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# The effect of information on drivers' toll lane choices and travel times expectations

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ABSTRACT

This paper reports on a study of drivers' toll lane choices and the effect of the type and content of information they are provided with on their travel time expectations and lane choices. In the data collection experiment, participants were asked about their travel time expectations. A mixed-effects regression model is developed to predict these expected travel times depending on the toll rates and type and content of travel information they are provided with. Then, a model to predict the choice whether or not to use the toll lane, using the expected travel times as explanatory variables, is formulated and estimated. The results show that drivers' expected travel times are affected by the information provided to them on the VMS. In particular, in the absence of precise travel time information drivers use the toll rate itself as an indicator to the expected travel times. In the choice model, there is a significant heterogeneity in preferences and the related values of time among drivers. In particular, there are large differences in values of time between drivers who pay the toll themselves and those whose employers pay the tolls.



## 1. Introduction

High Occupancy Vehicle lanes (HOV) are facilities that may be used only by public transportation and vehicles with at least a certain number of passengers. They are useful in reducing congestion through promotion of public transportation and higher vehicle occupancies. However, HOV lanes tend to be underused. High occupancy toll lanes (HOT), which permit other vehicles to use the lanes for a fee, have been promoted as an effective way of utilizing the excess capacity without reducing the time advantage to eligible vehicles and at the same time help finance new highway infrastructure (Burris, Ungemah, Mahlawat, & Pannu, 2009).

Understanding the demand for toll lanes and the factors that affect it is critical in planning for these facilities and in setting tolling schemes, in particular, when dynamic and real-time tolling are used. Models that predict drivers' choice of whether to use the tolled lane or the free lanes are essential for prediction of the demand on the HOT lane.

A typical scenario is a freeway section that consists of free and tolled lanes. Vehicles approaching the section receive information through variable message signs (VMS). Currently, most toll lane facilities provide drivers only with the toll rate (e.g. SR-91 Express Lanes in Orange County California and MnPass Express lanes in Minneapolis). Some facilities also show travel information in various forms. For example, the I-15 Express Lane in San Diego presents the travel times on the toll lanes. The TEXpress lanes in Texas and the Highway 1 Fast Lane in Israel provide qualitative information on traffic conditions and incidents on the free lanes.

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The classic behavioral model of toll lane choices assumes a tradeoff between cost and travel time saving (Burris et al., 2009; Devarasetty, Burris, & Shaw, 2012; Hess, Greene, Falzarano, & Muriello, 2011). This tradeoff is captured by the value of time (VOT), which is the marginal rate of substitution between these two variables in the utility functions of the various alternatives. The average VOT estimated in these studies vary greatly between 3.5 $/hr and 120 $/hr (Hess et al., 2011; Brownstone, Ghosh, Golob, Kazuimi, & Amelsfort, 2003; Burris & Shaw, 2012; Calfee & Winston, 1998; Janson & Levinson, 2014; Lam & Small, 2001 and the references within). Some of this variation has been explained by introducing to the model other attributes of the tolled and free alternatives that affect the lane choice. For example, travel time reliability (Patil, Concas, Burris, & Devarasetty, 2013), characteristics of the trip (e.g. purpose and urgency, Brownstone et al., 2003; Devarasetty, Burris, & Huang, 2014; Finkleman, Casello, & Fu, 2011) and socio-demographic characteristics of the drivers (e.g. income and household size, Lam & Small, 2001; Devarasetty et al., 2014). In the context of freight transportation, it has been shown that the identity of the entity responsible for paying the toll also affects VOT, with lower VOT for drivers that pay themselves compared to when a company bears the toll cost (Miao, Wang, & Adams, 2014; Toledo et al., 2013). In addition, explicitly accounting for the heterogeneity in preferences of different drivers can improve the model fit and explanatory power (Greene, Hensher, & Rose, 2006; Small, Winston, & Yan, 2005).

Another source of variability in toll lane use choices is that drivers make their decisions based on partial and inaccurate knowledge of the conditions, in paricular the travel times on the toll and free alternatives. As a results they systematically mispercieve travel times (Brownstone et al., 2003; Brownstone & Small, 2005). Devarasetty et al. (2014) found that drivers grossly overestimated their travel time savings on the Katy Freeway's managed lanes: They reported average savings of about 12 min, when the average observed savings were 3 min. Women, drivers with higher incomes, and those taking work trips tended to overestimate their travel time savings more than other drivers. Ghosh (2001) showed that drivers that overestimated travel times on the free lanes were more likely to use the toll lanes.

Brownstone et al. (2003) showed that in the absence of information about travel times, drivers use the toll rate as an indication to travel time savings and so are more likely to use toll lanes when the cost is higher than average. Owen, Janson, and Levinson (2014) analyzed data on tolls and flows in Minnesota. They found positive price elasticities during peak hours. The authors suggested that travelers perceive higher prices as indicating higher value, thus making the toll lane more attractive, as in luxury goods.

When information is provided, drivers' choices are affected by its content and presentation. For example, Basu and Maitra (2015) found that drivers that receive travel time information are more likely to use compensatory reasoning in making their route choice compared to those that do not receive any information. Dia (2002) found that quantitative and more exact qualitative information leads drivers to make decisions based on tradeoffs among attributes more than qualitative data. Erke, Sagberg, and Hagman (2007) found that drivers were more likely to comply with suggestions in variable message signs (VMS) when the information was more complex and detailed compared to more general and simple information. Recently, Brownstone, McBride, Kong, and Mahmassani (2016) tested the effect on route choices of various VMS schemes in incident scenarios. They developed a computer simulation experiment, in which multiple participants simultaneously chose routes based on VMS information, both descriptive and prescriptive. They found significant differences in drivers' behavior depending on the type and content of information. From the system optimal perspective, in most cases, qualitative description of the incident led to better diversion rates compared to quantitative and prescriptive guidance. Thus, in modeling toll lane choices it is useful to understand how drivers interpret information that they receive through VMS and consider it in their choices.

This paper reports on a study of drivers' toll lane choices and the effect of the type and content of information they are provided with on their travel time expectations and lane choices. The paper addresses two research questions: The first is how information provided on tolls and traffic conditions affect drivers' expectations of their travel time savings if they use a toll lane. The second is what the factors that affect the choice whether or not to use a toll lane are. In the data collection experiment, participants were asked to estimate their expected travel times using the information they received about toll rates and, in some cases, traffic conditions. In order to address the first research question, a mixed-effects regression model is developed to predict these expected travel times. Then, in order to address the second research question, a model to predict the choice whether or not to use the toll lane, using the expected travel times as explanatory variables, is formulated and estimated. The rest of the paper is organized as follows: the next section describes an experiment that was conducted in order to collect data for the estimation of the travel time expectation and lane choice models. The results of estimation of the two models are presented in the following two sections. Finally, concluding remarks are presented.

## 2. Data collection

### 2.1. Experiment

A stated preferences (SP) survey was developed to collect data on drivers' lane choice preferences and travel time expectations. The SP experiment was based on the hypothesized scenario shown in Fig. 1. Participants have a choice between a toll lane and parallel free lanes for a road section of 20 km as part of their trip. The travel time on the toll lane is guaranteed to be 12 min. Travel times on the free lanes vary based on the level of congestion. Before having to make the choice between the tolled and free lanes, a VMS is shown to the participant. The VMS provides information on the toll rate and in some cases on traffic conditions on the free lanes, in various formats.

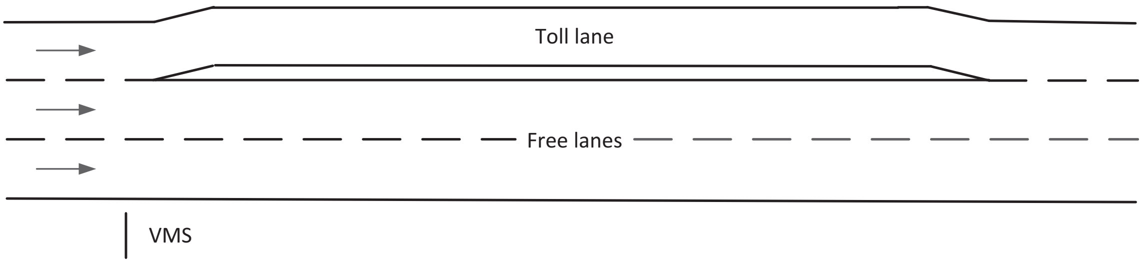


**Fig. 1.** Scenario for choice between tolled and free lanes.

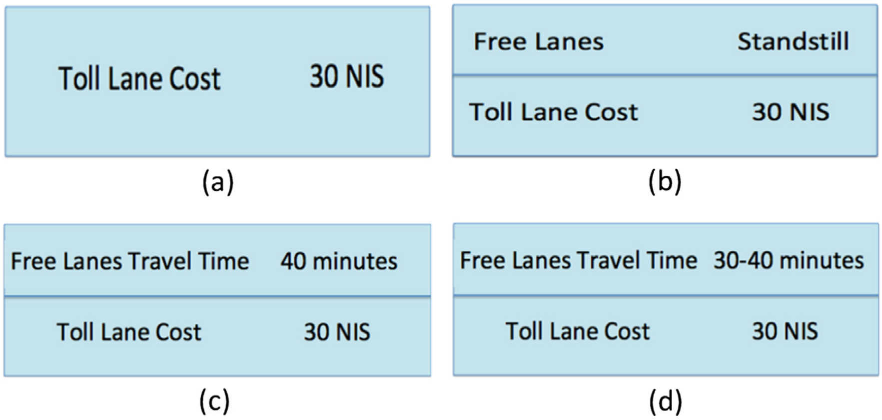


**Fig. 2.** Four formats of the information shown on the VMS in the experiment.

The four formats of VMS information that are shown in Fig. 2 were used in the experiment. Sign (a) shows only information about the toll rate. The other three also present travel time information on the free lanes: Qualitative description of the traffic condition (b), exact travel times (c), or a range of travel time (d). These sign formats represent typical configuration that are used by various road authorities (see guidelines in MUTCD, 2012; EasyWay, 2015; Chatterjee & McDonald, 2004 and the specific examples listed in the Introduction section).

The factors that were varied in the experiment were the toll rate, and depending on the format of the sign, the information about the free lanes: the travel time, both the travel time and the range of travel time uncertainty or the qualitative description of traffic conditions. These are consistently found to be the most relevant factors affecting route choices in the literature. Therefore, no additional factors were included in the experiment. The values of the various levels of these factors are presented in Table 1. The sign format dictated which information types and values are possible. The combinations of travel time and cost were chosen following experimentation in a pilot study. They represent a wide range of VOT values, ranging between 4 NIS/hr and 600 NIS/hr (3.8 NIS ≈ $1). The wording of the qualitative statements is similar to the one used in the Highway 1 corridor in Israel. They were not explicitly defined in the experiment, which is also the situation in the real-world. Thus, it is expected that there is variability in the perception of these terms in the drivers' population.

The participants were instructed to refer in their responses to a commute trip. They were also asked to indicate who will pay the toll, if they choose to use the toll lanes, and to assume the same payment responsibility in their responses. Participants were randomly allocated to one of the sign formats. They were then asked to choose the toll or free lanes in five different scenarios, with different combinations of the values of the factors. When information on the travel times was not provided at all or when only qualitative information was displayed, the participants were also asked to estimate the travel times on the free lanes. A full factorial design was produced and arranged in 13 blocks of five scenarios each using the Ngene

**Table 1**
Level values for the factors in the experiment.

| Factor | Values |
|---|---|
| Toll rate (NIS) | 2, 5, 10, 20, 30 |
| Travel time on free lanes (min) | 15, 20, 25, 30, 40 |
| Range of travel time uncertainty (min) | 1, 5, 10, 15, 20, 25 |
| Description of traffic conditions on free lanes | Flowing, congested, standstill |

(Wheeler & Braun, 2004) software. A built-in capability in Qualtrics was used to constrain even allocation of respondents to blocks.

Before starting the questionnaire, potential participants were asked, as a screening question, whether they own a drivers' license. The questionnaire itself also asked about the frequency that they use the Highway 1 Fast Lane corridor in Israel and about their socio-demographic characteristics: gender, age, education, employment type, and car ownership. The survey was administered using the Qualtrics online survey platform (Qualtrics, , 2012). The survey was distributed mainly through social media. In soliciting responses, emphasis was given to social groups that target residents of the area served by the Highway 1 Fast Lane in order to also obtain observations from individuals that make the toll lane choices in their real-world settings.

### 2.2. Sample

460 participants completed the web-based experiment. Table 2 presents a summary of the characteristics of the participants. The use of a web-based survey creates a sample that is not representative of the drivers' population. It over-represents males, younger participants and students. However, it should be noted that the participants are not endogenously sampled (selection is not conditional on the choices). In this case of an exogenous sample, corrections and weighing of the observations should not be made in model estimation using this data (Manski & McFadden, 1981).

Most participants would be paying the tolls themselves if they choose to use the toll lanes. A small fraction would be able to receive a partial refund through tax deductions, which is relevant to some trips taken by individuals who are self-employed. Most participants do not often face the toll use choice situation. Only 24% reported traveling on the Highway 1 corridor (regardless of whether they chose to use the toll lane or not) at least once a week.

## 3. Results

### 3.1. Travel time expectations

As noted above, in the experiments that involved no information or only qualitative information on travel times on the free lanes, the participants were asked to state what they expect the travel times on the free lanes would be. In all cases, they were told that the travel time on the toll lanes are expected to be 12 min.

The average and standard deviations of the travel time estimates with the different information provided are presented in Table 3. As expected, the information affects participants' travel time estimates, with indications of higher levels of congestion substantially increasing the travel time estimates. The coefficient of variation of the estimates decreases when information is provided in comparison to the no information cases.

In order to quantify the effect of information, toll rates and other factors on the participants' travel time expectations, a linear mixed-effects regression model was developed:

$$ETT_{nt} = X_{nt}\beta + X_{nt}\sigma_n + \varepsilon_{nt} \tag{1}$$

where $ETT_{nt}$ and $X_{nt}$ are the travel times in minutes estimated by individual $n$ in scenario $t$, and the explanatory variables that predict it, respectively. $\beta$ are the associated coefficients (fixed effects). $\sigma_n \sim N(0, \Sigma)$ are individual-specific random effects. $\varepsilon_{nt}$ is an i.i.d. normally distributed error term.

The model was estimated using the lme4 package in R (Bates, Maechler, Bolker, & Walker, 2015). The estimation results are presented in Table 4. The intercept of the model is 14 min, which is longer than the 12 min travel time reported for the toll lane. In the cases that negative information (i.e. congested, standstill) about traffic conditions on the free lanes is provided, the travel time expectations are strongly affected. These information increase the travel time expectations by approximately 10 and 24 min, respectively. In contrast, positive information (flowing) only slightly affects the travel time expectations: a decrease of less than 1 min. This result is consistent with a large body of literature on negativity bias, which suggests that negative information has a larger effect on perceptions compared to positive one. This is explained by negative information being more salient and that its processing attracts larger attention (e.g. Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001; Rozin & Royzman, 2001). The effect of positive information is also bounded by the provided benchmark of the travel time on the toll lanes. Very similar results, of a small insignificant effect for positive information and a large effect for negative information, are reported, for example, in the context of perception of potential employers (Kanar, Collins, & Bell, 2010).

**Table 2**
Characteristics of the participants in the experiment.

| Characteristic | Distribution |
|---|---|
| Gender | 70% male, 30% female |
| Age | 15% 24 or under, 45% 25–34, 38% 35–64, 1% 65 or over |
| Employment | 59% Hired employees, 24% students, 10% self-employed, 7% unemployed or retired |
| Toll payment | 75% driver, 18% employer, 3% family, 4% driver, but tax deductible |
| Frequency of using the highway 1 corridor | 54% less than once a month, 22% once or twice a month, 15% once a week, 9% more than once a week. |

**Table 3**
Average and standard deviations of travel time expectations.

| Travel time information | Sample size | Average (min.) | Standard deviation (min.) | Coefficient of variation |
|---|---|---|---|---|
| None | 210 | 23.5 | 11.1 | 0.47 |
| Qualitative – flowing | 228 | 16.3 | 7.6 | 0.47 |
| Qualitative – congested | 221 | 27.0 | 10.5 | 0.39 |
| Qualitative – standstill | 220 | 41.9 | 15.2 | 0.36 |

**Table 4**
Estimation results for the Travel time expectations model.

| Fixed effects | Estimate | Std error | | p-value | |
|---|---|---|---|---|---|
| Intercept | 14.05 | 1.62 | | <0.001 | |
| Qualitative information – flowing | −0.71 | 1.56 | | 0.65 | |
| Qualitative information – congested | 9.86 | 1.67 | | <0.001 | |
| Qualitative information – standstill | 24.20 | 1.88 | | <0.001 | |
| Toll rate | 0.086 | 0.03 | | 0.001 | |
| Toll rate × no information | 0.39 | 0.05 | | <0.001 | |
| High income × no information | 5.79 | 2.57 | | 0.02 | |
| Travel often on Highway 1 | 2.19 | 1.27 | | 0.09 | |
| Random effects | Estimate | Random parameters correlation matrix | | | |
| Standard deviation – Intercept | 7.37 | 1 | | | |
| Standard deviation – qualitative congested | 8.88 | −0.20 | 1 | | |
| Standard deviation – qualitative standstill | 15.15 | −0.34 | 0.91 | 1 | |
| Standard deviation – toll rate | 0.25 | −0.28 | −0.17 | 0.03 | 1 |
| Number of observations = 879 | | | | | |
| Number of respondents = 176 | | | | | |
| Log likelihood = −2939.2 | | | | | |

The toll also affects the travel time estimates. On average, when information on traffic conditions is provided, an increase of 11 NIS in the toll rate adds one minute to the travel time estimates. There was no significant difference in the effect of the toll rate on travel time expectations between the different qualitative information contents. However, when information is not provided at all, the cost becomes the only indicator to the potential travel time savings. Therefore, participants relied more heavily on the toll rate in forming their expectations. On average, one minute was added to their travel time expectation for every 2.1 NIS of toll. Fig. 3 demonstrates these effects. Fig. 3(a) shows the change in the travel time expectations as a function of the toll rate. The higher slope of the travel time expectation as a function of the toll rate is evident in the figure. Fig. 3(b) shows the median and 25th and 75th percentiles of the expected travel times for the various travel information options and for two levels of toll rates. The figure demonstrates the increase of expected travel times with the severity of the traffic flow description, from flowing to congested and standstill. It also shows the effect of the toll rate on the travel time expectations, and in particular when no other information is provided. A similar phenomenon was also observed by

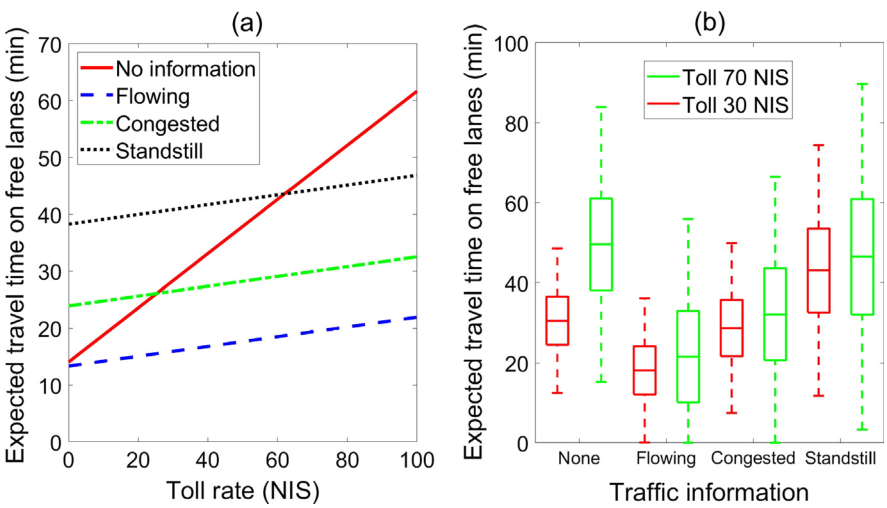


**Fig. 3.** Effect of toll rate and traffic information on travel time estimates.

Tenenboim and Shiftan (2018). These results are also consistent with theory and empirical finding in other domains. Rao and Monroe (1989) review literature on consumers' perception of product quality. The literature consistently shows positive relation between price and quality. Furthermore, when price is the only cue to quality, the positive effect is larger (Chang & Wildt, 1996).

The case of no information on traffic conditions, and the uncertainty associated with it, was also the only one in which any of the socio-demographic characteristics of the respondents affected the travel time expectations. In this case, respondents that reported high income levels estimated longer travel times on the free lanes. Finally, Respondents that travel the section of Highway 1 that has a toll lane option (regardless of whether they use the toll lanes or not) at least once a week, expected higher travel time on the free lanes than others. This may reflect their experience with the real-world facility in which the free lanes are often heavily congested with very high travel times.

The random effects included in the model account for a lack of independence among observations from the same respondent. They are assumed to vary by individual, and so capture the heterogeneity in expectations between individuals. Random effects that improved the model fit and were retained in the final model are the ones for the intercept, toll rate, and the congested and standstill qualitative information. For all four, the random effect is large, indicating high variability between individuals. It is especially large, compared to the mean coefficient value, for the toll rate. This suggests large variation in the way that the participants interpreted the toll rate as an indicator to the expected travel times. This is not surprising given the confusion and lack of understanding in the public on the mechanism used to set toll rates, which in Highway 1 is designed to prevent delays for vehicles on the toll lanes and does not explicitly consider congestion on the free lanes. The specification of the joint distribution of random coefficients allowed correlations among them. The correlation matrix based on the estimation results is shown next in the random effects part of Table 4. Among the random coefficients, a high positive correlation exists between the coefficients for the congested and standstill dummy variables. This seems plausible as both capture individuals' interpretations of similar types of information. The heterogeneity in travel times expectations is also illustrated in Fig. 3(b) by the error bars showing the 25th and 75th percentile values of the travel time expectations for the various information cases.

### *3.2. Toll lane use choice*

A mixed logit model was developed for the choice whether or not to use the toll lanes. A utility function is associated with the toll and free alternatives:

$$U_{int} = V_{int}(X_{int}, \beta_n) + \varepsilon_{int} \tag{2}$$

where $U_{int}$ and $V_{int}$ are the total and systematic part of the utility of alternative (lane) $i$ to individual $n$ in choice experiment $t$, respectively. $\varepsilon_{int}$ is an i.i.d. Gumbel error term. $x_{int}$ and $\beta_n$ are the explanatory variables in the utility function and the corresponding individual-specific parameters, respectively.

The individual-specific parameters are modeled as random coefficients. They capture taste heterogeneity among individuals. In the current model two coefficients are assumed to be distributed in the population: the coefficients of the toll rate and of travel time. Theoretically, and supported by the empirical literature, the travel time and cost coefficients should be negative. Prato (2009) shows that the lognormal distribution is commonly used for this purpose and recommends its use. The distribution also easily extends to estimation of the bivariate distribution. Therefore, the toll rate and cost coefficients are assumed to follow a bivariate lognormal distribution:

$$\ln\begin{bmatrix}\beta_{tollRate,n}\\ \beta_{tt,n}\end{bmatrix} \sim N\left(\begin{bmatrix}\beta_{tollRate}\\ \beta_{tt}\end{bmatrix}, \begin{bmatrix}\sigma^2_{tollRate} & \\ \sigma_{\mathrm{tollRate,\ tt}} & \sigma^2_{tt}\end{bmatrix}\right) \tag{3}$$

where $\beta_{tollRate,n}$ and $\beta_{tt,n}$ are the coefficients of toll rate and travel time for individual $n$, respectively. $\beta_{tollRate}$ and $\beta_{tt}$ are the corresponding mean parameters of the lognormal distribution. $\sigma^2_{tollRate}$ and $\sigma^2_{\mathrm{tt}}$ are their variances. $\sigma_{\mathrm{tollRate,\ tt}}$ is their covariance.

Under these assumptions, the predicted choice probabilities are given by:

$$P_{nt}(i) = \frac{1}{1 + \exp\left(V_{jnt}(x_{jnt}, \beta_n) - V_{int}(x_{int}, \beta_n)\right)} \tag{4}$$

The model was estimated with BIOGEME (Bierlaire, 2003) and using the simulated maximum likelihood method with 4000 Halton draws. The final systematic utility function is given by:

$$\begin{aligned} V_{tollLane,nt} &= \beta_{tollLane} + \beta_{tollRate,n} X^{tollRate}_{nt}\left(1 + \beta_{employerPays}\delta^{employerPays}_{n} + \beta_{taxDeduct}\delta^{taxDeduct}_{n}\right) \\ &\quad + \beta_{tt,n} X^{tt}_{tollLane,nt} + \beta_{oftenHighway1}\delta^{oftenHighway1}_{n} \\ V_{freeLane,nt} &= \beta_{tt,n} X^{tt}_{freeLane,nt} + \beta_{ttRange}\delta^{ttRange}_{nt} \end{aligned} \tag{5}$$

where $X^{tollRate}_{nt}$ is the toll rate in NIS. $X^{tt}_{tollLane,nt}$ and $X^{tt}_{freeLane,nt}$ are the travel times in minutes on the toll and free lanes, respectively. $\delta^{\mathrm{ttRange}}_{nt}$ is a dummy variable for the case that the VMS sign presented a range of travel times. $\delta^{employerPays}_{n}$ and $\delta^{taxDeduct}_{n}$ are dummy variables for the cases that the employer pays the tolls or that they are tax deductible, respectively. $\delta^{\mathrm{oftenHighway1}}_{n}$ is a dummy variable for drivers that use the Highway 1 corridor at least once a week. $\beta' s$ are the corresponding parameters. $\beta_{tollLane}$ is an alternative-specific constant.

The model estimation results are presented in Table 5. The toll lane constant is negative, which indicates a reluctance of drivers to use the toll lanes when everything else being equal. This objection to the toll lane is consistent with comments that some respondents made in an open question in the survey. Arguments that were repeated were that the state should provide road infrastructure freely and that the public has already paid for it through taxes.

As expected, both the travel time and toll rate coefficients are negative. Both these coefficients were estimated as random parameters. The estimated parameters of their standard errors are the Cholesky factorization of the covariance matrix. The coefficients' distribution is given by:

$$\ln\begin{bmatrix} -\beta_{tollRate,n} \\ -\beta_{tt,n} \end{bmatrix} \sim N\left(\begin{bmatrix} -0.635 \\ -1.120 \end{bmatrix}, \begin{bmatrix} 0.903 & \\ 0.346 & 0.558 \end{bmatrix}\right) \tag{6}$$

The estimated standard deviations are large, which indicates wide heterogeneity in preferences among individuals. The sensitivity of the utility to the toll rate is significantly lower, roughly by a factor of two, in the cases that the toll is paid by the respondent's employer or that the toll is a tax-deductible expense compared to when the respondent is responsible for the paying the toll. This implies that VOT are doubled when the driver is not responsible for the toll cost or when it is tax deductible. The mean estimated VOT is 54 NIS/hr ($\approx$ 14 \$/hr) for drivers that pay for the toll from their own pockets and 101 NIS/hr ($\approx$ 27 \$/hr) for drivers whose employers pay for the tolls. The corresponding median VOTs are 37 NIS/hr ($\approx$ 10 \$/hr) and 69 NIS/hr ($\approx$ 18 \$/hr), respectively. These VOT are in the lower part of the range of values reported in the literature. This can be partly explained by the use of SP data, which has been shown to produce lower VOT compared to studies that used revealed preferences data (Brownstone & Small, 2005). Another cause may be that the travel times used in this study were based on the expected ones reported by the participants. Most other relevant studies used objective measurements or travel times that were prescribed in SP scenarios. Research has shown that drivers tend to overestimate the potential travel time savings that toll lanes offer (Devarasetty et al., 2014). Thus, estimating VOT based on objective measurements may bias VOT upwards. The use of expected travel times reported by the participants avoids this potential bias. The estimated VOT distributions for drivers that pay the tolls themselves and for those whose employers pay the tolls are shown in Fig. 4.

The VOT values and their distribution may depend on the assumption about the distribution for the random coefficients of the cost and travel times. The results reported above are based on the assumption that these follow a bivariate lognormal distribution. Table 6 reports summary results for three other models with different assumptions about the mixing distributions. The overall fit, estimated parameter values and the resulting VOTs are similar with all four models. The best fit was obtained with Johnson's SB distribution and the normal distributions. However, these are unbounded at zero. As a result, they exhibit 4% and 5% respectively positive VOTs. Also, their mean VOT is not finite, since the probability density of zero cost coefficient is positive. A model using Johnson's Sb distribution, but with a lower bound fixed at zero, yields results and a fitted distribution that are very similar to those of the lognormal distribution. Thus, the selection of the mixing distribution does not substantially affect the results. The parsimonious and theoretically appropriate lognormal distribution is therefore preferred.

Travel time reliability has been shown to be an important factor affecting route choices (e.g. Patil et al., 2013). In the current experiment, drivers that were shown a VMS with a range of travel times on the free lanes were less likely to choose these lanes. However, in the model, no significant pattern was found with respect to the effect of the size of this range on the choice. Therefore, in the final model, a dummy variable indicating a VMS with a range of travel times was used.

Drivers that travel often on the section of Highway 1 that has toll lanes are faced with the choice scenario presented in the experiment in their real life. These drivers were less likely to choose the toll lane. A possible explanation is that drivers may be more willing to use the toll lane on infrequent trips compared to their regular ones. Finally, it should be noted that the

**Table 5**
Estimation results for the toll lane use choice model.

| Parameter | Estimate | Std error | p-value |
|---|---|---|---|
| Toll lane constant | −0.673 | 0.178 | <0.001 |
| Toll rate | −0.635 | 0.0933 | <0.001 |
| Employer pays toll | −0.463 | 0.0612 | <0.001 |
| Toll is tax deductible | −0.519 | 0.123 | <0.001 |
| Travel time | −1.120 | 0.0831 | <0.001 |
| Sign with travel time range | −0.221 | 0.255 | 0.38 |
| Travel often on Highway 1 | −0.622 | 0.218 | 0.004 |
| $\sigma_{toll\ rate}$ | 0.950 | 0.103 | <0.001 |
| $\sigma_{travel\ time}$ | 0.652 | 0.0509 | <0.001 |
| $\sigma_{toll\ rate,\ travel\ time}$ | 0.364 | 0.118 | 0.002 |
| Number of observations = 4367 | Number of respondents = 570 | | |
| Log likelihood = −1487.2 | $\rho^2 = 0.509 \bar{\rho}^2 = 0.505$ | | |

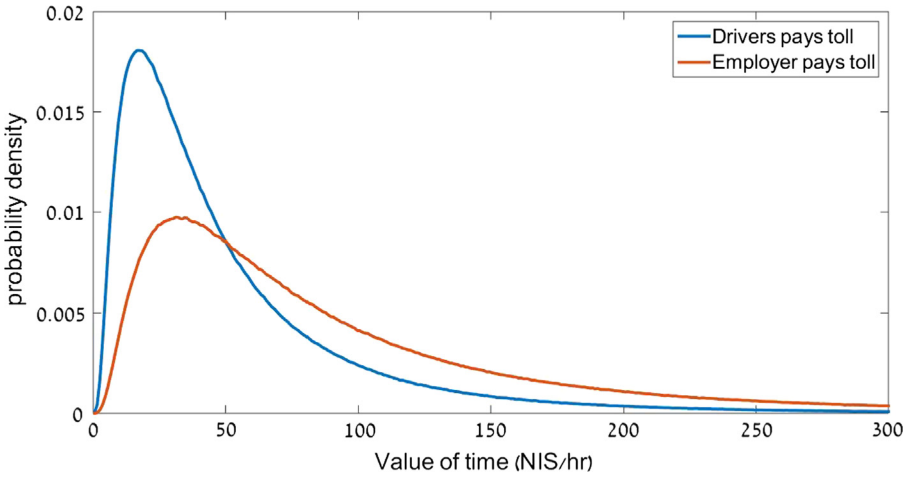


**Fig. 4.** Distribution of values of time.

**Table 6**
Estimation results for models with different distributions of random coefficients.

| Distribution | No. of parameters | Log likelihood | Goodness of fit | | VOT (NIS/hr) | | |
|---|---|---|---|---|---|---|---|
| | | | $\rho^2$ | $\bar{\rho}^2$ | Mean | Median | Remarks |
| Lognormal | 10 | 1487.2 | 0.509 | 0.505 | 54 | 37 | |
| Normal | 10 | 1481.3 | 0.511 | 0.507 | ND | 36 | 5% positive |
| Johnson's Sb | 14 | 1478.9 | 0.511 | 0.507 | ND | 37 | 4% positive |
| Johnson's Sb bounded at 0 | 12 | 1485.4 | 0.509 | 0.505 | 56 | 36 | |

socio-demographic characteristics of the drivers, such as age, gender and income were not found to be significant in the model and therefore omitted from the final model.

The effects of the various variables in the model on the toll lane choice probability are demonstrated by varying their values one at a time. Unless varied, the toll rate is 10 NIS, the travel time on the toll lane is 15 min shorter than on the free lanes. The driver pays the toll and does not use Highway 1 frequently. The VMS sign does not show a range of travel times. The results of this sensitivity analysis are shown in Fig. 5. The figure demonstrates the increase in the probability of choosing the toll lane when a range of expected travel time on the free lanes is displayed on the VMS. It also shows the lower probability of using the toll lane for drivers that are often faced with a toll lane choice scenario in their real life. For both the travel times and tolls the figure shows the median choice probabilities. Both plots illustrate the large difference between drivers that pay themselves and those whose employers pay the tolls.

In addition, there is large heterogeneity among drivers as captured by the random coefficients of toll and travel times. Fig. 6 demonstrates this by showing the toll lane choice probabilities for drivers at the median and the 75th and 25th percentiles of these distributions. For the travel time variable, the figure shows that drivers at the high end of the distribution would be willing to pay for the toll lane even for modest travel time savings. At the low end of the distribution, drivers are not willing to use the toll lane unless the savings are substantial. A similar pattern is observed for the toll rate coefficient. Note that the scenario shown in the figure assumes travel time savings of 15 min, regardless of how many drivers choose the toll lane. With this, when the toll rate is close to zero, practically all drivers choose the toll lane.

## 4. Discussion and conclusion

The results of this study show that traffic information provided to drivers affects their travel time expectations, as does the toll rate itself. When traffic information is provided to the drivers, it affects their travel time expectations and taken into account in choosing between the toll and free lanes. When travel times are not provided, drivers use the toll rate as an indicator to the potential travel time savings: Drivers' expectations of travel time savings increase substantially with the toll rates. However, in many cases, dynamic toll rates are set to keep the toll lanes flowing, regardless of traffic conditions on the free lanes. Therefore, they are only indirectly related to the travel time savings. This implies that drivers' travel time saving expectations based on toll rates may be misperceived and that their sensitivity to increases in the toll rate would be reduced by the perception that a higher toll implies larger travel time savings. This leads to inefficient lane choices, where drivers would tend to use the toll road more in the absence of travel time information. Thus, provision of travel time information in this context is desirable.

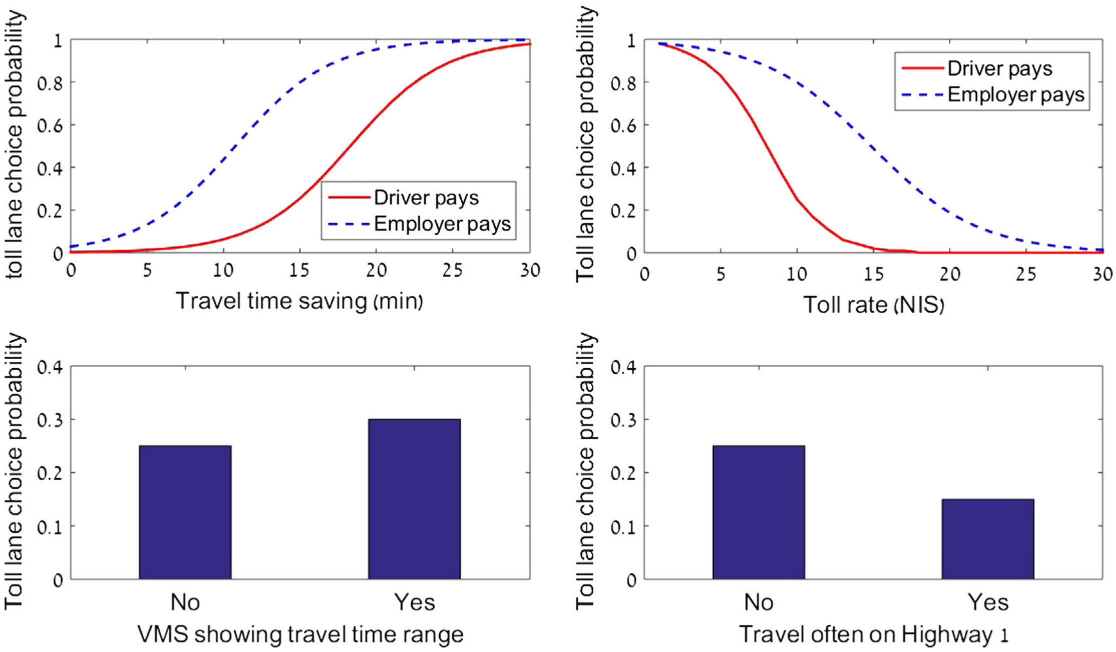


**Fig. 5.** Effect of explanatory variables on the choice to use the toll lane.

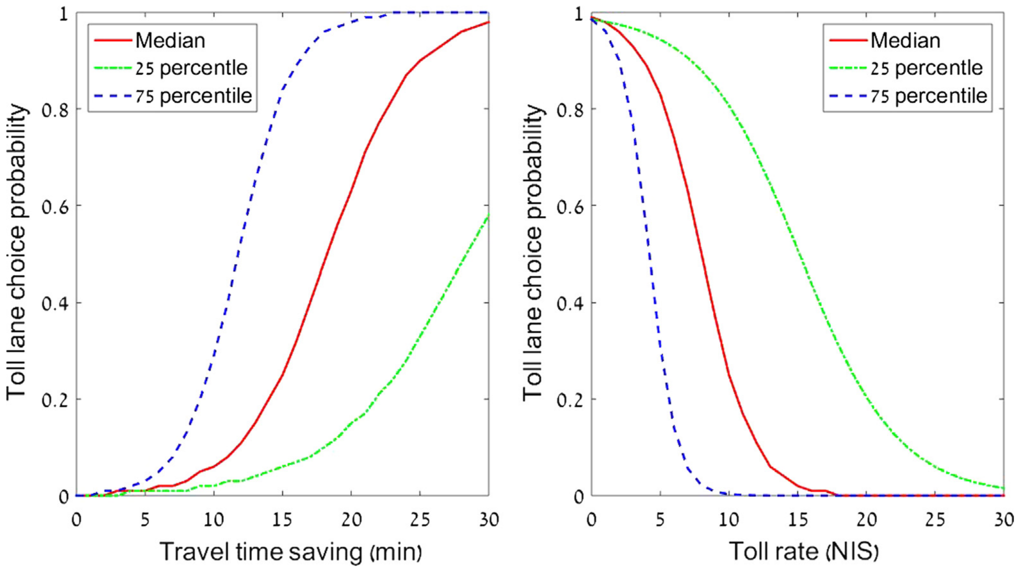


**Fig. 6.** Heterogeneity in choice to use the toll lane.

In predicting the usage of toll lanes and similar facilities, it is widely accepted that the demand is affected by the trade-off between travel time savings and the toll rate (VOT). Even when other variables are taken into consideration, VOT remains a key factor in drivers' choices. The effect of toll rates on travel time expectations also suggests that VOT calculated based on observed travel times would be lower compared to the ones calculated based on drivers' travel time expectations. Models that ignore this dependency would tend to overestimate drivers' sensitivity to the toll rate when travel time information is not provided.

The models developed in this study accounted for the heterogeneity in VOT in the population through the use of random cost and toll rate parameters and through the inclusion of variables that capture systematic sources of heterogeneity, such as the toll bearer identity. Estimation results found large coefficients of variation for the random parameters, and showed that the VOT of drivers whose employers pay the toll or have it tax deductible were roughly double of those that paid themselves.

Thus, overall, the results demonstrate the existence of wide variability in preferences. Modeling the sources of heterogeneity is in particular needed in the context of toll lanes, where facility operators only need to attract a certain, often not large, fraction of users in order to fill the available capacity. Thus, the ability to model not only mean VOT, but also distributions, and to distinguish different population segments is useful.

A limitation of the current study is the reliance only on SP data. SP data is subject to biases related to simplified decision protocols, lack of familiarity with the choice situation, ignoring situational constraints, lack of consequences of the choices made, and policy preferences of the participants. Previous studies have shown a tendency to underestimate VOT when using SP data compared to observed choices (Brownstone & Small, 2005). Despite its limitations, SP data is widely accepted and useful in situations where observations of actual behavior are not feasible. This is the case in this study due to the inability to experiment with the form and content of information and pricing in the real-world. Strategies to reduce SP biases include increasing the task complexity, hiding the study purpose and linking the incentives to response outcomes (e.g. Fifer, Rose, & Greaves, 2014; Lu, Fowkes, & Wardman, 2008). In the current experiment, the biases may be partly offset by variables that capture the familiarity of respondents with the choice situation (use of Highway 1), and the added complexity of the choice task induced by the situational description and constraints (commute trip, toll bearing identity) and the various information provided. The study was described to participants as an academic study to help understand drivers' preferences without reference to the toll lanes. The focus in the SP questions on information types may also curb policy biases related to attitudes towards toll lanes. It was not possible to link incentives to response outcomes, as was done, for example, in Brownstone et al. (2016). Participants did not receive incentives for participation, which would have been difficult with the online administration of the survey. Furthermore, it would not be clear what the desired outcome to link the incentive to would be.

Another limitation is related to the generation of the sample. It is a non-probability self-selected sample. Therefore, it is not possible to claim that the results presented can be generalized. However, it should be noted that in the recruitment of participants, they were not told about the purpose of the study. Thus, it is plausible that the sample is exogenous and that the models derived from the data have validity. In the context of political choices modeling, Alvarez, Sherman, and VanBeselaere (2003) found that there were no significant differences in results using different sampling strategies, including one that is similar to the one used in this study. Still, further research would be needed to strengthen the general validity of the findings.

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