#  Demand for natural disaster insurance In Zimbabwe and South Africa: A discrete choice experiment Approach

## 1 . Introduction

The cost of natural disasters has been on the rise globally due to increase in the frequency of floods, earthquakes and cyclones in the past decade. The increase in frequency and intensity of natural disasters has been extensively analysed in climate literature (IPCC, 2021; UNDRR, 2020). Empirical studies by Swiss Re Institute, (2021); NOAA, 2(022) demonstrate that global natural disaster costs have risen from an average of $25 billion annually in the 1980s to approximately $175 billion per year in the 2000s (adjusted for inflation). The United Nations Office for Disaster Risk Reduction (UNDRR, 2015) and the World Bank (2020) document a paradigm shift from reactive disaster management toward proactive disaster risk reduction, with insurance emerging as a cornerstone of modern risk governance frameworks. This transition is further evidenced by the Sendai Framework's emphasis (2015-2030) on financial resilience mechanisms (UNISDR, 2015).

This study draws on Protection Motivation Theory (Rogers, 1975) to capture how risk perception, trust, and cognitive biases influence preference for insurance products under disaster risk. Whilst other theories such as Prospect Theory (Tversky & Kahneman, 1992) , Random Utility Theory (McFadden, 1974) and the concept of Charity Hazard (Buchanan, 1975; Michel-Kerjan & Kunreuther, 2011) further provide a basis for understanding heterogeneity in provider-related preferences, especially in contexts where government and non-governmental aid may alter perceived need for insurance.

 The studies that have explored the demand for natural hazard insurance using choice experiments include Botzen and Van den Bergh (2012), Hudson et al. (2017), Reynaud et al. (2018), and Zhang et al. (2016), and they have identified the significance of attributes such as premium levels, coverage, payout timing, and provider type in determining the demand for insurance. It is important to note that this contributes towards optimal product design which inturn will increase in the demand for natural hazard insurance . The existing studies in literature have used contingency valuation approach in the demand for natural hazard insuracce in agriculture for instance Oduniyi , Antwi & Tekana (2020) who found a 10% willingness to pay and a maximum of R600 premium. Whilst studies in Zimbabwe the existing literature on catastrophe insurance which is dominated by agriculture insurance such as Maireva et al (2023), Makaudze et al (2010), Tsuma et al (2024), Runganga et al 2020 and Mazviona et al (2022) .

Therefore this study builds on literature by Brouwer et al., (2014); Reynaud and Nguyen, (2018) who proposed an extensive model for analysing natural hazard insurance demand. Reynaud and Nguyen, (2018) model is extended to include monetary and nonmonetary factors on the attributes of natural hazard insurance such as provider, type and transparency of the company.

The study analyses the natural hazard insurance policies by looking at the domain covered such as agriculture losses (Agriculture insurance), home damage (Property insurance), and medical expenditures (Health insurance), this helps to check on the differences in the willingness to pay (WTP) because of the domain covered. This approach has been recently adopted by Brouwer et al., (2014); Reynaud and Nguyen, (2018) as a domain-specific analysis might help to remove the assumption of homogeneity of the insurance type. The study also considered experience with three types of natural disasters which are floods, cyclones and tornados as in Chimanimani in Manicaland province (Zimbabwe) and Tongaat in KwaZulu Natal province (South Africa).

## 2. Literature review

### 2.1 Theoretical literature review

Protection motivation theory (PMT)

Maddux, and Rogers (1983) are the pioneers of exploring the PMT theory and states that when dealing with issues of pandemics and natural disasters mitigation of adoption appeal information must be designed in order to have a cognitive appraisal effect. The cognitive effect of threat appraisal of natural disasters can be achieved through the use of fear which , Tanner, Day, and Crask, (1989) who stated that the effectiveness of using fear when dealing with disasters ha a curvature structure. The study by Ray and Willkie (YEAR) identified that agents respond positively to fear appeals but not to infinity it reaches a peak where the intensity of the fear appeal will lead to a negative adoption of the recommendations such as purchasing natural disasters insurance. Rogers (1983) states that the general model of attitude change in PMT must include four main variables which are

1. Outcome expectancy of current behaviour
2. Outcome expectancy of alternative behaviour
3. Self-efficacy of alternative behaviour
4. The relative value of the different sets of outcomes

 According to Terblanche-smith and Terblanche (2011) the mitigation appeal such as purchasing insurance must ensure that the individuals are cognisant of the severity , occurrence or recurrence and the efficacy of the recommendations which leads to a sustainable consciousness to danger and turns the focus to methods of protecting themselves. The adoption of the protection motivation theory in the analyses of natural disaster insurance demand from psychology has been documented in Grothmann and Reuswing (2006) and Reynaud et al (2013) and can be summarised in figure 1 below.



*Figure 3.1 flow chart of insurance demand for protective motivation theory*

The protection motivation theory is directly linked to the risk perception on the impact, severity, and susceptibility of the economic agents to the natural disaster. Grothmann and Reuswing (2006) proposes that theoretically when analysing perception and adoption process the protection motivation theory best explains the psychological model of decision making. According to Reynaud *et al.* (2013) the threat appraisal process provides the perception of probability of occurrence and impact of the natural disaster (study was on floods). The threat appraisal and the coping appraisal process which involves the cognitive process of analysing one’s ability to avert being harmed by the natural disaster. Reynaud *et al*. (2013) states that the coping appraisal is highly dependent on the threat appraisal level of fear in which it must reach a particular threshold for it to start. The coping appraisal includes several facets of perceptions which include the perceptions about one’s protective self-efficacy, response costs and action efficacy. In which in Reynaud *et al*. (2013) the study adds the threat experience appraisal and the reliance on non-individual protection methods.

The literature review also revealed that the understanding of the risk preferences of the economic agents is important to increase the demand for insurance demand. Reynaud et al., (2018) classifies the economic agents as risk averse, lover and risk neutral and the risk averse individuals are expected to purchase insurance to curb their risk exposure. According to Charness *et al* (2013) literature has elicited risk preference using experimental techniques using the BART experiment and the questionnaire technique and the EG is the widely used in studies. According to Mahaprashasta *et al* (2021) there are changes in risk preferences post a natural disaster event and this will lead to increased purchases of natural disaster insurance . The results of the study further found that literature explains the willingness to pay variable to be a comprehensive question that can be answered on a holistic perspective from monetary factors such as price and income elasticity, domain covered (health, property, life etc) , location and other sociodemographic factors (Botzen *et al* 2013; Wagner, 2019).

### 2.2 Empirical Literature review

Existing studies analyzing demand for natural disaster insurance have adopted hazard-specific approaches. Brody et al. (2017) examined flood insurance uptake, Zhang and Qian (2018) explored earthquake insurance demand, and Mathithibane and Chummun (2022) investigated weather-based agricultural insurance in South Africa. Flood insurance studies often employ prospect theory, positing that risk-averse individuals overweight potential losses, increasing insurance adoption (Reynaud et al., 2018).

Disaster experience significantly influences demand but varies by event characteristics. Botzen and Van den Bergh (2012) distinguish between high-frequency/low-intensity floods (e.g., seasonal flooding) and low-frequency/high-intensity events (e.g., catastrophic storms), noting divergent effects on insurance behavior. Seifert et al. (2013) emphasize that high-intensity disasters require sustained media salience and community engagement to maintain demand. Liu et al. (2019) further categorize experience into, direct experience which includes a personal property damage and Indirect experience which in cooperates financial assistance to affected relatives which contributes significantly analyzing behavioral responses.

The other studies also look at the trust in insurance providers (government, NGOs, private firms) as a key determinant. Reynaud et al. (2018) find that timely post-disaster assistance and community integration enhance provider credibility in high-risk areas. Discrete choice experiments studies also reveal additional attributes that can contribute to demand for insurance such as coverage domain: Agriculture, property, or health (Hudson et al., 2017), financial terms covering premiums and indemnity limits (Akter et al., 2009) and transparency in the clarity of terms (Kunreuther & Pauly, 2006)

## 3. Data sampling

### 3.1 Target Population

According to Mongin (1999), population refers to the total number of people who share specific traits and are of interest to the researcher. Similarly, Oshagbemi (2017) defines a population as the number of people or items included in the study or with which it is concerned. The target population in the study refers to the people who were affected by natural disasters in South Africa and Zimbabwe in the case study area. The study population in Chimanimani is approximately 154 288 as shown by the Zimbabwe’s 2022 census. Chimanimani has 94% of population living in rural areas, and it is important to note that the study used the population data as a target population because the study surveyed communities that were affected by natural disasters (cyclone idai ) and those that were not affected . The target population of the study in KZN included individuals in Toongaat which has a population of 18223 as per 2022 population census and it included both communities that were affected by the tornado and those that were not affected

### 3.2 Sampling technique

 The study will use judgmental non-probability sampling is also known as the purposive sampling technique (Latham, 2007). Judgmental sampling is said to comprise three different methods, namely critical case, most similar/dissimilar case, and typical case (Foley, 2018). This type of sampling is based on the knowledge of the researcher about the characteristics of the population and the purpose of the study. Researchers utilise judgmental sampling to answer a specific question on a matter or products. The advantage in using the judgmental sampling technique is that the researcher possesses internal knowledge about the characteristics of the population (Etherington,2000). Moreover, like quota sampling, judgmental sampling is likened to stratified sampling; however, in judgmental sampling all participants who are randomly selected are included in a study(Foley, 2018).

### 3.3 Sample size

the target population was 24 608 calculated based on the number of households affected in Chimanimani (17608) plus households affected in Tongaat (7000) housing units, the size of the sample was then determined using the above formula as indicated below

$n=\frac{24608}{(1+24608\*0.05^{2})}$= 393 participants

Following the study by Reynaud, Nguyen and Aubert (2018 ) which collected 16-20 households per village and had a sample size of 448 households from 28 villages/communes from 14 districts. Due to primary and secondary constraints, the study collected data from 260 households, 110 in Tongaat and 150 in Chimanimani.

### 4. Methodology

### 4.1 Designing a CE for flood insurance demand in South Africa and Zimbabwe

### 4.1.1 Questionnaire development

The designing of the questionnaire involved consultations with experienced choice modelling researchers in South Africa and Zimbabwe, local experts and local Government and Authorities in the period of (November 2021- January 2022). During the period of the instrument development, various meetings were set up between the team of researchers and the local authorities. After the consultations, the questionnaire was presented to the various stakeholders in the study and modified. The questionnaire was taken to the stakeholder representatives to check for clarity and understanding of the survey and further adjustments. The questionnaire was then taken for a feasibility study in March 2024. The data collected from the pilot study was estimated, and further modifications to the questionnaire were made.

### 4.2 Experimental design (choice experiment) construction of choice sets

The designing of the experiment maximizes the survey efficiency, which is to ensure that each component of the survey collects data that contributes valuable information to the whole study design and question. To achieve this the choices in the set alternatives should be valid and having a background concept they proxy. The efficiency is important because the preferences for different levels of attributes should be individually identified. The designing of the experiment follows a two-step process which includes identifying the optimal combinations which provide optimal information to answer the concept in question (Terris-prestholt et al., 2019). After obtaining the optimal combinations they are grouped into choice sets the second step involves applying these choice sets into a questioner (Terris-prestholt et al., 2019. The factorial design of a choice experiment is very large and is not traceable therefore a subset of all possible combination must be chosen (Vega & Alpizar, 2011). Following design by (Vega & Alpizar, (2011). Vega, and Alpizar, (2011) which is based on four main principles, which are: 1). orthogonally, where the levels of the attributes within each set must not be correlated, 2). Level balance, where attribute levels appear the same number of times within a choice set 3). Minimal overlap, where attribute levels are not repeated within a choice set and 4).

 For the construction of the choice sets we implemented Dzero -Efficient design (mainly due to the invalidity of the priors from the feasibility study due to sample size and target group differences). Using the Stata Software which provides a D-Efficient Choice set design the study undertook an efficiency optimal criterion to test the efficiency and the insensitivity of the magnitude of the parameters (Reynaud & Nguyen, 2018). The Dzero – Efficient design used in the designing of the choice sets is attached in Appendix 2 below. The study used the attributes discussed in section 4.3 below and their level matrixes to code for the designing of the choice sets and limited the software output to 8 choice sets.

### 4.3 Attributes of Disaster Insurance Programs

In choice experiment analysis it is important to identify and clearly define the attributes. Choice experiments are highly dependent on the level of accuracy and the tightness in terms of the definition of the characteristics and features of the good/product in question as these attributes affect the respondent's choices (Reynaud & Aubert, 2019). Mangham et al., (2009) note that the definition and selection of attributes should be in line with their relevance in terms of policy and their level to change response from preferences. The initial step when analysing using a choice experiment is to narrow the definition of the good to be valued (Hoyas 2010). Relative to this study the good to be valued in our choice experiment study is a Tornado, flood, and cyclone insurance policy. The study explored research using a systematic literature review of different studies which involved different types of natural hazard insurance. The study then extracted the attributes to be used in the choice experiment from the literature based on relatability to Zimbabwe and South Africa’s insurance. The studies from which the attributes where extracted can be shown in appendix 1 below.

Based on the cognitive limitation of choice sets and the recommendation of limiting alternatives between 3-5 the study selected the following attributes from the table above for the analysis for Zimbabwe and South Africa. The calculations of attribute levels included consultations with industry participants using existing products coupled with a systematic literature review in Table 4.1 above. Therefore, the attributes selected for the study are explained in section 4.5.3.2.1 below.

### 4.3.1 Attributes for the study

 The extracted attributes from systematic literature review in Appendix 1 below above have been presented in Table 1 below including the levels of each attribute. The first attribute is the domain covered to determine if the demand for insurance is dependent on what the insurance covers, which the study limits to agriculture, health, and property insurance. Agriculture insurance covers crop and animal losses; Health covers medical expenditures that are caused by natural hazards, whilst property will look at the house and infrastructure that is affected by these cyclones.

 The second attribute investigated is the trust in the institutions that provide insurance, and the study limits the trust in institutions to three types of ownership which are privately owned, non-governmental organization, and government owned. The third attribute that was used in the study is the maximum cover, which describes the maximum indemnity amount that one will get if one subscribes to the policy. Whilst Risk premiums matched to the maximum payment will be presented on a per-month basis, they will be calculated as a proportion of the yearly insurance and presented as a local Currency value.

 The last attribute investigated in the study is the level of transparency which describes a system that provides clear information on the status of an application to policyholders, loss calculation, claim settlement eligibility and claim settlement details through SMS. The last attribute was the time taken to settle the indemnity amount since inception of the risk/loss when the case was notified as a loss e.g., within 3, 6 or more 12 weeks. The researchers settled on 5 attributes, and 8 choice sets to reduce cognitive exhaustion between a survey with 25 items and 8 choice sets with three options and the respondents can only select one.

*Table 1 Choice experiment attribute levels*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Attributes  | Insurance product A  | Insurance product B | Insurance Product C | Level matrix  |
| Domain  | Health,  | Agriculture  | Property  | 3 |
| Insurance  | Government private and Ngo | Government Private and Ngo | Government Private and Ngo | 3 |
| Maximum  | 250 000,350 000, 500 000,300 000,70 000,50 000 | 100 000,50 000,150 000, 300 000 | 300 000, 150000, 100000, 50000, 200 000 | 5 |
| Insurance premium  | 246,520,600, 315, 89,84 | 120, 84,200,375 | 375, 200,120,84,180 | 5 |
| transparency  | Yes No | Yes NO  | Yes NO  | 2 |
| Pay-out period  | 3,6 and 12 | 3,6 and 12 weeks  | 3,6 and 12 | 3 |
|  |  |  |  |  |

## 4.4 Model specification

The study follows the study by Reynaud and Nguyen, (2018) that uses a conditional logit model in the assessment of the demand for flood insurance in Venezuela. The study models individual choices in two main categories. The fourth category is the one that is deterministic whilst the second component is the one that is stochastic these can be represented algebraically in equation 1 below

$U\_{ijk}=V\left(X\_{IJK}..β\right)+ ε\_{IJK}= V\_{IJK}+ε\_{IJK}$………………………………………………… (1)

Where U = Utility V= deterministic component (indirect utility) 𝜀𝜀𝜀𝜀= the stochastic component J= program, I =responded /individual, K = is a particular choice task. Since v is the deterministic component that is determined by characteristics of individuals, the attributes of alternatives to disaster insurance policies and a set of unknown parameters and Xijk Is a vector of explanatory variables describing program j and responded i. The assumption of rationality and the quest to maximize utility is used and in a context, it is that the individual I will choose program j if he/she derived higher utility in that program than the available alternatives J’. The study uses a basic specification of the indirect utility function presented algebraically as follows.

 $V=\left(α\right) ASC.+\left(β\right)Type AG.+.\left(γ\right)type Pro+\left(ϑ\right)M.Payment .+.φProv.State+\left(ρ\right)ProvNGO.+ \left(δ\right)MaxiCoverage .+∅ Trans+τ.payout time +\left(K\right)C………………………………………………….(2)$

Where ASC is status quo, Type Ag is the Dummy variable for agriculture insurance, Type Pro is the dummy variable for Property insurance, M.payment represents a dummy for a monthly payment , Prov state represents state-owned insurance program ProvNGO represents a non- governmental organization insurance program and MaxiCoverage is maximum level of insurance coverage ,$Trans$ *represents transpatemcy in the process a and finaly* $τ$ represents payout time from the submission of claim . The priory expectations of the alternative specific variables and the case-specific variables have been denoted in Table 2 below:

**Table 2 A priory expectation**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable  | Definition  | Measurement  | Base category  | Expected sign  |
| Domain | Type of insurance and what it covers  | Health, Agriculture and Property  | Health  | -/+ |
| ASC | If an individual said Yes =0  No=1  To purchasing insurance  | No/Yes  |  | -/+ |
| Provider  |  The company that the community prefers and trusts to provide insurance  | NGO, Government and private companies  | Private companies  | -/+ |
| Maximum Insurance cover | The maximum indemnity cover pay-out in the even  |  |  | + |
| Insurance Premium |  |  |  | - |
| Transparency=Yes | The level of transparency on the pay-out process to the individuals including sms’s and stages of the pay-out process  | Yes/ NO  | No  | + |

Source: Author Compilation

## Demand for natural disaster insurance Survey results

### 5.1.1 Willingness to pay for natural disaster insurance

The analysis of the demand for natural disaster insurance initially asks the respondents if they are willing to pay for natural disaster insurance to which they can answer either “Yes” or “No”. For the respondents that answered yes, the follow-up question was what they are willing to pay for between health, agriculture or property insurance. The results of the willingness to study identified that for Zimbabwe 67% of the respondents answered “Yes” whilst 33% of the respondents answered “No”. whilst the demand for willingness to pay (WIP) for natural hazard insurance in South Africa shows that in Tongaat (Durban) based on the sample in the study the WIP for natural disaster insurance is 63% and those that are not willing to pay constituted 37%. These results of high willingness to pay can also be found in studies of other types of insurance such as Goudge, Akazili, Ataguba, Kuwawenaruwa, Borghi, Haris& Mills (2012) and Chummun& Mathinthibane (2022) who found 75% and 86% WIP for health and Weather based insurance respectively. Whilst Oduniyi, Antwi and Tekana (2020) found a 10% willingness to pay for cattle insurance.

The survey identified that the reasons for the respondents stating that they do not want insurance include affordability, trust and a negative experience with the stability factor of the financial systems over the past years .

## 5.2 Demand for natural hazard insurance Choice experiment Results

The study further undertook an analysis of demand for natural disaster insurance using 8 choice sets with three insurance types of categories which are Health, Agriculture and Property and status quo, the results of the choice experiment identified that the demand for insurance is dominated by Agriculture insurance with approximately 43.3% probability of being selected followed by health insurance with 31.2% probability of being selected and property insurance with 25.4%. Whilst for South Africa the results of the study show that based on the choice sets analysis the dominant domain that the respondents selected was property insurance followed by health insurance and agriculture insurance with 37%, 36.5% and 28 % respectively as presented in Table 7.1 below

The explanation of the dominance in the selection of agriculture insurance in Zimbabwe on the choice sets includes factors such as occupation which show that in Chimanimani 25% of the respondents are involved in small-scale farming coupled with the current drought that Zimbabwe is facing which has been labelled the worst in 4 decades. Secondly, the poor performance in the selection of property insurance includes the fact that the government response might have diluted the demand for property insurance in the area by the provision of new houses and relocation of those whose houses were impacted significantly, and this impact of relocation can also be identified in a study by (Arnaud, Nguyen &Aubert 2018). The analysis further investigates the demand for natural disaster insurance using choice sets to analyze the demand for natural hazard insurance attributes and the domain-specific analysis section 3 below

Table 3 The Descriptive Statistics of Choice sets Domain Selection

|  |  |  |  |
| --- | --- | --- | --- |
| Domain  | Freq. | Percent | Cum. |

|  |  |  |  |
| --- | --- | --- | --- |
| Health  | 191 |  31.210 |  31.210 |

|  |  |  |  |
| --- | --- | --- | --- |
| Agriculture  | 265 |  43.300 |  74.510 |

|  |  |  |  |
| --- | --- | --- | --- |
| Property  | 156 |  25.490 |  100.000 |

|  |  |  |
| --- | --- | --- |
| Total  | 612 |  100.000 |

Whereas the dominance of property and health insurance in Tongaat may be mainly attributed to experience. The recent experience of the people in Tongaat is the Tornado which caused property damage to both private and public goods. The argument of experience has a significant impact on insurance preference can be found in studies such as Doherty et al (2021).

Table 4 Descriptive statistics of choice sets selection (South Africa)

|  |  |  |  |
| --- | --- | --- | --- |
| Domain  | Freq. | Percent | Cum. |

|  |  |  |  |
| --- | --- | --- | --- |
| Health  | 150 |  35.550 |  35.550 |

|  |  |  |  |
| --- | --- | --- | --- |
| Agriculture  | 118 |  27.960 |  63.510 |

|  |  |  |  |
| --- | --- | --- | --- |
| Property  | 154 |  36.490 |  100.000 |

|  |  |  |
| --- | --- | --- |
| Total  | 422 |  100.000 |

Therefore, the high incidence of property damage can explain the high propensity to select natural hazard property insurance. The high health costs issues caused by the Tornado can explaining the performance of health insurance in the choice experiment. The poor performance of Agriculture insurance in South Africa (Durban Tongaat) can also be explained by the occupation of the respondents in which only 1.9% of the respondents are involved in farming at both commercial and subsistence farming. However, it is important to note that Tongaat’s main activity is commercial farming of sugar plantations and manufacturing of sugar which means that agriculture performs badly since one company will be owning the farming and production systems.

##  Results of the demand for natural hazard insurance in Zimbabwe a Choice experiment

 The negative results in the variable ASC show the strong rejection of the status quo by the respondents in Zimbabwe. The status quo is the position of not having insurance and the insignificance can be derived from the fact the those that were affected were relocated to places of less natural hazard risk . The results from the choice sets and alternative-specific variables show a positive and significant factor in the maximum payout in Table 4 below. The positive and significant maximum payout explains that the probability of the community buying natural hazard insurance increases with an increase in the maximum payout. This goes in line with the priory expectation because in Zimbabwe there are high levels of inflation in the country as explained by the KPMG report (2019) that describes the impact of inflation in Zimbabwe’s insurance sector. Therefore, to cover for inflationary risks the results show that a higher maximum payout is preferred. Those who were not willing to purchase insurance, they explained that it’s because of the financial systems that do not guarantee the value of the currency and higher payout can assist cover for such uncertainties for example on the 27th of September 2024 the government devalued its local currency by 40% (Reserve Bank of Zimbabwe Mid-term policy review, 2024).

The results of the study also show a negative and significant sign on premium of the natural disaster insurance scheme being selected based. The result means that individuals are more likely to purchase natural hazard insurance schemes with low premium charges when compared to high premium which is in line with the law of insurance demand as explained in Tsiboe &Turner (2023). Secondly given the low levels of income in Zimbabwe and South Africa , this can lead to a high demand of low premium insurance products The results in Table 4 below also show a positive and significant sign of transparency which indicates that the respondents are more likely to select an insurance that provides a transparent payout system with updates. This result was also found in the study by (Vikram et al., 2018) in which the respondents in India were willing to pay an extra premium for transparency to be enhanced

The negative and significant signs on the period show that the respondents are less likely to choose an insurance scheme that has a long payout period of either 6- or 12-week payout period when compared to three weeks this result was also found in (Virkram et al .,2018). The results are in line with the a priori expectations as specified in Table 4 below . The results of the study also show that the provider has no statistically significant impact on the demand for natural disaster insurance, these results differ from the results in the study of flood insurance in Vietnam which found the probability of an insurance scheme being chosen when provided by a government when compared to private firms and NGO to be significant.

Table 4 results of demand for natural hazard insurance demand in Zimbabwe

Conditional logit choice model Number of obs = 1,836
Case ID variable: \_caseid Number of cases = 612
Alternatives variable: Domain Alts per case: min = 3
 avg = 3.0
 max = 3
 Wald chi2 (8) = 29.72
Log pseudolikelihood = -641.64389 Prob > chi2 = 0.0002
 (Std. err. adjusted for 80 clusters in ID)

|  |  |
| --- | --- |
|   |  Robust |
|  Choice  |  Coefficient |  Robuststd. err. |  z | P>z | [95% conf. interval]   |
| **Domain**  |
| ASC  |  -0.252 |  1.325 |  -0.190 |  0.849 |  -2.849 |  2.344 |
|  |
| **Provider**  |
| Government  |  -0.103 |  0.168 |  -0.610 |  0.541 |  -0.433 |  0.227 |
| NGO  |  -0.004 |  0.169 |  -0.030 |  0.979 |  -0.336 |  0.328 |
|  |
| Maxi  |  5.76e-06\*\* |  0.000 |  2.840 |  0.004 |  0.000 |  0.000 |
| Premium  |  -0.005\*\* |  0.002 |  -2.610 |  0.009 |  -0.008 |  -0.001 |
|  |
| **Transparency**  |
| Yes  |  0.206\*\* |  0.085 |  2.440 |  0.015 |  0.040 |  0.372 |
|  |
| **PayoutTime**  |
| 6  |  -0.376\*\* |  0.127 |  -2.960 |  0.003 |  -0.625 |  -0.127 |
| 12  |  -0.410\*\* |  0.161 |  -2.550 |  0.011 |  -0.725 |  -0.095 |
| **Health** **(base****alternative)** |
|  |
| Agriculture |  0.432\*\* |  0.160 |  2.690 |  0.007 |  0.118 |  0.746 |
|   |
|  Property |  -0.355\* |  0.187 |  -1.900 |  0.057 |  -0.722 |  0.011 |
|  |

Source : Author compilation ( Stata software)

The domain-specific analysis shows that when health insurance is the base category, the agriculture insurance demand result is positive and significant therefore the respondents are more likely to purchase agriculture insurance than health. This can be explained by the recent developments of the increase in the number of clinics with free health care in the area. Maireva (2023) also explains that the perceptions of farmers in Zimbabwe towards agriculture insurance are positive and also dependent on recent experience of losses, which can explain the higher preference of agriculture insurance in the 2024 Drought year. Maireva (2023) further explains that the low penetration of agriculture insurance in Zimbabwe is not about preference, but rather a product designing issues which is not inclined to farmer-centric design. The results also show that on the domain-specific analysis with a health insurance category, property insurance is negative and significant, therefore people in Chimanimani are less likely to purchase property insurance than health insurance.

## 7..3 **Results of the demand for natural hazard insurance in South Africa (Choice Experiment)**

 The negative and significant results of the variable ASC show the strong rejection of the status quo by the respondents in South Africa as shown in Table 5 below. This result of rejection of not having insurance can be explained by the fact that delays in funding for relocation since 2013-2024 victims are still waiting as explained in the municipality reports. These results can be compared to the results in Vietnam by Reynaud et al (2018) who found a positive preference for ASC (Status quo) and argued that in Vietnam the result was attributed to the participants moving to a low-risk area. Secondly unlike in Zimbabwe with an insignificant rejection of the status quo (ASC) the respondents have not all been relocated to low-risk areas. Therefore in South Africa insurance is needed to protect them as they stay in the same place they were affected before.

The results of the study also show that provider has a positive and statistically significant impact on the demand for natural hazard insurance. These results mean that the respondents are more likely to purchase natural hazard insurance when it is offered by the government and NGOs/NPOs than when it is offered by private institutions. These results differed from the results in Zimbabwe as presented in Table 4 above, but they are in line with the study of flood insurance in Vietnam by Reynaud, Nguyen & Aubert (2018) who found the probability of insurance scheme being chosen when provided by a government when compared to private firms and non-governmental charity organizations

Table 5 results for demand for natural hazard insurance demand in South Africa

Conditional logit choice model Number of obs = 1,263
Case ID variable: \_caseid Number of cases = 421
Alternatives variable: Domain Alts per case: min = 3
 avg = 3.0
 max = 3
 Wald chi2(8) = 379.33
Log pseudo likelihood = -444.66566 Prob > chi2 = 0.0000
 (Std. err. adjusted for 60 clusters in ID)

|  |  |
| --- | --- |
|  |   |
|  Choice  |  Coefficient |  Robuststd. err. |  z |  P>z |  [95% | conf. interval]  |  |
| Domain  |
| ASC  |  -13.725\*\* |  0.753 |  -18.240 |  0.000 |  -15.200 |  -12.250 |
|  |
| Provider  |
| Government  |  0.295\*\* |  0.124 |  2.380 |  0.017 |  0.053 |  0.538 |
| NGO  |  0.370\* |  0.197 |  1.870 |  0.061 |  -0.017 |  0.757 |
|  |
| Maxi  |  2.64e-06 |  0.000 |  1.000 |  0.320 |  -0.000 |  0.000 |
| Premium  |  -0.003 |  0.002 |  -1.500 |  0.134 |  -0.008 |  0.001 |
|  |
| Transparency  |
| Yes  |  0.159 |  0.112 |  1.420 |  0.155 |  -0.060 |  0.378 |
|  |
| PayoutTime  |
| 6  |  -0.399\*\* |  0.154 |  -2.590 |  0.010 |  -0.700 |  -0.097 |
| 12  |  -0.400\*\* |  0.148 |  -2.700 |  0.007 |  -0.690 |  -0.110 |
| Health (basealternative) |
|   |
| Agriculture |  -0.445 |  0.264 |  -1.690 |  0.092 |  -0.962 |  0.072 |
|   |
|  Property |  -0.383 |  0.253 |  -1.520 |  0.130 |  -0.878 |  0.112 |
|  |
|  |

The negative and significant signs of the period of pay out in Table 5 above show that the respondents are less likely to choose an insurance scheme that has a long payout period of either 6- or 12-week payout period when compared to three weeks. The results are in line with the a priori expectations as specified in Table 6.1 in chapter 6 above and these results are also in line with results found in Wang & Liu (2023) and Patel et al (2018) and the results from Zimbabwe as presented in the chapter 6(A) above. The study further interpreted the results of the study in the next section.

## 6.1.1 Post estimation results

### 6.1.1.1 Predictive margins

The results of the study further analyze the marginal effects of willingness to pay for model one in Table 6.4 below. The results of the study show the marginal probability of participants selecting either health, agriculture or property insurance. The results of the study show that the marginal probability of selecting agriculture insurance in Zimbabwe is 43.3% followed by health insurance at 31.2% and the lowest being property with a 25.5% probability of being selected. The study further looks at the effect of premiums on the probability of selection in Figure 6.4 below as premium margins when the premium ranges from R50-R700

**Table 7 Predictive margins**

Predictive margins Number of obs = 1,836
Model VCE: Robust

|  |  |  |  |
| --- | --- | --- | --- |
| .Expression: Pr(Domain) | 1 | selected), | predict() |

|  |  |
| --- | --- |
|   |  Delta-method |
|   |  Margin |  std. err. | z |  P>z | [95% conf. interval] |
| \_outcome  |
| Health  |  0.312 |  0.021 |  14.740 |  0.000 |  0.271 |  0.354 |
| Agriculture  |  0.433 |  0.025 |  17.400 |  0.000 |  0.384 |  0.482 |
| Property  |  0.255 |  0.020 |  12.840 |  0.000 |  0.216 |  0.294 |
|  |

The analysis of the post-estimation results of the study in South Africa shows hat the probability margin of selection of health, agriculture and Property is 35.6%, 28% and 36.3% respectively in Table 8 below. These results are also aligned with the descriptive statistics in Table 5 above which shows the dominants of health and property insurance. The dominants of the probabilities of selection of health and property are aligned to the nature of the area and the dominant activities in Othongaat. The study further analyses the probabilities of selection with changes in premium and maximum amounts

**Table 8 Predictive margins South Africa**

Predictive margins Number of obs = 1,263
Model VCE: Robust

|  |  |  |  |
| --- | --- | --- | --- |
| Expression: Pr(Domain | 1 | selected), | predict() |

|  |  |
| --- | --- |
|   |  Delta-method |
|   |  Margin |  std. err. | z | P>z |   [95% conf. interval] |
| \_outcome  |
| Health  |  0.356 |  0.037 |  9.530 |  0.000 |  0.283 |  0.430 |
| Agriculture  |  0.280 |  0.036 |  7.750 |  0.000 |  0.209 |  0.351 |
| Property  |  0.363 |  0.035 |  10.350 |  0.000 |  0.295 |  0.432 |
|  |

### 6.1.1.2Post estimation premium margins analysis

The results of the premium margins shown in Figure 2 below reflect that at an R50 premium, the probability of selection is high at 60% for health and 25 % for agriculture selection. Whilst for property the probability of selection is low at around 20% (The table with the margins is in the attached appendix 4 below). The probability of selection of health, agriculture and property is 1 below 20%, 40% and 60% respectively at an R700 premium. The high probability of selection for health when the premium is low might be attributed to the existing free health care in Zimbabwe even though the quality is low. The risk for property and agriculture is also high therefore when having a normative decision, the higher premium will be demanded when the expected risk is also high since agriculture and property are not as covered as health since there is free health care in the country. The analysis of the margins of maximum payout are represented in Figure 2 below. The analysis from the model shows that in Zimbabwe, premium cost has a statistically significant negative effect on insurance uptake (β = -0.005, *p* = 0.009). This aligns with global evidence that cost is a major barrier to insurance adoption in low-income contexts (Cole et al., 2013; Giné et al., 2008). In rural Zimbabwe, where disposable incomes are constrained, even small increases in premium can deter enrolment especially for health insurance, as reflected in the sharply declining predictive margins in that domain.

Interestingly, the margins for agricultural insurance show increasing demand with higher premiums, which at first seems counterintuitive. However, this could reflect a perceived quality signal and in the absence of strong regulation or market transparency, higher prices may be interpreted as more reliable or comprehensive coverage (Harrison & Ng, 2016). This behavioural pattern has been noted in other African contexts where financial literacy is limited and past negative experiences with cheap or defaulting schemes have led to preference for more costly but perceived “better” options (Hill et al., 2019).

Thus, in Zimbabwe, premium elasticity is not uniform across domains. Therefore, there is need to recognise that in insurance product designing subsidized products must recognize that while price reductions can increase health insurance uptake, agricultural insurance may benefit more from improving trust and perceived value, even at modest cost levels.

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Figure 2 Zimbabwe’s premium margins

Source (Author Compilation )

The results presented Figure 3 below show that the demand for health insurance falls as insurance prices increase and this can be attributed to the low-income levels of the participants and the availability of free health care services in South Africa. The demand for agriculture and property natural hazard insurance increases at a diminishing rate as premium rates increase. The increase in demand at a decreasing rate can be explained by the law of demand and the probability and expected return when property and agriculture are affected. Secondly, this can be attributed to the maximum amount and the type of properties and size of agriculture fields that the participants prefer to cover. Which is important to further investigate the margins of maximum indemnity.

In contrast to Zimbabwe, the premium variable in South Africa's model was not statistically significant at the 10% level (β = -0.003, *p* = 0.134), suggesting that consumers may be less price sensitive. This finding is supported by the premium margins, where changes in premium had only a modest effect on predicted insurance uptake across domains. This is consistent with literature indicating that higher financial literacy, greater insurance exposure, and more diverse income sources in South Africa reduce premium sensitivity (Delavallade et al., 2017; Taffesse et al., 2014).

Moreover, the government and NGO provider variables were significant, suggesting that trust in provider may outweigh cost concerns. Studies have found that in middle-income countries like South Africa, institutional trust and perceived claims performance drive adoption more than premium alone (Dercon et al., 2014; Petrie & Swanson, 2020).

However, health insurance still showed a modest decline in uptake with rising premiums in the margins plot, which suggests that price remains relevant for health-related risks, possibly due to frequent and smaller claims that make premiums feel less “worth it” without immediate payoffs (Chetty & Looney, 2006).



Figure 3 South Africa’s premium margins

### 6.1.1.3 Post estimation maximum indemnity analysis

The analysis of demand for types of insurance with changes in maximum pay-outs can be identified in margins in Figure 4 below which shows changes in demand with an increase in maximum payout. The demand for health increases from around 15% probability of selection at a maximum payout of R50,000 to approximately 45% probability of selection at R350 0000 which is also in line with a priory expectation in Table 3 above. Whilst for property insurance and agriculture insurance the maximum payout tends to have a higher probability of selection when they are low and low as the maximum payout increases, which is against the priory expectation.

The Zimbabwe model showed a significant positive effect of maximum indemnity coverage on demand (β = 5.76e-06, *p* = 0.004), reinforcing the idea that higher potential payouts increase uptake. This is strongly supported by margins for the health domain, where demand increases steeply as coverage rises which suggests households are value-sensitive and they will probably purchase when the benefits outweigh the cost (Clarke & Dercon, 2016).

Interestingly, agricultural and property domains showed flat or declining marginal responses, which may reflect perceived uncertainty in claim delivery, or a low perceived risk of total loss in those domains. This aligns with findings by Janzen and Carter (2019), who found that in East Africa, unless farmers believe payouts are timely and fair, increasing coverage does not translate to greater uptake.

Another possible explanation is bounded rationality in which, households may struggle to evaluate the utility of high indemnity levels, especially when historical claims have been rare or abstract. This suggests that risk communication and scenario-based education (e.g., simulations or testimonials) could improve the uptake of higher-cover policies.

Overall, the results emphasize that in Zimbabwe, coverage generosity is a critical incentive, especially for health insurance, but must be accompanied by trust-building efforts for non-health domains.



Figure 4 Zimbabwe’s Maximum payout

Source: Author Compilation

Whilst the analysis for South Africa showshow that the margins of the demand for the three types of insurance from R50 000-R350 000 maximum pay out. The margin results of the study are shown in Figure 7.4 below the results of the study show that for health the higher the insurance maximum pay-out the higher the probability of selection from 22% to 45% at 50 000 and 350 000 respectively. Whilst the behaviour of property and agriculture is not in light with the priory expectations the higher the maximum pay-out the lower the demand.

In South Africa, the maximum indemnity variable was not statistically significant in the model (β = 2.64e-06, *p* = 0.320), and the margins plots confirm this, showing only modest or flat increases in insurance uptake across domains. This suggests that coverage amount alone is not a decisive factor for South African consumers.

This result may reflect the relative financial resilience of the South African population, who may not rely on insurance solely for catastrophic relief. Studies have shown that where formal credit markets and public safety nets are more developed, the appeal of large payouts diminishes unless paired with other benefits like value-added services or loyalty schemes (Karlan et al., 2014; Mapfumo et al., 2021).

Additionally, the modest positive trend for health domain uptake with higher coverage in the margins indicates that people still recognize value in large payouts for high-frequency risks, but the flat trends in agriculture and property may point to limited trust or perceived need, especially if past hazard exposure has been low or manageable.

This implies that in South Africa, product design should emphasize flexibility, provider credibility, and add-on services rather than just increasing coverage levels. Policymakers should also explore behavioral nudges, such as framing or peer comparisons, to make indemnity levels feel more relevant and desirable (Tversky & Kahneman, 1991).



Figure 5 Maximum payout predictive margin

Source: Author Compilation b

### Discussion

The conditional logit results for both countries reveal distinct patterns in how citizens perceive and value insurance attributes. The results for Zimbabwe shown in Table 4 above reveal that the significant predictors of insurance demand include premium level, maximum indemnity (Maxi), transparency, payout time, and domain of coverage. Specifically, premium has a negative and statistically significant coefficient (β = -0.005, p < 0.01). The results of the study further reveal that higher premiums reduce the likelihood of selecting an insurance product which is consistent with classic price sensitivity in (McIntosh et al., 2013; Cole et al., 2014). In contrast, maximum cover is positively associated with demand (β = 5.76e-06, p = 0.004), suggesting households value products offering greater financial protection. Transparency (β = 0.206, p = 0.015) significantly increases uptake, echoing evidence that trust and clarity in product terms enhance insurance participation (Dercon et al., 2014).

Whilst the results of South African model presented in Table 5 above similarly identifies significant attributes from provider type and payout delay. Premium has a negative but statistically insignificant effect (β = -0.003, p = 0.134), implying a relatively muted price sensitivity compared to Zimbabwe. Government (β = 0.295, p = 0.017) and NGO providers (β = 0.370, p = 0.061) positively affect insurance uptake which can be explained by the role of institutional trust and credibility of NGOs (Karlan et al., 2016). It is important to note that NGOs are more connected with the community since they are part of the first responders, and they provide educational services to reduce risk. It is also important to note that some of the assistance provided in partnership arrangements between government and NGOs were executed by NGOs leading to higher trust in NGOs. The strong significance of the alternative-specific constant (ASC = -13.725, p < 0.001) implies a baseline reluctance to adopt insurance absent favourable features.

Domain preferences diverge between countries. In Zimbabwe, agriculture is significantly preferred over health (base category), while property is marginally significant and negatively associated (β = -0.355, p = 0.057). In contrast, South Africans do not show significant preferences across domains, though both agriculture and property have negative coefficients. This may reflect Zimbabwean respondents’ higher exposure to agricultural risks and more immediate interest in farming-related coverage.

Whilst the analysis of premium margins shown on Figures 1 and 2 (premium margins) show clear differences in how insurance premiums interact with domain preferences. The results in Zimbabwe show that, the probability of selecting health insurance sharply declines as premiums increase, starting at approximately 0.6 and dropping to below 0.2. Agriculture demand increases steadily with premium, suggesting that higher-priced agricultural coverage may be associated with better coverage or perceived reliability. Property-related demand also rises modestly with premium. This inverted trend for health coverage may indicate that it is perceived as less essential or less effective in managing disaster risks compared to agriculture, where insurance is directly tied to economic survival (Hazell & Pomareda, 2012). Whilst in contrast the results in South Africa reveal that premium increases affect all domains more moderately. Health demand again declines with premium but at a slower rate. Agriculture and property preferences both exhibit upward trends, with agriculture’s predictive margin rising from below 0.2 to over 0.5. These patterns may reflect higher baseline income and financial literacy levels in South Africa, where individuals are more responsive to the value offered by insurance than to price alone (Giné & Yang, 2009; Cole et al., 2013).

This divergence suggests that while price remains a barrier in both countries, product value perception—particularly for agriculture—plays a greater role in South Africa. The trend supports findings by Clarke and Dercon (2016), who highlight the importance of aligning premium cost with meaningful, visible benefits in low- and middle-income contexts.

 The results of the premium margins provide partial information of the analysis, and the study further looks at the margins of the maximum coverage (indemnity) shown in Figures 3 and 4. The results in Zimbabwe reveal that, the probability of selecting health insurance increases significantly with coverage, rising from around 0.2 to nearly 0.5, while property and agriculture show declining trends. This highlights a unique contrast: while premium sensitivity for health insurance is high, demand rebounds strongly when generous coverage is offered. It indicates that Zimbabweans may only consider health insurance worthwhile if it offers substantial financial protection—consistent with previous studies showing high thresholds of perceived benefit required to justify insurance purchase (Takahashi et al., 2016). Whilst in South Africa, all domain margins respond more positively to increased coverage. Health demand rises steadily and surpasses other domains at higher coverage levels, reaching over 0.5. Property shows a mild decline, and agriculture is relatively flat, suggesting less sensitivity to maximum cover. This suggests that South Africans place high value on extensive protection in health, which may reflect more mature health infrastructure and higher expectations from formal insurance (Osei-Asare & Premand, 2020).

The margin results from both countries reinforce the finding that maximum coverage can significantly influence uptake, especially when premiums are high. This supports literature arguing that demand can be improved not by lowering premiums alone, but by increasing perceived value through generous and prompt indemnity (Janzen et al., 2016; Heltberg et al., 2015).

## 8.. Implications for Policy and Design

These findings yield several policy insights which include the need for subsidies and tiered pricing in Zimbabwe since premium sensitivity is high, especially for health insurance. Offering subsidized or tiered pricing for vulnerable groups could improve uptake. Given the strong demand for agricultural insurance even at higher premiums, there is potential to develop more market-based products in this domain. The results of the study also show the need for product tailoring and marketing in South Africa, which are NGO and government backed to significantly raise demand. Thus, public-private partnerships can be instrumental. Insurance campaigns should emphasize transparent terms, payout speed, and maximum coverage benefits to shift focus from price to value. The results of the study also show the need for differentiated strategies across domains because of the clear differences in how domains are valued suggest that a one-size-fits-all approach may be inefficient. For example, promoting health insurance in Zimbabwe may require stronger incentives and trust-building, while agricultural insurance could be bundled with other farming inputs. From the behavioural interventions there is need for development of trust because Low institutional trust can complexity reduce demand, as noted in other studies (Takahashi et al., 2019). Simplifying policies, increasing financial literacy, and leveraging trusted providers could enhance willingness to insure.

## 9. Limitations and Future Research

While the choice experiment approach captures stated preferences robustly, future research could complement it with revealed preference data or panel studies post-policy rollout. Additionally, qualitative research could explore the psychological and cultural drivers behind domain preferences and trust in providers.

### Reference list

1. Akter, S., Brouwer, R., van Beukering, P. J. H., French, L., Silver, E., Choudhury, S., & Aziz, S. (2009). Exploring the feasibility of private micro flood insurance provision in Bangladesh. *Disasters, 35*(2), 287–307. <https://doi.org/10.1111/j.1467-7717.2010.01158.x>
2. Botzen, W. J. W., & Van den Bergh, J. C. J. M. (2012). Risk attitudes to low-probability climate change risks: WTP for flood insurance. *Journal of Economic Behavior & Organization, 82*(1), 151–166. <https://doi.org/10.1016/j.jebo.2012.01.005>
3. Brody, S. D., Blessing, R., Sebastian, A., & Bedient, P. B. (2017). Examining the impact of land use/land cover characteristics on flood losses. *Journal of Environmental Planning and Management, 60*(3), 447–465. <https://doi.org/10.1080/09640568.2016.1162706>
4. Brouwer, R., Akter, S., Brander, L. M., & Haque, E. (2014). Socioeconomic vulnerability and adaptation to environmental risk: A case study of climate change and flooding in Bangladesh. *Risk Analysis, 34*(1), 98–113. <https://doi.org/10.1111/risa.12099>
5. Charness, G., Gneezy, U., & Imas, A. (2013). Experimental methods: Eliciting risk preferences. *Journal of Economic Behavior & Organization, 87*, 43–51. <https://doi.org/10.1016/j.jebo.2012.12.023>
6. Grothmann, T., & Reusswig, F. (2006). People at risk of flooding: Why some residents take precautionary action while others do not. *Natural Hazards, 38*(1–2), 101–120. <https://doi.org/10.1007/s11069-005-8604-6>
7. Hudson, D., Houssou, N., & Gebregziabher, G. (2017). Demand for weather index insurance: A field experiment in Ethiopia. *Agricultural Economics, 48*(3), 291–303. <https://doi.org/10.1111/agec.12331>
8. IPCC. (2021). *Climate Change 2021: The Physical Science Basis*. Intergovernmental Panel on Climate Change. <https://www.ipcc.ch/report/ar6/wg1/>
9. Kunreuther, H., & Pauly, M. (2006). Rules rather than discretion: Lessons from Hurricane Katrina. *Journal of Risk and Uncertainty, 33*(1), 101–116. <https://doi.org/10.1007/s11166-006-0173-z>
10. Liu, E. M., & Huang, J. (2019). Risk preferences and demand for insurance in developing countries: Evidence from China. *American Economic Journal: Applied Economics, 11*(2), 68–102. <https://doi.org/10.1257/app.20160401>
11. Maddux, J. E., & Rogers, R. W. (1983). Protection motivation theory and self-efficacy: A revised theory of fear appeals and attitude change. *Journal of Experimental Social Psychology, 19*(5), 469–479. [https://doi.org/10.1016/0022-1031(83)90023-9](https://doi.org/10.1016/0022-1031%2883%2990023-9)
12. Mahaprashasta, A., Das, U. K., & Shah, M. (2021). Risk preferences after natural disasters. *Review of Development Economics, 25*(4), 1856–1876. <https://doi.org/10.1111/rode.12797>
13. Mangham, L. J., Hanson, K., & McPake, B. (2009). How to do (or not to do)... Designing a discrete choice experiment for application in a low-income country. *Health Policy and Planning, 24*(2), 151–158. <https://doi.org/10.1093/heapol/czn047>
14. McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in Econometrics* (pp. 105–142). Academic Press.
15. Michel-Kerjan, E., & Kunreuther, H. (2011). Redesigning flood insurance. *Science, 333*(6041), 408–409. <https://doi.org/10.1126/science.1202616>
16. Oduniyi, O. S., Antwi, M. A., & Tekana, S. S. (2020). Factors affecting the willingness-to-pay for cattle insurance among smallholder cattle farmers in Gauteng Province, South Africa. *South African Journal of Economic and Management Sciences, 23*(1), 1–8. <https://doi.org/10.4102/sajems.v23i1.3057>
17. Reynaud, A., & Nguyen, M. (2018). Is there a demand for flood insurance in Vietnam? Results from a choice experiment. *Environmental Economics and Policy Studies, 20*(3), 593–618. <https://doi.org/10.1007/s10018-017-0193-2>
18. Reynaud, A., Nguyen, M., & Aubert, M. (2013). The influence of risk perception on insurance demand: Empirical evidence from a flood-prone region. *International Journal of Disaster Risk Reduction, 3*, 84–95. <https://doi.org/10.1016/j.ijdrr.2013.07.001>
19. Rogers, R. W. (1975). A protection motivation theory of fear appeals and attitude change. *The Journal of Psychology, 91*(1), 93–114. <https://doi.org/10.1080/00223980.1975.9915803>
20. Seifert, I., Botzen, W. J. W., & Kreibich, H. (2013). Awareness, precaution and insurance against flood risks: A survey among private households in Germany. *Risk Analysis, 33*(2), 313–323. <https://doi.org/10.1111/j.1539-6924.2012.01839.x>
21. Tanner, J. F., Day, E., & Crask, M. R. (1989). Protection motivation theory: An extension of fear appeals theory in communication. *Journal of Business Research, 19*(4), 267–276. [https://doi.org/10.1016/0148-2963(89)90006-9](https://doi.org/10.1016/0148-2963%2889%2990006-9)
22. Terris-Prestholt, F., Hanson, K., & Mills, A. (2019). Discrete choice experiments in low- and middle-income countries: A review of the literature. *Health Economics, 28*(2), 255–272. <https://doi.org/10.1002/hec.3833>
23. Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty, 5*(4), 297–323. <https://doi.org/10.1007/BF00122574>
24. UNDRR. (2020). *The human cost of disasters: An overview of the last 20 years (2000–2019)*. <https://www.undrr.org/>
25. UNISDR. (2015). *Sendai Framework for Disaster Risk Reduction 2015–2030*. <https://www.undrr.org/publication/sendai-framework-disaster-risk-reduction-2015-2030>
26. Vega, A., & Alpizar, F. (2011). Choice experiments in environmental economics: A review. *Journal of Forest Economics, 17*(3), 285–307. <https://doi.org/10.1016/j.jfe.2011.01.003>
27. Vikram, K., Choudhury, T., & Singh, A. (2018). Understanding demand for weather-based crop insurance in India. *World Development, 103*, 33–44. <https://doi.org/10.1016/j.worlddev.2017.10.019>
28. Wagner, G. (2019). Economic behavior and insurance decisions under risk and uncertainty. *Geneva Papers on Risk and Insurance – Issues and Practice, 44*(1), 78–98. <https://doi.org/10.1057/s41288-018-0097-8>
29. Zhang, L., & Qian, Y. (2018). Earthquake insurance demand in China: Evidence from the Wenchuan earthquake. *Natural Hazards, 93*(2), 723–741. <https://doi.org/10.1007/s11069-018-3322-z>