# ESTIMATING WILLINGNESS TO PAY FOR INVESTMENTS IN RESILIENCE USING BINARY AND ORDERED LOGIT MODELS

A Thesis

Presented to the Faculty of the Graduate School

of Cornell University

In Partial Fulfillment of the Requirements for the Degree of

Master of Science

by

Jiayi Sun

August 2016

## ABSTRACT

Resilience is the ability to function successfully after a natural disaster such as a flood or a hurricane. A resilient system would sustain minimal damage during a disaster and have the ability to bounce back quickly once such disasters have passed. However, resilience requires large investments and the funding is always limited. Willingness to Pay (WTP) has been widely used by researchers to measure people's preference on choosing a product or service. It is also the key to improving the resilience of an infrastructure to resist disasters. This paper is focused on estimating WTP for investments in resilience using binary and ordered logit models. The scope of standard models was extended and a mixed ordered logit model was formulated for the ordinal response data. In addition, the confidence interval and odds ratio for random parameter were properly calculated to interpret the results. Finally, conclusions and policy recommendations were provided.

**Keywords**: Resilience, Willingness to Pay, Binary Logit Model, Ordered Logit Model, Random Parameter, Mixed Ordered Logit Model

## BIOGRAPHICAL SKETCH

The author, Jiayi Sun, was born in Harbin, the capital city of the Heilongjiang province in the northeast of China. It is heralded as the "Ice City" for its well-known winter tourism and recreations. Spending 18 years in Harbin, he completed his elementary school and middle school education, upon which he built a strong interest in science and engineering at the Harbin No.3 High School. In Fall 2010, he was admitted in Department of Transportation Science and Engineering in Beijing University of Aeronautics and Astronautics (BUAA). There, he gained a multidisciplinary academic background across Transportation and Computer Science and earned the Bachelor Degree in Engineering after 4 years' study. He then decided to pursue higher education in this field and was admitted to the Master of Science degree program in Transportation System Engineering at Cornell University. In Fall 2014, he went to Cornell and started a new life there.

This thesis is dedicated to my parents: Xiaojun Sun and Hong Liang.

## ACKNOWLEDGMENTS

I would like to extend my sincerest thanks and appreciation to all who has helped me accomplish this thesis. Without their kind support and warm encouragement, this thesis would never have become a reality.

The first and foremost thanks go to Prof. Ricardo Daziano, my advisor and also chairman of my Special Committee. He provided me with insightful guidance when I was confused, steered me in the right direction with tireless discussion and review, and gave me the impetus to keep working on my study. It was the data from his lab that promoted the start of this thesis. The estimation models used in my study were learned from his course, Microeconometrics of Discrete Choice.

I would also like to thank Prof. Karthik Sridharan, who served as the minor advisor in my Special Committee. He was a nice professor in the Department of Computer Science, who gave me helpful comments on the thesis and also provided academic guidance. In his course, Machine Learning for Data Science, I opened my horizon on data science and raised the idea to solve transportation problems by coding.

Finally, I want to express my profound gratitude to my parents for providing me with unfailing support and continuous encouragement throughout my years of study. They are always my strong backing under any circumstances and their kindness, honesty, persistence and responsibility are the most valuable qualities that I will never stop learning from them through my lifetime.

TABLE OF CONTENTS

## TABLE OF CONTENTS

CHAPTER 1

# INTRODUCTION

Hurricane Sandy (also known as “Superstorm Sandy”) was the deadliest and most destructive hurricane of the 2012 Atlantic hurricane season. Moreover, it was also the second-costliest hurricane in United States history (Blake Eric S, 2013). Hurricane Sandy affected 24 states, including the entire eastern seaboard, with particularly severe damage to New Jersey and New York. Its storm surge hit New York City on October 29, 2012, flooding streets, tunnels and subway lines, cutting power in and around the city. Airlines canceled more than 150,000 flights around the world. Most gas stations in New York City were closed because of the power shortages and depleted fuel supplies.

Resiliency is the ability to function successfully after a natural disaster such as a flood or a hurricane. A resilient system would sustain minimal damage during and have the ability to bounce back quickly from these disasters. Resilience requires large investments but the funding is limited: The New York City mayor’s office in late November 2012 estimated total losses to the city to be $19 billion and asked $9.8 billion from the federal government to restore critical infrastructure including roads, schools and hospitals (FEMA, 2015).

The marginal rate of substitution between attribute k and the cost of the discrete good at constant utility is the Willingness to Pay (WTP) for a marginal improvement of an attribute that provides utility. WTP is widely used for measuring people’s preference on choosing a product or service and also a key to improving the resilience of city to resist on disasters. Unfortunately, research on WTP for resilience investments is limited due to lack of the data in that area.

Fortunately, in the year of 2015, the lab of Prof. Daziano developed a survey to gather information on the effects of Hurricane Sandy on daily life, especially with regards to transportation, and potential ways to improve resiliency for future disasters. Given the data, calculation the WTP for resilience using estimation models finally became possible.

In computer science, there are some studies based on Machine learning algorithms to estimate data. Support Vector Machines (SVM) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis (Corinna C., Vapnik, 1995). Given a training set, a model could be built from an SVM training algorithm that assigns new examples into one category or another, making it a non-probabilistic binary linear classifier. In general, SVM has a good use for category classification. There are also more powerful regression models called artificial neural networks (ANNs), which are a family of models inspired by biological neural networks (MacKay, 2003). ANNs have been used to solve a wide variety of tasks like computer vision and speech recognition that are hard to solve with high accuracy using ordinary tools. However, these two models are not fit for ordinal responses because they would see choices as discrete and omit the meaning of the order between choices. Moreover, since the WTP has economic meaning, it is a better choice in this study to use econometric models.

In Microeconometrics, there are studies on WTP (Louviere et al., 2000; Meyerhoff et al., 2009) for flooding risk deduction or stormwater control which could give us a view on how to estimate and analyze on WTP. In Cadavid et al.'s research (2013), a certain kind of stated preference tool was used. Choice experiment (CE) (Alriksson and Öberg, 2008; Hoyos, 2010) to evaluate people's WTP for several elements of stormwater management outcomes in an urbanizing area (Bateman et al. , 2006). MMNL (Louviere, 2000) were used as a supplement method to standard conditional logit (CL) because significant unobserved heterogeneity in the coefficients on most of the attributes were found, making it inappropriate to only use CL models for estimation. Their result showed that people were willing to pay to reduce flood frequency, but the value of flood reduction depended on how much flooding people currently experience. Moreover, citizens placed a high value on changes that would improve hydrologic function in a watershed, in addition to being willing to pay for improvements in conventional pollution-related stream water quality. In Marcella Veronesi's research (2014), the study elicited the willingness to pay to reduce the ecological and health risks (e.g., Kysely et al., 2011) from combined sewer overflows (CSOs) in rivers and lakes, and wastewater flooding of residential and commercial zones under the uncertainty of climate change. To analyze a large representative sample of the Swiss population, they implemented a discrete choice experiment. As a result, their sample showed that most of the respondents were willing to pay a higher annual local tax to reduce the risk of CSOs in rivers and lakes. Moreover, their findings also indicated that climate change perception had a great effect on the WTP to reduce these risks.

There are a number of studies on estimation model development. Binary logit model was developed by David Cox (1958) and used to estimate the probability of a binary response based on one or more predictor variables. Peter McCullagh (1980) first extended the logit model for ordinal dependent variables and developed ordered logit model. Both binary and ordered logit model were widely used for estimating WTP. Trudy (1987) used Multinomial logit model (MNL) to estimate WTP from survey data; Perez-pineda F (2001) estimated people's WTP for improved water using binary logit model. However, binary and ordered logit model have limitations because the parameter's value is assumed to be fixed. Mixed logit model was then created jointly by Boyd & Mellman (1980) and Cardell & Dunbar (1980). In mixed logit models, parameter values can vary across the population according to some pre-specified distribution, which makes the model itself more complex but more flexible.

Based on former studies on applications of WTP, binary, ordered and mixed logit models, this paper concentrates on WTP in resilience using both standard and mixed logit models. While most applications of the mixed logit models to date have focused on unordered choice contexts (Bhat C. R., 1999; Bhat C. R., 1998; Srinivasan, 1999; McFadden and K. Train, 2000), the scope to formulate mixed ordered logit model must be extended.

CHAPTER 2

# INSTRUMENT AND DATA

## 2.1 Structure of the survey

The survey contains information on the effects of Hurricane Sandy on daily life, especially with regards to transportation and resiliency for future disasters. The detailed summary of all questions listed in the survey is attached in the appendix of this paper.

The survey has 5 sections: describe daily trips, experience with floods, impact parts – improving preparedness for hurricanes, the game part and finally the demographics part. The first section contains 4 questions (Q1 – Q4) asking each respondent to describe his/her daily trips in the city. Questions about the choice of transportation modes, the frequency of certain transportation modes' usage, time cost of commuting to work or school are covered in this section. The second section contains 29 questions (Q5 – Q33) focused on respondent's experience with floods and extreme weather hazards. Questions such as, how many hurricanes have you been in, how many times have you evacuated from a hurricane, etc., are included in this section. Followed by impact section is the third section, which is also this paper's concentration and contains 5 questions (CV1 – CV2, Q34 – Q36) to gather respondent's willingness to pay for supporting infrastructure's recovery from the flood. Last but not least, we designed the fourth section – game part. In this section, respondent is presented with tables, each containing 3 different hypothetical recovery scenarios. The first scenario represents current funding conditions. Scenario A and B represent an improvement to the first scenario, based on a hypothetical annual payment to support the required investments. There are 16 questions (DCE1 – DCE16) in the game part. Finally, it is demographics section, which contains 17 questions (Q37 – Q53) to gather the social demographic information of the respondent's gender, age, work, income, etc.

## 2.2 Basic descriptive statistics

According to the table, there were fewer male than female respondents. Age was evenly distributed throughout the 25-74 age range. Most respondents were married and had a full-time job. For education, most respondents had equal to or higher than College Graduate education experience. 77% of respondents were White or Caucasian. Moreover, most respondents had a household income in a range \$30,000 to \$ 60,000. Table 2-1 presents standard descriptive statistics.

**Table 2-1: Demographic Statistics**

| Respondent Characteristics | Percentage |
|---|---|
| Male | 44.01 |
| Age from 18-24 | 8.25 |
| Age from 25-34 | 19.78 |
| Age from 35-44 | 17.91 |
| Age from 45-54 | 17.78 |
| Age from 55-64 | 19.78 |
| Age from 65-74 | 13.14 |
| 75 years or older | 3.35 |
| Living in evacuation zones | 22.81 |
| Single | 26.61 |
| In a relationship | 6.38 |
| Married | 49.42 |
| Living with partner | 4.83 |
| Divorced or separated | 8.05 |
| Widowed | 3.54 |
| Own pets | 48.00 |
| Full-time (>= 30 hours per week) job | 52.45 |
| Part-time/causal job | 14.56 |
| Homemaker | 3.67 |
| Full-time student | 3.80 |

| | |
|---|---|
| Retired | 1.22 |
| Less than High School | 0.32 |
| Some High School | 1.55 |
| High School Graduate | 11.79 |
| Some College | 20.30 |
| Trade/technical/vocational training | 3.93 |
| College Graduate | 34.60 |
| Some post-graduate degree | 5.03 |
| Post-graduate degree | 22.49 |
| White/Caucasian | 77.00 |
| Black or African American | 10.31 |
| Asian | 7.28 |
| American Indian or Alaska Native | 0.45 |
| Native Hawaiian or other Pacific Islander | 0.13 |
| Hispanic | 11.60 |
| Household income <= $30,000 | 22.43 |
| Household income > $30,000 and <= $60,000 | 34.01 |
| Household income > $60,000 and <= $90,000 | 23.82 |
| Household income > $90,000 | 19.74 |

Note: The white, black, Hispanic and Asian percentages sum to more than 100% because some of the respondents have multicultural backgrounds.

## 2.3 Survey highlights

People had difficulties getting food, water, fuel, loss of cell phone signal, electric power and so on. 72.99% and 70.88% of all respondents who got affected by Hurricane Sandy experienced difficulty in getting fuel and were affected by malfunctioning traffic signals. Among them, 74.13% and 59.01% of the respondents indicated that the problems lasted for more than 3 days. This meant most of the basic infrastructural problems regarding access to fuel and working traffic signals could not be handled with a fast response time.

From the transportation aspect, 65% of the respondents claimed that their normal commute was disrupted during or immediately following Hurricane

Sandy. 24% of the respondents believed that the disruption time was more than 7 days, while the average commute disruption time was actually 5.38 days. Moreover, the effects of Hurricane Sandy made people more inclined to use personal transportation modes. The ratios of cars to drivers and passenger commuting to work during Hurricane Sandy increased by 20%. Other people chose the subway as a public transportation mode more than they did the bus, ferry or commuter rail during Hurricane Sandy, indicating that the subway was perceived as more robust and resistant to the extreme weather events than other public transportation modes.

From the economic aspect, about 81.3% of respondents would like to pay less than $1,000 for the subway's recovery as a one-time payment and 3.61% would like to pay more than $4,000. The payment might be affected by the income, times of experiencing hurricanes, frequency of taking the subway, etc.

CHAPTER 3

**WILLINGNESS TO PAY**

## 3.1 Into and motivation

This paper is focused on analyzing the willingness to pay for investments in resilience given different choices of payment by using data from CV1.1 – CV2.1.

Concretely, CV1.1: “Suppose that the city is considering projects that would reduce the transportation recovery time from 1 week to 2 days. How likely would you be willing to pay the amounts below as a recurring annual payment to support these infrastructure investments.”

**Table 3-1 CV1.1 in Survey**

| | Very Unlikely (1) | Somewhat Unlikely (2) | Undecided (3) | Somewhat Likely (4) | Very Likely (5) |
|---|---|---|---|---|---|
| **\$50 (1)** | ○ | ○ | ○ | ○ | ○ |
| **\$100 (2)** | ○ | ○ | ○ | ○ | ○ |
| **\$200 (3)** | ○ | ○ | ○ | ○ | ○ |
| **\$400 (4)** | ○ | ○ | ○ | ○ | ○ |
| **\$800 (5)** | ○ | ○ | ○ | ○ | ○ |
| **More than \$800 (6)** | ○ | ○ | ○ | ○ | ○ |

CV1.2: “Suppose that the city is considering projects that would reduce the transportation recovery time from 1 week to 4 days. How likely would you be willing to pay the amounts below as a recurring annual payment to support these infrastructure investments.”

**Table 3-2 CV1.2 in Survey**

| | Very Unlikely (1) | Somewhat Unlikely (2) | Undecided (3) | Somewhat Likely (4) | Very Likely (5) |
|---|---|---|---|---|---|
| **\$50 (1)** | ○ | ○ | ○ | ○ | ○ |
| **\$100 (2)** | ○ | ○ | ○ | ○ | ○ |
| **\$200 (3)** | ○ | ○ | ○ | ○ | ○ |

| | | | | | |
|---|---|---|---|---|---|
| **$400 (4)** | | | | | |
| **$800 (5)** | | | | | |
| **More than $800 (6)** | | | | | |

CV1.3: "Suppose that the city is considering projects that would reduce the transportation recovery time from 2 weeks to 2 days. How likely would you be willing to pay the amounts below as a recurring annual payment to support these infrastructure investments."

**Table 3-3 CV1.3 in Survey**

| | **Very Unlikely (1)** | **Somewhat Unlikely (2)** | **Undecided (3)** | **Somewhat Likely (4)** | **Very Likely (5)** |
|---|---|---|---|---|---|
| **$50 (1)** | | | | | |
| **$100 (2)** | | | | | |
| **$200 (3)** | | | | | |
| **$400 (4)** | | | | | |
| **$800 (5)** | | | | | |
| **More than $800 (6)** | | | | | |

CV 2.1: "Suppose that the city is considering projects that would reduce the recovery time of transportation from 1 week to 2 days. How likely would you be willing to pay the amounts below as a recurring monthly payment to support these infrastructure investments."

**Table 3-4 CV2.1 in Survey**

| | **Very Unlikely (1)** | **Somewhat Unlikely (2)** | **Undecided (3)** | **Somewhat Likely (4)** | **Very Likely (5)** |
|---|---|---|---|---|---|
| **$5 (1)** | | | | | |
| **$10 (2)** | | | | | |
| **$20 (3)** | | | | | |
| **$40 (4)** | | | | | |
| **$80 (5)** | | | | | |
| **More than $80 (6)** | | | | | |

As the tables presented above show, given different amounts ($50, $100, etc.), information about how each respondent makes his/her choice of willingness range from very unlikely (1) to very likely (5) is gathered. These ordered choices of willingness can be seen as dependent variables while the payment can be seen as one of independent variables.

## 3.2 Methods - Econometrics

Binary and ordered models are used to predict the dependent variables in this paper. Each question (CV1.1 – CV2.1) would have its best model in both binary and ordered model, with fixed and random parameter. Also, a combined model with data from all four questions is developed to analyze the effect of time efficiency on the choice made.

**Binary model**

Binary logistic regression estimates the probability that a characteristic is present (in this thesis, it is likely to pay) given the values of independent variables.

**Model:**

$$\mathbf{y} = \mathbf{X}\beta + \varepsilon \qquad (1)$$

where y is a binary dependent variable:

$y_i = 1, if\ respondents\ chose\ somewhat\ likely\ or\ above$ ;

$y_i = 0, otherwise;$

$\mathbf{X} = (x_1, x_2, x_3, \dots, x_k)$ is a set of independent variables which could be continuous, discrete or a combination of the two. Note that $x_i$ is the observed value of the independent variables for observation i.

$$\pi_i = Pr(y_i = 1|X_i = x_i) = \frac{e^{x_i'\beta}}{1+e^{x_i'\beta}} = \Lambda(x_i'\beta) \qquad (2)$$

or,

$$\operatorname{logit}(\pi_i) = ln\frac{\pi_i}{1-\pi_i} = ln\frac{Pr(y_i = 1|X_i = x_i)}{Pr(y_i = 0|X_i = x_i)} = x_i'\beta \quad (3)$$

where $\Lambda(\cdot)$ represents the logistic CDF.

**Maximum likelihood estimation:**

Estimates $\hat{\beta}(\boldsymbol{y})$ are obtained by finding the parameters that maximize the likelihood of having sampled that particular set of $\boldsymbol{y}$. The likelihood function is the joint density of observing the sample data as a function of the parameters of the model.

In general,

$$\hat{\beta} = \arg\max_{\beta} = \{\ell(\beta; \boldsymbol{y}|\boldsymbol{X}) = \prod_{i=1}^{n}[F(x_i'\beta)]^{y_i}[1 - F(x_i'\beta)]^{1-y_i}\} \quad (4)$$

Specially for binary logit model, the likelihood equation becomes:

$$\sum_{i=1}^{n}\left(y_i - \Lambda\left(x_i'\hat{\beta}\right)\right)x_i = \sum_{i=1}^{n}(y_i - \hat{\pi}_i)\,x_i = 0 \quad (5)$$

**Odds ratio:**

exp ($\beta_0$): the baseline odds that the characteristic is present in an observation i, when $X_i$ is 0. $\exp(\beta_k)$: for every unit increase in $X_{ik}$, the odds that the characteristic is present is multiplied by $\exp(\beta_k)$.

**Standard error for odds ratio:**

In this thesis, we see the standard deviation of a large sample in normal distribution as standard error approximately.

For fixed parameter we have,

$$\beta = \hat{\beta} + \varepsilon \quad (6)$$

$$\text{odds ratio} = \exp(\beta) = \exp\,(\hat{\beta} + \varepsilon) \quad (7)$$

where $\varepsilon \sim \mathrm{N}(0, \mathrm{Std.\,error}(\hat{\beta})^2)$.

We could calculate the standard error of odds ratio by generating random sample in normal distribution $\mathrm{N}(\hat{\beta}, \mathrm{Std.error}(\hat{\beta})^2)$.

For random parameter we have,

$$\varepsilon \sim \mathrm{N}(0, \mathrm{Std.error}(\hat{\beta})^2) \quad (8)$$

$$\varepsilon_{sd} \sim \mathrm{N}(0, \mathrm{Std.error}(\widehat{\beta_{sd}})^2) \quad (9)$$

so we can get,

$$\hat{\beta} \sim \mathrm{N}(\hat{\beta}, \mathrm{Std.error}(\hat{\beta})^2) \quad (10)$$

$$\hat{\beta}_{sd} \sim \mathrm{N}(\hat{\beta}_{sd}, \mathrm{Std.error}(\widehat{\beta_{sd}})^2) \quad (11)$$

finally, we could get the standard deviation of odds ratio by simulation:

$$\text{odds ratio} = \exp\left(\beta + \beta_{sd} \cdot \xi\right) \quad (12)$$

where $\beta \sim \mathrm{N}(\hat{\beta}, \mathrm{Std.error}(\hat{\beta})^2)$, $\beta_{sd} \sim \mathrm{N}(0, \mathrm{Std.error}(\widehat{\beta_{sd}})^2)$, $\xi \sim \mathrm{N}(0,1)$.

**Confidence interval:**

The distribution of the odds ratio is positively skewed, but it could be approximately seen as normally distributed on a natural log-scale. So the confidence interval might be calculated on the natural log scale (LN), and finally use the EXP function to retrieve the original scale.

**Ordered model**

The ordered logit model is a regression model for ordinal variables, which could be seen as an extension of the binary logit model that applies to binary dependent variables, allowing for more than 2 response categories. Note that an alternative method utilizes the multinomial logit model, which has a drawback of ignoring the ordering of the categories.

**Model:**

$$\mathbf{y} = \mathbf{X}\beta + \varepsilon \quad (13)$$

where **y** is a dependent variable which represents the willingness to pay scaling from very unlikely (1) to very likely (5).

$\mathbf{X} = (x_1, x_2, x_3, \dots, x_k)$ is a set of independent variables which could be continuous, discrete or a combination of the two. Note that $x_i$ is the observed value of the independent variables for observation i.

Recall the logit model, which is

$$\text{logit}(\pi_i) = ln\frac{\pi_i}{1-\pi_i} = x_i'\beta. \quad (14)$$

Instead of considering the probability of an individual event, we consider the probability of that event and all event that are ordered before it. We may define $\pi_i$ as follow:

$$\pi_j = \frac{\Pr(y_i \leq j)}{\Pr(y_i > j)} \quad (15)$$

or,

$$\pi_j = \frac{\Pr(y_i \leq j)}{1-\Pr(y_i \leq j)} \quad (16)$$

Then, we could develop the ordinal logistic model for a single independent variable like below:

$$\pi_j = \alpha_j - \boldsymbol{X}\beta. \quad (17)$$

Where j goes from 1 to the number of categories minus 1, concretely 4 in this paper. Each logit has its own $\alpha_i$, which is called the threshold values.

**Maximum likelihood estimation:**

Based on previous equations, probabilities of individual event could be calculated using the formula:

$$\Pr(y_i = j) = \Pr(y_i \leq j) - \Pr(y_i < \text{j}). \quad (18)$$

Estimation of the parameter is very straightforward in maximum likelihood estimation like binary logistic regression goes. The log likelihood function can be represented as the following formula:

$$\mathcal{L} = \sum_{i=1}^{n} \sum_{j=0}^{J} \log\left[F\left(\alpha_j - x_i'\beta\right) - F\left(\alpha_{j-1} - x_i'\beta\right)\right] \quad (19)$$

where the constrains $\alpha_{-1} = -\infty, \alpha_0 = 0, \alpha_J = +\infty$ are hold.

**Random parameter model**

The random parameter model allows parameter values to vary across the population according to some pre-specified distribution, which makes the model itself more complex but more flexible. If a parameter is found to vary significantly across observations, it means that every observation has its own parameter. Here, we extend our ordered logit model to mixed ordered logit model.

Different from the standard logit model, where the "taste" coefficients βs are fixed, in random parameter models, every person k has its own $\beta_k$. The general representation of utility function is:

$$\boldsymbol{U}_n = \boldsymbol{X}_n\beta + \boldsymbol{P}_n\boldsymbol{T}\boldsymbol{\xi}_n + \varepsilon_n \quad (20)$$

where we have:

$\boldsymbol{U}_n$: vector of $\boldsymbol{J}_n$ indirect utility functions;

$\boldsymbol{X}_n$: ($\boldsymbol{J}_n \times K$) attribute matrix;

$\beta$: vector of K fixed taste parameters;

$\boldsymbol{P}_n$: ($\boldsymbol{J}_n \times F$) matrix of factor loadings including fixed or unknown parameter;

**T**: (F$\times F$) lower triangular matrix of (unknown) covariance parameters

$\boldsymbol{\xi}_n$: vector of F random variables with zero mean and variance;

$\varepsilon_n$: vector of $\boldsymbol{J}_n$ random terms iid EV1(0, $\lambda$).

Note that we would use θ to present the whole set of unknown parameters, including taste parameter $\beta$ and also parameters that represent random heterogeneity. Since it is an ordered logit model, we assume that:

$$y_i = j, if\ \alpha_{j-1} \leq U_i < \alpha_j \quad (21)$$

Conditional on $\boldsymbol{\xi}_n$, the choice probabilities is:

$$P_{in}(y_i = j|\boldsymbol{\xi}_n) = P_{in}\left(\alpha_{j-1} < U_i < \alpha_j \middle| \boldsymbol{\xi}_n\right)$$

$$= \Lambda\left(\alpha_j - (\boldsymbol{X}_{in}\beta + \boldsymbol{P}_{in}\boldsymbol{T}\boldsymbol{\xi}_n)\right) - \Lambda\left(\alpha_{j-1} - (\boldsymbol{X}_{in}\beta + \boldsymbol{P}_{in}\boldsymbol{T}\boldsymbol{\xi}_n)\right) \quad (22)$$

where $\Lambda(\cdot)$ represents logistic CDF.

Thus, the unconditional probability could be calculated by considering all possible values of $\boldsymbol{\xi}_n$,

$$P_n(y_i = j) = \int \Lambda\left(\alpha_j - (\boldsymbol{X}_{in}\beta + \boldsymbol{P}_n\boldsymbol{T}\boldsymbol{\xi}_n)\right) - \Lambda\left(\alpha_{j-1} - (\boldsymbol{X}_{in}\beta + \boldsymbol{P}_n\boldsymbol{T}\boldsymbol{\xi}_n)\right) f(\boldsymbol{\xi})\, d\boldsymbol{\xi} \quad (23)$$

where f(ξ) is the joint density function of ξ.

**Parameter estimation by simulation:**

The likelihood function of the model is:

$$\ell(\theta; y|\boldsymbol{X}) = \prod_{n=1}^{N} \prod_{i \in C_n} \left[\int \Lambda\left(\alpha_j - (\boldsymbol{X}_{in}\beta + \boldsymbol{P}_n\boldsymbol{T}\boldsymbol{\xi}_n)\right) - \Lambda\left(\alpha_{j-1} - (\boldsymbol{X}_{in}\beta + \boldsymbol{P}_n\boldsymbol{T}\boldsymbol{\xi}_n)\right) f(\xi)\, d\boldsymbol{\xi}\right]^{y_{in}} \quad (24)$$

which leads to the maximum log-likelihood problem as follows:

$$\max_{\theta} \mathcal{L}(\theta; y|\boldsymbol{X}) = \sum_{n=1}^{N} \sum_{i \in C_n} y_{in} \ln \left[\int \Lambda\left(\alpha_j - (\boldsymbol{X}_{in}\beta + \boldsymbol{P}_n\boldsymbol{T}\boldsymbol{\xi}_n)\right) - \Lambda\left(\alpha_{j-1} - (\boldsymbol{X}_{in}\beta + \boldsymbol{P}_n\boldsymbol{T}\boldsymbol{\xi}_n)\right) f(\xi)\, d\boldsymbol{\xi}\right] \quad (25)$$

Since there is no closed form for the integral that could enter the choice probability, it is a good way to estimate the model by simulation. We could use a maximum simulated likelihood estimator (MSLE) to replace the $P_{in}$ with $\widetilde{P_{in}}$, which is developed as follows:

$$\widetilde{P_{in}} = \frac{1}{S} \sum_{s=1}^{S} \Lambda\left(\alpha_j - (\boldsymbol{X}_n\beta + \boldsymbol{P}_n\boldsymbol{T}\boldsymbol{\xi}_n)\right) - \Lambda\left(\alpha_{j-1} - (\boldsymbol{X}_n\beta + \boldsymbol{P}_n\boldsymbol{T}\boldsymbol{\xi}_n)\right) \quad (26)$$

where $\xi_n^s$ is a random draw taken over the distribution of $\xi$. s = 1, …, S.

Then the simulated likelihood equation becomes:

$$\frac{\partial \tilde{\mathcal{L}}(\theta; y|\boldsymbol{X})}{\partial \hat{\theta}} = \sum_{n=1}^{N} \sum_{i \in C_n} y_{in} \frac{1}{\widetilde{P_{in}}(\hat{\theta})} \frac{1}{S} \sum_{s=1}^{S} P_n\left(i \middle| \hat{\theta}, \boldsymbol{\xi_n^s}\right) \frac{\partial ln P_n\left(i \middle| \hat{\theta}, \boldsymbol{\xi_n^s}\right)}{\partial \hat{\theta}} = 0 \quad (27)$$

## 3.3 Methods - data processing

Since the data needs to be applied in both binary and ordered models, processing of the transformation is needed to make it fit in the models. Part of the ordinary data for CV1.1 is listed below:

**Table 3-5 Data of CV1.1**

| CV1.1_1 | CV1.1_2 | CV1.1_3 | CV1.1_4 | CV1.1_5 | CV1.1_6 | … |
|---|---|---|---|---|---|---|
| 5 | 3 | 3 | 5 | 2 | 2 | … |
| 1 | 2 | 2 | 3 | 2 | 1 | … |
| … | … | … | … | … | … | … |

Each record represents a single respondent's choice. Concretely the first respondent's survey form might look like table 3-6 as below:

**Table 3-6 Response of CV1.1**

| | Very Unlikely (1) | Somewhat Unlikely (2) | Undecided (3) | Somewhat Likely (4) | Very Likely (5) |
|---|---|---|---|---|---|
| **$50 (1)** | ○ | ○ | ○ | ○ | ● |
| **$100 (2)** | ○ | ○ | ● | ○ | ○ |
| **$200 (3)** | ○ | ○ | ● | ○ | ○ |
| **$400 (4)** | ○ | ○ | ○ | ○ | ● |
| **$800 (5)** | ○ | ● | ○ | ○ | ○ |
| **More than $800 (6)** | ○ | ● | ○ | ○ | ○ |

For each record, transform the record format by adding variables like respondent id, payment, etc. Note that in order to fit in binary model, an additional column "dummyChoice" is added to present whether the respondent would like to pay given certain payment. This binary dependent variable is defined:

$$\text{dummyChoice} = \begin{cases} 1, & if\ likeness > 3. \\ 0, & otherwise\ . \end{cases} \quad (27)$$

Finally, the data can be found in the table below:

**Table 3-7 Example of One Respondent's Data for CV1.1**

| respondent ID | choice | dummyChoice | payment | Other variables |
|---|---|---|---|---|
| **1** | 5 | 1 | 50 | … |
| | 3 | 0 | 100 | … |
| | 3 | 0 | 200 | … |
| | 5 | 1 | 400 | … |
| | 2 | 0 | 800 | … |
| | 2 | 0 | 1200 | … |

In the table above, the payment of $1200 stands for the choice of “More than $800” in the original survey in case of evaluation. Moreover, for the combined models, add other 3 dummy variables called “data1.2”, “data1.3”, “data2.1” that were used to keep track of the origin of the data. (In CV2.1, the monthly payment is converted to the yearly payment by multiplying by 12.)

**Table 3-8 Example of One Respondent's Data for CV1.1-CV2.1**

| respondent ID | choice | dummyChoice | payment | Other variables | Data1.2 | Data1.3 | Data2.1 |
|---|---|---|---|---|---|---|---|
| **1** | 5 | 1 | 50 | … | 0 | 0 | 0 |
| | 3 | 0 | 100 | … | 0 | 0 | 0 |
| | 3 | 0 | 200 | … | 0 | 0 | 0 |
| | 5 | 1 | 400 | … | 0 | 0 | 0 |
| | 2 | 0 | 800 | … | 0 | 0 | 0 |
| | 2 | 0 | 1200 | … | 0 | 0 | 0 |
| | 5 | 1 | 50 | … | 1 | 0 | 0 |
| | 4 | 1 | 100 | … | 1 | 0 | 0 |
| | 4 | 1 | 200 | … | 1 | 0 | 0 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 3 | 0 | 400 | … | 1 | 0 | 0 |
| 2 | 0 | 800 | … | 1 | 0 | 0 |
| 1 | 0 | 1200 | … | 1 | 0 | 0 |
| … | … | … | … | … | … | … |

## 3.4 Hypotheses

### 3.4.1 Independent variables & recoding

Given dependent variables, independent variables are dedicatedly chosen for the model development.

- *PersLoss* refers to Q13(1): Did you experience any person loss from Hurricane Sandy, recoding "Yes" as 1, "No/Don't remember" as 0;
- *numHurr* refers to Q5: How many hurricanes have you been in, recoding "0" as 0, "1-2" as 1, "3-4" as 3, "5-6" as 5 and "7 or more" as 8.
- *numEvac* refers to Q6: How many times have you evacuated from a hurricane, recoding "0" as 0, "1-2" as 1, "3-4" as 3, "5-6" as 5 and "7 or more" as 8.
- *daysMissedW* refers to Q10 and Q11, recoding "No" as 0, "7 days or longer" as 8. lineInconv refers to Q26b How is the effect of subway line closures on daily life, recoding "Wouldn't affect me/Minor inconvenience" as 0, "Somewhat inconvenient/ Extremely inconvenient" as 1.
- *fullTime/worker* refers to the same question Q46: Which of the following best describes your current employment situation. For fullTime, recode "Full-time (more than 30 hours per week)" as 1, otherwise 0; for worker recode "Full-time" and "Part-time/ casual job" as 1, otherwise 0.
- *Income* refers to Q49: What is your estimated annual household income, recoding "Less than $10,000" as 7,500, "$10,000-$19,999" as 15,000, "$20,000-$29,999" as 25,000, "$30,000-$39,999" as 35,000, "$40,000-$49,999"

as 45,000, “$50,000-$59,999” as 55,000, “$60,000-$69,999” as 65,000, “$70,000-$79,999” as 75,000, “$80,000-$89,999” as 85,000, “$90,000-$99,999” as 95,000, “$100,000-$149,999” as 125,000, “More than $150,000” as 175,000. Note that *log(income)*, which is income applied to logarithm, is also considered as an independent variable.

- *White* refers to Q50: What do you consider yourself, recoding “White/Caucasian” as 1, others as 0. Hisp refers to Q51: Are you Hispanic or Latino, recoding “Yes” as 1, “No” as 0.
- *Lib/Cons* refers to Q53: When it comes to politics, you generally consider yourself to be…, recoding “Very Liberal” and “Liberal” as 1 in Lib; “Conservative” and “Very Conservative” as 1 in Cons; otherwise 0 in both.
- *TownHouse* refers to Q42: In what type of housing do you live, recoding “TownHouse” and “Brownstone” as 1, otherwise 0.
- *Married* refers to Q43 What is your current relationship status, recoding “Married” and “Living with partner” as 1, otherwise 0.
- *Children* refers to Q44 How many children, including adult children, are currently living with you, recoding “1-2” as 1, “3-4” as 3, “More than 4” as 5.

### 3.4.2 Hypotheses

Below is a table of hypotheses for each independent variable:

**Table 3-9 Hypothesis of Independent Variables**

| Variable | Sign of parameter | Odds ratio (Compare to 1) |
|---|---|---|
| **payment** | - | < |
| **persLoss** | + | > |
| **numHurr** | - | < |
| **numEvac** | + | > |

| | | |
|---|---|---|
| **daysMissedW** | + | > |
| **lineInconv** | + | > |
| **fullTime/worker** | + | > |
| **income/log(income)** | + | > |
| **white** | - | < |
| **hisp** | + | > |
| **lib** | + | > |
| **cons** | - | < |
| **townHouse** | + | > |
| **married** | + | > |
| **children** | + | > |

- *NumEavc*, *daysMissedW*, *children*: the higher value these variables have, the higher probability of the respondent is willing to pay to support investments in resilience. In statistical terms, a positive parameter is expected in binary models for each of these variables, corresponding to an odds ratio that is higher than 1.
- *Payment*, *numHurr*, *fullTime/worker*, *income/log(income)*, *hisp*, *lib*, *townHouse*, *married*, *children*: if these variables hold true, the probability of the respondent willing to pay to support investments in resilience are high. In statistical terms, a positive parameter is expected in binary models for each of these variables, corresponding to an odds ratio that is higher than 1.
- *White*, *cons*: if these variables hold true, the probability of the respondent willing to pay to support investments in resilience are low. In statistical terms, a negative parameter is expected in binary models for each of these variables, corresponding to an odds ratio that is lower than 1.

## 3.5 Results

After running in the R-lab studio, we are able to obtain the result of each kind of models.

**Binary models**

**Models for CV1.1:**

Fixed parameters model:

**Table 3-10 Result of Standard Binary Model for CV1.1**

| | Estimate | Std. Error | z-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| **constant** | -4.2649156 | 0.7727776 | -5.519 | 3.41E-08 | *** |
| **payment** | -0.0025892 | 0.0001692 | -15.303 | < 2e-16 | *** |
| **persLoss** | 0.5581879 | 0.1035475 | 5.391 | 7.02E-08 | *** |
| **numHurr** | -0.0641118 | 0.0209329 | -3.063 | 0.002193 | ** |
| **numEvac** | 0.4542661 | 0.0534395 | 8.501 | < 2e-16 | *** |
| **daysMissedW** | 0.0542808 | 0.0198276 | 2.738 | 0.006188 | ** |
| **lineInconv** | 0.3318013 | 0.0979254 | 3.388 | 0.000703 | *** |
| **worker** | 0.3352633 | 0.1239769 | 2.704 | 0.006846 | ** |
| **log(income)** | 0.2648828 | 0.0720469 | 3.677 | 0.000236 | *** |
| **white** | -0.2475424 | 0.1147005 | -2.158 | 0.030915 | * |
| **hisp** | 0.49338 | 0.139449 | 3.538 | 0.000403 | *** |
| **townHouse** | 0.5954412 | 0.1414354 | 4.21 | 2.55E-05 | *** |
| **children** | 0.2008143 | 0.0545042 | 3.684 | 0.000229 | *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Optimization of log-likelihood by Newton-Raphson maximization
Log Likelihood: -1405
BIC: 2915.866

Odds ratio:

**Table 3-11 Odds Ratio of Standard Binary Model for CV1.1**

| | Odds ratio | Odds Std Error |
|---|---|---|
| **payment** | 0.997414149 | 2.89817E-08 |
| **persLoss** | 1.747502979 | 0.018546443 |
| **numHurr** | 0.937900136 | 0.000418575 |
| **numEvac** | 1.575017054 | 0.004629422 |
| **daysMissedW** | 1.055781024 | 0.000419742 |
| **lineInconv** | 1.393475937 | 0.013459018 |
| **worker** | 1.398308511 | 0.021296705 |

| | | |
|---|---|---|
| **log(income)** | 1.303278223 | 0.006851025 |
| **white** | 0.780717118 | 0.010568579 |
| **hisp** | 1.637842783 | 0.031882827 |
| **townHouse** | 1.813831031 | 0.036184883 |
| **children** | 1.222397751 | 0.003556736 |

Random parameters model:

**Table 3-12 Result of Mixed Binary Model for CV1.1**

| | Estimate | Std. Error | z-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| **constant** | -4.6553245 | 0.7607722 | -6.119 | 9.40E-10 | *** |
| **payment** | -0.0025996 | 0.0001733 | -14.997 | < 2e-16 | *** |
| **persLoss** | 0.5471737 | 0.1056772 | 5.178 | 2.25E-07 | *** |
| **numEvac** | 0.4903989 | 0.0638441 | 7.681 | 1.58E-14 | *** |
| **daysMissedW** | 0.0604557 | 0.01952 | 3.097 | 0.001954 | ** |
| **lineInconv** | 0.3589551 | 0.0985886 | 3.641 | 0.000272 | *** |
| **log(income)** | 0.3066493 | 0.0683767 | 4.485 | 7.30E-06 | *** |
| **hisp** | 0.5360253 | 0.1420649 | 3.773 | 0.000161 | *** |
| **townHouse** | 0.6041217 | 0.1416433 | 4.265 | 2.00E-05 | *** |
| **children** | 0.1995406 | 0.0553851 | 3.603 | 0.000315 | *** |
| **mean.numHurr** | -0.0899206 | 0.0344726 | -2.608 | 0.009095 | ** |
| **sd.numHurr** | 0.0708516 | 0.0820495 | 0.864 | 0.38785 | |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Optimization of log-likelihood by BFGS maximization

Log Likelihood: -1411

BIC: 2918.732

Odds ratio:

**Table 3-13 Odds Ratio of Mixed Binary Model for CV1.1**

| | Odds ratio | Odds Std Error |
|---|---|---|
| **payment** | 0.997403776 | 3.11E-08 |
| **persLoss** | 1.728361241 | 1.93E-02 |
| **numEvac** | 1.632967481 | 6.63E-03 |
| **daysMissedW** | 1.062320536 | 0.000410628 |
| **lineInconv** | 1.431832511 | 0.013284275 |
| **log(income)** | 1.358864331 | 6.12E-03 |
| **hisp** | 1.709199787 | 0.03428855 |

| | | |
|---|---|---|
| **townHouse** | 1.829644526 | 3.76E-02 |
| **children** | 1.220841775 | 0.003623128 |
| **numHurr** | 0.914003754 | 0.083009465 |

Basic statistics for CV1.1 Models:

1. Frequencies of categories:

**Table 3-14 Frequencies of Categories for CV1.1**

| **0** | **1** |
|---|---|
| 0.7966 | 0.2034 |

2. Willingness to pay:

**Table 3-15 WTP for CV1.1**

| **WTP for** | |
|---|---|
| **persLoss** | 215.5831531 |
| **numHurr** | 24.76123899 |
| **numEvac** | 175.4465086 |
| **daysMissedW** | 20.9643133 |
| **lineInconv** | 128.1481925 |
| **worker** | 129.485285 |
| **log(income)** | 102.3029507 |
| **white** | 95.60574695 |
| **hisp** | 190.5530666 |
| **townHouse** | 229.9711108 |
| **children** | 77.55843504 |

**Models for CV1.2:**

Fixed parameters model:

**Table 3-16 Result of Standard Binary Model for CV1.2**

| | **Estimate** | **Std. Error** | **z-value** | **Pr(>\|z\|)** | |
|---|---|---|---|---|---|
| **constant** | -3.659435 | 0.8857442 | -4.131 | 3.60E-05 | *** |
| **payment** | -0.0026791 | 0.0002061 | -13.001 | < 2e-16 | *** |
| **numHurr** | -0.0791447 | 0.0242222 | -3.267 | 0.001085 | ** |
| **numEvac** | 0.3868017 | 0.0625801 | 6.181 | 6.37E-10 | *** |
| **daysMissedW** | 0.0939319 | 0.0220996 | 4.25 | 2.13E-05 | *** |

| | | | | | |
|---|---|---|---|---|---|
| **lineInconv** | 0.6342148 | 0.1138641 | 5.57 | 2.55E-08 | *** |
| **log(income)** | 0.2195002 | 0.0798548 | 2.749 | 0.005982 | ** |
| **cons** | -0.3431481 | 0.1442633 | -2.379 | 0.017377 | * |
| **townHouse** | 0.5684403 | 0.1593364 | 3.568 | 0.00036 | *** |
| **children** | 0.2038181 | 0.0568538 | 3.585 | 0.000337 | *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Optimization of log-likelihood by Newton-Raphson maximization
Log Likelihood: -1053
BIC: 2184.635

Odds ratio:

**Table 3-17 Odds Ratio of Standard Binary Model for CV1.2**

| | Odds ratio | Odds Std Error |
|---|---|---|
| **payment** | 0.997324486 | 4.37E-08 |
| **numHurr** | 0.923906226 | 0.000551026 |
| **numEvac** | 1.472264512 | 5.62E-03 |
| **daysMissedW** | 1.098484937 | 5.28E-04 |
| **lineInconv** | 1.885541033 | 2.51E-02 |
| **log(income)** | 1.245454097 | 0.008224824 |
| **cons** | 0.709533122 | 0.014548973 |
| **townHouse** | 1.765511235 | 0.047182968 |
| **children** | 1.22607511 | 0.003901025 |

Random parameters model:

**Table 3-18 Result of Mixed Binary Model for CV1.2**

| | Estimate | Std.Error | z-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| **constant** | -3.5443518 | 0.9173224 | -3.864 | 0.000112 | *** |
| **payment** | -0.0027381 | 0.0002333 | -11.739 | < 2e-16 | *** |
| **numEvac** | 0.4545171 | 0.0912091 | 4.983 | 6.25E-07 | *** |
| **daysMissedW** | 0.1021296 | 0.0240448 | 4.247 | 2.16E-05 | *** |
| **lineInconv** | 0.6326161 | 0.1179169 | 5.365 | 8.10E-08 | *** |
| **log(income)** | 0.207143 | 0.0825437 | 2.509 | 0.01209 | * |
| **townHouse** | 0.5878006 | 0.1675441 | 3.508 | 0.000451 | *** |
| **children** | 0.2040417 | 0.058623 | 3.481 | 0.0005 | *** |

| | | | | | |
|---|---|---|---|---|---|
| **mean.numHurr** | -0.1357666 | 0.056958 | -2.384 | 0.017143 | * |
| **sd.numHurr** | 0.1418302 | 0.0793949 | 1.786 | 0.074036 | . |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Optimization of log-likelihood by BFGS maximization
Log Likelihood: -1055
BIC: 2189.307

Odds ratio:

**Table 3-19 Odds Ratio of Mixed Binary Model for CV1.2**

| | **Odds ratio** | **Odds Std Error** |
|---|---|---|
| **payment** | 0.997265645 | 5.44E-08 |
| **numEvac** | 1.575412433 | 1.25E-02 |
| **daysMissedW** | 1.107526998 | 6.45E-04 |
| **lineInconv** | 1.865741473 | 2.41E-02 |
| **log(income)** | 1.230158472 | 0.008381833 |
| **townHouse** | 1.800025083 | 0.049509341 |
| **children** | 1.226349291 | 0.004266836 |
| **numHurr** | 0.873046378 | 0.120027494 |

Basic statistics for CV1.2 Models:

1. Frequencies of categories:

**Table 3-20 Frequencies of Categories for CV1.2**

| **0** | **1** |
|---|---|
| 0.8201 | 0.1799 |

2. Willingness to pay:

**Table 3-21 WTP for CV1.2**

| WTP for | |
|---|---|
| numHurr | 29.54152514 |
| numEvac | 144.3774775 |
| daysMissedW | 35.06099063 |
| lineInconv | 236.7268112 |
| log(income) | 81.9305737 |
| cons | 128.0833489 |

| | |
|---|---|
| townHouse | 212.1758426 |
| children | 76.07707812 |

**Models for CV1.3:**

Fixed parameters model:

**Table 3-22 Result of Standard Binary Model for CV1.3**

| | Estimate | Std. Error | z-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| **constant** | -2.02E+00 | 1.58E-01 | -12.778 | < 2e-16 | *** |
| **payment** | -2.93E-03 | 2.10E-04 | -13.942 | < 2e-16 | *** |
| **persLoss** | 7.85E-01 | 1.17E-01 | 6.689 | 2.24E-11 | *** |
| **numEvac** | 1.30E-01 | 5.18E-02 | 2.51 | 0.01207 | * |
| **daysMissedW** | 1.51E-02 | 2.28E-02 | 0.661 | 0.508664 | |
| **lineInconv** | 6.19E-01 | 1.12E-01 | 5.512 | 3.55E-08 | *** |
| **worker** | 2.67E-01 | 1.29E-01 | 2.065 | 0.038891 | * |
| **log(income)** | 2.34E-06 | 1.15E-06 | 2.031 | 0.042251 | * |
| **hisp** | 5.64E-01 | 1.48E-01 | 3.822 | 0.000132 | *** |
| **lib** | 2.99E-01 | 1.13E-01 | 2.654 | 0.007949 | ** |
| **townHouse** | 8.34E-01 | 1.55E-01 | 5.384 | 7.27E-08 | *** |
| **children** | 2.17E-01 | 5.57E-02 | 3.894 | 9.87E-05 | *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Optimization of log-likelihood by Newton-Raphson maximization:
Log Likelihood: -1092
BIC: 2284.073

Odds ratio:

**Table 3-23 Odds Ratio of Standard Binary Model for CV1.3**

| | Odds ratio | Odds Std Error |
|---|---|---|
| **payment** | 0.997073291 | 4.60E-08 |
| **persLoss** | 2.191311011 | 3.02E-02 |
| **numEvac** | 1.138828383 | 0.003135303 |
| **daysMissedW** | 1.015194277 | 0.000519944 |
| **lineInconv** | 1.857255759 | 2.30E-02 |
| **worker** | 1.305779264 | 0.02207502 |
| **log(income)** | 1.000002341 | 1.36E-12 |
| **hisp** | 1.757337712 | 0.037718425 |

| | | |
|---|---|---|
| **lib** | 1.349049135 | 0.016649566 |
| **townHouse** | 2.302280147 | 5.60E-02 |
| **children** | 1.242344102 | 3.88E-03 |

Random parameters model:

**Table 3-24 Result of Mixed Binary Model for CV1.3**

| | Estimate | Std. Error | z-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| **constant** | -2.5651085 | 0.9450581 | -2.714 | 0.006643 | ** |
| **payment** | -0.0044058 | 0.0004211 | -10.462 | < 2e-16 | *** |
| **persLoss** | 0.9382648 | 0.1503585 | 6.24 | 4.37E-10 | *** |
| **daysMissedW** | 0.0481898 | 0.0265621 | 1.814 | 0.069642 | . |
| **log(income)** | 0.0913843 | 0.0852531 | 1.072 | 0.283757 | |
| **hisp** | 0.6677966 | 0.1941093 | 3.44 | 0.000581 | *** |
| **lib** | 0.3419806 | 0.1360834 | 2.513 | 0.01197 | * |
| **townHouse** | 0.9781708 | 0.1973886 | 4.956 | 7.21E-07 | *** |
| **children** | 0.1774019 | 0.0714118 | 2.484 | 0.012984 | * |
| **mean.numEvac** | -0.5286906 | 0.2980724 | -1.774 | 0.076113 | . |
| **mean.lineInconv** | 0.6600591 | 0.1347863 | 4.897 | 9.73E-07 | *** |
| **sd.numEvac** | 2.9255999 | 0.6017394 | 4.862 | 1.16E-06 | *** |
| **sd.lineInconv** | 0.0197914 | 0.3797259 | 0.052 | 0.958433 | |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Optimization of log-likelihood by BFGS maximization
Log Likelihood: -1087
BIC: 2277.659

Odds ratio:

**Table 3-25 Odds Ratio of Mixed Binary Model for CV1.3**

| | Odds ratio | Odds Std Error |
|---|---|---|
| **payment** | 0.995603891 | 1.78E-07 |
| **persLoss** | 2.55554319 | 5.72E-02 |
| **daysMissedW** | 1.049369807 | 0.00077222 |
| **log(income)** | 1.095689998 | 0.007701612 |
| **hisp** | 1.949936095 | 0.076270439 |
| **lib** | 1.407732987 | 0.026865737 |
| **townHouse** | 2.659586873 | 1.05E-01 |
| **children** | 1.19411091 | 0.006079044 |

| | | |
|---|---|---|
| **numEvac** | 0.589376194 | 0.409857004 |
| **lineInconv** | 1.934906684 | 1.78E+00 |

Basic statistics for CV1.3 Models:

1. Frequencies of categories:

**Table 3-26 Frequencies of Categories for CV1.3**

| **0** | **1** |
|---|---|
| 0.8143 | 0.1857 |

2. Willingness to pay:

**Table 3-27 WTP for CV1.3**

| WTP for: | |
|---|---|
| persLoss | 212.9612783 |
| daysMissedW | 10.93780925 |
| log(income) | 20.7418176 |
| hisp | 151.5721549 |
| lib | 77.62054564 |
| townHouse | 222.0188842 |
| children | 40.26553634 |
| numEvac | 119.9987743 |
| lineInconv | 149.8159472 |

**Models for CV2.1:**

Fixed parameters model:

**Table 3-28 Result of Standard Binary Model for CV2.1**

| | **Estimate** | **Std. Error** | **z-value** | **Pr(>\|z\|)** | |
|---|---|---|---|---|---|
| **constant** | -2.63E+00 | 3.98E-01 | -6.615 | 3.72E-11 | *** |
| **payment** | -2.33E-03 | 8.17E-05 | -28.489 | < 2e-16 | *** |
| **persLoss** | 3.10E-01 | 5.82E-02 | 5.328 | 9.93E-08 | *** |
| **numHurr** | -2.20E-02 | 1.10E-02 | -2.004 | 0.04505 | * |
| **numEvac** | 2.44E-01 | 3.02E-02 | 8.08 | 6.66E-16 | *** |
| **daysMissedW** | 5.50E-02 | 1.09E-02 | 5.062 | 4.14E-07 | *** |
| **lineInconv** | 5.56E-01 | 5.40E-02 | 10.292 | < 2e-16 | *** |
| **worker** | 1.38E-01 | 6.18E-02 | 2.232 | 0.02563 | * |

| | | | | | |
|---|---|---|---|---|---|
| **log(income)** | 1.72E-01 | 3.72E-02 | 4.621 | 3.82E-06 | *** |
| **white** | -1.92E-01 | 6.29E-02 | -3.052 | 0.00227 | ** |
| **hisp** | 3.94E-01 | 7.83E-02 | 5.032 | 4.86E-07 | *** |
| **lib** | 2.45E-01 | 5.84E-02 | 4.203 | 2.64E-05 | *** |
| **cons** | -1.85E-01 | 6.98E-02 | -2.654 | 0.00795 | ** |
| **townHouse** | 3.95E-01 | 8.05E-02 | 4.908 | 9.21E-07 | *** |
| **children** | 1.98E-01 | 2.89E-02 | 6.86 | 6.91E-12 | *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Optimization of log-likelihood by Newton-Raphson maximization
Log Likelihood: -4573
BIC: 9281.538

Odds ratio:

**Table 3-29 Odds Ratio of Standard Binary Model for CV2.1**

| | Odds ratio | Odds Std Error |
|---|---|---|
| **payment** | 0.997675705 | 6.90E-09 |
| **persLoss** | 1.363425114 | 4.70E-03 |
| **numHurr** | 0.978269583 | 0.000120632 |
| **numEvac** | 1.275833895 | 1.19E-03 |
| **daysMissedW** | 1.056519484 | 1.25E-04 |
| **lineInconv** | 1.742986463 | 0.005010072 |
| **worker** | 1.147745978 | 0.004208941 |
| **log(income)** | 1.187559071 | 1.73E-03 |
| **white** | 0.825389403 | 0.003259083 |
| **hisp** | 1.482900549 | 9.22E-03 |
| **lib** | 1.278132464 | 4.36E-03 |
| **cons** | 0.83093808 | 0.004024363 |
| **townHouse** | 1.484384191 | 9.73E-03 |
| **children** | 1.219084296 | 1.02E-03 |

Random parameters model:

**Table 3-30 Result of Mixed Binary Model for CV2.1**

| | Estimate | Std. Error | z-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| **constant** | -2.73094 | 0.4010575 | -6.809 | 9.80E-12 | *** |
| **payment** | -0.002491 | 0.0001001 | -24.89 | < 2e-16 | *** |
| **persLoss** | 0.256465 | 0.0622467 | 4.12 | 3.79E-05 | *** |

| | | | | | |
|---|---|---|---|---|---|
| **daysMissedW** | 0.0578604 | 0.0111006 | 5.212 | 1.86E-07 | *** |
| **log(income)** | 0.1758936 | 0.0361485 | 4.866 | 1.14E-06 | *** |
| **hisp** | 0.4313197 | 0.0813295 | 5.303 | 1.14E-07 | *** |
| **lib** | 0.2766204 | 0.0612827 | 4.514 | 6.37E-06 | *** |
| **cons** | -0.179948 | 0.0722047 | -2.492 | 0.0127 | * |
| **townHouse** | 0.4028635 | 0.0852868 | 4.724 | 2.32E-06 | *** |
| **children** | 0.1965966 | 0.0302908 | 6.49 | 8.57E-11 | *** |
| **mean.numHurr** | -0.023371 | 0.0113317 | -2.062 | 0.0392 | * |
| **mean.numEvac** | 0.3590555 | 0.0507214 | 7.079 | 1.45E-12 | *** |
| **mean.lineInconv** | 0.583278 | 0.0559317 | 10.428 | < 2e-16 | *** |
| **sd.numHurr** | 0.0034343 | 0.0995997 | 0.034 | 0.9725 | |
| **sd.numEvac** | 0.6992469 | 0.1794058 | 3.898 | 9.72E-05 | *** |
| **sd.lineInconv** | 0.0376931 | 0.3216465 | 0.117 | 0.9067 | |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Optimization of log-likelihood by BFGS maximization

Log Likelihood: -4570

BIC: 9285.482

Odds ratio:

**Table 3-31 Odds Ratio of Standard Binary Model for CV2.1**

| | **Odds ratio** | **Odds Std Error** |
|---|---|---|
| **payment** | 0.9975121 | 9.79E-09 |
| **persLoss** | 1.292353533 | 5.05E-03 |
| **daysMissedW** | 1.05956707 | 1.28E-04 |
| **log(income)** | 1.19231119 | 1.62E-03 |
| **hisp** | 1.539287582 | 1.02E-02 |
| **lib** | 1.318665711 | 5.12E-03 |
| **cons** | 0.835313312 | 0.004110582 |
| **townHouse** | 1.49610266 | 1.10E-02 |
| **children** | 1.217252902 | 1.13E-03 |
| **numHurr** | 0.976899498 | 0.02276104 |
| **numEvac** | 1.431976274 | 5.67E-01 |
| **lineInconv** | 1.791902671 | 1.354639917 |

Basic statistics for CV2.1 Models:

1. Frequencies of categories:

**Table 3-32 Frequencies of Categories for CV2.1**

| 0 | 1 |
|---|---|
| 0.7053 | 0.2947 |

2. Willingness to pay:

**Table 3-33 WTP for CV2.1**

| WTP for | |
|---|---|
| **persLoss** | 133.0472103 |
| **numHurr** | 9.442060086 |
| **numEvac** | 104.72103 |
| **daysMissedW** | 23.60515021 |
| **lineInconv** | 238.6266094 |
| **worker** | 59.22746781 |
| **log(income)** | 73.81974249 |
| **white** | 82.40343348 |
| **hisp** | 169.0987124 |
| **lib** | 105.1502146 |
| **cons** | 79.39914163 |
| **townHouse** | 169.527897 |
| **children** | 84.97854077 |

**Analysis on models CV1.1 - CV2.1:**

**Table 3-34 WTP for CV1.1-CV2.1**

| | cv1.1(7 days) | cv1.2(7 days) | cv1.3(14 days) | cv2.1(7 days) |
|---|---|---|---|---|
| **daysSaved** | 5 | 3 | 12 | 5 |
| **recoveryTime** | 2 | 4 | 2 | 2 |
| **numEvac** | 175.4465086 | 144.3774775 | 119.9987743 | 104.72103 |
| **daysMissedW** | 20.9643133 | 35.06099063 | 10.93780925 | 23.60515021 |
| **lineInconv** | 128.1481925 | 236.7268112 | 149.8159472 | 238.6266094 |
| **log(income)** | 102.3029507 | 81.9305737 | 20.7418176 | 73.81974249 |
| **townHouse** | 229.9711108 | 212.1758426 | 222.0188842 | 169.527897 |

| | | | | |
|---|---|---|---|---|
| **children** | 77.55843504 | 76.07707812 | 40.26553634 | 84.97854077 |

According to the table 3-34 as above, people would be more likely to pay less money monthly to reduce the times of evacuation from hurricanes than they would to pay yearly. As the efficiency of recovery improves, the WTP for reducing the days absent from work would decrease. WTP for someone living in a townhouse is about the same in CV1.1 – CV1.3, but would decrease from 229.97 to 169.5, if the investment is paid monthly instead of yearly. As efficiency of recovery improves, respondent's WTP for children decreases.

**All combined models:**

Fixed parameter model:

**Table 3-35 Result of Standard Binary Model for All Combined Data**

| | Estimate | Std. Error | z-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| **constant** | 1.255862 | 0.268298 | 4.681 | 2.86E-06 | *** |
| **log(payment)** | -0.984771 | 0.023357 | -42.162 | < 2e-16 | *** |
| **persLoss** | 0.375123 | 0.044177 | 8.491 | < 2e-16 | *** |
| **numHurr** | -0.047006 | 0.008404 | -5.593 | 2.23E-08 | *** |
| **numEvac** | 0.302138 | 0.021804 | 13.857 | < 2e-16 | *** |
| **daysMissedW** | 0.059065 | 0.008141 | 7.255 | 4.02E-13 | *** |
| **lineInconv** | 0.581958 | 0.041083 | 14.165 | < 2e-16 | *** |
| **log(income)** | 0.166791 | 0.025884 | 6.444 | 1.17E-10 | *** |
| **hisp** | 0.396258 | 0.058808 | 6.738 | 1.60E-11 | *** |
| **cons** | -0.271913 | 0.050066 | -5.431 | 5.60E-08 | *** |
| **townHouse** | 0.5169 | 0.059492 | 8.689 | < 2e-16 | *** |
| **children** | 0.201989 | 0.021693 | 9.311 | < 2e-16 | *** |
| **log(payment):data1.2** | -0.0313 | 0.014495 | -2.159 | 0.0308 | * |
| **log(payment):data1.3** | -0.035513 | 0.014237 | -2.494 | 0.0126 | * |
| **log(payment):data2.1** | 0.213903 | 0.015376 | 13.911 | < 2e-16 | *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Optimization of log-likelihood by BFGS maximization
Log Likelihood: -7995
BIC: 16136.38

Odds ratio:

**Table 3-36 Odds Ratio of Standard Binary Model for All Combined Data**

| | Odds Ratio | Odds Std. Error |
|---|---|---|
| **log(payment)** | 0.373524754 | 0.008436337 |
| **persLoss** | 1.45517039 | 0.064503492 |
| **numHurr** | 0.954081673 | 7.92E-03 |
| **numEvac** | 1.352747893 | 0.028466606 |
| **daysMissedW** | 1.060844193 | 8.63E-03 |
| **lineInconv** | 1.78953892 | 0.073195356 |
| **log(income)** | 1.181507304 | 3.03E-02 |
| **hisp** | 1.486252721 | 8.67E-02 |
| **cons** | 0.761920545 | 3.98E-02 |
| **townHouse** | 1.676821438 | 0.099288399 |
| **children** | 1.223834546 | 0.02740589 |

Random parameter model:

**Table 3-37 Result of Mixed Binary Model for All Combined Data**

| | Estimate | Std. Error | z-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| **constant** | 1.550607 | 0.285942 | 5.423 | 5.87E-08 | *** |
| **log(payment)** | -1.0637 | 0.029775 | -35.701 | < 2e-16 | *** |
| **persLoss** | 0.335051 | 0.048285 | 6.939 | 3.95E-12 | *** |
| **daysMissedW** | 0.059052 | 0.008657 | 6.821 | 9.01E-12 | *** |
| **log(income)** | 0.167717 | 0.027161 | 6.175 | 6.62E-10 | *** |
| **hisp** | 0.410066 | 0.062711 | 6.539 | 6.19E-11 | *** |
| **cons** | -0.26401 | 0.05266 | -5.013 | 0.000000535 | *** |
| **townHouse** | 0.510047 | 0.064622 | 7.893 | 2.89E-15 | *** |
| **children** | 0.196903 | 0.023252 | 8.468 | < 2e-16 | *** |
| **log(payment):data1.2** | -0.03243 | 0.015526 | -2.089 | 0.036715 | * |
| **log(payment):data1.3** | -0.03343 | 0.015298 | -2.185 | 0.028873 | * |
| **log(payment):data2.1** | 0.230245 | 0.016767 | 13.732 | < 2e-16 | *** |
| **mean.numHurr** | -0.04261 | 0.010974 | -3.883 | 0.000103 | *** |
| **mean.numEvac** | 0.384109 | 0.038406 | 10.001 | < 2e-16 | *** |
| **mean.lineInconv** | 0.600752 | 0.043828 | 13.707 | < 2e-16 | *** |
| **sd.numHurr** | 0.022536 | 0.07185 | 0.314 | 0.753789 | |

| | | | | | |
|---|---|---|---|---|---|
| **sd.numEvac** | 0.829013 | 0.138415 | 5.989 | 2.11E-09 | *** |
| **sd.lineInconv** | 0.090463 | 0.208258 | 0.434 | 0.664011 | |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Optimization of log-likelihood by BFGS maximization
Log Likelihood: -7972
BIC: 16119.57

Odds ratio:

**Table 3-38 Odds Ratio of Mixed Binary Model for All Combined Data**

| | **Odds ratio** | **Odds Std. Error** |
|---|---|---|
| **log(payment)** | 0.345418 | 0.010158991 |
| **persLoss** | 1.398011682 | 0.068133144 |
| **daysMissedW** | 1.060830402 | 0.009044415 |
| **log(income)** | 1.182601887 | 0.032778453 |
| **hisp** | 1.506917238 | 0.090008859 |
| **cons** | 0.76796586 | 0.040842177 |
| **townHouse** | 1.665369465 | 0.109554819 |
| **children** | 1.217625925 | 0.026964073 |
| **numHurr** | 0.958283132 | 0.043514815 |
| **numEvac** | 1.468305478 | 0.639506008 |
| **lineInconv** | 1.823489549 | 1.448731697 |

Analysis for the model:

Category and frequencies is showed as below, where 75.93% of respondents have choice with value of 0, while 24.07% have choice with value of 1.

**Table 3-39 Frequencies and Categories**

| **0** | **1** |
|---|---|
| 0.7593 | 0.2407 |

- *Payment/log(payment)*: the higher *payment/log(payment)*, the lower probability of the respondent willing to pay to support the investments in resilience. The odds ratio is 0.3454, with 95% confidence interval (0.3258, 0.3662), which is lower than 1, indicating that if *log(payment)* increase by 1 unit, the probability of willing to pay would decrease by 65.46%.

- *PersLoss*: if respondents experience personal loss from hurricane, probability of willing to pay would increase. The odds ratio is 1.3980 with 95% confidence interval (1.2718, 1.5368), which is higher than 1, indicating that having experience of personal loss from hurricane would increase probability of willing to pay by 39.80%.
- *daysMissedW*: the more days that respondents missed from work, the higher probability of willing to pay. The odds ratio is 1.0608 with 95% confidence interval (1.0430, 1.0790), which is higher than 1, indicating that every unit increase on *daysMissedW*, the probability of willing to pay would increase by 6%.
- *Income/log(income)*: the more income respondents have, the higher probability of willing to pay. The odds ratio is 1.1826 with 95% confidence interval (1.1213, 1.2473), which is greater than 1, indicating that every unit increase of *log(income)*, the probability of willing to pay increase by 18%.
- *Hisp*, *con*, *townHouse*: if *hisp*, *townHouse* holds true for respondent, the probability of willing to pay will increase while if con holds true, the probability would decrease. Odds ratio of *hisp* is 1.5069, greater than 1, meaning that if the respondent is Hispanic or Latino, the probability of willing to pay would increase by 50%; odds ratio of *con* is 0.7680, lower than 1, meaning that if respondent is conservative, the probability of willing to pay would decrease by 23.2%; odds ratio of *townHouse* is 1.6653, greater than 1, meaning that if respondent live in town house, the probability of willing to pay would increase by 66.53%.

- *numHurr, numEvac*: the more people experience a hurricane, the lower probability of respondents willing to pay. On the contrary, the more people have been evacuated from hurricanes, the higher probability of respondents willing to pay. People with more experience with hurricanes might not care that much about recovery. The odds ratio of *numHurr* is 0.9583, with 95% confidence interval (0.8767, 1.0474), which is lower than 1, indicating that with every one-time increase in hurricane experience, the probability of willingness to pay decreases by 4.17%. For *numEvac*, the odds ratio is 1.4683, with 95% confidence interval (0.6864, 3.1410), which is greater than 1, indicating that for every one-time evacuation from hurricane, the probability of willingness to pay increases by 46.83%. This is reasonable because when people have been evacuated from their homes due to a hurricane, they are directly under influence of hurricane and might have personal loss or experience great inconvenience. The more times people have been evacuated from hurricane, the more willing those people are to invest.
- *lineInconv*: if the subway line closures greatly affect people, they are more likely to pay for support the resilience. The odds ratio of *lineInconv* is 1.8235, with 95% confidence interval (0.5595, 5.9427), which is greater than 1, indicating that if subway line closures affect people, probability of willing to pay would increase by 82%.

**Ordered logit models**

**Models for CV1.1:**

Fixed parameter model:

**Table 3-40 Result of Standard Ordered Model for CV1.1**

| | Estimate | Std. Error | z-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| **kappa.1** | 5.48E-01 | 2.67E-02 | 20.475 | < 2.00E-16 | *** |
| **kappa.2** | 1.52E+00 | 4.53E-02 | 33.613 | < 2.00E-16 | *** |
| **kappa.3** | 2.62E+00 | 6.69E-02 | 39.142 | < 2.00E-16 | *** |
| **constant** | -3.03E-01 | 9.69E-02 | -3.124 | 0.001786 | ** |
| **payment** | -1.66E-03 | 9.18E-05 | -18.129 | < 2.00E-16 | *** |
| **persLoss** | 3.46E-01 | 7.57E-02 | 4.57 | 4.88E-06 | *** |
| **numHurr** | -5.35E-02 | 1.43E-02 | -3.746 | 0.000179 | *** |
| **numEvac** | 3.80E-01 | 3.86E-02 | 9.851 | < 2.00E-16 | *** |
| **daysMissedW** | 6.41E-02 | 1.42E-02 | 4.502 | 6.74E-06 | *** |
| **lineInconv** | 3.82E-01 | 7.03E-02 | 5.43 | 5.62E-08 | *** |
| **worker** | 4.61E-01 | 8.12E-02 | 5.684 | 1.32E-08 | *** |
| **hisp** | 4.70E-01 | 1.02E-01 | 4.608 | 4.07E-06 | *** |
| **townHouse** | 4.73E-01 | 1.05E-01 | 4.502 | 6.73E-06 | *** |
| **children** | 2.25E-01 | 4.01E-02 | 5.611 | 2.01E-08 | *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Optimization of log-likelihood by BFGS maximization
Log Likelihood: -4186
BIC: 8486.874

Random parameter model:

**Table 3-41 Result of Mixed Ordered Model for CV1.1**

| | Estimate | Std. Error | z-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| **kappa.1** | 0.5699 | 0.02966 | 19.216 | < 2e-16 | *** |
| **kappa.2** | 1.579 | 0.054 | 29.235 | < 2e-16 | *** |
| **kappa.3** | 2.71 | 0.08131 | 33.326 | < 2e-16 | *** |
| **constant** | -0.2917 | 0.1005 | -2.902 | 0.003711 | ** |
| **payment** | -0.00171 | 0.0000974 | -17.602 | < 2e-16 | *** |
| **persLoss** | 0.3665 | 0.07965 | 4.602 | 0.00000418 | *** |

| | | | | | |
|---|---|---|---|---|---|
| **numEvac** | 0.4178 | 0.04584 | 9.115 | < 2e-16 | *** |
| **daysMissedW** | 0.0667 | 0.01475 | 4.524 | 0.00000607 | *** |
| **lineInconv** | 0.3844 | 0.0727 | 5.287 | 0.00000012 | *** |
| **worker** | 0.4789 | 0.08478 | 5.649 | 1.61E-08 | *** |
| **hisp** | 0.5093 | 0.1066 | 4.779 | 0.00000177 | *** |
| **townHouse** | 0.4964 | 0.1092 | 4.547 | 0.00000545 | *** |
| **children** | 0.2371 | 0.04193 | 5.654 | 1.57E-08 | *** |
| **mean.numHurr** | -0.0723 | 0.01833 | -3.944 | 0.0000801 | *** |
| **sd.numHurr** | 0.1254 | 0.03315 | 3.784 | 0.000155 | *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Optimization of log-likelihood by BFGS maximization
Log Likelihood: -4184
BIC: 8490.315

Basic statistics for models CV1.1:

1. Frequencies of categories:

**Table 3-42 Frequencies of Categories for CV1.1**

| **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|
| 0.52512 | 0.11069 | 0.16121 | 0.11390 | 0.08908 |

2. WTP：

**Table 3-43 WTP for CV1.1**

| **WTP for** | |
|---|---|
| **persLoss** | 208.4337349 |
| **numHurr** | 32.22891566 |
| **numEvac** | 228.9156627 |
| **daysMissedW** | 38.61445783 |
| **lineInconv** | 230.1204819 |
| **worker** | 277.7108434 |
| **hisp** | 283.1325301 |
| **townHouse** | 284.939759 |
| **children** | 135.5421687 |

**Models for CV1.2:**

Fixed parameter model:

**Table 3-44 Result of Standard Ordered Model for CV1.2**

| | Estimate | Std. Error | z-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| **kappa.1** | 0.4725258 | 0.0281004 | 16.816 | < 2e-16 | *** |
| **kappa.2** | 1.3979938 | 0.049841 | 28.049 | < 2e-16 | *** |
| **kappa.3** | 2.4886441 | 0.0768632 | 32.378 | < 2e-16 | *** |
| **constant** | -0.3657093 | 0.0972727 | -3.76 | 0.00017 | *** |
| **payment** | -0.0016629 | 0.0001077 | -15.444 | < 2e-16 | *** |
| **numEvac** | 0.2228377 | 0.0493004 | 4.52 | 6.18E-06 | *** |
| **daysMissedW** | 0.0576765 | 0.0165771 | 3.479 | 0.000503 | *** |
| **lineInconv** | 0.2740129 | 0.0839357 | 3.265 | 0.001096 | ** |
| **worker** | 0.2602678 | 0.0875143 | 2.974 | 0.002939 | ** |
| **hisp** | 0.3813145 | 0.1271837 | 2.998 | 0.002716 | ** |
| **lib** | 0.3367909 | 0.0879277 | 3.83 | 0.000128 | *** |
| **cons** | -0.2878286 | 0.1070418 | -2.689 | 0.007168 | ** |
| **townHouse** | 0.5422807 | 0.1175938 | 4.611 | 4.00E-06 | *** |
| **children** | 0.2631768 | 0.0417492 | 6.304 | 2.91E-10 | *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Optimization of log-likelihood by BFGS maximization
Log Likelihood: -3161
BIC: 6433.491

Random parameter model:

**Table 3-45 Result of Mixed Ordered Model for CV1.2**

| | Estimate | Std. Error | z-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| **kappa.1** | 0.4799518 | 0.0287187 | 16.712 | < 2e-16 | *** |
| **kappa.2** | 1.4240653 | 0.0520168 | 27.377 | < 2e-16 | *** |
| **kappa.3** | 2.5451316 | 0.0823197 | 30.918 | < 2e-16 | *** |
| **constant** | -0.357536 | 0.0985199 | -3.629 | 0.000284 | *** |
| **payment** | -0.001704 | 0.0001113 | -15.321 | < 2e-16 | *** |
| **daysMissedW** | 0.0536191 | 0.0169658 | 3.16 | 0.001575 | ** |
| **lineInconv** | 0.2852757 | 0.0851537 | 3.35 | 0.000808 | *** |
| **worker** | 0.2723348 | 0.0885916 | 3.074 | 0.002112 | ** |

| | | | | | |
|---|---|---|---|---|---|
| **hisp** | 0.3929551 | 0.1295216 | 3.034 | 0.002414 | ** |
| **lib** | 0.3347954 | 0.0894293 | 3.744 | 0.000181 | *** |
| **cons** | -0.280823 | 0.1086825 | -2.584 | 0.009769 | ** |
| **townHouse** | 0.4829654 | 0.1222013 | 3.952 | 0.0000774 | *** |
| **children** | 0.2612517 | 0.0424823 | 6.15 | 7.76E-10 | *** |
| **mean.numEvac** | 0.2762847 | 0.0640879 | 4.311 | 0.0000162 | *** |
| **sd.numEvac** | 0.3861427 | 0.1161393 | 3.325 | 0.000885 | *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Optimization of log-likelihood by BFGS maximization
Log Likelihood: -3158
BIC: 6434.35

Basic statistics for models CV1.2:

1. Frequencies of categories:

**Table 3-46 Frequencies of Categories for CV1.2**

| 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| 0.57746 | 0.09508 | 0.14758 | 0.10389 | 0.07599 |

2. WTP:

**Table 3-47 WTP for CV1.2**

| WTP for | |
|---|---|
| **numEvac** | 134.0054724 |
| **daysMissedW** | 39.68428649 |
| **lineInconv** | 164.7801431 |
| **worker** | 156.5144025 |
| **hisp** | 229.3069337 |
| **lib** | 202.5322629 |
| **cons** | 173.0883396 |
| **townHouse** | 326.1054182 |
| **children** | 158.2637561 |

**Models for CV1.3:**

Fixed parameter model:

**Table 3-48 Result of Standard Ordered Model for CV1.3**

| | Estimate | Std. Error | z-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| **kappa.1** | 0.4955464 | 0.0279265 | 17.745 | < 2e-16 | *** |
| **kappa.2** | 1.3931157 | 0.0482892 | 28.849 | < 2e-16 | *** |
| **kappa.3** | 2.2661302 | 0.0681873 | 33.234 | < 2e-16 | *** |
| **constant** | -0.2672628 | 0.0925094 | -2.889 | 0.00386 | ** |
| **payment** | -0.0016323 | 0.0001031 | -15.835 | < 2e-16 | *** |
| **persLoss** | 0.5273662 | 0.084281 | 6.257 | 3.92E-10 | *** |
| **numEvac** | 0.1314437 | 0.0404702 | 3.248 | 0.00116 | ** |
| **daysMissedW** | 0.038529 | 0.0161244 | 0.239 | 0.081115 | * |
| **lineInconv** | 0.3269679 | 0.0801981 | 4.077 | 4.56E-05 | *** |
| **worker** | 0.2955111 | 0.0851561 | 3.47 | 0.00052 | *** |
| **hisp** | 0.5369921 | 0.1067348 | 5.031 | 4.88E-07 | *** |
| **cons** | -0.5033826 | 0.10049 | -5.009 | 5.46E-07 | *** |
| **townHouse** | 0.5445323 | 0.1170563 | 4.652 | 3.29E-06 | *** |
| **children** | 0.2301458 | 0.0410609 | 5.605 | 2.08E-08 | *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood: -3350

BIC: 6811.052

Random parameter model:

**Table 3-49 Result of Mixed Ordered Model for CV1.3**

| | Estimate | Std. Error | z-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| **kappa.1** | 0.4982288 | 0.0292031 | 17.061 | < 2e-16 | *** |
| **kappa.2** | 1.4012348 | 0.0540991 | 25.901 | < 2e-16 | *** |
| **kappa.3** | 2.2782762 | 0.0785086 | 29.019 | < 2e-16 | *** |
| **constant** | -0.098353 | 0.0820718 | -1.198 | 0.23077 | |
| **payment** | -0.0016424 | 0.0001081 | -15.191 | < 2e-16 | *** |
| **persLoss** | 0.5063581 | 0.0864841 | 5.855 | 4.77E-09 | *** |
| **daysMissedW** | 0.036817 | 0.0157074 | 1.071 | 0.028433 | * |
| **hisp** | 0.5324143 | 0.1077141 | 4.943 | 7.70E-07 | *** |
| **cons** | -0.5132121 | 0.1021445 | -5.024 | 5.05E-07 | *** |

| | | | | | |
|---|---|---|---|---|---|
| **townHouse** | 0.5789314 | 0.1182295 | 4.897 | 9.75E-07 | *** |
| **children** | 0.2287251 | 0.0417036 | 5.485 | 4.15E-08 | *** |
| **mean.numEvac** | 0.1435923 | 0.0462133 | 3.107 | 0.00189 | ** |
| **mean.lineInconv** | 0.3414319 | 0.0821725 | 4.155 | 3.25E-05 | *** |
| **sd.numEvac** | 0.1082186 | 0.1178959 | 0.918 | 0.35866 | |
| **sd.lineInconv** | 0.2375109 | 0.3788559 | 0.627 | 0.53071 | |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Optimization of log-likelihood by BFGS maximization
Log Likelihood: -3356
BIC: 6830.67

Basic statistics for models CV1.3:

1. Frequencies of categories:

**Table 3-50 Frequencies of Categories for CV1.3**

| **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|
| 0.56871 | 0.10113 | 0.14447 | 0.09056 | 0.09514 |

2. WTP:

**Table 3-51 WTP for CV1.3**

| **WTP for** | |
|---|---|
| **persLoss** | 323.0816639 |
| **numEvac** | 80.52668014 |
| **daysMissedW** | 2.360411689 |
| **lineInconv** | 200.311156 |
| **worker** | 181.0396986 |
| **hisp** | 328.9788029 |
| **cons** | 308.3885315 |
| **townHouse** | 333.5981744 |
| **children** | 140.9947926 |

**Models for CV2.1:**

**Fixed parame**ter model:

**Table 3-52 Result of Standard Ordered Model for CV2.1**

| | **Estimate** | **Std. Error** | **z-value** | **Pr(>\|z\|)** |
|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| **kappa.1** | 4.52E-01 | 1.47E-02 | 30.722 | < 2e-16 | *** |
| **kappa.2** | 1.20E+00 | 2.34E-02 | 51.079 | < 2e-16 | *** |
| **kappa.3** | 2.08E+00 | 3.20E-02 | 64.839 | < 2e-16 | *** |
| **constant** | 1.97E-01 | 6.51E-02 | 3.024 | 0.002498 | ** |
| **payment** | -1.63E-03 | 5.32E-05 | -30.599 | < 2e-16 | *** |
| **persLoss** | 2.90E-01 | 4.53E-02 | 6.392 | 1.64E-10 | *** |
| **numEvac** | 1.68E-01 | 2.35E-02 | 7.131 | 9.93E-13 | *** |
| **daysMissedW** | 4.79E-02 | 8.69E-03 | 5.518 | 3.43E-08 | *** |
| **lineInconv** | 4.40E-01 | 4.32E-02 | 10.194 | < 2e-16 | *** |
| **worker** | 3.23E-01 | 4.60E-02 | 7.017 | 2.27E-12 | *** |
| **white** | -1.85E-01 | 4.88E-02 | -3.8 | 0.000145 | *** |
| **hisp** | 3.47E-01 | 6.21E-02 | 5.588 | 2.29E-08 | *** |
| **lib** | 2.05E-01 | 4.57E-02 | 4.475 | 7.63E-06 | *** |
| **cons** | -2.79E-01 | 5.50E-02 | -5.079 | 3.80E-07 | *** |
| **townHouse** | 3.59E-01 | 6.31E-02 | 5.683 | 1.33E-08 | *** |
| **children** | 2.18E-01 | 2.29E-02 | 9.523 | < 2e-16 | *** |

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Optimization of log-likelihood by BFGS maximization

Log Likelihood: -11850

BIC: 23842.34

Random parameter model:

**Table 3-53 Result of Mixed Ordered Model for CV2.1**

| | **Estimate** | **Std. Error** | **z-value** | **Pr(>\|z\|)** | |
|---|---|---|---|---|---|
| **kappa.1** | 4.64E-01 | 1.60E-02 | 29.041 | < 2e-16 | *** |
| **kappa.2** | 1.23E+00 | 2.75E-02 | 44.747 | < 2e-16 | *** |
| **kappa.3** | 2.13E+00 | 3.94E-02 | 54.093 | < 2e-16 | *** |
| **constant** | -9.53E-01 | 3.07E-01 | -3.099 | 0.001939 | ** |
| **payment** | -1.67E-03 | 5.72E-05 | -29.264 | < 2e-16 | *** |
| **persLoss** | 2.83E-01 | 4.76E-02 | 5.94 | 2.86E-09 | *** |
| **numEvac** | 1.99E-01 | 2.64E-02 | 7.55 | 4.35E-14 | *** |
| **daysMissedW** | 5.88E-02 | 8.76E-03 | 6.71 | 1.94E-11 | *** |
| **lineInconv** | 4.61E-01 | 4.43E-02 | 10.403 | < 2e-16 | *** |
| **worker** | 3.25E-01 | 4.82E-02 | 7.591 | 2.40E-12 | *** |
| **white** | -1.83E-01 | 5.07E-02 | -3.604 | 0.000313 | *** |
| **hisp** | 3.70E-01 | 6.36E-02 | 5.808 | 6.33E-09 | *** |
| **lib** | 1.95E-01 | 4.71E-02 | 4.138 | 3.50E-05 | *** |

| | | | | | |
|---|---|---|---|---|---|
| **cons** | -3.07E-01 | 5.67E-02 | -5.416 | 6.08E-08 | *** |
| **townHouse** | 3.89E-01 | 6.46E-02 | 6.015 | 1.80E-09 | *** |
| **children** | 2.10E-01 | 2.37E-02 | 8.837 | < 2e-16 | *** |
| **mean.numHurr** | -2.74E-02 | 9.95E-03 | -2.756 | 0.005842 | ** |
| **sd.numHurr** | 1.00E-01 | 2.13E-02 | 4.704 | 2.55E-06 | *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Optimization of log-likelihood by BFGS maximization
Log Likelihood: -11860
BIC: 23876.58

Basic statistics for models CV2.1:

1. Frequencies of categories:

**Table 3-54 Frequencies of Categories forCV2.1**

| 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| 0.4651 | 0.0963 | 0.1442 | 0.1319 | 0.1625 |

2. WTP:

**Table 3-55 WTP for CV2.1**

| WTP for | |
|---|---|
| **persLoss** | 177.9141104 |
| **numEvac** | 103.0674847 |
| **daysMissedW** | 29.38650307 |
| **lineInconv** | 269.9386503 |
| **worker** | 198.1595092 |
| **white** | 113.4969325 |
| **hisp** | 212.8834356 |
| **lib** | 125.7668712 |
| **cons** | 171.1656442 |
| **townHouse** | 220.2453988 |
| **children** | 133.7423313 |

**Analysis on models CV1.1 - CV2.1:**

**Table 3-56 WTP for CV1.1-CV2.1**

| WTP for: | cv1.1(7 days) | cv1.2(7 days) | cv1.3(14 days) | cv2.1(7 days) |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| **daysSaved** | 5 | 3 | 12 | 5 |
| **recoveryTime** | 2 | 4 | 2 | 2 |
| **numEvac** | 228.9156627 | 134.0054724 | 80.52668014 | 103.0674847 |
| **daysMissedW** | 38.61445783 | 39.68428649 | 2.360411689 | 29.38650307 |
| **lineInconv** | 230.1204819 | 164.7801431 | 200.311156 | 269.9386503 |
| **worker** | 277.7108434 | 156.5144025 | 181.0396986 | 198.1595092 |
| **hisp** | 283.1325301 | 229.3069337 | 328.9788029 | 212.8834356 |
| **townHouse** | 284.939759 | 326.1054182 | 333.5981744 | 220.2453988 |
| **children** | 135.5421687 | 158.2637561 | 140.9947926 | 133.7423313 |

According to the Table 3-56 as above, people would like to pay less money monthly rather than one payment yearly to reduce the times of evacuation from hurricanes. As the efficiency of recovery improves, the WTP for reducing the days absent from work would decrease. Different from the binary model, WTP for townhouse varies in CV1.1 – CV1.3. It would decrease from 284.93 to 220.24 if investments are paid by month instead of by year. The longer it takes the system to recover, the more people care about children, correspondingly the WTP for children would increase.

**All combined models:**

Fixed parameter model:

**Table 3-57 Result of Standard Ordered Model for All Combined Data**

| | Estimate | Std. Error | z-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| **kappa.1** | 0.484322 | 0.010942 | 44.263 | < 2e-16 | *** |
| **kappa.2** | 1.331371 | 0.018183 | 73.22 | < 2e-16 | *** |
| **kappa.3** | 2.283902 | 0.025544 | 89.412 | < 2e-16 | *** |
| **constant** | 2.649253 | 0.202638 | 13.074 | < 2e-16 | *** |
| **log(payment)** | -0.700303 | 0.015738 | -44.496 | < 2e-16 | *** |
| **persLoss** | 0.296508 | 0.033217 | 8.926 | < 2e-16 | *** |
| **numHurr** | -0.024277 | 0.006176 | -3.931 | 8.46E-05 | *** |
| **numEvac** | 0.220492 | 0.017139 | 12.865 | < 2e-16 | *** |
| **daysMissedW** | 0.045041 | 0.006275 | 7.178 | 7.06E-13 | *** |
| **lineInconv** | 0.421586 | 0.030946 | 13.623 | < 2e-16 | *** |

| | | | | | |
|---|---|---|---|---|---|
| **worker** | 0.301137 | 0.035023 | 8.598 | < 2e-16 | *** |
| **log(income)** | 0.034629 | 0.019616 | 1.765 | 0.0775 | * |
| **hisp** | 0.423388 | 0.044432 | 9.529 | < 2e-16 | *** |
| **cons** | -0.369681 | 0.037505 | -9.857 | < 2e-16 | *** |
| **townHouse** | 0.420002 | 0.045415 | 9.248 | < 2e-16 | *** |
| **children** | 0.223632 | 0.016652 | 13.43 | < 2e-16 | *** |
| **log(payment):data1.2** | -0.030576 | 0.009315 | -3.282 | 0.00103 | ** |
| **log(payment):data1.3** | -0.029312 | 0.009151 | -3.203 | 0.00136 | ** |
| **log(payment):data2.1** | 0.107062 | 0.010473 | 10.222 | < 2e-16 | *** |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Optimization of log-likelihood by BFGS maximization
Log Likelihood: -22430
BIC: 45055.24

Random parameter model:

**Table 3-58 Result of Mixed Ordered Model for All Combined Data**

| | Estimate | Std. Error | z-value | Pr(>\|z\|) | |
|---|---|---|---|---|---|
| **kappa.1** | 0.500741 | 0.011959 | 41.872 | < 2e-16 | *** |
| **kappa.2** | 1.374255 | 0.021337 | 64.407 | < 2e-16 | *** |
| **kappa.3** | 2.352925 | 0.03104 | 75.803 | < 2e-16 | *** |
| **constant** | 2.809291 | 0.212064 | 13.247 | < 2e-16 | *** |
| **log(payment)** | -0.72069 | 0.016901 | -42.642 | < 2e-16 | *** |
| **persLoss** | 0.302085 | 0.034867 | 8.664 | < 2e-16 | *** |
| **daysMissedW** | 0.046697 | 0.006476 | 7.21 | 5.58E-13 | *** |
| **lineInconv** | 0.42767 | 0.031861 | 13.423 | < 2e-16 | *** |
| **worker** | 0.308495 | 0.036212 | 8.519 | < 2e-16 | *** |
| **log(income)** | 0.030449 | 0.02023 | 1.505 | 0.072284 | * |
| **hisp** | 0.442277 | 0.045661 | 9.686 | < 2e-16 | *** |
| **cons** | -0.374765 | 0.038726 | -9.677 | < 2e-16 | *** |
| **townHouse** | 0.427619 | 0.04671 | 9.155 | < 2e-16 | *** |
| **children** | 0.229648 | 0.017165 | 13.379 | < 2e-16 | *** |
| **log(payment):data1.2** | -0.032237 | 0.009612 | -3.354 | 0.000797 | *** |
| **log(payment):data1.3** | -0.030645 | 0.00943 | -3.25 | 0.001155 | ** |
| **log(payment):data2.1** | 0.108221 | 0.010783 | 10.036 | < 2e-16 | *** |
| **mean.numHurr** | -0.037078 | 0.007512 | -4.936 | 7.98E-07 | *** |
| **mean.numEvac** | 0.250459 | 0.021185 | 11.822 | < 2e-16 | *** |
| **sd.numHurr** | 0.103793 | 0.014683 | 7.069 | 1.56E-12 | *** |

| | | | | | |
|---|---|---|---|---|---|
| **sd.numEvac** | 0.114701 | 0.062288 | 1.841 | 0.065553 | . |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Optimization of log-likelihood by BFGS maximization
Log Likelihood: -22420
BIC: 45055.01

Analysis for the model:

Category and frequencies is showed as below. 51.00% of respondents have chosen very unlikely, 9.962% of respondents have chosen somewhat unlikely, 14.801% of respondents have chosen undecided, 11.766% of respondents have chosen somewhat likely and 12.474% of respondents have chosen very likely.

**Table 3-59 Frequencies of Categories**

| **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|
| 0.50997 | 0.09962 | 0.14801 | 0.11766 | 0.12474 |

- *Payment/log(payment)*: this variable has significant effect on the model, the value of coefficient is -0.72069, which is lower than 0, indicating that the higher *payment/log(payment)*, the lower probability of the respondent willing to pay to support the investments in resilience.
- *PersLoss*: this variable has significant effect on the model, the value of coefficient is 0.3021, which is greater than 0, indicating that if respondents experience personal loss from hurricane, probability of willing to pay would improve.
- *daysMissedW*: this variable has significant effect on the model, the value of coefficient is 0.0467, which is greater than 0, indicating that the more days that respondents missed from work, the higher probability of willing to pay.
- *lineInconv*: this variable has significant effect on the model, the value of coefficient is 0.4267, which is greater than 0, indicating that if the subway

line closures greatly affect people, they are more likely to pay for support the resilience.

- *Worker*: this variable has significant effect on the model, the value of coefficient is 0.3085, which is greater than 0, indicating that if the respondent is a worker, the probability of willing to pay would be high.
- *Income/log(income)*: this variable does not have significant effect on the model.
- *Hisp*, *con*, *townHouse*: the values of coefficient of *hisp* and *townHouse* are 0.4423 and 0.4276, which are both greater than 0, while the value of coefficient of *con* is -0.3748, which is lower than 0, indicating that if *hisp*, *townHouse* holds true, the probability of willing to pay would increase while if *con* holds true, the probability would decrease.
- *numHurr*, *numEvac*: these two variables both have significant effect on the model, the value of coefficient of *numHurr* is -0.0371, greater than 0, which indicates that the more people experience with hurricane, the lower probability of respondents willing to pay. On the contrary, the value of coefficient of *numEvac* is 0.2505, greater than 0, which indicates that the more times people have been evacuated from their homes due to a hurricane, the higher probability of respondents willing to pay. People with more experience with hurricane might not care that much about recovery. People who are evacuated due to a hurricane are directly under its influence and might have got personal loss or experienced great inconvenience. The more times people have been evacuated from hurricane, the more willing those people are to invest.

CHAPTER 4

# CONCLUSIONS

## 4.1 Main results

**Table 4-1 Hypothesis Test**

| Variable | Sign of parameter | Odds ratio (Compare to 1) | Hypothesis test |
|---|---|---|---|
| **payment** | - | < | ✓ |
| **persLoss** | + | > | ✓ |
| **numHurr** | - | < | ✓ |
| **numEvac** | + | > | ✓ |
| **daysMissedW** | + | > | ✓ |
| **lineInconv** | + | > | ✓ |
| **fullTime/worker** | + | > | ✓ |
| **income/log(income)** | + | > | ✓ |
| **white** | - | < | ✕ |
| **hisp** | + | > | ✓ |
| **lib** | + | > | ✕ |
| **cons** | - | < | ✓ |
| **townhouse** | + | > | ✓ |
| **married** | + | > | ✕ |
| **children** | + | > | ✓ |

We can see that *payment/log(payment)*, *numHurr* and *cons* all have a negative and significant parameter, meaning that we cannot reject the hypothesis of *payment*, *numHurr con,* and *payment: data1.2*. Variables including *persLoss*, *numEvac*, *daysMissedW*, *lineInconv*, *worker*, *income/log(income)*, *hisp*, *cons*, *townHouse* and *children* all have a positive parameter that is significant, meaning that we cannot reject their hypothesis as well. Variables like *white*, *lib* and *married*, do not show significance in the model, meaning that the hypothesis for these variables don't hold true and we might simply believe that these variables are irrelevant in explaining investment support in resilience.

**Table 4-2 Result of Interaction Variables**

| | Estimate | Std. Error | z-value | Pr(>$\lvert z \rvert$) | |
|---|---|---|---|---|---|
| **constant** | 1.550607 | 0.285942 | 5.423 | 5.87E-08 | *** |
| **log(payment):data1.2** | -0.03243 | 0.015526 | -2.089 | 0.036715 | * |
| **log(payment):data1.3** | -0.03343 | 0.015298 | -2.185 | 0.028873 | * |
| **log(payment):data2.1** | 0.230245 | 0.016767 | 13.732 | < 2e-16 | *** |

The value of coefficient of *payment: data1.3* is expected to be positive because the efficiency is higher compared to the baseline (CV1.1). The reason for this counterintuitive result might be the lack of data and unequal rating scale. In this survey, not everybody answered all questions at the same time. They were randomly assigned to answer one question from CV1.1 – CV1.3. For CV2.1, all respondents were asked to answer it. Also, respondents might have individual specific rating ability, which means that rating scale across all respondents would not be equal.

### 4.2 Future Work

We should gather more data: ask respondents to answer all these 4 questions in order to have sufficient data analyzing the influence of recovery efficiency on WTP; We could also ask for ordered-response to have the rank of these payment choices of investments for resilience in case of the effect of unequal individual rating scale. Finally, we may ask respondents for how much the investment is the most willing to pay so that we could have a better view of analyzing the influence of payment on WTP for investments.

### 4.3 Policy Conclusions

According to the model, people have a higher probability of willing to pay monthly than yearly, it would be more successful to raise money monthly from people. The investment might not be in the area where people often have experience on hurricane, since the number of hurricane experienced has a negative effect on people's willingness to pay. Moreover, the inconvenience of subway line closure has a great effect on willingness to pay on resilience investment, which indicates that to resume service of subway system might be a very important task on hurricane recovery.

## BIBLIOGRAPHY

Blake E S, Kimberlain T B, Berg R J, et al. Tropical cyclone report: Hurricane sandy[J]. National Hurricane Center, 2013, 12: 1-10.

FEMA Sandy Recovery Office, Hurricane Sandy by the Numbers, October 21, 2015. http://www.fema.gov/sandy-recovery-office.

Cortes C, Vapnik V. Support-vector networks[J]. Machine learning, 1995, 20(3): 273-297.

MacKay D J C. Information theory, inference and learning algorithms[M]. Cambridge university press, 2003.

Louviere, J. J., D. A. Hensher, and J. D. Swait (2000), Stated Choice Methods: Analysis and Application, Cambridge Univ. Press, Cambridge, U. K.

Meyerhoff, J., U. Liebe, *and* V. Hartje (2009), Benefits of biodiversity enhancement of nature-oriented silviculture: Evidence from two choice experiments in Germany, *J. For. Econ.*, **15**(1–2), 37–58.

Alriksson S, Öberg T. Conjoint analysis for environmental evaluation[J]. Environmental Science and Pollution Research, 2008, 15(3): 244-257.

Hoyos, D. (2010), The state of the art of environmental valuation with discrete choice experiments, *Ecol. Econ.*, **69**(8), 1595–1603, doi:10.1016/j.ecolecon.2010.04.011

Bateman, I., M. Cole, S. Georgiou, and D. Hadley (2006), Comparing contingent valuation and contingent ranking: A case study considering the benefits of urban river water quality improvements, *J. Environ. Manage.*, **79**(3), 221–231, doi: 10.1016/j.jenvman.2005.06.010.

J. Kysely, L. Gaal, R. Beranova, E. Plavcova, Climate change scenarios of precipitation extremes in Central Europe from ENSEMBLES regional climate models**,** Theor. Appl. Climatol. (2011), pp. 529–542

Cox D R. Two further applications of a model for binary regression[J]. Biometrika, 1958, 45(3/4): 562-565.

McCullagh P. Regression models for ordinal data[J]. Journal of the royal statistical society. Series B (Methodological), 1980: 109-142.

Cameron T A, James M D. Estimating willingness to pay from survey data: an alternative pre-test-market evaluation procedure[J]. Journal of Marketing Research, 1987: 389-395.

Perez-pineda F. Using Binary Choice Models in Estimating Willingness to Pay for Improved Water[J].

Boyd J H, Mellman R E. The effect of fuel economy standards on the US automotive market: a hedonic demand analysis[J]. Transportation Research Part A: General, 1980, 14(5-6): 367-378.

Cardell N S, Dunbar F C. Measuring the societal impacts of automobile downsizing[J]. Transportation Research Part A: General, 1980, 14(5-6): 423-434.

Bhat C R, Koppelman F S. A retrospective and prospective survey of time-use research[J]. Transportation, 1999, 26(2): 119-139.

Bhat C R. Accommodating variations in responsiveness to level-of-service measures in travel mode choice modeling[J]. Transportation Research Part A: Policy and Practice, 1998, 32(7): 495-507.

Srinivasan S, Bhat C, Holguin-Veras J. Empirical analysis of the impact of security perception on intercity mode choice: A panel rank-ordered mixed logit model[J]. Transportation Research Record: Journal of the Transportation Research Board, 2006 (1942): 9-15.

McFadden D, Train K. Mixed MNL models for discrete response[J]. Journal of applied Econometrics, 2000: 447-470.

## APPENDIX : DATA SUMMARY

Sc1. Are you 18 or older?

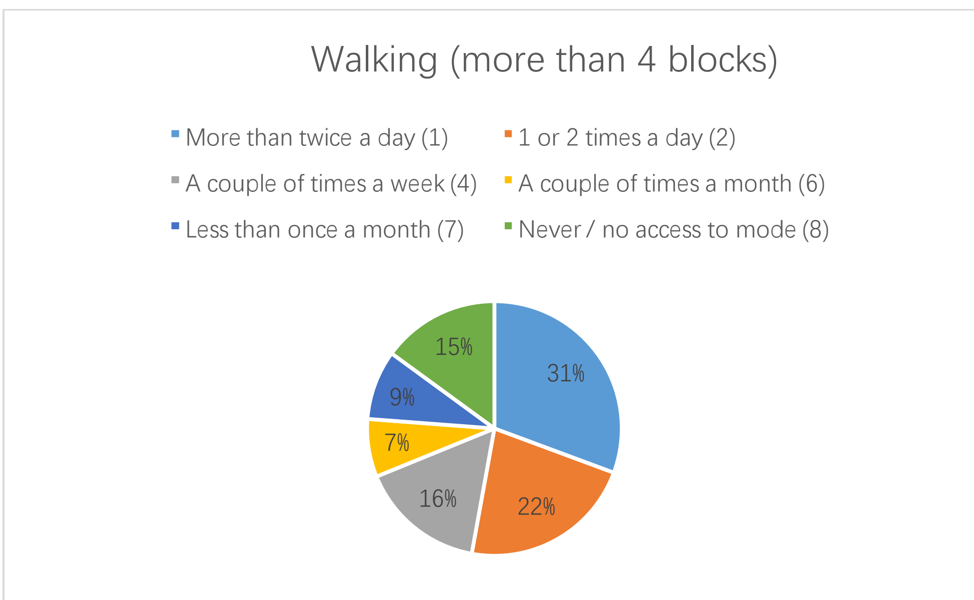
| | People, Percentage |
|---|---|
| Less than 18 | 35, 1.62% |
| 18 or older | 2132, 98.38% |

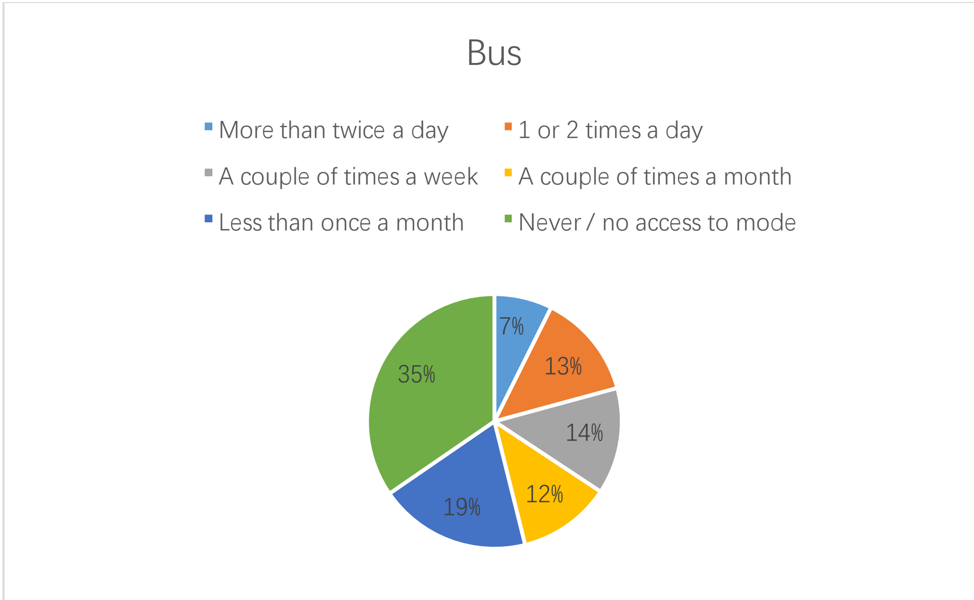
Sc2. Do you currently live in the New York Metropolitan Area?

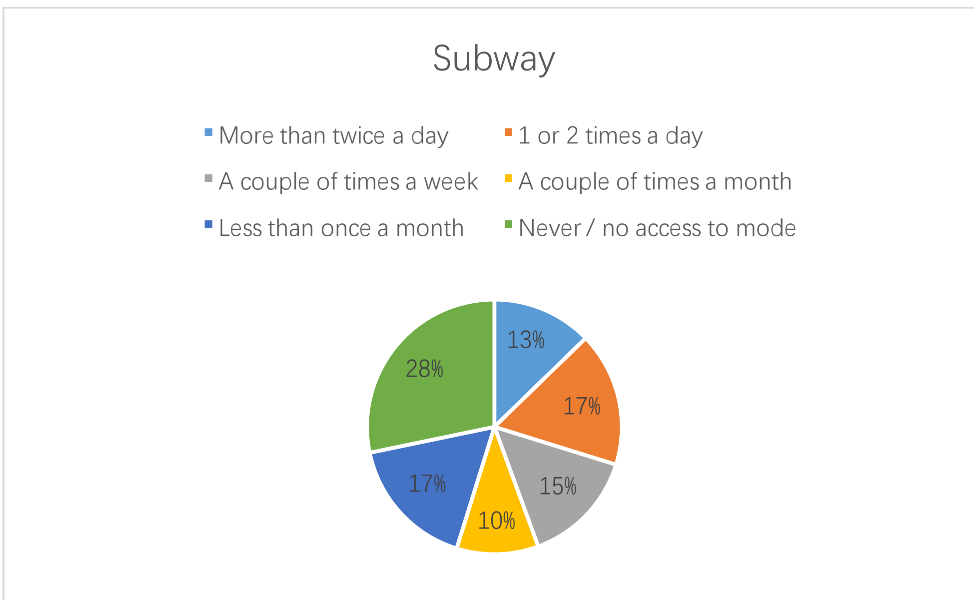
| | People, Percentage |
|---|---|
| New York Metropolitan Area | 1771, 81.73% |
| Others | 396, 18.27% |

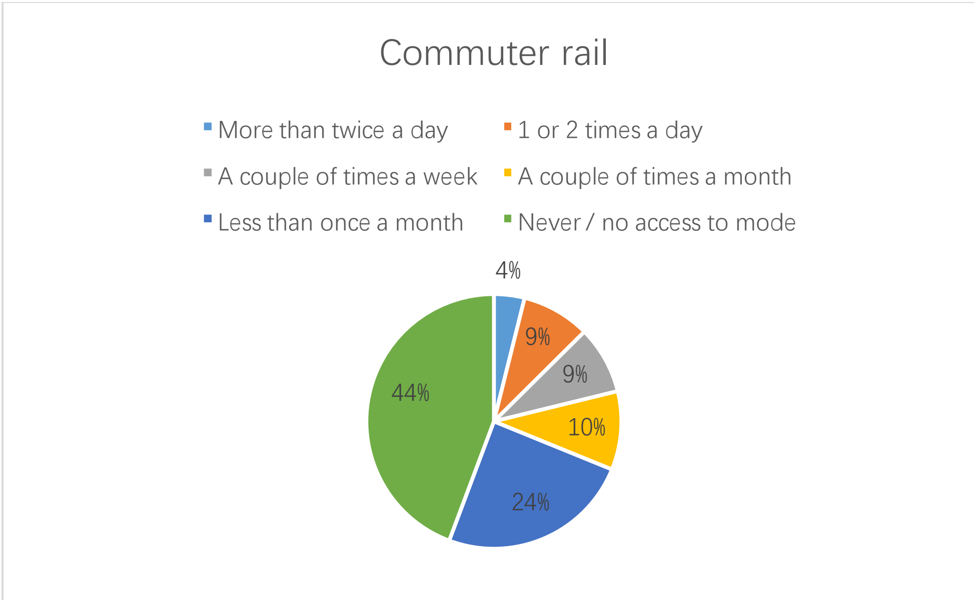
Questions: Valid tuples 1752 (older than 18, and live in New York Metropolitan Area)

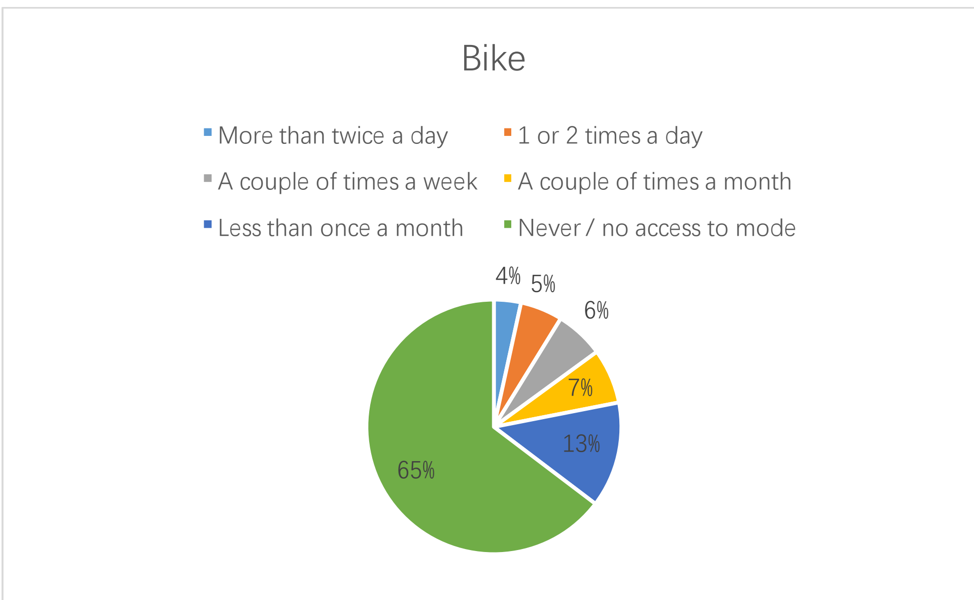
q1. During typical business days, how frequently do you use the following transportation modes?

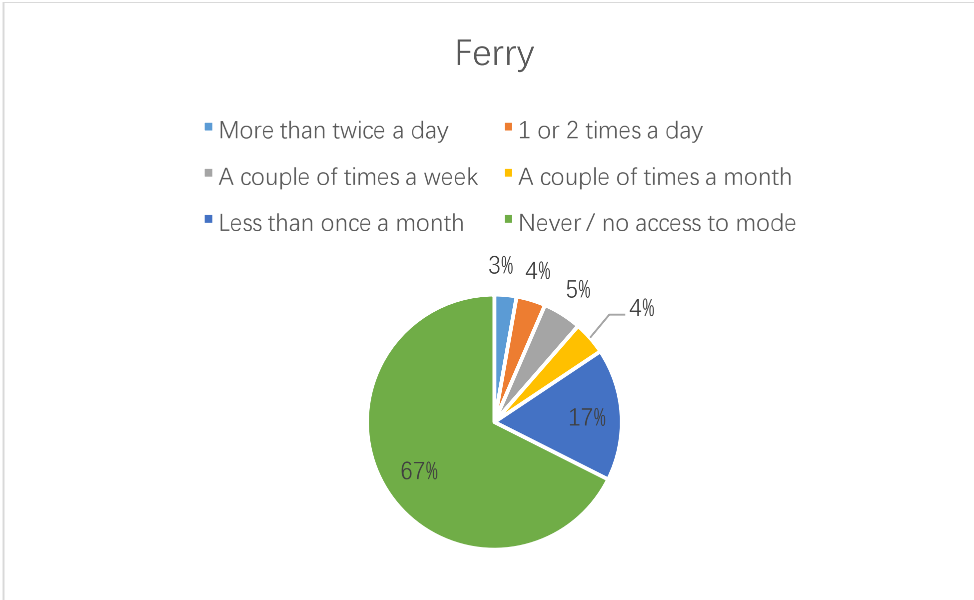


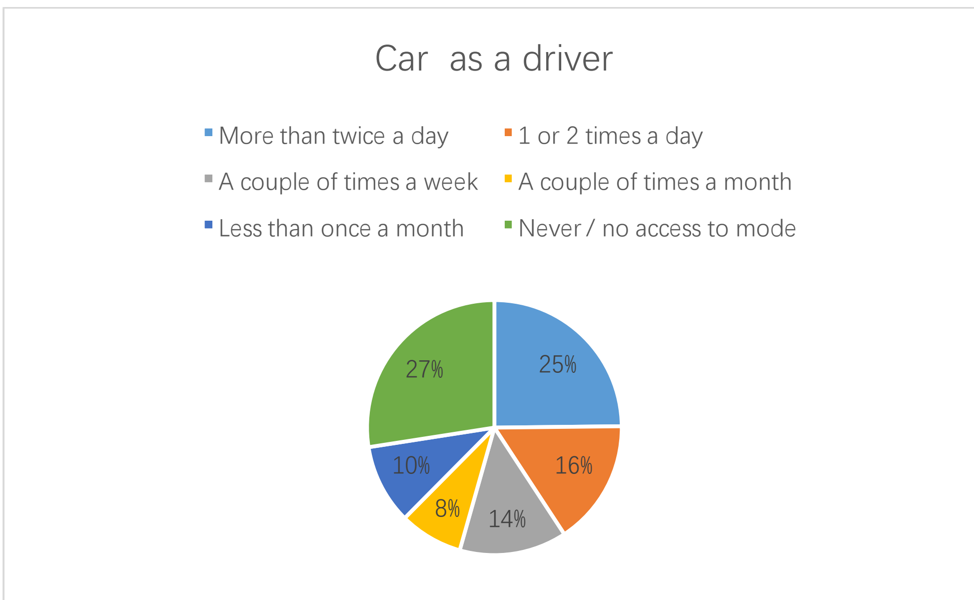

Bus
More than twice a day
1 or 2 times a day
A couple of times a week
A couple of times a month
Less than once a month
Never / no access to mode
7%
13%
14%
12%
19%
35%

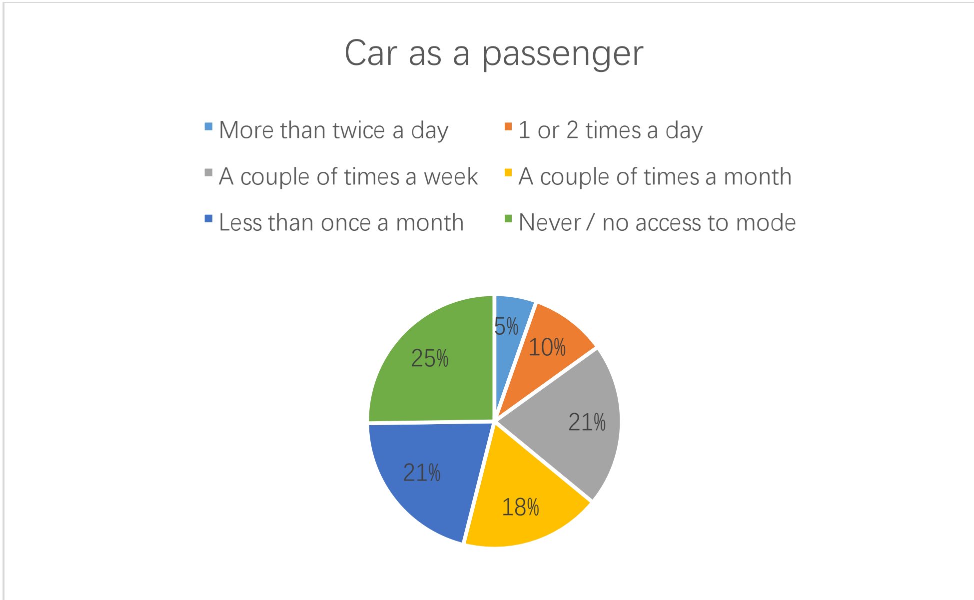

Subway
More than twice a day
1 or 2 times a day
A couple of times a week
A couple of times a month
Less than once a month
Never / no access to mode
13%
17%
15%
10%
17%
28%

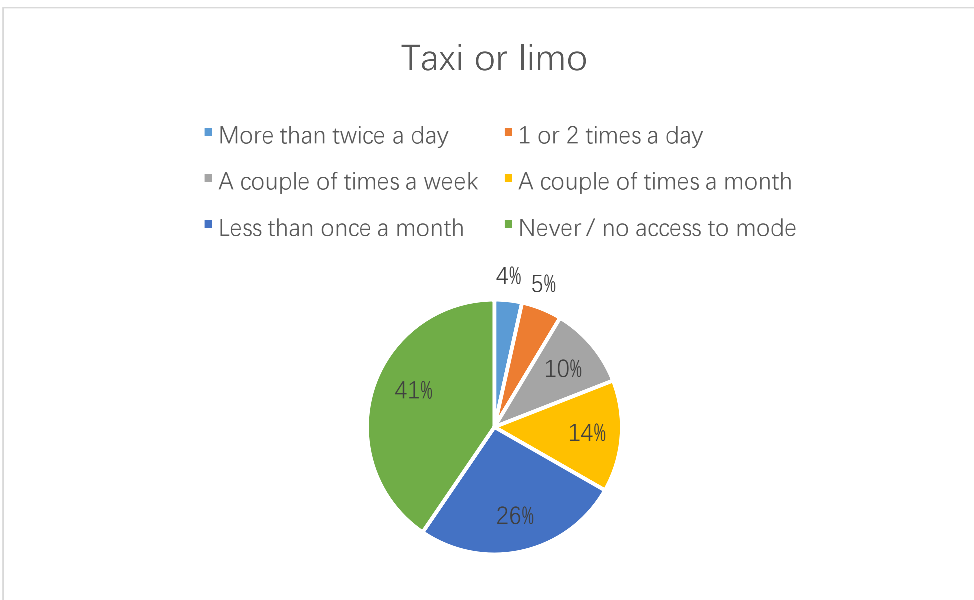

Commuter rail
More than twice a day
1 or 2 times a day
A couple of times a week
A couple of times a month
Less than once a month
Never / no access to mode
4%
9%
9%
10%
24%
44%

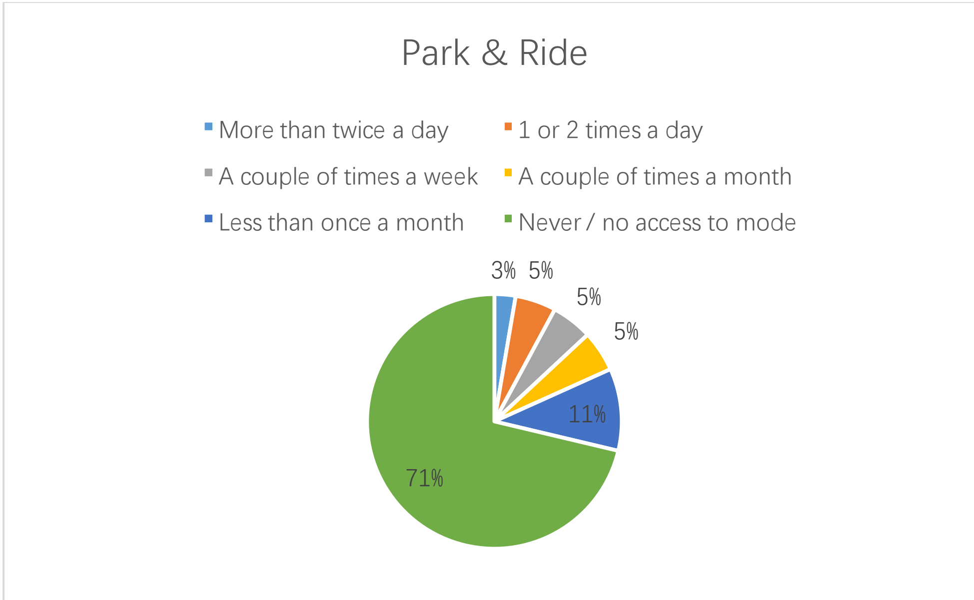

Bike
More than twice a day
1 or 2 times a day
A couple of times a week
A couple of times a month
Less than once a month
Never / no access to mode
4%
5%
6%
7%
13%
65%

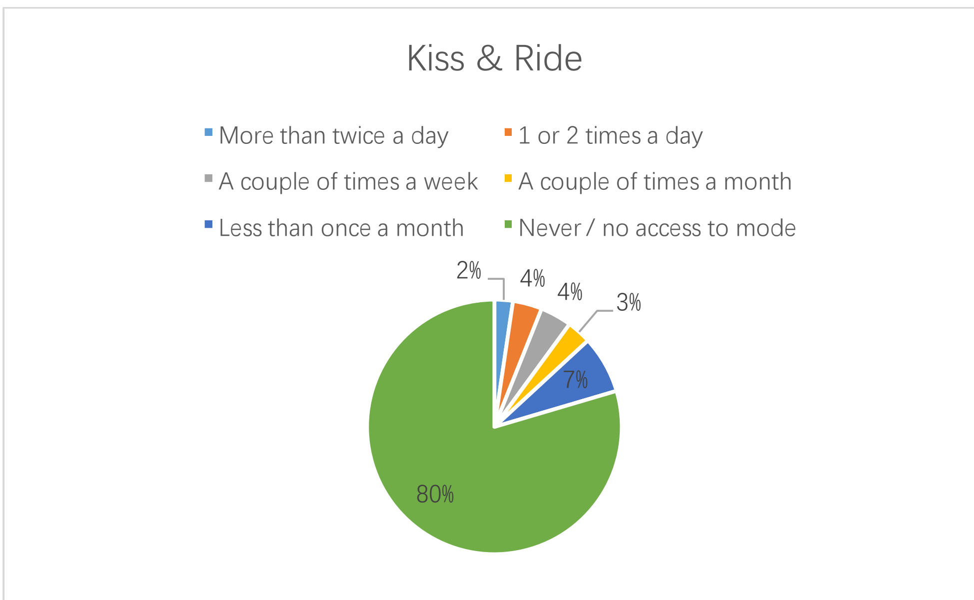

Ferry
More than twice a day
1 or 2 times a day
A couple of times a week
A couple of times a month
Less than once a month
Never / no access to mode
3%
4%
5%
4%
17%
67%

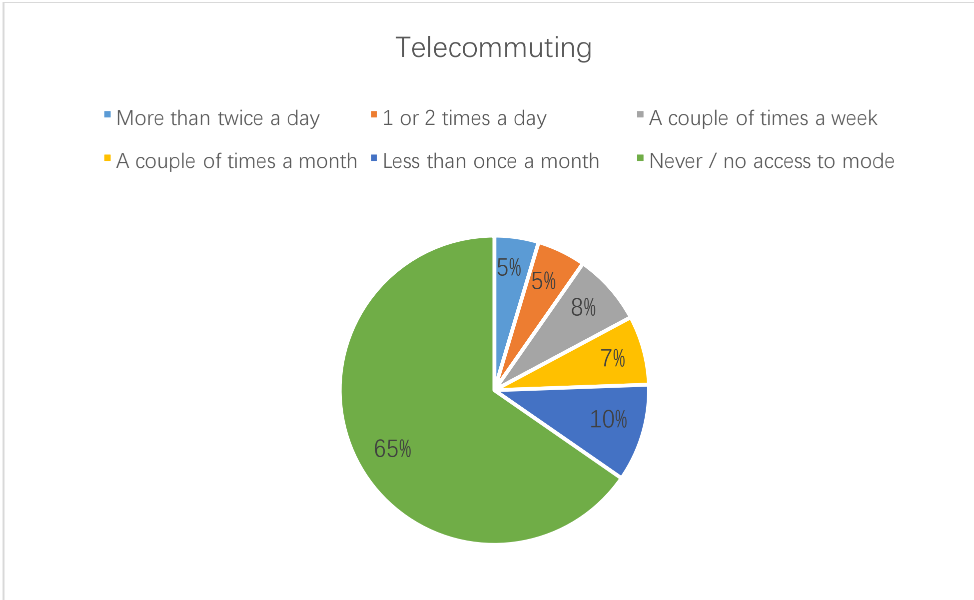

Car as a driver
More than twice a day
1 or 2 times a day
A couple of times a week
A couple of times a month
Less than once a month
Never / no access to mode
25%
16%
14%
8%
10%
27%


Car as a passenger
More than twice a day
1 or 2 times a day
A couple of times a week
A couple of times a month
Less than once a month
Never / no access to mode
5%
10%
21%
18%
21%
25%

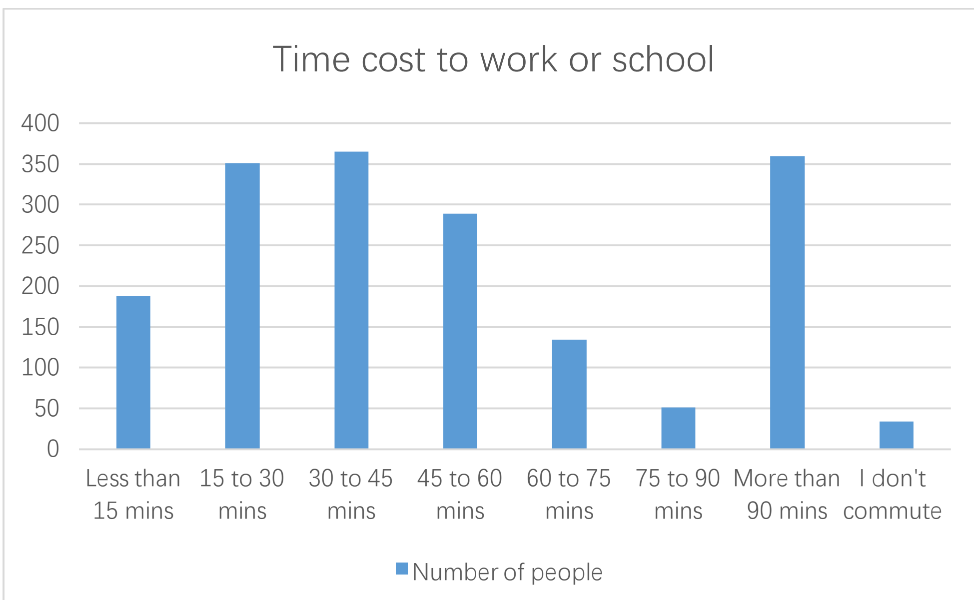

Taxi or limo
More than twice a day
1 or 2 times a day
A couple of times a week
A couple of times a month
Less than once a month
Never / no access to mode
4%
5%
10%
14%
26%
41%


Park & Ride
More than twice a day
1 or 2 times a day
A couple of times a week
A couple of times a month
Less than once a month
Never / no access to mode
3%
5%
5%
5%
11%
71%


Kiss & Ride
More than twice a day
1 or 2 times a day
A couple of times a week
A couple of times a month
Less than once a month
Never / no access to mode
2%
4%
4%
3%
7%
80%

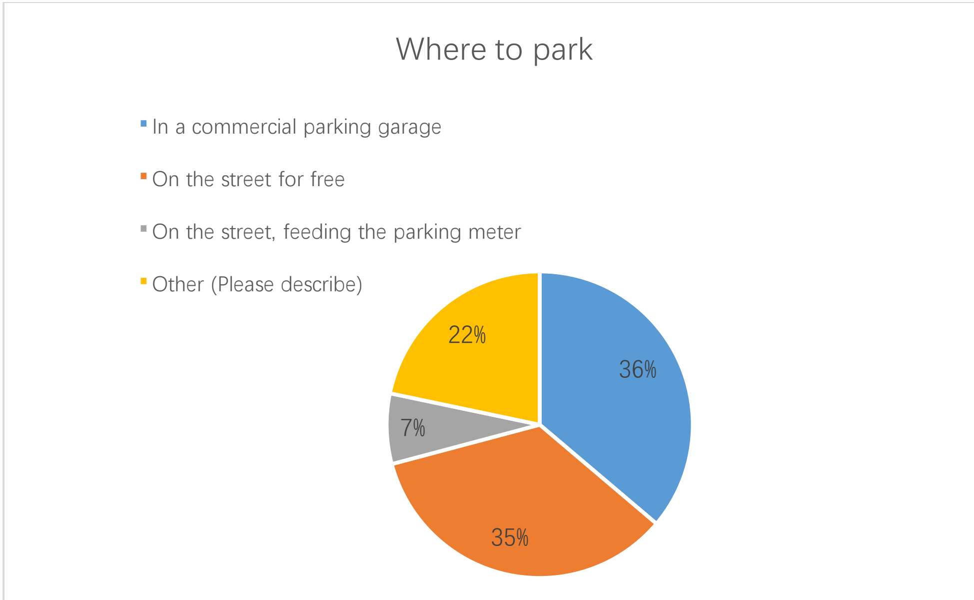



q2 How long does it take you on average to commute to work or school (one way trip)?

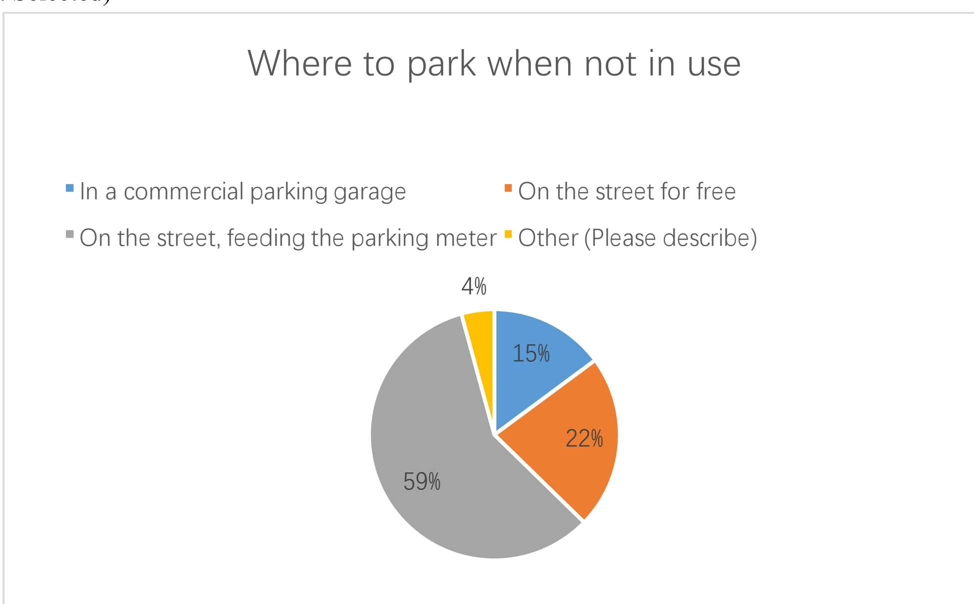



q3 Where do you park the car when you use it to go to work or school?

(Answer If During typical business days, how frequently do you use the following transportation modes? Car as a driver - Never / no access to mode Is Not Selected And How long does it take you on average to commute to work or school? I don't commute Is Not Selected)




q4. Where do you park the car when it is not in use? (Answer If During typical business days, how frequently do you use the following transportation modes? Car as a driver - Never / no access to mode Is Not Selected)




q5. How many hurricanes have you been in?

| | Number of people, Percentage |
|---|---|
| 0 | 127, 7.25% |
| 1-2 | 712, 40.64% |
| 3-4 | 476, 27.17% |
| 5-6 | 181, 10.33% |
| 7 or more | 256, 14.61% |

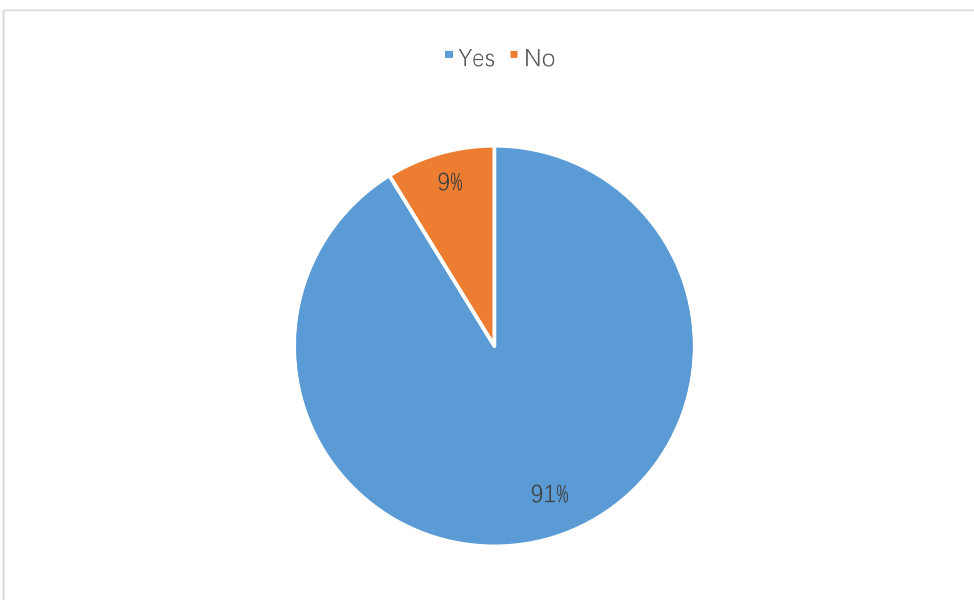
q6. How many times have you evacuated from a hurricane?

| | Number of people, Percentage |
|---|---|
| 0 | 1217, 69.50% |
| 1-2 | 426, 24.33% |
| 3-4 | 75, 4.28% |
| 5-6 | 25, 1.43% |
| 7 or more | 8, 0.46% |

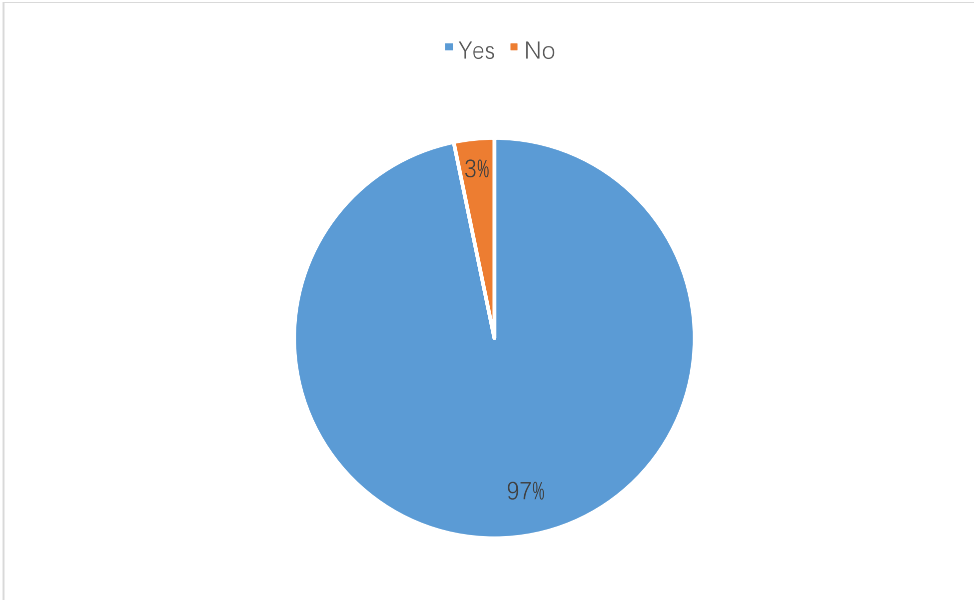
q7. How many times have you had property damage from a hurricane?

| | Number of people, Percentage |
|---|---|
| 0 | 798, 45.55% |
| 1-2 | 801, 45.72% |
| 3-4 | 123, 7.02% |
| 5-6 | 19, 1.08% |
| 7 or more | 11, 0.63% |

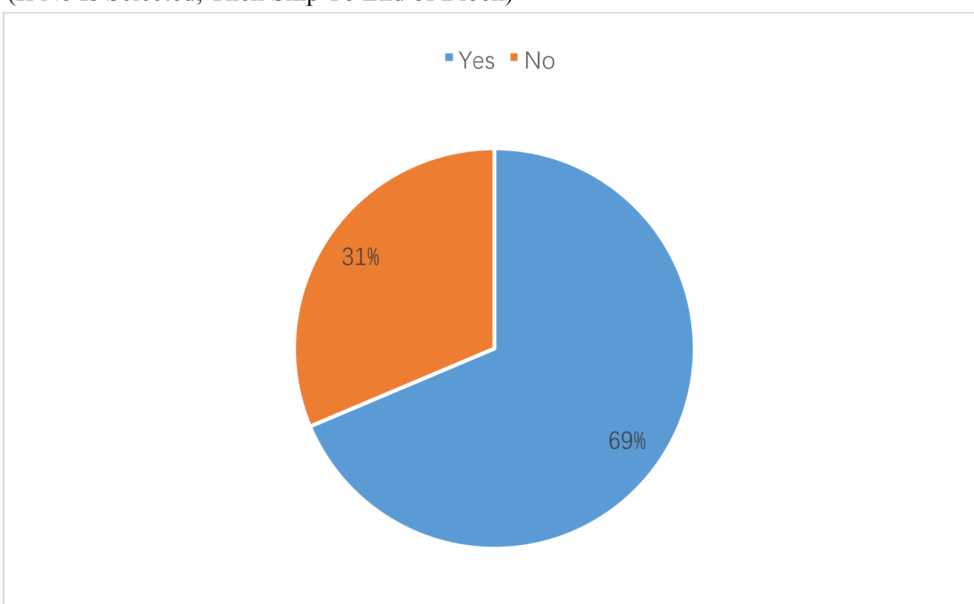
q8. Were you in the New York City metropolitan area before, during, or after Hurricane Sandy made landfall around New York City (October 29th, 2012)?
(If Yes Is Selected, Then Skip To Did you miss work during or immediate...)



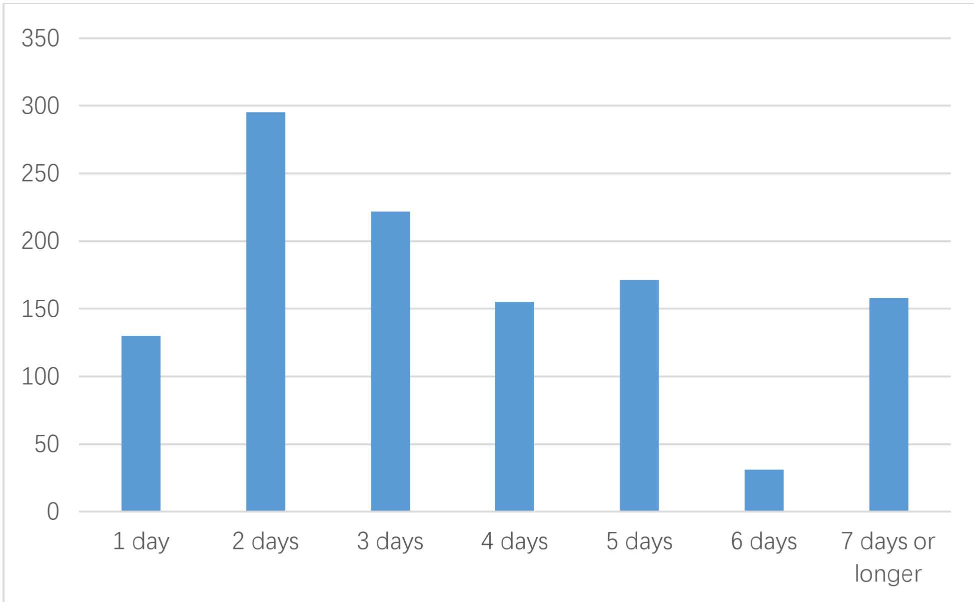

q9. Were you in another area that was affected when Hurricane Sandy made landfall on October 29th, 2012? (If No Is Selected, Then Skip To End of Block)



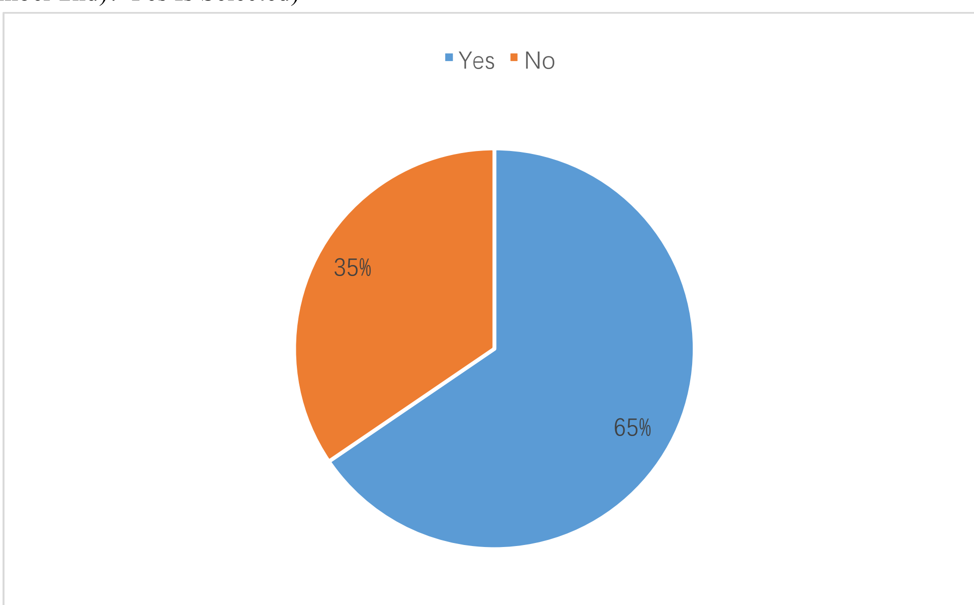

q10. Did you miss work during or immediately following Hurricane Sandy (October 29th-November 2nd)? (If No Is Selected, Then Skip To End of Block)




q11. For how long did you miss work?



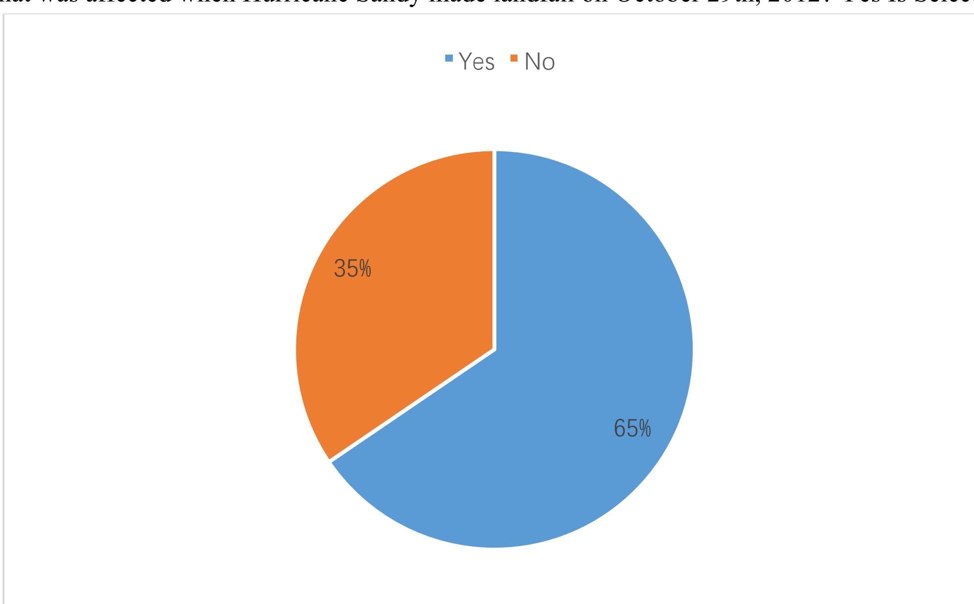

q12. When you missed work, were you paid for the days that you missed?
(Answer If Did you miss work during or immediately following Hurricane Sandy (October 29th-November 2nd)? Yes Is Selected)




q13. The following questions are about your experience with Hurricane Sandy:
(Answer If Were you in the New York City metropolitan area before, during, or after Hurricane Sandy... Yes is Selected Or Were you in another area that was affected when Hurricane Sandy made landfall on October 29th, 2012? Yes Is Selected) Total: 1693, 100%

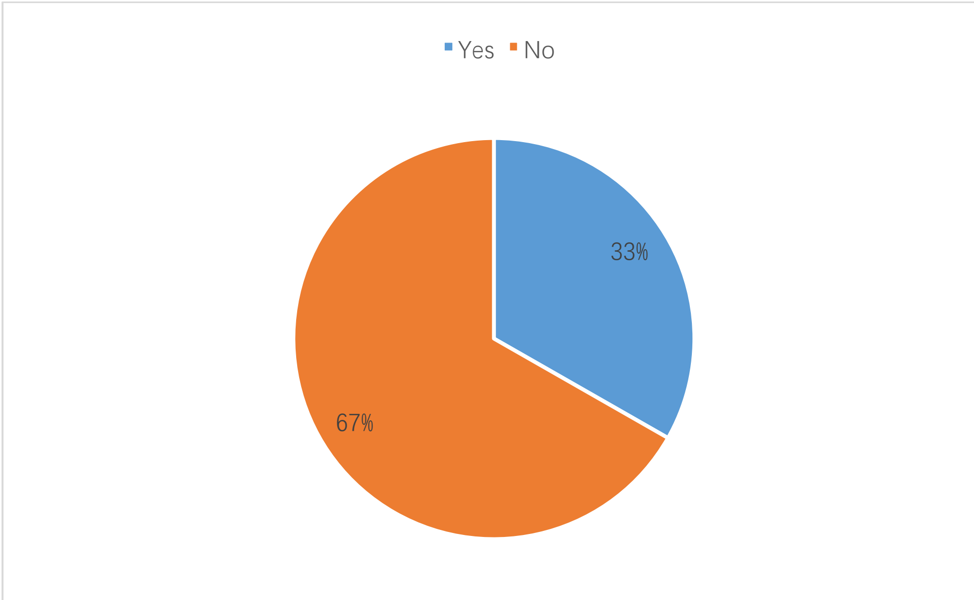
| | Yes | No | Don't know/can't remember |
|---|---|---|---|
| Did you experience any personal loss from Hurricane Sandy? | 33.90% | 64.32% | 1.78% |
| Did someone you know experience any personal loss from Hurricane Sandy? | 67.99% | 28.23% | 3.78% |
| Did your home experience any storm surge from Hurricane Sandy? | 27.64% | 69.70% | 2.66% |
| Did your neighborhood experience any storm surge from Hurricane Sandy? | 40.99% | 55.05% | 3.96% |
| Did your community experience any storm surge from Hurricane Sandy? | 49.88% | 45.15% | 4.96% |
| Was there an evacuation order for your area during Hurricane Sandy? | 23.33% | 72.18% | 4.49% |
| Did you actually evacuate? | 16.48% | 81.22% | 2.19% |

q14. Was your normal commute disrupted during or immediately following Hurricane Sandy (October 29th-November 2nd)?
(Answer If Were you in the New York City metropolitan area before, during, or after Hurricane Sandy made landfall around New York City (October 29th, 2012)? Yes Is Selected Or Were you in another area that was affected when Hurricane Sandy made landfall on October 29th, 2012? Yes Is Selected)

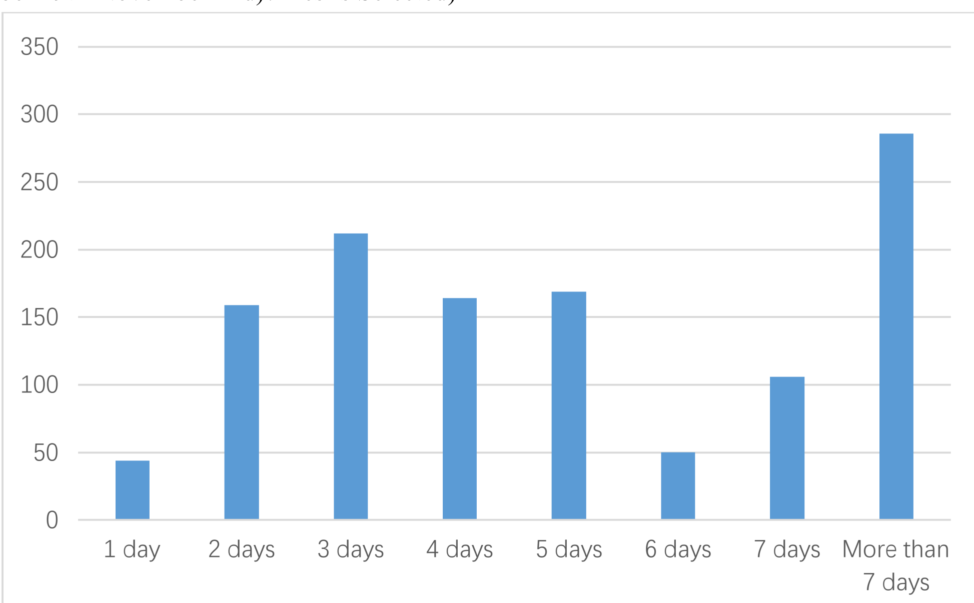



q15. Did you use social media to find open gas stations?

(Answer If Were you in the New York City metropolitan area before, during, or after Hurricane Sandy made landfall around New York City (October 29th, 2012)? Yes Is Selected Or Were you in another area that was affected when Hurricane Sandy made landfall on October 29th, 2012? Yes Is Selected)

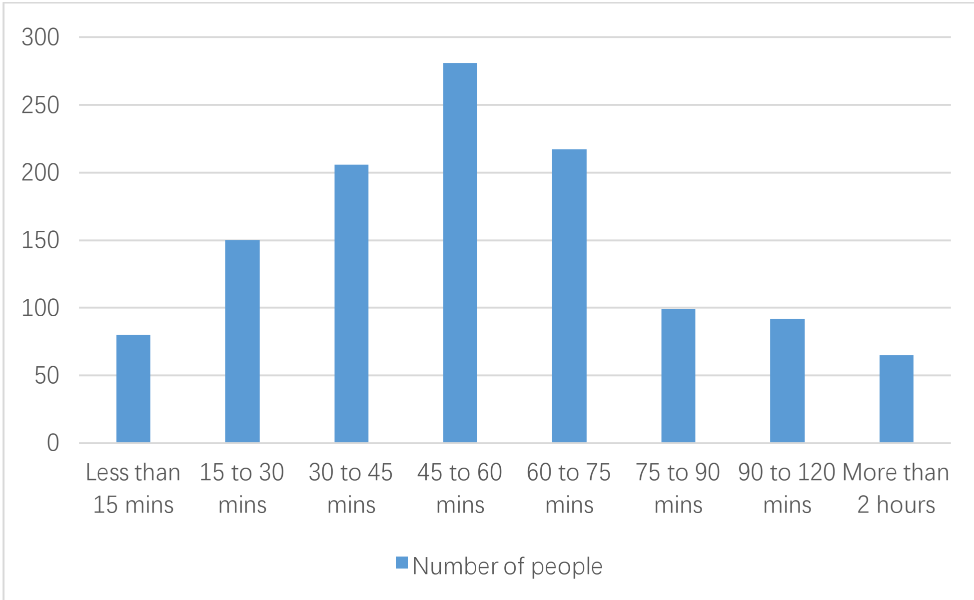



q16. How long was it before your commute returned to normal, in terms of both the modes of transportation you used and your average commute time?
(Answer If Was your normal commute disrupted during or immediately following Hurricane Sandy (October 29th-November 2nd)? Yes Is Selected)

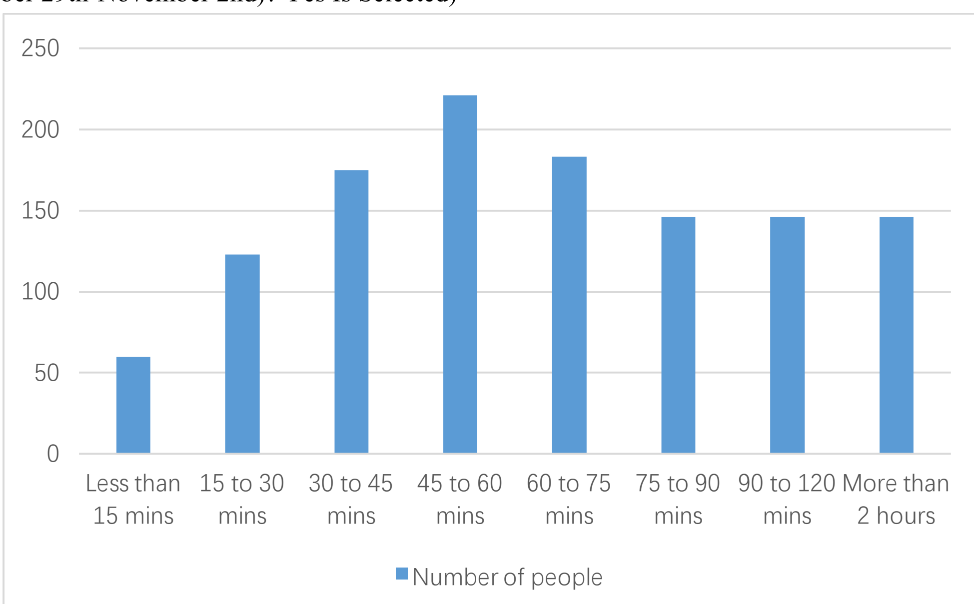



q17. How long was your commute on average the week immediately following Hurricane Sandy?

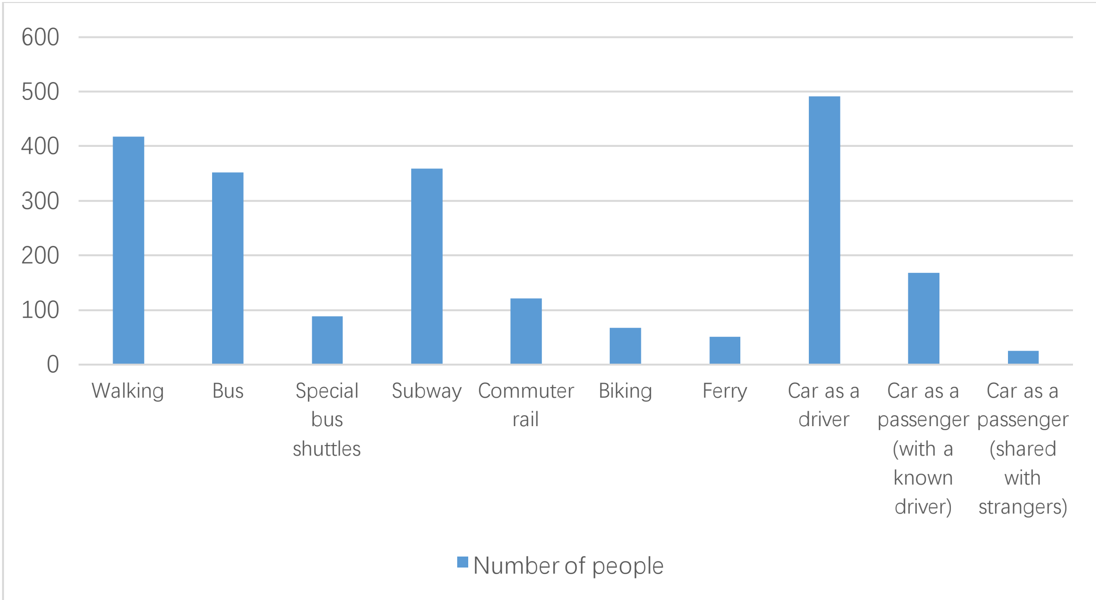
(Answer If Was your normal commute disrupted during or immediately following Hurricane Sandy (October 29th-November 2nd)? Yes Is Selected)



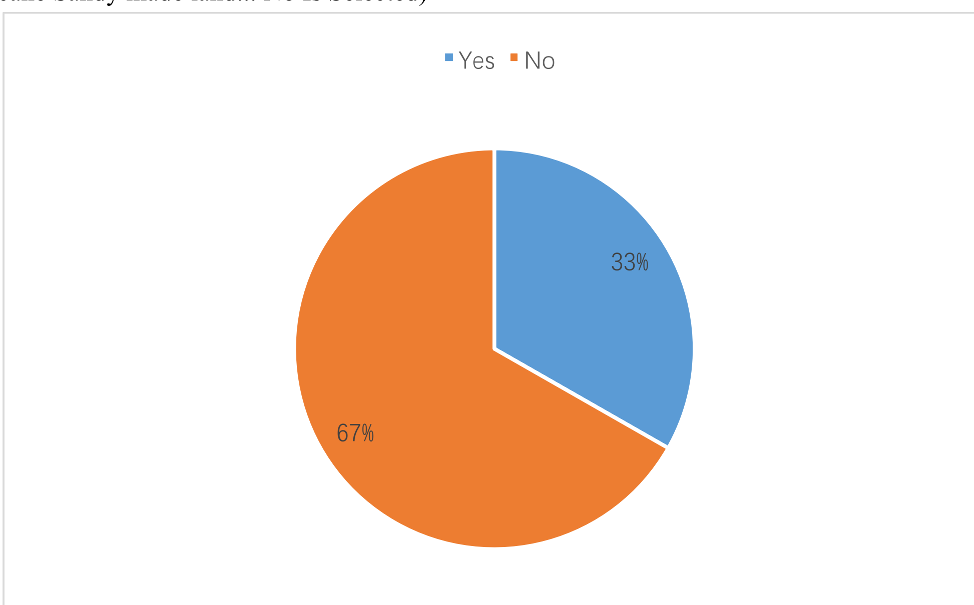

q18. How long was the longest commute that you experienced following Hurricane Sandy? (Answer If Was your normal commute disrupted during or immediately following Hurricane Sandy (October 29th-November 2nd)? Yes Is Selected)



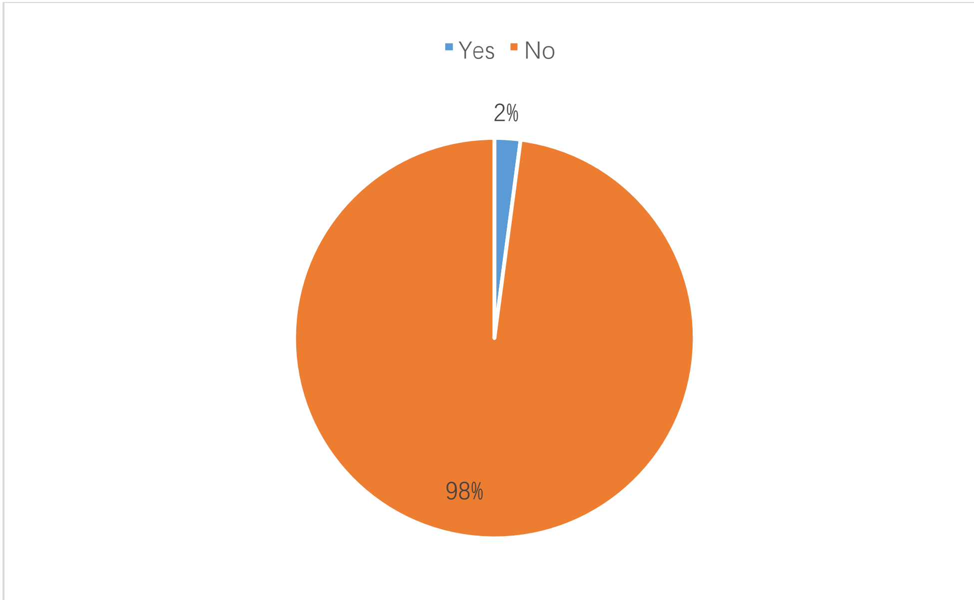

q19. What mode(s) of transportation did you use to commute the week immediately following Hurricane Sandy? (Answer If Was your normal commute disrupted during or immediately following Hurricane Sandy (October 29th-November 2nd)? Yes Is Selected)



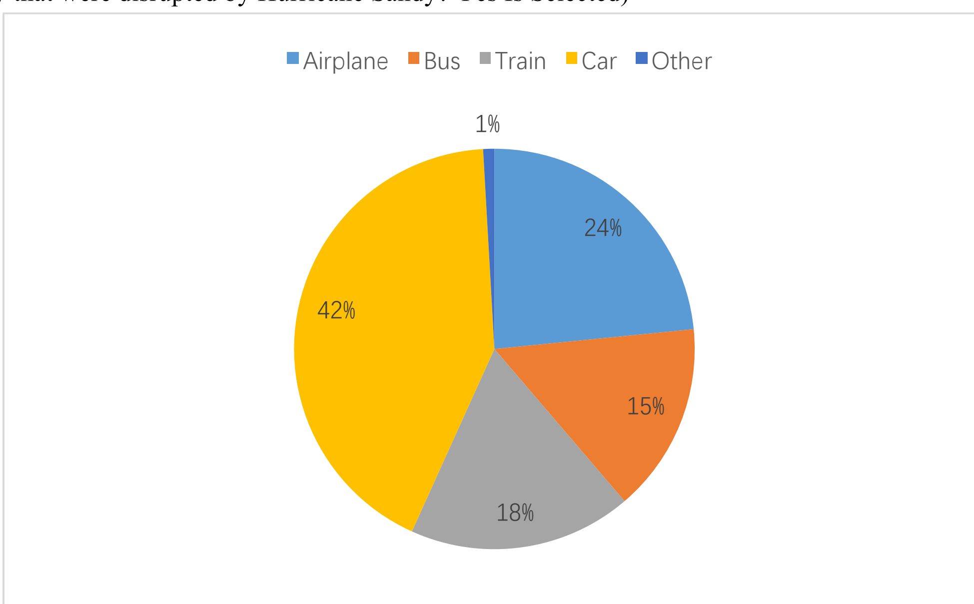

q20. A) Did you have plans to leave the New York City metropolitan area that were disrupted by Hurricane Sandy? (Answer If Were you in the New York City metropolitan area before, during, or after Hurricane Sandy made land... No Is Selected)



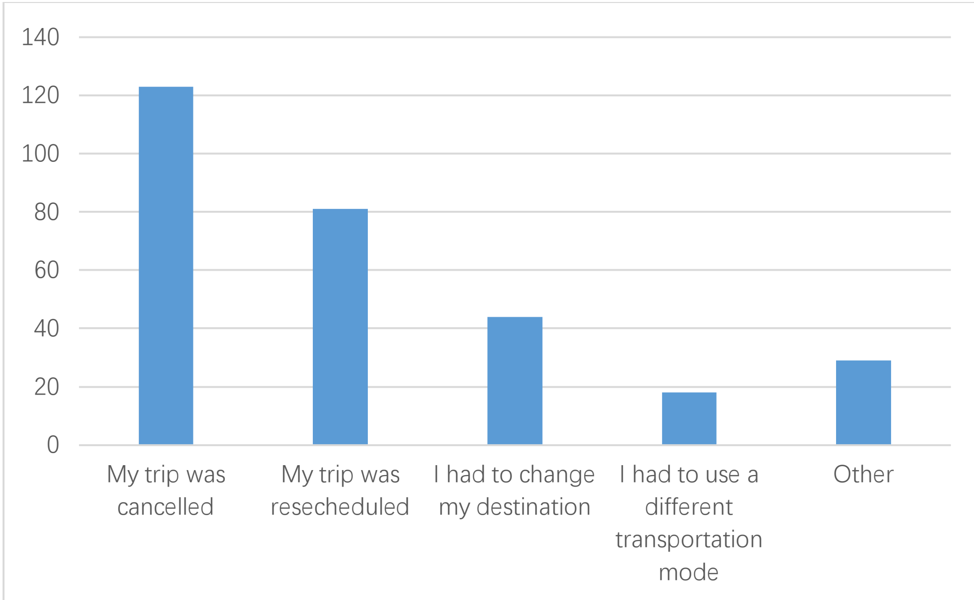

q20. B) Did you have any plans to move around New York, Connecticut or New Jersey that were disrupted by Hurricane Sandy? (Answer If Were you in the New York City metropolitan area before, during, or after Hurricane Sandy made land... No Is Selected)



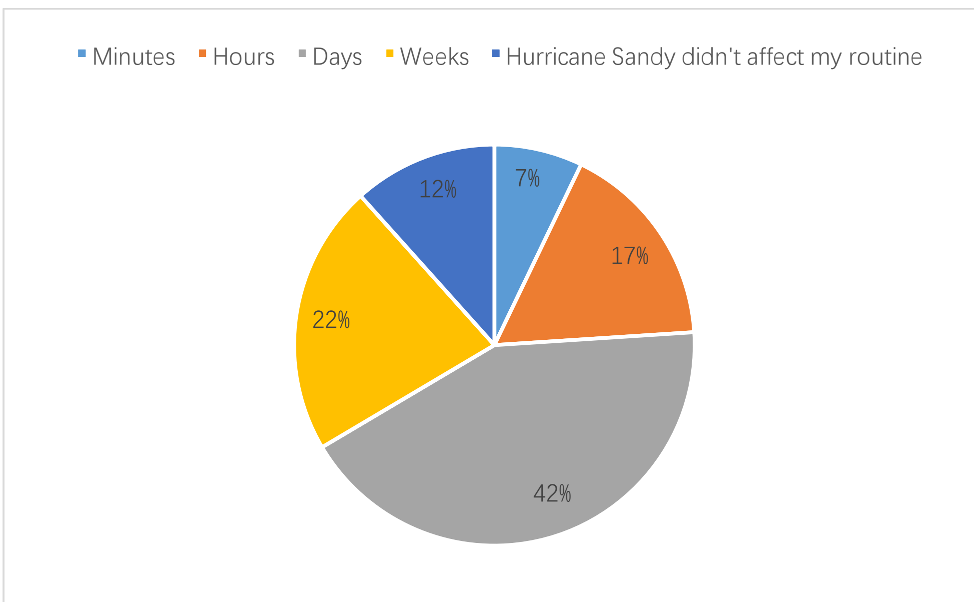

q21. What mode of transportation were you planning to use?
(Answer If Did you have plans to leave the New York City metropolitan area that were disrupted by Hurricane... Yes Is Selected Or Did you have any plans to move around New York, Connecticut or New Jersey that were disrupted by Hurricane Sandy? Yes Is Selected)



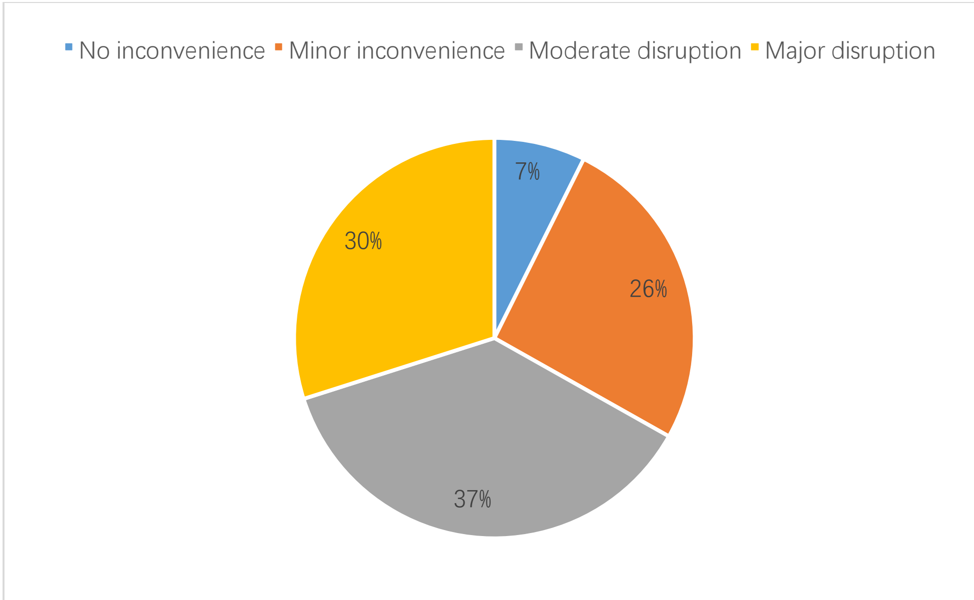

q22. How were your plans disrupted? (Select all that apply)
(Answer If Did you have plans to leave the New York City metropolitan area that were disrupted by Hurricane... Yes Is Selected Or Did you have any plans to move around New York, Connecticut or New Jersey that were disrupted by Hurricane Sandy? Yes Is Selected)



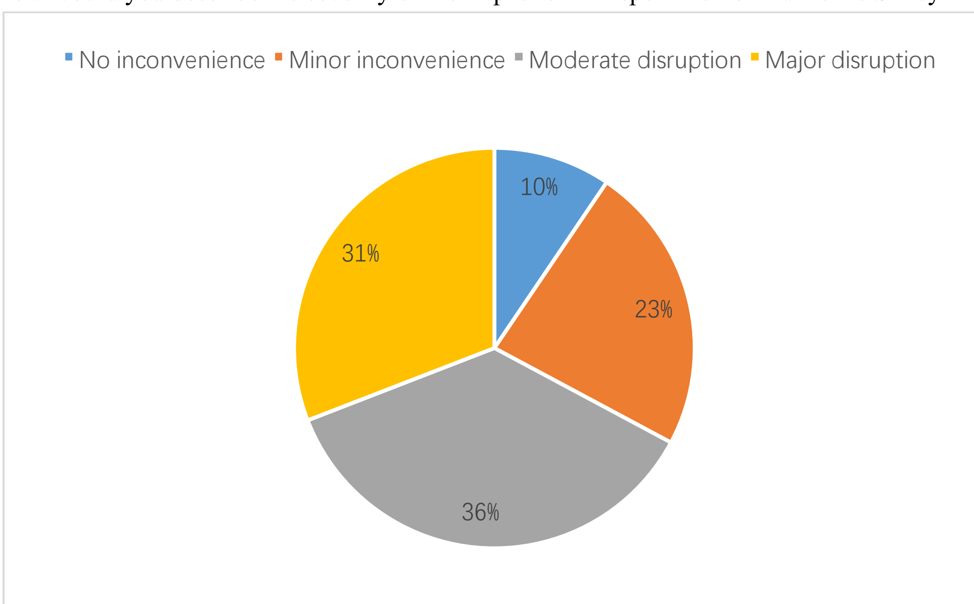

q23. How would you describe the duration of the overall impact of Hurricane Sandy on your daily routine?




q24. How would you describe the severity of the overall impact of Hurricane Sandy?




q25. How would you describe the severity of the impact on transportation of Hurricane Sandy?




q26. A) Did you experience any of the following disruptions as a result of Hurricane Sandy?

Total：1693

| | Not at all | Only for a few hours | For 1-2 days | For 3-5 days | For a week | For 1 - 2 weeks | For more than 2 weeks |
|---|---|---|---|---|---|---|---|
| Subway line closures | 42.00% | 6.97% | 17.90% | 12.82% | 7.97% | 6.26% | 6.08% |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Subway station closures | 42.65% | 6.67% | 16.77% | 11.70% | 8.74% | 7.03% | 6.44% |
| Closed bridges | 49.20% | 7.38% | 18.25% | 11.16% | 6.91% | 4.19% | 2.89% |
| Closed tunnels | 50.27% | 5.55% | 16.72% | 11.05% | 7.56% | 4.49% | 4.37% |
| Abnormal traffic congestion | 31.42% | 7.32% | 18.37% | 15.06% | 13.17% | 9.04% | 5.61% |
| Limited bus service | 41.29% | 6.62% | 17.66% | 13.88% | 10.40% | 7.03% | 3.13% |
| Commuting times more than twice as normal | 37.27% | 7.21% | 16.60% | 15.53% | 11.16% | 7.56% | 4.67% |
| Having to use alternate routes | 31.19% | 6.85% | 16.48% | 16.60% | 12.40% | 9.74% | 6.73% |
| Working at alternate sites | 59.60% | 4.13% | 10.22% | 9.75% | 7.62% | 4.96% | 3.72% |
| Severe crowding in mass transit | 45.36% | 5.43% | 13.29% | 11.40% | 10.63% | 7.97% | 5.91% |

q26. B) How would you rate the level of inconvenience of the following problems (due to the arrival of a hypothetical hurricane)?

Total: 1752

| | Wouldn't affect me | Minor inconvenience | Somewhat inconvenient | Extremely inconvenient |
|---|---|---|---|---|
| Subway line closures | 43.66% | 15.98% | 19.35% | 21.00% |
| Subway station closures | 43.84% | 15.75% | 20.72% | 19.69% |
| Closed bridges | 41.72% | 17.41% | 24.66% | 16.21% |
| Closed tunnels | 45.55% | 16.84% | 21.75% | 15.87% |

| | | | | |
|---|---|---|---|---|
| Abnormal traffic congestion | 27.11% | 21.58% | 29.28% | 22.03% |
| Limited bus service | 44.58% | 17.75% | 21.58% | 16.10% |
| Commuting times more than twice as normal | 29.57% | 17.35% | 26.48% | 26.60% |
| Having to use alternate routes | 25.23% | 24.54% | 32.13% | 18.09% |
| Working at alternate sites | 49.14% | 17.41% | 20.66% | 12.79% |
| Severe crowding in mass transit | 40.92% | 15.58% | 23.57% | 19.92% |

q27. Did you experience any of the following as a result of Hurricane Sandy?
(Answer If Were you in the New York City metropolitan area before, during, or after Hurricane Sandy made landfall around New York City (October 29th, 2012)? Yes Is Selected Or Were you in another area that was affected when Hurricane Sandy made landfall on October 29th, 2012? Yes Is Selected)

| | Not at all | Only for a few hours | For 1-2 days | For 3-5 days | For a week | For 1 - 2 weeks | For more than 2 weeks |
|---|---|---|---|---|---|---|---|
| Difficulty getting food | 46.01% | 9.21% | 20.26% | 10.63% | 6.91% | 4.31% | 2.66% |
| Difficulty getting water | 56.53% | 8.45% | 14.83% | 8.51% | 5.73% | 4.02% | 1.95% |
| Poor water quality | 61.78% | 6.91% | 10.57% | 7.27% | 6.14% | 4.31% | 3.01% |
| Difficulty getting fuel | 26.99% | 5.79% | 13.11% | 17.48% | 18.02% | 11.64% | 6.97% |
| Malfunction of traffic signals | 29.12% | 8.68% | 20.38% | 17.84% | 13.05% | 7.68% | 3.25% |
| Loss of cellphone signal | 38.81% | 17.90% | 15.95% | 12.64% | 8.09% | 4.67% | 1.95% |
| Loss of electric power | 28.59% | 11.52% | 12.17% | 17.07% | 12.99% | 12.52% | 5.14% |
| Elevators not working | 61.84% | 5.02% | 9.51% | 8.51% | 7.32% | 5.20% | 2.60% |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Lack of heating | 43.89% | 6.67% | 8.86% | 13.23% | 11.75% | 11.05% | 4.55% |
| Staying at home | 21.03% | 6.67% | 26.46% | 19.02% | 14.59% | 7.97% | 4.25% |
| Staying at a friend's/family member's home | 63.32% | 4.73% | 9.21% | 7.80% | 6.26% | 5.02% | 3.66% |

q28. Please indicate to what extent you agree or disagree with the following statements:

| | Completely Disagree | Somewhat Disagree | Neutral | Somewhat Agree | Completely Agree |
|---|---|---|---|---|---|
| I live near the coastline | 22.89% | 14.61% | 15.87% | 26.60% | 20.03% |
| If I had to evacuate my home, I could easily access a highway or other exit route | 5.94% | 8.85% | 17.87% | 39.27% | 28.08% |
| If I had to evacuate my home, I could easily access mass transit | 15.81% | 15.47% | 18.32% | 31.62% | 18.78% |
| The frequency of floods has been increasing in recent years | 4.74% | 7.02% | 23.46% | 40.01% | 24.77% |
| I live inland | 14.16% | 13.58% | 18.66% | 29.85% | 23.74% |
| The severity of floods has been increasing in recent years | 4.05% | 7.02% | 22.72% | 39.84% | 26.37% |
| The government is | 4.39% | 10.39% | 26.66% | 35.39% | 23.17% |

| | | | | | |
|---|---|---|---|---|---|
| solely responsible for financing projects that improve transportation infrastructure | | | | | |
| The frequency of natural disasters has been increasing in recent years | 4.00% | 6.74% | 18.32% | 39.33% | 31.62% |
| Communities should contribute to financing projects that improve resiliency | 4.74% | 6.74% | 27.28% | 41.44% | 19.81% |
| The severity of natural disasters has been increasing in recent years | 4.28% | 5.37% | 18.38% | 40.30% | 31.68% |
| Global climate change is a real and urgent issue | 6.45% | 5.65% | 17.81% | 29.34% | 40.75% |
| Select 'Neutral' | 1.54% | 1.54% | 88.64% | 4.51% | 3.77% |

Q29. a Suppose that hurricane Deirdre, a hurricane as strong as Sandy, is heading for your area. How likely is it that this hypothetical hurricane would harm:

| | Not At All Likely | Somewhat Likely | Moderately Likely | Extremely Likely |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| You and your family | 24.90% | 39.87% | 24.90% | 10.33% |
| Your home | 18.01% | 43.84% | 25.30% | 12.85% |
| Your local community | 9.93% | 39.60% | 29.93% | 20.53% |
| Your daily routine | 8.08% | 29.93% | 29.80% | 32.19% |
| Subway | 18.01% | 23.44% | 26.62% | 31.92% |
| Commuter rail | 13.11% | 24.37% | 27.81% | 34.70% |
| Buses | 10.60% | 25.30% | 32.32% | 31.79% |
| Tunnels for vehicles and trains | 14.04% | 24.50% | 27.68% | 33.77% |
| Bridges | 12.19% | 26.36% | 29.27% | 32.19% |
| Airports | 10.07% | 20.79% | 24.37% | 44.77% |
| Ferries | 13.77% | 20.93% | 24.77% | 40.53% |
| Electric Power | 5.17% | 19.87% | 32.72% | 42.25% |
| Telecommunication Infrastructure | 7.68% | 25.56% | 36.56% | 30.20% |
| Schools | 7.15% | 23.05% | 30.99% | 38.81% |
| Hospitals | 9.67% | 29.93% | 35.10% | 25.30% |

Q29b Suppose that super storm Deirdre, a super storm as strong as Sandy, is heading for your area. How likely is it that this hypothetical super storm would harm:

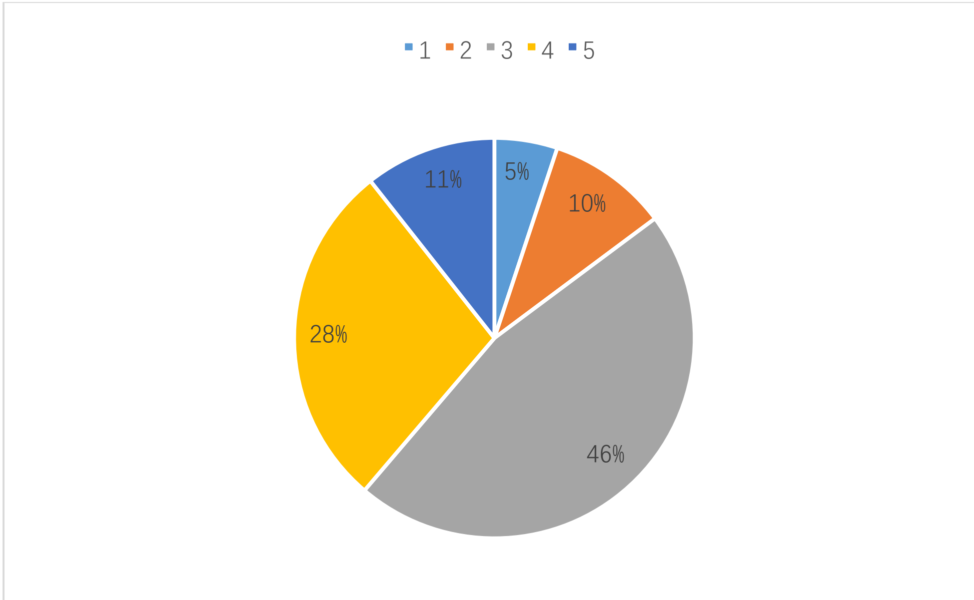
| | Not At All Likely | Somewhat Likely | Moderately Likely | Extremely Likely |
|---|---|---|---|---|
| You and your family | 23.56% | 42.23% | 21.43% | 12.78% |
| Your home | 21.18% | 41.35% | 23.68% | 13.78% |
| Your local community | 10.15% | 40.48% | 28.57% | 20.80% |
| Your daily routine | 7.52% | 29.32% | 26.82% | 36.34% |
| Subway | 16.79% | 22.68% | 26.44% | 34.09% |
| Commuter rail | 13.03% | 24.31% | 26.94% | 35.71% |
| Buses | 10.15% | 23.43% | 30.45% | 35.96% |
| Tunnels for vehicles and trains | 11.15% | 24.06% | 28.70% | 36.09% |

| | | | | |
|---|---|---|---|---|
| Bridges | 10.40% | 26.69% | 29.95% | 32.96% |
| Airports | 7.39% | 22.81% | 22.93% | 46.87% |
| Ferries | 10.65% | 21.80% | 25.19% | 42.36% |
| Electric Power | 3.63% | 20.30% | 28.70% | 47.37% |
| Telecommunication Infrastructure | 6.39% | 24.94% | 33.33% | 35.34% |
| Schools | 5.51% | 21.55% | 27.44% | 45.49% |
| Hospitals | 7.14% | 28.82% | 33.58% | 30.45% |

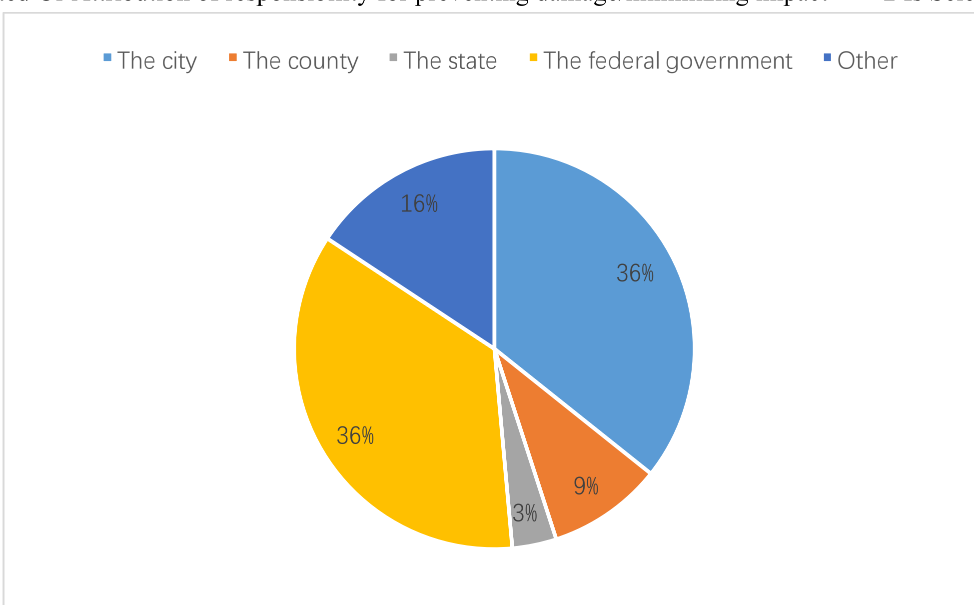
Q30 How likely is it that these extreme weather events would harm vital transportation infrastructure in your area:

| | Not At All Likely | Somewhat Likely | Moderately Likely | Very Likely | Extremely Likely |
|---|---|---|---|---|---|
| Heat wave | 31.75% | 25.43% | 24.02% | 12.11% | 6.70% |
| Heavy precipitation | 15.52% | 24.02% | 27.43% | 20.93% | 12.11% |
| Blizzard | 3.93% | 17.19% | 22.86% | 30.59% | 25.43% |
| Storm surge | 12.94% | 21.31% | 24.98% | 23.25% | 17.51% |
| Hurricane of category 1 | 15.39% | 26.08% | 26.53% | 20.35% | 11.65% |
| Hurricane of category 2 | 7.02% | 18.80% | 28.65% | 28.78% | 16.74% |
| Hurricane of category 3 | 3.73% | 12.75% | 22.22% | 30.20% | 31.10% |
| Nor'easter | 5.92% | 22.73% | 25.50% | 26.85% | 19.00% |
| Damaging winds | 6.44% | 24.15% | 27.11% | 25.24% | 17.06% |

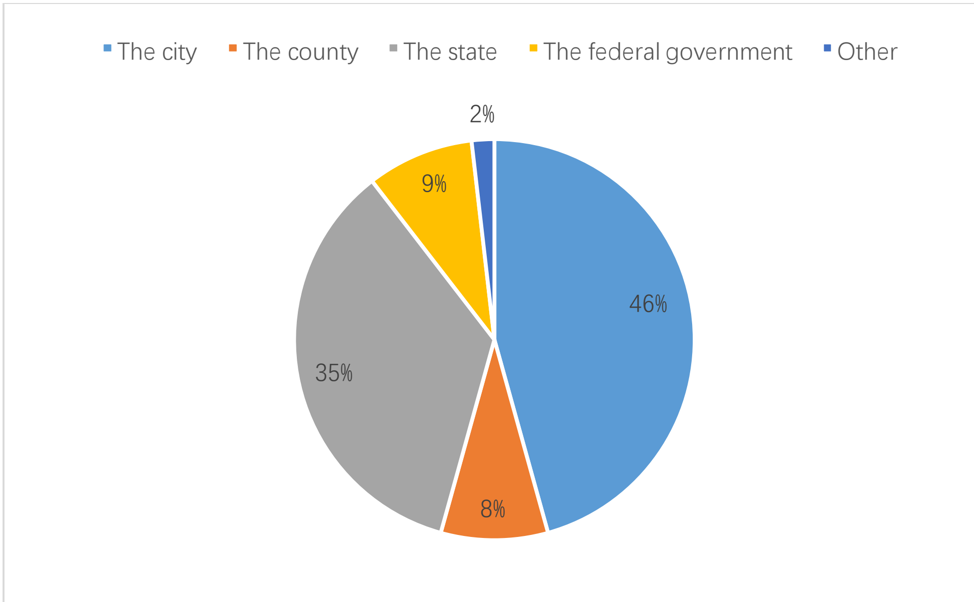
Q30 Please tell us whether you think government policies have made the transportation system in your area more or less prepared for hurricanes.




Q31.1 Who do you think should get the blame for the transportation system being less prepared for hurricanes?(Answer If Attribution of responsibility for preventing damage/minimizing impact - 1 Is Selected Or Attribution of responsibility for preventing damage/minimizing impact - 2 Is Selected)




Q31.2 Who do you think should get the credit for the transportation system being more prepared for hurricanes? (Answer If Attribution of responsibility for preventing damage/minimizing impact - 4 Is Selected Or Attribution of responsibility for preventing damage/minimizing impact - 5 Is Selected)




Q31.3 To what extent do you disagree or agree with the following statements:
(Answer If Attribution of responsibility for preventing damage/minimizing impact - 3 Is Selected)

| | Strongly disagree | Disagree | Neither disagree or agree | Agree | Strongly agree |
|---|---|---|---|---|---|
| Government has not been doing enough to prepare the transportation system for hurricanes | 1.11% | 8.32% | 48.68% | 37.03% | 4.85% |
| Government policies simply do not matter when it comes to the issue of hurricanes | 5.96% | 27.88% | 43.83% | 19.83% | 2.50% |

Q32 In your opinion, how trustworthy are the following:

| | Not at all trustworthy | Somewhat trustworthy | Moderately trustworthy | Very trustworthy | Extremely trustworthy |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| City Government | 15.07% | 29.23% | 39.28% | 12.69% | 3.73% |
| County Government | 14.55% | 30.78% | 40.18% | 11.78% | 2.70% |
| State Government | 17.00% | 30.14% | 36.25% | 12.49% | 4.12% |
| Federal Government | 22.60% | 30.07% | 32.07% | 11.59% | 3.67% |

Q33 Please rate the extent to which you disagree or agree with each statement.

| | Strongly Disagree | Disagree | Somewhat Disagree | Somewhat Agree | Agree | Strongly Agree |
|---|---|---|---|---|---|---|
| No level of government should be held accountable for what happened to the people affected by Hurricane Sandy in your state. | 21.51% | 23.44% | 23.44% | 18.48% | 9.85% | 3.28% |
| Subway operations recovered rather quickly | 4.31% | 12.88% | 23.31% | 41.98% | 14.17% | 3.35% |
| First responders (Fire, police and EMT personnel) did all they could to | 1.09% | 1.09% | 5.86% | 25.11% | 34.77% | 32.07% |

| | | | | | | |
|---|---|---|---|---|---|---|
| save people from rising flood waters during Hurricane Sandy | | | | | | |
| My local and state government did not convey to me the severity of the risks posed by Hurricane Sandy | 14.62% | 22.34% | 24.86% | 21.18% | 12.30% | 4.70% |
| TV media conveyed to me the severity of the risks posed by Hurricane Sandy | 2.06% | 2.96% | 7.98% | 29.62% | 34.51% | 22.86% |

Q34 After Hurricane Sandy, it took 3 weeks for subway operations to resume in highly affected areas (World Trade Center). How much would are you willing to pay, as a one-time payment, to support investments that would reduce the recovery time to from 3 weeks to only 3 days.

N/A

Q35 How much would are you willing to pay, as a recurring monthly payment, to support investments that would reduce the recovery time from 3 weeks to only 3 days.

N/A

Month In the previous question, you said you would be willing to pay per month for reducing recovery time of subway operations from 3 weeks to 3 days after a disruption provoked by an extreme weather event. Suppose that the monthly payment could be deferred to a recurring annual payment due at the end of each year. How likely would you be willing to pay the amounts below per year?

| | Very Unlikely | Somewhat Unlikely | Undecided | Somewhat Likely | Very Likely |
|---|---|---|---|---|---|
| Less than $ 50 per year | 16.63% | 4.75% | 15.26% | 21.24% | 42.12% |
| $ 100 per year | 18.36% | 6.12% | 18.21% | 21.17% | 36.14% |
| $ 200 per year | 20.88% | 9.07% | 20.09% | 18.43% | 31.53% |
| $ 400 per year | 24.69% | 10.37% | 21.60% | 15.19% | 28.15% |
| $ 800 per year | 28.51% | 12.17% | 20.16% | 13.32% | 25.85% |
| $ 1600 per year | 42.48% | 13.39% | 21.38% | 10.37% | 12.38% |
| More than $ 1600 per year | 15.05% | 3.31% | 13.97% | 18.50% | 49.17% |

CV1.1 Suppose that the city is considering projects that would reduce the transportation recovery time from 1 week to 2 days. How likely would you be willing to pay the amounts below as a recurring annual payment to support these infrastructure investments.

| | Very Unlikely | Somewhat Unlikely | Undecided | Somewhat Likely | Very Likely |
|---|---|---|---|---|---|
| $50 | 30.61% | 7.99% | 15.48% | 21.94% | 23.98% |
| $100 | 40.41% | 9.85% | 18.85% | 17.49% | 13.41% |
| $200 | 47.63% | 14.75% | 19.15% | 11.53% | 6.95% |
| $400 | 60.03% | 12.93% | 15.48% | 7.48% | 4.08% |
| $800 | 65.59% | 11.86% | 14.58% | 5.59% | 2.37% |
| More than $800 | 70.46% | 9.17% | 13.58% | 4.41% | 2.38% |

CV1.2 Suppose that the city is considering projects that would reduce the transportation recovery time from 1 week to 4 days. How likely would you be willing to pay the amounts below as a recurring annual payment to support these infrastructure investments.

| | Very Unlikely | Somewhat Unlikely | Undecided | Somewhat Likely | Very Likely |
|---|---|---|---|---|---|
| $50 | 33.76% | 9.03% | 13.98% | 21.94% | 21.29% |
| $100 | 44.52% | 9.68% | 18.28% | 15.05% | 12.47% |
| $200 | 54.62% | 11.18% | 18.49% | 11.18% | 4.52% |
| $400 | 64.52% | 11.18% | 15.05% | 6.45% | 2.80% |

| | | | | | |
|---|---|---|---|---|---|
| $800 | 70.32% | 9.68% | 13.98% | 3.87% | 2.15% |
| More than $800 | 76.13% | 6.24% | 11.61% | 3.87% | 2.15% |

CV1.3 Suppose that the city is considering projects that would reduce the transportation recovery time from 2 weeks to 2 days. How likely would you be willing to pay the amounts below as a recurring annual payment to support these infrastructure investments.

| | Very Unlikely | Somewhat Unlikely | Undecided | Somewhat Likely | Very Likely |
|---|---|---|---|---|---|
| $50 | 31.72% | 7.27% | 15.76% | 19.80% | 25.45% |
| $100 | 46.87% | 7.47% | 16.97% | 12.73% | 15.96% |
| $200 | 54.55% | 10.10% | 17.17% | 10.71% | 7.47% |
| $400 | 61.62% | 13.54% | 14.95% | 5.45% | 4.44% |
| $800 | 68.08% | 12.73% | 12.73% | 2.83% | 3.64% |
| More than $800 | 73.74% | 10.30% | 11.31% | 3.23% | 1.41% |

CV2 Suppose that the city is considering projects that would reduce the recovery time of transportation from 1 week to 2 days. How likely would you be willing to pay the amounts below as a recurring monthly payment to support these infrastructure investments.

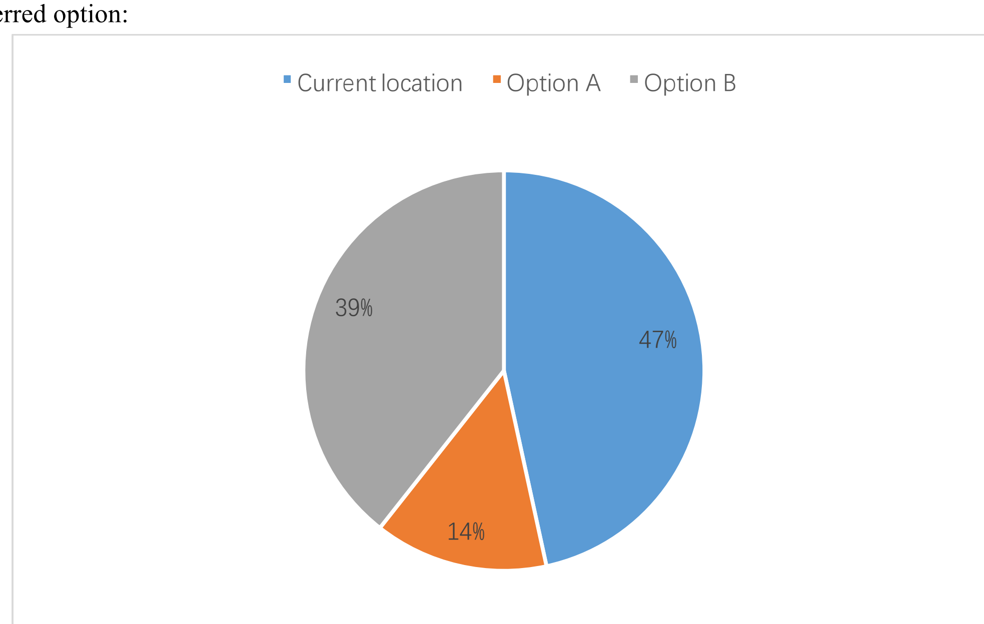
| | Very Unlikely | Somewhat Unlikely | Undecided | Somewhat Likely | Very Likely |
|---|---|---|---|---|---|
| $50 | 28.40% | 5.50% | 11.77% | 20.18% | 34.15% |
| $100 | 34.41% | 6.14% | 14.29% | 18.76% | 26.39% |
| $200 | 40.75% | 9.31% | 16.88% | 15.52% | 17.53% |
| $400 | 49.58% | 11.97% | 17.48% | 10.29% | 10.68% |
| $800 | 58.31% | 13.70% | 14.41% | 7.82% | 5.75% |
| More than $800 | 65.63% | 11.13% | 13.46% | 5.95% | 3.82% |

Q36 How likely would you be willing to pay any of the following in order to support funding of projects like those described previously that improve transportation infrastructure resiliency?

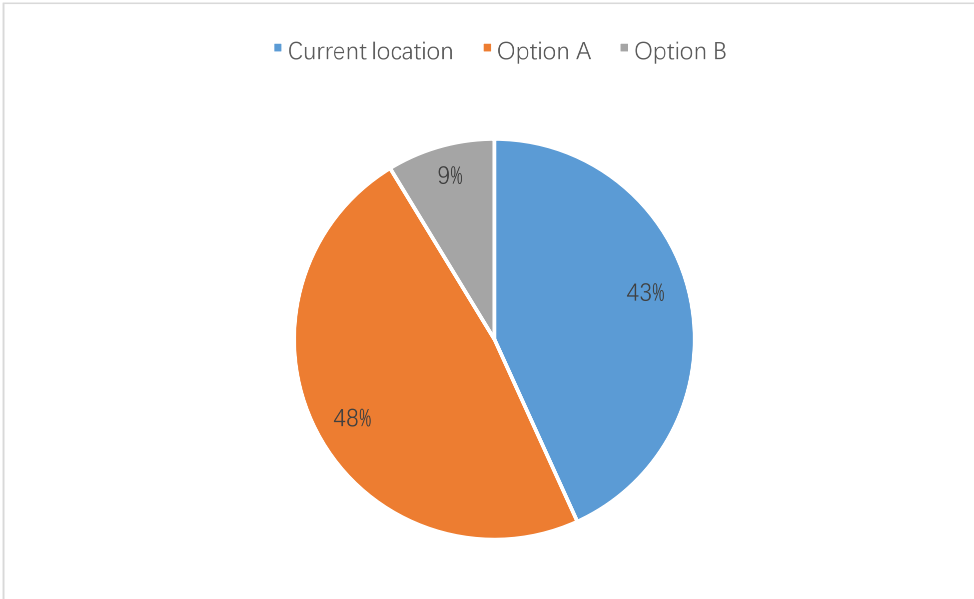
| | Very Unlikely | Somewhat Unlikely | Undecided | Somewhat Likely | Very Likely |
|---|---|---|---|---|---|
| Increased tax on vehicle sales | 36.70% | 11.14% | 20.80% | 22.09% | 9.27% |

| | | | | | |
|---|---|---|---|---|---|
| Increased tax on vehicle registration | 36.96% | 13.01% | 19.96% | 22.54% | 7.53% |
| Increased tax on gas | 42.69% | 17.06% | 17.39% | 15.65% | 7.21% |
| increased property tax | 49.71% | 16.48% | 17.77% | 12.11% | 3.93% |
| One-time increase in income tax | 43.72% | 13.46% | 21.51% | 15.58% | 5.73% |
| Insurance premium | 44.95% | 15.71% | 21.12% | 13.72% | 4.51% |
| Increased bus fares | 39.41% | 13.26% | 20.93% | 19.45% | 6.95% |
| Increased subway fares | 39.79% | 13.33% | 19.32% | 19.96% | 6.76% |
| Increased bridge tolls | 41.60% | 14.75% | 20.09% | 16.81% | 6.76% |
| Increased parking fees | 41.02% | 15.84% | 19.25% | 17.32% | 6.57% |

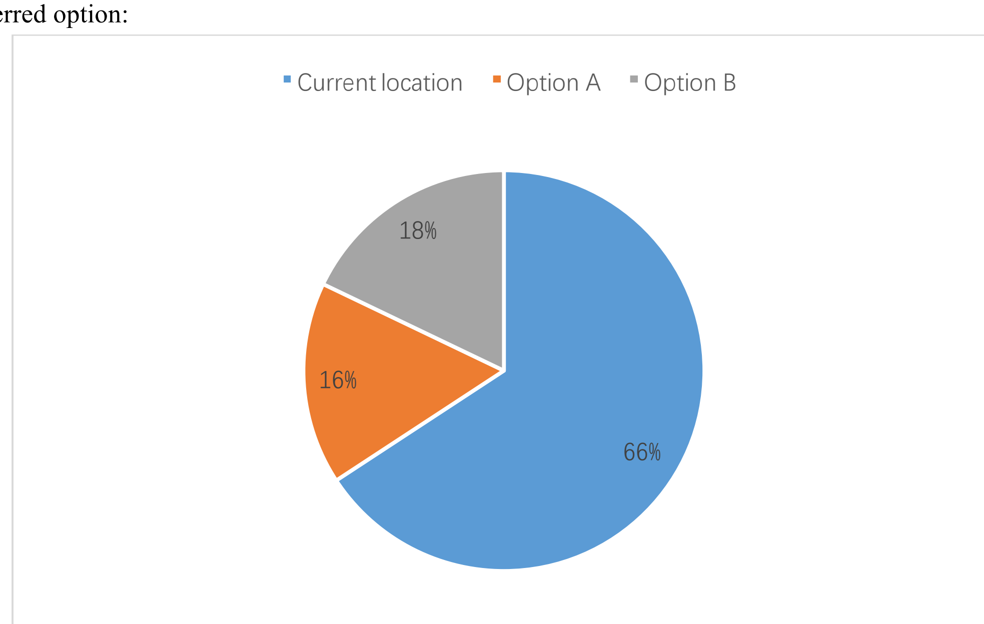
DCE1 Suppose that a super storm hits New York, causing serious disruptions in the transportation system of the city. Look at the recovery times and financial support required below, and choose your preferred option:



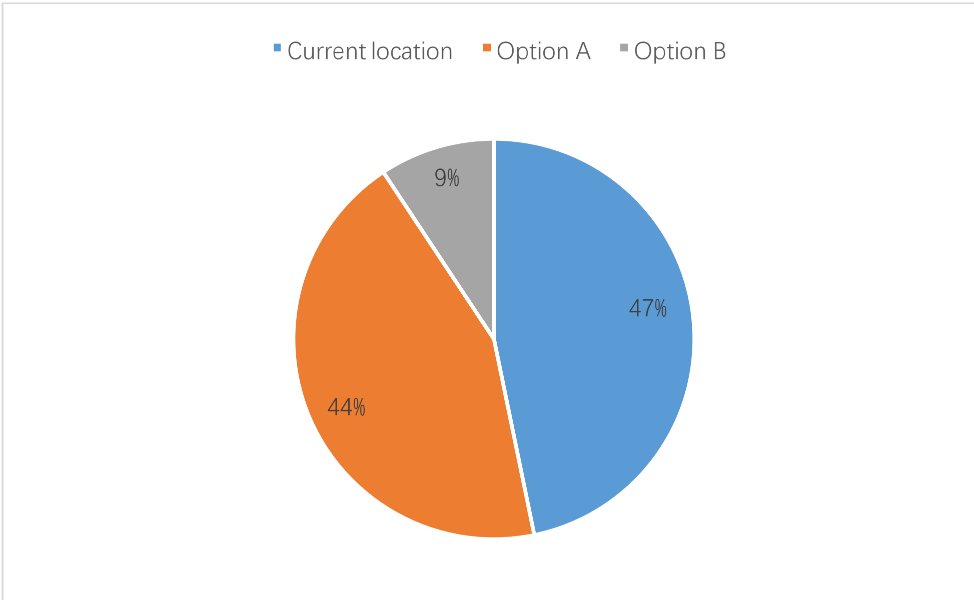
DCE2 Suppose that a superstore hits New York, causing serious disruptions in the transportation system of the city. Look at the recovery times and financial support required below, and choose your preferred option:



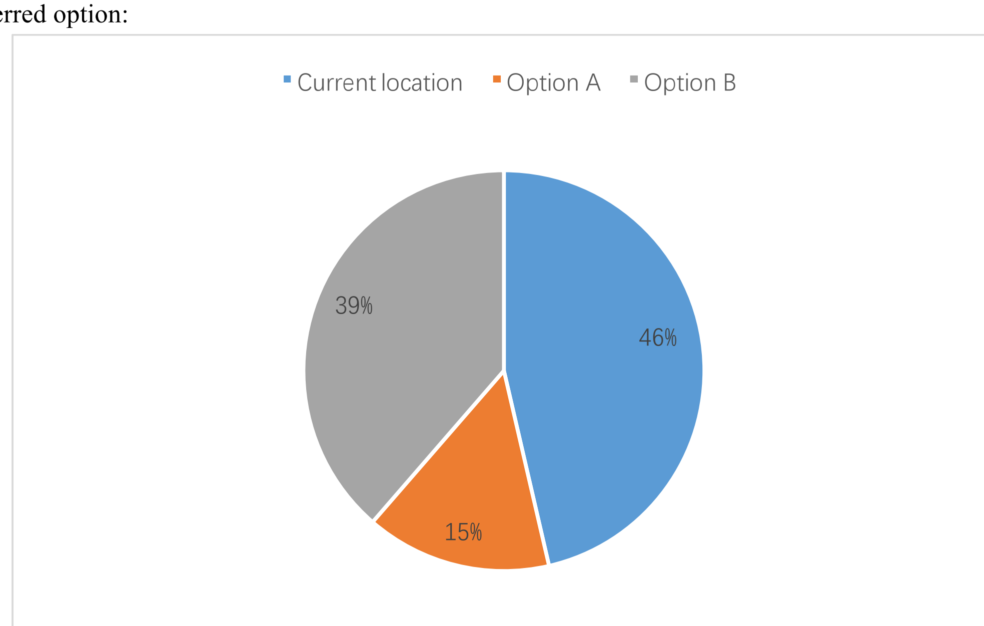

DCE3 Suppose that a super storm hits New York, causing serious disruptions in the transportation system of the city. Look at the recovery times and financial support required below, and choose your preferred option:



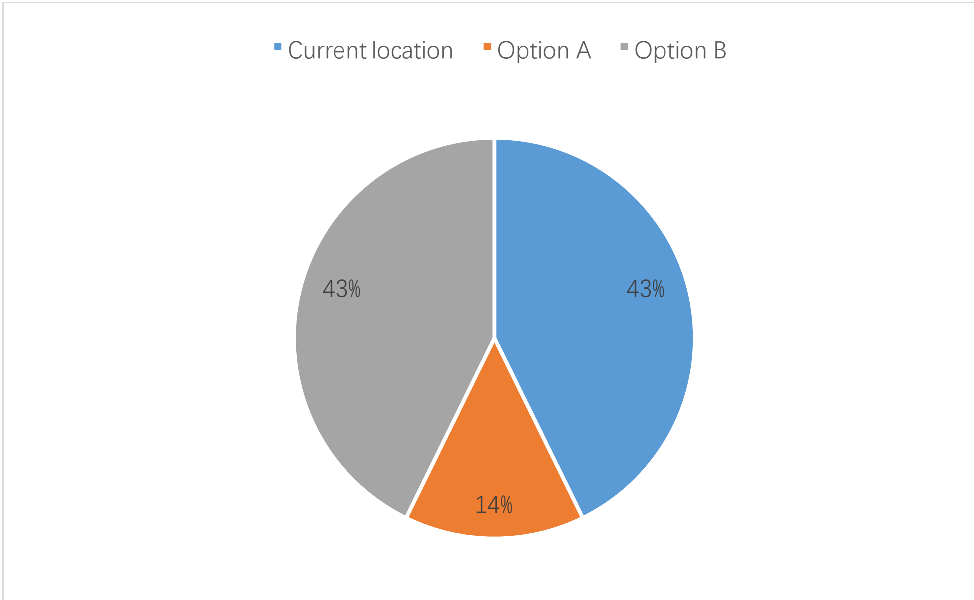
DCE4 Suppose that a superstore hits New York, causing serious disruptions in the transportation system of the city. Look at the recovery times and financial support required below, and choose your preferred option:



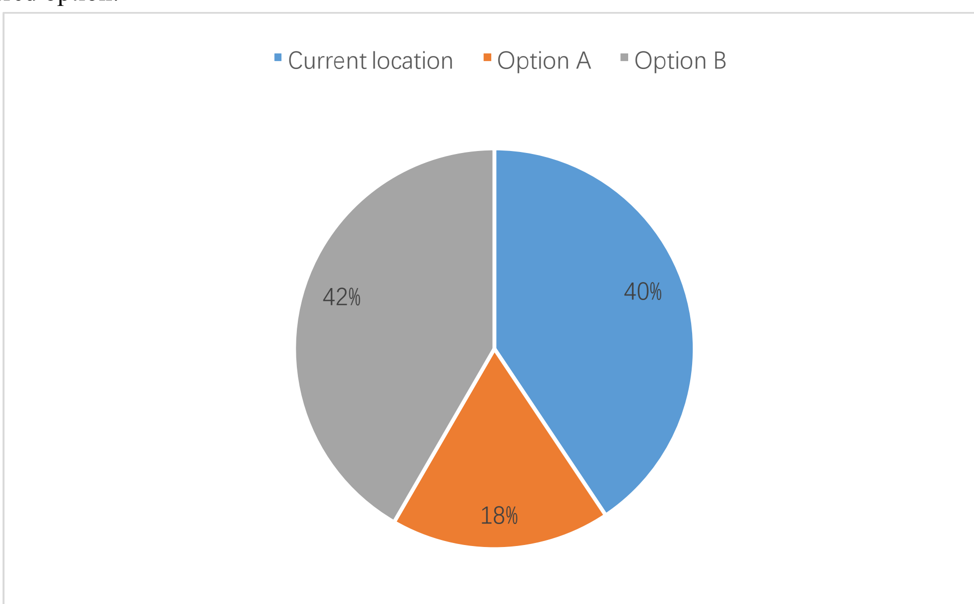

DCE5 Suppose that a super storm hits New York, causing serious disruptions in the transportation system of the city. Look at the recovery times and financial support required below, and choose your preferred option:



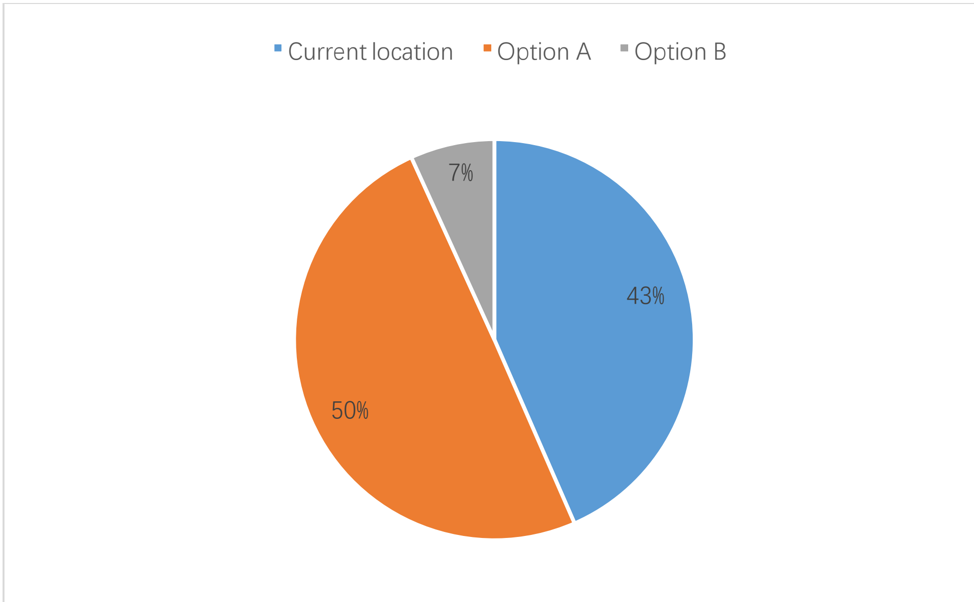

DCE6 Suppose that a superstore hits New York, causing serious disruptions in the transportation system of the city. Look at the recovery times and financial support required below, and choose your preferred option:



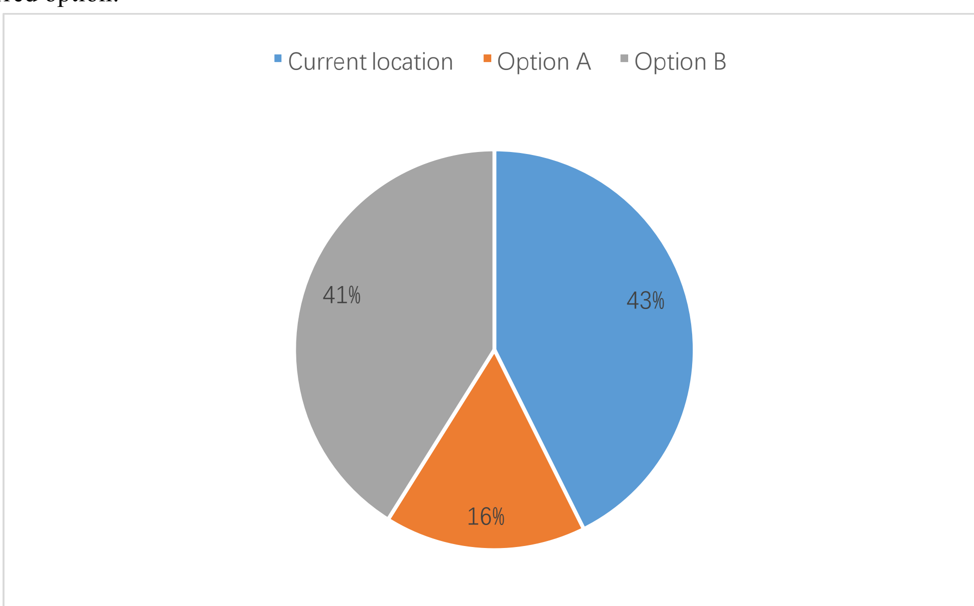

DCE7 Suppose that a super storm hits New York, causing serious disruptions in the transportation system of the city.   Look at the recovery times and financial support required below, and choose your preferred option:



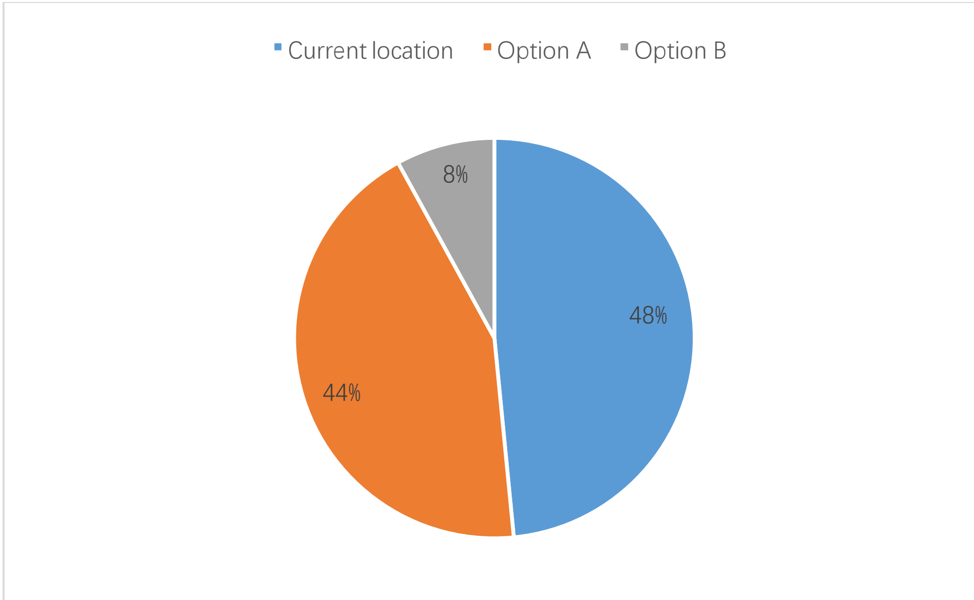

DCE8 Suppose that a superstore hits New York, causing serious disruptions in the transportation system of the city. Look at the recovery times and financial support required below, and choose your preferred option:



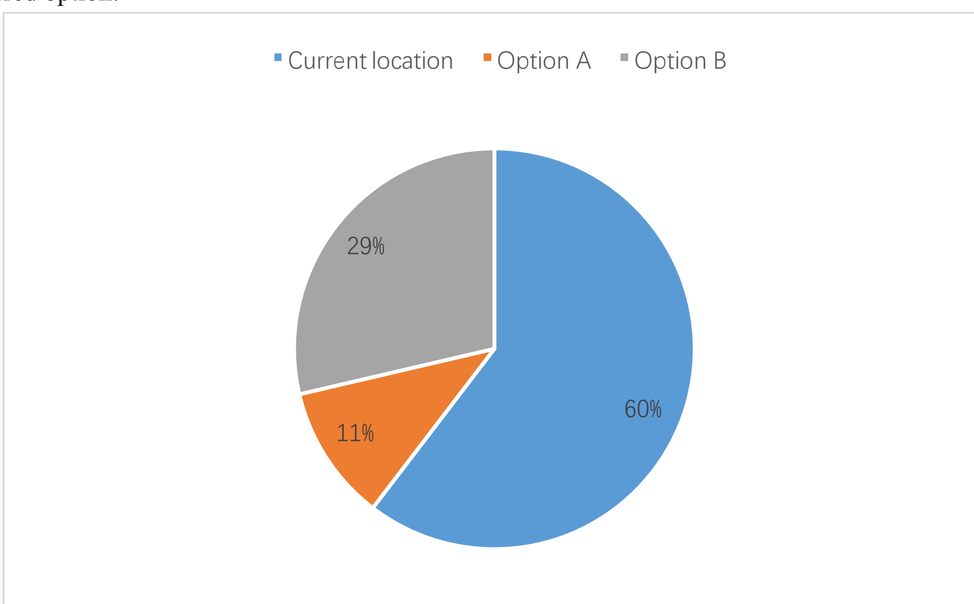

DCE9 Suppose that a super storm hits New York, causing serious disruptions in the transportation system of the city. Look at the recovery times and financial support required below, and choose your preferred option:



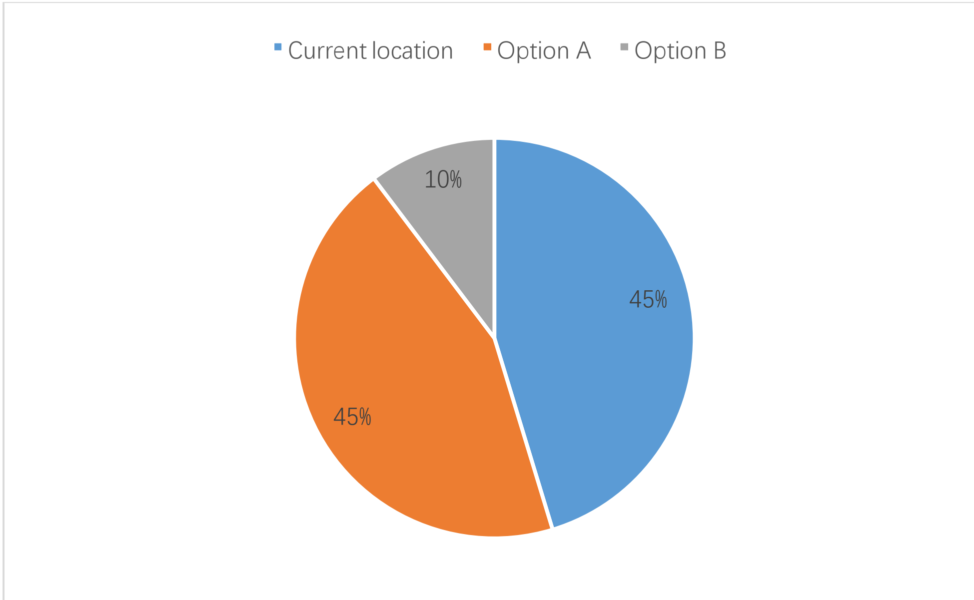

DCE10 Suppose that a superstore hits New York, causing serious disruptions in the transportation system of the city. Look at the recovery times and financial support required below, and choose your preferred option:



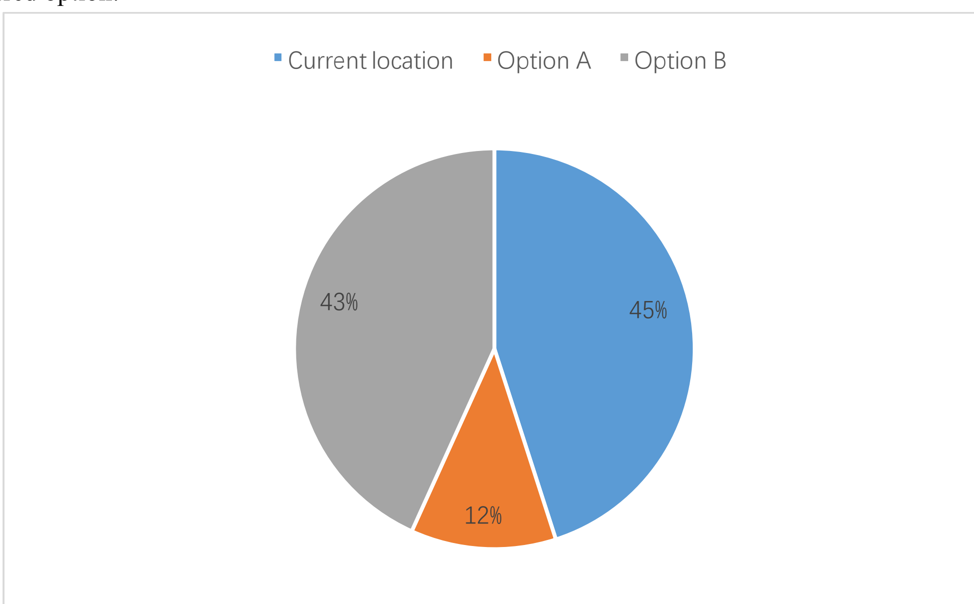

DCE11 Suppose that a super storm hits New York, causing serious disruptions in the transportation system of the city. Look at the recovery times and financial support required below, and choose your preferred option:



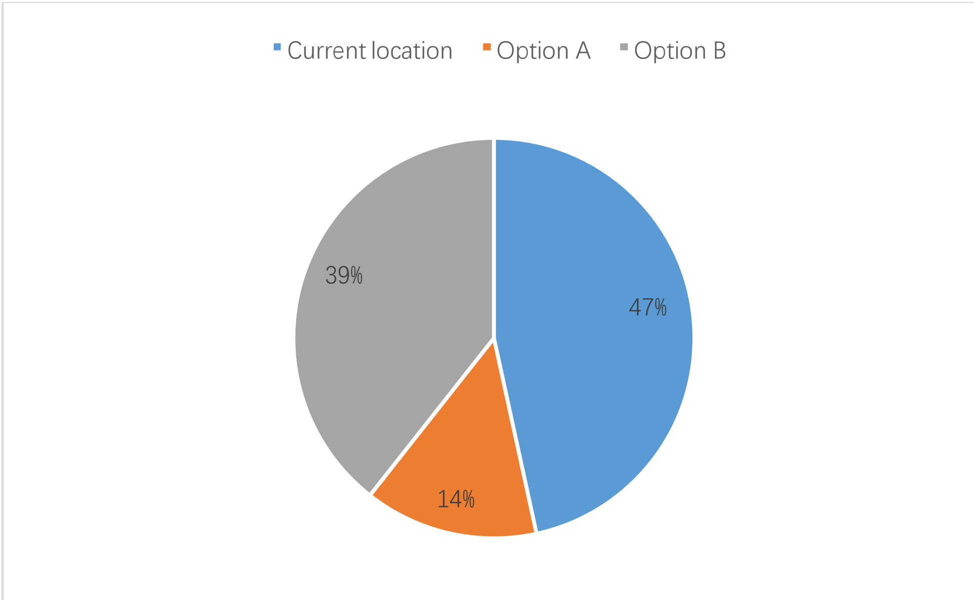

DCE12 Suppose that a superstorm hits New York, causing serious disruptions in the transportation system of the city. Look at the recovery times and financial support required below, and choose your preferred option:



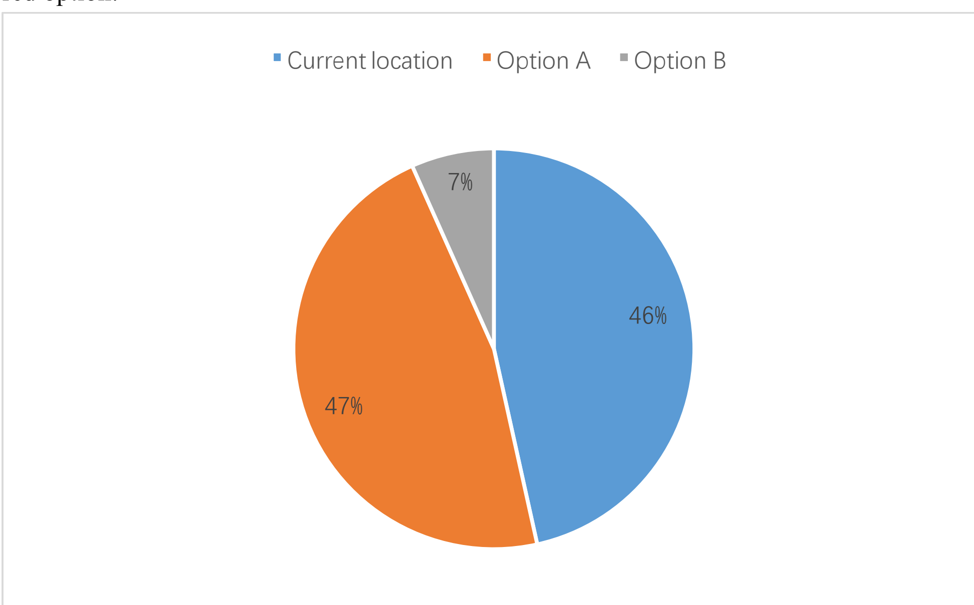

DCE13 Suppose that a super storm hits New York, causing serious disruptions in the transportation system of the city. Look at the recovery times and financial support required below, and choose your preferred option:



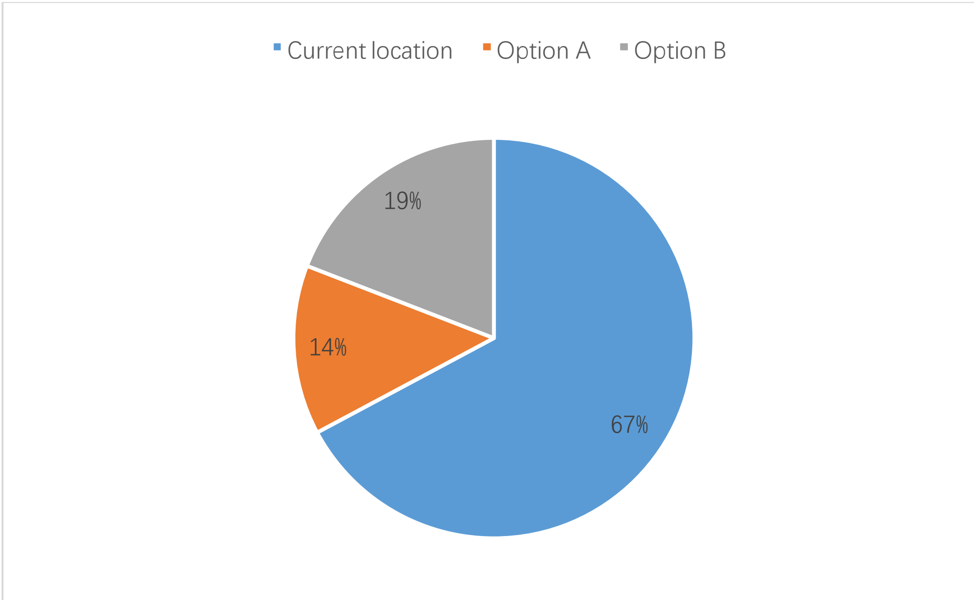

DCE14 Suppose that a super storm hits New York, causing serious disruptions in the transportation system of the city. Look at the recovery times and financial support required below, and choose your preferred option:



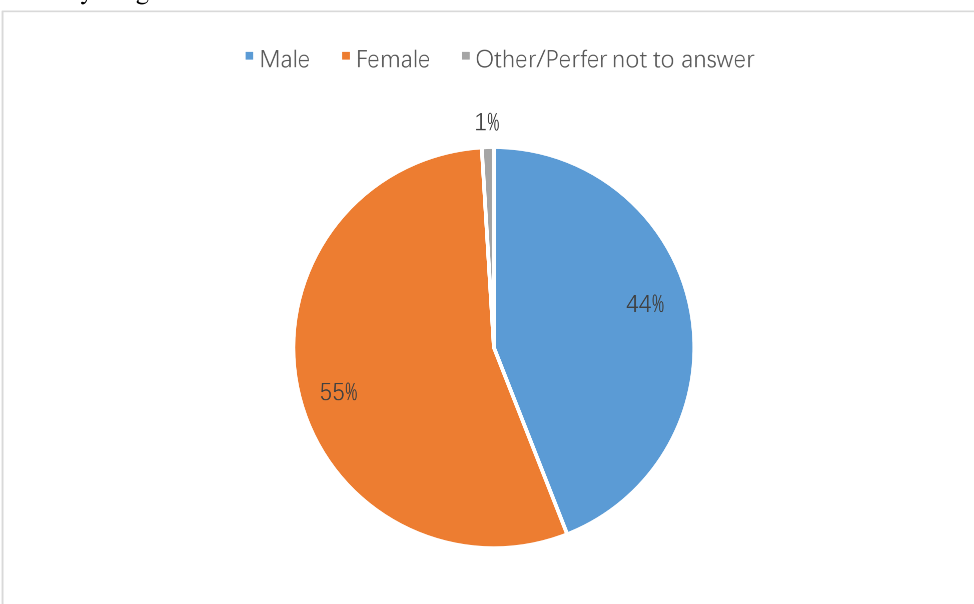

DCE15 Suppose that a super storm hits New York, causing serious disruptions in the transportation system of the city. Look at the recovery times and financial support required below, and choose your preferred option:



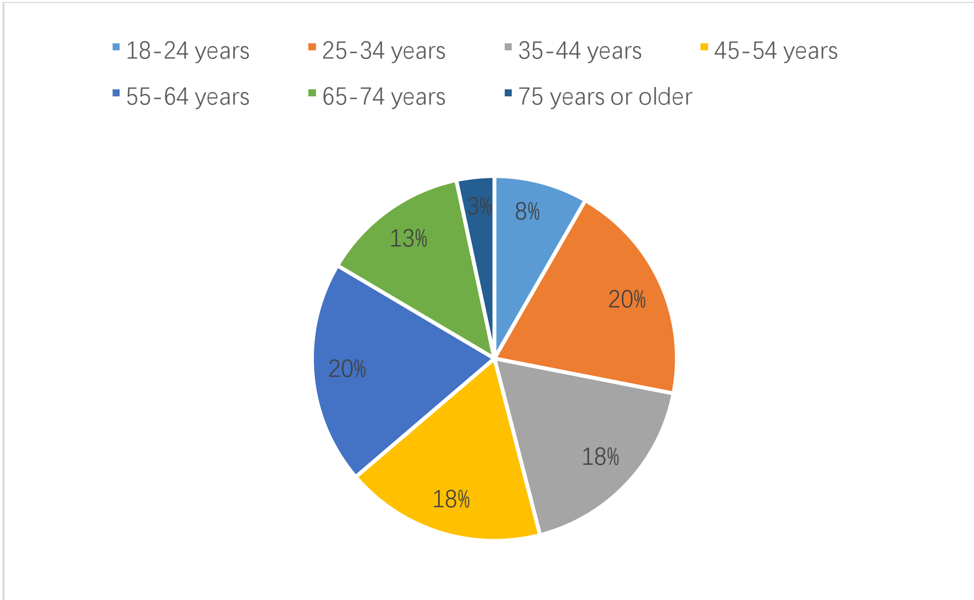

DCE16 Suppose that a super storm hits New York, causing serious disruptions in the transportation system of the city. Look at the recovery times and financial support required below, and choose your preferred option:



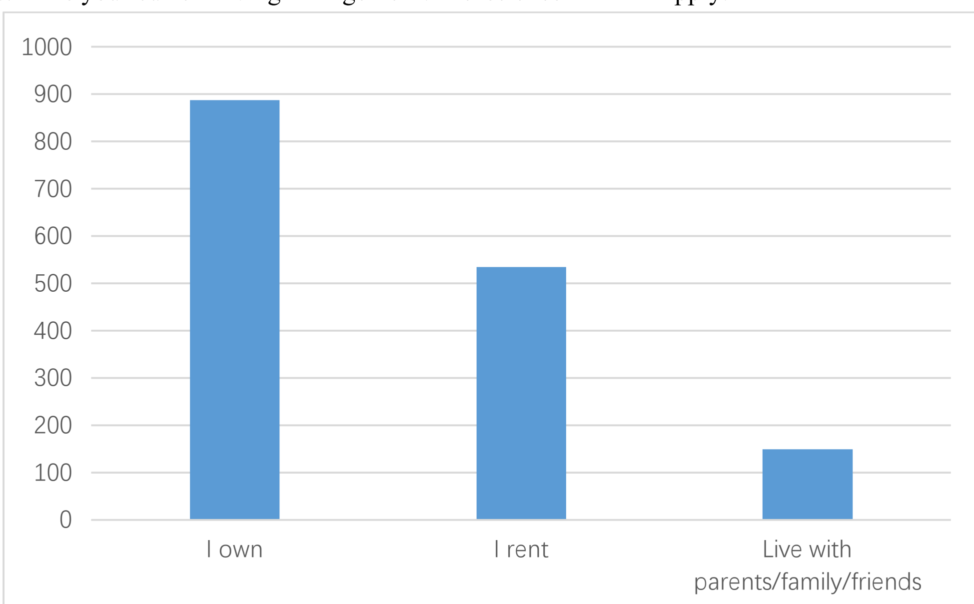

Q37 What is your gender?



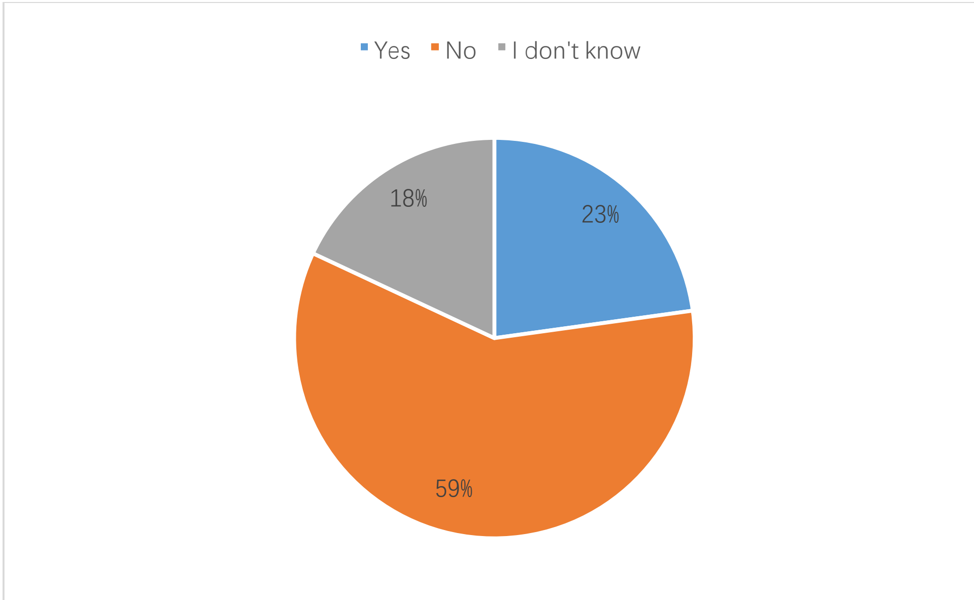

Q38 What is your age?




Q39 What is your current living arrangement? Please check all that apply.

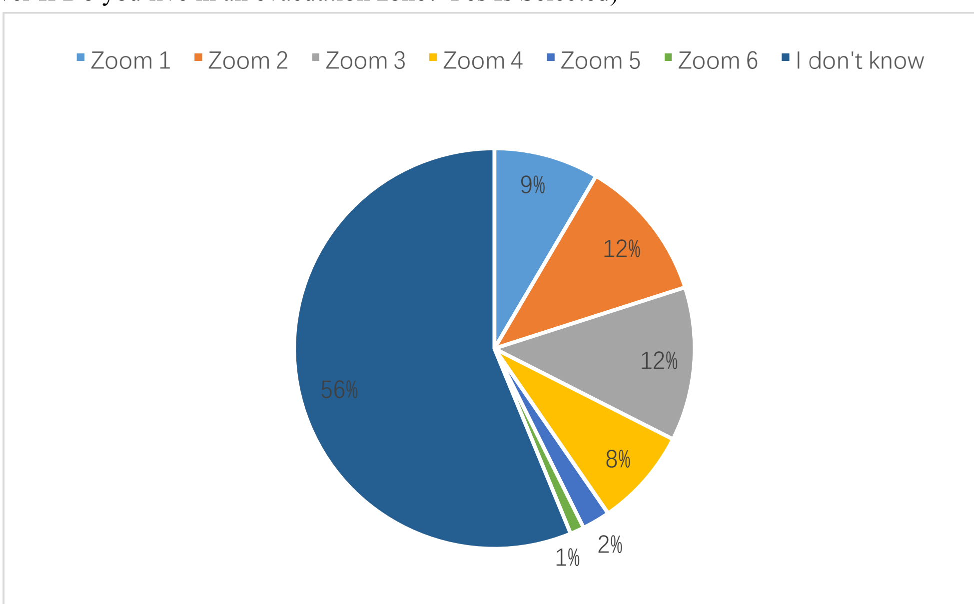



EvZone1. Do you live in an evacuation zone?




EvZone2. Do you know which is your evacuation zone?

(Answer If Do you live in an evacuation zone? Yes Is Selected)



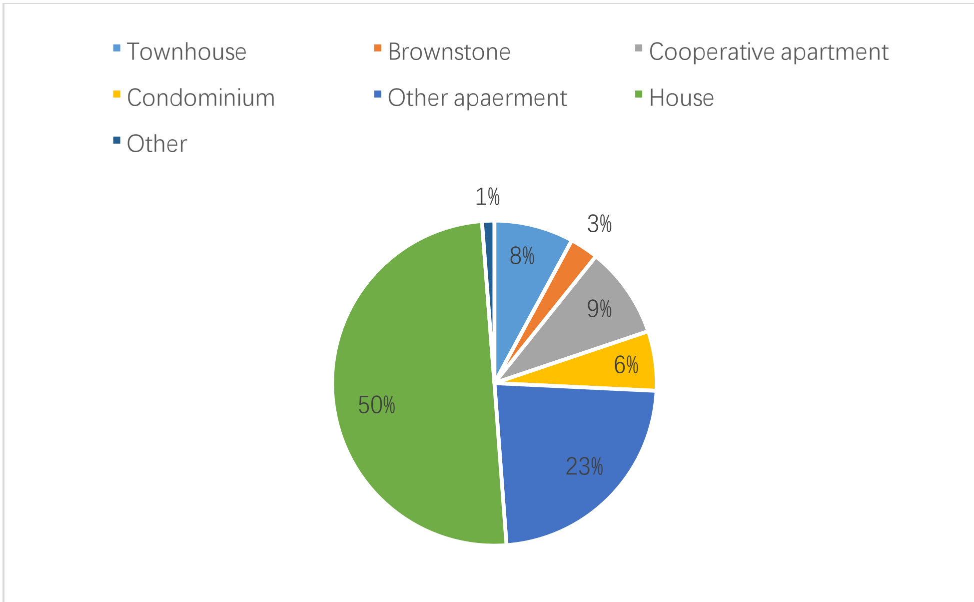

Q40 In what neighborhood do you live?

N/A

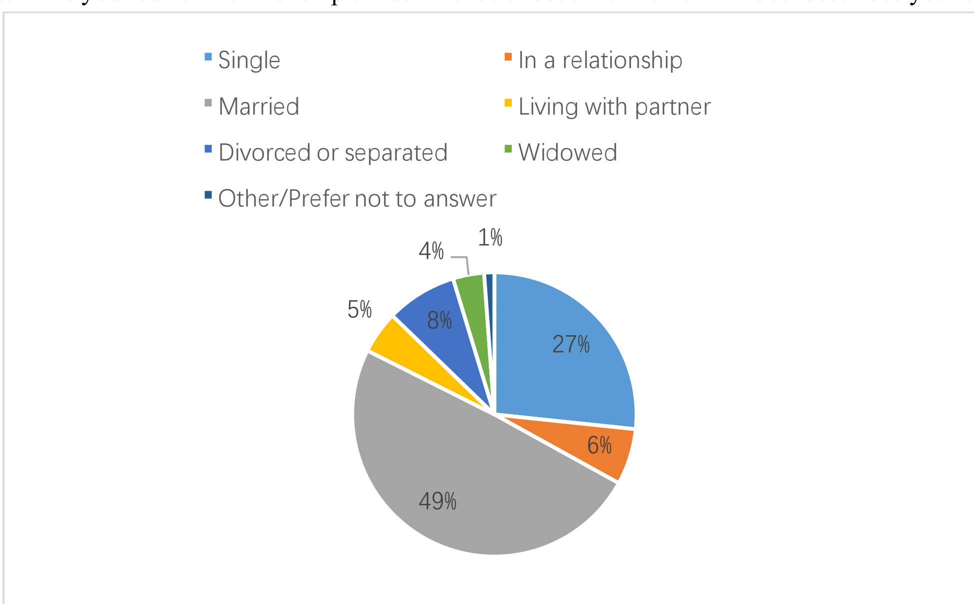
Q41 In what neighborhood do you work or study?

N/A

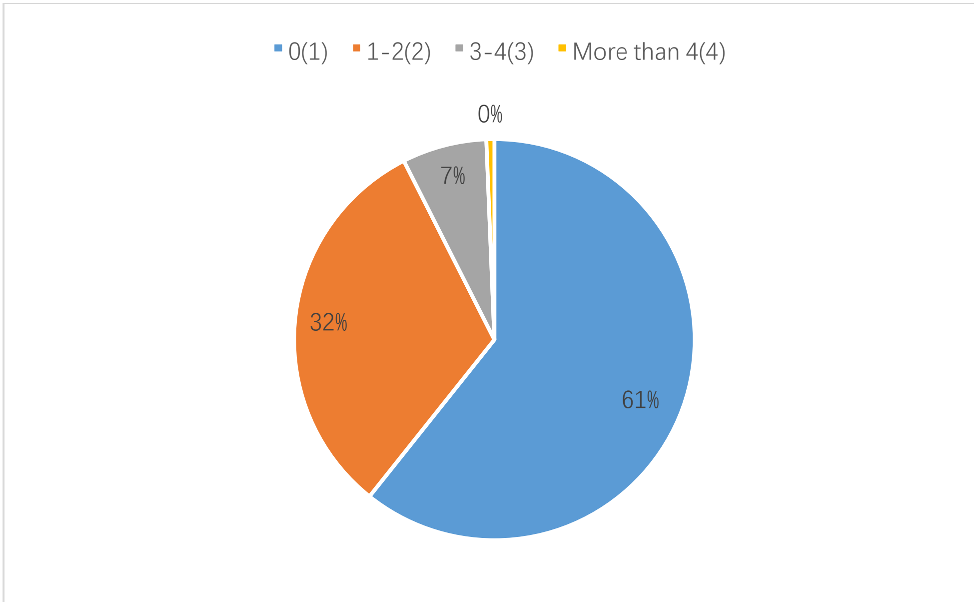
Q42 In what type of housing do you live?



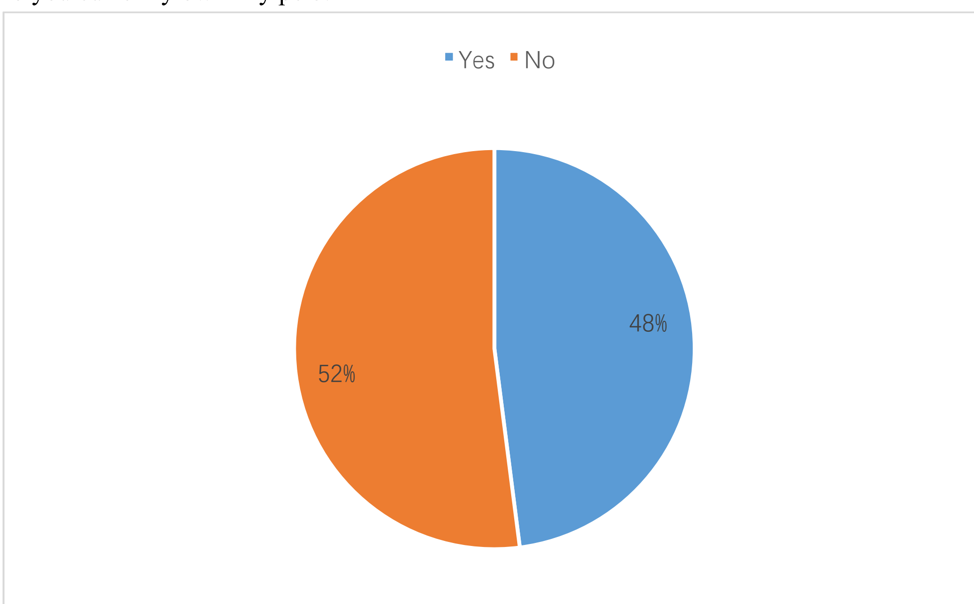

Q43 What is your current relationship status? Please choose the answer that best describes your status.



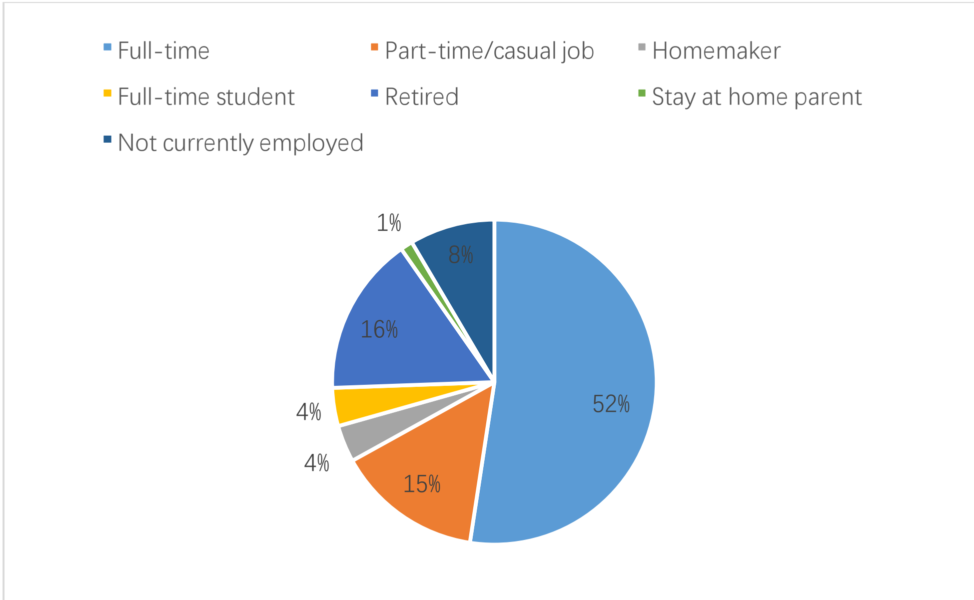

Q44 How many children, including adult children, are currently living with you?



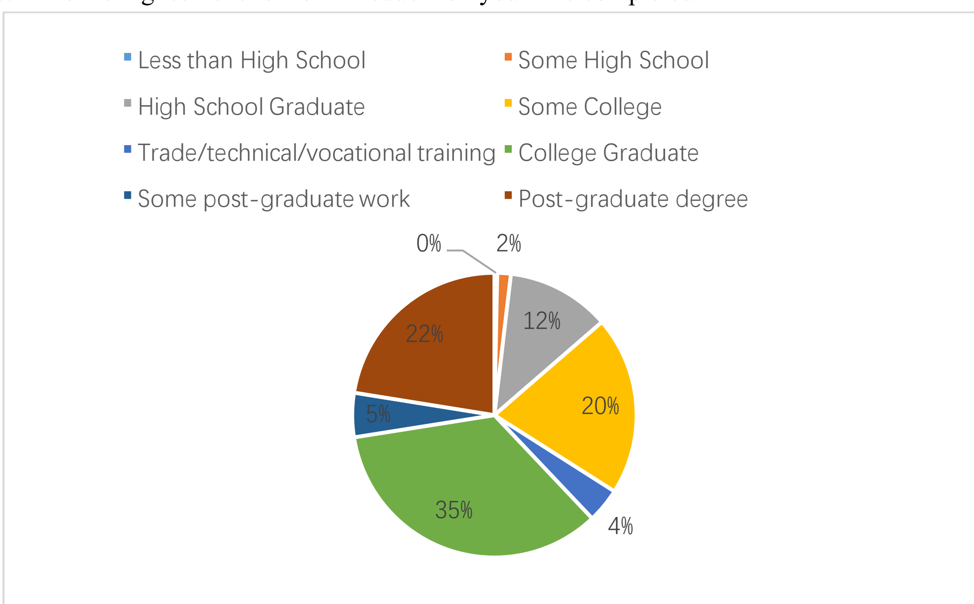

Q45 Do you currently own any pets?



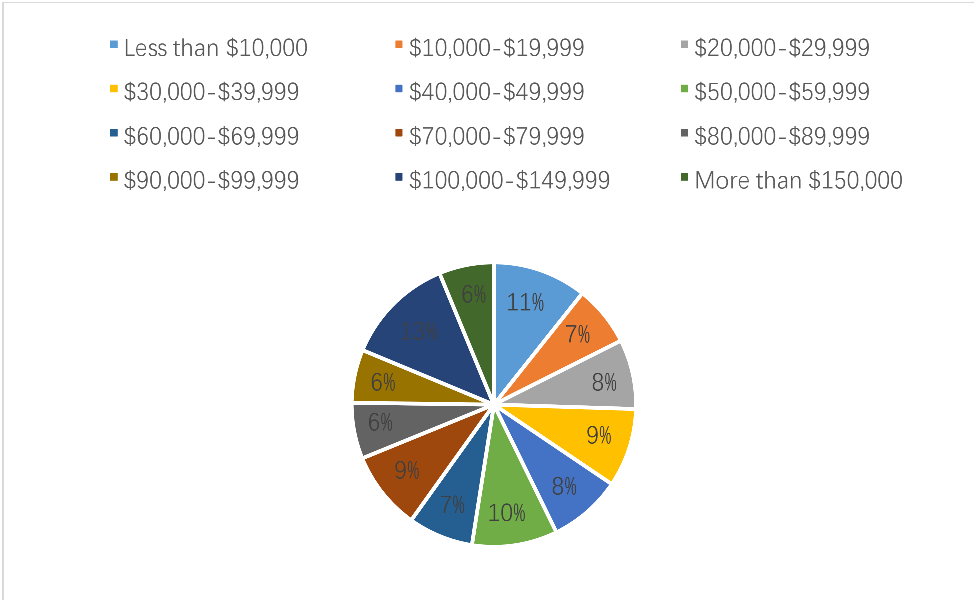

Q46 Which of the following best describes your current employment situation?



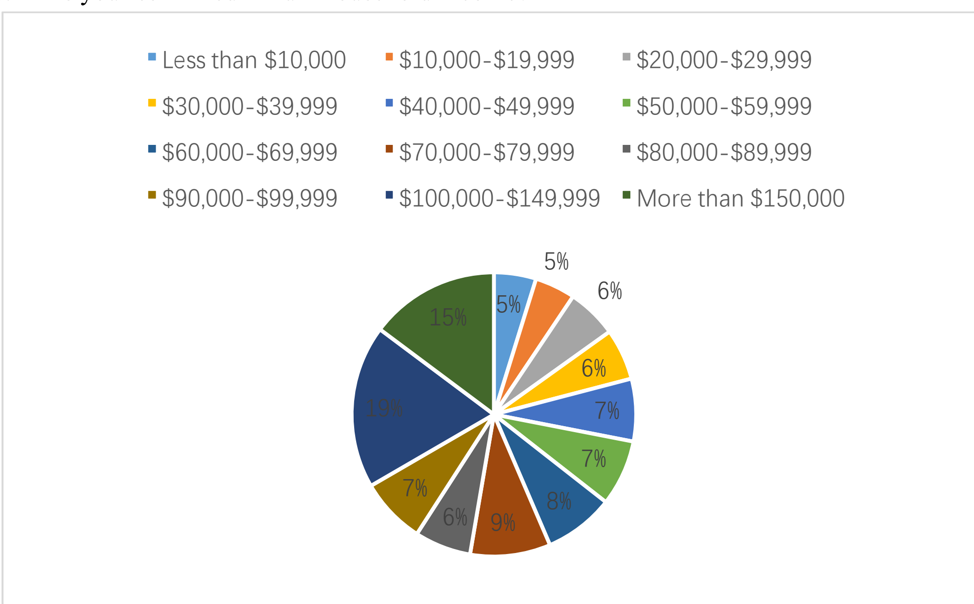

Q47 What is the highest level of formal education you have completed?



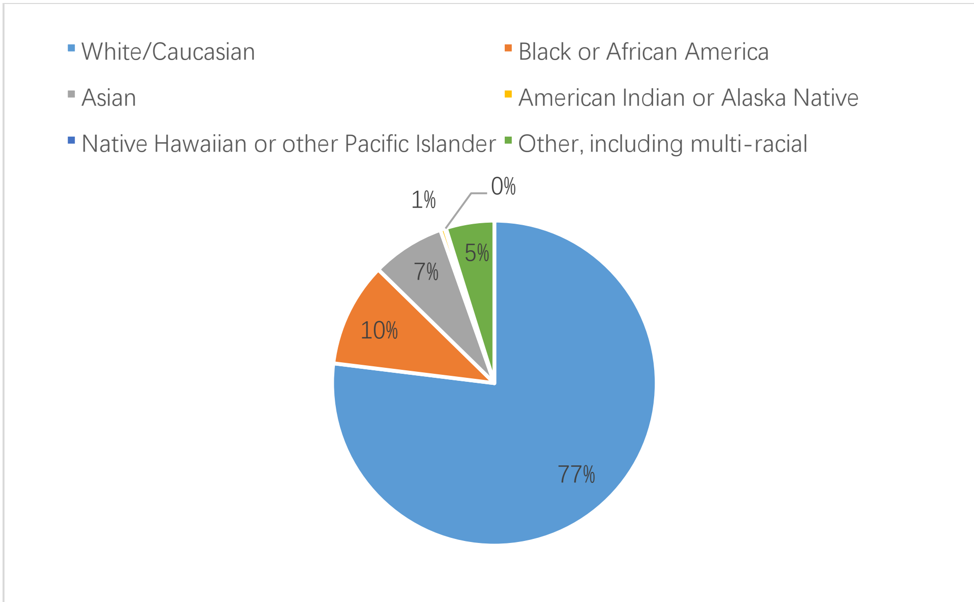

Q48 What is your annual income?



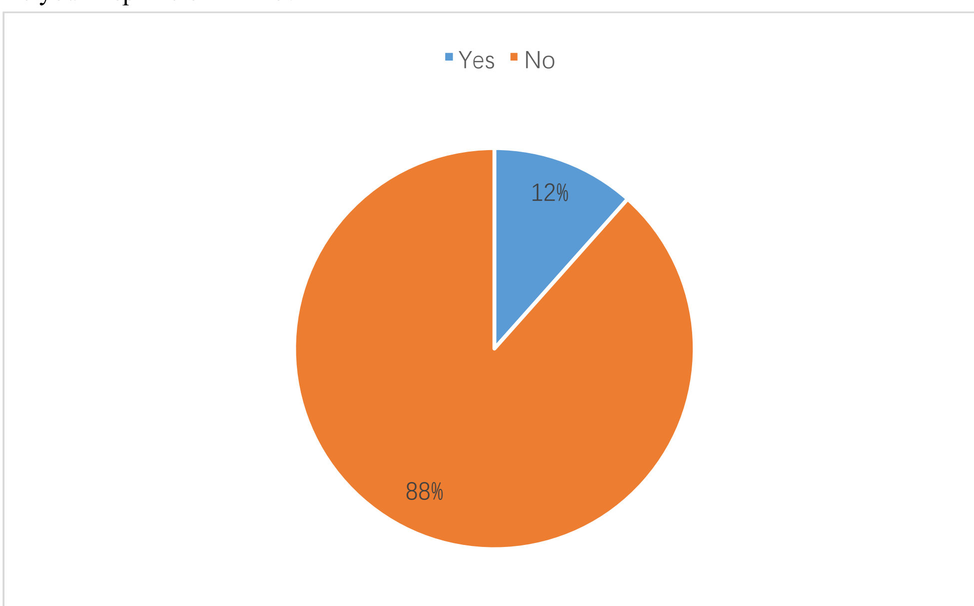

Q49 What is your estimated annual household income?



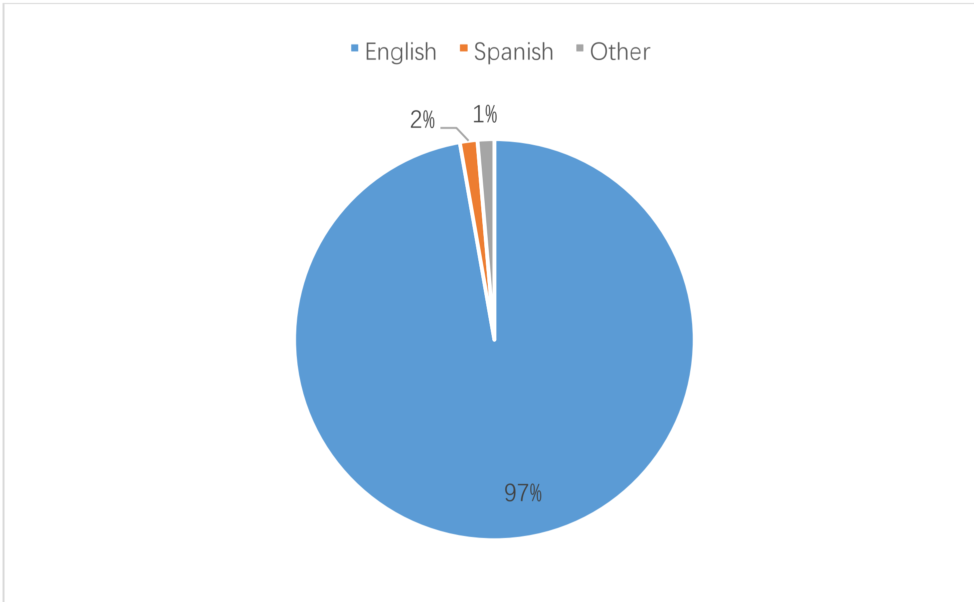

Q50 What do you consider yourself?




Q51 Are you Hispanic or Latino?




Q52 What is the primary language that you speak at home?




Q53 When it comes to politics, you generally consider yourself to be...