Analysis of Inter-City Travel Behavior in Metro Manila during Flooding

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Abstract: This paper presents the results of a preliminary survey aimed to characterize inter-city travel behaviour of people during flood events. In the survey, respondents were given four (4) travel choices for the flood event. Results show about 91% of the total respondents (n=159) were stranded and waited for conditions to improve while others continued to travel. Results also showed the absence of alternate travel plans which might explain the lack of response in mode or route changes. A binomial logit model was developed to determine the factors that affect inter-city travel behaviour during flood events. The model showed that trip purpose, flood experience, main public transport mode used, flood height, and travel distance are related in making a travel decision during flood events in Metro Manila.

Keywords: flooding, choice modelling, Metro Manila

1. INTRODUCTION

Growing and developing metropolitan regions face challenges of meeting daily transportation demands of travellers within the region. Each transport solution would have a corresponding impact which often manifests in the form of changes in travel behaviour. As such, it is important to have an idea of how travellers react or respond to any new transport proposal or how they adapt to certain system changes which may be caused by environmental conditions.

Travellers also respond to the varying conditions of transportation networks. For example, changes in traffic conditions would make certain travel options more attractive than the usual. The increasing attractiveness of certain travel activities may result in changes in travel demand for certain transport modes or travel routes.

It has been established in the literature that travel behaviour, transit ridership, and traffic conditions are affected by different weather conditions (for a review, the reader is referred to Böcker, Dijst, & Prillwitz (2013)). This paper aims to explore the effect of flooding to travel behaviour in inter-city travels in Metro Manila.

Flooding is a major issue felt all over Metro Manila especially during rainy seasons. Heavy rain cause flooding in areas and are known for causing property damages, fatalities, and injuries. Aside from this, flood waters are also responsible for disrupting transportation network and public transit services. In this event, passengers may get stranded or wait until flood waters have subsided. Meanwhile, most travellers are affected by an increase in overall travel times. A significant increase in waiting times at terminals due to lack of transit services and very congested transport vehicles are also observed.

Travelers in the urban area are faced with complex travel decisions involving their choice of mode, time of departure, selected route, for their morning and afternoon trips. These decisions often vary depending on the characteristics of the traveller, the household s/he belongs in, and the environmental conditions. It is not new that Metro Manila often experience flooding due to monsoon rainfall or tropical cyclones and faces several transport issues. However, it is significant to explore how travellers respond to the changes in travel conditions and how these responses differ in traveller characteristics. A better understanding of the impact of flooding is useful in the hope of further improving transportation system performance even during disruption events.

The structure of this paper is as follows: Section 2 discusses the relevant literature. Section 3 briefly describes the methodology. Section 4 summarizes the results of the preliminary survey and the developed binomial logit model. Section 5 concludes the paper.

2. LITERATURE REVIEW

2.1. Transit ridership, travel behaviour, and weather conditions

This section briefly discusses the effects of weather conditions to travel behaviour and transit ridership. In Spain, public bus trips for leisure, shopping, and personal business decreased due to wind and rain and increased when temperature rises (Arana, Cabezudo, & Peñalba, 2014). The authors used actual transit ridership data and used multilinear regression to establish the relationship between variables. Meanwhile, a group of researchers in Australia analysed the relationship of weather to transit ridership. The best model that they developed includes season, daily weather variations, and whole-day rainfall accumulation as variables in a regression model to explain localised investigation area ridership (Kashfi, Bunker, & Yigitcanlar, 2016).

In the analysis of travel behaviour, discrete choice models were often applied. A study of flooding and travel behaviour was done by performing stated choice experiments to examine differences in attitudes and responses to flooding and extreme weather in coastal and inland locations in Bangladesh. Results showed that road disruption, isolation by flood waters, and frequency of flooding are significant in travel behaviour choice (Lu, Zhang, Peng, & Rahman, 2014). The authors noted that common responses to travel disruptions are trip cancelations and changed destinations.

Weather conditions and trip purpose were also considered in the study of Cools, et al (2010). The authors made use of a stated adaptation approach wherein the choice sets are made of two or more attribute profiles and respondents are asked to choose the profile they like most. Travel behaviour changes were characterized in this study as changes in transport mode, the timing of the trip, the location where activity is performed, trip route, and cancelling of the trip. Their results show that for weather disturbances, rain influences timing changes, cancellation of shopping and leisure trips. Further analysis shows that changes in time of departure, locations, and cancellation of trips significantly depend on trip purpose (Cools, et al 2010).

The effect of extreme weather conditions to long distance travel behaviour was studied by Zanni & Ryley (2015). A binomial logit model was used to show the general cautiousness of travellers during extreme weather events. Results showed that a slight majority of air and public transport travellers did not considerably alter their travel plan after a disruption. It was also established that business trips are more flexible given that in such trips, companies usually cover travel costs. Significant factors in the binomial model were origin, destination, and presence of children. It should be noted that age did not have a significant effect on the model.

Finally, the study of Khattak and De Palma (1997) analysed the impacts of adverse weather conditions in Brussels. It was noted that a high percentage of respondents reported that weather has a strong influence on departure time change compared with route and mode. Departure time changes often reflect the time flexibility of individuals. It was established that those who have a low propensity in changing their departure times often drove alone and are constrained by family commitments. Meanwhile, those who have lower flexibility in work arrival time and longer travel times have higher propensities to change their departure times. The results of their study showed the importance of travel information and suggested that having accurate travel information can influence travel decision in both normal and adverse weather conditions.

The papers mentioned in this section generally show that effect of adverse weather conditions to travel behaviour and transit ridership. It shows the difficulty being experienced by travellers as they are often forced to adapt by making new travel choices. It was shown that some of the choices are changing their travel modes or routes, departure times, and trip cancelations. It was established that these decisions vary depending on the individuals' trip purpose, travel characteristics, and socio-demographic characteristics. This paper aims to perform a discrete choice analysis of the changes in travel behaviour during flooded conditions.

2.2. Discrete Choice Analysis

Discrete choice occurs when respondents select an option from a set of alternatives. In general, discrete choice models postulate that *"the probability of individuals choosing a given option is a function of their socioeconomic characteristics and the relative attractiveness of the option."* (Ortúzar & Willumsen, 2011)

The attractiveness of the alternatives is represented through the concept of utility. The utility of an alternative is derived from its characteristics and those of the individual. The Random Utility Theory is the most common framework of discrete choice models. This theory states that each individual act rationally and possess perfect information will select an option that maximizes their personal utility depending on different constraints. The theory assumes that the choice set of is already predetermined and the effects of the constraints have been taken care of. Since the analyst do not have complete information about all factors considered by the individual in making a choice, it is assumed that the utility is represented by two components: a measurable, systematic, or representative part (V_{jq}) and a random part (ε_{jq}) that reflects the tastes of individuals and errors made by the analyst. Hence, the utility equation:

$$U_{jq} = V_{jq} + \varepsilon_{jq} \tag{1}$$

Each individual q then selects the alternative which gives the maximum utility. It is understood that non-selected alternatives have lower levels of utility. The inclusion of the random error means that the choice now becomes probabilistic. Through this, the alternative with the highest observed utility shall have the highest probability of being chosen.

3. METHODOLOGY

3.1. Data Collection

Data was gathered using a questionnaire survey. The main purpose of this survey is to (1) characterize inter-city travellers in terms of their personal and travel characteristics; (2) have an idea of their flood experiences, and (3) evaluate the factors that affected their travel choice during flooded condition. The questionnaire had two parts:

(a) *Previous flood experience and travel attributes:* frequency of flood occurrences, details about recent flood experience (flood height, flood location, and flood duration, travel details in the event the flood occurred (origin, destination, trip purpose, travel group, travel frequency, time of departure, usual travel cost for the journey, usual travel time), travel decision during flood event and corresponding travel details

(b) *Socio-demographic characteristics:* age, gender, civil status, educational attainment, occupation, and individual monthly income

The pilot survey was conducted in pre-determined locations in Manila and Quezon City to capture inter-city travels. In this study, inter-city travel is defined as travel whose origins and destinations are different from each other. The focus on inter-city travels was selected to target public transport trips that would be heavily affected by a flood disruption event. Surveyors were positioned in the morning and afternoon on March 2015 along Monumento, Pedro Gil, North EDSA, and Quezon Avenue. In this pilot survey, a sample of 159 validated survey forms was collected and analysed.

3.2. Model estimation

Initially, there are four travel choices presented in the questionnaire. The four travel choices are: continue with travel (same as normal conditions), continued using a different mode or route, waited for conditions to improve, and stayed home for the day. Since all responses were limited to two choices (continue travelling as usual and wait then travel later), a binomial logit model was developed. In the model generation stage, the software NLOGIT 3.0 was used.

4. RESULTS AND DATA ANALYSIS

4.1. Descriptive statistics

The descriptive statistics of the socio-demographic characteristics are summarized in

Table 1. The majority of the respondents are male and single. Note that the sample sex ratio is different in the actual population (1.02). This is understandable considering that this is just the results of the pilot survey. Respondents are aged between 17 and 58. This implies that

majority of the respondents are employees and earns on their own. This is also important since the target sample of the survey are commute trips (from home or to home). The average individual monthly income is around P18,500 (which falls slightly above minimum wage level).

Table 1 Descriptive statistics of survey respondents (n=159)

Gender		**Civil Status**	
Male	*60.4%*	*Single*	*64.8%*
Female	39.6%	Married	35.2%
Individual Monthly Income			
less than P5,000	15.1%	P20,000 to P29,999	16.4%
P5,000 to P9,999	3.1%	P30,000 to P39,999	9.4%
P10,000 to P14,999	*25.8%*	P40,000 to P59,999	5.0%
P15,000 to P19,999	*25.2%*	**Average**	**P18,522.01**
Age			
Minimum	17	**Average**	**30.31**
Maximum	58		

Table 2 shows the summary of the most recent flood experience of the respondents. It was shown that respondents experience flooding annually. This is significant and somehow strengthen the need for resilient transport in Metro Manila. However, during the last 5 years, respondents perceived that their flood experiences have decreased. This could be true especially if respondents used past extreme flood events (Ketsana/Ondoy – 2009; Monsoon rains – 2012 & 2013) as reference. The decreased flood event perception might also reflect the positive impact of the additional flood control infrastructure and improved weather and flood reporting systems implemented by the government. Finally, the majority of the respondents who have experienced floods noted ankle-height floods that normally lasts for about an hour.

Table 2 Flood experience of respondents

Flood experience of respondents		**Changes in flood experiences over recent years**	
Once a year	38.4%	No change	20.1%
2-5 times a year	*58.5%*	Increased	8.2%
More than 5 times a year	3.1%	*Decreased*	*71.7%*
Experienced flood height		**Flood duration**	
Ankle and below	*69.8%*	*Less than an hour*	*83.0%*
Above ankle to knee	27.7%	1 to 3 hours	16.4%
Above knee to waist	2.5%	3 to 5 hours	0.6%

It was mentioned earlier that only two (2) of the 4 choices were chosen by respondents. Continue traveling was selected by about 9% of the respondents while the remainder reported being stranded and waited for conditions to improve. The absence of responses to change in transport mode or route and trip cancellation could be attributed to the hesitance of respondents in altering their usual travel patterns. Misunderstanding between the respondent and the surveyor during the survey process should not also be ruled out. For example, what qualifies as ‘being stranded’ and how it differs from a respondent leaving their origin and was not able to access public transportation.

It is also important to note that all respondents use only a single route for their journeys. In Figure 1, there are several reasons why travellers only use a single route. 75% of these respondents said that this single route was either the only route they know or the only route available to them. Lastly, about 50% of those who got stranded and waited had trouble of boarding transport vehicles because they are full. Another reason for experiencing long waits is unavailable or lacking transport services during the flood event. Overall, the results suggest the limited adaptive capacity of the traveller during traveller due to limited travel options.

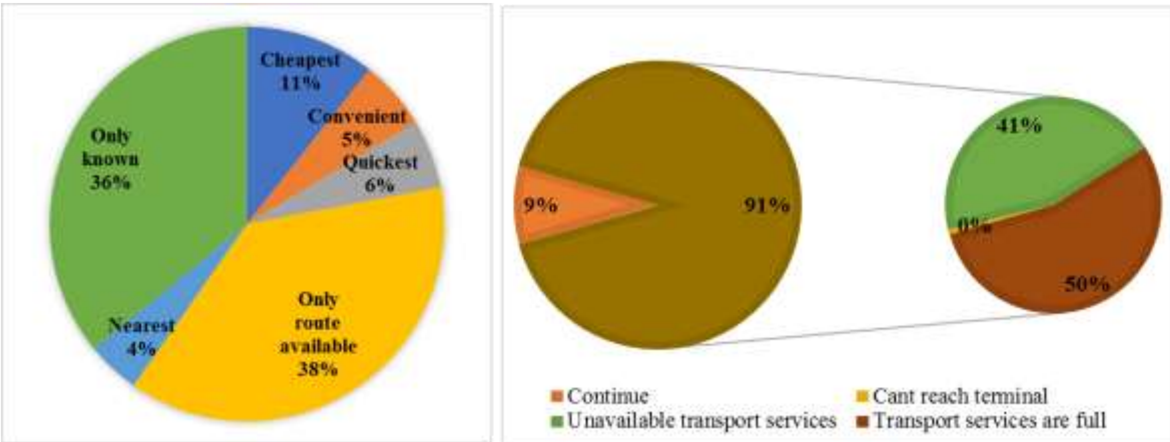

Figure 1 Respondents' reasons for only having one route and for being stranded

4.2. Binomial Logit Analysis

Binomial logit models were estimated using NLOGIT3.0. A base model was first estimated wherein only the alternative specific constant was included. The log likelihood function for this model was estimated as -47.3826. Various binomial models were estimated using different variables. The variables used in the final model estimation are tabulated in Table 3.

Table 3 Variables used in final binomial models

Variable	Description
A_A	Alternative specific constant for *continue travelling as usual* (Choice A)
AxTOW1	*Trip purpose* Dummy variable (1 – to work; 0, otherwise)
AxINC1	*Flood experience* Dummy variable (1 – increasing; 0, otherwise)
AXJEE1	*Main mode used* Dummy variable (1 – if the main mode is Jeepney; 0, otherwise)
AXBUS1	*Main mode used* Dummy variable (1 – if the main mode is Bus; 0, otherwise)
AXUVM1	*Main mode used* Dummy variable (1 – if the main mode is FX/UV; 0, otherwise)
AXRAI1	*Main mode used* Dummy variable (1 – if the main mode is Rail; 0, otherwise)
AxANK1	*Flood height* Dummy variable (1 – if ankle level and below; 0, otherwise)
AXKNE1	*Flood height*

	Dummy variable (1 – if above ankle to knee level; 0, otherwise)
AXSHO1	*Travel distance* Dummy variable (1 – travel distance is more than 5.0 kilometers; 0, otherwise)

The variables used in the final model were a result from initial models that used trip purpose, modal use, flood experiences, and transfers as variables. All variables used in the model were dummy variables as not all attributes were considered to have a linear effect on the choice parameter. The variables in the final model consider the purpose of the trip, flood experience perception, and travel characteristics of the respondent. As these variables are invariant across all alternatives, these would only appear on the first utility equation which pertains to the travel as usual option.

Table 4 Base and final binomial models

	Base Model		Model 1		Model 2	
Variables	**Coeff.**	**p-value**	**Coeff.**	**p-value**	**Coeff.**	**p-value**
A_A	-2.338	0.000***	-3.7848	0.0002***	-4.6000	0.0120**
AxTOW1			2.2163	0.0130**	2.1340	0.0179**
AxINC1			2.3466	0.0105**	2.6391	0.0082***
AxJEE1					3.1535	0.0105**
AxBUS1			-3.0113	0.0121**		
AxUVM1			-1.2362	0.3247	1.8613	0.2426
AxRAI1			0.0756	0.9669	0.4902	0.7918
AxANK1			2.3226	0.0259**	-0.0430	0.9772
AxKNE1					-3.2556	0.0850*
AxSHO1			-2.4675	0.0134**	-2.4100	0.0155**
No. of estimated coefficients	1		8		9	
LL function	-47.383		-31.4968		-30.0893	
$-2\left(L(c) - L(\hat{\beta})\right)$			31.7716		34.5865	
Degrees of Freedom			7		8	
χ^2 Critical value (α = 0.05)			14.0671		15.5073	
Equality Expression			31.7716 > 14.0671		34.5865 > 15.5073	
Findings			Reject H_0		Reject H_0	
Log Likelihood Value	-47.383		-31.4968		-30.0893	
R-squared (NLOGIT)	0.57007		0.7142		0.7270	
Corrected R-squared			0.6991		0.7160	
Pseudo-R^2			**0.3359**		**0.3650**	

**p<0.1*
***p<0.05*
****p<0.01*

Going over the coefficients for the models, A_A, AXSHO1, AXBUS1, and AXUVM1 were negative for model 1. A_A, AXANK1, AXKNE1, and AXSHO1 were negative for model 2. Consistency in signs was observed for the trip purpose (AXTOW1), increased flood experience (AXINC1), main mode rail (AXRAI1), and short travel distances (AXSHO1) for both models. Generally, the sign of the coefficient gives information to the analyst if the attribute increases or decreases the overall utility.

Analysing the trip purpose (AXTOW1) variable, the positive coefficient suggests that travellers going to work do not make changes in their travel arrangements. Employees are considered less flexible with their time and compel them to travel at whatever condition because getting to their workplaces are important. Flexibility in travel have a significant impact on changes in travel behaviour as reported in the studies of Khattak & De Palma (1997), Marsden, Anable, Shires, & Docherty (2016), and Zanni & Ryley (2015).

An increased perception in flood experience increases the utility of the *continue as usual* alternative. This positive sign could mean two things: (1) increased flood events made the traveller more experienced and more aware of possible areas or services that are affected to flood, or (2) increased flood events made travellers more aware of the negative impacts of flooding which may influence their decision to travel as soon as possible.

Flood heights were modelled differently in models 1 and 2. In model 1, ankle level floods showed a positive utility for the *continue as usual* alternative. Although positive in value, its coefficient is very minimal and only has a small effect on the overall utility of the alternative. In contrast to model 1, model 2 considers knee and above knee level flood heights. This was considered since increasing flood heights may decrease the travel as usual alternative. Both models suggest that ankle level flood height increases the utility of the continue as travel alternative. Although model 2 has better explanatory power than model 1, log-likelihood tests showed that introducing another flood dummy variable did not make it superior to model 1.

The main mode used and travel distances were analysed in the models to show the effect of the respondent's travel characteristics in their travel behaviour. The main mode was determined by obtaining the mode wherein the traveller spent the largest amount of time during their travel. The modes were modelled as dummy variables since it does not have a linear effect to the choice alternatives. Modelling the main modes used gives a sense of hierarchy of transport modes during flood events. Looking at the coefficients for the main modes, it shows that travellers who use the bus have the greatest disutility for the travel as usual alternative. It is then followed by UV Express (FX), jeepneys, then rail. This ranking could be attributed to the fact that the main mode was determined from travel times. The result may suggest that travellers who spend a significant amount of time for travel in buses are more likely to wait until conditions improve than other modes. Furthermore, this may also reflect the operating differences between these modes, especially during flood disruptions. As an aside, it is important to note that some main mode transport dummy variables were insignificant due. This could be due to the limited samples in the survey.

Short travel distances were defined as those who have travels that are less than five (5.0) kilometres. The short travel distance variable considers the minimum travel distance used in base fares and acceptable walking distances for access and egress. In both models, the AXSHO1 variables are negative. This could suggest that travellers are more flexible with their travels when travel distance is less than or equal to 5 kilometers. Travels longer than 5 kilometers might force travellers to leave as soon as possible to avoid the extent of travel disruption.

Finally, socio-demographic characteristics were not considered in the model as they were insignificant. This could still be a result of the low sample size and under-sampled values for the *continue as usual* alternative.

5. CONCLUSION

From the binomial logit model, variables related to trip purpose, flood experience, and travel characteristics have an influence on travel decision-making of individuals during flood events. Trip purpose, flood experience, and short travel distances were consistent with the developed binomial models. In the case of main transit mode used, a hierarchy was observed for the travel as usual alternative.

The model describes the decision-making of inter-city travellers in Metro Manila in the event of a flood. From the models, travellers who are going to work and have increased perception in flood occurrences over recent years are more likely to continue traveling as usual. Individuals who travel less than five kilometres are more flexible which allows them to stay for a period and travel when conditions are acceptable. For flood heights above ankle levels, road-based public transit services are severely affected and resulted to larger disutility for the continue as usual alternative. This implies that improvements in road-based public transit services or operations should be sought. Analysis of the main mode suggests that travellers who used buses as their main mode are least prone to travel as usual. This result may suggest that bus users are severely affected during this condition because of a large amount of travel time spent in this vehicle. Furthermore, the hierarchy highlights the differences in operating conditions of the travel modes in Metro Manila during the disruption. This could be used as a focus for policy makers in improving the robustness of the transportation network.

Considering that this research is in its preliminary stages, there is still a large amount of data that could be analysed. As a future step for this research, it is recommended to analyse the factors that would influence decision makers to try other travel options given that *wait for conditions* to improve was oversampled.

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