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15. SUPPLEMENTARY NOTES
Traffic incidents and other unexpected disruptions on roadways lead to extensive delays that diminish the quality of life for those that live and/or work in major cities nationwide. The effective management of these incidents is hindered by an incomplete understanding about how drivers respond to information provided by network operators.

16. ABSTRACT
39 subjects each controlled a simulated vehicle through a simple road network: one freeway, one alternate route with two traffic lights. All subjects traveled simultaneously (share the road) and in the same direction to their destination. Each participants started with $14.00 endowment that decreases at $0.15 per second until they reached their destination. Each subject began on the freeway, and were given one opportunity each round to switch to the alternate route. The simulation has a Changeable Message Sign (CMS) within 8 seconds before alternate route off-ramp is reached. The CMS varied based on the each scenario being tested. (See image section below for diagram of CMS content.)

The sessions presented the subjects with information that used publicly or privately visible vehicle identifiers to target the diversion recommendation at specific individuals. Another session presented standard Caltrans CMS information, and one of the sessions presented a dynamically updated desired diversion rate. Detailed statistical analyses of all treatments were completed, including the estimation of models describing the learning processes and behavioral changes of subjects in response to CMS content and the outcomes of previous route choices.

17. KEY WORDS
Changeable Message Signs (CMS), Dynamic Prices, Pricing Treatments, Traffic Incident Management (TIM), Road Pricing, Pricing Schemes,

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Final Report for: Experimental Studies for Traffic Incident Management

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Contents

Definitions

Acronym/Abbreviation	Meaning
VMS	Variable message signs
AI	Computer controlled vehicles
ESSL	UCI Experimental Social Science Laboratory
VOT	Value of time
IFF	If-and-only-if
Sc. 0 / Scen0 / s0	Incident severity level 0 (no traffic incident)
CRL	Color outline
Qual	Qualitative
Recs	Recommendations
Div	Diversion

1. Introduction

Non-recurring traffic incidents are responsible for nearly 60% of delay caused by roadway congestion, prompting the need for efficient incident management (FHWA, 2000). Network operators can often alleviate congestion and mitigate delays by diverting traffic from affected roadways onto alternate routes. One tool widely available for inducing such diversions is variable message signs (VMS) – programmable electronic roadside displays that can provide travelers with timely information regarding road conditions. Some of the earliest VMS systems in the U.S. were used in Detroit in the 1960's to direct motorists to alternate routes based on freeway traffic conditions (Dudek, 2002), and field studies by Dudek et al. (1978) and Weaver et al. (1977) have confirmed the ability of VMS to aid incident management on freeways by diverting traffic onto alternate routes. Under most circumstances, however, transportation agencies are hesitant to use VMS to encourage diversions. Although they possess tools to determine the optimal proportion of vehicles to divert (Cragg et al., 1995), they lack a reliable method for achieve the diversion rates they target. Prior research shows that when a high percentage of travelers are presented with route-choice information, myopic agents can make diversion decisions that, in aggregate, worsen road network performance (Mahmassani and Jayakrishnan (1991)) and that VMS systems deployed in Minnesota don't lead to significant reductions in travel times (Levinson and Huo (2003)). As a result, both the agencies and city officials share fears of overloading surface streets with an excessive diversion (FHWA 2000). Consider further research to optimize VMS systems.

Efficient incident management through VMS necessitates finding a type of public information that, when provided to all drivers, will produce the desired distribution of traffic across available routes. With the limited opportunity for drivers to coordinate, it is unlikely to achieve the desired response. This phenomenon is manifest in highly stylized route-choice games conducted by Selten et al. (2004) and Iida et al. (1992), where an efficient equilibrium distribution was extremely difficult to reach – even across repeated trials with full information and feedback. Instead, one might expect to see non-smooth changes in diversion rates as VMS content is varied. Field studies by Chatterjee et al. (2002) and Horowitz et al. (2003) confirm the unpredictability of diversion rates induced by VMS.

It is possible to mitigate many of these coordination issues through the selective provision of information privately to drivers via in-vehicle systems, such systems are not yet ubiquitous, and system operators cannot control for users receiving information from third parties. Given the extant presence of VMS infrastructure in the US and abroad, it is desirable to improve its effectiveness as a low-cost, readymade tool for incident management. To achieve this objective, we need to gain a better understanding of how VMS information affects time-limited decision-making in scenarios where drivers possess imperfect information of the environment and influence each other's behavior.

We seek to explore how the availability and manipulation of VMS content will affect driver decision-making in real-time. In particular, we focus on how an increase or decrease in the "intensity" of VMS content – that is, message adjustment intended to induce more or fewer drivers to divert – can produce a desired change in the diversion rate. To this end, we jointly designed a route-choice experiment to test a variety of different VMS messaging schemes using a 2-dimensional real-time driving simulator with a simple road network. We incentivize subjects with real monetary payments to induce a controlled value of time preference.

The next six sections describe how we conducted our research and provide an overview of the results. Section 7 gives a detailed description of the results from the individual treatments we used in this research.

2. Literature Review

There is a substantial body of research on VMS and other real-time public traffic information systems. Previous studies have demonstrated the efficacy of information in encouraging diversions[1], identified numerous factors that influence route-switching behavior[2], and confirmed the difficulty of attaining stable equilibria in route selection[3]. None of these studies has specifically examined the predictability of the diversion response as a function of message intensity, or considered how to mitigate the risk of over-diversion. Furthermore, the diversion rates observed and/or route choice models estimated in these studies do not reveal methods of control that operators can apply to their messages to achieve desired diversion responses over a full range of desired outcomes. One commonly recovered parameter in studies employing econometric analysis is the effect of an alternate route's travel time savings on the probability of an individual diverting. However, this type of analysis also does not offer operators a mechanism of control since time savings are endogenous to the aggregate diversion response on a dynamic real-world network and cannot be known a priori.

At least two studies identify ways to manipulate VMS content to produce specific aggregate changes in the diversion rate. Wardman et al. (1997) demonstrate the effects of different types of messages, while Peeta et al. (2000) establish a relationship between

[1] Horowitz et al. 2003, Levinson and Huo 2003, Chatterjee and McDonald 2012, Weaver et al. 1977, Dudek et al. 1978, Khattak et al. 1993

[2] Bonsall and Palmer 1995, Brocken and Van der Vlist 1991, Mahmassani and Liu 1999, Allen et al. 1991, Jou et al. 2005, Abdel-aty et al. 1997, Gan 2012, Mahmassani and Jayakrishnan 1991, Emmerink et al. 1996, Chatterjee 2002, Kattan and Habib 2009

[3] Iida et al. 1992 , Selten et al. 2004

information quantity and diversion rates. Neither study, however, shows if and how manipulation of such content features to predictably achieve desired changes in diversion rates.

Ben-Elia and Shiftan (2010) conducted a laboratory experiment to study the effect of real-time information on driver route-choice using an abstract route selection game. Using a learning-based model, they demonstrate that information, experience, and risk characteristics jointly affect individual driver behavior. Though informative, their study does not seek to analyze the collective effect of information on groups of drivers sharing the road. In addition, their experiment incorporates neither real incentives nor real driving.

3. Experiment Design

Seeking to incorporate many aspects of real world driving relevant to understanding route-choice in a manner that is feasible to implement on ordinary lab computers, we designed the experiment and driving simulator to support the following features: Firstly, vehicles move in real-time and obey simplified Newtonian kinematics, requiring drivers to exert effort to maintain course and speed. Secondly, a large number of human drivers share the same virtual roadway to create a sense of immersive traffic. Thirdly, traffic and congestion are generated endogenously from a combination of the large number of vehicles and the effects of reductions in route capacity. Fourthly, drivers are exposed to limited and dynamic forms of information based on that which their senses would perceive while driving on the freeway in real life. Finally, the road geometry is simplified yet retains a structure relevant to studying the questions of interest.

3.1 Driving Simulator

Our experiment platform is a 2D, real-time, top-down perspective-driving simulator implemented as a browser application using Node.js, JavaScript, and HTML5. Subjects see a top-down view of the roadway where vehicles are represented as small colored squares - the driver's own vehicle is colored blue while all other vehicles are colored red. The driver's viewport constantly tracks his/her vehicle and presents a fixed window of visibility around it - the driver can see farther ahead than behind to simulate the forward-focused vision of real-world drivers. From top to bottom, the driver's screen contains the following elements: the secondary information area that displays the current experiment round, the VMS display area, the driver's viewport, and the primary information area that displays the driver's earnings and percent completion of their itinerary in real-time.

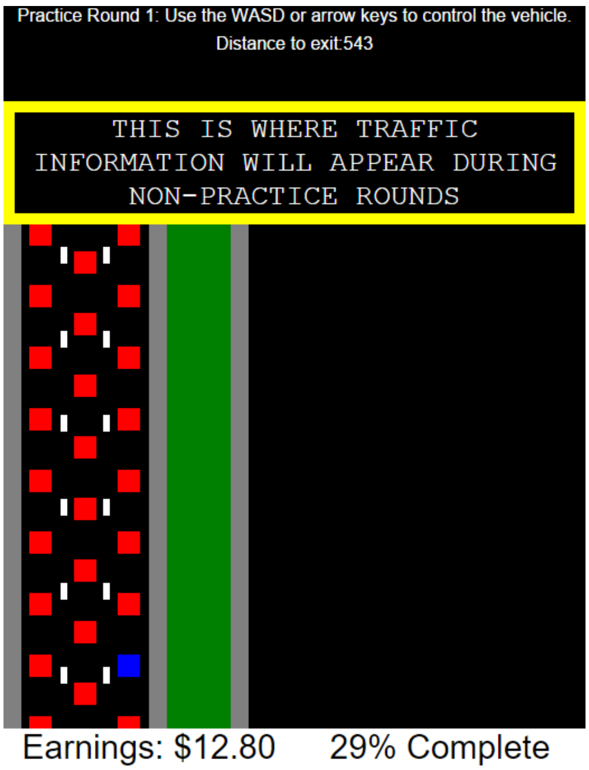


Figure 1: Driver's screen

Using the Up Arrow / W, Left Arrow / A, and Right Arrow / D keys, drivers control their vehicles to accelerate or change lanes left / right. All vehicles accelerate at the same rate and quickly reach the same maximum speed. If a driver stops accelerating, their vehicle will decelerate at a constant rate until it reaches the minimum speed - this minimum speed is designed to prevent a driver from completely blocking their lane and it is slow enough such that a driver who always travels at the minimum speed will never complete their itinerary before their entire endowment is expended. While cruising, vehicles are automatically guided to stay in the center of the nearest lane. A minimum following distance is enforced between cruising vehicles to allow space for lane changes to occur. If another vehicle when attempting to change lanes obstructs a driver's vehicle, their vehicle will be slowed down slightly to allow them to move in behind the obstructing vehicle. Drivers are informed that there are no rewards or penalties for colliding with other objects or vehicles. In addition to human controlled vehicles, computer controlled vehicles, which follow simple pre-defined control routines, are used to fill in the front of the driving platoon to create a sense of immersive traffic.

3.2 Road Geometry, Traffic Flow, and Incidents

We designed the roadway to provide drivers with the choice between traveling on a main highway and switching to an alternate surface street regulated by traffic signals. All vehicles start driving simultaneously at random locations on a grid within the starting area near the bottom of the map. Drivers travel from their starting point to a shared destination and are incentivized to complete their journey as quickly as possible - they are given a monetary endowment at the start of travel which decreases linearly over time. The roadway is comprised of a three lane main route that extends from the starting area to the finish line and a two lane alternate route with two traffic signals that branches off from the main route near the midpoint of travel. Throughput on the main route can be impacted by simulated traffic incidents - these incidents can variably reduce or completely stop traffic flow for a period. The incident area begins at a point upstream of the exit to the alternate route such that drivers must choose their route before any incident-induced congestion is visible. In the absence of traffic incidents, it is optimal for all drivers to use the main route. When flow on the main route is impeded, system performance is maximized when traffic is optimally split between the two routes. If enabled, drivers are shown the VMS message on their VMS display for approximately 7.5 seconds immediately before they reach the exit to the alternate route. Vehicles on the alternate route are hidden from view until drivers reach the off-ramp proper, at which point vehicles on the main route become hidden. This feature prevents drivers from knowing the condition of the route they did not select. The finding of Dong and Mahmassani (2009) that a flow breakdown can be very difficult, if not impossible to reverse motivates our choice of exit location. Therefore, subjects must make their decision before evidence of a breakdown is apparent, conditioning only upon their prior knowledge (experience) of the network, the actions of other subjects in their limited field of view, and any VMS and/or toll information presented.

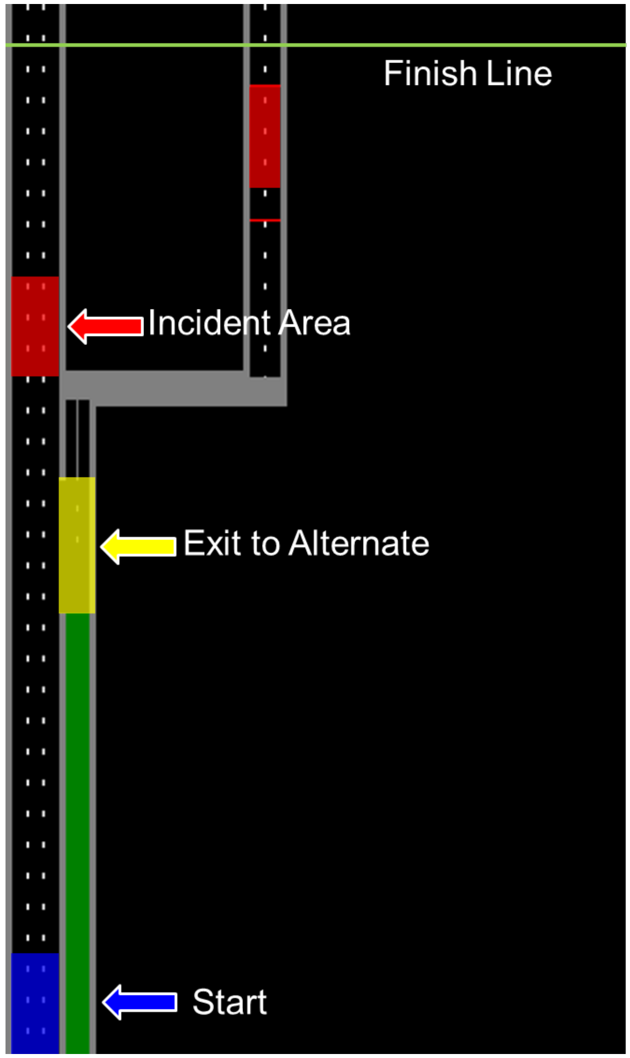


Figure 2: Road overview

3.3 Session Structure

We conducted a series of experiment sessions, which typically lasted for 1 hour and involved up to 39 participating subjects. Our human subjects were recruited through random selection from the population of UC Irvine undergraduate and graduate students from the Experimental Social Science Laboratory (ESSL) subject pool with IRB approval under HS #2011-8378. Subjects were not provided any information regarding the nature of the experiment until the start of the experiment session. Each session was divided into two parts: Part I featured a risk elicitation task in which subjects choose between three lotteries with differing risk characteristics and Part II featured the driving task. Part II is comprised of a series of 23 driving rounds, during which subjects complete the same driving itinerary while being exposed to a different traffic incident scenario each round. The first three rounds were guided practice rounds that had no impact on a subject's final earnings. Each subject's final earnings are the sum of their show-up payment, the realization of the lottery they selected in Part I, and the average of what they earned from three randomly chosen non-practice rounds in Part II. Since drivers' starting positions are randomized, averaging across three rounds helps to offset the effect on earnings of starting at the front or the back of the platoon. After completing Part I and Part II, we asked subjects to answer a post-experiment questionnaire to gather demographic information and optional feedback.

4. Treatment Design

We assembled treatment conditions from the combination of a sequence of incident scenarios, a VMS messaging scheme, a driver incentive scheme, and a road-pricing scheme. Within sessions, all treatments utilize the same pre-randomized sequence of incident scenarios where each incident severity occurs an equal number of times - this is designed to eliminate scenario-ordering effects and allow results to be compared across sessions. Between sessions, the VMS messaging, driver incentive scheme, and road-pricing scheme may vary.

Severity Level	**Effect on Traffic**	**Appears in Round**
0	No impediment, all lanes clear	1,3,6,16
1	One lane blocked	2,4,10,11
2	Two lanes blocked	5,14,18,19
3	Three lanes blocked, short traffic slowdown	8,12,17,20
4	Three lanes blocked, long traffic slowdown	7,9,13,15

Table 1: Incident severity levels

4.1 VMS Messaging Schemes

We generated messaging schemes from the combination of a message header presented on line one and a message body presented on lines two through three of the VMS display. Tables 2 and 3 summarize the message headers and bodies used in combination to generate messaging schemes. Each row contains the individual messages of a messaging scheme, and each column indicates which message would be displayed for a particular incident scenario. For each messaging scheme, the "VMS intensity" increases from left to right for every unique message.

Scenario	**0. No Incident**	**1. One Lane Blocked**	**2. Two Lanes Blocked**	**3. Three Lanes Blocked**			**4. Three Lanes Blocked, Longer Delay**		
				Short	Medium	Long	Short	Medium	Long
Message Header (First Line)									
Generic	N/A	ACCIDENT AHEAD							
Descriptive	ROAD CLEAR	MINOR ACCIDENT AHEAD	MEDIUM ACCIDENT AHEAD	MAJOR ACCIDENT AHEAD			SEVERE ACCIDENT AHEAD		

Table 2: Message headers

We used two types of messaging headers: a Generic header for which "ACCIDENT AHEAD" is displayed if any non-zero incident is present and a Descriptive header for which a qualitative description of incident severity is displayed. For select treatments, "ROAD CLEAR" is displayed in the header when there is no traffic incident.

Scenario	0. No Incident	1. One Lane Blocked	2. Two Lanes Blocked	3. Three Lanes Blocked			4. Three Lanes Blocked, Longer Delay		
				Short	Medium	Long	Short	Medium	Long
Message Body (Second and Third Line)									
Incident Severity	N/A	EXPECT MINOR DELAY	EXPECT MEDIUM DELAY	EXPECT MAJOR DELAY			EXPECT SEVERE DELAY		
Recommendation	ALL CARS: USE MAIN ROUTE	N/A	ALT RTE AVAILABLE AHEAD	N/A	ALT RTE AVAILABE AHEAD	USE ALT RTE AHEAD	N/A	ALT RTE AVAILABE AHEAD	USE ALT RTE AHEAD
Lanes Blocked	N/A	1 LANE BLOCKED	2 LANES BLOCKED	3 LANES BLOCKED			3 LANES BLOCKED		
Diversion Rate	N/A	1 IN 10 CARS SHOULD EXIT	1 IN 4 CARS SHOULD EXIT	1 IN 3 CARS SHOULD EXIT			1 IN 2 CARS SHOULD EXIT		
Numeric ID	N/A	IF YOUR CAR IS #1-4 USE ALT ROUTE	IF YOUR CAR IS #1-11 USE ALT ROUTE	IF YOUR CAR IS #1-18, USE ALT ROUTE			IF YOUR CAR IS #1-27, USE ALT ROUTE		
Color Outline	ALL CARS: USE MAIN ROUTE	GREEN OUTLINE CARS: TAKE EXIT. ALL OTHER CARS USE MAIN ROUTE							

Table 3: Message bodies

We used six types of messaging bodies in treatments without road pricing: an Incident Severity type, a Recommendation type, a Lanes Blocked type, a Diversion Rate type, a Numeric ID type, and a Color Outline type. The Incident Severity and Lanes Blocked bodies are always used in conjunction with a Generic header and may be combined with the Recommendation body. The Recommendation body is only used to augment the message body; it is never used by itself. The Lanes Blocked body only contains four levels of information for five levels of incident severity; it is used to test whether or not the diversion response can become more predictable when fewer levels of information is provided. The Diversion Rate body seeks to present the simulated optimal proportion of alternate route usage to the subjects in an intelligible manner. The Numeric ID and Color Outline bodies are used in conjunction with a publicly or privately visible graphical method of identifying particular drivers' cars in order to perform targeted messaging. For Numeric ID treatments, a unique number persistent across rounds is shown on the driver's vehicle. Then, a select subset of drivers can be instructed to divert to the alternate route using VMS. As shown in Table 3, the same subsets of drivers are always instructed to divert for a particular incident scenario. For Color Outline treatments, a bright green outline is displayed around cars selected to divert to the alternate route. Drivers are selected based on their starting position – a fixed subset of positions are selected for each incident scenario with preference to drivers who start in the rightmost lanes. Compared to using Numeric IDs, treatments using Colored Outlines attempt to maximize compliance with the targeted VMS instructions by providing select drivers closest to the exit with the clearest possible signal to divert.

4.2 Driver Incentive Schemes

We designed the simple monetary incentive scheme used in this experiment, in which an initial endowment depreciates over time at a constant rate, to induce a precise value of time preference in subjects. Within each session, the induced VOT preference was either homogeneous or heterogeneous among subjects. In the homogeneous case, each subject received an endowment of $14.00 at the beginning of a round, which then decreases at a constant rate of $0.15 per second for the duration of the round. In the heterogeneous case, the initial endowment and corresponding rate of decrease were assigned to subjects from a pre-randomized uniform distribution. Once assigned, subjects always received the same initial endowment with the same rate of decrease for the duration of the session. Endowments in this distribution ranged from $4.67 to $23.33, and the corresponding rate of decrease was calculated as Endowment*3/380. Thus, the average endowment and time to bankruptcy was approximately equal to those of the homogeneous case.

4.3 Road Pricing Schemes

In treatments with road pricing, a toll or subsidy was applied to subjects who took the main route, while the alternate route was always un-priced. When applicable, tolls and subsidies were added or subtracted from the subject's endowment once per round. The current road price was shown together with a messaging header on the VMS display when pricing was in effect. We tested two road pricing schemes: an intra-round dynamic pricing scheme that continuously updates the toll / subsidy amount as subjects commit to their route choice (a real-time pricing adjustment scheme) and an inter-round scenario-based pricing scheme that updates the toll / subsidy amount for a particular incident severity depending on the outcome of the previous round with that severity (a "day-to-day" pricing adjustment scheme). In the case of the intra-round dynamic scheme, a subject's road price was "locked-in" once they left the VMS area and entered the exit area in order to prevent last-second price updates from confusing the subject. For both pricing schemes, the road price started at $0.00 and adjusted upward / downward in increments of $0.50 - a positive price is considered a toll while a negative price is considered a subsidy. Prices were adjusted in reference to the proportion of subjects who chose the alternate route; if too many subjects selected the main or alternate route, than the price adjusted towards a toll or subsidy, respectively. These prices were designed to provide a simple feedback mechanism to nudge subjects towards the optimal route allocation.

4.4 Treatments and Sessions

The following table lists the treatment conditions that were conceived and the session codes in which they were tested. In the following sections of this report, experiment sessions will be referred to by the treatment codes shown in Table 4. Note that treatment codes generally follow from the combination of messaging, incentive, and pricing schemes used for the treatment condition. For example, the treatment with Incident Severity and Recommendation messaging, combined with messaging during no incident rounds, is termed "ISRN".

Any treatment with informative messaging should perform better than the baseline treatment NM with no messaging. Treatments with targeted messages that directly instruct drivers to choose a particular route should perform better than treatments that do not do so, treatments with more detailed and/or a greater variety of information should perform better than treatments with sparse information, and treatments that provide dynamically updating information should perform better than their static counterparts should. Given that subjects trusted the experimenters (system operators) to provide them with accurate information, directly targeted messaging schemes such as PCSN should perform the best as they provided a direct strategy for subjects to reach the best possible outcome each round.

Treatment Code	**Messaging Scheme**	**Description**	**Hypothesis**
NM	No Messaging	Baseline response with no VMS	Flat response, no reaction to incident severity
IS	Incident Severity (Updated)	Qualitative description of incident severity	Diversion response should increase as incident severity increases
ISR	Incident Severity w/ Recommendations	Same as IS, with added recommendations to divert to alternate route	Same as IS, recommendations should further increase diversion rate
ISRN	Incident Severity w/ Recommend., Sc. 0 Message	Same as ISR, with guidance during no-incident rounds	Same as IS, with more optimal response particularly during no-incident rounds
ISHT	Incident Severity w/ Heterogeneous VOT	Same as IS, with uniformly randomly distributed VOT	Same as IS
LB	Lanes Blocked	The precise number of lanes that are blocked during an incident is displayed	Same as IS, but with more muted response due to sparser information
DR_1	Diversion Rate (Variable Denominator)	Optimal diversion rate is shown as a fraction of cars that should divert	Diversion response should increase as displayed diversion rate increases
DR_2	Diversion Rate (Fixed Denominator)	Same as DR_1	Same as DR_1
DDR	Dynamic Diversion Rate	Same as DR_1, but diversion rate is updated dynamically to nudge subjects towards the optimal level	Diversion response should more closely match optimal response than DR_1 or DR_2
DDRS	Dynamic Diversion Rate w/ Incident Severity	Same as DDR, with incident severity description in header	Same as DDR, but with more variability in response due to additional information
ID_1	Numeric ID	Vehicles possess numeric ID and certain ID ranges are instructed to divert	Subjects should comply with the displayed directive according to their own ID
ID_2	Numeric ID (Revised)	Same as ID_1	Same as ID_2, with improved compliance due to revised verbiage
IDS	Numeric ID w/ Incident Severity	Same as ID_1, with incident severity description in header	Same as ID_1 or ID_2, but compliance may fall due to additional information.

PIS	Public Numeric ID w/ Incident Severity	Same as IDS, with publicly visible IDs on vehicles	Same as IDS, but public display of ID could improve compliance
PCS_1	Public Color Outline w/ Incident Severity	Vehicles with a publicly visible green outline are instructed to divert, with incident severity description in header	Same as PIS, with improved compliance due to ease of identification
PCS_2	Public Color Outline w/ Incident Severity (Revised)	Same as PCS_1	Same as PCS_2
PCSN	Public Color Outline w/ IS, Severity 0. VMS	Same as PCS_1, with additional guidance during severity level 0	Same as PCS_1 or PCS_2, with more optimal response particularly during no-incident rounds
DT	Round Dynamic Pricing w/ Incident Severity	Tolling scheme updates price dynamically within a round depending on route usage, with incident severity description in header	Diversion response should more closely match optimal response than static messaging
DTHT	Round Dynamic Pricing w/ IS, Heterogeneous VOT	Same as DT, with uniformly randomly distributed VOT	Same as DT
ST	Scenario Based Pricing w/ Incident Severity	Tolling scheme updates price between round to round depending on outcome of previous round of same incident severity	Response to tolls will be attenuated compared with DT
STHT	Scenario Based Pricing w/ IS, Heterogeneous VOT	Same as ST, with uniformly randomly distributed VOT	Same as ST

Table 4: Treatment conditions

5. Results and Discussion

5.1 Demographics

Date	Code	Avg. Age	M:F	Play Games	USA License	Driven Past Year	Avg. Hr / Week Driving (>0)	Seen VMS	Use Traffic Info	Risk Averse	Risk Neutral	Risk Loving
7/1/2015	NM	20.1	15:17	69%	88%	88%	10.7	97%	N/A	40%	43%	17%
7/14/2015	ISR	20.5	17:22	67%	92%	95%	7.5	79%	N/A	28%	51%	21%
8/11/2015	DR_1	20.6	20:19	49%	85%	85%	6.7	82%	72%	44%	28%	28%
8/18/2015	DR_2	20.6	13:26	51%	77%	87%	7.3	82%	64%	33%	51%	15%
8/28/2015	ID_1	20.5	19:19	55%	82%	87%	5.2	87%	58%	39%	32%	29%
10/6/2015	ID_2	20.2	17:21	47%	76%	87%	6.5	79%	68%	29%	42%	29%
10/8/2015	DDR	20.1	14:24	47%	84%	89%	7.1	100%	71%	42%	45%	13%
10/19/2015	IDS	20.1	12:27	33%	82%	90%	6.1	85%	54%	56%	31%	13%
10/22/2015	PIS	19.9	14:23	57%	73%	86%	7	86%	65%	43%	49%	8%
11/3/2015	IS	19.9	9:30	56%	77%	82%	8	87%	77%	33%	49%	18%
11/24/2015	PCS_1	20.2	13:25	49%	74%	90%	9.6	82%	62%	36%	49%	15%
2/9/2016	PCS_2	20.3	18:21	56%	79%	82%	6	87%	64%	28%	33%	38%
2/18/2016	DDRS	20.6	12:23	51%	77%	86%	8.0	86%	60%	26%	60%	14%
3/3/2016	PCSN	20.9	16:23	62%	72%	79%	8.0	85%	56%	41%	31%	28%
3/4/2016	DT	20.1	13:26	59%	82%	82%	6.4	82%	72%	41%	38%	21%
3/8/2016	ISHT	20.6	13:22	46%	86%	86%	11.6	80%	74%	37%	54%	9%
3/10/2016	LB	20.7	14:25	31%	87%	85%	6.7	79%	64%	38%	36%	26%
3/17/2016	ISRN	20.4	22:16	55%	84%	89%	7.6	84%	68%	26%	53%	21%
3/29/2016	DTHT	20.3	26:13	46%	95%	82%	8.0	92%	62%	51%	28%	21%
3/30/2016	ST	20.4	26:13	44%	85%	77%	5.1	90%	85%	28%	38%	33%
3/31/2016	STHT	19.7	19:15	47%	79%	79%	7.5	88%	76%	47%	44%	9%

Table 5: Subject demographics by experiment session

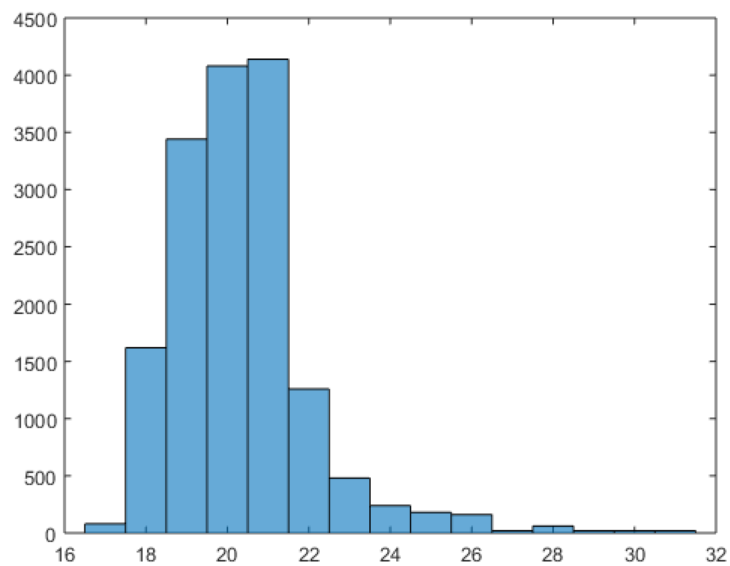


Figure 3: Distribution of subject age

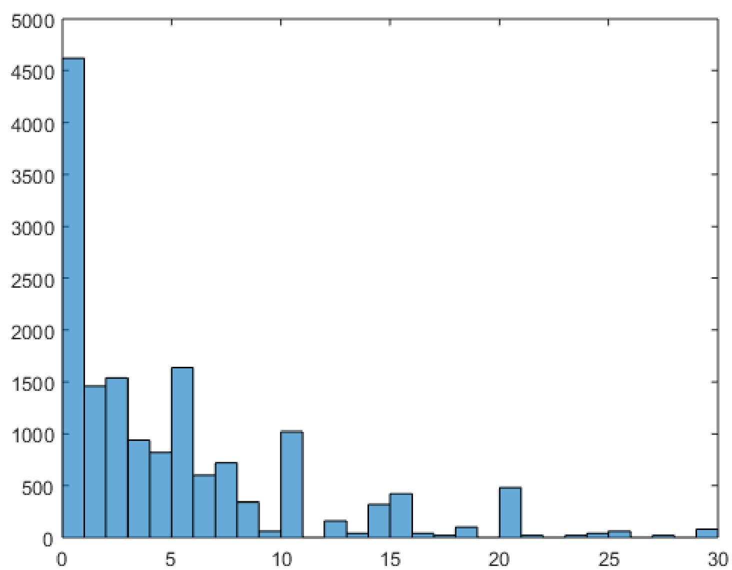


Figure 4: Distribution of hours driven per week reported by subject

Consistent with the composition of the undergraduate student body, subjects are 20 years old on average, and the vast majority both hold a valid US driving license and have driven a car within the past year. Most subjects reported that their typical driving locale is in Southern California. Therefore, it is likely that most have seen the variable messaging signs operated by

Caltrans. In addition, most subjects also report having received some form of real-time traffic information while driving. These statistics indicate that the majority of subjects should be familiar with the physical and mental aspects of driving as well as the various types of information that are available to them while driving. Notably, the gender composition of most of our sessions was skewed to have more female. Although driver composition in the US is split evenly between males and females, male drivers are known to drive more miles on average than their female counterparts within every age group. (FHWA 2015, Sivak 2015) Nonetheless, it is difficult to anticipate what effects, if any, gender may have on driver decision-making within our experimental setting. Based on our risk lottery task data, the majority of subjects in each session are either risk averse or risk neutral. With the exception of session PCS_2, subjects who are identified to be risk loving are always in the absolute minority. Although the absence of non-recurring incidents on the alternate route could potentially improve its appeal for risk averse drivers, the effect could be small in magnitude and its identification hindered by the imperfect ability of our risk elicitation task to sort drivers by risk preference. Finally, the distribution of average hours spent driving per week as reported by subjects is massed at zero hours; with very few subjects reporting more than 10 hours, (subjects who reported over 30 hours of driving per week are excluded from the histogram).

5.2 Aggregate Performance

To compare the overall outcomes of subjects in aggregate, subjects' average travel times per round were regressed on a treatment dummy both with and without individual characteristics (shown in Table 6). From this perspective, better treatment performance is characterized as lower average travel times among a session's group of subjects. Ignoring individual characteristics, the five treatments with lowest average travel times were ISRN, PCSN, ISHT, PIS, and IS. When individual characteristics are included, only the risk preferences show a significant effect on travel time, and these effects are small in magnitude compared to the treatment specific effects.

Variable	Meaning	Value	tStat	Value	tStat
(Intercept)		45.521	93.620	45.260	77.604
treatment = 'ISRN'		-3.048	-4.686	-3.240	-4.961
treatment = 'PCSN'		-3.079	-4.761	-3.146	-4.819
treatment = 'ISHT'		-2.814	-4.247	-3.013	-4.516
treatment = 'IS'		-2.701	-4.176	-2.909	-4.453
treatment = 'DDRS'		-2.589	-3.907	-2.818	-4.227
treatment = 'PIS'		-2.708	-4.139	-2.813	-4.275
treatment = 'PCS_2'		-2.618	-4.047	-2.792	-4.267
treatment = 'ST'		-2.483	-3.840	-2.693	-4.123
treatment = 'DT'		-2.543	-3.933	-2.664	-4.090
treatment = 'DTHT'		-2.583	-3.994	-2.651	-4.065
treatment = 'ID_2'		-2.410	-3.705	-2.625	-4.000
treatment = 'DDR'		-2.499	-3.842	-2.604	-3.984
treatment = 'STHT'		-2.481	-3.719	-2.573	-3.830
treatment = 'DR_2'		-2.403	-3.715	-2.538	-3.898
treatment = 'IDS'		-2.304	-3.562	-2.417	-3.692
treatment = 'LB'		-1.967	-3.042	-2.194	-3.348
treatment = 'ISR'		-1.902	-2.941	-2.040	-3.142
risk = 1	Risk Neutral	–	–	0.684	2.926
risk = 2	Risk Loving	–	–	0.475	1.620
gender = 'Female'	Female	–	–	0.023	0.101
playgames = 'Yes'	Plays Video Games	–	–	-0.334	-1.493
license = 'Yes'	Holds US Driver's License	–	–	0.081	0.246
seenvms = 'Yes'	Seen VMS on Hwy	–	–	-0.291	-0.952
drivemore = 1	Drive > 0.5 hrs / week	–	–	-0.229	-0.810
older = 1	Age > 23 years	–	–	-0.339	-0.853

Table 6: Linear regression of ***travel time*** *on treatment dummy and individual characteristics. The reference for the treatment variable is the no messaging baseline NM.*

Next, sessions are decomposed according to the degree of "mis-diversion" observed on average per incident scenario per round. The metric of mis-diversion is calculated as the difference between the proportion of subjects observed to divert to the alternate route and the optimal diversion proportion for a given scenario calculated using computer driver simulations from our software. It can be interpreted as the degree to which subjects overshot (positive mis-diversion) or undershot (negative mis-diversion) the optimal diversion rate for a given scenario.

Rank	No Incident	1 Lane Blocked	2 Lanes Blocked	3 Lanes Blocked, Short	3 Lanes Blocked, Long
1	PCSN	ISR	DR_2	DR_1	IDS
2	ISRN	PCSN	ISR	ID_1	PCS_1
3	ISR	ST	PCSN	DDR	PCS_2
4	ST	DT	DT	PIS	IS
5	DR_2	NM	PIS	DDRS	PCSN
6	IS	ISHT	ID_1	ST	ISRN
7	LB	DTHT	PCS_2	IS	PIS
8	LB	PCS_2	ISRN	STHT	DR_1
9	PIS	DDRS	NM	DT	DTHT
10	DDR	DR_2	DDR	PCS_2	LB
11	ID_2	LB	ID_2	DTHT	LB
12	DDRS	LB	ISHT	ID_2	ID_2
13	DT	PIS	IS	ISR	DT
14	ID_1	DDR	ST	ISHT	DDR
15	DR_1	PCS_1	DTHT	DR_2	ID_1
16	ISHT	IDS	DDRS	IDS	ISHT
17	DTHT	ISRN	STHT	PCSN	ST
18	PCS_1	STHT	IDS	PCS_1	ISR
19	STHT	IS	LB	LB	DR_2
20	IDS	ID_2	LB	LB	STHT
21	PCS_2	DR_1	DR_1	ISRN	DDRS
22	NM	ID_1	PCS_1	NM	NM

Table 7: Treatments ranked by degree of mis-diversion per incident severity level

Firstly, it is evident that providing any type of relevant messaging information improved subject travel times and reduced mis-diversion over the no messaging treatment. This was expected given that without VMS, subjects had no ability to anticipate the incident that would occur and respond to a reduction in route capacity. Consequently, session NM with no VMS had consistently longer average travel times and higher average rates of mis-diversion than other treatments. That said, it is somewhat surprising that simply providing a standard, static description of the incident severity (treatment IS) would perform relatively well compared to all other treatments that provide more information or adjust feedback in a dynamic manner. Combining a qualitative description of incident severity in the message header with other content in the message body usually performed better than having said content on its own with a generic header. Although the treatment in session ISHT, which combines incident severity messaging with heterogeneous value of time incentives, performed slightly better with respect to travel time than its counterpart session IS with homogenous incentives for all subjects, it is not clear that heterogeneous incentives are significantly responsible for the improvement.

The combination of direct targeted messaging, a description of incident severity, and informative VMS during no incident rounds enabled session PCSN to perform the best on average with respect to travel time and well with respect to mis-diversion. Notably, the addition of VMS messaging during no incident rounds enabled session PCSN to perform better than its counterpart session PCS_2. Since the most gains to be had are from preventing mis-diversion when there is no incident, it is arguable that providing VMS during those rounds will yield a significant performance improvement for any treatment under our experiment setting. Direct targeted messaging, whether using numerical vehicle IDs or vehicle outlines, generally performed well when subjects understood the meaning of the messages. In this respect, treatments with revised messaging verbiage such as PCS_2 and ID_2, performed slightly better than their counterparts, such as PCS_1 and ID_1. It is notable that targeted treatments where the form of identification was publicly visible to subjects also performed slightly better than their private identification counterparts did.

Treatments based on a statement of the optimal diversion rate did not perform significantly better than others did. Firstly, it is likely that most subjects interpreted those statements as noisy signals of the incident severity and proceeded to make their decisions accordingly. Secondly, dynamically updating the diversion message (sessions DDRS and DDR) to provide subjects with timely feedback to adjust their decision-making proved more effective than simply presenting the static message. Thirdly, the limited visibility subjects had of the platoon of cars limited their ability to judge how the current state of route choice compared with the displayed diversion rate and potentially hindered their ability to make use of that information.

Session DT, with a pricing scheme that updates dynamically within a round, performed similarly to other sessions (DDR, DDRS) utilizing a dynamically updating messaging scheme. The addition of heterogeneous VOT in session DTHT did not appear to produce an overall improvement in diversion response. Sessions ST and STHT, with scenario based pricing that updates between rounds depending on the outcome of the previous round of the same incident severity, performed significantly worse than their round dynamic counterparts. This indicates that if the pricing scheme adjusts too slowly or by too small of an increment, not enough feedback is generated to moderate the diversion response. Dynamic feedback, whether in the form of tolls/subsidies or diversion rate messages, may help nudge subjects towards making an optimal decision given the current state of the system. However, road pricing can be adjusted with finer resolution and to greater direct impact than informational messages, which, with sufficient calibration, may allow a dynamic pricing scheme to outperform a dynamic messaging scheme in our experiment setting.

Variable	Description
traveltime	travel time per round in seconds
divert	binary, 1: subject diverted to alternate route
comply	binary, 1: subject complied with VMS instruction to divert or not to divert
risk	0: risk averse, 1: risk neutral, 2: risk loving
toll	dollar toll/subsidy amount on main route
endow	dollar endowment
payoff	dollar earnings from current round
dframe	frames taken to complete trip
lane	0: left lane, 1: middle lane, 2: right lane, driver's starting lane
scenario	0-4, incident severity
VMS	0-4, VMS message intensity
DIV	0-2, VMS recommendation intensity
age	age in years
gender	Male' or 'Female'
older	binary, 1: age > 23
playgames	‘Yes' or 'No', play at least 1 hour of video games per week
license	‘Yes' or 'No', possess US driver's license
drivehours	average driving hours per week
drivemore	binary, 1: drivehours > 0.5
seenvms	‘Yes' or 'No', seen variable message signs before

*Table 8: Regression variables (**traveltime**, **divert,** and **comply** are dependent)*

5.3 Group Analysis

In the following section, sessions are analyzed in comparison with the no messaging baseline session NM and other sessions within the same messaging type group. A comparative plot of the mis-diversion rate for each group of sessions is provided. In each plot, the mis-diversion rate observed every round is grouped by incident scenario and stacked from left to right in the order in which the scenarios occurred. Each session will have five groups of columns representing incident scenarios 0 through 4. Additionally, logit regression models are estimated to compare how treatments affect the propensity of drivers to divert to the alternate route. In these regressions, the dependent variable is always the binary indicator of whether drivers diverted to the alternate route. Independent variables are taken from the treatment design parameters, observed subject behavior and outcomes, and subject’s individual characteristics as elicited by the post-experiment survey. Estimates, which are significant at the 5% level, are bolded. Common variables as listed in Table 8.

		NM		IS		ISR		ISRN		ISHT		IS, ISHT	
		Baseline		Incident Severity						Heterogeneous VOT			
Variable	**Meaning**	**Value**	**tStat**	**Value**	**tStat**	**Value**	**tStat**	**Value**	**tStat**	**Value**	**tStat**	**Value**	**tStat**
(Intercept)		0.221	0.484	**-1.537**	**-3.889**	**-2.573**	**-5.946**	**-3.210**	**-6.213**	**-1.339**	**-2.818**	**-1.880**	**-5.257**
risk = 1	Risk Neutral	-0.342	-1.524	-0.210	-1.086	**0.505**	**2.277**	0.202	0.986	-0.002	-0.009	-0.035	-0.274
risk = 2	Risk Loving	**0.969**	**3.580**	**-0.609**	**-2.196**	-0.138	-0.486	-0.160	-0.646	-0.080	-0.235	-0.203	-1.040
lane = 1	Middle Lane	0.030	0.131	0.070	0.353	-0.057	-0.274	0.003	0.016	0.016	0.078	0.047	0.333
lane = 2	Right Lane	0.273	1.238	0.334	1.711	0.371	1.837	**0.519**	**2.564**	0.329	1.610	**0.357**	**2.562**
VMS = 1	VMS Intensity 1	–	–	**0.620**	**2.193**	0.447	1.401	**1.233**	**3.731**	0.295	1.022	**0.460**	**2.293**
VMS = 2	VMS Intensity 2	–	–	**0.905**	**3.266**	**0.941**	**3.105**	**1.462**	**4.488**	**0.745**	**2.676**	**0.818**	**4.190**
VMS = 3	VMS Intensity 3	–	–	**1.445**	**5.308**	**1.772**	**5.637**	**2.496**	**7.297**	**1.511**	**5.506**	**0.818**	**4.190**
VMS = 4	VMS Intensity 4	–	–	**1.746**	**6.409**	**1.637**	**5.194**	**2.350**	**6.889**	**1.542**	**5.626**	**0.818**	**4.190**
DIV_1	Diversion Recommend. 1	–	–	–	–	0.108	0.380	0.340	1.163	–	–	–	–
DIV_2	Diversion Recommend. 2	–	–	–	–	0.266	0.939	-0.168	-0.587	–	–	–	–
scenario = 1	1 Lane Blocked	-0.112	-0.382	–	–	–	–	–	–	–	–	–	–
scenario = 2	2 Lanes Blocked	0.357	1.256	–	–	–	–	–	–	–	–	–	–
scenario = 3	3 Lanes Blocked, Short	0.179	0.624	–	–	–	–	–	–	–	–	–	–
scenario = 4	3 Lanes Blocked, Long	0.089	0.310	–	–	–	–	–	–	–	–	–	–
endow	Endowment Amount	–	–	–	–	–	–	–	–	0.008	0.475	0.009	0.548
toll	Toll/Subsidy Amount	–	–	–	–	–	–	–	–	–	–	–	–
license = 'Yes'	Holds US Driver's License	**2.368**	**4.017**	0.340	1.511	-0.463	-1.312	**0.793**	**2.562**	**0.781**	**2.159**	**0.541**	**2.961**
seenvms = 'Yes'	Seen VMS on Hwy	-0.427	-0.818	0.298	1.079	-0.119	-0.537	0.076	0.318	0.223	0.981	0.135	0.797
drivemore = 1	Drive > 0.5 hrs / week	**-1.470**	**-3.799**	**-0.767**	**-3.877**	0.199	0.675	-0.003	-0.011	**-0.720**	**-3.086**	**-0.700**	**-4.940**
gender = 'Female'	Female	0.214	1.040	**-0.451**	**-2.091**	-0.098	-0.532	0.073	0.396	0.363	1.737	-0.006	-0.043
playgames = 'Yes'	Plays Video Games	-0.198	-0.899	-0.493	-2.705	-0.139	-0.730	-0.128	-0.728	0.320	1.687	0.094	0.765

Table 9: Logit model of ***divert*** *for un-pooled treatments NM, IS, ISR, ISHT and pooled treatments [IS, ISHT]*

		DR_2		DDR		DDRS		ID_2		IDS		PIS	
		Diversion Rate						Numeric ID					
Variable	**Meaning**	**Value**	**tStat**	**Value**	**tStat**	**Value**	**tStat**	**Value**	**tStat**	**Value**	**tStat**	**Value**	**tStat**
(Intercept)		**-2.812**	**-4.575**	**-1.841**	**-5.132**	**-1.274**	**-3.140**	**-1.935**	**-4.454**	**-0.845**	**-2.542**	**-0.962**	**-2.202**
risk = 1	Risk Neutral	0.027	0.134	0.037	0.207	0.048	0.226	**0.486**	**2.342**	**-0.610**	**-3.130**	-0.251	-1.202
risk = 2	Risk Loving	-0.412	-1.409	-0.179	-0.667	**0.809**	**2.869**	**0.545**	**2.419**	**-0.559**	**-2.097**	-0.458	-1.293
lane = 1	Middle Lane	0.134	0.646	0.381	1.889	-0.056	-0.267	**0.392**	**1.965**	0.215	1.099	**0.558**	**2.719**
lane = 2	Right Lane	**0.529**	**2.634**	**0.796**	**4.003**	**0.462**	**2.271**	**0.431**	**2.181**	**0.487**	**2.515**	0.252	1.212
VMS = 1	VMS Intensity 1	0.560	1.958	0.506	1.782	0.475	1.605	**0.575**	**2.062**	0.098	0.368	0.536	1.832
VMS = 2	VMS Intensity 2	0.486	1.683	**0.839**	**3.038**	**0.989**	**3.461**	**0.795**	**2.898**	**0.546**	**2.125**	**0.716**	**2.485**
VMS = 3	VMS Intensity 3	**1.150**	**4.181**	**1.375**	**5.082**	**1.399**	**4.950**	**1.143**	**4.238**	**1.138**	**4.502**	**1.495**	**5.339**
VMS = 4	VMS Intensity 4	**1.422**	**5.206**	**1.517**	**5.607**	**1.488**	**5.264**	**1.526**	**5.683**	**1.436**	**5.667**	**1.834**	**6.536**
DIV_1	Diversion Recommend. 1	–	–	–	–	–	–	–	–	–	–	–	–
DIV_2	Diversion Recommend. 2	–	–	–	–	–	–	–	–	–	–	–	–
scenario = 1	1 Lane Blocked	–	–	–	–	–	–	–	–	–	–	–	–
scenario = 2	2 Lanes Blocked	–	–	–	–	–	–	–	–	–	–	–	–
scenario = 3	3 Lanes Blocked, Short	–	–	–	–	–	–	–	–	–	–	–	–
scenario = 4	3 Lanes Blocked, Long	–	–	–	–	–	–	–	–	–	–	–	–
endow	Endowment Amount	–	–	–	–	–	–	–	–	–	–	–	–
toll	Toll/Subsidy Amount	–	–	–	–	–	–	–	–	–	–	–	–
license = 'Yes'	Holds US Driver's License	-0.654	-1.788	0.071	0.269	**0.976**	**2.864**	-0.076	-0.274	0.181	0.655	0.056	0.205
seenvms = 'Yes'	Seen VMS on Hwy	0.072	0.269	–	–	-0.336	-1.354	-0.165	-0.776	0.338	1.419	0.482	1.522
drivemore = 1	Drive > 0.5 hrs / week	**1.042**	**2.278**	-0.115	-0.490	**-0.668**	**-2.329**	0.194	0.746	0.000	0.002	-0.165	-0.575
gender = 'Female'	Female	-0.223	-1.163	0.159	0.640	0.370	1.941	**0.459**	**1.998**	**0.937**	**4.763**	**1.003**	**4.464**
playgames = 'Yes'	Plays Video Games	-0.275	-1.580	0.146	0.600	0.122	0.606	0.095	0.440	-0.152	-0.783	-0.110	-0.546

*Table 10: Logit model of **divert** for un-pooled treatments DR_2, DDR, DDRS, ID_2, IDS, PIS*

		PCS_2		PCSN		DT		DTHT		ST		STHT		IS, DT	
		Color Outline				Tolling (DT is dynamic within round, ST is dynamic between rounds)									
Variable	**Meaning**	**Value**	**tStat**	**Value**	**tStat**	**Value**	**tStat**	**Value**	**tStat**	**Value**	**tStat**	**Value**	**tStat**	**Value**	**tStat**
(Intercept)		**-3.714**	**-9.240**	**-3.784**	**-7.489**	**-1.453**	**-4.614**	**-1.742**	**-2.759**	**-2.165**	**-4.388**	**-2.108**	**-4.408**	**-1.657**	**-6.496**
risk = 1	Risk Neutral	0.388	1.575	-0.212	-0.915	-0.250	-1.390	0.230	1.056	0.177	0.771	-0.092	-0.519	-0.118	-0.948
risk = 2	Risk Loving	**0.474**	**2.028**	0.235	0.997	-0.344	-1.513	0.237	1.145	**0.565**	**2.212**	-0.067	-0.206	**-0.387**	**-2.352**
lane = 1	Middle Lane	**1.548**	**6.437**	**0.798**	**3.276**	0.038	0.193	0.001	0.006	-0.133	-0.663	**0.540**	**2.558**	0.054	0.393
lane = 2	Right Lane	**2.577**	**10.573**	**2.365**	**9.546**	0.052	0.263	0.174	0.889	0.095	0.484	**0.951**	**4.567**	0.205	1.495
VMS = 1	VMS Intensity 1	-0.113	-0.398	**1.037**	**2.899**	0.207	0.723	0.224	0.804	0.525	1.735	0.380	1.274	**0.409**	**2.056**
VMS = 2	VMS Intensity 2	0.219	0.792	**1.428**	**4.072**	0.486	1.770	**0.690**	**2.591**	**1.061**	**3.761**	**0.698**	**2.562**	**0.689**	**3.558**
VMS = 3	VMS Intensity 3	**1.041**	**3.815**	**2.719**	**7.833**	**1.348**	**5.126**	**1.241**	**4.716**	**1.373**	**4.929**	**1.277**	**4.731**	**1.381**	**7.349**
VMS = 4	VMS Intensity 4	**1.425**	**5.172**	**2.786**	**7.986**	**1.536**	**4.924**	**1.408**	**4.570**	**1.394**	**4.509**	**0.917**	**2.673**	**1.626**	**8.160**
DIV_1	Diversion Recommend. 1	–	–	–	–	–	–	–	–	–	–	–	–	–	–
DIV_2	Diversion Recommend. 2	–	–	–	–	–	–	–	–	–	–	–	–	–	–
scenario = 1	1 Lane Blocked	–	–	–	–	–	–	–	–	–	–	–	–	–	–
scenario = 2	2 Lanes Blocked	–	–	–	–	–	–	–	–	–	–	–	–	–	–
scenario = 3	3 Lanes Blocked, Short	–	–	–	–	–	–	–	–	–	–	–	–	–	–
scenario = 4	3 Lanes Blocked, Long	–	–	–	–	–	–	–	–	–	–	–	–	–	–
endow	Endowment Amount	–	–	–	–	–	–	**0.067**	**4.133**	–	–	-0.014	-0.869	–	–
toll	Toll/Subsidy Amount	–	–	–	–	-0.273	-0.736	-0.077	-0.216	0.458	0.855	0.610	1.444	-0.307	-1.045
license = 'Yes'	Holds US Driver's License	-0.414	-1.692	0.060	0.218	-0.254	-0.976	0.188	0.499	0.075	0.271	0.029	0.077	0.131	0.803
seenvms = 'Yes'	Seen VMS on Hwy	0.332	1.103	0.000	0.000	0.210	0.902	-0.307	-0.982	**-0.643**	**-2.379**	**0.671**	**2.145**	0.241	1.430
drivemore = 1	Drive > 0.5 hrs / week	0.428	1.925	-0.222	-0.854	0.206	1.012	-0.271	-1.398	-0.209	-0.988	-0.165	-0.432	**-0.336**	**-2.514**
gender = 'Female'	Female	**0.818**	**3.402**	**0.532**	**2.448**	-0.016	-0.088	-0.178	-0.952	**0.817**	**3.142**	0.257	1.327	0.143	1.088
playgames = 'Yes'	Plays Video Games	-0.049	-0.222	0.015	0.076	-0.057	-0.336	**-0.823**	**-4.296**	**0.631**	**2.687**	0.054	0.274	**0.329**	**2.791**

*Table 11: Logit model of **divert** for un-pooled treatments PCS_2, PCSN, DT, and pooled treatments [IS, DT]*

Baseline: NM

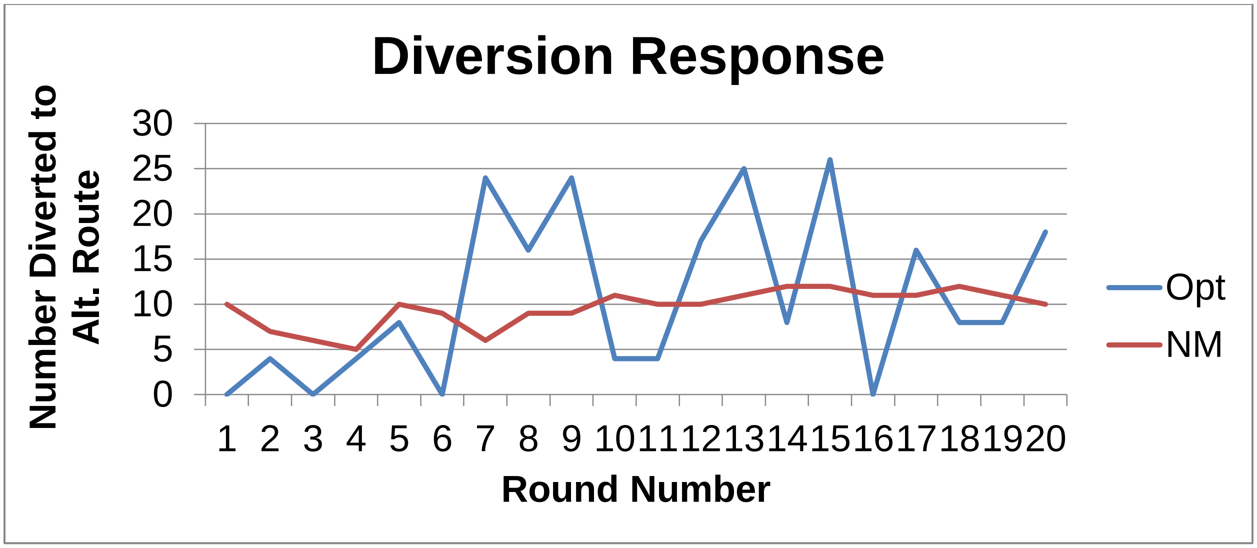


Figure 5: Diversion response of NM vs simulated optima

As shown in Figure 5, the diversion response of subjects is mostly flat and unreactive when no information is provided. In this stark environment, subjects are incapable of knowing whether, or not, an incident has occurred on the roadway before they choose routes. As shown in Table 9, the logit model estimates are significant only for select coefficients based on individual subject characteristics. In particular, subjects who were risk loving were more likely to divert, while subjects who did not hold a US driver's license or drove more than half an hour per week were less likely to divert.

Incident Severity - Group IS

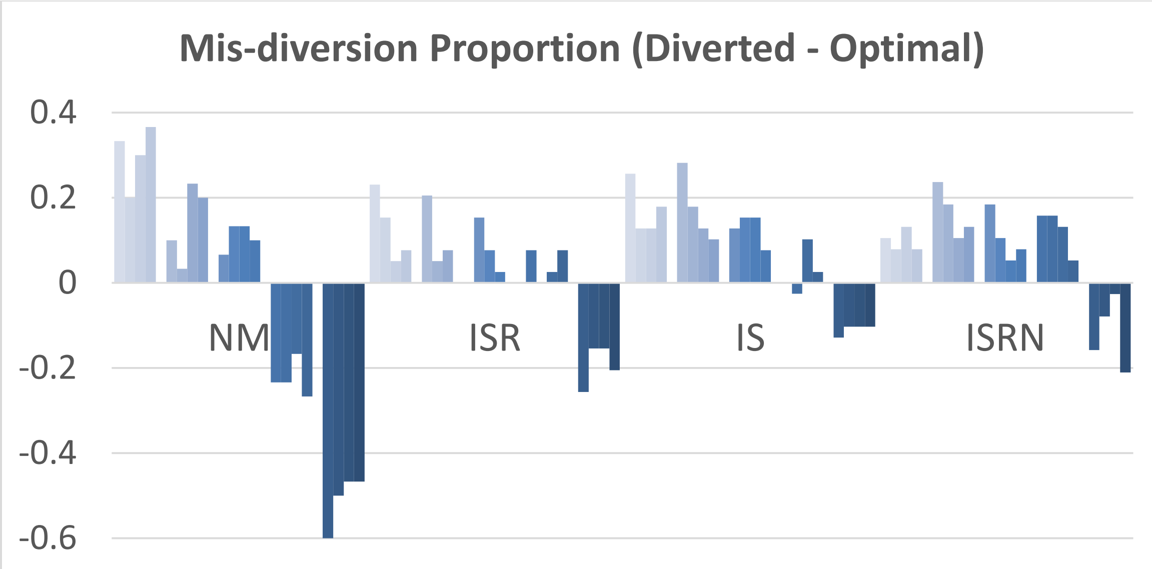


Figure 6: Degree of mis-diversion in NM, ISR, IS, ISRNs

As shown in Figure 6, the addition of incident severity information significantly reduced the degree of mis-diversion for most scenarios. Additionally, the degree of mis-diversion tended to decrease over time when subjects are provided with information, suggesting that subjects in aggregate are learning and adjusting their route choice based on prior experience. As shown in Table 9, the un-pooled logit model estimates for treatments IS, ISR, and ISRN are significant for many of the VMS intensity categorical variables. In general, subjects are more likely to divert as the VMS intensity increases. For treatment IS, significant effects are also found for gender and whether or not the subject regularly plays video games. For treatment ISR, the use of diversion recommendations has a slightly positive, but insignificant effect on subjects' propensity to divert. For treatment ISRN, the additional VMS guidance provided for non-incident (Scen. 0) rounds significantly reduces mis-diversion during those rounds.

Diversion Rate: Group DR

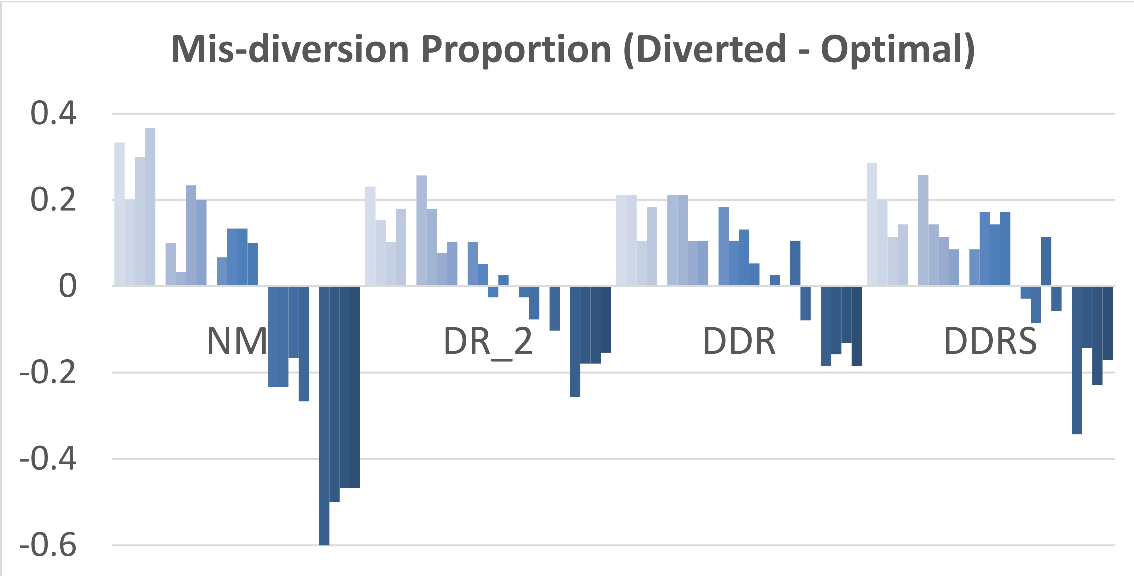


Figure 7: Degree of mis-diversion in NM, DR_2, DDR, DDRS

Similar to group IS treatments; group DR treatments show evidence of learning across rounds. However, group DR subjects appear to have higher initial mis-diversion rates for a longer period than their group IS counterparts. As shown in Table 10, logit model estimates for group DR treatments are positive and significant for most VMS intensity levels. Of note, VMS intensity in the dynamic messaging treatments DDR and DDRS appear to have a greater impact on subjects' propensity to divert than their static messaging counterpart DR_2. The estimates for lane_2 are positive and significant across group DR, indicating that being in the right lane at the start of the experiment increases the subjects' propensity to divert.

Numeric ID: Group ID

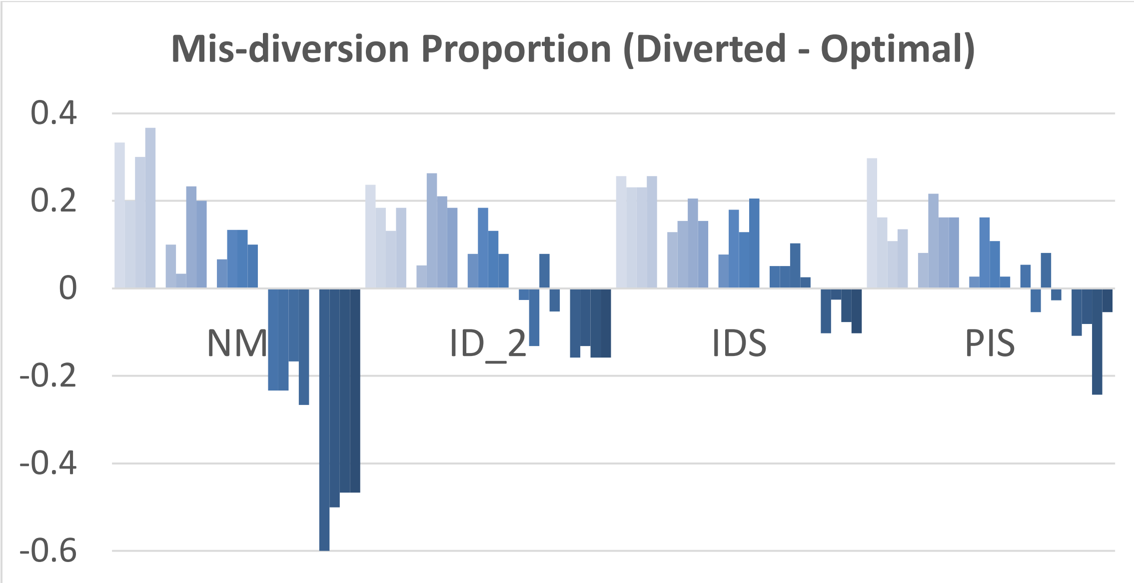


Figure 8: Degree of mis-diversion in NM, ID_2, IDS, PIS

As shown in Figure 8, the trend of mis-diversion rates over time is noticeably different for group ID in comparison with group IS or group DR. Diversion rates fluctuate up and down between rounds, indicating that subject compliance with VMS instructions did not improve over time. As shown in Table 10, logit model estimates for group ID indicate that being male gendered has a significant negative impact on subjects' propensity to divert. In addition, being in the middle or right lane has a positive impact on the propensity to divert. Risk preference coefficients are conflicting across treatments, but this could be attributed to the fact that VMS always instructs the same subset of individuals to divert for a given incident scenario.

Color Outline: Group C

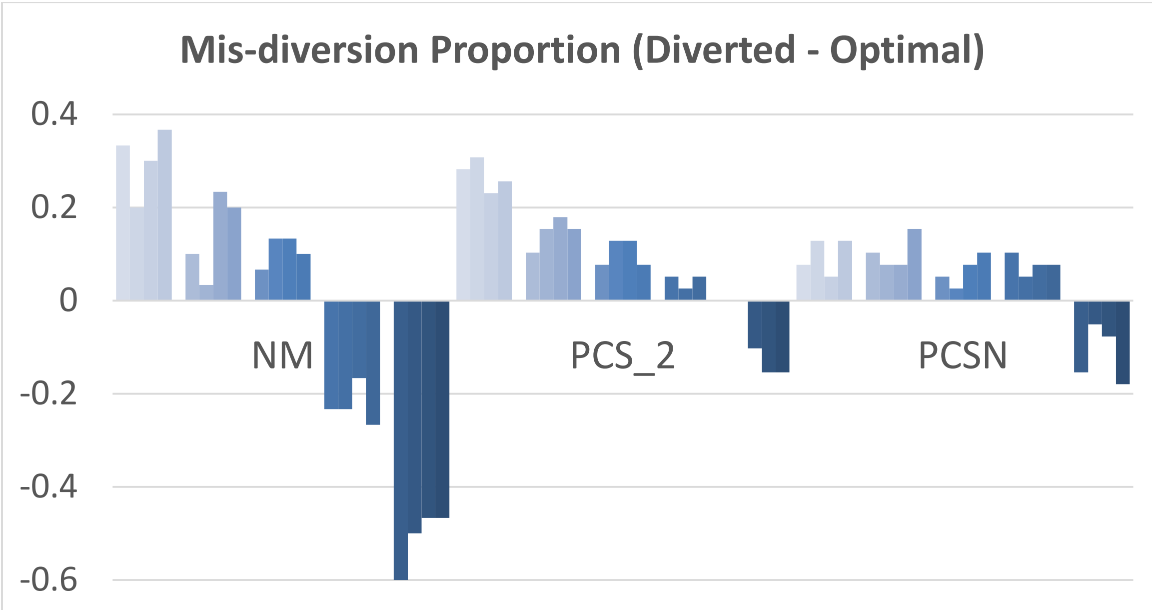


Figure 9: Degree of mis-diversion in NM, PCS_2, PCSN

Group C treatments generally have lower magnitudes and variability of mis-diversion than other groups. By providing subjects with direct guidance, it appears they are able to adapt stable strategies more quickly. As shown in Table 11, logit model estimates for group C indicate that individual characteristics do not have a significant impact on subjects' propensity to divert. Rather, it is evident that subjects are mainly influenced by whether or not their car was outlined and instructed to divert by VMS. Although the estimates for the starting lane categorical variable are significant, the starting lane position is endogenously related to the selection of cars that are outlined. As was the case with group ID, being male gendered has a significant negative effect on subjects' propensity to comply.

Compliance Analysis

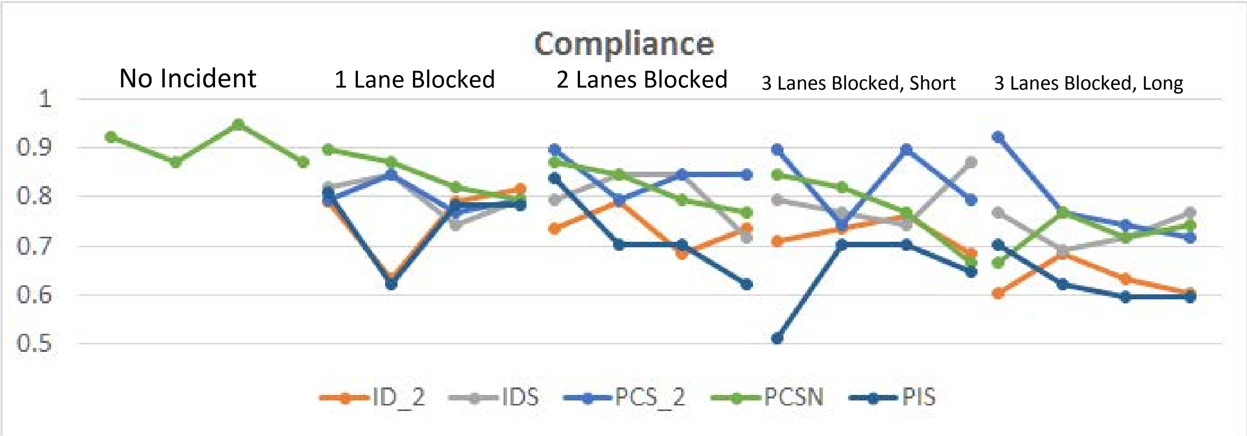


Figure 10: Compliance over time, grouped by scenario for treatments ID_2, IDS, PCS_2, PCSN, PIS

For group ID and group C treatments, compliance can be defined as the subject choosing to divert only when instructed to do so by VMS. In Figure 10, the compliance rate of each session is plotted over time and grouped by incident scenario (0-4 from left to right). As shown, compliance rates for each incident scenario does not typically improve over time. In fact, compliance tends to be downward sloping within treatments for many incident scenarios. Compliance rates also tended to decrease as the incident severity and VMS intensity (number of subjects instructed to divert) increased. Group C treatments tended to have significantly better compliance rates than group ID treatments. This can potentially be attributed to the ease with which group C subjects could interpret and understand the VMS instructions – they only needed to be aware of whether or not their car was outlined as opposed to tracking their numeric ID and the IDs selected by VMS.

ID_2, IDS, PIS, PCS_2, PCSN			
Variable	**Meaning**	**Value**	**tStat**
(Intercept)		**1.470**	**6.856**
treatment = 'IDS'		**0.324**	**2.359**
treatment = 'PIS'		-0.161	-1.237
treatment = 'PCS_2'		**0.653**	**4.627**
treatment = 'PCSN'		**0.437**	**3.188**
risk = 1	Risk Neutral	**-0.238**	**-2.371**
risk = 2	Risk Loving	-0.169	-1.413
lane = 1	Middle Lane	0.117	1.087
lane = 2	Right Lane	**-0.223**	**-2.159**
scenario = 2	2 Lanes Blocked	-0.040	-0.313
scenario = 3	3 Lanes Blocked, Short	-0.214	-1.729
scenario = 4	3 Lanes Blocked, Long	**-0.486**	**-4.032**
gender = 'Male'	Male	**-0.250**	**-2.482**
playgames = 'No'	Doesn't Play Video Games	-0.002	-0.020
license = 'No'	No US Driver's License	0.075	0.585
seenvms = 'No'	Never Seen VMS on Hwy	**-0.275**	**-2.105**
drivemore = 1	Drive > 0.5 hrs / week	0.195	1.631

Table 12: Logit model of ***comply****, pooled treatments ID_2, IDS, PIS, PCS_2, PCSN*

Table 12 contains the pooled logit model estimates for treatments ID_2, IDS, PIS, PCS_2, and PCSN. Outcomes from incident scenario 0 rounds are excluded from this regression as all treatments except for PCSN did not provide any VMS instructions for those rounds. Controlling for individual effects as well as the incident severity, treatments PCSN and PCS_2 had the highest baseline impacts on propensity to comply. Curiously, the negative effect of being male gendered on compliance retains significance when treatments are pooled.

Heterogeneous VOT

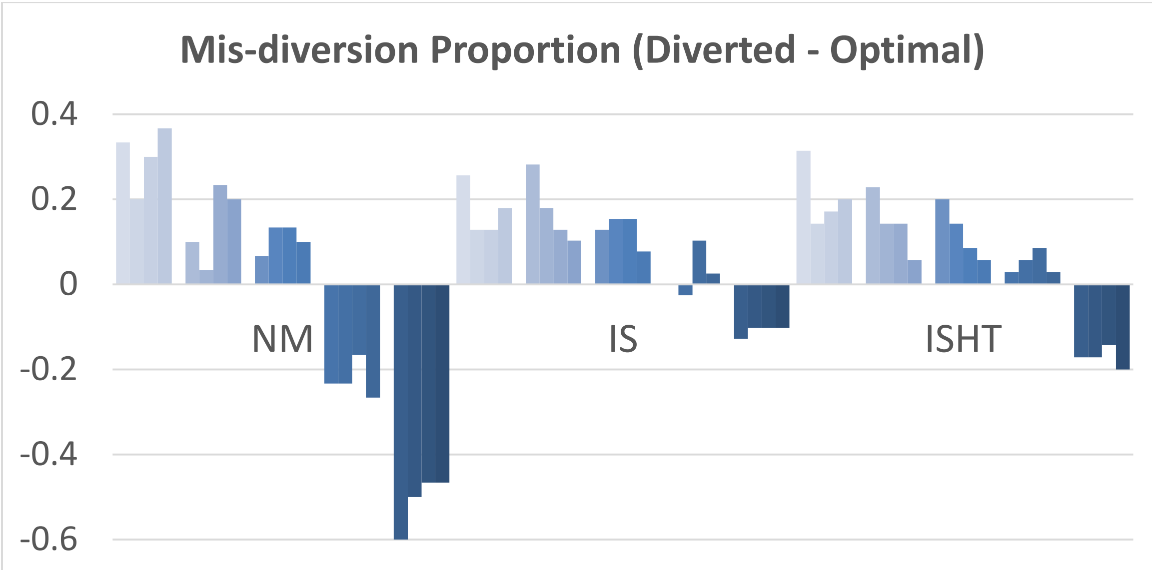


Figure 11: Degree of mis-diversion for NM, IS, ISHT

As shown in Figure 11, the degree of mis-diversion in treatment ISHT was similar to that of treatment IS. Table 11 contains the logit model estimate for treatment ISHT standalone, treatment IS, and ISHT pooled. In both regressions, the endowment of subjects had no significant impact on subjects' propensity to divert.

Pricing: Group T

In this group, treatment DT uses the dynamically adjusted within round pricing scheme, whereas treatment ST uses the scenario based, adjusted between rounds pricing scheme.

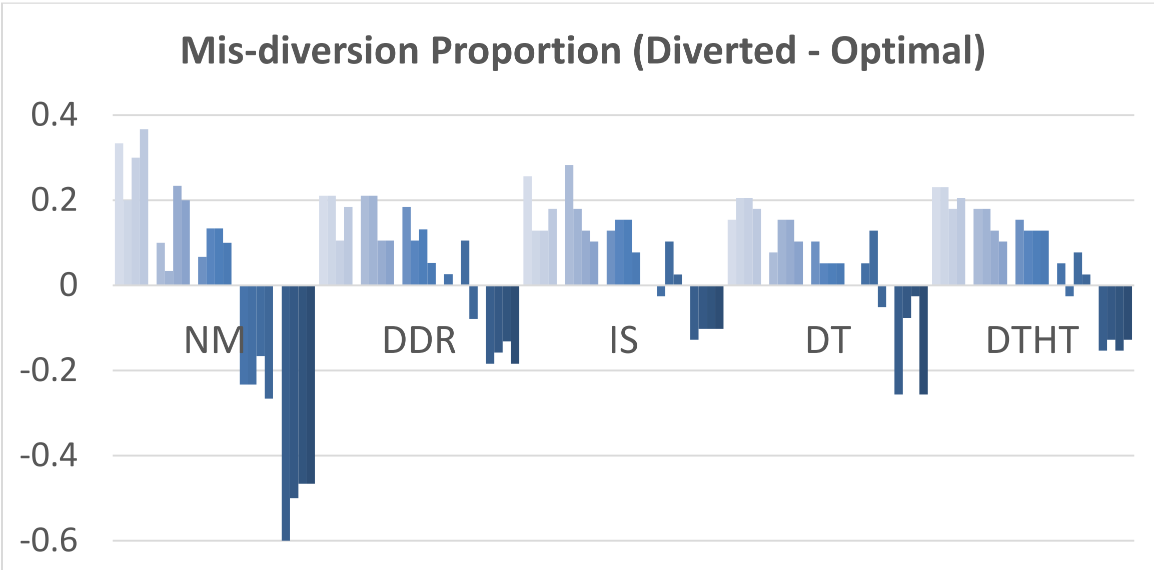


Figure 12: Degree of mis-diversion for NM, DDR, IS, DT, DTHT

As shown in Figure 12, mis-diversion rates in treatment DT remained relative constant across rounds except for those of incident scenario 4. Table 11 contains logit model estimates for treatments DT, DTHT, and treatments IS and DT pooled. Both DT regressions indicate that the price had a negative, but insignificant effect on the propensity of drivers to divert to the alternate route. Had the road price worked as anticipated, the effect would be positive instead of negative, as a positive price on the main route would be expected to influence drivers to take the alternate route instead. Compared to treatment DT, treatment DTHT with heterogeneous VOT had significantly higher levels on mis-diversion on average per scenario. The DTHT regression saw a diminished pricing effect and a highly significant, but slightly positive effect from the magnitude of subjects' endowments.

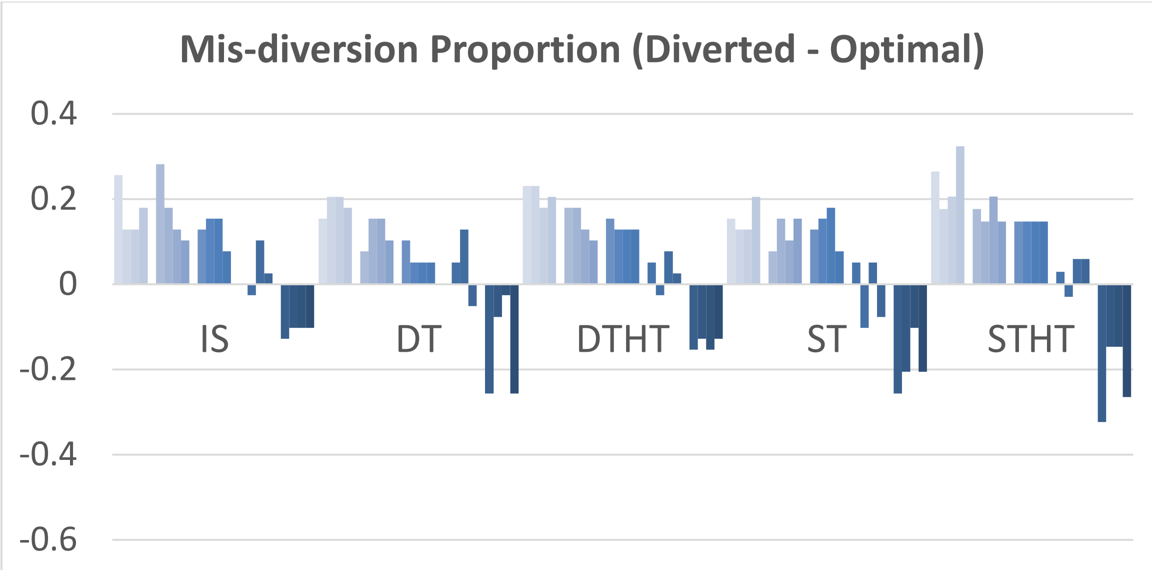


Figure 13: Degree of mis-diversion for IS, DT, DTHT, ST, STHT

As shown in Figure 13, scenario based pricing treatments ST and STHT generally performed equal to or worse than their dynamic within round pricing counterparts. The logit model estimates show positive, but not statistically significant effects for the road price in both treatments. It appears that subjects may have responded to positive prices under this scheme with diversion to the alternate route, but the magnitude and/or adjustment thresholds for the road price were not enough to generate the desired response level. Overall, both the dynamic and scenario based tolling schemes require further calibration in both the price amount and the threshold for price updates.

Pooled analysis

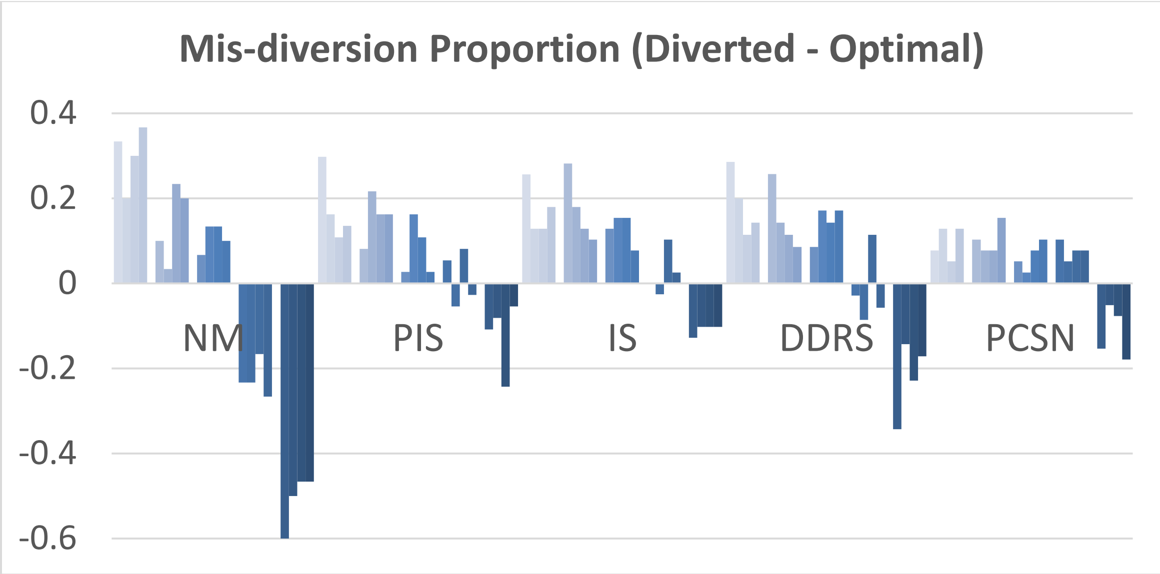


Figure 14: Degree of mis-diversion for NM, PIS, IS, DDRS, PCSN

NM, PIS, IS, DDRS, PCSN			
Variable	**Meaning**	**Value**	**tStat**
(Intercept)		**-0.867**	**-5.850**
risk = 1	Risk Neutral	-0.085	-1.009
risk = 2	Risk Loving	**0.221**	**2.038**
lane = 1	Middle Lane	**0.242**	**2.598**
lane = 2	Right Lane	**0.674**	**7.420**
VMS = 1	VMS Intensity 1	0.099	0.833
VMS = 2	VMS Intensity 2	**0.428**	**3.773**
VMS = 3	VMS Intensity 3	**1.119**	**10.257**
VMS = 4	VMS Intensity 4	**1.312**	**12.009**
gender = 'Female'	Female	**-0.382**	**-4.777**
playgames = 'Yes'	Plays Video Games	-0.125	-1.589
license = 'Yes'	Holds US Driver's License	**0.630**	**5.466**
seenvms = 'Yes'	Seen VMS on Hwy	0.056	0.479
drivemore = 1	Drive > 0.5 hrs / week	**-0.433**	**-4.282**
older = 1	Age > 23 years	**-0.364**	**-2.571**

*Table 13: Logit model of **divert**, pooled treatments NM, PIS, IS, DDRS, PCSN*

Table 13 contains the logit model estimates for treatments NM, PIS, IS, DDRS, and PCSN pooled. Across these different messaging schemes, it is clear that VMS intensity levels 2 through 4 have significant positive effects on the subjects' propensity to divert. VMS intensity level 1 does not have a significant effect, as the average proportion of drivers who diverted was similar to the baseline diversion rate. The subject's initial starting lane had a significant effect on the probability of diversion – the closer the subject was located to the exit on the right side, the more likely the subject was to divert. Among the individual characteristics considered, significant effects include a positive effect due to risk lovingness, a negative effect due to being female, a positive effect due to holding a US driver's license, a negative effect for subjects who drove more than half an hour per week, and a negative effect for subjects 23 years and older. The effect of risk preferences could be attributed to the following: First, subjects who start in the left and middle lanes will lose an uncertain amount of time when changing lanes to reach the exit to the alternate route. Second, subjects are provided with information regarding the traffic incident on the main route, but receive no information regarding the traffic levels on the more easily congestible alternate route, leading to the perception that the alternate route is more "risky" despite the fact that traffic incidents never occur there. The effects of holding a US driver's license, driving more frequently, and being older can be jointly interpreted as an indicator that both the least experienced and most experienced drivers are more averse to taking the alternate route. It is unclear why, controlling for risk preferences, gender still has a significant impact on driver's propensity to divert.

6. Conclusion

Our study has shown that a real-time 2D driving simulator experiment incorporating value of time incentives and key features of the real-world environment can shed new light on how drivers decide which route to take in the face of uncertainty on the roadway. On the aggregate level, introducing any type of meaningful incident-based information improves system performance relative to the no-information baseline. That being said, different information schema can have significantly different results on driver behavior. First, it is apparent that more information does not necessarily equate to better system performance – the qualitative description of incident severity by itself performed better on average across all scenarios than many treatments, which added additional information and/or active guidance. Second, providing dynamically adjusting information and feedback with or without the use of road pricing did not always improve system outcomes. This may be a result of the VMS display changed too quickly for some subjects to comprehend and/or indicative that the magnitude with which the information and incentives adjusted was not large enough. Clearly, VMS schemes that seek to provide dynamically adjusting feedback need to be calibrated over a range of parameters to be effective. Third, the idiosyncratic characteristics of drivers have different and potentially significant effects on different messaging schemes. For example, being male was found to have a significant negative effect on compliance with targeted messaging, and indicators of driver experience was found to have conflicting effects on all treatments. Taken as a whole, these results indicate that it is not straightforward to determine the level and nature of information that will be most conducive towards coordinating an optimal system response.

In the discussion of findings generated by our study, it is important for us to acknowledge suspected flaws, known limitations, and potential avenues of improvement with respect to the research methodology. Regarding the experiment design, we note the following issues: First, the system's optimal diversion rate for incident scenario 1 may be too low by design such that it would be difficult for subjects to reach the optimal equilibrium. Second, the baseline diversion rate is likely inflated due to the gamified driving dynamics and simplistic two-route road network. In upcoming experiments, we will attempt to incorporate more aspects of real world driving dynamics such as costly collisions as well as more complicated road geometries to make our simulator more representative of real world driving. Third, the use of some simplistic computer controlled drivers introduces artificial and unpredictable influences on the behavior of human drivers in the experiment. Although we have tried to minimize their usage, it is nonetheless desirable to eliminate computer controlled drivers from the within the main platoon of drivers. Finally, we are aware that the population of college students from which we sampled our participants is not 100% representative of the driving public in the US or even in Southern California. In upcoming studies, we will strive to sample from a greater subset of the adult driving populace to further eliminate sample bias and gain a better understanding of how demographic characteristics may interact with treatment conditions to affect driver behavior.

7. Detailed Description of Results

7.2 Qualitative VMS (group IS)

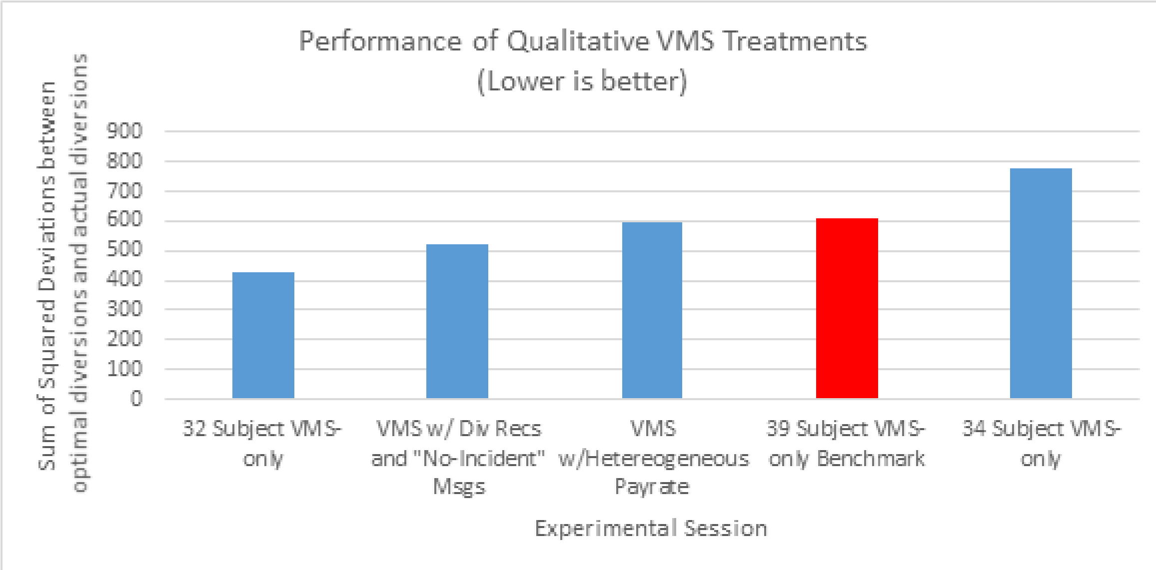
7.2.1 Qualitative VMS only (treatment IS)

Overview

During qualitative-VMS-only treatments, subjects are informed of an incident and given a one-word description of the incident type (minor, medium, major, severe); this description corresponds to a fixed loss of capacity on the main route in that round. By uniquely identifying each incident type, subjects are able to learn diversion strategies for each type and apply that knowledge for the appropriate incident type in future rounds. The qualitative description also allows subjects to rank the severity of each incident type; subjects know that more vehicles should divert for a major incident than a medium one, and so on.

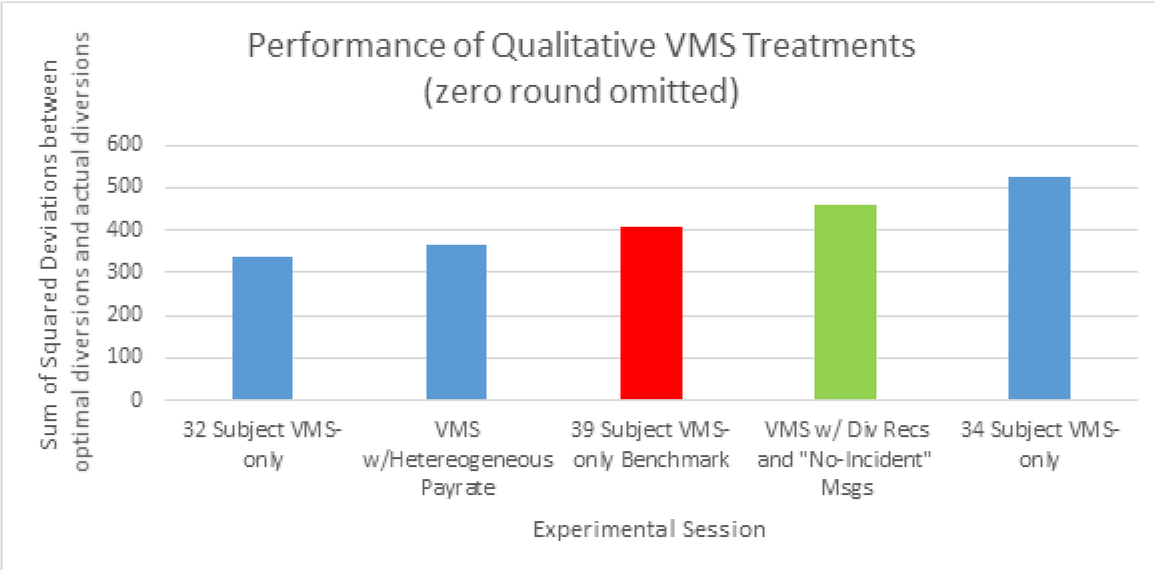
The drawbacks are that drivers do not know how many vehicles should divert during each incident type – this must be learned over time. Furthermore, even if subjects learn how many vehicles should divert, it will be difficult for them to coordinate on who diverts and who stays on the main route.

Several versions of this treatment were run with slight variations, which will be explained later in this section. There was significant variation in performance between these treatments; the sum of squared differences between the actual diversion rate and optimal diversion rate each round for the worst session were nearly twice that of the best-performing session.



The most basic and straightforward implementation of this treatment, which is a 39-subject (full session) qualitative VMS-only treatment, performs almost identically to the median and will be used as the reference case for comparison to other types of treatments. Performance is measured as the sum of squared deviations between the optimal number of diversions each round and the actual experimental number of diversions each round.

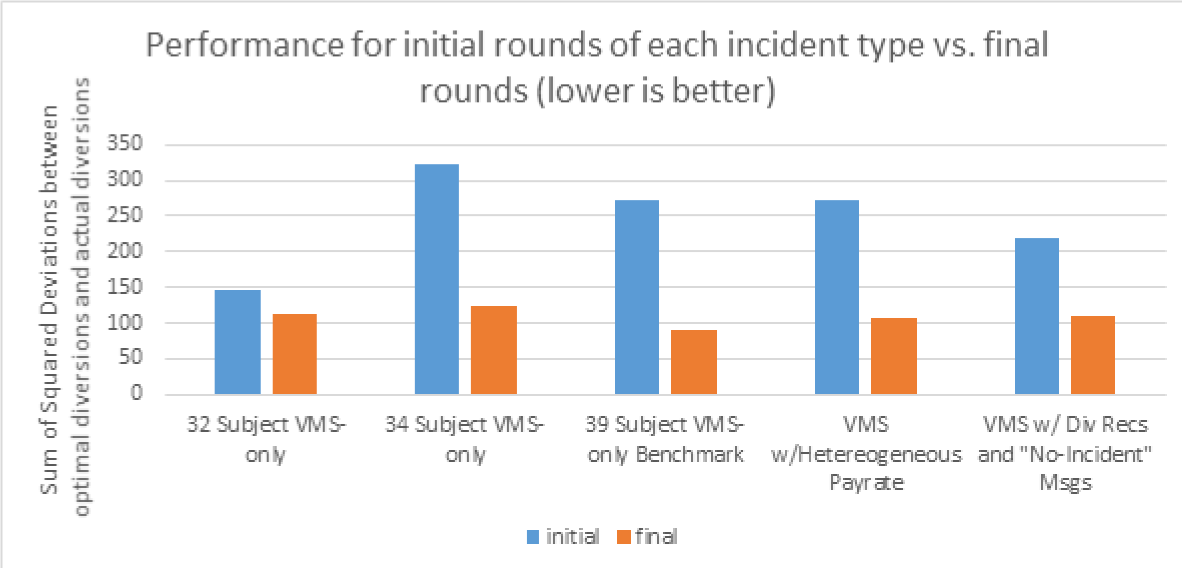
When ignoring rounds with no incident, for which no VMS information is provided, the differences between the various qualitative-VMS-only treatments are not as pronounced. It is possible that for these treatments, performance on rounds with no incident is random.



The basic qualitative-information-only treatment used as our reference (marked in red) is still the median; the performance rankings of some of the treatments changed, however.

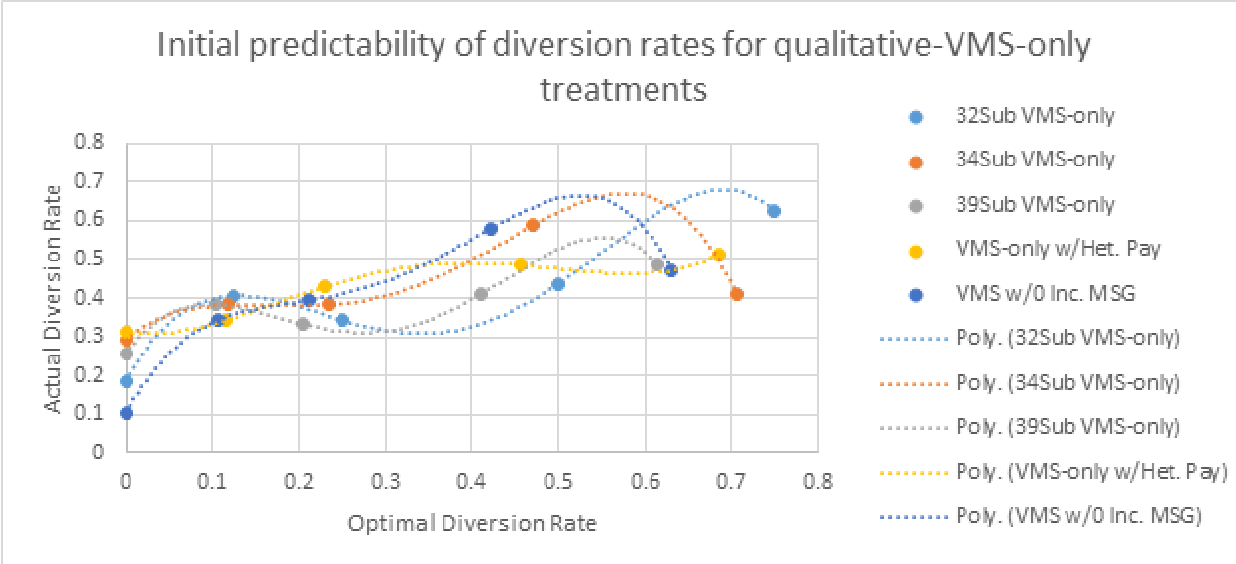
The change in ranking comes from the treatment highlighted in green, which is the sole VMS-only treatment that provides information on rounds with no incident. This round loses its advantage when these rounds are excluded, which explains the drop in ranking.

A consistent result from these treatments is that performance improves over time; performance on the later rounds is dramatically improved over early-round performance.   By the final round for each type of incident, performance among the various treatments is nearly identical, regardless of discrepancies in initial performance.

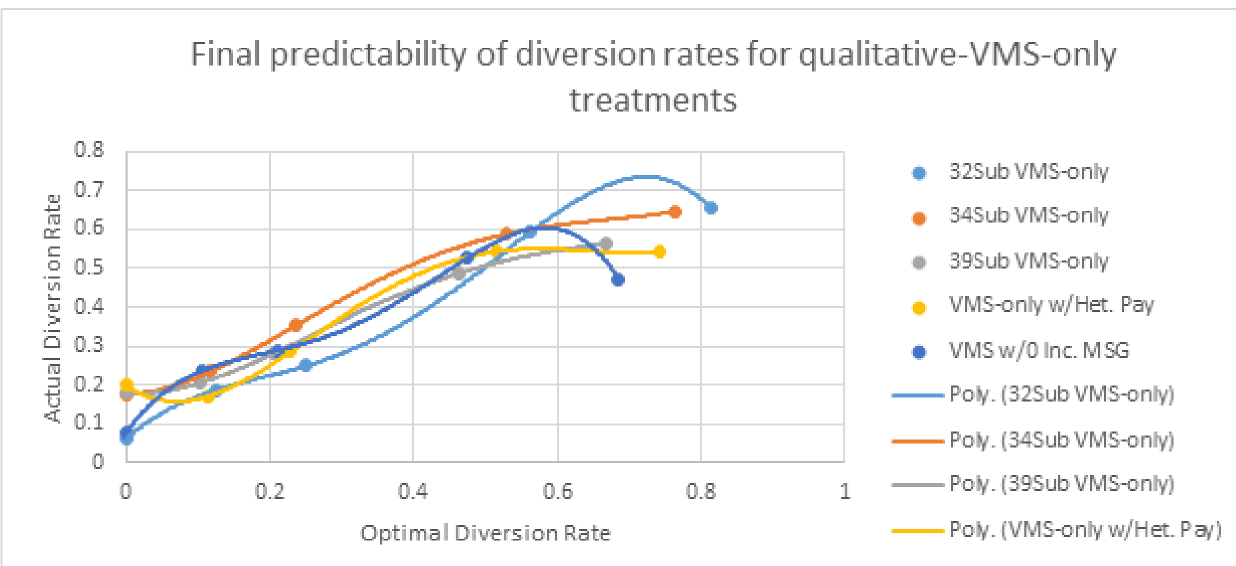


Thus, it appears as though these treatments are very conducive to subjects learning optimal diversion behavior. Subject behavior is consistent with reinforcement learning theory, in which subjects are more likely to choose a route after a good travel time on that route than after a bad one. A detailed analysis of subject learning during this experiment is described in a later section.

The predictability of diversion responses for the initial round for each incident type varied significantly from treatment to treatment. In nearly all cases, the response was non-monotonic with either a higher diversion rate for “minor” incidents than “medium” incidents or for “major” incidents than “severe” incidents. The lack of smoothness indicates that when subjects are first exposed to qualitative incident descriptions, one cannot reliably achieve a desired diversion rate by adjusting the “intensity” of the description based on past performance of other subjects.



There is much more similarity in the final round diversion response curves between the various treatments. Compared to the initial predictability curves, the patterns are much smoother and most are monotonic. This shows that as users gain experience, they respond to the VMS incident descriptions much more predictably.

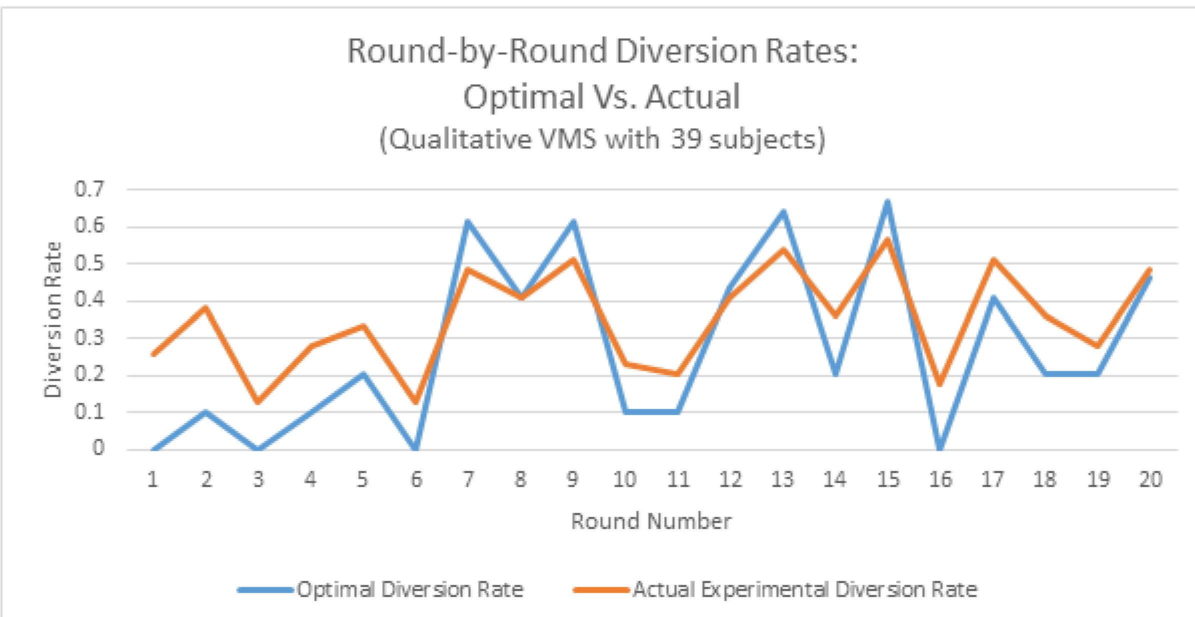


The curves resemble 45-degree lines, which indicate that well-differentiated and predictable responses to VMS are achieved for the finals rounds of these treatments.

To understand how variations to qualitative VMS treatments affect their performances, specific treatment results are explored below.

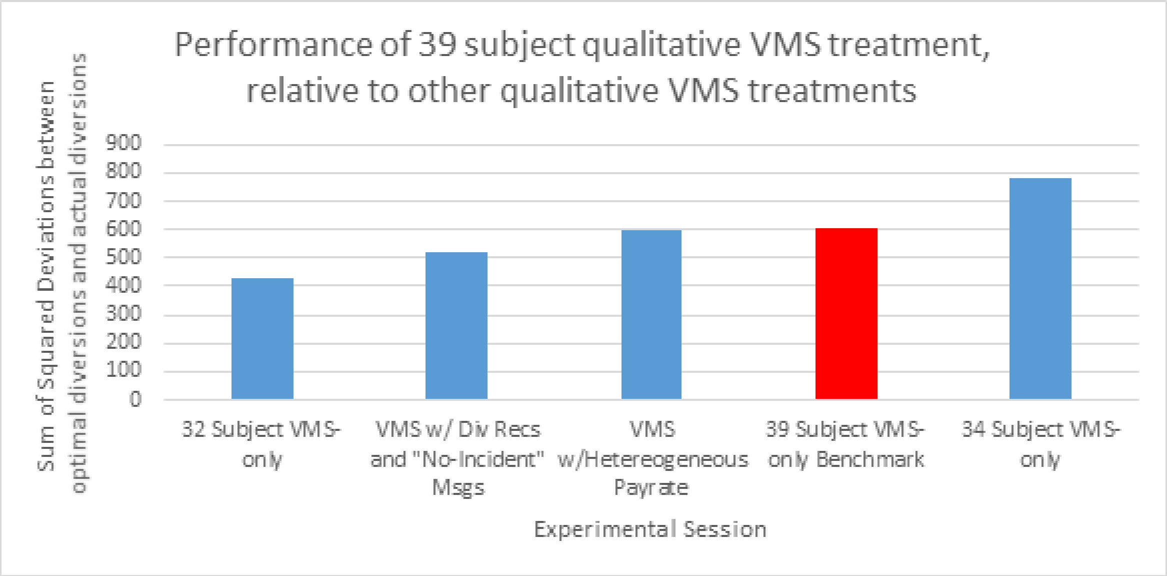
7.2.2 Qualitative VMS with 39 subjects (treatment IS, full session)

This is the most basic implementation of the treatment, with a one-word description ("minor", "medium", "major", "severe") to describe each incident type. 39 subjects constitute a "full" session, where the maximum number of subjects the software can accommodate are participating.

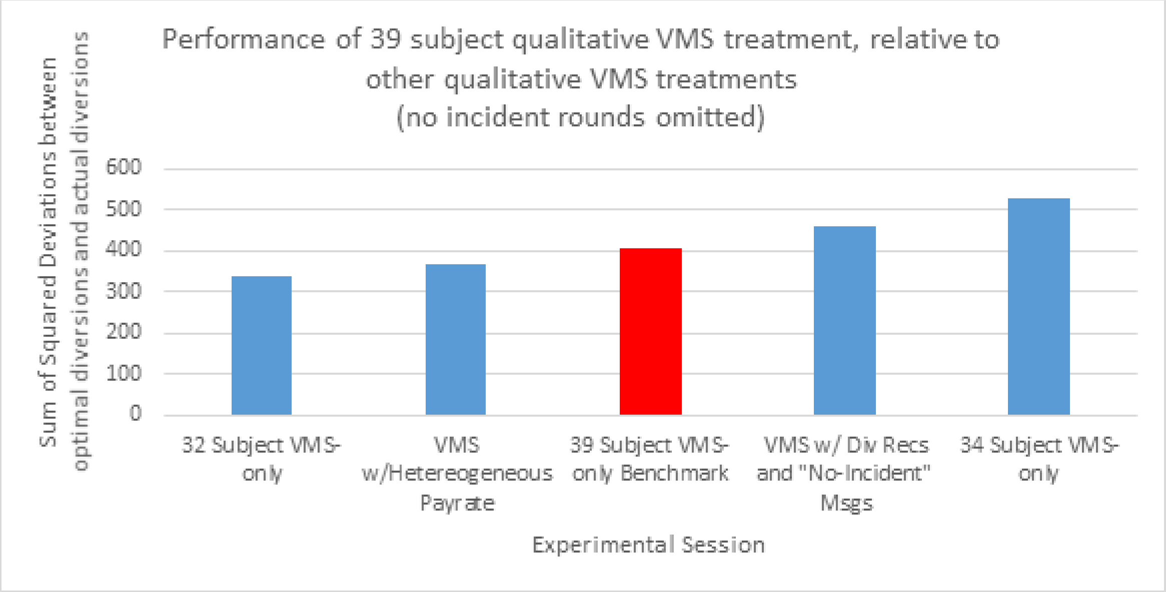


The graph indicates that subjects tend to over-divert on incidents that favor a low diversion rate, and under-divert on treatments that favor a high diversion rate. Thus, subject naturally avoid aggregate extremes, which is likely aided by the ability of subjects to observe the decisions of some of the other subjects in real-time. Over time, the gap between the optimal and actual diversion rates can be observed to shrink, suggesting that learning is taking place.

This treatment performs about average for qualitative VMS only treatments, with the sum of squared deviations being almost identical to the median value.

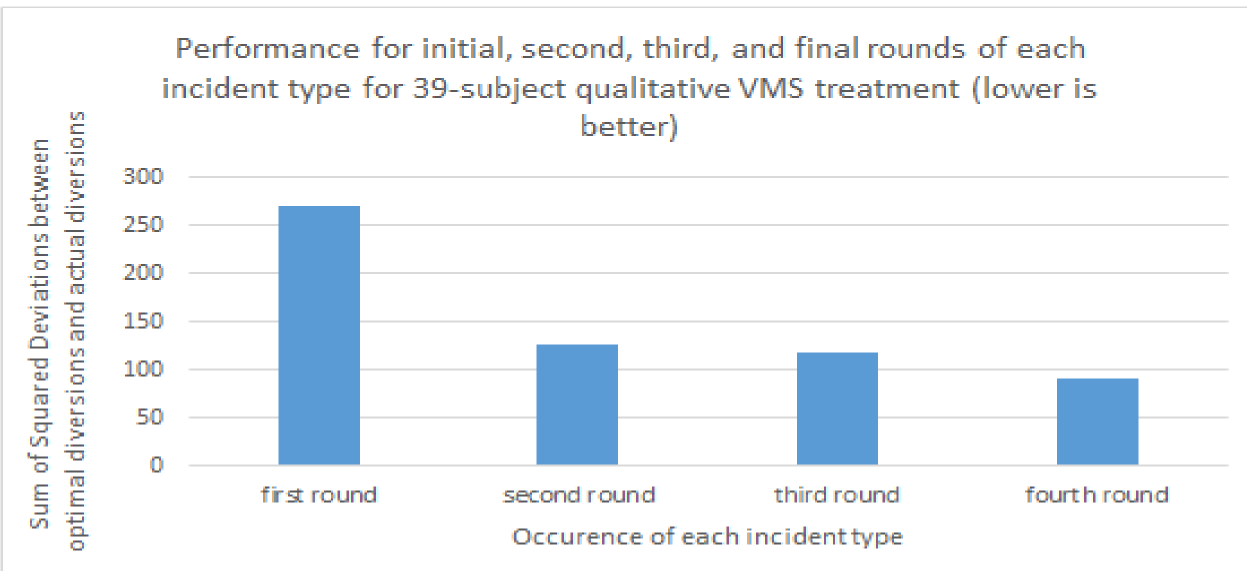


When omitting rounds with no incidents (and no VMS), performance also attains the median value.

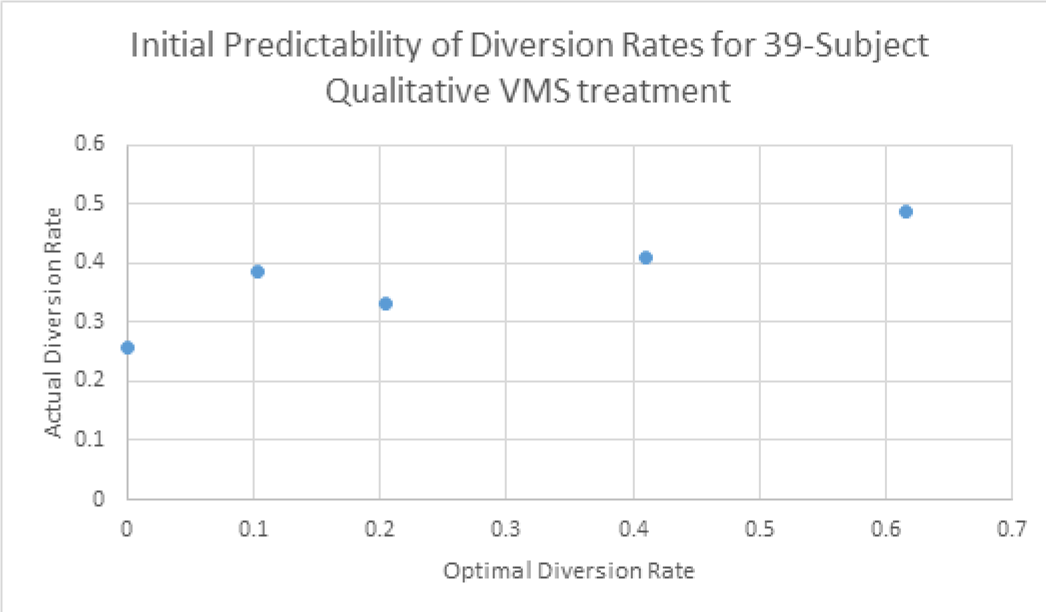


As with other qualitative-VMS-only treatments, there is a dramatic difference between initial and final performance. This confirms that learning effects are strong for this treatment. Learning is rapid; most of the improvement occurs between the first and second occurrence of each treatment.

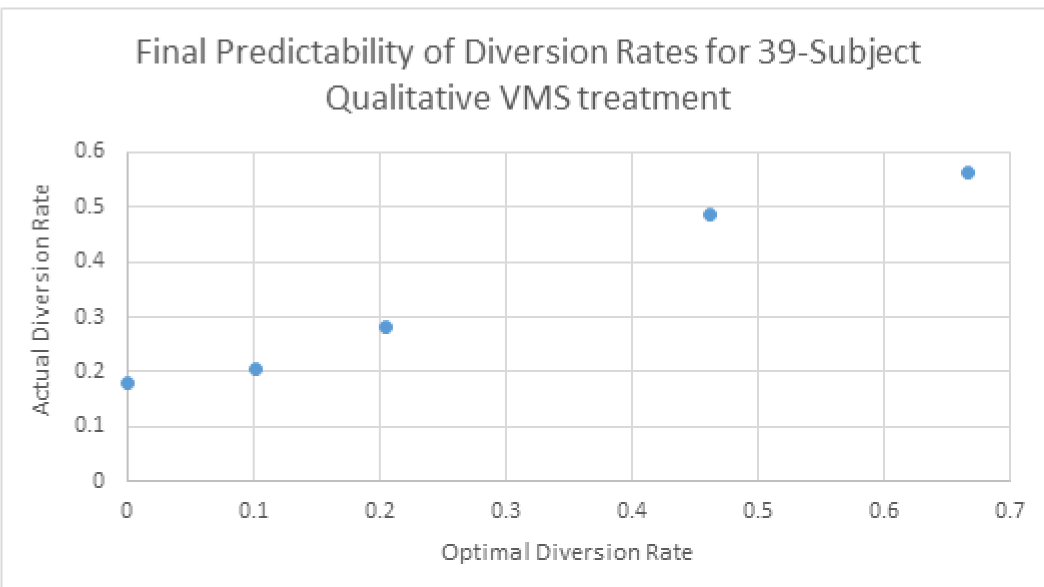
Treatment	Initial deviation from optimum	Second Round deviation	Third Round deviation	Final deviation from optimum
Qualitative Only w/ 39 Subs	271	127	118	91



The initial predictability for this treatment is reasonably smooth and is monotonic with the exception of the "minor" incident, for which there is a higher diversion rate than for the "medium" incident. The diversion response curve is also relatively flat, reflecting over-diversion for less severe incidents and under-diversion for more severe ones.



The diversion response curve is significantly better for the final rounds; the trend is smooth and monotonic, and the steepness is significantly closer to 45 degrees (which signifies a perfect correspondence between optimal and actual diversion rates).



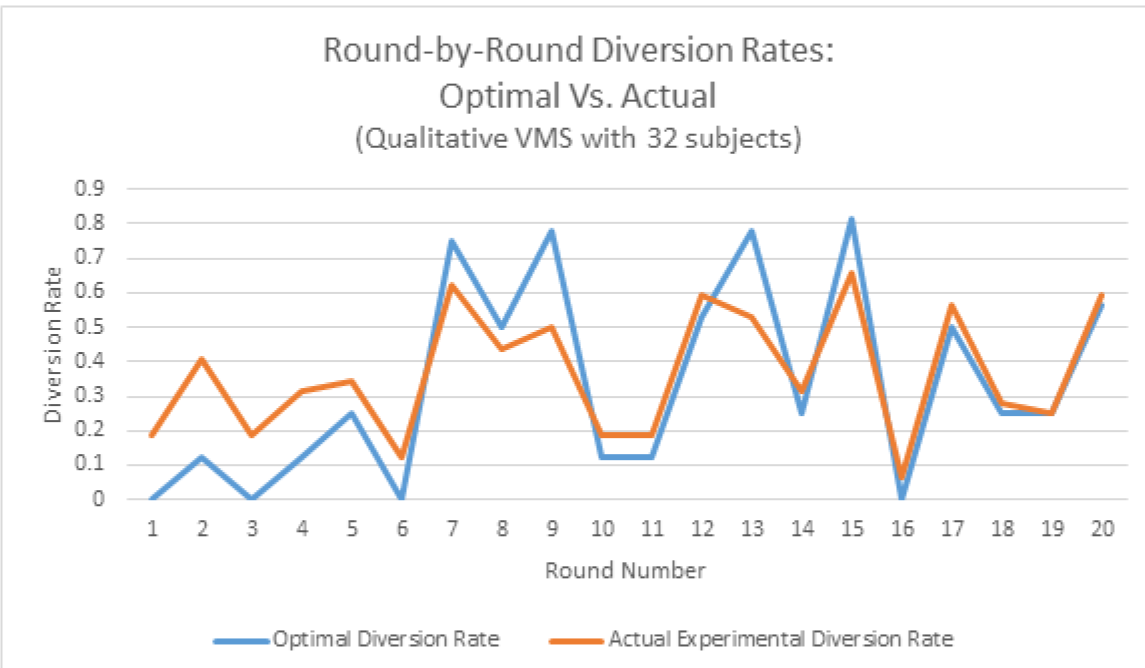
Lessons:

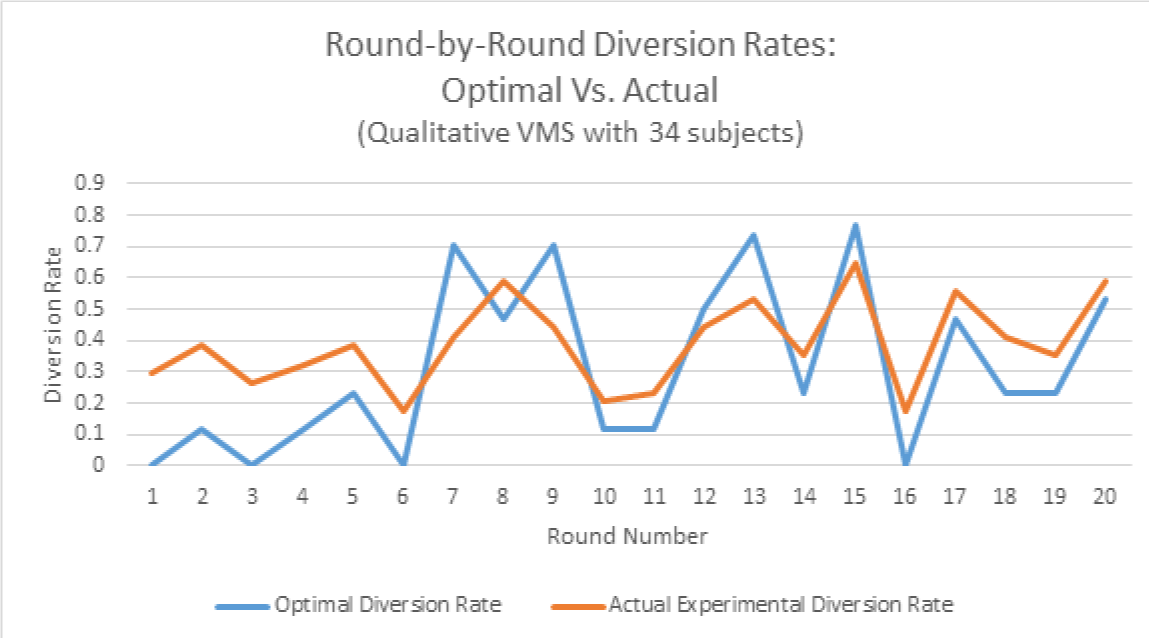
- VMS containing only a description of the incident does not achieve good results initially, but is conducive to rapid learning so that good results are achieved soon thereafter.

7.2.3 Qualitative VMS with a lower number of subjects (treatment IS)

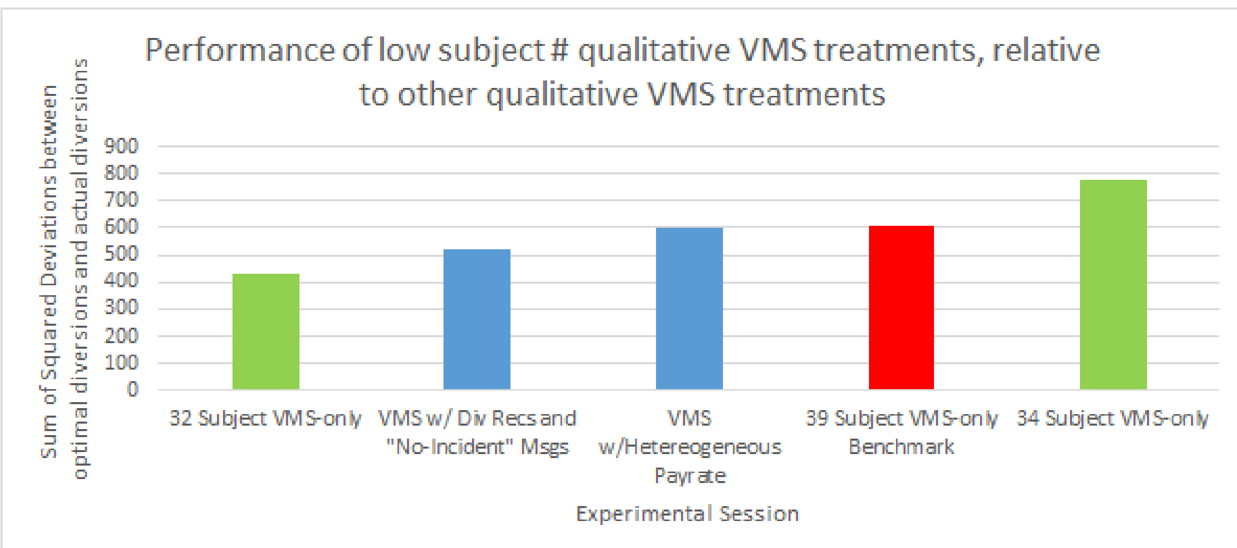
In these treatments, qualitative-information-only VMS sessions were conducted with insufficient subject turnouts to conduct full sessions. For one session, only 32 subjects participated and for another only 34 subjects participated. The treatments were not planned; instead, they were run as a backup for low turnout. However, because qualitative-only VMS was intended to be as the reference treatment, it was helpful to collect more data for this treatment type.

Surprisingly, the performance between the two sessions varied significantly.

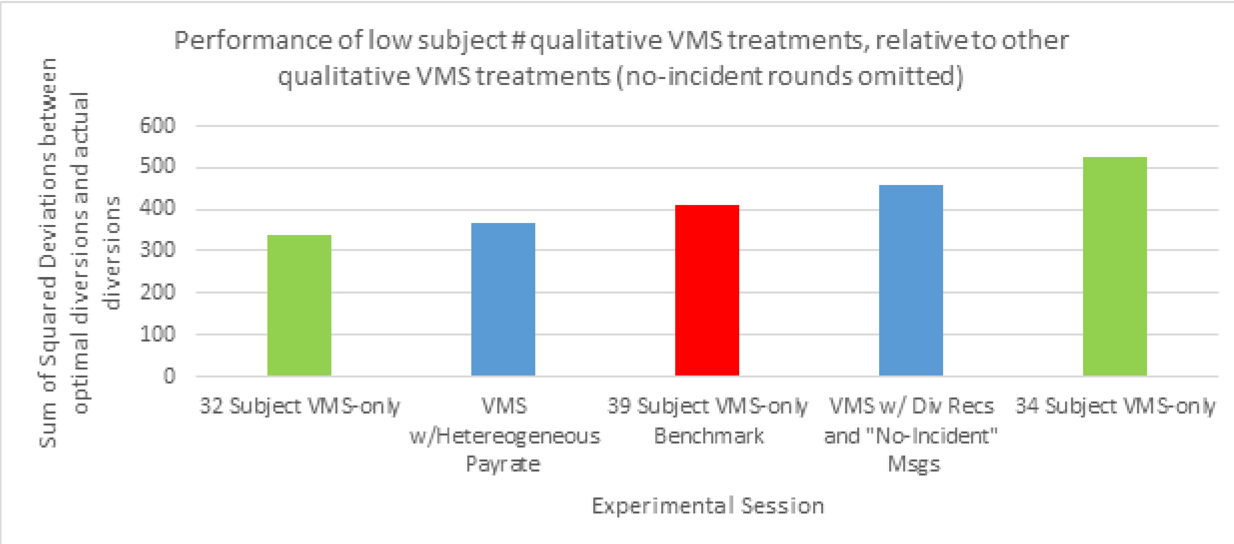




The 32-subject treatment had the best overall performance, while the 34-subject treatment had the worst.



It is unclear why such a wide difference in performance between the two treatments occurred. This result persists when rounds with no incident are omitted.

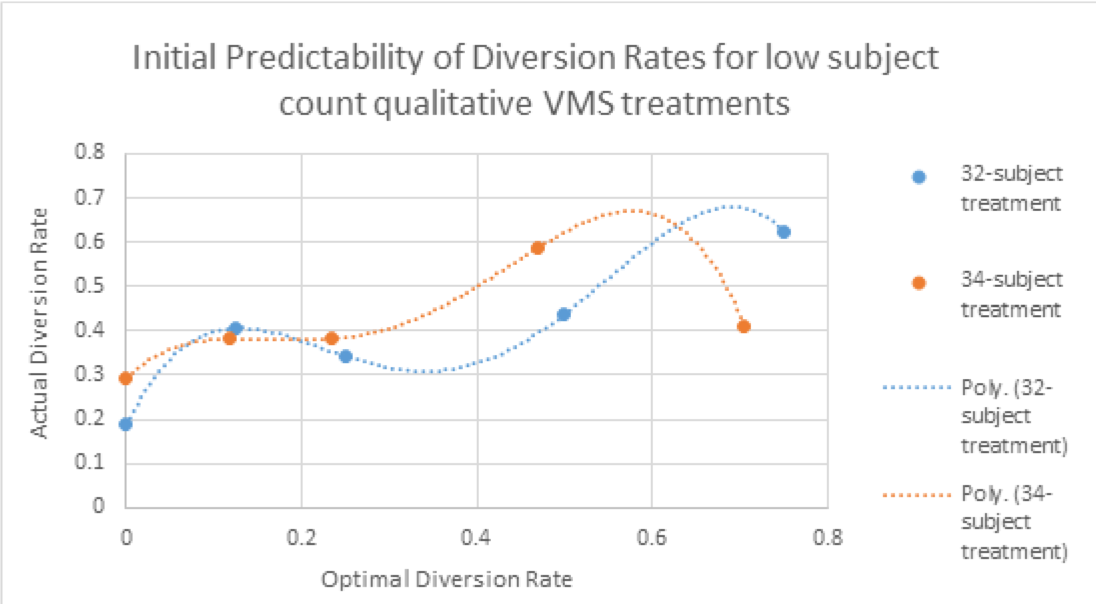


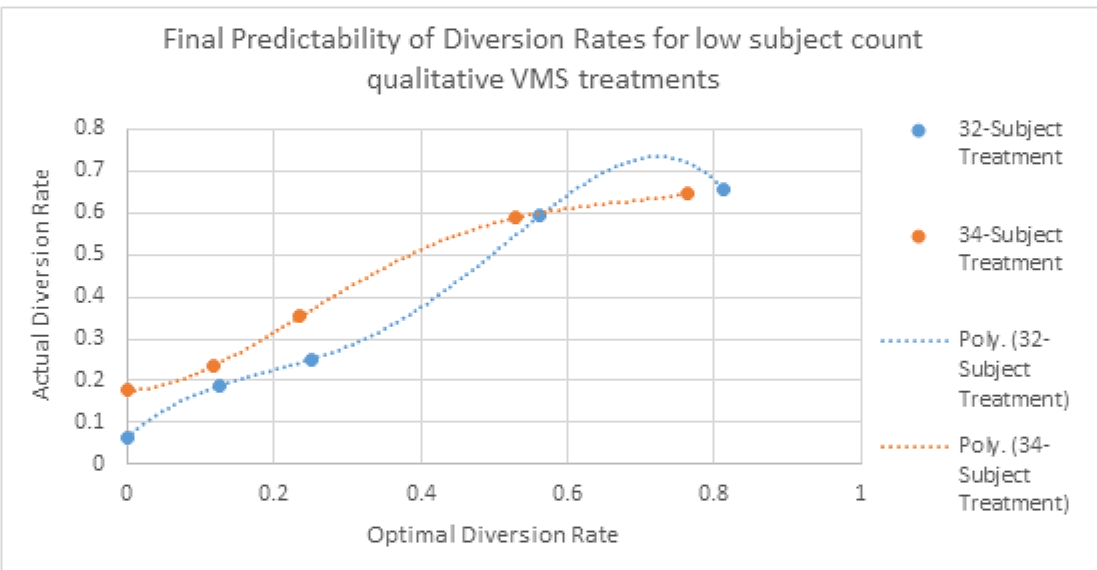
Also surprisingly, the difference between the two rounds is almost negligible by the final round.

Treatment	**Initial deviation from optimum**	**Final deviation from optimum**
Qualitative Only w/ 32 Subs	146	112
Qualitative Only w/ 34 Subs	322	124

Even with very poor initial performance, subjects are able to quickly learn and approach optimal behavior.

Similar improvement can be observed in the diversion response curves for these treatments. As with the 39 subject qualitative VMS treatment, the initial predictability of diversion rates lacks smoothness, while the final round predictability of the diversion rates is greatly improved.





The final curves are much smoother and closer to 45 degrees than the initial.

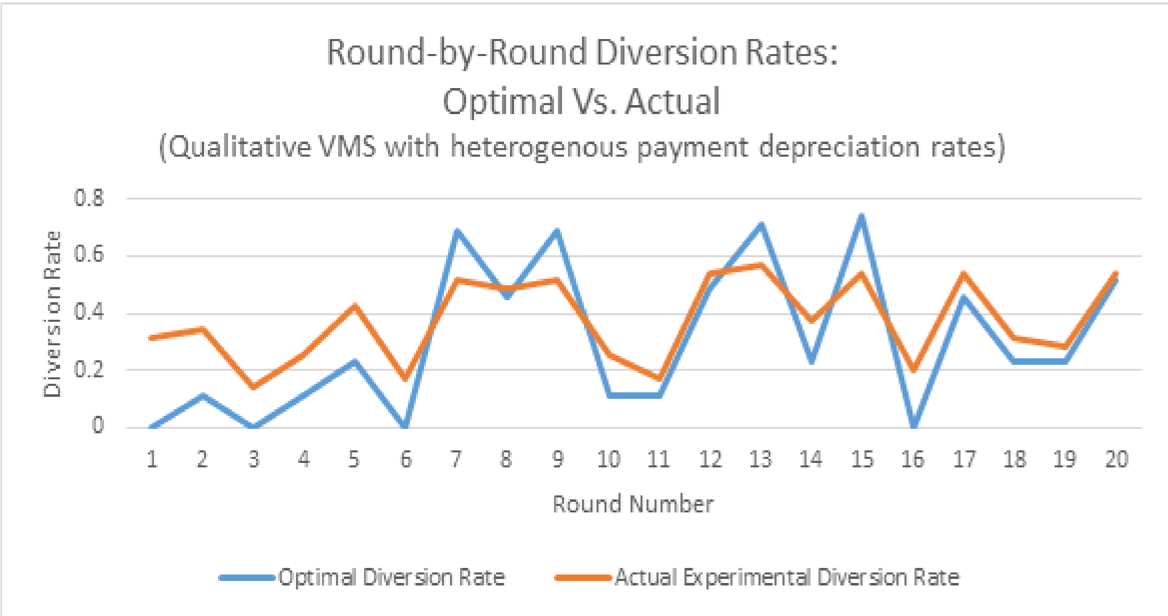
Lessons:

- Qualitative VMS treatments with a low number of subjects can achieve very different results for almost the same treatment, seemingly due only to the use of a difference subject sample. One reason why lower subject count treatments might have great disparity between them is that coordination becomes more important the fewer subjects there are; good coordination can produce very good outcomes while lack of coordination can produce very bad outcomes.

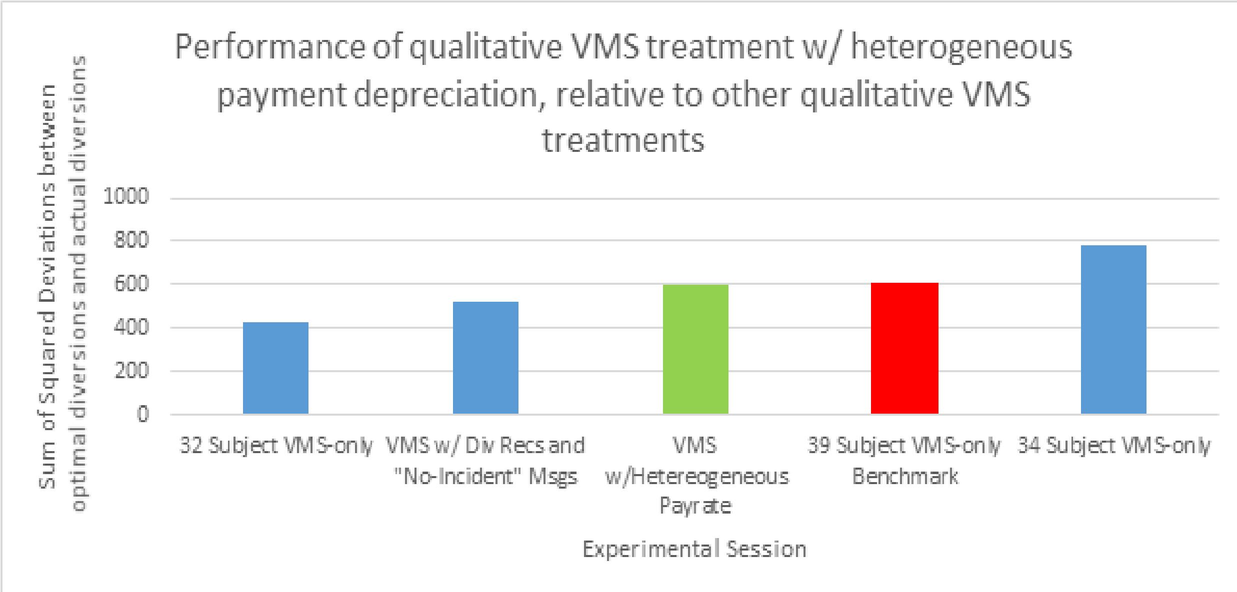
- Performance does not seem to be made better or worse on average by a lower number of subjects.
- Large initial differences in performance and predictability are soon made negligible through learning.

7.2.4 Qualitative VMS with heterogeneous payment depreciation rates (treatment ISHT)

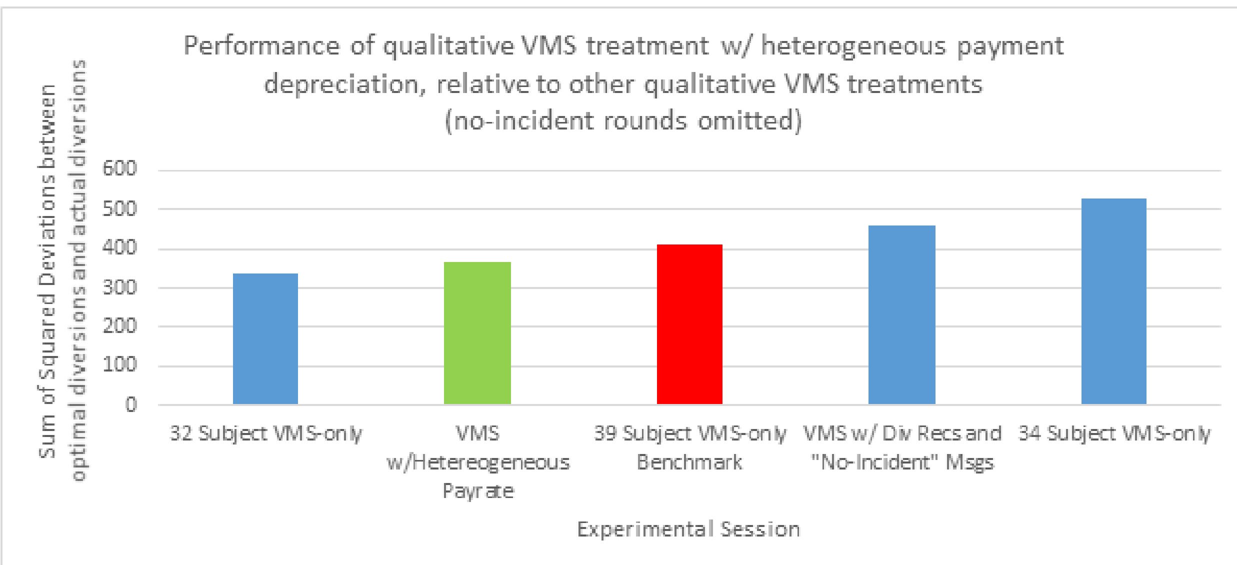
For this treatment, subjects were randomly assigned a unique payment depreciation rate from a uniform distribution, centered on the typical depreciation-rate used in this project. This was designed to emulate the real-world phenomenon of some people having a higher value of time than others do. While it is not expected to affect results in VMS only treatments, this treatment was intended to serve as a benchmark for comparisons to later treatments in which heterogeneous payment depreciation rates were used in conjunction with pricing mechanisms. Nonetheless, we felt it worthwhile to compare the results from this treatment to the basic qualitative-VMS-only treatment with homogeneous payment depreciation rates.



This treatment performs about the same as the reference treatment (basic qualitative VMS with 39 subjects).



When omitting rounds with no incident, performance is still similar to the reference case.

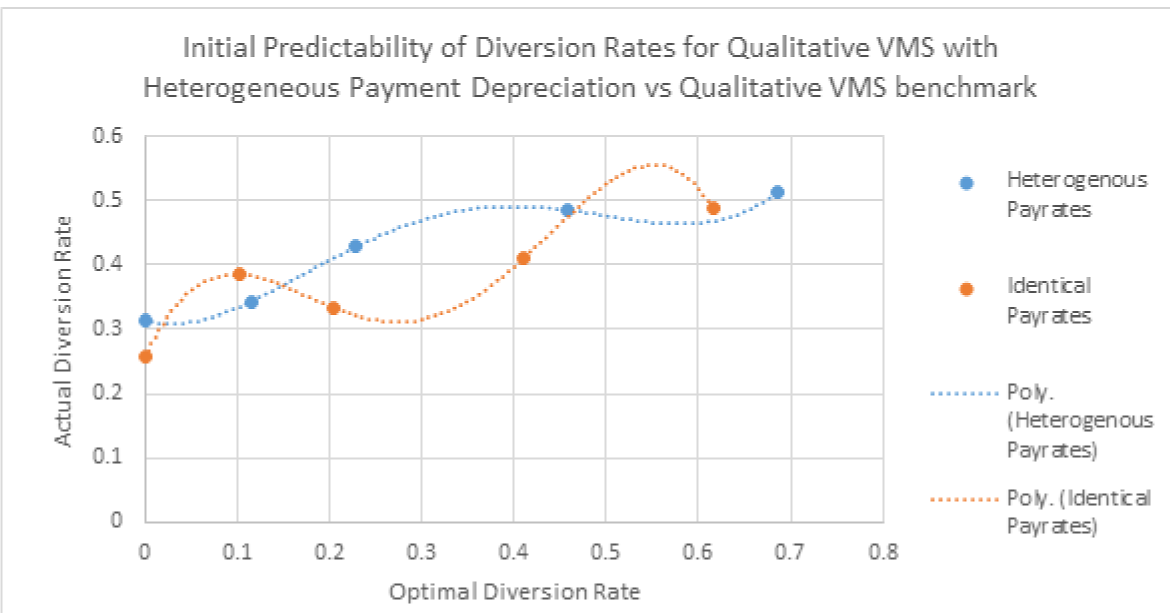


Subjects in this treatment also appear to learn at roughly the same rate as in the 39-subject qualitative-VMS-only reference case.

Treatment	Initial deviation from optimum	Final deviation from optimum
Qualitative Only w/ 39 Subs	271	91
Qualitative Only w/ heterogeneous payment depreciation	271	107

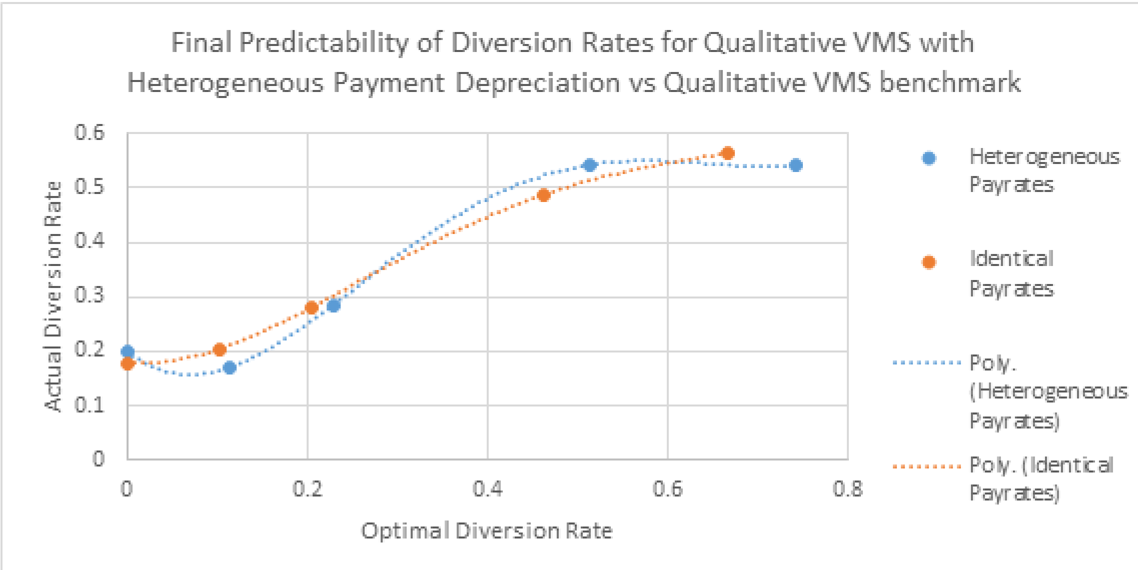
The difference between initial and final performance is roughly equivalent between the two treatments.

Initial predictability between this treatment and the reference treatment are similar as well; the diversion-response curve for the heterogeneous payment rate treatment is a bit smoother, however.



Both curves are very flat, indicative of over-diversion on less-severe incidents and under-diversion on more-severe incidents.

The final predictability is also very similar for both treatments.



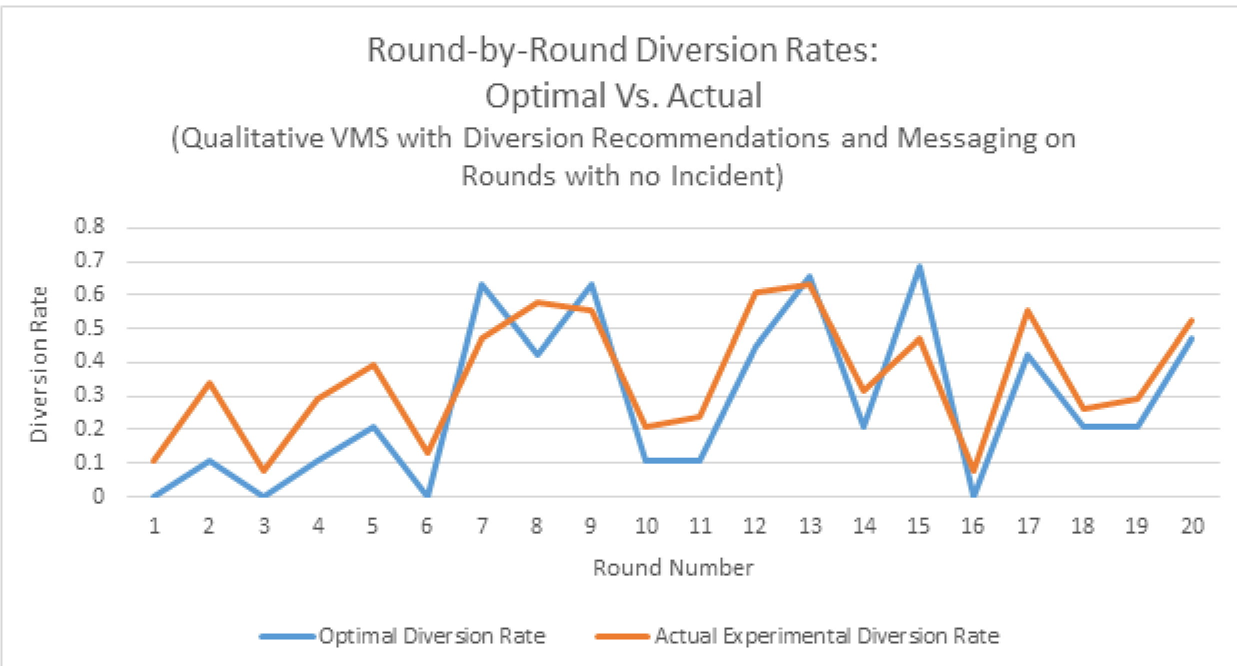
With the exception of significant under-diversion on the final "severe" incident round in the heterogeneous payment depreciate rate treatment; the diversion response curves are smooth and reasonably steep.

Lesson:

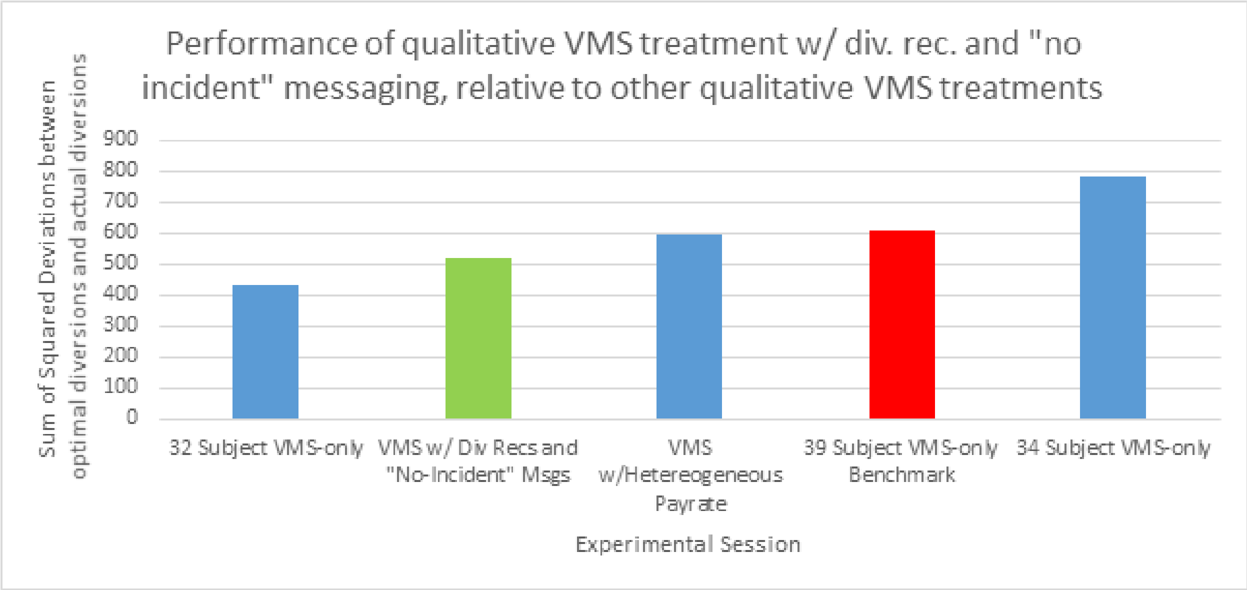
- Heterogeneous payment depreciation rates do not seem to affect performance for qualitative-VMS-only treatments.

7.2.5 Qualitative VMS with Diversion Recommendations and Messages on Rounds with no Incident (treatment ISRN):

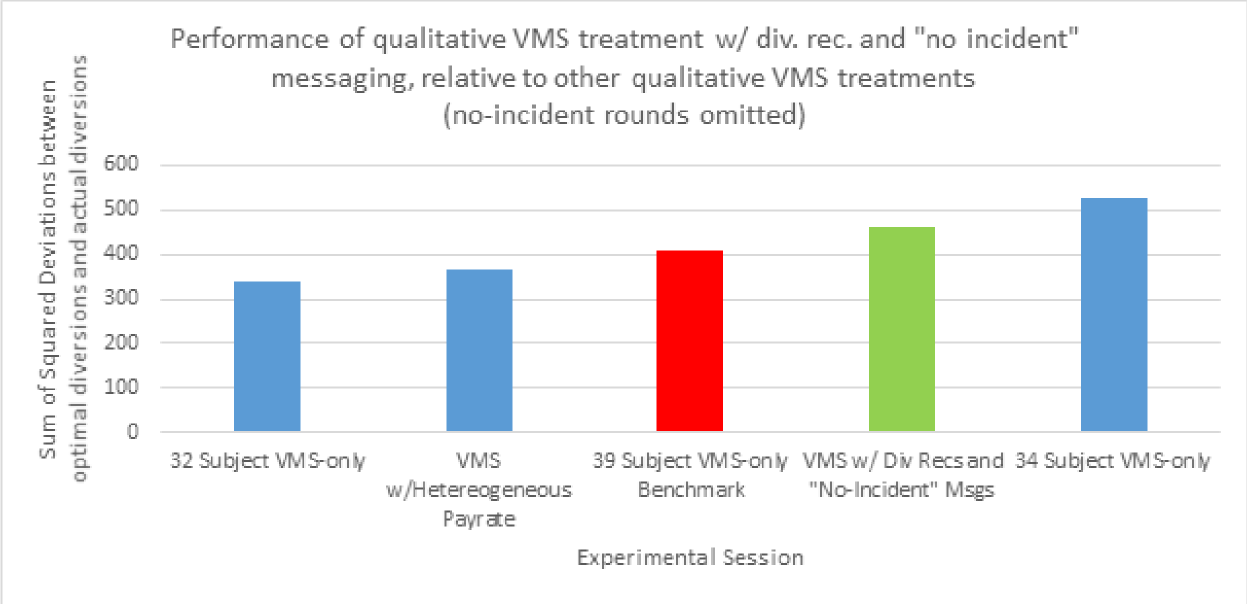
This treatment modifies the qualitative-VMS-only treatment in two ways. First, it provides messaging on rounds where there is no incident; the intent is to reduce the number of subjects who divert when there is no incident. Secondly, it includes explicit messages about the alternate route on some rounds, either mentioning the existence of the alternate route or explicitly providing a recommendation to divert that is visible to all subjects.



This treatment results in improved overall performance relative to the benchmark treatment.

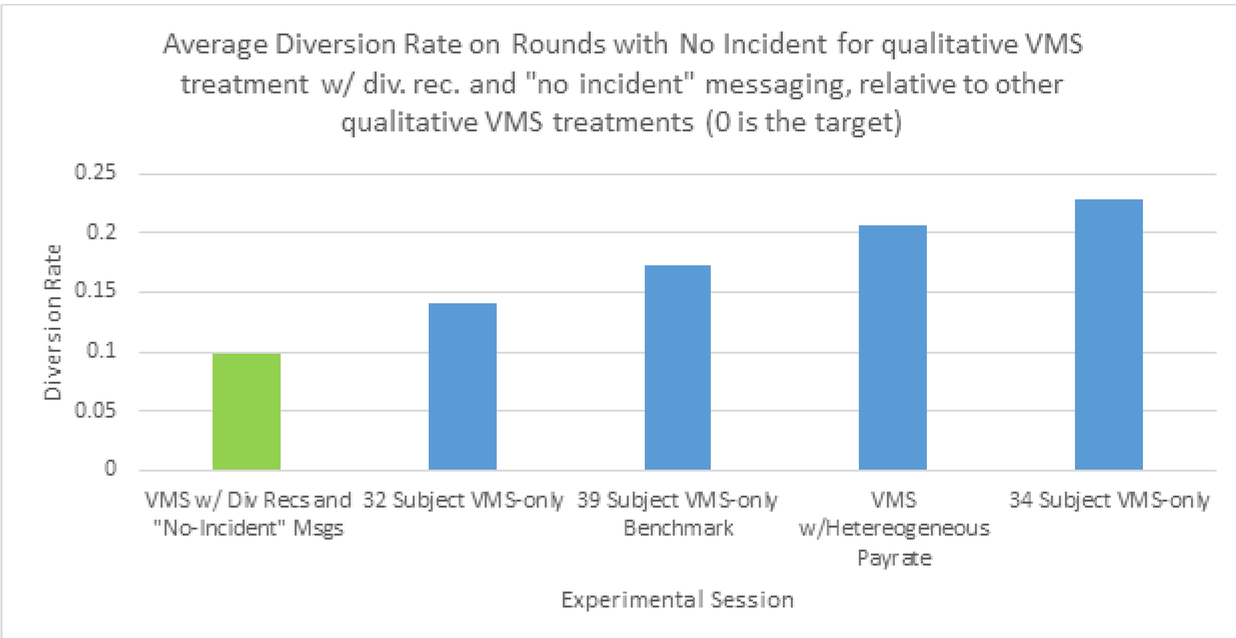


The advantage is driven by improved performance on rounds with no incident, due to the addition of VMS on these rounds. When "no-incident" rounds are omitted, this treatment does relatively worse by a significant amount.

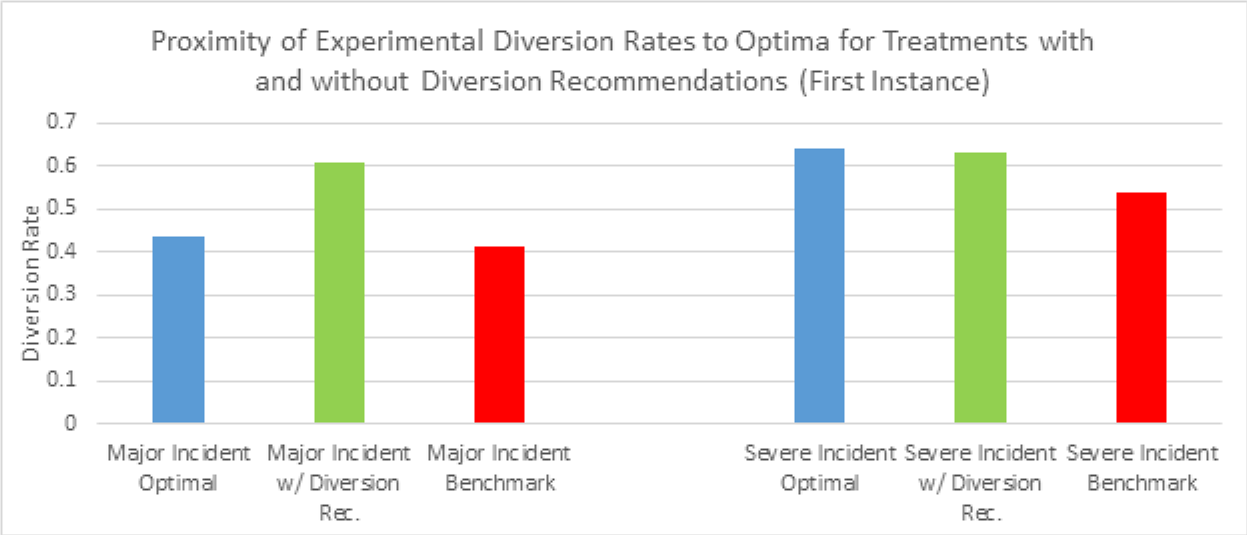


Omitting rounds with no incident leaves only the effect of the diversion recommendations, which judging by the chart above is detrimental.

To differentiate between the effects of diversion rate recommendations and messaging on rounds with no incident for this treatment, the effects of each are looked at individually. The graph below illustrates the ability of this treatment to achieve lower diversion rates on rounds with no incident compared to other qualitative VMS treatments; this is beneficial because the optimal diversion rate is zero when there is no incident.



The effects of the diversion rate recommendation are more complicated, with mixed pros and cons. The diversion recommendation is encountered four times, twice for both major and severe incidents. The diversion recommendation is effective in encouraging diversions the first time it is encountered for a given incident type, as shown below.

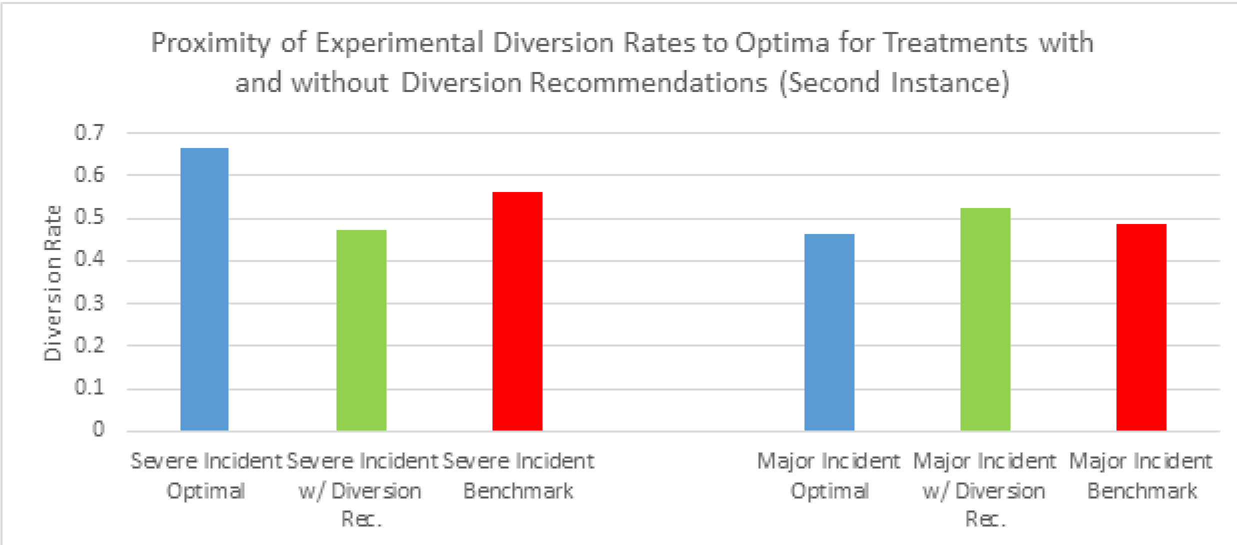


For the major incident round shown on the left, the treatment with diversion recommendations induces strong over-diversion on the first "major" incident type for which the recommendation appears. Subjects in the benchmark treatment perform quite close to the optimum.

For the severe incident round shown on the right, the treatment with diversion recommendations is nearly able to achieve the high optimum diversion rate for the first "severe" incident for which the recommendation appears, while the benchmark treatment is not.

The over-diversion for the "major" incident outweighs the improvement in the "severe" incident, leading to reduced overall performance.

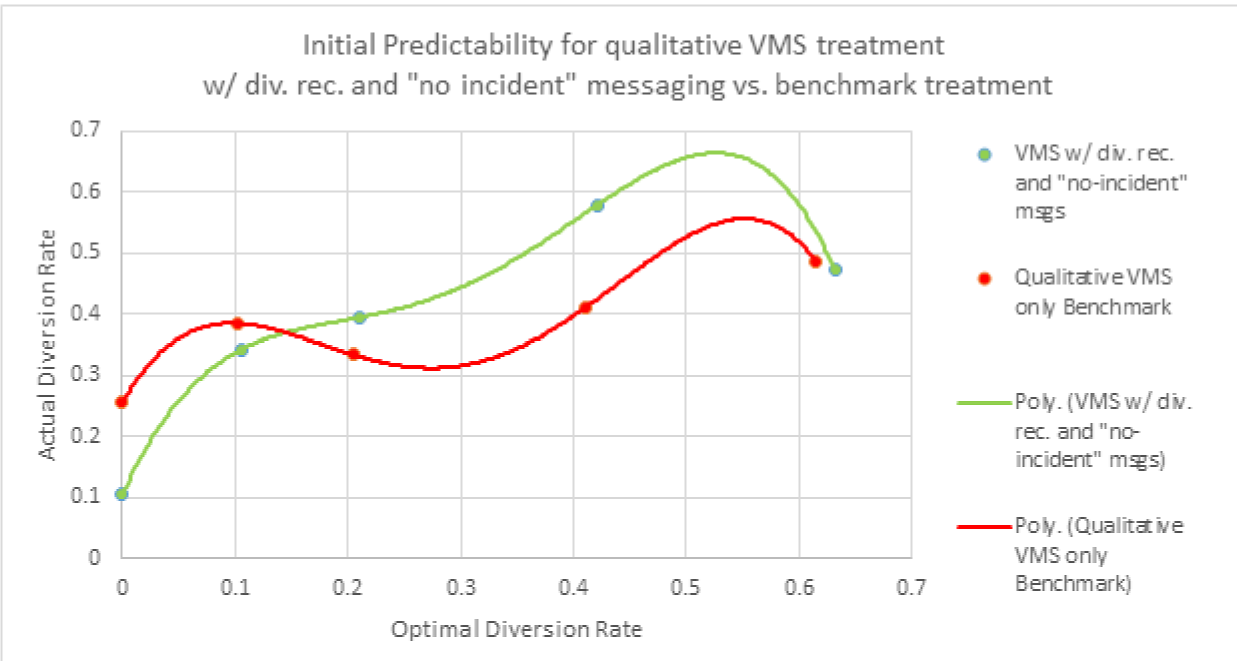
In the second instance of the diversion recommendation, there appears to be a counterintuitive effect of reduced diversions.



For the severe incident round shown on the left, the treatment with diversion recommendations yields a lower diversion rate on the second recommendation for a “severe” incident than the benchmark. This might be due to backlash against following either recommendations or diverting in general due to the over-diversion that took place during the first wave of diversion recommendations. The result is that under-diversion in this round is more pronounced for the treatment with diversion recommendations.

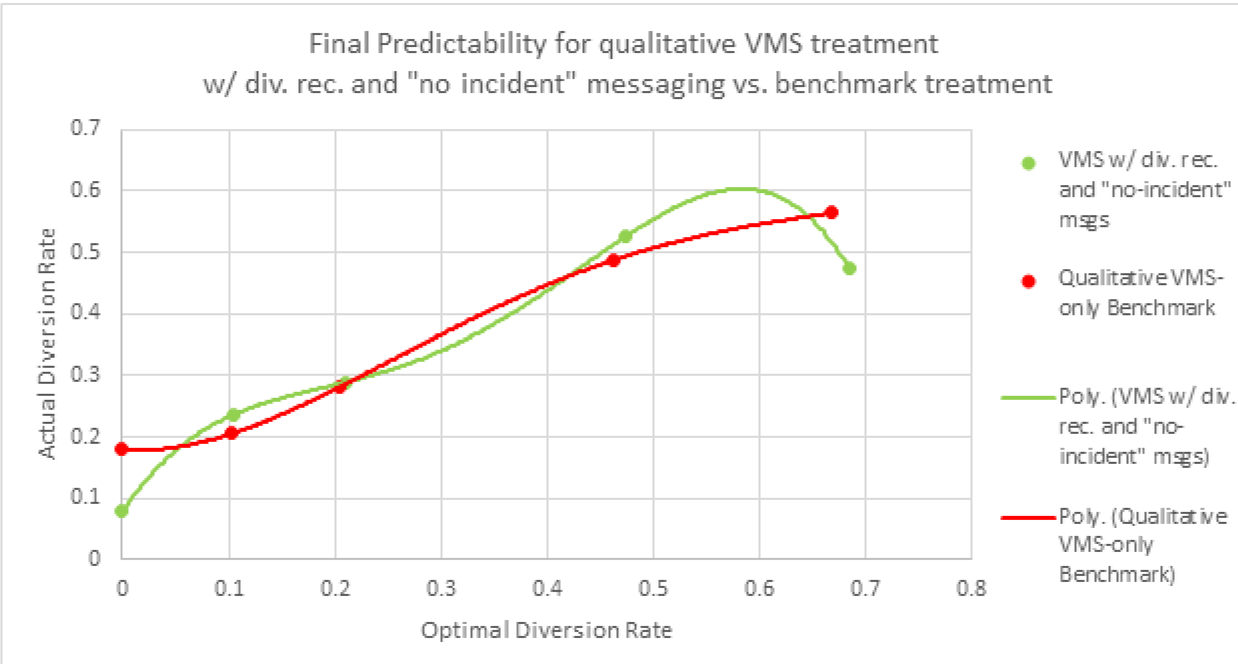
In the major incident, whose results are grouped on the right in the chart above, the treatment with diversion recommendations once again yielded a higher diversion rate, albeit slightly so, for the “major” incident the second time one was given. It is unclear whether this is due to subjects learning the best responses to the diversion message, or whether the time elapsed (four rounds) between the second severe incident with a diversion recommendation and the second major incident with a recommendation gave them time to forget the worsened performance from the first set of diversion recommendations.

Despite not containing any rounds for which a diversion recommendation was displayed, the initial predictability of diversion rates for this treatment was very different from that of the benchmark. This is partially due to the lower diversion rate on the round with no incident, which is explained by the VMS message displayed on the first “no-incident” round. Most notably, however, there was significant over-diversion on the “major” incident (though not as much as on the first major incident round with the diversion recommendation).



The combination of the “major” round over-diversion and “severe” round under-diversion result in non-monotonicity and a lack of smoothness in the initial diversion response. It is unclear whether the “major” incident over-diversion for this round is related to the presence of VMS on scenarios with no incident. Though there is no compelling reason why this might be the case, it is worth noting that a similar pattern is found in the initial diversion response curve for a different class of treatment (discussed later) that utilizes messaging on scenarios with no incident.

The final round diversion rate predictability was improved for this treatment, but it is negatively affected by the "major" incident over-diversion and "severe" incident under-diversion that resulted from diversion rate recommendations.



Lessons:

- Explicit public diversion recommendations increase diversions, at least initially, and should probably only be used on the most severe incidents.
- Over-diversion as a result of such messaging might lead to under-diversion in future rounds
- VMS on rounds with no incidents significantly reduces the diversion rate for those rounds, substantially improving performance. There is a possibility that other rounds are adversely affected, but it is unlikely and not enough to offset the benefits from the rounds with no incident

Overall lessons:

- Treatments utilizing only VMS with an incident description does not achieve good results early on, but is conducive to rapid learning so that good results are achieved soon thereafter
- Only use explicit public diversion recommendations increase diversions, at least initially, and should probably on the most severe incidents.
- VMS on rounds with no incidents significantly reduces the diversion rate for those rounds, substantially improving performance.

Recommended Additional treatment:

- Qualitative VMS with traffic-free practice rounds. Currently subjects travel on both the main and alternate route all-together during practice rounds. Experiencing the maximum level of traffic on each. By doing so, subjects are able to learn that the alternate route is considerably more congestible in the absence of incidents, which may result in lower diversion rates than might otherwise occur without this practice.
- Qualitative VMS with diversion recommendations for one or more “severe” incidents. This is likely to make the best use diversion recommendations with reduced risk of over-diversion (compared to when they were also given for "major" incidents)

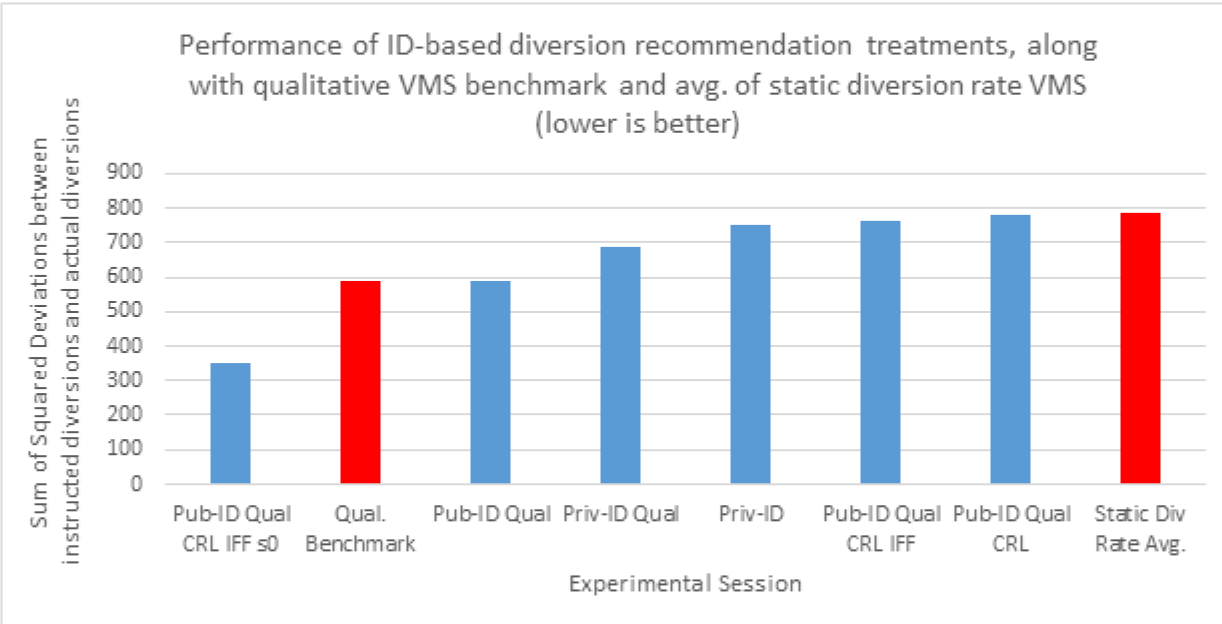
7.3 Individual Diversion Recommendations (group ID, C):

Overview

For treatments with individual diversion recommendations, each subject's vehicle is given an identifying characteristic such as a number so that individualized instructions can be given through public VMS. Each round, subjects are instructed to either stay on the main route or divert depending on the identifying characteristic assigned to their vehicles. The advantage of this strategy is that the optimal allocation of vehicles on each route is guaranteed to be achieved if everyone simply follows the instruction associated with their identifying characteristic. Subjects no longer face uncertainty over what the optimal diversion rate will be, and potentially no longer face difficulty in coordinating on known optimal diversion rates.

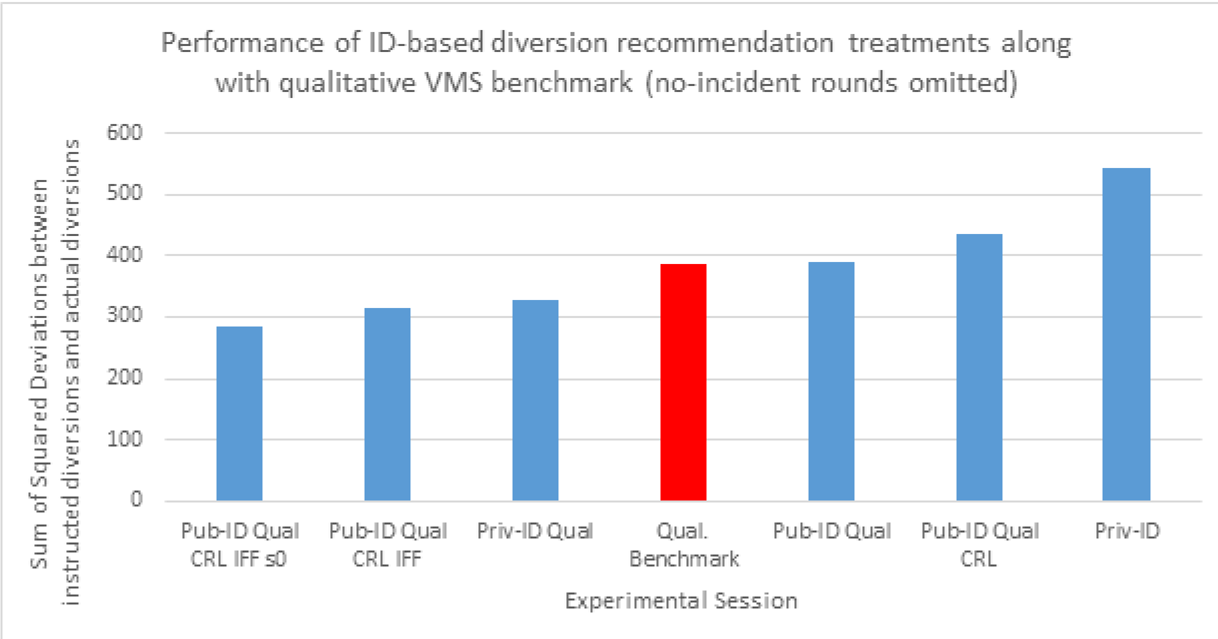
The drawbacks to this type of treatment are that drivers must override innate preferences for one lane over another for the sake of compliance. Furthermore, subjects actually have very little incentive to comply, since in equilibrium the difference in travel times between compliers and non-compliers will be negligible. Lastly, compliance is liable to break down and adversely affect performance if initial compliance is not sufficiently high.

Many variations of these treatments were run, which will be explained in depth later in the section. Comparisons were made between these treatments and both the qualitative-only benchmark and the simple-fraction diversion recommendation treatment. As with the simple-fraction diversion recommendation treatment, the ID-based individualized diversion recommendations were based on a slightly inaccurate assessment of what the optimal diversion rates actually were. Thus, the instructed diversion rates were used as the performance benchmark rather than the true optimal diversion rates.

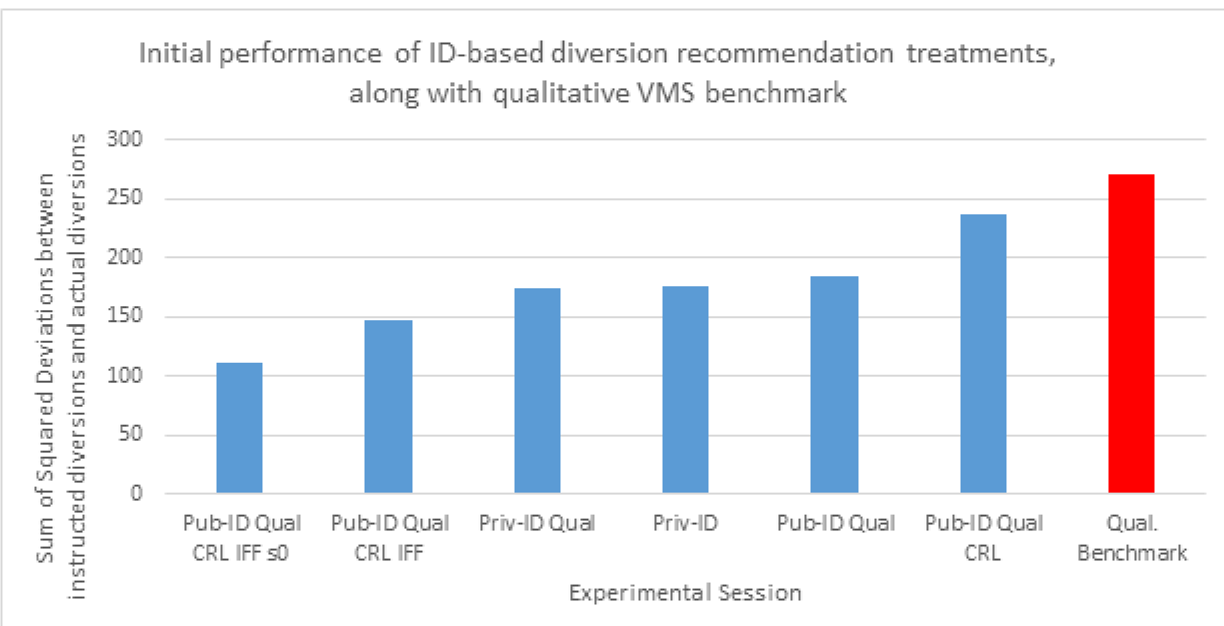


The inability of ID-based recommendation treatments to outperform the qualitative VMS benchmark overall is due largely to rounds with no incidents, where the qualitative-VMS-only benchmark strongly outperforms individual diversion recommendations. For both types of treatments, no information is provided on rounds with no incidents, yet for reasons which are not obvious, diversion rates on these rounds are much higher (and therefore further from optimal) for ID-based diversion recommendation treatments. One possibility is that in the ID-based recommendation schemes, subjects view these no-incident rounds as a chance to explore/experiment in the absence of instructions and choose the alternate route. In fact, the only ID-based diversion recommendation treatment that outperforms the qualitative VMS-only benchmark is the only one where diversion instructions are also given when there is no incident.

When ignoring these no-incident rounds, ID-based diversion recommendation treatments outperform qualitative-VMS-only treatments.



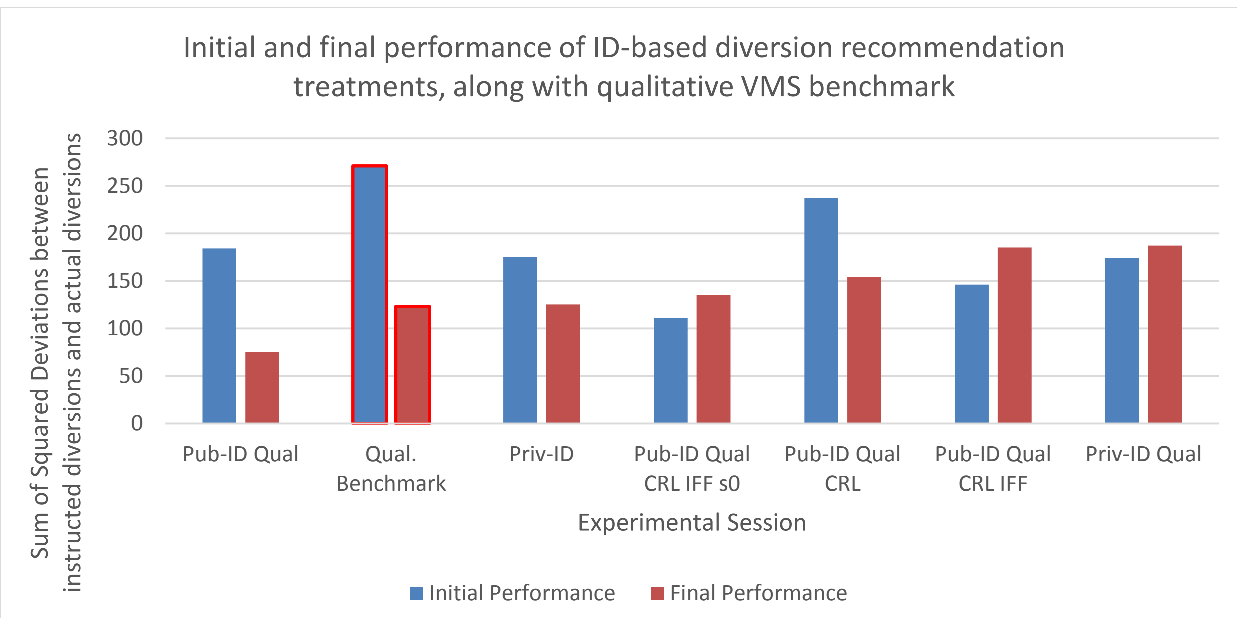
One consistent advantage that ID-based diversion recommendations have over qualitative-VMS only treatments is in initial performance.



Subjects in these treatments are always able to start out with a better idea of how many should be diverting and a way to coordinate who takes the main route and who takes the alternate route; this leads to improved initial performance.

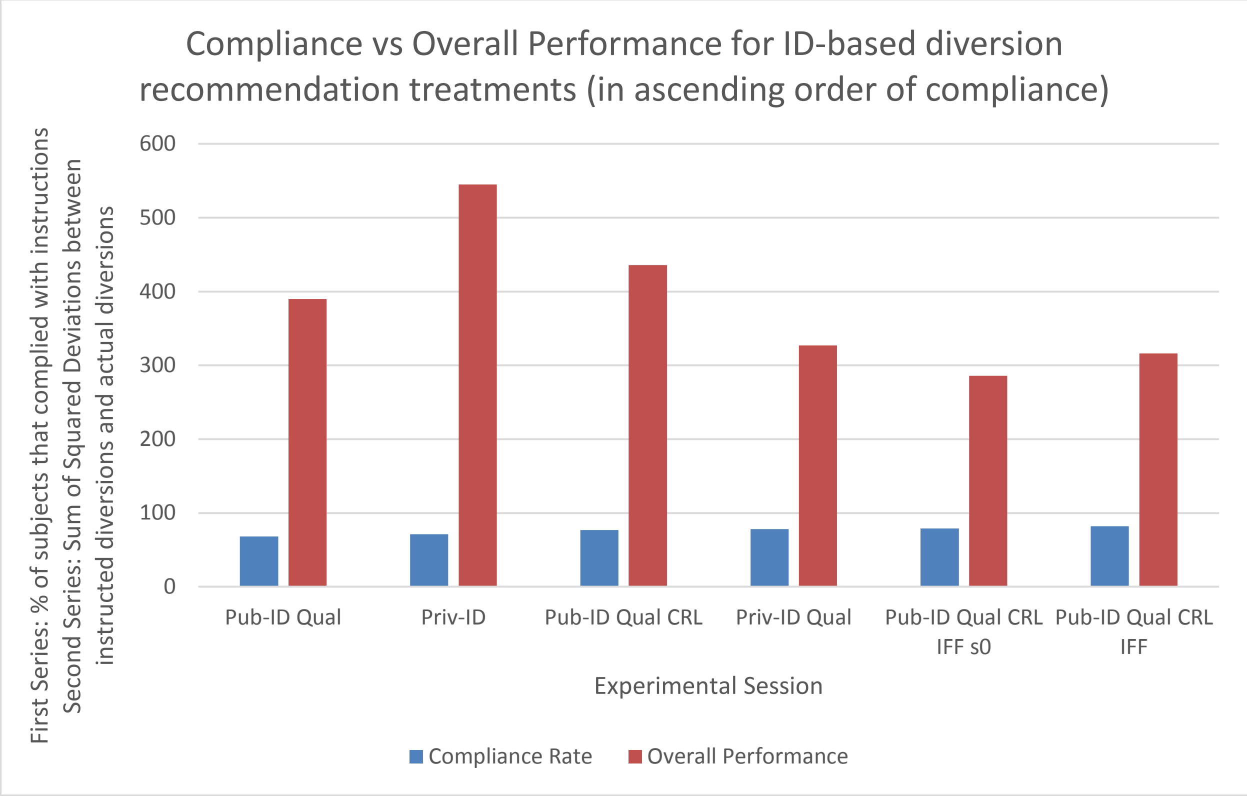
Subjects in these treatments are always able to start out with a better idea of how many should be diverting and a way to coordinate who takes the main route and who takes the alternate route; this leads to improved initial performance.

However, performance in qualitative-only-VMS treatments steadily improves over time, while in some ID-based diversion recommendation treatments it worsens. This is possibly due to drops in compliance as the session progresses; furthermore, reinforcement-based route learning is hindered in the ID-based diversion recommendation treatments for many subjects because the instructions may conflict with what experience indicates is the better route choice.



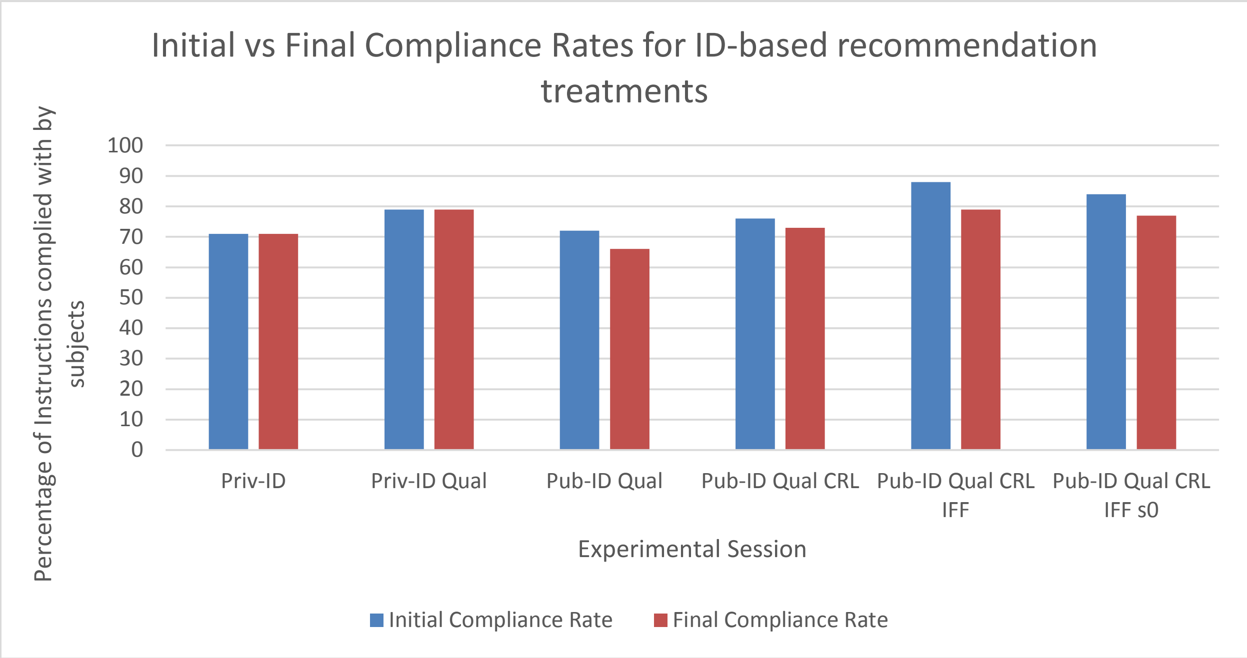
The qualitative-VMS-only treatment has better performance in the final round for each incident type than all but one of the ID-based diversion recommendation treatments, despite having the worst initial round performance. However, not all ID-based diversion recommendation treatments entailed later-round drop-offs in subject performance, emphasizing the importance of how such treatments are implemented.

Much of the difference in performance between the different treatments can be explained by what percentage of the time subjects comply with the instructions in each treatment.



For the most part, the lowest compliance treatments correspond to those with the worst performance, with the exception of the highest and lowest compliance treatments. Overall compliance ranges from 68% to 82%.

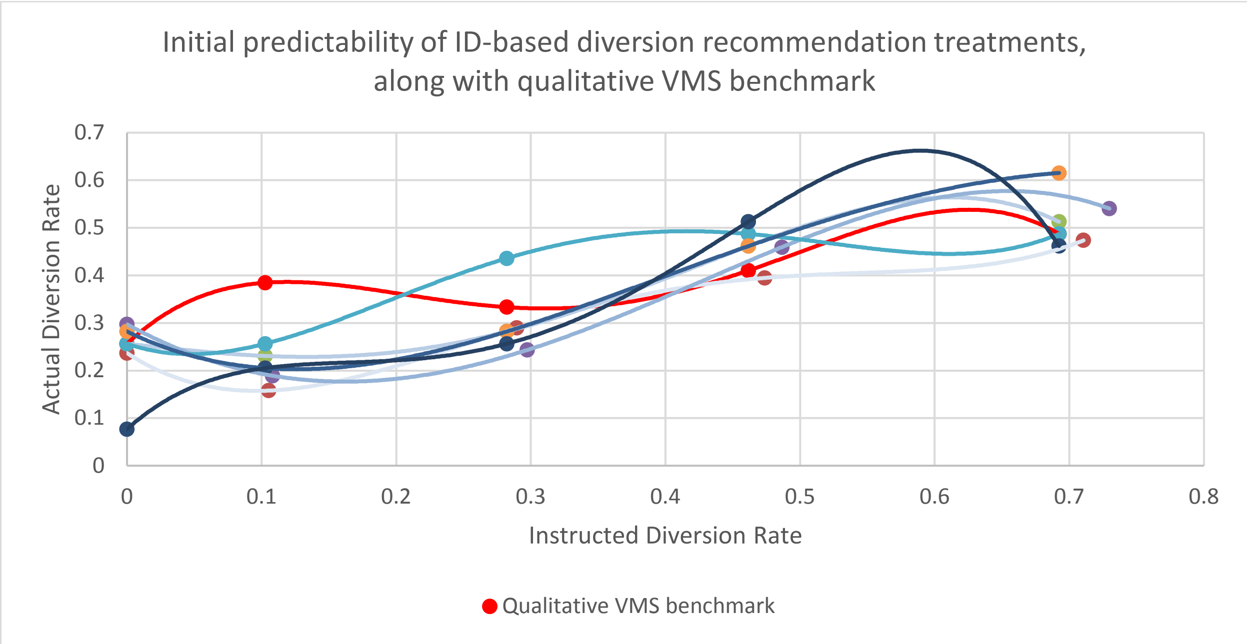
Long-run compliance either remains steady or decreases over time for each treatment.



The two treatments where the compliance rate remained steady over time involved private ID numbers, a treatment where subjects only know their own instructions, and not those of the other subjects. For treatments with public IDs, however, where subjects know the instructions of all other visible subjects, the compliance rate falls over time. The discrepancy between the two treatments is likely due the fact that in public ID treatments, subjects can observe whether, or not, other subjects are complying with the instruction, while in private ID treatments they cannot. One possible reason for the drop-off over time in compliance for public ID treatments is that subjects increasingly doubt the value and credibility of the instructions when they realize that others are not complying, and then simply ignore the instructions themselves. A more optimistic case is that subjects apply discretion in not complying in an attempt to balance out mis-diversion resulting from non-compliance. For example, if a subject told to take the main route observes other subjects who were told to divert ignoring the instructions and choosing the main route, that subject might choose to ignore the instruction and switch to the alternate route because they believe under-diversion will occur. There is evidence to support both cases depending on the specific public ID treatment.

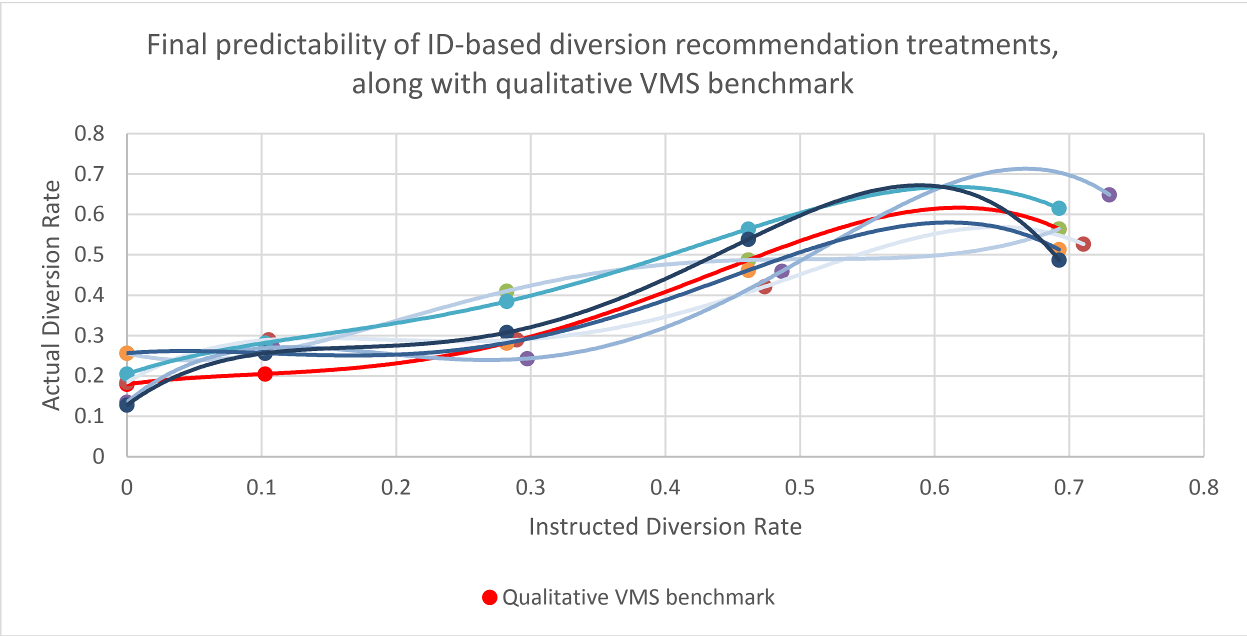
In any case, the fact that the compliance rate never increases suggests that subjects do not ever "learn" to comply.

The superior initial performance of ID-based recommendation treatments generally translates to superior initial predictability as well.



This is a busy graph, but it should still be clear that the diversion response curves of ID-based treatments are less flat and generally smoother than those from the qualitative-VMS only benchmark (marked in red). That is, they are closer to a 45-degree line.

The trends between the two treatment types are nearly identical in terms of final predictability, however.

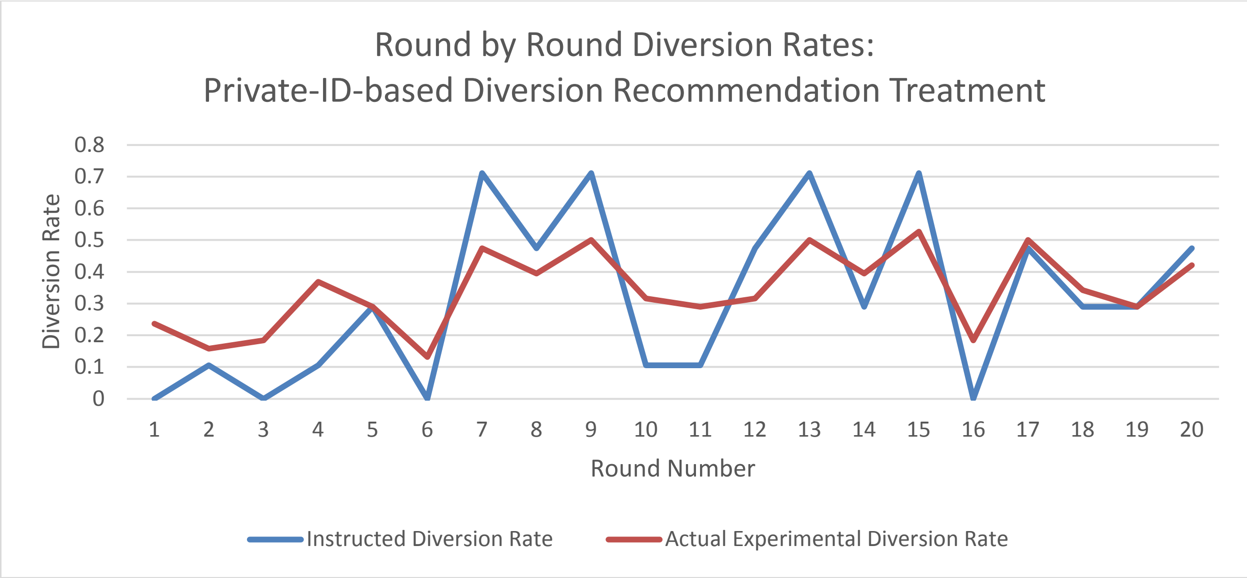


These curves are steeper and smoother than the initial diversion response curves, and monotonic.

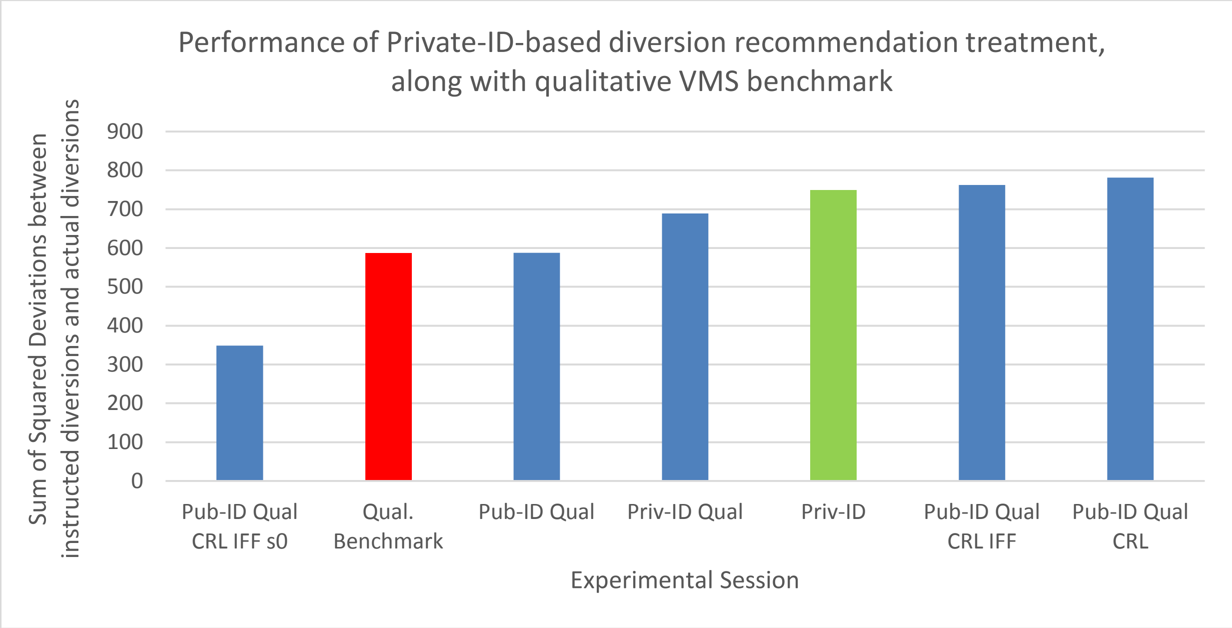
To understand which factors make ID-based recommendations more effective, specific treatment results are explored below.

7.3.1 Private-Number-Only Diversion Recommendation Treatment (treatment ID)

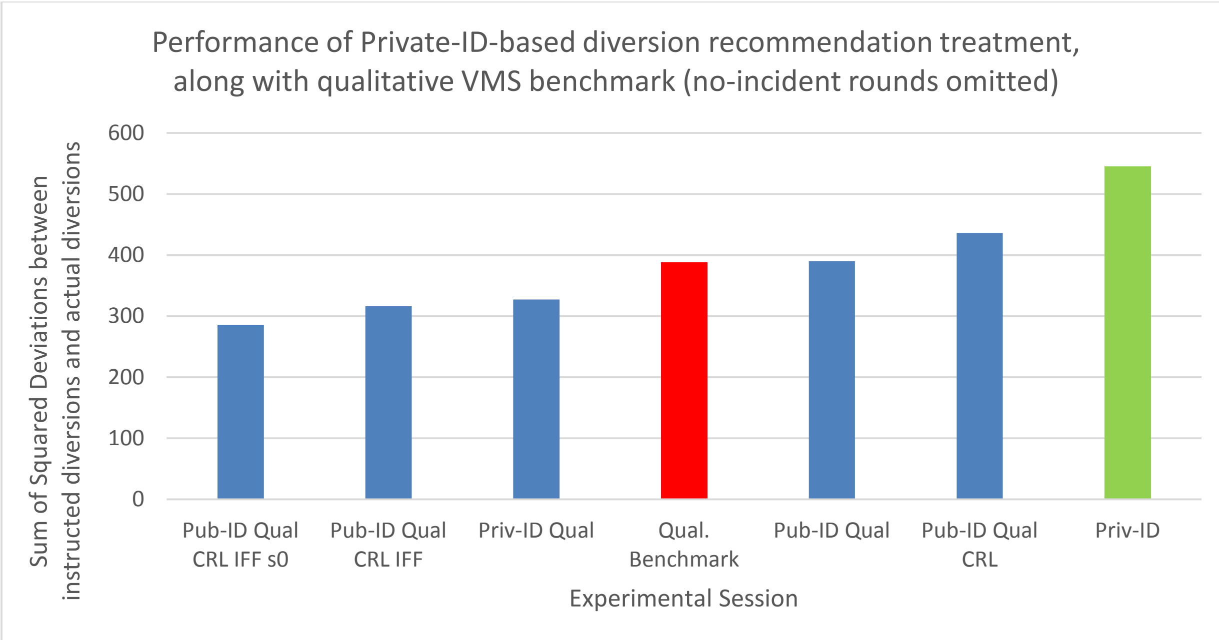
The first treatment with individual diversion recommendations entailed subjects being provided with a private number; the VMS told instructed specific subjects to divert each round based on their private ID number. The total share of subjects instructed to divert each round corresponds to the near-optimal diversion rate for the incident present during that round.



This treatment was around the middle of the pack for overall performance among ID-based diversion recommendation treatments, and was worse than the qualitative-VMS-only reference case.

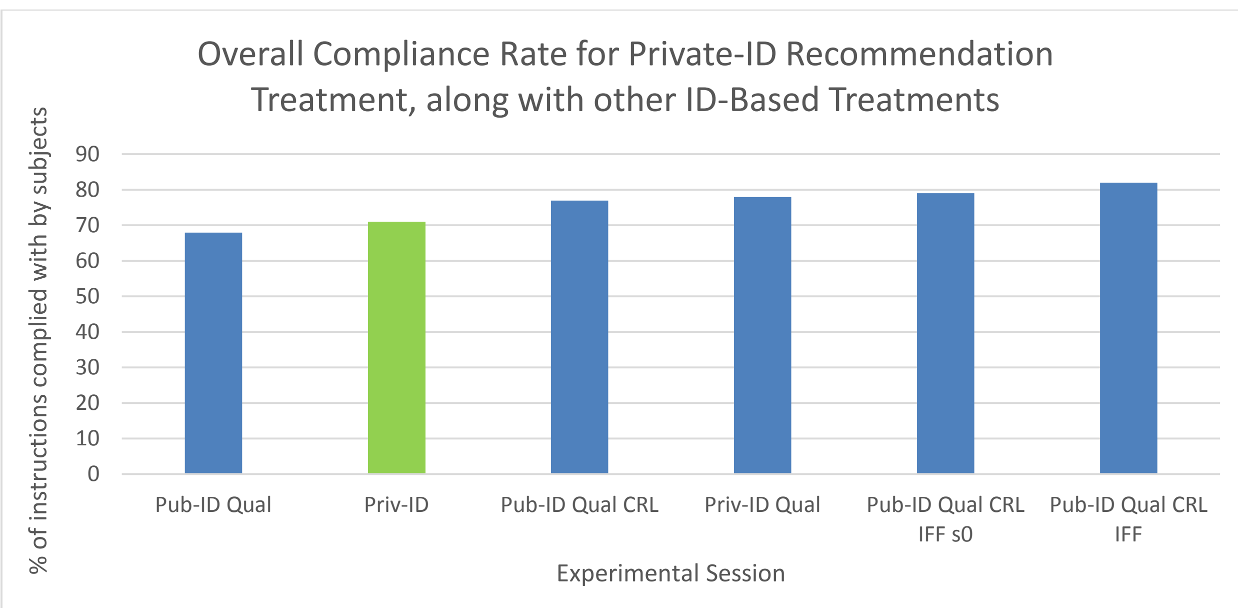


When one omits rounds with no incident, it is in fact the worst performing ID-based recommendation treatment.



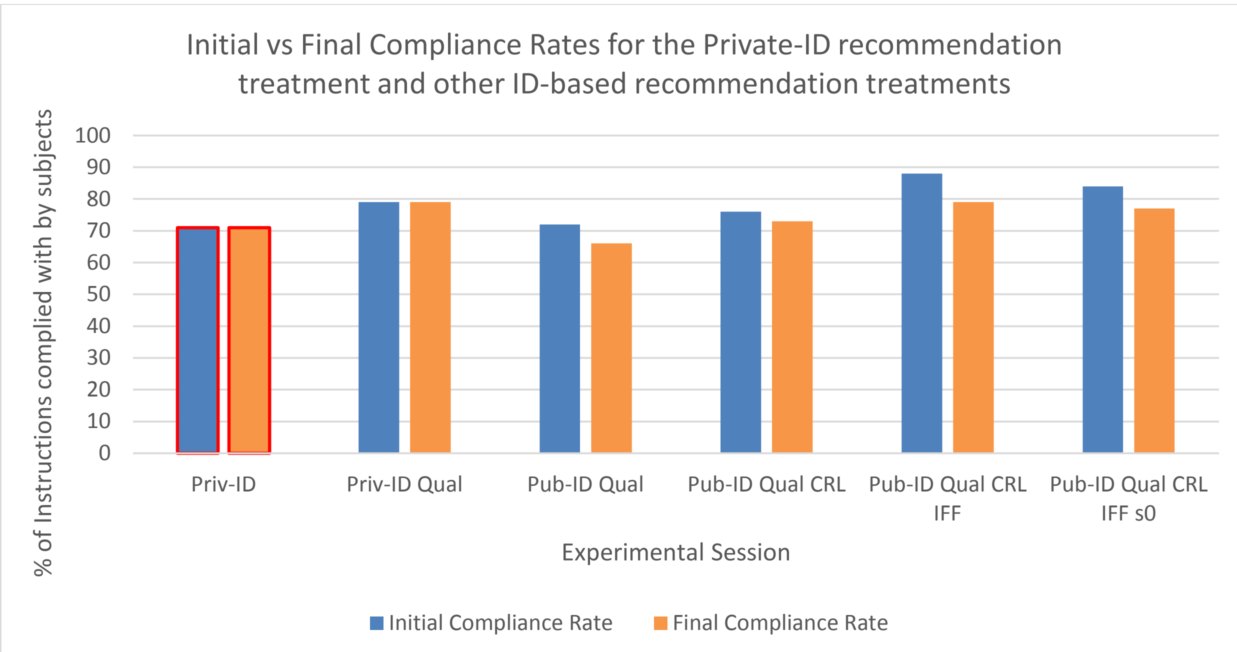
It is unclear why performance on no-incident rounds were better for this treatment compared to other ID-based recommendation treatments

The overall compliance rate for this treatment was 71%, which is the second lowest of all the ID-based recommendation treatments.



This low compliance rate is consistent with the treatment performing poorly on rounds with incidents.

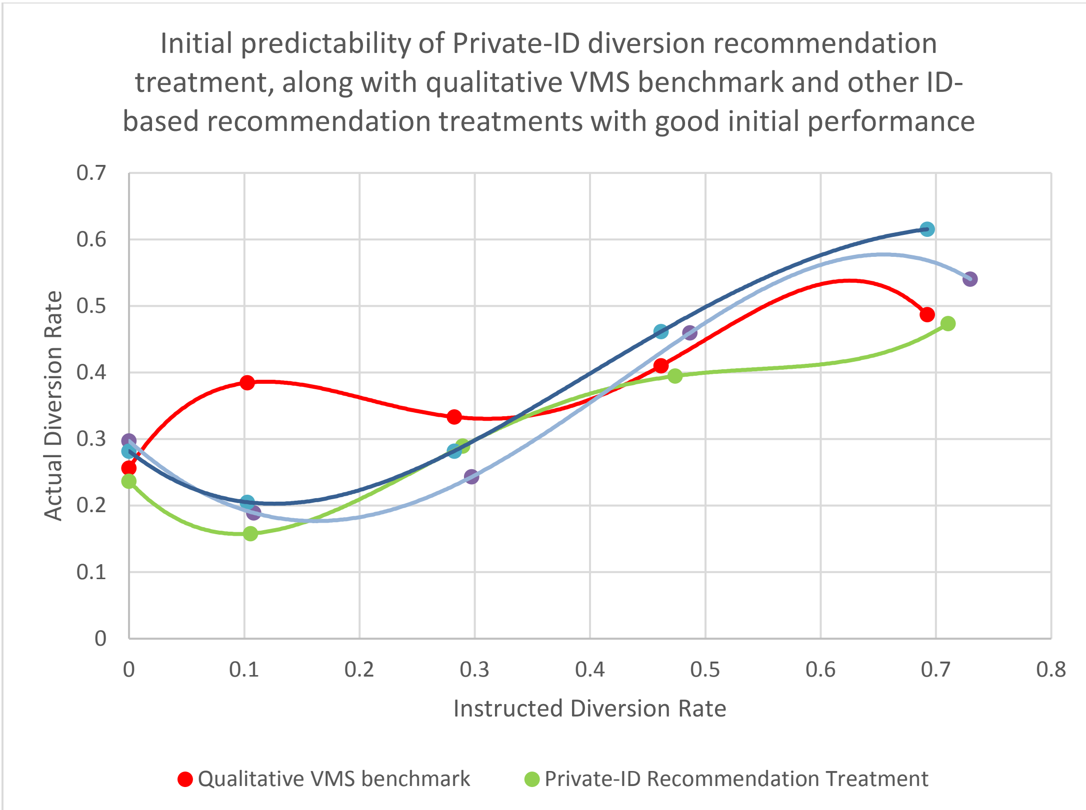
This treatment is also one of the two treatments with no drop-off in the compliance rate between the first and last rounds.



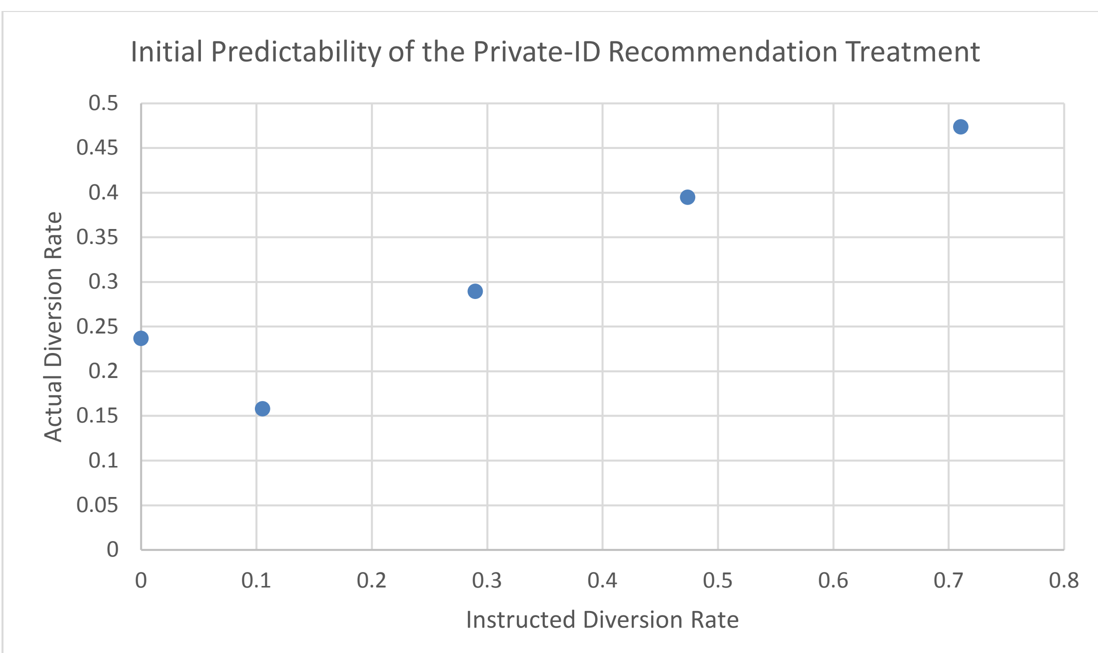
Most instances of non-compliance involve subjects who choose the main route after receiving instructions to divert.

Instructed Route	% Complied
Main Route	77
Alt Route	62

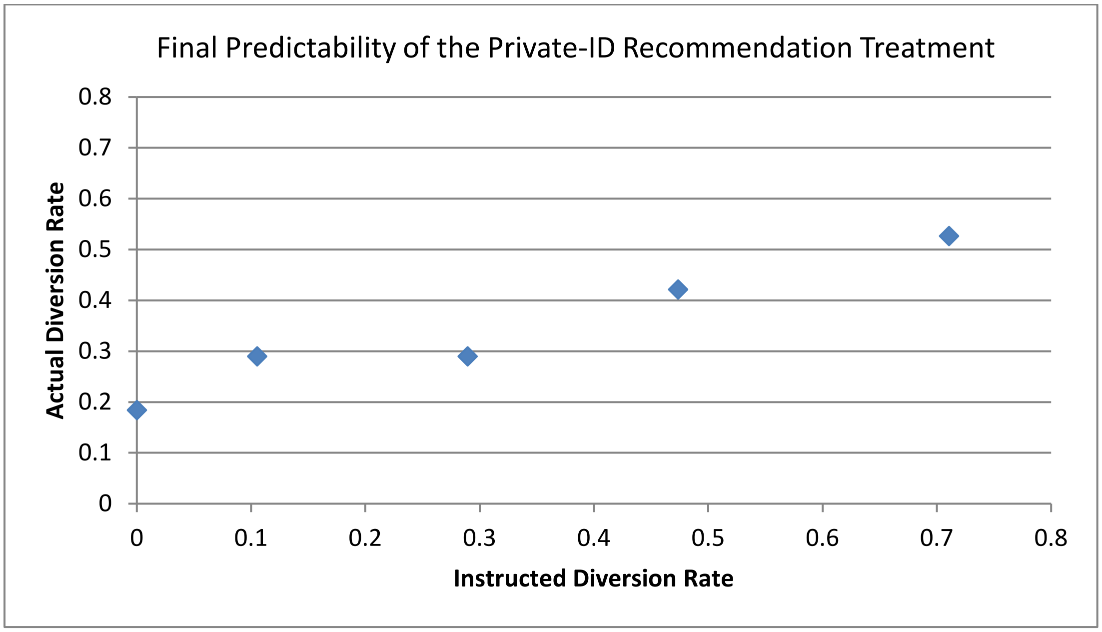
The initial predictability of this treatment is better than that of the qualitative-VMS-only benchmark, but not as good as that of some of the other ID-based recommendation treatments.



With the exception of the no incident round (during which no information or guidance is given), the curve is monotonic, reasonably smooth, and reasonably steep.



The final diversion response curve looks similar; the only real improvement is for the "no incident" scenario. As shown in the overview for ID-based recommendation treatments, the final round diversion response curves all look very similar to one another and to that of the qualitative VMS-only treatment.

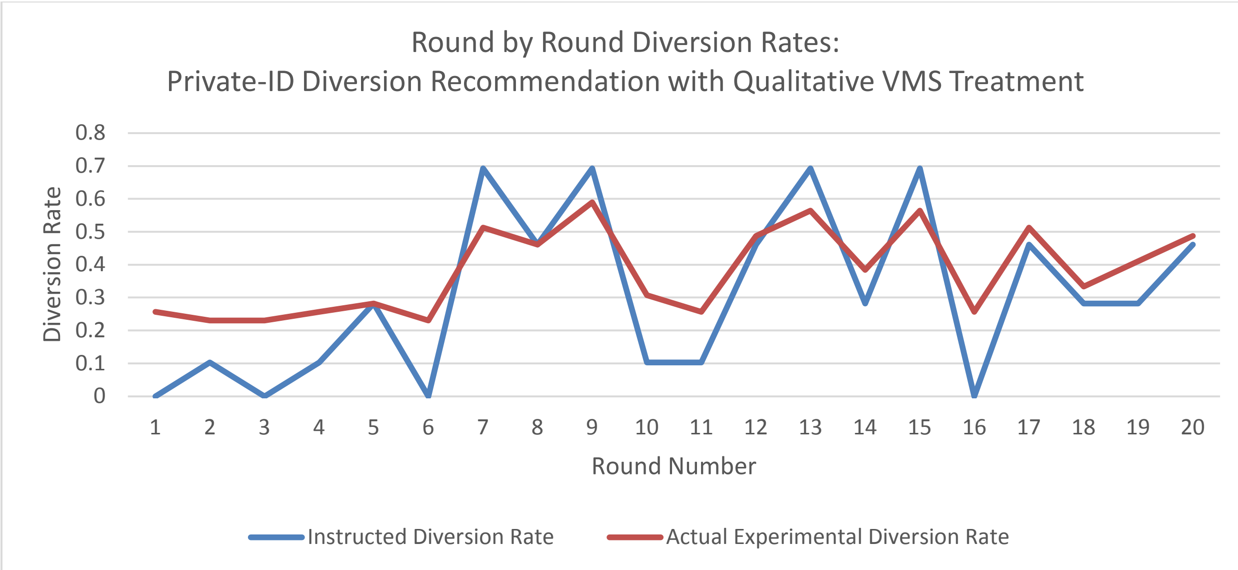


Lessons for Private-ID-based Recommendation Treatment

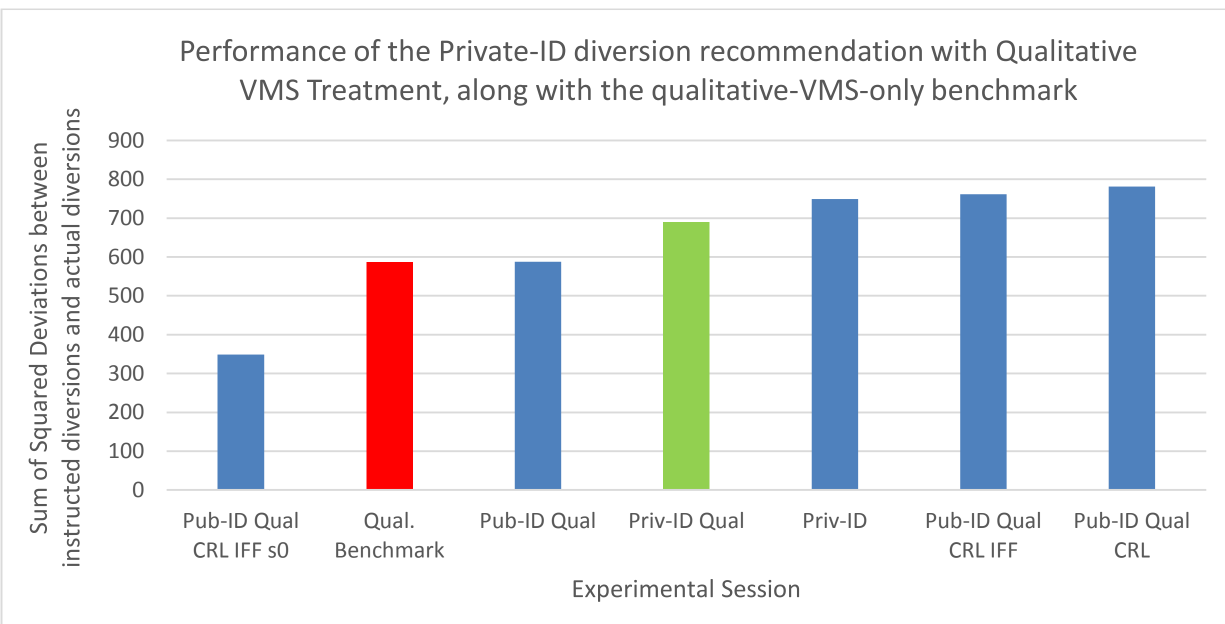
- This treatment has worse performance and lower compliance than most ID-based recommendation treatments
- This treatment has worse overall performance than the qualitative-VMS-only benchmark, but better initial performance and predictability.

7.3.2 Private Number Recommendation plus qualitative VMS Treatment (treatment IDS)

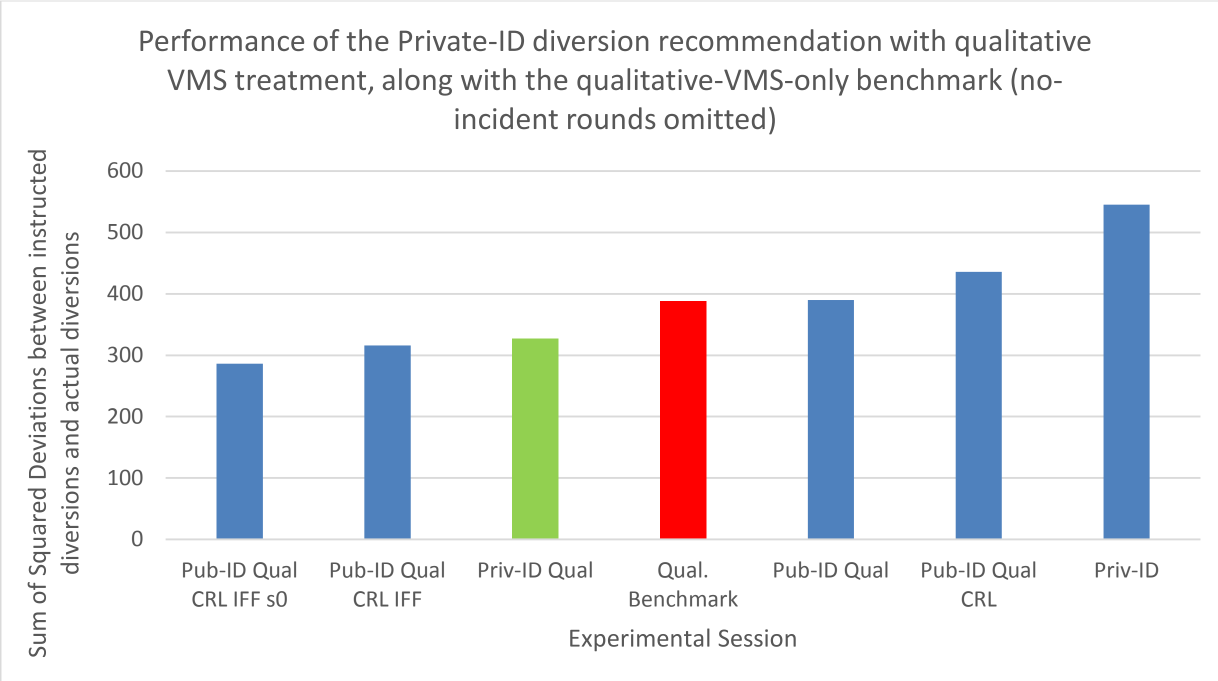
This treatment builds upon the previous treatment where subjects are provided with a private number and instructed to either divert or take the main route based on that number. This treatment adds an additional modification, which is a qualitative one-word (minor/moderate/major/severe) description of each incident present.



This treatment was around the middle of the pack for overall performance among ID-based diversion recommendation treatments, and was worse than the qualitative-VMS-only reference case. Its performance was superior to that of the private-ID-only recommendation treatment, however.

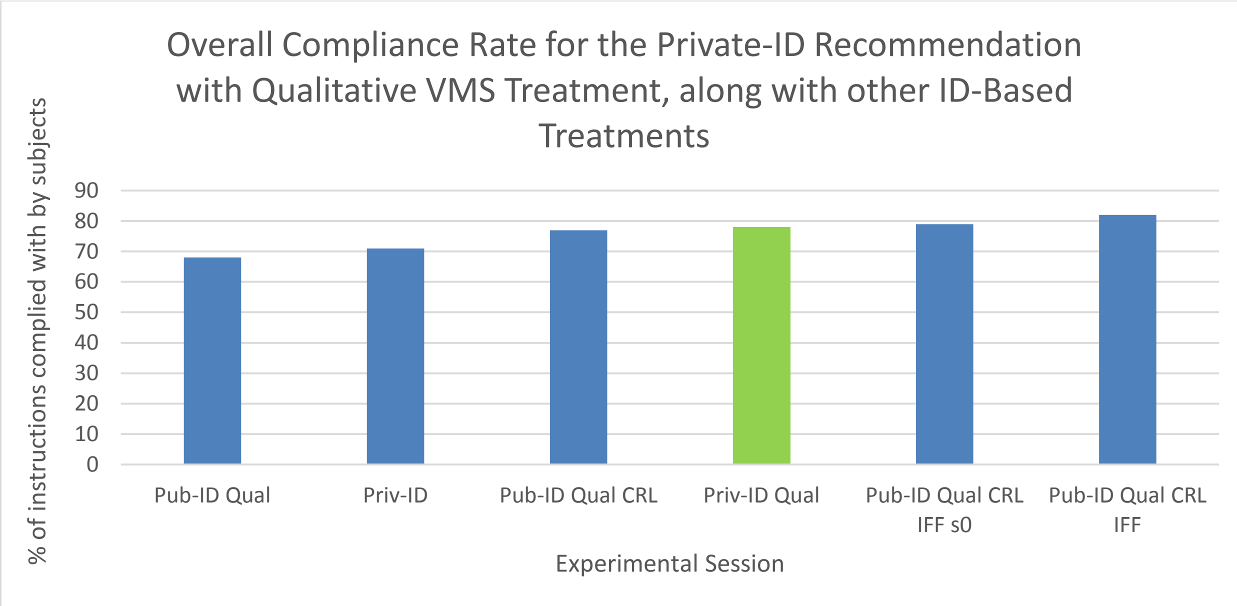


When ignoring rounds with no incidents (and no VMS), however, this treatment is among the best performers.

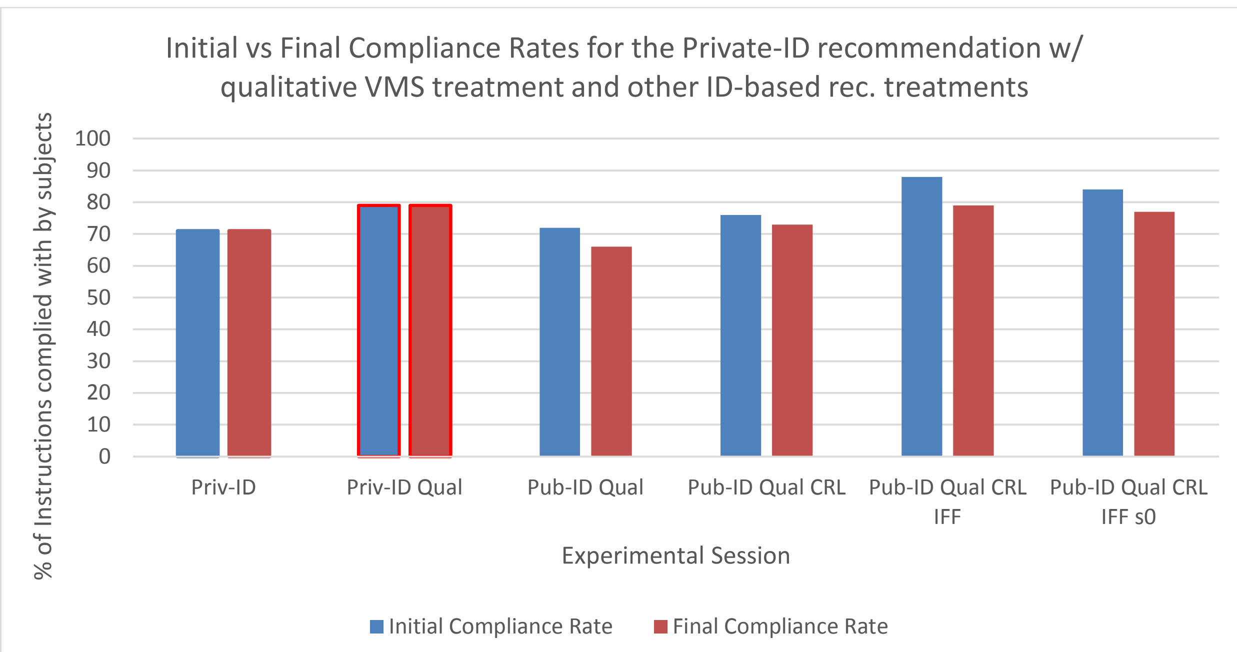


It outperforms the qualitative-VMS-only benchmark and the majority of ID-based recommendation treatments. It is unclear why performance is relatively worse on rounds with no incidents.

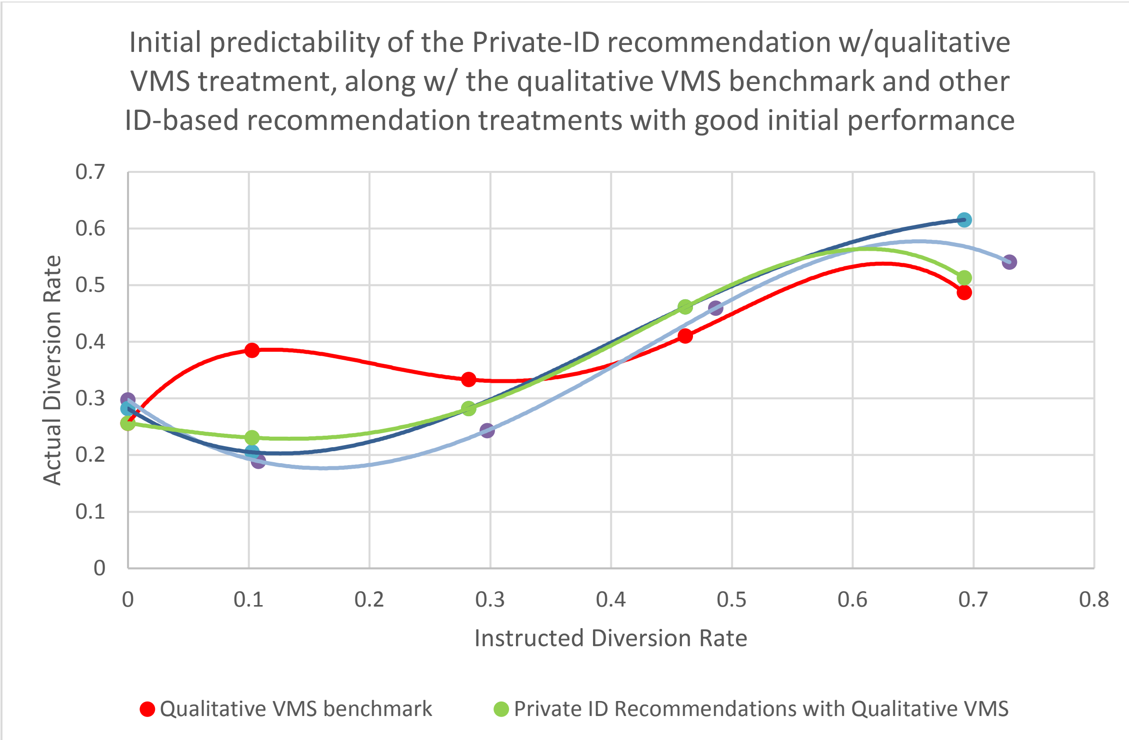
Compliance is also improved relative the private-ID recommendation-only treatment, which likely is responsible for the improved performance. This suggests that subjects are more likely to follow varied compliance instructions when they are given reasons for doing so; in this case the reason is provided by the qualitative description of the incident.



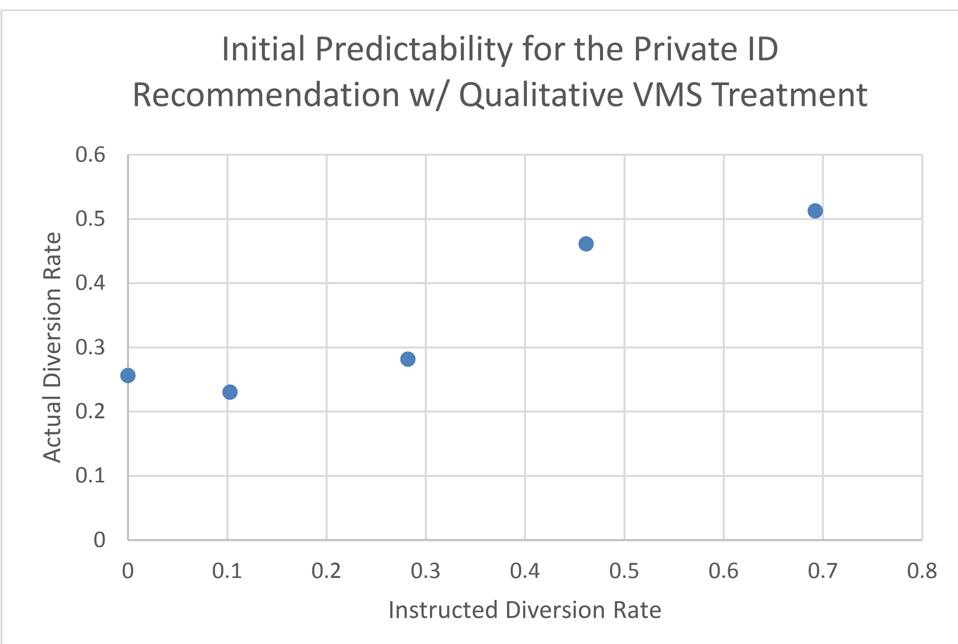
As is the case with the private-ID-only treatment, compliance in this treatment does not fall over time.



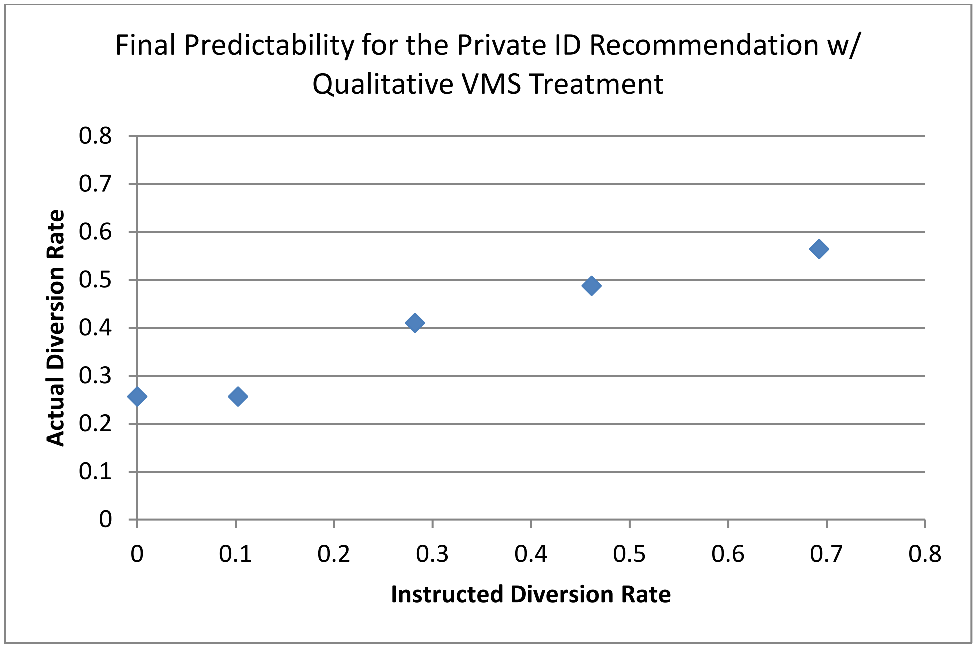
This is among the better ID-based recommendation treatments as far as initial predictability is concerned, and its predictability is much better than that of the qualitative-VMS-only benchmark treatment as well.



With the exception of the data point corresponding to the round with no incident (during which no information or guidance is given), the curve is monotonic, reasonably smooth, and reasonably steep.



The final-round diversion response curve is even steeper and closer to a 45-degree line.

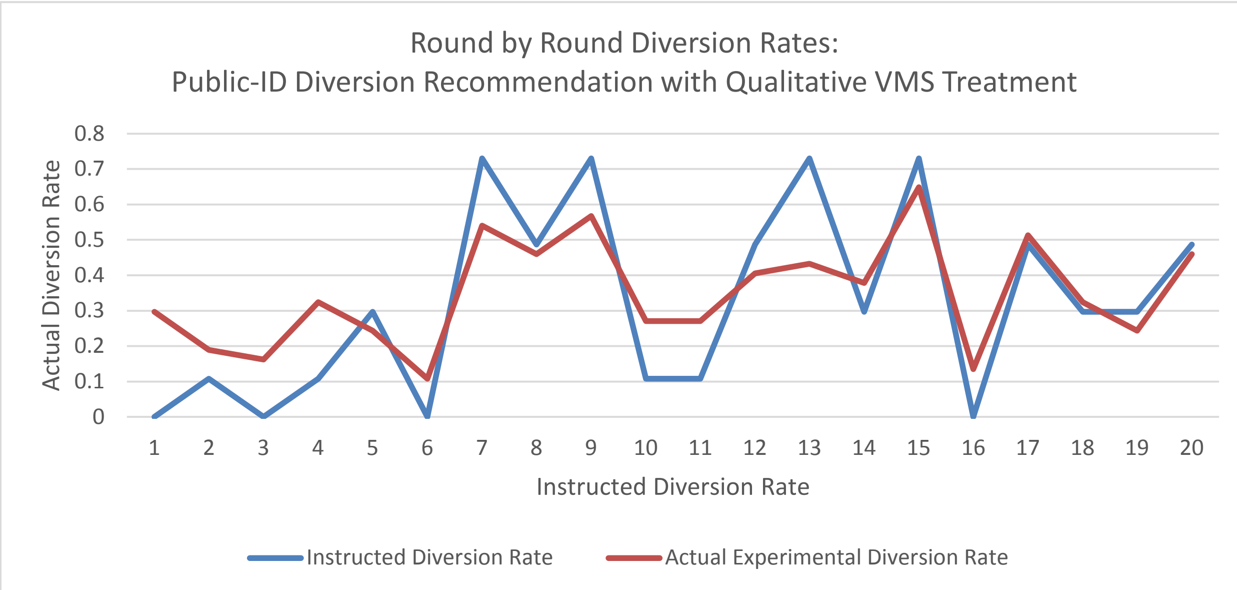


Lessons from this treatment:

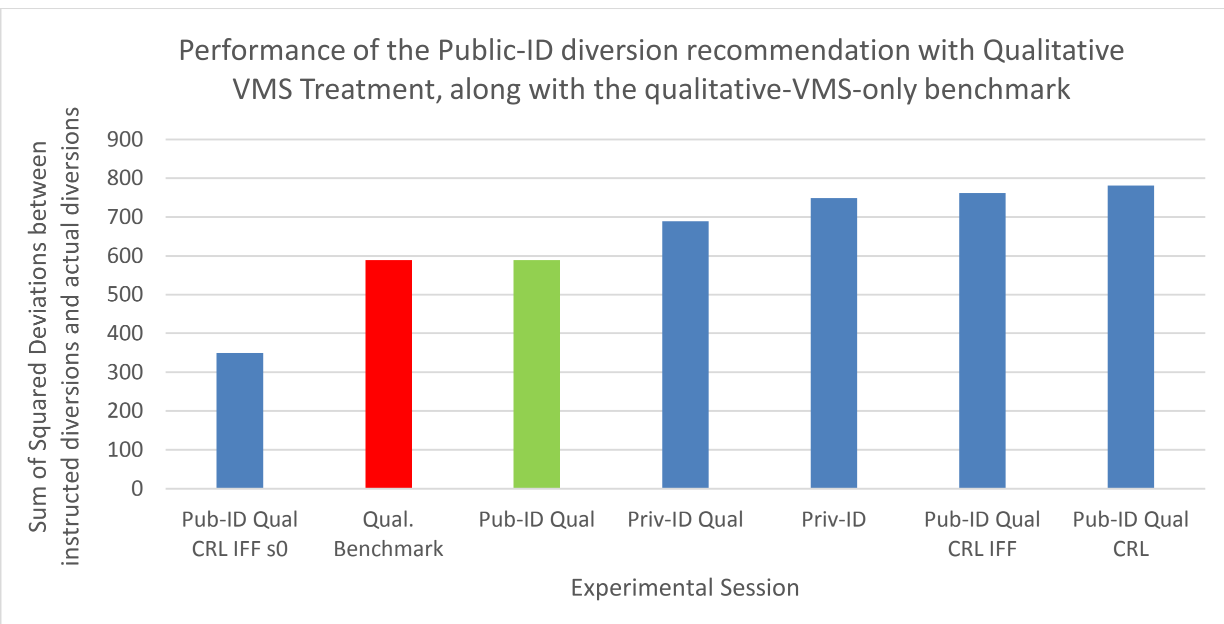
- Combining private-number diversion recommendations with qualitative messaging improves the performance and compliance achieved by the treatment significantly relative to a treatment with private-number diversion recommendations only. Subjects are perhaps more willing to comply with instructions when provided with an explanation of why they should.

7.3.3 Public Number Recommendation plus qualitative VMS Treatment (treatment PIS)

This treatment modifies the previous treatment where subjects are provided with a private number, which determines whether, or not, they are instructed to divert each round and a qualitative description of each incident present. The modification replaces private numbers with public numbers that can be viewed by any other subject nearby; thus, subjects know whether other subjects ahead are complying with instructions.

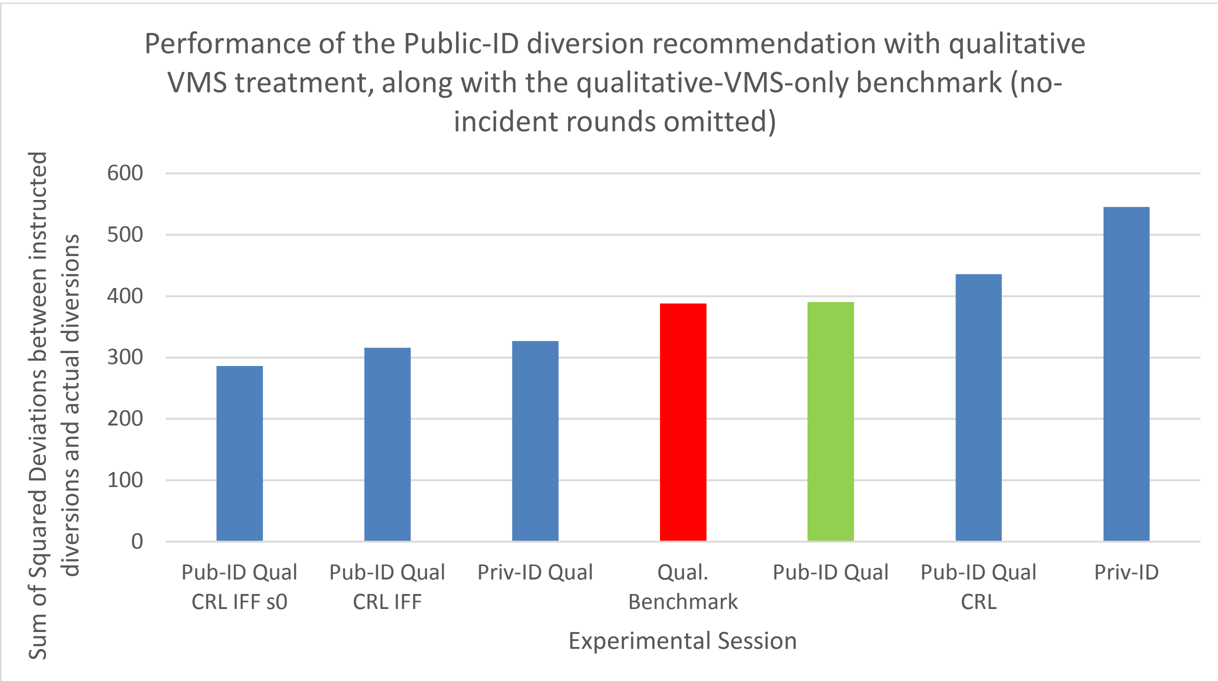


This treatment performed better overall than most ID-based recommendation treatments, and had almost identical overall performance to the qualitative-VMS-only reference treatment.



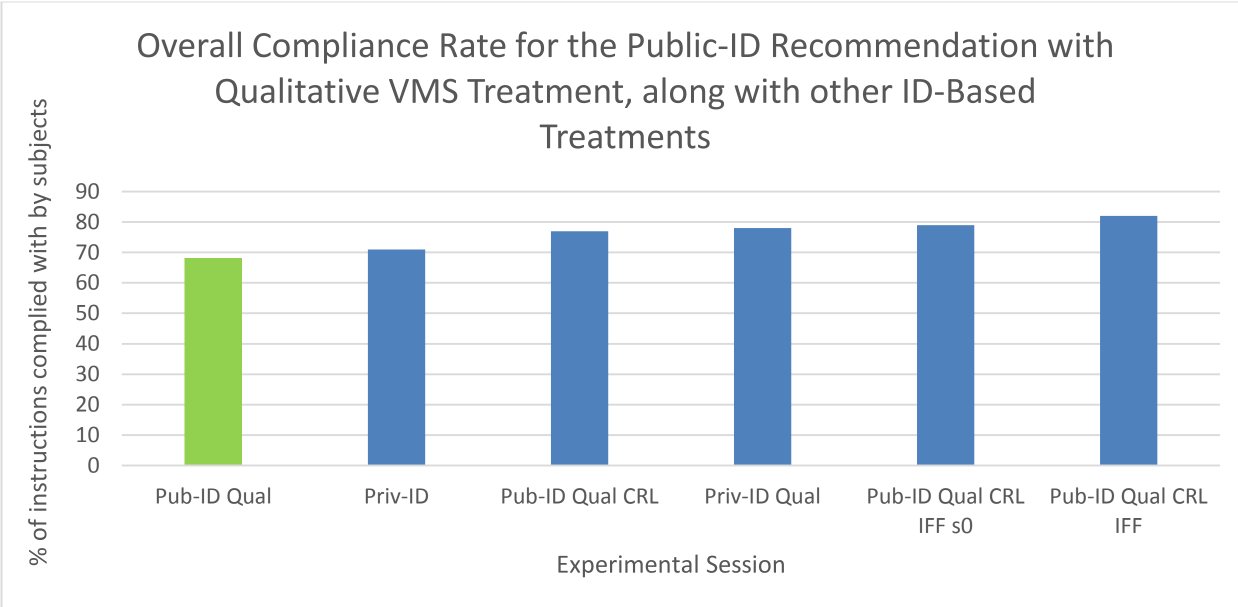
The use of public IDs slightly improved overall performance relative to the private ID treatment.

When ignoring rounds with no incidents (and no thus VMS), however, this treatment does not perform as well as relative to other treatments.



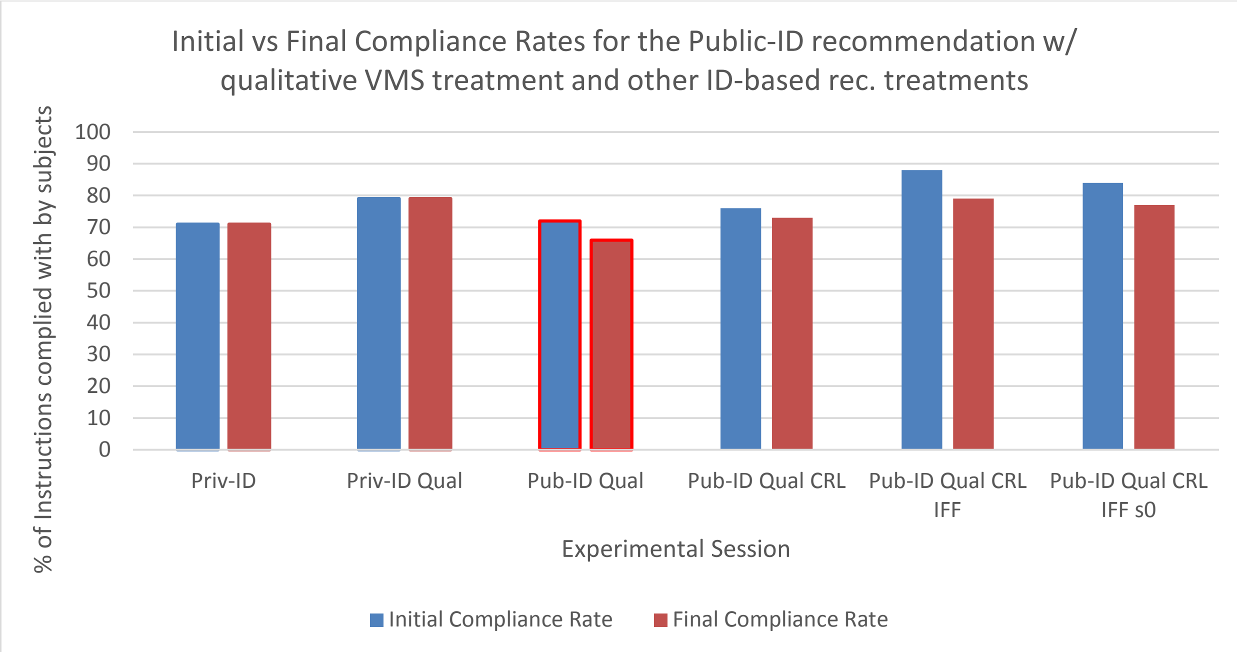
Though still equivalent to the qualitative-VMS-only treatment in terms of performance, it is outperformed by the private-ID recommendations with qualitative info treatment when only looks at rounds with incidents. It is unclear why this treatment does better on rounds with no incident.

This treatment also achieves a lower compliance rate than both private ID treatments, with and without qualitative incident descriptions. In fact, this treatment has the worst overall compliance rate of any of the ID-based recommendation sessions.



As theorized in the overview for this class of treatments earlier in the report, treatments that use public IDs likely achieve lower compliance rates than those that use private IDs because subjects are able to view the non-compliance of other subjects and see less value in complying themselves.

This conjecture is supported by the finding of a significant drop-off in this treatment between initial and final compliance.

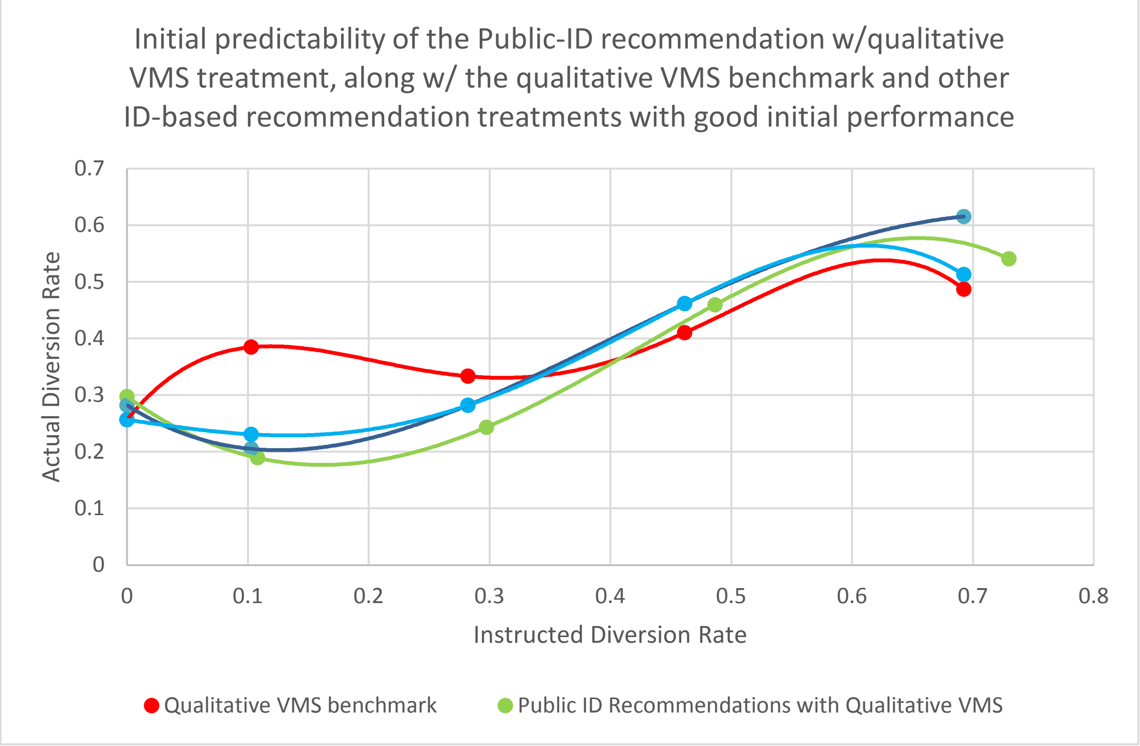


This drop-off in compliance does not directly translate to worse performance, however; final performance is still superior to initial performance, suggesting that the drop in compliance is not entirely maladaptive.

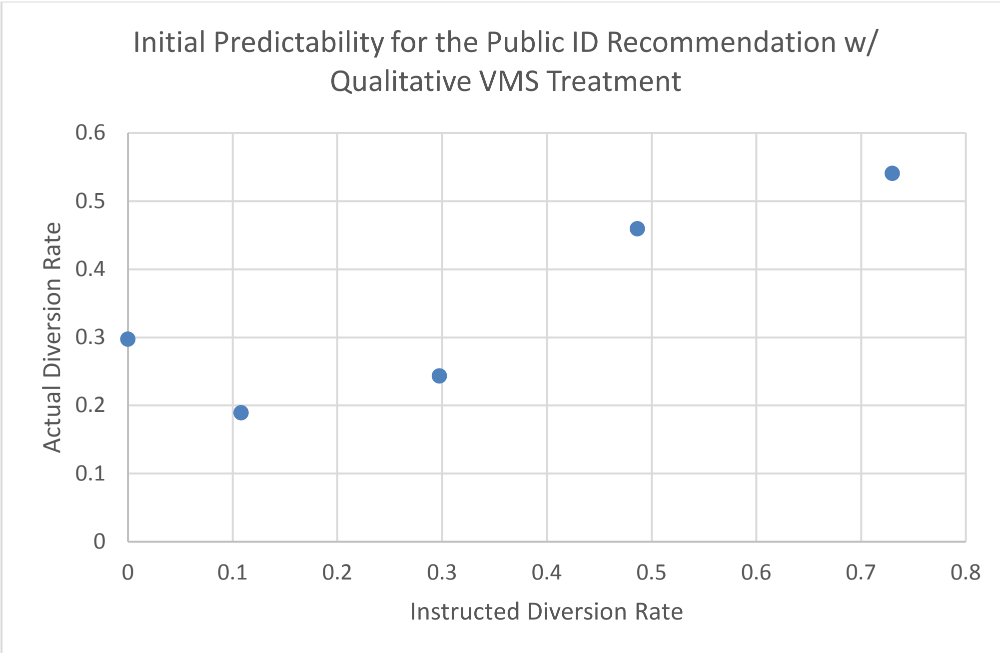
Performance during initial rounds for each incident type (lower is better)	Performance during final rounds for each incident type (lower is better)
184	75

This supports the more optimistic case theorized in the overview for this class of treatments earlier in the report, which states that increased non-compliance might originate from subjects attempting to balance out perceived mis-diversion. That is, rather than ignore instructions completely, a subject might observe that more non-compliance is due to subjects failing to divert when instructed, and thus choose to switch to the alternate route even though he himself was told to take the main route. This can explain why an improvement in performance was observed despite a drop in a compliance occurring. However, this treatment still performs worse on rounds with incidents than the private-ID recommendation with qualitative info treatment. Therefore, there is still some performance penalty to lower compliance.

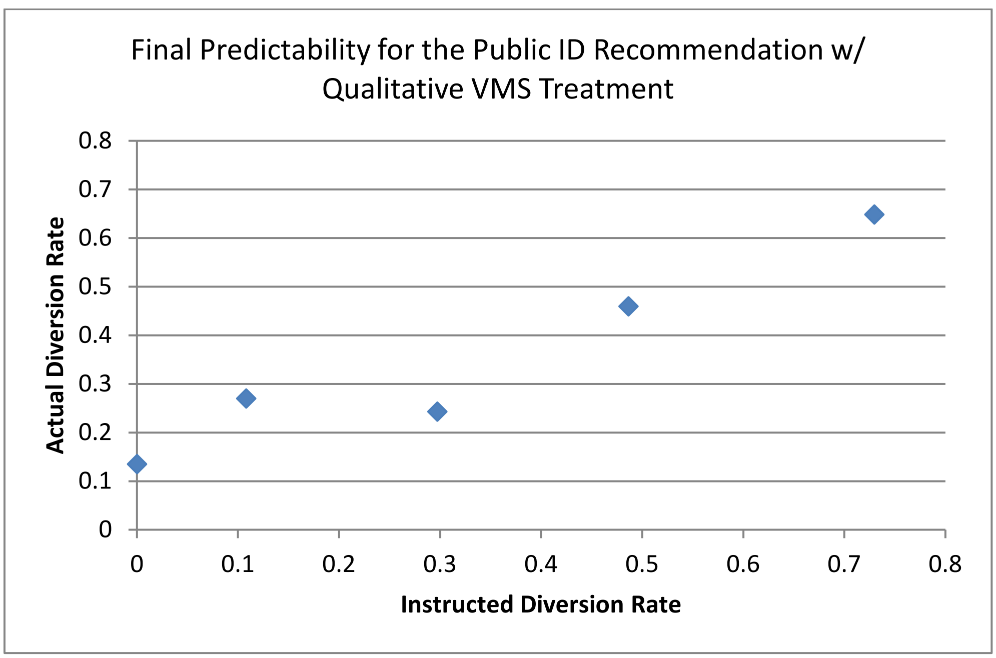
This treatment is among the better ID-based recommendation treatments as far as initial predictability is concerned; its initial predictability is much better than that of the qualitative-VMS-only treatment as well.



With the exception of the data-point corresponding to the round with no incident (during which no information or guidance is given), the curve is monotonic, reasonably smooth, and reasonably steep.



The diversion response curve for the final rounds of each incident type is still somewhat smooth and predictable, but lacks monotonicity due to significant over-diversion during the final "minor incident" round. This might be related to the drop-off in final round compliance.

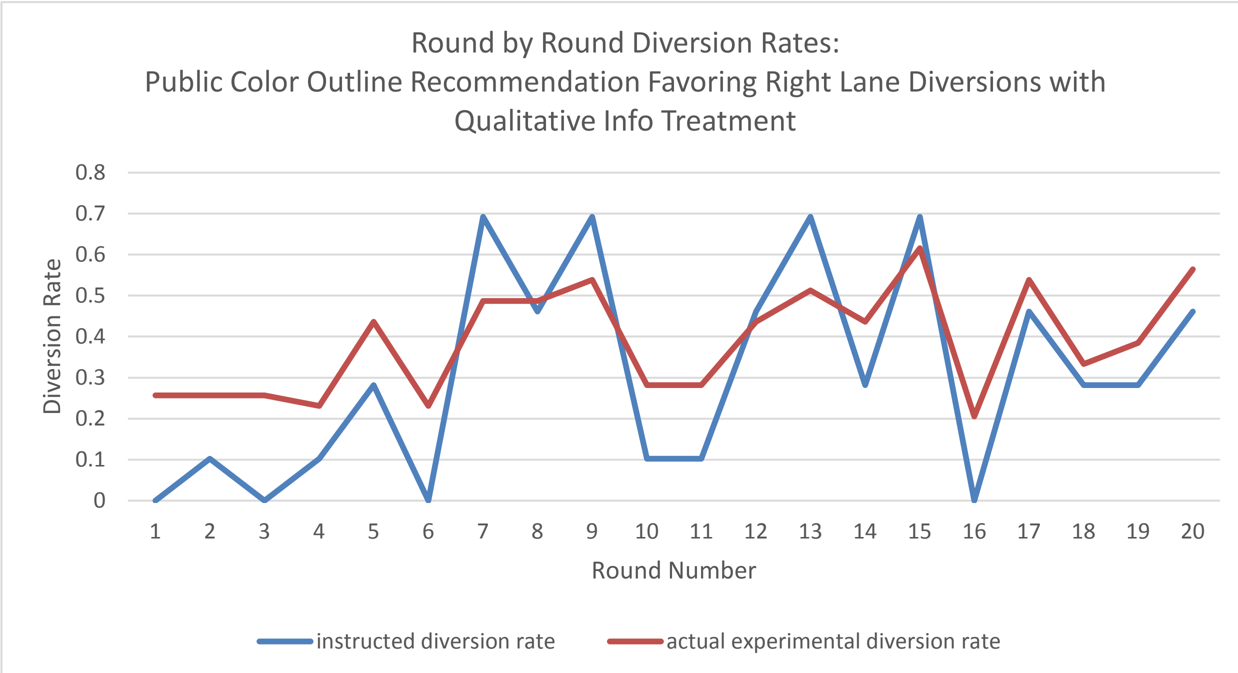


Lessons from the public ID diversion recommendation with qualitative info treatment:

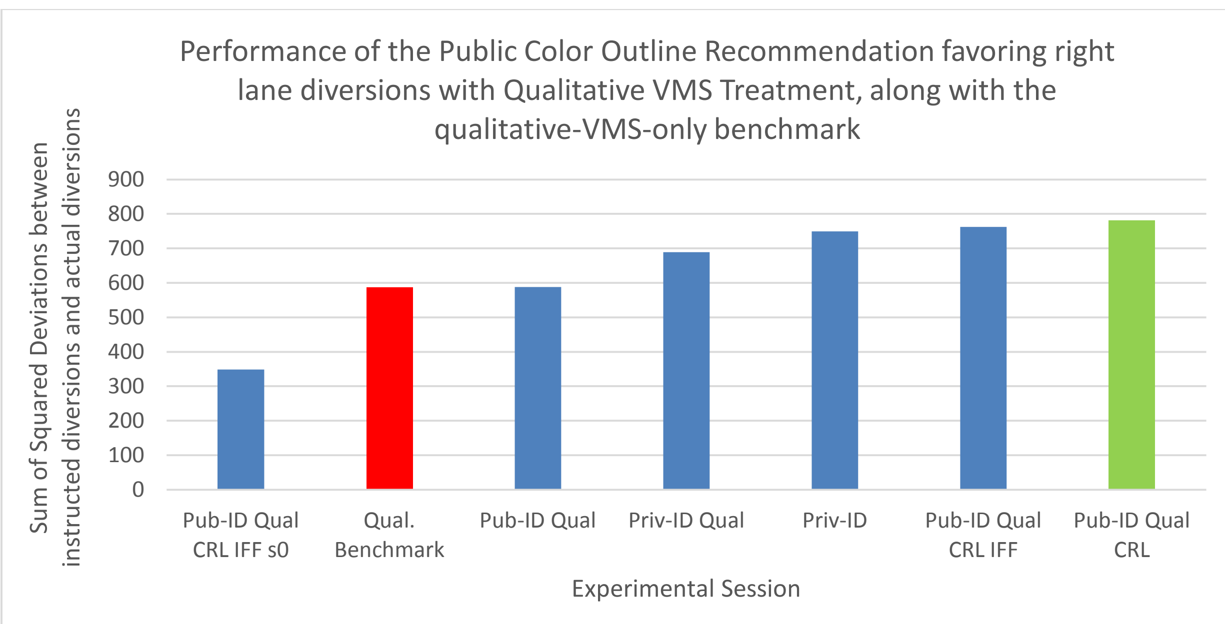
- When public IDs are used, subjects are less likely to comply than when using private IDs. Compliance drops as the experiment progresses for this treatment, which is not the case for private ID treatment.
- The drop in compliance is not entirely maladaptive because performance still improves over time, but likely is still largely responsible for lower performance during rounds with incidents compared to the private-ID recommendation with qualitative info treatment.

7.3.4 Public Color Outline Diversion Recommendation Favoring Right Lane plus Qualitative Information Treatment (treatment PCS_1)

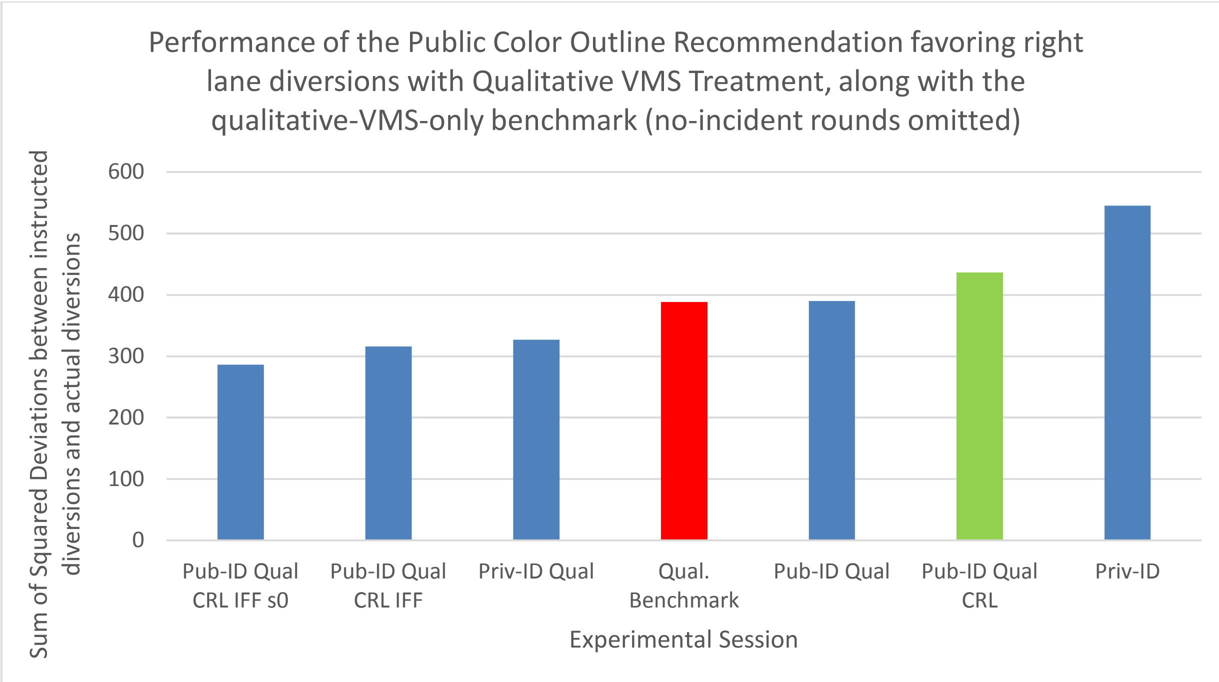
This treatment modifies the previous treatment where subjects are provided with a public number, which determines whether, or not, they are instructed to divert each round and a qualitative description of each incident present. The modification attempts to increase compliance by replacing ID numbers with colored outlines around the vehicle (visible to all) to increase the saliency of the identifier. It also attempts to increase compliance by choosing predominantly vehicles in the exit lane to receive diversion instructions. This makes it easier for vehicles to comply with diversion instructions since they do not have to change lanes. It also has the effect of randomizing who is told to divert each round, since vehicle positions are randomized each round. In the ID-number treatments, the same subjects receive the same number each round, and thus the same set of users are told to divert for each repeated incident type.



This treatment has the worst overall performance among all the ID-based recommendation sessions, and was much worse overall than the qualitative-VMS-only treatment.

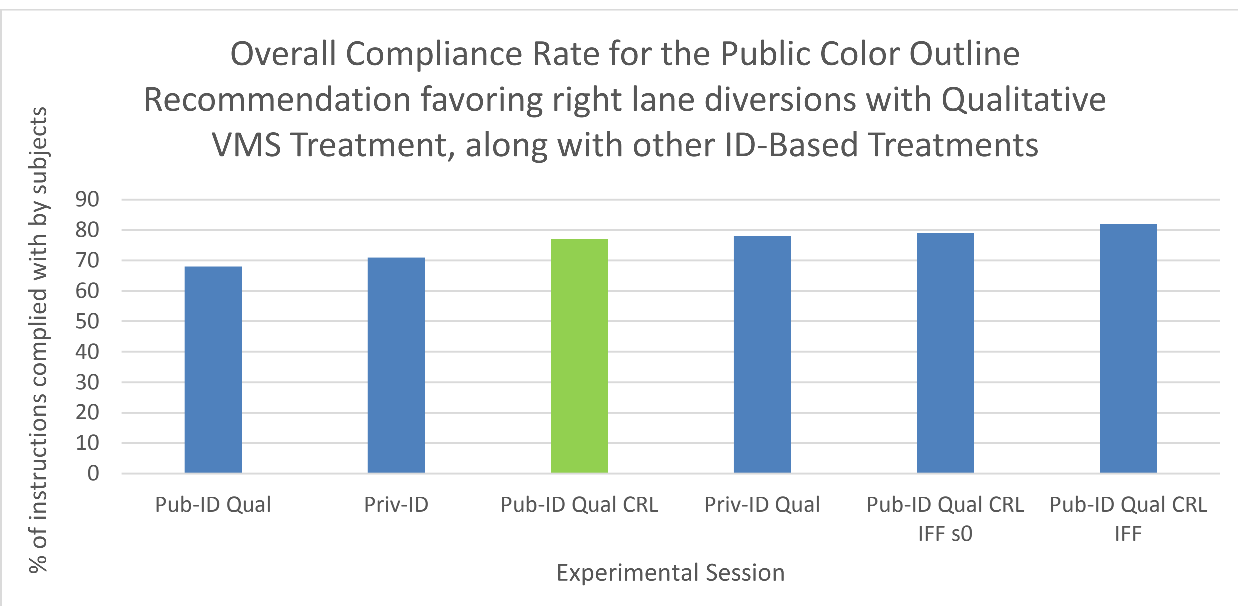


When ignoring rounds with no incidents (and thus no VMS), the treatment is still one of the worst performers.

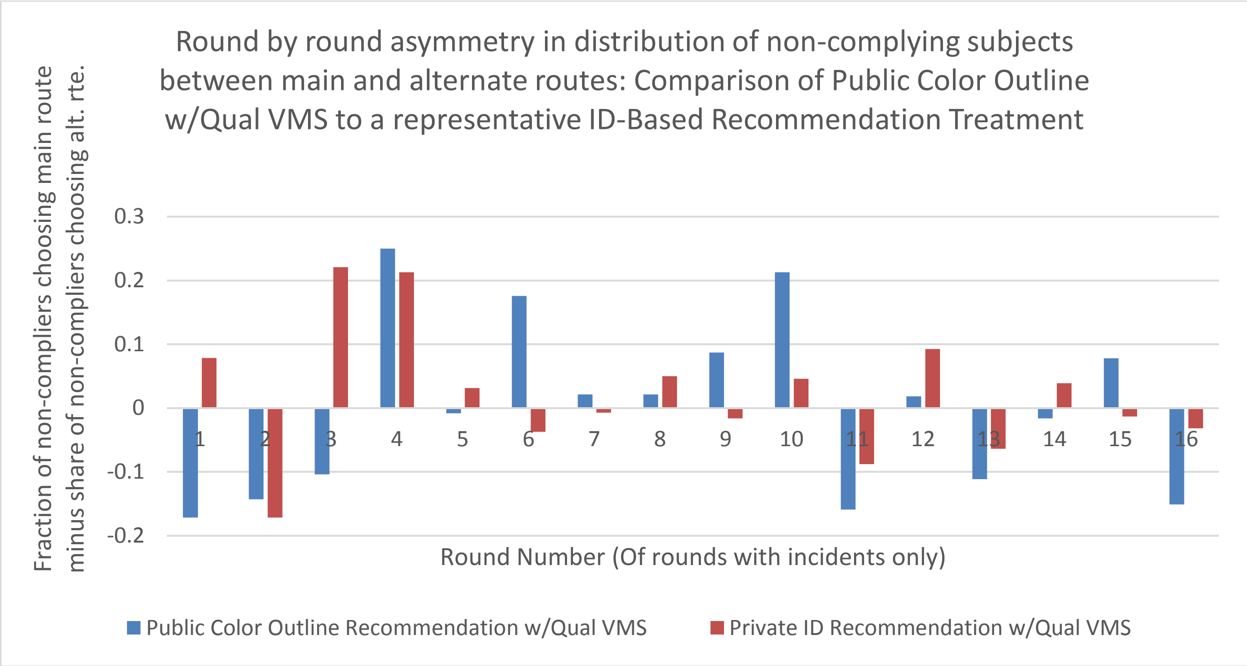


The modifications introduced with this treatment fail to achieve a performance improvement over the public-ID diversion recommended with qualitative VMS treatment.

The worsened performance is not a result of decreased compliance; this treatment actually increased compliance over the public ID recommendation with qualitative VMS treatment.



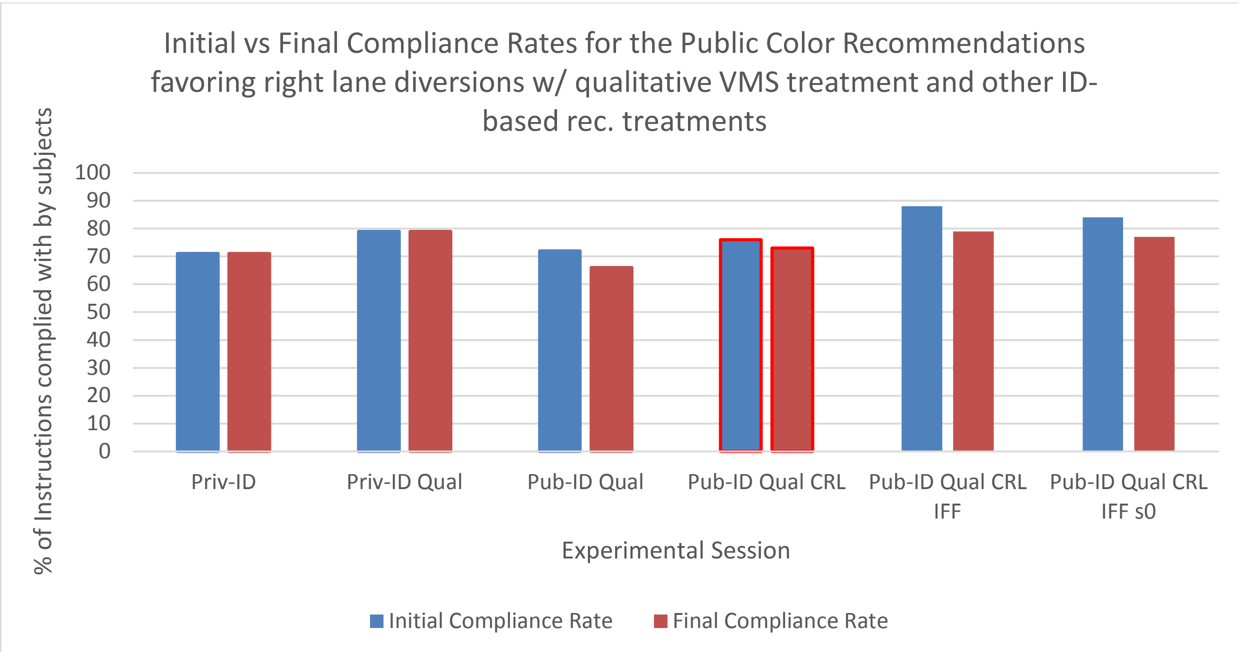
Instead, performance is diminished because instances of non-compliance result in more mis-diversion on average. On some rounds, non-compliance will overload the main route, and on others, the alternate route will be overloaded.



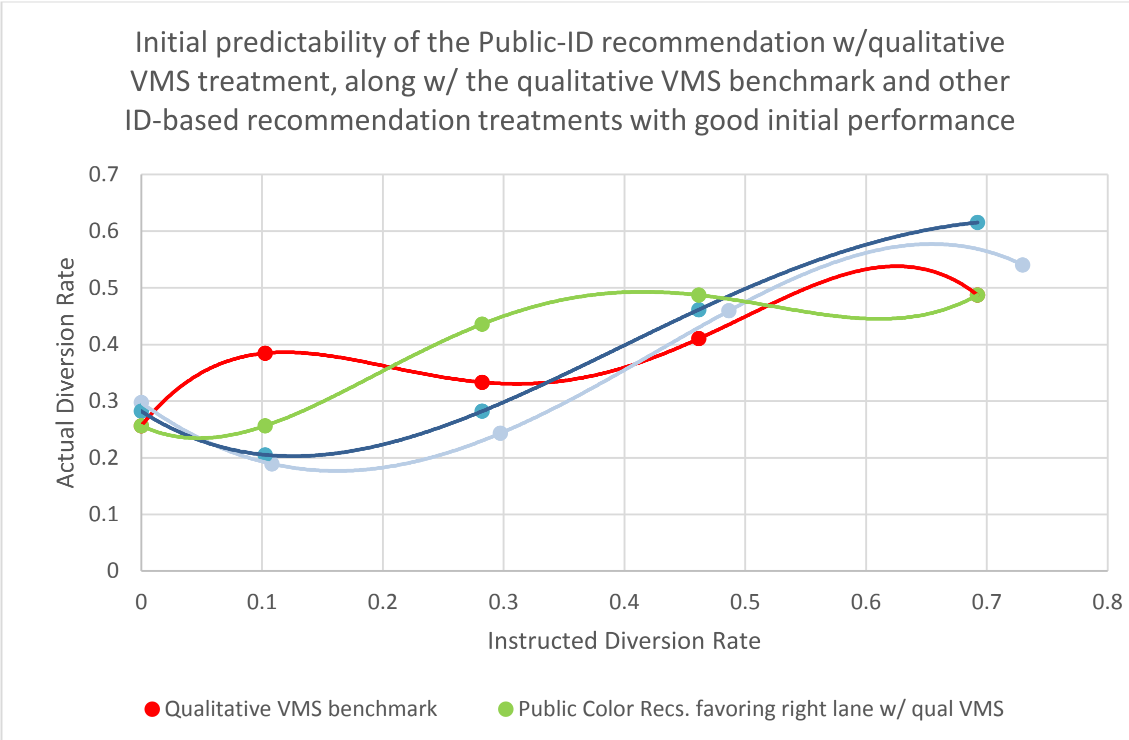
One possible explanation for greater mis-diversions originating from non-compliance is that the modifications introduced by this treatment (color outlines, subjects in right lane predominantly told to divert) were effective in reducing non-compliance among subjects told to divert, but did nothing to prevent non-compliance among those told to stay on the main route. This would lead to imbalance in which route was chosen by non-complying subjects (there would be greater over-diversion in minor and medium incident scenarios). This conjecture is supported by the fact that this treatment has the highest diversion rate among all ID-based diversion recommendation treatments.

It is also possible that the sorting of subjects told to divert into the right lane and vice-versa make it harder for subjects to compensate for perceived mis-diversion. For example, if a subject told to take the main route observed under-diversion, they would have to switch over one more or lanes to the right in order to exit and compensate for the under-diversion.

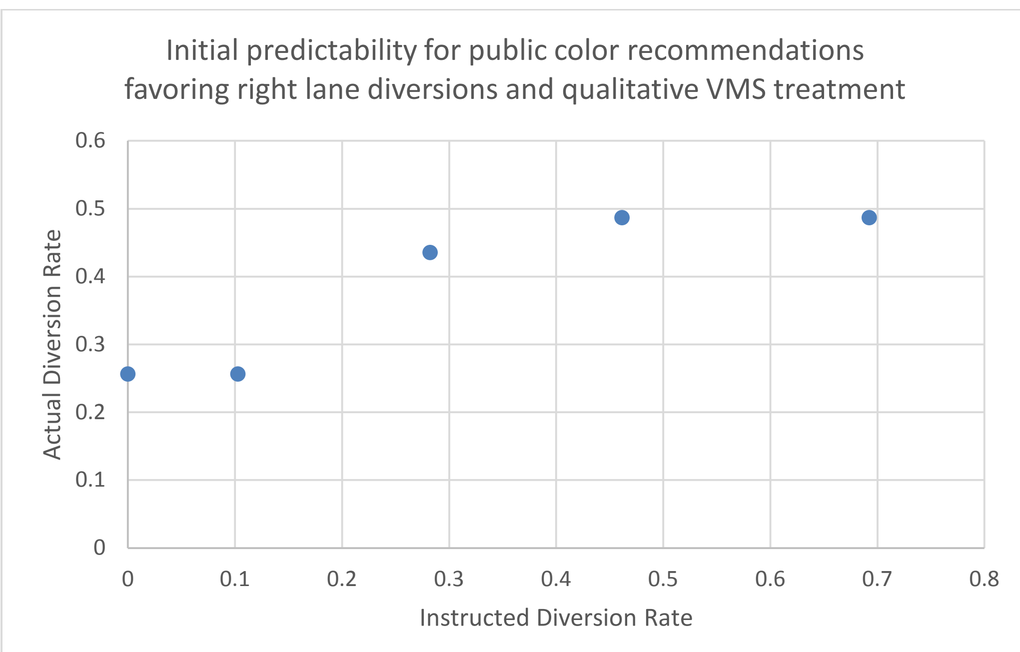
This treatment also produces a slight drop in compliance between the initial and final rounds of each incident type.



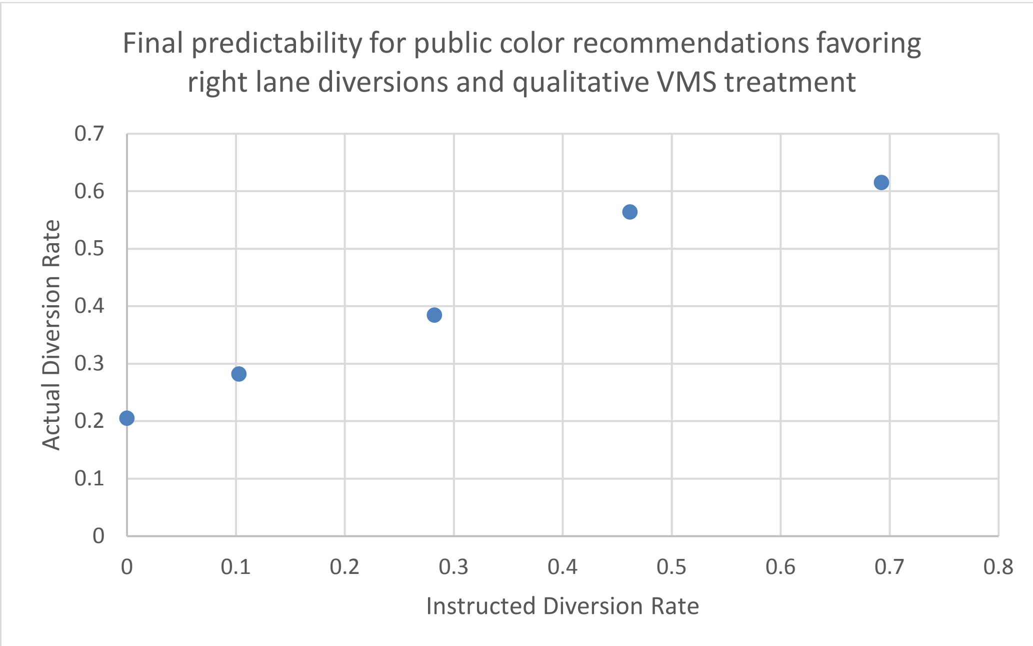
This relatively poor performance of this treatment is also reflected in the initial predictability of its diversion response curve. This treatment was the worst of the ID-based recommendation treatments as far as initial predictability is concerned, and its initial predictability is only slightly better than that of the qualitative-VMS-only treatment.



Though monotonic, the diversion response curve for this treatment is very flat which indicates that there is not much difference in the diversion rate for the different types of incidents.



As is usually the case for ID-based recommendation treatments, however, the final round diversion response curve is smooth, monotonic, and sufficiently steep.

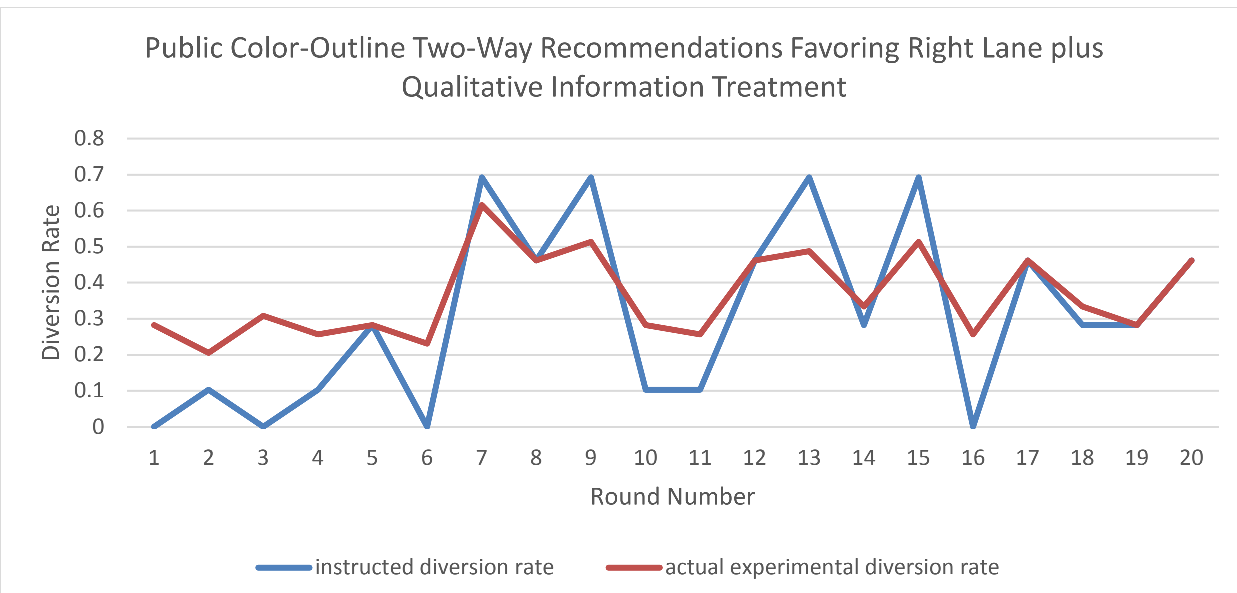


Lessons from Public Color Outline Diversion Recommendation Favoring Right Lane plus Qualitative Information Treatment:

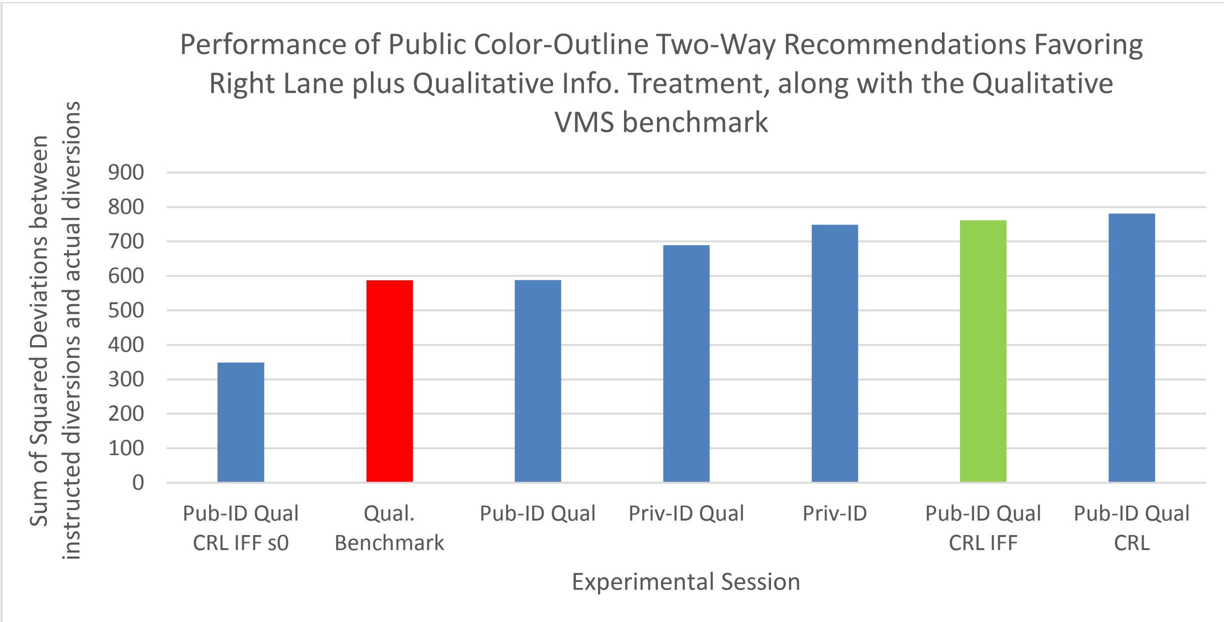
- This treatment, either through increasing the salience of identification through the colored outlines or through prioritizing right lane vehicles when instructing subjects to divert, improved compliance with instructions but hurt diversion performance and initial predictability relative to the public-ID diversion recommendation with qualitative information treatment.
- The increase in compliance came primarily from subjects instructed to divert as opposed to subjects instructed to take the main route. The decrease in performance associated with this treatment is evidence that it is not beneficial to unilaterally increase compliance with instructions to take one route without increasing compliance with instructions to take the other route.

7.3.5 Public Color-Outline Two-Way Recommendations Favoring Right Lane plus Qualitative Information Treatment (also referred to as IFF, short for If and Only IF, treatment PCS_2)

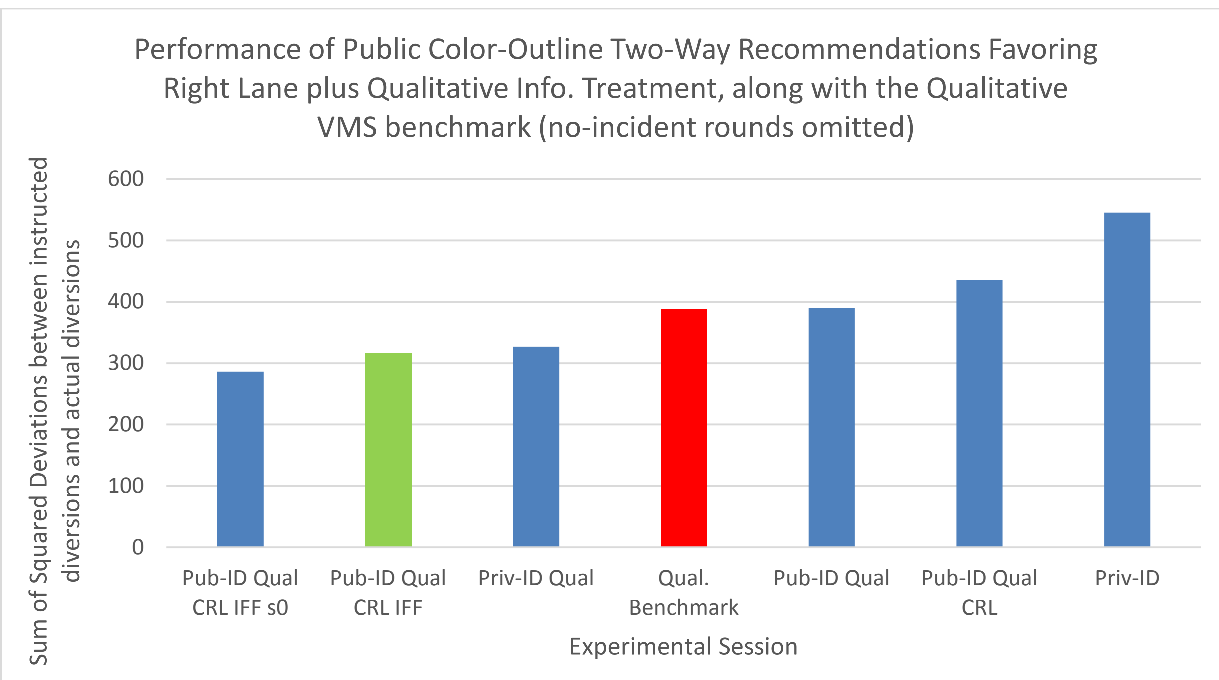
This treatment modifies the previous treatment where subjects predominantly in the right lane are provided with a public color outline, which determines whether, or not, they are instructed to divert each round and a qualitative description of each incident present. The modification changes the wording of instructions to make it clear the vehicles not explicitly told to divert should remain on the main route. Prior to this modification, subjects were only told to divert; not being told to divert was an implicit instruction to stay on the main route. The goal of the treatment is to increase the compliance rate of subjects "instructed" to take the main route by making the implicit instruction explicit.



As with the prior treatment, which was the same as this treatment except for a lack of two-way "IFF" messaging, overall performance was adversely affected by large over-diversion on rounds with no incident. As a result, this treatment's overall performance was worse than that of most of the ID-based recommendation treatments, and it was much worse than that of the qualitative-VMS-only treatment.

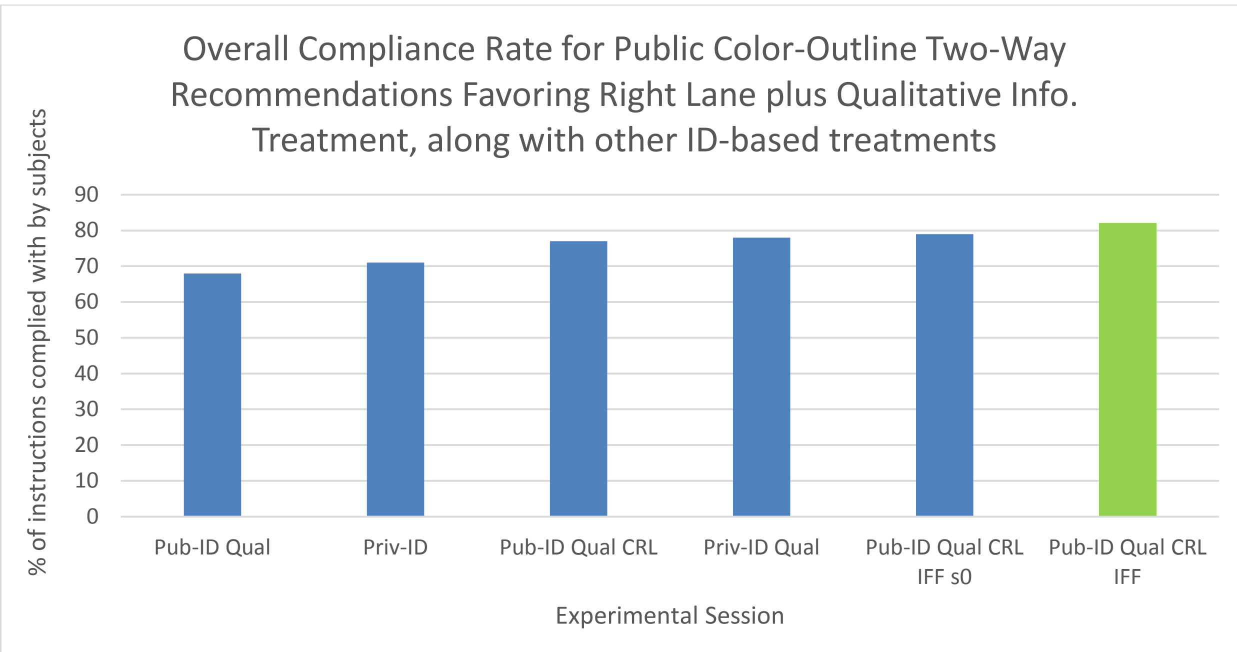


When omitting rounds with no incident, the relative performance of this treatment dramatically improves.



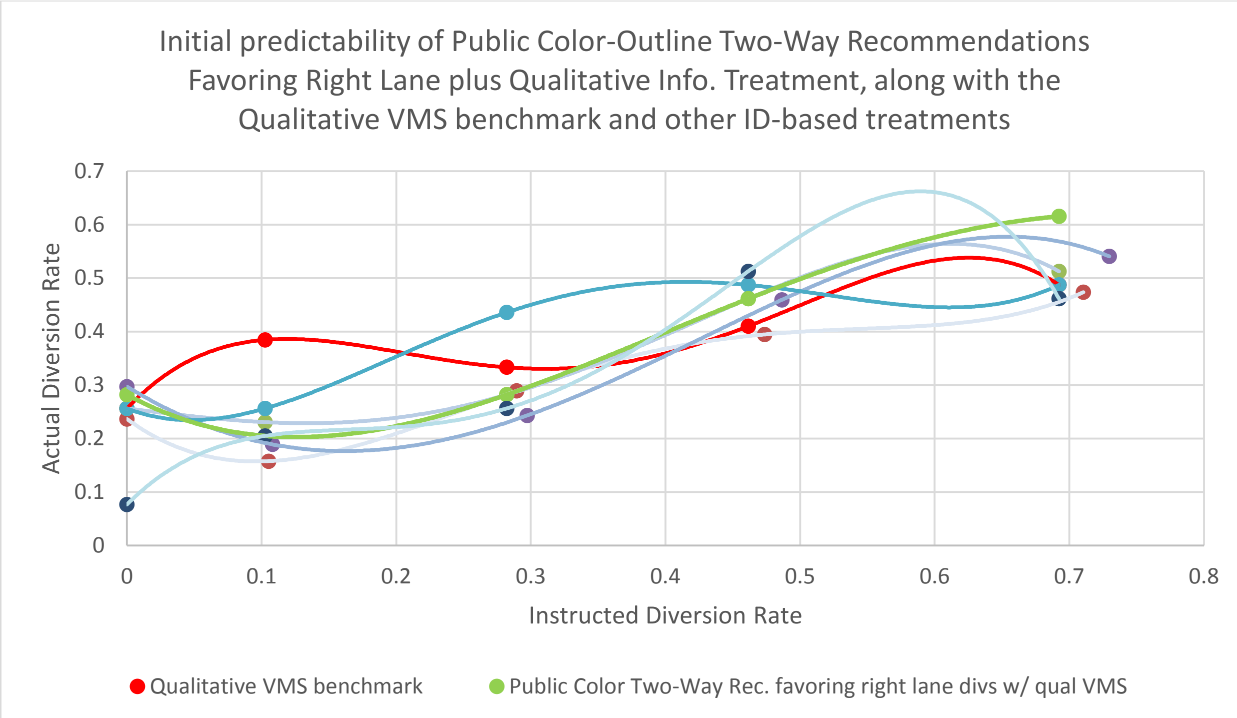
Modifying the wording of the diversion instructions significantly reduced over-diversion and improved the performance over most other ID-based instruction treatments. It is unclear why performance was so much worse on rounds with no incident.

This improvement in performance is accompanied by an equally significant improvement in compliance; a higher percentage of instructions are complied with for this treatment than any other.

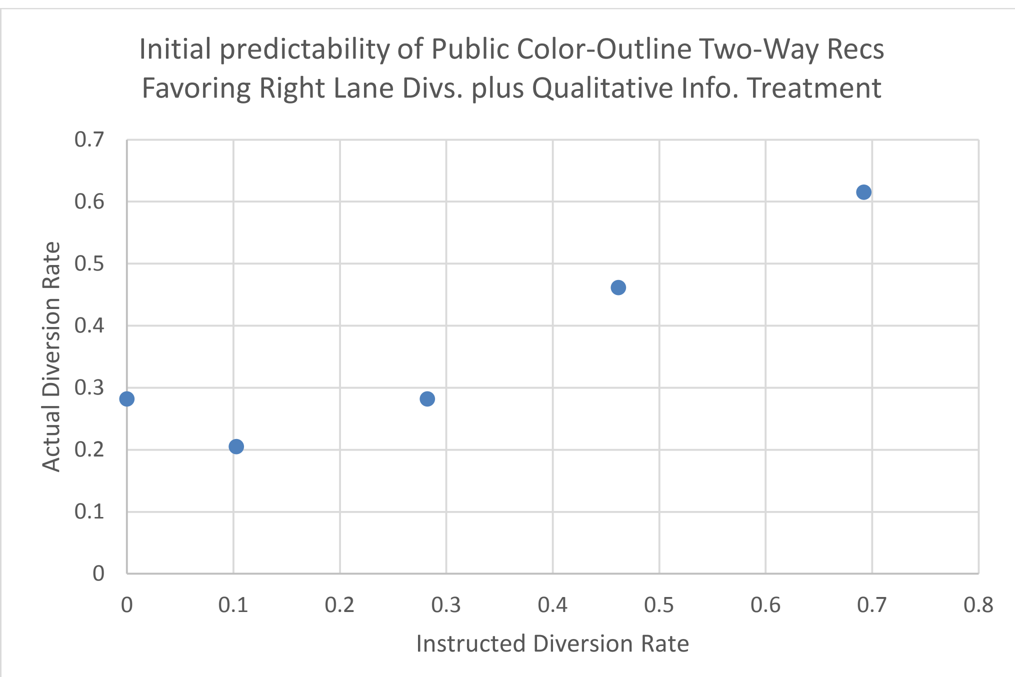


As with all other treatments that use public identifiers, compliance decreases over time for this treatment.

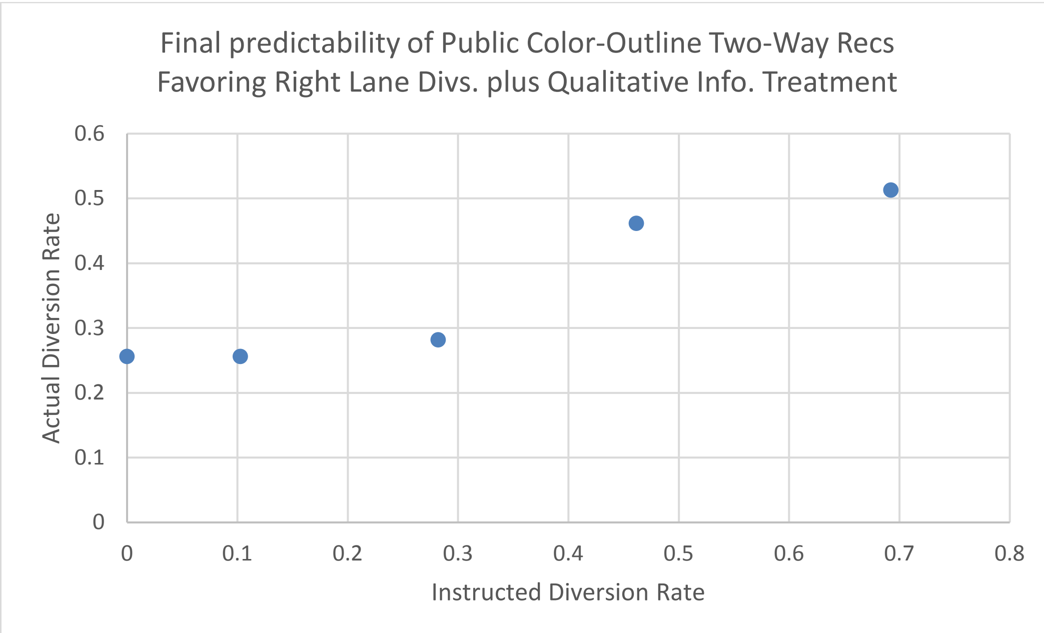
The initial predictability for this treatment is much better than that of any other ID-based recommendation treatment, and it is much better than that of the qualitative VMS only.



With the exception of the data-point from the round with no incident, the initial diversion response curve forms an almost perfect straight line.



Surprisingly, the diversion response curve for the final rounds was not as good as that of the initial round.



Though monotonic, the diversion response curve is somewhat flat.

The decrease in predictability coincides with a drop in performance; this treatment is one of the few whose final round performance that is worse than its initial round performance. However, the final round performance is still very good.

Treatment	Initial Delta	Final Delta
Public Color w/ Qual VMS, right lane, IFF	**25**	**85**

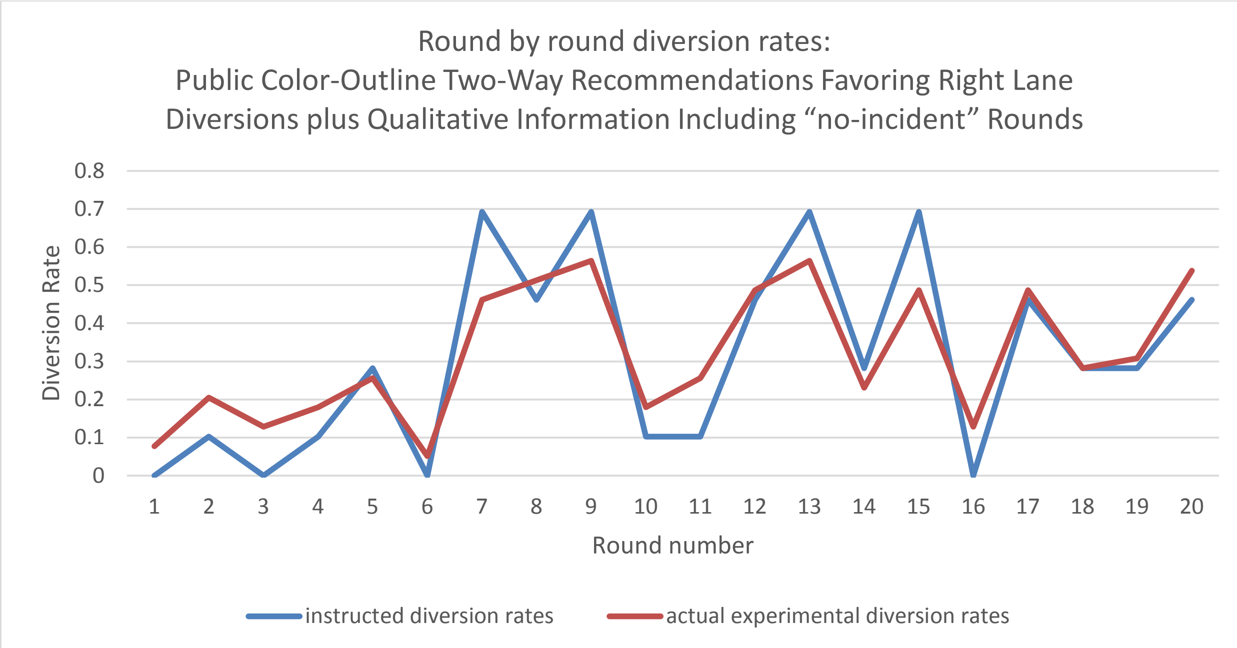
Lessons from Public Color-Outline Two-Way Recommendations Favoring Right Lane plus Qualitative Information Treatment:

- When subjects not told to divert are given explicit instructions to stay on the main route, compliance and performance are improved.

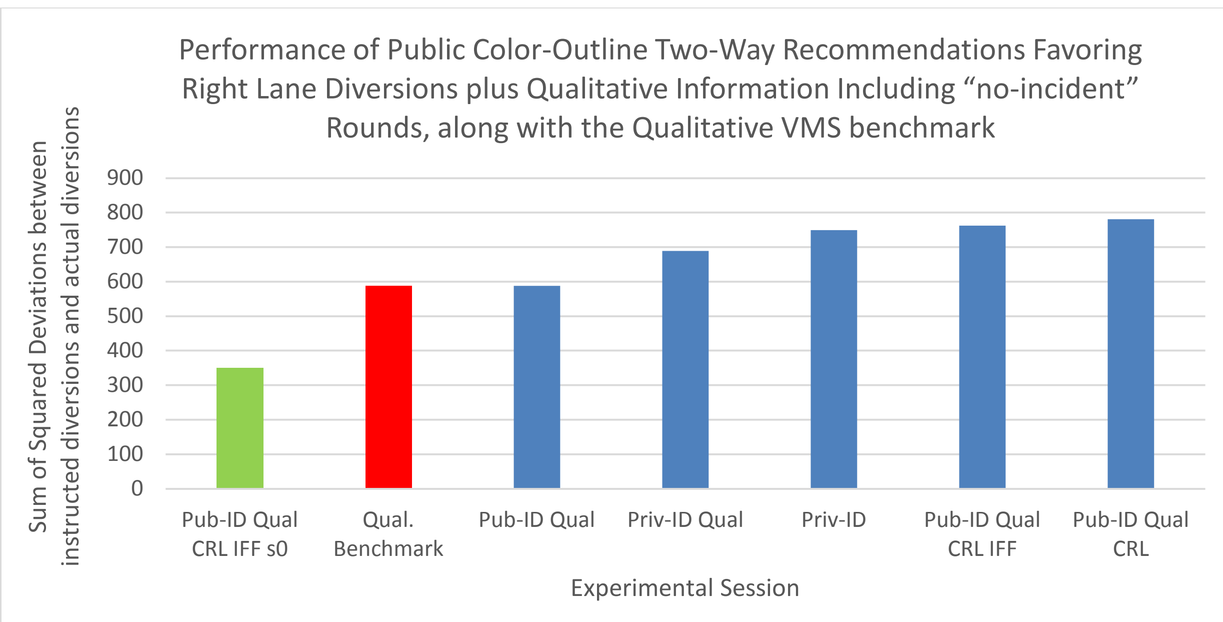
- It is possible however that this “intensive” messaging treatment might be adversely affecting performance when there is no incident. Higher compliance with instructions might result in more exploration during rounds with no incident, or might make subjects overly dependent on information.

7.3.6 Public Color-Outline Two-Way Recommendations Favoring Right Lane Diversions plus Qualitative Information Including “no-incident” Rounds Treatment (also referenced as IFF/Scen0, IFF s0, treatment PCSN)

This treatment extends the previous treatment where subjects predominantly in the right lane are provided with a public color outline, which determines which route they are explicitly instructed to take (IFF-style instructions) each round and a qualitative description of each incident present. The extension also provides instructions and incident information on rounds with no incident. Prior to this modification, subjects were not given any information on rounds with no incident. The goal of the treatment is to improve performance on rounds with no incident by reducing the number of subjects who divert on these rounds.

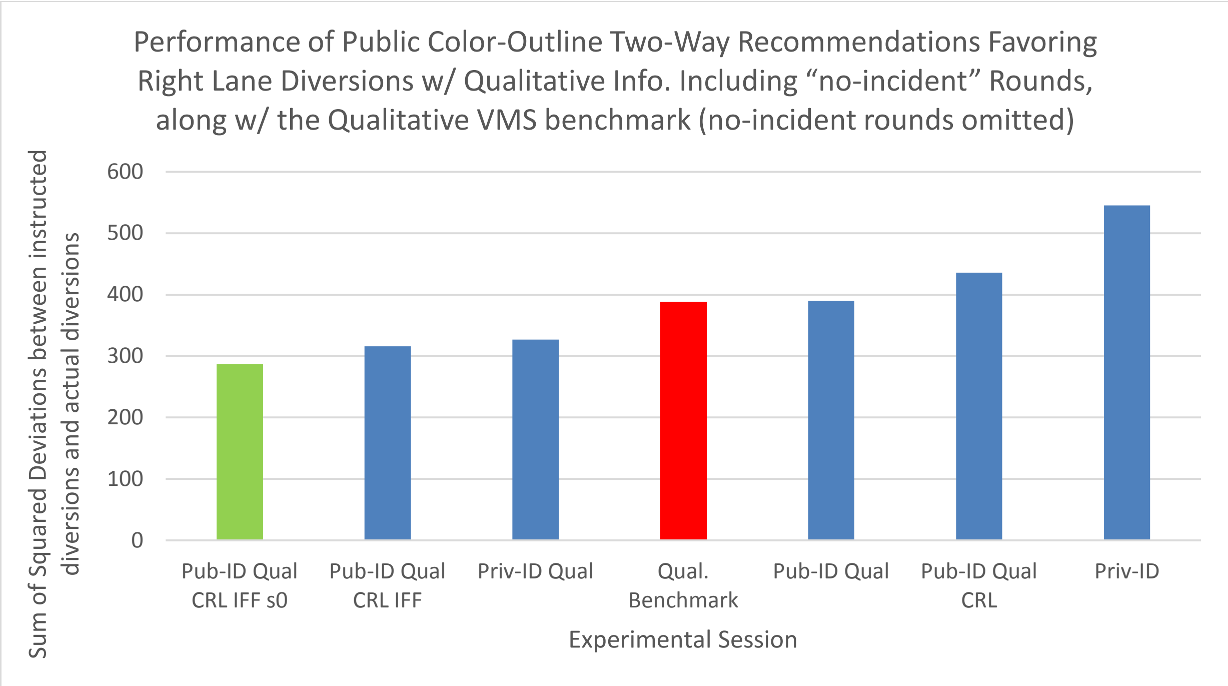


Giving instructions and information on the rounds with no incident dramatically improves overall performance; this treatment has the best overall performance of any treatment tested.



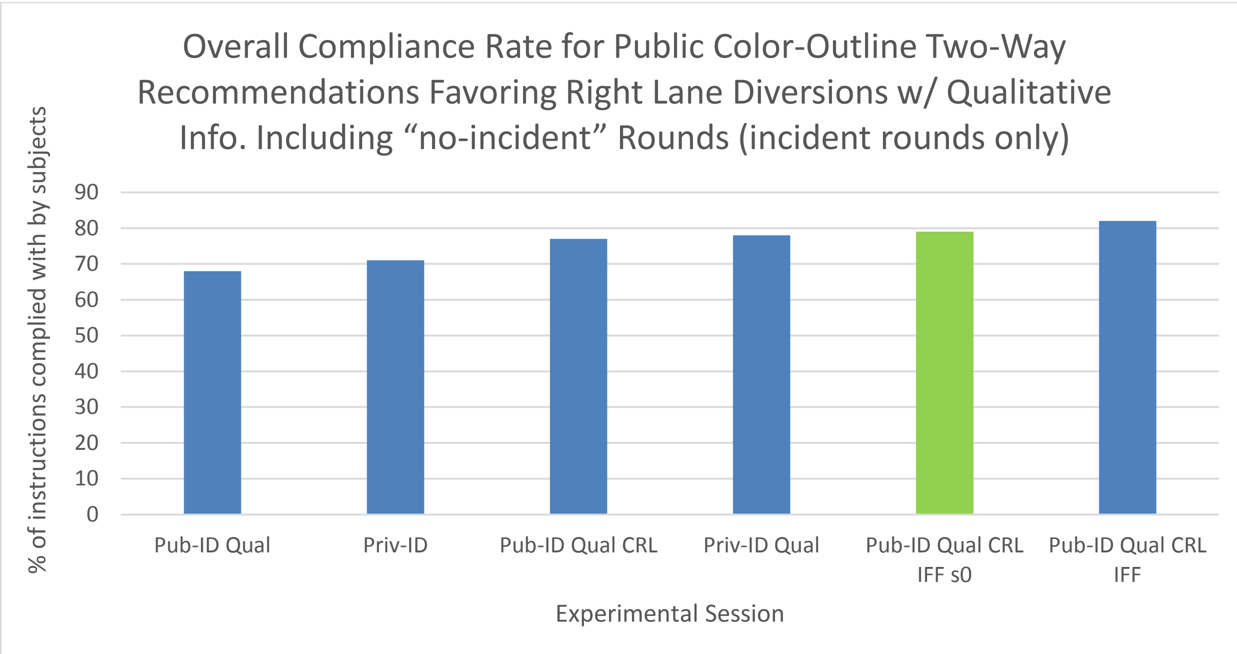
This suggests that in all other treatments, subjects either did not know that the main route always provides faster travel times with no incident, or did not know that a lack of messaging meant that there was no incident present.

Interestingly, this treatment is also the best performer when rounds with no incident are omitted.



The improvement in performance in rounds, with incidents relative to the prior treatment, (identical but lacking information on rounds with no incident) was not substantial enough to conclude that providing guidance on rounds with no incident can also help to improve performance on rounds with incidents. At the very least, however, it does not make performance on rounds with incidents worse.

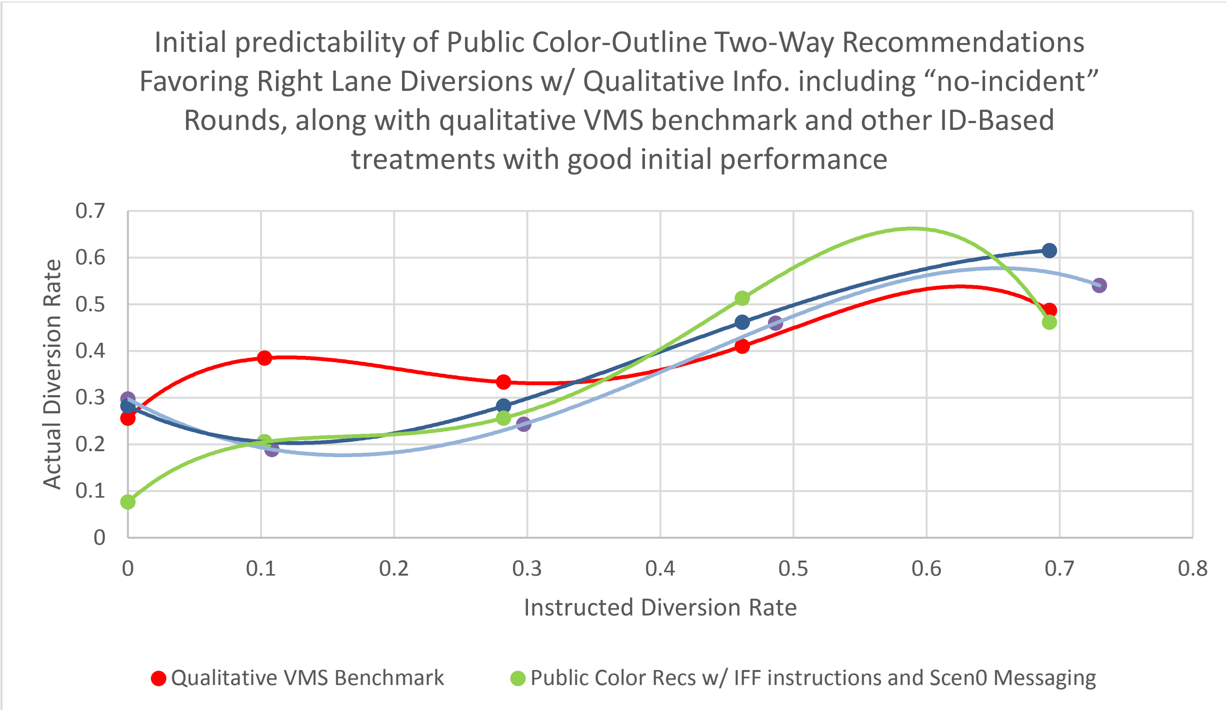
Although providing instructions and information for rounds with no incident-improved performance, it did not increase the compliance rate.



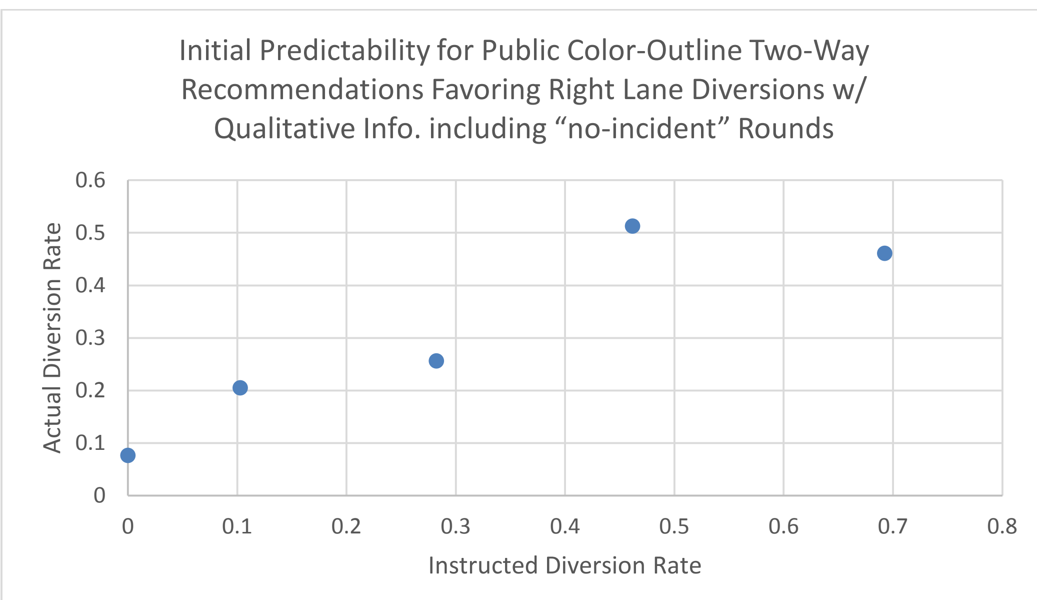
This is further evidence against the notion that providing VMS on rounds with no incident will improve performance on rounds with incidents.

As is the case for all other Public-ID-based diversion recommendation treatments, there was a drop-off between the initial and final compliance rates for this treatment.

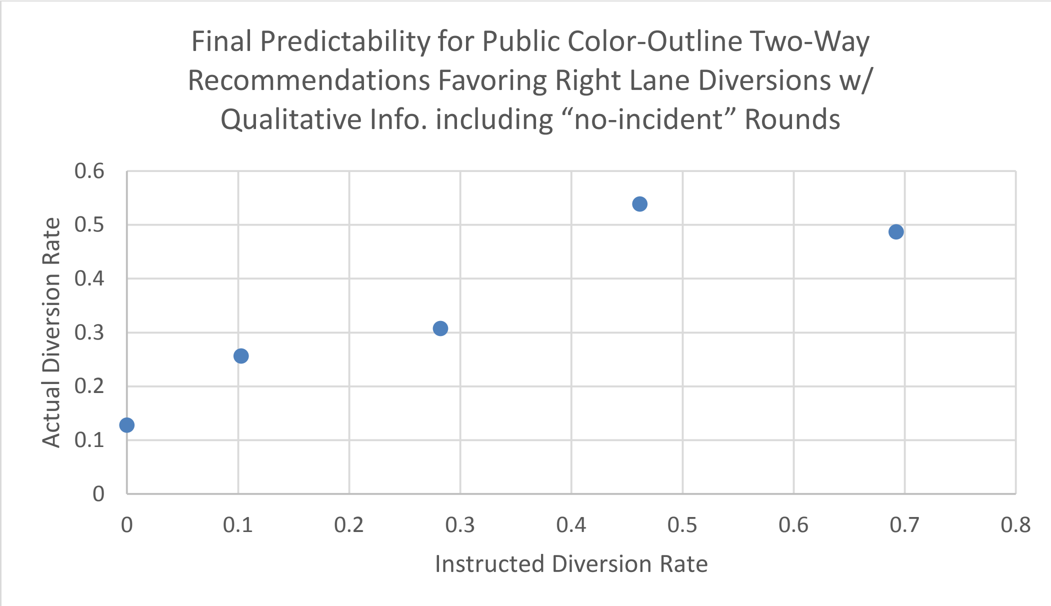
Surprisingly, the initial predictability for this treatment on rounds with no incident is not as good as that for other ID-based recommendation treatments. However, the data-point for the round with no incident improves the steepness and monotonicity of the initial diversion response curve for this treatment.



The initial diversion response curve for this treatment lacks smoothness and monotonicity due to slight over-diversion for the "major" incident followed by significant under-diversion for the "severe" incident.



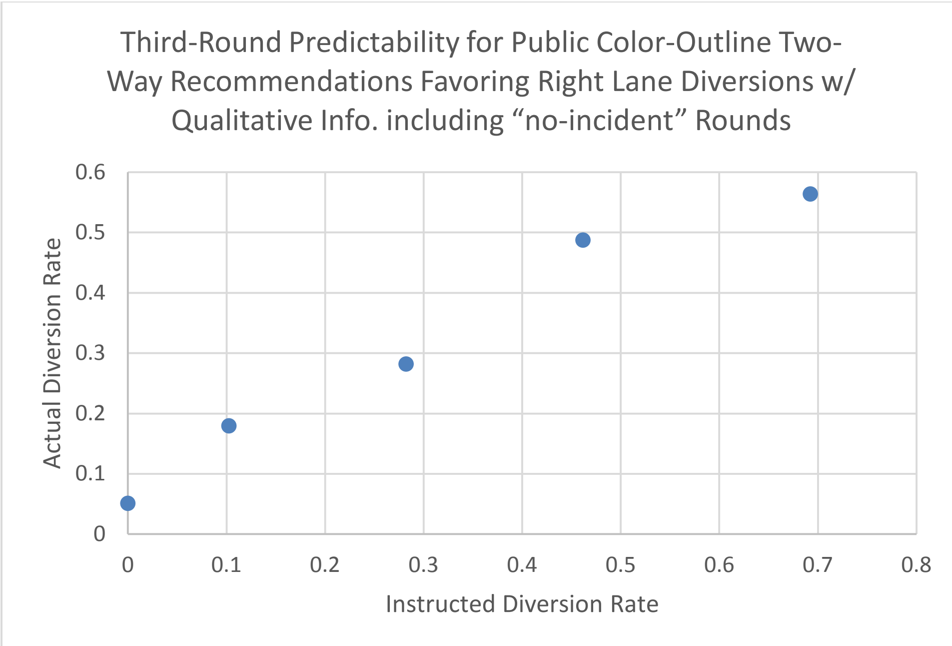
Surprisingly this non-monotonicity also occurs for the final diversion response curve; the same two incident types cause it.



It is difficult to reconcile the discrepancy between performance and predictability for this treatment. Although this treatment produced subject diversion rates that were closer to the optimum than that of any other treatment, it seems as though one cannot reliably achieve the desired diversion rate by adjusting the number of subjects told to divert – even once three rounds of learning for each incident type have occurred.

It is possible that the poor final round predictability was due to "bad luck" or exploration; by contrast, the diversion rates for "major" and "severe" incidents occurring during the second and third rounds of the treatment were much closer to the optimum.

The diversion response curve for the third round of each incident type, shown below, is excellent for this treatment.



Given these third-round results, it is difficult to determine whether, or not, late-round predictability is adversely affected by providing information to subjects on rounds with no incident.

Lessons:

- Providing messaging/instructions when there is no incident significantly improves performance on those rounds
- It is ambiguous whether performance and predictability concerning rounds with incidents is affected by the VMS provided on rounds with no incident.

Overall Lessons for ID-based recommendation treatments

- No matter how much information or verbal persuasion is given to subjects, perfect compliance with instructions seems to be unattainable.

- ID-based treatments are superior to static diversion-rate VMS treatments under all circumstances
- Although learning is hindered by ID-based recommendation treatments in all cases, superior initial performance can more than makes up for this drawback for certain implementations of this treatment, specifically private-ID recommendation with qualitative VMS treatments and ID-based treatments that provide explicit instructions both to subjects one wants to divert and subjects one wants to take the main route.
- If initial performance and predictability are a high priority, then ID-based recommendations will always be beneficial relative to qualitative-VMS-only treatments.
- If longer-term performance is important as well, ID-based recommendation treatments can be beneficial when combined with VMS and explicit instructions to both subjects one wants to divert and subjects one wants to take the main route.
- Private-ID-based treatments are preferable to Public-ID-based treatments.
- Explicitly instructing drivers to use the main route in addition to just the alternate route will improve compliance and performance
- Giving information and instructions to subjects when there is no incident greatly improves performance as well.
- Providing instructions to divert primarily to subjects in the right lane does not improve performance, but does increase diversion rates.

Suggested future treatment: Private-ID-based Recommendations with qualitative incident information, explicit instructions pertaining to both the main and alternate route, and VMS for rounds with no incidents.

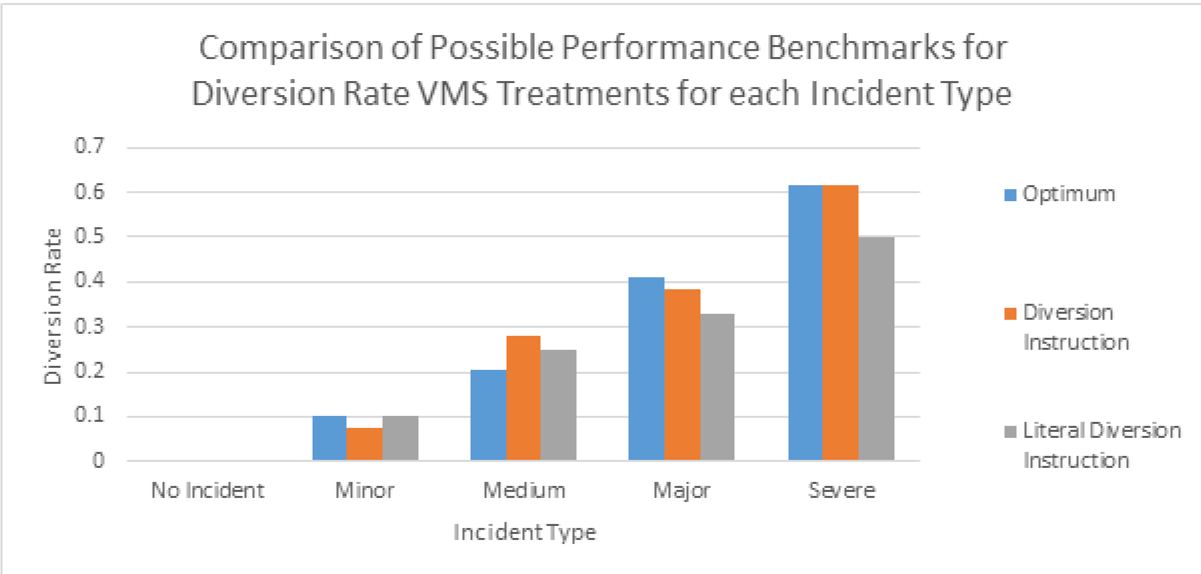
7.4 VMS Displaying Desired Diversion Rate (group DR):

For these treatments, VMS messaging displays the desired diversion rate. For example, during "minor" incidents subjects are told that 1 in 10 should divert, and during "major" incident, subjects are told that 1 in 3 should divert. As with the qualitative VMS treatments, displaying the desired diversion rate should enable subjects to uniquely identify each incident type and both respond and learn accordingly. An added feature is that displaying the optimal diversion rate removes the need for subjects to make an initial guess at what the ideal diversion rate should be for each incident type.

Of course, subjects are still faced with the challenge of coordinating amongst themselves to achieve this optimal diversion rate, however. Rational subjects, however, could play a strategy in which they divert with a probability equal to the known diversion rate and in aggregate achieve close to the optimum.

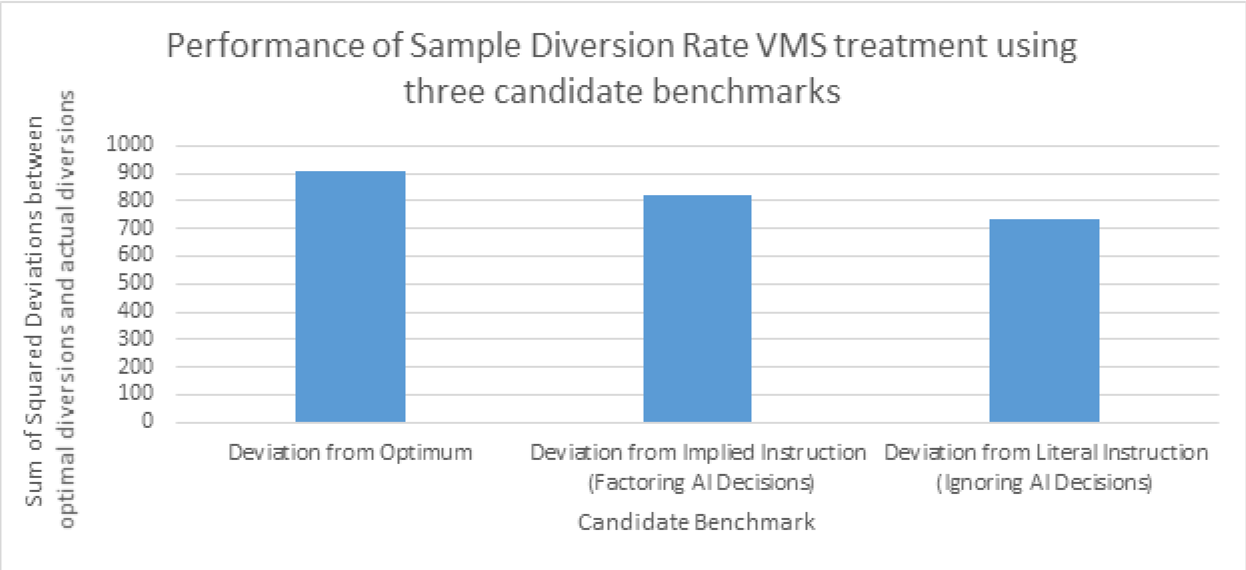
The results from these treatments were the most difficult to analyze and interpret, for two significant reasons. One reason is that at the time these sessions were run, we were mistaken about what the optimal diversion rates were due to an error in our simulation. Therefore, the fractions we display do not always correspond to what we now know are the true optima; this could lead to a conflict between what the displayed optimal diversion rate conveys and what subjects are learning about the optimum based on their experiences. Secondly, there are always a dozen artificial intelligent (AI) vehicles at the front of the platoon whose pre-programmed diversion rates do not match the displayed optimal diversion rate. The diversion rates we display each round factor in these vehicles, and thus reflect the assumption subjects would also consider these AI vehicles when attempting to coordinate to reach the optimal diversion rate. If this assumption is incorrect, and if in reality subjects are able to recognize and ignore the AI vehicles and only coordinate amongst themselves, then subjects would be attempting to coordinate on incorrect diversion rate.

Therefore, performance in these rounds could be feasibly evaluated based on a comparison of actual subject diversion rates to one of three different references: the true optimal diversion rates (considering AI diversions), the "implied" VMS diversion rates relevant to subjects once AI diversions are taken into account, and the “literal” VMS diversion rate that ignores AI behavior. A comparison of these benchmarks is shown below:



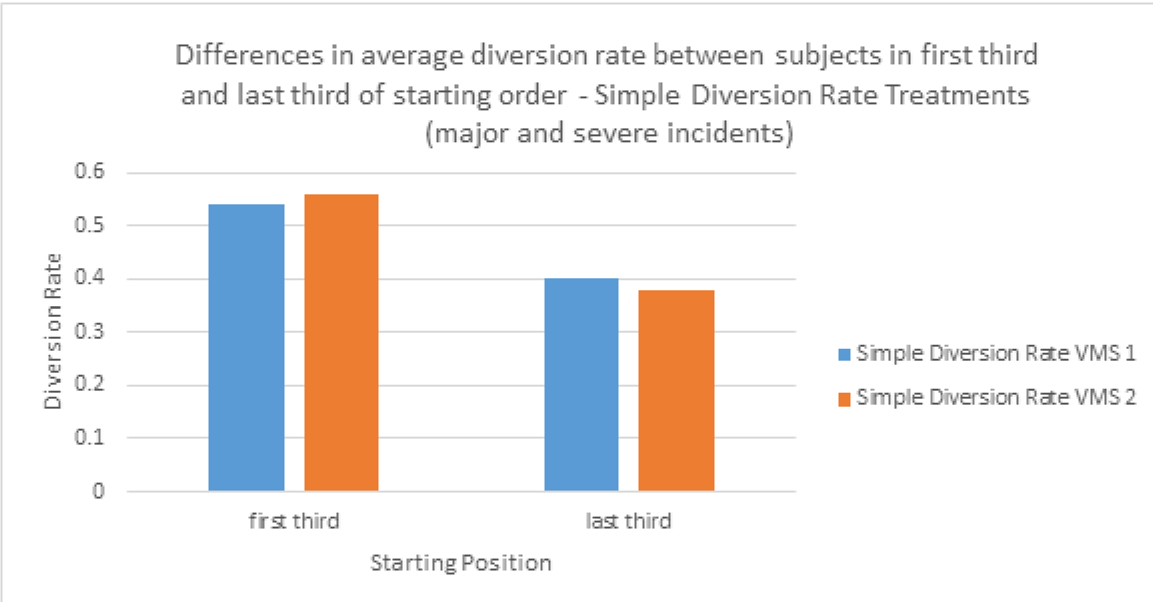
All, but the “Minor” and “No Incident” scenarios, have significant discrepancies among benchmark diversion rates; the literal interpretation of the diversion rate is significantly different from the optimum in the “Major” and “Severe” incident types, and the “diversion instruction” interpretation that considers AI decisions is significantly different from the optimum for the “Medium” incident type.

The graph below shows how much the performance metric (sum of squared deviations between actual diversion rate and benchmark) can vary based on which benchmark is used. The experimental diversion rate data comes from the most basic of the diversion rate VMS treatments and are compared to the three possible benchmarks.



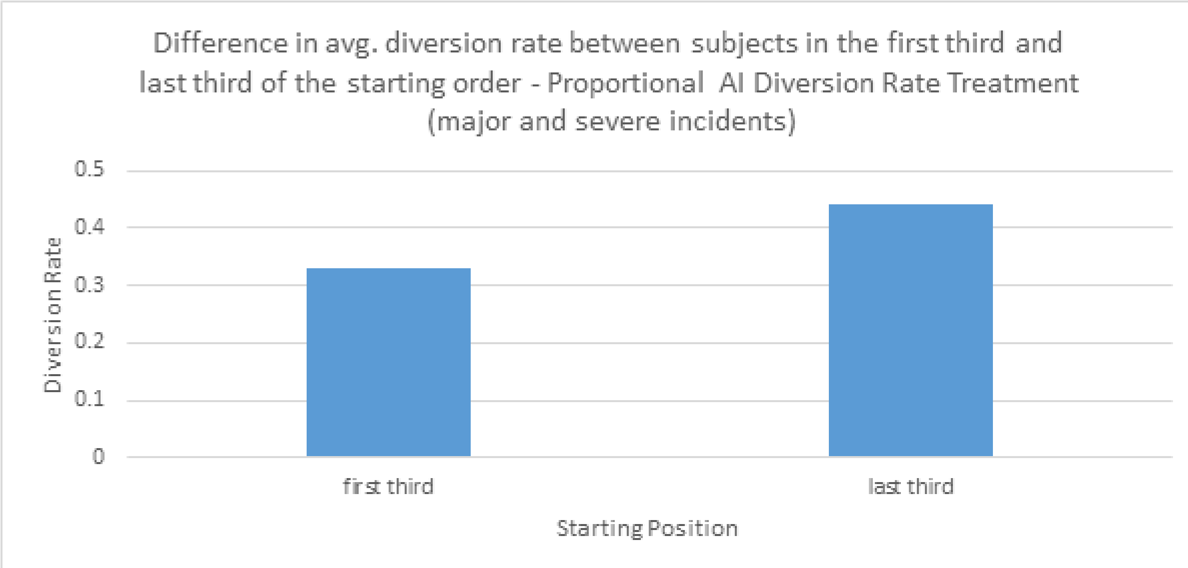
The discrepancy between these performance measures should be considered when making comparisons among diversion rate VMS treatments and between diversion rate VMS treatments and other types of treatments, especially qualitative-VMS-only treatments.

To investigate whether subjects seemed to ignore non-diverting AI up front or factor them into decision-making, the spatial pattern of diversions for diversion rate VMS treatments was examined. If subjects really were taking non-diverting AI at the front of the platoon into account, then for incidents that called for high diversion rates, one would expect subjects towards the front to have the highest diversion rate. This is because they are the ones observing all the AI vehicles that remain on the main route, and would react to this perceived under-diversion by choosing the alternate route. One would then expect subjects furthest towards the back, who see no AI vehicles, to have much lower diversion rates. To see whether this pattern is observed in the data, two of the most basic diversion rate VMS treatments were analyzed. The graph below shows the diversion behavior of the first third and last third of subjects by starting position.



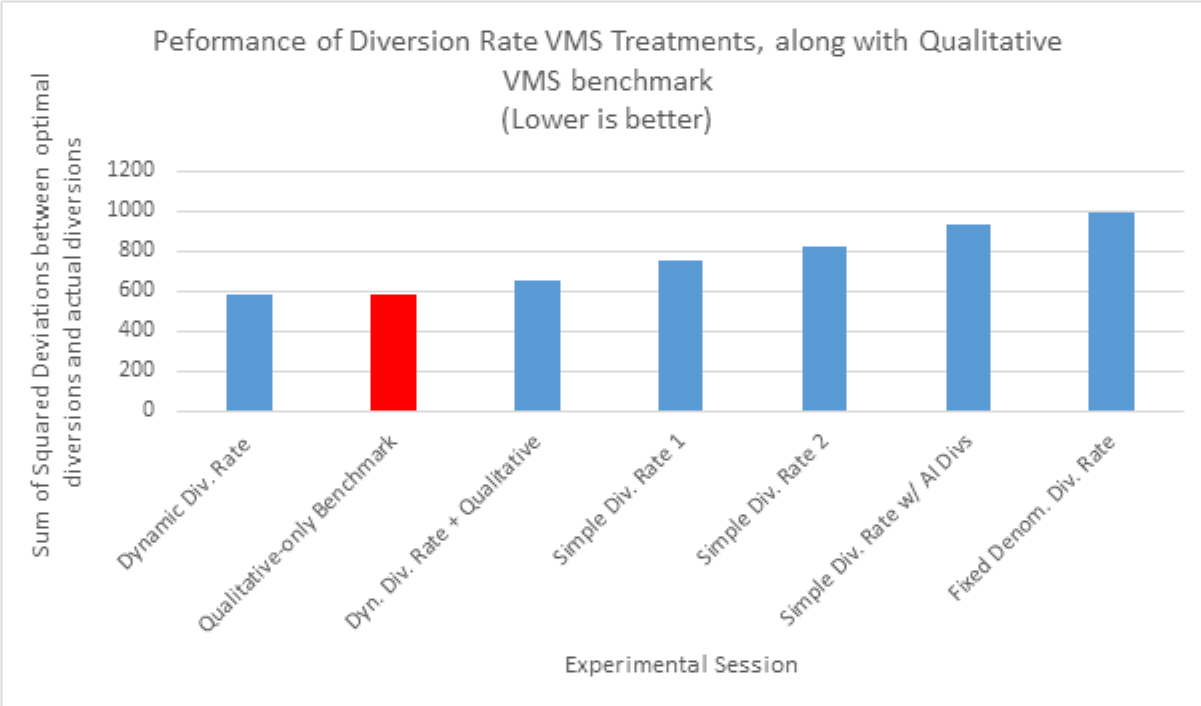
The diversion rates from the data conform to the pattern described above, where the vehicles closest to the front divert in a much higher proportion than vehicles in the back. This is evidence that subjects are incorporating the behavior of AI in the front of the platoon into their decision-making.

To be even more confident that this is the case, an additional experimental session was run in which the AI vehicles up front divert in the same proportion recommended by the VMS. With this treatment, the “literal” vs “implied” diversion rate benchmarks would be identical, since the number of subjects who should optimally divert is the same in both cases. For this treatment, one would expect no drop-off in the diversion rate between the subjects up front and those in the back during high-diversion rate incidents.



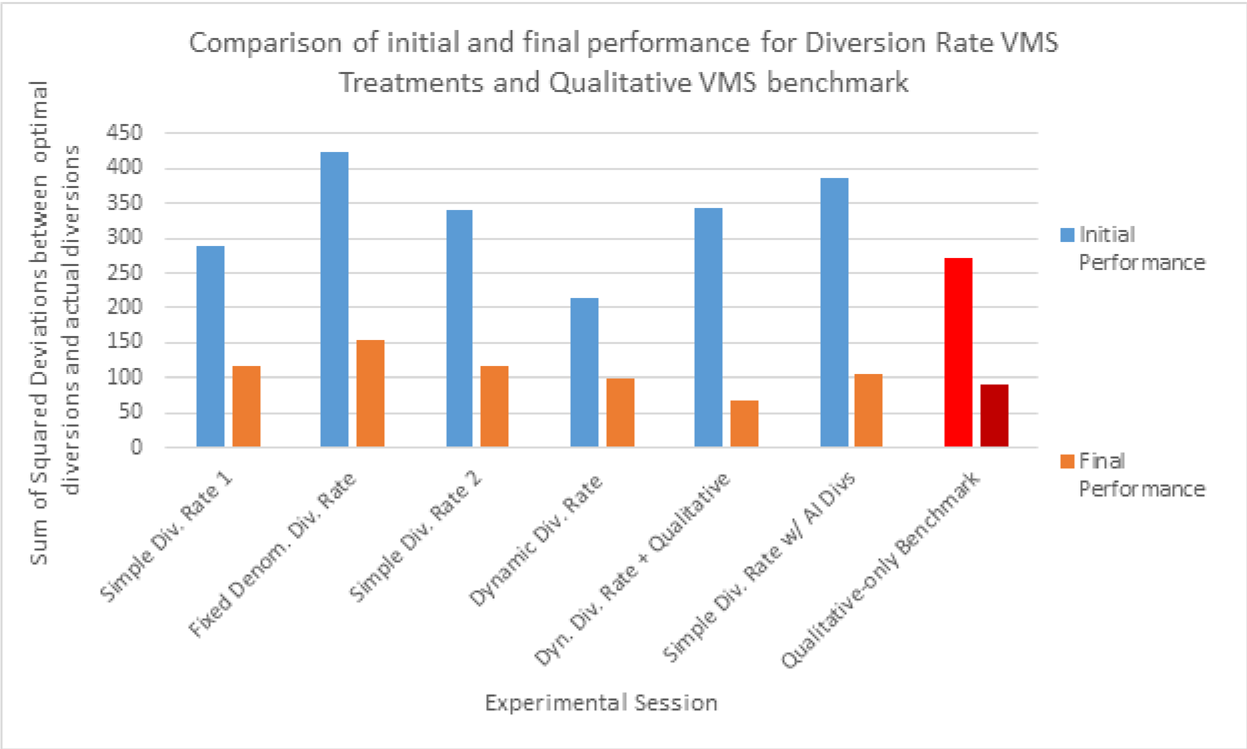
As expected, there was no drop off between vehicles in the first and last third of the starting queue. In fact, the vehicles towards the back diverted at an ever higher than those at the front. This makes it all the more significant that we found higher diversion rates among front vehicles compared to rear vehicles in typical Diversion Rate treatments with a constant number of non-diverting AI. Given this strong evidence for the conclusion that subjects able to observe non-diverting AI (i.e. subjects up front) are more likely to divert than those who cannot (subjects at the back), the "implied" diversion rate benchmark is chosen for performance analysis rather than "literal" diversion rate benchmark.

Several versions of this treatment design were run with varied wording and information. There was significant variation in the performance of these treatments; once again, the squared differences between the actual and optimal results for the worst session were nearly twice that of the best. Surprisingly, all but one treatment performed significantly worse than the qualitative-VMS-only benchmark.



Although these treatments provided more information than the benchmark qualitative-VMS-only treatment and theoretically should have performed better, it appears as though being given known fractions to coordinate on was actually a hindrance to subjects. Thus, subjects did not employ the optimal mixed strategy in which each subject diverts with a probability equal to the displayed desired diversion rate. It is possible that subjects attempted to dynamically coordinate amongst themselves, so that the fraction of diverters in their respective fields of view visibly matched the fraction given. It is unclear whether the significant mis-diversion in these treatments results from flawed beliefs about which route other subjects will choose, whether subjects are unable to perceive the proportion of diverting vehicles around them, or whether attempting to coordinate visibly in real-time is counterproductive.

In either case, the use of fractions does not seem to inhibit the ability of subjects to learn. Performance still rapidly improves in these treatments.



This means that whatever is responsible for poor performance in Diversion Rate VMS treatments is present from the start.

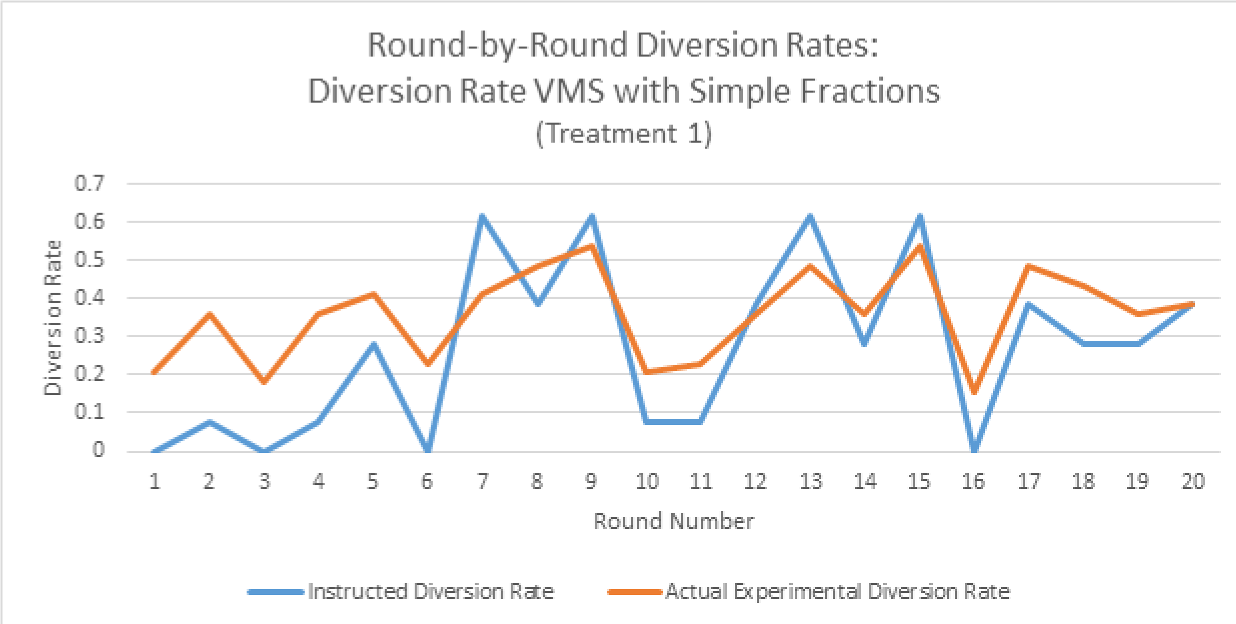
There was significant variation in both the initial and final predictability of these treatments, depending on the specific modifications made to the information provided. It is too difficult to characterize the predictability for this entire class of treatments with one comprehensive graph, so predictability for these treatments will be examined on a case-by-case basis in the specific section for each treatment variation.

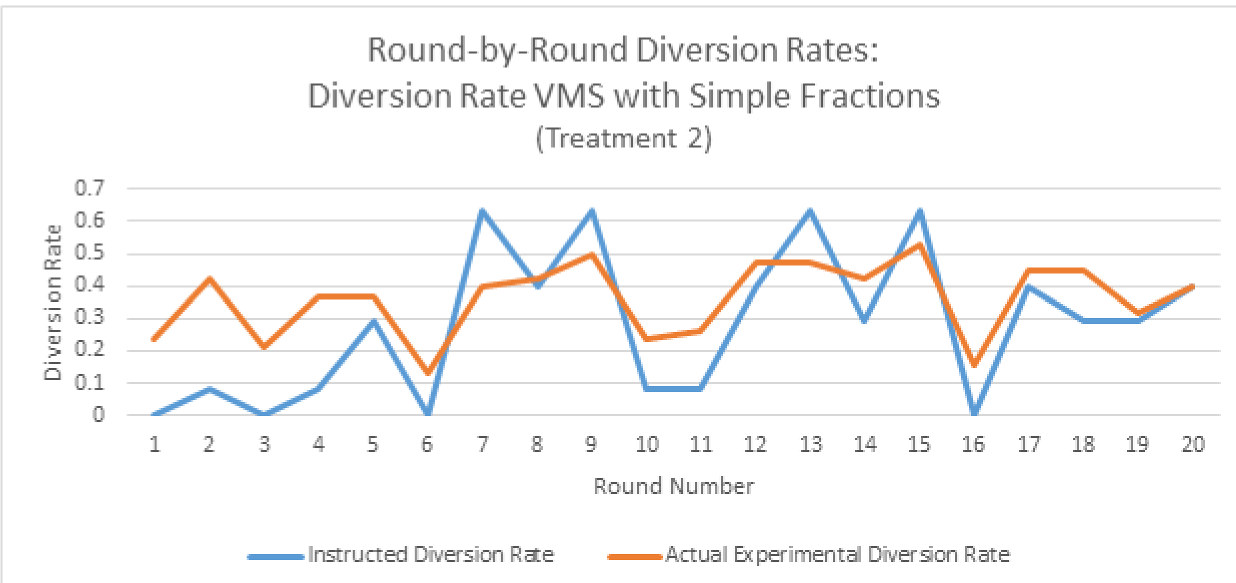
Although Diversion Rate VMS treatments do not perform as well as the Qualitative VMS benchmark, many useful insights can be gleaned from the results of these treatments that are applicable to other types of VMS treatments.

7.4.1 Optimal diversion rate using simple fractions (treatment DR):

This treatment is the most basic implementation of Diversion Rate VMS. Depending on the type of incident each round, subjects are informed of an incident and the desired diversion rate is displayed. The format of the fraction uses a "1" in numerator (e.g. 1/10, 1/4, 1/3, 1/2). This fraction remains static throughout the whole round, regardless of subject behavior.

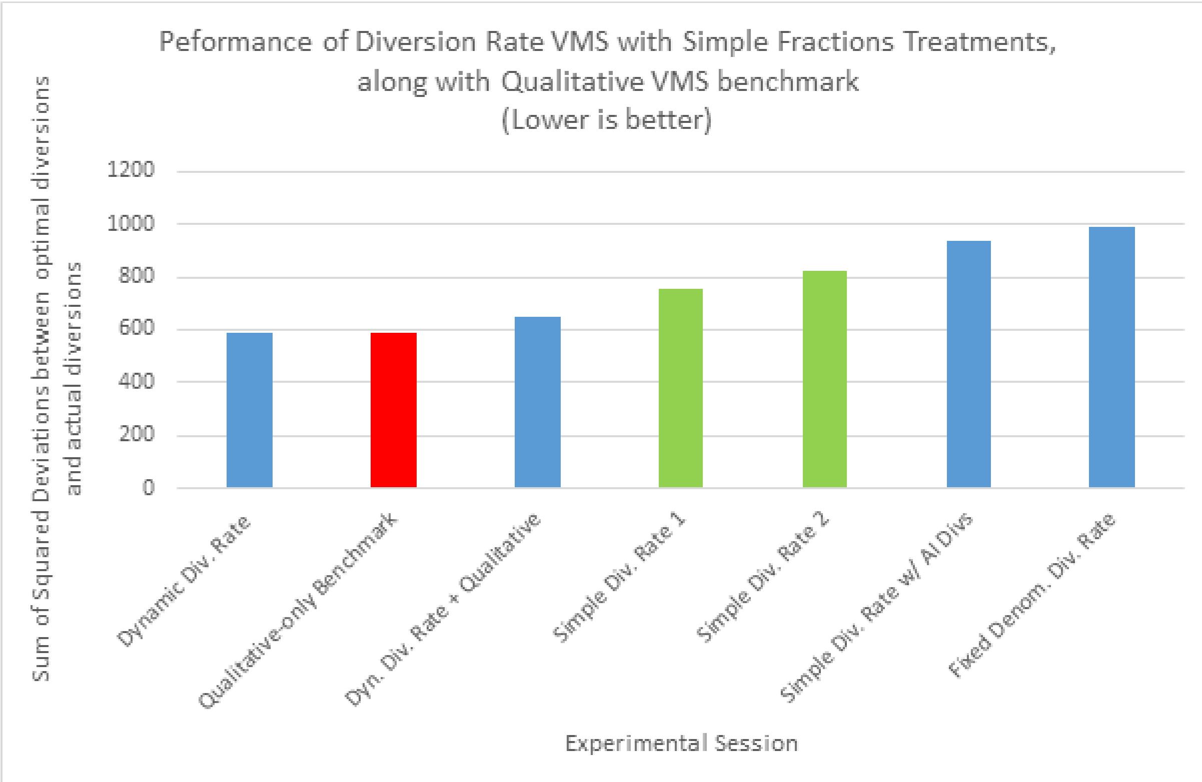
This treatment was conducted twice in the same exact fashion. Rather than comparing the diversion rates of subjects each round to the optimal diversion rates, we compared the subject diversion rates to the instructed diversion rate. We also used this performance benchmark for the Qualitative VMS reference treatment for the purpose of comparison. The instruction and optimal diversion rates are similar enough to where the results are not substantively changed by switching between the two.



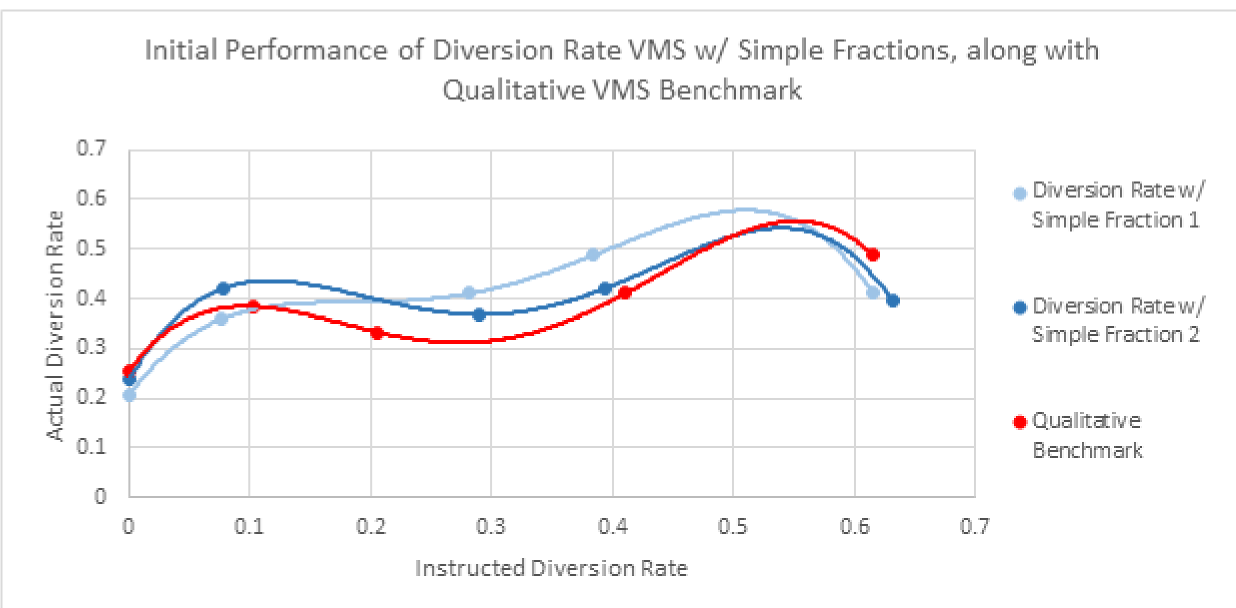


The patterns for the two treatments are very similar. In both cases, there was significant over-diversion for less severe incidents and significant under-diversion for more severe incidents.

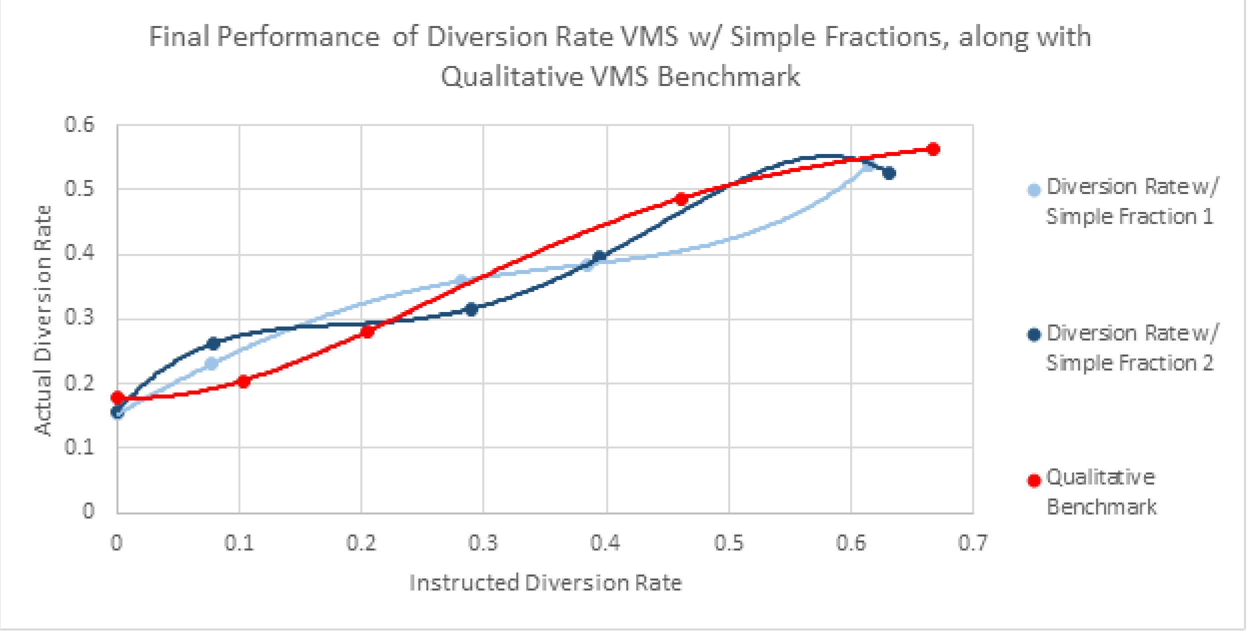
Both treatments performed significantly worse than the Qualitative VMS benchmark.



The initial predictability of these treatments are poor. The curves are nearly flat and there is significant non-monotonicity. The qualitative VMS benchmark is not much better, but the curve is slightly less flat.



The final diversion response curve is much smoother and steeper, reflecting the learning that has occurred. As with the initial predictability, however, the final predictability of the diversion response curves for diversion rate VMS treatments are not as smooth and steep as those of the qualitative VMS benchmark.



The overall nature of diversion responses was not dramatically different for this treatment from those of the qualitative VMS benchmark. Mis-diversion seemed to occur on the same rounds and in the same direction for the two types of treatments, but was slightly too moderately worse for diversion rate VMS treatments in most cases.

Lesson:

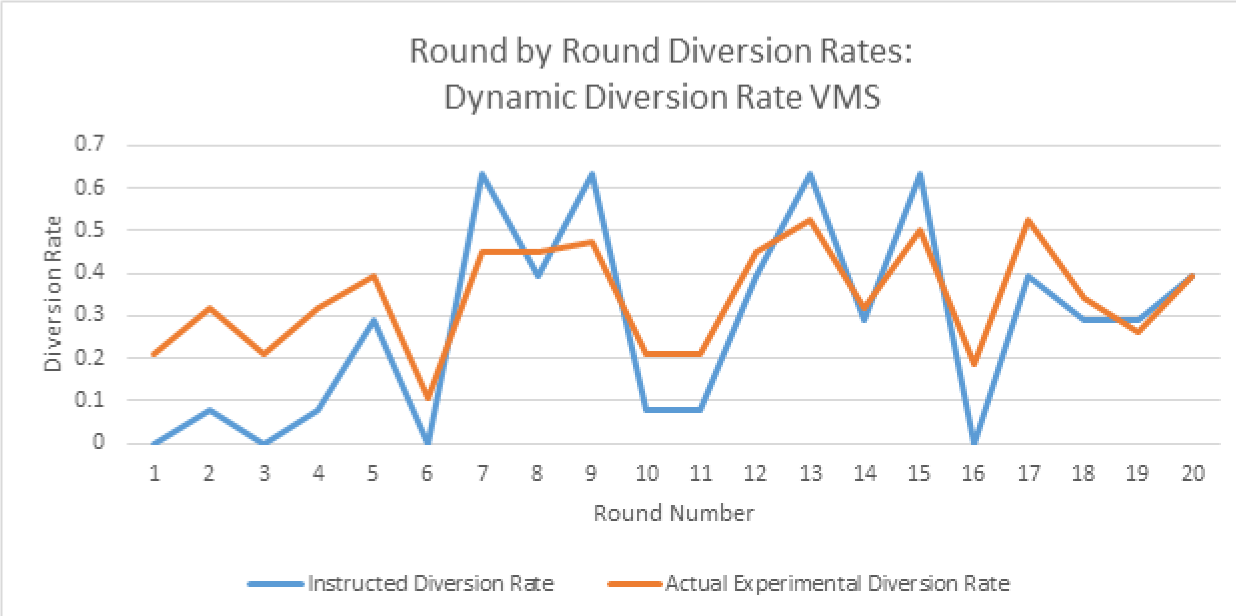
- Fixed diversion rate recommendation treatments are an ineffective treatment for achieving accurate or predictable diversion rates compared to qualitative incident descriptions.

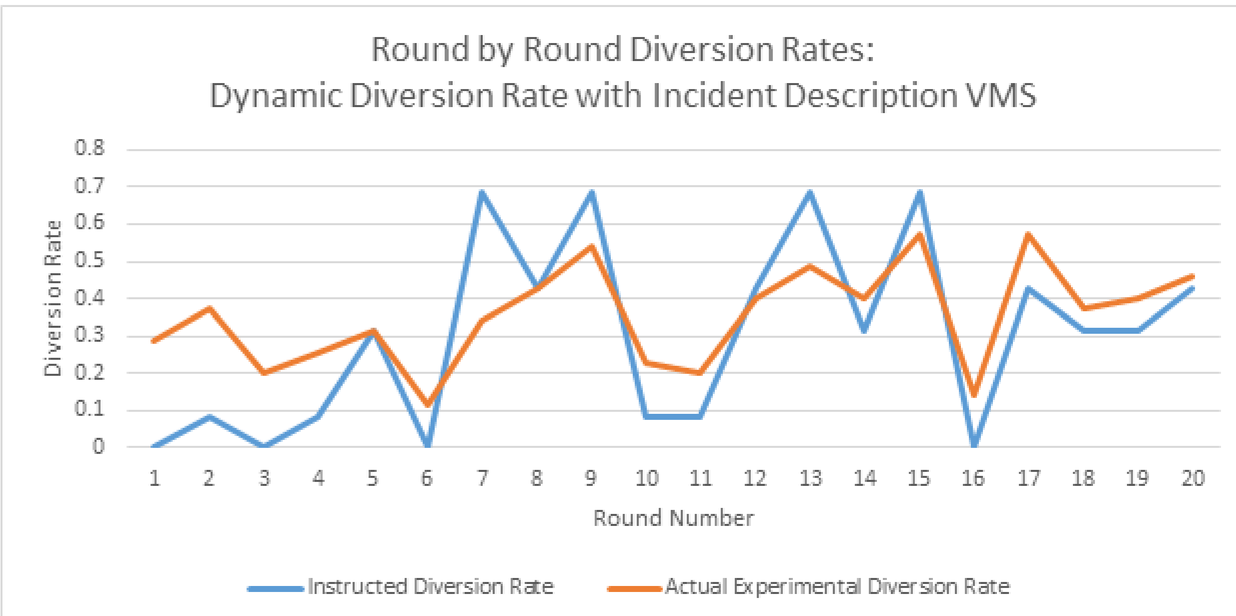
7.4.2 Dynamic diversion rate (treatment DDR)

This treatment modifies the previous treatment by dynamically adjusting the recommended diversion rate displayed by VMS. If over-diversion is occurring, the displayed diversion rate will adjust downward to reflect the new optimal diversion rate among the subject who have yet to reach the exit. If under-diversion is occurring, the displayed diversion rate will adjust upward.

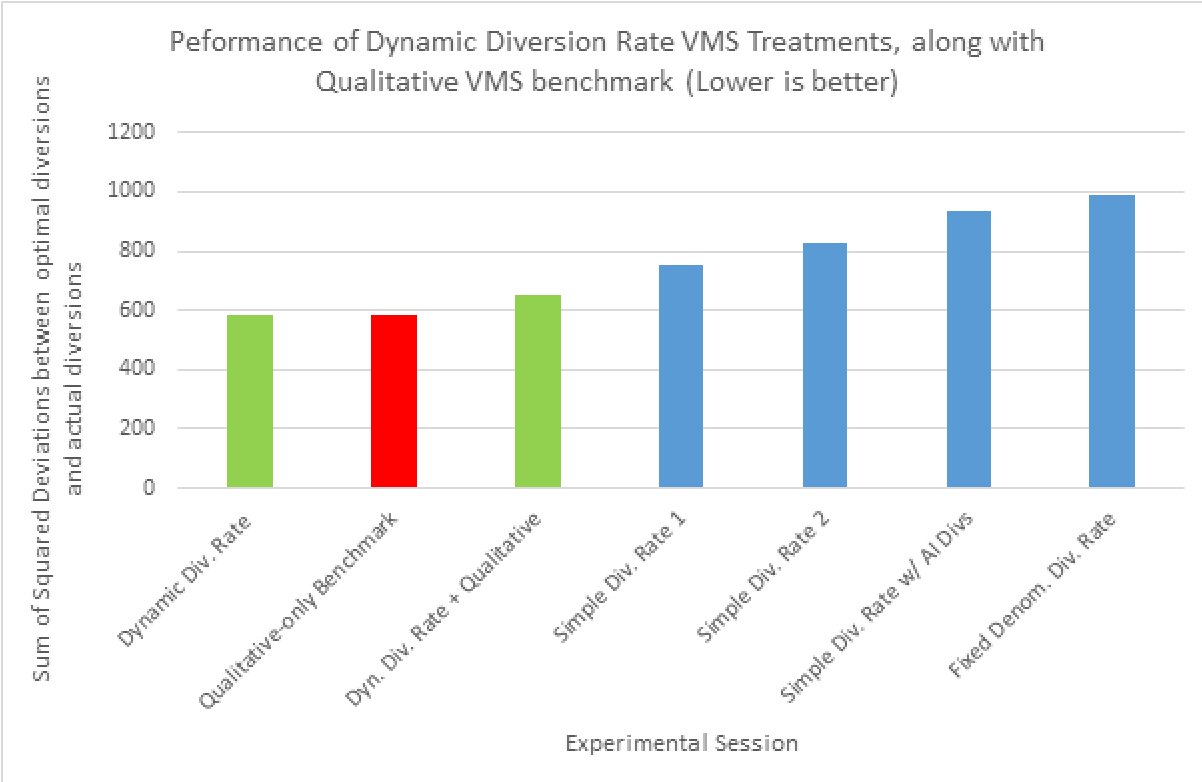
A significant advantage of this treatment is that it can help to prevent significant mis-diversion during early rounds before subjects have had sufficient learning experience. Much of the coordination challenges are resolved, since the dynamic nature of the rate display can help correct for errors. Furthermore, reinforcement learning might be accelerated since subjects have instant feedback mapping the behavior of other visible drivers to whether over-diversion or under-diversion is occurring.

Two versions of this treatment were implemented; one that supplements the diversion rate with a message informing subjects of an incident (just like in the aforementioned static diversion rate treatment), and one whose supplemental information consists of a qualitative description of the incident.





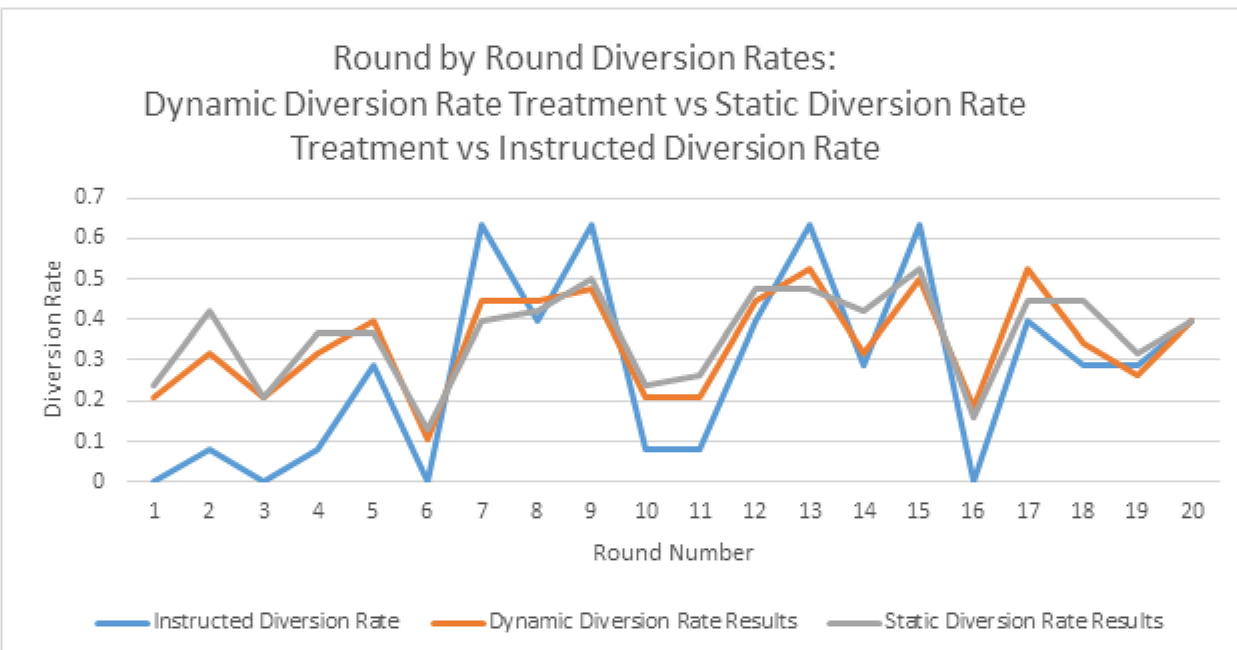
These treatments significantly improved performance of diversion rate messaging, showing much lower deviation from desired diversion rates than the two previous static diversion rate treatments.



The dynamic diversion rate VMS treatments still do not show improvement over the qualitative VMS benchmark, however. This is possibly due to the following reasons:

One is that displaying the desired diversion rate was already shown to be less effective than providing qualitative VMS only, so although making the diversion rate dynamic improved its performance, it wasn't enough to overcome the inherent disadvantage of diversion rate VMS. More importantly, the implementation of the dynamic rate was far from optimized. The threshold for the displayed diversion rate to begin changing was too high, so that the displayed rate often only changes for a relatively small fraction of subjects towards the back – and often didn't change at all even for significant mis-diversion. Furthermore, the presence of non-diverting AI at the front of the platoon of vehicles led to occasional initial recommendations that were counter-productive (i.e. instructions to divert even with over-diverting subjects) and made it very difficult for the diversion rate to adjust downwards in response to over diversion. Lastly, once the displayed diversion rate does begin changing, it can continue to change rapidly as subjects make their decisions, which may confuse other subjects. In summary, the fact the dynamic diversion rate was able to improve performance even slightly is impressive due to the limited opportunity it had to work.

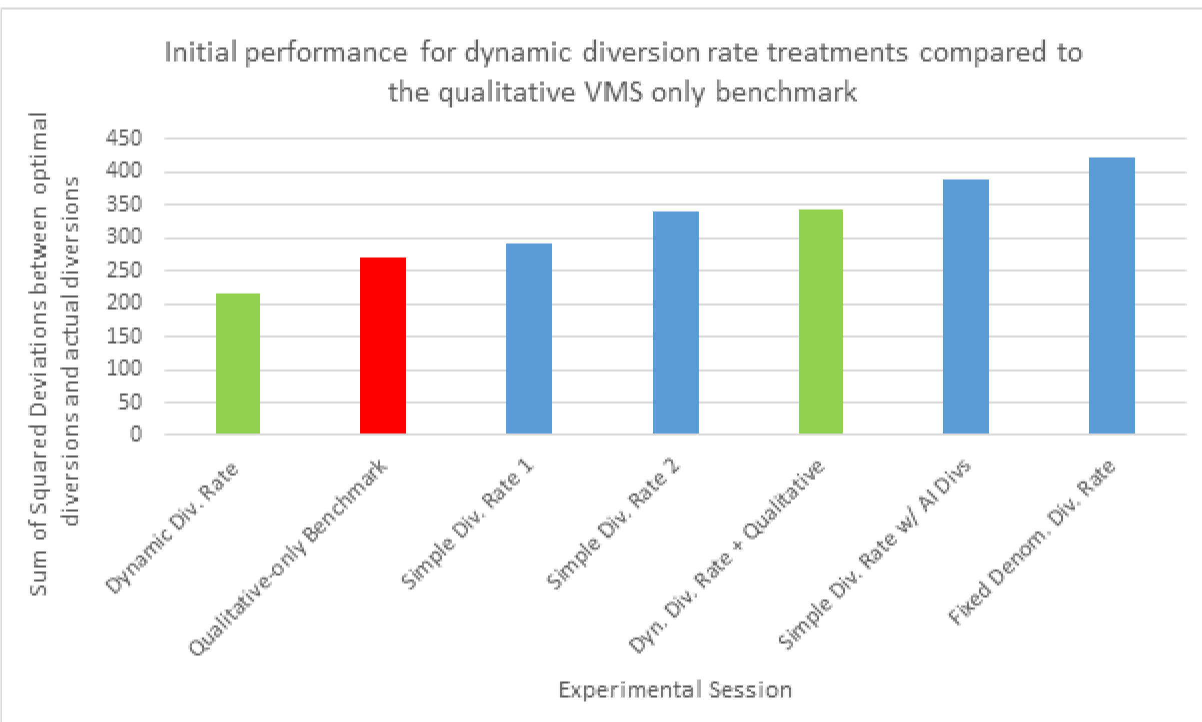
The most straightforward assessment of whether dynamic feedback results in an improvement in performance is to compare the dynamic diversion rate only treatment to the static diversion rate treatment.



With a couple exceptions, the dynamic results were generally equal or closer to the optimum than the static diversion rate, showing the dynamic feedback is clearly improving performance. There were about 7 or 8 rounds out of 16 possible in the static diversion rate treatment where the dynamic rate would have changed at all had it been implemented.

By contrast, there were only about three rounds of out 16 possible in the qualitative VMS only treatment where the dynamic rate would have changed had it been implemented. This is because qualitative VMS treatments induced diversion rates that were closer to the optima. Therefore, it makes a comparison between the dynamic diversion with qualitative VMS treatment and the qualitative-VMS-only treatment very difficult. Overall, the two treatments had very similar results.

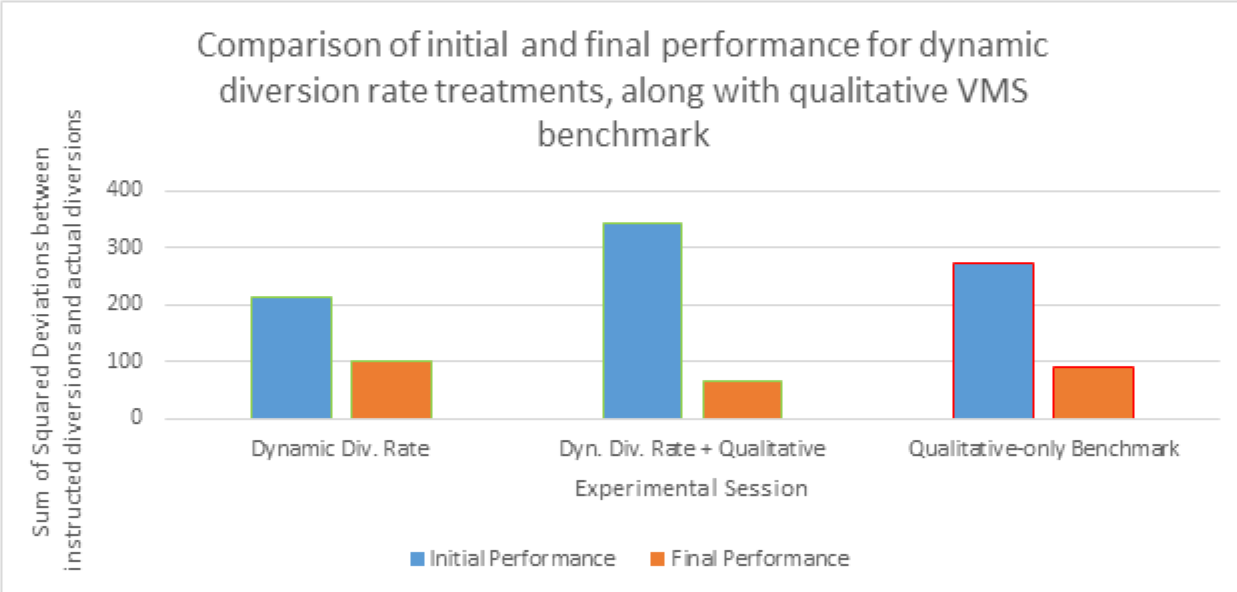
The two treatments offered mixed results regarding the hypothesis that dynamic diversion recommendations would improve initial diversion performance by providing immediate feedback on mis-diversion to obviate the need for reinforcement learning over several rounds. The graph of initial performance below both supports and contradicts this conjecture:



The dynamic diversion rate only treatment has the best initial performance of all the diversion rate treatments, and even surpasses that of the qualitative-VMS-benchmarks. However, the dynamic diversion rate plus qualitative VMS does significantly worse initially. This initial result for the dynamic diversion rate plus qualitative VMS treatment is driven almost entirely by the first “severe” incident encountered by subjects, during which there is worse under-diversion than any in other treatment conducted as part of this project. Ironically, that is the very situation that dynamic feedback aims to prevent.

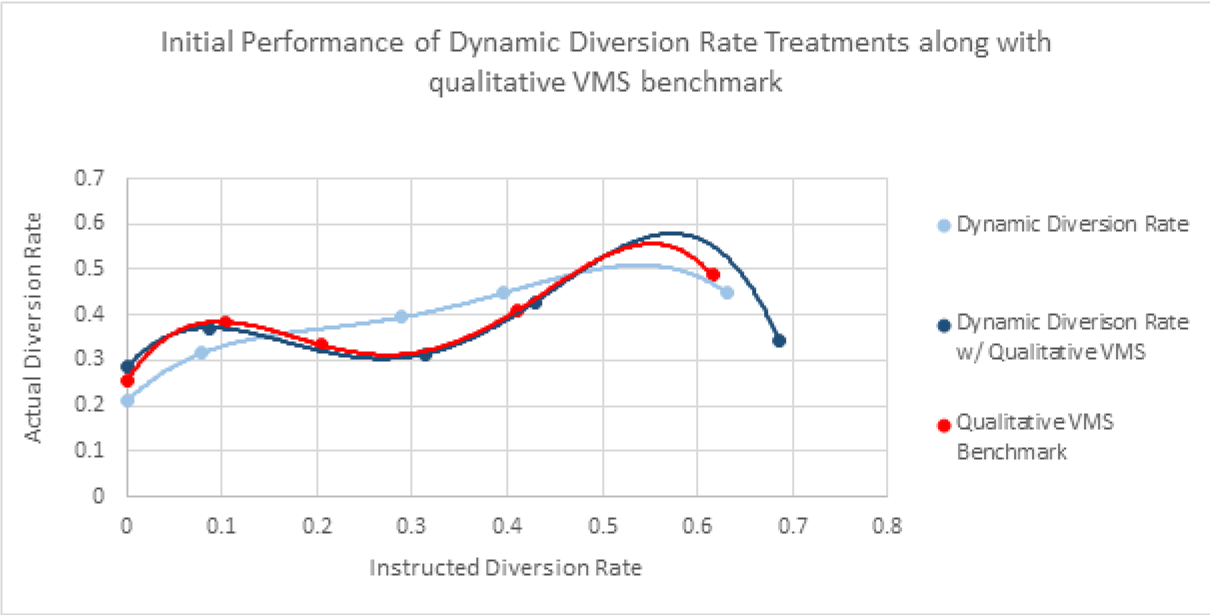
To explain how such a result occurred, we theorize that because subjects were not primed for this type of dynamic messaging treatment, it is possible that they did not initially understand what the dynamic feedback was signifying. It is noteworthy that if the average initial diversion rate for severe incidents is substituted into that round instead of the observed result, the dynamic diversion rate plus qualitative VMS treatment has better initial and overall performance the qualitative VMS benchmark.

It was also hypothesized that dynamic feedback would accelerate the learning process by helping subjects map the behavior of other subjects ahead of them to whether or not over-diversion is occurring. The dynamic diversion rate treatment results certainly do not refute this conjecture. The dynamic diversion rate with qualitative VMS treatment has one of the worst initial performances, yet ends with the best final performance of any treatment in the whole project. It is hard to know whether this should be attributed more to the provision of dynamic diversion rate instructions or qualitative incident descriptions, given that the next lowest final round performance in the entire project is from the qualitative VMS only treatment. The dynamic diversion rate only treatment has the third best final round of all treatments, providing more evidence that dynamic diversion rates do in fact have a positive effect on learning.



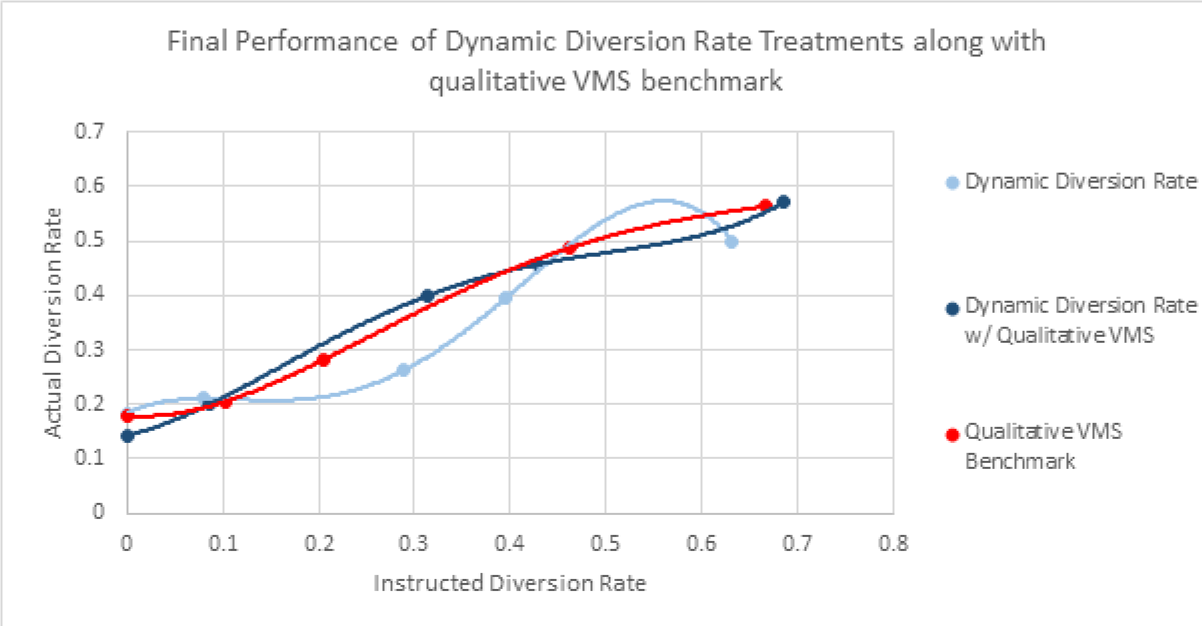
The initial predictability of the dynamic diversion rate with qualitative VMS treatment is almost identical to that of the qualitative VMS only benchmark, with the exception of the former's very poor "severe" incident round. It is probable that in the dynamic diversion rate treatment no changes in the diversion rate were displayed until the "severe" incident round, before which subjects only paid attention to the qualitative information (thus the similarity between the two treatments).

The initial predictability of the dynamic diversion rate treatment without an incident description is much smoother, though still relatively flat. The dynamic diversion rate only treatment has the best initial performance of any other diversion rate treatments and the qualitative VMS benchmark as well.



For final predictability, the dynamic diversion rate with qualitative VMS treatment is once again almost identical to that of the qualitative VMS only benchmark. Given the quick learning associated with qualitative VMS, it is unlikely that by the fourth set of incidents a large enough mis-diversion would even occur to even generate a change in the displayed diversion rate. Thus is makes sense that final diversion rates for both treatments would be extremely similar.

The final round predictability for the dynamic diversion rate only treatment is not as good; it is monotone but not particularly smooth.



Lesson:

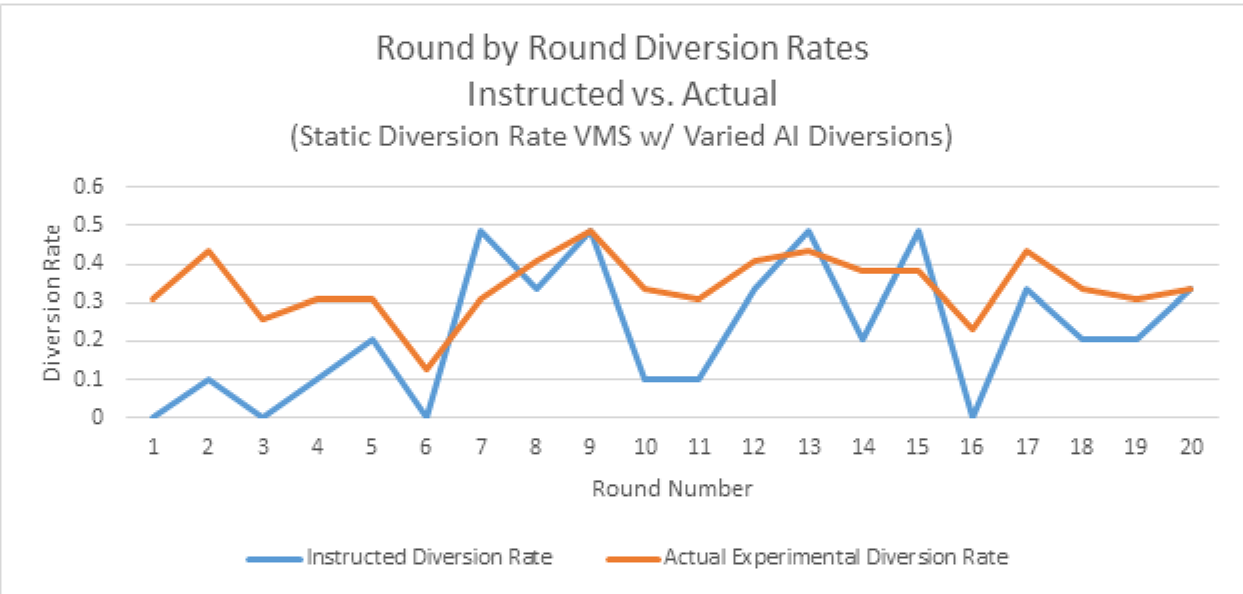
- Dynamic diversion rates yield significantly improvement over static diversion rate treatments.
- Dynamic diversion rates did not yield improvement over qualitative VMS in the experiment, but this is likely due to poor implementation of the treatment.
- Even if dynamic diversion VMS is not improvement over qualitative VMS per se, applying dynamic feedback has the potential to improve any type of treatment.
- There is potential for very poor initial performance if subjects do not understand how the dynamic diversion VMS works. Priming subjects as to how it functions might significantly improve the performance of the mechanism

Recommended future treatment:

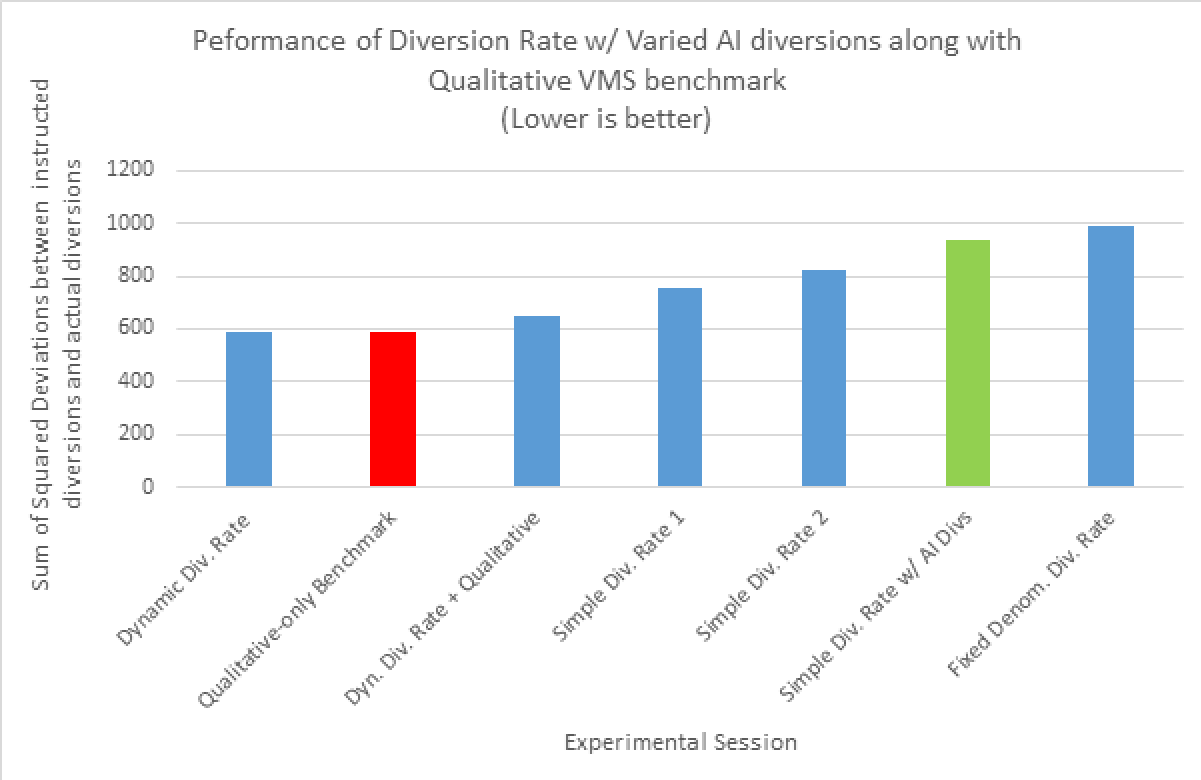
- Dynamic diversion rate with improved mechanics for adjusting the rate
- VMS with dynamic qualitative feedback.

7.4.3 Static diversion rate with varied AI behavior (treatment DR)

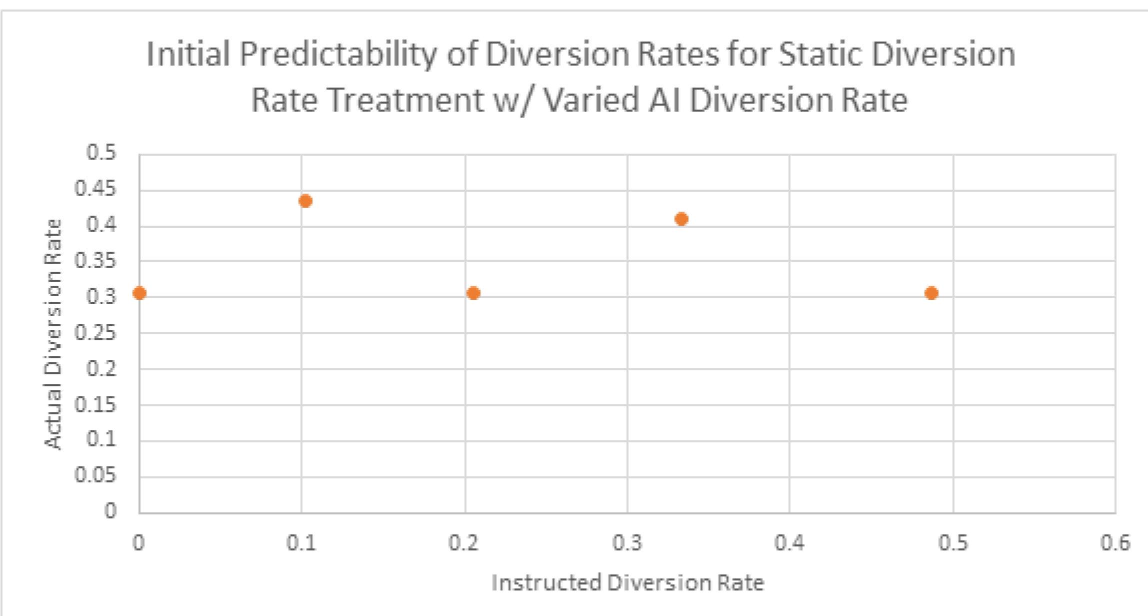
This treatment is the same as the static diversion rate with simple fractions treatments, except that the AI at the front of the vehicle platoon also divert in the same proportion as the VMS recommends. For example, if 1/3 is the displayed optimal diversion rate, then one in three AI vehicles will divert. The aim of this modification is to make whether or not subjects take AI diversions into account a moot point. With this treatment, the "literal" vs "AI-observing" implied diversion rate target for subjects would be identical.

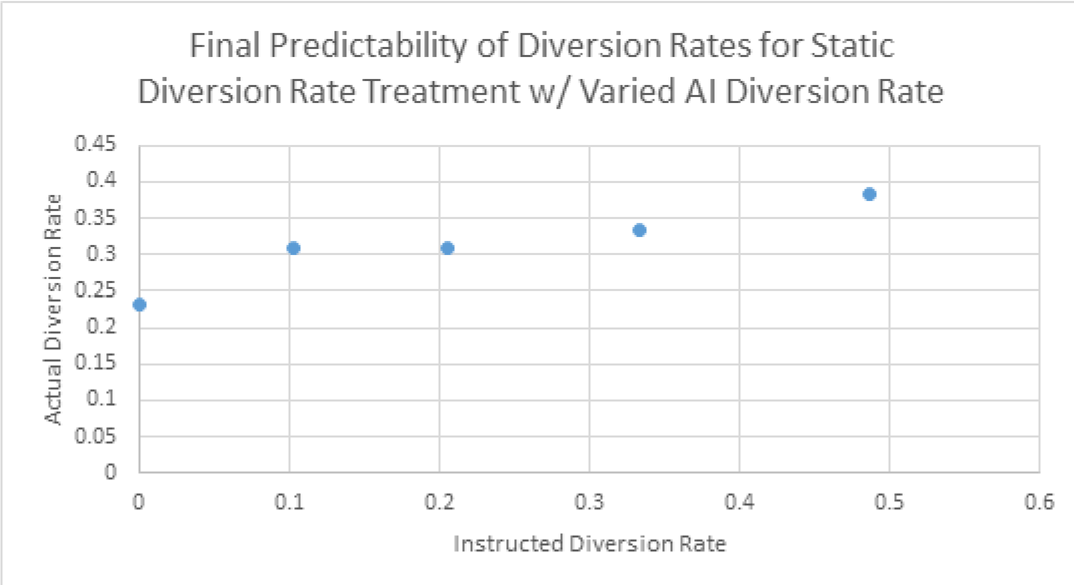


The results from this treatment confirm that subjects have a difficult time coordinating on known diversion rate optima, and that qualitative VMS treatments perform much better.



As expected, both the initial and final predictability of this treatment is poor as well. The initial diversion response curve is non-monotonic and non-increasing, and the final diversion response curve is almost flat.





Lessons:

- Even when there is no ambiguity for subjects as to whether or not they should incorporate the decisions of AI vehicles at the front of the platoon into their own decision-making, fixed diversion rate VMS is still a poor-performing treatment.

Overall lessons:

- Subjects have a great deal of difficulty coordinating on known optimal diversion rates, and are better off with a simple description of the incident
- Dynamic feedback is a promising tool for improving the performance and predictability of diversion rate responses to VMS. The mechanism has the potential to be counter-productive if poorly implemented, however.

7.5 Pricing Treatments (group T)

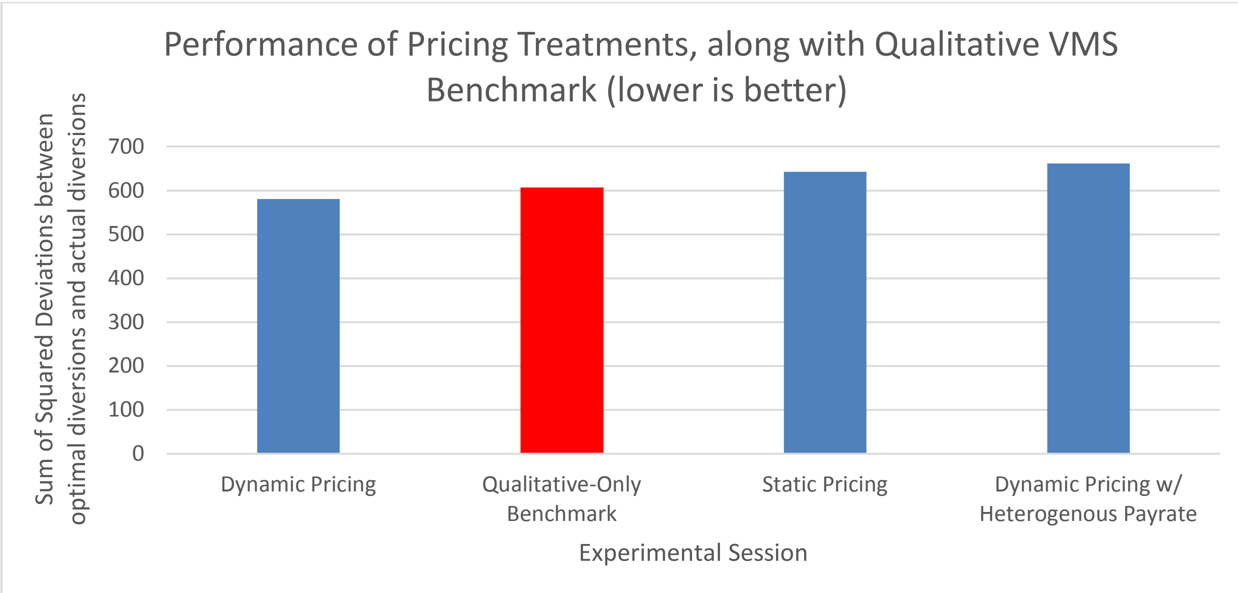
Overview:

For these treatments, prices are used to correct or prevent mis-diversion. Prices are either set once each round based on subject behavior during prior rounds, or adjusted dynamically throughout each round based on subject behavior during that round. Pricing is always implemented on the main route; a toll is used to encourage diversions when attempting to correct or prevent under-diversion and a subsidy is given to discourage diversions when attempting to correct or prevent over-diversion.

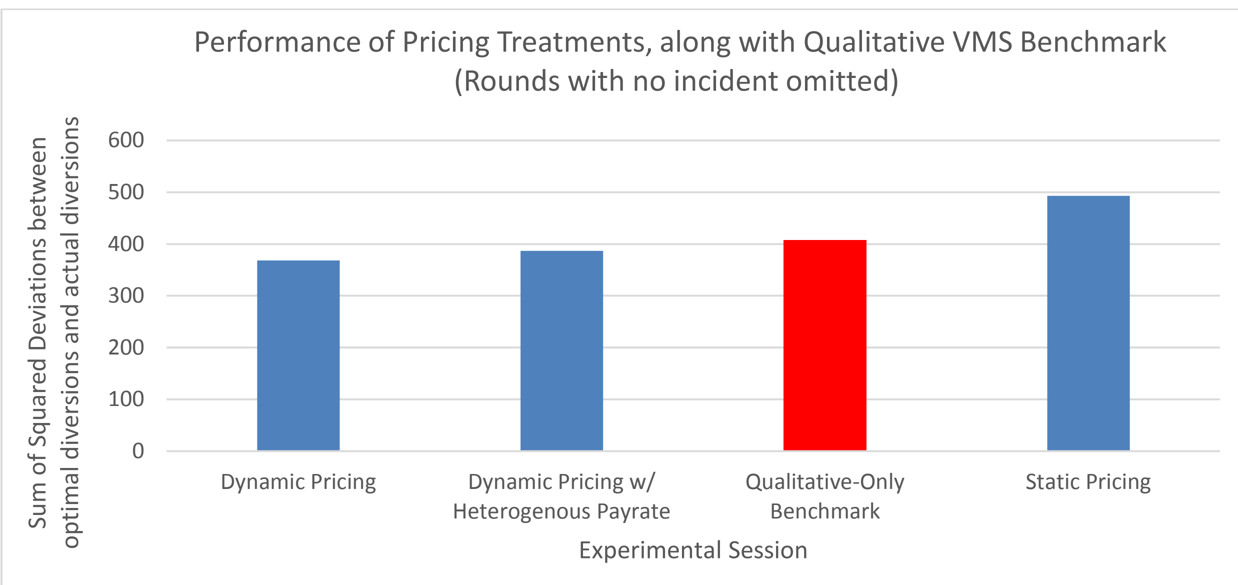
Prices are displayed using VMS, and are accompanied by qualitative incident descriptions so that prices are not interpreted as an indicator of incident severity. Instead, the qualitative incident descriptions serve to inform subjects of incident severity so that the prices can be instead interpreted as an indicator of past or current mis-diversion.

These treatments share many of the advantages of dynamic diversion rate treatments; pricing serves as additional feedback that helps to facilitate diversion-rate coordination and potentially accelerate learning. The use of pricing has additional advantages over dynamic diversion rates as well. One advantage is that while subjects might question the veracity of the "optimal" diversion rates being recommended via VMS, they will almost certainly not question whether a toll is real or not. A second advantage is that if heterogeneous values of time are assigned to users, then tolls/subsidies can naturally sort subjects into diverters and non-diverters based on their value of time preferences. This natural sorting could lead to more predictable diversion rates than are achievable through diversion rate treatments. Which require subjects to deliberately coordinate on known fractions.

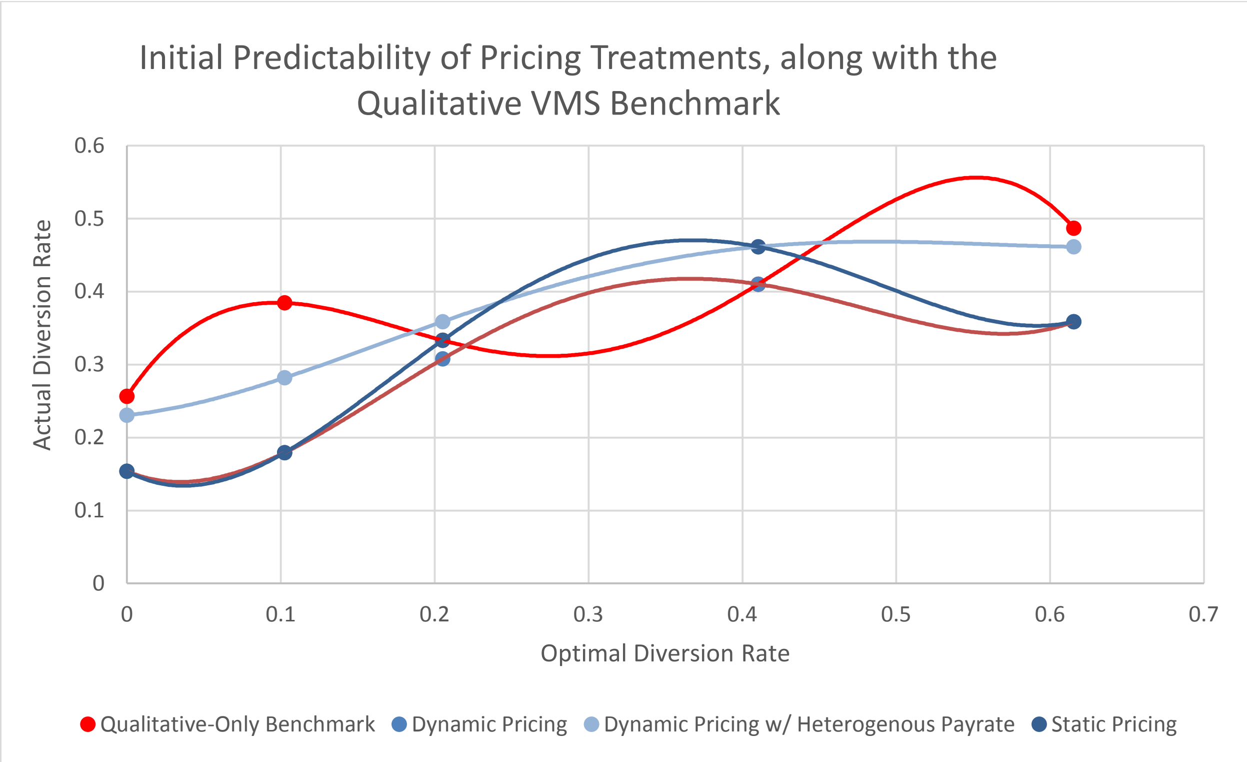
Overall, these treatments performed around the same level as the qualitative VMS benchmark, with one pricing treatment outperforming it slightly.



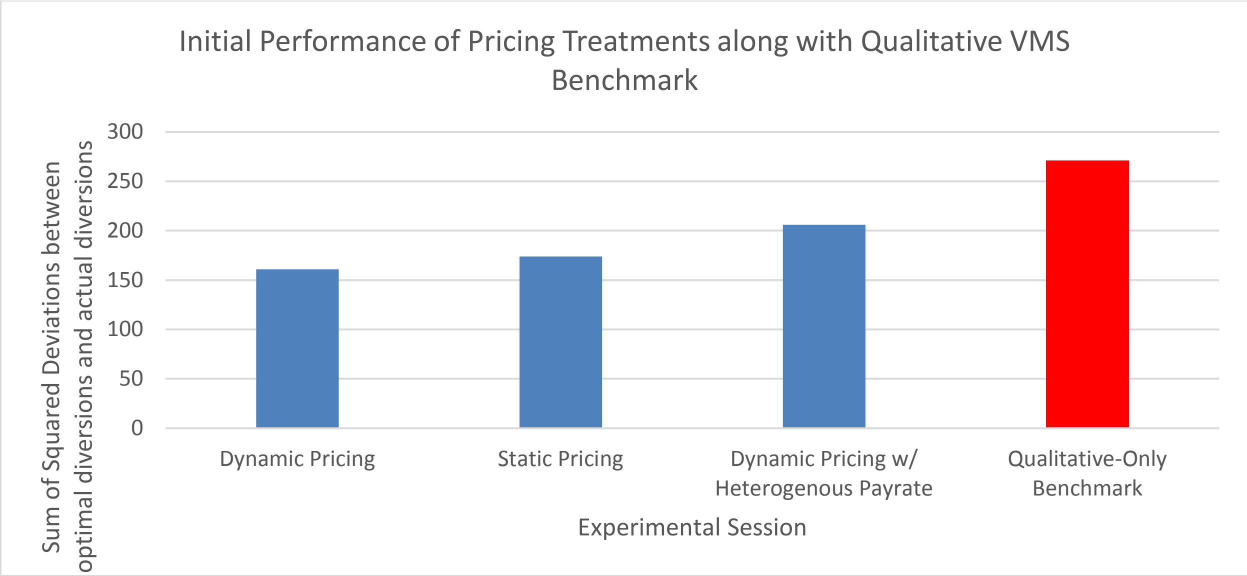
When rounds with no incident (and thus no VMS) are omitted, the performance of dynamic pricing treatments (those with prices that change throughout each round) is improved relative to the qualitative-VMS-only benchmark, while the performance of the static pricing treatment (whose toll is set only once per round) worsens.



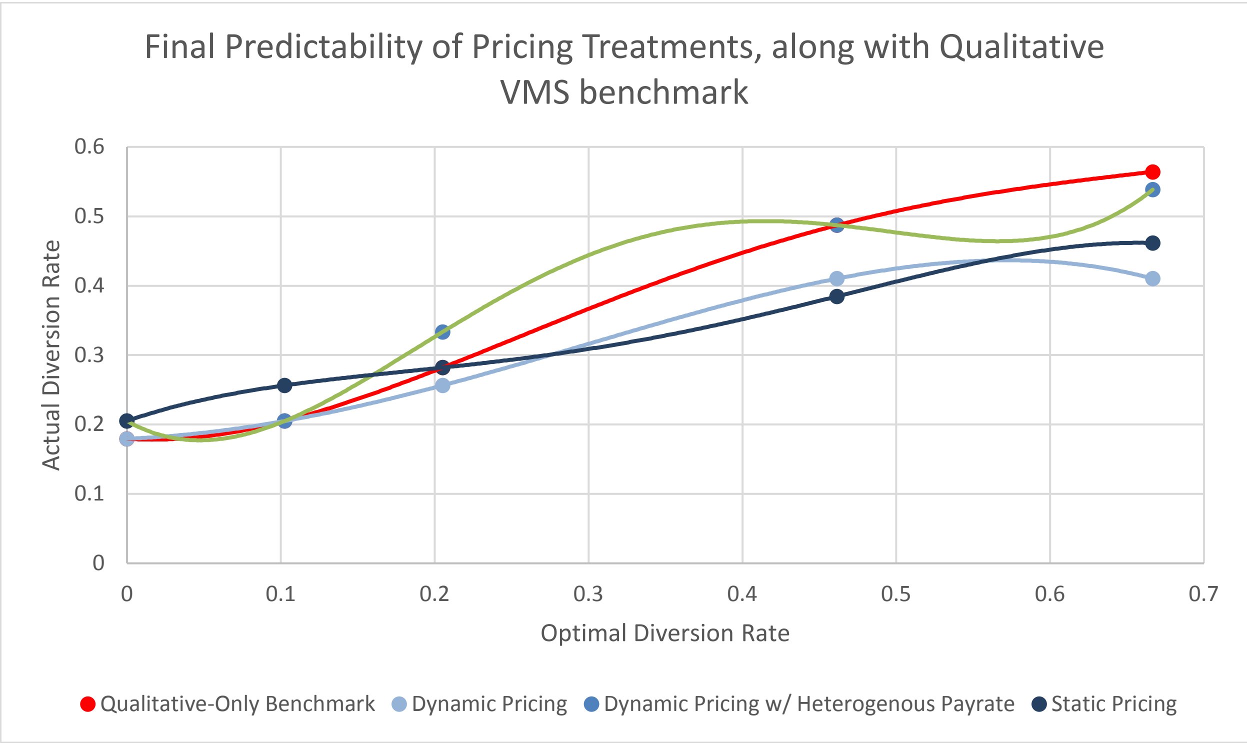
The initial predictability of diversion rates for the pricing treatments is better than or comparable to that of the qualitative VMS benchmark, depending on the treatment.



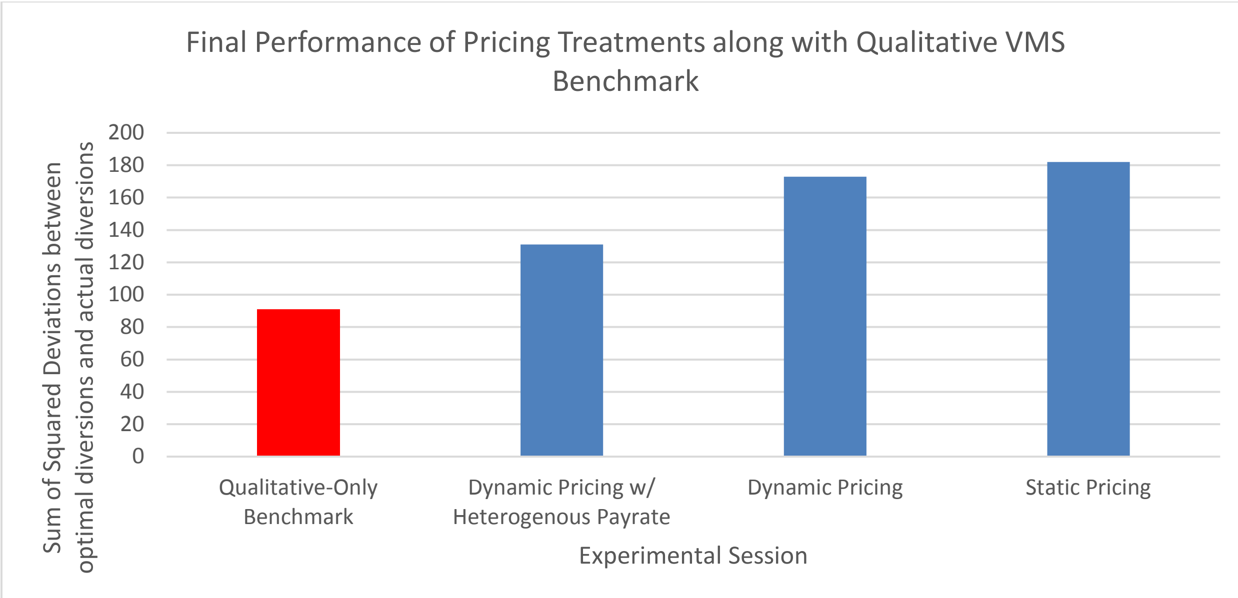
Although only one pricing treatment has unambiguously better initial predictability than the qualitative-VMS-only benchmark, all three pricing treatments have significantly better initial round performance.



In contrast to the initial predictability results, the predictability of the final rounds of each of the pricing treatments was worse than that of the qualitative VMS benchmark.



Similarly, the final-round performance results of pricing treatment are all worse than that of the qualitative VMS benchmark, despite the fact that the pricing treatments had better initial round performance.



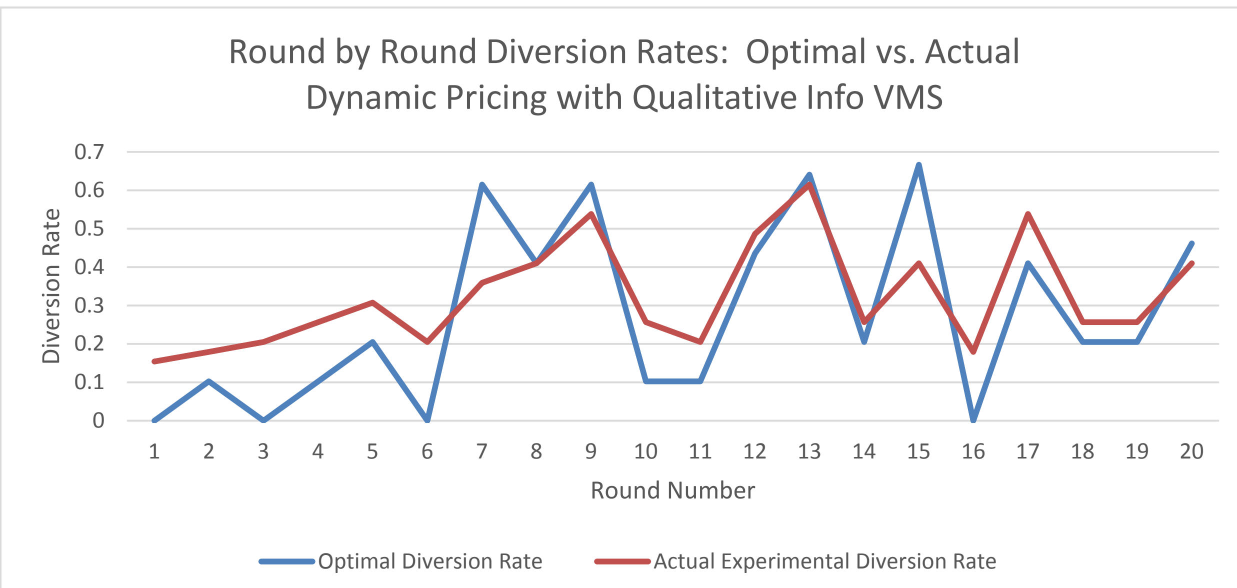
This result is surprising, because it implies that combining qualitative VMS information with pricing results in worse final round performance than using qualitative VMS information alone. Ironically, the final round diversion performance for the qualitative-only benchmark is close enough to the optimum such that prices would not even change from $0.00 had they been introduced for that round. Thus, it is possible that pricing treatments interfere with subject learning and hurt late round performance.

Pricing treatments were further examined on a case-by-case basis to gain more insights into the factors driving the performance and predictability results; this analysis is described below:

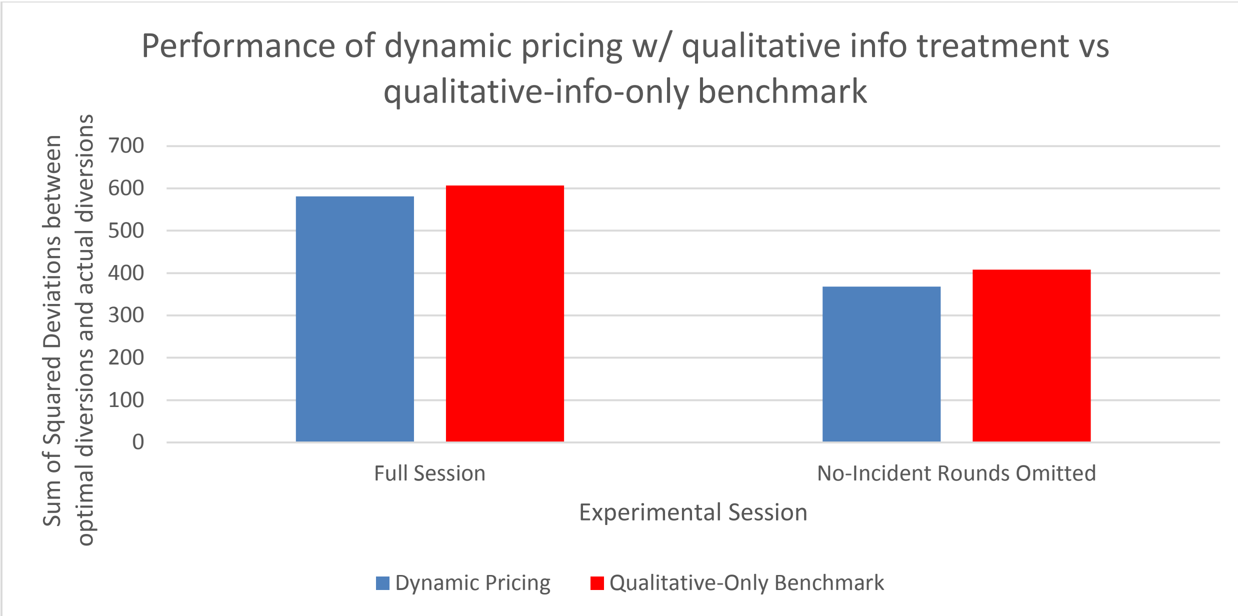
7.5.1 Dynamic pricing + VMS (treatment DT)

The dynamic pricing treatment operates similarly to the dynamic diversion rate treatment described in the diversion rate treatment section. For each incident type (except for no incident), subjects receive VMS content providing a qualitative incident description and a statement of how much the subsidy/toll on the main route is. The toll begins at zero dollars each round regardless of the incident type. If subjects begin diverting at a level exceeding the optimal rate by a certain threshold during a round, a subsidy is immediately introduced on the main route to discourage further diversion. If the level of diversions falls short of the optimal rate by a certain threshold during a round, a toll is immediately introduced on the main to route to encourage further diversion. After a round is over, the toll is reset so that it begins at $0.00 again for the next round.

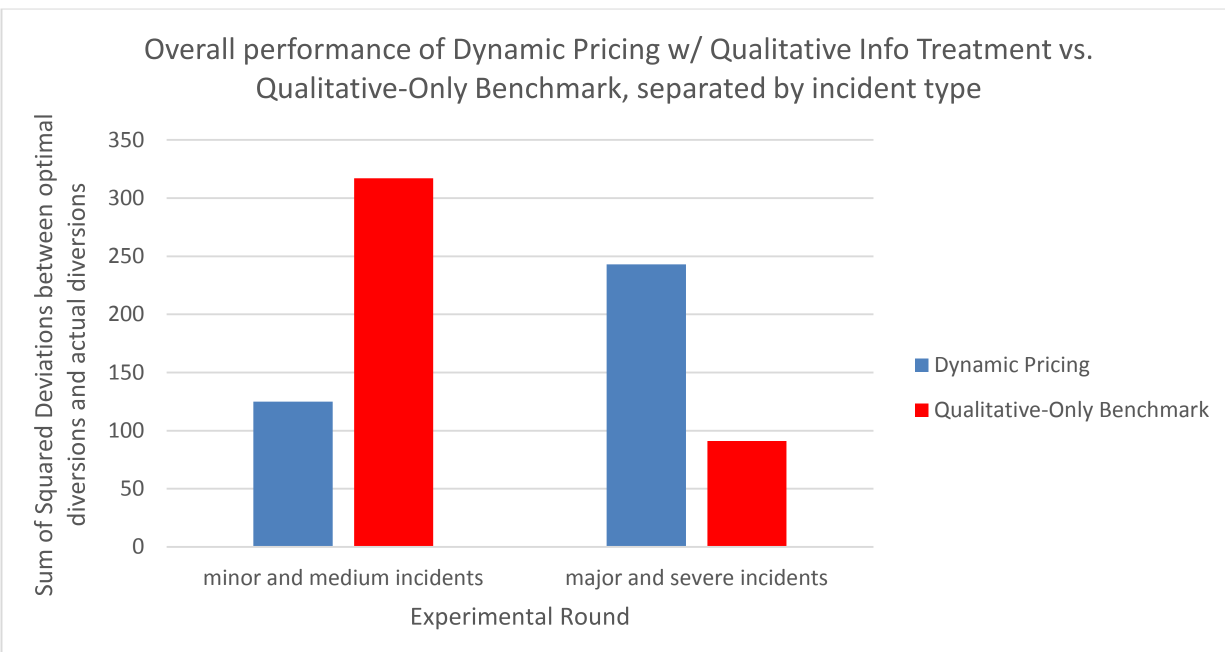
One advantage of this treatment is that it provides subjects with instant feedback on whether or not they are achieving the optimal diversion rate, and more specifically, whether they are over-diverting or under-diverting in aggregate. Another very important advantage is that the tolls/subsidies provide subjects with an extra incentive to correct mis-diversion by choosing the under-utilized route.



Combining qualitative information with dynamic pricing improved performance compared to information-only both overall and also when no-incident rounds were omitted, albeit slightly.

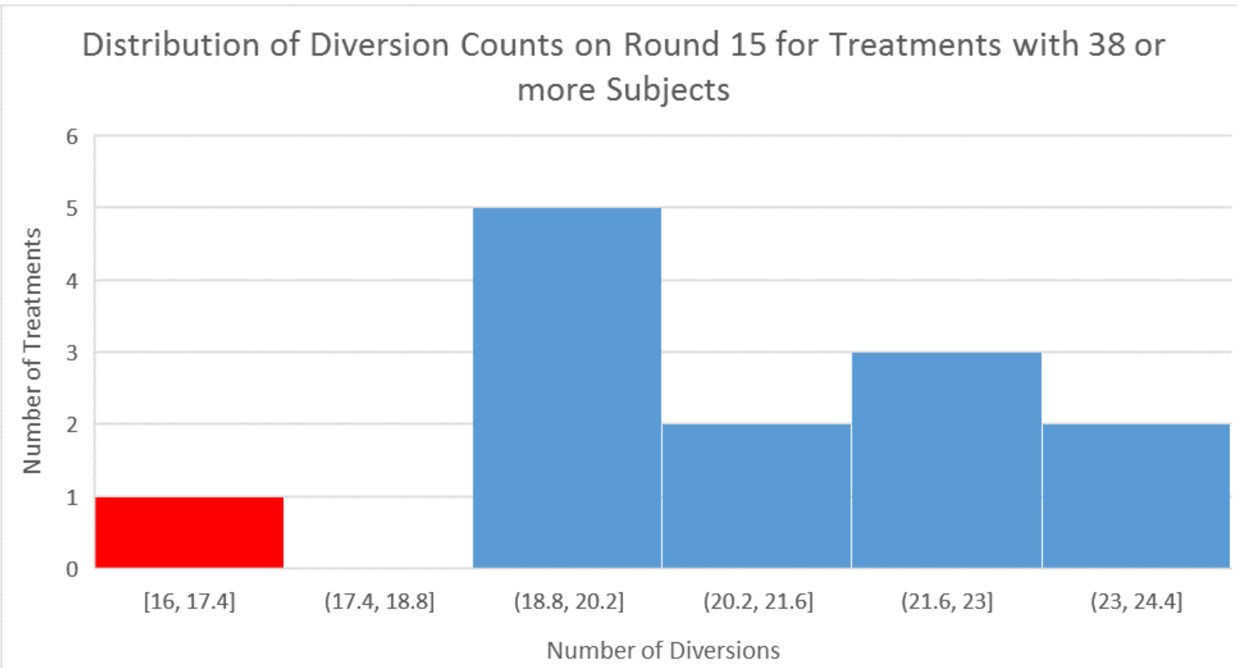


The slight improvement in performance is due to entirely subsidies, which significantly helped to prevent over-diversion. Tolls did little, if anything, to address under-diversion; in fact, this treatment had much worse performance than the qualitative-only benchmark on rounds where tolls were applied to the main route.



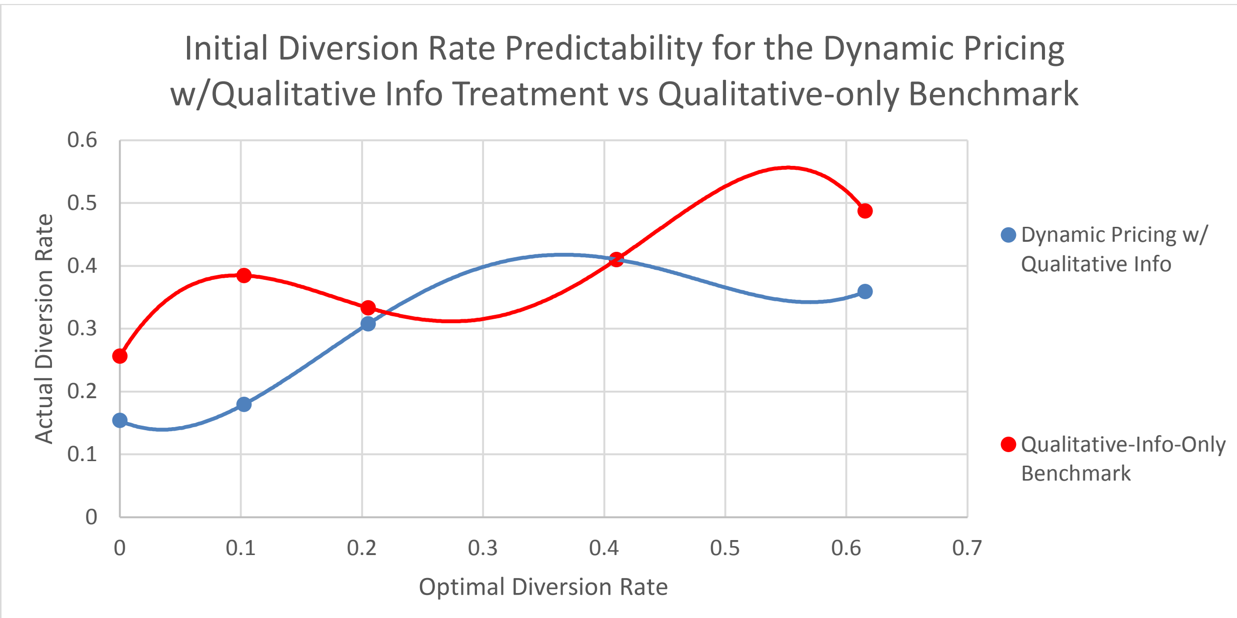
It appears as though subsidies were effective at discouraging diversions, but that tolls potentially were counterproductive for encouraging diversions.

One possibility for this discrepancy is that subjects occasionally had trouble differentiating between whether there was a subsidy or toll on the main route. Evidence of this comes from two “severe” incident rounds, 7 and 15, in which performance was unusually bad compared to virtually all other treatments. The low number of diversions on round 15 for this treatment was a significant outlier among other treatments.



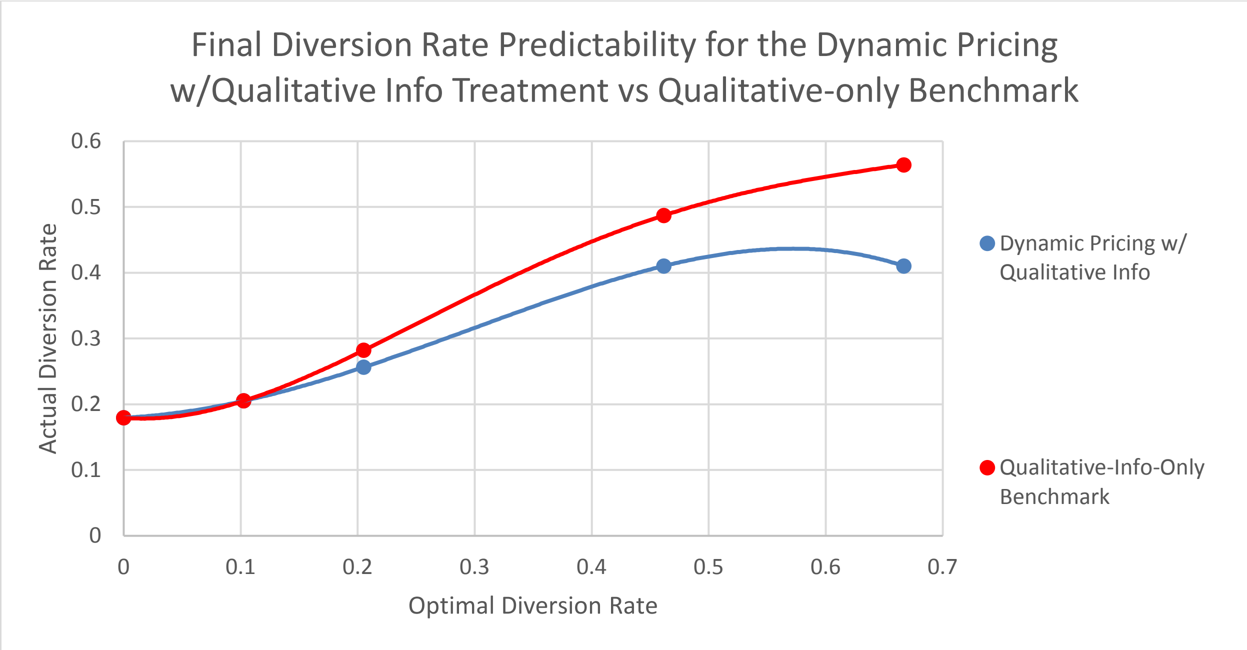
One explanation for how subjects could mistake tolls for subsidies is that the first few rounds with prices all offered subsidies. Thus, subjects might be conditioned to see any price, including tolls, and think that it is a subsidy, even though the VMS states “toll” and “pay” instead of “subsidy” and “receive.” In the post-experiment questionnaire, many subjects stated that they were confused by the tolls.

This issue also effects the initial predictability of this treatment's diversion rates; it is non-linear and made non-monotonic by the fact that the diversion rate for the first "severe" incident is less than that of the first "major" incident. Otherwise, the initial predictability of this treatment would have been quite good. However, if subjects cannot reliably differentiate between tolls and subsidies with a pricing mechanism, that is a significant liability for treatments using such a mechanism.



The initial predictability for this treatment is still no worse than that of the VMS only treatment, however.

The final round predictability is also adversely affected by the unusually low diversion rate on the first "severe" round. The diversion response curve for this treatment is noticeably flatter than that of the qualitative-only benchmark.

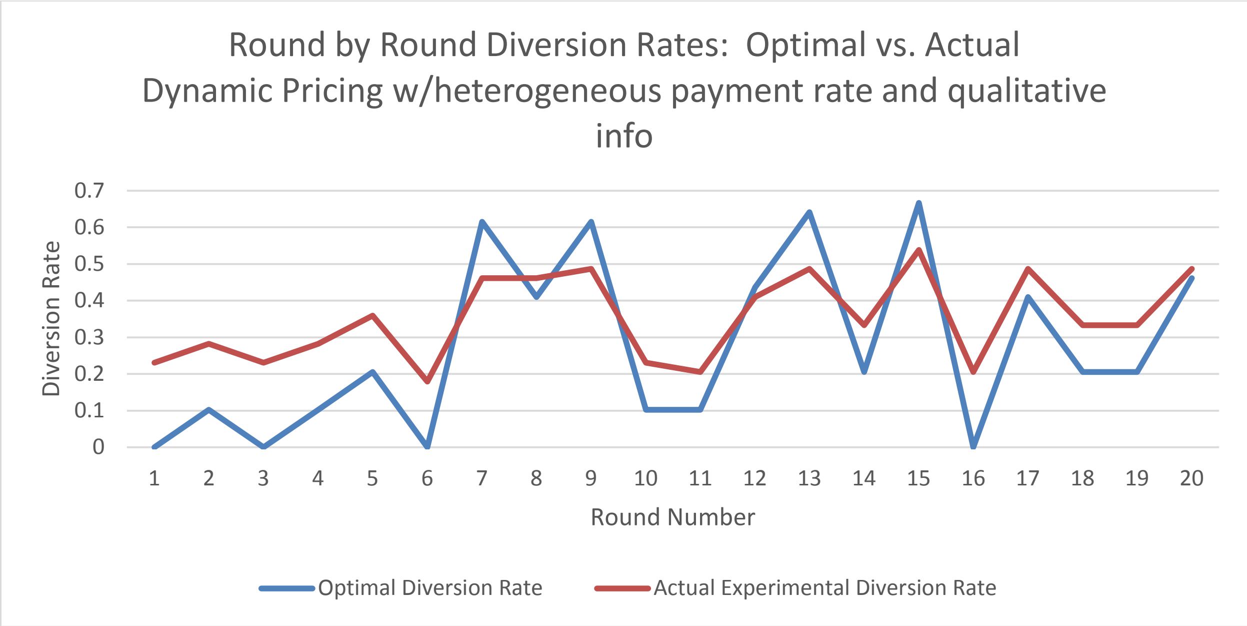


Lessons:

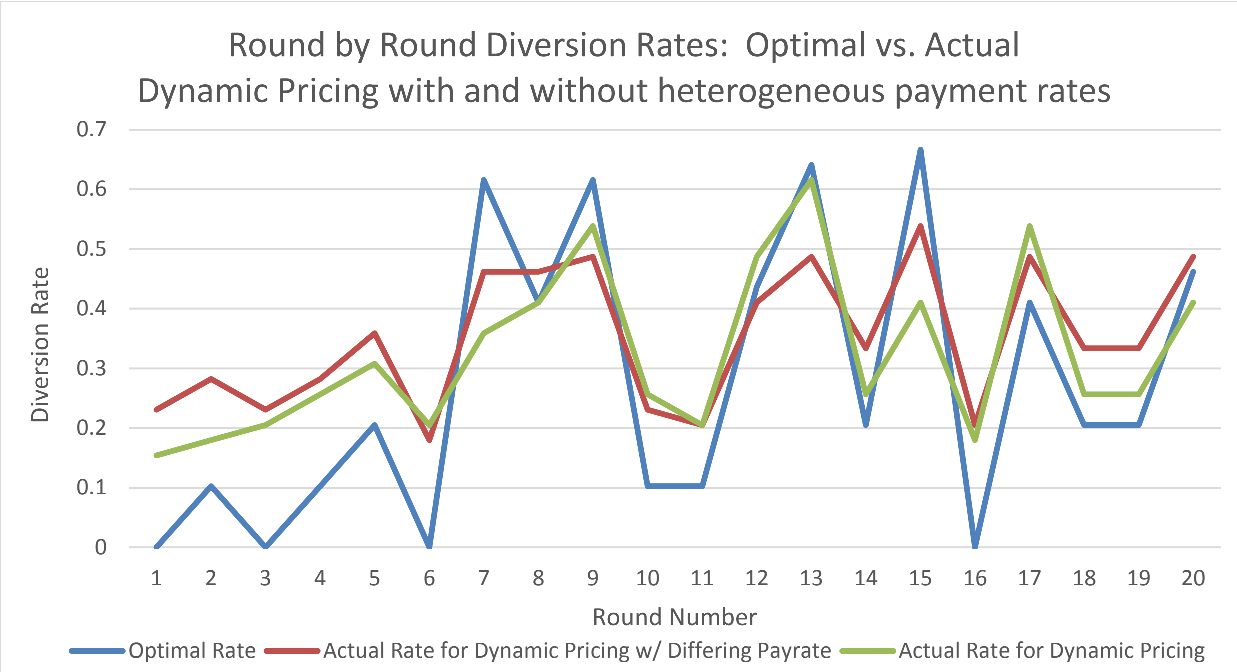
- Dynamic tolling showed some promise for improving diversion-rate outcomes, as it was able to strongly mitigate over-diversion.
- There is high potential for driver confusion if tolls and subsidies are administered on same route. Some subjects very likely confused tolls for subsidies, leading to very significant under-diversion on certain treatments – worse than for comparable treatments without pricing.

7.5.2 Dynamic Pricing with VMS and Heterogeneous Payment Depreciation Rates (treatment DTHT)

In reality, not all drivers on the road have the same value of time; some are in more of a hurry than others are. This variation might affect the willingness of a driver to pay a toll to take a route they prefer or think might be faster. Drivers with a high value of time will be a lot less sensitive to a toll, than those with a low value of time. These differences have the potential to change the aggregate behavior of drivers in response to tolls, and might make diversion response rates more predictable if subjects can simply sort themselves between tolled and un-tolled routes according to their value of time rather than try to consciously coordinate on a certain known diversion rate. To test for possible benefits from exploiting these differences in subject values of time, the Dynamic Pricing with Qualitative Information treatment was repeated with one important difference: subjects were given a randomly assigned a unique payment depreciation rate from a uniform distribution, centered around the typical value used in this project. Subjects with high payment depreciation rates essentially have a higher value of time imposed on them; since every second spent driving costs them more than the average subject, and vice versa for subjects with low payment depreciation rates.

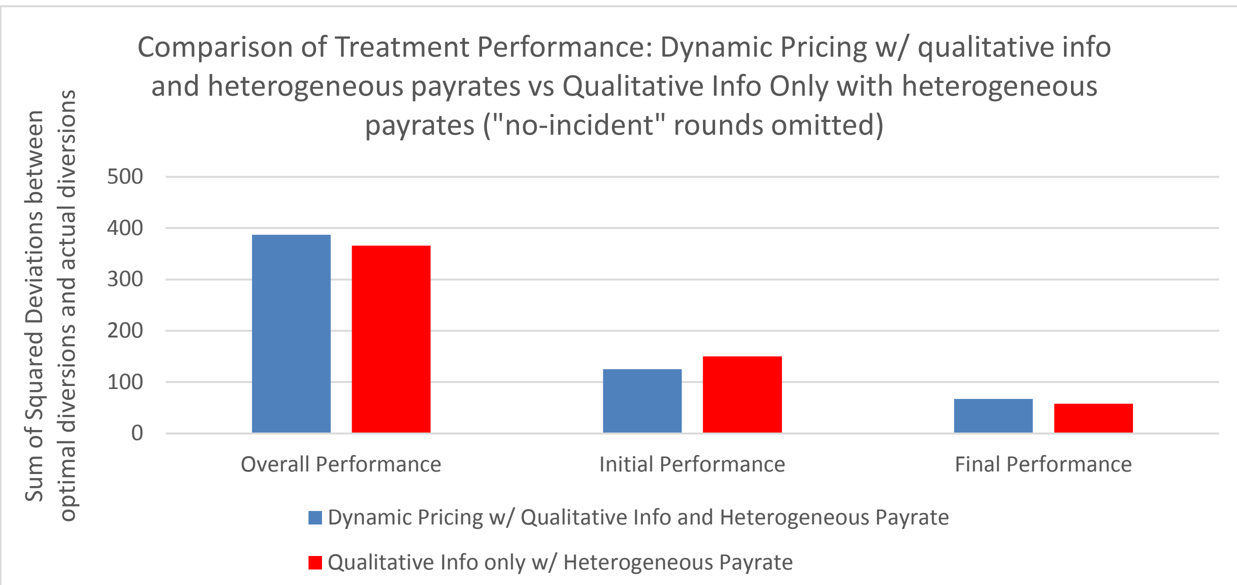


In contrast with the dynamic pricing treatment without heterogeneous payment depreciation rates, this treatment has relatively uniform mis-diversion. That is, as opposed to achieving many rounds of near-optimal diversion rates combined with some rounds with very high mis-diversion (as is the case with the dynamic pricing with identical payment rates, due to misinterpretation of the toll vs subsidy), this treatment has a consistent level of moderate mis-diversion typical of most treatments.



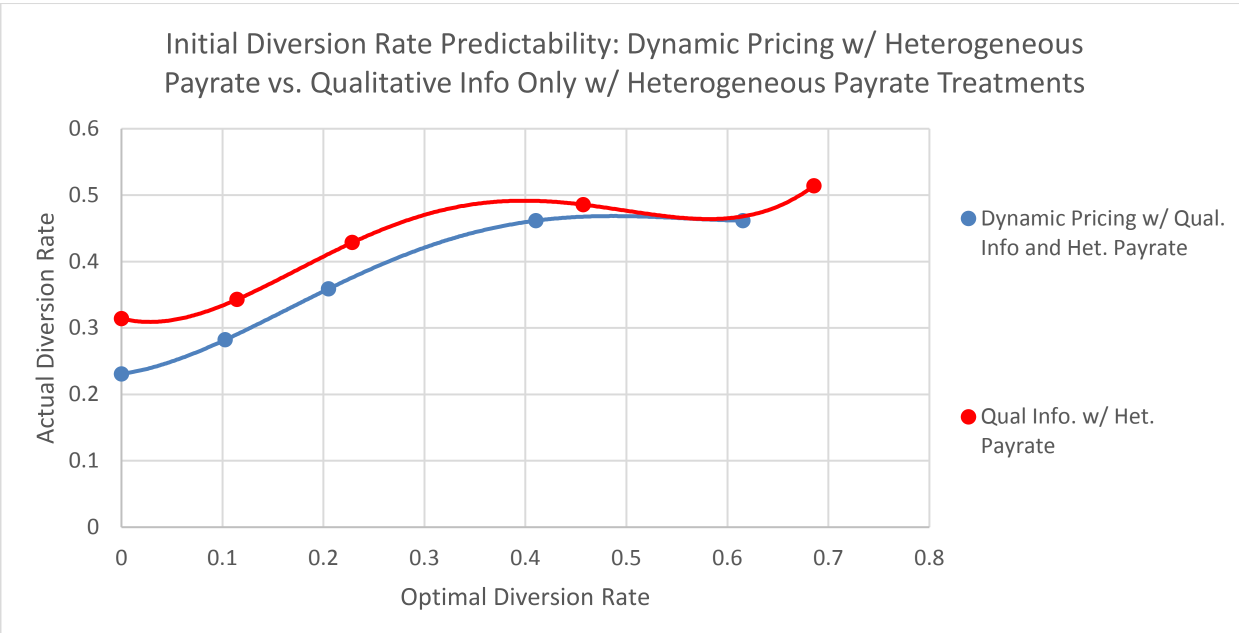
This difference in subject diversion responses to this treatment compared to the other dynamic pricing treatment is consistent with subjects simply being less responsive to pricing in this treatment. Evidence to support this is that only one in 39 subjects mentioned the toll as a factor in their decision-making in the post-experiment survey for this treatment, while many more subjects mentioned the toll in the survey for the session with the dynamic diversion rate without differing payment depreciation rates. However, there is no clear reason why heterogeneous payment rates would result in less people paying attention to the toll, given that subjects keep the same payment depreciation rate throughout the experiment and that the average payment depreciation rate is the same between the two dynamic pricing treatments. The experimental data support the notion that the increased range of payment depreciation rates is not a contributing factor to reduced responsiveness to tolls. Subjects with values of time that were closer to the median of the distribution were no more likely to respond to pricing than those with more extreme values. This means that treatments with subject payment rate heterogeneity should have similar responses to pricing than treatments with homogeneous subject payment rates, and that we are unable to draw meaningful conclusions from the fact that they did not.

The overall performance for this treatment is very similar to the qualitative-information-only VMS with heterogeneous payment depreciation treatment; the same holds true for both the initial and final rounds for each incident type.



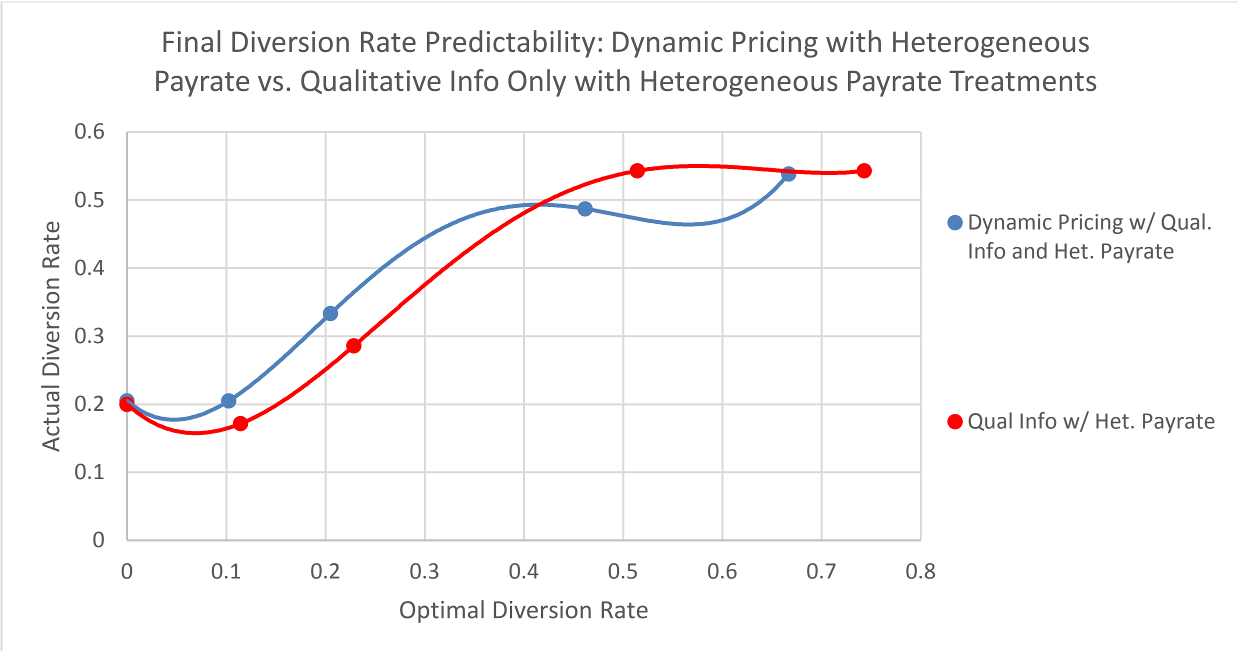
The post-experiment survey suggests that subjects did not pay much attention to the tolls, and these results are highly suggestive of this fact. For subject samples with heterogeneous depreciation rates, the addition of dynamic pricing did not result in even a slight improvement over the qualitative info only treatment. It would be worth exploring whether increasing the toll and subsidy amounts could lead to an improvement, given the apparent lack of responsiveness of subjects to the prices used. Currently, the amount of most tolls and subsidies set through the dynamic pricing algorithm equal 50 cents. There is also the possibility either that the pricing scheme confused subjects, or that the amount of time that the prices were displayed via the VMS was too short for subjects to react.

Just as the performance of this treatment was not an improvement over the qualitative info only with heterogeneous pay rate treatment, neither was the initial predictability of diversions for this treatment.



The similarity of the two diversion response curves is consistent with subjects not responding to the prices. If the prices were completely ignored by all subjects, then the two treatments would be functionally equivalent.

The final round predictability is also not substantively different between the two treatments, reinforcing the idea that tolling is having little effect

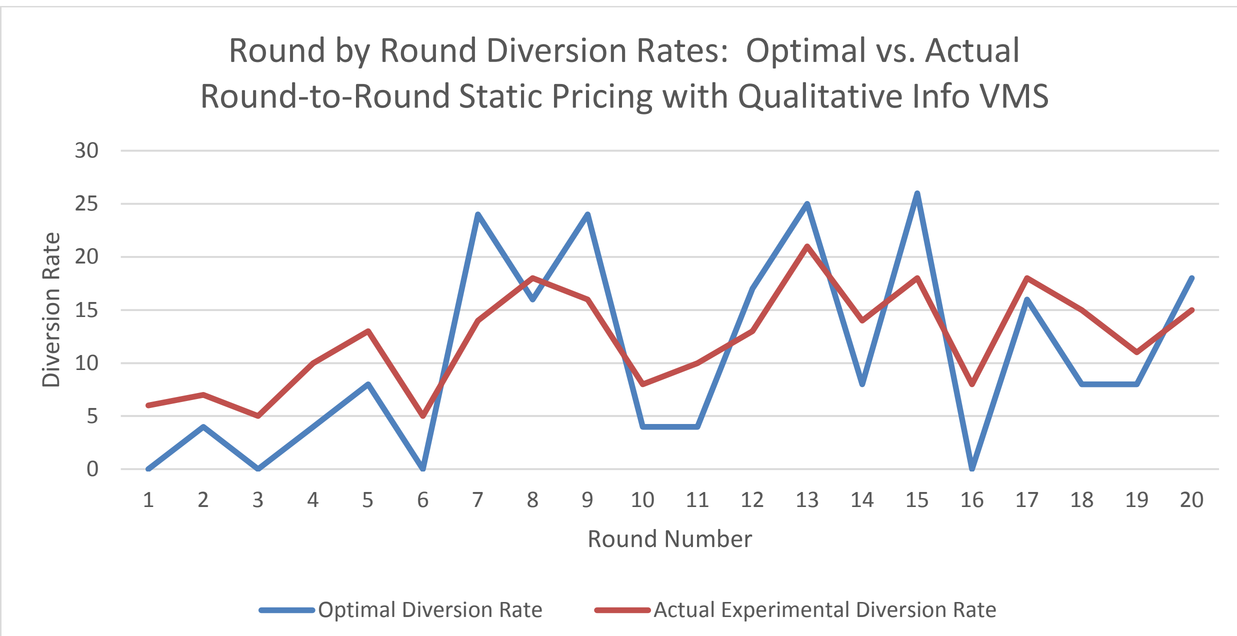


Lessons:

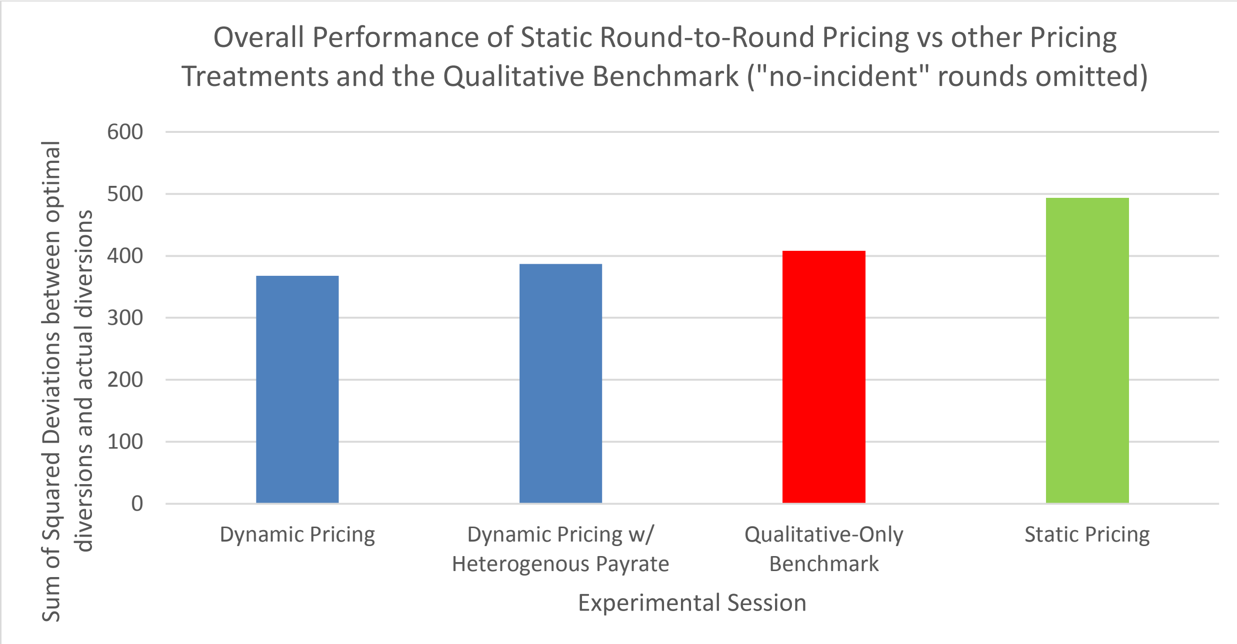
- In this treatment, subjects did not respond to pricing. It is unlikely that it is due to the assignment of heterogeneous payment depreciation rates to subjects. Thus, dynamic pricing may not always be an effective incident management strategy. It is possible that increasing the price level, or increasing the amount of time that prices are displayed, might be necessary to achieve positive results from dynamic pricing.

7.5.3 Static Round to Round Pricing (treatment ST)

In this treatment, a price is set on the main route at the beginning of each round; this price remains constant for the duration of the round. VMS displays both the toll and qualitative incident descriptions each round. As with the dynamic pricing treatments, tolls are used to encourage diversions and subsidies are used to discourage them. Prices are determined by subject diversion performance during prior rounds. For the first round of each incident type, the price will be set at the default value of $0.00 on the main route. If subjects under-divert, then the next round where that same incident type occurs, a toll will be applied proportional to the severity of the under-diversion. For example, if under-diversion occurs during a minor incident, then a toll will be applied on the main route the next time a minor incident occurs; this serves as an attempt to encourage diversions and prevent a repeat episode of under-diversion for the second minor incident. The reverse is true for over-diversion; a subsidy is applied the next round with the same incident to help limit diversions. Thus' the goal of the treatment is to provide extra reinforcement to subjects from round to round to mitigate mis-diversion. In theory, this should help subjects converge to the optimal diversion rate faster, since prices send a stronger and clearer signal than travel times alone.



This treatment has worse performance than the qualitative-information-only benchmark and other pricing treatments.



One reason this treatment did not improve performance over the qualitative-information-only treatment is that there simply were not enough rounds where there was a non-zero price on the main route. The threshold for mis-diversion required to trigger a nonzero price for future rounds was set too high; prices only appeared on 3 out of 12 possible rounds despite performance being far from optimal on many rounds.

When non-zero prices were applied to the main route, prices were able to improve diversion performance compared to other non-pricing treatments such as qualitative information, static diversion rate recommendation, and ID-based diversion recommendation treatments that rely solely on reinforcement learning to reduce mis-diversion from round to round. To make the comparison more valid, rounds from this treatment were only compared rounds from other treatments that followed similar levels of prior mis-diversion. For example, a “major” incident from this treatment that followed a prior “major” incident where there was under-diversion totaling five subjects would only be compared to a "major" incident from other treatments that also followed a prior "major" incident with under-diversion totaling close to five subjects.

Comparison of Next-Round (of the same incident type) Responses to Mis-diversion: Static Pricing Treatment vs. Treatments that Depend on Reinforcement Learning Only			
Optimal Prior-Round Diversion Total (vehicles)	Actual Prior-Round Diversion Total (vehicles)	Number of Additional Diverting Vehicles During the Next-Round of the Same Incident Type	
		Static Pricing Treatment	Other Treatment Average
24	14 - 15	2	2.666666667
4	9 - 10	-2	-1.666666667
24	16 - 17	5	2.75

The first instance displayed by the chart shows mis-diversion being corrected less strongly in the Static Pricing treatment (only 2 additional vehicles diverted after significant under-diversion during the prior round of the same incident-type, compared to 2.67 vehicles on average for non-pricing treatment). The next two instances, however, show mis-diversion being corrected more strongly in the Static Pricing treatment.

Unfortunately, the diversion rates in the static round-to-round pricing treatments reverted to their pre-price level once prices are reset. This phenomenon is illustrated in the chart below

Pattern of Vehicle Diversions in Response to Prices for the Static Round-to-Round Pricing Treatment		
Optimal Diversion Total (vehicles)	Actual Diversion Total (vehicles)	Main Route Price
4	10	$ 0.00
4	8	$ -0.50
4	10	$ 0.00

After mis-diversion was corrected in the presence of a toll, the next instance of that incident would not be accompanied by toll, resulting of a repeat of the mis-diversion that induced the initial toll in the first place. Thus, while prices can correct mis-diversion when they are present, the effects do not seem persist. This lack of a persistent effect does not occur in treatments that rely on reinforcement diversion only; once mis-diversion is corrected during these treatments, diversion behavior tends to remain improved for the remainder of the session.

If pricing-induced behavioral changes are in fact not as persistent as those from learning are, it is counterproductive for tolls to reset to zero once a desired diversion rate is achieved or nearly achieved. It would also suggest that subjects learn less effectively overall in the presence of round-to-round pricing. In fact, initial and final performance for this treatment were equal, indicative of virtually no learning-taking place at all. It is possible that subjects came to rely on the prices rather than trying to learn an optimal route-choice strategy based on experienced travel times. If this was the case, the preponderance of zero-price rounds (due to the unintentionally high threshold for price changes) possibly led subjects to falsely believe that they were achieving optimal behavior on their respective routes, and that there was no point in switching.

Lessons:

- Static round-to-round pricing was effective in correcting mis-diversion in the short term, but the effects did not persist when the price is removed. Therefore, the price should be allowed to persist longer than one round in response to mis-diversion.
- It is very possible that subjects came to rely on the prices rather than reinforcement learning to make route choices. Therefore, unless static round-to-round pricing treatments are well implemented, they might achieve worse performance than treatments with qualitative incident descriptions only due to detrimental effects that they have on subject learning.

Overall Lessons for Pricing Treatments:

- Pricing has potential as an effective tool for incident management using VMS. In experimental sessions, it improved diversion performance for some incident types. However, treatments using pricing mechanisms were not able to achieve substantial overall performance improvements. This is likely due in part to flaws in the experimental design of these treatments.
- For round-to-round pricing treatments, mis-diversion is corrected in the short-term, but the effects do not persist if the prices are reset.
- Proper implementation of pricing mechanisms is essential, otherwise performance might be worse off than with qualitative information only via VMS. For example: it should be made very clear whether a toll or subsidy is present on a given route, and prices set in response to

mis-diversion should persist for longer than only one future instance of the same incident type.

- Dynamic Pricing achieved better results than Static Round-to-Round Pricing

Recommended future pricing treatments:

- Dynamic tolling where the difference between tolls and subsidies is strongly emphasized to minimize confusion.
- Dynamic tolling, where both the main route and the alternate route are capable of being priced, so that a toll can always be used (as opposed to the need for both tolls and subsidies when only route is priced).
- Pricing treatments with higher tolls/subsidies to ensure that the prices are salient
- Static round-to-round pricing with both a lowered threshold for a non-zero price and prices that persist for multiple rounds.

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QUARTERLY POWER POINT PRESENTATIONS

Driver Responses to Variable Message Signs After a Traffic Incident

An Experimental Study

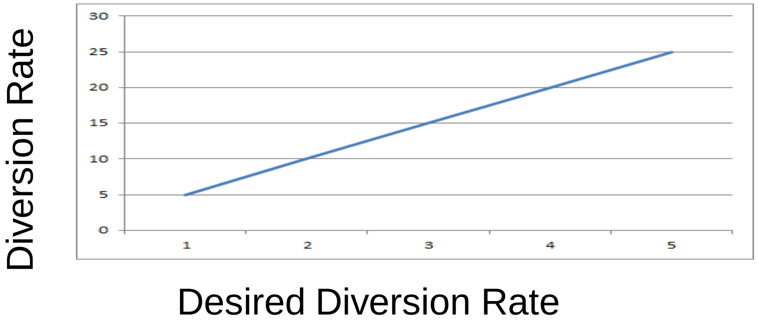
Si-Yuan Kong and Amine Mahmassani

Our Research Questions

Can predictable diversion rates be achieved through manipulation of VMS content?

We hope to find a type of “variable intensity” messaging scheme that can be adjusted to induce predictable changes in diversion rates.

Such a scheme would enable authorities to calibrate VMS systems to actively manage incidents with minimized risk of overburdening alternate routes



Our Experiment

40 subjects each control a vehicle

Simple road network: one freeway, one alternate route with two traffic lights

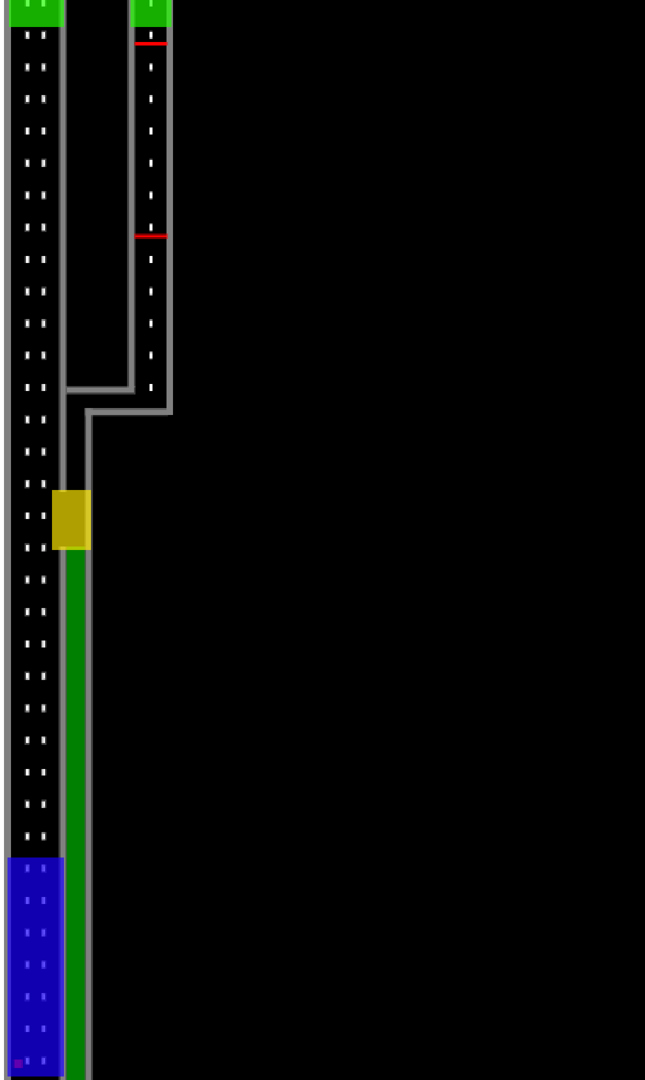
All travel simultaneously (share the road)

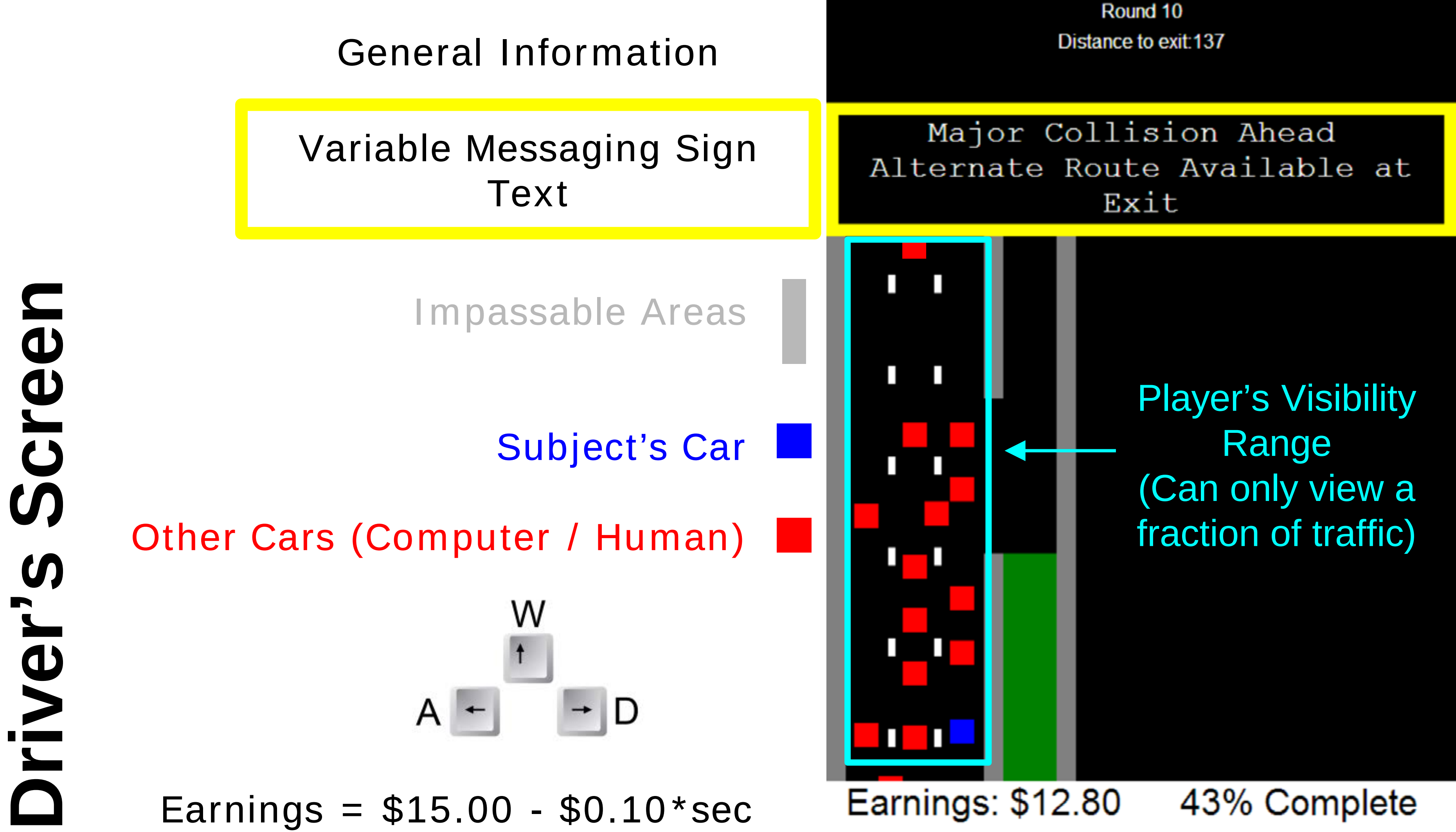
Drive in the same direction towards the same destination

Start with endowment that decreases linearly with time

Begin on the freeway, one opportunity each round to switch to the alternate route

2 practice rounds, payment averaged from 3 / 23 paying rounds



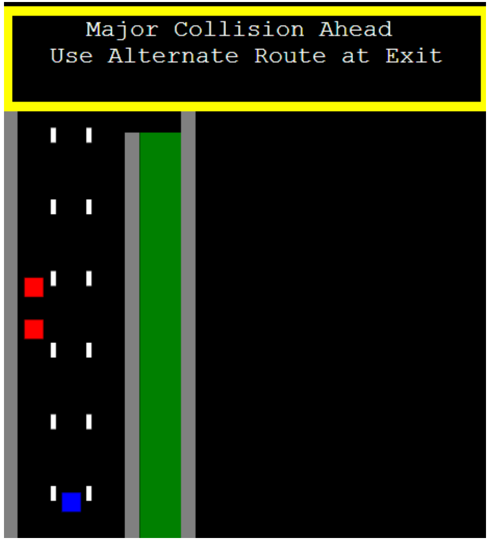

Driver's Screen
General Information
Variable Messaging Sign Text
Impassable Areas
Subject's Car
Other Cars (Computer / Human)
W
A
D
Earnings = $15.00 - $0.10*sec
Round 10
Distance to exit:137
Major Collision Ahead
Alternate Route Available at Exit
Player's Visibility Range
(Can only view a fraction of traffic)
Earnings: $12.80
43% Complete

Incidents and the role of VMS

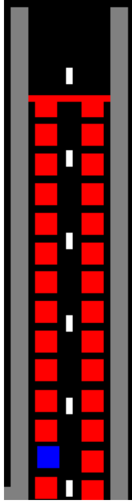
Drivers are informed of incidents via VMS and their own experience.

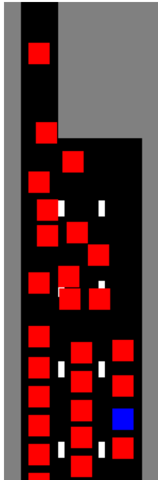
From this information, drivers must weigh the risk of congestion on the freeway from the incident against the risk of congestion on the alternate route from diverting drivers causing queues at the stoplights.

Due to the congestibility of both routes, there is no dominant strategy in making the diversion decision.



Congestion on the alternate route due to diverted traffic encountering a light.





Congestion on the main route due to a two-lane blockage

Our Treatments

The experiment is run for several sessions, each with a different group of 40 subjects and consisting of dozens of rounds.

Within groups: Vary the severity of our incident and the intensity of our VMS content, accordingly.

Between groups: Vary the language and information content of the VMS message

Within Subjects

Between Subjects

Scenario Main	No Incident	One Lane Blocked	Two Lanes Blocked		Three Lanes Blocked			Three Lanes Blocked 10 seconds		
Severity					20s	17s	14s	29s	26s	23s
No Messaging										
Incident Severity Only		Minor Collision Ahead	Medium Collision Ahead		Major Collision Ahead			Severe Collision Ahead		
Incident Severity + Recommendation		Minor Collision Ahead	Medium Collision Ahead. Alt. route available	Medium Collision Ahead	Major Collision Ahead. Use Alt. Route	Major Collision Ahead. Alt. route available	Major Collision Ahead	Severe Collision Ahead. Use Alt. Route	Severe Collision Ahead. Alt. route available	Severe Collision Ahead
Lanes Blocked + Recommendation (TBD)										

Driver Responses to
Variable Message Signs
After a Traffic Incident

An Experimental Study

Si-Yuan Kong and Amine Mahmassani

2015-08-10 Caltrans Webinar

VMS Messaging Schemes

Within Subjects

Between Subjects

Scenario	0. No Incident	1. One Lane Blocked	2. Two Lanes Blocked	3. Three Lanes Blocked			4. Three Lanes Blocked, Prolonged Delay		
Severity				Fastest	Medium	Slowest	Fastest	Medium	Slowest
Incident Severity Message	N/A	EXPECT MINOR DELAY	EXPECT MEDIUM DELAY	EXPECT MAJOR DELAY			EXPECT SEVERE DELAY		
Recommendation Message	N/A	N/A	ALT RTE AVAILABLE	N/A	ALT RTE AVAILABE AHEAD	USE ALT RTE AHEAD	N/A	ALT RTE AVAILABE AHEAD	USE ALT RTE AHEAD
Lanes Blocked Message	N/A	ONE LANE BLKD	TWO LANES BLKD	THREE LANES BLKD			THREE LANES BLKD		
Diversion Rate Message	N/A	1 IN 10 CARS SHOULD EXIT	1 IN 4 CARS SHOULD EXIT	1 IN 3 CARS SHOULD EXIT			1 IN 2 CARS SHOULD EXIT		

- All VMS messages begin with “ACCIDENT AHEAD”
- **Within Subjects** means subjects within the same session are exposed to different scenarios / severities
- **Between Subjects** means subjects across different sessions are exposed to different messaging schemes

- Example VMS message (Incident Severity + Recommendation):
  ACCIDENT AHEAD
  EXPECT MAJOR DELAY
  ALT RTE AVAILABLE AHD

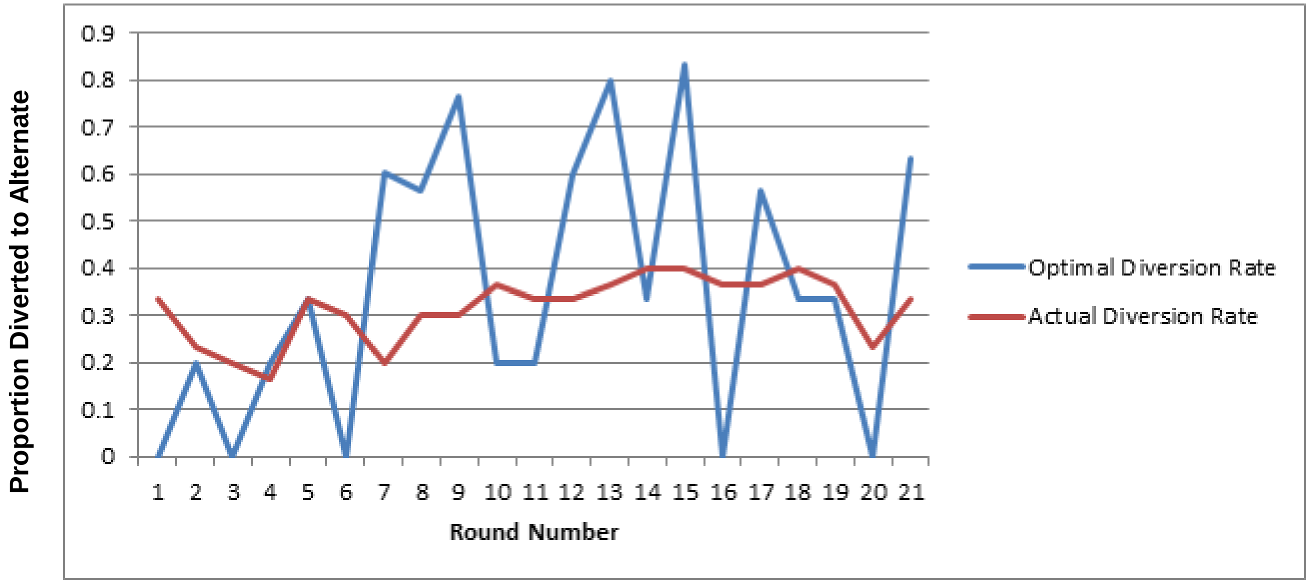
- Message formatting in this table is not representative of actual experiment formatting

Experiment Treatments

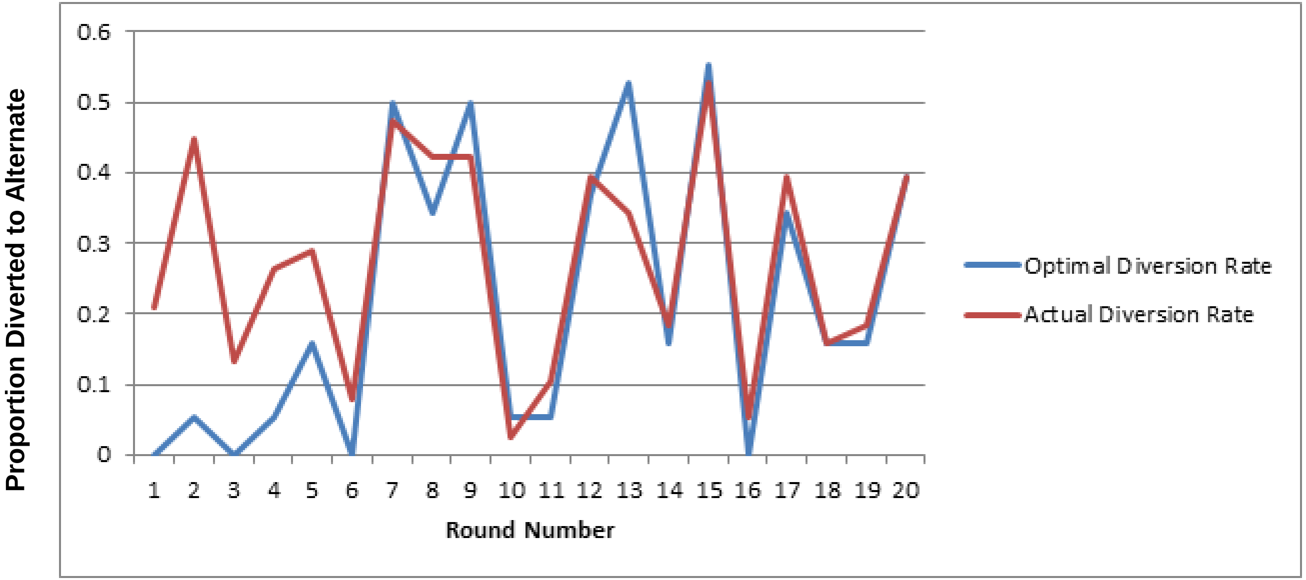
Treatment Code	Messaging Scheme	Session Date	# of Subjects
NM	No Messaging	7/1/2015	30
SM	Incident Severity	7/7/2015	38
RM	Incident Severity + Recommendation	7/14/2015	39
LM	Lanes Blocked	Future Session	N/A
DM	Diversion Rate	8/11/2015	39

- Each session consists of 3 practice rounds and 20 paying rounds
- Each session features the same pre-randomized order of incident scenarios
- Each session will have 51 vehicles total: up to 39 clients, the remainder are AI controlled

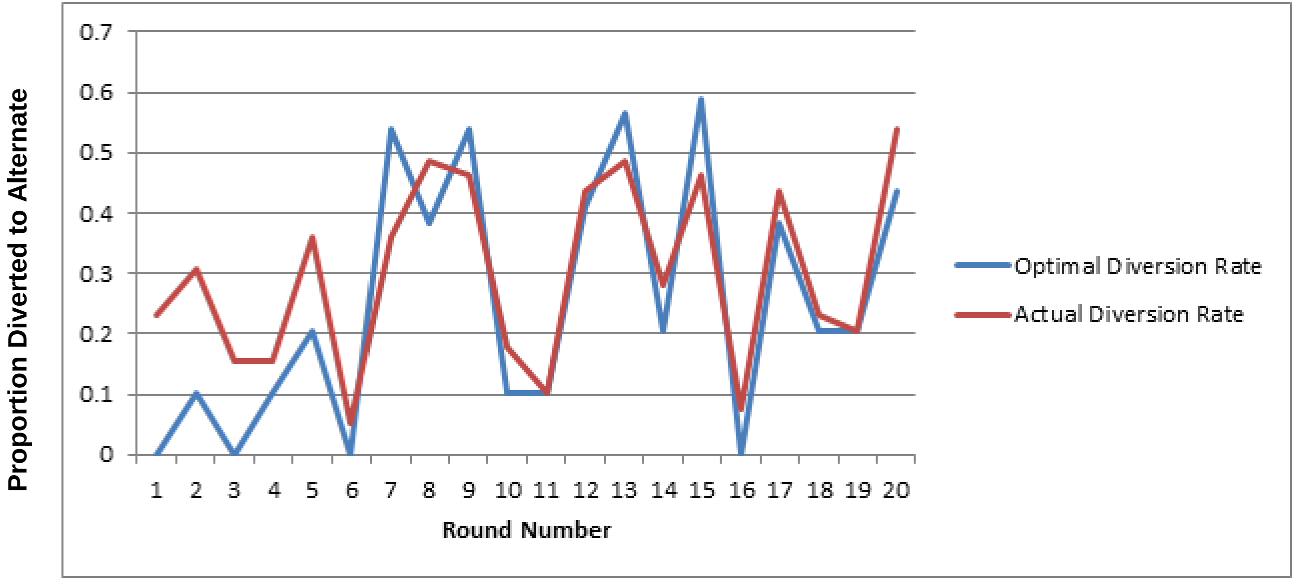
Session NM - No VMS



Session SM - Standard description of incident



Session RM - Description of incident and recommendation



Driver Responses to
Variable Message Signs
After a Traffic Incident

An Experimental Study

Si-Yuan Kong and Amine Mahmassani

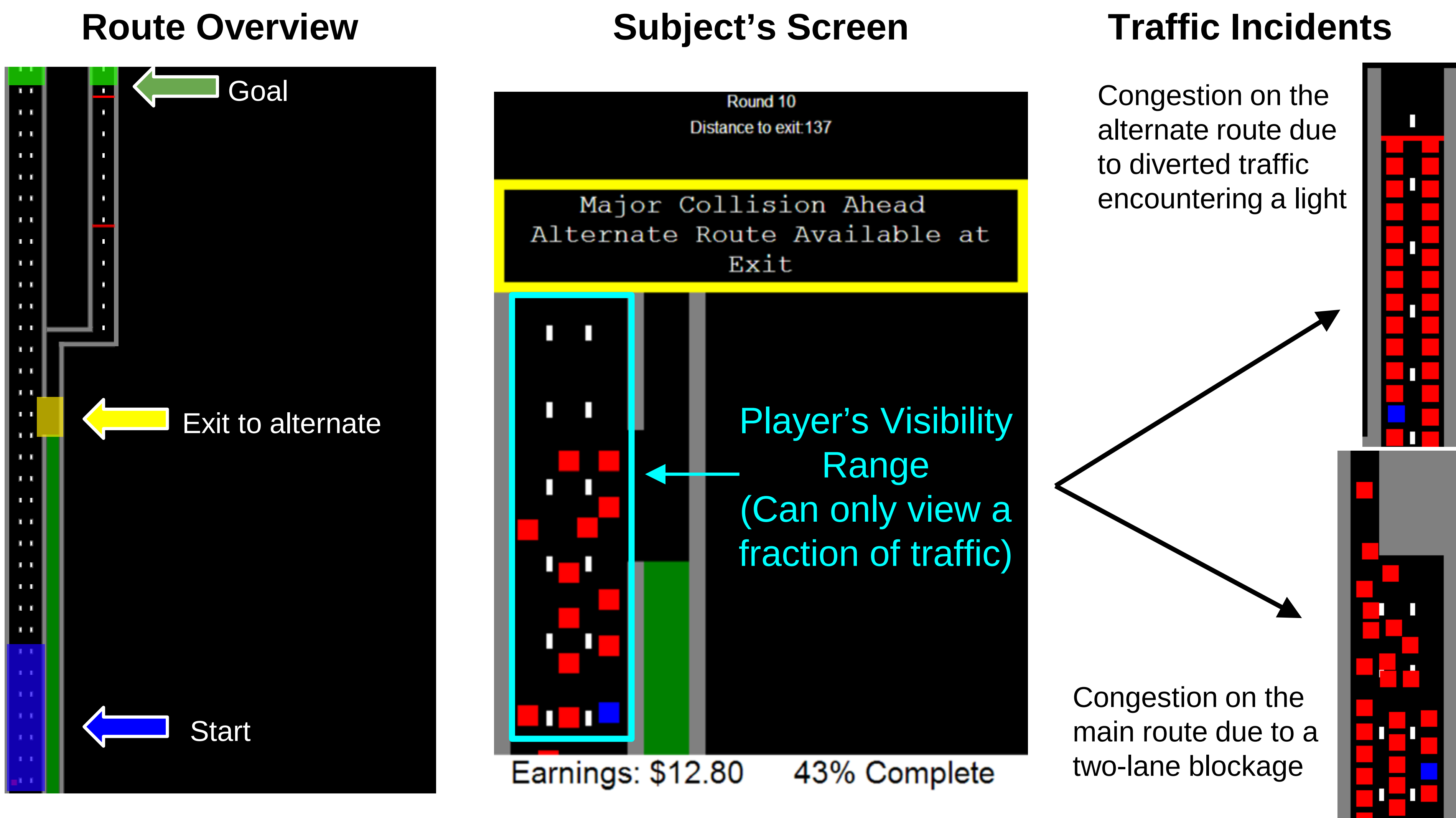
2015-09-17 Caltrans Webinar

Our Study

Can predictable diversion rates be achieved through manipulation of VMS content?

We search for a “variable intensity” messaging scheme capable of inducing predictable changes in diversion rates.

- 2D real-time driving simulator
- 40 subjects each control a vehicle
- All travel simultaneously (share the road)
- Drive in the same direction towards the same destination
- Start with endowment that decreases linearly with time
- Begin on the freeway, one opportunity each round to switch to the alternate route
- Incidents appear randomly, block portions of the freeway


Route Overview
Goal
Exit to alternate
Start
Subject's Screen
Round 10
Distance to exit:137
Major Collision Ahead
Alternate Route Available at Exit
Player's Visibility Range
(Can only view a fraction of traffic)
Earnings: $12.80
43% Complete
Traffic Incidents
Congestion on the alternate route due to diverted traffic encountering a light
Congestion on the main route due to a two-lane blockage

VMS Messaging Schemes

Within Subjects

Between Subjects

Scenario	**0. No Incident**	**1. One Lane Blocked**	**2. Two Lanes Blocked**	**3. Three Lanes Blocked**			**4. Three Lanes Blocked, Prolonged Delay**		
Severity				Fastest	Medium	Slowest	Fastest	Medium	Slowest
Incident Severity Message	N/A	EXPECT MINOR DELAY	EXPECT MEDIUM DELAY	EXPECT MAJOR DELAY			EXPECT SEVERE DELAY		
Recommendation Message	N/A	N/A	ALT RTE AVAILABLE	N/A	ALT RTE AVAILABE AHEAD	USE ALT RTE AHEAD	N/A	ALT RTE AVAILABE AHEAD	USE ALT RTE AHEAD
Lanes Blocked Message	N/A	ONE LANE BLKD	TWO LANES BLKD	THREE LANES BLKD			THREE LANES BLKD		
Diversion Rate Message	N/A	1 IN 10 CARS SHOULD EXIT	1 IN 4 CARS SHOULD EXIT	1 IN 3 CARS SHOULD EXIT			1 IN 2 CARS SHOULD EXIT		

- All VMS messages begin with “ACCIDENT AHEAD”
- **Within Subjects** means subjects within the same session are exposed to different scenarios / severities
- **Between Subjects** means subjects across different sessions are exposed to different messaging schemes

- Example VMS message (Incident Severity + Recommendation):
  ACCIDENT AHEAD
  EXPECT MAJOR DELAY
  ALT RTE AVAILABLE AHD

- Message formatting in this table is not representative of actual experiment formatting

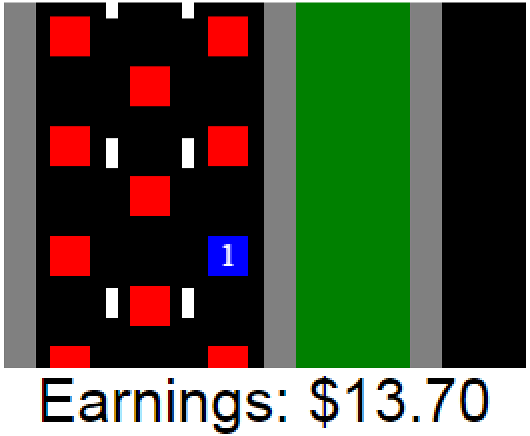
VMS Messaging Schemes

Within Subjects

Scenario	0. No Incident	1. One Lane Blocked	2. Two Lanes Blocked	3. Three Lanes Blocked			4. Three Lanes Blocked, Prolonged Delay		
Severity				Fastest	Medium	Slowest	Fastest	Medium	Slowest
ID'd / Targeted Message	N/A	MINOR ACCIDENT AHEAD IF YOUR CAR IS #1-4, USE ALT ROUTE	MEDIUM ACCIDENT AHEAD IF YOUR CAR IS #1-11, USE ALT ROUTE	MAJOR ACCIDENT AHEAD IF YOUR CAR IS #1-18, USE ALT ROUTE			MAJOR ACCIDENT AHEAD IF YOUR CAR IS #1-27, USE ALT ROUTE		

Between Subjects

- ID’d / Targeted Messaging is used in treatments where subject vehicles are uniquely identified with a number label
- Two sub-treatments are considered: one in which the label is publicly displayed, another in which it is only privately visible

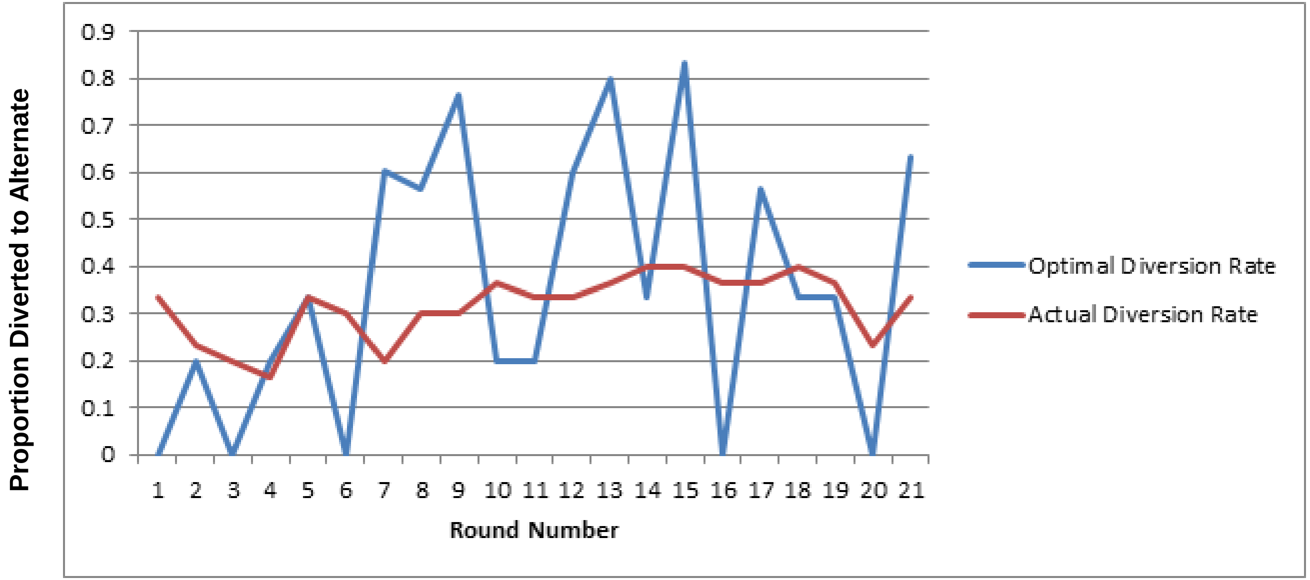


Experiment Treatments

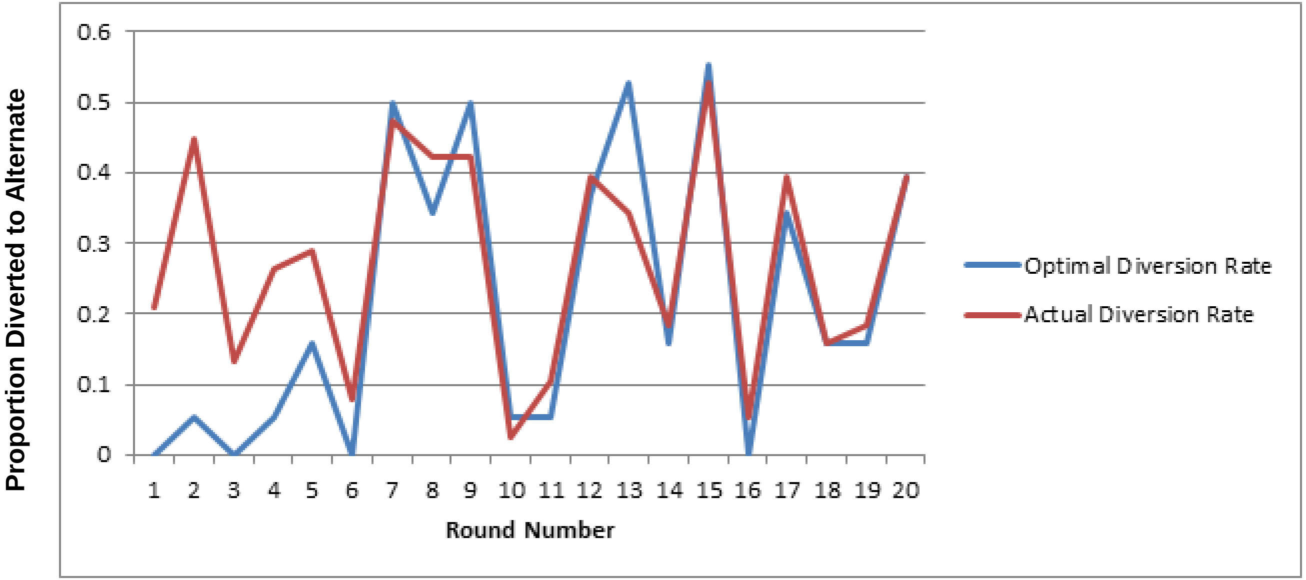
Treatment Code	Messaging Scheme	Session Date	# of Subjects
NM	No Messaging	7/1/2015	30
IS	Incident Severity	7/7/2015	38
ISR	Incident Severity + Recommendation	7/14/2015	39
LB	Lanes Blocked	Future Session	N/A
DR	Diversion Rate (Variable Denominator)	8/11/2015	39
	Diversion Rate (Fixed Denominator)	8/18/2015	39
DDR	Dynamic Diversion Rate	Future Session	
ID	Identified / Targeted	Future Session	
PID	Publicly Identified / Targeted	Future Session	

- Each session consists of 3 practice rounds and 20 paying rounds
- Each session features the same pre-randomized order of incident scenarios
- Each session will have 51 vehicles total: up to 39 clients, the remainder are AI controlled

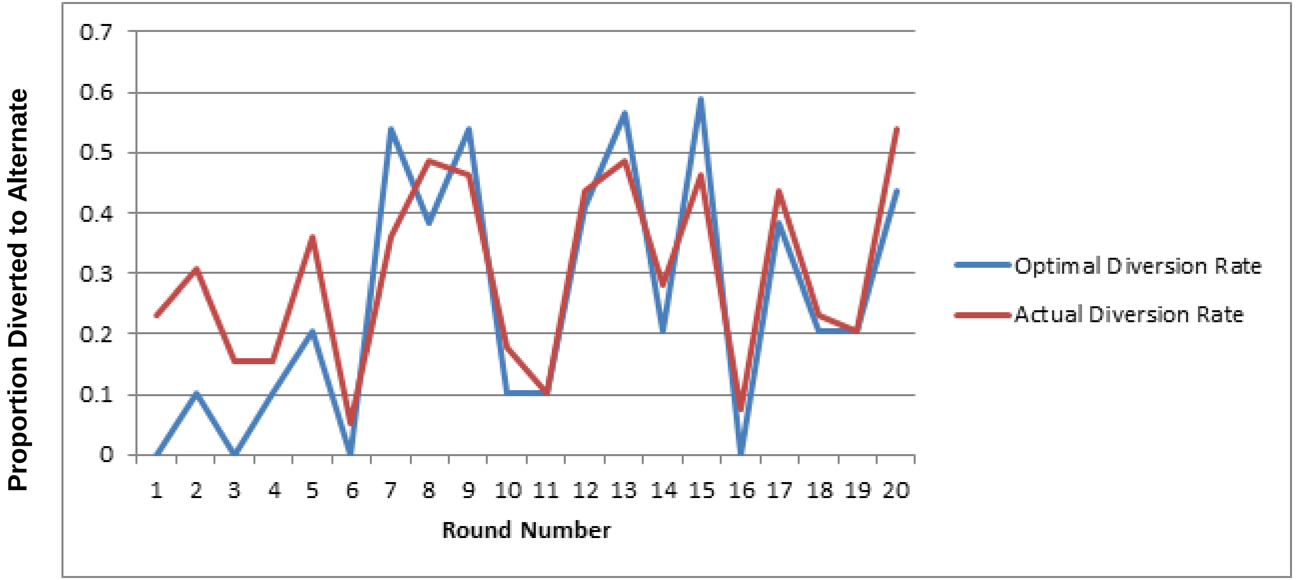
Session NM - No VMS



Session IS - Standard description of incident severity

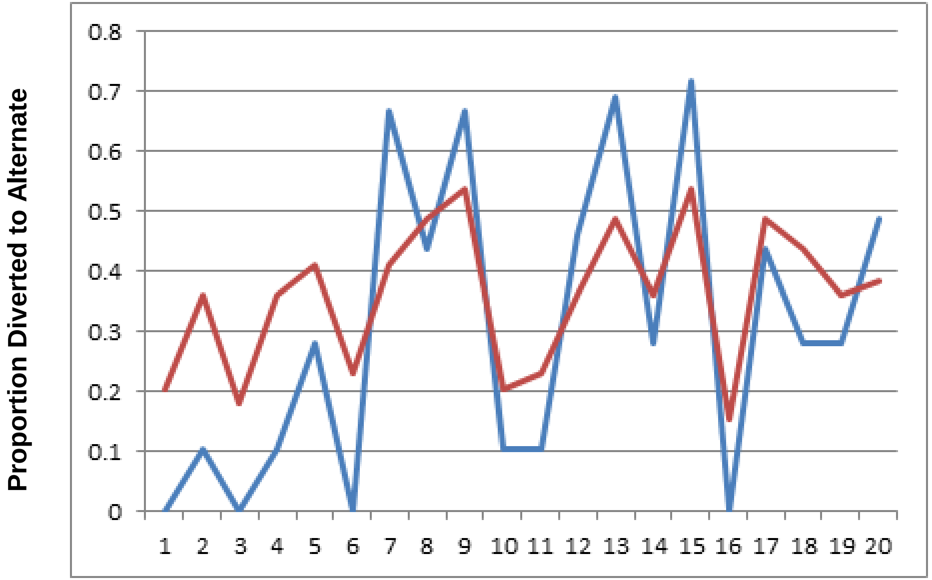


Session ISR - Incident severity with recommendation

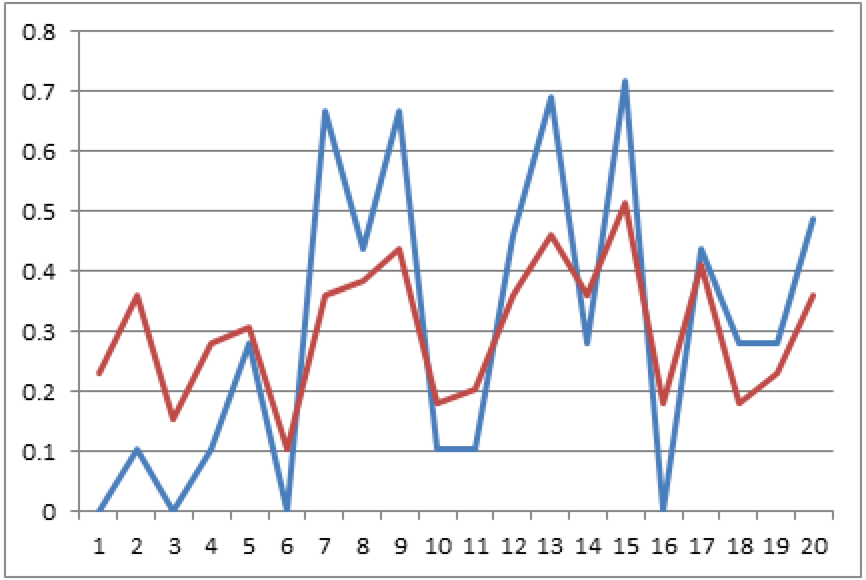


Session DR - Diversion rates presented as fractions

Variable Denominator



Fixed Denominator



Variable Denominator messages:

- 1 IN 10 CARS SHOULD EXIT
- 1 IN 4 CARS SHOULD EXIT
- 1 IN 3 CARS SHOULD EXIT
- 1 IN 2 CARS SHOULD EXIT

Fixed Denominator messages:

- 1 IN 10 CARS SHOULD EXIT
- 2 IN 10 CARS SHOULD EXIT
- 4 IN 10 CARS SHOULD EXIT
- 6 IN 10 CARS SHOULD EXIT

Field-study Prospects

Given the results of sessions conducted thus far, the standard description of incident severity appears to be the best candidate for field-testing.

A field-study conducted in the OC triangle can examine:

- driver response to VMS with / without diversion recommendations
- network performance with / without VMS
- changes in driver behavior over time due to repeated VMS interactions
- the impact of freeway VMS on local street traffic

Extension 1: Private information messaging

A rapidly increasing share of drivers have access to a private real-time traffic information source (smartphone apps, networked GPS devices, networked car infotainment systems). Direct messaging can be used to provide targeted traffic information, including incident alerts, diversion recommendations, and alternate route guidance to help further improve incident management.

A laboratory study using our software platform can provide insights regarding:

- the efficacy of private messaging in directing driver behavior during incident management
- the selection of optimal messaging content and verbiage unique to a private messaging system
- how private messaging compares to public messaging in the same controlled environment

Extension 2: Traffic signal control using VOT auctions

UCI PhD candidate Roger Lloret-Batlle, under UCTC funded dissertation research, has developed a novel traffic signal control algorithm that incorporates users' value-of-time (VOT) elicited via right-of-way auctions. The system is designed to improve user satisfaction / quality-of-life and also has the potential to optimize the economic value of the transportation system for many types of users.

A laboratory study using our software platform can provide insights regarding:

- the potential of the VOT-aware system to improve the economic outcomes of drivers compared to existing traffic signal control systems
- the most effective / efficient allocation and control algorithms
- the viability of the system from the perspective of traffic management
- the ease-of-use of the system from the perspective of drivers

Driver Responses to
Variable Message Signs
After a Traffic Incident

An Experimental Study

Si-Yuan Kong and Amine Mahmassani

2015-11-19 Caltrans Webinar

Experiment Treatments

Treatment Code	Messaging Scheme	Session Date	# of Subjects
NM	No Messaging	7/1/2015	30
IS	Incident Severity	7/7/2015	38
	Incident Severity (Updated)	10/15/2015	34
	Incident Severity (Updated)	11/3/2015	39
ISR	Incident Severity + Recommendation	7/14/2015	39
LB	Lanes Blocked	Future Session	N/A
DR	Diversion Rate (Variable Denominator)	8/11/2015	39
	Diversion Rate (Fixed Denominator)	8/18/2015	39
DDR	Dynamic Diversion Rate	10/8/2015	38
ID	Identified / Targeted	8/28/2015	38
	Identified / Targeted (Revised)	10/6/2015	38
IDS	Identified / Targeted w/ Severity Info	10/19/2015	39
PIDS	Public Id. / Targeted w/ Severity Info	10/22/2015	37

VMS Messaging Schemes - Diversion Rate Messaging

Scenario	**0. No Incident**	**1. One Lane Blocked**	**2. Two Lanes Blocked**	**3. Three Lanes Blocked**			**4. Three Lanes Blocked, Prolonged Delay**		
Severity				Fastest	Medium	Slowest	Fastest	Medium	Slowest
Fixed Diversion Rate Message	N/A	1 IN 10 CARS SHOULD EXIT	1 IN 4 CARS SHOULD EXIT	1 IN 3 CARS SHOULD EXIT			1 IN 2 CARS SHOULD EXIT		

Dynamic Diversion Rate

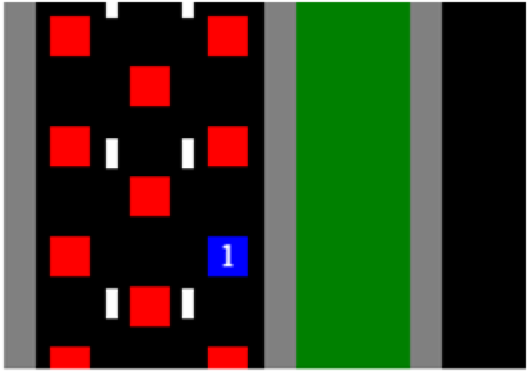
Diversion Message (__ CARS SHOULD EXIT)	**NO CARS**	**1 IN 10**	**1 IN 5**	**1 IN 4**	**1 IN 3**	**1 IN 2**	**2 IN 3**	**3 IN 4**
0. No Incident	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A
1. One Lane Blocked	0	.1	.2	.33	.5	.66	.88	1
2. Two Lanes Blocked	0	.1	.2	.33	.5	.66	.88	1
3. Three Lanes Blocked	0	.1	.2	.33	.5	.66	.88	1
4. Three Lanes Blocked, Prolonged Delay	0	.1	.2	.33	.5	.66	.88	1

- Dynamic diversion rate messages begin by stating the ideal diversion rate.
- This rate updates in real-time based on the share of drivers diverting; if too many are diverting, the message will change to recommend a lower rate - and vice versa
- The chart to the left shows which message will be displayed based on the share of remaining drivers who should divert to achieve the optimum.

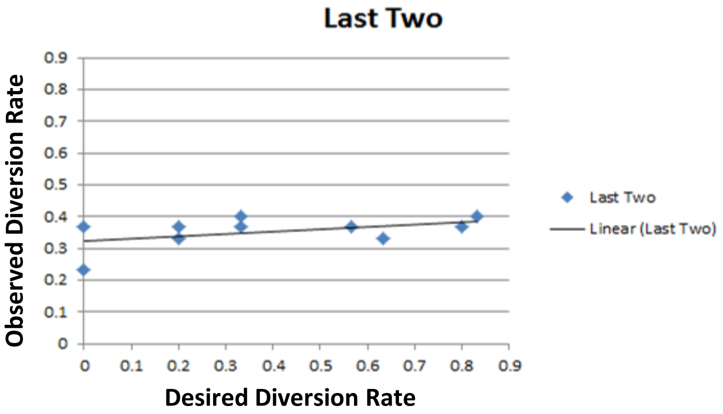
VMS Messaging Schemes - Targeted Messaging

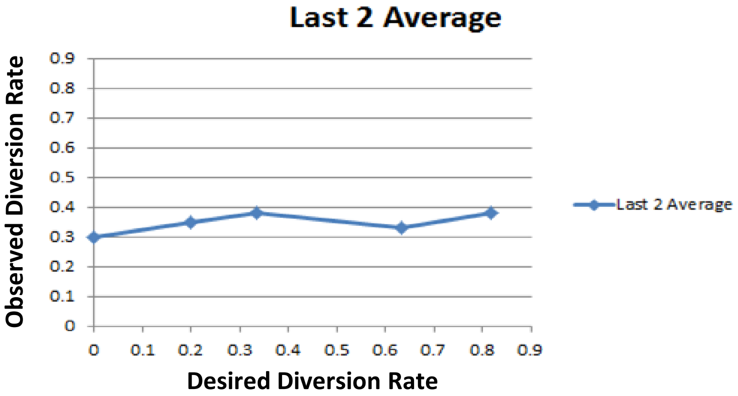
Scenario	**0. No Incident**	**1. One Lane Blocked**	**2. Two Lanes Blocked**	**3. Three Lanes Blocked**			**4. Three Lanes Blocked, Prolonged Delay**		
Severity				Fastest	Medium	Slowest	Fastest	Medium	Slowest
Incident Severity Line	N/A	MINOR ACCIDENT AHEAD	MEDIUM ACCIDENT AHEAD	MAJOR ACCIDENT AHEAD			SEVERE ACCIDENT AHEAD		
ID'd / Targeted Message	N/A	IF YOUR CAR IS #1-4, USE ALT ROUTE	IF YOUR CAR IS #1-11, USE ALT ROUTE	IF YOUR CAR IS #1-18, USE ALT ROUTE			IF YOUR CAR IS #1-27, USE ALT ROUTE		

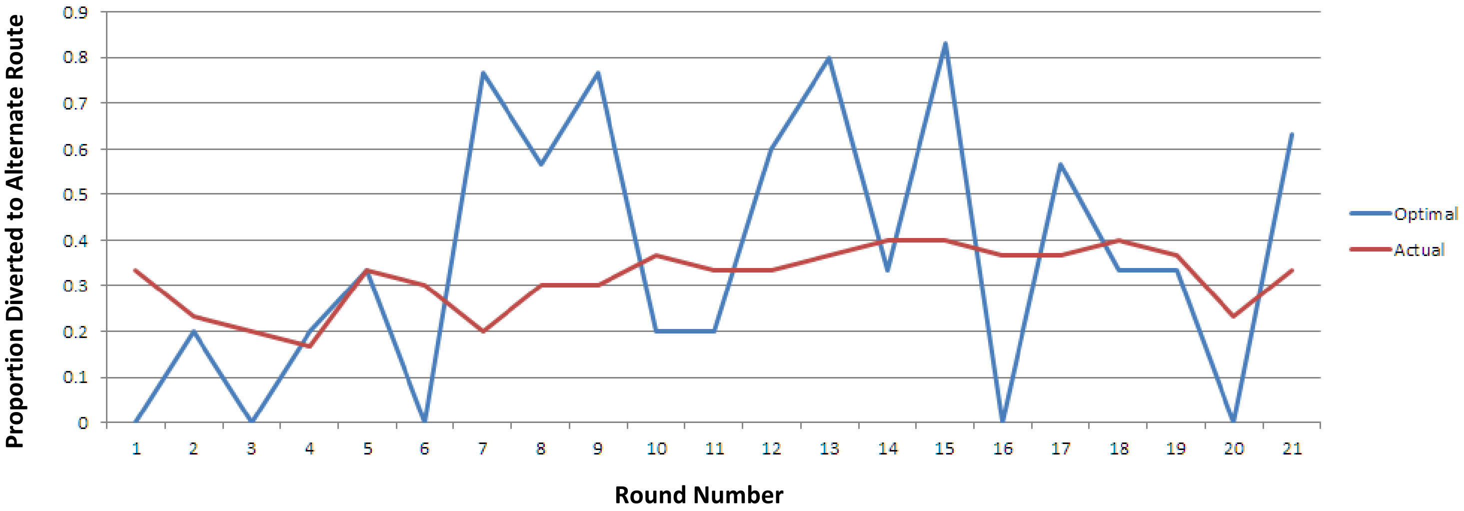
- ID’d / Targeted Messaging is used in treatments where subject vehicles are uniquely identified with a number label
- Sub-treatment 1: label is displayed publicly (visible on all cars) or privately (visible only to the driver on his car)
- Sub-treatment 2: first message line displays incident severity
- Number labels are persistent through all rounds within a session
- Example VMS:
  MEDIUM ACCIDENT AHEAD
  IF YOUR CAR IS #1-11,
  USE ALT ROUTE



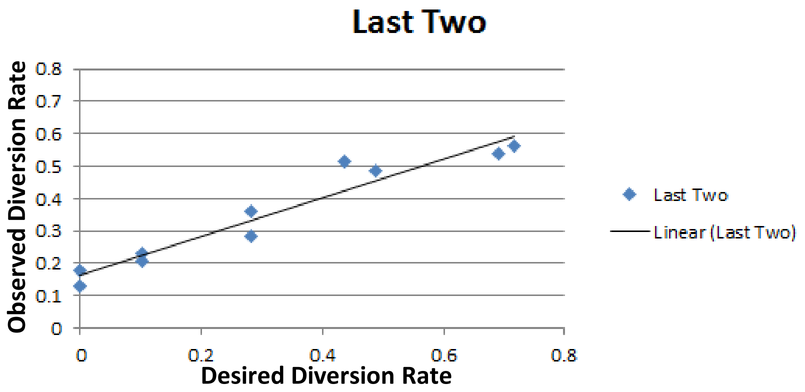
Session 0 - No VMS

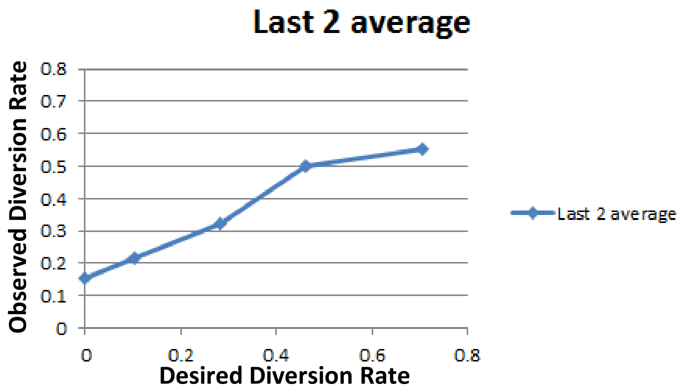


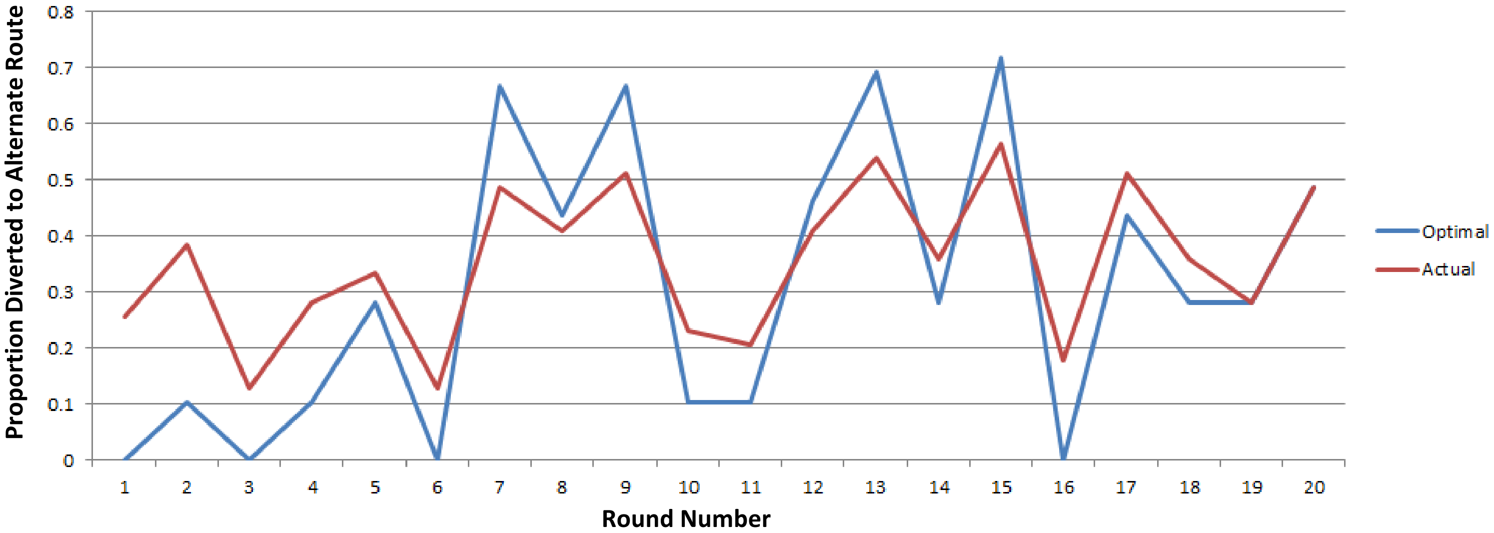




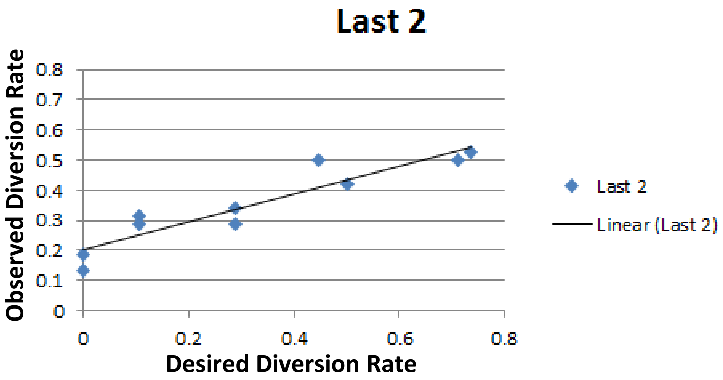
Session IS - Standard description of incident severity

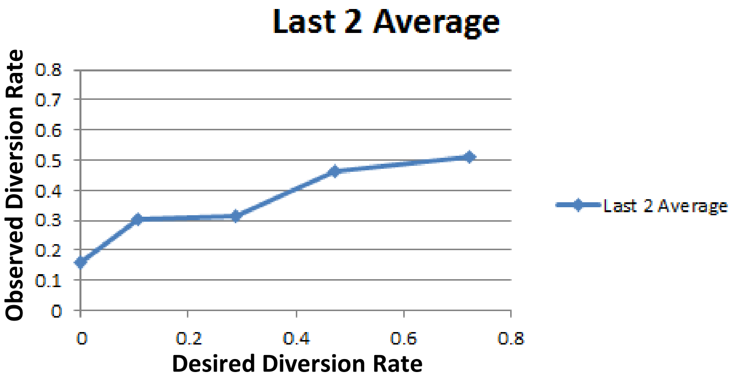


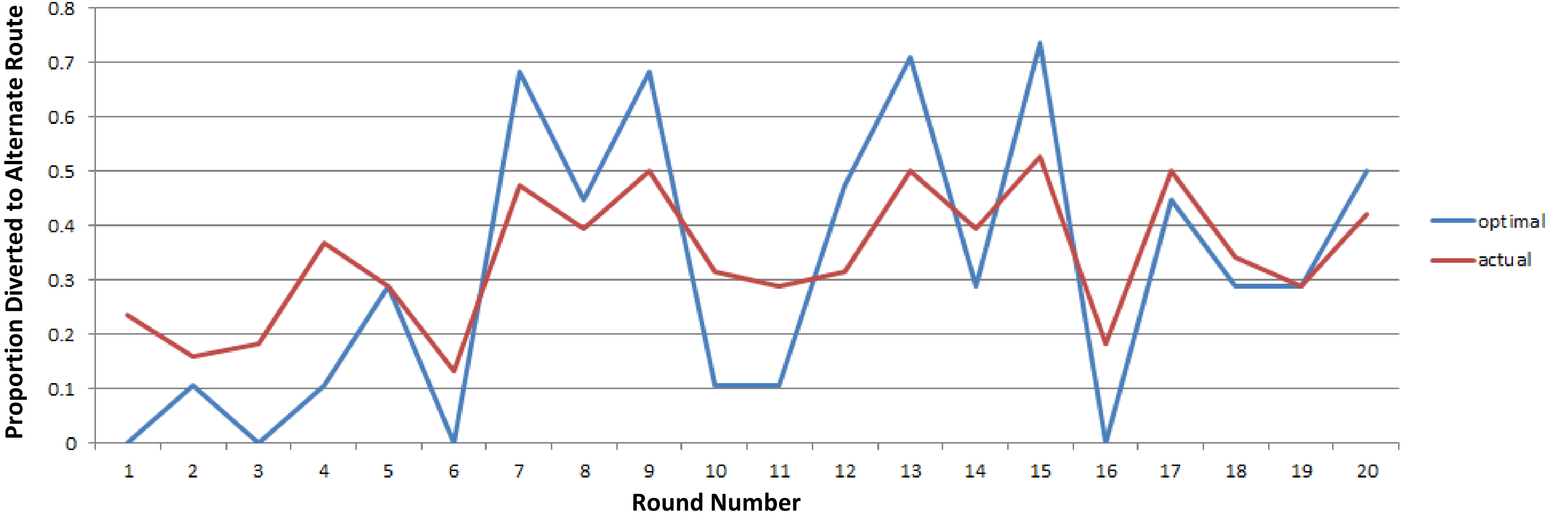




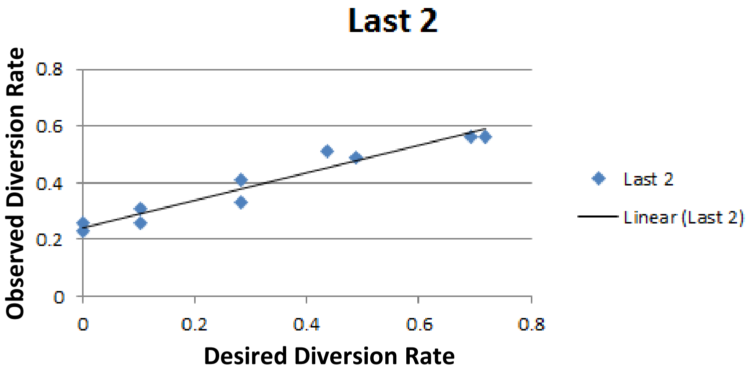
Session ID - Identified / Targeted Messaging

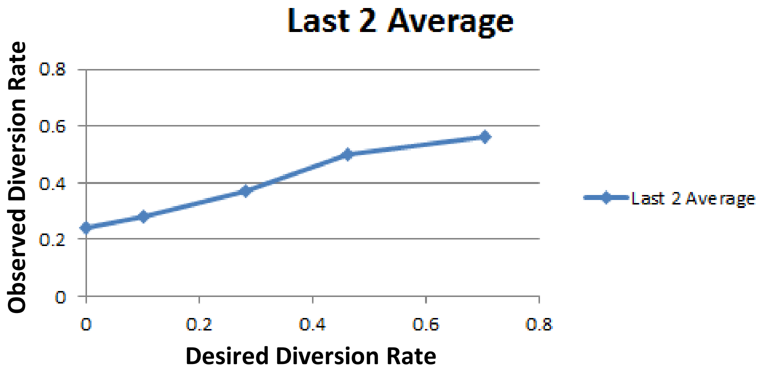


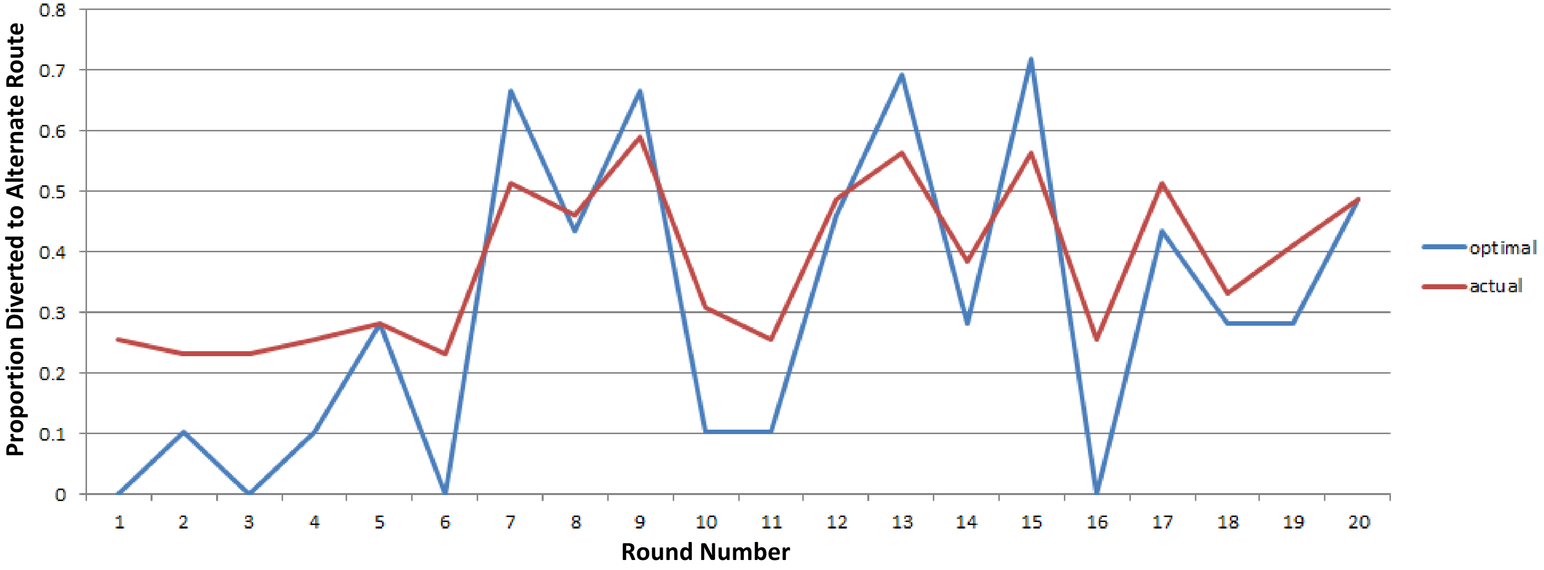




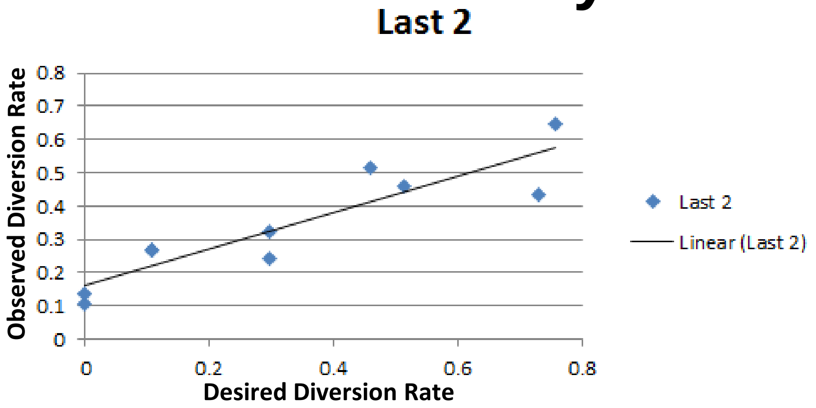
Session IDS - Identified / Targeted w/ Severity Info

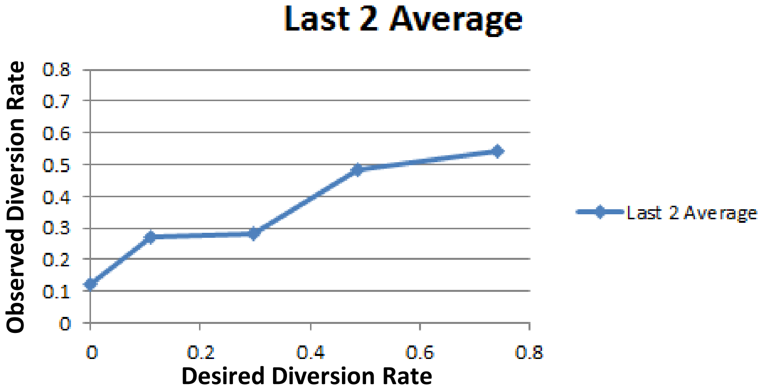


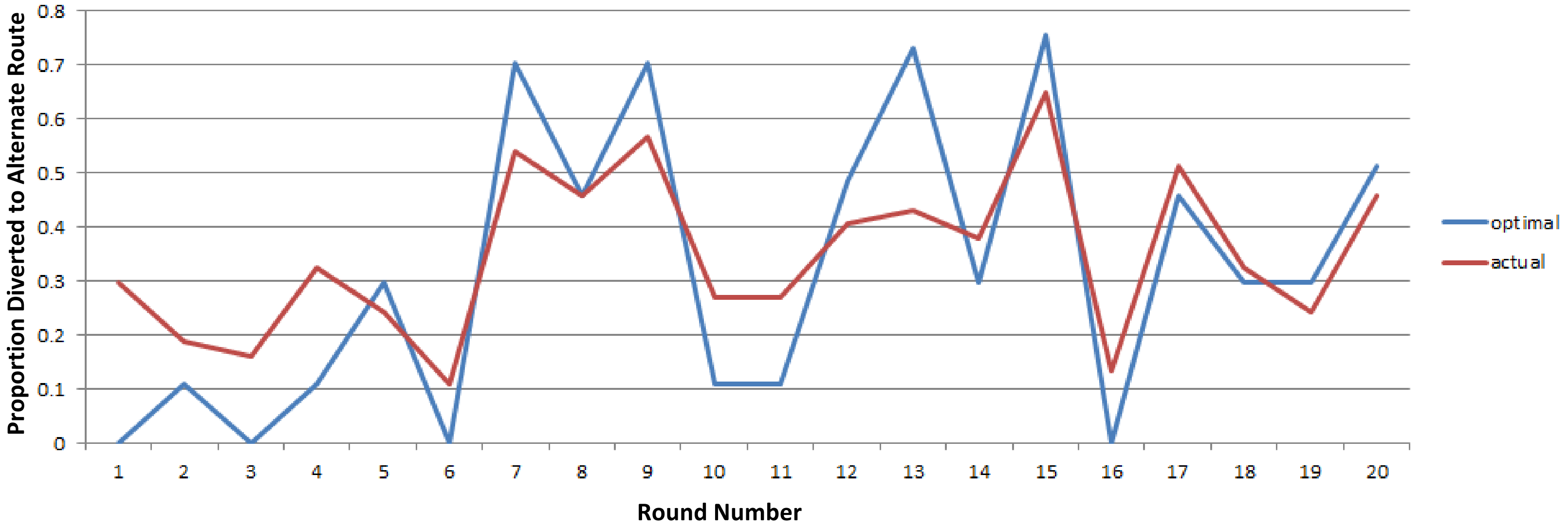




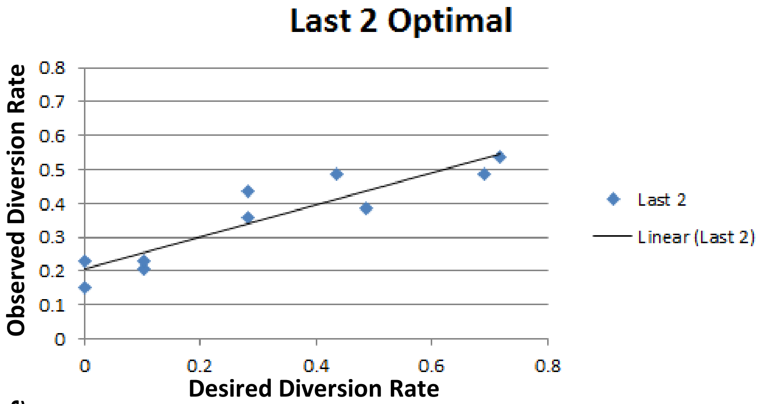
Session PIDS - Publicly Identified / Targeted w/ Severity Info

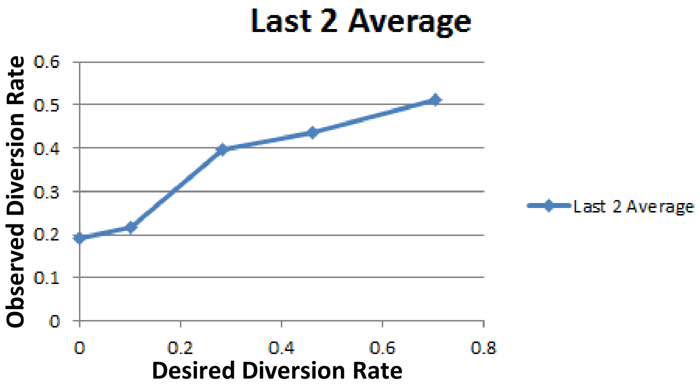


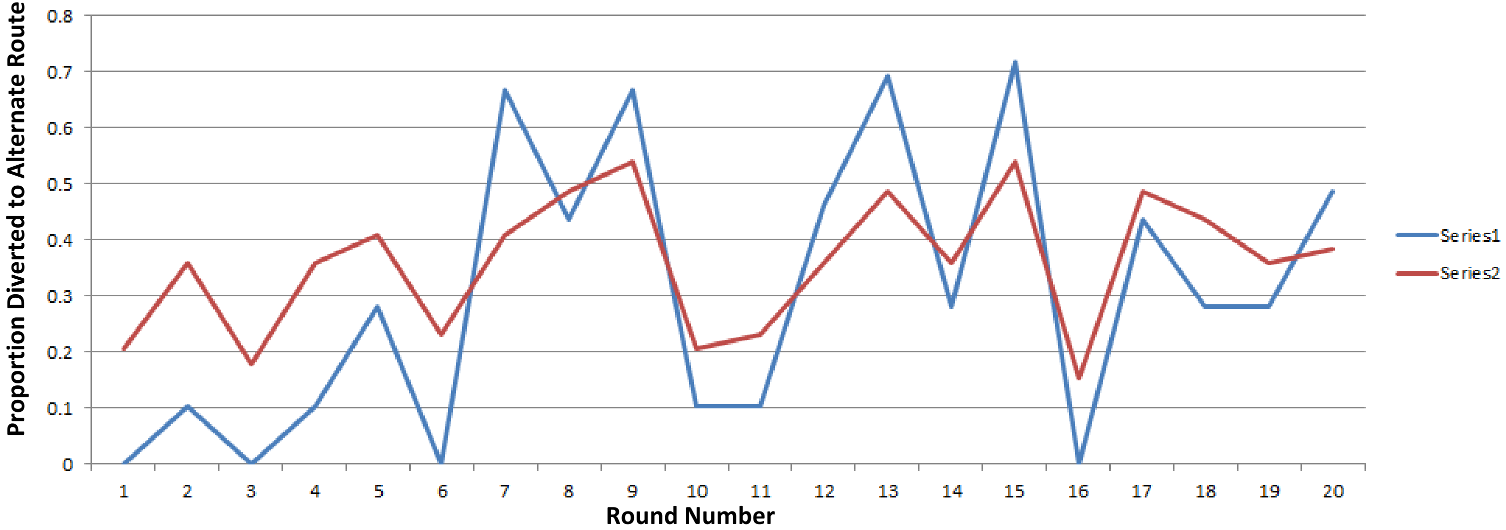




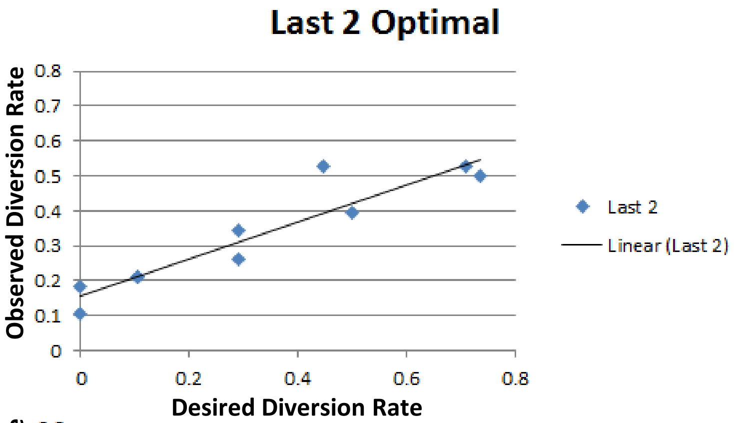
Session DR - Fixed Diversion Rate Messaging

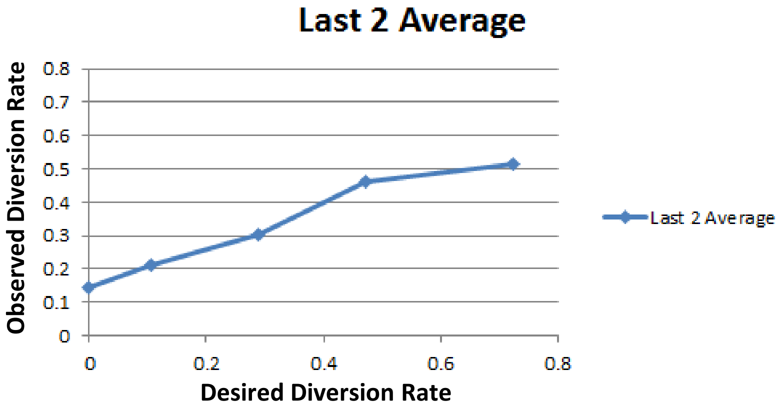


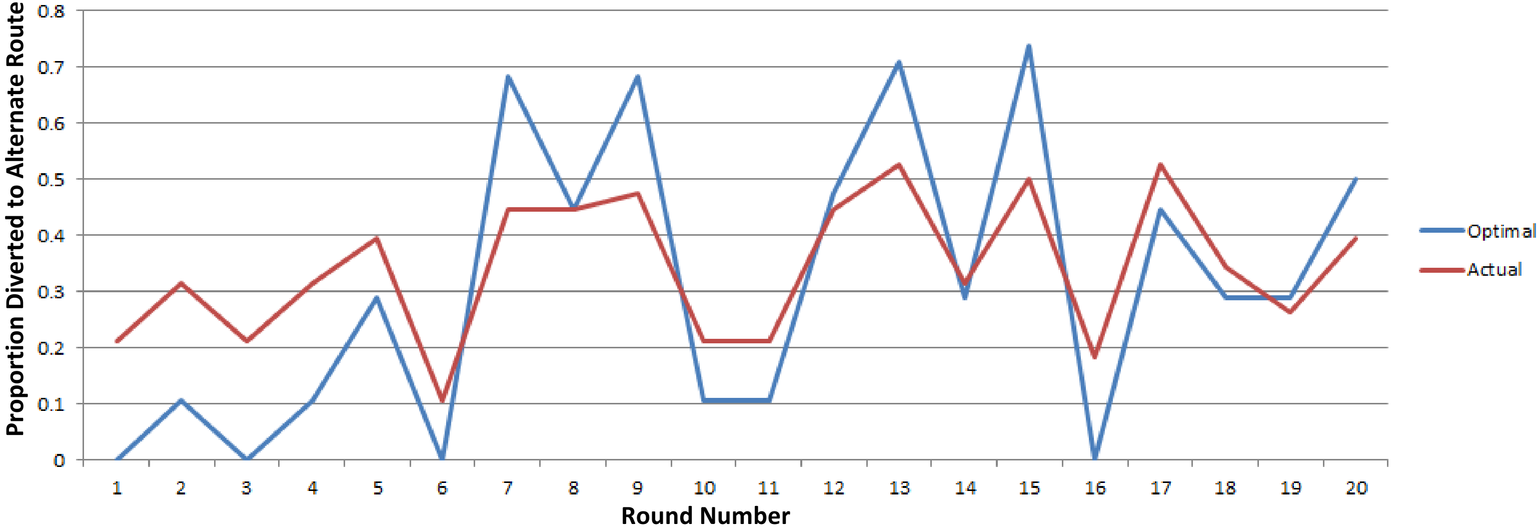




Session DDR - Dynamic Diversion Rate Messaging







Preliminary Lessons, Part 1

- **Slide 6, Standard Description of Incident Severity**: VMS incident descriptions offer dramatically better diversion performance than when no VMS content is provided at all
- **Slide 7, Identified/Targeted Messaging**: Without an explanation of why, drivers will not reliably comply with VMS instructions. One is better off simply describing the incident and providing no instructions
- **Slide 8, Identified/Targeted Messaging w/Severity Info**: VMS instructions are much more successful when accompanied by information explaining why. However, private number instructions + incident description is not a significant improvement over incident description only.

Preliminary Lessons, Part 2

- **Slide 9, Publicly Targeted/Identified w/Severity Info**: Public number instructions are more successful than private number instructions, likely because drivers get a sense of what other people are being told to do – increasing trust in the information and giving an opportunity to observe non-compliance and adapt. This is the most successful scheme.
- **Slide 10, Fixed Diversion Rate Messaging**: Drivers to not coordinate to achieve desired rates when told what share of them divert. This is due in part to coordination difficulties, and also likely because information credibility is reduced without an incident description.
- **Slide 11, Dynamic Diversion Rate Messaging**: Adjusting the displayed rate recommendation is able to improve performance by encouraging more diversions in real-time when too few drivers exit, and vice-versa. This is the most successful scheme that does not include an incident description. A follow-up treatment should combine a dynamic rate recommendation with an incident description.

Upcoming Treatments

Type of Scheme	Modifications	Purpose
Static pricing on main route	Normal value of time distribution	Study how pricing can be used to exploit value of time heterogeneity to achieve desired diversion rates
	Uniform value of time distribution	
Dynamic pricing on main route		Study whether real-time adjustments of pricing in response to diversion rates can improve outcomes
Static and/or dynamic pricing combined with incident description		Explore whether pricing and information can be used synergistically to improve route choice outcomes
Various robustness checks	Round ordering, practice rounds, instructions, maybe sampling	To ensure that promising rounds are still effective under reasonable variations in conditions