events. Furthermore, we are able to show that these tangential shock events can translate into changing preferences regarding government redistribution.

Our findings are in line with psychological research on witnessing traumatic events. However, we illustrate that the impacts of such events are also relevant in regard to adverse environmental shocks and individuals' subjective well-being dynamics. Hence, we add a new dimension to the research on subjective well-being determinants and provide new insights into individuals' behavioural patterns in the aftermath of a shock event. While we draw upon a sample taken from a rural population in Thailand and Vietnam, we argue that the relevance of our results may extend beyond this population. Various studies (Sarracino et al., 2013; Markussen et al., 2018; Reyes-García et al., 2016) have identified a so-called 'unique happiness function' and have found that determinants of subjective well-being hold for individuals across countries and cultures.

Our findings therefore call for a more cautious interpretation of behavioural responses and well-being measures, as well as a more thorough consideration of the circumstances in which individuals were encountered. Traditional survey instruments do not capture such tangential events. However, in light of our results, researchers might want to consider the dynamic environment respondents face and how they interact with changing conditions in their surroundings.

Moreover, our findings have implications for policy design in the aftermath of (environmental) shock events. Policies designed to alleviate the ramifications of adverse shocks may yield an inefficient usage of resources if target groups are not directly identified based on their true shock experience. Instead, it might be worthwhile to differentiate between individuals who actually suffered a decline in economic well-being due to the shock and those displaying transitory negative well-being dynamics. The former would require material relief, whereas the latter might benefit from information on how to cope with the risk of a recurring shock event.

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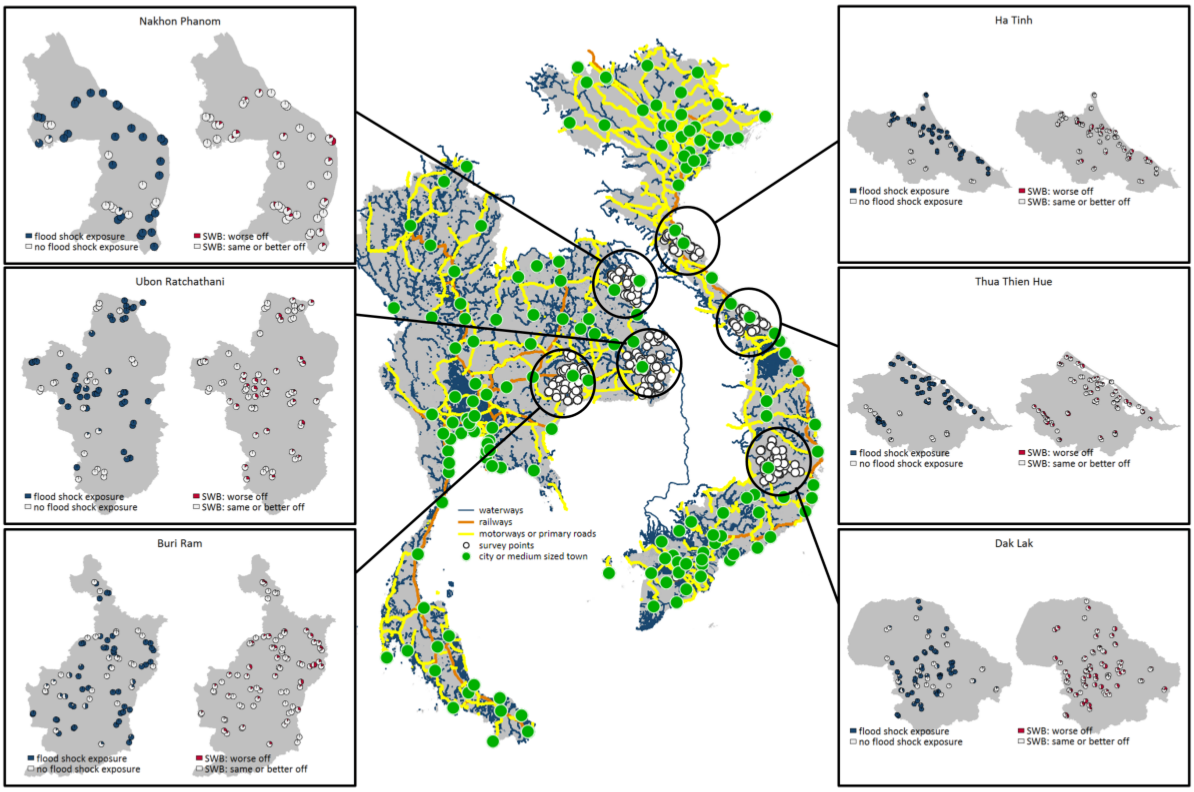
A Appendix

Table A.1: Overall descriptive statistics for model variables in the empirical analyses

Variable label	Short description	min	max	mean	std.dev.
Dependent variables					
past well-being dynamic	individual well-being compared to last year (1: better off 36.2%, 2: same 42.8%, 3: worse off 21.0%)	1	3	-	-
future well-being dynamic	individual well-being in one year (1: better off 51.3%, 2: same 38.3%, 3: worse off 10.4%)	1	3	-	-
shock expectations	flood shock expected to occur within the next five years	0	1	0.301	-
distributional preferences	support for more government redistribution	0	1	0.626	-
Control variables					
HH income p.c.	HH income per nucleus HH member relative to province median	0.000	205.921	1.604	3.338
HH income fluctuation	fluctuation of HH income (1: not at all 39.4%, 2: a bit 49.1%, 3: a lot 11.5%)	1	3	-	-
gender	respondent's gender (0: male, 1: female)	0	1	0.503	-
age	respondent's age	15	93	50.352	13.426
health dynamics	health status compared to one year before (1: worse 32.1%, 2: same 56.9%, 3: better 11.1%)	1	3	-	-
marital status	relationship indicator (1: unmarried 5.3%, 2: married 83.9%, 3: widowed 10.9%)	1	3	-	-
religion	respondent is religious (0: no, 1: yes)	0	1	0.595	-
educational attainment	highest completed educational attainment (0: no schooling 47.8%, 1: primary 27.2%, 2: lower secondary 16.3%, 3: upper secondary 8.6%	0	3	-	-
main occupational status	main occupational status in the last year (0: no occupation 4.4%, 1: housewife/HH-member caretaker 3.1%, 2: casually employed 9.3%, 3: permanently employed 3.6%, 4: own agriculture/hunting 68.8%, 5: own off-farm business 8.7%, 6: government official 2.0%, 7: student/pupil 0.1%)	0	7	-	-
Shock experience variables	(0: no, 1: yes, reversed in estimations for reasons of interpretability				
flood shock	flood shock experience in last 12 months	0	1	0.080	-
flood or heavy rain shock	flood or heavy rain shock experience in last 12 months	0	1	0.090	
severe flood or heavy rain shock	severe flood or heavy rain shock experience in last 12 months	0	1	0.051	
drought shock	drought shock experience in last 12 months	0	1	0.044	-
storm shock	experience of storm shock experience in last 12 months	0	1	0.019	-
ice or snow rain shock	ice or snow rain shock experience in last 12 months	0	1	0.005	-
Sensitivity analyses					
network (r=5000, m=12)	distance weighted share of village HH exposed to TSE in r and m	0	1	0.661	0.464
flood history (r=5000)	HH specific average maximum yearly TSE exposure in r	0	195.333	20.074	37.336
land-use (r=5000)	number of cultivation plots in r	0	28	3.186	1.857
mental issues	serious incidence of mental disease or depression (0: no, 1: yes)	0	1	0.03	
headache	serious incidence of headache in the last year (0: no, 1: yes)	0	1	0.012	

Note: Descriptive statistics for explanatory variables on the household / individual level and flood exposure variables are conditioned on the sample used in the main analysis (n=17,346). Variables from the sensitivity analyses refer to the corresponding sample of each analysis. The same holds for the variables used in Sections 4.3 and 4.4. In case of categorical variables, no means or standard deviations are reported. For binary indicators, the means indicate the share of responses coded as one.

Figure A.1: Environmental conditions, village-level shares of individuals with potential flood shock exposure and well-being dynamics in 2013



Note: Only villages with at least three interviewed households are depicted. The size of the provinces is not necessarily true to scale.

Table A.2: Ex-ante comparability in 2007, by direct shock experience and tangential shock exposure

	Vietnam						Thailand					
	direct experience			TS exposure			direct experience			TS exposure		
	no	yes	P(Test)	no	yes	P(Test)	no	yes	P(Test)	no	yes	P(Test)
N	1,058	447		171	1,334		1,393	243		106	1,530	
Continuous and binary variables												
rel. income p.c.	1.76	1.35	0.0050	1.34	1.68	0.1009	1.65	1.26	0.0256	1.28	1.61	0.1814
female	0.36	0.39	0.3117	0.34	0.38	0.3446	0.53	0.55	0.5568	0.58	0.53	0.3319
age	46.02	43.92	0.0052	42.52	45.77	0.0027	50.81	50.35	0.6068	49.91	50.8	0.4838
Categorical variables												
income fluct.			0.0000			0.0430			0.1460			0.366
health fluct.			0.0040			0.8180			0.2400			0.894
marital status			0.0920			0.0060			0.5200			0.661
education			0.0170			0.6540			0.8230			0.946
occupation			0.0000			0.1390			0.8390			0.3370

Note: For continuous and binary variables, we report group means and applied a T-test with H_0: Group means are identical. Groups are defined as having ever experienced a direct shock experience or having been exposed to a tangential shock (TSE). In case of categorical variables with three or more categories, the samples are evaluated based on a χ^2 test with H_0: Independence of categories and shock experience/exposure.

Table A.3: Overview of Tangential shock indicators

time horizon		Sphere of interest (radius) 1000	2000	3000	4000	5000
1 month	mean	0.209	0.457	0.766	1.143	1.507
	max	22	26	26	27	27
	sd	1.402	2.254	2.965	3.556	4.093
3 months	mean	0.667	1.421	2.322	3.419	4.537
	max	59	77	77	77	77
	sd	3.626	5.772	7.701	9.267	10.783
12 months	mean	4.565	8.712	13.074	17.291	21.522
	max	173	226	226	226	226
	sd	16.67	24.306	30.856	35.604	40.019

Note: Based on the sample used in the main analysis (17,346 observations). Minimum values across indicators, radii and time horizons are zero. The average numbers of included pixels for a given radius are 53, 493 and 1367.

Table A.4: Model comparison: Flood shock experiences and TSE (5 km radius, 12 months)

Specification	Main (Section 4.1)								Robustness (Section 4.2)							
Shock experience	Flood and heavy rain				Flood and heavy rain				Flood only				Severe flood and heavy rain			
TSE exposure	No				Yes				Yes				Yes			
	Δ^+		Δ^-		Δ^+		Δ^-		Δ^+		Δ^-		Δ^+		Δ^-	
	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
HH Income (p.c., rel.)	0.059***	(0.020)	−0.046**	(0.023)	0.059***	(0.020)	−0.046**	(0.023)	0.059***	(0.020)	−0.045**	(0.023)	0.059***	(0.020)	−0.045*	(0.023)
HH Income fluctutation																
Yes, a bit	−0.103***	(0.038)	0.632***	(0.048)	−0.103***	(0.038)	0.635***	(0.049)	−0.103***	(0.038)	0.634***	(0.049)	−0.102***	(0.038)	0.631***	(0.049)
Yes, a lot	−0.287***	(0.070)	1.623***	(0.066)	−0.287***	(0.070)	1.623***	(0.066)	−0.286***	(0.070)	1.624***	(0.066)	−0.285***	(0.070)	1.621***	(0.066)
Gender (female=1)	−0.001	(0.042)	0.051	(0.050)	−0.001	(0.042)	0.052	(0.050)	−0.001	(0.042)	0.051	(0.050)	−0.001	(0.042)	0.049	(0.050)
Age	0.011	(0.010)	0.026**	(0.011)	0.011	(0.010)	0.027**	(0.011)	0.011	(0.010)	0.027**	(0.011)	0.011	(0.010)	0.026**	(0.011)
Age^2	−0.000*	(0.000)	−0.000**	(0.000)	−0.000*	(0.000)	−0.000**	(0.000)	−0.000*	(0.000)	−0.000**	(0.000)	−0.000*	(0.000)	−0.000**	(0.000)
Health dynamics (1 year)																
worse	−0.003	(0.043)	0.591***	(0.047)	−0.003	(0.043)	0.592***	(0.047)	−0.003	(0.043)	0.591***	(0.047)	−0.002	(0.043)	0.591***	(0.047)
better	0.652***	(0.057)	0.124	(0.081)	0.652***	(0.057)	0.125	(0.081)	0.652***	(0.057)	0.124	(0.081)	0.652***	(0.057)	0.127	(0.081)
Marital status																
married	0.268***	(0.087)	−0.010	(0.098)	0.268***	(0.087)	−0.011	(0.098)	0.268***	(0.087)	−0.012	(0.098)	0.268***	(0.087)	−0.012	(0.098)
widowed	0.236**	(0.107)	0.061	(0.117)	0.236**	(0.107)	0.062	(0.117)	0.236**	(0.107)	0.062	(0.117)	0.236**	(0.107)	0.060	(0.117)
Religion (yes=1)	−0.292***	(0.078)	−0.060	(0.082)	−0.290***	(0.078)	−0.057	(0.082)	−0.291***	(0.078)	−0.058	(0.082)	−0.293***	(0.078)	−0.054	(0.082)
Educational attainment																
primary	0.102*	(0.055)	−0.126**	(0.059)	0.102*	(0.055)	−0.126**	(0.059)	0.102*	(0.055)	−0.127**	(0.059)	0.102*	(0.055)	−0.125**	(0.059)
lower secondary	0.288***	(0.063)	−0.070	(0.073)	0.287***	(0.063)	−0.070	(0.073)	0.286***	(0.063)	−0.071	(0.073)	0.287***	(0.063)	−0.070	(0.073)
upper secondary / tertiary	0.193**	(0.078)	−0.165*	(0.096)	0.191**	(0.078)	−0.166*	(0.096)	0.191**	(0.078)	−0.167*	(0.096)	0.191**	(0.078)	−0.164*	(0.096)
Main occupational status																
housewife / home nursing	0.269*	(0.144)	−0.056	(0.146)	0.270*	(0.144)	−0.053	(0.146)	0.269*	(0.144)	−0.056	(0.146)	0.269*	(0.144)	−0.054	(0.146)
casual labour	0.371***	(0.114)	0.074	(0.113)	0.371***	(0.114)	0.078	(0.113)	0.371***	(0.114)	0.078	(0.113)	0.370***	(0.114)	0.076	(0.113)
permanently employed	0.661***	(0.140)	0.090	(0.163)	0.661***	(0.140)	0.093	(0.163)	0.661***	(0.140)	0.090	(0.163)	0.660***	(0.140)	0.094	(0.163)
agriculture	0.486***	(0.103)	−0.096	(0.103)	0.486***	(0.103)	−0.093	(0.103)	0.486***	(0.103)	−0.094	(0.103)	0.487***	(0.103)	−0.095	(0.103)
own business	0.559***	(0.120)	0.128	(0.126)	0.559***	(0.120)	0.127	(0.126)	0.559***	(0.120)	0.128	(0.126)	0.558***	(0.120)	0.127	(0.126)
government official	0.542***	(0.173)	0.114	(0.208)	0.541***	(0.173)	0.116	(0.208)	0.541***	(0.173)	0.115	(0.208)	0.541***	(0.173)	0.116	(0.208)
student/pupil	0.205	(0.815)	−0.629	(1.172)	0.237	(0.831)	−0.541	(1.201)	0.230	(0.827)	−0.540	(1.201)	0.207	(0.816)	−0.609	(1.181)
no shock experience (s)	−0.011	(0.069)	−0.141**	(0.071)	−0.054	(0.079)	−0.252***	(0.081)	−0.031	(0.084)	−0.279***	(0.085)	0.069	(0.104)	−0.404***	(0.099)
TSE exposure (s^{TSE})					−0.002	(0.002)	−0.005**	(0.002)	−0.001	(0.002)	−0.005**	(0.002)	−0.000	(0.003)	−0.007**	(0.003)
$s \times s^{TSE}$					0.002	(0.002)	0.005***	(0.002)	0.001	(0.002)	0.006***	(0.002)	0.000	(0.003)	0.007**	(0.003)
N (HH cluster)	17,346 (3,543)				17,346 (3,543)				17,346 (3,543)				17,346 (3,543)			
LL	-17329.55				-17325.56				-17325.06				-17320.58			
df_m	56.00				60.00				60.00				60.00			
Wald chi2	1760.45				1768.45				1766.38				1785.54			
p(chi2)	0.0000				0.0000				0.0000				0.0000			

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

Note: All specifications include year and country FE. Standard errors are clustered at the household level. x denotes an interaction.

Table A.5: The influence of other types of shocks

Model	(1)		(2)		(3)	
	Δ^+	Δ^-	Δ^+	Δ^-	Δ^+	Δ^-
no flood shock experience (s)	-0.0522	-0.2283^{***}	-0.0596	-0.1880^{**}	-0.0668	-0.1866^{**}
	(0.0790)	(0.0815)	(0.0794)	(0.0824)	(0.0799)	(0.0826)
TSE exposure (s^{TSE})	-0.0021	-0.0046^{**}	-0.0019	-0.0041^{**}	0.0048	-0.0063
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0048)	(0.0055)
$s \times s^{TSE}$	0.0020	0.0052^{***}	0.0019	0.0046^{**}	0.0018	0.0048^{**}
	(0.0019)	(0.0020)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
no drought shock	0.1782^{***}	-0.1050^{*}	0.1708^{***}	-0.0444	0.1780^{***}	-0.0568
	(0.0530)	(0.0601)	(0.0535)	(0.0626)	(0.0576)	(0.0680)
no storm shock	-0.0392	-0.2394^{**}	-0.0386	-0.1931^{*}	-0.0990	-0.1544
	(0.0895)	(0.0979)	(0.0898)	(0.1003)	(0.1050)	(0.1186)
no snow / ice rain shock	0.0013	-0.4923^{***}	-0.0026	-0.4982^{***}	0.2268	-0.5526^{***}
	(0.1448)	(0.1422)	(0.1454)	(0.1447)	(0.1834)	(0.1782)
other shocks	No		Yes		Yes	
env. shock $\times s^{TSE}$	No		No		Yes	
N (HH clusters)	17,346 (3,543)		17,346 (3,543)		17,346 (3,543)	
Wald χ^2 (P $> \chi^2$)	1800.17 (0.0000)		1955.35 (0.0000)		1965.80 (0.0000)	

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

Note: All specifications include the full set of sociodemographic and socioeconomic controls, as well as year and country FE. Standard errors are clustered at the household level. $\times$ denotes an interaction.

Table A.6: Tangential shocks sensitivity analysis - Network effects, coping strategies and land usage

	(1)		(2)		(3)		(4)	
	Δ^+	Δ^-	Δ^+	Δ^-	Δ^+	Δ^-	Δ^+	Δ^-
				Panel A: 3000m, 3 months				
s (no shock)	−0.0360	−0.1342*	−0.0431	−0.0925	−0.0432	−0.0929	−0.0267	−0.0954
	(0.0721)	(0.0755)	(0.0762)	(0.0807)	(0.0762)	(0.0807)	(0.0766)	(0.0808)
s^{TSE}	−0.0079	−0.0138	−0.0112	−0.0150	−0.0106	−0.0177	−0.0099	−0.0177
	(0.0101)	(0.0115)	(0.0108)	(0.0124)	(0.0114)	(0.0132)	(0.0114)	(0.0132)
$s \times s^{TSE}$	0.0088	0.0197*	0.0111	0.0198	0.0110	0.0198	0.0109	0.0195
	(0.0100)	(0.0118)	(0.0104)	(0.0125)	(0.0104)	(0.0125)	(0.0104)	(0.0125)
Network			−0.0047	0.0210	−0.0006	0.0014	−0.0004	−0.0002
			(0.0674)	(0.0743)	(0.0722)	(0.0820)	(0.0722)	(0.0825)
Flood history					−0.0002	0.0010	−0.0001	0.0010
					(0.0015)	(0.0017)	(0.0015)	(0.0017)
Land use							0.0453***	−0.0154
							(0.0119)	(0.0141)
				Panel B: 3000m, 12 months				
s (no shock)	−0.0522	−0.1601**	−0.0650	−0.1148	−0.0690	−0.1227	−0.0521	−0.1245
	(0.0752)	(0.0790)	(0.0797)	(0.0842)	(0.0797)	(0.0843)	(0.0801)	(0.0844)
s^{TSE}	−0.0028	−0.0043*	−0.0031	−0.0040	−0.0062*	−0.0092***	−0.0059*	−0.0091***
	(0.0024)	(0.0025)	(0.0026)	(0.0027)	(0.0032)	(0.0034)	(0.0032)	(0.0035)
$s \times s^{TSE}$	0.0028	0.0055**	0.0033	0.0051*	0.0035	0.0054*	0.0034	0.0053*
	(0.0024)	(0.0026)	(0.0026)	(0.0027)	(0.0025)	(0.0027)	(0.0026)	(0.0027)
Network			−0.0837*	−0.0134	−0.0871*	−0.0199	−0.0893*	−0.0156
			(0.0470)	(0.0535)	(0.0471)	(0.0538)	(0.0472)	(0.0540)
Flood history					0.0033	0.0055**	0.0033	0.0055**
					(0.0022)	(0.0023)	(0.0022)	(0.0024)
Land use							0.0455***	−0.0155
							(0.0119)	(0.0141)
				Panel C: 5000m, 3 months				
s (no shock)	−0.0511	−0.1668**	−0.0570	−0.1233	−0.0572	−0.1240	−0.0392	−0.1269
	(0.0752)	(0.0783)	(0.0795)	(0.0837)	(0.0795)	(0.0838)	(0.0800)	(0.0838)
s^{TSE}	−0.0078	−0.0156**	−0.0071	−0.0161**	−0.0087	−0.0181**	−0.0079	−0.0178**
	(0.0070)	(0.0072)	(0.0074)	(0.0078)	(0.0079)	(0.0085)	(0.0079)	(0.0085)
$s \times s^{TSE}$	0.0074	0.0178**	0.0076	0.0172**	0.0076	0.0172**	0.0076	0.0169**
	(0.0070)	(0.0075)	(0.0072)	(0.0079)	(0.0072)	(0.0079)	(0.0072)	(0.0079)
Network			−0.0338	0.0370	−0.0436	0.0242	−0.0485	0.0213
			(0.0577)	(0.0641)	(0.0606)	(0.0684)	(0.0608)	(0.0686)
Flood history					0.0006	0.0008	0.0007	0.0008
					(0.0012)	(0.0014)	(0.0012)	(0.0014)
Land use							0.0472***	−0.0160
							(0.0118)	(0.0144)
				Panel A: 5000m, 12 months				
s (no shock)	−0.0596	−0.1880**	−0.0749	−0.1390	−0.0767	−0.1429	−0.0572	−0.1444
	(0.0794)	(0.0824)	(0.0842)	(0.0880)	(0.0843)	(0.0880)	(0.0848)	(0.0880)
s^{TSE}	−0.0019	−0.0041**	−0.0017	−0.0038*	−0.0026	−0.0055**	−0.0024	−0.0054**
	(0.0019)	(0.0019)	(0.0020)	(0.0020)	(0.0025)	(0.0026)	(0.0025)	(0.0026)
$s \times s^{TSE}$	0.0019	0.0046**	0.0021	0.0043**	0.0022	0.0043**	0.0021	0.0042**
	(0.0019)	(0.0019)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Network			−0.1066**	0.0090	−0.1075**	0.0070	−0.1111**	0.0168
			(0.0475)	(0.0546)	(0.0475)	(0.0547)	(0.0477)	(0.0550)
Flood history					0.0010	0.0019	0.0010	0.0018
					(0.0016)	(0.0019)	(0.0016)	(0.0019)
Land use							0.0478***	−0.0159
							(0.0118)	(0.0143)
N (HH cluster)	17,346 (3,543)		15,310 (3,159)		15,310 (3,159)		15,230 (3,159)	
Other shocks	Yes		Yes		Yes		Yes	

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

Note: All models include our full set of sociodemographic controls, as well as year and country FE. Standard errors (in parentheses) are clustered at the household level. Network refers to the distance weighted share of in-sample households within a village which have been exposed to a tangential shock in their maximum sphere of interest in the previous year. Flood history represents the household specific average yearly exposure to the corresponding tangential shock since 2004. The land-use control specification accounts for the number of cultivation area plots in a sphere of interest.

Table A.7: Tangential shocks and indirect psychological effects

	SWB				mental issues	headache
	Δ^{+}	Δ^{-}	Δ^{+}	Δ^{-}		
TSE radius / time horizon	5km / 3 months		5km / 12 months		5km / 12 months	
no shock experience (s)	−0.0610	−0.2400***	−0.0675	−0.2555***	−0.0004	0.0009
	(0.0779)	(0.0809)	(0.0823)	(0.0850)	(0.0015)	(0.0042)
TSE exposure (s^{TSE})	−0.0052	−0.0138*	−0.0013	−0.0035*	−0.0000*	−0.0001
	(0.0072)	(0.0077)	(0.0020)	(0.0020)	(0.0000)	(0.0001)
$s \times s^{TSE}$	0.0049	0.0170**	0.0013	0.0043**	0.0000	0.0001
	(0.0073)	(0.0080)	(0.0020)	(0.0021)	(0.0000)	(0.0001)
mental issues	0.2370	0.5719	0.2367	0.5735		
	(0.3496)	(0.4118)	(0.3495)	(0.4120)		
headache	−0.1902	0.2340	−0.1900	0.2314		
	(0.1831)	(0.1880)	(0.1832)	(0.1882)		
N	15,885		15,885		15,885	15,885

Note: All models include our full set of sociodemographic and socioeconomic controls, as well as year and country FE. Standard errors are clustered at the household level.

Table A.8: Attrition analysis - Shock-related estimates for negative SWB dynamics

radius (meter)	3000	4000	4000	5000	5000	5000
months	12	3	12	1	3	12
no shock experience (s)	−0.1994**	−0.1959**	−0.2176***	−0.1937**	−0.2144***	−0.2336***
	(0.0792)	(0.0770)	(0.0807)	(0.0770)	(0.0783)	(0.0824)
TSE exposure (s^{TSE})	−0.0037	−0.0155*	−0.0042*	−0.0314*	−0.0157**	−0.0040**
	(0.0026)	(0.0092)	(0.0022)	(0.0187)	(0.0074)	(0.0019)
$s \times s^{TSE}$	0.0047*	0.0178*	0.0046**	0.0371*	0.0177**	0.0045**
	(0.0027)	(0.0095)	(0.0022)	(0.0194)	(0.0077)	(0.0020)
N	16,809	16,809	16,809	16,809	16,809	16,809

Note: All models include the full set of sociodemographic and socioeconomic controls, as well as year and country FE. Standard errors are clustered at the household level.

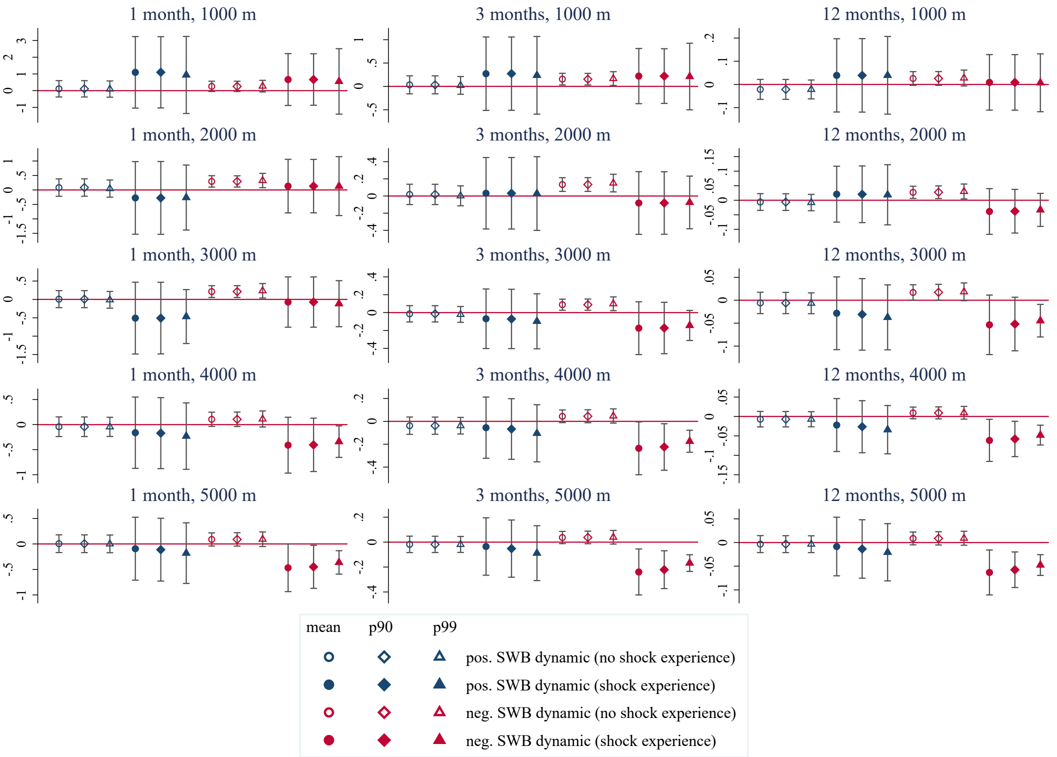
Table A.9: Tangential shocks in Fixed and Random Effects models for negative SWB dynamics

Model		(1)		(2)	(3)	(4)		(5)	(6)
Radius		3km				5 km			
Estimation		FEMlogit		FE	RE	FEMlogit		FE	RE
		Δ^{+}	Δ^{-}	Δ^{-}	Δ^{-}	Δ^{+}	Δ^{-}	Δ^{-}	Δ^{-}
	Months								
		Panel A: Respondent panel							
s (no shock)	1	0.0943	−0.1345	−0.0079	0.0012	0.0612	−0.1510	−0.0340**	−0.0343***
		(0.0951)	(0.1033)	(0.0073)	(0.0052)	(0.0981)	(0.1064)	(0.0152)	(0.0130)
s^{TSE}		−0.0328	−0.0667	−0.0314**	−0.0283**	−0.0341	−0.0560*	−0.0074*	−0.0037
		(0.0422)	(0.0484)	(0.0146)	(0.0125)	(0.0252)	(0.0305)	(0.0038)	(0.0030)
$s \times s^{TSE}$		0.0348	0.0527	0.0047	0.0010	0.0368	0.0367	0.0037	0.0048
		(0.0388)	(0.0449)	(0.0069)	(0.0054)	(0.0238)	(0.0276)	(0.0035)	(0.0031)
s (no shock)	3	0.1041	−0.1561	−0.0042	−0.0015	0.0607	−0.1713	−0.0371**	−0.0386***
		(0.0959)	(0.1035)	(0.0027)	(0.0020)	(0.0997)	(0.1075)	(0.0154)	(0.0132)
s^{TSE}		−0.0039	−0.0299	−0.0360**	−0.0325**	−0.0130	−0.0188	−0.0022	−0.0020*
		(0.0143)	(0.0190)	(0.0148)	(0.0127)	(0.0096)	(0.0121)	(0.0015)	(0.0011)
$s \times s^{TSE}$		0.0057	0.0287*	0.0039	0.0025	0.0117	0.0178	0.0020	0.0026**
		(0.0126)	(0.0173)	(0.0025)	(0.0021)	(0.0087)	(0.0109)	(0.0014)	(0.0012)
s (no shock)	12	0.0853	−0.1854*	−0.0014**	−0.0006	0.0559	−0.1818	−0.0393**	−0.0430***
		(0.1009)	(0.1077)	(0.0006)	(0.0004)	(0.1064)	(0.1123)	(0.0163)	(0.0140)
s^{TSE}		−0.0033	−0.0096**	−0.0400**	−0.0370***	−0.0025	−0.0046	−0.0007	−0.0006**
		(0.0041)	(0.0046)	(0.0155)	(0.0134)	(0.0030)	(0.0036)	(0.0005)	(0.0003)
$s \times s^{TSE}$		0.0023	0.0071**	0.0009*	0.0008*	0.0027	0.0042	0.0005	0.0007**
		(0.0031)	(0.0036)	(0.0005)	(0.0004)	(0.0024)	(0.0027)	(0.0004)	(0.0003)
N		12,958		15,534	15,534	12,958		15,534	15,534
		Panel B: Household panel							
s (no shock)	1	0.0591	−0.1368	−0.0129*	−0.0004	0.0373	−0.1633*	−0.0326**	−0.0332***
		(0.0812)	(0.0896)	(0.0067)	(0.0050)	(0.0845)	(0.0923)	(0.0137)	(0.0122)
s^{TSE}		−0.0227	−0.0888**	−0.0290**	−0.0273**	−0.0275	−0.0701***	−0.0094***	−0.0045
		(0.0358)	(0.0401)	(0.0132)	(0.0118)	(0.0217)	(0.0257)	(0.0036)	(0.0029)
$s \times s^{TSE}$		0.0270	0.0612	0.0080	0.0030	0.0252	0.0500**	0.0063*	0.0057*
		(0.0326)	(0.0376)	(0.0064)	(0.0052)	(0.0200)	(0.0233)	(0.0033)	(0.0030)
s (no shock)	3	0.0624	−0.1516*	−0.0051**	−0.0018	0.0333	−0.1839*	−0.0358**	−0.0371***
		(0.0821)	(0.0903)	(0.0025)	(0.0019)	(0.0859)	(0.0939)	(0.0140)	(0.0124)
s^{TSE}		−0.0060	−0.0338**	−0.0321**	−0.0311***	−0.0131	−0.0249**	−0.0031**	−0.0023**
		(0.0123)	(0.0169)	(0.0134)	(0.0119)	(0.0086)	(0.0104)	(0.0014)	(0.0011)
$s \times s^{TSE}$		0.0064	0.0297*	0.0044*	0.0029	0.0089	0.0226**	0.0029**	0.0029**
		(0.0106)	(0.0154)	(0.0023)	(0.0020)	(0.0076)	(0.0094)	(0.0013)	(0.0011)
s (no shock)	12	0.0394	−0.1796*	−0.0014**	−0.0006	0.0228	−0.1958**	−0.0384***	−0.0409***
		(0.0866)	(0.0938)	(0.0006)	(0.0004)	(0.0915)	(0.0982)	(0.0148)	(0.0132)
s^{TSE}		−0.0032	−0.0094**	−0.0358**	−0.0346***	−0.0032	−0.0052*	−0.0008*	−0.0006**
		(0.0035)	(0.0039)	(0.0140)	(0.0125)	(0.0026)	(0.0030)	(0.0004)	(0.0003)
$s \times s^{TSE}$		0.0028	0.0071**	0.0010**	0.0008*	0.0023	0.0052**	0.0007**	0.0008***
		(0.0027)	(0.0030)	(0.0005)	(0.0004)	(0.0021)	(0.0023)	(0.0003)	(0.0003)
N		16,289		17,313	17,313	16,289		17,313	17,313

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

Note: We report results for the 3 km (models 1-3) and 5 km (models 4-6) radius. Model (1) and (4) report results for the fixed effects multinomial logit model for positive and negative SWB dynamics. Model (2), (3), (5), and (6) show results for fixed effects (FE) and random effects (RE) models, with a binary dependent variable that is coded as one if a respondent reported to be worse off, and zero otherwise. The set of explanatory variables comprises the full set of sociodemographic and socioeconomic controls. Samples comprise those individuals (or households) for which we have at least two observations in the dataset. Standard errors (reported in parentheses) are clustered on the household level.

Figure A.2: Average marginal effects (%) for SWB dynamics - maximum days of flood exposure measure



Note: All marginal effects draw upon the main sample of 17,346 observations. The depicted response and shock experience specific average marginal effects have been calculated at the mean, the 90$^{\text{th}}$ and 99$^{\text{th}}$ percentile of the tangential shock variable (maximum days of flood exposure). The whiskers indicate the 90% confidence intervals.