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Determinants of household flood evacuation mode choice in a developing country

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Abstract Increasing frequency and severity of hazards that lead to devastating disaster impacts demand building substantial response capability. Evacuation is seen as one of the effective measures to avert disaster impacts. Planning and modeling of effective evacuation incorporate evacuation travel behavior. This study seeks to identify and understand the effects of determinants on households' mode choice behavior in a developing country. Discrete choice models were estimated and validated from original data collected in selected sub-districts in Quezon City, Philippines. Findings revealed important determinants that can help evacuation planners and managers develop strategies for future flood evacuation operations. Determinants to evacuees who traveled on-foot include departure timing, destination type, age, gender and educational attainment of the head of the household, presence of small children, presence of health problem, house ownership, number of years living in the residence, vehicle ownership, source of warning, distance traveled to safety and cost of evacuation. Results of this study provide insights that can be useful for the government to plan for future evacuations. For instance, the government can encourage the households with a personal vehicle to use them in future evacuations, while providing for those without a personal vehicle and needing to travel longer distances. The government can also encourage households living in high flood risk areas to prepare household evacuation plans.

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1 Introduction

Disasters have affected lives, properties, environments, and economies at different scales in the past two decades. The gravity of disaster impacts is becoming more severe due to increasing vulnerability as evident in areas with growing populations, even informal settlements that are common all over the world. With these, the countries are faced with increasing need of building disaster resilience. In March 2015, during the 3rd World Conference on Disaster Risk Reduction (WCDRR) in Japan, countries adopted the Sendai Framework for Disaster Risk Reduction 2015–2030 (UNISDR 2015). This new international agreement promotes greater disaster resilience in countries around the world, succeeding the Hyogo Framework for Action 2005–2015 (UNISDR 2012) that helped governments establish comprehensive national disaster risk management strategies and legislation, resulting in a significant change from an emergency response approach to increasing focus on disaster risk reduction (DRR). One of the four priorities for action in the Sendai Framework for DRR is the enhancement of disaster preparedness for effective response. One effective preparedness measure that helps minimize, if not eradicate, loss of lives is evacuation.

Effective evacuation depends greatly on careful planning which is fleshed out in an evacuation plan. Evacuation strategies can be evaluated through models that demonstrate probable evacuation scenarios during the actual operations. In modeling evacuation scenarios, consideration of travel behavior of evacuees is deemed important (e.g., Sorensen 2000; Pel et al. 2010, 2012; Fang and Edara 2013; Huang et al. 2015). Evacuation travel behavior is identified as: the decision to evacuate or stay, departure time, destination and shelter type, mode, and route choices. These have been the focus of evacuation modeling research (e.g., Sinha and Avrani 1984; Revi and Singh 2007; Paul and Dutt 2010; Paul 2012; Hasan et al. 2011; Mesa-arango et al. 2013; Lim Jr. et al. 2015a; Lim et al. 2015a). Mode choice behavior of evacuees has been investigated in several studies (e.g., Perry et al. 1981; Lindell and Perry 1992; Baker 2000; Dash and Morrow 2001; Dow and Cutter 2002; Lindell and Prater 2007; Siebeneck and Cova 2008; Lindell et al. 2011; Wu et al. 2012, 2013; Sadri et al. 2014). Understanding the mode of transportation that evacuees use when evacuating has implications on the traffic flow in road networks available during evacuation. In addition, understanding what mode evacuees take and the determinants that influence decision making can help government officials develop strategies that prioritize those in dire need while effectively assisting others to move to safety.

In one of the limited studies on understanding the mode choice behavior of residents in Miami Beach, USA, during hurricane evacuation, Sadri et al. (2014) emphasized the need for more studies to investigate and reveal other factors that are important to evacuees' decision making. Also, earlier evacuation planning studies were car-based and transit-based (e.g., Murray-Tuite 2007; Balakrishna et al. 2008; Chen and Xiao 2008; Klunder et al. 2009; Mastrogiannidou et al. 2009; Noh et al. 2009; Chan 2010; Huibregtse et al. 2010; Wang et al. 2010; Pel et al. 2011; An et al. 2013). These developments on mass transit and car-based evacuation modeling, however, are large-scale evacuations in developed countries such as the Netherlands and USA. Case studies in most developing countries are still lacking socio-demographic characteristics of the population, hazard-related information, and evacuees' travel-related decisions, in addition to available transportation infrastructures that are unique. Majority of people in developing countries do not have personal vehicles. They depend greatly on available modes of transport for evacuation. It was also recommended by Abdelgawad and Abdulhai (2010) in their large-

scale evacuation multimodal study that modes such as walking and cycling which are readily available in urban cities could be integrated to evacuation planning. Allowing people to evacuate on foot is believed to be faster than vehicular evacuation within a 2-km region (Shiwakoti et al. 2013). This is an important mode of evacuation at the onset of disasters especially when road networks are congested. The earthquake and tsunami reported by Lindell et al. (2015) prompted pedestrian evacuation as well as vehicular evacuation.

This study seeks to discover the determinants of households' evacuation mode choice in a developing country. Data used for analysis were collected from households in selected sub-districts in Quezon City, Philippines. Specifically, the behavior of walking evacuees in the event of flood was investigated. Other modes that were available to evacuees and the determinants that they considered upon choosing certain evacuation mode were also taken into account.

The rest of this paper is organized as follows. Section 2 includes literature related to evacuation planning and mode choice behavior. Section 3 presents the methodology used in model estimation and validation. Section 4 provides discussion of the data, variables included in the model, variable inter-correlations, and model estimation and validation results. Section 5 summarizes and concludes the findings with some key insights for evacuation planners and managers.

2 Earlier related studies

This section gives an overview and relationship of evacuation planning and evacuation mode choice behavior. It also provides a summary of the determinants that were investigated in the past studies for evacuees' mode choice behavior.

2.1 Evacuation planning and mode choice behavior

Evacuation planning is a proactive approach by modeling the hazard occurrence, redesigning and identifying shelters, conducting regular training to make sure that people understand their roles and know what to do, establishing contacts among all organizations involved in emergency management, conducting plan audits to ensure procedures remain appropriate, and regular field assessment of the plan given diverse scenarios, among others (Lindell 2013). Authorities, planners, and evacuation managers are assisted by evacuation models in employing strategies for effective and efficient operations. Alternative evacuation scenarios that can be integrated in the models are expected to establish suitable evacuation policies that help facilitate communication and transfer of information (Lumbroso et al. 2008). Evacuation modeling, usually done in a sequential manner, follows the classic four-step travel demand modeling (Abdelgawad et al. 2010). The first stage is evacuation demand generation which determines the number of evacuees and their departure time patterns. The second stage is the evacuation distribution of which the origin–destination are either assumed using the potential locations of shelters/evacuation centers or estimated from the destination choices of evacuees gathered from past evacuation events (Mesa-arango et al. 2013). In the third stage, mode split is primarily important in the withdrawal stage of evacuation process. It is one of the essential logistical considerations in evacuation planning and operation, because resources that require careful planning are often scarce. The last stage of evacuation modeling is the traffic assignment

where the evacuation route is taken into consideration. This also has implications on the network flow during evacuation.

Earlier evacuation planning studies have considered cars as the mode of evacuation (e.g., Cova and Johnson 2003; Jha et al. 2004; Han and Yuan 2005; Kwon and Pitt 2005; Mitchell and Radwan 2006; Murray-Tuite 2007; Williams et al. 2007; Balakrishna et al. 2008; Chen and Xiao 2008; Klunder et al. 2009; Noh et al. 2009; Huibregtse et al. 2010; Wang et al. 2010; Pel et al. 2011). According to studies such as that of Lindell and Prater (2007) and Deka and Carnegie (2010), households with vehicles are more likely to evacuate using their own vehicles. However, not all people at risk have their own vehicles (Murray-Tuite and Wolshon 2013). Recognizing this, researchers have investigated the needs of the carless people and those with special needs such as people with disabilities and the elderly (e.g., Renne et al. 2008, 2009). Results led to evacuation planning and modeling efforts toward multimodal evacuation plans (Wolshon et al. 2005; Elmitiny et al. 2007; Liu et al. 2008; Abdelgawad et al. 2010; Sayyady and Eksioglu 2010; Naghawi and Wolshon 2012; VanLandegen 2010). Evacuation studies have expanded to other modes of evacuation such as mass transit (e.g., Mastrogiannidou et al. 2009; Chan 2010; Bish 2011; An et al. 2013), a mode that has the capacity to move a large number of people to safety. It is seen to be effective in developed countries where it is established as a common mode of transportation in urban areas (Shiwakoti et al. 2013). Despite advances in multimodal evacuation models, evacuation travel behavior is not well represented nor realistically assumed in modeling (e.g., Thomas et al. 2010; Naghawi and Wolshon 2012). Development of a multimodal evacuation plan can then be explored in the context of disaster-prone areas in developing countries where comprehensive evacuation plans may be limited and resources such as vehicles are scarce, but where the adaptive capacity of people is high.

2.2 Evacuation mode choice behavior and related determinants

The mode of evacuation is influenced by a number of determinants such as characteristics of the hazards, distance from areas at risk to safety, location of the evacuees when an evacuation order is given, the capacity and size of the vehicles, types of vehicle (personal or transit), and population groups such as tourists or people conducting intermediate trips (Murray-Tuite and Wolshon 2013). Deka and Carnegie (2010) highlighted that the choice of other modes excluding private vehicles is determined by the familiarity of evacuees with transit options and not having personal vehicles.

In another study, Sadri et al. (2014) investigated how evacuees from Miami Beach chose their mode of evacuation. Data were gathered through a stated preference survey from hypothetical category four (major) hurricane scenarios. Special evacuation buses, taxis, and regular buses that had been aggregated from evacuees riding with persons from another household with other types of mode served as alternatives in the survey. Key findings were revealed with regards to mode choice of evacuees who are captive in using non-household vehicles. First, evacuees have a higher probability of taking special evacuation buses. Second, single evacuees have less likelihood of riding in a taxi. Third, evacuees with annual household incomes over US$80,000 have a higher probability of taking taxis. Fourth, when a household has adults more than 65 years old, the likelihood of riding with someone from another household is higher. Fifth, evacuees going to hotels are more likely to use the regular bus service. Evacuees going to public shelters have less likelihood of riding with someone else from another household. Lastly, evacuees going to their friends or relatives' home are less likely to use special evacuation buses. However, the authors emphasized the small sample size used in the study. Hence, future studies were

suggested to generate more data for the same kind of analysis. The authors also highlighted the need for more research effort to reveal and introduce new determinants which affect the mode choice behavior.

Studies also discovered that evacuating households take more than one vehicle (e.g., Wu et al. 2012; Yin et al. 2014). Age, gender, marital status, educational attainment, household size and income influence the number of vehicles taken in evacuation (Wu et al. 2012). Yin et al. (2014) found out that there is a higher likelihood of taking fewer vehicles when households travel long distances and during late evacuation. Additionally, households that had experienced hurricanes before the event and had pets have a higher likelihood of using more vehicles. Distance from the coast also indicated some level of significance to the number of vehicles taken.

This study was built from the above variables, that were found or suggested as influential factors to mode choice, to investigate determinants of this evacuation behavior. Also, variables categorized as socio-demographic characteristics of the decision maker, associated capacity and hazard-related ones, as mentioned in Lim et al. (2013), in addition to evacuation and mode-related variables, were explored in this study.

3 Methodology

This section provides the details of the context of the study area and methods employed in collecting the data used for analysis, parameter estimation and modeling framework, and internal model validation.

3.1 Context of the study area

Data used for analysis in this study were gathered from households in Quezon City, Philippines, the largest city among 16 in Metro Manila with a land area of about 16,112.58 ha. The City is Metro Manila's point of strategic convergence for various transportation infrastructures. As one of the key cities in the country, Quezon City can be considered as a melting pot of different cultures coming from other parts of the country. The City is located at the north-eastern portion of Metro Manila, bordering Manila City to the southwest, Caloocan City and Valenzuela City to the west and northwest, San Juan and Mandaluyong City towards the south, and Marikina and Pasig City to the southeast (Fig. 1). In 2012, the City's population was approximately 3.18 million (706,564 households), which is growing at the rate of 2.92 % per annum (Quezon City Government Planning and Development Office, QCGPDO 2013). This population is about 25 % of Metro Manila's population making it one of the most populated cities in the Philippines. It is also considered vulnerable to different types of hazards, one of which is typhoon-induced flooding which occurs several times in a year affecting 700,000 people (Quezon City Government and Earthquake and Megacities Initiative, QCG and EMI 2013). A factor that contributes greatly to the flood risk is the fact that the cities of Metro Manila are situated on a wide flood plain, the main river of which is the Pasig river, filled with tributaries (the Marikina River and San Juan River as major tributaries), and canals that branch out in various cities and towns. One of the worst recorded massive flooding from excessive rains in Metro Manila happened in September 2009, affecting millions of people in the Philippines and resulting in 100 deaths in Quezon City alone. During this flood event, the recorded cost of damage was approximately US$275 million including infrastructures and the agriculture
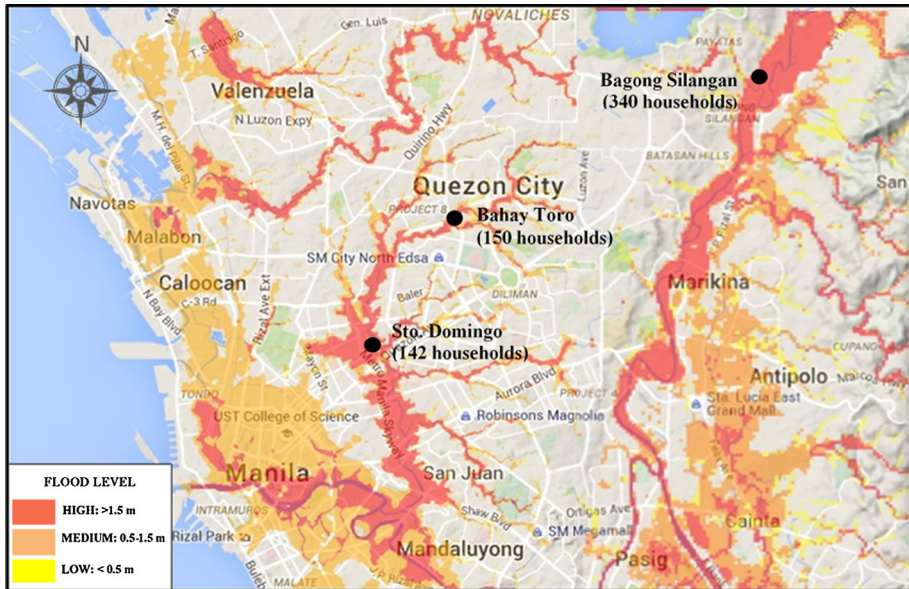
Fig. 1 Flood map of Quezon City with number of households interviewed. *Source*: Department of Science and Technology (2012)

sector (QCG and EMI 2013). Another flood event happened in 2012 when about 1000mm of rain fell in some parts of Metro Manila. Hundreds of residents were evacuated as water in affected villages reached up to the roofs of houses in many areas. This event was replicated in mid-August 2013 brought about by the heavy monsoon rains and tropical cyclone Trami that hit the Philippines. The flood resulted in more than US$14 million worth of damage, and also prompted the evacuation of up to 9000 households in Quezon City to assigned public shelters (Social Services Development Department, SSDD 2013). This flood event was the basis of the information collected from households used for analysis in this study.

A number of sub-districts were affected by the 2013 flood event. Among the five sub-districts suitable for the study as recommended by the government are Bagong Silangan, Bahay Toro and Sto. Domingo sub-districts. The criteria for selection were the history of evacuation and the number of flood vulnerable households in the sub-districts. Bagong Silangan has a population of 22,000 households, Bahay Toro has 74,987 households, and Sto. Domingo has around 15,560 households (QCGPDO 2013). During the flood, there were about 2864, 500, and 533 households that evacuated to public shelters from the Bagong Silangan, Bahay Toro and Sto. Domingo sub-districts, respectively (SSDD 2013).

3.2 Data collection, preparation for analysis and selection of determinants

Face-to-face interviews were conducted with randomly selected households in the sub-districts. Random selection of households was done using the cluster sampling technique. Here, villages in high flood risk areas were selected. Within the villages, simple random selection of interview households was done.

Prior to the commencement of the data collection, the interviewers were trained by the research team to make sure that quality interviews were made. The interviews were conducted from October 2013 to May 2014. Households in villages located in flood prone areas in Bagong Silangan, Bahay Toro, and Sto. Domingo were randomly approached for interviews. The data collection effort was part of a study in understanding evacuation-related behavior of households, such as route choice (Lim Jr. et al. 2015a, b). During the interview process, the respondents were given a brief introduction to the study being conducted. This was to ensure they understood the context which was the basis of their answers to the questions. The interviewers also made sure that the household experienced flooding during mid-August 2013 before proceeding with the interviews. To do this, interviewees were first asked if they had experienced flooding during the 2013 event. The flood details, including the level of flood in their house, the number of days they were flooded, the level of damage the flood caused their house, and whether they received evacuation warning and its source. Information on the distance of house location from the flood hazard, were also solicited. Then, information on evacuation-related decisions was also elicited including the type of evacuation decision, the timing of evacuation, their evacuation destination, and the mode they used when evacuating. The type of evacuation was indicated as full when the whole members of the household moved to safety, and as partial when most of the members moved to safety while leaving some others behind to look after the household's belongings. For departure timing, households that are risk-averse or risk-tolerant were indicated as those that evacuated before or during the flood. The destination type choice included those that went to the public evacuation centers, church/seminary or to friends/relatives' homes. The households' modes of evacuation ranged from vehicles provided by the government, rented or personal vehicles, and walking. The distance traveled in evacuating, and the costs incurred during evacuation, were also sought.

The second part of the interview solicited suggestions and comments for better situations in future evacuation from floods. The third part of the interview aided solicitation of socio-demographic information of the head of the household and other household information that included age, gender, marital status, educational attainment and type of work of the head of the household, presence of health problem and insurance, household monthly income, number of household members, age of members, the presence of small children and senior citizens, number of years the household had been living in that residence, type of house ownership and materials, the number of house floor levels, vehicle ownership, and pet ownership. The questionnaire was prepared in the English language and translated into Filipino. It was pilot-tested prior to the full survey in order to make necessary adjustments according to the context of the study area.

Six hundred thirty-two interviews were completed out of the 640 total number of households approached. This shows a response rate of nearly 99 %, equal to the total interviews completed divided by the total number of approached households. The high response rate shows the eagerness of the households in sharing their flood experiences wih the hope that results of the endeavor can assist in better evacuation situations in future flood events. Of the 632 interviews, 340, 150, and 142 were from Bagong Silangan, Bahay Toro, and Sto. Domingo, respectively. The locations of these sub-districts in Quezon City are indicated in Fig. 1. All the data collected were tabulated in Excel spreadsheets. The data were verified and cross-checked by ensuring that information provided by the households were according to the questions asked. Data obtained with a lot of missing information and inconsistencies in relation to the needed information were excluded from the analysis. Also, data from households which decided not to evacuate were not included

in the analysis. Therefore, the total number of observations used for analysis of the mode taken during evacuation is 427 of which 212, 132, and 83 are from Bagong Silangan, Bahay Toro and Sto. Domingo, respectively.

From the data gathered, households' modes of evacuation include vehicles provided by the government, rented or personal vehicle, and walking. Vehicles provided by the government, rented, or personal vehicles were merged as one category, "others", due to their small percentage of the data. These two categories (walking and others) were included in the analysis of mode choice behavior. Mode indicated as "others" served as the reference category for parameter estimation.

Determinants of mode choice included in the models were selected through the stepwise backward elimination method. The stepwise selection method is an effective way to find the best subset of variables that predict an outcome (Steyeberg et al. 2004). Variables including evacuation-related decisions, socio-demographic characteristics of the head of the household, household characteristics, and information related to the hazard and the mode, as mentioned earlier in this section, were included in the analysis. Data for each sub-district as well as pooled ones were subjected to stepwise selection of determinants.

3.3 Model estimation and validation

Mode choice models estimate how many people will use which available mode of transport. As the considerations of households in choosing the mode they took in evacuating were investigated in this study, the logit model under the maximizing utility framework was used. The mode choice model postulates that the probability of choosing a specific mode for a journey is based on relative values of determinants (Ortuzar and Willumsen 2011). Logit has been widely used in modeling mode choice during normal traffic conditions as in studies conducted by Cherry and Cervero (2007), Ashalatha et al. (2013), Miskeen et al. (2013), Danaf et al. (2014), and Mitra and Buliung (2015). Its usage is also becoming more popular in evacuation modeling due to its simplicity, closed form estimation, and its capability of capturing behavioral context of decision-making (e.g., Charnkol and Tanaboriboon 2006; Hasan et al. 2011; Mesa-arango et al. 2013; Lim Jr. et al. 2015b; Lim et al. 2015b).

The utility function in analyzing the mode choice behavior of households is shown in Eqs. 1 and 2, respectively, for any household, h, choosing to walk, w, or other modes of transport (owned/rented vehicle or vehicle provided by the government), v. The utility function is composed of observable determinants, X_{wh} and X_{vh}, for mode outcomes of walking and other modes, respectively; the corresponding vector of parameters to be estimated, $\boldsymbol{\beta}'_w$ and $\boldsymbol{\beta}'_v$, for walking and any other modes, respectively; and random terms ε_w and ε_v, which represent unobserved determinants of decision making.

$$U_{wh} = \boldsymbol{\beta}'_w X_{wh} + \varepsilon_{wh} \tag{1}$$

$$U_{vh} = \boldsymbol{\beta}'_v X_{vh} + \varepsilon_{vh} \tag{2}$$

The probability that a particular mode is chosen is given in Eqs. 3 and 4. P_{wh} and P_{vh} are the probabilities that a mode alternative, walking, w, or other modes, v, is chosen.

$$P_{wh} = \frac{e^{\boldsymbol{\beta}'_w X_{wh}}}{e^{\boldsymbol{\beta}'_w X_{wh}} + e^{\boldsymbol{\beta}'_v X_{vh}}} \tag{3}$$

$$P_{vh} = \frac{e^{\boldsymbol{\beta}'_v \boldsymbol{X}_{vh}}}{e^{\boldsymbol{\beta}'_w \boldsymbol{X}_{wh}} + e^{\boldsymbol{\beta}'_v \boldsymbol{X}_{vh}}} \tag{4}$$

The log likelihood (LL) function is presented in Eq. 5, where H is the number of households, and M is the type mode chosen by household, h. To fit the logit model, the maximum likelihood estimation was used with the aid of IBM SPSS Statistics.

$$\mathrm{LL} = \sum_{m=1}^{M} \sum_{h=1}^{H} \log(P_{mh}) \tag{5}$$

To evaluate the goodness of fit of the models, McFadden pseudo R^2 has been used. Further, the ability of the model to distinguish correctly the different outcomes based on a specified cut-off point (discrimination) has been evaluated using the area under the Receiver Operating Characteristics (ROC) curve (AUC). ROC analysis is being employed in many areas for as a common method for graphical analysis of classification models. Details about ROC have been documented in many publications and readers can refer to these for further details (e.g., Fawcett 2006; Hernandez-Orallo 2013). The use of AUC has become an important method for assessing and building classification models. It indicates the probability of a model to indicate a randomly chosen positive case (sensitivity) higher than a randomly chosen negative case (specificity). AUC ranging from 0 to 1, a general rule by Hosmer and Lemeshow (2000), is outlined as follows:

- $0.9 \leq \mathrm{AUC} \leq 1$ = outstanding discrimination
- $0.8 \leq \mathrm{AUC} < 0.9$ = excellent discrimination; and
- $0.7 \leq \mathrm{AUC} < 0.8$ = acceptable discrimination.

The base classification rate indicates the proportion of correct classification that occurs by chance alone is also presented in this study. It is determined by summing the squares of the percentages of outcomes in the data. The correct classification rate (CCR) is compared to the base rate to evaluate the predictive performance of the models. The increase in the CCR compared to the base rate indicates how much the model can improve predictive accuracy with the addition of significant variables in the model.

To further statistically investigate the validity of the models' specifications, a likelihood ratio (LR)-based test was employed. The test was conducted to check the significant difference between the parameters of the models estimated using pooled data and the models estimated using parts of the whole data (that is, using the sub-district data). The null hypothesis is that the pooled models are the same between sub-districts. The procedure as detailed in Sadri et al. (2014) was adopted in this study. Equation 6 shows the formula for calculating the LR, where $LL(\beta_{\mathrm{pool}})$, $LL(\beta_{\mathrm{sub1}})$ and $LL(\beta_{\mathrm{sub2}})$ are the log-likelihood at convergence of the model estimated using the pooled data, and the separate sub-district data (sub1 and sub2), respectively. The LR value which is χ^2-distributed with degrees of freedom equal to the number of parameters estimated (not including the model constant), is compared to the critical value at 5 % significance level. If the resulting LR is less than the critical value, the null hypothesis is not rejected. Hence, the validity of the pooled model specification is established. Otherwise, the results indicate that sub-district models may be more useful than the pooled model.

$$\mathrm{LR} = -2[\mathrm{LL}(\beta_{\mathrm{pool}}) - [\mathrm{LL}(\beta_{\mathrm{sub1}}) + \mathrm{LL}(\beta_{\mathrm{sub2}})] \tag{6}$$

4 Results and discussion

4.1 Descriptive statistics

The percentages of those who walked when evacuating and those who evacuated by other modes of transport in Bagong Silangan are 82.1 % and 17.9 %, respectively. Bahay Toro had about 65.9 % households that walked, while 34.1 % reported using other modes of transportat. In Sto. Domingo, 48.2 % reported evacuating by walking and the other 51.8 % took other available modes of transport. Due to the small number of cases for Bahay Toro and Sto. Domingo, these were combined and used to estimate and validate a pooled model. A model is also estimated using the combined cases for the three sub-districts.

The selected determinants that were included in the models are presented in Table 1. Information on the percentage under specified categories is also provided for each determinant with the corresponding models. Determinants included in the Bagong Silangan model (Model 1) are evacuation departure timing, the level of education of the head of the household, the presence of small children aged less than or equal to 10 years old, the presence of personal vehicles and the evacuation distance traveled. The Bahay Toro model (Model 2) includes evacuation departure timing, the age of the head of the household, the level of education of the head of the household, the number of years living in the residence, the presence of personal vehicles, and the source of warning. Determinants for the Sto. Domingo model (Model 3) include age and gender of the household head, the presence of a small child, the presence of health problems for the head of the household and the cost of evacuation. The determinants for the pooled model for the Bahay Toro and Sto. Domingo data (Model 4) are evacuation departure timing, their destination, age, and level of education of the head of the household, house ownership type, the presence of vehicles and the source of warning. Finally, for the model using pooled data from the three sub-districts (Model 5), determinants include the presence of vehicles, sthe ource of evacuation warning and evacuation distance traveled. Details of categories and percentage in the data are indicated in Table 1.

4.2 Inter-correlation of variables included in the model

The inter-correlations of the variables included in the logit models are first presented in Table 2, for two main reasons as outlined by Huang et al. (2015). First, is to determine possibilities of better model fit of a model to quite different estimated models. Gordon (1968) noted that the best model estimated on a sample could fit significantly less well in the population and, thus, in other samples. Second, the inter-correlation among all variables included in the logit is key information for conducting the quantitative meta-analyses, where the relative strength of effects among variables such as demographic and other behavioral ones can be determined. As presented in Table 2, the mode of evacuation is significantly correlated with departure timing ($r = 0.104$), vehicle ownership ($r = -0.180$), source of warning ($r = 0.118$), evacuation distance ($r = -0.257$), and cost of evacuation ($r = -0.121$). Low to medium level inter-correlations also exists among variables ($0.096 \leq r \leq 0.309$). In the next section, logit models are estimated in order to evaluate the effects of multiple variables on mode choice.

Table 1 Variables included in each model, categories, and corresponding percentage in the data

Variables	Categories	Percentage in the data (%)				
		Model 1	Model 2	Model 3	Model 4	Model 5
Dependent variable						
Mode choice (MDEC)	Evacuated by other modes	17.9	34.1	51.8	40.9	29.5
	Evacuated by walking	82.1	65.9	48.2	59.1	70.5
Evacuation-related decisions						
Departure timing (TDEC)	Evacuated during the flood	34.4	84.1	89.2	86.1	60.4
	Evacuated before the flood	65.6	15.9	10.8	14.0	39.6
Destination choice (DDEC)	Evacuation Center	61.3	50.8	8.4	34.4	47.8
	Church/seminary	14.6	9.9	72.3	34.0	24.4
	Friends/relatives	24.1	39.4	19.3	31.6	27.9
Characteristics of the head of household and other household information						
Age of the head of the family (AGE)	20–30 years old	16	20.4	16.9	19.1	17.6
	31–40 years old	36.8	28.0	20.5	25.1	30.9
	41–50 years old	22.6	20.5	22.9	21.4	22.0
	>50 years old	24.5	31.1	39.8	34.4	29.5
Gender of the head of household (GEN)	Female	12.7	22.0	22.9	22.3	17.6
	Male	87.3	78.0	77.1	77.7	82.4
Educational attainment of the head of the household (EDUC)	Elementary	28.8	20.5	18.1	19.5	24.1
	High School	49.5	54.6	56.6	55.4	52.5
	Diploma/undergraduate	14.2	13.6	20.5	16.3	15.2
	Graduate	7.6	11.4	4.8	8.8	8.2
Presence of small children (CHILD)	No small child	37.3	38.6	16.9	30.2	33.7
	Small child is present	62.7	61.4	83.1	69.8	66.3

Table 1 continued

Variables	Categories	Percentage in the data (%)				
		Model 1	Model 2	Model 3	Model 4	Model 5
Health problem (HPROB)	No health problem	74.5	86.4	73.5	81.4	78.0
	With health problem	25.5	13.6	26.5	18.6	22.0
House ownership (HOWN)	Rented	14.1	25.0	50.6	34.9	24.6
	Owned	85.9	75.0	49.4	65.1	75.4
Years of residence (YLIVE)	<10 years	30.2	26.5	33.7	29.3	29.7
	10–20 years	58.5	21.2	26.5	23.3	40.8
	>20 years	11.3	52.3	39.8	47.4	29.5
Vehicle ownership (VEH)	No personal vehicle	85.8	89.4	77.1	84.7	85.3
	With personal vehicle	14.2	10.6	22.9	15.4	14.8
Hazard-related variables						
Source of warning (SWARN)	Other sources (tv/radio/friends/relatives)	30.2	47.7	69.9	56.3	43.3
	From Sub-district official	69.8	52.3	30.1	43.7	56.7
Mode-related variables						
Evacuation distance (EDIST)	<200 m	33.0	0.8	6.0	2.8	17.8
	200–400 m	16.0	1.5	9.6	4.7	10.3
	>400 m	50.9	97.7	84.3	92.6	71.9
Cost of evacuation (ECOST)	No cost spent with mode	85.8	40.2	83.1	56.7	71.2
	Spent cost in evacuating through mode	14.2	59.9	16.9	43.3	28.8

Model 1 = Model for Bagong Silangan

Model 2 = Model for Bahay Toro

Model 3 = Model for Sto. Domingo

Model 4 = Model for combined Bahay Toro and Sto. Domingo

Model 5 = Model for combined Bagong Silangan, Bahay Toro and Sto Domingo

Table 2 Intercorrelations of variables included in the logit models

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. MDEC	1													
2. TDEC	.104*	1												
3. DDEC	.036	−.189**	1											
4. AGE	.080	−.050	−.049	1										
5. GEN	−.002	.072	−.050	−.224**	1									
6. EDUC	.009	.002	.080	−.198**	.019	1								
7. CHILD	−.060	.040	.025	−.227**	.126**	.057	1							
8. HPROB	−.016	.021	−.002	.278**	−.096*	−.027	−.027	1						
9. HOWN	.036	.151**	−.051	.199**	.008	−.001	−.131**	.159**	1					
10. YLIVE	−.049	−.078	.024	.294**	−.089	−.029	−.092	.097*	.309**	1				
11. VEH	−.180**	−.026	.074	−.024	.036	.127**	.101*	.034	.008	−.033	1			
12. SWARN	.118*	.157**	−.189**	.059	.106*	.005	−.074	.111*	.170**	.071	.004	1		
13. EDIST	−.257**	−.224**	−.256**	−.027	−.075	.010	−.045	−.043	−.113*	.057	.008	−.006	1	
14. ECOST	−.121*	−.050	.198**	−.153**	−.033	.066	.005	−.101*	.003	.116*	−.046	−.039	.183**	1

* Correlation is significant at the 0.05 level (2-tailed)

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

4.3 Parameter estimates

Parameter estimates for the logit models for households that walked during evacuation are presented in Table 3 and are discussed here. The zero-order correlations between the alternative mode and the determinants ($r_i Y$) for all the models estimated are also reported in Table 3.

4.3.1 Model 1: Bagong Silangan

Model 1 shows that significant variables include evacuation departure timing, the level of education of the head of the household (significant at $p < 0.01$), presence of small children, vehicle ownership and evacuation distance traveled (significant at $p < 0.001$). Households that evacuated before the floodwaters reached their home are more likely to walk ($\beta = 0.882$, OR = 2.415). Household heads with educational attainment higher than elementary level are less likely to walk compared to those who attained only elementary level education ($\beta = -0.497$; OR = -0.392). These households have higher probability of evacuating through a vehicle. Also, households with children that are less than or equal to 10 years old are less likely to walk compared to households that do not have small children. This is indicated by its coefficient ($\beta = -1.235$). An addition of a child in the household will reduce the odds of walking by 70.9 % (OR = -0.709). These households have a higher probability of evacuating through a vehicle available to them such as the one provided by the government or their personal or rented vehicle. Moreover, those that have a personal vehicle are more likely to use them when evacuating ($\beta = -1.436$; OR = -0.762). Similarly, households that traveled a distance of 200 m or further are less likely to walk when going to their destinations ($\beta = -1.038$; OR = -0.646).

The ability of Model 1 to discriminate was measured by the AUC, which is 0.801. This indicates an excellent level of discrimination (Hosmer and Lemeshow 2000). The CCR of 81.6 % indicates that the model is better than prediction by chance indicated by the increment from the base CCR which is 70.6 %.

4.3.2 Model 2: Bahay Toro

The significant determinants at 0.05 of Model 2 are the age of the head of the household, and the number of years living in the residence. In addition, the level of education of the head of the household and vehicle ownership are significant at 0.01, while the source of warning is significant at 0.001. The evacuation departure timing, although not significant, is still included as it is believed to have an effect to mode outcome (based from Ben-Akiva and Lerman 1985).

Households that evacuated before the flood are less likely to walk ($\beta = -2.848$; OR = -0.942). This indicates that households, after heeding the evacuation warning from the government, may have also traveled either by the vehicle provided by the government or their personal or rented vehicle. In addition, household heads older than 30 years have a higher likelihood of walking when evacuating compared to younger ones ($\beta = 0.426$; OR = 1.531). Those that have been living in their residence for more than 10 years have a lower probability of walking ($\beta = -0.518$, OR = -0.404). This indicates familiarity of the households of available transport modes and/or the provision of modes of transport by the government during evacuation, hence availing themselves of it. Further, household heads with educational attainment higher than elementary level are more likely to walk

Table 3 Parameter estimates of models for households that walked in evacuating

Determinants	Model 1: Bagong Silangan			Model 2: Bahay Toro			Model 3: Sto. Domingo		
	riY	b	S.E	riY	b	S.E	riY	b	S.E
Intercept	–	4.093****	0.707	–	−0.253	0.588	–	−2.203***	0.849
Evacuation-related decisions									
Indicators for TDEC (1 for households that evacuated before the flood, 0 otherwise)	0.050	0.882**	0.44	−0.343**	−2.848	0.695	–	–	–
Indicators for DDEC (1 for households that evacuated to friends/families homes or to church/seminary, 0 otherwise)	–	–	–	–	–	–	–	–	–
Characteristics of the head of household and other household information									
Indicators for AGE (1 for head ≥30 years, 0 otherwise)	–	–	–	0.085	0.426*	0.221	0.118	0.681***	0.259
Indicators for GEN (1 for male household head, 0 otherwise)	–	–	–	–	–	–	0.146	1.123*	0.624
Indicators for EDUC (1 if educational attainment of household head is higher than elementary level, 0 otherwise)	−0.127	−0.497**	0.236	0.258**	0.602**	0.307	–	–	–
Indicators for CHILD (1for households with small children ≤10 years old, 0 otherwise)	−0.131	−1.235***	0.479	–	–	–	–	–	–
Indicators for HPROB (1 if household head have health problem, 0 otherwise)	–	–	–	–	–	–	−0.142	−1.137*	0.587
HOWN (1 if household own their house, 0 if renting)	–	–	–	–	–	–	–	–	–
Indicators for YLIVE (1 for households living in the residence ≥10 years, 0 otherwise)	–	–	–	−0.083	−0.518*	0.285	–	–	–
Indicators for VEH (1 if household have their own vehicle, 0 otherwise)	−0.234**	−1.436***	0.474	−0.064	v1.571**	0.761	–	–	–
Hazard-related variables									
Indicators for SWARN (1 if the source of warning are authorities, 0 otherwise)	–	–	–	0.241**	2.047***	0.579	–	–	–
Mode-related variables									
Indicators for EDIST (1 if household traveled a distance ≥200 m, 0 otherwise)	−0.249**	−1.038***	0.276	–	–	–	–	–	–
Indicators for ECOST (1 if household spend cost in evacuating by mode, 0 otherwise)	–	–	–	–	–	–	0.209	1.705**	0.717

Table 3 continued

Determinants	Model 1: Bagong Silangan			Model 2: Bahay Toro			Model 3: Sto. Domingo		
	riY	b	S.E	riY	b	S.E	riY	b	S.E
Number of observations	212			132			83		
−2Log-likelihood at zero	132.544			140.538			53.664		
−2Log-likelihood at convergence	96.082			96.878			39.407		
Akaike Information Criterion (AIC)	108.082			110.878			49.407		
Bayesian Information Criterion (BIC)	128.221			131.057			61.501		
Likelihood ratio (LR) Chi square (χ^2)	36.462			43.660			14.257		
Degrees of freedom (DF)	5			6			4		
Prob > χ^2	0.000			0.000			0.007		
McFadden Pseudo-R^2	0.183			0.258			0.124		
Correct classification rate (CCR) (%)	81.6			73.5			69.9		
CCR for the base rate (%)	70.6			55.1			50.1		
Area under curve (AUC)	0.801			0.823			0.726		

Determinants	Model 4: Bahay Toro + Sto. Domingo			Model 5: Bagong Silangan + Bahay Toro + Sto. Domingo		
	riY	b	S.E	riY	b	S.E
Intercept	–	−1.013*	0.58	–	2.459***	0.408
Evacuation-related decisions						
Indicators for TDEC (1 for households that evacuated before the flood, 0 otherwise)	−0.129	−0.861*	0.441	–	–	–
Indicators for DDEC (1 for households that evacuated to friends/families homes or to church/seminary, 0 otherwise)	0.111	0.314*	0.189	–	–	–
Characteristics of the head of household and other household information						
Indicators for AGE (1 for head ≥30 years, 0 otherwise)	0.089	0.308**	0.143	–	–	–
Indicators for GEN (1 for male household head, 0 otherwise)				–	–	–

Table 3 continued

Determinants	Model 4: Bahay Toro + Sto. Domingo			Model 5: Bagong Silangan + Bahay Toro + Sto. Domingo		
	riY	b	S.E	riY	b	S.E
Indicators for EDUC (1 if educational attainment of household head is higher than elementary level, 0 otherwise)	0.156*	0.511**	0.203	–	–	–
Indicators for CHILD (1for households with small children ≤10 years old, 0 otherwise)	–	–	–	–	–	–
Indicators for HPROB (1 if household head have health problem, 0 otherwise)	–	–	–	–	–	–
HOWN (1 if household own their house, 0 if renting)	–0.073	–0.597*	0.333	–	–	–
Indicators for YLIVE (1 for households living in the residence ≥10 years, 0 otherwise)	–	–	–	–	–	–
Indicators for VEH (1 if household have their own vehicle, 0 otherwise)	–0.144*	–1.157***	0.419	–0.180**	–1.106***	0.299
Hazard-related variables						
Indicators for SWARN (1 if the source of warning are authorities, 0 otherwise)	0.181**	0.907***	0.323	0.118*	0.584***	0.227
Mode-related variables						
Indicators for EDIST (1 if household traveled a distance ≥200 m, 0 otherwise)	–	–	–	–0.257**	–1.028***	0.209
Indicators for ECOST (1 if household spend cost in evacuating by mode, 0 otherwise)	–	–	–	–	–	–
Number of observations	215			427		
–2Log-likelihood at zero	239.805			102.048		
–2Log-likelihood at convergence	207.594			48.565		
Akaike Information Criterion (AIC)	223.594			56.565		
Bayesian Information Criterion (BIC)	250.559			72.792		
Likelihood ratio (LR) Chi square (χ^2)	32.211			53.483		
Degrees of freedom (DF)	7			3		

Table 3 continued

Determinants	Model 4: Bahay Toro + Sto. Domingo			Model 5: Bagong Silangan + Bahay Toro + Sto. Domingo		
	riY	b	S.E	riY	b	S.E
Prob > χ^2	0.000			0.000		
McFadden Pseudo-R^2	0.111			0.103		
Correct classification rate (CCR) (%)	66.0			72.1		
CCR for the base rate (%)	51.6			58.4		
Area under curve (AUC)	0.720			0.711		

– Independent variable is not a determinant in corresponding model; riY correlation, r, of the independent variable i, to mode outcome, Y

* Significance at 95 %; ** Significance at 99 %; *** Significance at 99.9 %

when evacuating ($\beta = 0.602$, OR $= 1.825$). Those with personal vehicles are less likely to walk ($\beta = -1.571$, OR $= -0.792$). This means that those who have vehicles take them when evacuating. Households that received evacuation warnings from authorities are more likely to walk ($\beta = 2.047$, OR $= 7.745$).

The AUC of Model 2, which is 0.823, indicates an excellent discrimination ability (Hosmer and Lemeshow 2000). Also, the addition of the variables in the model results to a CCR of 73.5 %, which means that the model is better than predicting by chance. This is measured by the increment from the base CCR which is 55.1 %.

4.3.3 Model 3: Sto. Domingo model

In the case of Model 3, estimation results show that the gender and the presence of health problem of the head of the household are significant at 0.05, while the cost of evacuation and age of the head of the household are significant at 0.01 and 0.001, respectively. Males have a higher likelihood of walking compared to females ($\beta = 1.123$, OR $= 3.074$). On the other hand, those that have health problems are less likely to walk ($\beta = -1.137$, OR $= -0.679$). This is reasonable as they have constraints in walking a distance considering they have to carry some personal belongings with them. Household heads more than 30 years of age are more likely to walk ($\beta = 0.681$, OR $= 1.976$). If there is a cost associated with evacuating through a mode, the more likely that households choose to walk ($\beta = 1.705$, OR $= 5.501$). As shown in Table 2, the cost of evacuation is positively correlated with evacuation distance ($r = 0.183$) indicating that households that travel longer distances are more likely to spend in evacuating through a vehicle.

The ability of Model 3 to discriminate (AUC $= 0.726$) is at an acceptable level (Hosmer and Lemeshow 2000). Also, the addition of the variables in the model results to a CCR of 69.9 %, which is higher than 50.1 %. This shows that the model is better than prediction by chance.

4.3.4 Model 4: Pooled model for Bahay Toro and Sto. Domingo

The determinants in Model 4 are evacuation departure timing, their destination, house ownership type (significant at 0.05); age and level of education of the head of the household (significant at 0.01); and the presence of a vehicle and the source of warning (significant at 0.001). Households that evacuated before the floodwaters reached their home are less likely to walk ($\beta = -0.861$, OR $= -0.577$). Those that evacuated to their friends'/relatives' homes or to church/seminaries are more likely to walk ($\beta = 0.314$, OR $= 1.369$). This explains the fact that the government usually provides vehicles to evacuees which they take to public evacuation centers which are government-designated facilities. Moreover, households that own their own house are less likely to walk ($\beta = -0.597$, OR $= -0.450$). It can be observed from Table 2, that house ownership is positively correlated with the presence of health problems ($r = 0.159$). This explains their higher probability not to walk. In addition, household heads who are 30 years or older have a higher likelihood of walking when evacuating ($\beta = 0.308$, OR $= 1.361$). Similarly, household heads with educational attainment higher than elementary level have a higher probability to walk when evacuating ($\beta = 0.511$, OR $= 1.667$). Consistent with the effect in the models presented earlier, those with personal vehicles are less likely to walk ($\beta = -1.157$, OR $= -0.686$). An additional vehicle in the household reduces the odds of walking by 68.6 %. Also, those that received an evacuation warning from authorities are more likely to walk ($\beta = 0.907$, OR $= 2.477$).

The model's ability to discriminate (AUC = 0.720) indicates an acceptable level (Hosmer and Lemeshow 2000). The addition of variables in the model resulted to a CCR of 66 % with a significant increase from the base CCR of 51.6 %. This shows that the model is able to predict better than just by chance.

4.3.5 Model 5: Pooled model for all sub-districts

For Model 5, determinants include the presence of personal vehicles, the source of evacuation warning and evacuation distance traveled. Those with personal vehicles are less likely to walk ($\beta = -1.106$, OR = -0.669), while households that received evacuation warnings from authorities are more likely to walk ($\beta = 0.584$, OR = 1.793). Households traveling a distance greater than or equal to 200 m when going to their destinations have a lower likelihood of walking when compared to those that travel shorter distances ($\beta = -1.028$, OR = -0.642). Traveling more than 200 m reduces the odds of walking by 64.2 %.

The model's ability to discriminate also indicates an acceptable level (AUC = 0.711) (Hosmer and Lemeshow 2000). The resulting CCR of 72.1 % is higher than the base CCR of 58.4 %. This means that the model is better than predicting by chance.

4.3.6 Model comparisons

The following observations can be highlighted in comparing the model results.

- Vehicle ownership is a significant determinant to all models, except for Model 3. It is significant at 0.01 in all models with the same negative effects. This shows similar behavior of households with personal vehicles that use them when evacuating. This finding agrees with Deka and Carnegie (2010) and Lindell and Prater (2007).
- Common to Models 1, 2, and 4 is the educational level attained by the household head, significant at 0.01 in all three models. However, the effect of the variable to Models 2 and 4 are positive while having a negative effect to Model 1. Households in Model 1 which are educated higher than elementary level have a lower likelihood of walking contrary to households in Models 2 and 4. The difference may be due to the correlation existing between the level of education and vehicle ownership ($r = 0.127$) as shown in Table 2. These are both related to the economic status of the household.
- A determinant common to Models 2, 3, and 4 is the age of the household head with the same effects. Household heads that are 30 years or older have a higher likelihood of walking when evacuating.
- Departure timing is significant in Models 1 and 4 with opposite effects, while included in Model 3 although it is not significant, but believed to have an influence in the decision making. Opposite effects in Models 1 and 4, indicates differences in behavior of risk-averse households in Bagong Silangan against Bahay Toro and Sto. Domingo. Households in Bagong Silangan are more likely to walk while this is less likely in the other 2 sub-districts. The difference may be related to the greater distances that households in the other 2 sub-districts have to travel when going to their destinations. It is shown in Table 1 that almost 93 % of the households in Bahay Toro and Sto. Domingo travel distances greater than 400 m, while it is only more than 50 % in Bagong Silangan. Also in Table 2, there exists a negative correlation ($r = -0.224$) between departure timing and evacuation distance.

- Distance traveled during evacuation is common to Models 1 and 5 with the same level of significance and negative effect. The result is plausible as the greater the distance households have to travel, the more likelihood that they do not evacuate on foot.
- The destination type and presence of small children is unique in Model 1. Results regarding households' destination as a determinant to mode choice behavior support findings in Sadri et al. (2014). With regards to having small children in the household, it is logical that these households require assistance in evacuation through having a vehicle available.
- The number of years the households have been living in the residence is a unique determinant to households in Bahay Toro. The households living in the area for more than 10 years are less likely to walk. It should also be noted that the number of years in the residence is positively correlated with the presence of health problems ($r = 0.097$) and house ownership ($r = 0.309$). This specifies that those living in the area for 10 years or more may have health problems, own their house and are also aware of modes of evacuation that are available, and take them when evacuating instead of walking. On the other hand, the presence of health problems, the gender of the head of the household and the cost of evacuation are determinants taken into account only by households in Sto. Domingo, but not in the other 2 sub-districts. In addition, the type of house ownership is a determinant to Model 4, where households owning the house have a lower probability of walking.
- The R^2 of separate Models for each sub-district: Model 1 (0.183), Model 2 (0.258), Model 3 (0.124), are higher than that of the R^2 of pooled models (Model 4 = 0.111; Model 5 = 0.103). Model 2 has a slightly higher value compared to that of Sadri et al. (2014) with $R^2 = 0.236$, while the rest of the models have lower values. However, AUCs for Model 1 (0.801) and Model 2 (0.823) indicate excellent levels while for Model 3 (0.723) it is at an acceptable level slightly higher than those of the pooled models (Model 4 = 0.720; Model 5 = 0.711). This shows the usefulness of the models estimated.

4.4 Model validation

The LR-based validation was conducted to test the validity of the pooled model specifications versus separate sub-district models. The procedure described in Sect. 3.3 was employed. Model 4 was the first case tested against the parts of the data (Bahay Toro and Sto. Domingo) estimated with the same model specifications. The log-likelihood at convergence is recorded for each estimation result. The LR is then calculated using Eq. 6, where $-2LL(\beta_{model4}) = 207.59$, $-2LL(\beta_{Sto\ Domingo}) = 84.41$ and $-2LL(\beta_{Bahay\ Toro}) = 107.12$ are the log-likelihood at convergence of the model estimated using Model 4, Sto Domingo and Bahay Toro data, respectively. This results to an LR of 16.07, which is χ^2-distributed with degrees of freedom equal to 7. The critical value of χ^2 for the significance level of 5 %, $\chi^2_{0.05,7}$ equals 14.07, which is less than the resulting LR. Hence, the null hypothesis is not rejected. Therefore, the validity of the model specification is supported. This indicates that the Model 4 specification is established over sub-districts Sto. Domingo and Bahay Toro.

The second case tested was the Model 5, estimated using the pooled data of 427 observations against the data used for Model 4 and Model 1, estimating it with the same model specification as that of Model 5. The resulting $-2LL$ at convergence for the estimations for β_{model5}, $\beta_{Sto.\ Domingo\ +\ Bahay\ Toro}$ and $\beta_{Bagong\ Silangan}$ are 48.565, 31.867 and 30.776, respectively. Using the same Eq. 6, the resulting LR with degrees of freedom equal

to 3, $\chi^2_{0.05, 3}$ is -14.078. This indicates that the parameters of Model 5 are not established over the subsamples from the 3 sub-districts. Therefore, the separate Models 1 and 4 are more useful than the pooled Model 5.

5 Synthesis, conclusions and future research

The frequency and severity of hazards that lead to considerable disaster impacts are continuously increasing. The need to devise preparedness plans for future evacuations is imperative in order to minimize disaster impacts to people. Modeling helps in evacuation planning as it will predict the most probable evacuation outcomes (e.g., cumulative percentage of the risk area population who evacuate over time, location of bottlenecks, etc.) if the analysts use accurate inputs for evacuation demand and capacity. Within the modeling efforts, evacuation behavior has been realized as an important consideration in modeling; hence, this has been the focus of evacuation modeling research in the past. Incorporating evacuees' behavior is helpful for efficient evacuation operations in the future. Evacuation behavior aspects are identified as the decision to evacuate or stay, departure timing, destination and shelter type choice, mode choice, and route choice.

This study seeks to learn the determinants of evacuees' mode choice in a developing country. Data used for analysis were collected from households in selected sub-districts in Quezon City, Philippines. Specifically, determinants that households take into account when evacuating on foot or by taking other modes of transport, such as their own vehicle, rented vehicle or vehicle provided by the government, were investigated. Analysis using separate data for sub-districts as well as pooled ones has been presented and discussed.

Findings show that the pooled model for Bahay Toro and Sto. Domingo, and the separate model for Bagong Silangan are more useful than the pooled Model for all 3 sub-districts. Bagong Silangan households' mode choice is determined by a combination of determinants including evacuation departure timing, the level of education of the head of the household, the presence of small children who are 10 years or younger, the presence of personal vehicles and evacuation distance traveled. Pooled Bahay Toro and Sto. Domingo model determinants are evacuation departure timing, their destination, age, and level of education of the head of the household, house ownership type, the presence of vehicles and the source of warning. Similar behavior of households with personal vehicles has been observed; that is, taking their vehicles when evacuating. This finding is consistent with earlier studies such as Deka and Carnegie (2010) and Lindell and Prater (2007).

Results in this study provide insights that can be used by evacuation planners and managers in preparing plans for future evacuation. First, the government can encourage the households that have their own vehicle to use them in future evacuations. For those lacking vehicles, but needing them because of disability or evacuation distance, the government can arrange for rides with peers (friends, relatives, neighbors). Second, the government can encourage those that evacuate later to do pre-emptive evacuation and encourage those that travel shorter distances to walk, while providing vehicles for those that need to travel longer distances.

Overall, the government can mandate the households living in high flood risk areas to prepare a household evacuation plan that includes details such as the mode that they will take or need when evacuating, where they will go, and the resources such as food, water, and shelter they need. Home owners in specific villages can devise their own plans that can assist the sub-district level government to implement effective evacuations in the future.

Although the Bagong Silangan model shows an excellent predictive accuracy, the model for Bahay Toro and Sto. Domingo is only at an acceptable level. This indicates that there might still be determinants that are not captured in the pooled Bahay Toro and Sto. Doming model. Hence, further investigation is needed in order to develop a model that can be used to predict future percentages of evacuees who will use which type of evacuation mode. For further analysis, applying methodologies in handling missing data may add significant value to model estimates. Johnson and Young (2011) found that modern methodologies of handling missing data yield better results than using traditional ones. In addition, Graham (2009) gives a literature overview of the missing data, issues and challenges and suggests practical ways to handle bias. These useful insights and methodology recommendations may be applied in future analysis.

Predictive models can help evacuation planners and managers to plan for appropriate type and number of modes to provide for moving people to safety. These models can also help governments assess whether or not their resources in providing government vehicles are sufficient. If not enough, procurement of additional vehicles might be needed. If procurement is not possible, collaborations with other local governments or carefully planning the number of trips during evacuation can be done. Practical examples of the integrating mode choice model in the evacuation planning model are detailed in Yin et al. (2014).

In the context of this study, it is imperative to know how households choose their destination as the next step. Also, a study is needed to explore the possibility of developing models that can be generalized to cities in the Philippines. In addition, the growing need to understand how different genders are affected by disasters and the growing vulnerability of women is increasingly interesting. In the future, understanding key determinants of gender-based evacuation travel behavior in the area of evacuation decision, departure time, destination, mode and route choice behavior can be investigated, especially in the case of flood. Increasing sample sizes and collecting data in other sub-districts may be helpful.

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