The impact of local shocks on well-being: Only a matter of perception?

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Abstract: *This paper investigates how witnessing adverse events affects individuals´ perceptions and consequently their personal subjective well-being. In order to do so, we compare material well-being dynamics with changes in subjective well-being. We link GIS data on local flood shocks to an extensive household sample from rural Southeast Asia. This allows us to contrast individuals who actually experienced a shock with those who did not. We find that the mere proximity to a potentially adverse flood shock, without any direct impact on a household's material well-being, can be sufficient to affect subjective well-being.*

Keywords: perception; subjective well-being; GIS data; MODIS flood mapping

JEL codes: I31; Q51; R23

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1 Introduction

Over the past decades, researchers and scholars have developed a fierce interest in the dynamics of subjective well-being and produced manifold insights on its determinants.[1] Much of this literature concentrates on the effects of socio-demographic factors, income and wealth, and personal life circumstances, such as marriage or divorce and career situation (e.g. Dolan, 2008).

Recently, a strand of the literature began to examine to which extent directly experienced external shock-like events, e.g. a currency devaluation or extreme weather phenomena, may impact on well-being (for example Maddison and Rehdanz, 2011). However, until now there exists hardly any evidence on how shock events that are witnessed, but not directly experienced affect individual *subjective well-being* (SWB). Psychological and medical research, in contrast, has long discussed the impacts of traumatic events on individuals, who observed them or heard about them from others (e.g. Figley, 1995; Potter et al. 2010; Cocker & Joss, 2016). In this field, the phenomenon is known as *Secondary Trauma* or *Compassion fatigue*. Studies show that *Secondary Traumas* can cause severe mental stress and even symptoms of post-traumatic stress disorder, consequently resulting in a decrease of life quality. Yet, the topic has found no attention in the literature on subjective well-being or the economic literature in general. Thus, the potential ramifications 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 regarding the SWB of individuals who did not experience any direct loss or deterioration of their material situation? We call those events *tangential shock events (TSE)* and argue that a recorded decline in well-being may not exclusively reflect shock-related economic losses, but also entail a transitory shift in perception.

The scenario we study in order to demonstrate the impact of TSE on subjective well-being are flood events occurring in rural Thailand and Vietnam. Floods are especially suitable to examine the impact of TSE for three reasons: First, since flooding can be traced by satellites, we can combine household panel data with high-resolution satellite-based flood data from the MODIS near real-time flood mapping project (Nigro et al., 2014). This enables us to localise potentially observable shock events with 250 meters´ precision and link them to a household´s sphere of interest. Second, the fact that flood shocks are highly visible and may cause severe mental stress (Mason et al., 2010; Lamond et al., 2015; Walker-Springett et al., 2017) opens up a channel how perceptions might sway SWB. Third, the frequency and severity of flood shocks have increased in many regions and will likely become even more prominent in the future (IPCC, 2014). This suggests an increasing relevance of TSE in the future.

Within our analysis, we apply two different econometric modelling strategies to detect the potential interrelation between SWB and tangential flood shocks. In the first step, called the convergence approach, we establish the basic interrelation of subjective well-being and changes in material well-being. In doing so, we reproduce the findings from the literature, and thus, provide evidence that our subsequent results are not due to a highly distinct sample. In the second step, called the divergence approach, we account for the potential exposure to TSE and find that the mere presence of a flood event can indeed alter individual subjective well-being. Individual

[1] SWB can be described as a function of individuals' 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 different valuations people make regarding their lives, the events happening to them, their bodies and minds, and the circumstances in which they live".

behavioural reactions might thus not only be triggered by directly experienced events, but also by tangential shocks.

Our findings add an interesting new aspect to the literature on SWB and give important insights into the relevance of people´s perceptions for economic studies. We therefore take the existing literature on the effects of exogenous shocks on SWB one step further and incorporate theories from the field of psychology into our analysis.

The paper is organised as follows: we first present a short literature overview (Section 2). In Section 3, we explain our conceptual approach and the derivation of our tangential shock indicators. Afterwards we describe our data (Section 4), followed by our empirical analysis (Section 5). We end with a discussion of our results in Section 6.

2 Related literature

Within our research, we draw upon findings related to fundamental determinants of subjective well-being, such as socio-demographic and socio-economic factors. In addition, our research also relates to the literature on direct impacts of shocks events, both from an economic and a psychological perspective.

Socio-demographic factors. Socio-demographic characteristics as determinants of SWB have been reviewed extensively (e.g. Myers and Diener, 1995; Easterlin, 2003; Dolan, 2008; Reyes-García et al., 2016). Factors, such as age, gender, education, and personality explains a substantial degree of variation in SWB levels (Diener, 1996; Gutiérrez 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 (Myers and Diener, 1995; Gutiérrez, 2005; Dolan, 2008).[2] Many studies address the relationship between SWB and personal life events, such as unemployment, marriage / divorce, educational achievements, or death of a family member (Suh et al., 1996; Luhmann et al., 2012; Pedersen and Schmitt, 2014). Most of the authors argue that the impacts of such events only prevail in the short run (Luhmann et al., 2012; Diener, 1996).[3]

Socio-economic factors. Another intensively investigated group of determinants are material perspectives, i.e. income or assets. In general, these studies find a positive relationship between income levels and SWB (Diener et al. 1993). Yet, whether this relation is absolute or relative is an ongoing debate, which dates back to Easterlin (1974) and Veenhoven (1991). Nowadays, there is some consensus that income has positive but diminishing returns to SWB (Dolan, 2008). In lower-income countries, income plays a more prominent role for 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 (Clark et al., 2008; Dolan, 2008). For 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.

Economic and environmental shocks. Other recent studies assess the impact of external shocks on SWB levels. Hariri et al. (2015) evaluated cross-sectional data from Botswana and found macroeconomic shocks to exert strong negative impacts on SWB in the short run. Adverse ramifications to SWB may also result as a

[2] Although most studies on socio-demographic traits focus on high-income countries, it is worth noting that different studies find a sort of "unique happiness equation" (Sarracino, 2013; Markussen, 2014; Reyes-García et al., 2016). Ultimately, the most essential findings on SWB do not only hold in high-income countries, but also in lower and middle-income countries.

[3] Recent work on panel data 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).

consequence of 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) compared data from individuals living in flood prone regions in Bulgaria to those who live in areas without any flood occurrence. While they found a strong negative impact of flooding on SWB, they also pointed out that intangible factors, i.e. psychological damages 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 tie in with this idea on the consequences of severe flooding.

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

3 Conceptual framework

3.1 Econometric specification

The premise of our research is a potential divergence between material and subjectively perceived levels of well-being. Within our research, a first aspect of material well-being refers to income-related measures. The second aspect relates to those observable socio-demographic characteristics, which have been established in the literature on well-being (e.g. age, gender, health status).

The basic relationship between individual i's subjective well-being (SWB_i) and individual characteristics x_i can be represented by the linear model

$$SWB_i = x_i\beta + \varepsilon_i. \qquad (1)$$

The vector x_i comprises the set of socio-economic or socio-demographic attributes, known from the literature: age, age squared, health status, marital status, educational attainment, and occupational status.[4] Consumption opportunities, i.e. a household income measure, are represented in x_i as well.

In accordance with the literature on environmental shocks, adverse shocks (s_i) may not only have an indirect effect, e.g. by lowering income, but also an immediate impact on subjective well-being. Being hit by a shock translates into diminished levels of subjective well-being, for instance, by reducing quality of life, or deteriorating perspectives for the future. Aside from an aggregate variable, accounting for the shock frequency,[5] the vector s_i

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

[5] Within our household data, shock events may comprise a variety of adverse events, e.g. sickness of a household member, theft, price shocks or livestock diseases. Examples of environmental shocks are storm, flooding or drought. For the construction of the aggregate measure, we assume an idiosyncratic definition of shocks: events count as shocks when they are perceived by a respondent as such.

encompasses a binary indicator. This binary indicator reflects the individual exposure to a specifically relevant shock event.

In the data we use, subjective well-being is measured as 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. We therefore obtain as a modified version of equation 1:

$$\Delta SWB_{i,t} = x_{i,t}\beta + s'_{i,t}\gamma + \varepsilon_{i,t}. \qquad (2)$$

Our dependent variable (ΔSWB, further described in section 4.1) has three categories: subjective well-being may have increased, decreased or stayed the same – the latter being a natural reference point. A valid modelling approach to estimate such a categorical dependent variable is rephrasing the well-being response to fit a multinomial logit model (cf. Greene, 2012, p. 763), given by

$$Prob(\Delta SWB_{i,t} = j | x_{i,t}, s_{i,t}) = \frac{\exp(x_{i,j,t}\beta_j + s'_{i,j,t}\gamma_j)}{1+\sum_{k=1}^{2}\exp(x_{i,k,t}\beta_k + s'_{i,k,t}\gamma_k)}. \qquad (3)$$

For each of the two non-reference response categories (worse off and better off) we obtain a distinct set of parameter estimates. This approach thus allows for the modelling of asymmetric effects of explanatory variables across the response categories.

Ultimately, equation (3) enables testing for a fundamental positive (negative) relationship of income levels and increased (decreased) subjective well-being, accounting for directly interfering shocks. This is what we call the convergence approach. Moreover, it measures to what extent socio-economic traits and actual shock experience translate into changing overall well-being, thereby demonstrating the validity of our data.

In contrast to this, our research is guided by the conjecture that not only do actual shock experiences affect subjective well-being, but *tangential shocks* may also sway perceptions of well-being.[6] As *tangential shocks* we define events of potential shock exposure, i.e. shock events occurring in the local or social vicinity of an individual or household. These events may be merely observed by an individual without any immediate ramification on the observer's material well-being or health. Of special interest are those tangential shock events, which took place in a respondent's sphere of interest, yet were explicitly not reported as being a relevant or severe actual shock experience. A short distinction is that tangential shocks should only be *observed*, i.e. their occurrence *could* have been noticed, but actual shocks were *directly experienced* and reported as adverse event hitting a household or individual.

This divergence approach aims at decomposing the change in reported subjective well-being into two components: On the one hand, there are dynamics related to experienced adverse shocks which lowered actual levels of material well-being or the living standard. On the other hand, subjective well-being is also affected by potential shock exposure – a form of transitory cognitive overreaction or belief updating. Tangential shocks may thus be interpreted as important externalities.

The impact of observing such a local tangential shock s^T is modelled by an interaction with the reported shock experience (s_i):

$$P(\Delta SWB_{i,t} = j | x_{i,t}, s_{i,t}, s^T_{i,t}) = \frac{\exp(x_{i,j,t}\beta_{1,j} + s'_{i,j,t}\gamma_{1,j} + s^T_{i,j,t}\gamma_{2,j} + s_{i,j,t}s^T_{i,j,t}\theta_{1,j})}{1+\sum_{k=1}^{2}\exp(x_{i,k,t}\beta_{1,k} + s'_{i,k,t}\gamma_{1,k} + s^T_{i,k,t}\gamma_{2,j} + s_{i,k,t}s^T_{i,k,t}\theta_{1,j})} \qquad (4)$$

The interaction coefficient θ_1 allows us to contrast the distortionary influence of tangential shocks on individuals from households not reporting any actual shock experience against those having suffered a relevant shock.

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

3.2 Research hypotheses

Our most essential hypothesis is the 'tangential shock hypothesis': individual (or household) well-being dynamics are not only affected by directly experienced flood shocks leading to an economic loss, but by potential flood shock exposure as well. Referring to the multinomial logit specification depicted in equation (4), with the two categories of well-being dynamics of interest 'better off' (b) and 'worse off' (w) we expect $\gamma_2^b < 0$ ($\gamma_2^w > 0$). The presence of tangential shocks reduces (increases) the likelihood respondents perceive themselves to be better off (worse off). On the other hand, we further anticipate a significant interaction effect with actual flood shock experience $\theta_1^b < 0$ ($\theta_1^w > 0$), implying that individuals who explicitly did not report any direct flood shock experience still feel affected by a tangential shock. This is then evidence in favour of diverging levels of subjective and fundamental well-being, induced by the mere perception of shocks.

The 'recency hypothesis' acknowledges the potential dominance of tangential flood shocks in the recent past over comparable events in the more distant past. Tangential shocks in the last pre-interview month might weigh more heavily on subjective well-being than those having occurred during the complete reference horizon, i.e. 12 months. Since we are using externally identified measures of potential shock exposure, any resulting 'recency effect' (Atkinson and Shiffrin, 1968) is not related to a reporting error of tangential shocks due to a diminishing capacity to memorise and recall such events explicitly.

The relevance of an individual's spatial position, relative to tangential flood shock events, is mirrored in the 'household position hypothesis'. Tangential flood shocks occurring closer to a household's homestead or cultivation areas are more likely to be witnessed by an individual, even if no actual shock experience was recorded. This would be associated with either diminishing coefficients for potential flood exposure indicators in higher-order exclusive radii or a loss of significance beyond a certain distance threshold.

A related hypothesis is the 'shock subjectivity hypothesis': tangential shocks may enter the process of evaluating subjective well-being to a lesser extent if an individual disposes of more refined coping strategies or has more immediate access to emergency relief. In addition to location-specific moderating factors, individual traits might be relevant, i.e. individuals with a pronounced inherent ability to process and differentiate information may report a lower sensitivity of well-being to potential flood exposure.

3.3 Definition and identification of shock events

Relevant actual shock events in the convergence approach are adverse events that induce lower levels of well-being in general and in a material sense, i.e. if the event causes 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. In other words, the data we require for our analytical purposes have to provide information on actual experiences of severe shock events, which can hardly be prevented, and to consist of individuals or households displaying a sufficient degree of 'vulnerability'.

These two requirements are fulfilled in case of a dataset of households in rural areas of Southeast Asia, i.e. from the Thailand Vietnam Socio Economic Panel (further discussed in section 4.1). The households in the sample are mainly depending on agricultural or livestock production. Following the literature (cf. Klasen and Waibel, 2013), these households can be considered vulnerable to shocks.

Referring to the vulnerability of these households, two types of shocks are especially harmful: drought and flood events, both diminishing crop yields or livestock production, and with the potential to be existence threatening. Primarily flood shocks, however, bear the potential to destroy non-productive factor assets, such as homesteads. Another characteristic of flood shocks is their high degree of perceptibility: flooded fields or drowned livestock can be visually detected by respondents. Such a severe event will be recalled more easily and reliably at the interview. For these reasons, we focus on flood shocks in our analysis.

Our designated household data provide information on actual experience of flood or heavy rain shocks.[7] This further enables to identify those flood shocks that occurred within the 12 month reference period implied by the subjective well-being item.

In the next modelling step, which we call the divergence approach, we assess the impact of tangential shocks. Here, we rely on external information on shocks that go beyond self-reported shock events. Suitable data on tangential shocks have to satisfy three main requirements: reliable identifiability of a shock event, precise localisation of any occurring flood event, and adequate temporal coverage.

In contrast to the relevance criterion for self-reported shocks, the identifiability criterion for tangential shocks incorporates an additional dimension: it is not sufficient if the nature of a tangential shock event had the potential to harm a household's economic prospects, but it is necessary that it is externally observable. Therefore, identifiability requires that a potential shock event can be detected by a third party observer.

The localisation requirement ensures that a household's potential shock exposure can be plausibly inferred. In the case of households depending to a large extent on agricultural production, relevant shocks should occur in the vicinity of a household's cultivation areas, so they might be witnessed. The more precisely a tangential shock event can be located in relation to a household's sphere of interest, the more precisely its impact on the formation of this household's well-being levels can be assessed.

Lastly, adequate temporal coverage refers to the possibility of linking tangential shock events arising within a reference period. For our purpose, and predefined by the well-being items in the survey, we need data which allow us to detect shock events occurring in the 12 months before the interviews took place. In order to investigate the influence of memorability, we further need shock data which allow the investigation of several time horizons within the 12 month reference period; i.e. yearly aggregates are inadequate.

These three criteria are fulfilled by derivatives of the NASA/DFO MODIS near real-time global flood mapping product (Nigro et al., 2014). Based on satellite data, the flood mapping algorithm provides information on flood water (FW) events with a relatively high degree of spatio-temporal precision.[8]

Flood events are identified if the algorithm detects water-like electromagnetic emissions outside the areas of reference water, i.e. the sea, lakes or rivers. The information on flood water events is provided in a spatial resolution of approximately 250×250 meters: for each of these tiles (or pixels) the number of flood water days within an observation interval is recorded. Since the detection algorithm relies on surface reflections, cloud coverage imposes a severe limitation. In order to overcome this issue, we use the 14 day composite product[9]: each daily observation in this interval is included as non-missing if three cloud-free observations originating from

[7]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. Secondly, these events tend to coincide, therefore making it hard to discern them when interviewed several months after such an event.

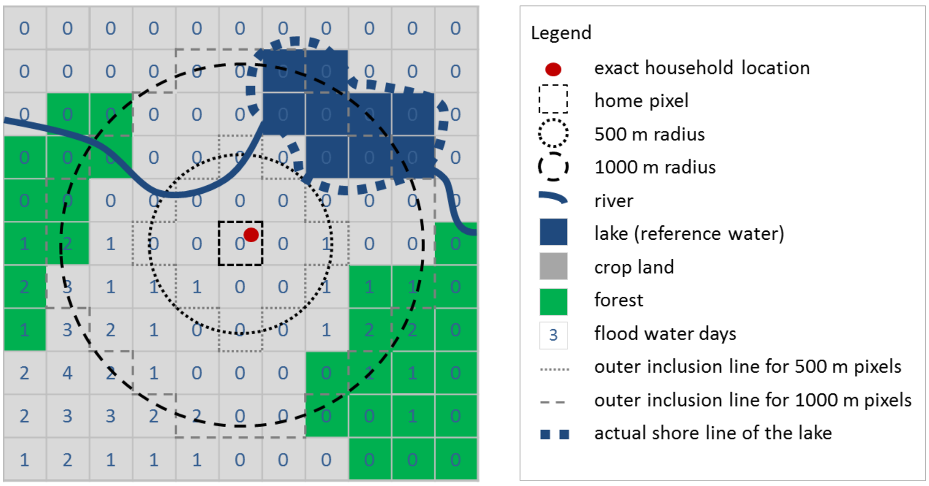
[8] The measuring instrument is called Moderate Resolution Imaging Spectrodiameter, hence the abbreviation MODIS.

[9] The corresponding product for Thailand and Vietnam, with the temporal coverage of 2004 to 2016, has been kindly provided by NASA on special request. We are grateful for their support.

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. 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.[10] Based on the derivation algorithm (Nigro et al., 2014), the day count of flood water can be interpreted as lower bound.

Using MODIS near-real-time flood mapping data, we construct various indicators for potential flood exposure, and thus integrate externally observed flood events into our analysis. For the majority of households homestead coordinates were collected in the years 2016 and 2017, allowing spatial matching. Based on these coordinates, the closest 250×250 meter tile in the MODIS flood data, labelled 'home pixel', is identified. In the next step, all relevant tiles within a radius of up to five kilometres are identified – defining a household's sphere of interest. This threshold has been chosen based on the observation that it comprises 95% of households' cultivation areas, and hence, encompasses the land most relevant for the livelihood of households depending on agricultural production. To investigate the impact of tangential shocks' proximity on well-being, we further identified those tiles included within stepwise increasing radii.

Figure 1: Stylised MODIS flood water data



The temporal matching refers to the identification of the closest 14 day observation interval, which ended before a household was interviewed. This ensures that only those flood water events which actually occurred in the last 12 months are used to examine the impact of tangential shocks on the reported well-being dynamics in the past year. We further construct for each radius, and the subsets of included tiles, corresponding flood indicators spanning three time horizons: the one month indicators include flood water days which were recorded in the two closest pre-interview observation intervals, the three month indicators enclose the six most recent observation intervals, and the twelve month indicators the previous 26 intervals.

Figure 1 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 1000 meter radii. Drawing on the stylised flood water data in Figure 1, also reporting the number of flood water days for each tile, Table 1 documents the resulting values for three different flood exposure indicators.

[10] In case of a year's last interval, the upper bound of daily flood detection is 15 or 16.

Table 1: Example of various flood water (FW) indicators

indicator type	concept	r_0 (home pixel)	r_{500}	r_{1000}
maximum FW days	maximum local severity	0	1	3
total number of FW pixels	spatial spread	0	2	16
mean FW days per pixel	relative exposure	0	2/13	22/57

The maximum flood water (FW) days indicator refers to the highest number of flooding days that affected any tile in a certain radius. Such a maximum day count provides an indicator for the maximum local severity of flooding: the longer it lasts, or the more events occurred within a time horizon, the more likely agricultural production will suffer. The total number of flood-affected pixels, in contrast, may prove informative regarding the overall spatial spread of flooding. The mean flood day indicator is a measure of relative exposure. It takes into account the size of a radius, i.e. the number of included tiles.

4 Data and descriptive statistics

4.1 Introduction to the TVSEP

We draw upon micro data originating from the Thailand Vietnam Socio Economic Panel (TVSEP; Klasen and Waibel, 2013). Data are collected via an extensive household survey in both countries, initiated in 2007. Since then, six additional waves were conducted in 2008, 2010, 2011, 2013, 2016 and 2017.

The survey is carried out in six rural provinces (cf. Figure A.1). Three of them are located in the northeastern part of Thailand (Ubon Ratchathani, Buri Ram and Nakhon Phanom) and three in Vietnam (Ha Tinh, Thua Thien Hue and Dak Lak). In order to identify a group that is representative for the rural population, about 2000 households in each country were selected through a three-stage cluster sampling strategy (Hardweg et al., 2013). When the survey started in 2007, 4,381 households in 440 villages were interviewed. The same households were interviewed in each wave (in 2011 only one province in each country was surveyed). Over the years, some of these households were lost, due to attrition. The overall attrition rate is low, which leaves us with 3,812 households in 2017.

The survey's comprehensive household questionnaire comprises nine sections, relating to household socio-demographic characteristics, agricultural production, investment decisions, income sources, wealth, assets, as well as a detailed section on experienced shocks and risk expectations. This section also contains questions relating to individual or household well-being.

For the purpose of this research, we use the data obtained in the years 2007-2013 (5 waves) and combine them with information on households' spatial location, which is available from 2016 onwards.[11] Household locations are recorded using GPS devices, which provides us with coordinates for most households still in the sample.

Across the different waves, respondents within households 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 a restricted sample.[12] This focus on the individual respondent is reasonable for two factors: For one, 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. Second,

[11] The 2016 and 2017 waves are not yet fully included, due to cleaning and availability reasons.

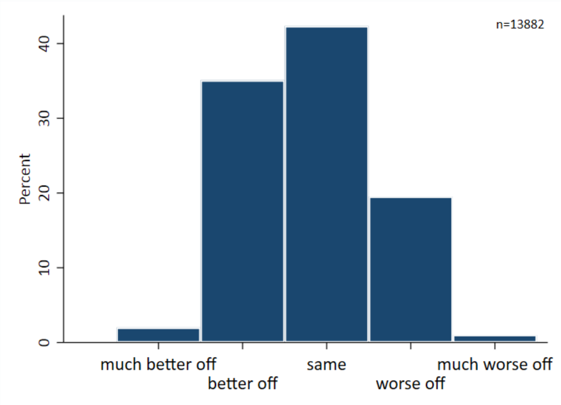
[12] We follow the idea of Ferrer-i-Carbonell and Frijters (2004), pointing out the relevance of unobserved, time-invariant factors correlated with likely determinants of subjective well-being. Therefore, we also present random and fixed effects specifications of binary response models (Table A.4).

reported well-being dynamics at the household and the individual level are highly correlated (see Figure A.2 for more details).

Respondents in our sample originate typically from rural multi-generational households. They are on average 50 years old, the majority is married (84%) and engaged in subsistence farming (70%). Gender-wise the sample is balanced and education levels are relatively low - 76% have completed primary schooling at best. The information on individual health dynamics provides a mixed overview; about 30% (11%) of the respondents stated that their health status is worse (better) than one year before. A detailed overview of all variables can be found in the appendix (Table A.1). For our analysis, we use a pooled sample that only includes respondents at least 15 years of age who lived in households which did not move between 2007 and 2016 and for whom the interview date could be identified reliably.[13]

Households, and consequently the respondents, experienced a variety of shocks. These shocks have been elicited by asking respondents to report any major shocks experienced since the last survey. These can be shocks on the household level, which affected all household members, as well as those experienced only by certain household members. In a second stage respondents were given a list of possible shock events and asked to report for each whether the event was experienced by the household or not. For our analysis, we focus on the total number of shocks experienced by the household (0.9 on average). We also differentiate between flood shocks (including heavy rainfall) and others. 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.

Figure 2: Distribution of subjective well-being on the individual level (5-point scale)



Note: The number of individual-year observations refers to the sample of the convergence approach (section 5.1) and includes respondents from all waves from 2007 to 2013.

Our measure of interest is individual self-reported subjective well-being.[14] The implemented survey item is formulated such that respondents identify their level of well-being in relation to one year ago. More precisely the question posed to the respondent is: "*Do you think you in person* [sic] *are better off than last year?"*[15] Each respondent can choose between five answers, namely *(1) Much better off, (2) Better off, (3) Same, (4) Worse off, (5) Much worse off*.

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

[14] A number of our explanatory variables is measured at the household level, we therefore perform a robustness check on household level well-being.

[15] The survey questionnaire also features a question with a time horizon of 5 years. However, such a long time horizon may lead individuals to understate their well-being back then, and thus, overstate positive well-being dynamics (Easterlin, 2003).

Figure 2 displays the relative frequency of individually reported subjective well-being dynamics: only a few respondents chose categories (1) or (5). 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 the three categories of well-being dynamics 'better off' (ΔSWB^{+}), 'same', and 'worse off' (ΔSWB^{-}).

4.2 The (geographic) distribution of well-being dynamics and flood shocks

Figure A.1 illustrates the location of villages in Thailand and Vietnam where at least three households have been interviewed in 2013. To provide a more refined idea of geographic conditions, the country-level map also displays the position of municipalities, major components of the traffic system, and waterways.

On each side of Figure A.1, three graphs present enlarged maps of the relevant provinces and villages. For each province, the left panel reports village aggregates on the occurrence of tangential shocks. This general potential exposure is based on a binary measure, indicating whether a tangential flood shock occurred in a radius of 5000 meters and a time horizon of 12 months. The right panels display unconditional well-being dynamics in the negative domain as village aggregates.[16] These aggregates refer to the relative share of respondents, in a given village, who were either exposed to a tangential shock (blue) or reported a negative well-being dynamic (red), i.e. they stated to be worse off than 12 months before.

In Ubon Ratchathani and Buri Ram, almost 50% of the circles representing village aggregates of potential flood shock exposure are empty. This implies that in 2013, the interviewed individuals in these villages were not exposed to any tangential shock within the vicinity of 5 kilometres in the last 12 months. The exposure to tangential shocks in Nakhom Phanom, however, seemed more pronounced. This can be rationalised by resorting to the country-level map: all villages at the eastern border of this province are in the direct vicinity of the Mekong. The picture regarding the distribution of unconditional adverse well-being dynamics is less clear cut. There is no *a priori* systematic pattern of the geographic distribution of villages where a higher share of respondents reported being worse off.

In Vietnam, one province (Dak Lak) is land locked and the other two are situated at the coastline. Both of the seaside provinces, Ha Tinh and Thua Thien Hue, also feature a river delta. Taken together with their flatness, they are predestined flooding areas – a fact which is mirrored by the MODIS flood water data used for the construction of the binary version of our tangential flood shock indicator. Most villages in these areas were exposed to such an event. As in the case of Thailand, the occurrence of adverse unconditional well-being dynamics in Vietnam seems not systematically related to the presence of tangential shocks. 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.

Table 2 documents the unconditional correlation structure of binary well-being variables and corresponds to the aggregates in Figure A.1, which are actual flood shock experience and some measures of tangential shock exposure. The maximum flood water (FW) days indicator refers to the highest number of flooding days that affected any tile in a certain radius. Such a maximum day count provides an indicator for the maximum local severity of flooding: the longer it lasts, or the more events occurring within a time horizon, the more likely it is that agricultural production will suffer. The total number of flood affected pixels, in contrast, may prove

[16] For the sake of improved readability, the well-being variable has been recoded into a binary one, which contrasts cases stating to be worse off with those reporting to be either better off or having experienced no well-being change.

informative regarding the overall spatial spread of flooding. The mean flood day indicator, however, is a measure of relative exposure. It takes into account the size of a radius, i.e. the number of included tiles.

Table 2: Selected unconditional correlations of well-being and flood experience or exposure

shock	type	radius	time horizon	ΔSWB_i^+	ΔSWB_i^-	ΔSWB_{HH}^+	ΔSWB_{HH}^-
experience	FWS	∞	12 months	-0.026 a	0.045 a	-0.031 a	0.044 a
	FWHRS	∞	12 months	-0.030 a	0.048 a	-0.039 a	0.046 a
	sev. FWHRS	∞	12 months	-0.039 a	0.061 a	-0.052 a	0.064 a
exposure	max FW	5 km	1 month	-0.005	-0.002	-0.025 a	0.012
		5 km	12 months	-0.011	-0.002	-0.025 a	0.013
	mean FW	5 km	1 month	-0.004	0.004	-0.024 a	0.017 c
		5 km	12 months	-0.003	-0.011	-0.024 b	0.001
	total FW	5 km	1 month	-0.006	0.004	-0.027 a	0.018 c
		5 km	12 months	-0.010	-0.003	-0.028 a	0.012

a: p<0.01, b: p<0.05, c: p<0.1

Note: A more complete overview of unconditional correlations is provided in Figure A.2.

All binary SWB indicators are strongly correlated with self-reported shock experience measures: The actual experience of a flood shock (FWS) or a flood or heavy rain shock (FWHRS) is negatively correlated with a positive well-being dynamic (SWB_i^+). Accordingly, individuals who stated they were worse off (SWB_i^-) did report an actual experience of such a shock more frequently. This also holds for household income, as documented in Figure A.2, which depicts the correlation structure of a wider set of indicators. This illustration also points out the high degree of correlation between SWB indicators on the household (SWB_{HH}) and individual (SWB_i) level. Significant unconditional correlations of MODIS-based tangential shock measures display the expected numerical sign, but solely for SWB dynamics on the household level: if any tangential flood shock occurred in the 12 pre-interview months in a radius of 5000 meter around the homestead, or the mean flood days per pixel were higher in the larger radius, individuals were less likely to report a positive well-being dynamic.

33: Tangential shock indicators in the sample

		maximum flood water days (any pixel)			average flood water days (per pixel)			number of affected pixels		
time horizon	radius (m)	max	mean	std.dev.	max	mean	std.dev.	max	mean	std.dev.
1 month	1000	19	0.21	1.31	4.74	0.01	0.09	33	0.15	0.93
	3000	25	0.75	2.80	1.83	0.02	0.09	120	1.62	7.01
	5000	26	1.48	3.94	1.29	0.02	0.08	165	5.04	17.11
3 months	1000	59	0.67	3.46	12.81	0.05	0.34	42	0.43	2.33
	3000	77	2.32	7.38	4.32	0.06	0.28	206	4.33	15.62
	5000	77	4.53	10.52	3.40	0.07	0.25	372	12.95	37.54
12 months	1000	173	4.67	16.65	59.43	0.61	3.22	53	2.45	7.35
	3000	226	13.19	30.84	33.51	0.80	2.92	460	25.00	59.54
	5000	226	21.37	39.61	22.97	0.81	2.54	1205	67.71	145.88

Note: Based on the divergence approach sample (13,879 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.

3 presents descriptive statistics for our three tangential shock measures for all considered time horizons and a selection of sphere of interest radii. The tangential shock indicators display a substantial degree of variation. Unsurprisingly, mean values for smaller radii or shorter time horizons can be relatively small. Extending the time horizon or the sphere of interest, however, reveals a notable share of households which might have observed severe flood events in their vicinity.

In the subsequent section, we will examine whether this variation allows for the detection of any robust micro-founded conditional interdependencies, pointing to the relevance of tangential shocks for the evaluation of subjective well-being.

5 Econometric analysis

5.1 The convergence of subjective and material well-being

Within the convergence approach, we establish the fundamental interrelation between socio-economic variables ($x_{i,t}$) and our measure of well-being dynamics on the individual level ($\Delta SWB_{i,t}$). Regarding the components of material well-being, we focus on household income per capita (in logs), income fluctuation and a household's relative income position. We also include reported shock experience in order to account for direct effects of shock experiences ($s'_{i,t}$) in general, and flood shock experience in particular, on the formation of subjective well-being.

For our analyses in the convergence approach, equation (3) depicts the resulting multinomial logit model. To account for systematic (measurement) error on the household level, we apply clustered standard errors at the household level. Potential year and country specific effects are absorbed by wave and country fixed effects. Due to a rather unbalanced panel on the respondent level, and to exploit a sufficient number of person-year observations, we apply at this point a multinomial logit model to our pooled sample.

The first model in Table 4 is our baseline model in the convergence approach. Typically, significant coefficients of variables related to material well-being exhibit the mathematical signs one would expect.[17] Higher per capita household income is associated with an increased likelihood of a positive well-being dynamic (Δ^{+}), and analogously, it translates into a lower probability of facing a negative well-being dynamic (Δ^{-}). More pronounced income fluctuations lower (raise) the probability of being better (worse) off.

Turning to the models accounting for actual shock experience over various pre-interview time horizons, the coefficient estimates of explanatory factors from the baseline specification prove to be robust. In the shock specifications, however, the coefficient for the binary indicator of actual flood or heavy rain shock experience remains insignificant. A similar pattern can be observed when the combined flood shock experience (flood and heavy rain) is substituted by the flood-only version (second last column) or a combined indicator for severe shock events (last column).

Whereas the overall number of all reported shocks decreases (increases) the likelihood to be better off (worse off), well-being dynamics of those without an actual flood shock experience are not significantly different from those being hit by such a shock. This lack of a direct flood shock effect could have, in principle, two reasons: unreliability of the self-reported flood shock measure or existing effects are otherwise absorbed. The existence of indirect effects of shocks, i.e. via lowered material well-being, is documented in a set of auxiliary estimations with log-income per nucleus household member as dependent variable (Table A.6). Households without an actual flood shock experience have a 14.7 to 23.9 % higher per capita income. These findings are highly significant and robust across all specifications. At the same time, these results indicate that self-reported flood events can be valid measures of shock experiences which affect material perspectives adversely. Therefore, the lack of any direct effects of shock experience on SWB is not due to a noisy self-reported shock measure.

[17] The same holds for non-pecuniary, i.e. socio-demographic variables, such as health (Table A.2).

Table 4: Income and shock-related coefficient estimates in the convergence approach

	base		environmental shock in last									
			1 month		3 months		12 months		12 months		12 months	
SWB response category	Δ^{+}	Δ^{-}	Δ^{+}	Δ^{-}	Δ^{+}	Δ^{-}	Δ^{+}	Δ^{-}	Δ^{+}	Δ^{-}	Δ^{+}	Δ^{-}
HH income p.c.	**0.229**a	**-0.058**c	**0.229**a	**-0.058**c	**0.228**a	**-0.056**c	**0.228**a	-0.049	**0.228**a	-0.049	**0.228**a	-0.048
(log)	(0.031)	(0.033)	(0.031)	(0.033)	(0.031)	(0.033)	(0.031)	(0.033)	(0.031)	(0.033)	(0.031)	(0.033)
HH income	**-0.138**a	**0.583**a	**-0.135**a	**0.580**a	**-0.135**a	**0.574**a	**-0.134**a	**0.556**a	**-0.134**a	**0.555**a	**-0.133**a	**0.553**a
fluctuation	(0.042)	(0.054)	(0.042)	(0.054)	(0.042)	(0.054)	(0.042)	(0.054)	(0.043)	(0.054)	(0.042)	(0.054)
	-0.214a	**1.551**a	**-0.210**a	**1.542**a	**-0.210**a	**1.533**a	**-0.205**b	**1.504**a	**-0.204**b	**1.504**a	**-0.206**b	**1.506**a
	(0.081)	(0.079)	(0.081)	(0.079)	(0.081)	(0.079)	(0.081)	(0.080)	(0.081)	(0.080)	(0.081)	(0.080)
low relative	0.027	**0.130**c	0.027	**0.128**c	0.026	0.132c	0.027	**0.133**c	0.026	**0.133**c	0.028	**0.130**c
income position	(0.066)	(0.074)	(0.066)	(0.074)	(0.066)	(0.075)	(0.066)	(0.075)	(0.066)	(0.075)	(0.066)	(0.075)
sum of shocks			**-0.135**b	**0.206**a	**-0.085**b	**0.291**a	**-0.048**b	**0.205**a	**-0.050**b	**0.200**a	**-0.040**b	**0.192**a
			(0.069)	(0.072)	(0.043)	(0.044)	(0.021)	(0.022)	(0.020)	(0.021)	(0.020)	(0.021)
flood +			0.624	0.322	0.566	0.329	-0.102	0.116				
heavy rain			(0.648)	(0.541)	(0.357)	(0.347)	(0.078)	(0.083)				
flood only									-0.133	0.071		
									(0.082)	(0.086)		
severe flood +											-0.034	-0.055
heavy rain											(0.096)	(0.096)
observations	13882		13882		13882		13882		13882		13882	
no. of HH clusters	3492		3492		3492		3492		3492		3492	

a: p<0.01, b: p<0.05, c: p<0.1

Note: All specifications include socio-demographic controls (age, age squared, gender, health dynamics, marital status, educational attainment and occupational status), as well as year and country FE. Standard errors (in parentheses) are clustered at the household level. The reference group for household income fluctuations is 'none'. Low relative income position refers to poor households (below 60% of a province's median income).

There is also evidence that the relation between our variables of interest and subjective well-being dynamics is not symmetric across the two dimensions of well-being dynamics: significant estimates vary not only with respect to their sign, but also notably in their absolute size. Concerning the overall shock experience, i.e. the sum of experienced shocks, the variation of coefficient estimates for positive well-being dynamics (Δ^{+}) suggests that the timing of shocks might be relevant too.

The main conclusion from the convergence approach is the general relevance of shock experience to subjective well-being. Estimates for direct flood shock experiences, however, remain below the threshold of significance. Therefore, there is no robust evidence of direct effects of experienced flood shocks on subjective well-being.

5.2 The divergence: How tangential shocks distort subjective well-being

Building on the convergence approach, this section focuses on the potential impact of tangential shocks on the formation of subjective well-being. Tangential flood shocks are defined as occurring in the vicinity of an individual, such that they are plausibly observable. They do not necessarily lead to an actual flood shock experience, e.g. by devastating relevant farm land. Instead, their potential impact on well-being is more subliminal, causing a distortion of stated well-being such that it may deviate more strongly from the latent fundamental well-being.

The underlying baseline estimation model is given by equation (4). Controlling for actual shock experience ($s_{i,t}$, as in the convergence approach), the coefficients γ_2 and θ_1 are informative with respect to the potential influence of tangential flood shocks ($s^{T}_{i,,t}$) on well-being: the first relates to the direct association of these tangential flood shocks and well-being. In our discussion, however, we will focus on the second, i.e. the coefficient related to the interaction of the binary flood experience indicator $s_{i,,t}$ and the continuous tangential shock measure $s^{T}_{i,t}$. This allows a further differentiation of the likely impact of tangential shocks on those individuals who also reported a severe actual shock experience (the reference group) and those who were either mere observers or perceived the shock to be of minor relevance.

Coefficient estimates for this tangential shock interaction θ_1 are reported in Table 5. Reported results originate from multinomial logit models where the tangential shock indicators varied with respect to the considered time horizons (1 month, 3 months and 12 months prior to the interview date), the radius of the sphere of interest (from 1 km to 5 km) and the aggregation of the MODIS flood data (see the panel labels).

Table 5: Tangential shock interaction estimates for θ_1, over various time horizons and spheres of interest

radius	1km		2 km		3 km		4 km		5 km	
SWB response category	Δ^+	Δ^-	Δ^+	Δ^-	Δ^+	Δ^-	Δ^+	Δ^-	Δ^+	Δ^-
Panel A: maximum number of flood days (on any pixel)										
1 month	-0.136	-0.053	0.035	0.053	0.044	0.065	0.005	**0.063**c	0.018	**0.049**c
	(0.101)	(0.117)	(0.057)	(0.069)	(0.041)	(0.048)	(0.030)	(0.035)	(0.026)	(0.027)
3 months	-0.047	-0.013	0.014	0.037	0.020	**0.039**b	0.006	**0.027**c	0.006	**0.024**b
	(0.042)	(0.048)	(0.020)	(0.027)	(0.016)	(0.018)	(0.011)	(0.014)	(0.010)	(0.010)
12 months	-0.007	-0.001	0.001	0.007	0.005	**0.009**b	0.002	**0.008**b	0.003	**0.007**b
	(0.008)	(0.008)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Panel B: average flood days (per pixel)										
1 month	-0.668	-0.746	0.867	-0.066	0.184	1.580	0.525	1.864	0.358	2.604
	(1.853)	(2.329)	(1.701)	(2.125)	(1.803)	(2.762)	(1.424)	(2.729)	(1.620)	(2.776)
3 months	-0.211	0.067	0.045	0.510	0.167	1.074	0.223	0.863	0.169	**1.079**c
	(0.670)	(0.835)	(0.622)	(0.855)	(0.535)	(0.775)	(0.477)	(0.621)	(0.500)	(0.600)
12 months	0.006	0.010	-0.005	0.025	-0.002	0.064	0.004	0.076	0.000	**0.085**c
	(0.033)	(0.031)	(0.033)	(0.040)	(0.035)	(0.048)	(0.036)	(0.048)	(0.037)	(0.048)

a: p<0.01, b: p<0.05, c: p<0.1

Note: All specifications include socio-demographic controls (age, age squared, gender, health dynamics, marital status, educational attainment and occupational status), 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 13,879 observations.

The results in Table 5 document significant interaction effects mostly for enlarged spheres of interest (with a radius of at least 3 km). These findings are asymmetric, i.e. restricted to negative well-being dynamics. A positive interaction coefficient θ_1 implies that well-being levels of individuals without any or a minor shock experience are indeed sensitive with respect to the exposure to a tangential shock: they are more likely to report a declining subjective well-being compared to those who reported a severe shock experience in the last 12 months.

Figure 3 illustrates the corresponding average marginal effects (AME) in the negative SWB domain (related to panel A of Table 5), derived over the tangential shock indicator's area of support.[18] Transforming coefficient estimates from our non-linear model into directly interpretable average marginal effects, conditional on the sample distribution, provides a refined interpretation. A first impression of the absolute size of the average marginal effects, suggests that they decrease with higher radii and increasing time horizons. This pattern provides support for both our household position and recency hypothesis.

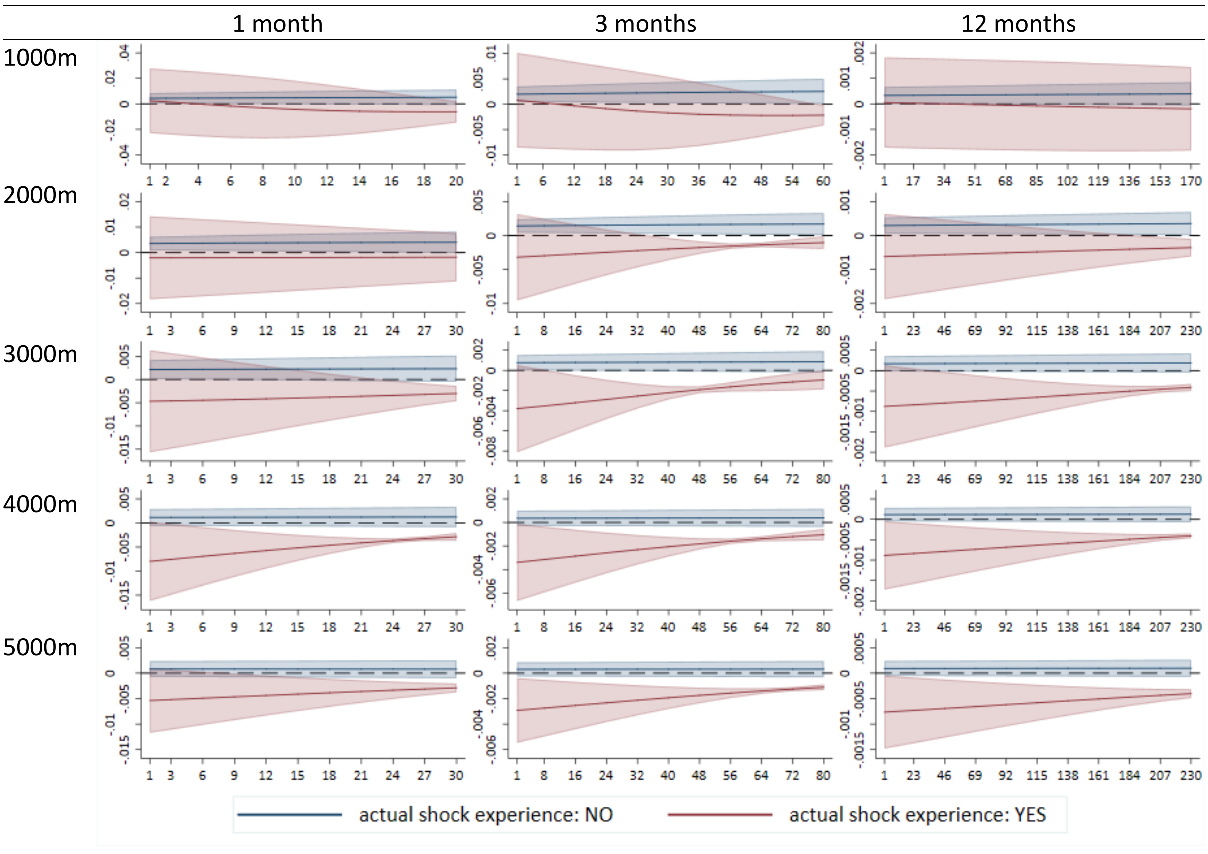
With the 90% confidence band being just above zero (dashed line), individuals without an actual shock experience (blue graph) are on average more likely to report negative well-being dynamics (relative to reporting a constant level of well-being) only for smaller spheres of interest. Typically, in the case of at least intermediate radii or time horizons the confidence bands of the two groups (with and without actual shock experience) do not overlap – 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 severe shock experience, prolonged tangential shocks do not increase the likelihood a respondent expresses a negative subjective well-being dynamic. In fact,

[18] Figure A.3 provides an overview for positive and negative SWB dynamics. AMEs are evaluated at the indicator's mean, 90th and 95th percentile.

those suffering by an actual shock are more likely to report unchanged well-being levels, since AMEs are interpreted relative to this reference category. A positive gradient for this group, however, indicates that long-lasting tangential shock exposure could eventually translate into a decreasing resilience, i.e. diminish the share of individuals reporting constant well-being levels instead of declining levels. Referring to the 5 km radius and a time horizon of 3 months, going from one day of maximum flood exposure to 40 days of maximum exposure would lessen the dampening effect of having been hit by an actual shock on the effect of one additional day of exposure from -0.3 percentage points to -0.2 percentage points.[19]

Figure 3: Average marginal effects for negative SWB dynamics - maximum days of flood exposure measure



Note: All marginal effects draw upon the baseline specification of the divergence approach (13,879 observations). The depicted response and shock-experience-specific average marginal effects have been evaluated over the range of the respective tangential shock measure (maximum days of flood exposure), depicted on the x-axis. The shaded areas indicate the 90% confidence intervals.

Returning to the comparison of tangential shock indicators in Table 5, the observed pattern is less prominent in the relative exposure indicator (Panel B), controlling for the size of the sphere of interest. Unreported results for the third indicator (the number of affected pixels) did not yield significant results.

Converting coefficients of the relative exposure measure into average marginal effects, however, supports previous findings to a large extent. For larger spheres of interest and longer time horizons, average marginal effects (Figure A.4) display a similar pattern as we observed in Figure 3. The differential behaviour between individuals with or without actual shock experience is retrieved, especially, for the intermediate range of the relative tangential shock exposure measure.

Considering the differing concepts incorporated in the three tangential shock measures, the somewhat weaker performance of the relative exposure measure and the lack of predictive power in the case of the affected area

[19] Given a basic response likelihood for the worse off category (20.56 %), even a seemingly small absolute effect of 0.1 percentage points for one additional flood day would translate into a notable response change in case of a typical flood event, lasting several days in total.

indicator can be rationalised. The number of flooded pixels may be indicative of the geographical expansion of a flood event, but it may say little regarding an event's potential impact on agricultural production. High values can refer to rather short events, which either did not fall into a growing season or did not last long enough to affect plant growth. Even in case of the longest time horizon and largest sphere of interest, the flooded area amounts to less than 5 % of a respective sphere of interest. A similar argument can be put forward for the relative exposure measure. Within a year and a radius of 5 km, the relative flood exposure remains below one day (cf. 3), thus the perceived severity of the flood exposure might be below a recognition threshold.

Maximum local flood severity, i.e. the maximum number of flood days on a pixel, mirrors potentially threatening events in a more precise manner. The sample average for the largest sphere of interest amounts to 4.5 days 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 a flood event is observed by an individual, and thus, might impinge on subjective well-being. Alternatively, this measure might be indicative of severe events which affected other households as well. Depending on a household's interdependencies within the village community, this local severity measure might pick up feed-back effects from other households even though a reporting household was not directly hit by a flood shock.

The aspects of tangential shocks correlating with growth periods, pointing to diverse effects for farming and non-farming households, and correlated household shock exposure will be further addressed in our sensitivity analyses.

5.3 Sensitivity analyses

Our first robustness check controls for the potential transfer of shock-related well-being dynamics across 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.[20] 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.3 documents for various time horizons (3 and 12 months) and spheres of interest (3 and 5 km) the robustness of our findings from the divergence approach.[21] Notably, our network variable displays significance across all specifications, yet only for positive well-being dynamics: the larger the share of other households exposed to a tangential shock, the lower 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, though it does not affect our main results.

A second sensitivity analysis captures 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. The second specification in Table A.3 displays the robustness of our findings, 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

[20] We also applied equal and linear distance weights. The results remain unaffected. We selected the log-distance weights due to a desirable feature, i.e. partially lowering the dominant impact of one very close neighbour over a number of more distant neighbours. We further restrict the construction of our network variable to households with at least three neighbours. The sample size remains fairly constant.

[21] The results for smaller sphere of interest radii remained insignificant. Those for unreported shorter time horizons and larger radii displayed the same significant patterns as in section 5.2.

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.

In a third specification, we investigate our results' robustness with respect to diverging practical importance of events in a given sphere of interest. Our baseline models account for respondents' main occupation - this factors in that farming households might be more susceptible to (tangential) flood shocks in general. Now, we further account for the size of the cultivation area in a general sphere of interest. However, although individuals with more farm land at stake, thus the relatively better-off, display more frequently positive well-being dynamics, we still observe the familiar impact of tangential shocks regarding negative well-being dynamics.

The vulnerability of farming households is further addressed by controlling for growth periods of major crops (rice, corn, peanuts, cassava or sweet potato, vegetables, fruits).[22] Whenever a household was cultivating a specific crop in the corresponding time horizon, the respective growth period variable is coded as one. Typically, derived coefficients are invariant with respect to the inclusion of this set of control variables.[23] An analysis of average marginal effects for this specification (Figure A.5) reveals insignificant effects for the group lacking direct shock experience. The declining resilience effect for the second group remains unaffected.

Aside from these specific sensitivity checks, we also performed analyses where we matched the time horizon of the self-reported actual shock experience (s) and the satellite-based tangential shock measure (s^T). Our main results (not reported) remain unchanged. However, we did encounter convergence and collinearity issues related to a notably diminished level of variation for shorter time horizons and smaller spheres of interest.

We also re-estimated our model with SWB on the household level as dependent variable. Considering the extremely high degree of correlation between these two alternative SWB concepts, shock-related coefficient estimates are robust (last column, Table A.3).

Our next robustness check assesses the reliability of our previous estimation results with respect to unobserved heterogeneity. So far, our estimations were based on a multinomial logit framework in a cross-sectional pooled sample where observations are linked on the household level. This allowed us to examine asymmetric relations between potentially relevant factors across the two well-being dynamic domains. These dynamics, however, are rooted in 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 within 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 divergence models (3 km / 5 km sphere of interest and 3 / 12 months time horizon) with the maximum flood exposure indicator in a panel setting. The dependent variable is now binary, where negative well-being dynamics are coded as one. Positive well-being dynamics and stable well-being levels are joined in the reference category.

Table A.4 reports the results from fixed and random effects models on the respondent level (panel A) and the household level (panel B).[24] In the respondent panel, significant interaction coefficients can be retrieved from the random effects model, but not from the fixed effects model. Controlling for unobserved heterogeneity on

[22] It is not possible to link growth periods of specific crops and sphere of interest-specific cultivation areas.
[23] The interaction coefficient (3 km, 12 months) in the positive well-being dynamics domain is the one exemption. The estimates for all other radii (1 km, 2km, 4 km, 5 km) and time horizons (1 month, 3 months) are insensitive to the inclusion of crop-specific growth period indicators.
[24] The set of explanatory variables corresponds to the baseline divergence approach, not those lacking the required variation for FE estimation (excluded are gender, marital status, education and occupation). RE estimations are conditioned to draw upon the FE sample.

the household level, both the direct flood exposure and its interaction with self-reported flood experience prove to be significant across both model specifications.

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

5.4 Moderating factors

So far, we pointed out that subjective well-being can be swayed by tangential shocks. Individual sensitivity to this sort of shock exposure also varies between individuals who actually experienced a shock and those who did not. However, there might be other factors moderating a tangential shock's impact: beyond the relative position of households and (tangential) shocks, previously represented by the concept of spheres of interest, a household's position within the geographic environment could be pivotal. Studying the impact of environmental shocks on SWB in Madagascar, for instance, Mills et al. (2004) found that low levels of market and transport infrastructure have negative impacts on SWB levels.

We therefore assume that location-specific moderating factors may affect the perception of tangential shocks and their evaluation with respect to the formation of subjective well-being. For instance, a household in a remote region might react differently to a tangential shock than a household close to a more developed municipality. In the latter case, related to proximity to larger markets and public services, a household might expect a higher likelihood of receiving emergency relief in case of an actual shock experience. Consequently, the adverse effects of tangential shock exposure in the last year on well-being might be mitigated.

Additionally, villagers might anticipate that awareness for their situation may be higher in regions which are nationally and internationally more connected. Therefore, the level of accessibility to the transportation system might play a mediating role as well.

Another potentially moderating factor is related to adaptation (Guiteras et al., 2015): households in regions which experience considerable flooding on a regular basis are likely to have developed strategies to alleviate the impact on their well-being. Similarly, these households' well-being dynamics might be less prone to be influenced by tangential shocks. In this regard, a measure of flooding potential may serve as proxy for adaptation.

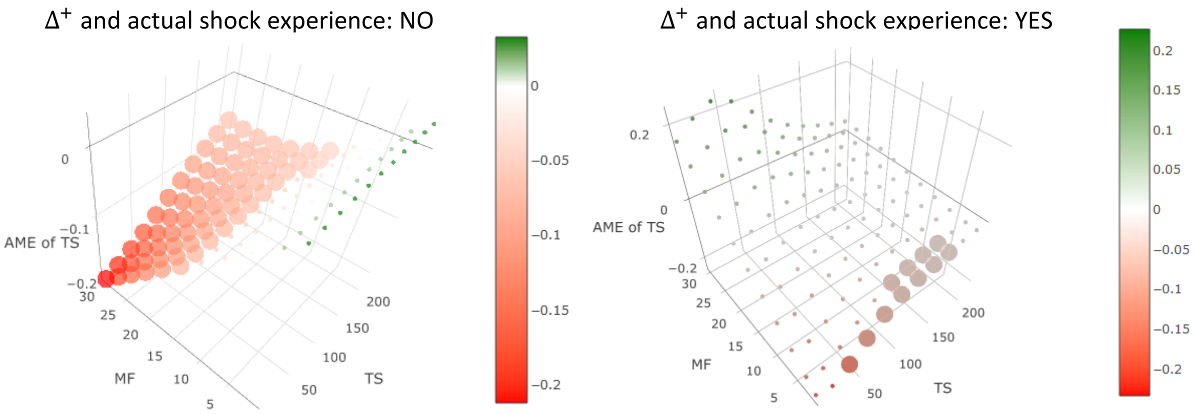
Using OpenStreetMap data, these three concepts - accessibility, urban development and flooding potential - will be incorporated into an extension of our analysis. The relevance of the moderating factor accessibility is evaluated based on the distance to the nearest transportation system, e.g. motorway or railway. Urban development indicators are based on the distance to the nearest municipality. An alternative measure refers to the proximity of nearest hospital. Flooding potential is inversely related to the distance to the nearest running water (stream or river) or body of water (lake or reservoir).

The impact of these localised moderating factors is modelled by adding a set of complete interactions of a moderating factor, the tangential shock variable (s^T) and the shock experience (s) to equation (4). In order to interpret the complex set of interactions, we calculated average marginal effects of one additional maximum flood exposure day across the range of the tangential shock variable and a respective moderating factor.[25]

[25] Coefficient estimates for the maximum sphere of interest and the 3 and 12 month time horizon are reported in Table A.5.

When we account for geographic moderating factors over their complete range, significant average marginal effects can be observed mainly for positive well-being dynamics. Figure 4 contrasts AMEs for individuals without shock experience (left panel) and those with shock experience (right panel). Individuals without an actual flood experience residing at a greater distance from a river, thus facing lower flood risk in general, are much less likely to report a positive well-being dynamic for low to medium levels of tangential shock exposure. Those with flood experience, in turn, are less likely to feel better off if their flood exposure increases further and they live in the vicinity of rivers.

Figure 4: AMEs for positive well-being dynamics, conditional on flood exposure and distance to a river



Note: TS refers to the maximum flood day indicator (radius of 5km, time horizon of 12 months); MF is the distance to the closest river (in km). Small dots indicate insignificant average marginal effects (AME). Large dots represent AMEs significant at least at the 10% level. AMEs have been scaled by the factor 100, i.e. -0.2 corresponds to an effect of -0.2 percentage points.

Amongst the other geographic moderating factors, distance to a motorway (Figure A.6) and the distance to hospitals provided interesting insights.[26] Given higher shock exposure, further increasing exposure levels diminish the likelihood of a positive (negative) well-being dynamic for individuals without actual shock experience in better (less) connected areas. In the case of the moderating factor accessibility, we also detect the resilience effect of individuals with actual shock experience: Individuals who are geographically better connected are also less likely to experience a negative well-being dynamic if their flood exposure increases (lower right panel).

Our findings therefore support our 'shock subjectivity hypothesis', i.e. the existence of asymmetric moderating effects, such as adaptation in regions with a higher flooding potential. Additionally, the sensitivity of individual well-being to tangential shocks and actual shocks varies in response to a village's geographic connectedness.

6 Conclusion

Employing a unique household sample from Southeast Asia, we investigate the sensitivity of subjective well-being dynamics to tangential shock events. We therefore study flood events in rural villages in Thailand and Vietnam. Capitalising on satellite-based near real-time flood event data, we compare well-being dynamics of individuals reporting an actual flood shock experience with those who did not report any experience, but do live in close proximity to the flood event. We show that merely witnessing a flood event can indeed be sufficient to

[26] Positive well-being dynamics of respondents without actual shock experience living in more remote areas (characterised by a larger distance to a hospital) are adversely affected by tangential shocks for a given medium to high level of flood shock exposure.

trigger negative well-being dynamics. The effects of these tangential shocks are found to be heterogeneous across households and to depend on geographic factors and the timing of the interview. Moreover, the analysis of marginal effects shows that individuals' with direct actual flood experience are more resilient regarding the exposure to additional shock events (i.e. additional flood water days) than individuals' merely observing the event. It seems that the lack of direct self-experience translates into an overemphasis of potentially adverse, yet not faced, consequences. We might think of three possible explanations for this. First, it is the consequence of a rational belief update. Observing the event makes people realize the threat of potentially adverse events. Second, the effect is an altruistic or emphatic reaction, i.e. individuals' care about the people in their close environment and feel for them if they are struck by negative events. Third, individuals might expect indirect financial repercussions from the event, related to social obligations to support their shock-affected neighbours or friends financially.

In conclusion, our findings show that subjective well-being levels are not only determined by observable and relatively easy measurable factors, but also by perceived factors, like tangential shock events. Subsequently, the individual perception of a specific situation is relevant when it comes to judging ones' own life satisfaction.

Relevance and implications. Our findings are in line with psychological research on 'secondary traumas'. We show that this phenomenon is also relevant when it comes to adverse environmental shocks and individuals' subjective well-being dynamics. Hence, we add a new aspect 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 that is representative of the rural population in Thailand and Vietnam, we argue that the relevance of our results may extend beyond this population. Different studies (Sarracino, 2013; Markussen, 2014; Reyes-García et al., 2016) have identified a so called 'unique happiness function'. They find that determinants of subjective well-being hold for individuals across countries and cultures.

Our findings thus call for a more cautious interpretation of behavioural responses and well-being measures, respectively a more thorough consideration of the circumstances individuals were encountered in. Traditional survey instruments do not capture such tangential events. In light of our results, researchers might want to consider the dynamic environment of the respondent and the interaction thereof.

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

Avenue for further research. Having established the adverse effects of tangential shocks on individual perceptions and well-being dynamics, future research might concentrate on three things. First, the interrelation of tangential shock events and behavioural and economic decision making. TSE might not only effect personal well-being dynamics, but also economic behaviour. Second, future studies might investigate if our findings translate to other adverse situations. If environmental shocks can cause such an effect, other situations might as well. Third, research on the origins of this effect is needed in order to adequately react to it. We discussed some possible explanations above. This is where future research might tie in.

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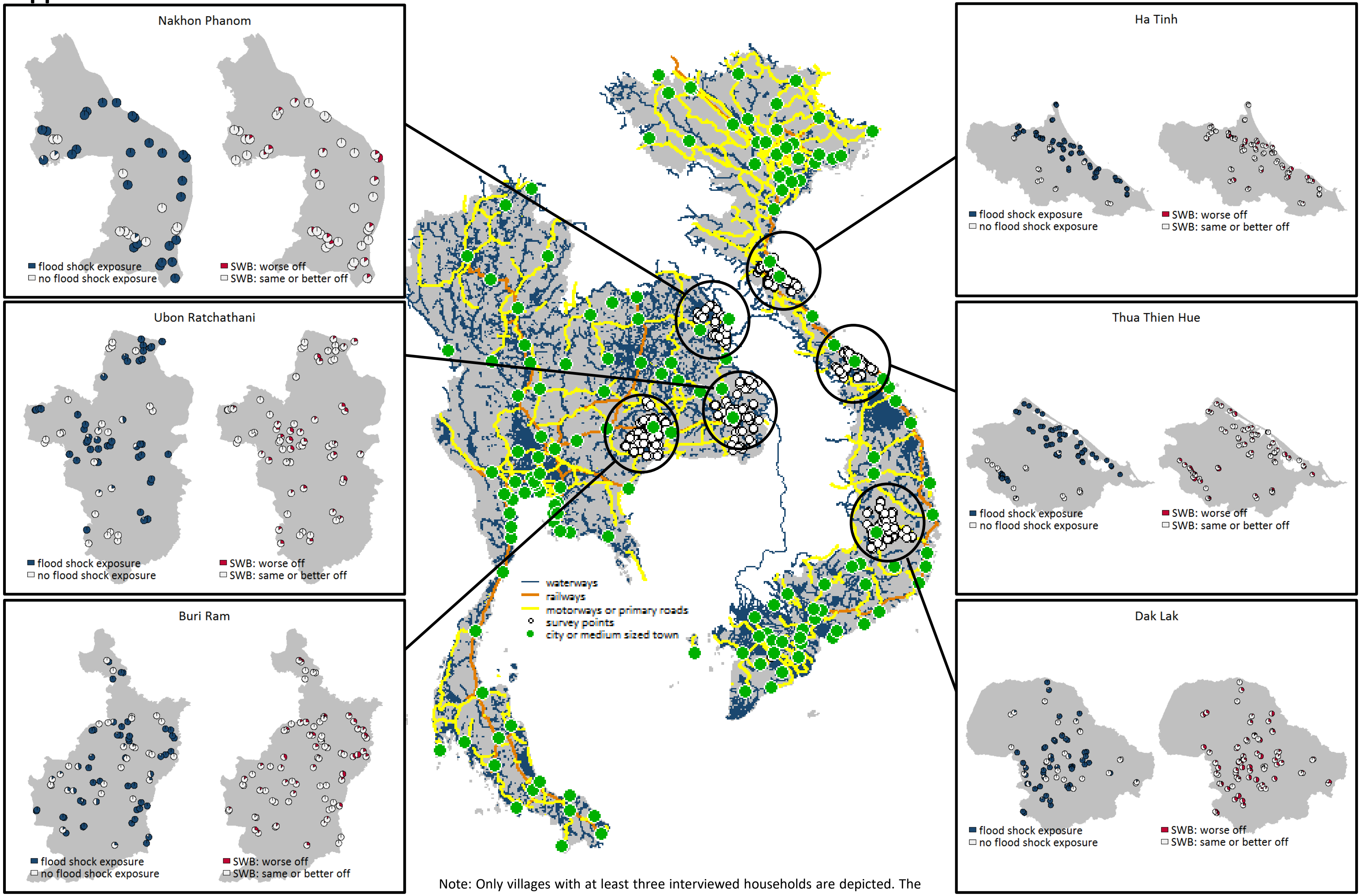
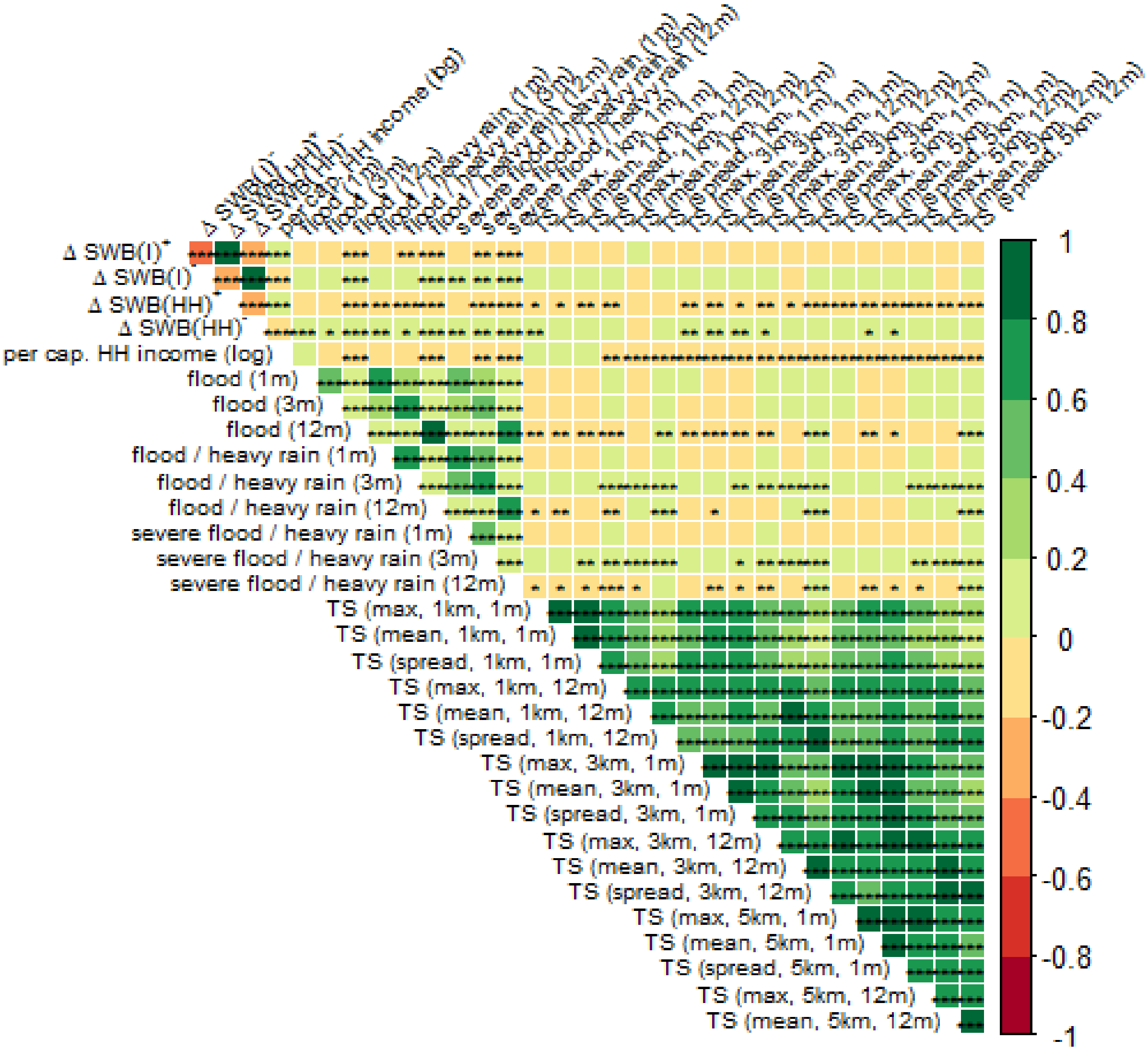
Appendix

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.

Figure A.2: Correlation plot for binary SWB indicators, various shock experiences and shock exposures



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

Note: Correlations are derived within the unconditional baseline sample from the convergence approach (sample size varies between 14,190 and 14,771 pairwise observations). Correlations with binary SWB variables on the household level ($\Delta SWB\ (HH)$) draw upon a smaller sample (between 11,320 and 11,323 observation) since the underlying item was only included in the waves from 2008 onwards.

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

category	variable label	short description	original scale	N	min	max	mean	std.dev.
dependent variable	*well-being dynamic*	individual well-being compared to last year (1: better off, 2: same, 3: worse off)	categorical	13789	1 (37.08%)	3 (20.56%)	-	-
explanatory variables (individual or HH level)	*HH income p.c. (log)*	log of HH income per nucleus HH member	cardinal	13789	-1.171	12.103	7.045	1.076
	HH income fluctuation	fluctuation of HH income (1: not at all, 2: a bit, 3: a lot)	categorical	13789	1 (39.27%)	3 (10.11%)	-	-
	relative income position	poverty indicator: household income below 60% of the in-sample median household income at the province level	binary	13789	0	1	0.300	-
	gender	gender of the respondent (0: male, 1: female)	binary	13789	0	1	0.520	-
	age	respondent's age	cardinal	13789	15	91	50.168	13.314
	health dynamics	health status compared to one year before (1: worse, 2: same, 3: better)	categorical	13789	1 (31.44%)	3 (11.15%)	-	-
	marital status	relationship indicator (0: unmarried 3.4%, 1: married 84.8%, 2: widowed 10.0%, 3: divorced/separated 1.9%)	categorical	13789	0	3	-	-
	educational attainment	highest educational attainment (0: no schooling 9.2%, 1: some years in elementary 41.3%, 2: primary 27.1%, 3: lower secondary 16.3%, 4: upper secondary or higher 8.1%)	categorical	13789	0	4	-	-
	main occupational status	main occupational status in the last year (0: no occupation 4.3%, 1: housewife/HH-member caretaker 3.3%, 2: casual employed 8.2%, 3: permanent employed 2.3%, 4: own agriculture/hunting 70.5%, 5: own off-farm business 8.7%, 6: government official 2.0%, 7: student/pupil 0.1%)	categorical	13789	0	7	-	-
	total no. of shocks experienced	aggregate number of all shocks in the last year a respondent has actually experienced (himself or on the HH level)	cardinal	13789	0	10	0.920	1.238
	flood shock experience	HH experienced an actual flood shock in the last year (0: no, 1: yes), reversed for reasons of interpretability in the estimations	binary	13789	0	1	0.092	-
	flood or heavy rain shock experience	HH experienced an actual flood or heavy rain shock in the last year (0: no, 1: yes), aggregated due to similarity of event	binary	13789	0	1	0.100	-
	severe flood shock experience	HH experienced a severe actual flood shock in the last year (0: no, 1: yes)	binary	13789	0	1	0.054	
	severe flood or heavy rain shock experience	HH experienced a severe actual flood or heavy rain shock in the last year (0: no, 1: yes)	binary	13789	0	1	0.059	-
TS indicators	*r=5000, m=1*	binary overview indicator, any flood detection within radius r around the homestead during the last m months	binary	13789	0	1	0.217	0.413
	r=5000, m=3		binary	13789	0	1	0.343	0.475
	r=5000, m=12		binary	13789	0	1	0.673	0.469
	other indicators	***see 3***						
sensitivity analyses	network (*r=5000, m=12*)	distance weighted share of village HH exposed to TS in r and m	cardinal	10068	0	1	0.673	0.461
	flood history (*r=5000*)	HH specific average maximum yearly TS exposure in r	cardinal	10068	0	195.333	19.279	35.736
	land-use (*r=5000*)	cultivation area size in r $(hectar)$	cardinal	10068	0	480	2.499	9.004
	growth season (*m=12*)	all crops in m	binary	10068	0	1	0.995	0.068
		rice in m	binary	10068	0	1	0.880	0.325
		corn in m	binary	10068	0	1	0.100	0.300
		peanuts in m	binary	10068	0	1	0.108	0.310
		cassava / sweet potatoes in m	binary	10068	0	1	0.165	0.371
		vegetables in m	binary	10068	0	1	0.192	0.394
		fruits in m	binary	10068	0	1	0.024	0.152
moderating factors	*min. dist. to lake*	distance (km) to the closest lake or reservoir	cardinal	10068	0.012	29.985	5.256	5.371
	min. dist. to river	Distance (km) to the closest river or stream	cardinal	10068	0.023	33.381	6.342	6.422
	min. dist. to city	distance (km) to the closest conurbation	cardinal	10068	4.047	529.680	194.051	177.545
	min. dist. to hospital	distance (km) to the closest hospital	cardinal	10068	2.867	197.669	63.404	57.666
	min. dist. rail	distance (km) to the closest rail	cardinal	10068	0.0387	195.093	47.490	41.003
	min. dist. to motorway	distance (km) to the closest motorway	cardinal	10068	53.005	331.963	193.106	59.880

Note: Descriptive statistics for explanatory variables on the household / individual level and flood exposure variables are conditioned on the sample in the divergence approach (n=13,879). Variables from the sensitivity analyses and moderating factors refer to the corresponding sample of from the extended divergence approach (n=10,068). 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.

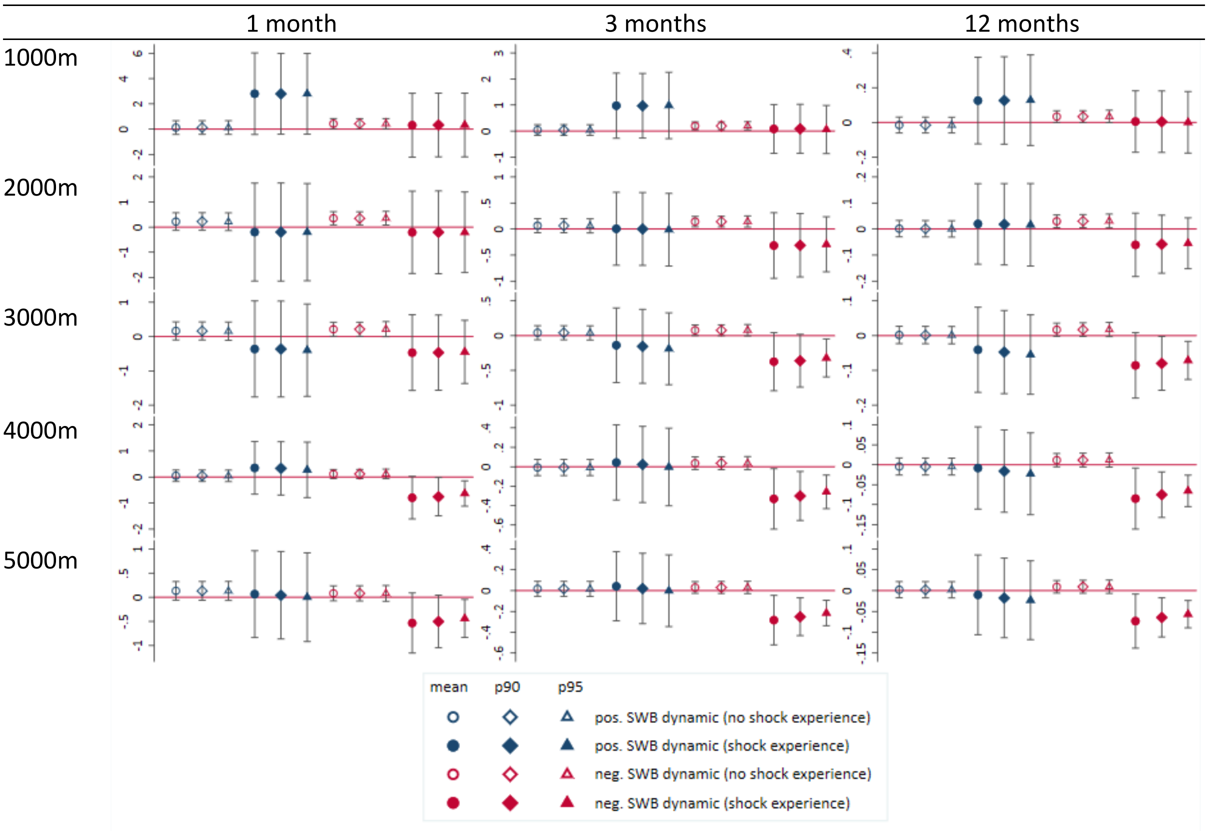
Table A.2: Coefficients in a benchmark model comparison

	convergence		divergence					
	baseline		baseline (r=5000, m=12) maximum flood exposure measure		baseline (r=5000, m=12) relative flood exposure measure		sensitivity specification (r=5000, m=12) maximum flood exposure measure	
	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. (log)	**0.228**a (0.031)	-0.048 (0.033)	**0.231**a (0.031)	-0.046 (0.033)	**0.232**a (0.031)	-0.047 (0.033)	**0.224**a (0.038)	-0.045 (0.040)
HH income fluctuation								
moderate	**-0.133**a (0.042)	**0.553**a (0.054)	**-0.132**a (0.043)	**0.557**a (0.054)	**-0.132**a (0.043)	**0.556**a (0.054)	**-0.139**a (0.050)	**0.560**a (0.066)
high	**-0.206**b (0.081)	**1.506**a (0.080)	**-0.205**b (0.081)	**1.505**a (0.080)	**-0.205**b (0.081)	**1.507**a (0.080)	**-0.249**a (0.094)	**1.537**a (0.094)
relative income position	0.028 (0.066)	**0.130**c (0.075)	0.032 (0.066)	0.132c (0.075)	0.035 (0.066)	**0.130**c (0.075)	0.000 (0.077)	0.121 (0.088)
gender (female=1)	-0.006 (0.046)	-0.003 (0.055)	-0.007 (0.046)	-0.004 (0.055)	-0.008 (0.046)	-0.004 (0.055)	0.010 (0.054)	0.042 (0.064)
age	0.008 (0.011)	**0.035**a (0.013)	0.008 (0.011)	**0.035**a (0.013)	0.007 (0.011)	**0.035**a (0.013)	0.011 (0.013)	**0.040**b (0.016)
age squared	**-0.000**c (0.000)	**-0.000**b (0.000)	-0.000 (0.000)	**-0.000**b (0.000)	-0.000 (0.000)	**-0.000**a (0.000)	-0.000 (0.000)	**-0.000**b (0.000)
health dynamics (1 year)								
worse	-0.005 (0.048)	**0.527**a (0.054)	-0.004 (0.048)	**0.530**a (0.054)	-0.002 (0.048)	**0.526**a (0.054)	-0.025 (0.057)	**0.518**a (0.064)
better	**0.655**a (0.064)	0.126 (0.092)	**0.656**a (0.064)	0.129 (0.092)	**0.657**a (0.064)	0.129 (0.092)	**0.673**a (0.074)	0.063 (0.109)
marital status								
married	0.192 (0.118)	0.149 (0.151)	0.194 (0.118)	0.152 (0.151)	**0.197**c (0.118)	0.150 (0.151)	0.153 (0.136)	-0.000 (0.169)
widowed	0.203 (0.141)	0.240 (0.171)	0.208 (0.141)	0.248 (0.171)	0.212 (0.141)	0.243 (0.172)	0.096 (0.164)	-0.040 (0.200)
divorced / separated	-0.127 (0.198)	0.321 (0.215)	-0.121 (0.198)	0.333 (0.216)	-0.114 (0.198)	0.325 (0.216)	-0.223 (0.264)	0.328 (0.265)
educational attainment								
some elementary	0.109 (0.092)	-0.124 (0.095)	0.111 (0.092)	-0.123 (0.095)	0.114 (0.092)	-0.127 (0.095)	0.128 (0.111)	-0.171 (0.115)
primary	0.141 (0.093)	**-0.189**c (0.098)	0.142 (0.093)	**-0.189**c (0.097)	0.146 (0.093)	**-0.192**b (0.098)	0.187 (0.114)	-0.163 (0.118)
lower secondary	**0.329**a (0.096)	-0.106 (0.107)	**0.330**a (0.096)	-0.105 (0.106)	**0.339**a (0.096)	-0.109 (0.107)	**0.343**a (0.118)	-0.104 (0.129)
upper secondary (and more)	0.181 (0.111)	-0.218 (0.134)	0.181 (0.111)	-0.218 (0.133)	**0.189**c (0.111)	**-0.222**c (0.134)	0.194 (0.136)	**-0.381**b (0.164)
main occupational status								
housewife / home nursing	0.249 (0.159)	0.096 (0.166)	0.247 (0.159)	0.095 (0.166)	0.248 (0.159)	0.098 (0.166)	**0.419**c (0.224)	0.259 (0.253)
casual labour	**0.250**c (0.131)	0.130 (0.136)	**0.250**c (0.131)	0.131 (0.136)	**0.251**c (0.131)	0.130 (0.136)	0.251 (0.195)	**0.394**c (0.214)
permanently employed	**0.477**a (0.163)	0.235 (0.195)	**0.474**a (0.162)	0.227 (0.196)	**0.475**a (0.163)	0.226 (0.196)	**0.502**b (0.238)	0.354 (0.296)
agriculture	**0.409**a (0.117)	-0.130 (0.121)	**0.410**a (0.117)	-0.128 (0.121)	**0.412**a (0.117)	-0.130 (0.121)	0.264 (0.169)	0.086 (0.186)
own business	**0.418**a (0.133)	0.213 (0.145)	**0.415**a (0.133)	0.208 (0.145)	**0.414**a (0.133)	0.212 (0.145)	**0.402**b (0.194)	**0.375**c (0.222)
government official	**0.564**a (0.190)	0.280 (0.235)	**0.554**a (0.190)	0.286 (0.235)	**0.557**a (0.190)	0.283 (0.235)	0.185 (0.256)	0.424 (0.323)
student / pupil	0.048 (0.810)	0.389 (0.904)	0.043 (0.810)	0.378 (0.905)	0.023 (0.817)	0.377 (0.906)	-0.094 (0.811)	0.625 (0.936)
sum of shocks	**-0.040**b (0.020)	**0.192**a (0.021)	**-0.040**b (0.020)	**0.191**a (0.021)	**-0.039**c (0.020)	**0.191**a (0.021)	**-0.045**b (0.023)	**0.178**a (0.024)
no flood shock experience (s)	-0.034 (0.096)	-0.055 (0.096)	-0.087 (0.112)	**-0.182**c (0.109)	-0.033 (0.102)	-0.115 (0.102)	-0.150 (0.120)	**-0.218**c (0.119)
s^T			-0.002 (0.003)	**-0.006**b (0.003)	0.010 (0.037)	**-0.080**c (0.048)	-0.005 (0.003)	**-0.009**b (0.004)
$s \times s^T$			0.003 (0.003)	**0.007**b (0.003)	-0.000 (0.037)	**0.085**c (0.048)	0.003 (0.003)	**0.007**b (0.003)
network							**-0.136**b (0.057)	0.023 (0.069)
flood history							0.003 (0.002)	**0.004**c (0.002)
land-use							0.004 (0.004)	0.003 (0.007)
growth season: rice							-0.058 (0.080)	**-0.182**b (0.086)
corn							-0.044 (0.092)	0.068 (0.098)
peanuts							0.021 (0.087)	**0.169**c (0.094)
cassava / sweet potatoes							**0.113**c (0.068)	-0.067 (0.083)
vegetables							-0.020 (0.064)	-0.108 (0.074)
fruits							0.148 (0.155)	-0.184 (0.182)
observations (HH clusters)	13882 (3492)		13879 (3492)		13879 (3492)		10068 (2983)	
LL	-13787.59		-13781.78		-13781.99		-9970.83	
df (model)	60		64		64		82	
Wald χ^2 (prob > χ^2)	1539.23 (0.0000)		1540.81 (0.0000)		1537.64 (0.0000)		1130.00 (0.0000)	

a: p<0.01, b: p<0.05, c: p<0.1

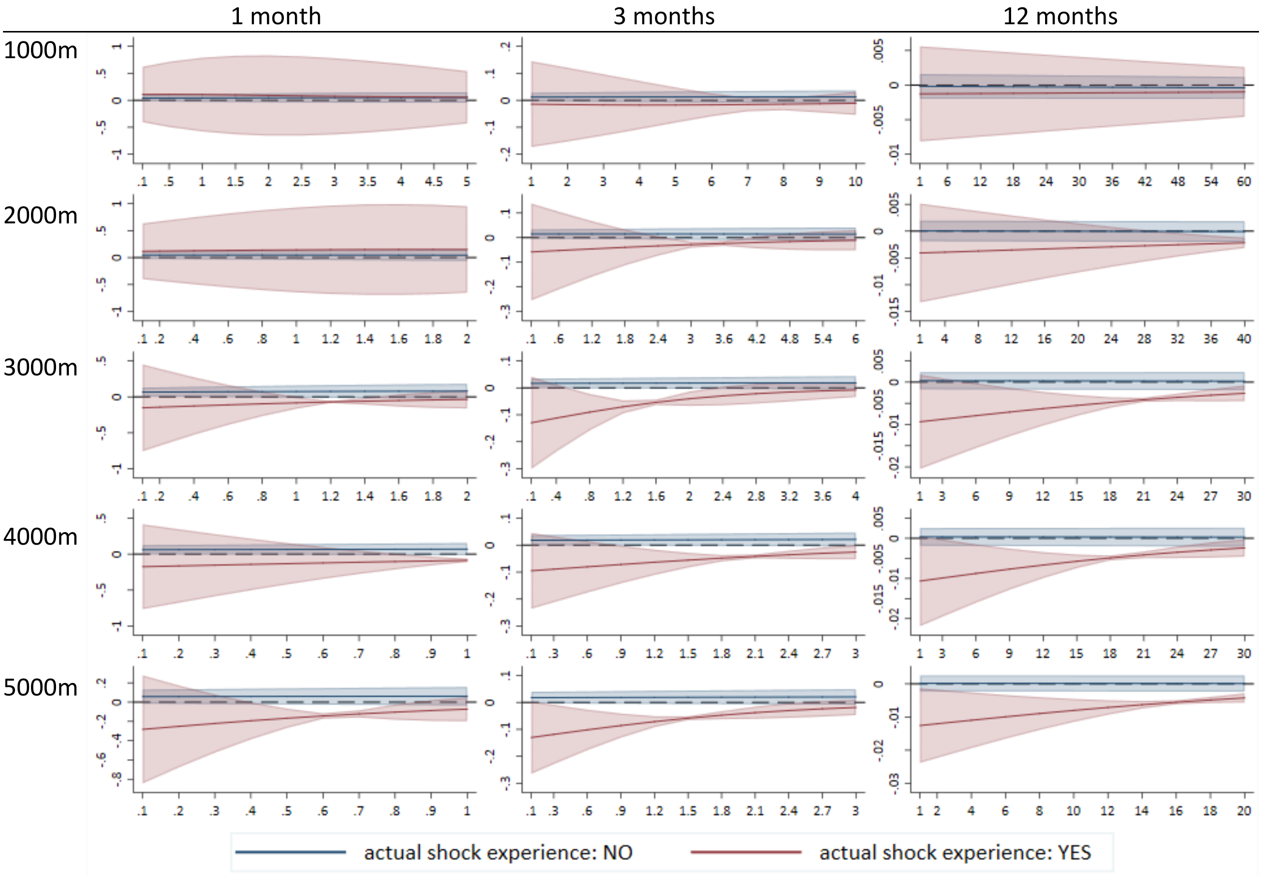
Note: All specifications include year and country FE. Standard errors are clustered at the household level. '×' denotes an interaction.

Figure A.3: Average marginal effects (%) for both SWB dynamics - maximum days of flood exposure measure



Note: All marginal effects draw upon the baseline specification of the divergence approach. Each comprised the identical sample of 13,879 observations. The depicted response and shock experience specific average marginal effects have been calculated at the mean, the 90th and 95th percentile of the tangential shock variable (maximum days of flood exposure). The whiskers indicate the 90% confidence intervals.

Figure A.4: Average marginal effects for negative SWB dynamics - relative flood exposure measure



Note: All marginal effects draw upon the baseline specification of the divergence approach. Each comprised the identical sample of 13,879 observations. The depicted response and shock experience specific average marginal effects have been evaluated over the range of the respective tangential shock measure (average flood days per pixel). The shaded area indicate the 90% confidence intervals.

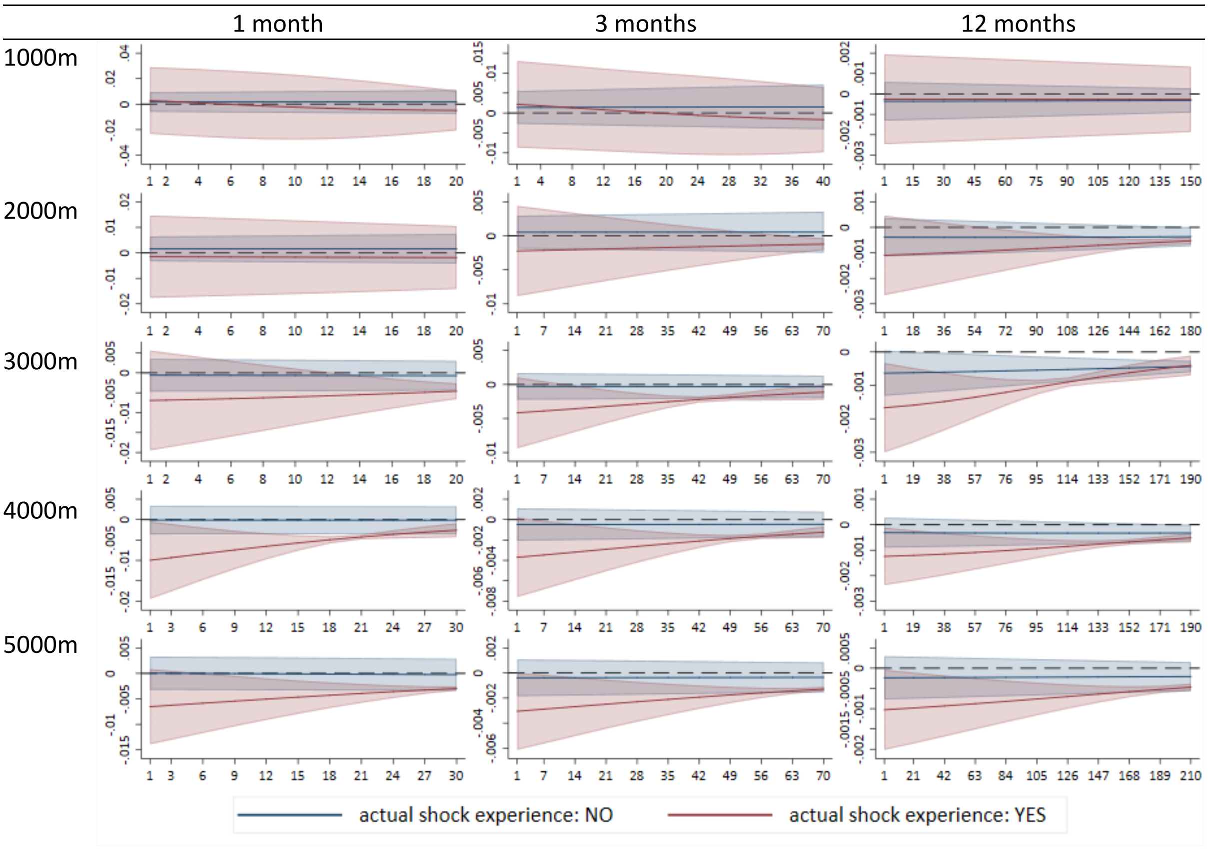
Table A.3: Tangential shocks sensitivity analysis – maximum shock exposure

	r	**SWB (respondent level)**								**SWB (household level)**	
	r	Δ^{+}	Δ^{-}	Δ^{+}	Δ^{-}	Δ^{+}	Δ^{-}	Δ^{+}	Δ^{-}	Δ^{+}	Δ^{-}
Panel A: 3 months											
s^T		-0.017	**-0.032**c	-0.021	**-0.040**b	-0.021	**-0.040**b	-0.021	**-0.037**c	-0.026	-0.029
		(0.016)	(0.018)	(0.017)	(0.019)	(0.017)	(0.019)	(0.019)	(0.022)	(0.020)	(0.021)
$s \times s^T$		0.023	**0.039**b	0.023	**0.040**b	0.023	**0.039**b	0.025	**0.038**c	0.025	**0.034**c
		(0.016)	(0.018)	(0.016)	(0.018)	(0.016)	(0.018)	(0.018)	(0.021)	(0.019)	(0.020)
network		**-0.135**a	0.041	**-0.144**a	0.024	**-0.135**a	0.025	**-0.112**b	-0.013	-0.050	-0.018
	3000	(0.048)	(0.056)	(0.049)	(0.058)	(0.050)	(0.058)	(0.056)	(0.067)	(0.063)	(0.076)
flood history				✓		✓		✓		✓	
land-use						✓		✓		✓	
growth season								✓		✓	
N		13115		13115		13026		10068		7879	
Panel B: 12 months											
s^T		-0.004	**-0.007**c	**-0.009**b	**-0.015**a	**-0.009**b	**-0.015**a	**-0.011**a	**-0.016**a	**-0.012**a	**-0.013**b
		(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$s \times s^T$		0.005	**0.009**b	0.006	**0.010**b	0.006	**0.010**b	0.007c	**0.010**b	0.008c	**0.011**b
		(0.004)	(0.004)	(0.004)	(0.004)	(0.04)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
network		**-0.134**a	0.042	**-0.141**a	0.032	-0.131a	0.033	**-0.124**b	0.009	-0.051	-0.041
	3000	(0.049)	(0.058)	(0.049)	(0.058)	(0.050)	(0.058)	(0.056)	(0.067)	(0.064)	(0.076)
flood history				✓		✓		✓		✓	
land-use						✓		✓		✓	
growth season								✓		✓	
N		13115		13115		13026		10068		7879	
Panel C: 3 months											
s^T		-0.004	**-0.021**b	-0.009	**-0.028**b	-0.009	**-0.028**b	-0.007	**-0.024**c	-0.018	**-0.030**b
		(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)
$s \times s^T$		0.008	**0.023**b	0.007	**0.023**b	0.007	**0.023**b	0.006	**0.021**c	0.010	**0.027**b
		(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
network		**-0.138**a	0.053	**-0.152**a	0.031	**-0.145**a	0.036	**-0.124**b	0.019	-0.049	-0.014
	5000	(0.049)	(0.058)	(0.050)	(0.059)	(0.051)	(0.060)	(0.057)	(0.069)	(0.065)	(0.078)
flood history				✓		✓		✓		✓	
land-use						✓		✓		✓	
growth season								✓		✓	
N		13115		13115		13026		10068		7879	
Panel D: 12 months											
s^T		-0.002	**-0.006**b	-0.005	**-0.010**a	-0.005	**-0.010**a	**-0.005**b	**-0.009**b	**-0.007**b	**-0.008**b
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
$s \times s^T$		0.003	**0.007**b	0.003	**0.007**b	0.003	**0.007**b	0.003	**0.007**b	0.005	**0.008**a
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
network		**-0.142**a	0.051	**-0.146**a	0.045	**-0.140**a	0.050	**-0.132**b	0.017	-0.040	-0.030
	5000	(0.050)	(0.059)	(0.050)	(0.059)	(0.051)	(0.060)	(0.058)	(0.069)	(0.065)	(0.078)
flood history				✓		✓		✓		✓	
land-use						✓		✓		✓	
growth season								✓		✓	
N		13115		13115		13026		10068		7879	

a: p<0.01, b: p<0.05, c: p<0.1

Note: All specifications include socio-demographic controls (age, age squared, gender, health dynamics, marital status, educational attainment and occupational status), 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 cultivation area size in a sphere of interest. Growth season specifications introduce controls for six major crop types (rice, corn, peanuts, cassava or sweet potato, vegetables, fruits). The estimation on the household level (last column) is based on a reduced sample from 2008 onwards.

Figure A.5: AMEs for negative SWB dynamics in the sensitivity analysis - maximum flood exposure measure



Note: All marginal effects draw upon a specification controlling for network, flood history, land-use and growth period (cf. model 4 in Table A.3). Each comprised the identical sample of 10,068 observations. The depicted response and shock experience specific average marginal effects have been evaluated over the range of the respective tangential shock measure (maximum days of flood exposure). The shaded area indicate the 90% confidence intervals.

Table A.4: Tangential shocks in Fixed and Random Effects models for negative SWB dynamics

	months	3 km FE		3 km RE		5 km FE		5 km RE	
		Panel A: Respondent panel							
s^T		**-0.008**b	(0.004)	-0.004	(0.002)	-0.003	(0.002)	**-0.003**c	(0.001)
$s \times s^T$		0.006	(0.004)	**0.005**b	(0.003)	0.002	(0.002)	**0.003**b	(0.001)
observations (individuals)	3	13880 (5779)		13880 (5779)		13880 (5779)		13880 (5779)	
F (prob > F) / Wald χ^2 (prob > χ^2)		26.73 (0.000)		1140.78 (0.000)		26.50 (0.000)		1135.51 (0.000)	
s^T		**-0.002**b	(0.001)	-0.001	(0.001)	-0.001	(0.001)	**-0.001**c	(0.001)
$s \times s^T$		0.001	(0.001)	**0.001**b	(0.001)	0.000	(0.001)	**0.001**b	(0.000)
observations (individuals)	12	13880 (5779)		13880 (5779)		13880 (5779)		13880 (5779)	
F (prob > F) / Wald χ^2 (prob > χ^2)		26.95 (0.000)		1141.09 (0.000)		26.55 (0.000)		1137.48 (0.000)	
		Panel B: Household panel							
s^T		**-0.009**a	(0.003)	**-0.004**c	(0.002)	**-0.004**b	(0.002)	**-0.003**b	(0.001)
$s \times s^T$		**0.008**b	(0.003)	**0.005**b	(0.003)	**0.003**c	(0.002)	**0.003**b	(0.001)
observations (households)	3	13880 (3492)		13880 (3492)		13880 (3492)		13880 (3492)	
F (prob > F) / Wald χ^2 (prob > χ^2)		37.34 (0.000)		1132.62 (0.000)		37.07 (0.000)		1127.11 (0.000)	
s^T		**-0.002**a	(0.001)	**-0.001**c	(0.001)	**-0.001**b	(0.001)	**-0.001**b	(0.000)
$s \times s^T$		**0.002**b	(0.001)	**0.001**b	(0.001)	**0.001**c	(0.001)	**0.001**b	(0.000)
observations (households)	12	13880 (3492)		13880 (3492)		13880 (3492)		13880 (3492)	
F (prob > F) / Wald χ^2 (prob > χ^2)		37.52 (0.000)		1132.97 (0.000)		37.13 (0.000)		1129.16 (0.000)	

a: p<0.01, b: p<0.05, c: p<0.1

Note: The binary dependent variable is coded as one if a respondent reported to be worse off, and zero otherwise. The set of explanatory variables comprises only those factors which displayed sufficient levels of variation over time (and individual) to be included in the FE specification (excluded are: gender, marital status, educational attainment and occupation). For the sake of comparability, RE specifications are conditioned on the same sample. The reference group for household income fluctuations is 'none', and for health dynamics it is 'same'. Standard errors (reported in parentheses for the two shock variables) are clustered on the household level.

Table A.5: Coefficient estimates in the moderating factors analysis

	(r=5000, m=3) maximum flood exposure measure				(r=5000, m=12) maximum flood exposure measure			
	Δ^{+}		Δ^{-}		Δ^{+}		Δ^{-}	
	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
HH income p.c. (log)	**0.230**a	(0.038)	-0.045	(0.039)	**0.230**a	(0.038)	-0.046	(0.039)
HH income fluctuation								
moderate	**-0.133**a	(0.050)	**0.569**a	(0.066)	**-0.133**a	(0.050)	**0.565**a	(0.066)
high	**-0.227**b	(0.094)	**1.546**a	(0.094)	**-0.235**b	(0.094)	**1.539**a	(0.094)
relative income position	0.007	(0.078)	0.111	(0.088)	0.009	(0.078)	0.115	(0.088)
gender (female=1)	-0.003	(0.055)	0.048	(0.064)	0.002	(0.055)	0.046	(0.064)
age	0.009	(0.013)	**0.039**b	(0.016)	0.009	(0.013)	**0.039**b	(0.016)
age squared	-0.000	(0.000)	**-0.000**b	(0.000)	-0.000	(0.000)	**-0.000**b	(0.000)
health dynamics (1 year)								
worse	-0.024	(0.057)	**0.513**a	(0.064)	-0.025	(0.057)	**0.513**a	(0.064)
better	**0.676**a	(0.074)	0.075	(0.109)	**0.671**a	(0.074)	0.071	(0.109)
marital status								
married	0.132	(0.137)	-0.017	(0.169)	0.140	(0.137)	-0.009	(0.168)
widowed	0.084	(0.164)	-0.036	(0.199)	0.083	(0.165)	-0.028	(0.199)
divorced / separated	-0.247	(0.266)	0.328	(0.263)	-0.237	(0.266)	0.349	(0.265)
educational attainment								
some elementary	0.111	(0.113)	-0.145	(0.116)	0.111	(0.112)	-0.162	(0.115)
primary	0.166	(0.115)	-0.135	(0.118)	0.166	(0.115)	-0.154	(0.118)
lower secondary	**0.299**b	(0.119)	-0.067	(0.129)	**0.296**b	(0.119)	-0.093	(0.130)
upper secondary (and more)	0.147	(0.138)	**-0.330**b	(0.166)	0.143	(0.138)	**-0.355**b	(0.166)
main occupational status								
housewife / home nursing	**0.427**c	(0.224)	0.255	(0.254)	**0.417**c	(0.224)	0.234	(0.254)
casual labour	0.247	(0.194)	**0.402**c	(0.215)	0.242	(0.194)	**0.394**c	(0.214)
permanently employed	**0.486**b	(0.239)	0.388	(0.298)	**0.480**b	(0.240)	0.356	(0.298)
agriculture	0.262	(0.168)	0.091	(0.186)	0.256	(0.168)	0.079	(0.186)
own business	**0.384**b	(0.193)	**0.377**c	(0.223)	**0.377**c	(0.193)	**0.368**c	(0.223)
government official	0.179	(0.254)	0.408	(0.323)	0.163	(0.256)	0.400	(0.323)
student / pupil	-0.201	(0.849)	0.518	(0.927)	-0.190	(0.840)	0.533	(0.930)
sum of shocks	**-0.048**b	(0.023)	**0.177**a	(0.024)	**-0.052**b	(0.023)	**0.172**b	(0.024)
no flood shock experience (s)	**0.969**b	(0.431)	0.009	(0.382)	**1.060**b	(0.490)	-0.238	(0.419)
s^{T}	0.150	(0.104)	-0.136	(0.094)	**0.027**c	(0.016)	**-0.041**b	(0.017)
$s \times s^{T}$	-0.152	(0.105)	**0.161**c	(0.096)	**-0.029**c	(0.016)	**0.043**b	(0.017)
network	-0.048	(0.076)	-0.099	(0.090)	**-0.127**b	(0.060)	0.029	(0.073)
flood history	-0.001	(0.002)	0.003	(0.002)	0.002	(0.002)	0.003	(0.002)
land-use	0.004	(0.004)	0.002	(0.007)	**0.004**	(0.004)	0.002	(0.007)
growth season	-0.046	(0.057)	**-0.214**a	(0.067)	-0.200	(0.361)	-0.560	(0.381)
MF1: min. dist. to lake	**0.044**a	(0.016)	**-0.030**c	(0.018)	**0.043**b	(0.018)	**-0.038**c	(0.019)
MF2: min. dist. to river	-0.019	(0.017)	-0.010	(0.014)	-0.019	(0.018)	-0.014	(0.015)
MF3: min. dist. to conurbation	**0.002**b	(0.001)	0.001	(0.001)	**0.002**b	(0.001)	0.000	(0.001)
MF4: min. dist. to hospital	-0.006	(0.007)	0.002	(0.007)	-0.007	(0.007)	0.006	(0.008)
MF5: min. dist. to rail	-0.003	(0.003)	0.002	(0.003)	-0.005	(0.003)	0.001	(0.003)
MF6: min. dist. to motorway	**0.006**a	(0.002)	**0.004**b	(0.002)	**0.007**a	(0.002)	0.003	(0.002)
year FE	✓				✓			
country FE	✓				✓			
$s \times MF$	✓				✓			
$s^{T} \times MF$	✓				✓			
$s \times s^{T} \times MF$	✓				✓			
observations (HH clusters)	10068 (2983)				10068 (2983)			
LL	-9921.40				-9927.92			
df (model)	120				120			
Wald χ^2 (prob > χ^2)	1235.73 (0.0000)				1218.89 (0.0000)			

a: p<0.01, b: p<0.05, c: p<0.1

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

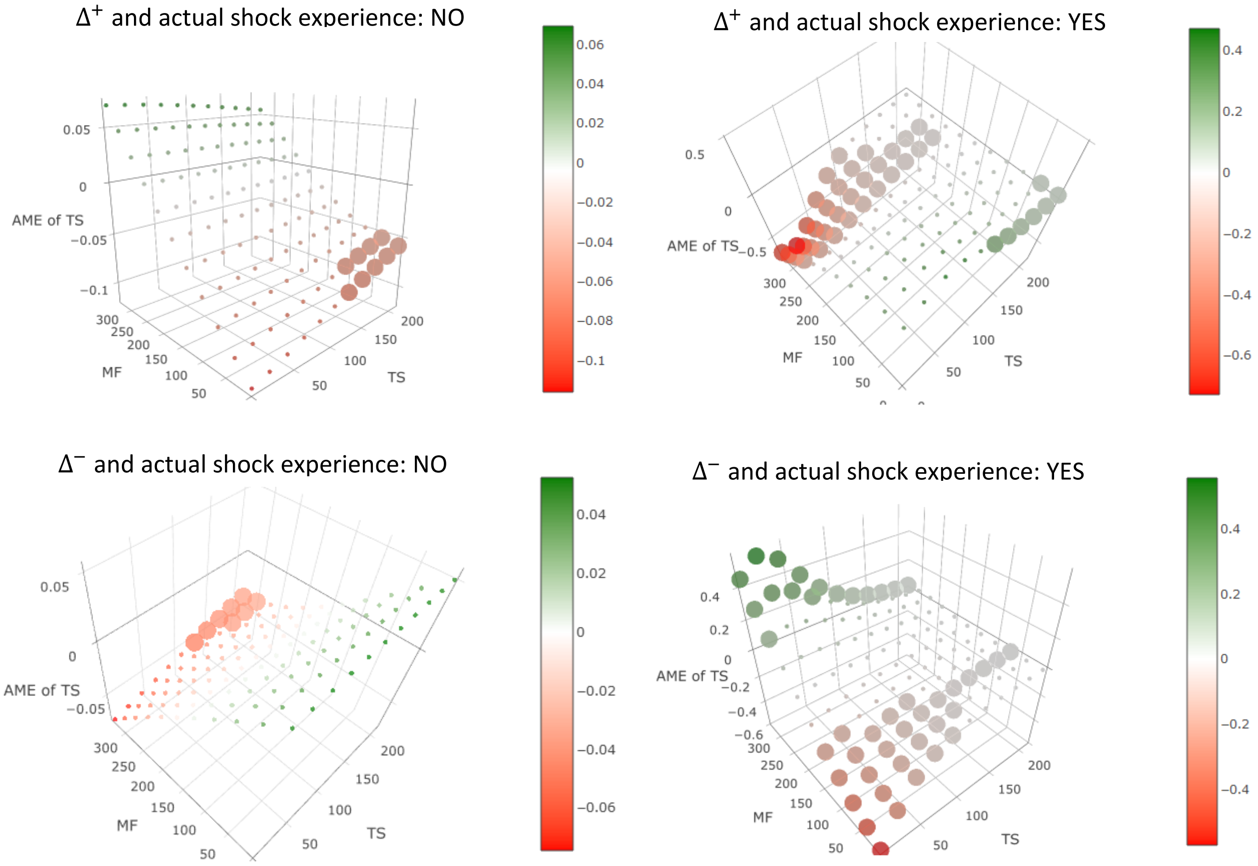
Table A.6: Flood shocks and material well-being (log HH income per nucleus member)

		3 km		5 km	
		TS	sensitivity analysis	TS	sensitivity analysis
	months	**Panel A: maximum flood exposure measure**			
sum of shocks		**-0.046**a (0.008)	**-0.053**a (0.009)	**-0.045**a (0.008)	**-0.053**a (0.009)
no flood shock experience (s)		**0.186**a (0.042)	**0.147**a (0.043)	**0.211**a (0.044)	**0.165**a (0.045)
s^T		0.007 (0.006)	0.007 (0.008)	**0.010**a (0.003)	**0.010**b (0.004)
$s \times s^T$	3	-0.006 (0.006)	-0.005 (0.007)	**-0.009**a (0.003)	**-0.008**b (0.004)
observations (HH clusters)		13879 (3492)	10068 (2983)	13879 (3492)	10068 (2983)
F		52.25	34.29	52.43	34.25
R^2		0.145	0.161	0.145	0.162
sum of shocks		**-0.046**a (0.008)	**-0.053**a (0.009)	**-0.045**a (0.008)	**-0.053**a (0.009)
no flood shock experience (s)		**0.200**a (0.044)	**0.164**a (0.045)	**0.239**a (0.046)	**0.196**a (0.048)
s^T		0.002 (0.001)	**0.005**a (0.002)	**0.003**a (0.001)	**0.004**a (0.001)
$s \times s^T$	12	-0.002 (0.001)	-0.002 (0.002)	**-0.003**a (0.001)	**-0.003**a (0.001)
observations (HH clusters)		13879 (3492)	10068 (2983)	13879 (3492)	10068 (2983)
F		52.27	34.66	52.60	34.51
R^2		0.145	0.163	0.146	0.163
		Panel B: relative flood exposure measure			
sum of shocks		**-0.046**a (0.008)	**-0.053**a (0.009)	**-0.046**a (0.008)	**-0.053**a (0.009)
no flood shock experience (s)		**0.189**a (0.041)	**0.151**a (0.042)	**0.195**a (0.042)	**0.153**a (0.043)
s^T		**0.405**a (0.144)	**0.484**b (0.189)	**0.431**b (0.172)	**0.421**b (0.009)
$s \times s^T$	3	**-0.381**a (0.147)	**-0.442**b (0.191)	**-0.382**b (0.174)	**-0.369**c (0.043)
observations (HH clusters)		13879 (3492)	10068 (2983)	13879 (3492)	10068 (2983)
F		52.27	34.43	52.30	34.12
R^2		0.145	0.161	0.145	0.161
sum of shocks		**-0.046**a (0.008)	**-0.053**a (0.009)	**-0.046**a (0.008)	**-0.053**a (0.009)
no flood shock experience (s)		**0.193**a (0.042)	**0.159**a (0.044)	**0.200**a (0.043)	**0.164**a (0.045)
s^T		0.024 (0.016)	**0.043**c (0.022)	**0.033**b (0.014)	**0.047**a (0.016)
$s \times s^T$	12	-0.022 (0.016)	-0.029 (0.022)	**-0.029**b (0.014)	**-0.031**b (0.015)
observations (HH clusters)		13879 (3492)	10068 (2983)	13879 (3492)	10068 (2983)
F		52.32	34.74	52.40	34.46
R^2		0.145	0.163	0.145	0.163

a: p<0.01, b: p<0.05, c: p<0.1

Note: All specifications include socio-demographic controls (age, age squared, gender, health dynamics, marital status, educational attainment and occupational status), as well as year and country FE. Standard errors (in parentheses) are clustered at the household level. Columns labelled 'TS' correspond to the specification in the divergence approach, net all material well-being indicators. Columns labelled 'sensitivity analysis' integrate the corresponding four additional types of control variables: network, flood history land-use and growth season controls for six major crops

Figure A.6: AMEs, conditional on flood exposure and distance to a motorway



Note: TS refers to the maximum flood day indicator (radius of 5km, time horizon of 12 months), MF is the distance to nearest motorway (in km). Small dots indicate insignificant average marginal effects (AME). Large dots represent AMEs significant at least at the 10% level. AMEs have been scaled by the factor 100. All marginal effects draw upon the sensitivity analysis in the divergence approach, introducing a complete set of interaction terms of moderating factors and the tangential shock measure (model two in Table A.5). Each comprised the identical sample of 13,879 observations.