Content of Variable Message Signs and On-line Driver Behavior

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ABSTRACT

Variable Message Signs (VMS) are programmable traffic control devices that convey non-personalized real-time information on network traffic conditions to drivers encountering them. Especially useful under incidents, VMS aim to influence driver routing decisions to enhance network performance. This paper investigates the effect of different message contents on driver response under VMS. Presumably, if the message content is a significant factor in driver response, the traffic controller can use it as a control variable to positively influence network traffic conditions without compromising on the integrity of information. This issue is addressed through an on-site stated preference (SP) user survey. Logit models are developed for drivers' diversion decisions. The analysis suggests that content in terms of the level of detail of relevant information significantly affects drivers' willingness to divert. Other significant factors include socioeconomic characteristics, network spatial knowledge, and confidence in the displayed information. Results also indicate differences in the response attitudes of semi-trailer truck drivers compared to other travelers. They provide substantive insights for the design and operation of VMS-based information systems.

Key words: variable message signs, message content, diversion rates.

INTRODUCTION

Advanced Traveler Information Systems (ATIS), a key component of the intelligent transportation systems (ITS) architecture, assist motorists in making more informed decisions on departure time, congestion avoidance, route selection, and en-route diversion. In a prescriptive mode, they can be used by traffic controllers to improve network performance by triggering favorable route choice and/or diversion decisions by travelers. This implies the need to understand the factors that influence drivers' response to supplied information.

Variable message signs (VMS), the most visible manifestation of ATIS, are programmable traffic control devices located in close proximity to the roadway. They display non-personalized real-time information on traffic conditions to drivers encountering them, either as advisories or as proactive guidance. While they have an obvious role under incidents in terms of improving network performance, they have the potential to contribute positively under endemic recurrent congestion and special events as well. In all cases, their effectiveness in real-time traffic operations is highly dependent on user response to the displayed information. This motivates the need to study the relationship between information displayed through the VMS and user response behavior. A compounding factor is that unlike an in-vehicle navigation system (IVNS) which can provide personalized routing information, VMS are constrained to display generic information. This places a higher premium on the message displayed through a VMS vis-à-vis its relative effect on system performance. This is further accentuated by the path-specific access to VMS information and the limited ability to display messages.

This paper focuses on the relationship between the content of VMS message and driver route diversion rates. Presumably, if different message contents to describe the *same* situation prompt different diversion rates, then message content can be used as a control variable by the traffic controller to generate favorable network conditions in the real-time operation of the system while conserving the integrity of information. This has key implications for the design and operation of VMS-based traffic information systems, primarily in terms of credibility and effectiveness of information for motorists. Controlling the level of detail of displayed VMS information without impinging on its veracity can potentially aid user confidence in VMS-based information provision. Also, solution methodologies for networks installed with VMS can focus on message content as a primary mechanism to improve network performance. It should be noted here that message content in our study does not imply human factor related details such as number of words or lines, size of words, or graphics issues. Message content refers to the amount of information provided on the incident situation.

The task of eliciting relationships between VMS message content and driver response is not trivial, and is characterized by several technical, technological, and logistical impediments. Previous studies (*1*) suggest that some messages conveyed through VMS are not understood or perceived to be relevant, while yet others may be misinterpreted. Others (*2*) report a wide range of diversion rates due to a VMS message. Yet other studies (*3,4*) have suggested that driver response to traffic information conveyed through any dissemination source is highly dependent on the information content. While these further strengthen the case for the value of VMS message content and highlight the technical issues, the key problem nevertheless is how to capture these relationships under a variety of message contents. In a technologically sophisticated scenario, each vehicle could be equipped with tracking devices (subject to privacy issues being adequately addressed) that provide the analyst the user response to the displayed VMS message in the field. In the absence of such capabilities, Revealed Preference (RP) surveys entail impractical logistic mechanisms like stopping and interviewing motorists on the road after they encounter a VMS message. However, such studies (*5,6*) exist, but their results are limited to the messages displayed during the survey period.

Stated Preference Studies

Previous studies have focused on driver response to VMS through Stated Preference (SP) methods involving user surveys (*7*), on-screen driving simulators (*8*) or full-scale driving simulators (*9*). The SP methodology is a valuable tool to test the behavior of individuals under a variety of controlled scenarios. It has been used to understand the effect of well-observed factors vis-à-vis VMS such as network spatial knowledge, message content, and confidence in the supplied information. However, it suffers from a number of key limitations. Its main shortcoming is that users may not respond the way they state, in a real situation. In the VMS context, this is primarily because SP is not effective in capturing the situational behavior of users. It is not a reliable method to capture the effect of variables such as weather, time of day, destination, and actual traffic conditions, all of which are key situational elements in the driver's decision-making process given the generic nature of VMS messages. The ability of SP approaches to reasonably infer on these factors requires recreating driving environments that closely replicate real world conditions (e.g., flight simulators used by the aviation industry to train pilots). Second, stated preference surveys can be lengthy depending on the key variables that need to be considered. To illustrate this issue, let us assume that we are trying to capture the effect of a set of situational variables X_i ($i = 1, 2, 3, \ldots, n$) on the dependent variable Y (divert or not divert). For simplicity, assume that each of these n variables contain m categories. Then, there are m^n unique combinations of these variables. Ideally, we would like to observe the value of the dependent variable for each of these m^n combinations. In a SP survey, since each of these scenarios represents a question for the respondent, the survey may become impractical. Also, as discussed earlier, users' actual actions may be different.

Study Objectives

The main objective of this study is to build driver behavior models that predict the diversion probability of an individual under a specific VMS message type (content). In building these models, the study examines the relative importance of various VMS message types in influencing drivers to divert. It also seeks insights on attitudinal differences among different population segments, for more effective use of VMS in on-line traffic operations.

The remainder of this paper is organized as follows. The next section describes the SP survey design and implementation. This is followed by a brief summary of survey results. The modeling framework for VMS route diversion using the survey data is then discussed. Insights and limitations from the estimated models are described. Some concluding comments are presented.

METHODOLOGY

VMS Messages

VMS messages are classified into two main categories from the perspective of their utility for drivers: passive and active. A passive message provides descriptive information on the problem that the driver may encounter. It provides information such as the type of the incident, its location and/or expected delay. An active message provides the driver explicit route guidance to avoid the bottleneck, such as the best available alternate route. The passive information may be further classified as qualitative or quantitative. Qualitative information refers to the problem generically (such as accident, work zone, congestion) whereas quantitative information focuses on specifics (expected delay, location, etc.). This study analyzes whether route diversion rates differ based on the amount and type of VMS information displayed.

Survey Design

A stated preference study is conducted through an on-site survey in the form of a questionnaire. The questionnaire was designed after identifying key factors that influence driver route diversion decisions under VMS. It was organized as follows. First, the respondents were asked about their socioeconomic characteristics including gender, age, education level, and household size. Next, they were asked a series of questions concerning their preferences and attitudes towards traffic information conveyed through a VMS and their propensity to divert under certain situations. The last part of the questionnaire addressed diversion intentions under generic descriptions of VMS messages in terms of the level of detail of information, as illustrated in Table 1. The messages were specified in a random order to avoid potential directional bias for the messages. The responses were recorded on a five point Likert scale (1-5), where 1 meant low willingness to divert and 5 meant high willingness to divert.

The survey was conducted in the Borman Expressway region in northwestern Indiana. It consists of the Borman Expressway, a sixteen-mile segment of interstates 80 and 94 that is characterized by heavy traffic volumes, surrounding arterials, and nearby interstates, I-90 and I-65. The Indiana Department of Transportation (INDOT) is currently installing an advanced traffic management system (ATMS) on the Borman Expressway (*10*) to alleviate congestion and incident situations, both of which are magnified by the high percentage of trucks (30% during peak periods and up to 70% at nights). VMS is the primary information dissemination source being planned for this ATMS. Two survey locations were identified. The first is a truck stop on the Borman Expressway. Hence, most respondents at this location were truck drivers. There are no rest areas on the Borman Expressway. Hence, a rest area on I-65 a few miles south of the Borman Expressway was used as the other survey location. The Borman Expressway represents part of the journey for most drivers who stop at this rest area. Most drivers surveyed here were non-truck drivers. The surveys on both locations were conducted using a 4-person crew for two days each. Potential respondents were approached and informed about the objectives of the survey. The refusal rates were 20% and 10% at the truck stop and the rest area, respectively. The data collection effort resulted in 248 respondents; 116 truck drivers and 132 non-truck drivers.

SURVEY RESULTS

Socioeconomic Characteristics

Table 2 shows the socioeconomic characteristics of the sample. About 79% of the respondents were males. The distribution of the respondents in terms of age groups was mostly even, except for the less than 20 and greater than 65 age groups. 59% have at least some college experience and 41% received at least one college degree.

Network Familiarity

About half the respondents (50.4%) stated that they were regular drivers in the Borman Expressway region. This does not necessarily imply that such drivers are familiar with alternate routes other than their regular route. Hence, regular drivers in the region were asked about their familiarity with alternate routes. Amongst this group, 65% were familiar with at least one alternate route besides the Borman Expressway. Also, 61% of the respondents stated that they would divert to an alternate route under a work-related trip if that alternate route offered travel time savings ranging from 5 to 30 minutes. However, only 47% stated that they would divert on a personal trip for identical savings. This reaffirms the notion of higher value of time for work-related trips.

Diversion Characteristics

53% of the respondents indicated that they would divert when the expected delay on the current route is at least 10 minutes. More than 70% of the respondents stated that they would divert to an alternate route under adverse weather conditions if a VMS message suggested it. This could be due to the effect of incident clearance time, as bad weather conditions may increase it. In such situations, drivers prefer to avoid excessive delays by diverting to the suggested alternate route. Also, a significant number of participants (65%) stated that they would consider diverting to an alternate route at night. While the survey obtains responses on weather and night variables, these responses are not based on the consideration of other factors (such as incident severity) that make driver responses to these variables more meaningful. Such a capability entails providing the drivers several specific situations involving many factors through SP to elicit their response attitudes. As discussed earlier, this is a limitation of the SP approach.

Content of Messages

Table 1 summarizes the drivers' willingness to divert to an alternate route when different types of VMS messages are displayed. It indicates that as information content increases, driver propensity to divert also increases, provided the information type is considered valuable. The survey suggests no significant difference in diversion response to VMS message types 1 and 2. In other words, messages displaying the *Occurrence of Accident* and *Location of Accident* have similar effect on driver behavior, all other factors being equal. *Expected Delay* and *Best Detour Strategy* are considered valuable information in terms of influencing drivers' route diversion decisions. *Location of Accident* and *Occurrence of Accident* have added value only in conjunction with information on *Expected Delay* or *Best Detour Strategy*.

MODELING FRAMEWORK

We now develop VMS route diversion prediction models for the Borman Expressway using the survey data. The focus is on estimating the diversion rate in response to information conveyed through a specific message type.

Model Structure

The choice set C_n of each individual consists of only two alternatives (divert or not divert), motivating the use of a binary logit model to predict the probability of a user diverting under a VMS message. The utility functions are represented by:

$$U_{in} = V_{in} + \varepsilon_{in} \tag{1}$$
$$U_{jn} = V_{jn} + \varepsilon_{jn} \tag{2}$$

where:

i = alternative representing user diverting,

j = alternative representing user not diverting,

V_{in} = systematic component of the utility of diverting from the current route,

V_{jn} = systematic component of the utility of not diverting from the current route, and

ε_{in} and ε_{jn} = disturbances or random components.

The probability of an individual n diverting is equal to the probability that the utility of alternative i, U_{in}, is greater than or equal to the utility of alternative j, U_{jn} (*11*). This can be written as follows:

$$P_n(i|C_n) = Pr\left[U_{in} \geq U_{jn}, \forall j \in C_n\right] \tag{3}$$

Then, the probability of user n diverting is given by:

$$P_n(i) = \frac{1}{1 + e^{-(V_{in} - V_{jn})}} \tag{4}$$
$$P_n(j) = 1 - P_n(i) \tag{5}$$

In our context, the difference in the systematic components can be represented as follows:

$$V = (V_{in} \text{-} V_{jn}) = ONE + \beta \boldsymbol{X} + \alpha \boldsymbol{VMS} \tag{6}$$

where,

ONE = alternative specific constant corresponding to divert,

X = vector of those explanatory variables other than VMS message type that may influence a driver's decision to divert,

β = vector of estimated parameters corresponding to ***X***,

VMS = vector of dummy explanatory variables representing each of the VMS message types provided to drivers, and

α = vector of estimated parameters corresponding to ***VMS***.

The third element of the right hand side of equation (6) can be represented as:

$$\alpha \boldsymbol{VMS} = \sum_{k=2}^{8} \alpha_k VMS_k \tag{7}$$

where:

VMS_k = dummy variable representing VMS message k, and

α_k = coefficient of VMS_k,

The list of all explanatory variables included in the utility function is shown in Table 3.

Construction of the Dependent Variable

As illustrated in Table 1, the diversion propensities of respondents under the various VMS message types are obtained in the form of a five point Likert scale from 1 to 5, where '5' indicates a strong willingness to divert and '1' indicates a strong unwillingness to divert. However, the dependent variable in the modeling process is a binary (*Yes* or *No)* variable to indicate diversion decision. This is because the response of the driver in actual situations is discrete: either he/she diverts or does not. In the context of VMS message display for incident management, our objective is to display messages that optimize the network performance. The VMS message aims at influencing users' decisions to divert or not to divert under incident scenarios. Hence, the binary logit model is chosen for our analysis. While the use of a Likert scale lends itself to the estimation of models such as ordinal logit or ordered probit, the current focus is on estimating diversion probabilities rather than those of the different degrees of the willingness to divert. However, there are some advantages to using the Likert scale instead of the Yes/No format in our survey. The Likert scale enables the collection of a richer array of data to better understand the differences in responses to the eight VMS message types. It allows us to obtain finer insights on response attitudes towards message types that seemingly produce similar responses or responses that are not significantly different. More importantly, a finer resolution than Yes/No, for example a tertiary dependent variable such as Yes/Neutral/No, is more versatile in the context of on-line operations, where some on-line factors (such as weather, time of day, destination data, traffic conditions) can be weighted in conjunction with the survey data to obtain the diversion decisions of the "Neutral" drivers. A Yes/No approach is not as flexible in the context of on-line implementation. Thereby, the use of the Likert scale allows us to explore several alternative on-line models in determining the most representative ones.

In the current context, the focus is on the binary Yes/No choice to obtain insights from the survey. To compromise the Likert scale used in the survey with the binary choice, the actual survey responses can be grouped in different ways to obtain the dependent variable for model estimation. Two possible ways are:

$$y_n = \begin{cases} 1, \text{if willingness to divert} \geq 4 \\ 0, \text{otherwise} \end{cases} \tag{8}$$

$$y_n = \begin{cases} 1, \text{if willingness to divert} \geq 3 \\ 0, \text{otherwise} \end{cases} \tag{9}$$

In the first method, respondents who answered 4 or 5 are assumed to divert while those who answered 1, 2 or 3 are assumed unwilling to divert. In the second method, respondents answering 3, 4 and 5 are assumed to divert while respondents answering 1 or 2 are assumed unwilling to do so. The difference between the two methodologies lies in the treatment of the respondents answering 3. If respondents answering 3 are assumed to divert, the models may overestimate the final diversion rates. However, if they are assumed not to divert, the opposite effect is likely. While a limitation here, the Likert scale is beneficial in practice as it allows more refined modeling, as discussed earlier. The models here use the first method in determining the dependent variable.

ANALYSIS OF MODELS

Preliminary Models

As a first step in the model building procedure, a general model was constructed with the survey data (8 VMS message types per person × 248 persons = 1984 pooled observations). Table 4 shows the results from the estimation of this binary logit model. All explanatory variables were included in the estimation procedure. Insignificant variables, as determined from intermediate models, were omitted at the corresponding stages. Also, the categories shown in Table 3 for some variables (SEX, AGE, EDU, TRUCK, DRIV, FAM, TRUST, VMS_k) were obtained after grouping survey sub-categories that were not statistically different. Since the estimation procedure uses pooled data over individuals, the models were tested for the presence of heterogeneity using a Hausman specification test (*12*). The test results indicate that there is no evidence of the presence of heterogeneity.

The variable ONE is the alternative specific constant. It represents the utility of diverting for a driver exposed to VMS_1, and whose socioeconomic and other characteristics are given by the base cases of the relevant variables (that is, they take a zero value) included in the model. The negative sign implies a natural aversion to diversion. It illustrates the potential of information systems in "convincing" drivers to divert through information provision. When any of the message types VMS_1, VMS_2 or VMS_3 are displayed, there is no combination of socioeconomic variables that will produce a positive utility difference. This suggests that users exhibit an inclination to stay on their current route when they do not have much information on the incident, reaffirming the conclusions of previous studies (*3, 13, 14*).

SEX and AGE are socioeconomic characteristics that significantly influence the diversion behavior of an individual. SEX has a positive sign implying that males are more likely to divert than females under similar conditions. AGE has a negative coefficient indicating that younger drivers are more likely to divert compared to older drivers when all other conditions are the same. These results are intuitive because females and older drivers are, on average, more risk averse than males and younger drivers, respectively.

The models also suggest that the education level of a driver (EDU) may be an important factor. Well-educated individuals exhibit greater compliance with VMS compared to their less educated counterparts under similar conditions. Since education is a proxy for income, well-educated people are likely to have a higher value for time and hence, may be more sensitive to delays on their planned route. Another aspect vis-à-vis education relates to the level of comfort with technology. Well-educated individuals are likely to be at greater ease with technological innovations, at least initially, and hence may not exhibit as much *a priori* inertia to VMS messages. A related issue is that most truck drivers in the sample belonged to the less educated category and a large proportion of the non-truck drivers belonged to the well-educated category. Therefore, EDU might act as a proxy for truck drivers, as discussed in the next subsection.

Dummy variables corresponding to VMS messages 2 through 8 were included in all models (VMS_1 is the base case). The VMS variables are very significant and provide the largest increases in log-likelihood amongst all variables. As mentioned earlier, VMS messages from 1 through 8 are in the order of increasing amount of information (see Table 1). In all models presented, coefficient values increase with information, implying that more relevant information on a VMS leads to higher diversion. These results are important because they suggest that drivers' diversion behavior can be influenced by controlling the amount of information displayed on the VMS. The traffic controller can use this variable to improve network performance without compromising the integrity of the system. There is no statistical difference between messages VMS_1 and VMS_2, seemingly suggesting no value for the location of the incident. This highlights the limitations of the SP approach in the VMS context. Location plays a significant role in the diversion decision based on the actual destination. However, unlike expected delay which can be perceived irrespective of the actual situation, the value of the location of incident is revealed only in real situations. Hence, the lack of statistical differences between one or more VMS variables might be an artifice of the SP methodology as opposed to a behavioral effect. Therefore, irrespective of the t-statistic, all VMS variables were included in the models.

Models for Truck and Non-truck Drivers

We now explore whether significant differences in response attitudes exist between truck drivers and other travelers in the Borman Expressway region. By assuming the same coefficients for both groups in the general model, truck and non-truck drivers are assumed to exhibit similar diversion behavior. However, the diversion behavior of truck drivers can be significantly different from that of non-truck drivers. This is because not all alternate routes available to a non-truck driver are feasible for trucks. Hence, truck drivers may exhibit more resistance to diversion than other drivers. These issues are especially important in commercial highway corridors such as the Borman Expressway region where trucks can represent a significant fraction of the total traffic. To address them, the survey data was separated into truck and non-truck observations and separate binary logit models were estimated for them. The results are illustrated in Table 4.

A major difference between the Truck and Non-Truck models is the effect of the DRIV (regular driver) and FAM (familiarity with alternate routes) variables. These variables are significant for truck diversion, but not for non-truck diversion, suggesting that being a regular driver and being familiar with alternate routes is important for truck drivers in route diversion decisions. This implies that they may *a priori* hesitate to consider all alternate routes as legitimate alternatives. Therefore, unless a truck driver is familiar with alternate routes, he/she may not risk diverting. TRUST is an important explanatory variable in all three models (General, Truck, Non-Truck). The positive sign of TRUST suggests that people who trust messages displayed through the VMS are more likely to divert as compared to those who do not.

The trends in the VMS variables for the truck and non-truck models are similar to those observed in the general model. There is a small decrease in coefficient values as one goes from VMS_6 to VMS_7 in the Truck model and from VMS_3 to VMS_4 in the Non-Truck model. However, these are not statistically significant differences. For the Truck model, VMS_2 and VMS_3 are not statistically different from the base case (VMS_1). Similarly, for the Non-Truck model there is no statistical difference between VMS_1 and VMS_2. These are possibly because of the limitations of the SP approach, as discussed in the previous subsection.

Interaction Model

The preceding subsection concentrated on specific trends for the Truck and Non-Truck models. However, the models cannot compare their coefficients. For instance, is the effect of TRUST on diversion probability different for truck and non-truck drivers? To address such questions, truck and non-truck data was pooled and a combined model with interaction variables was estimated, as shown in Table 4.

The effect of age on diversion propensities is similar for truck and non-truck drivers, and is hence not a significant interaction variable. As discussed earlier, DRIV and FAM are important factors for truck drivers. Hence, (DRIV*TRUCK) and (FAM*TRUCK) are significant variables in this model. Also, the effect of the TRUST variable seems to differ for truck and non-truck drivers. From Table 4, the TRUST variable has a coefficient value of 0.924 and the interaction variable (TRUST*TRUCK) has a coefficient value of –0.525. Hence, the contribution of the TRUST variable will be (0.924 - 0.525) = 0.399 for a truck driver but 0.924 for a non-truck driver. The positive sign for the combined coefficient (0.399) for truck drivers implies that trusting truck drivers exhibit a higher diversion propensity compared to non-trusting ones. Also, since 0.399 is less than 0.525 (TRUST), it suggests that trusting truck drivers exhibit a slightly lower propensity to divert than trusting non-truck drivers. Hence, the TRUST variable does not have similar effects on truck and non-truck drivers. The same line of reasoning can be extended to the VMS interaction variables. (VMS_3*TRUCK), (VMS_5*TRUCK) and (VMS_7*TRUCK) are all negative. This implies that if the message VMS_3, VMS_5, or VMS_7 is shown, a truck driver is less likely to divert than a corresponding non-truck driver. It highlights the relatively greater importance of location for truck drivers. However, when one of the other VMS messages is displayed, there is no significant difference in their diversion probabilities.

CONCLUSIONS AND FURTHER RESEARCH

This study focuses on the potential of VMS to improve system performance under real-time traffic operations by analyzing the relationships between driver route diversion propensity and the content of VMS messages. In this regard, an on-site SP survey is conducted on the Borman Expressway in northwestern Indiana and logit models are developed using the survey data.

The commonly used SP methodology has a number of well-understood limitations. First, the SP responses may not satisfactorily reflect actual behavior. Second, in the context of VMS driver response, SP surveys can be lengthy (to address the multiple actual scenarios possible). However, the current sparsity in VMS behavior field data suggests SP methodology as a valuable tool to address driver behavior under a variety of scenarios. Our on-going research focuses on the effective use of available technology in SP surveys. The interactive and dynamic capabilities of the internet are being used to enhance the reliability of the stated responses, compared to on-site surveys. Hence, the aim is to develop more reliable and cost effective SP surveys.

The current SP study provides some important insights on VMS survey design and driver attitudes for on-line traffic operations. The strong correlation between VMS message type and driver response suggests message content as an important control variable for improving system performance without impinging on the integrity of the information provided. Significant differences were found in the attitudes of truck and non-truck drivers. This is important for the use of VMS-based information systems to influence network performance in commercial corridors such as the Borman Expressway region where trucks represent a significant percentage of the traffic. The use of a Likert scale in the SP survey in the context of VMS message content enables a finer resolution in understanding the differences between driver response to various message types. It also provides flexibility in practice while developing hybrid driver response models. A shortcoming of using generic variables is illustrated by the perceived relative values of expected delay and location. While expected delays are perceivable in terms of magnitude without the need for specific scenarios in SP surveys, the value of location is perceivable only in actual situations or specifically constructed SP scenarios for a particular network. Hence, information on the location of an incident was not a significant VMS message in our study, though it is in the real world.

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TABLE 1 Effect of VMS Message Content

VMS Message Type	Message Content	Relative Willingness to Divert				
		1 %	2 %	3 %	4 %	5 %
1	Occurrence of accident only	13.7	33.9	26.6	13.3	12.5
2	Location of the accident only	20.2	33.1	22.6	11.3	12.9
3	Expected delay only	9.3	12.9	39.5	23.8	14.5
4	The best detour strategy only	7.7	18.5	30.2	25.0	18.5
5	Location of the accident and the best detour strategy	2.0	4.0	22.6	35.1	36.3
6	Location of the accident and the expected delay	0.8	0.8	19.8	38.3	40.3
7	Expected delay and the best detour strategy	2.0	2.0	13.7	33.5	48.8
8	Location of the accident, expected delay, and the best detour strategy	1.2	2.0	5.6	19.8	71.4

TABLE 2 Socioeconomic Characteristics

Attribute	Range	Non-truck Drivers (%)	Truck Drivers (%)	Aggregate (%)
Gender	Male	63.6	95.7	78.6
	Female	36.4	4.3	21.4
Age Group	< 20	4.5	2.6	3.6
	20-29	21.2	26.7	23.8
	30-39	28.0	27.6	27.8
	40-49	22.7	24.1	23.4
	50-64	12.9	15.5	14.1
	≥ 65	10.6	3.4	7.3
Education Level	High School or Less	18.2	35.3	26.2
	Some College	15.2	52.6	32.7
	College Graduate	40.2	12.1	27.0
	Post Graduate	26.5	0.0	14.1
Persons in Household	1	17.4	11.2	14.5
	2	26.5	22.4	24.6
	3	25.0	22.4	23.8
	≥ 4	31.1	44.0	37.1

TABLE 3 Explanatory Variables in the Driver Response Model

Explanatory Variable	Mnemonics
Alternative specific constant	ONE
Sex = 1, if male = 0, if female	SEX
Age group = 1, if age ≥ 40 years = 0, if age < 40 years	AGE
Level of education = 1, if education ≤ some college = 0, if education ≥ college	EDU
Dummy variable for truck drivers = 1, if respondent is a truck driver = 0, otherwise	TRUCK
Regular driver in the Borman Expressway region = 1, if Yes = 0, if No	DRIV
Familiarity with alternate routes = 1, if familiar = 0, if not familiar	FAM
Trust in information provided = 1, if high = 0, otherwise	TRUST
Dummy variables corresponding to each VMS message type, k = 2 to 8	VMS_k

TABLE 4 Logit Models for Driver Response Under VMS

Variable	Model			
	General	Truck Drivers	Non-truck Drivers	Interaction
	Coeff. (t-ratio)	Coeff. (t-ratio)	Coeff. (t-ratio)	Coeff. (t-ratio)
ONE	-1.897 (8.92)	-1.665 (-5.30)	-2.586 (-10.52)	-2.426 (-10.90)
SEX	0.433 (3.26)	-0.643 (-1.63)	0.416 (2.45)	0.266 (1.91)
AGE	-0.458 (-4.17)		-0.238 (-1.53)	-0.422 (-3.77)
EDU	-0.308 (-2.74)			
TRUCK				0.371 (1.29)
DRIV	0.207 (1.87)	0.434 (2.36)		
FAM		0.570 (2.73)		
TRUST	0.666 (5.84)	0.435 (2.58)	0.916 (5.61)	0.924 (5.82)
VMS_2	-0.090 (-0.43)	-0.158 (-0.56)	1.27E-04 (3.62E-04)	-0.095 (-0.44)
VMS_3	0.611 (3.05)	0.191 (0.69)	1.154 (4.48)	1.004 (3.90)
VMS_4	0.842 (4.23)	0.781 (2.83)	1.046 (4.03)	0.890 (4.34)
VMS_5	2.083 (10.00)	1.636 (5.56)	2.671 (10.10)	2.511 (9.59)
VMS_6	2.490 (11.38)	2.372 (7.12)	2.864 (10.60)	2.636 (11.59)
VMS_7	2.731 (12.02)	1.995 (6.43)	3.577 (11.78)	3.395 (11.39)
VMS_8	3.548 (13.02)	3.231 (7.68)	4.057 (11.92)	3.729 (13.27)
DRIV*TRUCK				0.549 (2.92)
FAM*TRUCK				0.713 (3.35)
TRUST*TRUCK				-0.525 (-2.27)
VMS_3*TRUCK				-0.712 (-2.31)
VMS_5*TRUCK				-0.762 (-2.33)
VMS_7*TRUCK				-1.279 (-3.45)
Sample size	1984	928	1056	1984
L(0)	-1375.20	-643.24	-731.96	-1375.20
$L(\hat{\beta})$	-1037.66	-490.92	-519.34	-1009.68
ρ^2	0.245	0.237	0.290	0.266

Note: See Table 3 for definition of variables.