Modeling Of Students Travel Behavior During Class Suspension Due to Bad Weather

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Abstract: Yearly, the Philippines experiences heavy rainfall, resulting to flooding. In this circumstances, everybody is put to risk and vulnerable when commuting. Understanding students' behavior and decision making are still unclear during and after a heavy rainfall and flooding. This study modelled and tried to understand the general decisions made by tertiary students in the city of Manila during heavy rainfall and flooding such as route choice, go home decision and others. Trend on the decision was investigated including the selection of important explanatory variables that affect the decision. Results showed that 30% of the sample would most likely to remain in school during heavy rainfall and flooding and 70% would go home immediately after a class suspension. The study uses discrete choice to identify significant variables that affect the choice of students. When bad weather scenario is compared under normal scenario, travel time, waiting time were seen to increase drastically.

Keywords: Discrete Choice Modeling, Disaster Related, Travel Behavior

1. INTRODUCTION

In Metro Manila, there is a systematic process laid by the Department of Education (DepEd) and Commission on Higher Education (CHED) regarding the suspension of classes during inclement weather. For tropical cyclone impending to hit the locality, automatic suspension for preschool level is enforced when Public Storm Warning Signal No. 1 (PSWS#1) is issued by the official weather agency of the Philippines, PAGASA (Philippine Atmospheric Geophysical, Astronomical Services Administration). Elementary and secondary levels are suspended when Public Storm Warning Signal No. 2 is raised. Colleges and work are suspended when Public Storm Warning Signal No. 3 is enforced. PAGASA normally issues cyclone bulletin every 6 hours (5AM, 11AM, 5PM, 11PM) when there is an impending typhoon.

When it comes to heavy rainfall events, there are no guidelines on implementing automatic suspension. The Department of Education has authorized local government units and school heads to suspend the classes if they feel it is unsafe to conduct such activities (DepEd, 2008). There are instances where students were asked to attend classes in the morning then a sudden suspension is called in the afternoon during or after a heavy rainfall event.

An example of this scenario happened in 2013 of mid-July. Unexpected rainfall amounts fell over the metropolis and surrounding provinces during the day, prompting the immediate suspension of classes by noontime. Students were dismissed immediately, but clogged the transportation network system of the metropolis. The immediate release of students and staffs added to the demand on that hour as road capacity continues to fall as roads start to be inundated by floods.

Several people got stranded on their way home as floods partially/ fully submerge the road networks. Transportation modes were rendered useless due to the unexpected flood heights. Train operations were grounded, as the operator suspended the services which leave people clueless on how to go to their respective destinations. PNR suspended its' operation since PNR trains run on the ground which are also flooded. On the other hand, LRT is operational but its ground stations such as Roosevelt, 5^{th} Avenue and Balintawak Stations are flooded (LRTA, 2013) which is rendered useless also for commuters since people were unable to get down on the stations. There were also reports of injuries and deaths of students and other people due to electrocution as they cross the flooded roads in Espana Avenue in the city of Manila.

In order to alleviate the situation the Department of Public Works and Highway (DPWH), has devised plans to lessen the effects of the flooding in the Metropolis (DPWH, 2015), but until now it is far from being completely done and operational. On the other hand, MMDA (Metropolitan Manila Development Authority) has no intensive studies yet regarding heavy rainfall scenarios on its transportation network. There is also limited studies regarding the possible routes that can be used when a particular amount of rain has fallen.

2. LITERATURE REVIEW

2.1 Exceptional and Unwanted Scenario

Studies concerning exceptional scenario in the past uses the same traffic simulation under normal condition. Both scenarios uses all four (4) basic step transportation model. Though there is a major difference when it comes o decision making (Setunge et al. 2014). Most of the studies done in the past and until now are modelling of traffic and commuter's behavior under a normal weather condition. When an exceptional event happens such as flooding or massive evacuation, congestions is likely to happen at a different level (Pe et al, 2010 and Bujed, 2014). It is also expected to change the travel behavior as well as the supply of the network and infrastructure (Hoogendoorn, 2009), thus making it essential to model the behavior and operation when it occurs. Few studies have been conducted where the scenario is under an unwanted event such as disaster and terrorist attack, which occasionally happens.

Table 1. Hazard Type and Potential Effects and Impacts (Source: FHWA)

Hazard Type	Possible Impacts and Effects on Road Operation, Capacity and People
Strong Winds	- Debris blown by strong winds can block the roads, which lessens the capacity and performance.
Precipitation	- Visibility is to decrease, which tends for driver to slow down - Lessens the friction of the roads, which tends for driver to slow down
Flooding	- Reducing road capacity due to inundation

Weather impacts the operation and capacity of roads, mobility, and as well as the choice of people towards different transportation option, which includes route and mode choice, behavior and trip generation, according to past studies conducted and collected by Federal Highway Administration (FHWA, 2015). Traffic speed, flow, travel time and accident risk is expected to be affected as adverse weather affects the network (FHWA, 2015). According to past studies, there is a change in behavior of commuters on whether to take pre trip route or en route. An example of this is the study conducted by (Ahmed et al, 2010) which shows the changes of ridership of bicycles due to different weather hazards (Ahmed et al, 2010). It also affects the modal and route choice of people. Some examples of hazard and its effects from FHWA (Federal Highway Administration, U.S.A.) is seen in Table 1.

In terms of costs, there are additional costs that needs to be included. According to the study of Chang et al (2011), which focuses on the flooding disaster, the cost depends on the severity of the event. The study also categorized the cost into 5 types focusing on the directness and type of sectors (public or government) involved. The following are the types suggested by Chang et al.:

A. **Direct costs towards the government** are additional costs due to immediate effects of the disaster. It considers the damages and other cost such as emergency response cost and repair cost.
B. **Direct costs towards the public** are costs due to immediate effects of disaster towards the individual/ citizens. It includes the health cost and the property damage cost.
C. **Indirect costs** are costs due to the aftermath of the event. This is towards the government and/ or citizens. Under this type, it focuses on the congestion cost, delay cost, loss of economic activities
D. **Tangible costs** are costs to improve the preventive measure against disaster.
E. **Intangible costs** are due to changes of perception of risk by individual.

2.2 Risk Attitude and Behavior

There are many factors that affect the behavior of the commuter; it depends on the situation factor, demographic factors and etc. When an unwanted or exceptional event strikes, it changes the way individual respond and behaves on transportation choice (Otto, 2010) as well as the driving attitude and psychological impacts (Hoogendorn, 2009). In terms of decision-making, we are to consider the type of risk attitude a person has. This is categorized into 3 types: risk averse, risk seeking and risk neutral (Kisky, 2015). This factor is not to be generalized since it depends on how one sees the event. When unexpected events are to be extracted from interviewee, it is important to obtain ones' personal experience and the location's risk (Viscusi and Zeckhause, 2006). Though it was also stated that people has a limited comprehension level when it comes to risk. People may tend to overestimate or under estimate (Gutscher and Siegrist, 2006). This is due to the past experience of the interviewee. Meanwhile, time plays a very big role and influence as well in risk (Hufschmidt et al, 2005).

A study conducted by Song et al (2012) focuses on the selection of emergency evacuation route. The following parameters and characteristics where included in the study as they select important evacuation routes: road condition, intersection density and etc. Song et al considered road condition to be the most influential factor in choosing the route as this influences the comfort and safety of people.

In terms of cost, this is solely dependent on the magnitude, type and duration of the disaster (Chang et al, 2011). According to the study it is classified into 2 types of cost, direct cost and indirect cost. As Chang explained it, direct cost solely came from the disaster's immediate effect.

2.3 Decision Making Flow

In real life scenarios, decision making under disaster conditions is continuous. As presented by Pel et al (2011), it can be presented as a continuous binary logit model as seen in figure 1. This is done in order to simulate the "dynamically" decision making process and travel demand.

Under this type of scenario, the model would continue to split until the respondent chose to evacuate, to stop the process in the scenario of evacuation. Other factors may also play a role in a dynamic decision making process especially the prevailing conditions, current hazard level of the area and etc.

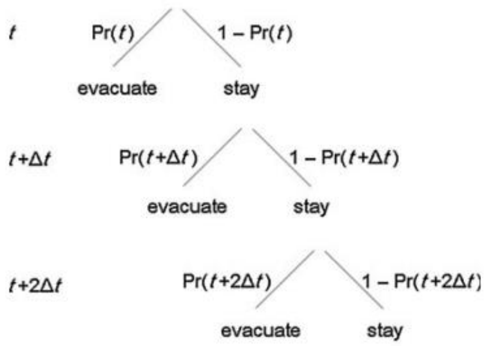

Figure 1. Repeated and Continuous Binary Logit Model by Pel, etal (2011)

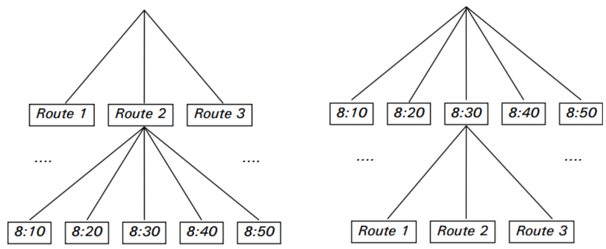

Figure 2. Multidimensional Choice Decision Making by Ben-Akiva (2008)

As also presented by Ben-Akiva (2008), this type of scenario is focused on multidimensional choices where in departure time plays a role in choosing a particular route as presented in figure 2. Under this type of choice scenario, it is then formulated as a continuous nested logit model. The nest can either be the route alternative or the time parameter (departure time).

2.4 Other Studies

Majority of disaster related transportation-modeling studies only cover the evacuation and movement of people. In terms of heavy rainfall and flooding, the scenario usually focuses on the forecast period rather than after the event itself. Lim et al conducted an example, which focuses on the flood evacuation route modeling for sub districts. It uncovers the important explanatory variables and behavior that must be considered in modeling evacuation route and decision (Lim etal, 2015). Some of the variables/ attributes included in this research are the mode used by the people, the departure time, level of education, house ownership and etc. The variables included in the analysis are socio-demographic information of evacuees, some hazard-related and evacuation-related information. It also included personal experiences. Logit models were used in identifying the necessary attributes. It has also introduced some possible routing categories it would be used such as shortest path, familiar path, usual path and etc (Lim etal, 2010).

Another study regarding the commuter's behavior towards the heavy rainfall forecast was conducted in Nagoya prefecture of Japan (Sakamoto et al, 2015). The study finds the relationship of people's behavior towards their trip, focusing more on the return trip. The researcher in the study also used Logit model. Characteristics and attributes such as socio demographics, frequency of information access, and other transportation attributes were considered (Sakamoto etal, 2015).

A study regarding the emergency path selection was done before. Attributes that were included in choosing a path are road quality, safety, time, cost and etc. (Ruan et al, 2012). Other studies include disaster resiliency, mobility, serviceability and evacuation modeling. There were also a handful of researches regarding travel and evacuation behavior before without the inclusion of travel characteristics and attributes in the study.

3. METHODOLOGY

The research focuses on disaggregate modeling; data were collected from individuals rather than by group or zones. Primary data collection were obtained directly from respondents through a questionnaire survey. For this research, primary data were gathered through surveys, which include on-campus survey and online survey using google maps. For the on-campus questionnaire survey, this was administered to students in universities, private or government institution (Manila City Only) through face to face interviews while the online survey was sent to individual students interested to join the study. Personal travel information during god and bad weather were obtained from the respondents and these include the socio-economic characteristics of the individual as well as personal travel characteristics including travel time, usual route taken, cost of travel, type of public transportation used, for both normal and inclement weather conditions. These variables were considered in the choice modeling behavior and experience of the students. Perception of students regarding the situation was also asked.

The city of Manila is the capital of the Philippines, where it is expected to be also the center of education of the country. There are no official list of records of complete institutions available in the database of the CHED website. By looking visually, there are big concentrations of schools in the University Belt Area, then followed by the stretch of Taft Avenue and the least concentration is found in the Intramuros Area. There are also some higher educational institutions not located in any of the cluster. For this study, a total of 1,544 respondents were collected through Internet and paper survey. By approximation, the breakdown of samples from the school clusters are as follows: 10% for Intramuros, 35% for Taft Avenue and 55% for University Belt Area. This is obtained by collecting all the schools listed in the Internet that fell under these three clusters. Some schools were deliberately not considered due to proximity to bigger schools and inconvenience of the surveyor to collect data.

After the collection of survey results, these were processed in a data processing software in order to extract the route, school and personal attributes and characteristics. Since choice modeling is a trail-and-error approach to obtain satisfactory models, simple models were first tested using a choice modeling software with only few route- and school- specific variables considered. This was repeatedly done by adding more variables until a significant combination of attributes and characteristics were achieved. Utility equations of each choice were then developed. Only of the MNL and NL model varieties were developed.

One of the major categories included in the questionnaire was the experience of the student. The set was grouped according to their answer in that question and were compared to each other in the modeling.

Theoretically, it was impossible to recreate the past scenarios especially with lack of information of flood levels and rain intensity in all areas of Metro Manila and nearby provinces. In spite of this problem, a stated preference survey was also included where a hypothetical scenario was formulated by using the flood hazard map by LiDARPH and Project NOAH. Data regarding the flood hazard map came from Project NOAH of Department of Science and Technology (DOST). Detailed flood hazard map of the city of Manila was readily available and was subdivided into three levels, low, moderate and high. The assumption was that all areas under the hazard is being slowly inundated. (First sample would focus on high threat level, thus inundating all high threat areas, while the following samples would include other levels). A 5-year return period was used since this is the smallest year flood return period created by the agency, which recreates and gives the highest probability of mimicking general bad weather in the Philippines.

Risk levels were used in order to deduce different information and turn this attributes into specific decisions, depending on the school and home location of the student. A general trend of risk level types was also provided in the latter part of the study.

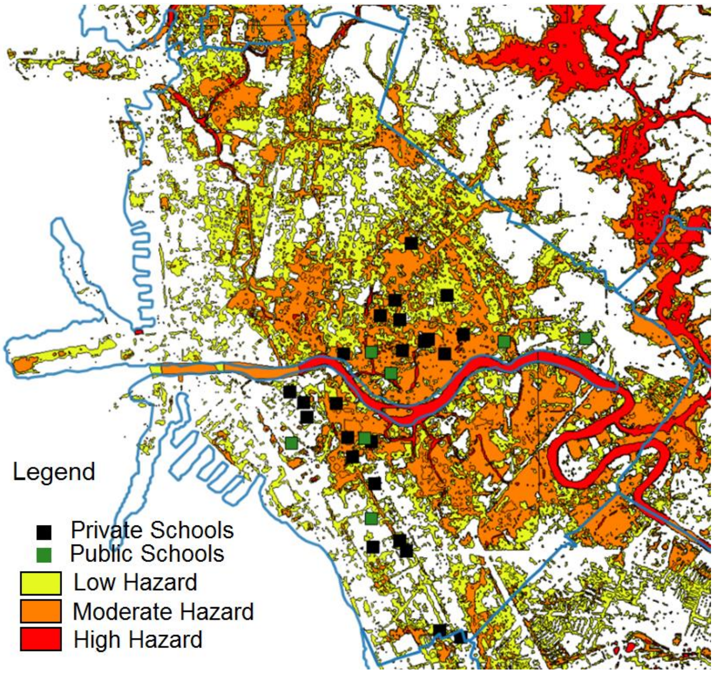

Figure 3. School location overlaid over the flood hazard map

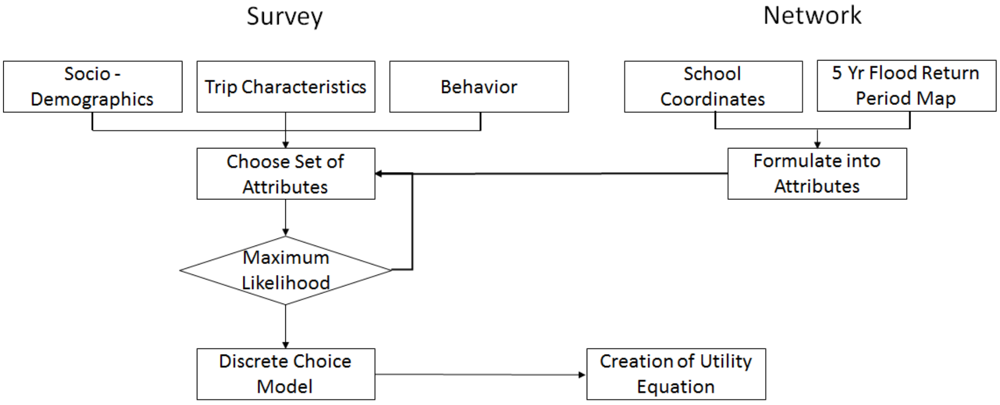

Figure 4. Methodological flow chart of the research

In summary, the following logit models were developed (a) Binary Logit (Usual vs. Alternative Route), (b) Binary Logit (Go Home vs. Stay Model), (c) All Decision Model (MNL vs. NL Model). The restuls of these models are discusses in the succeeding section.

4. RESULTS AND ANALYSIS

4.1 The Variables Considered

The following variables (e.g. mode- and route-related variables and individual-specific and related variables) in Table 2 were considered in the choice modeling process.

Table 2. Variables considered in choice modelling process

Variable	**Model Name**	**Description**
Mode- and route-related variables		
Constant	ASC	Alternative-specific constant
Travel Time	TOTTIME	Total travel time (minutes) of a student from school to home
No. of Transfer	TRANSFR	Number of transfers using public transport
Wait Time	WAIT	Waiting time (minutes) before riding a vehicle from school to home after classes are suspended
School Wait Time	SCHWAIT	Waiting time (minutes) inside the school campus after classes are suspended before deciding to go home
Individual-specific and related variables		
Flood Height	FLODHT	The usual flood height encountered by the student along the route from below ankle to chest deep (in inches)
Try Alternative Route	TRYALT	A dummy variable indicating if the student have tried another alternative route, 1 if tried, 0 otherwise
Risk Seeker	SEEKER	A dummy variable, 1 if risk seeker, 0 otherwise. A risk seeker is aware of the possible risk, but will continue to travel
Risk Averse	AVERSE	A dummy variable, 1 if risk averse, 0 otherwise. A risk averse is person who wanted to be safe than to be sorry, thus will not gamble with the risk
School location in a Hazard Area	HAZARD	A dummy variable, 1 if school is located in a hazard area, 0 otherwise
From Province	PRVNC	A dummy variable, 1 if home location is from the province, 0 otherwise
Decision is by self	DECME	A dummy variable, 1 if decision is influenced by self when deciding to go home or stay put, 0 otherwise
Decision is influenced by friend	DECFRI	A dummy variable, 1 if decision is influenced by a friend when deciding to go home or stay put, 0 otherwise
Decision is influenced by news report	DECNEW	A dummy variable, 1 if decision is influenced by a news report when deciding to go home or stay put, 0 otherwise
School is from University Belt	UNIVB	A dummy variable, 1 if the university of the student is located in the University Belt area, 0 otherwise

4.2 Risk Breakdown

Respondents were asked to assess themselves on which type of risk attitude they fall in. This research categorized the risk behavior into three (3) types: risk seeker, risk averse and risk neutral as defined by Otto (2010). *Risk Seekers* are people who are aware of their risk but would continue to travel. *Risk Averse* are people who wanted to be safe than to be sorry, thus would not gamble with the risk they know. Lastly, *Risk Neutral* are people who are in between these two types. The breakdown of risk attitudes is shown in figure 5. Majority of the respondents categorized themselves as risk averse; risk seeker then follows this category. About 10% were risk neutral. This is an important attribute to be used in the model, which falls under categorical variables.

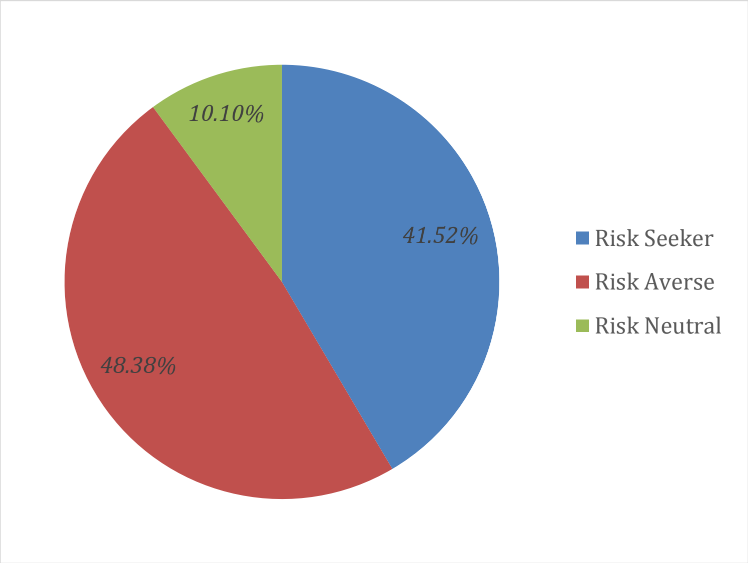

Figure 5. Risk type breakdown

4.3 Disaster Related Variables

One of the most important variables in this research is the usual flood level being experienced by the respondent during bad weather. In this kind of situation, it is easy for people to remember the usual flood level they encounter when commuting. Figure 6 shows the distribution of the usual inundation level encountered by students when commuting. More than half of the respondents who took part of the survey almost always experience ankle level floods with 52.66% of the total sample. This is followed by Knee Level (39.05%), Waist Level (4.92%), Below Ankle Level (2.78%) and Chest (0.58%). No one answered above person flood level.

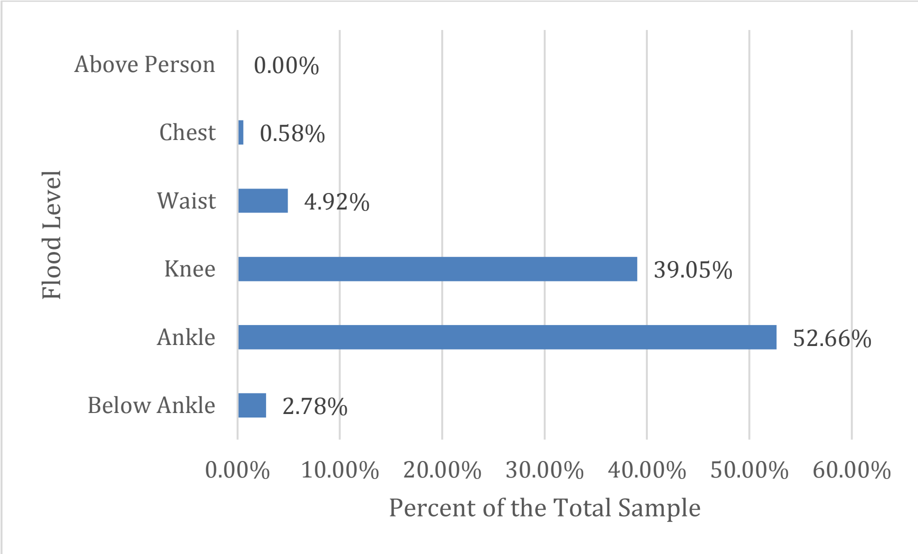

Figure 6. Flood level encountered distribution taken from the survey

Respondents were also asked about their willingness to go home or stay depending on the flood level. As shown in Figure 7, majority of the students are willing to go home immediately after suspension as long as the flood level is within ankle level and below. More than half of the total respondents are said to stay at school if the flood level hits knee level. This is then followed by ankle level. There are responses who chose to go home and to remain at the same flood level indicating a 50-50 chance of doing the said action.

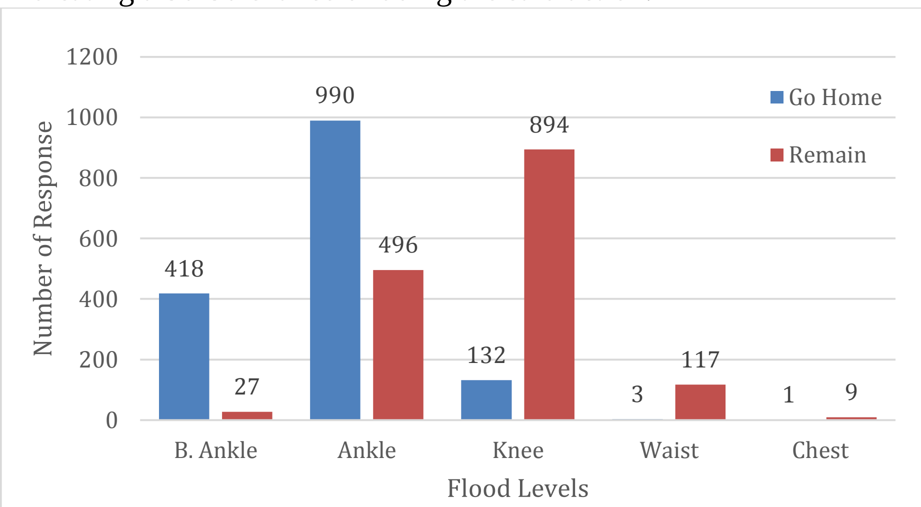

Figure 7. Students' willingness to go home/stay

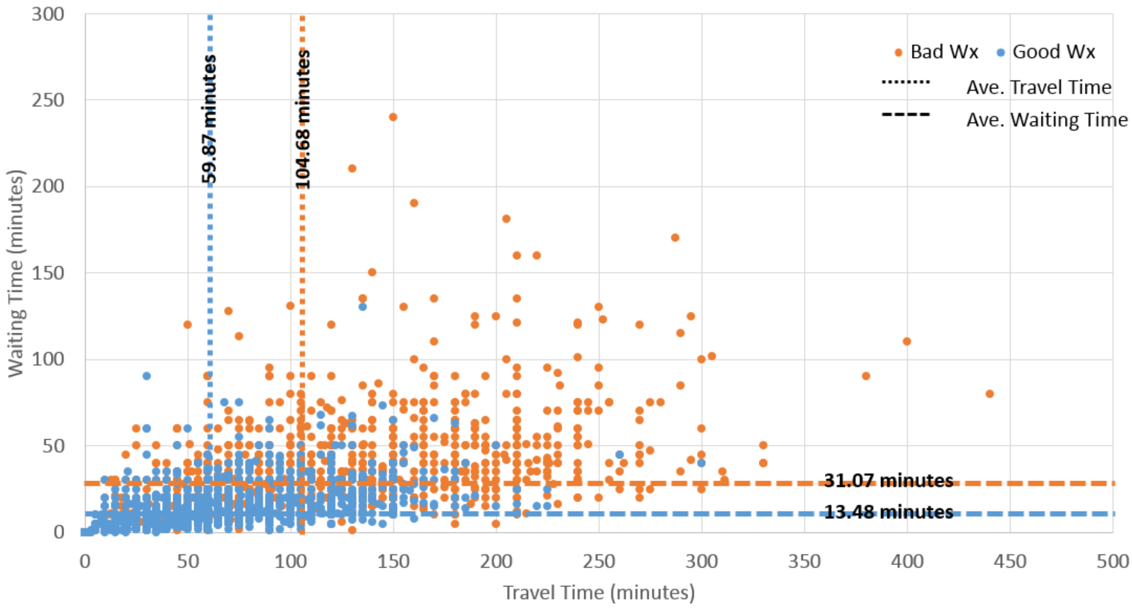

Figure 8. Data plots of waiting versus travel time of good and bad weather (Wx) scenario

When good and bad weather scenario travel variables are compared, it is evident that there is a higher waiting and travel times for bad weather condition. This can be also seen using the average line of the travel and waiting times. As shown in figure 8, people tend to wait more and travel more as the weather condition changes from good to bad. Averagely, about 44.709 minutes additional travel time increase is seen and 17.504 minutes waiting time is added from people's travel. This finding strongly supports the theory of change in capacity and demand of roads and other transport infrastructure (Hoogedorn, 2009) as the condition changes from normal to unwanted scenarios, since there is longer travel time recorded.

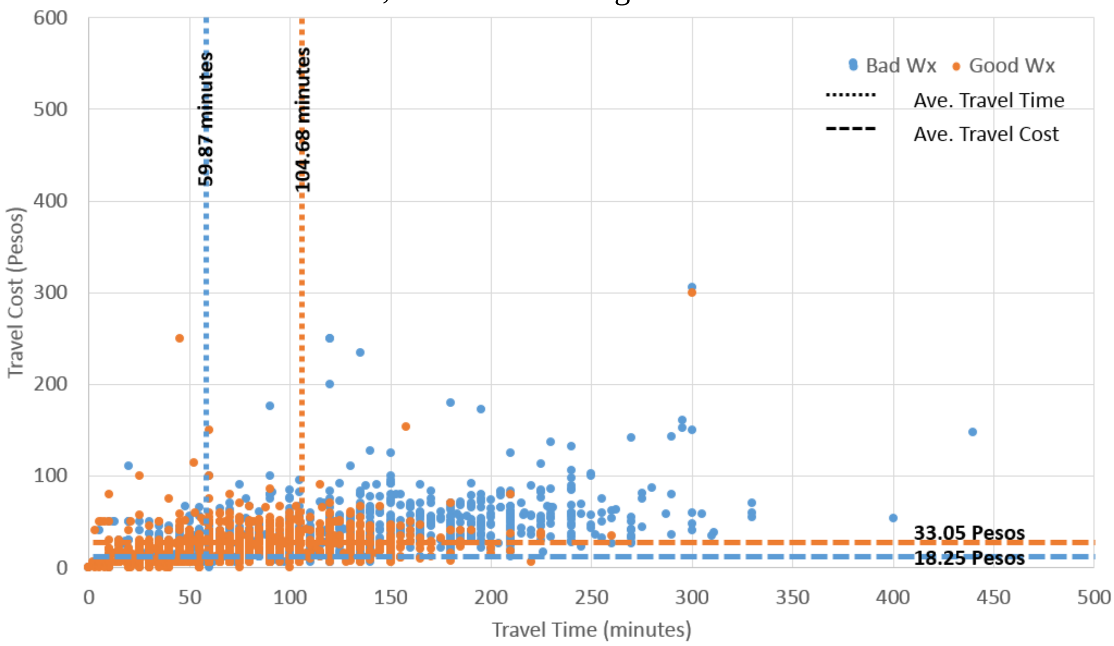

Figure 9. Data plots of travel cost versus travel time of good and bad wx scenario

Travelers tend to travel longer under bad weather condition, which was also seen in the previous figure. It is also seen in figure 9 that there is also an increase in travel cost but it is not evident from the scatter plot alone as it is concentrated on the same level with the good weather condition. By computing the average, there is an increase of 11.4 pesos in travel cost when normal and bad scenario are compared with each other.

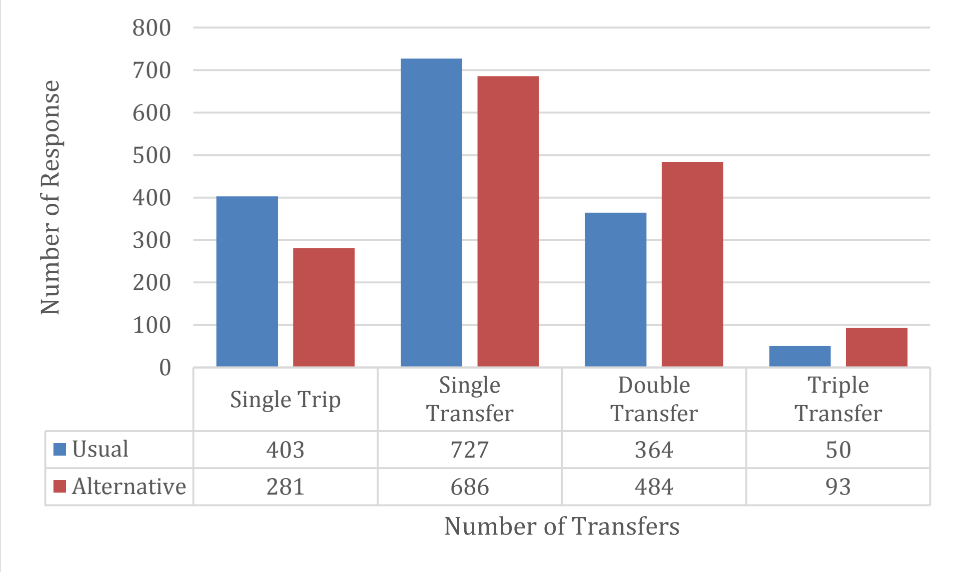

Figure 10. Usual and alternative route transfers

By looking at figure 10, there are more counts in double transfer trips and triple transfer trips as the route taken are the alternative routes they know. There are fewer single trips under the alternative routes compared to the usual routes taken by the respondents. With the figure presented above, this simply means that majority of the usual route taken is probably the most convenient way to go home from school as there are lesser transfer from their trips compared to the alternative routes presented to respondents presented. Still, there are respondents who have the same number of transfers regardless of which routes they took to different factors such as the proximity of their homes to the schools, road availability and etc.

4.4 Discrete Choice Modeling Result

Binary Logit (Usual vs. Alternative Routes). For the first model, the choices are the usual and alternative path known to the individual. This was modeled in order to see which of the routes known to the decision maker is selected during bad weather scenario and what factors affect their decisions. For the scenario considered, this is very appropriate due to the fact that school officials do not permit a prolonged or overnight stay in school campuses. Therefore, capturing the general route/itinerary choice was done. It considered all the 1544 observations, since every respondent is covered under this modeling scenario even though they chose to stay for some time.

Out of 1544 observations, there were 72.93% who chose the usual path to travel during bad weather and 27.07% chose an alternative path. As seen from table 3, *TOTTIME (Travel Time), TRANSFR (Number of Transfers), FLODHT (Usual Flood Height) and TRYALT (Having tried other route)* have negative coefficients, which indicate these variables are disutilities. These would mean when trip-related variables increases, the chances of choosing this alternative decreases. Attributes such as *Flood Height, and Tried Alternative Rout*e also contribute greatly to the chances of choosing the usual path alternative as it is seen to be 99% significant.

Table 3. Usual and alternative route models

Variables	Coefficient	T-Stat	P-Value
ASC***	3.3074	8.603	0.0000
TOTTIME ***	-0.0116	-8.654	0.0000
TRNSFR***	-0.3442	-4.078	0.0000
TRYALT***	-2.3249	-6.914	0.0000
PRVNC*	0.3425	1.915	0.0555
FLODHT***	-0.0070	-3.184	0.0014
DECME***	1.266	2.578	0.0099
SEEKER***	0.3806	2.992	0.0028
UNIVB***	0.3632	2.871	0.0007
No. of obs	1544		
Pseudo R^2	0.26626		
Log-Likelihood	-785.2597		
LR chi^2 (8)	232.80769		
Prob > chi ^2	0		
Correct Prediction	65.67 %		

*significant @ 10%, ** significant @5%, *** significant @1%

The only attribute in the model at 95% significance is *PRVNC (Home Location is Province)*. This attribute has a positive coefficient together with *SEEKER* and *DECME*. People who are risk seeking would tend to continue the usual path even the risk along the route is known. On the contrary, risk averse people would tend to choose the alternative path in order to avoid the known risk along the usual path they usually use. A localized attribute of the university (*UNIVB*) is also seen to have a positive sign, meaning students from this cluster tends to use their usual routes rather than their alternative routes. Possibly due to very limited alternative path choices or alternative routes not attractive enough especially during bad weather. Lastly, students who lived outside Metro Manila (PRVNC) tend to also use the usual path rather than change their paths as the coefficient shows a positive sign.

Binary Logit (Go Home vs. Stay Model). For the second model, the choices are **Go Home** or **Stay (Wait)**. These are the possible choices of students after a suspension or dismissal of classes during bad weather. For this research, it is only focused on the decision-making made right immediately after suspension/dismissal during bad weather. It considered all the 1544 observations, since every respondent is covered under this modeling scenario.

All attributes were seen to be 99% significant in terms of predicting the chances of choosing an alternative and interaction among other attributes except for *WAIT* and *HAZARD* that are only 95% significant. About 70.08% chose to immediately go home and 29.92% chose to stay inside the campus. Coefficients for *WAIT*, *FLODHT*, and *DECFRI* are seen to have negative signs indicating disutilities. The longer the students need to wait outside school grounds are more likely to stay as indicated in the model. Also, the higher the flood usually experienced in their travel would prompt students to choose stay more than going home immediately.

Attributes such as *HAZARD*, *SEEKER*, and *SCHWAIT* have positive signs. People who are risk seeker would most likely go home than people who are averse and neutral. This is the propensity of risk seeking attitude people. In terms of *HAZARD* (*School's Hazard Level Location*), the higher hazard level of school translates to the higher likelihood of students going home immediately.

SCHWAIT (waiting time inside the school campus) is a relatively new parameter introduced in this study. This parameter is also new in the study of disaster decision making since the scenario is to either move immediately or wait. The scenario of the study is very different from typical evacuation scenario where people has the choice to either stay permanently or move. In the Philippines, students are asked to leave the campus most of the time, thus staying permanently inside the campus is almost impossible. In the model presented in table 4, waiting time inside the school campus is seen to have a positive coefficient indicating a utility rather than a disutility.

Table 4. Go Home and Stay Models

Variables	Coefficient	T-Stat	P-Value
ASC ***	1.9664	10.64	0.0000
WAIT **	-0.0052	-2.172	0.0299
SCHWAIT ***	0.0108	9.820	0.0000
FLODHT ***	-0.0073	-3.407	0.0007
HAZARD **	0.1569	2.275	0.0290
SEEKER ***	0.3567	2.888	0.0039
DECFRI ***	-0.6625	-3.221	0.0013
No. of obs	1544		
Pseudo R^2	0.21023		
Log-Likelihood	-845.2316		
LR chi^2 (6)	195.5467		
Prob > chi ^2	0		
Correct Prediction	63.67%		

*significant @ 10%, ** significant @5%, *** significant @1%

SCHWAIT can be considered as a perception on the uncertainty or risk the traveler see. As seen from the statistics previously, people tends to wait more as their destination distance increases. As the destination distance increases, the uncertainty of negative events also increases along the way. The model tries to capture on which is safer and better rather than which is the best choice in terms of the utility alone. Compared to *WAIT*, where it is perceived as a disutility, *SCHWAIT* can increase the ease of travel during unwanted scenarios. It is also translatable to waiting outside the school is more dangerous (disutility) than waiting inside the campus. Nonetheless, the study failed to capture further reasons on why students tend to wait inside the school which may affect the decision making and model as well.

This model tries to capture the decision making only after immediate suspension of classes. Since the study focuses on the static (time frame) decision making, the time frame to be considered only is the first set of decision making to be done. Therefore it is either only travel now or wait for a particular duration of time and disregard the decision to be done, if he/she chose to stay, in the future which is continuous until a person chooses to go home.

With that reasoning, it is evident waiting time outside the campus is expected to be zero, thus it is not included in the stay utility equation and vice versa with the school waiting time attribute.

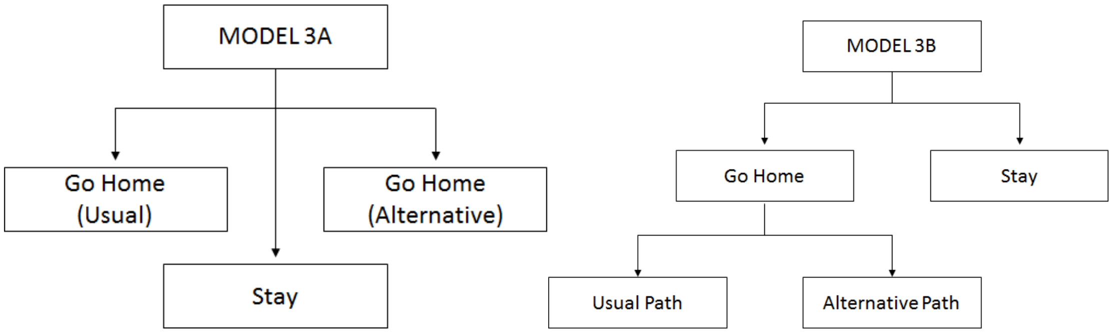

Figure 11. Model 3A(MNL) & 3B(NL) structures involving all decision choices

Table 5. MNL and NL Model for Route and Go Home/ Stay Model

	MNL Model			NL Model		
Variables	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
ASCA	2.5673***	14.858	0.0000	2.3019***	13.949	0.0000
ASCB	0.8885***	5.764	0.0000	1.774***	12.577	0.0000
TOTTIME	-0.0047***	-4.664	0.0000	-0.0031***	-3.053	0.0023
WAIT	-0.0035	-1.417	0.1564	-0.0018*	-1.656	0.0978
FLODHT	-0.0093***	-4.671	0.0000	-0.0028**	-2.417	0.0157
DECNEW	1.2254***	2.944	0.0032	0.3327*	1.813	0.0699
AVERSE	-0.3562***	-3.304	0.0010	-0.0963*	-1.866	0.0621
SCHWAIT	0.0106***	9.921	0.0000	0.0113***	11.029	0.0000
PRVNC	-0.5270***	-2.847	0.0044	-0.3433*	-1.85	0.0643
IV parameter				0.2888***	2.947	0.0032
No. of obs	1544			1544		
Pseudo R^2	0.21808			0.22194		
LogLikelihood	-1423.246			-1416.222		
LR chi^2	224.141			807.9643		
Prob > chi ^2	0			0		

*significant @ 10%, ** significant @5%, *** significant @1%

All Decision Model (MNL vs. NL Model). By combining all alternatives, two (2) models were formulated by using of multinomial and nested logit models. Under multinomial logit, all alternatives are on the same level. Thus go home-usual, go home-alternative and stay decision fall under a single level. For nested logit, usual and alternative routes fall under the nest of go home while stay is a degenerate branch, since it has no other choice on the nest of stay. All except one attribute under MNL model is significant at 99%. *WAIT* is not significant at all in the MNL Model. On the other hand, all attributes are significant under NL Model with at least 90% significance. All signs of the coefficients in all attributes are the same regardless of what model is used. *TOTTIME*, *WAIT*, *FLODHT*, *AVERSE* and *PRVNC* are all disutilities, which would mean, these attributes lessen the chance of an alternative being picked. *SCHWAIT* stays to be a utility even under this decision-making scenario. The attribute *PRVNC* is present under Stay utility since it affects the decision of either going home or staying rather than usual or alternative path choices.

The significant attributes in the NL model are the best developed after several tries of attributes in different utility equations. The NL model is found to be the better model between the two due to its better statistical measures.

5. CONCLUSION

The main purpose of this research is to determine the probable behavior of students when going home after an immediate suspension of classes due to a bad weather condition which results to flooding. The student's alternative are whether to use the usual route or the alternative route when going home or stay for a while in the school campus. The following conclusion can be deduced form the results of this study:

1. College students of Manila would most likely choose the usual path in travelling from school to home after a sudden suspension of classes due to bad weather.
2. College students of Manila would most likely to choose to go home immediately rather than staying in school for a period of time before going home.
3. Travel variables such as total travel time, number of transfers, total waiting time play significant roles in the decision making of students. Disaster specific variables such as flood height experienced and hazard level of school are also important decision variables. Moreover, attitudes towards risk and decision influencer have significant effects in the decision model.
4. Indirect variable such as school waiting time also has a significant effect towards the decision-making under an unwanted scenario.
5. There are also significant changes in the capacity of the network, such as changes in travel time and waiting time, when a change in scenario took place (good weather to bad weather).

The results of this study can provide government policy makers especially those involved in disaster risk management and transport to improve the current and alternative transport paths of students including the general public, during this kind of event. School administration officials can also coordinate with government officials and parents an how to provide safer and faster way for students to go home during bad weather.

6. RECOMMENDATION

To further improve the study and expand the research under the field of unwanted scenario modeling, the researcher would like to recommend the following:

1. To focus on a single bad weather that resulted to flooding under a class suspension scenario in order to have controlled and more event-specific factors. This will also avoid varied flood scenario situations and wide range of trip related variables. This study only captured the general bad weather condition in Metro Manila which may have happened under different bad weather and flooding events.
2. It is also important to capture more variables and reasoning about what the respondent is doing or how he/she spends his/her time inside the campus if he/she chose to stay. This is to further strengthen the explanation and analysis for the new parameter 'school waiting time' or simply known as indirect variables.
3. To analyze the scenario dynamically, wherein there is a continuous decision-making done until the respondent gets to choose to go home. Further expansion to other types of discrete choice models are highly recommended.
4. To include more schools in different cities in order to capture more detailed decision making done by students as a whole in the National Capital Region (Metro Manila).
5. To include transport mode choice analysis as part of the study under the unwanted scenario which is also relatively new study under a bad weather and flooding event.

Finally, this study demonstrated how the effect of climate change through flooding would alter the travel routine (those using public transport) of everyone by remembering no one escapes Mother Nature since everyone uses the transportation network.

REFERENCES

Ahmed, F. (2010). Impact of weather on commuter cyclist behavior and implications for climate change adaptation. Australia Transportation Research.

Akbarzadeh, M. and Wilmot, C. (2015). Time- dependent route choice in Hurricane Evacuation. Natural Hazard Review.

Ben-Akiva, M. (2008). Discrete Choice Analysis II. Transportation System Analysis. Massachusetts Institute of Technology.

Ben-Akiva, M. and Bierlaire, M. (1999). Discrete Choice Methods and Their Application to Short Term Travel Decisions. Transportation Science Handbook. Massachusetts Institute of Technology.

Bujed, P. (2014). Commute Behavior Changes During Rainy Season in Jakarta Metropolitan Area. University of Tokyo.

Cascetta, E. (2009). Transportation System Analysis: Models and Applications. Springer. Chapter 2 and 4.

Chang, H., et al (2011). Future Flooding Impacts on Transportation Infrastructure and Traffic Patterns Resulting from Climate Change. Geography Faculty Publications and Presentations. Portland State University. 14-15.

Daligdig, J. and Besana, G. (1993). Seismological Hazard in Metro Manila in Disaster Prevention and Mitigation in Metropolitan Manila. Quezon City, DOST- Phivolcs.

Frejinger, E. (2008). Route Choice Analysis: Data, Models, Algorithms and Applications. Ecole Polytechnique Federale de Lausanne, Switzerland.

Greene, W. (2007). NLOGIT Verison 4.0 Reference Guide. NSW, Australia.

Gutscher, H., et al (2006). Flooding risks: a comparison of lay people's perceptions and expert's assessments in Switzerland.

Hensher, D., etal (2009). Applied Choice Analysis. University of Cambridge, London, England, United Kingdom Press.

Hoogendoorn, S. (2009). Transportation Modeling and Management for Emergencies. Delft Technological University.

Hufschmidt, G., et al. (2005). Evolution of natural risk: research framework and perspectives, Nat. Hazards Earth Syst. Sci., 5, 375-387.

Kousky, C., et al (2015). Understanding Flood Risk Decision making: Implications for Flood Risk Communication Program Design. Washington DC.

Lim, H., et al (2015). Household Flood Evacuation Route Choice Models at Sub-district Level. EASTS 2015 Conference.

Otto, S., et al (2010). The psychology of Transport Choice. Corpus. Institute for Ecological Economic Research.

Pel, A., et al (2011). A review on travel behavior modelling in dynamic traffic simulation models for evacuations. Springer.

Ruan, J., et al (2013). Scenario-based path selection in uncertain emergency transportation networks. Journal of Innovative Computing, Information and Control.

Sadri, A., et al (2015). How to evacuate? A Model to Understand Routing Strategies During Hurricane Evacuation. Journal of Transportation Engineering.

Sakamoto, J. and Fujita, M. (2015). Empirical Analysis on the Impact of Rain Intensity on Commuters' Departure Decision on Torrential Rain Day. EASTS 2015.
Setunge, S., et al (2014). Influence of Decision Making During Disasters and How It Impacts a Community. 10th International Conference of the International Institute for Infrastructure Resilience and Reconstruction. 176-188.
Song, C., et al (2012). Research on Route Selection Model of Road Network Emergency Evacuation under Ice and Snow. Trans Tech Publication. 144-145
Train, K. (2009). Discrete Choice with Simulation. University of California. Cambridge University Press, New York.
Viscusi, K., et al (2006). National Survey Evidence on Disasters and Relief: Risk Beliefs, Self-Interest, and Compassion. Journal of Risk and Uncertainty, Springer, vol. 33(1), 13-36.
Williams, R., (2016). Marginal Effects for Continuous Variables. University of Notre Dame.