# Tracking changes in resilience and recovery after natural hazards

## Insights from a high-frequency mobile-phone panel survey

Lindsey Jones[1,2] and Paola Ballon[3]

[1] *London School of Economics and Political Science, Grantham Research Institute for Climate Change and the Environment*

[2] *Overseas Development Institute*

[3] *University of Oxford*

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Knowing how resilience changes in the aftermath of a shock is crucial to targeting effective humanitarian responses. Yet, heavy reliance on face-to-face household surveys often means that post-disaster evaluations of resilience are costly, time-consuming and difficult to coordinate. As a result, most quantitative assessments are either carried out via one-off snapshots or by combining surveys conducted years apart. Doing so severely restricts our understanding of the temporal dynamics of resilience, particularly as it relates to inter- and intra-annual fluctuations.

In this paper we examine how household's resilience to multi-hazard risk changes over time. To do so we combine two novel approaches. Firstly, we use a high-frequency mobile-phone panel survey to conduct remote interviews in Eastern Myanmar. Surveys took place every six weeks over a one-year period. Secondly, we adapt a self-evaluated subjective measure of resilience to allow it to be administered via mobile phone. Shortly after the first survey was conducted, monsoonal flooding affected the site, allowing for the effects of flood exposure on resilience to be compared over time.

Our findings reveal how self-evaluated levels of resilience fluctuate considerably over the course of a year. To probe the effects of the monsoon floods, we compare resilience scores between households directly and indirectly affected by flooding. Scores drop sharply for the first three months amongst directly affected households, before slowly converging up to a year later. We also compare the effects of flood exposure on different socio-economic groups, revealing how female-headed households are particularly affected in the aftermath of flooding. Insights from the study highlight the dangers of using one-off resilience surveys to measure resilience, and underscore the need for development actors to account for shorter-term changes in the design of resilience-building interventions. Lastly, our findings showcase the potential of methodological innovations in addressing many of the resource, time and logistical constraints of traditional resilience measurement practices.

## 1. INTRODUCTION

Tracking the resilience of households and communities is essential to ensuring that development and humanitarian resources are targeted at those most in need (Bahardur et al. 2015; Carter 2004). Unfortunately, accurately measuring resilience remains a critical challenge (FSIN 2014; Levine 2014). Definitional and methodological ambiguities not only mean that resilience measurement is hotly contested (Alexander 2013), it contributes to the myriad of toolkits that have sprout in recent years. As such, many development actors have their own interpretations of what resilience is and how it should be measured (Schipper and Langston 2015).

Excessive data collection costs and the impracticalities of coordinating large household survey exercises mean that our understanding of resilience – at least when it comes to capacity-based quantitative evaluations – is often restricted to snap-shots: one-off surveys carried out at a single point in time (Gregorowski et al. 2017; Platt, Brown & Hughes 2016; Jones 2018). Little is therefore known about how a household's capacity to deal with risk evolves over shorter-term timescales – from days, to months to years (IFAD 2015). This knowledge gap is particularly evident in the aftermath of shocks and stresses, environments where humanitarian and development actors take keen interest.

Here we provide novel insights into the temporal aspects of resilience in hazard-affected contexts. In doing so, we take advantage of two innovations. The first is a mobile phone panel survey to collect high frequency data after seasonal flooding in Eastern Myanmar. Mobile surveys have been used in a number of academic survey initiatives across Africa and Asia in recent years, capitalising on the rapid proliferation of cellular networks and mobile phone availability globally (Berman et al. 2017; Chesterman et al. 2017; Labrique et al. 2017). Phone surveys can be carried out in a number of formats, including via Short Message Services (SMS), Interactive Voice Recording (IVR) and computer-assisted telephone interviews (CATI) (Gibson et al. 2017). In the context of this study we focus on the latter: voice interviews conducted via a team of enumerators.

The advantages of mobile surveying are manifold: they allow respondents to be contacted remotely at a time of their convenience; provide timely and low-cost alternatives to traditional face-to-face survey administration; and permit results to be fed back to evaluators in near-real-time (Dabalen et al. 2016). They are particularly useful in post-disaster contexts, where access to field sites may be compromised due to political sensitivities, conflict or hazardous environments (Jones et al. 2018).

The second innovation is the use of subjective modes of evaluation. In recent years, a range of subjective toolkits for resilience measurement have emerged (Marshall and Marshall 2007; Lockwood et al. 2015; Nguyen and James, 2013; Béné et al. 2016; Jones and Samman 2016; Jones and D' Errico 2019). These offer a viable alternative to traditional objective methods which rely on external characterisations and evaluations of resilience (Jones, 2018). Rather than assuming that outside actors – typically NGOs or evaluation experts – are best placed to evaluate the resilience of others, subjective approaches take a contrasting epistemological stance. They seek to capture people's understanding of their own resilience and factor perceived capacities directly into the measurement process (Jones and Tanner 2017). Subjective methods are therefore concerned with measuring perceptions, judgements and preferences of the individuals being evaluated. They draw heavily on conceptual and methodological developments made in related fields like subjective wellbeing (Diener et al. 2000; Kahneman and Kruger 2006; Dolan et al. 2008), risk perception (Slovic 1987; Sjöberg 2000) and psychological resilience (Bonanno et al. 2007; Fletcher and Sarkar 2013).

An additional advantage of subjective methods for resilience measurement is the rapidity with which they can be administered (Claire et al. 2017). While objectively-evaluations of resilience can involve surveys made up of hundreds of separate questions (and up to two hours of survey administration), many subjective modules offer far quicker alternatives (see Jones 2018). For example, subjective modules used by Marshall and Marshall (2007), Béné et al. (2016) and Jones and Samman (2016) can be administered with just a handful of questions and completed in less than five minutes. Indeed, it is the brevity of subjective evaluations that lends them to being administered via mobile surveys, with time limitations of 12-16 minutes before high risk of call termination (Dabalen et al. 2016; Gibson et al. 2017).

By combining the advantages of these two innovations, this paper provides novel insights into how resilience-capacities change in the aftermath of natural hazards. More specifically we are interested in three important questions. Firstly, we examine whether (and how) self-evaluated levels of resilience fluctuate on intra-annual timescales by comparing scores across our panel dataset. Secondly, we focus on the impacts of seasonal flooding, looking at whether directly affected households fare worse than those indirectly affected. Lastly, we see if there are differences in the length of time that floods impact on resilience scores across different socio-economic groups. Insights into these questions not only speak to the evidence needs of humanitarian and development actors, they shed valuable light on the validity of combining subjective methods with mobile phone surveys.

In tackling these three questions we use data collected in conjunction with the Building Resilience and Adaptation to Climate Extremes and Disasters (BRACED) programme in the Hpa An township of Eastern Myanmar. As part of the programme, we carried out face-to-face household surveys with 1,072 residents in June 2017. Roughly one month after the baseline survey the area was hit by monsoon flooding. In order to investigate the effects of flooding on survey respondents, call centre enumerators carried out successive phone surveys every six-to-eight weeks for a period of twelve months. In total, eight separate waves of data collection were carried out allowing rapid evolutions in resilience and recovery to be quantified for the first time.

In this paper, we first provide background on resilience, and its application in measurement approaches. We then detail data collection methods used in the survey, including descriptions of the subjectively-evaluated resilience module and steps taken in mobile surveying. Results are showcased, before we then discuss the paper's main research questions. Lastly, we provide methodological challenges and routes forward for resilience measurement.

## 2. CONCEPTUALISING RESILIENCE AND HOW IT EVOLVES OVER TIME

Resilience means many things to many different people; a term heavily contested not only across academic disciplines, but within them (Brown 2014). Much of this confusion stems from the fact that resilience has been applied across a range of different fields, from engineering and ecology to its recent adoption within the social sciences (Olsson et al. 2015). More recently, resilience has come to prominence as a guiding framework for development and humanitarian actors (Brown, 2015). Indeed, resilience is now seen as an important international policy issue, with firm targets embedded into various United Nation's frameworks (UN 2015a; UN 2015b).

While the rise of resilience is an encouraging political development, its proliferation makes measurement particularly challenging. Unlike some health or poverty outcomes, resilience – at least as it relates to individuals or households – is neither directly observable nor measurable using a single indicator (Paloviita & Järvelä 2015). It also partially explains the dominance of qualitative analyses in our understanding of the resilience of socio-ecological systems to date (Adger, 2000; Walker et al. 2004; Folke, 2006; Cote and Nightingale, 2012). Indeed, some decry attempts at quantification as futile altogether (Levine, 2014).

Yet, this hasn't stopped a large number of quantitative assessment tools from emerging in recent years. The supply is in large part driven by calls for better ways of tracking the effectiveness of large international investments flowing into resilience-building. One way of measuring resilience is to compare how people's wellbeing changes in response to a shock – usually measured through consumption, GDP or food security (Kimetrica, 2015; Arouri et al. 2015; Lazzaroni, et al. 2014). While informative, these approaches often make use of unrealistically narrow definitions of wellbeing (and resilience), and struggle to account for the influence of confounding factors (Shipper and Langston 2015; Bahadur and Pichon 2017). Moreover, they are severely limited in needing a shock to occur for someone's level of resilience to be revealed.

As a result, most quantitative assessments take a different approach: evaluating resilience-capacities instead of outcomes. Resilience is commonly thought of as constituting a suite of related capacities (Kelman et al. 2016). For example, the elaborate definition of resilience used by the Intergovernmental Panel on Climate Change's Fifth Assessment Report includes references to: 'coping', 'responding', 'reorganising', 'maintaining structure', 'adaptation', 'learning' and 'transformation' (IPCC 2014: 23). Capacity-based approaches concentrate on measuring these constituent capacities, often through use of objectively-evaluated proxy indicators (FAO et al. 2016; Smith et al. 2015; Sylvestre et al. 2012). Given that many of the capacities are themselves difficult to observe, indicators are often bunched together requiring considerable amounts of socio-economic data gathered from household surveys (Shipper and Langston 2015; FSIN 2014).

One key advantage of capacity-based frameworks is that they encourage the recognition of resilience as a process (or set of processes) that continually evolve over time:

> *"[Social resilience] recognises uncertainty, change and crisis as normal, rather than exception. The world is conceived of as being in permanent flux. In consequence, social resilience is perceived as a dynamic process, rather than as a certain state or characteristic of a social entity.*" (Keck and Sakdapolrak 2013, pp 9)

Conceptualising it in this way recognises not only that resilience constitutes the capacity to respond to changing shocks and stresses, but that a household's resilience will itself persistently changing over time (Waller, 2001; Meadows et al. 2016). In other words, at any one moment in time, a household may exhibit comparatively low levels of resilience in responding to multi-hazard risk (say the plight of farming household following the death of an income generator), while there may be other times when the household's resilience-capacity is far higher (perhaps following harvest of a bumper crop).

Despite this, most resilience assessments are limited to single cross-sectional surveys (acting as a snap-shot in time). While well-resourced development programmes occasionally include mid-term and/or end-line surveys into their monitoring and evaluation (Yaron et al. 2017), panel surveys are sadly rare. One-off evaluations will therefore only measure resilience as it relates to the precise moment of data collection – failing to recognise that levels of resilience may have quickly shifted thereafter (Meadows et al. 2016).

The high financial and logistical costs of household surveys are largely to blame here, meaning that quantitative evidence of the temporal dimensions of resilience is limited – particularly on intra-annual timescales. Yet, there is good reason to believe that resilience may fluctuate on timescales shorter than a year. For example, the sustainable livelihoods literature has a long history documenting the influence of seasonality and intra-seasonal dynamics on livelihood outcomes and poverty – both of which contribute significantly to a household's resilience (Chambers et al. 1981; Longhurst et al. 1986; Deveroux et al. 2013). In recent years, some of this thinking has permeated the resilience literature. Though much of this relates to the adoption of adaptation and transformation as core components of the resilience of socio-ecological systems – concepts that are more commonly associated with multi-annual and decadal fluctuations (Kates et al. 2012). In what follows, we seek to fill a gap in quantitative evidence on the short-term dynamics of resilience by using high-frequency surveys administered before and after flooding in Myanmar.

## 3. STUDY APPROACH

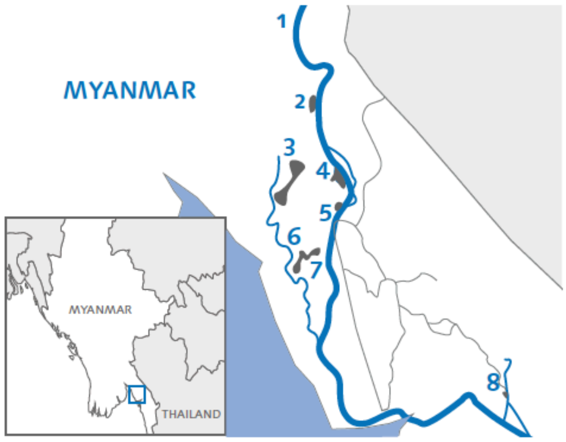
In order to track changes in resilience-capacities over time we use survey data collected from Hpa An township in Eastern Myanmar. Access to the site was facilitated through the BRACED Myanmar Alliance, a consortium of NGOs led by Plan International and consisting of five partner agencies: ActionAid, World Vision, BBC Media Action, the Myanmar Environment Institute and the UN Human Settlements Programme (UN-Habitat). The project was in operation between March 2015 to January 2018, delivering a range of resilience-related activities in eight townships across the country (see http://www.braced.org for further details).

The choice of Hpa An was taken on the basis of a number of factors (see Jones et al. 2018). Principally, the site is prone to flooding during the monsoon season owing to its proximity to the Thanlwin river. Indeed, a month after the first set of baseline surveys, Hpa An was subjected to a series of heavy flood events that damaged communal infrastructure and livelihoods in the area. Unlike a number of other BRACED sites, Hpa-An is not affected by political instability. Lastly, the site in Hpa-An is made up of eight individual villages, each with different livelihoods, socioeconomic characteristics and risk profiles allowing for comparisons of resilience-capacities to be made.

### 3.1. Survey design and set-up

The first step in our survey design involved collecting baseline information through a traditional face-to-face household survey in June 2017. The exercise was carried out for all households across the eight villages served by the BRACED programme in Hpa An– essentially constituting a census of the area. After completing the surveys, each household was handed a mobile phone (a Singtech G9) and a small solar array. Handouts were done irrespective of whether respondents were previously in possession of a phone or not. Phone numbers of any other household members, as well as immediate neighbours, were collected to help ensure that respondents were easily contacted for the mobile surveys that followed.

**Figure 1: List and location of the eight villages in the mobile panel survey**




| | VILLAGES INCLUDED IN THE RRR |
|---|---|
| 1 | Ta Kaung Boe |
| 2 | Wet Gyi |
| 3 | Kaw Yin (Upper) |
| 4 | Mote Ka Di |
| 5 | Hlar Kar |
| 6 | Pann Kone |
| 7 | Ya Thae Pyan |
| 8 | Kha Yae Kannar |

*Notes: Dark blue line represents the Thanlwin river (thick line) and its tributaries (thin lines). Grey shaded areas relate to village locations within Hpa An.*

Immediately after the baseline survey a call centre was set up in the city of Yangon. Call centre enumerators comprised of individuals that took part in the initial survey and were trained in the use of computer-aided systems – involving automated dialling and the completion of online forms. Once set up, the call centre was used to remotely contact each of the households via the mobile phones distributed (or the alternative numbers collected).

A short oral survey was administered covering a range of resilience-related topics. The survey also gathered relevant socio-economic data. Given the risk of drop-out and survey fatigue (Debalen et al. 2015), mobile surveys were limited to 10-12 minutes in duration. In instances where respondents were unable to speak, an alternative time was arranged. Respondents were also given a small financial incentive to take part in the survey in the form of $0.50 airtime credit delivered remotely to the phone after completion. Previous research has shown that small incentives like these can help to ensure high response rates without biasing results (see Leo et al., 2015). Each individual wave took roughly six weeks in length, with seven phone waves completed across the study period. In total eighth survey rounds were completed: the initial face-to-face baseline followed by seven waves of mobile phone surveys.

Answers from the baseline were used to create a detailed profile of the socio-economic characteristics of each household. In some cases, households were unable to provide answers to all socio-economic questions.

In addition, data on flood exposure started as of the first phone survey. Owing to the fact that a small number of households (5 in total) were solely affected by flooding in between Waves 1 and 2, and are likely to act as confounders, we remove these from the sample entirely.

Given that flood exposure is unlikely to be random, we weight our main analyses using an Inverse Propensity to Treat Weighting. Details of the IPTW process are described below, though require all households to be matched to a selection of socio-economic characteristics gathered during the baseline survey. We therefore exclude the small number of households that fail to answer all socio-economic questions in the initial survey. This limits the main sample to a partially balanced panel of 1072 households[1]. In addition, owing to the fact that drop-out rates in subsequent Waves of the survey appear non-random (and higher) amongst directly affected households, we also run the main analyses with a fully-balanced panel dataset comprised of 925 households. Result from the two datasets are compared later in Section 4.2, revealing similar trends against the main outcomes of interest.

Alongside the quantitative surveys, a series of semi-structured interviews were conducted using the mobile phone set-up. A total of 25 respondents were randomly selected from the survey population and asked a series of questions relating to resilience and coping strategies taken in response to flooding. Interviews lasted roughly 40 minutes in duration and were conducted using the same team of survey enumerators. Interviews were fully transcribed, providing insights to supplement findings from the quantitative survey. Given restrictions in the length of the interviews, respondents were asked only a handful of questions relating to factors associated with resilience. We augment as many of the quantitative results with qualitative insights, though recongise that this is far from uniform.

### 3.2. Measuring resilience using people's perceptions

Resilience can be measured in relation to a range of scales and systems. Here we clarify what we mean by resilience in the context of this study, *whose* resilience we refer to and resilience to *what*.

Our primarily interest is in examining social resilience – i.e. the ability of a social system to respond to external threats and changes while maintaining similar states of wellbeing or livelihood opportunity (Marshall and Marshall 2007; Adger et al. 2002). Core to this definition is the notion that social systems may need to re-organise in responding to evolving risk profiles: adapting and potentially transforming core functions as well institutional set-ups or power relations in order to sustain societal outcomes (Béné et al. 2014; Carr 2019). Viewed in this way, resilience can be seen as a process rather than a static outcome, and is typically characterised as made up of a range of inter-related capacities (FSIN 2014).

In narrowing down our focus on social resilience, we are especially interested in a particular unit of analysis: the household (Alinovi et al. 2008). By doing so we recognise the importance of the household system as a crucial decision-making body in responding to external threats:

> '*As the decision-making unit, the household is where the most important decisions are made regarding how to manage uncertain events, both ex ante and ex post, including those affecting food security such as what income-generating activities to engage in, how to allocate food and non-food consumption among household members, and what strategies to implement to manage and cope with risks'*. (Alinovi et al, 2008:5).

Household resilience can be seen as sub-system of wider social resilience, and thus similarly concerned with the ability of individual household units to maintain levels of wellbeing and livelihood outcomes in the face of external threats. Indeed, household-systems have been the primary unit of focus for a number of resilience measurement studies (see D'Errico & Di Giuseppe 2018; d'Errico et al. 2018; Alinovi et al. 2010), allowing us to compare resilience outcomes from this study with a range of objectively-oriented evaluations.

While our focus on household units addresses the question of *whose* resilience, we must also clarify to *what*? One option is to treat resilience as hazard-specific. For example, a focus on flood resilience is concerned

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[1] The original face-to-face baseline was conducted with 1203 households, meaning that the partially-balanced panel constitutes 89% of the original sample

solely with the characteristics and indicators that reflect a household's ability to deal with flood risk. Yet, external threats rarely affect households in isolation. The impacts of flooding are likely to interact with, and be further compounded by, a whole host of wider socio-economic and environmental factors. Many of which may manifest through hybrid (or additional) threats further down the line – whether in the form of food price spikes or pest outbreaks.

Accordingly, resilience is increasingly framed in relation to multi-hazard risk. This recognises that the characteristics and indicators of resilience to different types of threats are often closely matched. In this study, we adopt this same multi-hazard framework, and seek to measure a household's capacity to respond to a broad range of socio-economic and environmental shocks (rather than a single specified threat). This approach is used in a range of household resilience measurement frameworks, including the Resilience Index Measurement and Analysis (RIMA) popularised by the United Nations Food and Agriculture Organisation (FAO) (Alinovi et al. 2008; Alinovi et al. 2010; D'Errico & Di Giuseppe 2018).

To measure household resilience, we use the Subjective self-Evaluated Resilience Survey (SERS) module (Jones and Samman 2016; Jones et al. 2018; and Jones and D'Errico 2019). SERS capitalises on people's knowledge of their own resilience and asks people to self-evaluate themselves accordingly. Perception based tools like SERS have gained traction in recent years and are seen as a way of complementing traditional objectively-evaluated approaches to resilience measurement (Clare et al. 2017).

The SERS approach is based on a series of questions aggregated to form a single module (see Annex Table 1). Each question is comprised of a short statement linked to a specific resilience-related capacity. Statements are phrased in relation to a household's ability to deal with hypothetical future threats. Respondents are asked to rate their levels of agreement with the statements using a 5-point Likert scale (see Annex Table 1). Answers to each question are numerically converted, with scores calculated using an equal weighted mean for all capacity questions. Scores are then normalised, resulting in a single resilience score ranging from 0 (lowest resilience) to 1 (highest resilience).

SERS is designed to be flexible. The choice and number of statements can be changed in order to mimic a range of resilience frameworks. In the context of this study, we define resilience in accordance with the '3As' model first introduced by Bahadur et al. 2015 – referred to herein as the SERS-3A model, or simply SERS. Under the 3A model, resilience is viewed as consisting of three core capacities: anticipatory capacity (the ability to anticipate threats and respond ahead of time); absorptive capacity (the ability to bounce back after a threat) and adaptive capacity (the ability to change core societal structures and functions in response to changing risk profiles). This model of resilience has been used widely by a range of development actors and forms the conceptual basis of the $130M BRACED programme. While the majority of our analysis makes use of the 3As, we also compare results to other popular resilience frameworks, including those that feature transformative capacity (Béné et al. 2014).[2]

When evaluating SERS, it is important to clarify what the measure actually represents. Specifically, SERS is meant as a momentary marker of a household's resilience to deal with future threats (expressed as multi-hazard risk rather than a singular hazard). Self-evaluations aim to be forward-looking, gauging the extent to which households can deal with forth-coming hypothetical threats at a given moment in time. While the SERS model inherently cannot cover all aspects of resilience, and other capacities undoubtedly remain, it gives a useful indication of the household's resilience and is comparable with similar objectively-oriented resilience measures.

[2] We return to examine differences amongst SERS variants in the Robustness checks section and Section 6.2

**Table 1: List of resilience-related capacity questions used in the 3A variant of the Subjectively-Evaluated Resilience Score**

| Preamble: 'I am going to read out a series of statements. Please tell me the extent to which you agree or disagree with them.' [Read out each statement and ask] 'Would you say that you strongly agree, agree, disagree, strongly disagree or neither agree nor disagree that:' | |
|---|---|
| Resilience-related capacity | Survey question |
| Absorptive capacity | Your household can bounce back from any challenge that life throws at it |
| Adaptive capacity | If threats to your household became more frequent and intense, you would still find a way to get by |
| Anticipatory capacity | Your household is fully prepared for any future disasters that may occur in your area |

*Notes: For a full list of the original capacity questions, as well as other SERS variants see Annex Table 1 and Jones and D'Errico (2019).*

In the context of this paper we are primarily interested in how hazards impact on resilience scores over short periods of time. We note that there are many factors that can affect a household's resilience. Indeed, changes in resilience are likely to occur whenever there are factors that influence the status of resilience-related capacities – many of which are likely to take place in the absence of a hazard. However, the occurrence of a shock (in this case heavy seasonal flooding) can be expected to have an immediate and consequential impact on household's resilience capacities (Linnenluecke 2012) - akin to a natural experiment. This allows us to easily infer how exposure to one hazard influences resilience levels going forward, isolating the temporal nature of this impact using our unique high-frequency panel. It is for this reason that we focus on the impacts of the June flooding in Hpa An in this study. Yet, we note that the same methodology could easily be applied to tracking slower onset changes to resilience capacities in other contexts.

## 4. RESULTS

Below we present findings from across the various waves of surveying in Hpa An (for clarity, we refer to the initial face-to-face survey as the baseline, and the subsequent seven rounds of mobile phone surveys as waves 1-7). We begin by describing socio-economic and environmental risk conditions of our study site, followed by insights into the three research questions addressed in this paper.

The left-hand column of Table 2 presents unweighted summary statistics of socioeconomic characteristics of households (we return to describe the nature of the weighted sample in the right-hand columns later). The sample is characterised by low socio-economic wellbeing and high levels of disaster risk (further visual breakdowns are presented in Annex Figure 1). Around 30% of respondents have not completed any form of formal education. This compares with the national average of 16% for those aged 25 and over (GoM 2017a).

Agriculture is the primary source of livelihood with casual labour and remittances playing an important role. Close to one in five head-of-households classifies themselves as a widower – with the national average being 10.4% for women and 3.1% for men (GoM 2017b). Moreover, the mean Progress Out of Poverty (POP) score[3] for households in the survey is 41 – roughly equivalent to a 16% likelihood of being below the 2010

[3] The Progress out of Poverty Score was created by the Grameen Foundation, it uses 10 simple questions, such as "What material is your roof made out of?" or "How many of your children are in school?" to determine the likelihood that a particular

national poverty line (see Schreiner 2012). While this indicates that poverty is present, it is not prevalent, and is similar to Myanmar's average of 19.4% of households below the national poverty line in 2015 (World Bank 2017).

**Table 2: Summary statistics for the Hpa An panel survey (unweighted and weighted)**

| | Unweighted sample | | | | Weighted sample | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | Overall (n = 1072) | No hazard (n = 994) | Floods (n = 78) | p | Overall (n = 1072) | No hazard (n = 994) | Floods (n = 78) | p |
| Baseline resilience score | 0.54 (0.18) | 0.54 (0.18) | 0.56 (0.13) | 0.17 | 0.5 (0.0) | 0.5 (0.0) | 0.6 (0.0) | 0.65 |
| Dummy for education of household head | | | | 0.33 | | | | 0.78 |
| None | 312 (29.1) | 285 (28.7) | 27 (34.6) | | 312 (30.0) | 285 (29.1) | 27 (30.9) | |
| Some schooling | 760 (70.9) | 709 (71.3) | 51 (65.4) | | 760 (70.0) | 709 (70.9) | 51 (69.1) | |
| Age of respondent | 47.2 (13.0) | 47.2 (12.9) | 47.0 (13.5) | 0.86 | 46.8 (1.1) | 47.2 (0.4) | 46.4 (2.3) | 0.74 |
| POP poverty score (high score = higher likelihood of not in poverty) | 41.7 (13.3) | 42.1 (13.5) | 37.4 (9.6) | < 0.001 | 40.6 (0.5) | 41.7 (0.4) | 39.4 (1.0) | 0.03 |
| Mean number of HH occupants | 4.66 (2.03) | 4.66 (2.04) | 4.58 (1.97) | 0.71 | 4.8 (0.2) | 4.7 (0.1) | 4.8 (0.3) | 0.56 |
| Dummy for farmer as primary income source | | | | 0.006 | | | | 0.60 |
| Farmer | 506 (47.2) | 457 (46.0) | 49 (62.8) | | 506 (45.5) | 457 (47.2) | 49 (43.8) | |
| Non-farmer | 566 (52.8) | 537 (54.0) | 29 (37.2) | | 566 (54.5) | 537 (52.8) | 29 (56.2) | |
| Dummy for remittance as primary income source | | | | 0.73 | | | | 0.99 |
| Non-remittance | 727 (67.8) | 676 (68.0) | 51 (65.4) | | 727 (67.9) | 676 (67.8) | 51 (67.9) | |
| Remittance | 345 (32.2) | 318 (32.0) | 27 (34.6) | | 345 (32.1) | 318 (32.2) | 27 (32.1) | |
| Gender of HH head | | | | 0.25 | | | | 0.83 |
| Male | 830 (77.4) | 765 (77.0) | 65 (83.3) | | 830 (78.1) | 765 (77.4) | 65 (78.8) | |
| Female | 242 (22.6) | 229 (23.0) | 13 (16.7) | | 242 (21.9) | 229 (22.6) | 13 (21.2) | |
| Respondent gender | | | | 0.72 | | | | 0.87 |
| Male | 563 (52.5) | 520 (52.3) | 43 (55.1) | | 563 (52.0) | 520 (52.5) | 43 (51.4) | |
| Female | 509 (47.5) | 474 (47.7) | 35 (44.9) | | 509 (48.0) | 474 (47.5) | 35 (48.6) | |

*Notes: For continuous variables means are presented with standard deviations in parentheses, an unequal variance t-test is used to compare means; for categorical variables frequencies are presented with percentages in parentheses, a Pearson's chi-square test is used to examine differences in distributions across groups. Statistics are provided only for households that complete all eight waves of the panel survey (reducing the sample from 1203 to 985).*

During the baseline interview, respondents were also asked a number of questions related to risk perception. Annex Figure 2 shows that, while the area is occasionally affected by drought and cyclones, floods are by far the most frequently occurring climate hazard.

To get a better sense of levels of resilience in pre-monsoon conditions, we also look at associations between subjectively-evaluated resilience and various socio-economic traits by running a series of multivariate regressions (see Annex Section 1). Using this single cross-section of the survey, we observe that baseline resilience scores are associated with a number of socio-economic traits. Higher education of the household head, higher POP poverty scores (i.e. lower likelihood of being in poverty), female headed-households, greater life satisfaction, higher numbers of household occupants and reliance on remittance as a primary source of income are all positively associated with subjectively-evaluated resilience. Conversely, high dependence on farming as well as distance from the Thanlwin river are negatively associated with resilience. Reassuringly, many of these socio-economic characteristics appear to align with quantitative and qualitative understandings of the drivers of household resilience within the resilience literature (D'Errico and Di Giuseppe 2018). The age and gender of respondents also exhibit statistically significant relationships with SERS scores.

household is living below a given poverty line. The likelihood is derived from the value of the score, which ranges between 0 (extremely poor) to 100 (not poor). Thus, the lower the score the higher the likelihood for a household to be poor. For more see Schreiner (2012).

### 4.1. Changes in resilience over time

While the baseline results are of some interest, the real value from the Hpa An dataset is found in the full panel dataset. As outlined above, a few weeks after the baseline survey was conducted a series of flood events struck the area between June-July 2017. Direct observations of flood exposure for the area are lacking. However, we present simulated discharge of the Thanlwin for Hpa An town (adjacent to the 8 surveyed villages) using ensemble forecasts from the Global Flood Awareness System (GloFAS) for the period of the survey in Figure 12a (Alfieri et al. 2013). We also overlay dates of the various survey waves shown as vertical lines. As respondents were contacted on different days during each wave of the mobile survey, lines represent the average length of time from the baseline (the solid vertical line) for all households in subsequent waves (dashed lines).

A sharp uptick in river discharge occurs just after the baseline survey, with levels decreasing gradually thereafter. Large seasonal fluctuations like this are not uncommon in Hpa An. Indeed, insights from the baseline survey show that one in five households report being hit by floods at least once a year (20.8%) – see Annex Figure 2. Another 42.1% are affected by floods every couple of years. Accordingly, while Figure 23c shows that monsoonal river discharge in 2017 was not especially exceptional, various accounts from the semi-structured interviews point to the extent of localised impacts:

> '*The roof of our house was damaged. As the roof of our house is made with leaves, it was blown away by wind. We had to sleep on the floor under our house because the whole house was wet. We fixed the house by buying leaves for the roof of the house. We didn't get any help from others. We fixed it with money of our own. The water level rose up to our knee from the ground.*' (ID#1, Female, Seamstress)

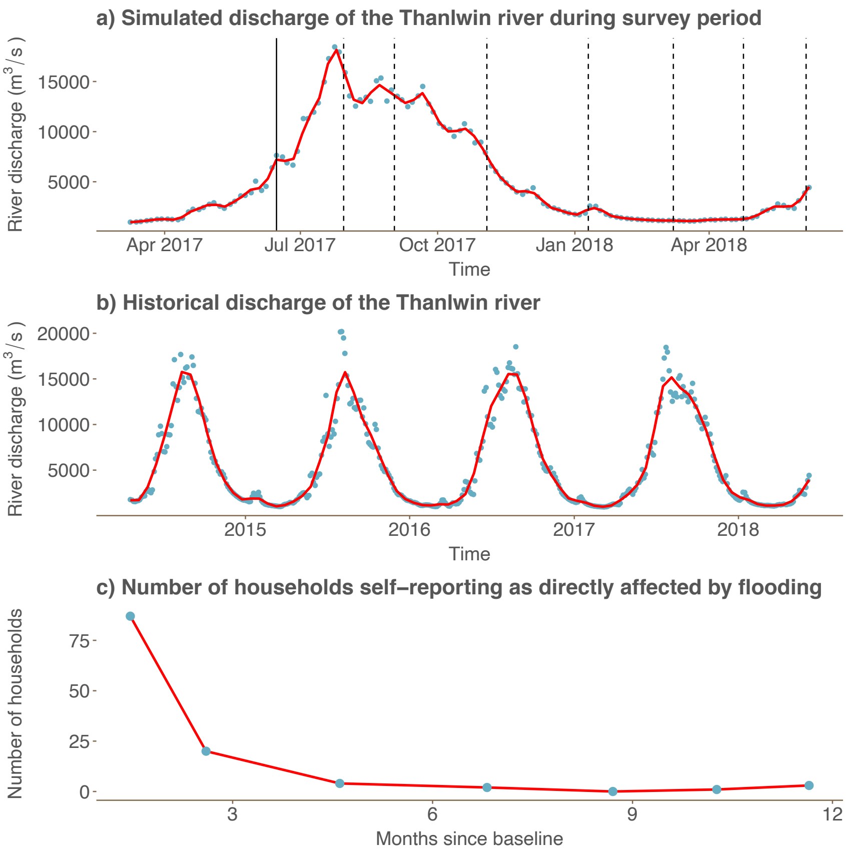
Note that the above quote also illustrates the importance of framing resilience in relation to multi-hazard risk. Even though the principle threat came from water inundation, high wind speeds also played a damaging role in the Hpa An floods. Interviewees report numerous other instances of damage to household property and negative implications for livelihoods, with similar impacts on communal infrastructure and local markets.

Figure 12c) reports the extent of flood exposure amongst surveyed households. At the start of each round of surveying, households were asked whether they had been impacted by a flood event since the last point of contact – defined as one inflicting a large negative effect on the household's way of life[4]. As Figure 12c shows, a number of households reported as directly impacted by flooding between the baseline and Waves 1 (n=87) and 2 (n=19) of the survey, coinciding with peak discharge of the Thanlwin river[5].

[4] See Annex Table 3 for survey question wording

[5] Note that these numbers are limited to n=78 (W1) and n=5 (W2) in the partially balanced dataset – owing to the exclusion criteria outlined in 3.3.1

**Figure 2: Thanlwin River discharge and frequency of self-reported flooding during the course of the Hpa An survey**




*Notes: Vertical dashed lines in Panel a) represent different waves of the mobile phone panel survey. Households classified as directly affected in Panel c) are those that self-report as having experienced a flood event with serious negative impacts the household's way of life in the previous month (baseline) or since the last wave of the survey (for mobile phone waves).*

Given the extent of flooding and localised impacts, we might expect to see this reflected in changes in levels of resilience-capacities amongst households in Hpa An. To investigate this further we plot mean SERS scores across the entire panel for the full Hpa An sample in Figure 13a. We also show the distribution and density of subjectively-evaluated resilience scores for each of the survey waves in Annex Figure 4.

Owing to the fact that two different methods of survey administration were used (face-to-face during the baseline and mobile for all remaining panel waves) we mark the period between the baseline and first wave of the mobile survey with a dotted line. Indeed, insights from related academic fields reveal well documented differences between these two modes of administration. For example, Dolan and Kavestos (2017) note that subjective wellbeing scores are significantly higher for phone surveys than for face-to-face interviews (2016).

Coincidently, the gap between the face-to-face and phones surveys is greatest when the majority of flood events are reported to have taken place in Hpa An. Thus, while it may be surprising to see a large jump in resilience scores between the baseline and Wave 1 of the survey, a large part of this is likely due to mode effects[6]. The fact that scores immediately drop after Wave 1 is also supportive of this interpretation. However, we choose to retain data from the baseline survey as it contains useful information on pre-flood conditions. In doing so we operate on the assumption that any differences between the two modes are

[6] A similar jump in scores between face-to-face and mobile phone modes is registered in a parallel BRACED survey run in the adjacent town of Mudon, providing further confidence in the existence of positive mode effects.

systematic and consistent across socio-economic groups. We note that results should be carefully interpreted with this caveat in mind.

As is clear, despite the rise in mean resilience scores between the baseline and first wave, there appears to be a dramatic and consistent reduction between Waves 1 and 4 (roughly 1-7 months after the baseline). Scores then rebound sharply during Wave 5 before appearing to level off somewhat for the final wave of the survey just over 10 months since the baseline survey.

**Figure 3: Change in subjectively-evaluated resilience scores over time**


*Notes: Shaded red areas in Panels a-c) represent periods of active flooding. Dotted lines in panels a-c represent the difference between face-to-face and mobile phone phases of the panel survey. Horizontal coloured lines are baseline resilience scores. The shaded blue area in Panel d) shows a stylised representation of the area used to calculate the Area Under the Curve (AUC). The face-to-face baseline (prior to flooding) is used as the reference period with the X-axis showing coefficients to the number of months since the baseline.*

We can also look at differences in resilience scores based on self-reported flood exposure. Figure 13b differentiates between households directly and indirectly affected by flooding between the baseline and first two waves of the phone survey. Here it is important to note that given the survey is a census of eight villages on the banks of the Thanlwin, we assume that flooding during this period had some degree of impact on all households. This could relate to access to: the status of communal assets; effects on local markets and livelihood opportunities; or demands of support from immediate family and neighbours. This assumption is supported by qualitative insights from the key informant interviews that report a wide range of localised impacts across all households in the area. As such, we classify all remaining households as 'indirectly' affected by the flood events, rather than 'unaffected'.

Directly affected households have lower resilience scores immediately after the main flood period. This is despite resilience levels being slightly higher for this group prior to flooding. Scores do appear to converge towards the fourth wave of mobile surveying and rebound similarly towards the end of the survey (though with slightly lower scores than indirectly affected households). It is also possible to account for different starting values prior to flooding by normalising baseline resilience scores. Figure 13c reveals starker differences between directly and indirectly affected households with similar patterns of convergence (and divergence) towards the end of the panel.

### 4.2. Examining the impact of natural hazards on resilience over time

It is clear from Figure 13 that levels of resilience drop sharply for all households after flooding. However, a host of wider shocks, seasonal factors and psychological traits could also be affecting changes in self-reported scores. To get a better sense of the specific role that floods played in influencing resilience scores over time, we employ a series of difference-in-differences regression specifications. Given the issue of spillover in flood impacts and coping strategies as highlighted earlier, we do not see these exercises as formal impact evaluations. Neither are they an attempt to formally quantify the magnitude of flood impacts on resilience. Rather, we use them to address a more basic question of whether differences in exposure to natural hazards affect self-reported resilience scores over time. We see this as a key test of the validity of the SERS module.

Our first method uses a generalised difference-in-differences approach with multiple time periods (Angrist & Pischke, 2008; Bertrand 2004). Here $\boldsymbol{Resilience_{ht}}$ corresponds to the SERS resilience score for household h during time period (wave) t.

$$Resilience_{ht} = \beta_1 post_t + \beta_2 f_h + \beta_3 (post_t \cdot f_h) + \psi_h + \emptyset_t + e_{ht} \qquad 1)$$

$post_t$ is an indicator of period, with 0 given for the pre-flood baseline and 1 for all post-flood waves. $f_h$ denotes the severity of the flood's impact on the household (0 for households that are indirectly affected by the flooding and 1 for those directly affected). $\psi_h$is an individual fixed effect (corresponding to each household in the survey), and $\emptyset_t$ is a time fixed effect (with separate dummies for each individual wave of the survey).

The $post_t \cdot f_h$ interaction estimates the change in pre- and post- resilience scores between those directly and indirectly affected by flooding, with the main entity of interest given by the coefficient $\beta_3$. To account for the fact that flood exposure is likely to have varied across the eight surveyed villages, we cluster-standard errors at the village level (though we repeat the analysis with errors clustered at the individual level as a robustness check). Given the small number of village-level clusters (n=8), standard errors are estimated using a Wild clustered bootstrap (Cameron, Gelbach and Miller 2008)[7].

A key assumption in difference-in-differences models is parallel trends between comparison groups (Angrist & Pischke 2008). While we do not have much data on household outcomes prior to flooding, it is reassuring to see that household characteristics between directly and indirectly affected households (shown in the unweighted sample in Table 2) appear to be relatively homogenous during the baseline. To further account for the risk that imbalances in composition may be affecting trends over time, we also combine the difference-in-differences model in Equation 1 with a weighting procedure (Stuart et al. 2014). Specifically, we use an Inverse Propensity to Treat Weighting (IPTW).

The first step involves running a logistic regression to determine the probability of being directly affected by the floods, p. A probability is obtained by regressing $f_h$ against a range of socio-economic baseline variables (those listed in Table 2). A weight is then given to each household, using an inverse probability of treatment (Imbens 2000), with households that are directly affected assigned $\frac{1}{p}$, and those indirectly affected given $\frac{1}{1-p}$. These weights are then used in calculating Equation 1.

[7] We also see no differences in main outcomes of interest when using traditional cluster-robust or bootstrapped standard errors as an alternative

**Table 3: Difference-in-differences between direct and indirectly affected households across all waves of the survey**

| | Resilience-over-time (DID) (Unweighted) | Resilience-over-time (DID) (Weighted using IPTW) |
|---|---|---|
| f · post (Difference in Differences) | -0.08*** (0.02) | -0.06*** (0.02) |
| f (1=Directly affected by flooding) | -0.13*** (0.02) | -0.14*** (0.02) |
| post (1=Periods after flooding) | -0.01 (0.01) | 0.004 (0.01) |
| Household fixed effects | YES | YES |
| Wave fixed effects | YES | YES |
| Observations | 8,765 | 8,765 |
| Adjusted R-Squared | 0.29 | 0.21 |
| Residual Std. Error | 0.707 (df = 8740) | 0.981 (df = 8740) |

*Note: Values indicate Beta coefficients with Standard Errors clustered at the village-level using a wild cluster bootstrap (with 200 replications) and shown in parentheses, *p<0.1** p<0.05 ***p<0.01*

Table 3 reports the estimates for the two models. In both cases, the coefficient for differences in resilience scores between the two groups (f · post) is negative and significant. While the effects are somewhat reduced for the weighted sample, results from both specifications suggest that households directly impacted by the floods have lower resilience scores over time than those that are indirectly affected (8% lower for the unweighted sample, and 6% lower for the IPTW sample).

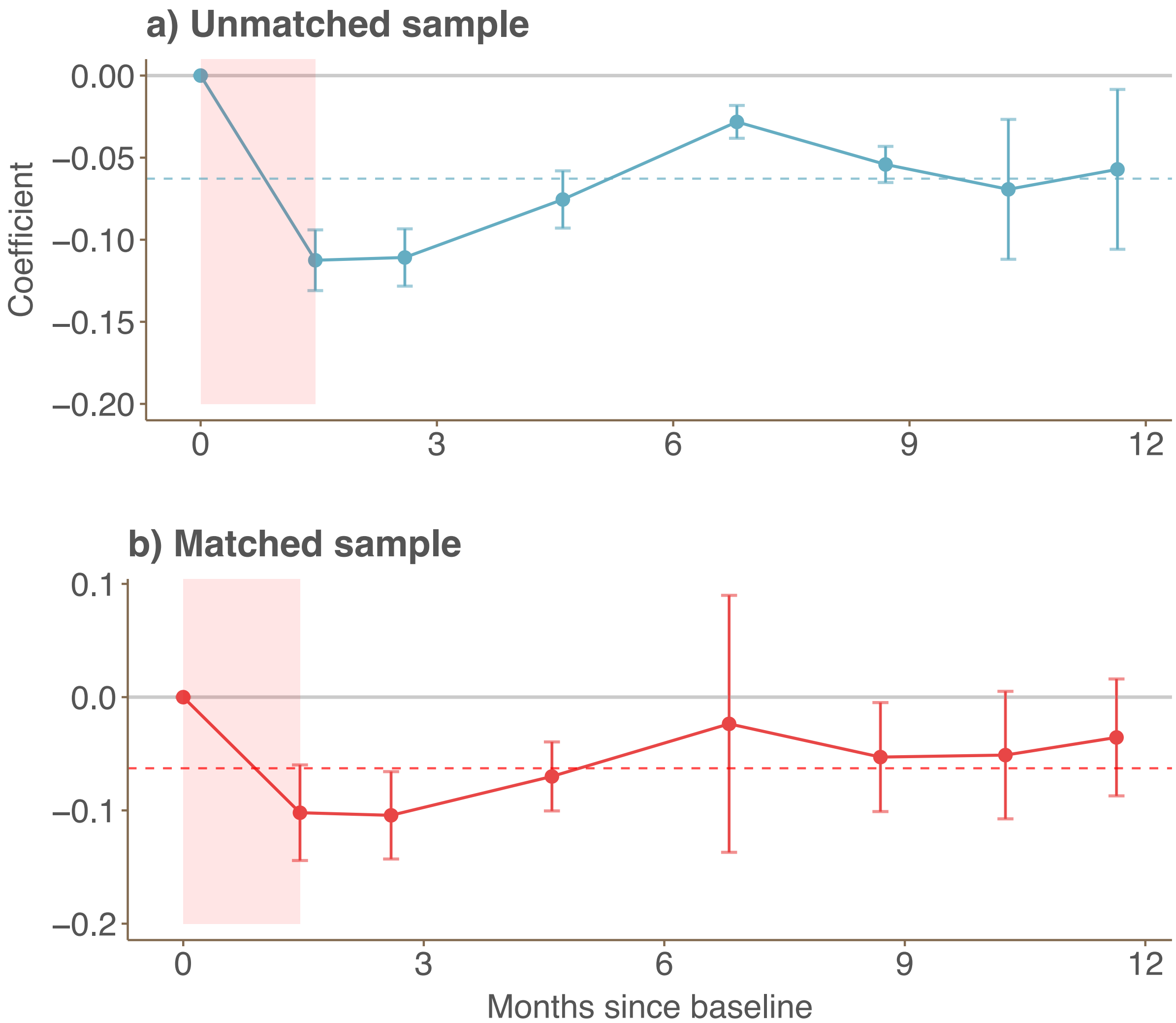
So far, we have focused the analysis on comparisons between the pre-flood baseline and all post-flood periods at once. However, we are also keen to have a more detailed look at how resilience scores vary over time, gaining insights into length of impact. To do so we modify Equation 1 to run an event study specification with interactions between the flood impact variable, $\boldsymbol{f_{hv}}$ and time dummies for all waves during the survey.

$$Resilience_{ht} = \sum_{k=1}^{7} \beta_k 1\ (t_h = t^* + k\ ) \cdot f_t + \psi_h + \emptyset_t + e_{ht}$$

2)

Here $f_t$ is an indicator of whether the household experienced a flood during the survey period. $\mathbf{1}\ (t_h = t^* + k\ )$ indicates the number of waves relative to the face-to-face baseline $t^*$, with k ranging from 1-7 (representing the seven Waves of mobile phone survey after flooding). The baseline survey is omitted as the reference period.

**Figure 4: Differences in self-evaluated resilience scores for households directly and indirectly affected by flooding over time**




*Notes: Graph shows outputs from the event study specification. Dots represent beta coefficients, with whiskers as 95% confidence intervals. The red shaded area represents the period of time when extensive seasonal flooding affected the Hpa An area. The dashed horizontal lines represents the average of all coefficients for survey waves after the period of flooding (waves 1-7). Standard errors are clustered at the village level using a Wild clustered bootstrap (200 replications). Coefficients are in relation to the number of months since the initial face-to-face baseline survey.*

Figure 14a shows a sharp drop in resilience scores for directly affected households in the first months following the baseline. Scores do appear to rebound somewhat, though convergence is somewhat inconsistent. The negative value of coefficients for all lead waves suggests that the impacts of flooding on directly affected households persist for some time. Outcomes from the weighted sample (Figure 14b) also reveal how directly affected households fare worse compared with those indirectly affected – closely matching those in the unweighted sample. Noticeably, scores for both approaches rebound somewhat towards the end of the panel survey – though this is inconsistent in nature, with a slight jump in Wave 4 (large standard errors present in the IPTW sample).

### 4.3. Calculating recovery rates using a resilience-over-time score

The generalised DID and event study estimates tell an interesting story of how flood exposure affects household's perceptions of resilience over time. Yet, these approaches do not make use of all information across survey waves. For example, each post-flood score is weighted evenly, even though there are differences between the time taken to collect each wave (see Figure 12 for average dates of wave completion). It is also difficult to compare associations with a range of time invariant factors – such as wealth and education. To shed further light on how flooding affects resilience over time we examine our survey data using a second method: an Area Under the Curve (AUC) approach.

AUC approaches are commonly used in comparing temporal changes in aggregate outcomes, such as subjective wellbeing (Kimball et al. 2015), stress-level monitoring (Eckhardt 2001) as well as various other health-related outcomes (Mohiyeddini el atl. 2015; Pruessner er al. 2003). More recently, they have been used to analyse resilience and recovery rates for hard infrastructure and ecological systems in the aftermath of disasters (Todman et al. 2016; Zobel 2014). Here, we borrow from these approaches and extend their application to examine social systems through tracking household-level outcomes.

Specifically, we calculate the total AUC for resilience scores of each individual across all waves of the panel. As shown in the stylised example in Figure 13d, this constitutes the shaded area under the resilience curve. Here, the AUC, $Resilienceovertime_{ht}$, can be expressed as the integral of the resilience curve $Resilience_h(t)$ between baseline (t=0) and the remaining seven waves of the mobile phone survey.

$$Resilienceovertime_{ht} = \int_{t=0}^{7} Resilience_h(t)dt$$

3)

In essence, we take $Resilienceovertime_{ht}$ (herein referred to as a 'resilience-over-time') to represent cumulative levels of resilience for households over the course of the survey: a proxy for recovery rates. As scores are unique to each household, they can be used to compare recovery levels across socio-economic groups.

For simplicity and ease of interpretation, intervals between each wave are assumed to be linear (and any missing values interpolated relative to the nearest scores on either side). Households with more than three missing values across the various waves, as well as those lacking in resilience scores for the baseline and endline surveys are removed entirely from the sample.

A key advantage of the AUC analysis is that it weights resilience scores according to the length of time taken for each wave to be completed since the last. In theory, households that are heavily impacted by the flood events will exhibit sharper and most sustained drops in average resilience scores in the months that precede reporting. This would in turn be reflected in lower resilience-over-time scores compared with households indirectly affected by flooding.

To formally examine the impact of the floods, and factors commonly associated with resilience-over-time scores, we run a series of regressions estimate by OLS. In Equation 4 we present a basic model set-up with the dependent variable $Resilienceovertime_{hv}$ as the AUC for the period up to 12 months after the baseline. This mimics a similar set up used by Kimball et al. (2015) in tracking the impacts of life events on levels of subjective wellbeing over time.

Here, the impact is a dummy variable, $f_{hv}$, for households that self-report as directly impacted by flooding between the baseline and the first two months of the survey. Controls for socio-economic variables, $s_{hv}$, and factors commonly associated with resilience, including risk perception, $p_{hv}$ are added. Importantly, each household's resilience score during the baseline, $Resilienceovertime_{hv,-1}$ is added to account for baseline imbalances in mean scores as recommended by Manca et al. (2005). Lastly, $\xi_v$ represents a village-level fixed-effect with the error term captured by $e_{hv}$.

$$Resilienceovertime_{hv} = \beta_1 Resilienceovertime_{hv,-1} + \beta_2 f_{hv} + \beta_3 s_{hv} + \beta_4 p_{hv} + \xi_v + e_{hv}$$

4)

To account for potential differences in the makeup of directly and indirectly affected households, we repeat the exercise using an inverse probability of treatment weighting (IPTW), as per the DiDs above.

Results of the regression models are shown in Table 4. Differences in resilience-over-time scores between those directly and indirectly-affected households are statistically significant and consistent across all models, with directly affected households exhibiting lower overall scores than those indirectly affected.

In terms of associations with wider socio-economic variables, age of the household head has a strong positive association with resilience-over-time scores for both unweighted and weighted samples. Reasons for this are likely to do with a lack of economic opportunities available to younger individuals – particularly in relation to work outside of Hpa An – as well as more established social networks and capital. This is well reflected in the qualitative interviews, with one interviewee observing that '*households where members are not old enough to stay and work in Thailand are in unstable conditions in the village, they struggle to earn for their family*' (ID#18, Female, Farmer). The number of household occupants is also strongly associated with resilience, with greater occupancy associated with higher resilience-over-time.

Households that derive a primary livelihood from farming are linked with higher resilience-over-time (though the effect is inconsistent for the IPTW). Numerous interview responses also reflect this trait, noting how '*people without a farm are unstable, they have difficulty in living*' (ID#3, Male, Farmer). Interestingly, while the household's poverty index (measured through the POP poverty score) exhibits a positive relationship with resilience-over-time scores for most models, the strength of associations with education of the household head is far less pronounced (though positive effects are seen across all models).

When it comes to risk factors, higher perceived flood sensitivity and flood exposure are negatively linked with resilience (though only the former is statistically significant). Life satisfaction is positively associated with resilience-over-time, while distance to the nearest road is negative and statistically significant – likely reflecting wider socio-economic circumstances such as access to markets and ease of movement. Female-headed households have significantly lower resilience-over-time scores compared to male-headed households. Lastly, it is curious to note that income diversity is negatively associated with resilience (households with more sources of income are linked to lower resilience-over-time scores).

**Table 4: Factors associated with resilience-over-time for the entire Hpa An sample**

| | AUC for unweighted sample | | | AUC for IPTW sample | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Dummy for flood impact (0=Indirect; 1=Direct) | -8.26** (4.18) | -7.87** (3.25) | -9.98*** (2.55) | -11.44** (4.64) | -12.03*** (4.47) | -10.06*** (3.80) |
| Dummy for education of household head (0=None; 1=Some schooling) | | 0.29 (1.32) | 2.31 (1.88) | | 3.00 (3.13) | 4.96* (2.66) |
| Age of respondent | | 0.24*** (0.03) | 0.27*** (0.04) | | 0.18*** (0.05) | 0.28*** (0.04) |
| POP poverty score (high score = higher likelihood of not in poverty) | | 0.13*** (0.05) | 0.13** (0.06) | | 0.14** (0.06) | 0.08 (0.06) |
| Mean number of HH occupants | | 1.07*** (0.26) | 1.19*** (0.46) | | 1.69*** (0.62) | 1.68** (0.68) |
| Dummy for farmer as primary source of income (1=Farmer) | | 4.66*** (1.05) | 7.19*** (1.37) | | 2.63 (1.96) | 3.23* (1.84) |
| Dummy for remittance as primary source of income (1=Remittance) | | -1.13 (1.68) | -1.93 (2.21) | | 4.00* (2.11) | 3.19 (2.02) |
| Gender of HH head (1=Female) | | -4.30*** (1.10) | -4.92** (2.00) | | -7.09** (2.84) | -7.86** (3.39) |
| Respondent gender (1=Female) | | -1.71 (1.40) | -1.18 (1.22) | | -1.18 (1.44) | 0.88 (1.90) |
| Risk perception: dummy for flood sensitivity (0= Not at all a problem; 1=Very serious problem) | | | -6.85*** (1.67) | | | -6.19** (3.10) |
| Risk perception: dummy for flood exposure (0 = Fewer than once a year; 1=Once a year or more) | | | -1.86 (1.22) | | | -2.04 (2.26) |
| Life satisfaction (higher score = higher life satisfaction) | | | 3.74*** (1.26) | | | 5.05*** (1.49) |
| Dummy for more than one source of livelihood (1=More than one) | | | -6.29*** (1.61) | | | -7.12*** (2.26) |
| Distance to the river (log+1) | | | 0.19 (1.18) | | | 0.38 (1.06) |
| Distance to nearest road (log+1) | | | -7.16*** (1.14) | | | -8.34*** (1.83) |
| Observations | 1,072 | 1,072 | 1,052 | 1,072 | 1,072 | 1,052 |
| Adjusted R2 | 0.21 | 0.23 | 0.20 | 0.26 | 0.28 | 0.31 |
| Residual Std. Error | 28.75 (df = 1062) | 28.51 (df = 1054) | 29.09 (df = 1035) | 39.17 (df = 1062) | 38.54 (df = 1054) | 37.90 (df = 1028) |

*Note: The outcome variable in all models consists of the resilience-over-time score (i.e. the area under the curve for the SERS-3A module over the course of the 8 rounds of surveying) weighted using IPTW. All models include controls for baseline resilience scores and Village fixed effects. Models 1-3 consist of the full Hpa An sample, while Models 4-6 are restricted to households directly affected by flooding between the baseline and Wave 1 of the survey. Values indicate Beta coefficients with Standard Errors clustered at the village-level using a wild cluster bootstrap with (1000 replications) shown in parentheses, *p<0.1** p<0.05 ***p<0.01*

### 4.4. Examining the impact of natural hazards on different socio-economic groups

The analysis above helps us in understanding the associations between resilience-over-time and a variety of socio-economic traits for all households in the Hpa An sample. While these are informative, we are especially interested in knowing whether exposure to the floods affected socio-economic groups in different ways. In other words, did particular social groups fare better or worse when directly exposed to flooding (compared to those indirectly affected)?

To explore this in more detail we augment Equation 4 by adding interactions between flood exposure ($f_{hv}$) and covariates for both socio-economic status ($s_{hv}$) and risk perception ($p_{hv}$) as shown below.

$$Resilienceovertime_{hv} = \beta_1 Resilienceovertime_{hv,-1} + \beta_2 f_{hv} + \beta_3 s_{hv} + \beta_4 p_{hv} + \beta_5(f_{hv} \cdot s_{hv}) + \beta_6(f_{hv} \cdot p_{hv}) + \xi_v + e_{hv}$$

5)

We carry out the analysis with the partially balanced sample. However, we recognise that drop-out rates for directly affected households are higher and are unlikely to be non-random. We therefore also run the analysis with a fully balanced dataset – noting that this further reduces the sample group of directly affected households (n=46 as opposed to than n=78 in the partial sample).

Table 5 presents results from the interacted variables in both samples. Although the group size of directly affected households is relatively small in both cases, a number of variables are seen as significantly associated with resilience-over-time scores when interacted with the flood exposure ($\boldsymbol{f_{hv}}$).

**Table 5: Associations with resilience-over-time scores with interactions between flood exposure and a range of socio-economic and risk factors**

| | Partially balanced sample | | Fully balanced sample | |
|---|---|---|---|---|
| | Unweighted | IPTW | Unweighted | IPTW |
| | (1) | (2) | (3) | (4) |
| Dummy for household head education (0=None; 1=Some schooling) * Flood exposure (0= Indirect; 1=Direct) | 0.55 (4.03) | 5.49 (5.40) | 8.63 (7.60) | 7.30 (12.60) |
| Age of respondent * Exposure to flooding | 0.04 (0.24) | 0.07 (0.23) | 0.35 (0.48) | 0.42 (0.51) |
| POP poverty score (high score = higher likelihood of not in poverty) * Exposure to flooding | -0.05 (0.34) | 0.002 (0.34) | 0.49 (0.39) | 0.58 (0.39) |
| Mean number of HH occupants * Exposure to flooding | 1.15 (2.61) | 2.29 (2.36) | 2.97 (2.72) | 2.34 (1.72) |
| Dummy for farmer as primary source of income (1=Farmer) * Exposure to flooding | -8.99 (8.63) | -13.64* (7.45) | -1.59 (6.19) | -9.25 (7.16) |
| Dummy for remittance as primary source of income (1=Remittance) * Exposure to flooding | 5.37** (2.26) | 10.06*** (2.77) | 1.95 (4.94) | 13.26* (7.18) |
| Gender of HH head (1=Female) * Exposure to flooding | -15.59** (6.13) | -11.45* (6.07) | -28.73*** (9.19) | -31.48*** (5.88) |
| Respondent gender (1=Female) * Exposure to flooding | 6.33 (9.45) | 6.91 (8.74) | 14.82 (9.86) | 13.77 (10.00) |
| Risk perception: dummy for flood sensitivity (1=Very serious problem) * Exposure to flooding | -6.72* (3.83) | -12.35** (5.27) | -11.08 (6.86) | -27.72** (12.80) |
| Risk perception: dummy for flood exposure (1=Once a year or more) * Exposure to flooding | -7.69 (8.16) | -12.42 (8.65) | -24.04*** (7.28) | -17.00 (10.58) |
| Life satisfaction * Exposure to flooding | 1.08 (3.06) | 2.77 (3.47) | 0.44 (2.93) | 3.97 (4.40) |
| Number of sources of livelihood * Exposure to flooding | -8.30** (4.07) | -11.10** (4.34) | 0.69 (5.91) | -12.49 (9.42) |
| Distance to the river (log+1) * Exposure to flooding | -0.98 (1.94) | 1.33 (2.27) | 1.65 (3.55) | 0.78 (4.04) |
| Distance to nearest road (log+1) * Exposure to flooding | -4.44 (6.89) | -3.37 (6.21) | -0.89 (11.04) | 0.21 (13.16) |
| Baseline resilience FE | YES | YES | YES | YES |
| Village-level FE | YES | YES | YES | YES |
| Observations | 1,052 | 1,052 | 925 | 925 |
| Adjusted $R^2$ | 0.24 | 0.35 | 0.26 | 0.37 |
| Residual Std. Error | 28.36 (df = 1014) | 36.90 (df = 1014) | 27.95 (df = 887) | 35.62 (df = 887) |

*Note: The outcome variable in all models is resilience-over-time scores (i.e. area under the curve for SERS over time). Only results of interactions between flood exposure and socio-economic risk factors are shown. Values indicate Beta coefficients with Standard Errors clustered at the village-level using a Wild cluster bootstrap (1000 replications) shown in parentheses. *p<0.1** p<0.05 ***p<0.01*

Consistent with Table 4, results from the interactions show that differences between male and female-headed households are even more pronounced for those directly affected by flooding. Effect-sizes are large and statistically significant across all models (though to differing extents), suggesting that flood exposure has strong negative impacts on female-headed households. This finding is similarly supported by qualitative insights from Hpa An, with a number of interviewees noting the challenges faced by female-headed households – widows in particular – in seeking support from relatives and family support networks:

> '*Households that are led by widows face difficulties. Of course, they do. If they ask others for help, no one will come. They do so only when they are paid. Widows are especially in trouble.*' (ID#1, Female, Seamstress)

Another distinction can be seen with regards to perceived exposure and sensitivity to flooding. Resilience-over-time scores for those directly hit by the June floods were significantly lower amongst households that generally viewed flooding as a serious threat, as well as those frequently affected by seasonal flooding. However statistical significance is inconsistent between samples and weighting procedures.

We also find that differences in resilience scores for households with more than one source of livelihood are pronounced for those directly-affected by flooding – similar to results in Table 4. However, the strength of associations (and sign) are inconsistent, with no statistical significance found in the balanced sample. Lastly, households that receive remittance payments during heavy flood exposure fare better than those without (though, again, the association is less pronounced for the fully balanced sample).

## 5. ROBUSTNESS CHECKS AND OTHER TESTS OF VALIDITY

As with any large quantitative analysis, our results come with caveats and assumptions. As such, we run a series of robustness checks to test the impact of different specifications on the paper's main findings. In Annex Section 2 we examine a range of potential confounders, including: differences between variants of the SERS module (both in terms of composition of resilience capacities and weighting); mode effects (differences between face-to-face and phone surveys); acquiescence bias; non-response; comparisons with an objective measure of flood impact (using monthly income); and controls for the timing of household-level interviews. Though small differences are apparent throughout, all alternative specifications are largely consistent and supportive of the main findings.

## 6. DISCUSSION

The Hpa An mobile phone panel survey yields a wealth of information on how resilience is affected in the aftermath of natural hazards. To make sense of the many tests and results presented above we re-focus our discussion on the original research questions.

### 6.1. Do self-evaluated levels of resilience fluctuate on intra-annual time-scales?

Of the three research questions, this is perhaps the easiest to answer. Results from the Hpa An survey clearly show how perceived resilience scores fluctuate over the one-year period of study. The extent of this change is visually apparent in Figures 12a and Annex Figure 4. From a high-point in Wave 1 to a low in Wave 4 (three months post floods), mean resilience scores in Hpa An drop by 34% between the two periods before rebounding at Wave 7.

These findings have notable implications for resilience policy and programming. For one, efforts to monitor and evaluate resilience-building interventions should be conscious of the perils of relying on one-off surveys. If resilience can fluctuate sharply from one month to the next, then evaluators must be careful in deciding time periods for comparison. The issue is perhaps of greater relevance to non-disaster related contexts, where levels of household resilience are often assumed to be constant in the absence of a shock. One way to help address this would be to encourage more widespread use of panel surveys – collecting data over multiple timescales before, during and after an intervention. Another is to more carefully design studies when inferring causality. This is particularly important when it comes to choosing control groups and ensuring that the time periods of data collection are commensurate (e.g. in large household surveys it is typical to measure different groups one after the other, often with a notable time gap between data collection rounds).

Admittedly, the findings apply specifically to resilience as measured subjectively (with all the caveats that come with it). However, the rapid changes in perceived resilience for Hpa An point to an inherent weakness in traditional objective approaches. These often rely on long lists of socio-economic indicators and household assets – things that are easier to see and measure. They also frequently rely on immutable indicators (i.e. those that change slowly over time), such as household assets or livelihood activities. Yet, while this survey suggests that a household's resilience-capacities can fluctuate rapidly in the face of shocks, many traditional indicators are unlikely to change in the shorter-term (as is the case for the income comparison in Annex Section 2). This can paint an inaccurate picture of a household's immediate resilience status. Ways to better accounting for this should be urgently sought – perhaps through improved integration of objective and subjective approaches, or more widespread of use of non-immutable indicators.

### 6.2. Do natural hazards impact on perceived resilience over time?

Households' perceived resilience in Hpa An clearly fluctuates over time. Yet, can we infer possible causes for this change? This is a harder question to answer. Given the drop in resilience scores immediately after the flood events, it seems intuitive that exposure to floods could be driving some (if not most) of this. The conclusion is further supported both by the DiD analyses as well as the AUC calculations for resilience-over-time (Table 4). Each suggests that the resilience of directly affected households fared significantly worse in the aftermath of the floods when compared with indirectly affected households.

Yet, a number of other intriguing insights remain. For one, why do resilience scores drop dramatically for both directly and indirectly affected households after the flood events? One reason for this might be that the floods impacted on community assets and infrastructure – like roads or access to local markets. Insights from the qualitative interviews support this claim, with reports of widespread localised impacts. Thus, even though households may not have been physically impacted by the flooding, these indirect impacts may have caused households to report lower resilience scores. It may also reflect that the fact that the survey is a census, with households closely networked; indirectly-affected households may have offered support (financial or otherwise) to directly-affected households nearby - whether family, neighbours or friends.

More importantly, could other factors such as response biases or seasonal fluctuations be partly driving changes in resilience scores (together with, or instead of the floods)? While we try to account for the former by randomising questions and ensuring that priming effects are kept to a minimum, we can do little to account for the influence of the latter in the absence of multi-year data. However, so long as seasonal fluctuations and wider shocks are systematic across the population, they should not change the fact that significant differences are observed between directly and indirectly affected groups (as measured by the DiD estimates). Indeed, that the pattern of gaps is consistent with expectations (starting off large and appearing to converge slowly over time) provides some reassurance of the role of flooding in influencing resilience scores. Moreover, when we exclude households that report other socio-economic shocks during the course of the survey, we see few differences – further discounting the role of wider shocks as playing a large role.

Perhaps the most interesting finding from the study is insight into the length of post-flood impacts. Not only do we see scores fall immediately after the floods, we witness a large up-tick in levels of resilience roughly five months after the baseline surveys (Wave 5). A similar pattern is seen when comparing the differences between directly and indirectly affected households over time (though slight differences in timing for weighted and unweighted samples). Insights like these can prove invaluable guidance for development and humanitarian actors in understanding the extent and nature of recovery on the ground, as well the length of time that households may be susceptible to the impacts of follow-on shocks.

Lastly, we look at whether there are differences in the extent to which the three resilience-related capacities used in devising the SERS module influence post-flooding outcomes. To examine this, we re-run the main difference-in-difference setup (as per Equation 1) replacing the SERS outcome variable with each of the three capacities included in the 3A framework for resilience (Bahadur et al. 2015): anticipatory capacity; absorptive capacity; and adaptive capacity (see Annex Table 1 for wording). Results are shown in Annex Table 10 (models 1-6), revealing that scores for each of the resilience-related capacities drop for households directly affected by the floods (when compared with those only indirectly affected).

Differences are statistically significant for all models (except for anticipatory capacity in the IPTW weighted sample). These findings provide interesting conceptual insights into the extent to which difference components of resilience change both over time and in response to a natural hazard. More specifically, they suggest that each of the three capacities used in the 3A variant acts (relatively) uniformly in influencing resilience-over-time in Hpa An. For comparison, we carry out additional DiD analyses (Annex Table 10, models 7-8) using transformative capacity as the outcome variable - noting its use in a number of other resilience frameworks (including Béné et al. 2014 and Pelling 2010). The effect of direct flood exposure is similarly negative for transformation, though not shown to be statistically significant. However, when we re-run the main DiD with SERS scores calculated using the AAT variant (made up of absorptive, adaptive and transformative capacities) in Annex Table 11, we find similar negative and significant outcomes – significance drops somewhat for the IPTW sample.

Together with findings in Annex Table 4, these results suggest that while individual capacities may differ somewhat (particularly in comparing scores over time), alternative resilience frameworks appear to produce similar outcomes (whether the 3As or the AAT variants). Indeed, this matches findings from Jones and D'Errico (2019) that show how different variants of the SERS module produce similar resilience outcomes in a cross-sectional survey in Northern Uganda. The reduced effect size and lack of significance for the transformation DiD (Annex Table 10, models 7-8) is especially interesting, and may reflect the fact that households' ability to transform relates more strongly to underlying issues of power and agency (Carr 2019). These are factors that are undoubtedly entrenched, and unlikely to be altered by exposure to seasonal flooding. We hope that further research, through both quantitative and qualitative means, can be used to shed light on these issues going forward. This includes better targeting of subjective questions to reflect issues of power as it relates to transformation (and resilience more generally).

#### 6.2.1. Does exposure to subsequent shocks affect perceived resilience scores?

The SERS module is meant to measure the ability of a household, at any given moment in time, to deal with a range of (hypothetical) future threats. Accordingly, it is not necessarily a measure of the length of time it takes for households in Hpa An to bounce back from the initial period of flooding (though it may be seen as a proxy for this). Rather, SERS measures the extent that households are able to deal with subsequent threats in the aftermath of the floods – whether in the form of further flooding or wider socio-economic shocks. As such, we might expect that any follow-on shocks experienced by households are likely to exhibit further negative impacts on SERS scores. This is especially the case for those directly affected by the initial floods. Testing this is inherently difficult, particularly considering the small sample size of households directly affected by initial flooding.

Despite this, we can explore parts of this hypothesis by making use of follow-up questions asked during the Hpa An survey. For example, after the main period of flooding, all households were asked whether they had been affected by any socio-economic or environmental shocks in the period since the last survey Wave (see Annex Table 3 for wording). While exposure to follow-on shocks was relatively uncommon (comprising less than a quarter of households over the course of the entire panel), interesting insights can be learned by comparing the impacts of subsequent shocks on resilience scores between households directly and indirectly affected by the initial floods.

To do so, we carry out two additional tests for heterogeneous effects. The first is to augment Equation 4 with an interaction between flood exposure and a dummy for whether the household was affected by a shock in the subsequent waves (similar to the setup in Equation 5). This measures differences in the resilience-over-time score (i.e. the area under the curve for resilience scores) between those affected by subsequent shocks for households directly affected by flooding (compared to those indirectly affected). A second approach is to run a difference-in-difference-in-differences setup (akin to triple-differencing). This essentially augments Equation 1 by adding a further interaction to the original difference-in-difference estimate (see Annex Section 3 for equations and full results). Both are similarly interpretable, with the former comparing resilience-over-time scores, and the latter comparing differences in SERS scores directly.

Results from both tests in Annex Section 3 show that subsequent shocks are negatively associated with resilience (as seen by the negative coefficients in Annex Tables 11 and 12). The association is statistically significant (at $p<0.05$) for the first approach, though not for the triple differencing setup. While inconsistencies in the strength of the associations between the two tests suggest that care should be taken in deriving firm conclusions, the negative effects across all models provide some reassurance that SERS may be: i) responsive to successive external threats (and not just a measure of how long it takes to bounce back from a single event); ii) and responsive to different types of threats. However, the group affected by both June flooding as well as any subsequent shocks totals only 17 in number. Follow-up work is therefore needed to firmly establish the nature and strength of these underlying assumptions.

### 6.3. Which social groups fare better or worse in the aftermath of a natural hazard?

There are two factors to consider when examining which groups fared better or worse in the aftermath of the Hpa An floods. Firstly, we can look at the fate of all households in the sample - combining both directly and indirectly affected households. Here, Table 4 points to significant associations between resilience-over-time and: age (older respondents fare better); levels of poverty (poorer households are less resilient); gender of household head (female heads are worse off); higher life satisfaction (happy respondents are more resilient over time); livelihood type (farmers are better off compared with non-farmers); livelihood diversity (those with more sources of income fare comparatively worse); flood sensitivity (those that view flooding as a serious problem are negatively affected); and distance to nearest road (those further away from a road are worse off).

One interesting finding is that the number of household occupants has a significant positive association with resilience-over-time scores (though with a modest effect size). This link is not well explored within the resilience literature, and may reflect the fact that larger households are likely to have more developed social networks and higher human capital available to them. It may also suggest that development actors consider targeting smaller (and likely younger) households in seeking to prioritise vulnerable groups.

It is also interesting to see that education exhibits a weak statistical relationship with resilience-over-time. Moreover, while poverty levels are seen as significant across all unweighted samples, associations in the IPTW sample are inconsistent. These findings conflict somewhat with traditional measurement frameworks that typically assume that higher education and wealth are some of the strongest predictors of resilience (D'Errico and Di Giuseppe 2018). Yet, the survey findings are consistent with previous subjective assessments in other contexts, such as Béné et al (2016) that carry a multi-country comparison and Jones and Samman (2017) that conduct a nationally representative survey of Tanzania. It is also worth noting that education and poverty likelihood are strongly associated with baseline resilience scores (see Annex Table 2), suggesting that any lack of association may be in relation to flood impacts rather than stabilised resilience levels.

A second way to look at the results is to focus specifically on the plight of households directly affected by the floods (see Table 5). In many ways this question has more policy relevance: these are households that face the worst consequences. Any differences are therefore more likely to be caused by the floods themselves, rather than being drowned out by the wider sample. Here, two points are noteworthy. First is that female-headed households fare considerably worse than male-headed households (with effect sizes large compared with other household traits). Together with the qualitative data collected, it points to challenges that female-headed households face in gaining access to valuable support networks, capitalising on livelihood opportunities and having a voice in community-level recovery efforts (Islam, 2017).

A second interesting observation is that livelihood diversity (defined as the number of sources of income) is negatively associated with resilience-over-time. The link is statistically significant for both the full sample (Table 4) and the interaction with flood exposure for the partially balanced sample (Models 1-2 of Table 5). In other words, households with a single source of income appear to be better off than those with multiple sources (when controlling for a range of other factors). These findings conflict somewhat with traditional assumptions of resilience and disaster recovery (Adger et al. 2005b; Allison and Ellis 2001). The underlying reasons for this are unclear, though may suggest that promotion of a variety of livelihoods may be an inefficient means of supporting households in recovering from floods (at least in the context of Hpa An). It also adds weight to the conclusions of Liao et al. (2015) that challenge the orthodox of livelihood diversification as applied in the context of Chinese pastoral households. However, we are careful to note that the association between the livelihood diversity and resilience-over-time when interacted with flood exposure is not significant in the fully balanced panel (as per Equation 5 and Table 5). Further evidence – particularly drawing on qualitative insights – is needed in drawing firm policy conclusions.

Lastly, we highlight the importance of strong associations between measures of risk perception and resilience-over-time (particularly when interacted with flood exposure). In essence, this implies that households have some grasp of the factors contributing to their own resilience. More importantly, given that risk perception was measured during the baseline survey (prior to the floods), it may suggest that perceptions of risk (particularly flood sensitivity) have some predictive power in both determining levels of resilience-over-time as well as distinguishing between households likely to be hardest hit by natural hazards. While this has considerable implications for measurement efforts, more can be done to further explore these links, particularly with regards to causal drivers – noting that risk perception is likely to play a role in people's evaluations of resilience (Béné et al. 2019).

### 6.4. Challenges and ways forward for resilience measurement

By combining subjective evaluations with mobile phone surveys, insights from the Hpa An panel survey are an important first step in better understanding (and quantifying) how resilience changes over time. Our findings confirm the well-documented influence a range of drivers for resilience and post-disaster recovery. They also challenge a number of long-held assumptions. To get a better sense of the implications of these findings, as well as whether they apply in contexts outside of Hpa An, a number of research gaps and avenues for further exploration need addressing.

For one, further testing of the validity of subjective assessments and comparisons with the wide range of existing objective approaches is crucial (building on earlier work by Clare et al. 2018 and Jones and D'Errico 2019). In particular, a better understanding of the impact of various cognitive biases on subjective responses will aid in drawing firmer conclusions on the outcomes of perception-based surveys such as this. This includes further exploration of the potential role of psychological adaptation in explaining recovery of SERS scores – similar to the effects experienced in measures of subjective wellbeing (Dolan 2008). In addition, more consistent collection of longer-term panel datasets (from a variety of different contexts) will be crucial in helping to disentangle causal effects, and discounting any confounding influences on resilience outcomes (such as seasonal or mode effects).

With all of this in mind, our results point to the considerable potential for subjective and mobile-phone survey tools. The simplicity of their use, cost-efficiency and near-real-time nature of remote data collection may provide a valuable complement to existing approaches for monitoring and evaluation. If household resilience does fluctuate over shorter timescales (as suggested by the Hpa An survey) then development and humanitarian actors should take note in accounting for this in their vulnerability assessments, project designs and post-intervention evaluations. This is particularly relevant in the aftermath of a natural hazard where resilience-capacities are likely to change rapidly. Greater innovation in designing and applying resilience measurement tools that can capture momentary, transient and longer-terms changes is needed. Doing so may be key to ensuring more effective resilience-building interventions on the ground.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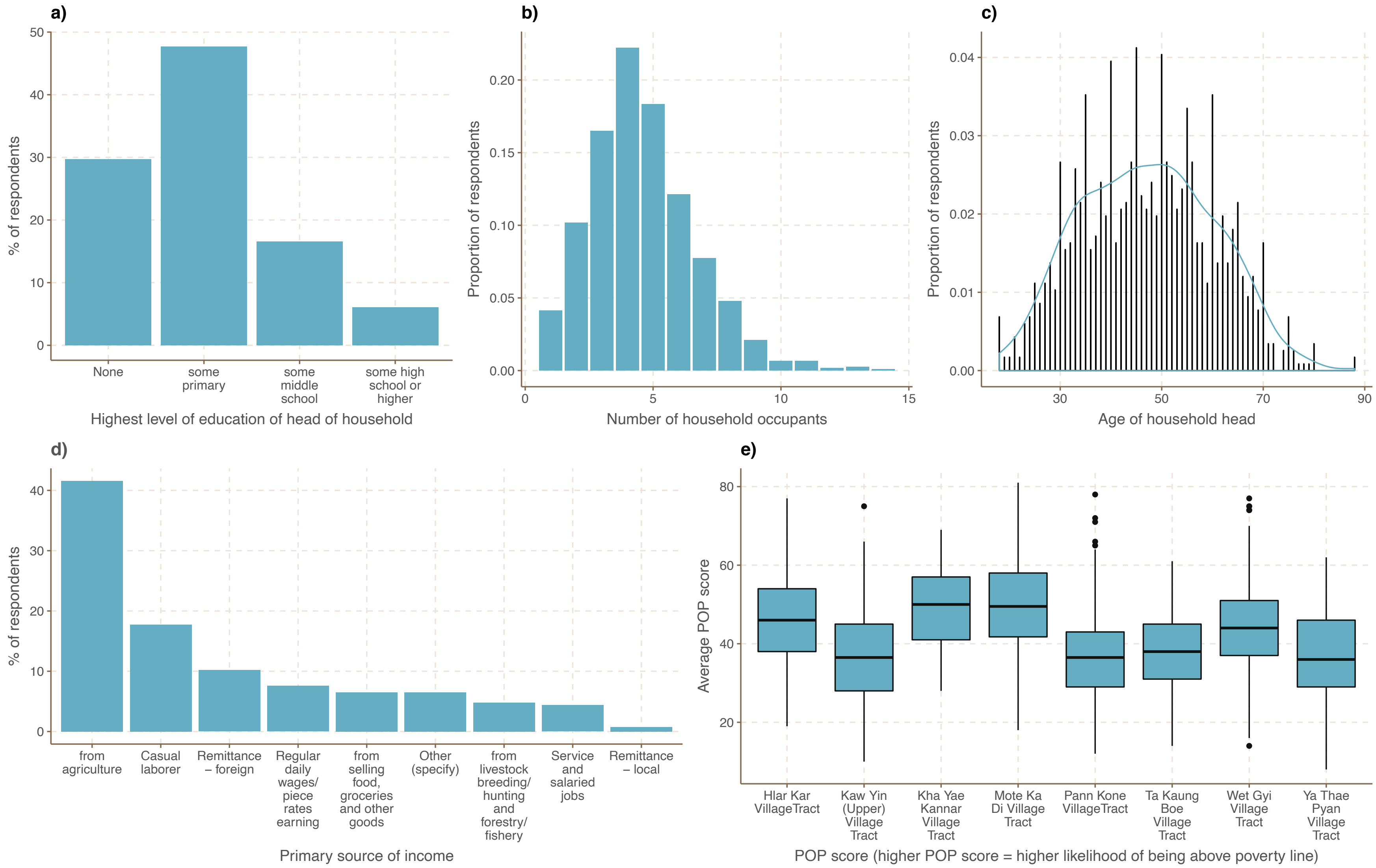
# Annexes

**Annex Table 1: List of resilience-related capacity questions used in the numerous variants of the Subjective self-Evaluated Resilience Score**

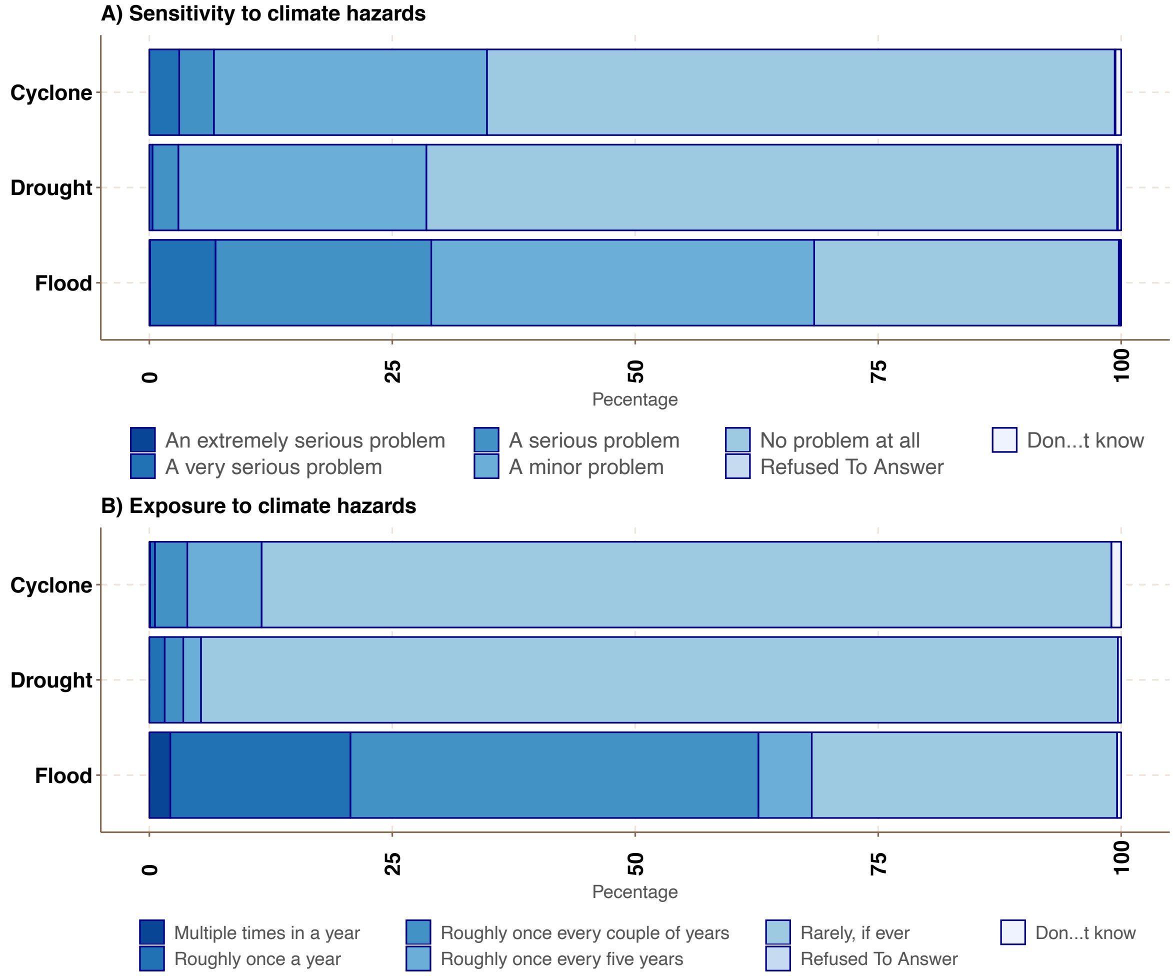
| Preamble: 'I am going to read out a series of statements. Please tell me the extent to which you agree or disagree with them.' [Read out each statement and ask] 'Would you say that you strongly agree, agree, disagree, strongly disagree or neither agree nor disagree that:' | |
|---|---|
| Resilience-related capacity | Survey question |
| Absorptive capacity | Your household can bounce back from any challenge that life throws at it |
| Adaptive capacity | If threats to your household became more frequent and intense, you would still find a way to get by |
| Anticipatory capacity | Your household is fully prepared for any future disasters that may occur in your area |
| Transformative capacity | During times of hardship, your household can change its primary income or source of livelihood if needed |
| Financial capital | During times of hardship, your household can access the financial support you need |
| Social capital | Your household can rely on the support of family and friends when you need help |
| Political capital | Your household can rely on support from politicians and government when you need help |
| Learning | Your household has learned important lessons from past hardships that will help you better prepare for future threats |
| Early warning | Your household receives useful information warning you about future risks in advance |

*Notes: The full SERS model uses all nine resilience-capacity questions, named the 9-C model. For the purposes of this study, we use the shortened 3A variant of the SERS model with uses Absorptive, Adaptive and Anticipatory capacities. Jones and D'Errico (2019) also use another variant, named AAT, comprising of Adaptive, Absorptive and Transformative capacities.*

**Annex Figure 1: Key socio-economic characteristics of survey respondents**



**Annex Figure 2: Risk perception: self-reported sensitivity and exposure to cyclones, droughts and floods in Hpa An**




*Note: For sensitivity respondents were asked, 'Please rate the following extreme weather events in accordance with how serious a problem they have been to your household's ability to survive and thrive in the past 5 years'; For exposure respondents were asked, 'On average, how often would you say your household is affected by the following extreme weather events?'*

**Annex Section 1**

What factors are associated resilience during the baseline survey?

One important aspect of the survey is understanding baseline levels of resilience. As highlighted in Table 2 (main text) mean subjectively-evaluated resilience score across all households is 0.54 (SD=0.18). Yet, this is somewhat uninformative without comparing across households. To do so we regress baseline SERS scores, $Resilience_{hv}$ against a number of key social-economic and demographic variables, $Socio_{hv}$. In addition, $Capacity_{hv}$ is a list of factors commonly associated with household resilience and $\xi_{hv}$are village-level fixed effects.

$$Resilence_{hv} = \beta_0 + \beta_1 Socio_{hv} + \beta_2 Capacity_{hv} + \xi_v + e_{hv} \quad 1)$$

Results from the model show that baseline resilience scores are positively associated with a number of socioeconomic traits, including education of the household head, lower likelihood of poverty, gender of household head and number of household occupants. Age of household head appears to be negatively associated with resilience, as does the gender of respondent. As respondent gender (1=Female) is randomised this potentially signals a difference in the way that males and females perceive their respective households – though note the low-level of statistical significance (p<0.1). With regards to factors commonly associated with resilience, higher life satisfaction is strongly significant (those with higher life satisfaction have higher resilience scores). Lastly, households that are further away from the main river (the Thanlwin) also appear to have lower resilience scores when controlling for all other factors (note here that the SERS resilience module is not specific to flood resilience).

**Annex Table 2: Factors associated with subjectively-evaluated resilience for the Hpa-An baseline survey**

| | (1) | (2) |
|---|---|---|
| Dummy for education of household head (0=None; 1=Some schooling) | 0.05*** (0.01) | 0.05*** (0.01) |
| Age of respondent | -0.001*** (0.0004) | -0.001*** (0.0004) |
| POP poverty score (high score = higher likelihood of not in poverty) | 0.002*** (0.001) | 0.002*** (0.001) |
| Mean number of HH occupants | 0.01*** (0.002) | 0.01*** (0.002) |
| Dummy for farmer as primary source of income (1=Farmer) | -0.03** (0.01) | -0.03* (0.01) |
| Dummy for remittance as primary source of income (1=Remittance) | 0.02 (0.01) | 0.02** (0.01) |
| Gender of HH head (1=Female) | 0.03*** (0.01) | 0.03** (0.01) |
| Respondent gender (1=Female) | -0.02* (0.01) | -0.02** (0.01) |
| Risk perception: dummy for flood sensitivity (1=Very serious problem) | | 0.01 (0.01) |
| Risk perception: dummy for flood exposure (1=Once a year or more) | | 0.001 (0.02) |
| Life satisfaction | | 0.03*** (0.01) |
| Number of sources of livelihood | | 0.001 (0.01) |
| Distance to the river (log+1) | | -0.02* (0.01) |
| Distance to nearest road (log+1) | | -0.01 (0.01) |
| Observations | 1,072 | 1,052 |
| Adjusted R2 | 0.17 | 0.19 |
| Residual Std. Error | 0.16 (df = 1056) | 0.16 (df = 1030) |

*Note: All models include Village fixed effects. Values indicate Beta coefficients with Standard Errors clustered at the village-level using a Wild cluster bootstrap with 1000 replications and shown in parentheses, *p<0.1 **p<0.05 ***p<0.01*

For details on question wording see Annex Table 3

**Annex Table 3: Questions and response items for variables of interest in the Hpa An survey**

| Variable | Question | Response items | Notes |
|---|---|---|---|
| Flood impact | Since we last called you on [DATE], has your household been affected by any significant shocks or events that have had a large negative effect on your household's way of life? | Yes<br>No<br>Don't know | Respondents that answer as affected are asked a follow up question: 'What is the primary cause of this shock or event?' (with Flood one of the options available). Responses are then collapsed into binary variables, including: Floods, Landslides, Irregular/Unseasonal rain, Strong wind/tornado, Disease destroying crop, Sudden loss livestock, Social unrest, Fall in price of a good that the HH sells, Increase in price of food or other essential item, Medical emergency, Serious accident at work or home, Death of the income generator, Sudden loss of productive assets, Loss of job. |
| Risk perception: flood sensitivity | Would you say that flooding poses an extremely serious problem, a very serious problem, a serious problem, a minor problem or no problem at all? | An extremely serious problem<br>A very serious problem<br>A serious problem<br>A minor problem<br>No problem at all<br>Refused to Answer<br>Don't know | Premable: "I would like to ask you about what would happen if a flood were to affect your household in the near future. By severe flood I mean one that is likely to negatively affect your household, or harm your dwelling, fields, or resources. Please rate how serious a problem flooding has been to your household's ability to survive and thrive in the past 5 years." Question asked during the baseline of the survey. Responses then collapsed into binary variable (extremely serious/very serious/serious=serious problem; minor/no problem=not serious problem) |
| Risk perception: flood exposure | On average, how often would you say your household is affected by flooding? | Multiple times in a year<br>Roughly once a year<br>Roughly once every couple of years<br>Roughly once every five years<br>Rarely, if ever<br>Refused to Answer<br>Don't know | Question asked during the baseline of the survey. Category collapsed into binary variable (multiple times/roughly one a year=once a year or more; every couple/once every five/rarely=less than once a year) |
| Life satisfaction | All things considered, how satisfied are you with your life as a whole these days? | Very dissatisfied with life<br>Dissatisfied with life<br>Neither satisfied nor dissatisfied<br>Satisfied with life<br>Very satisfied with life<br>Refused to Answer<br>Don't know | Question asked during the baseline of the survey. Treated as a cardinal variable. |
| Self-assessment of local environmental change | Has the health of the natural environment around you changed in recent years? | It is improving considerably<br>It is improving slightly<br>It is not changing<br>It is worsening slightly<br>It is worsening considerably | Question asked during Wave 6 of the survey. Treated as a cardinal variable and time invariant. |

**Annex Table 3 continued: Questions and response items for variables of interest in the Hpa An survey**

| Variable | Question | Response items | Notes |
|---|---|---|---|
| Coping mechanisms | 'What coping mechanisms has your household employed in responding to the<br>shock event since its occurrence? Please list up to three' | 1. Household members migrated<br>2. Engaged in spiritual efforts - prayer, sacrifices, divine consultations<br>3. Obtained credit<br>4. Ask for remittances from those outside the household<br>5. Received help from NGO/religious institution<br>6. Received help from government<br>7. Sought new forms of livelihood or work<br>8. Rely on own saving<br>9. Changed eating patterns (relied on less preferred food): options, reduced proportion or number of meals/day, or household members skipped days of eating, etc)"<br>10. Received help from relatives/friends<br>11. Sent children to live elsewhere<br>12. Reduced expenditures on household good<br>13. Took child out of school<br>14. Sold agricultural assets or goods<br>15. Did not do anything | Question only asked to households that self-report as affected by a disaster. Responses are post-coded afterward. Responses are then formed into a binary variables, with a primary coping mechanism constituting a response to any recovery mechanism (each households was able to choose up to three). |
| Primary livelihood | 'What is main source of income for this household?' | 1. From agriculture<br>2. from livestock breeding/<br>3. hunting and forestry/ fishery<br>4. from selling food, groceries<br>5. and other goods<br>6. Income from services<br>7. Salary<br>8. Regular daily wages/ piece<br>9. rates earning<br>10. Casual laborer<br>11. Remittance - local<br>12. Remittance - foreign<br>13. Other (specify) | Question asked during the baseline survey. Responses to formed into binary variables used in the regression analyses |
| Access to climate information during last flood | Do you have access to weather forecasts and climate information? | Yes<br>No | Question asked to all respondents in Wave 5 of the survey, irrespective of flooding |
| Early warning information | Did you receive information warning your household about the flood in advance? | Yes<br>No | Question only asked to respondents that self-reported as directly affected by a flood since the last round of the survey, and asked in relation to the flood event in question |

**Annex Section 2:**

A key decision made early on in the analysis is use of a reduced form of the SERS model; we opt for a version with three resilience-capacity questions rather than the full model with nine questions. To test the implications of this decision we run side-by-side analyses of different variants of the SERS module for the baseline survey in Annex Table 4 (set-ups are similar to Annex Table 2). Model 1) shows results from the 3A variant of the SERS module used in the main analysis, Models 2) and 3) use the 9C (all 9 questions) and AAT (including questions related to adaptive, anticipatory and transformative capacities) variants respectively[8]. Though statistical significance varies across some variables, signs and magnitudes of effect sizes are broadly similar across all three, implying that results are somewhat consistent across different characterisations of resilience. We also re-rerun the analysis with a variant of the SERS that weights based on a principal component analysis (rather than the standard methods of equal mean weighting) and see no large qualitative differences in key trends.

Turning to the validity of resilience-over-time scores, a number of selection choices should be considered. The first is whether to include data from the face-to-face survey alongside the wider phone panel. This is particularly important given well-documented differences in subjective scores between the two modes of administration (Dolan & Kavetsos 2016). The second, is how to deal with missing values when calculating a resilience-over-time score (as any such values need to be interpolated). In order to test these formally we replicate Equation 4 with three different specifications.

In Annex Table 5, Model 1) is the same set-up as in the main analysis and removes only households that have three or more missing resilience scores, or a missing value for either the starting (baseline) or finishing waves (wave 7). Model 2) excludes any household that has a missing value for a resilience score across any wave of the survey. While Model 3) excludes resilience scores from the face-to-face survey and starts calculating the area under the curve as of the first phone survey. Given that Model 3) includes one fewer survey than the rest, we calculate the resilience-over-time score as the area under the curve for 6 subsequent waves (rather than 7 in the main analysis). As is clear from Annex Table 5, though small differences exist, results appear to be similar in sign and significance across most variables of interest for the three specifications.

In rare cases, the original respondent was unable to pick up the phone and another member of the household carried out the survey in their place. Given the potential for confounding individual influences we rerun the main difference in difference analyses with a subset of the dataset that excludes values obtained from non-original respondents (Annex Table 6). Again, we see few differences in the main outcome.

Another crucial aspect to consider is how many time periods to include in calculating the resilience-over-time scores. While use of data from a larger number of waves provides more nuanced information on a household's recovery, it also risks being influenced by other external factors (like wider socio-economic of environmental threats) that make it difficult to make comparisons across groups. The choice of all 7 waves of phone survey data in calculating the AUC is borne of the desire to use all information available. However, in Annex Table 7 we compare multiple resilience-over-time scores, starting with the use of just three waves and adding an additional wave each time, up to a total of 7 waves. We also plot distributions of resilience scores in Annex Figure 3. While small differences are apparent, signs and levels of significance are largely consistent.

We recognise that assessments of perceived levels of resilience are subjective in nature. Unfortunately, limitations in mobile surveys (typically restricted to 10-12 mins in duration) do not lend themselves to

[8] The AAT variant is meant to mimic the framework proposed by Béné et al. 2012. For full details of the questions and methods used in the variants see Jones (2017)

applying 'objective' measures of resilience such as the RIMA toolkit (FAO 2016[9]). However, we can make a useful comparison with changes in self-reported levels of monthly income – often considered a proxy for a household's economic resilience (Sturgess 2016) – collected during two waves of the survey (one prior to the floods and the other a number of months after). In Annex Table 8 we compare self-reported incomes between the baseline and Wave 5 of the survey using a difference-in-differences set-up similar to the main analysis. In doing so we see no statistically significant differences between direct and indirectly affected households. While this may point to differences in definitional outcomes of resilience, we refrain from drawing firm conclusions as it is far from a like-for-like comparison. Well-documented weaknesses in self-reported income measures (Fukuoka, et. al 2007) also mean that consumption-based measures (such as the POP poverty score used in the main analysis) are far preferred. Still, we believe that dedicated future analyses comparing subjective resilience and other proxies for resilience will have considerable merit.

Lastly, subjective assessments may be prone to different societal and environmental cues (Metcalfe et al. 2016). As such, we re-run the main difference-in-differences set-up for resilience scores with the inclusion of controls for day-of-the-week of the interview, time-of-the-day of the interview and weather on the day of interview (including average temperature, precipitation, dew point). Reassuringly, Table 9 show few differences in the paper's main outcome.

[9] For more on direction comparisons of objective and subjectively-evaluated resilience see Jones and D'Errico (2019).

**Annex Table 4: Comparison of associations with resilience using different versions of the SERS module**

| | SERS-3A<br>(1) | SERS-9C<br>(2) | SERS-AAT<br>(3) |
|---|---|---|---|
| Dummy for education of household head (0=None; 1=Some schooling) | 0.05*** (0.01) | 0.14*** (0.04) | 0.21*** (0.07) |
| Age of respondent | -0.001** (0.0003) | -0.003*** (0.001) | -0.01*** (0.002) |
| POP poverty score (high score = higher likelihood of not in poverty) | 0.002*** (0.0005) | 0.003*** (0.001) | 0.002 (0.002) |
| Mean number of HH occupants | 0.01*** (0.002) | 0.03*** (0.004) | 0.02** (0.01) |
| Dummy for farmer as primary source of income (1=Farmer) | -0.03* (0.01) | -0.08** (0.04) | -0.11*** (0.04) |
| Dummy for remittance as primary source of income (1=Remittance) | 0.02** (0.01) | 0.07*** (0.03) | 0.07 (0.05) |
| Gender of HH head (1=Female) | 0.02*** (0.01) | 0.08*** (0.03) | 0.08* (0.05) |
| Respondent gender (1=Female) | -0.02** (0.01) | -0.06** (0.03) | -0.13*** (0.05) |
| Risk perception: dummy for flood sensitivity (1=Very serious problem) | 0.01 (0.01) | 0.01 (0.01) | -0.01 (0.04) |
| Risk perception: dummy for flood exposure (1=Once a year or more) | 0.001 (0.02) | 0.03 (0.05) | 0.09 (0.06) |
| Life satisfaction (higher score=higher life satisfaction | 0.03*** (0.01) | 0.04*** (0.01) | 0.12*** (0.02) |
| Number of sources of livelihood | 0.0002 (0.01) | -0.002 (0.01) | -0.01 (0.02) |
| Distance to the river (Log+1) | -0.02* (0.01) | -0.04 (0.03) | -0.02 (0.02) |
| Distance to nearest road (Log+1) | -0.01 (0.01) | -0.002 (0.01) | -0.01 (0.03) |
| Observations | 1,057 | 1,057 | 1,057 |
| Adjusted $R^2$ | 0.18 | 0.20 | 0.21 |
| Residual Std. Error (df = 1034) | 0.16 | 0.41 | 0.69 |

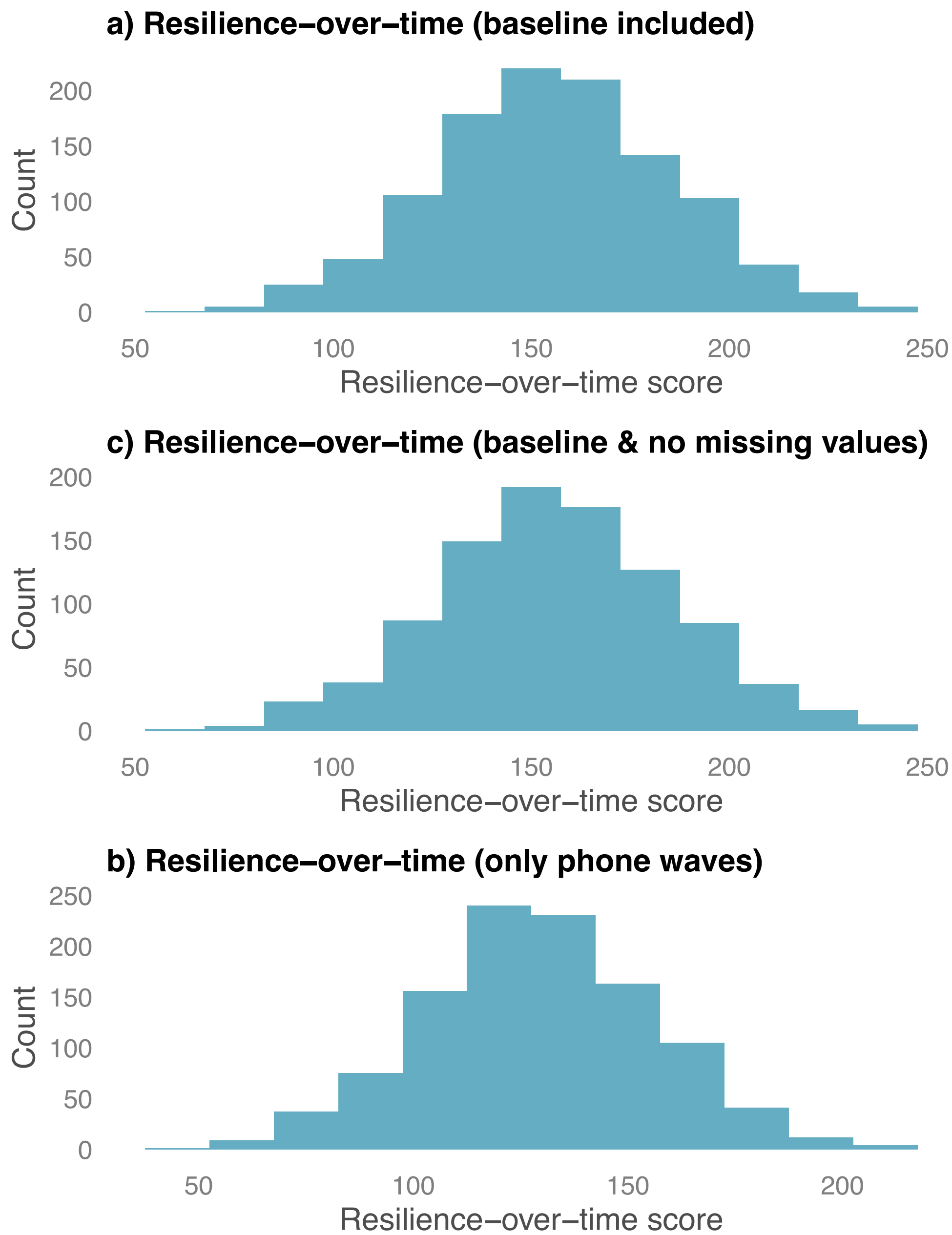
*Note: All models include Village-level fixed effects. Values indicate Beta coefficients with Standard Errors clustered at the village-level using a Wild cluster bootstrap with 200 replications and shown in parentheses, *p<0.1** p<0.05p***p*

**Annex Table 5: Associations with resilience-over-time for different methods of dealing with missing values**

| | Fewer than 3 missing responses (phone & baseline) (1) | No missing responses across all waves (phone and baseline) (2) | Phone only (3) |
|---|---|---|---|
| Dummy for education of household head (0=None; 1=Some schooling) | 0.17 (2.45) | -0.71 (2.12) | 0.65 (2.18) |
| Age of respondent | 0.22*** (0.04) | 0.22*** (0.04) | 0.19*** (0.03) |
| POP poverty score (high score = higher likelihood of not in poverty) | 0.09 (0.06) | 0.12** (0.05) | 0.11* (0.06) |
| Mean number of HH occupants | 0.82 (0.58) | 1.09* (0.61) | 0.87 (0.60) |
| Dummy for farmer as primary source of income (1=Farmer) | 5.53*** (1.96) | 4.83** (1.94) | 5.07*** (1.74) |
| Dummy for remittance as primary source of income (1=Remittance) | -1.30 (1.33) | -1.79 (1.11) | -0.97 (1.22) |
| Gender of HH head (1=Female) | -2.87 (2.71) | -3.35 (2.84) | -2.11 (2.82) |
| Respondent gender (1=Female) | -1.48 (1.27) | -0.69 (1.88) | -1.39 (1.03) |
| Risk perception: dummy for flood sensitivity (1=Very serious problem) | -3.91 (2.49) | -4.45* (2.70) | -3.63 (2.67) |
| Risk perception: dummy for flood exposure (1=Once a year or more) | -0.66 (2.04) | -0.43 (2.55) | -0.91 (2.12) |
| Life satisfaction | 4.01*** (1.14) | 3.84*** (1.30) | 3.34*** (1.27) |
| Number of sources of livelihood | -1.39 (0.92) | -0.54 (0.99) | -1.42 (1.00) |
| Distance to the river (log+1) | -1.52** (0.67) | -0.76 (0.92) | -1.61*** (0.60) |
| Distance to nearest road (log+1) | -5.61*** (1.42) | -4.19** (1.94) | -4.35*** (1.35) |
| Baseline control | YES | YES | YES |
| Village fixed effects | YES | YES | YES |
| Observations | 1,040 | 925 | 1,009 |
| Adjusted R2 | 0.24 | 0.26 | 0.18 |
| Residual Std. Error | 26.25 (df = 1017) | 25.83 (df = 902) | 24.41 (df = 986) |

*Note: To ensure comparability across the models, the AUC resilience-over-time scores are calculated up to Wave 6 for models 1 and 2 (rather than Wave 7 in the main analyses) owing to the fact that the phone-only variant in Model 3 has one fewer wave (i.e. no baseline). Values indicate Beta coefficients with Standard Errors clustered at the village-level using a Wild cluster bootstrap with 1000 replications and shown in parentheses, *p<0.1 **p<0.05 ***p<0.01*

**Annex Figure 3: Histogram of Resilience-over-time scores for difference variants amongst the entire Hpa An sample**



## Annex Table 6: Difference in differences for sample of same respondents only

| | Unweighted | IPTW |
|---|---|---|
| f · post (Difference in Differences) | -0.09*** (0.02) | -0.07*** (0.03) |
| Household fixed effects | YES | YES |
| Wave fixed effects | YES | YES |
| Observations | 7,520 | 7,520 |
| Adjusted R-Squared | 0.31 | 0.29 |
| Residual Std. Error | 0.17 (df = 6572) | 0.23 (df = 6572) |

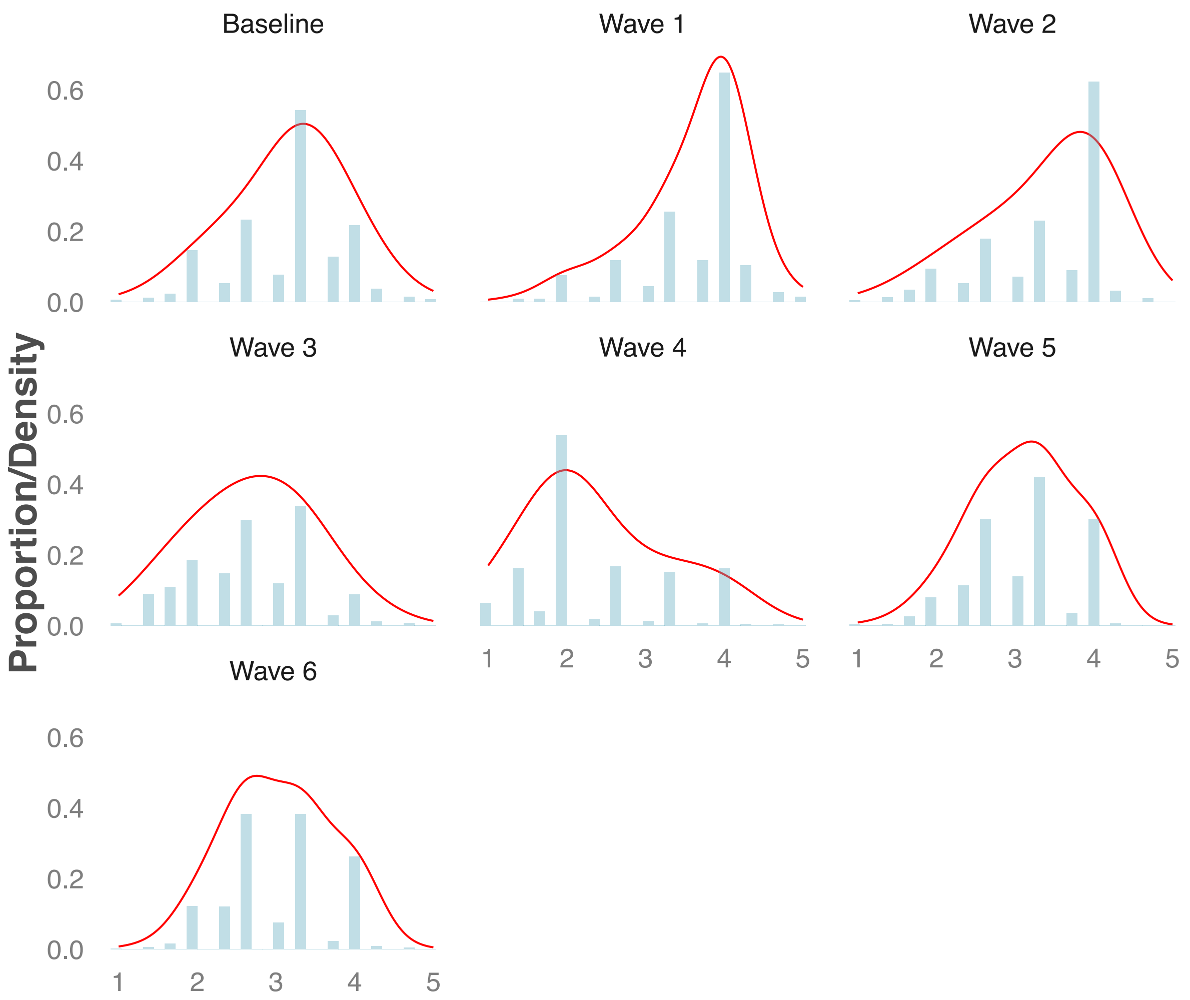
*Note: Values indicate Beta coefficients with Standard Errors clustered at the village-level using a Wild cluster bootstrap with 200 replications and shown in parentheses, *p<0.1 **p<0.05 ***p<0.01*

**Annex Table 7: Differences in associations with Resilience-over-time for different end-points of the AUC**

| | 3 waves | 4 waves | 5 waves | 6 waves | 7 waves |
|---|---|---|---|---|---|
| Dummy for flood impact (0=Indirect;1=Direct) | -6.58*** (1.10) | -5.13* (2.87) | -5.35* (2.76) | -6.28* (3.43) | -7.87* (4.05) |
| Baseline resilience score | 34.43*** (3.12) | 43.25*** (3.29) | 48.35*** (3.30) | 51.73*** (4.00) | 54.10*** (4.17) |
| Dummy for education of household head (0=None; 1=Some schooling) | -1.93* (1.10) | -2.20 (1.89) | -0.89 (2.22) | -1.35 (2.50) | 0.29 (2.76) |
| Age of respondent | 0.13*** (0.03) | 0.17*** (0.03) | 0.18*** (0.04) | 0.20*** (0.04) | 0.24*** (0.05) |
| POP poverty score (high score = higher likelihood of not in poverty) | 0.04 (0.04) | 0.07 (0.06) | 0.08 (0.05) | 0.13** (0.06) | 0.13** (0.05) |
| Mean number of HH occupants | 0.48* (0.27) | 0.65* (0.39) | 0.66 (0.49) | 0.84 (0.58) | 1.07* (0.57) |
| Dummy for farmer as primary source of income (1=Farmer) | 2.48** (1.11) | 2.65* (1.60) | 3.76** (1.90) | 4.92*** (1.87) | 4.66** (1.81) |
| Dummy for remittance as primary source of income (1=Remittance) | -1.45*** (0.51) | -1.72** (0.85) | -1.06 (1.00) | -1.36* (0.72) | -1.13 (0.93) |
| Gender of HH head (1=Female) | -2.07** (1.01) | -3.65** (1.44) | -3.49 (2.18) | -3.30 (2.59) | -4.30* (2.60) |
| Respondent gender (1=Female) | 0.43 (0.67) | 0.25 (0.88) | -1.33 (1.17) | -1.72 (1.35) | -1.71 (1.25) |
| Baseline resilience FE | YES | YES | YES | YES | YES |
| Village-level FE | YES | YES | YES | YES | YES |
| Observations | 1,064 | 990 | 1,065 | 1,056 | 1,072 |
| Adjusted $R^2$ | 0.23 | 0.22 | 0.21 | 0.22 | 0.23 |
| Residual Std. Error | 14.79 (df = 1046) | 19.95 (df = 972) | 24.17 (df = 1047) | 26.41 (df = 1038) | 28.51 (df = 1054) |

*Note: Values indicate Beta coefficients with Standard Errors clustered at the village-level using a Wild cluster bootstrap with 1000 replications and shown in parentheses. Sample sizes differ owing to differences in exclusion for missing values in subsequent waves of the survey. *p<0.1 **p<0.05 ***p<0.01*

**Annex Figure 4: Densities and proportion of responses across the various waves of the Hpa An survey**




*Note: Density functions are represented with the red line, while proportion of responses are indicated in blue/grey bars. X-axis for all panels feature SERS resilience scores ranging from 1-5.*

## Annex Table 8: Difference in differences between incomes in Baseline and Wave 5 outcomes

| | Log(Income+1) | |
|---|---|---|
| | Unweighted<br>(1) | IPTW<br>(2) |
| f · post (Difference in Differences) | 0.13 (0.09) | -0.03 (0.11) |
| f (1=Directly affected by flooding) | -1.04*** (0.04) | -0.96*** (0.05) |
| post (1=Periods after flooding) | -0.18*** (0.04) | -0.17*** (0.04) |
| Household fixed effects | YES | YES |
| Wave fixed effects | YES | YES |
| Observations | 2,187 | 2,187 |
| Adjusted $R^2$ | 0.35 | 0.41 |
| Residual Std. Error (df = 1066) | 0.55 | 0.81 |

*Note: Values indicate Beta coefficients with Robust Standard Errors in parentheses. Results are weighted using IPTW. *p<0.1 **p<0.05 ***p<0.01.*

**Annex Table 9: Difference in differences with inclusion of weather, time of day, and day of week fixed effects**

| | Unweighted | IPTW sample |
|---|---|---|
| f · post (Difference in Differences) | -0.08*** (0.02) | -0.06*** (0.02) |
| f (1=Directly affected by flooding) | -0.07*** (0.02) | -0.10*** (0.02) |
| post (1=Periods after flooding) | -0.01* (0.01) | -0.01 (0.01) |
| Time of day FE | YES | YES |
| Day of week FE | YES | YES |
| Weather FE | YES | YES |
| Wave FE | YES | YES |
| Village controls | YES | YES |
| Observations | 8,241 | 8,241 |
| Adjusted R2 | 0.30 | 0.30 |
| Residual Std. Error | 0.17 | 0.23 |

*Note: SERS scores are used as the outcome variable. Values indicate Beta coefficients with Robust Standard Errors in parentheses. Results are weighted using IPTW. *p<0.1 **p<0.05 ***p<0.01.*

**Annex Table 10: Difference-in-differences for the three resilience-related capacities used in the SERS module**

| | Anticipatory | | Absorptive | | Adaptive | | Transformative | |
|---|---|---|---|---|---|---|---|---|
| | Unweighted (1) | IPTW (2) | Unweighted (3) | IPTW (4) | Unweighted (5) | IPTW (6) | Unweighted (7) | IPTW (8) |
| f · post (Difference in Differences) | -0.07*** (0.02) | -0.05 (0.03) | -0.07*** (0.02) | -0.06*** (0.02) | -0.09*** (0.03) | -0.08** (0.03) | -0.03 (0.04) | -0.004 (0.04) |
| f (1=Directly affected by flooding) | -0.15*** (0.02) | -0.16*** (0.03) | -0.12*** (0.02) | -0.13*** (0.02) | -0.11*** (0.03) | -0.12*** (0.03) | -0.13*** (0.03) | -0.15*** (0.03) |
| post (1=Periods after flooding) | 0.12*** (0.01) | 0.14*** (0.02) | -0.01 (0.01) | -0.02* (0.01) | -0.13*** (0.01) | -0.11*** (0.01) | 0.06*** (0.01) | 0.06*** (0.01) |
| Household fixed effects | YES | YES | YES | YES | YES | YES | YES | YES |
| Wave fixed effects | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 8,667 | 8,667 | 8,678 | 8,678 | 8,689 | 8,689 | 8,674 | 8,674 |
| Adjusted $R^2$ | 0.18 | 0.16 | 0.26 | 0.27 | 0.19 | 0.19 | 0.08 | 0.12 |
| Residual Std. Error | 0.25 (df = 7539) | 0.35 (df = 7539) | 0.23 (df = 7550) | 0.31 (df = 7550) | 0.26 (df = 7561) | 0.36 (df = 7561) | 0.25 (df = 7546) | 0.35 (df = 7546) |

*Note: Values indicate Beta coefficients with Robust Standard Errors in parentheses. Results are weighted using IPTW. *p<0.1 **p<0.05 ***p<0.01.*

**Annex Table 11: Difference in differences with resilience-scores calculated as a combination of absorptive, adaptive and transformative capacities**

| | Unweighted<br>(1) | IPTW<br>(2) |
|---|---|---|
| f · post (Difference in Differences) | -0.06*** (0.02) | -0.04* (0.02) |
| f (1=Directly affected by flooding) | -0.12*** (0.01) | -0.14*** (0.02) |
| post (1=Periods after flooding) | -0.03*** (0.004) | -0.02*** (0.004) |
| Household fixed effects | YES | YES |
| Wave fixed effects | YES | YES |
| Observations | 8,666 | 8,666 |
| Adjusted R2 | 0.24 | 0.25 |
| Residual Std. Error (df = 1066) | 0.17 | 0.24 |

*Note: Values indicate Beta coefficients with Robust Standard Errors in parentheses. Results are weighted using IPTW. *p<0.1 **p<0.05 ***p<0.01.*

**Annex Section 3: Testing for the impact of subsequent shocks amongst directly affected households**

In our first setup, we regress resilience-over-time scores (i.e. the area under the curve for resilience scores across the panel) against the same covariates as those included in Equation 4. In addition, we interact $f_{hv}$ (a variable for flood impact) with a dummy variable, $d_{hv}$, which indexes for whether the household has experienced an additional shock in any of the subsequent Waves. To account for non-random rates of drop-out amongst households affected by subsequent shocks we limit the analysis to the fully balanced dataset.

$$Resilienceovertime_{hv} = \beta_1 f_{hv} + \beta_2 d_{hv} + \beta_3 (f_{hv} \cdot d_{hv}) + \beta_4 Resilienceovertime_{hv-1} + \beta_5 s_{hv} + \beta_6 p_{hv} + \xi_v + e_{hv} \qquad 5)$$

The main feature of interest is $\beta_3$, representing the effect of subsequent shocks on households directly affected by flooding (compared with those indirectly affected).

**Annex Table 12: Interactions between flood exposure and subsequent shock events**

| | Unweighted sample | IPTW sample |
|---|---|---|
| | (1) | (2) |
| Dummy for additional shocks (1=Shocks) * Flood exposure (1=Directly exposed) | -12.89** (6.57) | -9.62** (4.81) |
| Socio-economic and risk perception FE | YES | YES |
| Baseline resilience FE | YES | YES |
| Village-level FE | YES | YES |
| Observations | 925 | 925 |
| Adjusted $R^2$ | 0.26 | 0.26 |
| Residual Std. Error | 27.91 (df = 899) | 37.55 (df = 899) |

*Note: Resilience-over-time scores (i.e. area under the curve for SERS scores over time) are used as the outcome variable. Only results of interactions are shown. Values indicate Beta coefficients with Standard Errors clustered at the village-level using a Wild cluster bootstrap with 1000 replications and shown in parentheses. *p<0.1 **p<0.05 ***p<0.01*

As part of the second analysis we run a difference-in-difference-in-differences setup (akin to triple-differencing). This essentially augments Equation 2 by adding a further interaction to the original difference-in-difference estimate ($post_t \cdot f_h$). Here $d_h$, is a dummy variable for whether the household experienced an additional shock subsequent to the main period of flooding between the baseline and Wave 1 (1 = subsequent shock).

$$Resilience_{ht} = \beta_1 post_t + \beta_2 f_h + \beta_3 d_h + \beta_4 (post_t \cdot f_h) + \beta_5 (post_t \cdot d_h) + \beta_6 (f_h \cdot d_h) + \beta_7 (post_t \cdot f_h \cdot d_h) + \psi_h + e_{ht} \qquad 6)$$

In the context of this study, it is $\beta_7$ that is of primary interest, representing the difference between the DiD (i.e. seen in Equation 2) for those hit by subsequent shocks compared to those that weren't. In other words, it indicates the effect of follow-on shocks on resilience scores for households directly affected by flooding (when compared to those indirectly affected by flooding).

## Annex Table 13: Triple difference estimates on SERS resilience scores

| | (1)<br>Unweighted sample | (2)<br>IPTW sample |
|---|---|---|
| post · f · d (Triple differences) | -0.05 (0.04) | -0.06 (0.04) |
| Household fixed effects | YES | YES |
| Wave fixed effects | YES | YES |
| Observations | 7,512 | 7,512 |
| Adjusted $R^2$ | 0.31 | 0.29 |
| Residual Std. Error (df = 6563) | 0.17 | 0.23 |

*Note: SERS scores are used as the outcome variable. Only results from the triple interaction are shown. Values indicate Beta coefficients and Standard Errors clustered at the village-level using a Wild cluster bootstrap with 200 replications shown in parentheses. Results in Model 2 are weighted using IPTW. *p<0.1 **p<0.05 ***p<0.01*