An investigation of Residential Insurance Demand-side Reaction Pre- and Post- Natural Catastrophe: A Case for 2010-11 Christchurch Earthquakes

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ABSTRACT

This paper gives an empirical analysis of post-Christchurch earthquakes insurance reactions using survey data. The paper aims to deduce a model framework that explains how the insurance marketed reacted and the insurance demand for residential property post natural disaster. This study starts by carrying out a descriptive statistical analysis, correlation analysis and simple regression using SPSS to tests the first research hypothesis. Next, a multinomial logistic regression model is used to assess the association between a set of household, insurance and natural disaster features that affect the level of insurance coverage while controlling for some of the characteristics. The regression model is employed to survey data collected from insured homeowner in Christchurch City. The paper uses multinomial logistic regression model to deduce an econometric framework that has dummy independent variables.

My goal is to use these categorical independent variables to explain variation in the quantitative dependent variable; change in the level of coverage, used to proxy insurance demand. In the end then, the analysis of the demand for residential and contents insurance using the survey data will not seek to put a specific number on the level of insurance demand post-Christchurch earthquakes. The result of the analysis demonstrates how the demanders' characteristics significantly contribute to the change in the level of insurance coverage hence change in insurance demand.

KEY: Residential Insurance; Christchurch Earthquakes; Natural Disaster.

Introduction

Insurance sector played a very pivotal role in the re-build of Canterbury region after the devastation quakes of 2010/2011. This paper is as a result of investigations that we began in January 2014 to examine the reactions, both supply-side and demand-side, of the insurance industry in the wake of these two catastrophes. The paper focuses on the demand-side aspect of residential property insurance coverage. The key interests in the demand-side reactions centres on analysis of the change in the level of insurance coverage and all the variables that contributes to changes in insurance demand post-loss. In this analysis of residential and contents insurance demand, the study does not seek to calculate a specific value on the demand for insurance post-earthquakes. The study will instead seek to first demonstrate how the amount of premium the property owners a willing to pay in the new contract arrangement is associated with the property value and the income of the property owner. The study goes further to investigate how various insurance demand variables affect the level of insurance coverage post-catastrophe using a multinomial logistic regression model. Lastly, the study formulates a central research question that investigates how the demand and supply for residential insurance reacted to changes caused by the quakes. This research question is crucial in understanding how the insurance demanders have adjusted their level of insurance as a result of the contracts modifications and insurance demand determinants variables.

We thus start with simple statistic for determinants of insurance demand and other demand associated variable to examine whether this variable have significant association with the some specific household demographic characteristics. In essence then, the first step is to carry out a descriptive statistical analysis, correlation analysis and simple regression using SPSS to tests our first research hypothesis. The descriptive statistical analysis will be based on results of Frequencies-tabulations and Crosstabulation. Crosstabulation is a powerful technique that helps to describe the relationships between categorical (nominal or ordinal) variables. With

Crosstabulation, we can produce statistics such as, Observed Counts and %ages, Expected Counts and %ages, Residuals and Chi-Square. Chi-Square tests the hypothesis that the row and column variables are independent, without indicating strength or direction of the relationship.

All the analysis will input a set of household independent variable that determines insurance level coverage, a set insurance coverage parameters that determines insurance demand and supply and the natural disaster characteristics that affect residential insurance coverage. Survey responses to these three combinations of variables are rigorously analysis to examine how the Canterbury catastrophe has impacted the residential property and contents insurance industry and how insurance consumers have reacted to these catastrophic events.

First is the category of characterises that tells us about the insured individual who want to buy insurance coverage which includes; age, income, gender, education. For the two genders we would like to see how different gender adjusts their insurance level post-disaster. So in the end, we would be able to look at, for example how female property owner think about residential insurance compared to their male counterpart property owner categories. Similarly, the analysis looks at age categories: young, middle-aged and old-aged property owners to identify if there are any age-differences in residential insurance buying characteristics. Rather than using ages in years in the multinomial logistic regression model, we use age dummies to allow for the flexible and non-linear age effects. Thus, we create three age dummies: 18-40 (for young), 41-60(for middle-aged) and 61 years and older (for old-aged). "61 years and older'' is the reference age group. Next we look into the education category, so here we would be looking at the differences in education attainment levels and how these affect the change in coverage level. Why we use education level in the survey questionnaire is because, education level is a key demographic determinant that is expected to have a positive impact on the insurance demand (Dragos, 2014). In most academic literatures, the education attainment levels for an individual is used as a proxy for risk aversion, however there are differences in the results obtained for both non-life and life insurance sectors. For example in non-life an individual's education level is positively related to greater risk aversion. Since my analysis puts emphasis on the effects of the education level to the residential insurance which belongs to non-life insurance sector; this study adopts research opinion that converge towards the proposition, education positively influences the insurance demand for residential property. For the purposes of our multinomial logistic regression model, we set three dummy variables; high school graduate, university graduate and postgraduate and others. When interpreting our regression results, we use "postgraduate and others'' as the reference education level category.

Similar transformation is done to create dummy for all the variables of interest such that we come-up with a new set of dummy variables that can be regressed in our model. Once all this is done we do not need to put the entire dummy variable into the regression model all at once. Therefore we end-up with primary independent dummy variable of interest grouped in to two categories: a set of household general features that affect the level of insurance coverage, which includes; age, gender, income and property value and specific insurance coverage and post-natural disaster perceptions that affect how insured make decision and attitude toward insurance coverage , which includes; probability of occurrence of natural disaster, amount of premium charged, changed in the premium rates, change in risk perception and change in the perception of insurance coverage per dollar post-catastrophe. More importantly we can also look at how age, gender and education influence some of the other household characteristics like income and property value. For example, it is safe to suggest that a highly educated middle-aged male who earns more income or own property of high value have different risk perception than their less educated young-age male.

Review of Previous Literature on Post Catastrophe Experience

There is varying evidence of how post-catastrophe experience impacts insurance for demand. (Slovic, Kunreuther, & White, 1974) was the first to postulate in over-reaction by economic agents in the aftermath of a new disaster. Since then, natural disasters have gained attention because there are increasing findings, more recently from (Aseervatham, Born, Lohmaier, & Richter, 2015; R. E. Dumm, Eckles, Nyce, & Volkman-Wise, 2015), to show insurance consumers over-react to the occurrence of a new disaster. (Seog, 2008) theoretically demonstrate that catastrophic events leads to increases in insurance demand when there is increase in public information regarding a disaster.(Browne & Hoyt, 2000) analyse effect of catastrophic events on demand for insurance using state-level from U.S. for a period of 10 years. The authors found that higher premium rates post-disaster leads to depressed demand when considering flood insurance. However, the authors point that this pattern could be consistent with the low demand seen prior to a disaster, but does not support the increased demand post-disaster, when premium rates are higher.

Working on the same U.S. National Flood Insurance Program (Michel-Kerjan & Kousky, 2010) finds policy limits associated with this flood insurance program are increased and more policies are purchased after a flood occurs. This sends signals that once there is extreme catastrophic event like heavy floods, individuals over-weight the probability of a future flood and demand more insurance. (Gallagher, 2010) tries to estimate the change in probability that occurs in the aftermath of floods using panel dataset of floods and the take-up of flood insurance in the US. The author provides new evidence on how individuals update their beliefs over an uncertainty of rare events. Most importantly, they found out that the consumption of insurance is completely flat in the years before a flood, prickle immediately following a flood, and then steadily diminishes to pre-floods level. (Camerer & Kunreuther, 1989; Cohen, Etner, & Jeleva, 2008; Ganderton, Brookshire, McKee, Stewart, & Thurston, 2000; Kirsch, 1986; McClelland, Schulze, & Coursey, 1993; Palm, 1995; Shanteau & Hall, 1992) analysis on insurance demand reactions in the aftermath of a catastrophe, they suggest that insureds have the belief that the probability of an event is lowered when that event has already occurred. (Papon, 2008) study also suggests that prior risk occurrences influence subsequent insurance choices. Although several papers make the case for risk perceptions affecting natural disaster insurance decisions (Braun & Muermann, 2004; Kousky, Luttmer, & Zeckhauser, 2006; Kunreuther, 1984; Kunreuther, Meszaros, Hogarth, & Spranca, 1995; Manson, 2006; Michel-Kerjan & Kousky, 2010), shows that there is very little empirical work on how insurance demanders use their heuristic probability rule to update their past insurance coverage. (Born & Viscusi, 2006) finds that major catastrophes may reduce the quantity of insurance written, because of the higher rates and insurance rationing, as well as exiting of firms from the market. Similarly (West & Lenze, 1994) argues that heavily flooding hurricanes are exemplified by relatively low insurance coverage.

In the analysis of determinants for insurance demand, (Browne & Kim, 1993) explains that a higher level of education is a good proxy to measure the risk aversion. Thus, more risk-averse individuals due to higher education attainment positively influence the demand for non-life products. (J Francois Outreville, 1996) also supports the view expressed by (Browne & Kim, 1993). In the same line (Dzaja, 2013) suggested that education increases individuals risk aversion and encourages people to demand insurance. (Treerattanapun, 2011) points out that high education attainment increases the understanding of risk and threats to financial stability, helping the understanding of insurance benefits. (Park & Lemaire, 2012) analysis on 82 countries for a period of 10 years also found a positive relation between education and non-life insurance demand levels. (Ofoghi & Farsangi, 2013) demonstrated a significant and positive relationship between risk aversion and auto insurance demand, in which those with insurance knowledge are more risk-averse.

Research Hypothesis

Based on findings of previous studies and empirical observation of the New Zealand insurance industry in the aftermath of Canterbury two major earthquakes, we construct three research hypotheses. The aftermath of Canterbury disasters necessitated the insurance and the re-insurance companies to modify the residential insurance contracts. The insured are supposed to nominate a sum insured to which the insurer is liable to pay in the event of another disaster. This means the premium rates will be heavily depended on value of sum insured as nominated by the insured. This contract modification motivates the first research hypothesis.

Hypothesis I: *There is positive association between annual premium the insurance demanders are willing to pay to fully protect their property and contents through insurance mechanism, their property value and their annual household income.*

This particular research hypothesis tests if indeed the household income and the property value affect how much premium an insurance demander will be willing to pay to protect their property. In general the test will show whether there is any association between the three variables by carrying out a descriptive analysis. In the end then, this study using the above hypothesis will establish how the catastrophes affect expenditure on insurance coverage for a predetermine sum insured and hence demand for residential and contents insurance coverage.

The hypothesis draws from the findings in the prior literature. For example, in (Tooth, 2015), the implied income elasticity for the take-up of house insurance is around 0.02, suggesting that (after controlling for other factors) a 1 per cent increase in income would only result in a 0.01 to 0.02 per cent increase in the likelihood a household has house insurance cover. The other important findings is by (Showers & Shotick, 1994) which analysed data from the 1987 US Consumer Expenditure Survey to assess the effects of age, income and household characteristics on total insurance expenditure. Of note they found insurance expenditure to be positively related to income, age and size of household and that the marginal importance of income to be greater for small households.

Hypothesis II: *Demographic characteristic of households positively influences the demand for residential insurance cover in the aftermath of a Natural Disaster.*

Individual insurance consumers' risk aversion is highly affected by some of the major demographic characteristics like, value of insured asset, income, age amongst other features. The degree of risk aversion is a key determinant of insurance demand: this study uses the demographic characteristic of households living in Canterbury region to proxy risk aversion. Our demographic characteristic of household includes; age, gender, level of education, incomes, and property value.

In the insurance literature, the level of risk aversion is hypothesised to be positively correlated with insurance consumption of an individual. Numerous empirical studies (Beck & Webb, 2003; Browne & Kim, 1993; Hwang & Gao, 2003) have demonstrated a positive and significant relationship between insurance demand and the level of education which would hence imply a higher level of education may lead to a greater degree of risk aversion and greater awareness of the necessity of insurance coverage. However, in macroeconomic and cross-section studies, this hypothesis does not always hold and it cannot always be suggested that there is a positive correlation between risk aversion and the level of education. For instance,(J François Outreville, 2014) survey of the relationship between risk aversion and education shows negative relationship. Implying that, higher education leads to lower risk aversion that in turn leads to more risk-taking by highly-educated individuals.

(Aliagha, Jin, Choong, Nadzri Jaafar, & Ali, 2014) examines the role of income level and education level while purchasing flood insurance for residential properties. Their study finds that the propensity to purchase flood insurance increases significantly with income levels while education level does not make much difference. They suggest that, the increase is likely as a result of property owners suffering greater losses of wealth (accumulated savings from income) from the previous catastrophic floods that increases their risk aversion. With (Guiso & Paiella, 2008) pointing that households that face income uncertainty or suffered loss of income from severe natural disaster show evidence of a greater degree of risk aversion. Similarly, (Showers & Shotick, 1994) used US consumer expenditure survey to assess the effects of age, income and household characteristics on total insurance expenditure: they found insurance expenditure to be positively related to income, age and size of household and that the marginal importance of income to be greater for small households.

Hypothesis III: *Change in risk perception influences the demand for residential insurance cover in the aftermath of a Natural Disaster.*

Insurers normally assess risk by making best estimates of the frequency and severity of a hazard using statistical techniques or catastrophe models. However, expert's generated perception risk information often has small influence on decision making about risk by lay person (Kunreuther, Novemsky, & Kahneman, 2001). (R. E. Dumm et al., 2015; Papon, 2008; Viscusi, 1985) suggests that, individuals often use heuristics simple rules when they are assessing risk. Thus, individuals may judge an event as risky if it is easy to imagine or recall; for example, individuals who have experienced the Christchurch earthquakes may find it easier to imagine that the disaster could happen again in the future and therefore feel a higher perceived risk than individuals without this experience. Thus with this analysis, we are in a position to study how this sentimental feeling is used to judge the level of risks. Obviously, we expect people in the affected region to have a higher risk perception. If natural hazard are associated with negative feeling which can have been caused or reinforced by experiences of damage caused by natural hazard then we hypothesis this will drive the demand for residential insurance up and this will be reflected in our proxy increase in the level of insurance coverage.

Research Question I: *How the supply and demand for residential insurance reacts to changes in the aftermath of a catastrophic event?*

So far, using the intertemporal model for two period (pre- and post-loss) our findings shows that demand for insurance after loss increases and if no loss demands for insurance falls. Research Question One seeks to go further, using empirical data from the survey, to show how variables that affect demand have changed post-Canterbury earthquakes. To examine the post-catastrophe insurance supply and demand reactions, we set out four variables that prior literature suggests have an immediate reaction from natural disaster. The four set of variable are used to explore out if there are any general reaction that in the end affect the insurance demand or insurance supply.

The first variable examined the perception by the survey respondents towards the probability of loss from another earthquake. Since many insurance demanders do not mathematical compute the level of risk they use heuristic rule as a strategy that reduces the complex tasks of assessing probabilities and predicting values to simpler judgmental operations (Raschky & Weck-Hannemann, 2007; Rothschild & Stiglitz, 1992; Slovic, Fischhoff, Lichtenstein, Corrigan, & Combs, 1977).

The second variable examines the supply-side reaction from demander's perspective. The survey question set-out to investigate whether natural disaster impacts the supply of insurance to the affected market. This looks at the availability of insurance coverage post-quakes. Previous literature suggests catastrophes suppress insurance supply. (Parker & Steenkamp, 2012) studies immediately after the Canterbury quakes finds that; A few insurers were in the process of exiting the New Zealand market or limiting their exposures. For households and businesses, they also find restricted availability of insurance to cover construction of new buildings hampered investment and the rebuild process.

The third variable examines how insured property value reacts to catastrophes. The study on this variable want to reveal out if there are any changes in property value post natural disaster and how the property value impacts on the insurance premium. It seems reasonable to postulate that rational property buyer behaviour in regard to residential insurance should reflect price-efficient policies relative to disaster risk exposure. In the end, it is possible to show in general how the property value and insurance premium have impacted insurance demand. Natural disaster literatures try to outline the various social and economic impacts of different disasters by examining changing property values in disaster prone areas. These studies have essentially had the same goal of modelling disaster impacts to property value, but their methods have differed and the findings have often been contradictory. While it would seem reasonable to hypothesize that an event like floods or earthquake would have a negative effect on property value; this has not always been supported by the literature. (R. Dumm, Nyce, Sirmans, & Smersh, 2012) model implies that increases in insurance premiums due to a re-evaluation of expected loss following a natural disaster would lower property values. (Parker & Steenkamp, 2012) finds that property prices suggested that the loss of residential properties outstripped the loss of population, generating some excess demand for housing around Canterbury. Rents for new rental contracts had increased by 18 % in Christchurch since the end of 2010, compared with the 7 % increase nationwide.

The fourth variable examines how household expenditure on insurance changed in the aftermaths of the quakes.

Research Method

Our Modelling Framework

Our modelling framework is based on the logistic regression analysis model. In regression analysis, the common discussion is about how to find a relationship between endogenous variable y_i and a set of explanatory variables $x_1, x_1, ..., x_n$ expressed as: $y_i = f_i(x_1, x_1, ..., x_n)$.

If the outcome of endogenous variable y_i is a dichotomy with values 1 and 0, and say define $p_i = E(y_i / x_{ni})$, which is now the probability that y_i is 1, given some value of the explanatory variable x.

Then a logistic regression model can be derived from a linear probability models as follow

$$p_i = \alpha_0 + \alpha_1 x_{1i} + \alpha_2 x_{2i} + ... + \alpha_n x_{ni}$$

Since the logistic model assumes that the natural log of the odds $p/(p-1)$ is a linear function of the explanatory variables. This can be written in the form:

$$ln[p_i/(p_i - 1)] = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_n x_{ni} + \varepsilon_i$$

Thus, using (equation 2) the multinomial logistic regression model for this study is expressed in form:

$$y_i = \alpha_i + \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_n x_{ni} + \varepsilon_i$$

The multinomial logistic regression model used is generally effective where the dependent variable is composed of a polychromous category having multiple choices. The basic concept was generalized from binary logistic regression as proposed in (Agresti & Kateri, 2011; Starkweather & Moske, 2011).

In this study, our model framework aims to explain the demand for residential property and contents insurance post natural disaster. In our survey data, this is measured by the proxy changed in level of insurance coverage. When we replace the parameters of multinomial logistic regression equation above with our survey variables; then, the modelling equation to estimate the changed in the level of insurance coverage (used to proxy demand for insurance)is given as:

$$
\begin{aligned}
&\textit{Change in level of} \\
&\textit{insurance coverage} = \alpha + \beta_1(\textit{measure of INCOME}) \\
&\qquad + \beta_2(\textit{change in PREMIUM post-loss}) \\
&\qquad + \beta_3(\textit{NATURAL DISASTER consideration before purchase of property}) \\
&\qquad + \beta_4(\textit{measure of PROPERTY VALUE to be insured}) \\
&\qquad + \beta_5(\textit{change in LEVEL OF RISK post-loss}) \\
&\qquad + \beta_6(\textit{dummy household demographic features: AGE, GENDER \& EDUCATION} \\
&\qquad + \textit{error term}
\end{aligned}
$$

To this end then, the above modelling equation is used to assess the association between household, insurance and natural disaster features that affect the level of insurance coverage. Thus why our analysis uses multinomial logistic regression model, which can be a useful tool for modeling where the dependent variable is a discrete set of more than two choices (Agresti, 1996). The multinomial logistic regression model used in this study estimates the effect of the individual variables on the probability of changing the level of insurance coverage.

Data

This study uses data from online survey conducted through random sampling of employees from four major public organisations, University of Canterbury, Christchurch Polytechnic Institute of Technology (ARA Institute), Christchurch Airport and Christchurch Women's Hospital: all these organisations are domiciled in Canterbury region. This organisation where selected to provide the region's representative estimates of residential properties affected by the 2010/11 quakes. The survey was designed for the primary purpose of collecting data on pre- and post- catastrophe reactions specifically focusing on purchase of Home Insurance. The sample of interest consisted of those homeowners insured with the local private insurance companies. The survey aimed to collect individual-level information that literature suggests should be important determinants of home insurance demand. In compiling this dataset, we intended to examine the influence of each of these factors on home insurance demand in a multinomial logistic regression framework.

Detailed Data Collection Process

The process of putting together a survey questionnaire began in the early months of 2015. After a series of refinement editing, and taking in to account all the comments from varying stakeholders, the first draft of the questionnaire was ready by May 2015.

All data collection activities necessitated conformity to standard procedures for conducting household surveys. In this light, the process sought survey approval (i.e. sampling, survey design, and reporting methodologies) from the University of Canterbury ethics committee which was cleared by June 2015.

In the aftermaths of the quakes, many homeowners left their damaged homes to new suburbs or relocated to other cities. Online survey was hence considered as the most efficient survey method. The University's Qualtrics survey tool, which is jointly administered by Academic

Services Group and the Centre for Evaluation and Monitoring, was the preferred survey tool. Most importantly, the use of a number survey tools such as SurveyMonkey, is discouraged for official University research purposes. (To delete)

The University Communication Office distributed the qualtric survey link on June 28, 2015 via the University weekly e-newsletter on my behalf. However, this did not yield anticipated results, only got a paltry 7 responses from the University Communications invitation. Next, I took a more direct approach and emailed the staff directly appealing to them of their research support by taking time to complete the survey. The second survey invitations included the Christchurch Polytechnic Institute of Technology, Christchurch Airport and Christchurch Women Hospital whose emails were gathered from publicly available websites. In total, 1600 emails were sent between September and November 2015 some of which I had no means of ascertaining their email address validity. The participation rate in the second data gathering exercise was better; an additional 229 responses was received by end of December 2015. In total, the survey was closed with 254 responses. The next stage entailed sorting and cleaning the compiled data. A close look into all the completed log-ins found that 24 of questionnaires were started but not totally completed. In addition, 18 participants responded via my email expressing their ineligibility to participate; 3 all their claims were covered by EQC, 8 didn't own residential property and 7 were not residing in Christchurch during the earthquakes. In the end, 212 responses out of 254 have the required information for analysis.

Pilot Tests

One pilot test was conducted to ensure that the survey design and materials would capture the data necessary to meet the survey objectives. First, focus groups of 10 emails were sent to examine the respondent rate and factors that affect participation in the post-catastrophe survey or might hinder accurate completion of the survey. Focus group results were used to revise survey questionnaire and other respondent materials prior to the full survey. Based on the pilot test results, improvements were made in the invitation email and minor text changes were made to the questionnaire title.

Results and Discussions

This section gives summary of results and discussions of descriptive analysis and multinomial logistic regression to answer our research hypothesis.

In order to investigate the association between annual premiums insurance demanders are willing to pay to fully protect their homes, property value and annual household income, this study employed descriptive analysis using SPSS.

The results of the analysis are reported in Tables 1- 8.

Table 1: Correlation analysis for Hypothesis I (Premium versus Income)

		Annual income	Amount of premium willing to pay per annum to fully protect property and contents through insurance
Annual income	Pearson Correlation	1	.233**
	Sig. (2-tailed)		.001
	N	208	205
Amount of premium willing to pay per annum to fully protect property and contents through insurance	Pearson Correlation	.233**	1
	Sig. (2-tailed)	.001	
	N	205	208

**. Correlation is significant at the 0.01 level (2-tailed).

If we refer to the first hypothesis, the computed correlation coefficient value for premium versus income is reported in **Table 1** as 0.233 and the associated *p*-value is 0.001. Because the observed *p*-value is less than alpha value (i.e. *p*-value = 0 .001< 0.05) the results are considered statistically significant. While the data is significant at the 0.05 level, the computed coefficient value is closer to 0 than to +1. Therefore with results, R = 0.233, N = 211, *p*-value = 0.001, it can be concluded that the study finds a weak positive linear relationship between the annual premium an insurance demanders are willing to pay and their income. The weak relationship of premium and income is not surprising given that the analysis excludes other variables such as the value of contents and age that are closely correlated with income. The results for income versus premium are consistent with the analysis on house insurance in that controlling for other factors, income by itself should not be a major determinant of demand for insurance cover or the amount of premium demanders are willing to pay. This argument can be furthered by looking into a contingency table summary of income distribution against the hypothetical annual premium options. This crosstabulation analysis depicts the number of times each of the possible category combinations occurred in sample data on the two variables (annual premium an insurance demander is willing to pay and the annual household income).

Across all income categories, the vast majority of the sample respondent 42.4 % observed that they are willing to pay annual premium in the rage of $900 - $1200 to fully protect their property and contents through insurance mechanism; 31.7 % , of the sample respondents are willing to pay annual premium in the rage of above $1200; 20.5 % , of the sample is willing to pay annual premium in the rage of $600 - $900; and tiny minority 5.4 % , of the sample is willing to pay annual premium in the rage of below $600. The profile for income categories; below $14000 which is (0.00 %, 0.00 %, 0.0 % and 0.0 %) has been dropped out of the analysis. The profile for income categories $14001 - $48000 is (21.4 % , 7.4 % , 35.7 % and 35.7 %); for income categories $48001 - $70000 is (7.5 % , 35.8 % , 37.3 % and 19.4 %); and for income categories above $70000 is (2.4 % , 13.7 % , 46.0 % and 37.9 %) which essential do not departs from the total %ages profile of (4.4 % , 20.5 % , 43.4 % and 31.7 %).

Table 2 shows that the willingness to pay premium option $901 - $1200 among the sample insurance demanders on income bracket $48001 - $70000 and premium option above $1200 among the insurance demanders on income bracket above $70000 are relatively higher than other premium options and salary brackets in this study. Most importantly in this survey is that the vast majority of the respondents preferred maximum annual premium in the regions $901 - $1200. The same conclusions can also be justified by looking at the adjusted residuals (-0.5, -1.0 and 1.3) across all income brackets across this premium option.

Table 2: Crosstab of the amount premium insurance demander is willing to pay per annum to fully protect property and contents through insurance mechanism * Annual household income

			Annual income			
			b) $14001 - $48000	c) $48001 - $70000	d) Above $70000	Total
Amount of premium willing to pay per annum to fully protect property and contents through insurance	a) Below - $600	Count	3	5	3	11
		% within Amount of premium	27.3 %	45.5 %	27.3 %	100.0 %
		% within Annual income	21.4 %	7.5 %	2.4 %	5.4 %
		Adjusted Residual	2.8	.9	-2.3	
	b) $600 - $900	Count	1	24	17	42
		% within % within Amount of premium	2.4 %	57.1 %	40.5 %	100.0 %
		% within Annual income	7.1 %	35.8 %	13.7 %	20.5 %
		Adjusted Residual	-1.3	3.8	-3.0	
	c) $900 - $1,200	Count	5	25	57	87
		% within Amount of premium	5.7 %	28.7 %	65.5 %	100.0 %
		% within Annual income	35.7 %	37.3 %	46.0 %	42.4 %
		Adjusted Residual	-.5	-1.0	1.3	
	d) Above $1,200	Count	5	13	47	65
		% within Amount of premium	7.7 %	20.0 %	72.3 %	100.0 %
		% within Annual income	35.7 %	19.4 %	37.9 %	31.7 %
		Adjusted Residual	.3	-2.6	2.4	
Total		Count	14	67	124	205
		% within Amount of premium	6.8 %	32.7 %	60.5 %	100.0 %
		% within Annual income	100.0 %	100.0 %	100.0 %	100.0 %

This argument is based on the fact that under the null hypothesis that the two variables are independent, the adjusted residuals will have a standard normal distribution, i.e. have a mean of 0 and standard deviation of 1. So, an adjusted residual that is more than 1.96 (2.0 is used by convention) indicates that the number of cases in that cell is significantly larger than would be expected if the null hypothesis were true, with a significance level of 0.05. An adjusted residual that is less than -2.0 indicates that the number of cases in that cell is significantly smaller than would be expected if the null hypothesis were true. In summary the adjusted residual is a measure of how significant the cells (observed minus expected value) are to the chi-square value. Therefore when the cells are compare, the adjusted residual makes it easy to see which cells are contributing the most to the value, and which are contributing the least. Looking at the Crosstab, the computed Pearson Chi-Square statistics (26.672) and the associated *p*-value (0.001) figures alone, we could reject the null hypothesis, and report that there is a significance association between the annual premium the insurance demanders are willing to pay to fully protect their property and contents through insurance mechanism and the annual household income.

Table 3: Test for association between annual premium insurance demanders are willing to pay to fully protect property and contents through insurance mechanism and their annual household income

				Monte Carlo Sig. (2-sided)			Monte Carlo Sig. (1-sided)		
					99 % Confidence Interval			99 % Confidence Interval	
	Value	Df	Asymp. Sig. (2-sided)	Sig.	Lower Bound	Upper Bound	Sig.	Lower Bound	Upper Bound
Pearson Chi-Square	26.672[a]	6	.000	.000[b]	.000	.001			
Likelihood Ratio	24.022	6	.001	.001[b]	.000	.001			
Fisher's Exact Test	24.005			.000[b]	.000	.000			
Linear-by-Linear Association	11.092[c]	1	.001	.002[b]	.001	.002	.001[b]	.000	.002
N of Valid Cases	205								

a. 4 cells (33.3 %) have expected count less than 5. The minimum expected count is .75.

b. Based on 10000 sampled tables with starting seed 1993510611.

c. The standardized statistic is 3.330.

From Table 3, the *p-value* based on the Chi-square test is the tail area to the right of 26.672 from a chi-square distribution with 6 degrees of freedom. The computed *p-value* is 0.001 which is the basis for the rejection of the null hypothesis. However, the Chi-square test does not give any information on how the two variables are related or how strong the relationship is.

The statistics in Table 4 provides a measure of the strength of the association between the two variables. In this case, the low significant values for the Contingency Coefficient indicates that there is some relationship between the two variables (annual premium insurance demanders are willing to pay to fully protect property and contents through insurance mechanism and annual household income).

Table 4: Measure of the strength of association between annual premium insurance demanders are willing to pay to fully protect property and contents through insurance mechanism and annual household income

						Monte Carlo Sig.		
							99 % Confidence Interval	
		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.	Sig.	Lower Bound	Upper Bound
Nominal by Nominal	Contingency Coefficient	.339			.000	.000[c]	.000	.001
Interval by Interval	Pearson's R	.233	.075	3.416	.001[d]	.002[c]	.001	.002
Ordinal by Ordinal	Spearman Correlation	.242	.070	3.559	.000[d]	.001[c]	.000	.001
N of Valid Cases		205						

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on 10000 sampled tables with starting seed 1993510611.

d. Based on normal approximation.

The value of the test statistics is small, 0.339, an indication that the positive relationship between the two variables is a fairly moderate one. In the previous, an attempt was made to make the contingency coefficient to always range between 0 and 1 but not all conform to this (Janson & Vegelius, 1979; Mehta & Patel, 1989).

Figure 1: Distribution of annual premium insurance demanders are willing to pay Vs Annual income

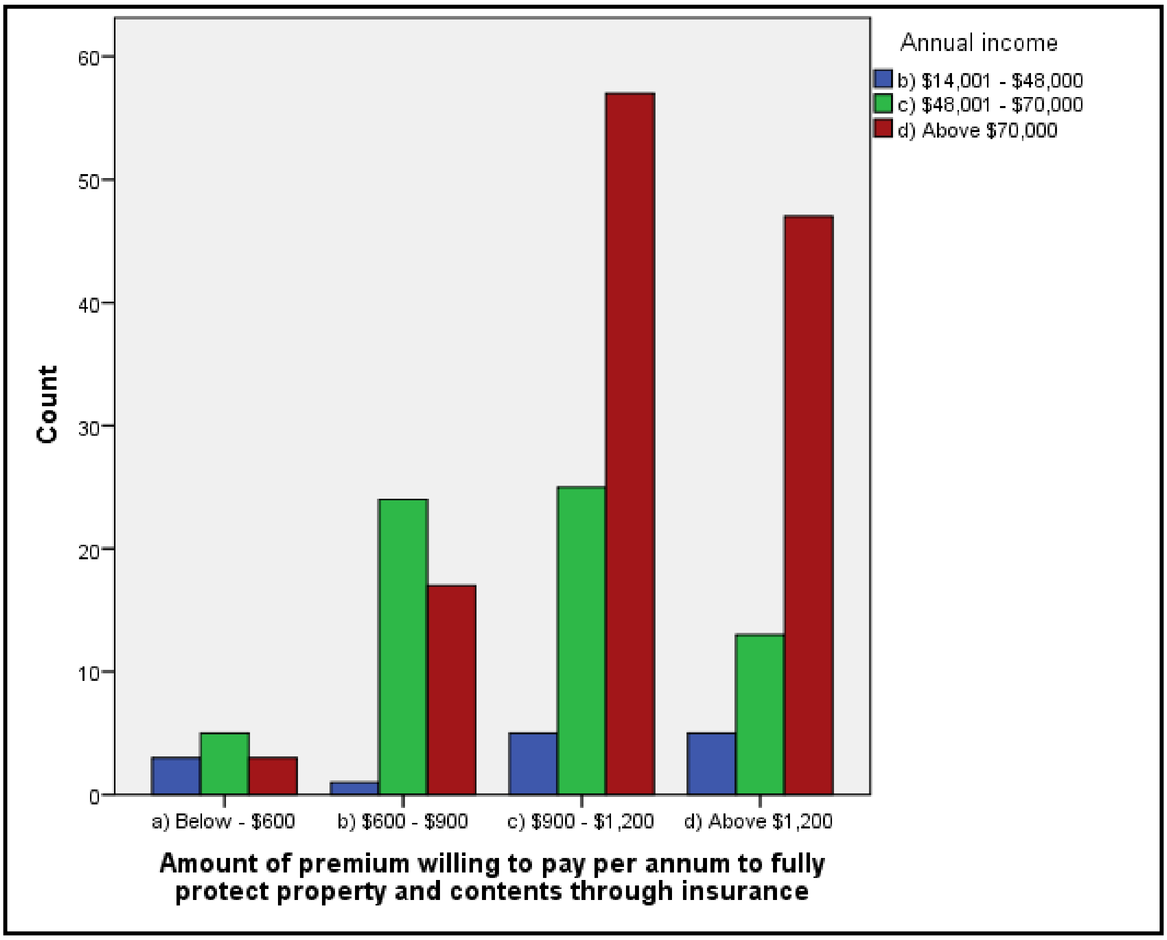


Figure 1 gives a clear picture of the sample distribution of annual premium insurance demanders is willing to pay to fully protect their residential property through insurance mechanism against annual household income.

Similarly, if we refer to the first hypothesis, the computed correlation coefficient value for premium versus property value is reported in **Table** 5. The computed correlation coefficient value is 0.536 and the associated *p*-value is 0.000. Because the observed *p*-value is less than alpha value (i.e. *p*-value = 0 .000< 0.05, so reject H_0) the results are statistically significant. Therefore with results, R = 0.536, N = 211, *p*-value = 0.000, it can be concluded that the study finds a strong positive linear correlation between the annual premium an insurance demander is willing to pay to fully protect his/her property and contents through insurance mechanism and the property value.

Table 5: Correlation analysis for hypothesis I (premium versus property value)

		Amount of premium willing to pay per annum to fully protect property and contents through insurance	Approximate property value
Amount of premium willing to pay per annum to fully protect property and contents through insurance	Pearson Correlation	1	.536**
	Sig. (2-tailed)		.000
	N	208	204
Approximate property value	Pearson Correlation	.536**	1
	Sig. (2-tailed)	.000	
	N	204	207

**. Correlation is significant at the 0.01 level (2-tailed).

This argument can be furthered by looking into a contingency table summary of income distribution against the hypothetical annual premium options. This crosstabulation analysis depicts the number of times each of the possible category combinations occurred in sample data on the two variables (annual premium an insurance demander is willing to pay and the annual household income).

Table 6: Crosstab of the amount of premium willing to pay per annum to fully protect property and contents through insurance * Approximate property value

			Approximate property value						
			Below $30,000	$300000 - $400000	$400000 - $500000	$500000 - $600000	$600000 - $700000	Above $700000	Total
Amount of premium willing to pay per annum to fully protect property and contents through insurance	a) Below - $600	Count	5	3	0	0	0	0	8
		% within Amount of premium	62.5 %	37.5 %	0.0 %	0.0 %	0.0 %	0.0 %	100.0 %
		% within property value	33.3 %	15.0 %	0.0 %	0.0 %	0.0 %	0.0 %	3.9 %
		Adjusted Residual	6.1	2.7	-1.4	-1.4	-1.3	-1.7	
	b) $600 - $900	Count	9	7	9	7	4	6	42
		% within Amount of premium	21.4 %	16.7 %	21.4 %	16.7 %	9.5 %	14.3 %	100.0 %
		% within property value	60.0 %	35.0 %	23.1 %	17.1 %	11.1 %	11.3 %	20.6 %
		Adjusted Residual	3.9	1.7	.4	-.6	-1.5	-1.9	
	c) $900 - $1,200	Count	1	10	22	19	19	16	87
		% within Amount of premium	1.1 %	11.5 %	25.3 %	21.8 %	21.8 %	18.4 %	100.0 %
		% within property value	6.7 %	50.0 %	56.4 %	46.3 %	52.8 %	30.2 %	42.6 %
		Adjusted Residual	-2.9	.7	1.9	.5	1.4	-2.1	
	d) Above $1,200	Count	0	0	8	15	13	31	67
		% within Amount of premium	0.0 %	0.0 %	11.9 %	22.4 %	19.4 %	46.3 %	100.0 %
		% within property value	0.0 %	0.0 %	20.5 %	36.6 %	36.1 %	58.5 %	32.8 %
		Adjusted Residual	-2.8	-3.3	-1.8	.6	.5	4.6	
Total		Count	15	20	39	41	36	53	204
		% within Amount of premium	7.4 %	9.8 %	19.1 %	20.1 %	17.6 %	26.0 %	100.0 %
		% within property value	100.0 %	100.0 %	100.0 %	100.0 %	100.0 %	100.0 %	100.0 %

Looking at the Crosstab, the computed Pearson Chi-Square statistics from Table 7, the Chi-square test value is the tail area to the right of 97.127 from a chi-square distribution with 15 degrees of freedom. The computed *p*-value is .000 which is the basis for the rejection of the null hypothesis.

Table 7: Test for association between annual premium insurance demanders are willing to pay to fully protect property and contents through insurance mechanism and their property value

				Monte Carlo Sig. (2-sided)			Monte Carlo Sig. (1-sided)		
					99 % Confidence Interval			99 % Confidence Interval	
	Value	Df	Asymp. Sig. (2-sided)	Sig.	Lower Bound	Upper Bound	Sig.	Lower Bound	Upper Bound
Pearson Chi-Square	97.127[a]	15	.000	.000[b]	.000	.000			
Likelihood Ratio	89.384	15	.000	.000[b]	.000	.000			
Fisher's Exact Test	75.984			.000[b]	.000	.000			
Linear-by-Linear Association	58.346[c]	1	.000	.000[b]	.000	.000	.000[b]	.000	.000
N of Valid Cases	204								

a. 9 cells (37.5 %) have expected count less than 5. The minimum expected count is .59.
b. Based on 10000 sampled tables with starting seed 2000000.
c. The standardized statistic is 7.638.

The statistically significant statistics; contingency coefficient value of 0.568 and correlation coefficient value of 0.536 indicates a very strong positive association between the annual premium insurance demanders are willing to pay and the approximate property value

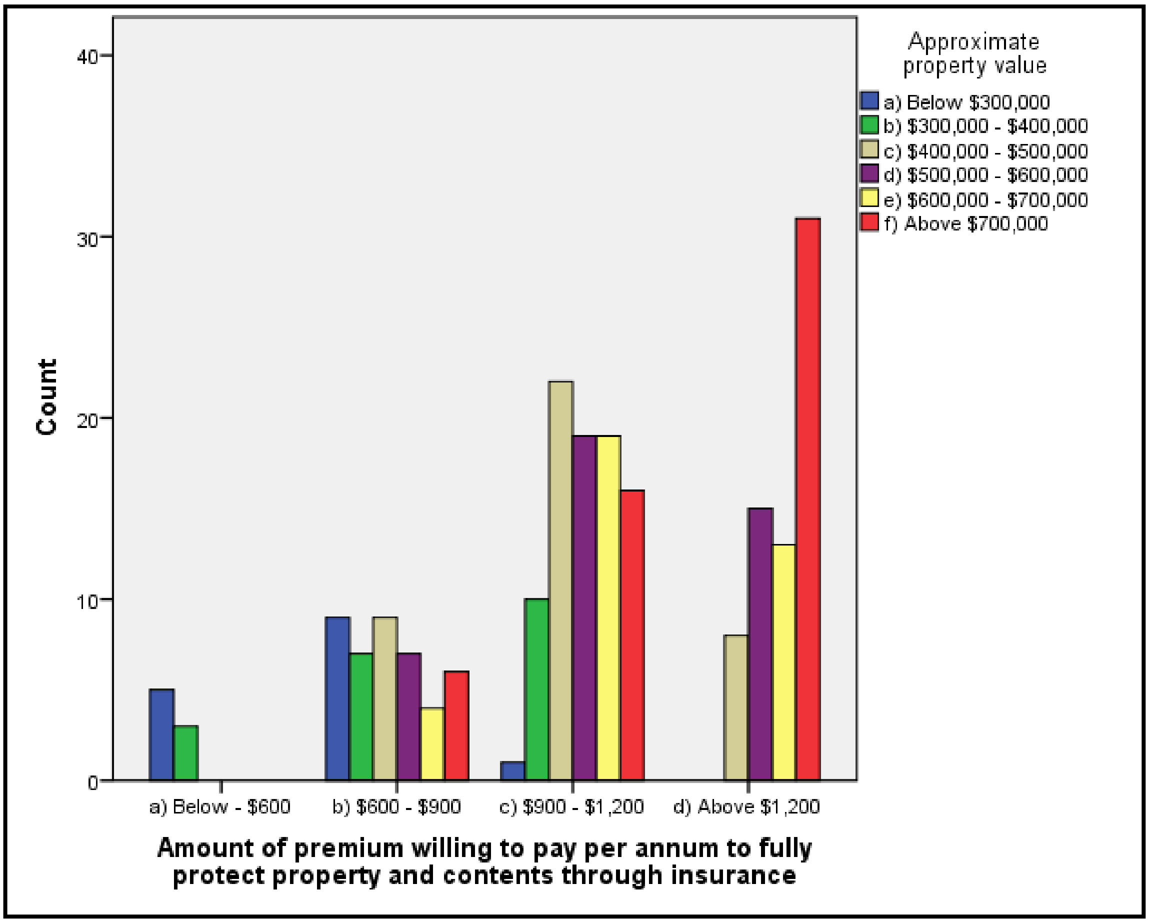
Table 8: Measure of the strength of association between annual premium insurance demanders are willing to pay to fully protect property and contents through insurance mechanism and property value

						Monte Carlo Sig.		
							99 % Confidence Interval	
		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.	Sig.	Lower Bound	Upper Bound
Nominal by Nominal	Contingency Coefficient	.568			.000	.000[c]	.000	.000
Interval by Interval	Pearson's R	.536	.053	9.026	.000[d]	.000[c]	.000	.000
Ordinal by Ordinal	Spearman Correlation	.492	.058	8.031	.000[d]	.000[c]	.000	.000
N of Valid Cases		204						

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Based on 10000 sampled tables with starting seed 2000000.
d. Based on normal approximation.

Although hypothesis does not examine the influence of the property value on insurance take-up rates; for the analysis of the annual premium insurance demanders are willing to pay and the property value, an increase in the value of property increases average level of insurance coverage, holding all else constant. Figure 2 gives a clear picture of the sample distribution of annual premium insurance demanders is willing to pay to fully protect their residential property through insurance mechanism against approximate property value.

Figure 2: Distribution of annual premium insurance demanders are willing to pay Vs property value



Findings I

From the results and conclusions of the tests on research hypothesis I (premium versus income), the study finds that; There is a fairly moderate relationships between the amounts of premium insurance demanders are willing to pay and their income. The vast majority, 42.4 %, of the sampled insurance demanders elected to pay an annual maximum premium in the region of $900 to $1200.

From the results and conclusions of these tests on research hypothesis I (premium versus property value), the study finds that; there is a strong positive linear association between the annual premiums an insurance demander is willing to pay to fully protect his/her property and contents through insurance mechanism and the property value. It's observed that the vast majority, 42.4 %, of the sampled insurance demanders elects to pay an annual maximum premium in the region of \$900 to \$1200. Holding all other factors constants this hypothesis finds that; the vast majority, 58.5 %, of those willing to pay premium above \$1200 have property valued above \$700000, the vast majority, 56.4%, of those willing to pay premium options \$900 - \$1200 have property valued between \$400000 - \$500000 and the vast majority of those willing to pay premium options \$600 – 900 and below \$600 have property valued above \$300000.

Next, if we refer to the second hypothesis, demographic characteristic of households would positively influences the demand for residential insurance cover in the aftermath of a natural disaster and the third hypothesis, change in risk perception influences the demand for residential insurance cover in the aftermath of a natural disaster. The objective here is to run a regression analysis with the level of insurance coverage as our dependent variable so as to address the two research hypothesis. To achieve this objective we bring a list of different explanatory independent variables together to run a multinomial logistic regression, we report output results as seen in Table 9-13.

In general the output result shows that the effect of a number of the explanatory variables is not-statistically significantly. For example, one statistically significant predictor variable, increase in level of coverage due to higher risk, affects more significantly the level of coverage than other predictor variable with *p-value* .000. This can also be seen from the actual proportion (92.9%) of those who perceive high risk as the cause of change in the level of insurance coverage.

More importantly, the initial run of the model shows that, when looked as a whole, the model is significant with a *p*-value .000 and chi-square statistics 40.824. This implies that at least one or more of the regression coefficients in the model are not equal to zero. When looking at the results of the regression all variable may not be significant, few of them are significant, but because we are predicting it is very important for us to keep all the variable of the mode. Even when most of the regression variables are not statistically significant, it would be wrong to remove them from the model. This is because even if they may not have the explanatory power within the model, some may have predictive powers in the overall regression model.

To run the multinomial logistic regression, we selected question number fifteen from the survey questionnaire that captures the change in the level of insurance coverage as our dependent variable and a set of thirteen independent variables from a set of eight survey questions.

We use the **nomreg** command in the SPSS programme to estimate a multinomial logistic regression model. The regression output for the increase in the level of insurance coverage dummy against a range of explanatory dummy variables as shown in the case processing summary on Table 9 gives the response propotions where the selected explanatory variables have been transfer to dummy variables.

```
NOMREG Q15_1 (BASE=LAST ORDER=ASCENDING) BY Q1_1 Q1_2 Q2_1 Q3_1
Q3_2 Q4_1 Q4_2 Q8_1 Q8_2 Q9_1 Q13_1 Q13_2 Q16_2a
  /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20)
LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE)
ENTRYMETHOD(LR) REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=PARAMETER SUMMARY LRT CPS STEP MFI.
```

Table 9: Case Processing Summary

		N	Marginal Percentage
Change in Level of Coverage	0.00	125	59.2%
	1.00	86	40.8%
Young Age	0.00	194	91.9%
	1.00	17	8.1%
Middle Age	0.00	82	38.9%
	2.00	129	61.1%
Male	0.00	89	42.2%
	1.00	122	57.8%
High School Graduate	0.00	194	91.9%
	1.00	17	8.1%
University Graduate	0.00	144	68.2%
	2.00	67	31.8%
Low Income	0.00	199	94.3%
	1.00	12	5.7%
High Income	0.00	22	10.4%
	2.00	189	89.6%
Lower Property Value	0.00	176	83.4%
	1.00	35	16.6%
Medium Property Value	0.00	128	60.7%
	2.00	83	39.3%
Natural Disaster consideration before purchase	0.00	85	40.3%
	1.00	126	59.7%
Increase in premium rates post- earthquakes	0.00	199	94.3%
	1.00	12	5.7%
Decrease in premium rates post- earthquakes	0.00	28	13.3%
	2.00	183	86.7%
Increase in level of coverage due to higher risk	0.00	196	92.9%
	1.00	15	7.1%
Valid		211	100.0%
Missing		0	
Total		211	
Subpopulation		99[a]	

a. The dependent variable has only one value observed in 76 (76.8%) subpopulations.

The data summary in Table 9 shows that, 59.2% of the sampled insurance demanders reported an increase in the level of their coverage with 92.9% attributing this change as a result of higher perception of risk and 94.3% attributing the change as a result of increase in premium rates post- earthquakes. This points that the change in the level of insurance coverage might not necessary mean a change in demand rather an increase in coverage level due to incease in price of insurance coverage post-catastrophe.

Table 10: Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	Df	Sig.
Intercept Only	189.558			
Final	148.734	40.824	13	.000

Table 10 indicates the parameters of the regression model for which the model fit is calculated: With "Intercept Only'', we describes a model that does not control for any predictor variables and simply fits an intercept to predict the outcome variable, in this case our intercept in this case is 189.558. With "Final'', we describe a model that includes the specified predictor variables by an iterative process that maximizes the log likelihood of the outcomes as seen in the outcome variable. So by including the predictor variables and maximizing the log likelihood of the outcomes as seen in the data, the final model should improve upon the intercept only model. The new -2(Log Likelihood) value associated with the final model is 148.734. From this two values (intercept only and final) we could compute the associated Chi-Square test statistics which tells us that at least one of the predictors' regression coefficients is not equal to zero; in this model the value is 40.824. The small *p-value* from the LR test, .000 < .00001, would lead us to conclude that at least one of the regression coefficients in the model is not equal to zero. The parameter of the chi-square distribution used to test our null hypothesis is 13 as defined by the degrees of freedom in table.

Logistic regression does not have an equivalent to the R-squared that is found in OLS regression; however, many researchers have tried to come up with one.

Table 11: Pseudo R-Square

Cox and Snell	.176
Nagelkerke	.237
McFadden	.143

Table 11 reports the three pseudo R-squared values of our multinomial logistic regression model. There are a wide variety of pseudo R-squared statistics which can give contradictory conclusions (Bruin, 2006). Because these statistics do not mean what R-squared means in OLS regression, the proportion of variance of the response variable explained by the predictors, their interpretation will be ignored for now.

Table 12: Likelihood Ratio Tests

	Model Fitting Criteria	Likelihood Ratio Tests		
Effect	-2 Log Likelihood of Reduced Model	Chi-Square	Df	Sig.
Intercept	148.734[a]	.000	0	.
Young Age	149.436	.703	1	.402
Middle Age	148.761	.027	1	.869
Male	148.850	.116	1	.733
High School Graduate	149.306	.572	1	.450
University Graduate	148.857	.124	1	.725
Low Income	148.894	.161	1	.688
High Income	148.780	.046	1	.830
Lower Property Value	148.734	.000	1	.983
Medium Property Value	148.824	.091	1	.763
Natural Disaster consideration before purchase	149.747	1.013	1	.014
Increase in premium rates post- earthquakes	156.206	7.473	1	.006
Decrease in premium rates post- earthquakes	154.517	5.783	1	.016
Increase in level of coverage due to higher risk	174.500	25.767	1	.000

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

In order to estimate our regression model, we used 13 explanatory variables from 8 survey questions as reflected in the overall model fit in Table 10. The estimated chi-square test statistics is reported in Table 12.

Table 13 reports the parameter estimates for the explanatory variables coefficient and the associated *p-values.*

Table 13: Parameter Estimates

Change in Level of Coverage[a]		B	Std. Error	Wald	Df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
.00	Intercept	-21.297	1.867	130.175	1	.000			
	[Young Age=.00]	.531	.632	.706	1	.401	1.701	.493	5.874
	[Young Age=1.00]	0[b]	.	.	0	.	.	.	.
	[Middle Age=.00]	.060	.365	.027	1	.869	1.062	.519	2.173
	[Middle Age=2.00]	0[b]	.	.	0	.	.	.	.
	[Male=.00]	-.110	.323	.116	1	.733	.896	.476	1.687
	[Male=1.00]	0[b]	.	.	0	.	.	.	.
	[High School Graduate=.00]	-.490	.661	.549	1	.459	.613	.168	2.239
	[High School Graduate=1.00]	0[b]	.	.	0	.	.	.	.
	[University Graduate=.00]	.125	.357	.124	1	.725	1.134	.563	2.281
	[University Graduate=2.00]	0[b]	.	.	0	.	.	.	.
	[Low Income=.00]	.404	1.011	.160	1	.689	1.498	.207	10.861
	[Low Income=1.00]	0[b]	.	.	0	.	.	.	.
	[High Income=.00]	.159	.747	.045	1	.831	1.172	.271	5.064
	[High Income=2.00]	0[b]	.	.	0	.	.	.	.
	[Lower Property Value=.00]	-.010	.486	.000	1	.984	.991	.382	2.566
	[Lower Property Value=1.00]	0[b]	.	.	0	.	.	.	.
	[Medium Property Value=.00]	-.108	.360	.091	1	.763	.897	.443	1.818
	[Medium Property Value=2.00]	0[b]	.	.	0	.	.	.	.
	[Natural Disaster consideration before purchase=.00]	.327	.326	1.005	1	.016	1.386	.732	2.625
	[Natural Disaster consideration before purchase=1.00]	0[b]	.	.	0	.	.	.	.
	[Increase in premium rates post-earthquakes=.00]	2.176	1.053	4.267	1	.039	8.808	1.118	69.416
	[Increase in premium rates post-earthquakes=1.00]	0[b]	.	.	0	.	.	.	.
	[Decrease in premium rates post-earthquakes=.00]	2.498	1.207	4.284	1	.038	12.160	1.142	129.503
	[Decrease in premium rates post-earthquakes=2.00]	0[b]	.	.	0	.	.	.	.
	[Increase in level of coverage due to higher risk=.00]	18.728	.000	.	1	.	135975952.541	135975952.541	135975952.541
	[Increase in level of coverage due to higher risk=1.00]	0[b]	.	.	0	.	.	.	.

a. The reference category is: 1.00.
b. This parameter is set to zero because it is redundant.

We recall that, an important feature of the multinomial logistic model is that it estimates $p-1$ models, where p is the number of levels of the outcome variable. In this case, the model treats no change in insurance coverage level as the reference group and therefore estimated a model for increase in insurance coverage level relative to no change in insurance coverage level. Therefore, since the parameter estimates are relative to the reference group, in each dummy variable, our standard interpretation of the regression results in Table 13 is that for a unit change in the predictor variable, the logistic of outcome significance level relative to the reference group is expected to change by its respective parameter estimate (which is in log-odds units) given the variables in the model are held constant. For example, the intercept value gives the multinomial logistic estimate for increase in insurance coverage level relative to no change in insurance coverage level when the predictor variables in the model are evaluated at zero. Thus, the logistic for probability of increase in insurance coverage level relative to no change in insurance coverage level is -21.297. Table 13 also gives the standard errors of the individual regression coefficients for the model estimates, the Wald chi-square test that the null hypothesis estimates equals zero, the degrees of freedom for each of the variables included in the model (Note: for each of these variables, the degree of freedom is 1 unless where the variable is redundant), the p-values of the coefficients within a given model, which tells us that the null hypothesis that a particular predictor's regression coefficient is zero given that the rest of the predictors are in the model, the odds ratios for the predictors which indicates how the risk of the outcome falling in the comparison group compared to the risk of the outcome falling in the reference group changes with the variable in question and the 95% Confidence Interval (CI) for Exp(B) - This is the CI for an individual multinomial odds ratio given the other predictors are in the model for outcome significance level relative to the referent group.

Findings II

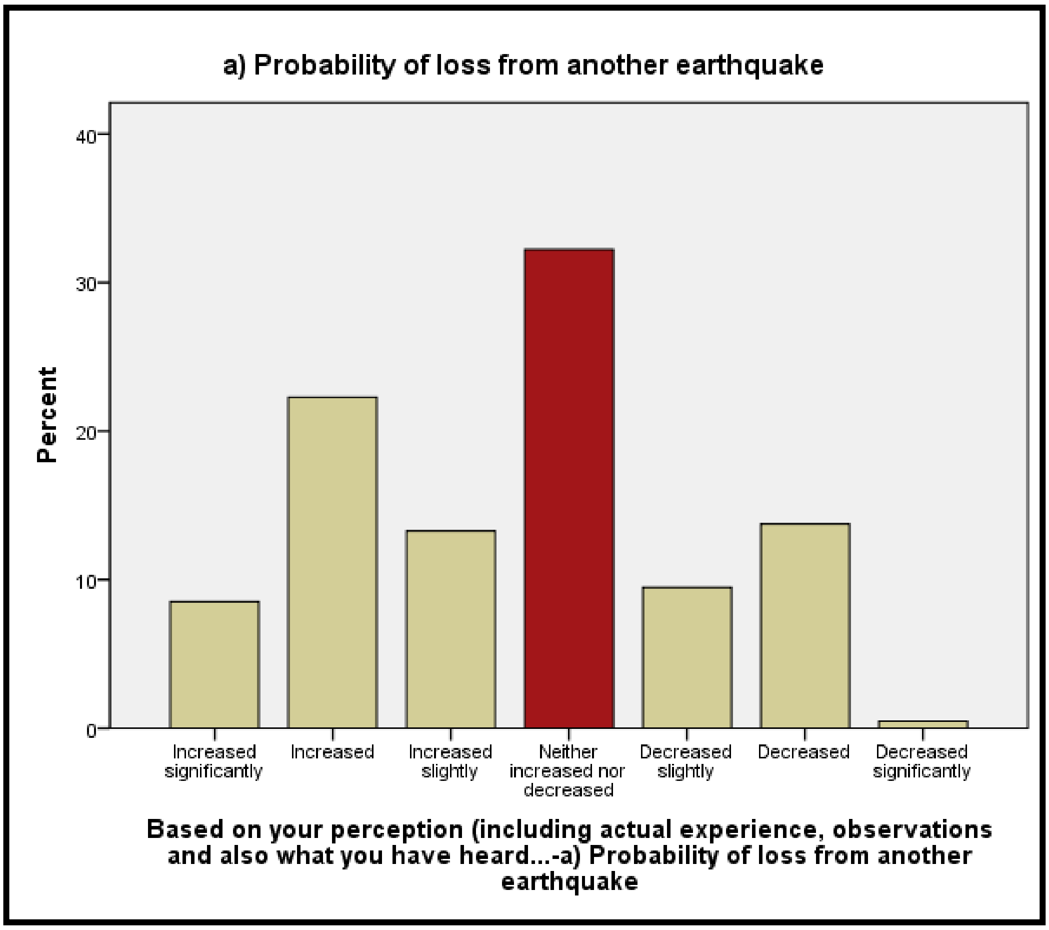
If we refer to the research hypothesis II and III, the regression analysis finds that; from the survey data, 59.2% of the sampled insurance demanders reported an increase in the level of their coverage with 92.9% attributing the change as a result of change in perception of risk and 94.3% attributing the change as a result of increase in premium rates post- earthquakes.

The results of the regression give likelihood ratio chi-square of 40.824 with an associated *p-value* < 0.0001 which tells us that our regression model as a whole fits significantly better than an empty model (i.e. a model with no predictor variables). Thus we conclude age, gender, education, income, property value, natural disaster, premium rates and risk perceptions substantially affect the level of insurance coverage post-natural disaster. From the parameter estimates of our regression model, vulnerability to natural disaster, change in premium rates and change in risk perception are the most statistically significant explanatory variables. These parameters would positively influence the demand for residential insurance cover in the aftermath of a natural disaster. However, it is difficult to show how much of the change in insurance level can be attributed to increase in premium. In such case change in premium rates would not reflect demand of insurance coverage.

The vast majority of insurance consumers who had previously filed claims for natural disaster reported to have higher risk perception. This is in line with the numerous research findings that postulate that higher risk perception is recorded from those who have prior experience of catastrophes than those who have not. To address our research question; how the supply and demand for residential insurance reacts to changes in the aftermath of a catastrophic event, we plot figures that depict how the catastrophes have impacted the demand-side . We have so far proved demand for insurance post-loss increases using a theoretic inter-temporal insurance model. Using the four most pronounced variables of interest, the results of our analysis are given below;

The first result gives reports for the change in the perception of probability of loss; The respondents were asked to identify their perception (including actual experience, observations and also what they have heard from others), in relation to their current residential property and contents insurance policy how the probability of loss from another earthquake had changed.

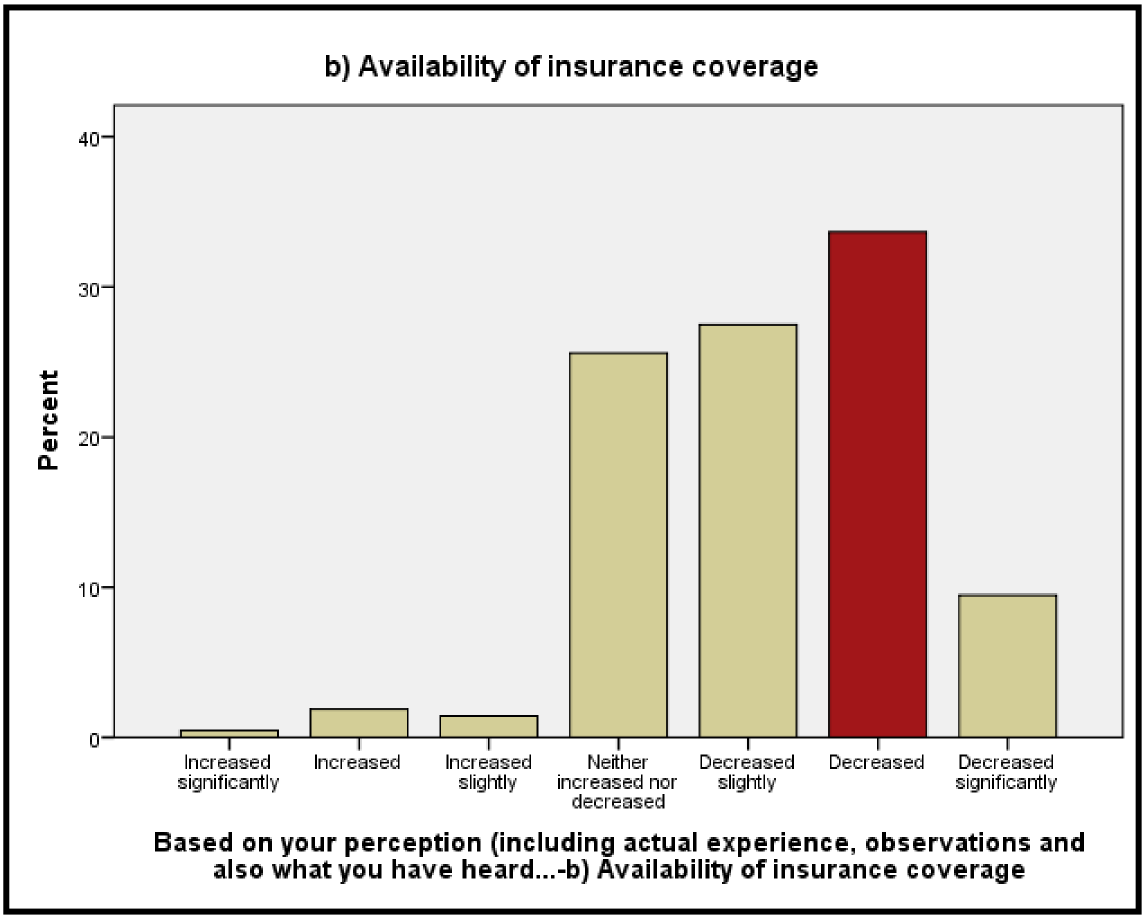
Figure 3: Probability of loss from another earthquake



In line to previous research findings that suggests, demand would increase with an increase in risk, 44.1% of the sample perceives the probability of loss from another quake to have increased, while 23.7 % of the sample perceives the probability to have decreased and 32.2 % were in neutral position regards the perceived post-quake probability of loss. It can be further argued, looking into the respondent observation on the level of insurance coverage, that the 40.8% of the sample who elected to voluntarily increase level of past insurance converge and the 92.9% of the who elected the change in the coverage to have be motivated by higher risk, are of as a rational responses to perceived increase in the probability of loss from another earthquake.

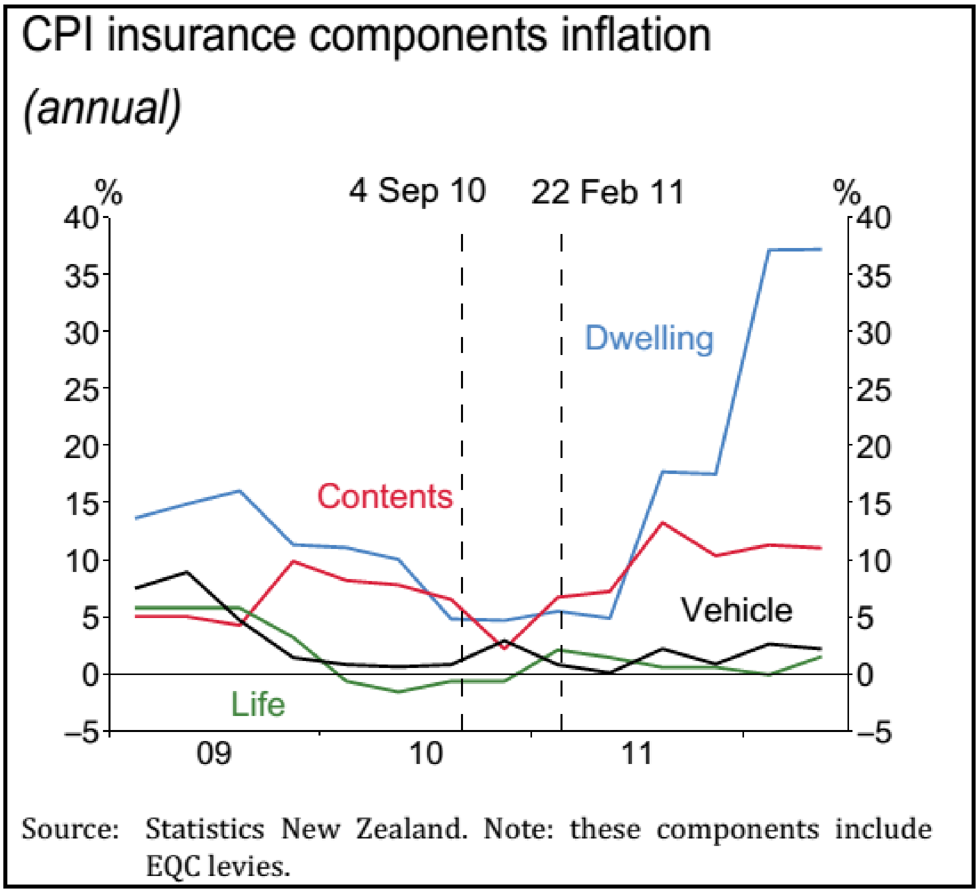
The second plot presented gives results for the reaction in relation to the availability of insurance coverage. On Figure 4 results of plot of the survey responses on the availability of insurance coverage post-quake is seen above. The survey question here examines respondent's perception and rating on overall changes in the availability of insurance coverage to insurer residential property and contents in the aftermath of 2010 and 2011 Canterbury earthquakes.

Figure 4: Availability of insurance coverage



The vast majority 70.6 % indicated that availability of insurance coverage has decreased, 25.6 % of the sample respondents were neutral as to whether the availability of insurance coverage has increased or decreased and only tiny minority 3.8 % observed that insurance availability has increased post-quakes. When this question is examined with the data on CPI insurance components inflation for households throughout New Zealand (source from the Statistic New Zealand) and the responses on post-quake premium changes as seen in Figure 6 below, the results suggest that the Christchurch earthquakes had a strong effect on the residential property and contents insurance coverage. Figure 6 reports an insurance component inflation of residential property raising at about 40% high.

Figure 6: CPI insurance components inflation for households and for businesses throughout New Zealand

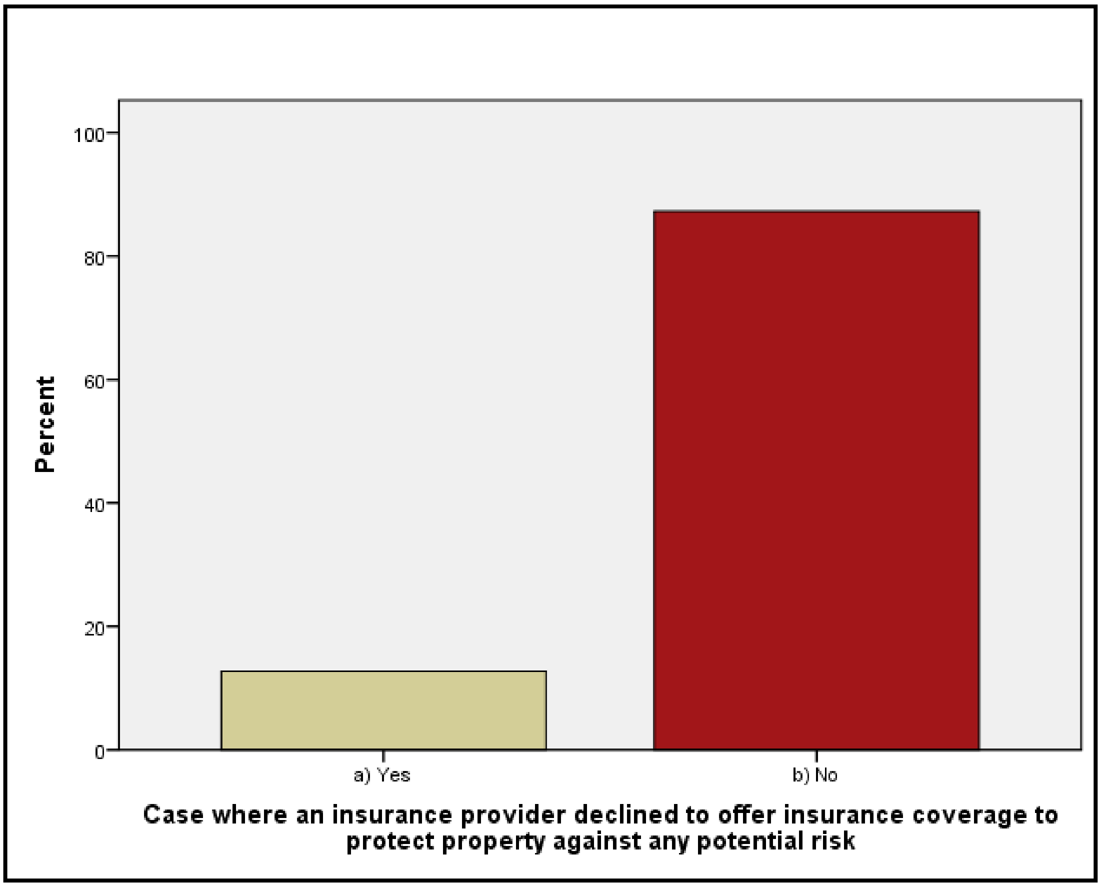


To shed more light, these results can further be jointly examined with the responses on cases where an insurance provider consciously declined to offer insurance coverage to protect property against any potential future risk for some customers. On the question regarding whether an insurance provider declined to offer insurance coverage; of 24 respondents who provided specific comments on reasons for insurance coverage declined, 11 states that the cover was declined because of the following specific reasons as stated by the provider of the insurance cover;

- *Claimed on the driveway damage and now they will not cover the driveway to the same extent as before;*
- *Did not have a kitchen;*
- *Immediately after the February earthquake the company wasn't taking on any new insurance;*
- *New building, many companies wouldn't undertake new policies;*
- *No companies are taking on new customers;*
- *No response to request for quote;*
- *Not stated;*
- *Paid-out not repaired therefore uninsurable except for public liability yet fit to live in;*
- *Received pay-out. Company unwilling to offer 3^rd^ party fire cover;*
- *Too soon after the September 2010 earthquake; and*
- *Was not providing contents cover for Canterbury.*

The above comment depicts a pragmatic reactions experience by the insured which clearly captures the actual supply/demand reactions and relationship of the insurance market post catastrophe.

Figure 7: Case where an insurance cover was declined

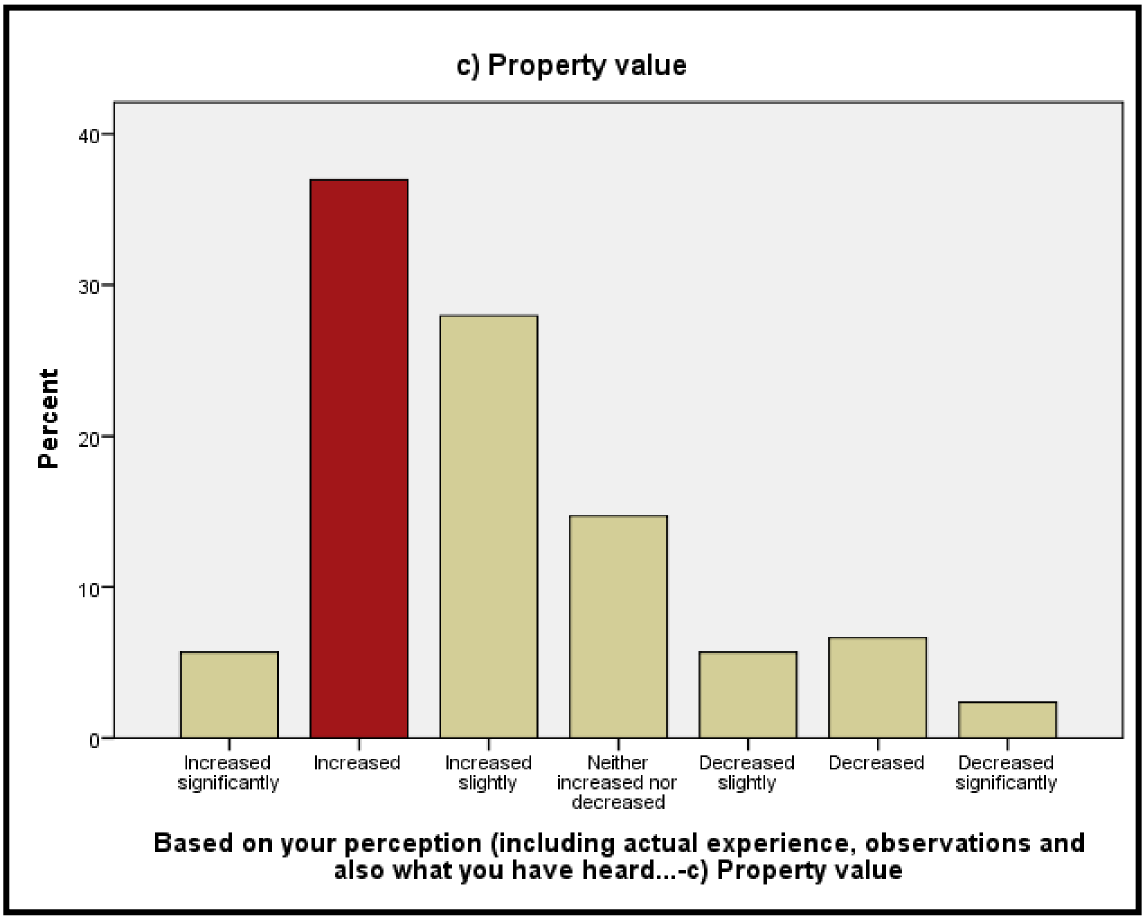


The survey results on the availability of coverage and cases where some insurance demanders where turned away sheds light on the experiences and opinions of people purchasing coverage post-quakes. The study can therefore generally infer that following a catastrophe, insurance providers approach the market more cautiously.

The third reaction that this study analysis is the change in property value (insured assets). As reflected in our survey questionnaire: the perceived change insurance coverage per dollar of property insured is an important parameter to understand how the insured feels about return for every dollar spent to purchase insurance cover.

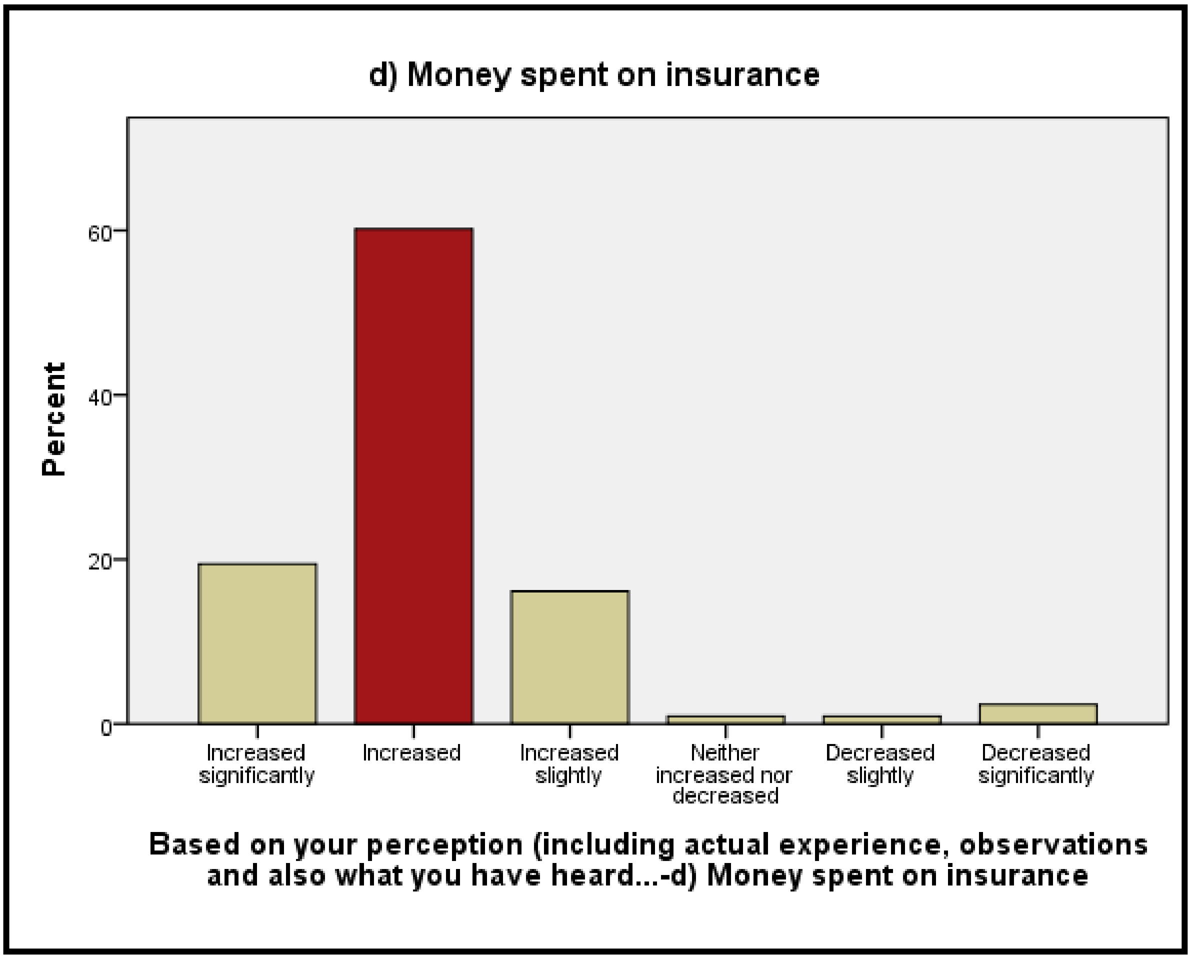
Most of the respondent as seen on Figure 8 observed that there was a sharp increase in property value after the earthquakes. 37 % observed the property value to have increased while 28 % observed some slightly increase in property value. In general it can be said that, 70.7 % observed an upward change in property value while 14.7 % observed no change in property value with the same percentage observing downward change.

Figure 8: Insured property value post-earthquakes



The forth plot give changes in the expenditure on insurance in the aftermath of catastrophic loss. Past studies shows that consumers would choose insurance policy that yields the highest benefit per additional dollar of insurance expenditure holding other factors constant. Thus, the questions regarding how the respondents have generally changed their expenditure on insurance depict how quakes affected the total expenditure associated with insurance policies. This study finds a whopping majority 95.7 % have in general increased the total amount of money they spend on insurance post-quakes. Only 3.3 % observed to have decreased their spending on insurance while a 0.9 % neither increased nor decreased the amount of money spent on insurance.

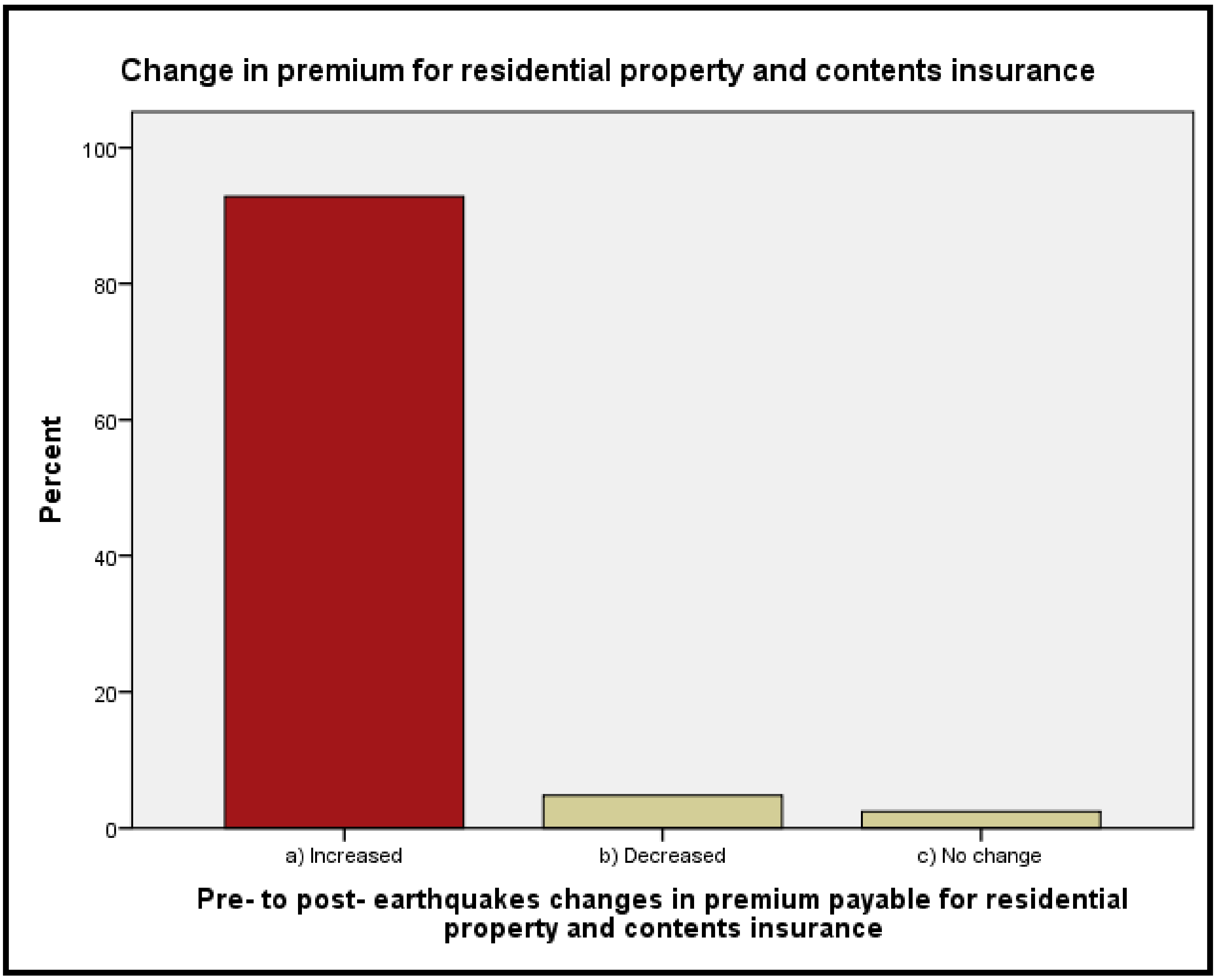
Figure 9: Expenditure on insurance



Further analysis of insurance expenditure as the dependent variable with incomes, and the value of property to insure reveal that there is a strong association between these variable as shown in the results of hypothesis one. The survey finds expenditure on insurance to be consistent with the literature on the choice to insure. In general the results of the study on money spent on insurance when linked with key household characteristics indicates that insurance expenditure generally increases with, and greater incomes, greater value of property to insure. To quote (McCormick & Kempson, 1998) "…e*xpenditure* on *home contents insurance accounted* for *2.0 per cent* of *income* for the *poorest fifth* of *households compared* to *just 0.5 per cent* for the *richest fifth…"*.

Moreover, Figure 9 and 10 gives a possible suggestion a relationship between the increase in premiums post-quakes and the increase in insurance expenditure. With the respondents in both cases observing increments above 91 % , it can be argued that most of the increase in insurance expenditure might have been majorly due to increased premium rates rather than change in level of coverage.

Figure10: Change in premium rate



Findings III

In addressing our research question; this analysis finds that the vast majority of insurance consumers update their perception of catastrophic risk. Especially those who have had a recent experience with natural disaster events, with policyholders involved in Canterbury quakes claims reporting 44.1% higher perception of a likelihood of loss from another similar disaster. Our results are in fact in line with heuristic rule which is supported by numerous literatures. On the insurance policy availability, our study finds that there was a noticeable decline and moratorium of new insurance contracts. The vast majority of respondents at 70.6 % reported a decline in availability of new insurance contracts. New policyholders found it difficult to meet the new insurance requirement and policy exclusions.

The catastrophic on Christchurch affected stability of many building with many of the property owners be temporally displaced or the suburb declared as red zone. Our survey shows that the displacement pushed the demand for houses which resulted to increase in rents and property value with 70.7% of the respondents reporting an increase in property value. Having shown insurance expenditure is positively related to income and property value; this study finds a whopping majority at 95.7% reporting an increase in the total amount of money spend on insurance policy in the aftermath of the earthquakes catastrophe.

Conclusions

The results of the first hypothesis suggest that, the value of homes is highly correlated with income (and can be used to proxy wealth) collectively influence the amount of premium the insurance demanders are willing to pay and the level of insurance coverage. These two parameters are an indication of expected losses, which would suggest that those with higher income and higher property values would purchase higher coverage amounts. Using the finding from this study we conclude that, an increase in an individual’s income should have no major effect on demand if insurance is actuarially fair. More often, however, positive loading exists, reflecting transaction costs and possibility of adverse selection. In such cases, the direction of the effect depends on whether an increase in income increases losses and on whether the insurance demander has increasing or decreasing absolute risk aversion.

Our findings suggest that perceptions play an important role in insurance decisions to voluntarily change their insurance cover. Thus, if the insurance demander perceives a higher possibility of natural disaster then, they adjust their coverage appropriately. They confirm this study's hypothesis that a household's decision to increase, decrease or no change of the insurance coverage level post-loss is influenced unequally by perceptions relating to occurrence of natural disaster in the future. Perceptions relating to the risk post-loss and considerations of the existence of disasters and the market insurance premiums adjustments are found to be the most significant and important parameter estimates. Thus insurance providers and the government regulators need to recognize individual perceptions regarding risk and anyother market policy modification to be a key factor in post-disaster insurance demand reactions, and to invest in understanding them in their design of interventions to stimulate more demand for insurance coverage as well as protect the insurance market from ruin

However, this study acknowledges that recognizing and addressing the entire past catastrophe reaction and the factors that shape them will only provide a partial solution to the complex problem of the aftermaths of natural disaster and the necessary rebuild with sufficient insurance compensation measures thereof

As the composition of the Christchurch dwellers evolves as the city gets back to normality, changes in individual characteristics will affect the demand for insurance, for example, individuals who have experienced the Christchurch earthquakes may find it easier to imagine that the disaster could happen again in the future and therefore feel a higher perceived risk than individuals without this experience. Maximizing these important subjective judgements in decision making will require understanding all these multiple factors involved using a variety of methodological approaches and addressing them through multifaceted interventions.

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