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Direct Shock Experience vs. Tangential Shock Exposure: Indirect Effects of Flood Shocks on Well-Being and Preferences

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Abstract

With extreme weather events on the rise, the question of how witnessing adverse weather events may affect individuals' perception, and consequently their subjective well-being, gains in relevance. To identify events that have been witnessed, i.e., tangential exposure to a weather shock, satellite-based data on flooding is linked to an extensive household panel survey from rural Southeast Asia. Contrasting direct shock experience with tangential shock exposure, we find that mere proximity to a potentially adverse shock, without reporting any actual direct shock experience, could be sufficient to reduce subjective well-being. This effect is not only restricted to the present but can also impinge on expected future well-being dynamics. Eventually, such a persistent effect from witnessing a weather shock may have further politico-economic repercussions, for instance, by altering support for redistribution policies.

JEL classification: I31, Q51, R23

Keywords: environmental shocks, perception, subjective well-being, GIS data, MODIS flood mapping, Thailand Vietnam Socio Economic Panel

1. Introduction

Extreme weather events, such as floods and heavy rain, may not only affect individuals' economic well-being but can have repercussions on their subjective well-being as well.[1] Eventually, this implies that

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1 Subjective well-being can be defined as a function of an individual's personality and their 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

weather shocks have the potential to influence quality of life in a much broader sense. Considering these far-reaching ramifications, it is essential to develop a better understanding of how well-being dynamics across individuals may differ depending on their level of exposure to the underlying shock event.

Previous studies investigate the impact of natural disasters, such as flooding or storm, on subjective well-being (SWB) and demonstrate that adverse shock events can lower SWB (e.g., Maddison and Rehdanz 2011; von Möllendorff and Hirschfeld 2016; Sekulova and Van den Bergh 2016). Until now, however, there has been little evidence on how shock events, which are witnessed but not directly experienced, affect individual SWB. Due to a lack of data on individual shock experience, existing studies mainly compare regions exposed to shocks to regions without shock exposure. This approach does not differentiate whether an individual in an exposed region was indeed directly affected by the shock or not.

This research extends the existing literature by assessing the effects of witnessing nearby shock events on SWB. It contrasts effects between those who experienced a shock (reported at the household level) and those that did not report any shock experience but potentially witnessed a shock (inferred through an external shock measure). Eventually, it can be analyzed whether the SWB levels of these two groups converge in response to witnessing nearby shock events. We call such events *tangential shock events (TSE)* 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 perception. Therefore, this paper also relates to studies from the psychological and medical fields, which discuss 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.

The scenario in which the relevance of TSE exposure will be evaluated is flood events in rural villages in Southeast Asia. Floods pose a severe threat to livelihoods, in particular to rural agricultural communities. Their frequency and severity have increased in many regions and will become even more prominent in the future (IPCC 2021). This also suggests an increase in the relevance of TSEs in the future.

The analysis employs data from an extensive household panel survey in Thailand and Vietnam, as well as high-resolution satellite-based flood data. Ultimately, the main analysis reveals that the mere presence of a flood event can translate into negative SWB dynamics, even if individuals were not affected by the flood itself. Individual behavioral reactions might thus be triggered not only by directly experienced events but also by tangential shocks. This effect is found to be a robust phenomenon, e.g., it also materializes controlling for correlated shocks, potential village network effects, local economic opportunities, flood history, or indirect psychological effects.

Having established a robust relation between TSEs and SWB, the study further investigates whether this is merely a temporary phenomenon. Results indicate that the phenomenon not only emerges for evaluations of retrospective SWB dynamics, but it impacts the formation of expected future SWB dynamics. Such a persistent effect may, in turn, influence decision-making processes or preferences.

Related to the focus on the perception of weather shocks in developing countries, the emergence of shifting preferences regarding redistribution policies as a consequence of altered SWB expectations is investigated. Ultimately, this research illustrates how observing an environmental shock (without being directly affected) may alter policy preferences within the population. Such local changes in redistribution preferences could be an important aspect to be considered when designing disaster relief policies.

The paper is organized as follows: A short literature overview on (environmental) shocks and well-being is followed by an introduction to the data sources and the derivation of TSE indicators. The empirical approach contrasting direct shock experiences and tangential shock exposure is then explained. This is followed by a presentation of the main results, including a detailed sensitivity analysis. Further

different valuations people make regarding their lives, the events happening to them, their bodies and minds, and the circumstances in which they live."

lasting consequences and potential politico-economic implications of TSE are discussed next. The final section synthesizes the findings and concludes.

2. Shocks and Subjective Well-Being in the Literature

There exists an extensive body of literature on the determinants of SWB. A substantial part of these studies focuses on the role of demographic factors, such as age, education, health, personality, and life events (e.g., Myers and Diener 1995; Easterlin 2003; Helliwell 2006; Reyes-García et al. 2016) or socioeconomic aspects, such as income and assets (e.g., Easterlin 2008; Dolan, Peasgood, and White 2008; Reyes-García, et al. 2016). We control for these established factors in the analysis but abstain from providing a more substantive overview of these studies here.[2]

In addition, a number of external circumstances have been found to directly or indirectly affect SWB. For example, high aggregate unemployment rates have been found to negatively affect the SWB of the employed (Clark, Knabe, and Rätzel 2010; Luechinger, Meier, and Stutzer 2010). Metcalfe, Powdthavee, and Dolan (2011) find that the September 11 attacks negatively affected SWB levels in the UK. More recently, scholars have started to assess the impacts of natural disasters, such as droughts (Carroll, Frijters, and Shields 2009; Lohmann, Pondorfer, and Rehdanz 2019), earthquakes (Sapkota 2018), flood events (Luechinger and Raschky 2009; Maddison and Rehdanz 2011; Sekulova and Van den Bergh 2016; von Möllendorff and Hirschfeld 2016; Ahmadiani and Ferreira 2021), forest fires (Kountouris and Remoundou 2011; Ambrey, Fleming, and Manning 2017), or storms (Kimball et al. 2006; von Möllendorff and Hirschfeld 2016; Ahmadiani and Ferreira 2021) on SWB. Most of these studies find that such potentially traumatic events have a negative impact on SWB.

Flood events, in particular, can have a persistent and strong negative effect on SWB (von Möllendorff and Hirschfeld 2016). Luechinger and Raschky (2009) analyze SWB data in 16 European countries to quantify utility losses associated with flooding and find a significant negative effect of flood exposure on SWB. 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 and find a strong negative impact of flooding on SWB. Analyzing data from the United States, Ahmadiani and Ferreira (2021) find a negative effect of extreme weather events, including flooding, on SWB for individuals living in affected areas. Yet, they do not find an impact of such events on the SWB of individuals living in neighboring counties. A cross-section analysis of weather events, including floods, on German households by Osberghaus and Kühling (2016) does not find a direct negative effect of flood events on SWB. However, they find a negative relation between climate change expectations and current SWB, i.e., individuals expecting negative climate effects in the future report lower levels of current SWB. Tu Le (2020) employs data from the same database used in this study and analyzes the effects of floods on household welfare. She observes a negative effect of floods on an aggregated SWB score.

In extension to this literature, a handful of studies assessed the effects of disaster risks on SWB. Two of those studies are concerned with the effects of the nuclear disaster at Fukushima and another two analyze the effects of hurricane risk. Rehdanz et al. (2015) find a negative effect of the Fukushima disaster on SWB for people living in the directly affected areas but not for people that live close to a nuclear power plant in general. However, using a sample from 23 European countries, Welsch and Biermann (2014) show that the Fukushima disaster affected the relationship between SWB and the share of nuclear power in Europe. Berlemann (2016) utilizes data from the World Value Survey to study the effects of hurricane risks on happiness and life satisfaction in several countries around the world. He finds differential effects between

2 It is worth noting that different studies find a sort of "unique happiness function" (Veenhoven 2010; Sarracino et al. 2013; Reyes-García et al. 2016; Markussen et al. 2018). More precisely, the most essential findings on SWB not only hold in high-income countries but also in lower- and middle-income countries. This is relevant as we study effects among a rural population in Thailand and Vietnam.

richer and poorer countries, with the negative effects of hurricane risks being greater in relatively poor countries. Eurich and Berlemann (2020) combine hurricane data from the United States with household data from the Gallup Daily Tracking Survey and study the effect of hurricane risk on self-reported life satisfaction. They identify hurricane risk by zip-code areas and compare regions with relatively higher hurricane risk to those with lower risk. The results reveal a significant negative effect of hurricane risk on life satisfaction, i.e., individuals in regions with higher hurricane risk report lower levels of life satisfaction compared to those from regions with lower hurricane risk.

Overall, there is substantial evidence that the potential exposure to natural disasters, respectively regional disaster risk, can impact negatively on SWB. The study at hand contributes to this literature by investigating heterogeneous effects based on actual shock experiences. In contrast, existing studies typically identify (potential) shock exposure rather than actual shock experience, i.e., the treatment status is defined based on administrative boundaries, like zip-code areas or state lines. This study is distinct in that it identifies actual reported shock experience at the household level and compares it to shock exposure around the homestead using satellite data that provide a spatial resolution of approximately 250 × 250 meters.

3. Introduction to Data Sources and Shock Measurements

3.1. Rural Households in Thailand and Vietnam: Sample Description

This research is based on microdata originating from an extensive household panel in rural Thailand and Vietnam, called the Thailand Vietnam Socio Economic Panel (TVSEP) (Klasen and Waibel 2013).[3] Since 2007, eight TVSEP waves and several smaller add-on surveys have been conducted in Thailand and Vietnam. The survey is conducted in six rural provinces, three in each country.[4] When the survey started in 2007, 4,381 households in 440 villages were interviewed.[5] The same households have been interviewed in each wave.[6]

For the purposes of this research, we use the data obtained from the seven waves between 2007 and 2017.[7] The base sample includes respondents who are at least 15 years old.[8] To account for survey attrition, only observations from households who were still represented in the 2017 wave and at least one additional earlier wave are included.[9] For the analysis, detailed information on households' locations is required. Coordinates for households' homesteads are available from 2016 onward and were collected via GPS devices. Hence, we use the coordinates from 2016 and backdate these coordinates to obtain geolocations for the previous waves. For those without coordinates or not interviewed in 2016, coordinates from 2017 and the same backdating approach are used. This approach provides coordinates for most households in the sample.

Respondents in the sample typically originate from rural, multigenerational households. They are on average 52 years old; the majority are married (83 percent) and engaged in subsistence farming (68 percent). The sample is balanced in terms of gender, and education levels are relatively low, i.e., 75 percent

3 More information and data access can be obtained via the project webpage: https://www.tvsep.de/.

4 The provinces in Thailand are Nakhon Phanom, Ubon Ratchathani, and Buri Ram; Ha Tinh, Thua Thien Hue, and Dak Lak are the Vietnamese provinces.

5 To identify a group that is representative of the rural and vulnerable population within the selected provinces and areas with similar conditions, approximately 2,000 households in each country were selected through a three-stage cluster sampling strategy (cf. Hardeweg, Klasen, and Waibel (2013)).

6 In 2011 only one province in each country was surveyed.

7 The waves took place in 2007, 2008, 2010, 2011, 2013, 2016, and 2017.

8 Across the different waves, the respondents within households have varied in a number of cases. This is accounted for in the sensitivity analysis, where results from panel estimations on the household level are contrasted with those on the respondent level.

9 The sensitivity analysis applies two even stricter non-attrition conditions.

have completed primary schooling at best. The information on individual health dynamics is mixed: approximately 33 percent (11 percent) 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 1.

3.2. Measuring Subjective Well-Being

The variable of interest is self-reported SWB. The relevant survey item is formulated such that respondents identify their level of well-being in relation to one year ago. These recorded changes are referred to as SWB dynamics across this paper. 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: (1) Much better off, (2) Better off, (3) Same, (4) Worse off, (5) Much worse off. Respondents rarely chose either of the two extreme categories (see fig. 1). A total of 35.3 percent of all respondents across the seven waves reported feeling better off or much better off; they display positive well-being dynamics. Some 21.2 percent expressed feeling worse off or much worse off, i.e., they exhibit negative well-being dynamics. The focus of the main analyses is on explaining the emergence of negative well-being dynamics.[10]

The SWB measure in the TVSEP deviates somewhat from standard well-being measures, which typically elicit overall SWB at the interview date on a Likert scale. However, the implemented SWB item corresponds to such measures in that it retrieves levels of change (i.e., dynamics) in SWB over time.[11] The SWB dynamics measure also offers a distinct advantage for our setting: it reflects well-being dynamics over a time horizon of 12 months, which can be directly matched to (shock) events occurring during the same period. In the case of irregular intervals between waves, a constant 12-month reference frame fosters a high degree of comparability of the resulting SWB measure. Moreover, this reference frame with a clear anchor point may facilitate the recall of potentially relevant events occurring during a year with all its seasonal variations.

3.3. Flood Shock Experiences

Since the TVSEP survey has a particular focus on the effects of shocks on vulnerable households in Southeast Asia, respondents answered detailed questions about their own and their household's shock experiences. Based on information from this section, a measure for flood shock experience during the prior 12 months is identified. This time horizon corresponds to the reference period of reported SWB dynamics. The flood shock measure also utilizes information on shock intensity (moderate or severe flood shock experience). In the TVSEP, some 8.1 percent of respondents stated that their household was hit by a flood or heavy rain shock during the respective time horizon; slightly more than half of these households were affected by a severe shock event. The consequences of such shock experiences can be severe: on average, households hit by a severe flood shock suffered a 10.3 percent drop in per capita income (table S1.1).

10 The sensitivity analyses include estimations drawing upon the three main well-being dynamics (better off, same, worse off). While the corresponding results confirm the main findings, they are more difficult to interpret.

11 Using data from a TVSEP add-on survey (Klühs, Koch, and Stein 2019), conducted in November 2017 in Ubon Ratchathani, we can investigate to which extent SWB dynamics are related to SWB components (life satisfaction and happiness). The sample includes 520 respondents who answered both the TVSEP questionnaire and the add-on survey. Respondents expressing positive well-being dynamics reported an average life satisfaction level of 8.01 (median: 8) on an 11-point scale (from not satisfied at all to completely satisfied); the mean for those expressing negative well-being dynamics is 7.16 (median: 7). For happiness levels, the mean in the group reporting positive well-being dynamics amounts to 7.73 (median: 8) and the mean for those with negative well-being dynamics is 6.58 (median: 7). All differences are statistically significant. While reassuring, this correlation between SWB dynamics and SWB levels is not required for this study focusing on SWB changes, attributable to events occurring in the same time horizon. A subjective deterioration of well-being, resulting in preference adjustments, may emerge for overall high levels of well-being as well. Similarly, improvements in the form of positive well-being dynamics may also occur at low levels of SWB.

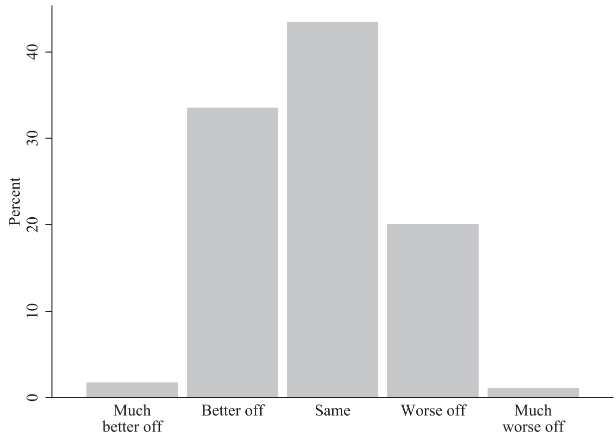
Table 1. Variable Descriptions and Descriptive Statistics

Variable label	Short description	*N*	Min	Max	Mean	Std. dev.
Dependent variables						
Past neg. SWB dynamic	SWB deteriorated over last 12 months	21,839	0	1	0.212	—
Future neg. SWB dynamic	SWB will deteriorate over next 12 months	17,892	0	1	0.105	—
Shock expectations	Flood shock expected to occur within the next five years	17,892	0	1	0.271	—
Redistribution preferences	Support for more government redistribution	2,879	0	1	0.627	—
Control variables						
Rel. HH income p.c.	HH income per nucleus HH member relative to in-sample province median	21,839	0.000	205.921	1.587	3.168
HH income fluctuation	Fluctuation of HH income (1: not at all 38.9%, 2: a bit 49.6%, 3: a lot 11.6%)	21,839	1	3	—	—
Gender	Respondent's gender (0: male, 1: female)	21,839	0	1	0.520	—
Age	Respondent's age	21,839	15	105	52.085	13.551
Health dynamics	Health status compared to one year before (1: worse 32.7%, 2: same 56.7%, 3: better 11.1%)	21,839	1	3	—	—
Marital status	Relationship indicator (1: unmarried 5.4%, 2: married 84.8%, 3: widowed 11.8%)	21,839	1	3	—	—
Educational attainment	Highest completed educational attainment (0: no schooling 47.3%, 1: primary 27.8%, 2: lower secondary 16.1%, 3: upper secondary (or higher) 8.9%	21,839	0	3	—	—
Main occupational status	Main occupational status in the last year (0: no occupation 4.9%, 1: only non-farming occ. 17.8%, 2: farming main occ. 68.8%, 3: farming sec. occ. 9.5%)	21,839	0	3	—	—
Shock experience variables						
Flood or heavy rain shock	Flood or heavy rain shock experience in last 12 months	21,839	0	1	0.089	—
Flood or heavy rain shock severity	Severity of severe flood or heavy rain shock experience in last 12 months (0: none 91.1%, 1: moderate 4.1%, high 4.9%)	21,839	0	2	—	—
Drought shock	Drought shock experience in last 12 months	20,769	0	1	0.129	—
Storm shock	Storm shock experience in last 12 months	20,769	0	1	0.041	—
Ice or snow rain shock	Ice or snow rain shock experience in last 12 months	20,769	0	1	0.016	—
Sensitivity analyses						
Network ($r = 5,000$, $m = 12$)	Distance weighted share of village HH with flood or heavy rain shock experience in past 12 months	20,769	0	1	0.089	0.167
Village agg. (savings)	Share of households in village with access to savings	20,769	0	1	0.599	0.304
Village agg. (transfers)	Share of households in village receiving public transfers	20,769	0	1	0.488	0.350
Village agg. (no occ.)	Share of households in village without occupation	20,769	0	0.571	0.051	0.082
Village agg. (non-farm occ.)	Share of households in village with non-farm occupation	20,769	0	1	0.190	0.179
Flood history ($r = 5,000$)	HH specific average maximum yearly TSE exposure in r	20,769	0	195.333	20.183	37.049
Cultivation plots ($r = 5,000$)	Number of cultivation plots in r	20,769	0	28	3.209	1.919
Rice cultivation ($r = 5,000$, $m = 12$)	Rice was cultivated within r and in growth season during m	15,139	0	1	0.893	—
Mental issues	Serious incidence of mental disease or depression (0: no, 1: yes)	19,723	0	1	0.003	—
Headache	Serious incidence of headache in the last year (0: no, 1: yes)	19,723	0	1	0.013	—

Source: Authors' own calculations based on TVSEP flood data from 2007 to 2017 and MODIS flood data for respective years.

Note: Descriptive statistics for explanatory variables are conditioned on the sample used in the main analysis (21,839 observations). Variables from the sensitivity analyses refer to the corresponding sample of each analysis. The same holds for variables used in the analysis of further implications of TSE. In the case of categorical variables, no means or standard deviations are reported. For binary indicators, the means indicate the share of responses coded as 1.

Figure 1. Distribution of Subjective Well-Being Dynamics on the Individual Level



Source: Authors' own calculations based on TVSEP data from 2007 to 2017.
Note: Displayed subjective well-being dynamics refer to the base sample (21,839 observations).

3.4. Quantifying Tangential Shock Events

We define tangential shock events 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 no actual shock was *directly experienced* or reported as an adverse event hitting a household or individual.

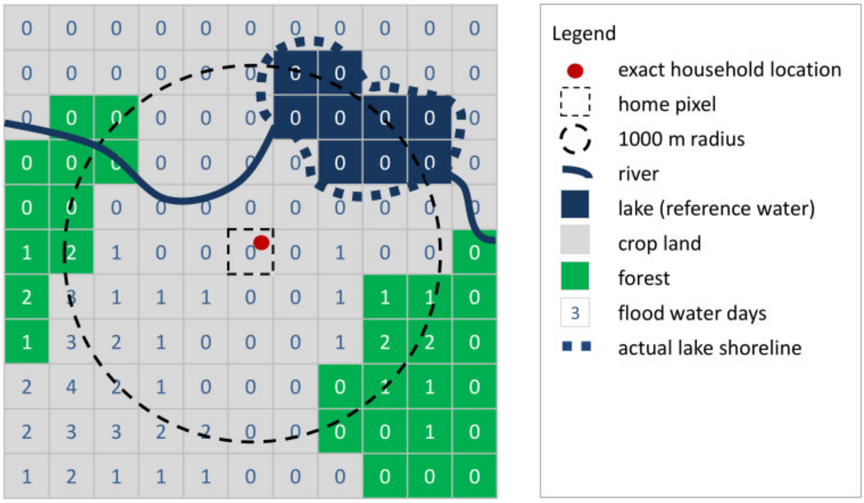
The analysis contrasts tangential flood shock exposure with direct flood shock experiences. Whereas direct shock experience can be identified based on the self-reported shock measure from the survey, the identification of tangential shock events is more challenging. To quantify tangential shock exposure, an *external measure* of shock occurrences is required. To precisely evaluate whether an individual could have observed a shock event, i.e., whether such an event happened near an individual's homestead, these data have to be of sufficient spatiotemporal resolution.

The MODIS near-real-time flood mapping product (Nigro et al. 2014) satisfies the criterion of *external measurability* to construct an indicator for TSE exposure.[12] Based on satellite data, collected twice daily, the MODIS flood mapping algorithm provides information on floodwater 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 rivers. The information on floodwater events is provided at a spatial resolution of approximately 250 × 250 meters: for each of these tiles (or pixels), the number of floodwater days within the observation interval is recorded. 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.[13] Each daily observation in this interval is included as non-missing if three cloud-free observations originating from the respective reference day

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

13 The utilized 14-day composite product has been kindly provided by NASA on special request for 2004 onward (based on the validated MODIS Near Real-Time (NRT) Global Flood Mapping 3-Day Product (3D3OT) v4.9 and augmented by version 5.1). A further merit of flood identification based on multiple water detection 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.

Figure 2. Stylized MODIS Floodwater Data



Source: Authors' own representation based on a fictitious example of MODIS flood data.

or the two previous days are available. A floodwater day is only recorded if water has been detected at least three times among the six satellite transits within this three-day interval. Based on this derivation algorithm, the day count for floodwater can be interpreted as a lower bound.

Based on MODIS flood data, different TSE indicators are constructed according to the following procedure: Using households' homestead coordinates from the TVSEP, the closest 250 × 250-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 kilometers 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 percent of a household's cultivation areas and hence comprises the land most relevant for the livelihood of households that are dependent on agricultural production. A stylized representation of the MODIS floodwater data for a fictitious household, showing the number of flood days within a respective time horizon, is displayed in fig. 2. In addition to the home pixel, it also depicts the relevant pixels in the 1,000-meter radius.

The TSE indicator captures the highest number of flood days that affected any tile within a certain radius of the home pixel over the past 1, 3, or 12 months. The time horizon is conditioned on the exact interview date. Such a maximum day count provides an indicator for the maximum local severity of flooding: the longer it lasts, or the more events occur within a given time horizon, the more likely agricultural production will suffer.

Evaluating TSE exposure over the last 1-month, 3-month, or 12-month horizon allows testing whether any potentially observed tangential shock effects are temporary or more permanent. Hence the derived measure reflects the highly localized household-specific TSE intensity (number of days with floodwater detection on a pixel) within the household's sphere of interest (radius) for a given time horizon.

Descriptive statistics for the TSE indicator across all considered time horizons (1 month, 3 months, 12 months) and spheres of interest (1 km, 2 km, 3 km, 4 km, and 5 km) can be found in table 2. While 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 (5 km radius) amounts to 4.5 days of flooding over 3 months, and 21 days for the 12-month horizon. Some 10 percent of respondents were exposed to flood events covering at least 17 days over 3 months or 76 days over 12 months. These values reflect a

Table 2. Descriptive Statistics of the Tangential Shock Event Indicator

Time horizon		Sphere of interest (radius in meters) 1,000	2,000	3,000	4,000	5,000
1 month	Mean	0.190	0.431	0.740	1.083	1.440
	90th percentile	0	0	0	3	5
	Max	22	25	25	25	26
	Std. dev.	1.290	2.094	2.782	3.335	3.845
3 months	Mean	0.657	1.434	2.403	3.391	4.469
	90th percentile	0	2	6	11	17
	Max	59	77	77	77	77
	Std. dev.	3.607	5.765	7.745	9.141	10.568
12 months	Mean	4.412	8.591	13.063	16.946	21.077
	90th percentile	8	28	45	60	76
	Max	173	226	226	226	226
	Std. dev.	16.040	23.732	30.372	34.929	39.091

Source: Authors' own calculations based on MODIS flood data.
Note: The tangential shock event (TSE) indicator is measured as the maximum number of flood days on any pixel within a certain sphere of interest and time horizon. Results are based on the sample used in the main analysis (21,839 observations). Minimum values across indicators, radii, and time horizons are zero. The average numbers of included pixels (ca. 250 × 250 meters) overlapping with a sphere of interest (increasing from 1,000- to 5,000-meter radius) are 53, 271, 491, 872, and 1,368.

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 SWB.

4. Estimating the Impact of Tangential Shock Events

4.1. Econometric Approach

To examine the impact of tangential shock events on individual SWB, the main analysis estimates a linear probability model (LPM). In the context of the household panel data used, fixed or random effects estimations are employed. The estimation model can be written as

$$P(\Delta \mathrm{SWB}^{-}_{i,t} = 1) = \beta_0 + \beta_1 s^{D}_{i,t} + \beta_2 s^{\mathrm{TSE}}_{i,t} + \beta_3 s^{D}_{i,t} \times s^{\mathrm{TSE}}_{i,t} + \mathbf{x}_{\mathbf{i},\mathbf{t}}\gamma + \phi_i + \mu_{p_i,t} + \varepsilon_{i,t},$$

where $\Delta \mathrm{SWB}^{-}_{i,t}$ is a binary indicator, coded as 1 if an individual reports to be worse or much worse off, and 0 otherwise. The above model thus denotes the probability of individual i displaying negative SWB dynamics in a given year t, i.e., to feel worse off compared to 12 months before. We denote by $s^{D}_{i,t}$ an indicator of direct shock experience during the previous 12 months. In the main specifications, it is a categorical indicator, which not only indicates whether there was any reported shock experience but also reflects the severity of the shock (none, moderate, or severe). This approach accounts for potentially heterogeneous recall probabilities, depending on shock severity. Exposure to TSE is represented by the continuous variable $s^{\mathrm{TSE}}_{i,t}$. This measure reflects the highest number of floodwater days for a given time horizon (1, 3, or 12 months) and sphere of interest (1, 2, 3, 4, or 5 kilometers). Thus, both the direct shock experience measure ($s^{D}_{i,t}$) and the TSE measure ($s^{\mathrm{TSE}}_{i,t}$) capture variations in a respective shock's intensity.

The main objective of this research is to identify the impact of observing a tangential shock (TSE) while not being directly hit by the shock itself. To isolate this effect, two groups of respondents are compared: group one comprises those individuals with direct (severe) shock experience ($s^D = 1, s^{\mathrm{TSE}} > 0$), and group two comprises those not suffering from a direct shock experience but who were exposed to a tangential shock within their sphere of interest ($s^D = 0, s^{\text{TSE}} > 0$).[14]

This comparison is enabled via an interaction between the actual shock experience indicator and the TSE measure: $s^D_{i,t} \times s^{\text{TSE}}_{i,t}$. The resulting set of interaction coefficients β_3 allows to retrieve the impact of observing TSE for those not reporting any direct shock experience. In general, tangential shocks play a role if $\beta_3 \neq 0$ is observed for the group without direct shock experience. If increasing levels of TSE exposure increase the probability of being worse off $P(\Delta\text{SWB}^-_{i,t})$, we would expect $\beta_3 > 0$ for this group. Eventually, the overall effect of TSE exposure, accounting for varying TSE intensities, is the difference in the probability of observing a negative SWB dynamic between individuals from group one and group two.

The analysis controls for a range of individual and household characteristics, which have been found to be important predictors of SWB (cf. Helliwell 2006) and are used in other studies focusing on the effects of environmental shocks on SWB (e.g., Ahmadiani and Ferreira 2021). The vector $x_{i,t}$ includes the following variables: age, age squared, gender, health status, marital status, educational attainment, occupational status, a measure of relative household income,[15] and income dynamics.[16] Depending on the estimation approach, ϕ_i represents panel fixed or random effects; $\mu_{p,t}$ denotes year and year-by-province specific effects. To account for potential measurement errors on the panel level, the preferred specifications employ standard errors clustered at the household level. To partly address potentially correlated flood shock experiences, baseline results with standard errors clustered at the village level are available as well.

Implementing the above-described linear probability model provides easily interpretable insights into how the various shock types impact the probability of observing negative SWB dynamics. However, this approach may not fully account for all information provided in the categorical SWB measure. Therefore, the sensitivity analyses implement ordered logistic regression and a multinomial logit model to exploit more of the information contained in the underlying SWB variable. Since the sets of coefficient estimates obtained from the two models offer a less intuitive interpretation and are generally in line with the results from the panel LPM, the latter is the preferred estimation approach.[17]

We also evaluate the ex ante comparability of respondents across sociodemographic characteristics, with respect to the occurrence of flood shocks, and their comparability in terms of pre-shock SWB outcomes in order to validate the estimation approach. To examine the underlying parallel trend assumption in a short panel with shock experience distributed across all waves, two synthetic treatment and control designs are created: In the static design, the control group comprises households that never experienced a shock across all seven waves, whereas the treatment group are households who experienced a shock only in the last two waves. In the partly dynamic design, the control group consists of households that

14 We are mainly interested in a comparison between these two groups. Technically, however, two other groups of respondents can be identified: group three are those without any direct shock experience and no tangential shock exposure ($s^D = 0, s^{\text{TSE}} = 0$), and group four represents those with direct shock experience and no tangential shock exposure within their immediate sphere of interest ($s^D = 1, s^{\text{TSE}} = 0$). The last group potentially includes cases where remote property had been damaged by a flood shock, while there were no flood events in the vicinity of the homestead. Since over 95 percent of all relevant plots are within 5 kilometers, the potential existence of such cases does not adversely affect the main findings.

15 Relative household income per capita is calculated as households' income per nucleus member, divided by the year and province-specific in-sample median household income per nucleus member. This reflects aspects of the relative income hypothesis (Duesenberry 1949). Since the relative income position will change eventually, low (or high) levels of income will not mechanically translate into ever-increasing probabilities of a certain SWB dynamic.

16 This measure accounts for perceived income fluctuations over the past year. Please refer to table 1 for further information on all variables.

17 The multinomial logit model produces two sets of coefficient estimates by design in this context. Due to a frequent violation of the parallel line assumption in the case of the ordered logit model, a generalized ordered logit estimation is used but it produces two (fully or partially) different sets of estimates as well.

have not yet had a shock experience. Once such an experience is made, they are assigned treatment status for the remaining waves. There are relatively small differences across groups in the respective synthetic pre-shock periods and a widening gap for the synthetic post-shock years (cf. fig. S1.1).

There are some differences in terms of sociodemographic characteristics between those who experienced a direct shock and those lacking such an experience, mostly among Vietnamese respondents (cf. table S1.2). To address this, the respective sociodemographic variables (relative income measures, age, marital status, health dynamics, educational attainment, and occupation) are included as control variables in all models.

After establishing a robust relation between tangential shocks and SWB dynamics, the consequences of TSE for respondents' future SWB expectations are examined. Furthermore, the implications of TSE regarding respondents' redistributive preferences will be evaluated. The estimations in these sections mirror those of the main specification.

4.2. Main Results

This section presents results for the base sample as described in the introduction to the data sources. Several versions of the linear probability model with household fixed or random effects are estimated. Each includes the full set of feasible individual or household control variables, and complete year-by-province fixed effects.

4.2.1. Baseline Determinants of SWB Dynamics

The first set of results originates from a baseline analysis of SWB determinants for the sample. The underlying specification is a modified version of the main estimation, i.e., without the TSE exposure measure. Results are reported in table 3. Direct flood experience (s^D) is first included as a binary indicator (no shock experience versus a shock experience of any severity) to measure whether individuals who experienced any flood shock (models (1) and (2)) are more likely to display negative SWB dynamics. Models (3) and (4) then introduce the previously described categorical flood experience indicator that measures severity (none, moderate, severe). Results show the expected effects of the control variables on SWB dynamics. The higher that per capita income is, relative to the year and province-specific in-sample median income, the lower the probability of observing negative SWB dynamics. Higher income fluctuations raise the probability of being worse off.

In line with the literature, a direct effect of actual flood shock experience on SWB can be observed: compared to individuals having experienced a flood shock (the reference group), those without such an experience are 2 to 2.2 percentage points less likely to display negative SWB dynamics. Differentiating by reported shock severity, those with no (or moderate) direct shock experience are ca. 4.8 to 6 percentage points less likely to display negative SWB dynamics than those with the most severe flood shock experiences. Estimates originating from fixed and random effect estimations are highly comparable.

4.2.2. Introducing the Effects of TSE

Having established the basic determinants of SWB dynamics in the sample, tangential shock measures (s^{TSE}) are included in the analysis and interacted with the respective flood experience indicator (s^D). Benchmark results, which draw upon TSE exposure within a 5-kilometer sphere of interest and a 12-month time horizon, are presented in table 3. When introducing the TSE measure, estimates for the direct shock experience become slightly larger in absolute terms (models (5) to (8)). The TSE interaction estimate for the binary direct flood experience measure and the group without any direct shock experience ($s^D = 0, s^{\text{TSE}} > 0$) turns out to be positive and significant at the 5 percent level in the case of the random effects model. Individuals who did not report being hit by any flood shock were increasingly more likely to report negative SWB dynamics if they observed longer-lasting tangential shock events. When replacing the binary indicator with the categorical flood shock severity indicator, both random and fixed effects

Table 3. Model Comparison for Negative Subjective Well-Being Dynamics—Flood Shock Experiences and Tangential Shock Events (TSE)

	(1) FE		(2) RE		(3) FE		(4) RE		(5) FE		(6) RE		(7) FE		(8) RE	
Estimation method	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 (relative, pc.)	−0.0045***	(0.0011)	−0.0044***	(0.0009)	−0.0045***	(0.0011)	−0.0044***	(0.0009)	−0.0045***	(0.0011)	−0.0044***	(0.0009)	−0.0045***	(0.0011)	−0.0044***	(0.0009)
HH income fluctuation																
Yes, a bit	0.0763***	(0.0060)	0.0897***	(0.0054)	0.0760***	(0.0060)	0.0893***	(0.0054)	0.0765***	(0.0060)	0.0899***	(0.0054)	0.0763***	(0.0060)	0.0896***	(0.0054)
Yes, a lot	0.2778***	(0.0112)	0.3117***	(0.0103)	0.2773***	(0.0112)	0.3110***	(0.0104)	0.2779***	(0.0112)	0.3115***	(0.0103)	0.2774***	(0.0112)	0.3109***	(0.0104)
Age	0.0017	(0.0020)	0.0013	(0.0014)	0.0017	(0.0020)	0.0012	(0.0014)	0.0017	(0.0020)	0.0013	(0.0014)	0.0017	(0.0020)	0.0013	(0.0014)
Age^2	−0.0000	(0.0000)	−0.0000	(0.0000)	−0.0000	(0.0000)	−0.0000	(0.0000)	−0.0000	(0.0000)	−0.0000	(0.0000)	−0.0000	(0.0000)	−0.0000	(0.0000)
Gender (female=1)	0.0006	(0.0079)	0.0032	(0.0062)	0.0002	(0.0079)	0.0029	(0.0062)	0.0006	(0.0079)	0.0032	(0.0062)	0.0003	(0.0079)	0.0029	(0.0062)
Health dynamics (1 year)																
Worse	0.0844***	(0.0072)	0.1075***	(0.0064)	0.0840***	(0.0072)	0.1071***	(0.0064)	0.0843***	(0.0072)	0.1075***	(0.0064)	0.0839***	(0.0072)	0.1071***	(0.0064)
Better	−0.0127	(0.0088)	−0.0198**	(0.0081)	−0.0127	(0.0088)	−0.0197**	(0.0081)	−0.0127	(0.0088)	−0.0198**	(0.0081)	−0.0126	(0.0088)	−0.0196**	(0.0081)
Marital status																
Married	−0.0177	(0.0171)	−0.0242*	(0.0125)	−0.0180	(0.0171)	−0.0243*	(0.0125)	−0.0180	(0.0171)	−0.0243*	(0.0125)	−0.0184	(0.0171)	−0.0244*	(0.0125)
Widowed	−0.0037	(0.0205)	−0.0097	(0.0153)	−0.0043	(0.0205)	−0.0102	(0.0153)	−0.0036	(0.0205)	−0.0096	(0.0153)	−0.0042	(0.0205)	−0.0099	(0.0152)
Educational attainment																
Primary	−0.0159	(0.0122)	−0.0348***	(0.0076)	−0.0160	(0.0122)	−0.0347***	(0.0076)	−0.0159	(0.0122)	−0.0349***	(0.0076)	−0.0160	(0.0122)	−0.0348***	(0.0076)
Lower secondary	−0.0128	(0.0151)	−0.0378***	(0.0095)	−0.0129	(0.0151)	−0.0377***	(0.0095)	−0.0129	(0.0151)	−0.0378***	(0.0095)	−0.0129	(0.0151)	−0.0377***	(0.0095)
Upper secondary/tertiary	−0.0447**	(0.0185)	−0.0460***	(0.0108)	−0.0445**	(0.0185)	−0.0458***	(0.0108)	−0.0445**	(0.0185)	−0.0462***	(0.0108)	−0.0443**	(0.0184)	−0.0460***	(0.0108)
Occupation																
Only non-farming	−0.0051	(0.0171)	−0.0173	(0.0153)	−0.0050	(0.0171)	−0.0172	(0.0153)	−0.0050	(0.0171)	−0.0173	(0.0153)	−0.0050	(0.0171)	−0.0173	(0.0153)
Farming (main)	−0.0050	(0.0172)	−0.0359**	(0.0149)	−0.0050	(0.0172)	−0.0359**	(0.0149)	−0.0050	(0.0172)	−0.0358**	(0.0149)	−0.0050	(0.0172)	−0.0358**	(0.0149)
Farming (secondary)	−0.0096	(0.0194)	−0.0387**	(0.0169)	−0.0094	(0.0194)	−0.0385**	(0.0169)	−0.0097	(0.0194)	−0.0386**	(0.0169)	−0.0095	(0.0194)	−0.0383**	(0.0169)
Shock experience (s)																
None (vs. any)	−0.0201*	(0.0112)	−0.0221**	(0.0102)	—	—	—	—	−0.0304**	(0.0132)	−0.0334***	(0.0118)	—	—	—	—
None (vs. severe)	—	—	—	—	−0.0475***	(0.0159)	−0.0495***	(0.0142)	—	—	—	—	−0.0656***	(0.0183)	−0.0670***	(0.0163)
Moderate (vs. severe)	—	—	—	—	−0.0583***	(0.0207)	−0.0595***	(0.0189)	—	—	—	—	−0.0738***	(0.0238)	−0.0722***	(0.0217)
TSE exposure (s^{TSE})	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	
s(none) × s^{TSE}	—	—	—	—	—	—	—	—	0.0005	(0.0003)	0.0006**	(0.0003)	—	—	—	—
s(any) × s^{TSE}	—	—	—	—	—	—	—	—	−0.0007*	(0.0004)	−0.0005*	(0.0003)	—	—	—	—
s(none) × s^{TSE}	—	—	—	—	—	—	—	—	—	—	—	—	0.0009**	(0.0005)	0.0009**	(0.0004)
s(moderate) × s^{TSE}	—	—	—	—	—	—	—	—	—	—	—	—	0.0008	(0.0006)	0.0007	(0.0005)
s(severe) × s^{TSE}	—	—	—	—	—	—	—	—	—	—	—	—	−0.0011**	(0.0005)	−0.0009**	(0.0004)

Source: Authors' own calculations based on TVSEP data from 2007 to 2017 and MODIS flood data for respective years.

Note: TSE indicator refers to a 5 km sphere of interest and a 12 months time horizon. Sample size across all fixed effects (FE) or random effects (RE) household panel estimations is 21,839 (3,721 HH clusters). All specifications include the full set of feasible year-by-province FE. Standard errors are clustered at the household level. The symbol × denotes an interaction. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

estimation uncover a significant positive effect of TSE exposure for those who did not experience a severe flood shock. Obtained estimates are also larger in size.

Deriving predicted probabilities, based on the results from table 3 (model 7), we can directly evaluate the overall effect, for instance, for individuals with average TSE exposure during the previous 12 months and a 5 km sphere of interest.[18] For 21 days of TSE exposure, individuals without direct (severe) shock experience are still less likely to report negative SWB dynamics (21.04 percent predicted probability of being worse off) than those being hit by a severe flood shock (25.65 percent predicted probability for negative SWB dynamic). Relative to respondents without TSE exposure, however, this gap shrinks by 1.9 percentage points (0.0009×21).

Results become even stronger for respondents within the top decile of TSE exposure: for those without any direct shock experience ($s^D = 0$, $s^{\text{TSE}} \geq 76$) the predicted probability of reporting negative SWB dynamics amounts to 19.9 percent. This probability is half a percentage point larger than for the comparable group of respondents, who experienced a severe flood shock ($s^{D,\text{ severe}} = 1$, $s^{\text{TSE}} \geq 76$).

4.2.3. TSE Effects across Varying Spheres of Interest and Time Horizons

Tangential shock interaction coefficient estimates (β_3) for models building on the interaction of categorical shock experiences and TSE exposure, which account for various spheres of interest and time horizons, are reported in table 4. Each set of estimates originates from a separate estimation and refers to the group without any direct shock experience and to the group with moderate shock experience. All are derived within the same sample and based on the same model specification.[19]

The results in table 4 document significant interaction effects, mostly for larger radii (with a radius of at least 3 km). A positive and significant interaction coefficient implies that negative well-being dynamics become relatively more likely for individuals without any shock experience if they are exposed to more intensive or frequent TSE. These results are robust both in terms of magnitude and precision across estimation methods.[20] Furthermore, the uncovered effects of being exposed to one additional TSE day seem to decrease monotonically with an increasing sphere of interest and time horizon: focusing on TSE during the previous 12 months, the estimate from fixed effects estimations declines from 0.0013 (3 km sphere of interest) to 0.0011 (4 km), and then to 0.0009 (5 km). Correspondingly, for a 5 km sphere of interest, estimates decline from 0.01 (1-month time horizon) via 0.004 (3 months) to 0.0009 (12 months).

The estimates presented in table 4 show average effects, attributable to incrementally increasing TSE exposure. As discussed above, however, the overall effect on SWB dynamics accumulates over the range of TSE exposure levels and may be more pronounced for those with higher levels of TSE exposure. Therefore, fig. 3 illustrates to which extent predicted probabilities to observe negative SWB dynamics gradually become more similar across the groups of respondents without any shock experience and those with (severe) shock experience. The point of congruent negative SWB probabilities is reached when their difference is zero, i.e., $P(\Delta\text{SWB}^-|s^D = 1) - P(\Delta\text{SWB}^-|s^D = 0) = 0$. In fig. 3, this point is represented by the intersection of the black downward sloping line, representing the difference, and the black dashed horizontal line. The grey solid curve depicts p-values, testing for zero difference, across the range of observed TSE exposure levels.

Initially, for lower levels of TSE exposure, the observed difference in predicted probabilities is positive and significant: Respondents actually suffering from a (severe) shock are much more likely to express

18 Predicted probabilities are derived based on the estimates from the previously estimated model, fixing shock experience at its respective levels (none, moderate, or severe) and TSE exposure at its average (or 9th decile), and iterating over the remaining control variables.

19 We abstain from presenting full regression outputs for all specifications for the sake of simplicity. Results are available upon request.

20 Applying alternative standard error clustering approaches, e.g., on the village level to account for correlated shock exposure, yields highly comparable statistical inference (table S1.3).

Table 4. Main TSE Interaction Estimates (Various Time Horizons and Spheres of Interest)

		1 month		3 months		12 months	
		FE	RE	FE	RE	FE	RE
1 km	s(none) × s^{TSE}	−0.0072	−0.0101	−0.0006	−0.0033	−0.0007	−0.0009
		(0.0184)	(0.0160)	(0.0055)	(0.0052)	(0.0014)	(0.0013)
	s(moderate) × s^{TSE}	−0.0002	0.0043	−0.0017	−0.0021	−0.0009	−0.0009
		(0.0227)	(0.0205)	(0.0064)	(0.0062)	(0.0016)	(0.0015)
2 km	s(none) × s^{TSE}	0.0014	−0.0012	0.0025	0.0016	0.0006	0.0006
		(0.0123)	(0.0104)	(0.0036)	(0.0033)	(0.0008)	(0.0007)
	s(moderate) × s^{TSE}	−0.0014	0.0003	0.0018	0.0015	0.0003	0.0002
		(0.0144)	(0.0122)	(0.0044)	(0.0039)	(0.0010)	(0.0009)
3 km	s(none) × s^{TSE}	0.0102	0.0066	0.0056**	0.0040	0.0013**	0.0011*
		(0.0085)	(0.0072)	(0.0028)	(0.0024)	(0.0006)	(0.0006)
	s(moderate) × s^{TSE}	0.0112	0.0104	0.0053	0.0042	0.0009	0.0009
		(0.0102)	(0.0089)	(0.0033)	(0.0029)	(0.0008)	(0.0007)
4 km	s(none) × s^{TSE}	0.0119**	0.0107**	0.0047**	0.0041**	0.0011**	0.0011**
		(0.0057)	(0.0051)	(0.0021)	(0.0019)	(0.0005)	(0.0005)
	s(moderate) × s^{TSE}	0.0128*	0.0124*	0.0045*	0.0037	0.0010	0.0009
		(0.0073)	(0.0066)	(0.0025)	(0.0023)	(0.0007)	(0.0006)
5 km	s(none) × s^{TSE}	0.0102**	0.0087**	0.0038**	0.0035**	0.0009**	0.0009**
		(0.0044)	(0.0040)	(0.0016)	(0.0015)	(0.0005)	(0.0004)
	s(moderate) × s^{TSE}	0.0103*	0.0081	0.0035*	0.0027	0.0008	0.0007
		(0.0057)	(0.0053)	(0.0020)	(0.0019)	(0.0006)	(0.0005)

Source: Authors' own calculations based on TVSEP data from 2007 to 2017 and MODIS flood data for respective years.
Note: Displayed results are from 30 separate regressions, i.e., 15 fixed effects (FE) and 15 random effects (RE) estimations, all estimating the probability of observing negative SWB dynamics. Reported estimates are for the group without any shock experience or with moderate shock experience (both have as reference group those with severe shock experience) and originate from household panel estimations (21,839 observations), including the full set of control variables, as well as the full feasible set of year-by-province FE. Standard errors are clustered at the household level. Results for clustering at the village level can be found in table S1.3. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

negative SWB dynamics than those without any shock experience. Yet with increasing TSE exposure levels this difference diminishes. Once TSE exposure reaches 5 days during the previous month, 15 days within the previous quarter, or 70 days over the last 12 months, individuals without any direct shock experience are as likely to feel worse off as those with severe shock experience. For even higher levels of TSE exposure, the difference becomes negative, suggesting that individuals without direct shock experience are more likely to report negative well-being dynamics in absolute terms.[21]

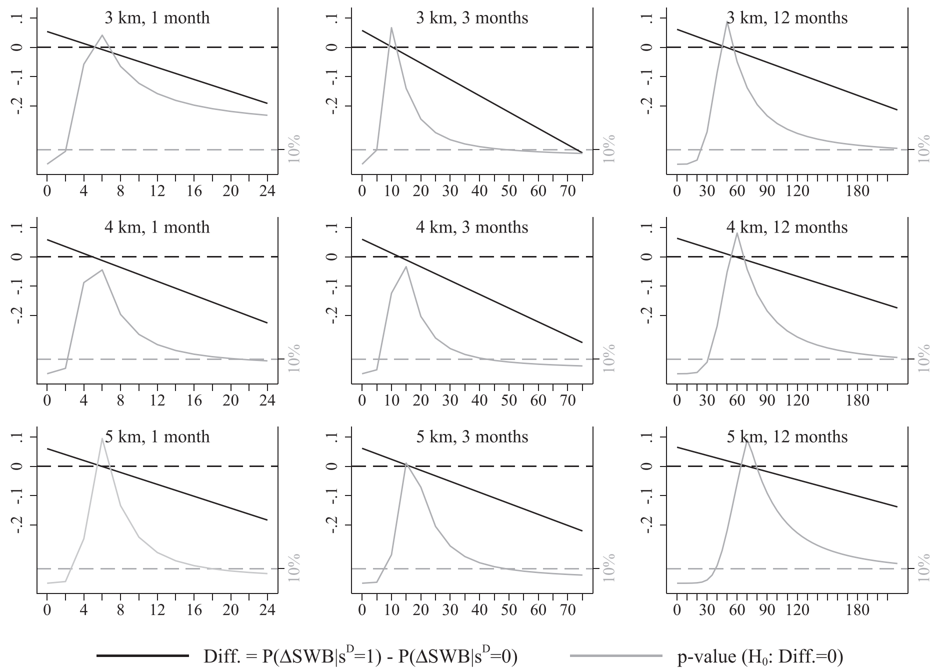
These results emphasize the adverse consequences of flood shocks. In line with the literature, they demonstrate that directly experiencing a flood has a negative impact on SWB. Beyond this, however, we show that merely witnessing a nearby shock event influences SWB as well. Furthermore, the closer to the interview date such TSE exposure occurs, the stronger the observed effects. These results relate to findings from the literature on the effects of disaster risk on SWB (e.g., Welsch and Biermann 2014; Berlemann 2016). These findings may thus have important implications for the measurement of SWB during a season with frequent TSE exposure.

4.3. Sensitivity Analyses

Households in the sample may vary across a variety of unobserved characteristics, which are related to both SWB dynamics and shock experiences. While the implemented household panel estimations ad-

21 The resulting negative difference remains insignificant up to high TSE exposure levels. Thus, it should be interpreted with some caution for intermediate levels of TSE exposure.

Figure 3. Between-Group Differences in Predicted Probabilities for Negative Subjective Well-Being Dynamics



Source: Authors' own calculations based on TVSEP data from 2007 to 2017 and MODIS flood data for respective years.
Note: Depicted differences are based on a comparison of the predicted probabilities, drawing upon the estimates in table 4. Horizontal axes show the days of TSE exposure within a given time horizon and radius. The black downward sloping line depicts the difference in observing negative SWB dynamics between the two groups (severe shock experience vs. no shock experience). The magnitude of these differences is depicted on the left vertical axes. The intersection of the black downward sloping line and the auxiliary black dashed horizontal line represents the point when the difference between the groups is zero. Grey curves represent *p*-values, originating from tests for zero differences. Group differences are significant if the grey curve is below the grey dashed line, which corresponds to the 10 percent significance level (right vertical axes).

dressed both the issue of time-constant omitted variables on the panel level and year or province-specific idiosyncrasies, heterogeneous adjustment patterns or prior exposure to shock events could lead to biased results. This section, therefore, describes various robustness checks addressing concerns about unobserved heterogeneity, but also evaluates the results' sensitivity regarding the set of control variables, alternative sample definitions, and estimation methods. Output tables are presented in the supplementary online appendix.

Other environmental shocks. Households are largely involved in agricultural activities, which explains the effects of flood shocks on SWB. However, other (possibly correlated) environmental shocks could also impact agricultural activities and thus SWB dynamics. To this end, the following further environmental shock experiences during the last 12 months are integrated: drought, storm, and snow or freezing rain.[22] This does not impact the TSE estimates. However, drought appears to be a relevant predictor for negative SWB dynamics (cf. table S1.4, columns (1) and (3)). The robustness of the TSE estimates can also be observed in the specification controlling for a full set of shocks, including falling victim to a property crime, experiencing a job loss, adverse financial shocks, and the death of a household member (see table S1.4, columns (2) and (4)).

22 Provinces in the Vietnam sample include villages located in mountainous areas where snow or ice rain events occur. Ten percent of Vietnamese households in our sample lived above 564 meters altitude, some above 1,000 meters.

Network shock propagation. Another sensitivity check controls 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 community. The network variable corresponds to the log-distance-weighted share of households (in the same village) who experienced a flood shock during the corresponding time horizon.

The shock experience of neighboring households is weighted more heavily than for remote households. With a range between 0 and 1, the network variable is a proxy for the likelihood of interacting with a fellow villager with a flood shock experience. Table S1.5 documents the robustness of the findings. Insignificant estimates for the network shock propagation variable itself across all specifications suggest that such interdependencies do not play a central role when controlling for direct shock experiences.

Local economic opportunities. A flood-shock-induced change in local economic opportunities in a village may, eventually, also negatively impact households without direct shock experience. Such feedback would then potentially bias estimates of interest. To control for dynamic economic opportunities, two types of village aggregates are introduced: Financial aggregates comprise the share of households having access to savings and the share of households receiving public transfers. Both are related to households' capability of coping with adverse shocks. Labor market aggregates are measured as the share of respondents without any occupation and those active in a non-farm occupation.[23]

Worsening local conditions would be captured by an increasing share of individuals without any occupation; increasing non-farm occupation shares could imply an adjustment strategy in response to the destruction of agricultural livelihoods.[24] Results (table S1.5) indicate that changing local economic opportunities do not impact TSE estimates. At the same time, some are associated with negative SWB dynamics: for instance, a 30 percentage point increase in the share of public transfer recipients is indicative of a 1 percentage point reduction in the probability of observing negative SWB dynamics.

Flood history. Next, the presence of coping strategies is evaluated. Households with frequent past exposure to flood shocks might have adapted, and their well-being could be unaffected by tangential shocks. Models (5) and (12) in table S1.5 display the robustness of the findings when 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 the findings. The same holds for alternative measures (results not reported), focusing on flood history in the two years prior to the 12-month pre-interview time horizon or deviations from average levels of exposure.

Cultivation activities. Depending on their level of reliance on agricultural production, some farming households might be more susceptible to (tangential) flood shocks than others. The relevance of households' exposure to adverse agricultural outcomes is assessed by accounting for the overall number of cultivation plots used or owned by the household in a sphere of interest. Accounting for individuals with more farmland at stake, the familiar impact of tangential shocks on negative SWB dynamics emerges once more (table S1.5). Exploiting additional information on cultivated crops in a reduced sample, the concern that the prevalence of rice farming biases TSE estimates can be addressed. This could be the

23 We explored alternative measures of local economic opportunities based on available village head surveys in 2007, 2010, and 2011. The following harmonized measures, related to economic conditions, could be derived: the presence of social problems, percentage of villagers working outside the village, number of small enterprizes, and unemployment rate (only 2011). All of them have to be interpreted as guesstimates, subject to potentially non-random reporting errors as well. The sample size decreases severely in the panel specifications, preventing any meaningful comparative analysis. Correlation analyses of village head guesstimates and our measures reveal significant levels of correlation. Considering this strong correlation, our measures seem capable of absorbing some of the potential bias resulting from an omission of local economic opportunities.

24 Year and village level shares are calculated for all villages with at least three respondents represented in a given year.

case as moderate levels of flooding may be beneficial for rice cultivation. Integrating an indicator for rice cultivation during the three months prior to the interview produces estimates which are between 15 and 30 percent increased and more precisely estimated. Moreover, a significant rice cultivation estimate implies that households who have already brought in a harvest, or expect to do so soon, are less likely to display negative SWB dynamics.

Psychological factors. When examining the impact of potentially traumatic events on SWB, omitted psychological factors could be a potential source of 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, worsening mental health can be expected to affect SWB. To account for indirect psychological effects, we resort to the self-reported prevalence of *mental issues* and *headaches* as predictors for underlying mental health conditions.[25] This specific sensitivity analysis comes with two caveats: sample size decreases by ca. 10 percent, and a low general prevalence of both conditions. Only 0.3 percent of respondents declare mental issues, and 1.3 percent report headaches.

Table S1.6 illustrates that individuals suffering from mental issues are 14 percentage points more likely to display negative SWB dynamics. The retrieved TSE interaction coefficients, however, correspond to those from the in-sample baseline specification without mental health proxies.[26] Overall, TSE effects do not seem to be driven by unobserved psychological effects.

Over-controlling. In the presence of indirect effects, the overall effects of actual shock experience or TSE exposure may be diluted. Shock exposure could impact health and directly translate into negative SWB dynamics. Health dynamic controls would then absorb some of the overall effect attributable to shock exposure, which is known as an over-controlling problem (Dell, Jones, and Olken 2014). Table S1.7 reports shock estimates obtained from a specification excluding particularly shock-sensitive variables relating to income and health, the other only controls for basic sociodemographic factors, immutable by shocks. While estimates of direct shock experiences increase slightly in magnitude, TSE estimates remain robust across the alternative specifications.

Sample attrition. Overall, sample attrition is relatively low (ca. 2 percent between each wave). The non-attrition condition applied so far required households to be represented in the 2017 wave (and at least one previous year). An alternative non-attrition condition, following Gröger and Zylberberg (2016), restricts the sample to households who have been represented in all waves. A third condition led to the inclusion of households represented in at least three waves, where the last wave's observation is discarded.[27] Derived results are highly comparable to previously presented baseline results (cf. table S1.8, presenting joint attrition and coordinate accuracy sample restrictions). Auxiliary regressions revealed no correlation between any of the shock measures (direct shock experience and tangential shock exposure for any sphere of interest or time horizon) and the probability of a household being absent in the subsequent wave. These results on attrition are also in line with Gröger and Zylberberg (2016), who show that panel attrition is unrelated to treatment, i.e., a typhoon, and that households in the TVSEP tend to rely on remittances from internal migrants rather than migrating to other places altogether.

25 TVSEP respondents are asked about impairments over the past year. We chose 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 psychological disorders (Baskin, Lipchik, and Smitherman 2006; Mercante, Peres, and Bernik 2011; Lampl et al. 2016).

26 Table S1.6 also presents the direct correlation structure between flood shock experience or exposure and the mental health proxies. There is a minor but significant correlation between mental issues and TSE exposure, suggesting an indirect channel of flood shocks impacting SWB via mental health dynamics.

27 Compared to the initial non-attrition condition, the sample size decreases by 5.8 percent and 16.5 percent, respectively.

Measurement errors. The reliability of households' TSE exposure depends on the precision of available coordinates. Thus, another sensitivity analysis restricts the sample to households whose location has been recorded with high accuracy. Using additional GPS information on coordinate accuracy, the high accuracy condition is defined as being within a 250-meter margin of error.[28] Across the three alternative non-attrition conditions (cf. table S1.8), estimates originating from the high accuracy specification follow the previously observed patterns. TSE estimates tend to be slightly larger in absolute size yet estimated with a similar degree of precision. This is remarkable considering that the high accuracy sample is between 33 percent and 44 percent smaller than the baseline sample. Eventually, the baseline sample produces estimates, which can be interpreted as lower bounds.

To account for potential enumeration bias, i.e., an under-reporting in the self-reported direct shock experience, which may be correlated with the outcome as well, the preferred model is reestimated, controlling for interview duration and integrating enumerator fixed effects. While auxiliary regressions indicated some correlation between interview duration and the probability of reporting a shock experience, this does not bias the tangential shock estimates in a somewhat reduced sample (table S1.9).

Lastly, TSE effects are evaluated in a respondent panel (table S1.10). Due to changing respondents for numerous households, the sample size decreases by ca. 10 percent. As in the baseline results, TSE effects of comparable magnitude emerge in the random effects specifications for larger radii.

Alternative estimation methods. Using panel-ordered logit estimation and a fixed effects multinomial logit model (Pforr 2014), additional information contained in the underlying categorical SWB variable can be exploited. The former treats the three SWB categories (worse off, same, better off) as ordered outcomes;[29] the latter allows differential impacts of explanatory factors on the emergence of positive or negative SWB dynamics relative to a natural reference group (same category) to be modeled. Due to convergence issues during the estimation for some models integrating the full set of year-by-province fixed effects, the comparison is based on estimations with simple year fixed effects. Potential violations of the proportional odds assumption of the ordered logit model had to be evaluated in a pooled sample.[30] Respective tests indicated a frequent violation and, thus, SWB dynamics are reestimated using a generalized ordered logit model. For larger radii and time horizons, once more, the emergence of negative SWB dynamics becomes more likely for those without direct shock experience, yet with higher levels of TSE exposure (cf. table S1.11). Similarly, the results from panel fixed effects of multinomial logit estimations indicate that TSE exposure drives the emergence of negative SWB dynamics.

Ultimately, the presence of TSE effects could be confirmed across a variety of sensitivity analyses. Moreover, these analyses suggest that the results presented in the main analysis could be interpreted as conservative lower bound TSE effects.

5. Further Implications of TSE

The previous sections have shown that tangential shock exposure may sway retrospective SWB dynamics. Negative SWB dynamics for respondents without any direct flood shock experience become more and more likely if they simply observed flood events. Eventually, they may exhibit similar (or even higher) probabilities of reporting negative SWB dynamics as those who were actually hit by a flood shock (cf. fig. 3).

28 This threshold corresponds to the resolution of the MODIS flood data.

29 If respondents applied a latent 11 point SWB scale (0: low, 10: high) to report SWB dynamics, this may be a strong assumption: a 12-month change from 0 to 1 would be reported as being better off, whereas stable SWB (9 in both years) would be in the *same* category, leading to a questionable ordering. This can be avoided by comparing outcomes relative to a natural reference group in multinomial logit models.

30 Results in table S1.11 (column (2), respectively (3) and (4)) highlight that neither discarding year-by province FE nor household FE affects the estimates' overall robustness.

Table 5. Belief Updates and Future Subjective Well-Being Expectations

	(1) FW shock belief update s_F			(2) Future SWB expectations ΔSWB_F^-			(3) Future SWB expectations ΔSWB_F^-		
Sphere of interest	1,000	3,000	5,000	1,000	3,000	5,000	1,000	3,000	5,000
Time horizon	3	3	12	3	3	12	3	3	12
Flood experience									
s(none)	−0.3221***	−0.3242***	−0.3211***	0.0007	−0.0018	−0.0063	−0.0294	−0.0320	−0.0336
	(0.0161)	(0.0167)	(0.0186)	(0.0118)	(0.0123)	(0.0137)	(0.0265)	(0.0268)	(0.0272)
s(moderate)	−0.0004	−0.0032	0.0109	−0.0091	−0.0092	−0.0108	−0.0326	−0.0326	−0.0319
	(0.0221)	(0.0229)	(0.0253)	(0.0152)	(0.0159)	(0.0176)	(0.0317)	(0.0321)	(0.0326)
TSE exposure									
s(none) × s^{TSE}	−0.0011	0.0006	−0.0002	0.0059***	0.0027***	0.0005*	0.0060***	0.0027***	0.0005*
	(0.0049)	(0.0026)	(0.0005)	(0.0022)	(0.0010)	(0.0003)	(0.0022)	(0.0010)	(0.0003)
s(moderate) × s^{TSE}	−0.0019	0.0009	−0.0006	0.0016	0.0007	0.0002	0.0018	0.0007	0.0001
	(0.0073)	(0.0037)	(0.0006)	(0.0026)	(0.0014)	(0.0003)	(0.0027)	(0.0014)	(0.0003)
s(severe) × s^{TSE}	0.0038	−0.0019	−0.0007	−0.0057**	−0.0028**	−0.0006	−0.0059**	−0.0028**	−0.0005
	(0.0056)	(0.0028)	(0.0005)	(0.0025)	(0.0013)	(0.0003)	(0.0025)	(0.0013)	(0.0003)
ΔSWB^-	—	—	—	0.1556***	0.1554***	0.1554***	0.1556***	0.1554***	0.1555***
				(0.0081)	(0.0081)	(0.0081)	(0.0081)	(0.0081)	(0.0081)
FW shock belief update									
s_F × s(none)	—	—	—	—	—	—	0.0419	0.0419	0.0389
							(0.0292)	(0.0292)	(0.0291)
s_F × s(moderate)	—	—	—	—	—	—	0.0288	0.0287	0.0263
							(0.0353)	(0.0353)	(0.0353)
s_F × s(severe)	—	—	—	—	—	—	−0.0344	−0.0345	−0.0317
							(0.0287)	(0.0287)	(0.0286)

Source: Authors' own calculations based on TVSEP data from 2008 to 2017 and MODIS flood data for respective years.
Note: For model (1) the outcome variable is 1 if the respondent is expecting a flood shock in the next five years. The outcome variable in models (2) and (3) is 1 if the respondent expects to be worse off (negative SWB dynamics) next year, and zero otherwise. All specifications originate from panel fixed effects estimations (on the household level) with a sample size of 17,892. They include the full set of control variables, as well as feasible year-by-province fixed effects. Standard errors are clustered at the household level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In the next step, we are interested in the consequences of this effect. Therefore, a related question is whether the impact of TSE exposure is restricted to evaluations of well-being dynamics in the recent past or whether it propagates into the formation of well-being expectations for the future. The latter may have far-reaching implications when it comes to decision-making.

5.1. The Propagation of TSE into Future Expectations

To investigate a potential forward-carrying effect of TSE exposure, but also flood experience, the first step is to examine whether TSE exposure is associated with an update to beliefs about future flood shocks, i.e., respondents are more likely to expect floods in the future.[31] Subsequently, the investigation focuses on whether belief updates are relevant drivers of expectations for future well-being.

Estimates from a linear probability model predicting respondents' flood shock belief updates are documented in table 5 (model 1). Here, the dependent variable is 1 if an individual expects a flood shock to

31 The underlying TVSEP question posed to respondents is "Do you think that [shock xyz] will occur in the next five years?" We use this question to measure a respondent's belief updates. A respondent updates their belief if they become more likely to expect a future flood shock in response to a past flood shock experience or TSE exposure.

occur in the next five years. The model specification mirrors the main specification.[32] Individuals without an actual flood shock experience are 32 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.

Model (2) presents results for the formation of negative future SWB expectations ($\Delta \mathrm{SWB}_F^-$).[33] Significant positive TSE interaction coefficients for expected negative SWB dynamics can be observed in the group without any shock experience. Interestingly, and in contrast to previous results for past SWB dynamics, this result is retrieved for smaller spheres of interest as well: individuals without actual flood shock experience seem to be less optimistic about their future prospects when their TSE exposure is more pronounced. The closer to the present or the closer to the respondents' homestead, the higher the magnitude. Furthermore, expectations of future SWB dynamics are conditional on current SWB evaluations. Individuals reporting negative SWB dynamics over the last year expect a further downward spiral in the future: they are 15.5 percentage points more likely to expect negative SWB dynamics in the coming 12 months.

Turning to model (3), which accounts for flood-shock belief updating, two interesting insights emerge: (a) 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 (b) the influence of tangential shock exposure also remains prevalent in this setting.

Future SWB expectations are 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 about 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, seems sufficient to trigger negative expectations for future well-being.

5.2. Indirect Politico-economic Implications of TSE

Thus far, it has been shown 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. Further suggestive evidence will demonstrate 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 organizations aim to redistribute resources toward affected individuals. In the case of governmental measures, public support for such a policy with inherent redistributive 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 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 percent agree,

32 The full set of variables is only available for the years 2008 to 2017, hence the smaller sample.

33 Future SWB expectations are captured through the following question: "Do you think you personally will be better off next year?" Answer categories are the same as for past SWB dynamics.

Table 6. Support for Government Redistribution in the Presence of Negative Subjective Well-Being Dynamics

Sphere of interest/ Time horizon	1 km/3 months				5 km/12 months			
Flood experience								
s(none)	−0.0782	−0.0786	−0.0791	−0.0933*	−0.0765	−0.0785	−0.0793	−0.0864
	(0.0551)	(0.0558)	(0.0554)	(0.0566)	(0.0604)	(0.0611)	(0.0607)	(0.0626)
s(moderate)	−0.0241	−0.0260	−0.0263	−0.0382	−0.0148	−0.0189	−0.0200	−0.0249
	(0.0809)	(0.0813)	(0.0810)	(0.0818)	(0.0889)	(0.0892)	(0.0889)	(0.0900)
TSE exposure								
s(none) × s^{TSE}	−0.0573*	−0.0600*	−0.0609*	−0.0467	−0.0008	−0.0007	−0.0007	−0.0008
	(0.0342)	(0.0345)	(0.0342)	(0.0379)	(0.0016)	(0.0016)	(0.0016)	(0.0015)
s(moderate) × s^{TSE}	−0.0365	−0.0388	−0.0400	−0.0301	−0.0005	−0.0003	−0.0003	−0.0006
	(0.0344)	(0.0347)	(0.0344)	(0.0379)	(0.0023)	(0.0023)	(0.0023)	(0.0021)
s(severe) × s^{TSE}	0.0588*	0.0620*	0.0629*	0.0449	0.0013	0.0012	0.0012	0.0008
	(0.0342)	(0.0345)	(0.0342)	(0.0380)	(0.0016)	(0.0016)	(0.0016)	(0.0017)
ΔSWB_F^-	—	0.1105***	0.1188***	0.1202***	—	0.1106***	0.1189***	0.1185***
		(0.0337)	(0.0353)	(0.0355)		(0.0335)	(0.0351)	(0.0354)
ΔSWB^-	—	—	−0.0227	−0.0206	—	—	−0.0227	−0.0207
			(0.0262)	(0.0265)			(0.0261)	(0.0265)
s_F	—	—	—	−0.0082	—	—	—	−0.0115
				(0.0241)				(0.0243)
Sensitivity controls	No	No	No	Yes	No	No	No	Yes

Source: Authors' own calculations based on TVSEP data from the 2013 wave and MODIS flood data for the respective year.
Note: The outcome variable for all regressions is a binary indicator turning 1 if the respondent indicates support for government redistribution. Since this question was included in the 2013 questionnaire only, results are based on a reduced sample (2,879 observations, robust standard errors). All specifications include the baseline sociodemographic (age, age squared, gender, health dynamics, marital status, educational attainment, and occupational status) and socioeconomic (relative income, income dynamics) controls, as well as province FE. Sensitivity controls comprise the full set of shock experience controls, village aggregates, flood history, as well as cultivation and network (flood experience and TSE exposure) controls. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

21 percent disagree, and the remainder are indifferent.[34] Overall, there seems to be strong support for governmental redistribution among rural households in Thailand and Vietnam.

The results from various linear probability models where the binary dependent variable indicates support for such governmental redistribution are reported in table 6. In this approach, the focus is not on any immediate effect of TSE exposure on the outcome. Instead, we ask how individual SWB dynamics, which are affected by TSE, may change support for redistribution.

The results show that there is, indeed, only a weak direct association between TSE exposure and support for government redistribution for smaller spheres of interest and time horizons. For larger spheres of interest and longer time horizons, or for specifications drawing on the full set of controls used in the sensitivity section, flood experiences or TSE exposure lose their predictive power. Yet there is strong evidence of an indirect link via expected future SWB dynamics. Individuals expecting deteriorating future SWB are 11 to 12 percentage points more likely to support government redistribution. This also holds when accounting for flood exposure within the village network, which reflects the relevance of shared flood exposure or potential altruistic tendencies. Moreover, support for redistributive policies is not related to belief updates.[35] Expecting to be hit by a flood in the future does not translate into stronger support.

34 The exact survey question is "Please indicate if you agree or disagree with the following statement: The government should redistribute income between richer and poorer households in [Vietnam/Thailand]".

35 In unreported auxiliary results, accounting for various shock-coping strategies, only one type displayed predictive power: individuals with shock experience using insurance payouts to mitigate the adverse consequences were ca. 15 percentage points less likely to support government redistribution policies.

Turning back to table 5, which displays the relation between TSE exposure and future SWB expectations, the following can be concluded: Individuals without direct shock experience but with TSE exposure become increasingly more likely to expect negative future SWB dynamics. Eventually, their expectations for future SWB dynamics may be as negative as for 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, with negative SWB dynamics acting as a mediating factor, endorsing government redistribution may become more likely among those who were only exposed to a tangential shock.

6. Conclusion

Employing a unique household panel from Southeast Asia, this research investigates the sensitivity of subjective well-being (SWB) dynamics to the observation of environmental shocks. The implications of an exposure to such tangential shock events (TSE) are investigated by studying flood events in rural villages in Thailand and Vietnam. Capitalizing on satellite-based, near-real-time flood event data, SWB dynamics of individuals reporting an actual flood shock experience are compared with the dynamics of those who were not directly hit but lived in close proximity to a flood event.

Four essential findings originate from the analysis: (a) Those without a direct flood shock experience are 2–6 percentage points less likely to display negative SWB dynamics compared to those who experienced a flood within the past 12 months, depending on the severity of the shock. Hence, those who experienced a flood shock are more likely to feel worse off than last year. This finding is in line with the existing literature. For example, von Möllendorff and Hirschfeld (2016) find that individuals living in regions affected by a flood within the past 12 months exhibit a reduction in life satisfaction by 0.021 on an 11-point Likert scale. (b) Flood shocks can have negative consequences for those that only witnessed the event, i.e., merely observing a flood event can be sufficient to increase the prevalence of negative well-being dynamics. The effects of such TSE 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, for increasing TSE exposure levels, individuals without direct flood experiences may display similar probabilities of negative SWB dynamics as do those who were actually hit by a severe flood shock. Ultimately, if witnessed flood events were rather extreme (e.g., in the top decile in terms of severity), negative SWB dynamics may become more likely in the group of TSE observers than for those directly affected by a shock. (c) TSE exposure not only affects retrospective SWB dynamics but may affect the formation of expectations for the future too. Witnessing flood shocks, without actually being hit, translates into less optimistic expectations regarding the future development of SWB. Notably, this outcome is not the consequence of a rational belief update. (d) The potential effects of TSE on SWB expectations translate into changed preferences towards government redistribution. The results reveal a higher preference for redistribution among individuals with less optimistic future well-being expectations, which are possibly affected by prior TSE exposure.

In conclusion, our findings indicate that present and future SWB are determined not only by direct (shock) experiences but also by subjective perceptions related to the observation of tangential shock events. Furthermore, there is suggestive evidence that these tangential shock events can translate into changing levels of support for government policies.

These findings are in line with psychological research on witnessing traumatic events. However, they illustrate that the repercussions of such events are also relevant in regard to adverse environmental shocks and SWB dynamics. Furthermore, the study at hand adds to the literature on the effects of disaster risk by providing new insights into SWB determinants and individuals' behavioral patterns in the aftermath of a shock event. While results are based on a sample of rural households in Thailand and Vietnam, we argue that the relevance of these findings may extend beyond this population. Various studies (Sarracino et al. 2013; Reyes-García et al. 2016; Markussen et al. 2018) have identified a so-called "unique happiness function" and have found that determinants of SWB hold for individuals across countries and cultures.

In addition, this study's findings call for a more cautious interpretation of behavioral 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, these 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 financial or material relief, whereas the latter might benefit from information and support on how to cope with the risk of a recurring shock event.

Data Availability Statement

Household Panel Data Data from the Thailand Vietnam Socio Economic Panel (TVSEP) (Klasen and Waibel 2013) can be accessed via the project webpage (https://www.tvsep.de/).

MODIS Near Real-Time (NRT) Global Flood Mapping Data The utilized 14 day composite product has been kindly provided by NASA on special request for 2004 onward (based on the validated MODIS Near Real-Time (NRT) Global Flood Mapping 3-Day Product (3D3OT) v4.9, and augmented by version 5.1).

To replicate the derivation of TSE exposure measures used in this project, the MODIS/Aqua+Terra Global Flood Product L3 NRT 250 m 3-day (MCDWD_L3_F3_NRT.061) product can be accessed via https://earthdata.nasa.gov/earth-observation-data/near-real-time/mcdwd-nrt. Please be advised that occasional updates by the data provider may affect the degree of comparability.

For easier replication of the main results, the authors can provide a file of TVSEP household IDs and the respective TSE measures derived within this project upon request.

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