

# DOES GREEN MAKE A DIFFERENCE: THE POTENTIAL ROLE OF SMARTPHONE TECHNOLOGY IN TRANSPORT BEHAVIOUR

## Abstract

The rise of smartphone applications within the transport sector has created new and exciting opportunities to provide users with a wide range of previously unavailable information services. Unlike previously available information sources, smartphone technology enables users to access individual and trip specific information both pre-trip and en route in real-time. The combination of journey planning applications and carbon calculators, allows for the provision of trip specific information regarding the potential environmental impact of personal transport options. While these applications are becoming more readily available in the market place, little in terms of scientific research has been undertaken to examine their influence on users. This paper presents the results of a stated preference experiment examining influence of carbon dioxide emissions information on user mode choice, as part of a survey undertaken in the Greater Dublin Area in November 2012. Acknowledging research findings arising from the field of behavioural economics, this study recognizes that mode choices are also influenced by factors other than the attributes presented to the user. Results indicate that, for all non driving modes, emissions play a significant role in the respondents' mode choice, with reduced associated emissions contributing to enhanced mode utility.

## 1. Introduction

### 1.1. New Opportunities for Smartphones and Transport Behaviour

As an ever increasing proportion of individuals have access to smartphone handsets, new and exciting opportunities are emerging with regard to the transport sector. Smartphone applications can simultaneously fulfil the roles of multiple existing technologies. Traffic alerts provided by variable message signs and radio updates, real time public transportation information transmitted by on street signage, and navigational instructions previously only available from dedicated satellite navigation devices, are all now available on a platform to which a large section of the population has easy access to. In terms of the provision of transport information, smartphone users in numerous cities worldwide are now able to access an ever increasing array of instant transport information. Applications currently provide real time information concerning, amongst other things, traffic congestion on selected routes, public transit arrival and departure times, city bicycle schemes availability, as well as route planning and navigational functions. While this market is still developing,

1 and therefore it is not yet apparent exactly what shape it will take in the future, smartphone  
2 technologies present an exciting departure from tradition forms of information provision and  
3 therefore have potential to have significant impacts upon individuals' transport behaviours (Tseng et  
4 al, 2013). One area in particular where smartphones have the potential to effect travellers' behaviour  
5 is with regard to the environmental impacts of mode choices.  
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## 8 9 10 1.2. Transport and the Environment

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12 Climate change resulting from the emission of greenhouse gases associated with human economic  
13 activities has the potential to create an unstable global climatic future. In line with Hardin's Tragedy  
14 of the Commons (Hardin, 1968), seemingly insignificant actions undertaken by unexceptional  
15 individuals, in this case numbering in the billions, sum together to drastically impact upon the fragile  
16 environmental balance of the global commons. Everyday individuals are making unsustainable  
17 transport choices that imperceptively erode away the stability of the planet's ecosystem.  
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21 While it must be acknowledged that many individuals face restricted mobility choices due  
22 factors such as poor quality sustainable transport infrastructure, the impact of behavioural barriers  
23 must also be considered. One such barrier has been identified as the lack of clear and consistent  
24 information about the environmental impact of personal travel (Browne et al, 2011; Anable et al,  
25 2006). Without access to quantifiable and comparable trip specific information, how can individuals  
26 be asked to make an informed choice between available alternatives? Research indicates that  
27 individuals lack the necessary information and internal reference parameters to make informed  
28 mode choices based upon associated carbon dioxide emissions (Brazil and Caulfield, 2013). The  
29 result of this is that ignorance of consequences of ones actions can legitimately be considered as an  
30 excuse for behavioural inertia, with regard to sustainable mode choice. Even individuals who possess  
31 sustainable aspirations have, up until very recently, not had the ability to make informed choices in  
32 line with their personal beliefs.  
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36 While it may be beyond this research to suggest what actions individuals should or should not take: it  
37 seems appropriate that they should at least be provided with enough information to informed  
38 choices in line with their personal environmental beliefs. This approach is not without recent  
39 precedents, as the provision of targeted information is currently being used to encourage behaviour  
40 change across a wide range of sectors. Nutritional information is now mandated on food products  
41 sold within the European Union (EU, 2000), and retailers display calorific information in tandem with  
42 prices on in store displays. Similarly alcoholic beverages are required display their relevant alcohol  
43 content and tobacco products must to provide information on their ingredients. In each case the  
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1 individual is free to make their choice, in line with their person beliefs, but cannot reasonably claim  
2 that they were not in some way aware of the consequences of their actions.  
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### 4 1.3. Carbon Calculators and Journey Planning Applications 5 6

7 While carbon calculators have existed in an online format for a number of years, it is their  
8 incorporation into journey planners that may enable them to make emissions more relevant to  
9 individuals' mode choices. If emissions information is not actively sought after or its provision legally  
10 required, one solution is to incorporate it into services that individuals consult for other purposes.  
11 While it is questionable as to whether an individual would consult a carbon calculator when planning  
12 a trip, the inclusion of emissions calculators into journey planning applications enables the provision  
13 of emissions estimates at a time when the individual is making their route/ mode choices. By  
14 providing information at the moment when the decision is made, it is more likely that the role of  
15 environmental concerns in the decision making process will become more prominent (Renes, 2012).  
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### 24 1.4. Existing Journey Planners and Applications 25

26 The Irish website hittheroad.ie (Hitheroad, 2013), and its accompanying smartphone application,  
27 provides users with emissions information in addition to available public transport routes and real  
28 time public transport information with the Greater Dublin Area (NTA, 2013). This information is  
29 presented in terms of emissions reduction in comparison to undertaking the same route in a car. The  
30 Reittiopas journey planner in Helsinki similarly provides users with emissions information in terms of  
31 the emissions associated with their trip, annual emissions per commuter trip and an estimated  
32 annual reduction in to driving (Reittiopas, 2013). This website also allows users to view the calorific  
33 consumption associated with walking or cycling the trip. The online journey planner Transport Direct  
34 enables users to plan a public transport trip within the United Kingdom and compare their selected  
35 route with other modes in terms of associated carbon dioxide emissions, while also providing ticket  
36 purchasing options (Transport Direct, 2013). Privately developed applications such as Ride Off  
37 Carbon (CityRyde LLC, 2011) and Carbon Diem (Carbon Hero Limited, 2013) allow users to enter their  
38 mode details when beginning a trip and use the Smartphone's GPS location function to calculate the  
39 emissions associated with their trips.  
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52 While the provision of emissions information is not yet a standard feature of all journey planning  
53 websites and smartphone applications, these applications demonstrate that it is possible to provide  
54 emissions information without determinate to the primary function of providing travel information.  
55 The incorporation of emissions information into journey planning applications and websites has the  
56 possibility of educating individuals about the environmental consequences of their decisions and  
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1 making carbon emissions more relevant to the decision maker, while providing information of value.  
2 These applications are becoming more prominent in the market place and therefore there is a need  
3 to examine the impact that this information has upon the decision maker. As there is currently little  
4 in terms of empirical research into this area (Averneri and Waygood, 2013), the research presented  
5 in this paper aims at addressing this gap in the knowledge.  
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## 8 9 **2. Discrete Choice Modelling:**

10 Discrete choice modelling refers to an experimental approach where a respondent is presented with  
11 a number of options or “alternatives” and asked to make a choice. Unlike other modelling methods  
12 such as alternative ranking, the discrete choice approach aims at replicating real world situations  
13 where consumers choose one good or service over another.  
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### 19 **2.1. Stated Preference**

20 The stated preference approach is a powerful tool for analysing individual’s preferences in relation to  
21 new or planned transport services. The deployment of this approach in examining preferences for  
22 new technologies has been extensively used (Tseng et al 2013; Razo and Gao, 2013; Tang and  
23 Thakuriah, 2013). Stated preference experiments involve presenting respondents with a number of  
24 hypothetical scenarios, in the case of the research presented in this paper the trips were commuter  
25 trips, and asking them to state which alternative they would choose given the information present. In  
26 contrast to revealed preference methods, which involves real world observations, stated preference  
27 methods allows the researcher to examine the effect of specific attributes in isolation from other  
28 attributes. This controlled experimental set up is particularly advantageous when examining new or  
29 emerging technologies such as emissions information.  
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### 41 **2.2. Random Utility Theory**

42 Random Utility Theory (RUM) is an economic theory that states that a consumer will seek to choose  
43 an alternative from a choice set that maximises his/her “utility”. Utility is a latent property of the  
44 alternative and is a function of the attributes associated with that alternative. In the case of this  
45 study the alternatives are the five mode choices (Drive, Rail, Bus\_Rail, Bus, Park and Ride) and the  
46 attributes under examination are the trip time and the carbon dioxide emissions associated with  
47 each available mode. The attributes and attribute levels for this study are presented in Section 3.2  
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55 This theory states that given a finite set of alternatives, the individual will choose the alternative  
56 from which he/she derives the greatest level of utility. Utility is assumed to be composed of both  
57 deterministic ( $V$ ) and a random component ( $\epsilon$ ).  
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$$U_i = V_i + \varepsilon_i \quad (1)$$

The random element cannot be measured and it is therefore assumed to be set to a probability distribution defined by the model used to analysis the data. The probability that an individual will choose one alternative over another is therefore the probability that he/she derives more utility from that alternative.

### 2.3. Multinomial Logit Model

The Multinomial Logit (MNL) model has been used in a large number of transport studies, including those examining the effect of information on transport decisions (Abdel-Aty et al, 1997; Chorus et al 2013). The model assumes that the error component of the utility function is Gumbell distributed and hence the probability of picking a given alternative is as:

$$P_i = \frac{\exp^{v_i}}{\sum_{j=1}^J \exp^{v_j}} \quad (2)$$

Where  $P_i$  is the probability that the individual will choose alternative  $i$ ,  $V_i$  is the deterministic component of utility for alternative  $i$  and  $J$  is the number of alternatives in the choice set.

### 2.4. Transport and the Environment: Discrete Choice Experiments:

While traditional transport research has concentrated on attributes such as trip time, cost, comfort etc (Commins and Nolan, 2011); only a few studies have applied discrete choice methods to environmental issues with the transport sector. Johnansson et al (2006) and Rieser-Schussler and Axhausen (2012) examined the role of latent environmental variables with regard to the mode choices of Swedish and Swiss commuters respectively, while Caulfield and Brazil (2011) assessed the impact of calorific and emissions information on individuals mode choices for non work based short trips. Studies from other sectors have also applied similar modelling techniques when considering the role of energy labelling in the retail sector (Sammer and Wustenhagen, 2011).

### 3. Survey Methodology

#### 3.1. Survey Distribution

The stated preference experiment formed paper of a wider survey that was conducted via a number of large governmental agencies and departments in late 2012. Care was taken to include organisations outside the city centre to ensure that on radial commuters were included in the survey sample. Table 1 presents the composition of the survey sample.

TABLE 1 HERE

#### 3.2 Experimental Design

**Alternatives:** Respondents were presented with a hypothetical 10km commuter/trip to education in the Greater Dublin Area (NTA). Five alternatives were made available: Drive, Rail, a combined Bus-Rail trip, Bus, and Park and Ride. These modes were chosen to reflect both the majority of trips undertaken in the Greater Dublin Area (Central Statistics Office, 2012), and the trip types likely to be recommended by journey planning applications. Specifically the combined Bus-Rail trip and Park and Ride were chosen to represent multimodal options that although infrequently undertaken, represent sustainable alternatives for individuals with non radial origin-destination pairs or with limited access to high quality public transport.

**Attributes:** To reflect the nature of existing journey planners and smartphone applications, it was decided to include trip time and emissions as the only scenario attributes. While cost was considered for inclusion as an attribute, difficulties in calculating trip cost due to factors such as complex public transport ticketing structures and the sunk cost of driving, make cost comparisons unsuitable for this experiment.

**Carbon Budget:** As individuals are likely to have little in terms of internal references to compare emissions estimates with, it was decided to provide them with a trip specific carbon budget. This budget was defined with 1.25kg/km or 12.5kg or carbon dioxide emissions as one hundred per cent. This is in line with transport projections under Ireland's commitment to the Kyoto protocol and previous research conducted on carbon budgeting in Ireland (McNamara and Caulfield, 2011) As research indicates that individuals have varying preferences with regard to the presentation of emissions information (Brazil et al, 2013) it was decided to provide a traffic light inspired colour coding scheme in tandem with the percentage figures. Emissions falling between 0-50 percent were displayed in green text, those falling between 50-100 percent in orange text and those exceeding 100 percent in red.

TABLE 2 HERE

FIGURE 1 HERE

### 3.3. Decision rule

The analysis of Discrete Choice models can often be complex and while significance of terms can be extrapolated, it is difficult to be sure of the exact role the respective attributes played in the respondents stated choice. When presented with similar tasks individuals often quickly develop decisions rules to help them process their choices with as little cognitive strain as possible. As the scenarios presented contained only two attributes, it was decided to ask respondents select a decision rule that best summarised how they had processed the information contained in the scenarios. Respondents were asked to select from the following four choices: First look at time and then consider emissions, first look at emissions and then consider time, only consider time, only consider emissions.

## 4. Results

Table 3 displays the results of the initial model in terms of the coefficients associated with each mode. From the purpose of this model only the influence of the time and emissions attributes for each of the modes is considered.

$$U = \beta_{const} + \beta_t * time + \beta_e * emissions \quad (3)$$

Where:

U= Utility of the Mode,  $\beta_{const}$ =Constant term,  $\beta_t$ =Time coefficient,  $\beta_e$ = emissions coefficient.

### 4.1. Base Model

Examination of the base model coefficients reveals that all terms, with exceptions of emissions for Driving and Park and Ride, are statistically significant at 95% confidence level. All coefficients of statistical significance display negative signs suggesting that decreases in both trip cost and associated emissions increases the utility of the mode. In terms of time this is as expected both from the literature and on an intuitive level. The negative signs associated with the emissions levels indicate, that for public transport journeys at least, the utility associated with the alternative decreases with respect to rises in emissions.

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5 4.2. Expanded Model  
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7 Table 4 displays the results of the expanded model. A wide range of socio economic variables were  
8 tested and this model includes only those that proved statistically significant for their respective  
9 modes. To account for respondents travel habits and any biases that might arise from this source,  
10 habitual terms have been included in the model. For the Bus\_Rail option, the frequency with which  
11 respondents took both modes was examined, however only the Bus Habits term for the Bus\_Rail  
12 alternative proved significant. For both socio economic and habitual variables, the Park and Ride  
13 option was held as the reference option. No additional variable proved statistically significant for this  
14 mode. Results indicate that the more frequently a respondent uses a given mode, the more likely  
15 the greater utility they accord it. Gender was coded as 1 for male and -1 for female, resulting in  
16 females being more likely to take the Bus\_Rail option. Respondents' residence was coded 1-5, with  
17 higher values indicating increased distance from the city centre. Somewhat counter-intuitively this  
18 would indicate that individuals living closer to the city would be more likely to drive than those  
19 residing in more peripheral locations. Perceived access to modes was only observed to be significant  
20 for the bus mode, where stated access to that mode increased its utility.  
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35 4.3. Decision Rule  
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37 The inclusion of the decision rule was intended to provide a simple guide to how the respondents  
38 processed the information presented them. As respondents completed three scenarios it is assumed  
39 that they quickly established a decision rule with regard to the processing and weighting of the  
40 available information. This would represent a cognitive shortcut where the user would discard  
41 information that he/she deemed irrelevant or less important, and concentrate upon the more primary  
42 attribute of interest. While this rule must be treated as a rough guide, as it does not account for  
43 random error, such as the latent variables not included in the experiment, it provides an insight into  
44 the respondents' consideration of the two attributes. It is clear that time is the dominant variable as  
45 it is either the primary or only attribute considered by 72% of the sample. It is also notable that only  
46 3% of respondents stated that they only considered emissions when choosing a mode.  
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#### 4.3.1. Decision Rule Model

Table 5 presents the results of the Decision Rule model. This model involved the incorporation a variable based upon the responses stated method of processing the information displayed in scenarios. Responses were coded as below:

1. Only look at time
2. First look at time then emissions
3. First look at emissions then time
4. Only look at emissions

The decision rule variables were added to the drive, rail, bus\_rail and bus utility equations as linear terms. These terms are labelled as Drive\_Drule, Rail\_Drule, Bus\_Rail\_Drule, and Bus\_Drule respectively. Decision rule coefficients were found to be statistically significant for all modes at either 95 % of 99% significance. The Park and Ride alternative was held as the reference mode and therefore there is no decision rule coefficient associated with it. The sign of the coefficients associated with the Rail, Bus\_Rail, and bus alternatives were observed to be positive in sign. Given the coding approach applied to the decision rule variable, these coefficients would indicate that the more attention individuals pay to emissions information, the more the utility of these modes increases. Conversely the coefficient for the decision rule associated with the driving alternative is positive in sign suggesting that individuals who ignore or accord little attention to emissions information are more likely to choose the car option.

TABLE 5 HERE

#### 4.4 Goodness of Fit of Models

For studies examining mode choice experiments within the transport sector, models are regarded to be good fits for the data given rho squared (with respect to constants) values of between 0.2-0.4 (Hensher et al, 2005). The initial model displayed a value of 0.097 which can be considered poor, although the inclusion of habitual and socioeconomic variables rises this to 0.1765. The further incorporation of variables reflecting the respondents' decisions rule brings this vale to 0.2379 which falls within the expectable bounds of a good model. Standard random utility theory is based upon the premise of the rational individual who assesses all the attributes presented in an equal manner before making a choice. However, in real world situations individuals often engage in cognitive shortcuts, ascertaining essential information and discarding or ignoring any information they deem superfluous. The marked improvement in model fit result from the inclusion of the decision rule

1 highlights how variables arising from behavioural economics can improve upon standard random  
2 utility models, at least in the area of information provision.

### 3 4 **5. Discussion**

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6 This study was undertaken to examine the role that emissions information, provided by journey  
7 planning smartphone applications, can play in an individual's mode choice. While several studies  
8 focus upon the technical ability to provide individuals with various types of real-time information,  
9 this study seeks to examine what information impacts upon users. The research presented provides  
10 some insights as to what information should be provided to users of smart phone devices. The  
11 experiment was based upon the format of existing journey planners and hence omitted attributes  
12 such as trip cost or comfort that may be included in more traditional mode choice experiments.  
13 Emissions coefficients proved to be statistically significant and negative in sign for the purely public  
14 transport based alternatives under consideration. This indicates that the utility of these alternatives  
15 increases as emissions levels decrease. Time is observed to be significant for all modes and the  
16 associated coefficient signs are negative, indicating a decrease in travel time is linked to an increase  
17 in the utility of the respective modes.  
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19 While the fit of the base model can be considered poor, the inclusion of habitual travel and  
20 socio economic variables provide an improvement. As this experiment examined the use of journey  
21 planning applications in the provision of travel information, it was important to incorporate variables  
22 that acknowledged varying methods of processing information presented. This was achieved by the  
23 inclusion of a decision rule variable based upon a post experiment question. Results indicate that  
24 individuals are more likely to drive than take public transport options if they give greater weight to  
25 time considerations than environmental consequences.  
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27 Carbon dioxide emissions associated with transport can be considered a latent attribute of  
28 any trip, as it very unlikely that it will be considered by an individual in the normal course of events.  
29 However, the results of this experiment would suggest that by displaying the relatively low per  
30 passenger emissions associated with public transport, especially in comparison to driving, the  
31 perceived utility of these modes can be increased. Smartphone applications represent a previously  
32 unavailable method of including emissions information as part of a value added service. If  
33 applications can be designed in such a fashion that emissions information can be displayed, without  
34 detracting from the primary functionality of the application, it seems logical that developers,  
35 particularly public transport providers, should facilitate its inclusion.  
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Figure 1

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Figure 1: Stated Preference Scenario

Mode	Time	Emissions
	35 Minutes	1.2 KgCO <sub>2</sub>
	25 Minutes	0.65 KgCO <sub>2</sub>
	20 Minutes	0.24 KgCO <sub>2</sub>
	30 Minutes	0.35 KgCO <sub>2</sub>
	50 Minutes	1 KgCO <sub>2</sub>

96% of Budget

52% of Budget

19% of Budget

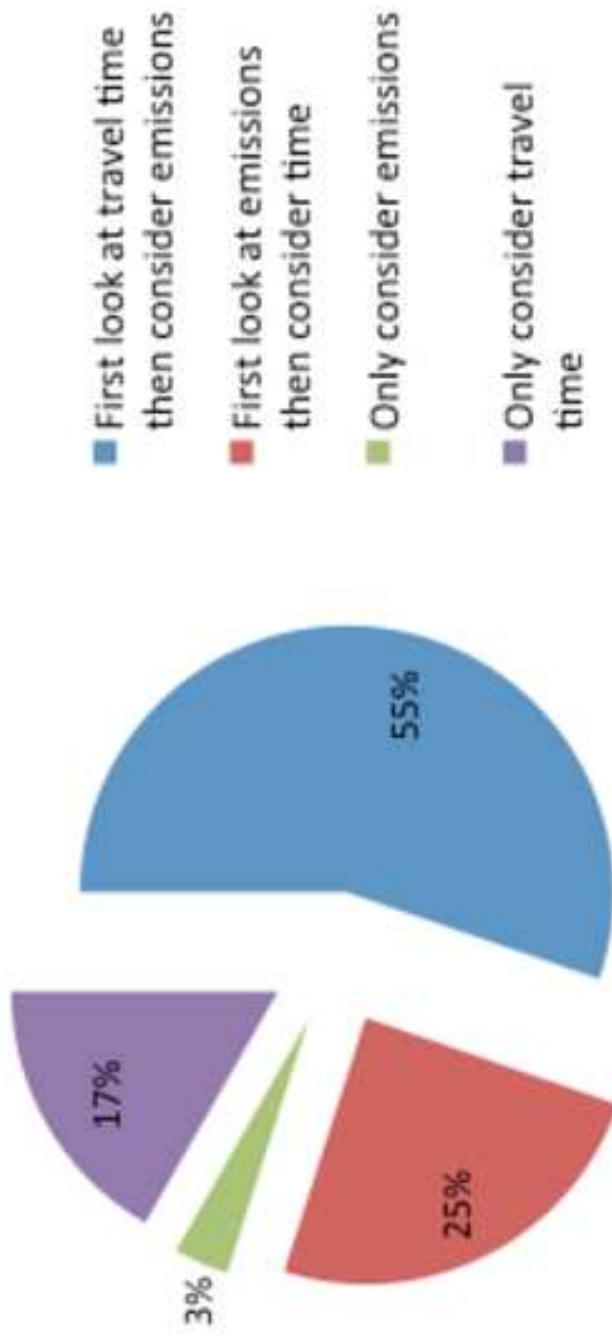
28% of Budget

80% of Budget

**Figure 2**  
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**Figure 2 Decision Rule**



**Table 1: Sample Properties**

Gender	Male	Female	(No Answer)			
	42.8 (34.8)	57.2 (46.5)	(18.7)			
Age	15-24	25-34	35-44	45-54	55+	(No Answer)
	15.7 (12.3)	25.5 (20.1)	24.7 (19.5)	25 (19.7)	9.1 (7.2)	(21.3)
Education	High School	Diploma	Bachelors Degree	Higher Degree	(No Answer)	
	25.4 (20.5)	17.7 (14.3)	22.9 (18.5)	34 (27.4)	(19.3)	
Income	€0-24K	€25-49K	€50-74K	€75-99K	€100k+	(No Answer)
	22.2 (17.9)	44.6 (36)	20.9 (16.9)	6.4 (5.2)	2 (1.6)	(22.5)

**Table 2**[Click here to download high resolution image](#)**Table 2: Scenario Attributes**

<b>Alternative</b>	<b>Emissions (kg CO<sub>2</sub>)</b>			<b>Time (Minutes)</b>		
<b>Driving</b>	<b>1.2</b>	<b>1.5</b>	<b>1.8</b>	<b>20</b>	<b>35</b>	<b>50</b>
<b>Rail</b>	<b>0.3</b>	<b>.475</b>	<b>.65</b>	<b>25</b>	<b>30</b>	<b>35</b>
<b>Bus_Rail</b>	<b>.21</b>	<b>.34</b>	<b>.47</b>	<b>20</b>	<b>35</b>	<b>50</b>
<b>Bus</b>	<b>.15</b>	<b>.35</b>	<b>.55</b>	<b>30</b>	<b>45</b>	<b>60</b>
<b>Park and Ride</b>	<b>.75</b>	<b>1</b>	<b>1.25</b>	<b>20</b>	<b>35</b>	<b>50</b>

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Table 3

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Table 3: Base Model

Observations N=1189					
Variable	Drive=152	Rail=495	Bus_Rail=275	Bus=225	P&R=42
	Coefficient				Z Stat
Drive Time					-4.08
Drive Emissions					.42
Rail Time					-2.18
Rail Emissions					-5.04
Bus_Rail Time					-10.65
Bus_Rail Emissions					-3.94
Bus Time					-7.03
Bus Emission					-7.36
Park and Ride Time					-2.07
Park and Ride Emissions					-1.58
Log Likelihood					-1655.71
Rho Squared Constants only					0.097
Rho Squared No Coefficients					0.271

\* Indicates Statistical Significance at  $\alpha=0.1$ , \* Indicates Statistical Significance at  $\alpha=0.05$ , \*\* Indicates Statistical Significance at  $\alpha=0.01$

Table 4

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Table 4: Expanded Model

Observations N=1029					
Variable	Coefficient	Z Stat	Variable	Coefficient	Z Stat
Drive Time	-.03***	-3.51	Bus_Rail Emissions	-7.06***	-4.79
Drive Emissions	.23	.54	Bus_Rail Bus_Habit	.355***	3.18
Driving Habit	.718***	6.15	Bus_Rail_Gender	-.331***	-3.87
Drive Age	-.03***	-2.78	Bus Time	-.05***	-7.15
Drive Live	-.154*	-1.65	Bus Emission	-4.64***	-7.37
Rail Time	-.033*	-1.87	Bus Habit	.316***	3.11
Rail Emissions	-2.40***	-4.69	Bus Bus_Acc	.3415***	3.11
Rail Habit	.33**	5.28	Bus Rail_Habit	-.1932**	-2.04
Rail Age	-.0193***	-2.97	Park and Ride Time	-.0328**	-2.32
Rail Edu	.212***	3.53	Park & Ride Emissions	-1.00	-1.21
Bus_Rail Time	-.077***	-10.42			
Log Likelihood		-1172.23			
Rho Squared Constants only		0.1765			
Rho Squared No Coefficients		0.333			

\* Indicates Statistical Significance at  $\alpha=0.1$ , \*\* Indicates Statistical Significance at  $\alpha=0.05$ , \*\*\* Indicates Statistical Significance at  $\alpha=0.01$

**Table 5**  
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Table 5: Decision Rule Model

Observations N=960					
Variable	Coefficient	Z Stat	Variable	Coefficient	Z Stat
Drive Time	-.04362***	-4.28	Bus_Rail Emissions	-8.31***	-5.26
Drive Emissions	.0653	.13	Bus_Rail Bus_Habit	.365***	5.19
Driving Habit	.588***	4.77	Bus_Rail_Gender	-.241***	-2.64
Drive Age	-.023*	-1.81	Bus_Rail D_Rule	1.68***	5.67
Drive Live	-.249**	-2.34	Bus Time	-.0541***	-7.25
Drive D_Rule	-.638**	-1.98	Bus Emission	-5.33***	-7.65
Rail Time	-.028	-1.55	Bus Habit	.362***	4.5
Rail Emissions	-2.50***	-4.57	Bus Bus_Acc	.237**	2.02
Rail Habit	.295***	4.55	Bus Rail_Habit	-.205**	-2.05
Rail Age	-.016**	-2.31	Bus D_Rule	1.6***	5.29
Rail Edu	.214***	3.37	Park and Ride Time	-0.035**	-2.45
Rail D_Rule	.679**	2.43	Park & Ride Emissions	-.987	-1.17
Bus_Rail Time	-.083***	-10.7			
Log Likelihood		-1009.46			
Rho Squared Constants only		0.2379			
Rho Squared No Coefficients		.381			

\* Indicates Statistical Significance at  $\alpha=0.1$ , \* indicates Statistical Significance at  $\alpha=0.05$ , \*\* indicates Statistical Significance at  $\alpha=0.01$