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Red-light cameras at intersections: Estimating preferences using a stated choice model

Aklesso Egbendewe-Mondzozo, Lindsey M. Higgins, W. Douglass Shaw

A B S T R A C T

Red-light cameras placed at intersections have the potential to increase safety, but they are often viewed as an invasion of privacy. Preferences for these cameras were explored using a stated choice model that presents key attributes of camera placements. Stated choice models involve careful experimental design, akin to experimental control in laboratory settings. A variety of design approaches were used, settling on a composition of the choice sets people face in the survey. To illustrate the approach, an internet survey was used with a convenience sample containing a high percentage of college students. The results show that while not the case independently, as the number of cameras and fines for violators are simultaneously increased, the preferences for one particular red light cameras program are likely to improve.

1. Introduction

In this manuscript, we apply the stated choice model (SCM) approach to analyze preferences for a traffic photo enforcement or red-light camera (RLC) program that is purported to increase the safety of pedestrians, motorists, and bicyclists at traffic intersections. SCMs are frequently used in modeling outcomes related to transportation policies (e.g., Rizzi and de Dios Ortúzar, 2003). They are ideal in situations where policy makers wish to gauge responses and public support to newly proposed transportation routes or facilities that may affect demand. Because RLC programs are relatively new, and because they can be controversial, SCM can similarly be applied to gauge preferences for RLC programs.

More than one million crashes occur each year at traffic signals in the US and, between 1992 and 1998, about 6000 people died in red-light running collisions (Retting et al., 2003). Red-light camera programs are an increasingly used traffic enforcement method that attempts to abate this problem (Maccubbin et al., 2001; Milazzo et al., 2001; Retting et al., 1999). In such programs, the cameras take photographs of automobiles that run monitored red lights and the registered owner of the vehicle is sent a fine. While at the outset, it may seem that the public might be overwhelmingly in favor of RLC programs because of enhanced safety, many object to paying a fine without due process of law. Other objections include complaints against privacy invasions, complaints that the cameras are ineffective, and complaints that the local government administering the program is wasting public funds.

A SCM was developed that allows people to choose among various options for what was to be a relatively new local RLC camera program. Key questions in a survey questionnaire were asked to gauge resident preferences and feelings related to the program. In SCMs where all of the attributes and their levels are hypothetical, the critical, but sometimes overlooked, part of the analysis is in the choice set design. As will be seen below, the best design involves a blend of careful mathematical and statistical methods, but also some common sense in terms of the correlations of attributes (see Kanninen, 2006). In addition, this paper presents an exploration of several design issues relevant to SCMs.

2. Background on RLCs

Photos and videos of automobiles have been used for many years to enforce traffic regulations, such as speed limits (e.g., Chen and Warburton, 2006). However, photo enforcement uses have now been extended to assess tolls on roads that require fees (Hensher, 1991), to watch pedestrian behavior at intersections (e.g. Yang et al., 2006), and to try to enforce violations at intersections, such as a driver running a red light. Typically in the United States, an arrangement is made between a private contractor who supplies and installs the cameras and a city government that monitors the camera film and sends out tickets. The two parties somehow share the proceeds of the revenue generated by a collected fine for violations (Obeng and Burkey, 2008). The use of RLCs was authorized with legislation in many locations [Maccubbin et al., (2001) mention Arizona, California, Colorado, Delaware, Georgia, Hawaii, Illinois, Maryland, New York, North Carolina, Ohio, Oregon, Texas, Virginia, Washington, and the District of Columbia], yet the implementation of RLC programs in several cities across the US has resulted in citizens who are taking, or have already taken, action to have the cameras removed. Marell and Westin (1999) point out that acceptance of a traffic safety program is key to allowing that program to move forward and improve traffic safety.

RLC programs are not cheap. Maccubbin et al. (2001) reported that RLCs cost approximately $50,000, plus installation costs of about half of that, plus monthly maintenance costs of $5000. Fines generally range from $50 to $271. The cost-effectiveness of such red-light camera programs are frequently called into question (Chen and Warburton, 2006). Citizens unhappy with red-light camera programs often cite them as either a way for the city to make money or as a significant cost to cities without subsequent improvements in traffic safety (Delaney et al., 2005).

The question of safety effectiveness for RLC programs generally fall into an argument about the cameras' inability to prevent accidents or an increase in accidents as a result of RLC programs. The US Federal Highway Administration stands by national data supporting a reduction in red-light violations and collisions as a result of RLC. However, they note that RLCs may increase more minor rear-end accidents (Connell, 2008; Obeng and Burkey, 2008). Additional research suggests that internationally, red-light cameras may reduce red-light violations by 20–87% (Maccubbin et al., 2001). [Note that Retting, Ferguson and Hakkert, in their 2003 study, offer a narrower range of 40–50%].

Walden (2008) reports on camera effectiveness for 26 cities or towns in the state of Texas, including the city where this study takes place. Using data for 56 traffic intersections, Walden (2008) reports that there was a 30% decrease in crashes after installation of the cameras. He cautions against making the inference of causality, i.e. he is not claiming that his analysis proves that cameras reduce crashes at intersections, as he does not control for other factors that could have reduced crashes in the time interval after installations occurred.

Whatever the success story is, many states and cities around the US have adopted RLCs. As examples, Boulder, Colorado has six cameras, the fine for a violation is $75, and the city issued 18,895 citations for alleged violations in 2007 (Urie, 2008). Los Angeles, California has 32 cameras, fines are $159, and that city issued 30,000 tickets in 2007 (Connell, 2008).

In a recent paper, Obeng and Burkey (2008) consider whether drivers of automobiles actually engage in offsetting behavior that may affect the impact of RLCs on crashes. On one hand, drivers who know of the cameras may drive more safely near intersections that have them, but on the other hand, they might stop too quickly, panic, or speed if they believe they can beat the camera from taking the photo as they go through an intersection. Drivers who stop too quickly as the yellow-light occurs may in fact encourage a collision from the rear, when perhaps otherwise they would have gone through the intersection and not have been hit from behind. Obeng and Burkey (2008) suggest that this offsetting behavior may help explain results reported by others (e.g. Andreassen, 1995; Maccubbin et al., 2001) that the RLCs have the perverse and unexpected effect of increasing, not decreasing accidents, especially rear-end accidents. Using data for their empirical study from North Carolina, Obeng and Burkey (2008) find that offsetting behavior results in a higher frequency of rear-end crashes at intersections with RLCs, but offer a caution that these results may not be generalized to any city.

The red-light camera program of interest in this research pertains to a program initiated in January of 2008 in the twin cities area of Bryan and College Station, Texas (commonly referred to as BCS). The CARES (Cameras Advancing Red Light Enforcement Safety) program began with the installation of four cameras at intersections throughout the city of College Station. The CARES program cameras were installed to monitor traffic through intersections and are triggered when an automobile runs a red light, thus catching a safety violation in progress. Violations result in a fine.

In the BCS program analyzed, the cameras record a short video of the red-light violation and takes pictures of the front and rear license plates. The cameras do not necessarily photograph the driver, so there is no visual proof that a particular person broke the law, only that the automobile registered to a person did so. Nevertheless, the program involves monitoring the film from the cameras, which is done by law enforcement agents. Upon verifying that the vehicle did run the light, registered motor vehicle owners are sent a citation and told they have to pay a fine of $75. The video clips and the photographs are available for the vehicle's owner to view online.

In the BCS area, the public was informed via various media outlets that the cameras were installed at four intersection locations and the associated fine for violators. Safety officials hoped that the cameras would act as a deterrent against running red lights, result in fewer collisions, and thus, increase safety at these intersections. Cameras are typically placed at intersections with the highest recorded red-light violations, or at least those that resulted in accidents. As suggested in the introduction, a downside of the camera program involves the "big brother" syndrome. Many do not like having cameras placed in public locations, even if this is supposedly for enhanced safety. In addition, some people may not believe that the cameras improve safety at all, but are merely a revenue-generating device for the local government (Chen and Warburton, 2006; Connell, 2008). Either way, a person sharing these views will not show support for the camera program which has proven to be detrimental to other attempts at establishing RLC programs.

A good deal has been written about red-light camera programs from perspectives other than economics (see Retting et al., 2003). Within the context of this paper, focus is restricted to individual behavioral aspects and the incentive structure the RLC programs are setting forth. This focus eliminates the ability to explore the underlying "why" of red-light violations that a psychologist may pursue in experimental/laboratory or survey research. The theoretical model of stated choices involving red-light cameras and their locations of placement does not, therefore, allow us to analyze why people may engage in violations, but it does allow us to consider whether they appear to support the RLC program and what factors contribute to explaining individual preferences.

3. Theoretical model

As the introduction suggests, SCMs are now in vogue in a variety of settings, and have long been used in the area of transportation. The random utility model (RUM), originally developed by Marschak (1960), underlies the SCM. Within a RUM, attributes of an alternative i are faced by the decision maker n during choice situation t, all denoted by x_{nit}. For example, one may wish to model the choice of toll versus no-toll roads with different attributes such as commuting times. For this RLC research, attributes were defined using alternatives that pertain to RLC programs. An RLC program might include having very few or many cameras or, in some cases, an alternative may be to have no cameras at all. The modeler specifies a utility function that relates the observed attributes to the individual's decision regarding possible choices.

Formally, let $V_{nit} = V(x_{nit}, \beta)\ \forall i, t$ be a utility function which has a vector of parameters β. The parameters and all elements of choice are assumed to be known to the decision maker, but are assumed to be unknown to the researcher. Choice decisions are based on the magnitude of V, conditioned on the choice, and, naturally, it is assumed that individuals choose the alternative as if they know which has the larger magnitude. To encompass unknown elements for the researcher, the utility function is rewritten as $U_{nit} = V_{nit} + \varepsilon_{nit}$ where the ε_{nit} captures the random part of the utility that is unobserved to the researcher but assumed to have a known density function $f(\varepsilon_{nit})$. The probability of choosing i will be:

$$\begin{aligned} P_{nit} &= \mathrm{Prob}(U_{nit} > U_{njt}, \quad \forall i \neq j) \\ &= \mathrm{Prob}(V_{nit} + \varepsilon_{nit} > V_{njt} + \varepsilon_{njt}, \quad \forall i \neq j) \\ &= \mathrm{Prob}(\varepsilon_{nit} - \varepsilon_{njt} > V_{njt} - V_{nit}, \quad \forall i \neq j) \\ &= \int_{\varepsilon_n} I(\varepsilon_{nit} - \varepsilon_{njt} > V_{njt} - V_{nit}, \quad \forall i \neq j) f(\varepsilon_n) d\varepsilon_n \end{aligned} \tag{1}$$

where $I(\bullet)$ is an indicator function that equals 1 if the expression in the parentheses is true and 0 otherwise.

Various assumptions about the mathematical form for the error distribution lead to multiple versions of the discrete choice model, and the conditional logit model is the most often used specification by researchers in the field of environmental economics, marketing, and transportation economics. As popular as conditional logit modeling is, it has a restrictive substitution pattern corresponding to the well-known independence of irrelevance alternative (*IIA*) property. Allowing heterogeneity across individuals leads to a different, and now popular, variant on the basic logit model (Train, 1998, 1999).

McFadden and Train (2000) have shown that by assuming that the coefficient vector β, or a subset of the vector, is random with a known distribution a more flexible model can be derived. This is now well-known as the mixed or random parameters logit (RPL) model (Train, 1998, 1999). The RPL can in fact approximate results of any random utility model (Train, 2003), and an attractive feature is that it allows for heterogeneity in tastes for the different attributes. The probabilities that correspond to the RPL are of the form:

$$P_{nit}(\theta) = \int P_{nit}(\beta) f(\beta|\theta) d\beta. \tag{2}$$

In practice, estimation of the log-likelihood function that uses the probabilities in (2) is carried out through simulation methods to avoid an integration problem in.[1] In the next section, a discussion of the design of the stated choice survey is provided, which is perhaps the most critical part of this analysis. As will be seen, because stated choice modeling depends on the description of the alternatives that are generated by the researcher, these must be well thought out in advance of conducting the choice analysis.

[1] See Train (2003) for an extensive treatment and discussion of the simulated likelihood method used in the estimation of θ.

4. Survey and choice set design

The tendency is to include every possible alternative and all of the attributes that will explain the choices that people make in establishing a preference for RLC programs within a SCM. However, extensive research has shown that an individual respondent's ability to make choices between alternatives diminishes as the number of alternatives each person considers increases (Siikamaki and Layton, 2007). In the simplest of experimental designs, each individual in the study sees two alternatives, A and B, and is asked to choose between only those. While it might be initially appealing to ask each individual to choose between say, 32 such pairs, it is easy to imagine exhaustion setting in and failure in comprehension as the number of alternatives increases. Based upon precedent set in prior applications of SCM, our study experiment was limited to eight choice pairs.

The levels of attributes used to describe alternatives presented to potential respondents should enrich the analysis, but, unfortunately, here again too many attribute levels may tremendously complicate the analysis. After some basic focus group work, four attributes were identified as being key to participants' formation of RLC preferences and, thus, those four attributes were identified as being of interest for our analysis of RLC programs: the cost of the ticket or fine incurred by red-light runners, the number of cameras in place, the nature of the camera location intersections, and the speed on the roads. Average speed on the roads is an issue that pertains to the clogging of intersections with traffic signals and has been found to be important in many transportation studies (Al-Madani, 2003; Hossain, 2001). The nature of the intersections mainly pertains to vehicle volume and to the presence of pedestrians. Pedestrians are well-known to cause problems at intersections when they decide to violate crossing signals (see Yang et al., 2006).

One goal of the experimental design is to obtain statistical efficiency, i.e. to reduce the estimated variance on the parameter estimates. Unfortunately, it is quite easy to formulate attributes and levels such that a large degree of correlation exists between the attribute levels, thus, increasing parameter variance. The levels for each attribute were selected based upon the initial CARES program implemented by College Station and also on the results of the focus group discussions. Before our study took place, the CARES program was initially implemented using $75 citations for red-light runners and four red-light cameras. Fines slightly above and below the initial citation fine of $75 were used, resulting in three levels of the fine: $50, $75, and $100. Red-light camera levels were selected at four, eight, and twelve cameras. Breffle (2008) discusses the importance of using choice pairs that are realistic alternatives. Therefore, it was decided that a "no cameras" alternative would not be presented at the time, as it was not realistic.

The nature of the camera intersections and the average speed on roads were considered as categorical (dummy value) variables. Rather than specifically identifying the exact camera intersections, labels were used to emphasize the desired characteristic associated with an intersection, including the amount of traffic volume and the degree to which pedestrians used the intersection. The locations incorporated into the design were the current locations (i.e., placing the four cameras in their existing or current locations), high volume intersections, high pedestrian intersections, and intersections that had a mix of high volume and high pedestrian characteristics. Speed levels were incorporated at the current speed or at a decrease of 5 mph. Table 1 summarizes the attributes or factors and their attribute levels.

The SAS optex procedure was utilized to select an efficient design using these attributes. The G-efficiency criteria, an information based criterion that uses average prediction variance, was used to first select an efficient set of 16 different alternatives. Main effects between all the variables and the cross effects between the numerical variables, cameras, and costs, were included in the model specification.

The resultant efficient design was put through a set of basic checks (see Kuhfeld, 2005). First, correlation between main effects was measured with canonical correlation. Using a criterion for correlation between linear combinations of factors of .316, used to measure the 10% level as suggested by Kuhfeld (2005), significant canonical correlation was present in the efficient set. Next, the frequencies of the attribute levels were checked as a measure of balance within our design, which ensured that the efficient set had equal or nearly equal one-way and two-way frequencies.

There are numerous ad hoc approaches to combining the efficient set of alternatives into choice pairs, but the mix-and-match method of Johnson et al. (2006) was followed here. The base design was randomized and then rotated to obtain a second set of 16 alternatives. The two candidate sets, the base and the rotated, were independently shuffled. At random, one profile was drawn from each of the candidate sets; this is the first choice pair. The randomized profile selection was repeated without replacement until eight choice pairs were selected. These are the choice pairs given to respondents.

The organization and presentation of the survey was refined based upon additional focus group sessions. The final survey layout consisted of four "warm-up" questions to assess the individual's prior knowledge of the CARES program, eight stated

Table 1
Summary of choice characteristics.

Attributes	Description of the levels	Levels
Cost of the ticket	50, 75, 100	3
Number of cameras	4, 8, 12	3
Type of location	Current, high traffic, high pedestrian, mixed	4
Speed on the roads	Current, decrease of 5 mph	2

choice questions, 19 scaled attitudinal questions, six questions on commuting patterns, and 10 demographic questions. The scaled attitudinal questions that were incorporated asked respondents to provide a numerical rank or score to indicate their agreement with statements which were presented. The commonly used scale let respondents strongly disagree (=1), to strongly agree (=5), with the middle value of three denoting a neutral feeling about the statement. Statements were selected based upon concerns expressed in our initial focus group, prior research on the perceptions of RLCs and prior research on the characteristics of red-light runners (Lum and Wong, 2003; Retting and Williams, 1999; Ruby and Hobeika, 2003; Yang et al., 2006).

Scaled responses were obtained for statements relating to driver safety perceptions, general driver behavior of the respondent, perceptions of other driver's behaviors on the roads, perceived effectiveness of traffic safety laws, perceived enforcement of traffic laws, perception of the existing BCS RLC program as being a revenue-generating tool, and perceptions of the safety of intersections for driving, bicycling, and walking.

5. Survey implementation and basic statistical results

The survey was hosted on a departmental web server and administered to residents of the Bryan-College Station community. Potential respondents were contacted via email, told that the survey was being done to gauge public opinion on the CARES program, and were asked to navigate to the survey webpage to anonymously participate in the survey. These respondents also spread the word about the survey being available on the internet, generating more potential respondents. A total of 261 survey responses were generated, though, as will be seen, and as is true in any survey, not every respondent completed every question in the survey.

Basic descriptive statistics on the demographic survey responses revealed that the sample was comparable to the population demographics of the BCS college community, with 48% of the respondents being male, 52% of the respondents being single, the average respondent age being 32 (note that the median age is 29), and 54% having at least some graduate education. Commuting pattern responses indicated that the average respondent spends 15–18 min commuting each morning and evening. The BCS area is relatively hot and humid during many months of the year and is not particularly well-suited for walking or biking as a form of commuting as compared to communities with other climates. The university runs a bus service for students to and from many neighborhoods, but otherwise there is no public transportation in the area. The BCS community is a place where driving one's private automobile dominates. This is reflected in the data on commuting patterns of the respondents, and should be kept in mind when assessing whether results can be generalized to other diverse communities.

As noted above, the BCS area already had four cameras in place. However, when asked specifically about the BCS RLC program, the majority (58%) of the respondents could not identify more than two intersections with existing RLCs. This does not mean they were completely unfamiliar with the cameras, as 60% of the respondents said they went through at least one of the RLC intersections on their daily commute.

Several of the agree/disagree statement responses revealed interesting characteristics about the sample of respondents. Table 2 presents frequencies and percentages of the full responding sample ($N = 261$) on the level of disagreement (scale = 1 for strongly disagree) or agreement (scale = 5 for strongly agree). Note that the general pattern for each question is that the largest frequency is in the middle, reflecting a neutral sentiment. However, note that a significant portion of the sample strongly disagrees that RLCs will make the area safer in general, for traffic, or for those on bicycles, and the vast majority do not think preventing drivers from running red lights in the most important issue, or are neutral about this.

In addition, an overwhelming majority of the respondents felt they were generally safe drivers, as measured by responses to several questions. These included being asked whether they were focused on the road when they drove, whether they followed the legally posted speed limit, and a question that asked whether they considered themselves to be safe drivers, which admittedly may be a loaded question (i.e., there may be a social stigma attached to admitting to being an unsafe driver). Finally, while respondents think themselves to be safe drivers, the majority of respondents believed that other drivers in the BCS area were not. Additional statistical results pertain to variables that are used in the choice model and are discussed in the next section.

Table 2
Frequencies on selected statement agreement for full sample ($N = 261$).

Statement	1	2	3	4	5
RLCs make BCS safer	41/16%	44/17%	71/27%	56/21%	43/16%
Additional RLCs will improve traffic safety	47/18%	40/15%	67/26%	61/23%	43/16%
Additional RLCs will further improve pedestrian and bicycle safety	40/15%	42/16%	74/28%	56/21%	44/17%
Preventing drivers from running red lights in the most important issue for improving road and traffic safety in BCS	62/24%	63/24%	65/25%	43/16%	26/10%

1 = Strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree. First number in the columns is the frequency, second is the percentage of the sample.

Table 3
Summary statistics for estimating sample ($N = 206$).

Variable/definition	Mean	SD	Min	Max
SPEED = 1 if 5 mph slower than current speed at intersections	0.50	0.50	0	1
COST: fines for violations	75	19.76	50	100
CAMERAS: total number of cameras in BCS*	7.25	2.90	4	12
LOCHP = 1 if high volume of pedestrians at intersections	0.31	0.46	0	1
LOCMIX = 1 if high auto and pedestrian volumes at intersections	0.31	0.46	0	1
LOCHV = 1 if high auto traffic volume at intersection	0.13	0.33	0	1
BCOLLEGE = 1 if resident of BCS	0.20	0.40	0	1
STUDENT = 1 if college student	0.66	0.47	0	1
AGE = reported age of respondent	31.68	12.49	17	99
SAFED = 1 if respondent believes him/herself to be a safe driver	4.46	0.64	2	5
RDCMSAFE = 1 (disagree) to 5 (strongly agree) that RLCs make conditions safer	3.05	1.28	1	5
CAREV = 1 (disagree) to 5 (strongly agree) that RLCs are mainly to collect revenue	3.26	1.27	1	5
ACCIDENT = 1 if respondent has ever been in an accident	0.69	0.46	0	1
CHILDREN = 1 if respondent has children under age 18	0.19	0.39	0	1
GENDER = 1 if male	0.49	0.50	0	1

* BCS is Bryan-College Station area of Texas. All variables that have definitions for values of 1 are equal to 0 otherwise. SD is the standard deviation.

6. Specification of the model and model estimation results

The modeling data set is also obtained from responses to the survey, and key responses for certain variables are used to estimate the choice model. Some omitted key responses result in dropping some individuals when estimating the model. The total number of respondents used in the estimation of the choice model is 206 out of the original 261 sample. Table 3 offers summary statistics on the basic model variables for this estimating sample. Two key attribute variables indicate the number of cameras (*CAMERAS*) and the cost (*COST*) of the fine, both of which are continuous variables. The variables for *SPEED* and intersection location type are dummy variables, and may enter the choice model as to influence a constant term (shifting it up or down), a slope parameter for another variable, or both. Respondents may have answered the question from the viewpoint of a driver who might be caught or they may have answered the question from the viewpoint of an innocent third party who hopes the RLC program protects them, as well as other people. Therefore, it is difficult to know what direction of influence these variables will have. Drivers who worry about being caught on film would see higher costs and more cameras as bad attributes, so these variables would have a negative influence (and signs on the parameters) in the model. However, parties who want other people caught and do not worry about their own driving may see these attributes as good ones, resulting in a positive sign.

The camera location types are divided into four distinct categorical or dummy variables (see Table 4 below). High pedestrian intersections (*LOCHP*), high traffic volume (*LOCHV*), and mixed high volume and high pedestrian locations (*LOCMIX*) dummy variables are used, with the current camera location types being the base case in the model. Our a priori expectations are that respondents would prefer intersections with smaller volumes of traffic (pedestrian and auto) than the current camera locations, resulting in negative signs, however, it may also be that these other types indicate preference to relocate the

Table 4
Results.

Variables	Coefficients	SE	Asymptotic-*z*	$P > \|z\|$
Mean				
LOCHP	2.278	0.364	6.260	0.000
LOCMIX	2.377	0.431	5.510	0.000
LOCHV	0.916	0.305	3.000	0.003
ACCIDENT ∗ *CAMERAS*	0.051	0.085	0.600	0.549
GENDER ∗ *CAMERAS*	−0.081	0.078	−1.040	0.300
CHILDREN ∗ *CAMERAS*	0.060	0.100	0.600	0.549
AGE ∗ *CAMERAS*	0.012	0.003	3.720	0.000
STUDENT ∗ *CAMERAS*	0.004	0.099	0.040	0.970
COST ∗ *CAMERAS*	0.007	0.002	3.580	0.000
CAREV ∗ *COST*	−0.012	0.003	−3.690	0.000
CAMERAS	−1.216	0.253	−4.800	0.000
SPEED	−1.516	0.225	−6.730	0.000
COST	−2.791	0.335	−8.330	0.000
Standard deviation				
CAMERAS	0.416	0.049	8.500	0.000
SPEED	1.869	0.180	10.330	0.000
COST	0.802	0.193	4.150	0.000
LR	256.230			0.000
Log *L*	−805.75			
Observations	3296			

See Table 3 for definitions of variables.

cameras away from their current intersections. If the latter is the case, this would lead to positive coefficients on these dummy variables.

In addition to the attribute variables, Table 3 defines several other demographic variables which are frequently used in modeling choices. These include the dummy variables *BCOLLEGE*, *STUDENT*, and the respondent's age (*AGE*). As noted above, the median age is 29, suggesting a young sample, but there are 27 people in the full sample of 261 who are in their 50s, 10 who are in their 60s, and one person stated that they were 99 years old, so older people are indeed present.

The variables *SAFED*, *RDCAMSAFE*, and *CAREV*, all of which are preference variables, indicate the respondent's agreement with statements. One would expect that residents of BCS may want a program more than non-residents, resulting in a positive coefficient, and that those who believe they are safe drivers (*SAFED* = 1) and who believe the cameras lead to more safety (*RDCAMSAFE* = 1) would be more likely to support an RLC program. Believing that the RLC programs are only there to generate revenue might have either influence, as some residents might believe revenue generation for the city is a positive factor.

Several other variables for which data are available relate to the respondent's safety perceptions or conditions. The *ACCIDENT* indicator might have a positive influence on choosing to support RLC programs if the respondent's own past experience in an accident makes them want to see safer conditions at intersections, and, similarly, having young children in the home may have a similar positive influence. Finally, the respondent's *GENDER* may play a role in choices. Several studies have found that perceptions of risk and safety issues differ by gender.

From Table 3, it can be seen that the sample mostly consists of students (66%), but most live elsewhere than the BCS area, and that the average age is somewhat high for a student population. One can also see in Table 3 that the mean response for *SAFED* is high; most respondents see themselves as safe drivers. The mean agreement responses for *RDCMSAFE* and *CAREV* are close to the mid-point in the range of 1–5; about 26% (15%) of the sample responded with a three for the *RDCAMSAFE* variable and 30% (10%) responded with a three for *CAREV*, while the proportions of those who very strongly agreed in each case (response = 5) were 16% and 22%, respectively.

7. Model estimation results

Results for estimation of the model are presented in Table 4. To keep the paper of manageable length, presentation is limited to only the most robust and best fitting specification of the several models estimated, based on the usual goodness of fit criteria (*LR*, *Log L*). To begin, while the parameters or coefficients on all of the attribute variables were first allowed to have individual heterogeneity, the standard deviations on the intersection types of variables were insignificant. Insignificance indicates that a fixed coefficient is sufficient for these variables in the model, as would be true in the usual, simplified, conditional logit specification. However, the standard deviations or variances on the other key variables are significant, supporting use of the mixed logit or RPL model for these variables.

In specifying the RPL, one typically assumes the normal, lognormal, or triangular distribution for the random parameters. The coefficients on the variables *SPEED* and *CAMERAS* were assumed to be normally distributed. The normal distribution takes into account heterogeneity in tastes for these variables, but use of it makes no assumption about the sign of the variable (i.e., the direction of influence of the variable on the choice). In contrast, our a priori assumption was that the cost coefficient should be negative because it reduces the opportunity of the consumer to use that income for something else (i.e., demand curves slope downward). Train (1998, 1999) illustrates that cost and price variable coefficients used in choice models can typically be assumed to be log-normally distributed. Train (1998, 1999) suggests multiplying the coefficient by negative one before the simulation exercise.[2]

The intersection dummy variables are all significant and positive, indicating that the individuals prefer cameras in the high pedestrian, high volume, and mixed locations relative to the types of intersections where the cameras are currently located. For high pedestrian intersections, this positive sign may indicate support to protect the pedestrians, and the positive sign on the high auto traffic intersection similarly may reflect support for RLCs to reduce accidents there. Based upon the magnitude of the coefficients, the camera locations with high volumes of pedestrians are most preferred. This may be consistent with the literature that indicates concern about pedestrians being hit at intersections with traffic signals (e.g., Yang et al., 2006).

The coefficients on the variables *CAMERA*, *SPEED* and *COST* are all significantly different from zero and all provide negative marginal utility. Respondents, on average, prefer fewer to more cameras. Recall that the cameras not only capture other drivers' violations, increasing one's own safety, but also increase the individual's own likelihood of being caught, so on average the respondents may appear to be more concerned about getting caught themselves.

College Station is a college town, with many younger people who may tend to drive faster. The results on *SPEED* show that a higher (current) speed near intersections is preferred to lower speeds, consistent with other literature on delays at intersections with traffic signals (Al-Madani, 2003; Hossain, 2001). This is not surprising, given that a majority of the sample are college students. The fine or cost is of expected negative sign, when considered alone (holding other attributes constant) indicating a preference for smaller fines.

Many interaction effects between the demographic (individual) variables and the main attributes were tried in the estimation of the models, and the log-likelihood value was higher with these interaction terms than without them (−813.884 as compared to the one reported −805.75). Thus, they improve overall fit of the model. Significant interactions were between

[2] For an extensive review on the lognormal distribution in such models, the reader is referred to Casella and Berger (2002).

the *CAMERA* and individual-specific *AGE*, *STUDENT*, and *COST* variables. Older respondents are influenced by cameras in a positive fashion, and more strongly than younger respondents. The combined *CAMERA–COST* variable also has a positive influence on utility and choice, suggesting that if cameras are allowed to increase in combination with the fines, the probability of choosing that alternative increases. The negative sign on the interacted *CAREV* and *COST* variable suggests that those who believe the cameras are there for revenue generation have an even stronger negative reaction to the fines.

8. Summary/conclusions

Red-light camera (RLC) programs have been instituted in more than 70 communities in the US (Insurance Institute for Highway Safety, 2002) and they are increasingly used in several European countries (Maccubbin et al., 2001). Stated choice models have been used in transportation analysis of policies such as these, but have yet to be applied to study preferences for RLC programs. Here, an SCM was used to assess whether people support RLC programs and the strength of four key attributes of signaled intersections that determine this support, as well as the role of demographic and safety preference variables. While it may seem that everyone would support more safety, recent studies have indicated that there might be unexpected behavior at intersections with RLCs (see Obeng and Burkey, 2008), and it is not a given that people will support the use of cameras that invade privacy, nor is it clear that people believe that RLC programs are cost-effective.

A sample of 261 people living in and around Bryan-College Station was used to evaluate the impact of the RLC program there and preferences to future potential changes in the program. As noted above, this area is not necessarily representative of every city, nor even representative of all college communities in the US, as the area may be disproportionately high in people who commute by automobile. With this in mind, on average, respondents in our sample wanted programs with fewer, not more red-light cameras. They also prefer the actual current speed near intersections to a possible decrease, and prefer cameras in high pedestrian use locations, high volume intersections, or a mixed high-volume/high-pedestrian location, relative to the current placements at four existing intersections. Even though our model suggests that people get disutility from an increase in fines and the total number of cameras separately, an increase in both the cost and the cameras together (i.e., the interaction of these two variables) is seen as having a probable safety gain. Thus, this interacted variable positively influences RLC program preference because it increases utility from the RLC program. The results also suggest that older respondents are positively and more strongly influenced by having more cameras at the intersections in the community than younger people. This may be because older individuals are more aware of safety concerns.

The survey implementation and data collection for this project occurred several years ago, when there were four existing red-light cameras in the community. Since then, a great deal of controversy in the community ultimately led to a local referendum on whether the city should continue to use and collect revenue from violations recorded by the existing cameras. The majority vote, in the fall of 2009, was to have the cameras removed (see Smith, 2009). This type of anti-camera sentiment is not uncommon today in many communities in the United States. Thus, it is important that researchers continue to examine the safety and cost-effectiveness of red-light camera programs nationwide. This research has helped to identify some of the key features that could have led to one RLC program's acceptance.

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Appendix A:. Key survey questions

Example of choice question
Choose which you prefer: alternative A or B?

Alternative A	Alternative B
Four additional cameras placed at intersections with high pedestrian traffic $100 citation for running a red-Light Speed reduced by 5 miles per hour	Eight additional cameras placed at intersections with a mixture of pedestrian and vehicle traffic $50 citation for running a red-Light Speed unchanged from current
I choose: alternative A B (circle one)	

Do you strongly disagree, or strongly agree with the following statement?

I am always focused on the road when I am driving. (If you do not drive, please select N/A).

Strongly disagree 1 2 3 4 5 Strongly agree {circle appropriate number}.

Similar Statements (all have the scale above).

I always follow the posted speed limit. (If you do not drive, please select N/A).

Overall, I am a safe driver. (If you do not drive, please select N/A).

Other drivers are always focused on the road when they are driving.

Overall, other drivers are safe drivers.

The roads in College Station are generally in good condition for driving.

The roads in College Station are safe to bicycle.

There is an adequate network of bicycle lanes in College Station.

The roads in College Station are safe to walk along.

There is an adequate network of sidewalks in College Station.

It is safe for pedestrians to cross at intersections in College Station.

The area under construction on S. Texas Avenue is safe to drive.

Speed limits are too slow in College Station.

There is adequate police enforcement of traffic laws in College Station.

Red-light cameras make College Station roads safer.

Additional red-light cameras will further improve traffic safety.

Additional red-light cameras will further improve pedestrian and biker safety.

The CARES Program is designed primarily to generate revenue for College Station through citations.

Preventing drivers from running red lights is the most important issue for improving road and traffic safety in College Station.

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