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Understanding the Decision of Flood Evacuation Departure Time Using Discrete Choice Model

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Abstract: Modeling evacuation departure time is primarily essential in evacuation demand modeling. In this study, a discrete choice model is used to understand the decision of evacuation departure time of households in flood affected areas in Quezon City, Philippines. Specification of the model is also validated. Results of the study provide useful insights for evacuation planners. Households put importance on hazard-related factors and their capacity to cope with flood when making their decisions. Factors that determine the flood evacuation departure time constitutes the type of work of the head of the household, house ownership, the number of house floors, distance of their homes from the source of flood, and the flood level.

Keywords: Evacuation, Discrete Choice Model, Travel Behavior, Evacuation Modeling, Departure Time, Flood

1. INTRODUCTION

The occurrence of hydro-meteorological hazards such as hurricanes and floods can be anticipated in advance. Their impacts can also be estimated at a certain level. With this, possible that people at risk can prepare so that impacts of future disasters could be averted. One effective measure that all level of governments do before disaster strikes an area at risk is evacuation. In fact, in the context of the Philippines the National Disaster Risk Reduction Management Framework of the Philippines or Republic Act 10121 specifies two types of evacuation that can be enforced by the local governments based on timing, which are preemptive evacuation and forced evacuation (NDRRMC, 2010). Preemptive and forced evacuations are executed prior and during the disaster event, respectively. Regardless of the type of evacuation orders, careful planning, simulation and drills are carried out to prepare community people for possible evacuation in the future. Evacuation planning is a way to identify the best strategy for evacuation under the most probable disaster scenario. However, the success relies on complex factors, like warning time, public preparedness and response time, the way information and instructions are distributed, available routes, network traffic conditions, and traffic management measures (Lindell and Prater, 2007). Because of the complexity of the processes involved with overwhelming factors that affect these processes, model-based methods are useful in analyzing and planning for future evacuations (Hardy *et al.,* 2010). Evacuation modeling is used to understand network conditions and the effect of traffic regulations and control measures. This is accomplished by knowing useful information such as predicted departure and arrival patterns, travel times, average speeds, queue lengths, and traffic flow rates (Pel *et al.*, 2011). With this information, planners could propose strategies that are appropriate for evacuation to safe destinations before disaster strikes threatened areas (Stopher *et al.*, 2004). Understanding the decision of evacuation timing is vital to help government officials decide when to issue emergency evacuation orders.

The importance of understanding decision making in terms of evacuation timing has been highlighted in studies. For instance, Pel *et al.* (2011) in their study on evacuee behavior analysis relaxed some of the limitations in traffic models used. Results of their study made the authors stress the need for more behavioral analysis on departure timing of evacuees. Further, the authors suggested that parameter settings in traffic models should be given careful attention. This is due to limitations of traffic models that are used in evacuation studies to suffer from lack of suitable real-life data. This limitation, if not addressed could result to models that are not correctly calibrated because of the use of traffic data that represent regular daily traffic conditions. Moreover, Li *et al.*, (2013) constructed an evacuation response curve using traffic data collected in 2011. Findings in their study also made the authors recommended that more empirical data from different cases are needed to have reliable evacuation response model. The authors have strongly noted that the behavior analysis is very important in order to better understand the evacuation decision making process.

Evacuation time has been mostly analyzed using response curves using traffic data during evacuation (e.g. Radwan *et al.*, 1985; Tweedie *et al.*, 1986; Lindell and Prater, 2007). However, using the response curve do not provide disaggregate information on where evacuees came from, the types of households and their characteristics, the type of evacuation warning they received from the government, among others. This information is important for capturing behaviors that could allow planners to design appropriate evacuation strategies. In addition, studies conducted on this line are mostly in the context of hurricane hazard and in developed countries. Departure time choice of households has not been fully understood in the Asia’s context. Hence, analyzing evacuation timing behavior in Asia could be analyzed and modeled.

Towards contributing to the needs of more behavior studies in understanding evacuation response behavior, this study is conducted to understand the factors that determine evacuation departure time choice. A binary logit model was estimated using the data collected from households in Quezon City, Philippines which was affected during the wake of the big flood in 2013 that affected the whole Metro Manila. This study is primarily useful in understanding the timing response of evacuees in flood disasters. Thereby, governments can make use of the results of the study to develop strategies to increase compliance of preemptive evacuation, hence, reducing casualties during flood events.

2. EARLIER LITERATURE

This section gives an account of previous studies on evacuation travel behavior particularly on evacuation departure time.

2.1 Approaches in Modeling Evacuation Departure Time Choice

Departure time of evacuees is essential in determining the demand for evacuation. Evacuation demand models are used to determine the number of people who will evacuate and their departure time patterns. Usually, evacuation demand modeling is done in three steps. Firstly, that region needs to be evacuated is identified. Then number of people that will evacuate is determined. The third step is to identify the departure time or loading rates of evacuees. Evacuees' departure timing can be modeled in a couple of ways. It is either sequentially or simultaneously modeled with evacuation decision (Pel *et al.*, 2012).

In the sequential modeling approach, evacuees' departure time choice is modeled after estimating the share of people who will evacuate. This is usually done through the application of exogenous response curve indicating the percentage of evacuees leaving in each time interval. The departure curve has significant impact on traffic operations, congestion, and therefore the network clearance time in emergency evacuation. Loading the evacuation demand in stages has the potential to better utilize the existing capacity of the transportation system as opposed to simultaneous evacuation which potentially gridlocks in the network (Abdelgawad and Abdulhai, 2010). Generation of evacuation departure curves can be done in two ways. First, response curves are constructed based on post evacuation surveys. Second, planners' knowledge and judgment with the use of data to create more general functions is employed for estimating departure time. The first approach applies response curve of different rates such as slow, medium and fast. Example of this is the one developed by the United States Army Corps of Engineers (2000) from post-evacuation surveys and behavioral analyses. This incorporates the zero time point where the decision is done when the evacuation order is issued, which reflects the share of people who evacuated before the order is given. Although this approach is simple to use, the transferability of such profiles to other evacuation events is an issue as well as its insensitivity to the dynamics of the evacuation process (Abdelgawad and Abdulhai, 2010). In the second approach, the departure response curve has been assumed to follow many different distributions such as instantaneous departure, uniform distribution, Rayleigh distribution, Poisson distribution, Weibull distribution and sigmoid curve. The Weibull distribution and sigmoid curve are most often used and claimed to be most realistic (Pel *et al.*, 2012).

In the simultaneous modeling approach, evacuation decision and departure time choice is modeled using the binary logit model that shows time-dependence (e.g. Fu and Wilmot, 2004; Fu *et al.*, 2006). For simultaneous modeling of the evacuation decision and departure time choice, binary logit model is repeatedly estimated in time to predict the share of people who decide to evacuate and depart presently, or postpone the decision to evacuate. As detailed in Pel *et al.* (2012), the performance of the repeated binary logit model depends evidently on how accurately the relative evacuation utilities are estimated. Another approach in simultaneous modeling is the development of mathematical models using data from surveys, and evacuation demand scheduling optimization (staging). This approach determines the optimal or "near-optimal" evacuation schedule that achieves a certain objective such as minimizing network clearance time (Pel *et al.*, 2011). However, solving this problem is mathematically and computationally demanding and requires the interaction between an optimization model and a dynamic model of the transportation system.

2.2 Recent Developments in Modeling Evacuation Departure Time Choice

Findings from research that focused on behavioral analysis of evacuation departure timing are reviewed here. These studies, that have identified important variables that significantly affect evacuation departure time choice, include that of Charnkol and Tanaboriboon (2006) in case of tsunami, Pel *et al.* (2010), Li *et al.* (2013), Dixit *et al.* (2012) and Hasan *et al.* (2013) in case of hurricane.

Charnkol and Tanaboriboon (2006) investigated the time at which the evacuees were expected to begin their evacuation in the case of hypothetical tsunami in Thailand. A behavioral analysis for transients and permanent residents was carried out to gain some insights into determining evacuees' response patterns. The response patterns were fast, medium, and slow, under four preparation and response time intervals (60 minutes, 45 minutes, 30 minutes, and 15 minutes). In the analysis, the age, number of family members, distance from the seashore, presence of disaster knowledge prior to the disaster, the number of children in the family, type of employment, marital status and educational attainment was found to influence evacuation departure decision making. Insights could be derived from the study. Transients were more likely to evacuate faster than the permanent residents. The probability of being in a quick response pattern diminishes with an increase in the number of family members. Respondents, who are living closer to the shore, are more likely to evacuate earlier than those living further away from the shore. Also, the respondents who themselves or whose relatives had experienced the Indian Ocean tsunami, were more likely to evacuate faster than those who had not. Likewise, respondents, who have disaster knowledge, are more likely to evacuate faster than those who do not have any disaster knowledge. As expected, the number of children in the household decreases the probability of being in the quick response group, and teenagers are more likely to be in a slow response group due to lack of experience as they tend to underestimate the risks of an approaching disaster and its destructive potential. Private employees were more likely to be in the quick response group than others. Although marital status and educational level was found to be significant at some level, the authors recommended future investigation in these factors.

On the other hand, Pel *et al.* (2010) in his earlier work focusing on departure time choice, proposed a model of integrating traveler information and compliance behavior using macroscopic simulation package. Their findings show the need to incorporate traveler information and compliance into evacuation models. They suggested that there is a need to understand the impacts of changing information and evacuation decision results that are obviously related to many behavioral aspects. Moreover, Li *et al.* (2013) constructed an evacuation response curve based on traffic data collected during Hurricane Irene (2011) in Cape May County, New Jersey. The evacuation response curve follows a general S-shape with sharp upward changes in slope following the issuance of mandatory evacuation notices. The widely used S-curves with different mathematical functions and the state-of-art behavior models are calibrated and compared with empirical data. The results show that the calibrated S-curves with Logit and Rayleigh functions best fit empirical data. The evacuation behavior analysis and calibrated evacuation response models based on this recent Hurricane evacuation event may benefit evacuation planning in similar areas.

Hasan *et al.* (2013) presented the results of a hurricane evacuation time model using a random-parameter hazard-based modeling approach. Several important factors that influence a household's evacuation timing decision are household's geographic location, type of the shelter, location and time to reach the destination in normal time, time between decision and actual evacuation, whether or not to live in a mobile house, educational attainment, income, and type of evacuation notice received. Three factors are found to have random parameters. These variables include usual travel time to reach the destination, location of household and the number of children. Insights can be taken from this study for evacuation planning. First, travel time to destinations under normal condition influences the timing decision; households moving to places that usually require longer time to be reached in normal situations will evacuate earlier. Second, households that evacuate late are likely to leave shortly after making the evacuation decision (i.e., low mobilization time) compared to the households evacuating earlier. Third, low-income households are likely to evacuate later and households receiving evacuation notice (either mandatory or optional) are likely to evacuate earlier.

Dixit *et al.* (2012) conducted a study in understanding the behavior of evacuees by using the theory of risk developed and connecting it to economic theory with behavior under threat. This study provides the first step toward explicitly incorporating risk aversion into the modeling framework for estimating time-dependent evacuation demand. Using Hurricane Andrew response data, evacuation departure time choice model is proposed. A constant relative risk aversion specification is used to model risk attitudes. The results show that the presence of children affected the amount of time spent preparing if the family decided to stay. The time of day, length of time spent in a region, and whether a mandatory evacuation order was issued affected risk attitudes. Further research will be needed to use actual revealed mobilization time and the time used to prepare to weather the storm, to develop robust estimates.

Although above-mentioned studies in understanding departure timing of evacuees provided more information on what are taken into account with this type of decision making, findings are mostly in the context of hurricane hazard in developed countries. This current study aims to investigate further in case of evacuation timing during flood event based on post flood event household surveys. Considering above-mentioned variables found to significantly influence the departure timing of evacuees, this study is conducted as another effort towards understanding evacuees' decision making, specifically in the context of households in flood prone areas in developing country.

3. METHODOLOGY

The section describes the data collection and basic modeling framework of the study.

3.1 Data Collection

Data used for analysis were collected from households in selected sub-districts in Quezon City, Philippines. Selected sub-districts were recommended by the Quezon City Government (QCG). Quezon City is a flood prone area in Metropolitan Manila and regularly experiences floods of different magnitudes every after heavy rain occur. This is mainly due to the presence of 700-hectare dam at 100-meter above sea level in the Northern part, and the low grade terrain at the Southern portion of the City. When heavy rainfall pours, the water level at the reservoir can reach the limit and cause excess water to flood downstream areas. Moreover, clogged canals, illegal settlements, poor urban planning and lack of preparedness of the people add to the level of negative impacts caused by floods (QCG and Earthquakes and Megacities Initiative, 2013).

The city's population of more than 2 million is nearly one-fourth of Metro Manila's population among 16 cities (QCG, 2013). It is a densely populated city with increasing number of settlements. From the flood risk assessment for the City, about 700,000 people are estimated to be affected. 16% of these people reside in low susceptible areas. 30% of them live in moderate flood susceptible areas while 54% live in high flood susceptible areas (QCG and EMI 2013). In 2013, another flood event happened during the August monsoon rains worsened by the tropical cyclone Trami. This event prompted several households to evacuate in many parts of Metro Manila including those in Quezon City. Flood levels reached up to the roofs of houses near the source of flood. This flood was the basis for the post flood survey in this study which was conducted to understand the evacuation behavior of the households.

In order to study evacuation behavior of households in the study area, courtesy call was done at the office of the Head of Quezon City, then to the sub-districts and villages. This was important to ensure safety of researchers, easier access to target households, and building rapport with households in flood prone villages that were the prospects for data collection.

The flood risk areas in Quezon City were identified from initial interviews with government officials. According to officials' recommendations, sub-district areas selected for this study include Bagong Silangan, Bahay Toro, Sto. Domingo and Roxas with 2013 projected population of 101,806, 74,987, 15,560 and 13,563 respectively (QCG, 2013). Initial interviews were also conducted with household heads in selected sub-districts in order to validate appropriateness of the survey questionnaire developed. The full face to face household interviews was then conducted between December 2013 and April 2014.

The exact number of population located in high flood risk areas is unknown. In determining the number of appropriate number of samples, it was assumed that the population is normally distributed. The empirical formulas used to determine the sample size is shown in Equations 1 and 2, according to Levy and Lemeshow (2008).

$$n_0 = \frac{Z^2 pq}{e^2} \qquad q = 1 - p \tag{1}$$

Where n_0 is the sample size for infinite population; Z is the statistical parameter corresponding to confidence level (Z =1.96 for 95% confidence level); e is the specified error margin (5% in this case); p is the hypothesized true proportion for population (equal to 0.5 to account for worst case).

$$n = \frac{n_0}{\left[1 + \frac{(n_0 - 1)}{N}\right]} \tag{2}$$

Where n is the sample for finite population; N is the size of the population. After calculating the sample size using Equations 1 and 2, the minimum number of samples obtained in 385. In this study, a total of 740 interviews with randomly approached households covering high flood risk villages were completed. During the interviews, 10 of approached households refused to undergo such interview. Hence, the total household approached for interviews was 750. From this, the response rate, which represents the total number of fully and partially completed interviews (740), divided by the sum of the number of fully and partially-completed interviews plus those who refused to undergo interview (750) is 98.7%. The response rate is high as every household approached were very cooperative and willing to share their experiences, motivated by the hope that the study results could reach concerned people, who in turn could help them have a better situation during future evacuations. In addition, coordination with relevant officials from the city level down to the village level contributed to the high interview response rate. Information gathered from households include the socio-demographic characteristics of the households, some hazard-related information and their evacuation experience during the flood event in 2013, and their comments and suggestions for improving situations in future evacuations. The face to face survey took an average of 15 minutes for every household interviewed.

After interviews were completed, data were verified, cross-checked and all those with missing information were removed from the data included for analysis. The data were then summarized and coded according to the requirement of statistical tool used for modeling method employed. Resulting valid samples used for analysis of departure time choice is 465. The departure time choices of households were grouped into two categories. The first group consists of risk-averse households that evacuated before the flood, after hearing recommended evacuation advice from the government (evacuation timing referred to as before). The other group consists of risk-tolerant households that evacuated when floodwaters are in their vicinity (evacuation timing referred to as during). These then are coded and analyzed according to the modeling framework presented in the next subsection.

3.2 Modeling Framework

The households' behavior regarding evacuation departure timing is analyzed using the discrete choice modeling framework. The departure timing choice include before or during the flood. Discrete choice models postulate that an alternative is selected if the utility is higher than the utility of any other alternatives. There are many applications of discrete choice models existing in the literature. Examples are in the field of economics (e.g. Pryanishnikov and Zigova, 2003), transportation (Zhang *et al.*, 2009) and evacuation modeling (e.g. Sadri *et al.*, 2014a). One form of discrete choice model is logit as detailed in Train (2009).

The question of whether to evacuate according to evacuation warning before or during the flood are modeled in this study through binary logit, a simple closed form solution which has the ability to capture behavioral representations, and to represent systematic taste variation (Train, 2009). The binary logit model for any household, *h*, evacuating before the flood, *b* or during the flood, *d*, respectively, is represented by the utility functions in Equation 3 and Equation 4. In these equations, $\boldsymbol{\beta'}_b$ and $\boldsymbol{\beta'}_d$ are vectors of parameters to be estimated for the model for households, *h*, that evacuated before, *b* and during, *d*, the flood, respectively. $\boldsymbol{X}_{bh}$ and $\boldsymbol{X}_{dh}$ are vectors of the factors that households put importance to, in their evacuation departure time decision-making of either before, *b,* or during the flood, *d* respectively. ε_{bh} and ε_{dh} accounts for the effects of unobserved attributes and preferences on observed choice *b* and *d*, respectively.

$$U_{bh} = \beta'_{bh} X_{bh} + \varepsilon_{bh} \tag{3}$$

$$U_{dh} = \beta'_{dh} X_{dh} + \varepsilon_{dh} \tag{4}$$

The probability that a household evacuates before or during the flood is denoted by P_{bh} and P_{dh}, respectively, which are presented in Equation 5 and Equation 6.

$$P_{bh} = \frac{e^{\beta'_{bh} X_{bh}}}{e^{\beta'_{bh} X_{bh}} + e^{\beta'_{dh} X_{dh}}} \tag{5}$$

$$P_{dh} = \frac{e^{\beta'_{dh} X_{dh}}}{e^{\beta'_{bh} X_{bh}} + e^{\beta'_{dh} X_{dh}}} \tag{6}$$

The maximum likelihood estimation method is used to determine the parameters (***β**s)*. Statistical test of model significance is conducted with the null hypothesis that all coefficients in the utility function take the value of zero. The null hypothesis can be statistically rejected if any relevant model parameter is different from zero at a 0.05 significance level. The significance of independent variables to departure timing decision outcome is assessed using the t-statistics. Moreover, model fit is assessed using pseudo R^2. The correct classification rate (CCR) is also determined to assess the predictive ability of the model. The area under the Receiver Operating Characteristics (ROC), with values between 0 and 1 was also determined to test the ability of the model to distinguish a randomly chosen positive case (sensitivity) higher than a randomly chosen negative case (specificity). As specified in Hosmer and Lemeshow (2000), AUC indicates outstanding discrimination if the value ranges from 0.9 to 1, excellent discrimination with values ranging from 0.8 to less than 0.9, and acceptable discrimination with values ranging from 0.7 to less than 0.8.

4. RESULTS AND DISCUSSION

4.1 Data and Variable Correlations

Data used for analysis consists of 38.7% households that evacuated before the flood, and 61.3% that evacuated during the flood. For analysis of the variables that are included in the model for departure time choice, several variables were initially considered. Most of these variables were collected based from findings in earlier literature. These variables were age, gender, marital status, educational attainment of the head of the household, type of work of the head of the household, household monthly income, number of household members, presence of children, presence of senior citizen and pet in the household, vehicle ownership, distance from the source of hazard, flood level, the level of flood damage and source of warning. Moreover, variables such as the number of floors of their house and the type of house material were included in the analysis. These variables were revealed by households during the interviews as factors they take into account in making their decision. Then, the stepwise selection method was used to determine variables included in the model. This method provides fast and effective way to screen a large number of variables, and to fit logit models simultaneously (Steyeberg et al., 2004). First, all variables were included in the model and assessed for inclusion using resulting p-values. Variables with highest p-value ($p \geq 0.05$) were removed one at a time. Remaining variables were subjected to the same procedure until significant variables were retained while having a significant model. The resulting variables included in the model are presented in Table 1. Information on the variables, description and the corresponding percentage in the data is presented in the Table.

Table 1. Summary of variables included in the model

Variable code and description	Variable categories	Frequency	Percent
TDEC (evacuation timing of households)	evacuated before flood	180	38.7
	evacuated during the flood	285	61.3
TWORK (type of work of the household head)	Part- time worker	156	33.5
	Full-time worker	309	66.5
HOWN (House ownership type)	Rented	114	24.5
	Owned	351	75.5
FLOOR (Number of house floor levels)	1 floor level	284	61.1
	>1 floor level	181	38.9
DIST (Distance from the source of flood hazard)	0-10 meters	283	60.9
	11-20 meters	39	8.4
	21-30 meters	26	5.6
	>30 meters	117	25.2
FLEVEL (level of flood experienced by the household)	< 1 meter	354	79.1
	≥ 1 meter	111	23.9

The correlation matrix, indicating the overall statistical relationship between variables is presented in Table 2. The relationship of departure timing with selected independent variables included in the model is indicated. The correlation between any two variables, r, are calculated by the formula in Equation 7, where x_h and y_h are corresponding variables being investigated for any existing relationship, for household h; and $\bar{x}$ and $\bar{y}$ are the mean values of sample x and y, respectively.

$$r = \frac{\sum_i \left(x_i - \overline{x}\right)\left(y_i - \overline{y}\right)}{\sqrt{\sum_i \left(x_i - \overline{x}\right)^2} \sqrt{\sum_i \left(y_i - \overline{y}\right)^2}} \tag{7}$$

The interrelationships among variables indicate low to medium level correlation. The result in the table indicates that households choose the timing of evacuation based on some characteristics and hazard related factors such as the type of work, the house ownership, the number of house floor levels, distance of house from the source of flood, and flood level. Departure time during the flood is positively correlated with the full-time worker, owned house located at a distance of more than 10 meters from source of flood. On the other hand, departure timing during flood is negatively correlated with number of floor levels (more than one), and the level of flood (greater than one meter). Since the correlation provides information on the effect of only one variable at a time on the departure timing, a binary logit model is estimated in order to evaluate the effects of multiple variables on the departure time choice. The detailed result of the estimation is presented in Section 4.2.

Table 2. Correlation matrix of selected variables

	TDEC	TWORK	HOWN	FLOOR	DIST	FLEVEL
TDEC	1					
TWORK	0.078	1				
HOWN	0.135**	-0.034	1			
FLOOR	-0.209**	0.025	0.014	1		
DIST	0.321**	-0.024	0.110*	-0.273**	1	
FLEVEL	-0.259**	-0.013	-0.049	0.178**	-0.361**	1

*significant at 5% level; **significant at 1% level

4.2 Model's Parameter Estimation

Table 3 presents the estimation results for departure timing. Result here shows the coefficients for the model of households that evacuated during the flood. Evacuation before the flood was the basis for parameter estimation. According to results, the Likelihood Ratio (LR) χ^2 –distributed, is equal to 76.589 with associating p-value of 0.000 which is significant at level of 0.05. This indicates the significance of the model parameters. Therefore, the existence of relationship between the dependent variable and the independent variables is supported. In addition, factors that households take into account when deciding when to evacuate include the type of work of the head of the household, house ownership, the number of floors their house have, distance from the source of flood and the flood level.

The type of work, with coefficient of -0.474 indicate that household heads working full-time are less likely to evacuate during the flood. This means that they evacuate before the flood which is reasonable. They need to secure members of the household before even going to work. Related to findings of Charnkol and Tanaboriboon (2006), private employees were more likely to be in the quick response group. Although the threshold of comparison differs between these studies due to data availability (private/public employment in Charnkol and Tanaboriboon (2006); full time/part-time workers in this current study), similar result is observed.

The house ownership has a negative coefficient of -0.646, which indicates that households that own the house are more likely to evacuate before the flood. This confirms the significant correlation (r = -0.209) between departure timing and house ownership indicted in the correlation matrix in Table 2. Households that own their house could prepare and keep their belongings well ahead of time, secure their homes before leaving the house when compared to those renting. This may be related to security and looting issues as elicited from interviewed households renting their homes. According to them, they do not leave until flooding occurs to ensure as possible their belongings are intact.

On the other hand, the number of house floor levels with coefficient 0.629 shows that households living in a house with more than a floor level have higher likelihood of evacuating, when floodwaters are already in their home vicinity. Also, households that live at a distance of more than 10 meters (farther) from the source of flood are less likely to evacuate during the flood. This is according to the negative coefficient of -0.371. As indicated in the correlation matrix (in Table 2), the medium level correlation between departure timing and distance (r=0.321) is significant at 0.01 level. There is also some level of correlation between floor and distance (r = -0.273). This means that those who are living nearest the source of flood may have built additional floors on their houses so they plan to decide to evacuate only when floodwaters have reached their homes. This can also be observed in the context of the study area and revealed in the interviews. Households nearest flood source mentioned that it is a way for them to adopt to flood risk to build higher floor levels.

Additionally, flood level indicator variable shows a coefficient of 0.771. This is an indication of a higher probability of evacuating during the flood for households that experience flood level more than 1 meter high. This also confirms the significant level of correlation between departure timing and the flood level (r = -0.259) as indicated in Table 2. This indicates the flood risk tolerance of households who decides to wait until their house is at a flood level they could bear before deciding to move to safer places. Table 2 also shows a significant medium level correlation between flood level and distance from the flood source (r=-0.361). This indicates the high flood risk that households located nearer the flood source experience higher flood level. This may also indicate that households nearer the source of flood have been adopting to floods by building higher floor levels as shown by significant correlation between floor and flood level (r = 0.178), hence, significantly influencing their timing of evacuation.

Table 3. Summary of estimated parameters

Variable	Coefficient	Standard error	t-stat	p-value
Constant	0.852	0.364	2.343	0.019
Indicator variable for TWORK (1 for full-time worker, 0 for part time worker)	-0.474*	0.225	-2.106	0.035
Indicator variable for HOWN (1 for households that own the house, 0 otherwise)	-0.646*	0.257	-2.516	0.012
Indicator variable for FLOOR (1 for households with house floor levels more than 1, 0 otherwise)	0.629**	0.225	2.792	0.005
Indicator variable for DIST (1 for households living from source of flood more than 10 meters, 0 otherwise)	-0.371***	0.084	-4.420	0.000
Indicator variable for FLEVEL (1 for households who experienced flood level more than 1 meter, 0 otherwise)	0.771**	0.248	3.108	0.002
Number of observations		465		
LR (χ^2) (5)		76.589		
Prob > (χ^2)		0.000		
Pseudo R-squared		0.123		
Log likelihood at convergence		-272.061		
Log likelihood at 0		-310.356		

*significant at 5% level; **significant at 1% level; ***significant at 0.1% level

The factors found here to affect the evacuation timing such as the distance of house location from the source of flood, house number of floors and flood level, indicates that households put importance on hazard-related factors when making their evacuation time decisions.

4.3 Validation of Model Specification

The ability of the model to discriminate, measured by the AUC which is equal to 0.744 with correct classification rate of 76%. This indicates acceptable level of discrimination according to the general rule outlined by Hosmer and Lemeshow (2000). In order to further statistically investigate the validity of the model specification, an LR based test employed. The objective of performing the LR is to test if there is no significant difference between the parameters of the model estimated using parts of the whole data. This is the null hypothesis, which when failed to be rejected, establishes the validity of the model specification.

The procedure as detailed in Hasan *et al.* (2013) and Sadri *et al.* (2014b) is employed in this study. The whole data of 465 observations which was used to estimate the model as presented in Table 3 is randomly divided into two parts. The two partitions are named here as sample 1 and sample 2, respectively. The two separate partitions were used to estimate separate models with the same specifications. Then the log-likelihood at convergence is recorded for each estimation result. The LR is then calculated using Equation 6, where $LL(\beta_{full})$ is the log-likelihood at convergence of the model estimated using the whole data, $LL(\beta_{sample1})$ and $LL\ (\beta_{sample2})$ are the log-likelihood at convergence of the model estimated using sample 1 and sample 2, respectively.

$$LR = -2\left[LL(\beta_{full}) - LL(\beta_{sample1}) - LL(\beta_{sample2})\right] \tag{8}$$

The calculated values for $LL(\beta_{full})$, $LL(\beta_{sample1})$ and $LL\ (\beta_{sample2})$ are –272.06, –135.95 and −131.26, respectively. From these values, LR is equal to 9.68. LR is χ^2 distributed with degrees of freedom equal to 5. Since the critical value of χ for 5% level of significance or 95% level of confidence and degrees of freedom equal to 5, $\chi^2_{0.05,\,5}$ is equal to 11.07, the null hypothesis is failed to be rejected. Hence, the validity of the specification of the model is supported.

5. SUMMARY, CONCLUSIONS AND FUTURE RESEARCH

The occurrence of hydro-meteorological hazards such as floods can be expected in advance, impacts estimated, hence certain level of preparedness could be done. Evacuation is one effective measure to move people at risk to safety before a disaster strikes so that impacts of future disasters could be minimized. At the level of authorities, planning for evacuation is a way to identify the best strategy for the most probable disaster scenario. In doing this, modeling is helpful in taking into account complexities involved in decision making processes. Evacuation modeling can be applied to obtain a better understanding of the network conditions and the effect of traffic regulations and control measures hereon, by predicting departure and arrival patterns, travel times, average speeds, queue lengths, traffic flow rates, among others. Understanding evacuation timing behavior of evacuees is one important subject that government officials need to know in order to decide when to issue emergency evacuation orders.

Evacuation timing behavior has been mostly analyzed using response curves using traffic data during evacuation. However, using the response curve do not provide disaggregate information which are important for capturing behaviors that could allow planners to design appropriate evacuation strategies. Therefore, understanding decision making in terms of evacuation timing is needed as fundamental analysis for better evacuation planning and management (e.g. Pel *et al.*, 2011; Li *et al.*, 2013).

This study was conducted to understand the evacuation timing behavior of flood evacuees. Data were gathered from household heads in selected sub-districts in Quezon City, Philippines. Using these data, a binary logit model was estimated. Findings from the model also contribute to a better understanding of household evacuation timing behavior. Several important factors that influence a household's evacuation timing decision is found from our empirical analysis. These factors include the household head's type of work, house ownership, number of house floor levels, distance of house from the source of flood, and the flood level.

Insights for evacuation planning could be derived from results of this study. First, households put importance on hazard-related factors and their security when making their decision to either evacuate before or during the flood. Households that have house with more than a floor level, living very near the source of flood, and those located in areas susceptible to flood level more than 1 meter high, are more likely to evacuate when floodwaters are already in their home vicinity. This indicates the flood risk tolerance of households who decides to wait until their house is at a flood level they could bear before deciding to move to safer places. Authorities could design appropriate strategies to encourage those that are living very near the source of flood and have house floor levels more than a floor to evacuate immediately once the government recommended them to evacuate. This can be done by educating and/or providing them with benefits of evacuating earlier such as highly prioritizing them to be moved to secured evacuation centers with provision of vehicles as needed, food, water, medical assistance and other basic needs. Second, since households that own their house, with the head working full time, are more likely to evacuate before the flood, the government can encourage these groups to do the same in future evacuation and involve them in leading evacuation movements. Third, in order to encourage households who are renting their homes to also evacuate well ahead of time, security guards should be provided in areas of residence to keep them from worries of looting and house security. Above all, government officials, when issuing future evacuation advice, should also specify the timing of evacuation by specific groups of households in addition to other evacuation related content of the message (e.g. routes to take when evacuating according to specified destinations such as evacuation centers). The model developed here can be used to predict the number of households evacuating at specific timing which can be utilized to plan for staged evacuation movement in the future.

This study is subjected to couple of limitations. First, evacuation analyzed in this study considered only those at high flood risk areas. Households who were recommended to evacuate or those who voluntarily evacuated should also be taken into account. This has some implications in network traffic conditions during evacuation. Future studies could also include modeling departure time choice based on their actual evacuation timing for better understanding of the distribution of evacuees at specific time interval within the given evacuation time period.

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