Which is the biggest carrot? Comparing non-traditional incentives for demand management

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Abstract

While congestion charging has been heavily studied, relatively little literature focus on incentives and none is comparing different incentivization schemes. This paper investigates the impact of providing incentives on travelers' choices for their commute to work. In contrast to road pricing, an approach of offering incentives to decongest is gaining interest with field test in Europe, India, the US or Singapore. Many forms of incentives exist and the objective of this study is to analyze the potential of a variety of incentive schemes including offering monetary rewards such as cash, credit towards Apple Store, donations, lottery, or in-kind rewards such as HOV pass, guaranteed parking, free coffee or privileged status. This study analyzes the results of a stated-preference survey conducted in the San Francisco Bay Area. In this survey the participants were presented with hypothetical scenarios where they could change their commute for an incentivized alternative. A nested-logit model was estimated from the SP survey and forecasts were made using the 2000 Bay Area Travel Survey. We found that our subjects are willing to change their commute, exhibiting a range of willingness to be paid \$6.95-\$18.98 per hour of travel time or \$10.60-\$28.93 per hour of schedule delay. Apple credit and cash proved to be the more efficient monetary rewards while HOV pass was value at \$10.85 by the participants. As predicted by behavioral economics, travelers are much more sensitive to charges than to rewards. While application of the model within a traffic simulator is outside of the scope of this study, more limited forecast explore the direct demand response. Illustrative forecasts show that the main contribution to a shift outside the peak hour relies in an earlier departure time and the use of an alternative road or that the use of incentives to shift people follows a law of increasing returns.

1 Introduction

Congestion is caused by massive commuting at more or less a common timeframe (e.g. the morning rush-hour), and it is a collective, synchronic phenomenon. Therefore, shifting commuters' departure times to less congested times, before or after the rush-hour, rerouting some portion of the flow, changing transport mode (from car to transit) or changing work mode (working from home), should, in theory, lead to considerable time savings, greater travel time certainty and lower external costs of congestion. To achieve these changes, most urban economists and a growing number of other policy analysts agree that the best policy to deal with congestion would be some form of road pricing. However, politically, congestion pricing can be difficult to implement and the use of incentives has emerged as an alternate way to decongest transport facilities.

Several incentivization fields tests implemented in Europe, India or Singapore proved to be efficient in reducing congestion. The notion of using rewards to achieve desired outcomes in travelers' behavior was implemented in 2006 in the Netherlands within the Spitsmijden program (the Dutch term for peak traffic avoidance). The pilot study, involving 340 participants and lasting over 13 weeks, was aimed to investigate the potential impacts of rewards on commuters' behavior during the morning rush hour. The results of the study indicate that positive incentives are able to reduce the amount of peak traffic of the participants by about 60%, mainly through a shift of the car trips to the periods before and after the peak period. Similarly, between October 2008 and April 2009, Merugu and Prabhakar (*1*) successfully deployed a lottery incentive mechanism over a six-month period in Bangalore, India, for encouraging commuters to travel at off-peak hours. In Singapore, the "Incentive for Singapore's Commuters" (Insic) has been launched early 2012 with the aim of encouraging off-peak commuting and build loyalty towards the public transit system. Participants earn credits per kilometers traveled by rail and can then use the credits to redeem cash prizes, or money credited straight into their public transportation travel card, for more trips.

While previous studies have typically tested one incentive scheme at a time, the aim of this paper is to investigate and compare the impact on commute behavior of 7 different incentivization schemes (cash, lottery, donation, credit to Apple Store, HOV pass, guaranteed parking, free coffee and status) and one congestion charge scheme. To do so, we administrated a stated-preference (SP) survey to commuters in the San Francisco Bay Area and modeled their behavioral responses using discrete choice analysis. The rest of this paper is organized as follows: Section 2 reviews the literature about the use of rewards to alleviate congestion. Section 3 describes the research approach. Experimental setup and presentation of the survey are presented in section 4. Results, based on a nested logit model are presented in Section 5. A calibration of the model and forecast based on the estimation results are presented in Section 7, followed by the conclusions in Section 8.

2 Literature

The intention of both road pricing and incentivization is to alter people's travel behavior enough so that the behavioral response leads to an increased efficiency of the transportation system. However, while the effects and the concerns raised by road pricing have been well documented in the literature, the literature is very sparse when it comes to the use of rewards to decongest transport facilities.

Most of the literature about the use of rewards to decongest transport facilities stems from the Spitsmijden experiment. Prior to the field experiment and using a stated-preference survey, Jasper Knockaert, Michiel Bliemer, Dick Ettema and Albert Mulder, Jan Rouwendal (*2*) determined reward-based values of time of €4.55 and value of schedule delay early and late of respectively €2.98 and €2.80. During the field experiment, participants could earn either €3 to €7 cash reward or credits to keep a Smartphone handset by deciding to drive to work earlier or later, switch to another travel mode or by teleworking. Based this revealed preference data, Ben-Elia and Ettema (*3*) showed that, while a monetary reward might be framed as a prospective gain, in-kind rewards had similar effects as monetary rewards. However, although the experiment was intended to achieve a structural change in travel behavior, it was observed that travelers returned to the peak period when the incentives ended (Ettema et al. (*4*)). Similarly to the Spitsmijden experiment, the scheme developed by Merugu and Prabhakar (*1*) awarded credits each day to employees based on their arrival times. Each week, the cumulative number of credits of each commuter was used by an algorithm to choose commuters who would win monetary rewards. The project has been a success: it succeeded in attracting a large number of commuters to travel at off-peak hours, led to a advancement of pickup times in the bus schedule, was greeted with enthusiasm by commuters, shortened the commute times by at least 30 minutes, reduced fuel consumption, pollution and overall congestion. However, like many other active programs who incentivize commuters to change their behavior (e.g. 12 counties around the San Francisco Bay Area offer various incentive program encouraging commuters not to drive alone (Metropolitan Transportation Commission (*5*)) or the "Speed Camera Lottery" in Stockholm (Schultz (*6*))), the impacts of the incentives are analyzed at an aggregate level. A more detailed analysis provides the drivers of the behavioral change and helps the transportation planner play with these drivers to manage travel demand.

Even though literature related to incentivization in the transportation field is closely tied to the Spitsmijden experiment, connected fields can provide insights on how effective the rewards are for motivating behavior change. Micro-economic theory, which has been dominant in transportation research, assumes that users have a symmetrical elasticity towards price increase and decrease. On the contrary, literature in behavioral economics (Kahneman and Tversky (*7*)) has demonstrated a difference in valuation of gains and losses and subsequently shown that people may respond differently when they are rewarded rather than punished (Kahneman and Tversky (*8*)). Moreover, Thorndike's law of effect (Thorndike (*9*)) stated originally that behavior that was followed by satisfying effects would be repeated more often in the future (Galef (*10*)). Behavior followed by annoying effects, conversely, would be less likely to be repeated. Moreover, rewards can be shaped to establish interest in activities that lack initial interest (Bandura (*11*)), to maintain or enhance effort and persistence at a task (Eisenberger (*12*)). Thus, the potential of rewards as a tool to reduce congestion is well worth considering, provided it is based on robust behavioral foundations.

Literature about congestion pricing is also a great source of insight when it comes to assess the impact of rewards on travel demand. Indeed, the design of new congestion charge schemes often used stated preference techniques to move from the traditional road pricing regimes (such as fuel taxes, parking fees, and car registration fees) to a more economic efficient variable user charge schemes. Therefore, similar means of study can be used to assess what should be the type of reward regime or the structure of the reward. Stated preference (SP) techniques represent the state of art and practice approach to understand the potential impacts of a new product or policy such as a incentivization scheme, and the behavioral responses towards it. Li and Hensher (*13*) identify the extend to which 20 published SP studies have contributed to a better appreciation of the behavioral consequence of a specific congestion charge scheme and reveal common strengths and weaknesses of these experiments.

It is based on the existing incentivization schemes, the insights of behavioral economics and inspired by the construction of new congestion charge scheme that we developed our experiment to test various incentivization schemes.

3 Research contribution and approach

While previous studies have typically tested only one incentive scheme at a time, we are studying the potential impact of 7 different incentivization schemes (cash, lottery, donation, apple credit, HOV pass, guaranteed parking, free coffee and status) and one congestion charge scheme on commute behavior. We focus on analyzing the changes in behavior when people are offered a reward or a charge to change their commute, identifying key factors that influence the response to the reward and ranking the different kind of rewards in terms of effectiveness.

Here we present experimental results in which our subjects (commuters from the Bay Area who drive to work at least two times per week) are presented hypothetical scenarios regarding various discrete commute decisions and asked to state their preference. The choice set is made of 7 options for their commute of which 6 are incentivized as they are involving an effort and one corresponds to their usual commute (Section 4 provides a detailed description of the experiment). In stating their preferences, the subjects reveal information regarding the trade-offs they are willing to make between the incentives (the benefit) and the travel time, cost, departure time or modal preference (the costs). We then estimate a nested logit model to infer these trade-offs.

4 Experiment

Our web-based SP survey was administrated to 46 staff at UC Berkeley and 152 workers in companies from the Bay Area who were driving to work alone at least two times per week. The Experimental Social Science Laboratory in the Haas Business School recruited the former subjects and the latter were recruited through partnerships with these companies. All the 198 participants were paid between \$10 and \$15 to take the survey, which took an average 20 minutes to complete. The survey included questions about the following topics: demographics, the commute habits (mode, personal and work constraints), information about the respondent's last commute by car and series hypothetical scenarios in which the respondent had to make a choice between several options for a future commute. The respondents were evenly distributed between the gender categories (49% of female and 51% of male) and the age categories (18% between 21 and 30, 29% between 31 and 40, 28% between 41 and 50, 24% between 51 and 60). Our sample gathered people who were regularly driving alone to work as, on average, 81% of their trips to work were made using this mode. The sample was not really flexible as most of them (85%) could not work at home at all and 61% of them did not see public transportation as a realistic alternative for their commute. Given our recruitment constraints (people who are driving to work), all the respondents were employed with 86% of them having a full time job and the 14% remaining working part time.

Imagine your next commute will be in a similar context to the one you told us about. You receive a notification from the public agency **<u>one day</u>** before your next commute to work.
In this notification, you are given the following options and associated incentives for your commute to work, which option would you choose?

Ignore the transit fare if you have a pass for the transit mode offered, and note that the alternative road uses only arterials.

Option	Incentive	Departure time	In vehicle travel time	Transit mode	Transit walk time	Number of transfers	Transit fare
◯ Do what you did last time	-	8:45 AM	0:50	-	-	-	-
◯ Leave earlier	\$2	Leave 45 min earlier	Trip is 13 min shorter	-	-	-	-
◯ Leave later	\$15	Leave 1 hour later	Trip is 25 min shorter	-	-	-	-
◯ Take an alternative road	\$6	8:45 AM	Trip is 13 min longer	-	-	-	-
◯ Take transit	\$12	8:45 AM	Trip is 13 min longer	Bart	20 min	1	\$2
◯ Walk / Bike	\$2	-	-	-	-	-	-
◯ Work at home	\$12	-	-	-	-	-	-

FIGURE 1 Screenshot of commute choice options in a scenario where cash rewards were offered

To make the hypothetical scenarios more realistic to the respondent, the presented scenarios were pivoted off of the last commute to work by car. Finally, the respondents were invited to consider commute alternatives in a similar context to the one in which they last commuted (see Figure 1). The alternatives available to the respondents were *(a)* do the same thing as they did before, *(b)(c)* drive and change their departure time (earlier, later), *(d)* drive and change their route, *(e)* take transit, *(f)* walk or bike, or *(g)* work at home. Here we want to analyze the travelers' willingness to change their commute if offered a reward or if charged. Therefore all the shifting options are associated with a reward and we have chosen a congestion charge scheme that applied to the road they used for their last commute by car, thus only the choices *Do as you did before*, *Leave earlier* and *Leave later* were concerned with the congestion charge. The following rewards were offered:

- Cash reward
- Credit towards an Apple Store gift card
- Entries to a lottery for a cash prize
- Cash donation to a charity
- Credits towards a HOV pass or a Guaranteed parking place at their workplace
- Credits towards a free coffee
- Credits towards being on the being on the Bay Area Green and Connected commuters' list

In order to not confuse the respondent with different scenarios, each respondent was randomly assigned a single incentive scenario and asked 5 different questions as in Figure 1. However, to be able make the options of comparable cost (Cash, Apple Credit, Donation and Lottery), the expected value of the levels of the incentives were the same (see Table 2 for more details).

In a stated preference context, it is up to the analyst to develop the set of choice tasks presented in Figure 1 (which constitutes the experimental design) as this set affects the parameter estimates and their reliability. We chose to use an orthogonal fractional design it has the ability to produce unconfounded estimates of the population parameters due to the enforced statistical independence between the attributes contained within the design (Rose and Bliemer (*14*)). Moreover, this experimental design that have worked well over the year ensures that the attribute levels (see Table 2 & 3) are nicely spread over all choice tasks and that attribute level combinations do not exhibit a correlated pattern (Bliemer and Rose (*15*)).

5 Model specification

We employ nested logit specifications to model the choices of the subjects and infer how they value different attributes relative to each other. After specification testing, the final nesting structure used four nests such that incentivized alternatives sharing the same mode belong to the same nest and the base alternative has its own nest (see Figure 2).

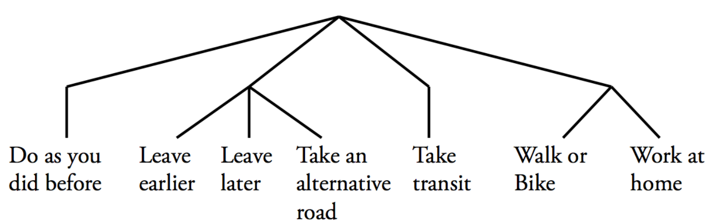

FIGURE 2 Nesting structure

In such models, the utility U that individual n associates with alternative i in nest C_m is given by the equation $U_{in} = \beta_n^{'} x_{in} + \varepsilon_{in} = V_{in}(\beta_n) + \varepsilon_{mn} + \varepsilon_{imn}$, where $V_{in}(\beta_n) = \beta_n^{'} x_{in}$ with x_{in} a column vector of explanatory variables (characteristics of the decision maker and attributes of the alternative), β_n a column vector of taste parameters, and ε_{in} the error that is the sum of two components. The first ε_{mn}, is nest specific, and is the same for all alternatives in the nest. The second, ε_{imn}, is alternative specific. ε_{mn} captures the unobserved attributes shared by alternatives in nest m, while ε_{imn} captures unobserved attributes specific to alternative i. If the parameters do not vary across the population (i.e., $\beta_n = \beta \, \forall \, n$) and assuming that the alternative with maximum utility is chosen, the probability with which person n chooses alternative i from nest C_m is:

$$P_n(i) = P(i|m)P(m) = \frac{exp(\mu_m V_{in})}{\sum_{j \in C_m} exp(\mu_m V_{jn})} \frac{exp(\mu \tilde{V}_{mn})}{\sum_{l=1..M} exp(\mu \tilde{V}_{ln})} \quad (1)$$

with:

$$\tilde{V}_{mn} = \frac{1}{\mu_m} ln \sum_{i \in C_m} exp(\mu_m V_{in}) \quad (2)$$

Ben-Akiva and Lerman (*16*) and Train (*17*) provide further information on nested logit models.

Our primary focus is to estimate the value of time (VOT) for each incentive. VOT is the marginal rate of substitution (MRS), equal to the trade-off that one can make between two attributes and maintain the same level of utility. In a linear in parameters model where $U_{in} = ...\beta_k x_{ink} + \beta_r r_{in} + ...\varepsilon_{in}$ (where r_{in} is the reward, x_{ink} is the quantity of attribute k), the marginal rate of substitution of x for r is:

$$MRS_{xr} = \frac{\partial U}{\partial x_{ink}} / \frac{\partial U}{\partial r_{in}} = \frac{\beta_k}{\beta_r} \quad (3)$$

We specify our utility functions to be linear in parameters, and therefore VOT is the parameter of time divided by the parameter of reward. The parameters are estimated via maximum (simulated) likelihood estimation using the free discrete choice estimation software Biogeme (Bierlaire (*18*)).

6 Estimation Results

In this section, we present and discuss results estimated from the nested logit model which are shown in Table 1. For this model we include as explanatory variables all of the attributes that were presented to the respondents. Concerning the Lottery, although we offered different odds, we include the expected value of the lottery in the utility specification as we were not able to identify significant results that capture the impact of the odds (e.g, high odd of small reward versus low odd of high reward).

TABLE 2 Levels for the incentives attributes

Attribute	Levels							
Cash, Donation, Apple Credit, Congestion	$0.5	$1	$2	$3	$6	$8	$12	$15
Lottery	1 in 10 to win $5	1 in 10 to win $12	1 in 10,000 to win $20,000	1 in 10 to win $30	1 in 1000 to win $6,000	1 in 10,000 to win $60,000	1 in 10,000 to win $120,000	1 in 10 to win $150
HOV pass & Guaranteed parking	5% credit towards a HOV pass	10% credit towards a HOV pass	25% credit towards a HOV pass	50% credit towards a HOV pass	HOV pass	Guaranteed parking	Guaranteed parking	Guaranteed parking
Coffee	10% credit towards a free coffee	25% credit towards a free coffee	50% credit towards a free coffee	Free coffee	-	-	-	-
Status	1% credit towards being on the Bay Area Green and Connected commuters' list	3% credit towards being on the Bay Area Green and Connected commuters' list	5% credit towards being on the Bay Area Green and Connected commuters' list	10% credit towards being on the Bay Area Green and Connected commuters' list	-	-	-	-

TABLE 3 Levels for other attributes

Attribute	Levels			
Travel time impact	+/- 0%	+/- 10%	+/- 25%	+/- 50%
Schedule delay	+/- 15 min	+/- 30 min	+/- 45 min	+/- 1 hour
Walking time	0 min	5 min	10 min	+20 min
Transit fare	$0	$1	$2	$5
Notification time	- 15 min	- 30 min	- 1 hour	- 1 day

TABLE 1 Estimation results

Parameter	Utility equation							Estimate	std. error	p-value	
	Do as you did before	Leave earlier	Leave later	Take an alternative road	Take transit	Walk/bike	Work at home				
Alternative specific constants											
ASC - Leave earlier		x						0.746	0.200	0.00	
ASC - Leave later			x					0.394	0.180	0.03	
ASC - Alternative road				x				0.131	0.200	0.51	*
ASC - Take transit					x			-0.767	0.304	0.01	
ASC - Walk/Bike						x		-1.900	0.269	0.00	
ASC - Work at home							x	-1.740	0.229	0.00	
Reaction to the incentives / congestion charge											
Congestion charge ($)	x	x	x					-0.442	0.095	0.00	
Apple Store credit incentive ($)		x	x	x	x	x	x	0.107	0.023	0.00	
Cash incentive ($)		x	x	x	x	x	x	0.085	0.019	0.00	
Lottery incentive ($)		x	x	x	x	x	x	0.049	0.017	0.00	
Donation incentive ($)		x	x	x	x	x	x	0.039	0.015	0.00	
HOV pass incentive (HOV pass)		x	x	x	x	x	x	0.923	0.271	0.00	
Guaranteed parking incentive (Guaranteed parking)		x	x	x	x	x	x	-0.368	0.290	0.20	*
Free coffee incentive (Free coffee)		x	x	x	x	x	x	0.308	0.382	0.42	*
Status incentive (Credits)		x	x	x	x	x	x	-1.010	3.480	0.77	*
Impact on the level of service											
Travel time by car (min)	x	x	x	x				-0.012	0.002	0.00	
Travel time by transit (min)					x			-0.017	0.005	0.00	
Schedule delay early (min)		x						-0.019	0.005	0.00	
Schedule delay late (min)			x					-0.018	0.005	0.00	
Walking time to transit (min)					x			-0.029	0.017	0.09	
Dummy = 1 if transfer for transit					x			-0.400	0.245	0.10	
Fare - Take transit ($)					x			0.049	0.109	0.65	*
Nest 1	x							1.000	fixed		
Nest 2		x	x	x				1.870	0.412	0.03	
Nest 3					x			1.000	fixed		
Nest 4						x	x	2.020	0.710	0.15	*
Number of observations	198 × 5 responses each										
Log-likelihood	-1636.372										
Adjusted rho-square	0.139										

First, the model performs well in that most parameters have the expected signs and most are highly significant. The fact that some parameters are not significant over a large number of observations means that the respondents did not take the associated attributes into account when they made their decisions. The coefficients for the transit fare, the guaranteed parking, the free coffee and status scenarios fall in this category. The layout of the SP design might have altered the transit fare because it was located at the very right of the choice matrix and thus might not have been taken into account in the decision process. As 77% of the respondents already had access to a parking spot at their work location they had no incentive to take an alternative offering a *Guaranteed parking*. Concerning the *coffee* and the *status* incentives, these clearly did not offer enough value in the travelers' eyes to make them shift from their usual behavior.

Using equation 3, we estimate a reward-based value of time for each incentive which correspond to the amount the respondents are willing to be paid to increase their travel time (Value of travel time noted VOTT) or shift their departure time (Value of schedule delay early and late noted VOSDE and VOSDL respectively). Similarly, we estimate a cost-based value of time which correspond to the amount the users are ready to pay to save a quantity of time. With these definitions, a reward-based VOT is negative and conversely a cost-based VOT is positive. Our results indicate that our subjects have different VOT depending on the kind of rewards they were offered and on the type of time (travel time vs. schedule delay - see Table 4).

TABLE 4 Values of time for different incentives

Incentive	Value of travel time	Value of schedule delay early	Value of schedule delay late	Unit of values of time	Value in cash $
HOV pass	-0.81	-1.23	-1.16	HOV pass / hour	10.85
Apple Credit	-6.95	-10.60	-10.04	$ of Apple credit / hour	1.26
Cash	-8.74	-13.33	-12.62	$ of cash / hour	1.00
Lottery	-15.18	-23.14	-21.92	$ of lottery / hour	0.58
Donation	-18.98	-28.93	-27.40	$ of donation / hour	0.46
Congestion charge	1.68	2.57	2.43	$ of congestion charge / hour	-
Spitsmijden experiment[1]	-6.48	-4.24	-3.99	$ of cash / hour	-

Both VOSDE and VOSDL are almost two times more important than the value of travel time VOTT. This can be explained by the fact that we had a pool of people with fixed work time or personal constraints that were preventing them from changing their departure time (132 out of 198 people are in this case i.e. 66%). When compared to the Spitsmijden experiment, we see that the VOTT values are slightly higher. The main difference relies in the fact that they had lower VOSDE and VOSDL but Jasper Knockaert, Michiel Bliemer, Dick Ettema and Albert Mulder, Jan Rouwendal (*2*) acknowledged that they had low VOSDE and VOSDL.

Concerning the effect of the monetary reward, the distribution of credit to Apple store is surprisingly more effective than the use of cash. However, this confirms anecdotal feedback obtained during the design of the survey. While seemingly irrational to prefer Apple credit to unrestricted money (which they could spend to buy Apple credits), results show a $1.26 cash incentive is equivalent to a $1 Apple credit incentive. That is, for the same behavioral shift, people require less Apple credit than cash. Then, in a decreasing order of effectiveness the cash alternative comes after the Apple incentive, followed by the Lottery and the donation. Concerning the non-monetary rewards, only the credit towards an HOV pass had an influence on the choice of the respondents. The value of an HOV pass can be obtained using the MRS (equation 3) between the HOV parameter and the cash parameter $\frac{\beta_{HOV}}{\beta_{Cash}} = \$10.85$, this means that providing an HOV pass is equivalent to a cash reward of $10.85.

The parameter on the congestion charge suggests that people react strongly to the introduction of a congestion charge as the introduction of a charge of $1.68 is enough to make people increase their travel

[1]The conversion from Euro to US dollar takes into account the inflation since 2006, year of the Spitsmijden experiment, and an exchange rate of €1 = $1.3

time by one hour. This cost-based value of time is lower than the levels observed in other studies in the US (Brownstone and Small (*19*) exhibit a VOT between \$20 and \$40 with RP data, Calfee and Winston (*20*) exhibits a VOT of \$3.88 with SP data). Results obtained by Brownstone and Small (*19*) show that the use of SP data can lead to undervalued VOT. Moreover, behavioral economics exhibit the asymmetry between the valuation of gains and losses. Kachelmeier and Shehata (*21*) and Borges and Knetsch (*22*) showed that they was a factor 2 between the willingness to pay (here to pay to decrease one's travel time) and the willingness to accept (here to accept money to increase one's travel time). In our case we have a stronger asymmetry as the factor between the willingness to pay and the willingness to accept is 4.

7 Policy Analysis and Forecasting

7.1 Approach

The objective of this work is to inform policy related to incentive schemes. In this section we discuss the policy implications of our results. Above we emphasized the value of time results that provide an indication of the ranking of the various incentive schemes in terms of effectiveness. To summarize, for the cash schemes, we found Apple credit to be most effective, followed by cash, lottery, and donation. One caveat on the relative ineffectiveness of lottery is that we studied here fairly high payouts (\$0.50 - \$15.00 per trip) as used in the Spitsmijden experiment, and it is possible that with very low stakes the lottery would be more effective than direct payouts. The provision of HOV passes also proved to be effective (valued at almost \$11), but parking access, coffee coupons, and status did not. The HOV option is intriguing because this is along the lines of the airline frequent flier programs, in which the reward provides something that would otherwise be impossible or very expensive to obtain. While these results are themselves informative, the models are also useful in terms of quantifying the magnitude of the impact of any incentive scheme, which we emphasize in the rest of this section.

The model such as we present in this paper provides a key input to any forecast of incentive schemes. A forecast, in general, requires knowing the probability with which travelers will accept the offered incentives and change their behavior. Because there are also network impacts, it is necessary not only to know that the driver did not drive on the congested route, but also to know how and when the person traveled (different route, different time, different mode, etc.). This model provides such probabilities given a particular trip and the incentive offered. The model can be incorporated into traffic simulation models, for example those that have been developed to manage transportation facilities and that currently reflect impacts of management tools such as congestion pricing and information (such as Ben-akiva (*23*) and Hao et al. (*24*)). The transport modeling framework (and interaction with supply) is required to capture the impacts on the network, including the dissipation of congestion during targeted times/routes and increase of demand during non-targeted times/routes/modes. Further, there may be feedback effects as the travelers react to the new status of the network.

In order to use the SP model in such a forecasting framework, it is necessary to first calibrate the model. While the trade-offs (ratios of the parameters, such as the VOT calculations) are generally considered a reasonable estimate to use in forecasts, the error component of the SP utility is not. Calibration of the SP model involves calibrating the mean and variance of the error to match real world data, and this translating to calibrating the alternative specific constants and the scale (inversely proportional to the variance) of the error. Calibrating the SP model requires real-world data, ideally disaggregate but also aggregate data can be used. As we will discuss below in the application, calibration of the model at this point is difficult due to the lack of real-world data available from incentive programs. As with any behavioral study, the inference will increase in accuracy as more data is acquired, including both more stated preference data and the addition of revealed preference data. The revealed preference data would not only be used for calibration (a necessary step for application of SP models), but also in estimation for example by estimating a behavioral response model using both RP and SP responses to take advantage of their relative strengths (not necessary, but very useful).

One other aspect of the behavioral response necessary to understand the potential impact of any incentivization scheme is to predict the participation rate, including how many people will register in the program and how frequently they will adjust their behavior. While we asked questions regarding these aspects in the survey, we have not yet modeled them.

7.2 Case study

While application within a traffic simulator is outside of the scope of this study, here we explore results from a more limited forecast to demonstrate output and also provide further insight on the behavioral response. These results explore the direct demand response, and do not consider the network effects or the secondary demand shifts that may occur.

We consider the application of different incentive schemes in the San Francisco Bay Area. We use microsimulation (Ben-Akiva and Lerman (*16*)) to generate forecasts, using the sample of the 2000 BATS data who commute to work by car during the morning peak 7:00-9:00am (Metropolitan Transportation Commission (*25*)). We assume that the incentivization scheme aims to divert drivers from their regular route and time, either to a different route, time, mode, or not to travel. We chose this scenario to be consistent with the Spitsmijden field test, which we use to calibrate the model.

Calibration is difficult due to the lack of adequate revealed preference data. For these purposes, we use the aggregate results of the Netherlands field test. We calibrate 2 parameters: the base constant related to do what one did before (we assume the relative magnitudes of our estimated constants for the different schemes is correct) and the scale. One thing to note is that in the Netherlands case, there was an extremely large demand shift observed in their sample. For the €3 reward, 47.2% shifted out of the peak, and when the reward was increased to €7, 61.8% shifted. As we calibrate to these datapoints, our forecasts reflect this large demand shift. This demand shift only considers the sample of participants in the pilot study, so is in effect conditioned on one participating in the program. For a forecast we also need to estimate the percent of people participating. As an estimate of this, we use the 70% positive response rate to the survey question asking the respondents if they were willing to participate in an incentivization scheme. These calibrations are admittedly rough, and would improve with better data. However, the emphasis in the results below is not so much on the absolute values of the forecast, but rather the relative shifts across incentivization schemes and the relative magnitudes of behavioral responses.

To generate the forecast, for each sample point in the BATS data, we have to make assumptions about the level of service of the current commute and of the alternatives. For this illustrative forecast, we use rough estimates of these values that were generated as follows. First, it is to be noted that the BATS data we use has been augmented by the San Francisco County Transportation Authority (SFCTA) using level of service skims produced by the SFCTA model (giving all the travel times and travel costs for the different modes available for the trip). Therefore, we consider the information provided by the BATS data (current commute time, alternative availability, transit time) as the level of service of the current commute. Then, based on empirical estimations from travel times in the Bay Area, we consider that for each sample point in the BATS data, taking an alternative road leads to a 10% increase in the travel time while traveling outside of the peak hour experience a 10% decrease. Finally, we control the type of incentive, its association with an alternative, the level of incentivization and the schedule delay.

Below we highlight three different outputs of the forecast. Our base case corresponds to a distribution of trips within the morning peak hour with 95% of trips by car and 5% distributed between take transit, walk or bike and work at home.

First we want to have a rough approximation of where in the transport network the demand diverts when people are incentivized to shift out of the peak hour. Figure 3 illustrates the shift out of the peak hour when people are offered a given incentive to leave either 30 min earlier or later, take an alternative road, take transit, walk or bike or work at home. One can notice that a change in departure time and the use of an alternative road represent 95% to the total shift. This result is consistent with the literature on traveler information, which shows that people mostly shift route and time of day. The offering of an incentive, more than the increase of the the latter enticed the drivers to switch as we can notice that the shift rises from 36.7% to 50.3% when the incentive was multiplied by a factor 10 from $1 to 10$. Compared to the shifts obtained in the Spitsmijden experiment where all the subjects were participating, the consideration of a participation rate mitigates the effect of an increase in the reward level.

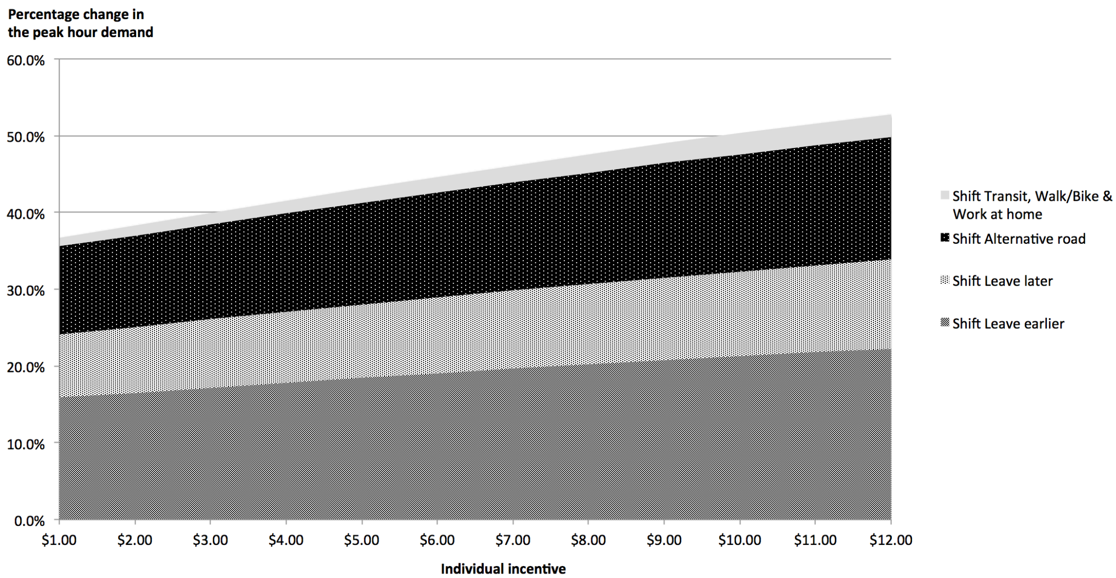

FIGURE 3 Breakdown of the total shift out of the peak hour expressed as a relative change to the base case versus the individual incentive offered to the commuters for not driving during the peak hour

Another scenario that is likely to be implemented in a field experiment could be the use of an incentive to shift people onto an underused road to relieve a congested road. Figure 4 shows the evolution of individual incentive as a function of the share of travel demand of the alternative on which we want to shift the people. The decreasing marginal incentive shows that the incentive follows a law of increasing returns meaning that each additional dollar of incentive increases the shift onto the alternative road more than the previous additional dollar. Figure 4 also compares the difference of incentivization required to achieve a given shift under the assumptions of a 5%, 10% and 15% increase in the alternative road travel time. This difference of incentivization is around 0.7$ and slightly increases with the level of shift on the alternative road as expected.

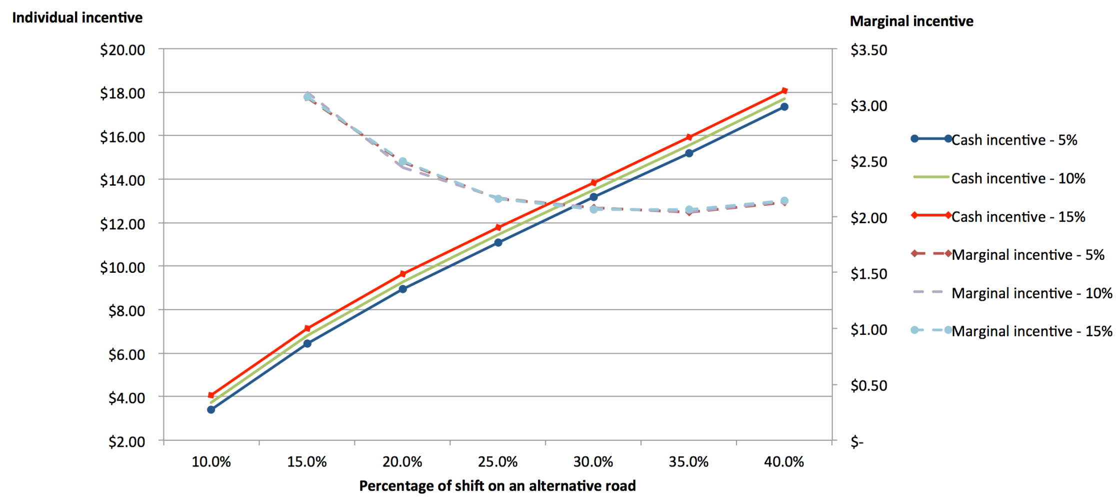

FIGURE 4 Individual incentive vs. share of travel demand (expressed as a percentage of the total travel demand) for an incentivized alternative road on which the travel time is increased by 5%, 10% and 15%

Figure 5 shows the relative effect of different incentives schemes on the shift out of the peak hour. The assumptions of Figure 3 applies to Figure 5.

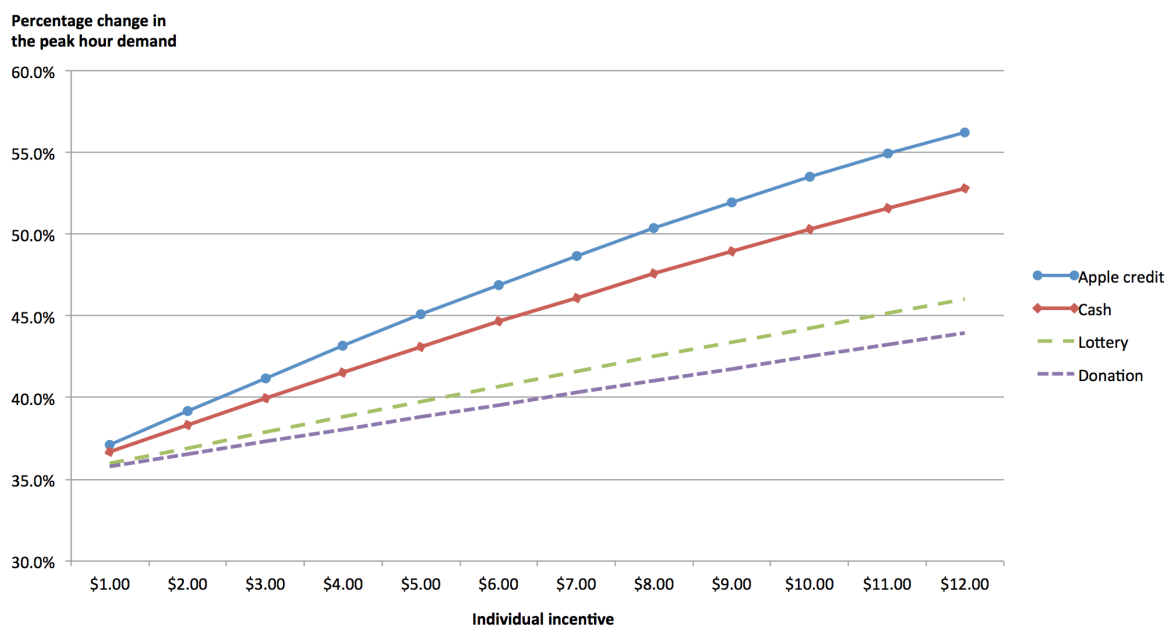

FIGURE 5 Total shift out of the peak hour expressed as a relative change to the base case versus the individual incentive offered to the commuters for not driving during the peak hour.

As the rewards increases, we can distinguish 2 groups in terms of efficiency of shifting people out of the peak hour. The most efficient one with tangible rewards such as cash or Apple credit and the less efficient one with monetary rewards which include risk (Lottery) or empathy (Donation). Even though the model says that cash and Apple credit performs better, the 4 monetary incentives perform similarly when offering low incentives.

8 Discussion and conclusion

In this investigation into how our subjects respond to incentivization, we found a large variability towards the kind of rewards they were offered to change their commute. Our basic model indicates a value of travel time that varies between \$6.95/hour for the Apple credit incentive to \$18.98/hour for the donation incentive, which shows the choice of the type of incentive is a key element of the incentivization scheme's design. While non-monetary incentives such as parking access, free coffee and status proved to be ineffective, the offering of a HOV pass was highly considered by the participants as that providing an HOV pass is equivalent to as cash reward of \$10.85. As predicted by behavioral economics, travelers are more sensitive to charges than to rewards. We found an stronger asymmetry between charge and rewards than the one foreseen by behavioral economics.

Under a set of assumptions, the results of the model were used to assess a direct demand response towards various incentivization schemes. The calibration of the stated preference model was made using revealed preference data from the Spitsmijden experiment. A first rough forecast of the trips distribution when people are incentivized to travel outside the peak hour showed that the main contribution to a shift outside the peak hour relies in a change of departure time and the use of an alternative road. A second illustrative forecast exhibit increasing returns when using incentives to shift people and a third one demonstrates a similar impact of the 4 monetary incentives when low incentives are offered.

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