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Natural Disasters, Social Protection, and Risk Perceptions*

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Abstract

Natural disasters give rise to loss and damage and may affect subjective expectations about the prevalence and severity of future disasters. These expectations might then in turn shape individuals' investment behaviors, potentially affecting their incomes in subsequent years. As part of an emerging literature on endogenous preferences, economists have begun studying the consequences that exposure to natural disasters have on risk attitudes, perceptions, and behavior. We add to this field by studying the impact of being struck by the December 2012 Cyclone Evan on Fijian households' risk attitudes and subjective expectations about the likelihood and severity of natural disasters over the next 20 years. The randomness of the cyclone's path allows us to estimate the causal effects of exposure on both risk attitudes and risk perceptions. Our results show that being struck by an extreme event substantially changes individuals' risk perceptions as well as their beliefs about the frequency and magnitude of future shocks. However, we find sharply distinct results for the two ethnicities in our sample, indigenous Fijians and Indo-Fijians; the impact of the natural disaster aligns with previous results in the literature on risk attitudes and risk perceptions for Indo-Fijians, whereas they have little to no impact on those same measures for indigenous Fijians. To provide welfare implications for our results, we compare households' risk perceptions to climate and hydrological models of future disaster risk, and find that both ethnic groups over-infer the risk of future disasters relative to the model predictions. If such distorted beliefs encourage over-investment in preventative measures at the cost of other productive investments, these biases could have negative welfare impacts. Understanding belief biases and how they vary across social contexts may thus help decision makers design policy instruments to reduce such inefficiencies, particularly in the face of climate change.

1 Introduction

Natural disasters affected 232 million people, killed over 100,000 people, and caused more than US$ 100 billion worldwide in damage each year between 2001 and 2010, on average (Guha-Sapir et al., 2012). Strömberg (2007) observes that people in low-income countries

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are 12 times more likely to die from natural disasters and are similarly more likely to suffer serious economic consequences of disasters, despite the fact that high- and low-income countries do not differ significantly either in terms of the number of disasters experienced, nor in terms of the number of people affected.

Moreover, the number of natural disasters recorded per year has increased markedly since 1940 (Munang et al., 2013), and factors such as population pressure and infrastructure development in risk-prone areas have increased the risk of loss and damage from natural disasters (IPCC, 2012; Munang et al., 2013). It is likely that climate change will amplify the number and severity of such disasters over the next century (Preston et al., 2006; Bates and others, 2008).

To reduce the vulnerability of at-risk populations, policy makers are increasingly turning toward climate-change adaptation, defined by IPCC (2014) as "an adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities." Examples of adaptation may involve altering land-use patterns, adjusting crop choices, and building protective infrastructure.

The existing literature points to potentially significant barriers to developing and implementing adaptation strategies for climate change that relate to the institutional and social dimensions of adaptation (Biesbroek et al., 2013). Recent research has emphasized not only the need for adaptation, but also the opportunities and constraints inherent in these adaptive efforts (Dovers and Hezri, 2010; Berrang-Ford et al., 2011). As a result, there has been an increased focus on policy initiatives to encourage adaptation, creating an opportunity to identify correlates of effective adaptation in practice as well as the practical steps necessary to undertake adaptation (e.g. Tompkins et al., 2010). For example, Adger et al. (2005) and Tullos et al. (2010) observe that successful adaptation stresses effectiveness, efficiency, equity, and legitimacy. They also note that adaptation can be motivated by preserving economic well-being, improving safety via market exchanges, and extending social and insurance networks.

Climate-change adaptation on small island states like Fiji is perceived to generate larger benefits when delivered in conjunction with other activities such as disaster-risk reduction and community-based approaches to development that address important social, economic, and environmental challenges (IPCC, 2014). Raising awareness and communicating risks to communities while acknowledging traditional institutions can also increase human and environmental resilience to the long-term impacts of climate change (Nunn et al., 2014).

To reduce the vulnerability of at-risk populations, policy makers are increasingly turning their attention toward climate-change adaptation. Adaptation may involve altering land-use patterns, adjusting crop choices, and building protective infrastructure, and although individuals may have limited say in broader adaptation policy, they may adapt their expectations or risk behaviors in less conspicuous ways, including altering their risk attitudes and risk perceptions. The importance of these subjective factors looms large in an environment that involves multiple hazards (Sullivan-Wiley and Gianotti, 2017) and heterogeneity in resilience (Arouri et al., 2015; Cutter et al., 2008).

Economists have recently begun examining the impact of negative shocks on risk attitudes (that is, risk tolerance), perceptions, and behaviors, including natural disasters as well as violent conflicts (Callen et al., 2014; Kim and Lee, 2014; Voors et al., 2012), macroeconomic shocks (Malmendier and Nagel, 2011), and early life traumatic experiences (Bernile et al., 2016). This article belongs to a growing subset of this literature that focuses on the effect of natural shocks on risk attitudes, risk perceptions, and risk-taking behavior. The evidence on risk attitudes is mixed, and the literatures on risk perceptions and behaviors largely focus on developed countries.

Our contribution to this literature is fourfold: First, we complement the literature on risk attitudes and perceptions via a natural experiment in the form of a cyclone, the path of which was unpredictable and random. Second, we explicitly measure individuals' subjective expectations of future loss and damage using an experimental method that allows us to explore impacts on both the perceived frequency and perceived magnitudes of natural disasters. Third, our data include two populations affected by the same disaster but who respond very differently to the event. Fourth, to provide welfare implications for our results, we compare households' perceptions to predicted future disaster risk from climate and hydrological models, showing that average perceptions greatly exceed baseline predictions, even for households who did not suffer material loss and damage from Cyclone Evan.

Different theoretical models have contrasting predictions concerning the impact of exposure to natural disasters on risk perceptions and risk attitudes. In the disaster risk literature, perceptions of risk are shown to increase sharply after exposure to flooding in a variety of settings, including the Netherlands (Botzen et al., 2009), New Zealand (Lawrence et al., 2014), Slovenia (Brilly and Polic, 2005), Switzerland (Siegrist and Gutscher, 2006), Taiwan (Ho et al., 2008; Lin et al., 2008) and post-Katrina New Orleans (Viscusi and Zeckhauser, 2006). For example, Botzen et al. (2009) find that the perceived probability of future flooding is significantly higher for individuals who have previously been evacuated due to flooding.[1] Similar results have been established for avalanches (Leiter, 2011), earthquakes (Kung and Chen, 2012), landslides (Lin et al., 2008) and hurricanes (Peacock et al., 2005).[2]

Imagine an individual who observes whether a disaster occurring in any given year and its magnitude if it does occur. If she is a Bayesian learner, she will update her expected probability of occurrence and expected magnitude given her prior observations and the new observation according to Bayes' rule (Gerrig et al., 2011; Gallagher, 2014). Whether she personally experiences losses due to the disasters or observes neighbours who face similar likelihoods of suffering losses should not influence her perceptions for future risks. However, the psychological literature suggests that individuals often employ an "availability heuristic", meaning that the weights that people to signals accord to the ease with which

[1]Botzen et al. (2009) also find that expected damages from future flooding falls with evacuation experience. The authors suggest that most of those who were evacuated did not experience property damage, thus lowering expectations of damage from flooding despite high perceived probabilities of flooding.

[2]As for risk attitudes, Cameron and Shah (2015) find that individuals in Indonesia who suffered loss and damage from flooding and/or earthquakes in the previous three years exhibit more risk aversion within the framework of a lab-in-the-field experiment. Similarly, Cassar et al. (2017) find that individuals affected by the 2004 Asian tsunami are substantially more risk-averse four and half years after the disaster. In contrast, Eckel et al. (2009) analyze the risk attitudes of individuals who were displaced by Hurricane Katrina and Page et al. (2014) analyze risk attitudes of home owners who suffered large losses in the Australian floods in 2011. Both studies find that respondents demonstrate high levels of risk-loving immediately after the disaster.

they can bring an instance to mind (Tversky and Kahneman, 1974). If more recent and more salient observations are easier to retrieve from memory, then recent exposure to severe disasters will dramatically increase expectations of future risks. Meanwhile, empirical evidence also suggests that emotions or feelings with respect to risk play a role in how risk is perceived (see Baron et al., 2000, Finucane et al., 2000, and Loewenstein et al., 2001). For example, Lerner et al. (2015) find that experimentally induced fear causes people to express more pessimistic risk perceptions and to make more risk-averse choices. Recent disasters can trigger feelings of fear, helplessness, and loss of control (Rüstemli and Karanci, 1999; Sartore et al., 2008; Botzen et al., 2015) and therefore evoke more pessimistic perceptions of risk.[3]

Furthermore, the availability of social protections can alter both the availability of a disaster memory in the cognitive process and the emotion that a disaster triggers; specifically, as unprotected individuals suffer from exposure to disasters, they have more salient and readily retrievable memories and may be more fearful of future events. Thus, Liebenehm (2017) attributes the lack of impact on risk attitudes stemming from idiosyncratic shocks (as compared to significant impacts stemming from covariate shocks) to the fact that individuals can insure idiosyncratic risks through social networks. Kosec and Mo (2017) find supporting evidence of this mechanism, studying Pakistan’s devastating 2010 floods: social protection mitigates the negative impacts of natural disasters on aspirations, which can potentially be related to risk perceptions. Similarly, Jones et al. (2013) observe that the strength of social networks significantly contributes to risk perceptions.

As such, individuals with fewer social protections are likely to deviate more from Bayesian probability updating after experiencing losses in natural disasters. We investigate the exogenous impact of a natural disaster directly on subjective expectations in a developing-country context. We find that individuals who belong to one ethnic group over-infer the probability and severity of future risks after being struck by a cyclone in 2012, while individuals who belong to another ethnic group do not change their subjective expectations. We find a similar pattern of the impact of disasters on risk aversion.

The next section describes the research context. The following section describes the survey data and sampling strategy, followed by a detailed description of the empirical strategy and summary statistics. We then turn to the results, which are followed by a discussion of differing institutions for the two ethnice groups in the sample and a comparison of the resulting inferences to likely loss and damage based on disaster modeling. We find that institutions are likely to play a vital role in the differing responses of the two ethnicities and

[3]With respect to behavior, Burn (1999) finds that victims of past flooding undertake more preventative measures against future flooding than people who have not experienced flooding but face similar future flooding risks. Lawrence et al. (2014) further find that people with previous exposure to flooding are more willing to make household-level changes and are better prepared against future flooding. Hoffmann and Muttarak (2017) find that individuals with recent experience of natural disasters in Philippines and Thailand are more likely to take preparedness actions, Cameron and Shah (2015) find that disaster victims in Indonesia exhibit more risk aversion in real-world behaviors, and Kousky (2010), Atreya et al. (2013), and Bin and Landry (2013) demonstrate that the price premium on housing located outside of flood plains rises significantly after extreme weather events in the United States. Furthermore, Botzen and Van den Bergh (2012) find that survey respondents in the Netherlands over-infer potential loss and damage from hypothetical flooding scenarios in that willingness to pay for low-probability flood insurance exceeds the expected value of losses from flooding. In contrast, Hanaoka et al. (2015) provide evidence that risky behaviors such as smoking and drinking increases with the intensity of exposure to earthquakes among Japanese men. Regardless, it is not clear whether changed behaviors stem from changed attitudes toward risk or changed perceptions of risk.

that subjective expectations vastly exceed probable risks even under severe climate-change scenarios, suggesting that the welfare implications of over-inference may be substantial if individuals adjust their investment behavior in response to their expectations. The last section concludes.

2 Context

2.1 Frequent natural disasters

The World Bank (1995) reports that natural disasters cause average direct losses of US$284 million in the Pacific each year. With a combined population of fewer than 10 million people, the Pacific is by population the second-most affected world region by natural disasters (Strömberg, 2007) behind Asia, and its losses are the highest in the world on a per-capita basis (World Bank, 1995). The Fiji Islands consists of more than 300 remote volcanic islands in the South Pacific, of which approximately 100 are inhabited.

Like other small island developing states, the Fiji Islands are highly vulnerable to natural disasters (Weir and Virani, 2011; McGree et al., 2014). Between 1983 and 2012, for example, 106 natural disasters were officially recorded for Fiji, costing an estimated USD 1.2 billion (Holland, 2014). In 2012, three major natural disasters – one 50-year flood, one 25-year flood, and one Category 4 cyclone – ravaged the northern and western parts of Viti Levu, the largest island of Fiji with 60% of the land mass and an equal share of the population.[4]

Flooding in January 2012 resulted in 11 deaths and the temporary displacement of 1,300 people while flooding in March 2012 resulted in four deaths and the temporary displacement of 15,000 people. Tropical Cyclone Evan – the strongest cyclone in Fiji's written record until Cyclone Winston in 2016 – brought peak winds of 230 km per hour in December 2012, destroyed more than 2,000 homes, and temporarily displaced between 11,000 and 14,000 people.

2.2 Ethnicity in Fiji

Fiji's population of 837,000 is largely comprised of two ethnic groups (Fiji Bureau of Statistics, 2012). *iTaukei* (57% of the total population of Fiji) arrived in Fiji from elsewhere in Melanesia 3,500 years ago. In the 1880s, the colonial government instituted a legal land-tenure system nominally based on the customary land-tenure system[5] and deeded 87% of all land in Fiji to *iTaukei* via inalienable customary title. Since 1940, all land not immediately required for maintenance and support has been surrendered to the *iTaukei* Land Trust Board, which administers and negotiates leases and licenses agreements on behalf of the *iTaukei* landowners. This institution embodies the principle of communal tenure while providing a guaranteed stream of income.[6]

[4]The terms "a 25-year flood," "a 50-year flood," etc. refer to the flood return period and describe the estimated probability of a flood event happening in a given year. That is, a 100-year flood has a 1/100 probability, or 1 percent, of occurring in any given year. These probabilities are estimated using historical weather and hydrological data.

[5]The colonial Native Lands Ordinance specified that land may be held by *iTaukei* according to "customs as evidenced by usage and tradition". However, Chapelle (1978) argues that the colonial government fundamentally altered the relationship between *iTaukei* and land.

Indo-Fijians (38% of the total population) are largely descended from indentured laborers brought to Fiji to work on colonial sugar cane plantations between 1879 and 1916. With the abolishment of indentured labor, many of these workers remained as independent farmers and/or small business holders (Foley, 2005). Fiji's sugar production continues to be dominated by Indo-Fijians, who often live in scattered settlements close to cane fields that the Indo-Fijians lease from *iTaukei* owners (Kumar and Prasad, 2004).

3 Data

The foundation for this study is an extensive socioeconomic survey designed to assess ecosystem-based adaptation to flooding in the Ba and Penang River catchments on Viti Levu, Fiji. The survey was designed by the four authors of this manuscript and was enumerated by staff and graduate students from the University of the South Pacific (two authors remained in the field throughout the survey period for enumerator training and field support).

Ethnically *iTaukei* team members enumerated the survey in iTaukei households and ethnically Indo-Fijian enumerators surveyed Indo-Fijian households. At the beginning of each survey, enumerators identified themselves as university staff/students and explained the purpose of the study (to conduct research on vulnerability to future flooding). Enumerated just two months after Cyclone Evan struck Viti Levu, the survey also collected information pertaining to damages caused by the cyclone. Enumerators made clear that the information collected would not be used to compensate households for past or future losses, although each household received nominal (and identical) compensation for participating in the survey.

3.1 Location of the survey sample

Located in north-western Viti Levu (Figure 1), Ba is the second largest province in Fiji by area and the largest by population, with 232,000 residents according to the 2007 census (Fiji Bureau of Statistics, 2012). Viti Levu's population remains largely rural, and sugar production, timber harvesting, and fishing constitute important commercial activities. It is by no means a wealthy region: Narsey (2008) reports that the province-wide poverty rate is 34%. Just under 46,000 people live within the boundaries of the Ba River catchment, one-third of whom are *iTaukei* and the remaining two-thirds of whom are Indo-Fijian.

Neighboring Ra Province has 29,000 residents, 8,300 of whom lived in the Penang River catchment at the time of the census (Fiji Bureau of Statistics, 2012). Approximately 45% of the population is rural, living in scattered rural settlements and villages. Sugar production is the main economic activity, although tourism and cattle rearing are other locally important industries. Narsey (2008) reports that 53% of the population of Ra Province earns less than the poverty line, making Ra the poorest region in the country. Nearly 42% of the population

[6]Indeed, terms for ordinary land owners have improved considerably in recent years. Prior to 2011, 30% of the net value of leases were reserved for heads of *yavusa* and *mataqali*; since 2011, however, land rents are equally distributed to "all living members of the proprietary unit, in equal proportion" (Native Land Trust (Leases and Licenses) (Amendment) Regulations, 2010).

in the Ba River catchment and over two-thirds of the population in the Penang River catchment are *iTaukei*, and virtually all others are Indo-Fijian.

3.2 Sampling and survey details

Respondents were drawn from villages (officially recognized entities that are exclusively *iTaukei*) and settlements (loosely organized clusters of houses that are largely occupied by Indo-Fijians) based on a probability sample with both geographic and ethnic stratification. In this way, 295 households from 14 rural villages (58% of all villages in the catchment) and 14 rural settlements (representing approximately 32% of the Indo-Fijian residences in the catchment) were surveyed in the Ba River catchment. Similarly, 74 households from three villages (60% of all villages in the catchment) and five settlements (representing approximately 50% of the Indo-Fijian residences in the catchment) were surveyed in the Penang River catchment. Maps of the villages and settlements are shown in Figures 2 and 3.

The household survey consisted of questions on demographics, education, and health; cropping, livestock, fishing, and forestry; labor income, remittances, durable goods, and housing; time allocation; and risk preferences. The survey also included several elements pertaining to the socioeconomic impacts of natural disasters, including Cyclone Evan. In particular, respondents were asked about crop losses, direct damage to housing and assets, and indirect damage in the form of lost labor, money spent on cleaning supplies, medical costs, and money spent on packaged food during evacuation.

The most recent official data on household income comes from the Household Income and Expenditure Survey (Fiji Bureau of Statistics, 2008) and our households appear to be representative of the province populations. For Fiji's Western Division (which includes the Ba and Ra provinces), average rural household income is FJD 9,960. The average household incomes by community based on our survey results were FJD 7,849 in the Ba River catchment and FJD 10,133 in the Penang River catchment. Given that growth of GDP fluctuated between –1% and 2% between 2009 and 2013, that these households were exposed to three major natural disasters in 2012, and that 25% of Fiji's poor live in Ba Province (Narsey, 2008), our income figures are consistent with the official figures.

4 Empirical strategy

Our basic estimation equation is the following:

$$y_{i,k} = \alpha_0 + \alpha_1 * T_{i,k} + \alpha_2 * E_{i,k} + \alpha_3 * T_{i,k} * E_{i,k} + \mathbf{X}'_{\eta} + \delta_k + \varepsilon_{i,k} \qquad (1)$$

where $y_{i,k}$ denotes the outcome variable for household i in community k, $T_{i,k}$ is an indicator variable for whether or not the household was struck by Cyclone Evan, $E_{i,k}$ is a dummy variable for ethnicity that equals one for Indo-Fijians, **X** is a vector of baseline controls, and δ_k are community dummy variables.

The indicator variable for whether or not a household was struck by Cyclone Evan is defined by loss and damage: a household is treated as being struck by the cyclone if it suffered material loss and/or damage in the cyclone, and as not struck otherwise.[7] We use an indicator variable here rather than a continuous measure of the actual losses incurred since wealthier individuals have more to lose, and may also expect to have greater losses in the future, making the continuous measure endogenous.

Apart from marriage, there is very little rural-to-rural migration in Fiji: *iTaukei* are tied to ancestral villages and Indo-Fijian farmers primarily work land that they obtain through leases of 30-90 years. There is thus little or no endogenous sorting in this context,[8] which supports our view that whether or not a household was struck by the cyclone is random. We believe that the error terms for individuals belonging to the same community may be correlated (but that they are uncorrelated across communities), and we therefore cluster our standard errors at the community level.

4.1 Outcome variables

4.1.1 Subjective expectations of future losses from natural disasters—The main outcome variable of interest is average subjective annual expected losses from all natural disasters. This variable derives from an experimental survey module that elicits a probability distribution over future losses. Directly eliciting probabilities can be difficult in poor countries with lower average levels of education because respondents generally have a weaker understanding of probabilities than do respondents in the developed world (Delavande et al., 2011). We overcome this challenge by using visual aids to elicit probability distributions.

Specifically, respondents were asked to estimate the replacement value of their loss and damage from all natural disasters in the worst year that they can imagine.[9] Respondents then forecast the number of years that they would be struck by natural disasters in the next 20 years by sorting shells into two piles, one for being struck and one for not being struck. Enumerators provided a brief explanation of probabilities and emphasized the subjective nature of the question to ensure that respondents reported their beliefs rather than trying to guess the “correct” answer.[10]

Based on the respondent’s worst-case expected loss and damage (henceforth “maximum expected value of loss and damage”), five evenly spaced bins were computed and drawn on a board as shown in Figure 4. The respondent was then asked to allocate the shells between the bins according to his or her perceived likelihood of occurrence. Using these probabilities,

[7]While acknowledging the literature on “loss and damage” (e.g., Mathew and Akter, 2015) “loss” in this manuscript refers primarily to crop losses and “damage” refers to the replacement value of totally or partially destroyed physical assets and to money spent as a result of the disaster. These definitions are consistent with those developed by the US Economic Commission for Latin America and the Caribbean in 1972 subsequently revised by the World Bank, UNESCO, WHO, and others (see for example World Bank, 2003).

[8]See the discussion in Section 4.3 for more detail.

[9]The question was worded as follows: “Think of the worst year for natural disasters that you can. How much do you think it would cost to rebuild and replace everything that you would lose to natural disasters during such a year (in Fijian dollars)?”

[10]The module begins by emphasizing that there are no correct answers to this question: “I will now ask you some hypothetical questions about natural disasters. There are no right or wrong answers; I am just asking for your ideas.” The prompt for the number of years was worded as follows: “Over the next 20 years, how many years do you think you will be affected by natural disasters in some way? For example, if you think that natural disasters will affect you in 10 out of the 20 years, it means that you are just as likely to be affected as not affected in any given year. If you say that natural disasters will affect you in 11 out of the next 20 years, this means that it is slightly more likely to happen than to not happen in any given year. If you say that natural disasters will affect you in 20 out of the 20 years, this means that you are sure it will happen every year.”

we calculate the average yearly expected loss and damage for each household. Field testing showed that *iTaukei* and Indo-Fijian households understood the module equally well.

Delavande et al., 2011 review evidence from several developing countries and conclude that people generally understand probabilistic questions and that carefully designed questions yield expectations that are useful predictors of future behavior and economic decisions. Other studies have used this methodology to examine farmers' beliefs about rainfall (see e.g. Lybbert et al., 2007), and McKenzie et al. (2012) use subjective expectations elicitation to explore potential migrants' beliefs about earnings abroad.

4.1.2 Other outcome variables—Because average expected yearly loss and damage is the product of an individual's perceived probability of loss and damage and the perceived magnitudes of those losses and damages, it is not ex ante clear which of these components would be more likely to be affected by a natural disaster. We therefore separately examine respondents' maximum expected value of loss and damage and the expected frequency of disasters, each elicited as described in the previous section.

Since individual risk attitudes are important determinants of economic behavior, we also analyze the effects of being struck by Cyclone Evan on risk aversion. Our measure of individuals' willingness to take risks follows Dohmen et al. (2011), who show that questions about willingness to take risks "in general" correlate with experimental measures of risk aversion as well as real-life risky behaviors. In addition, a recent review and test by Chuang and Schechter (2015) shows that answers to survey-based risk-aversion measures remain quite stable over time while experimental measures are only weakly correlated over time.

4.2 Summary statistics

Table 1 provides summary statistics for the correlates of subjective expectations of future losses and household demographic variables. As noted above, 41% of the sample is comprised of Indo-Fijians. Average wealth among Indo-Fijian households exceeds that of *iTaukei* households by 84%, consistent with the institutional characteristics described in Section 6.1. The distribution is positively skewed for both ethnicities, with small numbers of *iTaukei* having significant plantations of *yaqona* (a valuable cash crop) and some Indo-Fijians having accumulated significant assets through off-farm businesses.

The mean household has experienced flooding in 1.5 of the previous 12 years, most commonly in 2009. Nearly 90% of household heads are male, the average age of whom is 51 regardless of ethnicity. Househols consist of 4.5 people on average, and respondents have lived in their communities for over 40 years, again regardless of ethnicity. Both *iTaukei* and Indo-Fijian household heads have completed eight years of schooling, on average. *iTaukei* respondents suffered an average of FJD 4,703 in loss and damage to Cyclone Evan while Indo-Fijians suffered FJD 3,506 in loss and damage, a difference that is not statistically significant.

Figure 5 depicts the distribution of subjective expectations of future losses by ethnicity and whether the household was struck by Cyclone Evan. In general, Indo-Fijians have higher mean subjective expectations of future loss and damage (p=0.0000). Additionally, being struck by Cyclone Evan has little bearing on subjective expectations of future loss and damage among *iTaukei*. Among Indo-Fijians, however, being struck by Cyclone Evan shifts up the mean subjective expectation of future loss and damage.[11]

We also compare the households that were struck by Cyclone Evan with those that were not on other baseline characteristics and find that the number of flood events in the past 10 years is both statistically and economically significantly different between the two groups,[12] which we address by controlling for past flooding in our preferred estimates. Flooding is also correlated within communities, so community fixed effects are included to soak up some of these differences. Additional details on the balance between the two groups can be found in Table 2.

4.3 Causality

The causal interpretation of our results relies on two main assumptions. First, we assume that the likelihood of being struck by the cyclone is exogenous to unobservable characteristics at the household level, i.e. that households that were struck by the cyclone do not systematically differ from those that were not struck. The path of cyclones is difficult to predict, with 72-hour track errors in the range of 300 km (Elsberry, 2007). In comparison, Viti Levu – similar in size to the Big Island of Hawaii – is nowhere wider than 150 km. Figure 6 presents the paths of cyclones across Viti Levu between between 1969-2009, revealing no obvious patterns. Furthermore, the affected and unaffected households appear to be similar on observable characteristics, as noted above.

Second, in many settings where we may wish to study the impact of natural disasters, locational preferences and migration prove problematic. For example, risk-averse individuals may choose to live in areas with lower risk of natural disasters or individuals may selectively relocate after being affected by particularly severe storms. In Fiji, this concern is mitigated by the fact that migrating to rural areas is very uncommon.[13]

Several additional aspects of our data help to further alleviate potential concerns about endogenous sorting: First, data collection began less than two months after Cyclone Evan struck, so any migration response would have had to have been extremely rapid. Moreover, the sampled households were randomly selected from rosters that were based on pre-cyclone information, and enumerators located all of the heads of the sampled households in the homes in which they lived prior to the cyclone. In addition, 70 percent of the respondents in our data have lived in their current communities for their entire lives, and less than 14 percent have lived in their current community for less than half of their lives. As such, endogenous sorting is highly unlikely to drive our results. Finally, despite these reassuring facts, our preferred estimates control both for respondent age and for the number of years that the respondent has lived in his or her current community.

[11]A simple *t*-test of the equality of the mean subjective expectations for *iTaukei* that were and were not struck by Cyclone Evan has a p-value of 0.8997; for the Indo-Fijians the p-value for the same test is 0.0003.

[12]Households who were struck by Cyclone Evan experienced 0.7 more floods than did those who were not struck by the cyclone.

[13]Rural migration outside of marriage is unusual largely because *iTaukei* households belong to communities and Indo-Fijians farm land on long-term leases. See Chandra (2002) for more detail.

5 Results

5.1 Effects of Cyclone Evan on expected future losses

Tables 3–4 are structured as follows: Column (1) shows the results from a parsimonious regression that controls only for the household's physical assets and ethnicity. Physical assets are a key control variable since asset ownership provides an upper bound on how much a household could foreseeably lose. Column (2) adds community fixed effects while column (3) additionally controls for the number of floods that the household experienced in the past ten years.[14]

The number of past flood events proxy for the level of background risk that households face, and as such, are an important control variable when examining subjective expectations. The past number of flood events control for the key aspect of household vulnerability, such that any effects are estimated holding vulnerability constant. Finally, column (4) adds household demographics and other control variables, including the age and education of household head and land ownership.

As noted in our empirical strategy, the ethnicity dummy variable is weakly identified once we introduce community fixed effects because all but two of the sample communities are ethnically homogeneous. However, the interaction between the indicator variable and variables that vary within community (i.e. how the impact of these community-varying variables on the outcome variable varies by ethnicity) can be estimated.

To make this point, appendix table A-A.1 shows the results from a regression of respondents' expected loss and damage on a dummy variable for whether the household was struck by Cyclone Evan. Once community fixed effects are introduced in column (2), the coefficient on the ethnicity dummy, which is large and significant in column (1), diminishes and becomes statistically indistinguishable from zero. Importantly, the coefficients on Cyclone Evan and physical assets do not change substantially with the inclusion of community fixed effects, nor once past flooding is accounted for in column 3, nor when additional covariates are introduced in column (4).

Table 3 shows the impacts of being struck by Cyclone Evan on expected future loss and damage and how this effect varies by ethnicity. Panel A shows the regression coefficients from OLS estimation of equation 1, and Panel B shows the marginal effects of being struck by Cyclone Evan separately for *iTaukei* and Indo-Fijians for readibility and ease of interpretation.[15] Our preferred results are shown in column (4), which includes both community fixed effects and household demographic controls, but it is worth noting that the estimated impact of the cyclone is fairly consistent across specifications. Indo-Fijians who were struck by the cyclone expect to lose about FJD 5,400 more per year from natural disasters over the next 20 years than do Indo-Fijian households who were not struck,[16] an

[14]The past flooding events were elicited using the following question: "In which of the last 10 years have members of this household been affected by flooding other than the January 2012 flood, the March 2012 flood, and flooding caused by Cyclone Evan?" The questionnaire then asked specific questions about the January and March floods, as the impacts of these floods was the main purpose of the survey. The variable that we use here includes the January and March floods.

[15]The relevant hypothesis test here is that of the combined effect of the ethnicity dummy variable and the interaction term with being struck by the cyclone.

amount equivalent to roughly 14 percent of current Indo-Fijian household assets. Thus, the impact is both statistically and economically significant. The *iTaukei* point estimates do not exceed 4.4 percent of baseline *iTaukei* assets – even the upper bound of the 95 percent confidence interval on the effect on *iTaukei* expectations is below 13 percent of *iTaukei* baseline assets.

5.2 Frequency or magnitude?

These results raise questions about how expectations are formed and which components of subjective expectations are likely to be affected by exposure to natural disasters. This section thus explores the impact of Cyclone Evan on both the frequency with which households expect to experience loss and damage from natural disasters and the maximum expected value of loss and damage in any given year.

In Panel A of table 4, we present results for whether being hit by Cyclone Evan impacts the number of years that respondents expect to incur loss and damage from natural disasters.[17] The differences between the two ethnicities persists: *iTaukei* do not significantly alter their beliefs about how frequently they will be affected while Indo-Fijians who were struck by Cyclone Evan believe that they will incur losses roughly two additional years out of the coming twenty. Since the sample average is 11 years out of 20 (9 for *iTaukei* and 13 for Indo-Fijians), the increase for Indo-Fijians is close to 15% of the sample average.

Panel B of table 4 shows how Cyclone Evan affects households' maximum expected value of loss and damage. The effects here are substantial both in statistical and economic terms: being struck by Cyclone Evan increases an Indo-Fijian respondent's maximum expected loss and damage by more than FJD 12,000 while being struck by Cyclone Evan does not significantly change the perceptions of *iTaukei* households. Thus, being struck by Cyclone Evan impacted both components of households expected yearly losses, i.e., both the expected frequency and the expected magnitude of loss and damage.

Another way in which natural disasters may affect individuals is via risk attitudes. As discussed in the introductory section, there is no consensus in the literature on the size or even the direction of this effect. Panel C of table 4 reports the marginal impacts of being struck by Cyclone Evan on respondents' agreement with the statement "In general, I am willing to take risks," a common method of eliciting general risk preferences via survey questions. Given that Chuang and Schechter (2015) report that survey-based measures of risk aversion tend to be very stable over time, we anticipated little impact on this variable, but the effects are large. The question was elicited using a sliding scale from −100 to 100 on which respondents self reported using tablet computers, and the effect for Indo-Fijians is a 30-point difference (a 15 percentage-point change). For *iTaukei* respondents, we detect no statistically significant effect of Cyclone Evan on risk attitudes.

[16]At the time of the survey, FJD 5,400 corresponded to about USD 3,000.
[17]The full regression tables are shown in Appendix B.

6 Extensions

6.1 Ethnic institutions

Like other Melanesian peoples, *iTaukei* have complex social structures that provide membership in multiple groups. For example, they are born members of bito or tokatoka (family clans). Each *tokatoka* is part of a *mataqali* (clan); each *mataqali* is part of a *yavusa* (tribe); and each *yavusa* is part of a *vanua* (a community of people associated with a specific geographic area).[18] Membership in these concentric groups contributes to a social structure that Belshaw (2013, p. 123) calls "collectivist in organization and spirit." Moreover, Belshaw (2013) argues that this quintessential structure has remained in place through the colonial and post-colonial eras despite significant political change and socioeconomic development.[19]

In contrast with *iTaukei* social organization, De Vries (2002) and Rao et al. (2011) argue that Indo-Fijian society is individualistic and self-reliant. Reddy (2001) surveys a cross section of Fijian society and finds that business is considered to be "high status" among Indo-Fijians and "moderately low" status among *iTaukei*. As such, wage employment among Indo-Fijians is much higher than among *iTaukei* (Kumar and Prasad, 2004), and the World Bank (1995) reports that the vast majority of entrepreneurs are Indo-Fijian. Indeed, of the 11,000 businesses registered in Fiji in 2001, only 100 were owned by *iTaukei* (Rao et al., 2011).

Such stark institutional differences across Fiji's two largest ethnic groups may explain their vastly different responses to natural disasters. Specifically, the conspicuously "collectivist" social structure of *iTaukei* may provide *iTaukei* with well-functioning risk-sharing networks. On the one hand, *iTaukei* households who did not suffer direct loss and damage may have nevertheless experienced the shock through their risk-sharing networks, and hence, when they are asked to consider future risk, the recent cyclone is as salient in their memory as it is for those who were struck directly. On the other hand, because risk-sharing networks are strong for iTaukei and because the land-tenure system provides an underlying income guarantee for *iTaukei* but nor for Indo-Fijians, *iTaukei* society is better placed to absorb idiosyncratic shocks.

It is also plausible that *iTaukei* have better collective knowledge of the frequency and magnitude of natural disasters. Specifically, Dakuidreketi (2012) notes that *iTaukei* culture was until recently exclusively oral, and Bridges and McClatchey (2009) observe that Pacific peoples have survived major, unpredictable, and locally devastating disasters over 100+ generations. As McNamara and Prasad (2013, p.2) write, "This local knowledge in the Pacific, which is deeply embedded in practice and belief systems, is a crucial resource." (see also Salick and Ross, 2009). Indeed, environmental knowledge transmitted orally by successive generations is fundamental to Pacific peoples' wider holistic understanding of the

[18]Belshaw (2013, p. 35) observes that the *iTaukei* village "is a residential unit, conveniently located with respect to land, with a symbolic and ceremonial significance derived from *yavusa* and *mataqali* which make it up, and linked patrilineally with the yavusa and vanua of neighboring areas. Marriage connections reinforce these links, but spread them beyond into other territories, increasing the reality of social contact and mobility."

[19]Belshaw (2013, p. 114) writes "Kinship organization is essentially unchanged from that 100 years ago."

natural and spiritual world (King et al., 2007), and oral traditions frequently include detailed information about natural disasters.

For example, Blong (1982) analyses 54 different oral traditions of a *bingi* (impenetrable darkness) that covered central Papua New Guinea; he concludes that – despite stylistic variation – they similarly and accurately describe the ashfall (an indicator of severity) and timing of the eruption of Tibito Tephra some three centuries earlier (Cashman and Cronin, 2008). Aotearoa Māori oral histories describe a tidal wave off the coast of Wai-iti (Mitchell and Mitchell, 2007) and a tsunami that inundated Potiki-taua (Smith, 1910) in the 15th-16th centuries, each of which has subsequently been verified by western science (McFadgen and Goff, 2007). Mangaia Cook Islanders have names for more than 30 different directions in which the wind blows (Anderson 1995), yet the first written record of storms in the South Pacific – which did not appear until 1853 – described them simply as "revolving" (i.e., as being cyclonic) and recorded frequency rather than severity (Dobson, 1853; Kerr, 1976).

Reliable measures of the magnitude of cyclones in the South Pacific were not systematically recorded until 1953 (Kerr, 1976), and the Fiji Meteorological Service's earliest surviving records of cyclones date only as far back as 1969. If the long collective memory of *iTaukei* helps them to better contextualize individual storms and/or to better recover after storms hit, then *iTaukei* may have a more complete information set, and any one storm provides just one additional data point. Within a Bayesian updating framework, this would predict that expectations would not change much after a single storm.

6.2 Disaster modeling

iTaukei estimate that they will incur $4,381 in losses and damages to natural disasters in each of the next 20 years, on average; for Indo-Fijians, this figure is $15,044. The empirical loss and damage (including crop losses, direct losses, and indirect losses) for the three major natural disasters that impacted residents of the Ba and Penang River catchments in 2012 are shown in table 5.

The mean total loss and damage from Cyclone Evan is FJD 4,703 for *iTaukei*, 7% above the mean subjective expectation of future annual losses. That is, *iTaukei* respondents expect to be affected by a natural disaster of similar magnitude to a category IV cyclone in each of the subsequent 20 years. Among Indo-Fijians, the mean subjective expectation of future annual loss and damage is 430% of the empirical total loss and damage from Cyclone Evan of FJD 3,506.

To evaluate the veracity of these apparently high subjective expectations, we model damages from different flood regimes in the Ba and Penang River catchments; we focus on flooding rather than cyclonic activity because flood regimes are well understood and flood models are better developed. Specifically, we employ the US Army Corps of Engineers Hydrologic Engineering Center's River Analysis System HEC-RAS[20] using the US Army Corps of Engineers' HEC-GeoRAS extension to facilitate the transfer of information between ArcGIS

[20]This hydrological model has been used to estimate flood magnitudes and flood control options in the Pacific, including New Caledonia (Terry and Wotling, 2011) and Samoa (Woodruff, 2008).

and HEC-RAS. Channel geometry data is developed and cut in to an existing 25m digital elevation model (PacRIS, 2013) to run a steady-flow analysis across each catchment. Manning's N values – surface roughness coefficients used to estimate the amount of friction that must be overcome to enable water to flow over the surface – for each land-use type in the catchment are estimated from Arcement and Schneider (1989), Aldridge and Garrett (1973), Schneider et al. (1977), and Hicks and Mason (1991), and range from 0.04 for marginal floodplains and stream beds to 0.18 for closed upland forests.

The model is calibrated to match the empirical extent of the January 2012 flood (a 1-in-50 year flood) and March 2012 flood (a 1-in-20 year flood). Following calibration, the model is used to estimate flood extent under a range of flood regimes. We use the flood height and damage figures from these two events to construct non-linear flood exceedance probability curves for 1-in-500 (0.2% chance of a flood in any given year), 1-in-200 (0.5%), 1-in-100 (1%), 1-in-50 (2%), and 1-in-20 (5%) year events for each of the villages surveyed. The baseline 1-200 and 1-in-500 events were respectively assumed to cause four and eight times the damage of the 1-in-50 year event. See Daigneault et al. (2016) and Brown et al. (2017).

Catchments are highly idiosyncratic geographic features; therefore, the estimated damages under each type of flood regime is reported by ethnicity and catchment in table 6. Under these estimates, *iTaukei* households in the Ba River catchment would have to experience flooding that is more severe than a 1-in-100 flood every year to meet their subjective expectations of future losses (assuming no other natural disasters strike the household in any given year). *iTaukei* households in the Penang River catchment would have to experience flooding that is more severe than a 1-in-200 flood every year, again assuming that no other natural disasters strike the household in any given year. Analogously, Indo-Fijian households in the Penang River catchment would have to experience flooding nearing the intensity of a 1-in-500 year flood each year to meet their subjective expectations while those in the Ba River catchment would have to experience 1-in-500 year flooding event and a tropical storm akin to Cyclone Evan.

Lata and Nunn (2012) report that awareness of climate change among Fijians in the Rewa River Delta of Viti Levu is low, although it may be possible that survey respondents in the Ba River and Penang River catchments have internalized climate change projections in their subjective expectations of future loss and damage. That is, Australian Bureau of Meteorology and CSIRO (2014) project that a 1-in-20-year daily rainfall event in Fiji will become, on average, a 1-in-4-year event under Relative Concentration Pathway 8.5 by 2090. However, even if climate change shifts flood return periods by two (i.e., if a 1-in-100 year flood occurs every 20 years), then extreme flooding events would still need to occur every year to reach losses in the magnitude of survey respondents' expected losses.[21]

[21]Moreover, Australian Bureau of Meteorology and CSIRO (2014) report a high level of confidence in models that show 10-40% reductions in the number of cyclones in the south-east basin of the Pacific.

7 Conclusion

We hypothesize that objective probabilities and magnitudes of future risks should not differ by exposure to a single idiosyncratic shock. To test whether there are belief-biases that lead to a gap between baseline risks and perceived risks, we use the December 2012 Cyclone Evan as a natural experiment to identify the impact of direct experience on subjective expectations. A unique finding in our study is that the impact of shocks on subjective expectations differs sharply for the two ethnic groups in the sample.

Specifically, the effect of being struck by Cyclone Evan on subjective expectations among Indo-Fijian respondents aligns with previous studies such as Cameron and Shah (2015) in that being struck increases future expectations of loss and damage over the next 20 years. Similar to Cameron and Shah (2015), we find that such pessimistic beliefs are accompanied by a shift in risk attitudes toward risk aversion. Furthermore, we disentangle the subjective expectation of future disasters into perceived frequency and perceived magnitude, finding substantial effects on both margins. In contrast, being struck by Cyclone Evan affects neither *iTaukei* respondents' expectations about future disaster risk nor their risk attitudes.

Differing social institutions The conspicuously "collectivist" social structure of *iTaukei* may explain these results as multiple levels of "belonging" for *iTaukei*, which may may *iTaukei* better placed to absorb shocks than Indo-Fijians. distinctive results as the concentric circles of relationships provide *iTaukei* with well-functioning risk-sharing networks. On the one hand, *iTaukei* households who did not suffer direct loss and damage may have nevertheless experienced the shock through their risk-sharing networks, and hence, when they are asked to consider future risk, the recent cyclone is as salient in their memory as it is for those who were struck directly. On the other hand, because risk-sharing networks are strong for *iTaukei* and because the land-tenure system provides an underlying income guarantee for *iTaukei* but nor for Indo-Fijians, *iTaukei* society is better placed to absorb idiosyncratic shocks. Thus, we might expect that natural disasters invoke less "fear" in *iTaukei* than in Indo-Fijians, and therefore induces a smaller "treatment effect" on their risk perceptions. Similarly, longer and more detailed knowledge of past disasters and their impacts passed down through oral tradition may make *iTaukei* villages more resilient than Indo-Fijian communities.

Another possibility is that *iTaukei* are closer to standard Bayesian learners than Indo-Fijians because they have long oral histories regarding natural disasters while Indo-Fijians rely on the much shorter written record (Dakuidreketi, 2012). That is, because *iTaukei* oral history not only records occurrences of natural disasters but also practical knowledge for enduring such hardship (McNamara and Prasad, 2013), exogenous shocks may have lesser influence on the beliefs of *iTaukei* than those of Indo-Fijians.

To provide welfare implications for our results, we use climate and hydrological models to predict future disaster risk, allowing us to determine whether surveyed households over-infer risk based new information provided by Cyclone Evan. Regardless of whether or not they suffered material loss and damage from Cyclone Evan, we find that both ethnic groups over-infer the risk of future disasters relative to baseline predictions and that over-inference is especially acute among Indo-Fijians. Victims' distorted beliefs may prevent optimal take-up of insurance and may encourage over-investment in preventative measures and/or under-invest in productive activities. Understanding culture-specific belief biases may thus help decision makers to consider policy instruments that might reduce such inefficiencies, particularly in the face of changing disaster profiles under climate change.

A – Ethnicity and community

Table A.1

Effect of Being Struck by Cyclone Evan on Subjective Expectations of Future Damages

Dependent variable: Mean expected damages

	(1)	(2)	(3)	(4)
Struck by cyclone (0/1)	1970.7*	3255.4**	2229.7*	2334.6*
	(980.2)	(1314.3)	(1219.0)	(1337.7)
Indo-Fijian (0/1)	7145.0***	32.00	−595.2	−660.1
	(1180.1)	(3766.5)	(3913.0)	(3173.0)
Value of physical assets (USD)	0.202***	0.218***	0.210***	0.205***
	(0.0351)	(0.0358)	(0.0375)	(0.0377)
Number of floods			1159.7***	1173.9**
			(414.8)	(436.1)
Nr. of years lived in community				15.96
				(34.09)
Male household head (0/1)				−286.4
				(2165.3)
Age of household head				65.75
				(55.16)
Household size				204.5
				(230.5)
Years of education, hh head				287.6
				(175.0)
Land leased (hectares)				107.2
				(148.7)
Land owned (hectares)				−66.31
				(146.7)
Engaged in cropping activities (0/1)				−1896.1
				(3087.8)
Constant	−1587.7	5010.9	4135.1	−1219.2
	(1289.5)	(3595.3)	(3682.9)	(4365.3)
Community FE?	NO	YES	YES	YES
N	369	369	369	367
adj. R^2	0.423	0.458	0.478	0.476

Standard errors in parentheses; standard errors are clustered by community

*p<.1,

** p<.05,
*** p<.01

B – Full regression tables from Table 4

Table B.1
Effect of Cyclone on Expected Frequency of Future Damages

Dependent variable: Number of years household expects to experience losses from natural disasters

Panel A	(1)	(2)	(3)	(4)
Struck by cyclone (0/1)	−1.229	−1.703	−1.843	−1.648
	(1.709)	(1.870)	(1.864)	(1.802)
Indo-Fijian (0/1)	0.615	−5.907***	−5.549***	−5.985***
	(1.893)	(1.950)	(1.977)	(1.990)
(Indo-Fijian) x (Cyclone)	2.868	3.937*	3.287	4.026*
	(1.987)	(2.158)	(2.234)	(2.227)
Value of physical assets (USD)	0.00000106	0.00000484	0.00000221	0.00000364
	(0.0000100)	(0.0000104)	(0.00000962)	(0.00000893)
Number of floods			0.474**	0.515**
			(0.229)	(0.250)
Nr. of years lived in community				−0.0114
				(0.0256)
Male household head (0/1)				1.516
				(0.992)
Age of household head				0.0219
				(0.0439)
Household size				−0.0280
				(0.174)
Years of education, hh head				−0.0518
				(0.136)
Land leased (hectares)				0.0512
				(0.0700)
Land owned (hectares)				−0.0725
				(0.153)
Engaged in cropping activities (0/1)				−2.518**
				(1.231)
Constant	10.98***	17.36***	16.73***	16.62***
	(1.671)	(1.687)	(1.735)	(3.361)
Community FE?	NO	YES	YES	YES
N	369	369	369	367
adj. R^2	0.084	0.116	0.129	0.134

Standard errors in parentheses; standard errors are clustered by community

* p<.1,

** p<.05,

*** p<.01

Panel B reports the F-test for joint significance of Cyclone Evan and its interaction with ethnicity

Table B.2

Effect of Cyclone Evan on Maximum Losses from Natural Disasters

Dependent variable: Value of losses from natural disasters in worst possible year

Panel A	(1)	(2)	(3)	(4)
Struck by cyclone (0/1)	−290.7	4762.0 *	4215.6	3043.1
	(2731.8)	(2508.9)	(2571.2)	(2885.9)
Indo-Fijian (0/1)	8869.3 **	6542.1	7932.5	3232.4
	(3970.8)	(5799.1)	(5700.4)	(6197.3)
(Indo-Fijian) x (Cyclone)	10739.1 ***	9379.1 *	6852.4	9224.5 *
	(3820.6)	(5164.1)	(5031.0)	(5066.1)
Value of physical assets (USD)	0.773 ***	0.828 ***	0.817 ***	0.808 ***
	(0.136)	(0.135)	(0.141)	(0.142)
Number of floods			1840.4 *	1896.1 **
			(938.7)	(898.9)
Nr. of years lived in community				115.2
				(75.81)
Male household head (0/1)				−5167.8
				(4702.2)
Age of household head				63.16
				(125.1)
Household size				630.4
				(714.4)
Years of education, hh head				428.6
				(501.1)
Land leased (hectares)				156.1
				(365.6)
Land owned (hectares)				−564.0
				(363.0)
Engaged in cropping activities (0/1)				−3667.7
				(4285.3)
Constant	232.2	−9392.1 **	−11819.8 ***	−15333.7 **
	(3647.5)	(3770.5)	(3499.3)	(7037.3)
Community FE?	NO	YES	YES	YES
N	369	369	369	367
adj. R^2	0.576	0.620	0.625	0.626

Standard errors in parentheses; standard errors are clustered by community

* p<.1,

** p<.05,

*** p<.01

Panel B reports the F-test for joint significance of Cyclone Evan and its interaction with ethnicity

Table B.3

Effect of Cyclone Evan on Risk Aversion

Dependent variable: How strongly does the respondent agree with the statement "In general, I am willing to take risks."

Panel A	**(1)**	**(2)**	**(3)**	**(4)**
Struck by cyclone (0/1)	8.090	4.040	5.019	2.111
	(6.248)	(8.187)	(8.133)	(9.396)
Indo-Fijian (0/1)	14.12	32.37	29.88	20.27
	(10.94)	(22.34)	(22.63)	(22.56)
(Indo-Fijian) x (Cyclone)	−32.57***	−41.32***	−36.79***	−32.85*
	(11.07)	(9.779)	(11.27)	(16.21)
Value of physical assets (USD)	0.0000980	0.0000498	0.0000681	0.0000703
	(0.000107)	(0.000134)	(0.000124)	(0.000122)
Number of floods			−3.298	−2.911
			(2.790)	(2.933)
Nr. of years lived in community				−0.325*
				(0.183)
Male household head (0/1)				−5.639
				(6.488)
Age of household head				0.593
				(0.358)
Household size				0.818
				(1.584)
Years of education, hh head				−1.523
				(1.506)
Land leased (hectares)				−0.241
				(0.723)
Land owned (hectares)				−2.314*
				(1.290)
Engaged in cropping activities (0/1)				7.430
				(12.67)
Constant	63.60***	58.36***	62.71***	62.93**
	(5.635)	(20.97)	(21.01)	(24.82)
Community FE?	NO	YES	YES	YES
N	369	369	369	367
adj. R^2	0.017	−0.028	−0.023	−0.008

Standard errors in parentheses; standard errors are clustered by community

* p<.1,

** p<.05,

*** p<.01

Panel B reports the F-test for joint significance of Cyclone Evan and its interaction with ethnicity

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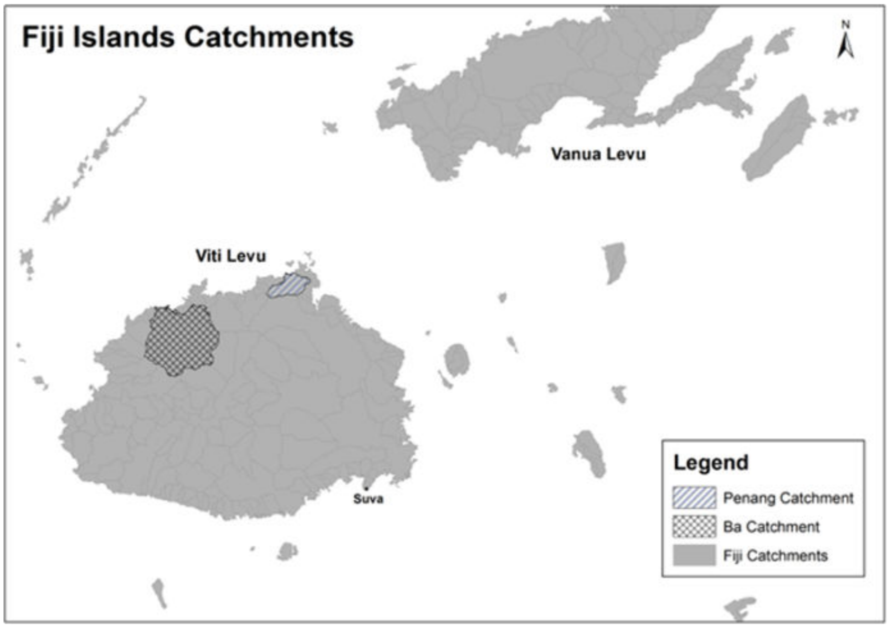

Figure 1.
Location of survey catchments

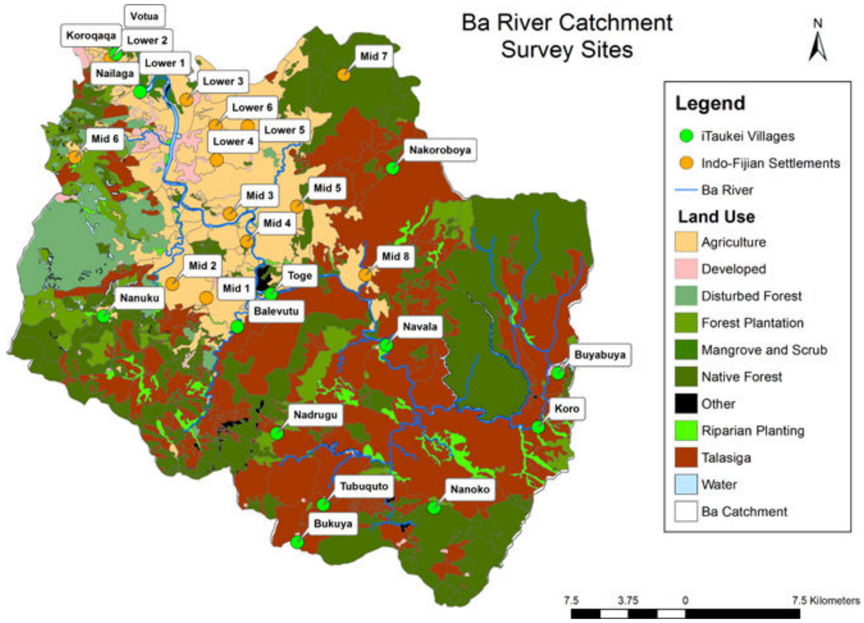

Figure 2.
Map of survey sites, Ba River Catchment

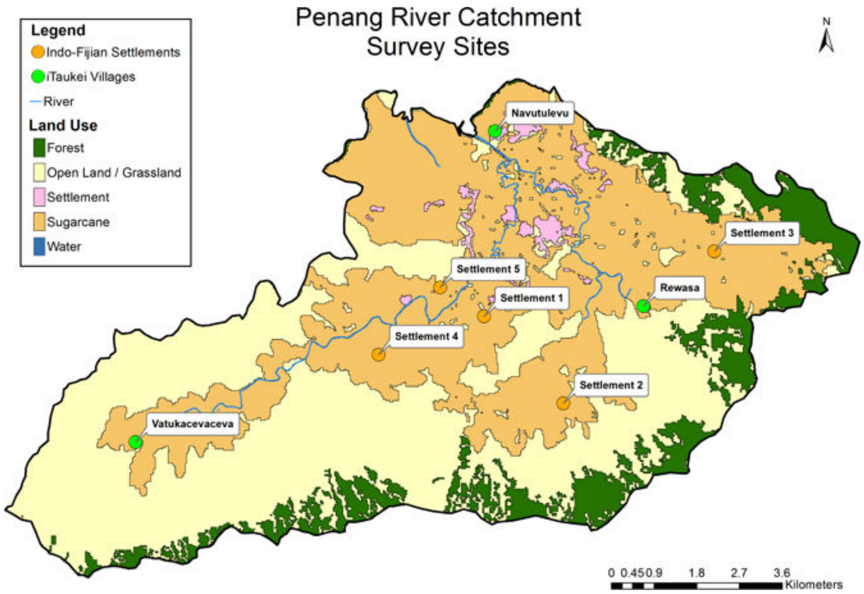

Figure 3.
Map of survey sites, Penang River Catchment

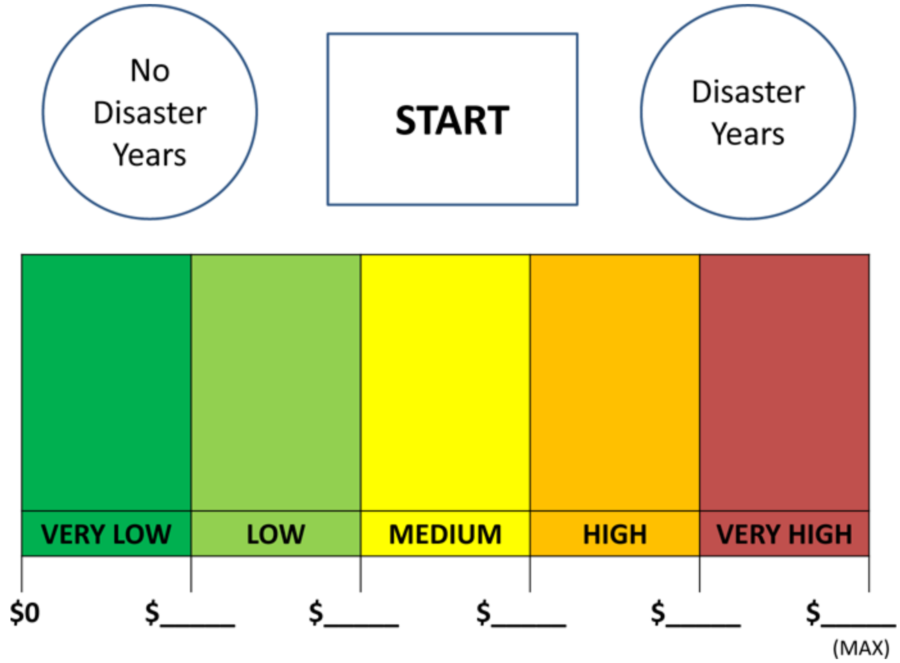

Figure 4.
Subjective expectations board

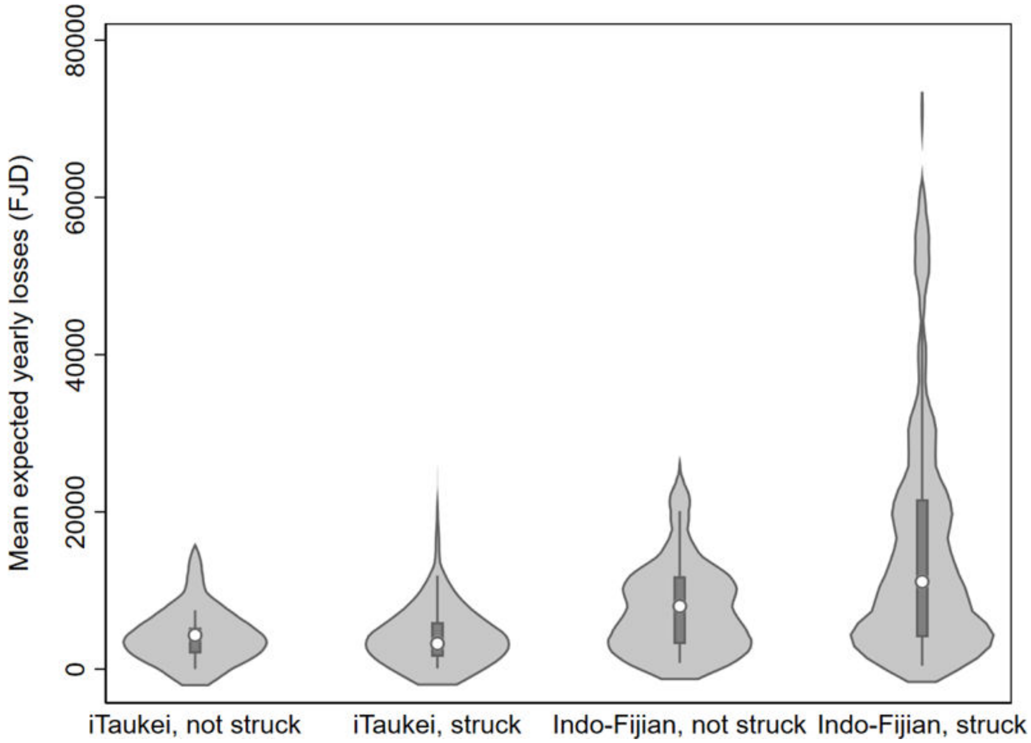

Figure 5.

Distributions of subjective expected losses by Cyclone Evan damage and ethnicity

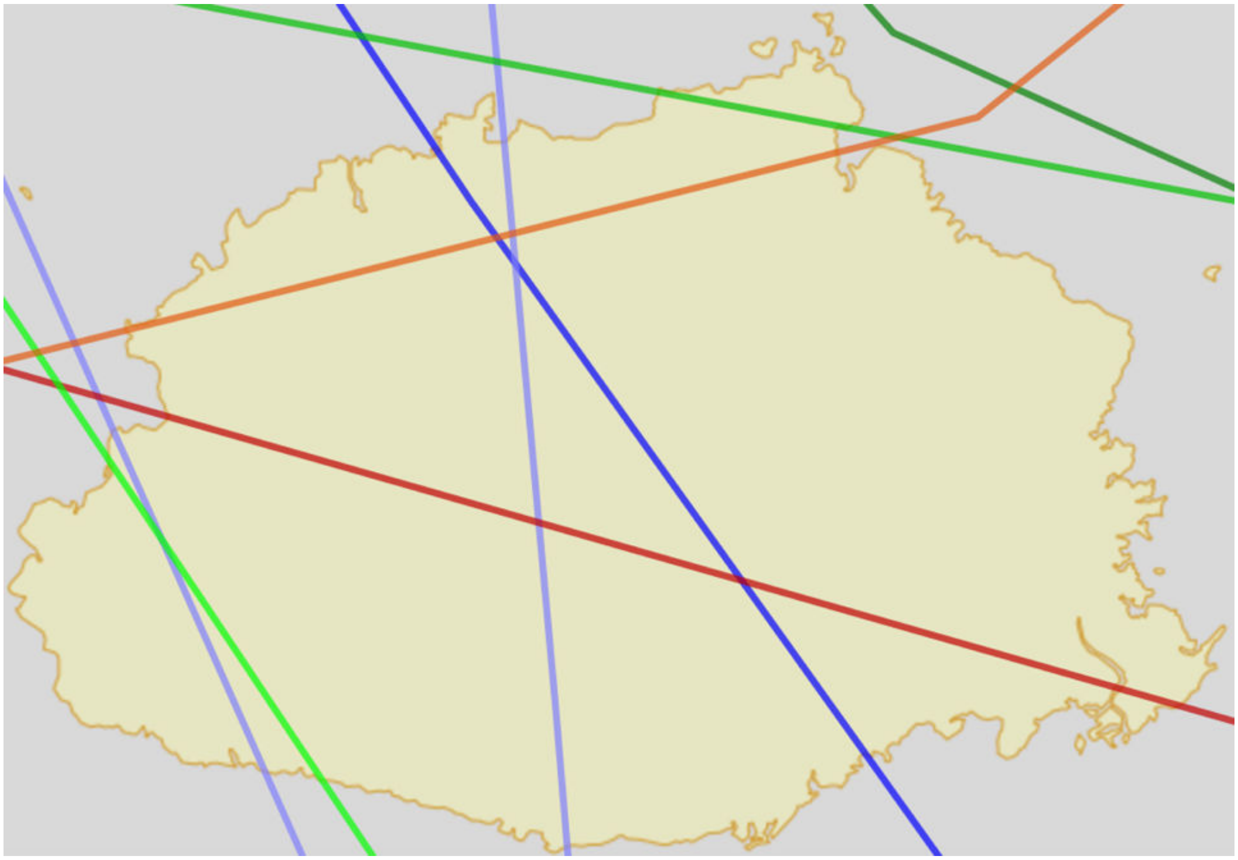

Figure 6.
Cyclone paths crossing Viti Levu, Fiji, 1969-2009
Source: Australian Bureau of Meteorology, 2016

Table 1

Summary Statistics

	Overall mean	*iTaukei*	Indo-Fijians
Is household Indo-Fijian? (0/1)	0.41	0	1
Wealth (FJD)	28248.30	20964.25	38647.25
Nr. of floods that hit household in past 10 years	1.45	1.11	1.94
Age of household head	51.53	51.73	51.24
Household head male? (0/1)	0.89	0.89	0.89
Education of household head	8.27	8.32	8.19
Household size	4.52	4.60	4.40
Nr. of years household head has lived in village	43.34	44.77	41.31
Amount of own land (acres)	2.13	3.52	0.15
Total damages from Cyclone Evan (FJD)	4210.37	4703.47	3506.41

Table 2

Balance Test

	Mean, not struck	Mean, struck	Difference	
Is household Indo-Fijian? (0/1)	0.46	0.41	0.0509	(0.64)
Wealth (FJD)	23077.21	28984.74	−5907.5	(−1.54)
Nr. of floods that hit household in past 10 years	0.78	1.54	−0.762***	(−5.03)
Age of household head	52.13	51.44	0.688	(0.41)
Household head male? (0/1)	0.76	0.91	−0.146**	(−2.23)
Education of household head	7.93	8.31	−0.381	(−0.76)
Household size	4.04	4.59	−0.542*	(−1.79)
Nr. of years household head has lived in village	38.85	43.98	−5.138	(−1.52)
Amount of own land (acres)	2.47	2.08	0.387	(0.58)

t statistics in parentheses

* p<.1,

** p<.05,

*** p<.01

Table 3

Effect of Being Struck by Cyclone Evan on Subjective Expectations of Future Damages, Interacted with Ethnicity

Dependent variable: Mean expected damages

Panel A	**(1)**	**(2)**	**(3)**	**(4)**
Struck by cyclone (0/1)	−35.01	935.1	609.5	457.2
	(838.3)	(985.0)	(1014.6)	(1085.6)
Indo-Fijian (0/1)	3272.3**	−5086.9	−4258.4	−5512.9
	(1493.5)	(4159.0)	(4323.3)	(4060.9)
(Indo-Fijian) x (Cyclone)	4505.2**	5421.6**	3915.8	4953.4*
	(1917.5)	(2412.3)	(2467.1)	(2713.7)
Value of physical assets (FJD)	0.198***	0.214***	0.208***	0.202***
	(0.0353)	(0.0360)	(0.0376)	(0.0379)
Number of floods			1096.7**	1127.0**
			(436.1)	(456.7)
Nr. of years lived in community				16.93
				(33.40)
Male household head (0/1)				−368.9
				(2170.0)
Age of household head				67.27
				(53.72)
Household size				216.1
				(228.7)
Years of education, hh head				287.9
				(176.2)
Land leased (hectares)				94.24
				(151.5)
Land owned (hectares)				−80.83
				(138.8)
Engaged in cropping activities (0/1)				−2589.3
				(3078.6)
Constant	253.5	7237.7**	5791.0	1263.6
	(1033.8)	(3315.7)	(3541.5)	(4234.6)
Community FE?	NO	YES	YES	YES
Panel B – marginal effects				
Marginal effect of Evan, *iTaukei*	−35.0	935.1	609.5	457.2
	(838.3)	(985.0)	(1014.6)	(1085.6)
Marginal effect of Evan, Indo-Fijian	4470.1**	6356.7***	4525.3**	5410.6**
	(1705.1)	(2198.5)	(2279.0)	(2670.9)
N	369	369	369	367

Panel A	**(1)**	**(2)**	**(3)**	**(4)**
adj. R^2	0.426	0.462	0.479	0.479

Standard errors in parentheses; standard errors are clustered by community

* p<.1,

** p<.05,

*** p<.01

Panel B reports the F-test for joint significance of Cyclone Evan and its interaction with ethnicity

Table 4

Effect of Cyclone Evan on Alternative Outcome Variables

	(1)	(2)	(3)	(4)
Panel A – Nr. of years out of 20 hh expects to incur losses from disasters				
Marginal effect of Evan, iTaukei	−1.23	−1.70	−1.84	−1.65
	(1.71)	(1.87)	(1.86)	(1.84)
Marginal effect of Evan, Indo-Fijian	1.64*	2.23**	1.44	2.38**
	(0.97)	(1.08)	(1.20)	(1.22)
Panel B – Value of losses from all natural disasters in worst possible year				
Marginal effect of Evan, iTaukei	−290.7	4762.0*	4215.7	3043.1
	(2731.8)	(2508.9)	(2571.2)	(2885.9)
Marginal effect of Evan, Indo-Fijian	10448.4***	14141.2***	11068**	12267.7**
	(2860.5)	(4563.7)	(4453.0)	(4639.5)
Panel C – Extent of agreement with the statement "In general, I am willing to take risks." Scale: −100 to 100				
Marginal effect of Evan, iTaukei	8.09	4.0	5.0	2.1
	(6.25)	(8.2)	(8.1)	(9.4)
Marginal effect of Evan, Indo-Fijian	−24.5***	−37.3***	−31.8***	−30.7**
	(9.0)	(4.8)	(7.4)	(12.6)

Standard errors in parentheses; standard errors are clustered by community

* p<.1,

** p<.05,

*** p<.01

Column (2) controls for community FE; column (3) adds number of past floods;

column (4) includes full set of covariates

Table 5

Mean Empirical Damage from Three Natural Disasters in 2012, in FJD

	Jan 2012 flood	March 2012 flood	Cyclone Evan	Expected annual loss
iTaukei	1,446	526	4,703	4,381
Indo-Fijian	1,594	1,183	3,506	15,044

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Table 6

Projected Loss and Damage under Different Flood Regimes, by Ethnicity and Catchment, in FJD

	1-in-20 year flood	**1-in-50 year flood**	**1-in-100 year flood**	**1-in-200 year flood**	**1-in-500 year flood**
Ba River catchment					
Avg. *iTaukei* hh	519	1,636	3,272	6,544	13,089
Avg. Indo-Fijian hh	866	1,403	2,805	5,610	11,221
Penang River catchment					
Avg. *iTaukei* hh	678	986	1,972	3,943	7,887
Avg. Indo-Fijian hh	1,250	2,178	4,355	8,710	17,421