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Evaluation of the effectiveness of accident information on freeway changeable message signs: A comparison of empirical methodologies

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ABSTRACT

In this paper, we study the effectiveness of accident messages that are displayed on freeway changeable message signs (CMS). Motivated by the lack of empirical studies and the mixed results reported in the limited empirical studies, this paper focuses on the comparison of different aggregate analysis methodologies and their corresponding results, using the same empirical data set. We have two major findings. First, we find that the CMS accident messages do not seem to have any significant immediate effect on driver diversion based on our empirical data. Visible congestion, on the other hand, seems to be an important factor for driver diversion. Second, we show how the conclusion could have been if wrong methodologies were to be adopted. Methods that rely on correlation alone but not the timing of events (what we call correlation method) yield high correlation between CMS accident messages and driver diversion, which is typically and incorrectly interpreted as CMS accident messages being effective.

1. Introduction

In this paper, we use empirical data to evaluate drivers' response to messages displayed on freeway changeable message signs (CMS, also known as variable message signs or dynamic message signs).

We are generally interested in the effect of information on traveler behavior. As a starting point, we focus on the information conveyed through freeway CMS for two reasons. First, CMS has been in use in the field for a long time, at least since the 1960s. Second, the CMS system is expensive: Typical installation cost is around $200,000 for each freeway CMS, excluding the cost for operation and maintenance. In California alone, there are about 771 such signs on the freeway, which cost at least $150 million for installation. Therefore, we would like to understand the worth of this system.

However, we have very limited understanding of how effective CMS messages are. According to a recently published NCHRP report (Robinson et al., 2012), only 30 percent of the agencies reported having evaluation data that demonstrate the benefits of providing information to the traveling public, and only 40 percent have an ongoing program for evaluating the provision of traveler information. To most public agencies, the empirical effect of CMS is largely anecdotal and difficult to quantify. Most of the literature on the effect of CMS, as described in the next section, is based on stated preference surveys or simulations. Therefore, there is a need to study the effect of CMS with empirical data.

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2. Literature review

The literature on the effect of CMS is summarized into the following categories:

2.1. Idealized assumptions

Earlier efforts to quantify the effect of traveler information (Kanafani and Al-Deek, 1991; Al-Deek and Kanafani, 1993) tend to make idealized assumptions about driver response, for example that drivers will fully comply with route diversion suggestions, either for system optimal assignment or to avoid incidents. The purpose of these studies is typically not to model driver response accurately, but rather to estimate the upper bound of the benefit of traveler information.

2.2. Stated preference surveys or simulations

The most commonly used method to study the effect of CMS is stated preference (SP) surveys (Khattak et al., 1993; Mannering et al., 1994; Madanat et al., 1995; Benson, 1996; Emmerink et al., 1996; Polydoropoulou et al., 1996; Wardman et al., 1997; Abdel-Aty et al., 1997; Peeta et al., 2000; Lappin and Bottom, 2001; Abdel-Aty and Abdalla, 2004; Chatterjee and Mcdonald, 2004; Chorus et al., 2006; Ben-Elia et al., 2013; Razo and Gao, 2013). Lappin and Bottom (2001), Chorus et al. (2006) provide good literature review on the findings from SP surveys. Typically, participants are asked what they would do if they see certain CMS messages. SP survey is an effective method to obtain information from individuals on their thought process. These and many other studies have offered insights into factors that affect drivers' decision for route diversion, including purpose of travel, schedule flexibility, travel distance, cause of congestion on current route, familiarity with alternative routes, information availability on alternative routes, and previous experiences with traveler information.

Studies using driving simulator (Dutta et al., 2004; Chorus et al., 2007, 2013) provide a comparatively more realistic setting to identify factors that affect the readability of information as well as the behavior of drivers. For example, Dutta et al. (2004) identifies the following factors that significant affect driver performance: visual obstructions of message signs, the displaying sequence of content, the message content, and the number and direction of lane changes required.

However, travelers' stated preference (or their behavior in the driving simulator) can be different from their actual behavior, due to the lack of commitment. For example, Xu et al. (2011) finds that SP survey overestimates the number of drivers who take diversion routes. Therefore, results obtained through SP surveys or simulations may not be appropriate for operational applications. For example, if CMS is used to divert traffic to arterial streets, the amount of traffic diverted needs to be estimated so that traffic signals on local streets can account for it. SP methods generally do not provide the level of accuracy needed for such operational purposes.

2.3. Empirical data

Alternatively, one can study the effect of CMS with empirical data to see what travelers actually did. This is the approach taken in this paper. The number of studies we are aware of in this category is much smaller compared with those using SP methods, and these studies are summarized in Table 1.

We find that the effect of CMS reported by these studies varies over a wide range. While almost all the studies report the effect of CMS to be statistically significant, the magnitude can sometimes be small and insignificant for operational purposes, such as in Dudek et al. (1982). Of course, the mixed results could be due to the differences in site location. But we also identify two problems in the methodologies adopted by these studies, which we think contribute to the mixed results.

The first problem is that many studies regard CMS as the only information source, while failing to account for the potential effect of visible congestion. However, the effect of visible congestion on diversion is well documented (Dudek et al., 1982; Ullman, 1992, 1996; Bushman et al., 2004; Liu et al., 2011; Wu et al., 2011; Xu et al., 2011). It has been empirically observed that many drivers change their routes when serious congestion is visible, and visible congestion is potentially the explanation for the observation in Foo et al. (2008) that sometimes the turning rate changes before the message changes.

The second problem is in the method used to derive the effect of CMS. Two types of methods are mainly used in the literature. The first method compares driver behavior with and without CMS messages, which we will call the correlation method. The second method compares the behavior right before and after CMS message changes, which we will call the causality method. The correlation method is more likely to capture a mixed effect from various information sources, while the causality methods is more likely to reveal the effect of CMS.[1]

As a summary, the number of empirical studies on the effect of CMS is small. Of the limited empirical studies, the reported effect of CMS varies greatly. Besides difference in site location, we speculate the mixed results can also be attributed to the different methodologies adopted by the studies. The comparison between methodologies has not been done to our knowledge, and typically only one methodology is adopted by each study.

[1] Strictly speaking, the term causality is too strong for the second method. In addition to correlation, the second method accounts for the timing of the events, which is a necessary but not sufficient condition for causality.

Table 1
Summary of empirical studies on the effect of CMS.

Reference & year	Site location	Event type	Info sources considered	Method to derive the effect of CMS
Dudek et al. (1978)	TX, USA	Special events	CMS*	Average with and without CMS message (alternating message and blank screen)
Turner et al. (1978)	TX, USA	Work zone	CMS*	5-min average before and after CMS message
Dudek et al. (1982)	TX, USA	Accident	CMS* Congestion*	Average with and without CMS message
Kuhne et al. (1996)	Munich, Germany	Normal	CMS*	No explanation
Yim and Ygnace (1996)	Paris, France	Normal	CMS*	5-min average before and after CMS message
Horowitz et al. (2003)	WI, USA	Work zone	CMS*	Average with and without CMS message
Bushman et al. (2004)	NC, USA	Work zone	CMS** Congestion*	Average with and without CMS message, controlling for congestion
Chu et al. (2005)	CA, USA	Work zone	CMS*	Average with and without CMS message
Lee and Kim (2006)	CA, USA	Work zone	CMS*	Average with and without CMS message
Huo and Levinson (2006)	MN, USA	Accident	CMS*	10-min average before and after CMS message
Foo et al. (2008)	ON, Canada	Normal	CMS*	30-min average before and after CMS message
Liu et al. (2011)	WI, USA	Work zone	CMS*	Average with and without CMS message
Wu et al. (2011)	WA, USA	Normal	Congestion*	Threshold based method
Xu et al. (2011)	Shanghai, China	Accident	CMS* Congestion*	5-min average before and after CMS message

* The effect of this factor (either CMS or visible congestion) on driver diversion is statistically significant.
** The effect of CMS on driver diversion is statistically significant only with both delay and alternative route advisory.

Therefore, the goal of this paper is twofold: to empirically evaluate drivers' response to CMS messages and to compare these methodologies on the same data set. During this study, we will focus on accident messages. Compared with other types of information that CMS can display, such as travel time or planned events, accident messages are not foreseeable and more urgent, and therefore more likely to be valuable to travelers and motivate their behavior change.

3. Experimental design

When drivers receive CMS messages about an accident somewhere downstream on the freeway, the only action they can take, if any, is to divert around the accident location through parallel arterial streets. To represent drivers' change of routes, we define turning rate $R(t)$ at each off-ramp between the CMS and the accident location to be the proportion of total flow that heads to the off-ramp at time t:

$$R(t) = \frac{Q_R(t)}{Q_{ML}(t) + Q_R(t)}, \quad (1)$$

where $Q_{ML}(t)$ and $Q_R(t)$ are mainline flow and off-ramp flow as shown in Fig. 1. This turning rate is generally determined by the destination of drivers and varies slowly with the time of day. Therefore, rapid change in the turning rate is an indicator for drivers' change of routes.

Note that flow data are aggregate in nature, so they can only be used to study aggregate behavior, e.g., how many people take a certain exit. To study individual behavior, we need data that can trace individual travelers, such as GPS data, which is beyond the scope of this paper.

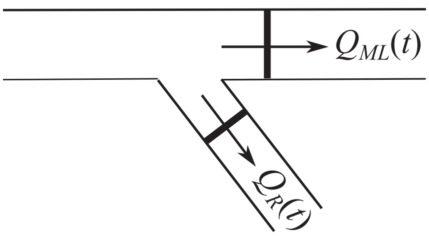

Fig. 1. Definition of turning rate.

3.1. Sites

Because of the data-driven nature of this study, the study sites are restricted to freeway sections that are well instrumented with loop detectors, especially on the off-ramps. We try to select freeway sections that start with a freeway CMS, and have most of the downstream exits instrumented.

So far, we have identified three study sites that we think are appropriate for exploration. The first site is along I-210E in Caltrans District 8 (San Bernardino/Riverside). A sketch of the site with mainline and off-ramp detectors is shown in Fig. 2(a). The total distance from the CMS (indexed 808866) to Milliken is about 11.1 km (6.9 miles). The second site is along I-15N in Caltrans District 11 (San Diego/Imperial), and the third site is along I-15S, also in Caltrans District 11. Similar sketches are shown in Fig. 2(b) and (c). At site 2, the total distance from CMS 1106507 to Clairemont Mesa is about 12.6 km (7.9 miles). At site 3, the total distance from CMS 1106508 to Adams is about 13.8 km (8.6 miles). At site 2, there is another CMS indexed 1117651 at Aero and I-15N. This CMS displayed no accident message (only travel time) in our study and is thus ignored.

3.2. Data

The California Department of Transportation (Caltrans) provides a live feed of the CMS messages posted on all 771 freeway CMSs in its 12 districts (Caltrans, 2013a). The messages are mostly updated every minute. We archive all the messages starting from November 2012 into a database. For this paper, CMS data from November 2012 to October 2013 are used. During this period of time, a total of 39 accidents are studied: 15 from Site 1, 17 from Site 2, and 7 from Site 3.

Besides CMS messages, we use flow and occupancy data from both mainline and off-ramp loop detectors from Caltran's Performance Measurement System (PeMS) (Caltrans, 2013b). The raw PeMS data are aggregated in 30-s intervals. We also use data from November 2012 to October 2013, to be consistent with the CMS data.

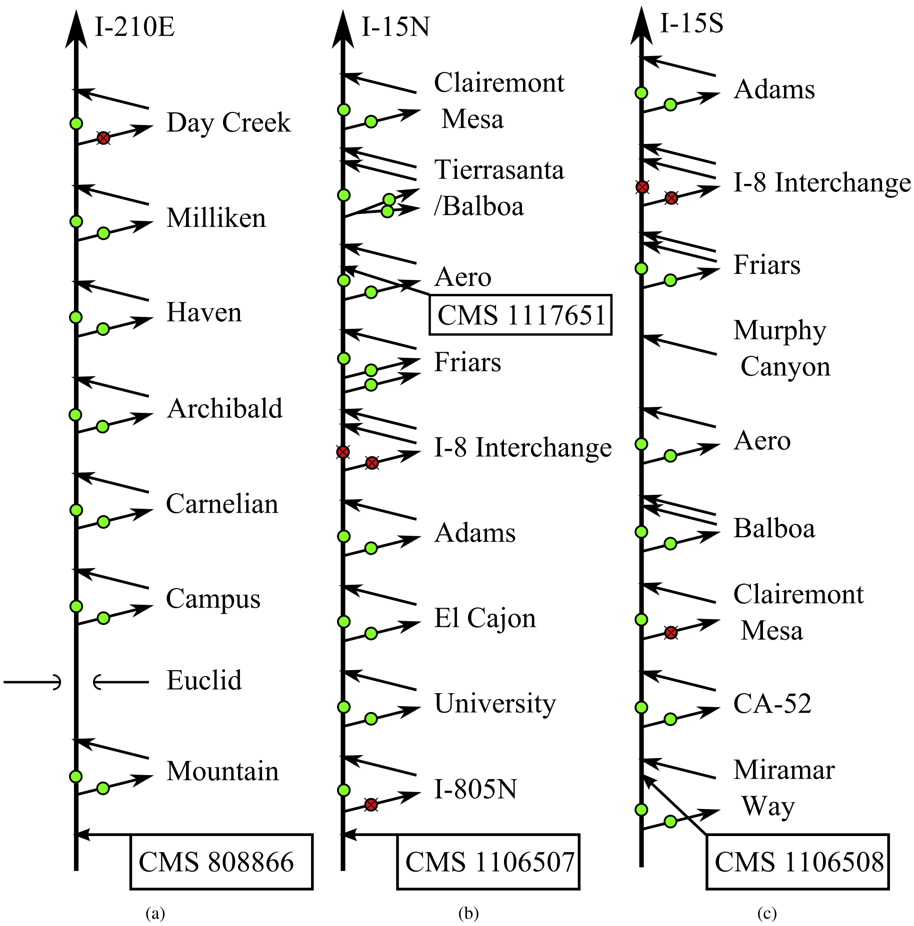

Fig. 2. Study sites. (a) Site 1: I-210E in Caltrans District 8 (San Bernardino/Riverside). (b) Site 2: I-15N in Caltrans District 11 (San Diego/Imperial). (c) Site 3: I-15S in Caltrans District 11 (San Diego/Imperial). The circles and those with a cross indicate functioning and non-functioning mainline and off-ramps detectors. Only relevant detectors are shown, ignoring on-ramp and other mainline detectors.

4. Case studies

We start our analysis with two case studies to draw insights into the effect of CMS on driver diversion.

4.1. Case study 1

The first case occurs on the afternoon of Tuesday, November 27, 2012, when CMS 808866 showed information on an accident on I-210E around Euclid Avenue at Site 1. The content and duration of the messages on that day are shown in Fig. 3. Note that Euclid Avenue does not connect directly to the freeway. The only path to circumvent this accident is to take the Mountain Ave exit, so we focus on this off-ramp for the first case study.

Fig. 4(a) shows the turning rate as a function of the time of day. Also shown is the travel time on the CMS. The gap in CMS travel time is the period of time when accident information was displayed. First, we see that the turning rate is fairly constant, except for some high values around the time of the accidents. However, closer inspection reveals that the timing of the high turning rate does not overlap with the timing of the CMS message. The turning rate starts to increase around 16:14, and the CMS accident message is not displayed until 16:25. Actually, at 16:14 the travel time on CMS is still the free flow travel time. Therefore, it seems that other factors are affecting driver diversion besides the CMS messages. Also, no obvious pattern can be observed between the turning rate and the CMS travel time.

Based on the literature, we suspect that visible congestion is a possible cause for diversion. This suspicion is supported by Fig. 4(b), which shows both the turning rate and mainline occupancy versus the time of day. The timing of visible congestion (as indicated by an increase in mainline occupancy) seems to coincide better with the timing of the increase in turning rate.

4.2. Case study 2

In the first case, drivers are already in congestion when they see the CMS accident message. So the second case is selected that congestion has not yet reached the location of the CMS when drivers see the CMS accident message.

The second case occurs on the morning of Monday, December 3, 2012, when CMS 1106507 showed information on an accident on I-15N to the south of CA-52 at Site 2. The content and duration of the messages on that day are shown in Fig. 5. Data are not available on the interchange from I-15N to I-805N, so we use the first downstream off-ramp with data available, University Avenue, for the second case study.

The finding is similar to that in the first case study: visible congestion, rather than CMS, is more likely to be the reason for diversion. As shown in Fig. 6(a), the accident message appears at 7:16. Before that time, drivers may also get some clue from the increased CMS travel time to both CA-52 and CA-56. However, the turning rate does not seem to increase until 7:30. Other off-ramps downstream of University Avenue exhibit similar patterns. As shown in Fig. 6(b), the timing of the increase in turning rate coincide better with the timing of the visible congestion. Also, the finding does not seem to be affected by which piece of information (CMS or visible congestion) is received first.

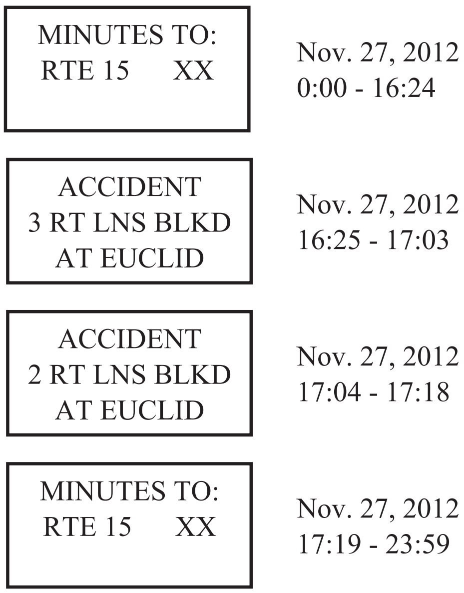

Fig. 3. Message on CMS 808866 on Tuesday, November 27, 2012. The "XX" in the messages are numbers for travel time.

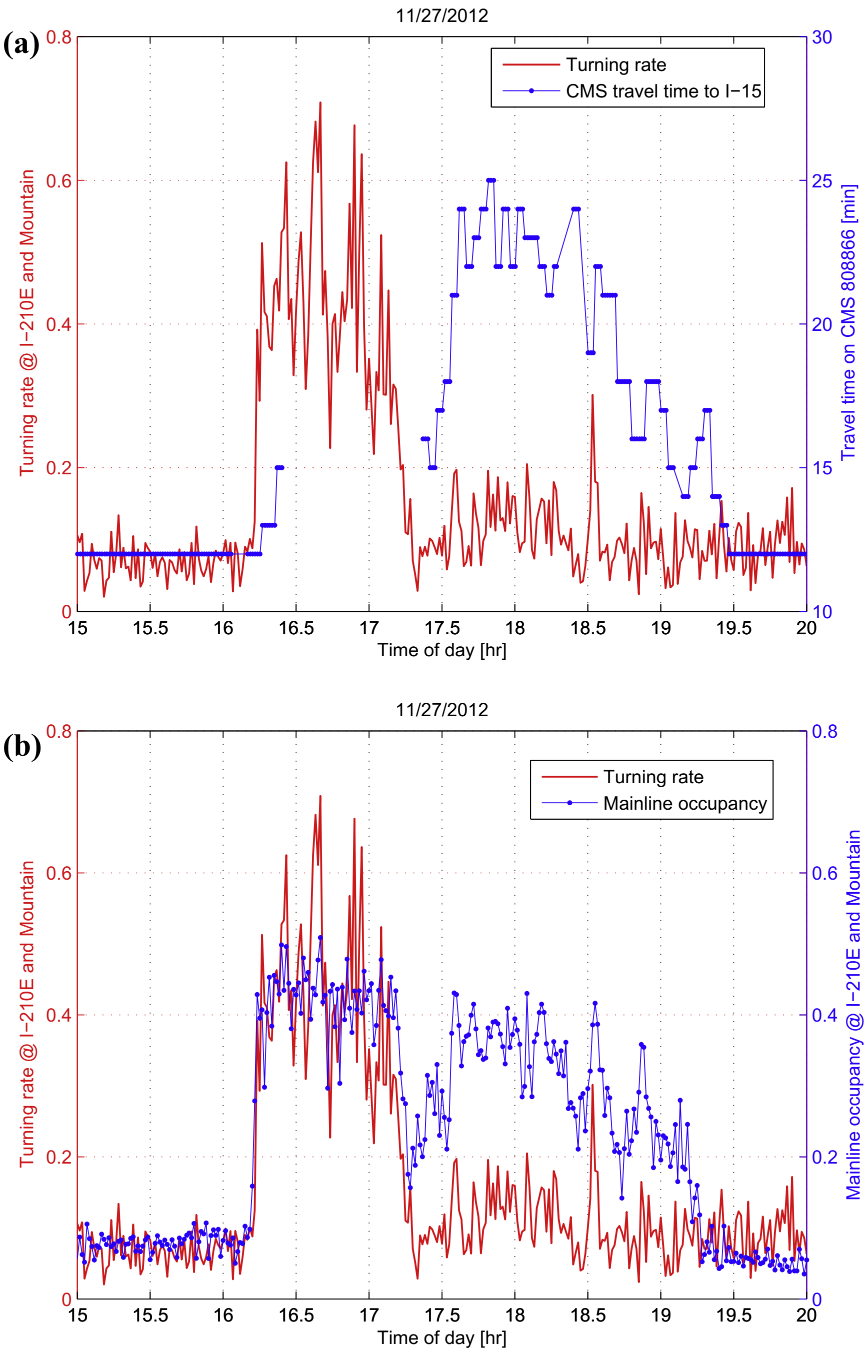

Fig. 4. Turning rate and CMS travel time versus the time of day, (a) on I-210E at Mountain Avenue, on November 27, 2012, (a) on I-15N at University Avenue, on December 3, 2012. The gap in CMS travel time is the period of time when accident information was displayed.

5. Statistical analysis

The two case studies provide us with good insights, notably the seemingly minor effect of CMS messages on driver diversion and the comparatively stronger effect of visible congestion. In this section, we will apply statistical analysis over the whole data set to explore the generality of the insights. During the analysis, we will describe and compare the different methodologies mentioned in the literature review: the correlation method and causality method, as well as whether the effect of visible congestion is accounted for.

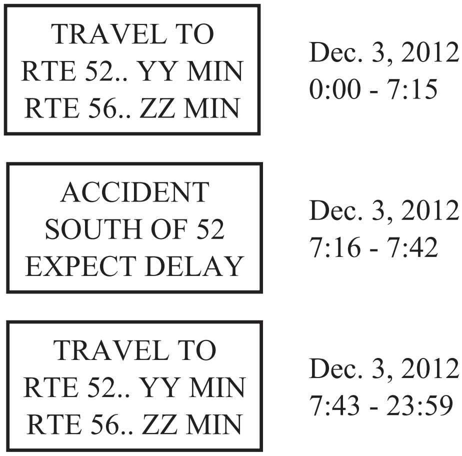

Fig. 5. Message on CMS 1106507 on Monday, December 3, 2012. The "YY" and "ZZ" in the messages are numbers for travel time.

5.1. Correlation method

This method compares the turning rates with and without CMS accident messages. We term it the correlation method because we gain insights into the correlation between turning rate and the presence of CMS accident messages. We will control for visible congestion first, and then show what happens if we do not.

5.1.1. Setup

We compare the turning rate R, controlling for mainline occupancy and the presence of CMS accident messages, both of which are the explanatory variables. The presence of CMS accident messages is a binary variable, x_1. Note that the duration CMS accident messages are displayed is different from the effective time of the messages at a downstream off-ramp. This is because when drivers see the message, they have to wait until arriving at the off-ramp of interest to take any action if they so desire. For x_1 to be properly defined, we need to estimate the travel time from the CMS to the downstream off-ramp of interest.

We use the flow and occupancy measured from all the mainline loop detectors to estimate the travel time between the CMS and the off-ramp. The travel time estimation algorithm is similar to the G-factor method in Jia et al. (2001), with minor differences.[2]

To understand the quality of the estimation algorithm, we apply the estimation algorithm to two different sites and validate the travel time estimates against travel time measurements from FasTrak (the electronic toll collection system in California) data. The validation on a 17.3-km (10.8-mile) section of US-101S (in Caltrans District 4) yields a root mean square error (RMSE) of 1.3 min. The validation on a shorter 4.8-km (3.0-mile) section of I-80W (also in Caltrans District 4) yields a RMSE of 1.0 min. Therefore, we expect the accuracy of the travel time estimation at the three study sites (with a length of 11.1–13.8 km, or 6.9–8.6 miles) also to be on the order of one minute.

Assume that a CMS accident message starts at time t_1 and stops at time t_2 and that the estimated travel time from CMS to the off-ramp is T_1 and T_2 if drivers arrive at the CMS at time t_1 and t_2, $[t_1 + T_1, t_2 + T_2]$ is the period of time when the CMS message is effective at the downstream off-ramp location. Therefore, we label $x_1 = 1$ when time $t \in [t_1 + T_1, t_2 + T_2]$ and $x_1 = 0$ otherwise.

Mainline occupancy is our indicator for visible congestion. Instead of using the occupancy as a continuous variable, we will use two binary variables x_2 and x_3 to describe the qualitative level of visible congestion: $x_2 = 0, x_3 = 0$ when mainline occupancy $0 < \Omega_{ML} < 0.15; x_2 = 1, x_3 = 0$ when $0.15 \leqslant \Omega_{ML} < 0.35; x_2 = 0, x_3 = 1$ when $\Omega_{ML} \geqslant 0.35$. So, x_2 is an indicator of medium congestion, x_3 is an indicator of heavy congestion, and x_2 and x_3 will not be 1 at the same time.

5.1.2. Nonparametric regression

Mainline occupancy is our indicator for visible congestion. Instead of using the occupancy as a continuous variable, we will use two binary variables x_2 and x_3 to describe the qualitative level of visible congestion: $x_2 = 0, x_3 = 0$ when mainline

[2] First, we estimate the point speed at each loop detector. To simplify calculation, we assume G-factor to be a constant. In this case, density is a linear function of occupancy, and the ratio of flow over occupancy (Q/Ω) is proportional to the point speed. We use historical data to estimate the average ratio of flow over occupancy r_f in free flow condition (i.e., data with occupancy < 0.1). Assuming the free flow speed equals the speed limit v_f (65 mph, or 104.6 km/hr), we estimate the point speed at time t to be $v(t) = Q(t)/\Omega(t)/r_f * v_f$. Second, we estimate the experienced travel time from point speed estimates at various loop detectors. Assuming that the average speed between two consecutive loop detectors is the average of the two point speed estimates at these two locations, travel time is estimated by summing up the travel time between consecutive loop detectors.

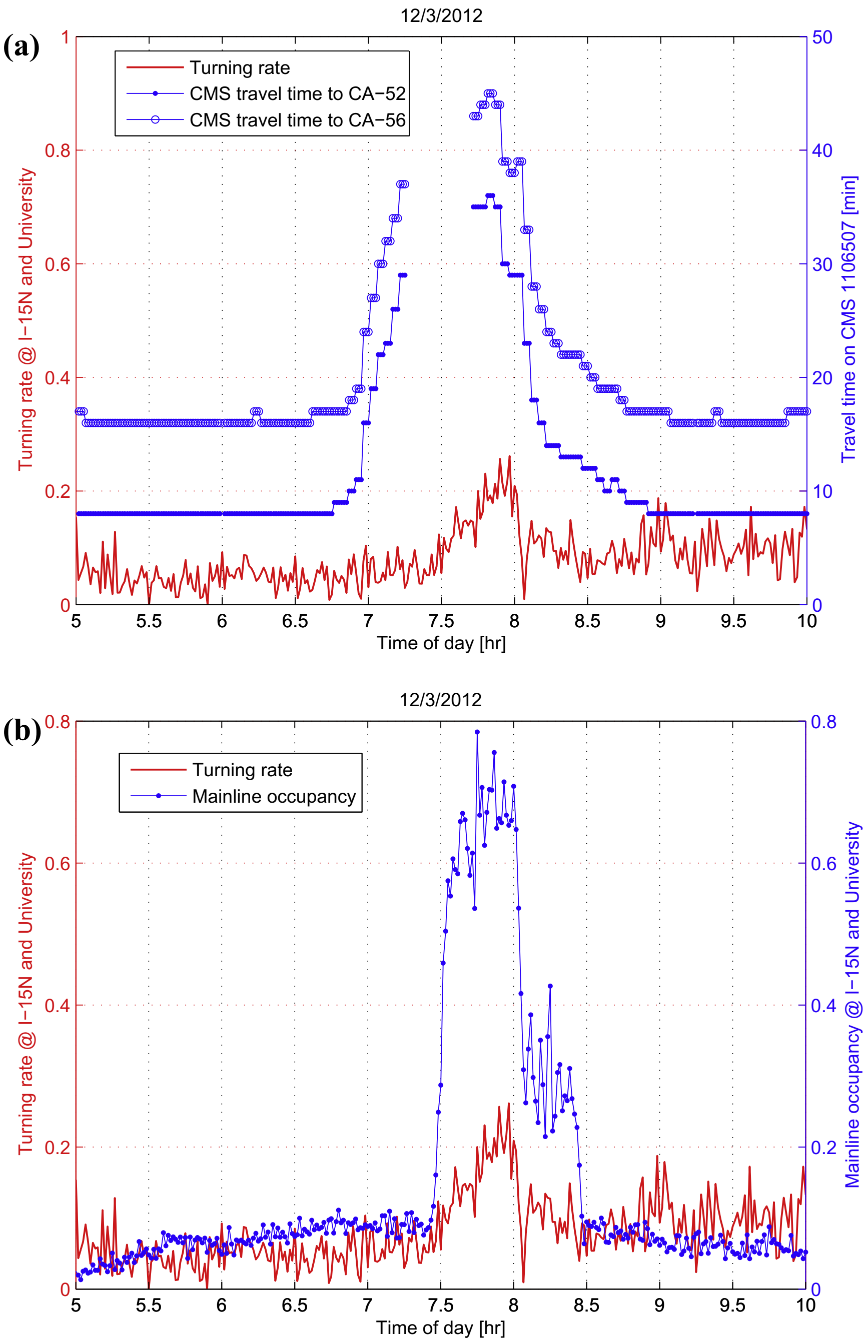

Fig. 6. Turning rate and mainline occupancy versus the time of day, (b) on I-210E at Mountain Avenue, on November 27, 2012, (b) on I-15N at University Avenue, on December 3, 2012.

occupancy $0 < \Omega_{ML} < 0.15; x_2 = 1, x_3 = 0$ when $0.15 \leqslant \Omega_{ML} < 0.35; x_2 = 0, x_3 = 1$ when $\Omega_{ML} \geqslant 0.35$. So, x_2 is an indicator of medium congestion, x_3 is an indicator of heavy congestion, and x_2 and x_3 will not be 1 at the same time.

Given that our explanatory variables are all binary variables (or dummy variables), nonparametric regression of the following form is carried out to assess the effect of CMS accident messages and visible congestion on the turning rate

$$R = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_2 x_3 + \gamma_1 x_1 x_2 + \gamma_2 x_1 x_3. \tag{2}$$

The regression is nonparametric, because we do not assume any specific functional form between turning rate R and mainline occupancy Ω_{ML}, which are both continuous variables. By discretizing Ω_{ML} into x_2 and x_3, instead of using the continuous variable, the model only estimate the level but not the slope. The interaction terms x_1x_2 and x_1x_3 are added to account for the correlation between explanatory variables.

Table 2 shows the result at Mountain Avenue on I-210E. The coefficient of $x_1(1-x_2)(1-x_3)$ is the effect of CMS accident messages without congestion, which is very small and insignificant. The rest of the terms are all statistically significant. The coefficients of x_2 and x_3 are the effect of medium congestion and heavy congestion respectively. The coefficients of x_1x_2 and x_1x_3 are the effect of CMS accident messages in medium congestion and heavy congestion respectively. Fig. 7 provides visual confirmation for the results. The x-axis is mainline occupancy (indicator of visible congestion), and the y-axis is turning rate (indicator of driver route change). The dots are for the instances when there is no CMS accident message, and the circles are for the instances when CMS accident messages are displayed. The nonparametric analysis shows that the effect of CMS is significant during congestion. Visually, this corresponds to higher positions of the circles than those of the dots in the region with occupancy >0.1.

One may notice the low R-squared value (<0.1) of this model. This is due to the fact that the turning rate also changes with the time of day and the day of week. Fig. 7, for example, shows that the range of turning rate is very wide at a given occupancy value, so prediction of turning rates based on occupancy value alone will likely be poor. One way to increase the R-squared value of the model could be to exploit the time of day and day of week information, such as a cluster method based on historical data. But the model then would no longer be linear, and regression would be difficult. We think the choice of factors and model to obtain higher R-squared value is a different topic and will not discuss it further in this paper.

Results from other ramps show mixed results. Four other ramps (I-210E at Milliken; I-15N at University, El Cajon, and Adams) show similar results: The coefficients for both x_1x_2 and x_1x_3 are statistically significant. At the rest of the ramps, either there is no data for statistical inference, or the coefficients for x_1x_2 and x_1x_3 are not statistically significant.

Although site-dependent, there is evidence for positive correlation between the presence of CMS accident messages and higher turning rate during congestion. However, these are simply correlations and we cannot conclude that the higher turning rate is due to CMS accident messages. A good use for the correlation method is to predict the turning rate, if all the other factors (beyond congestion and CMS) that affect the diversion behavior remain the same.

5.1.3. Neglecting visible congestion

Now we will carry out a similar nonparametric regression, only accounting for the presence of CMS accident messages and deliberately neglect visible congestion. As shown in Table 3, the coefficient for x_1 is small but statistically significant. The result based on this methodology suggests that CMS accident messages has a small but statistically significant effect on driver diversion.

As is shown in the next section, the presence of CMS accident messages does not have any immediate effect on driver diversion. But the presence of CMS accident messages is highly correlated with visible congestion, which (exemplified in the case studies) is correlated with driver diversion. We build a linear regression model with the presence of CMS accident messages x_1 being the response variable and mainline occupancy Ω_{ML} being the explanatory variable, over the same data set. The coefficient for Ω_{ML} is statistically significant (with a t-statistics of 3.2 and a p-value of 0.0014), meaning the presence of CMS accident messages is highly correlated with congestion. Therefore, the results here are simply capturing the correlation among the presence of CMS accident messages, visible congestion, and driver diversion.

One can also compare the R-squared value of this model with the R-squared value in Table 2. The R-squared value is much small for this model, which means most of the variations in driver diversion cannot be explained by the presence CMS accident messages. This is consistent with our finding that CMS accident messages does not seem to be the cause of driver diversion.

5.2. Causality method

This method compares the turning rates right before and after CMS accident messages are turned on or off. We term it the causality method because it is more likely to reveal the causal effect of CMS on driver diversion. The underlying assumption,

Table 2
Nonparametric regression for turning rates (R) versus presence of CMS accident messages (x_1) and severity of visible congestion (x_2, x_3).

Term	Estimate	S.E.	tStat	pValue
Constant	0.058	0.00013	432.5	0
$x_1(1-x_2)(1-x_3)$	0.00065	0.0011	0.57	0.57
x_2	0.036	0.00071	51.2	0
x_3	0.104	0.0014	71.9	0
x_1x_2	0.074	0.0063	11.7	1.1×10^{-31}
x_1x_3	0.191	0.0065	29.6	4.8×10^{-192}

Goodness of fit:
Number of observations = 130432, Error degrees of freedom = 130426.
Root Mean Squared Error = 0.0471.
R-squared = 0.0721, Adjusted R-Squared = 0.072.
F-statistic vs. constant model = 2.03×10^3, p-value = 0.

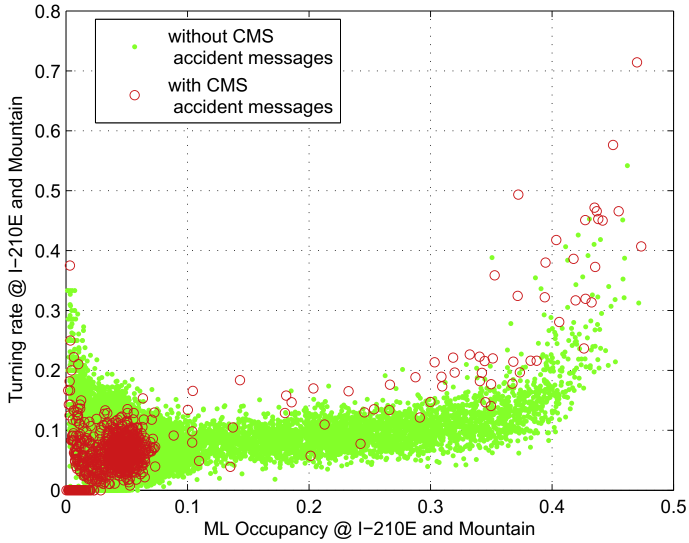

Fig. 7. Turning rates versus mainline occupancy with and without CMS accident messages at the Mountain Ave exit on I-210E.

Table 3
Nonparametric regression for turning rates (R) versus presence of CMS accident messages (x_1) only.

Term	Estimate	S.E.	tStat	pValue
Constant	0.060	0.00014	442.9	0
x_1	0.011	0.0011	9.32	1.2×10^{-20}

Goodness of fit:
Number of observations = 130432, Error degrees of freedom = 130430.
Root Mean Squared Error = 0.0489.
R-squared = 0.000666, Adjusted R-Squared = 0.000658.
F-statistic vs. constant model = 86.9, p-value = 1.16×10^{-20}.

similar in nature to that of regression discontinuity, is that in a small time window before and after CMS accident messages are turned on or off, other factors that have an effect on the turning rate will not change significantly. Therefore, changes in turning rate should be attributed to CMS accident messages. The caveat is that if some other sources of information happen to occur at exactly the same time when CMS accident messages are turned on or off, their effects would be captured as the effect of CMS accident messages, and our estimate would be biased.

5.2.1. Setup

We will compare the turning rates before and after time $t_1 + T_1$ and $t_2 + T_2$ at all the off-ramps between the CMS and the location of the accidents, adopting the same definition of t_1, t_2, T_1, and T_2 as in Section 5.1. To obtain the average turning rate and mainline occupancy before and after $t_1 + T_1$ (or $t_2 + T_2$), using a single data point (on turning rate or mainline occupancy) would be too noisy, so some form of local smoothing is needed. There are various types of kernel functions (or weighting functions) that can be used for local smoothing. Rectangular kernel carries equal weights and will yield the arithmetic mean, which is a reasonable choice. But it also makes sense for data points to carry less weight as the time gets further away from $t_1 + T_1$ (or $t_2 + T_2$), because of the increasing likelihood for turning rate to be affected by factors that we are not capturing. A unilateral triangular kernel, as illustrated below, is chosen for this purpose.

Assume $\Delta T = 30$ seconds is the sampling interval, $Q_{ML}(t)$ and $Q_R(t)$ are the mainline flow and ramp flow at time t. Define $Q(t) = Q_{ML}(t) + Q_R(t), R(t) = Q_R(t)/Q(t)$. The average turning rate before time $t_i + T_i, \bar{R}_{ib}$ and that after time $t_i + T_i, \bar{R}_{ia}$ are defined as:

$$\bar{R}_{ib} = \frac{\sum_{k=1}^{N} R(t_i + T_i - k\Delta T) Q(t_i + T_i - k\Delta T) w(k)}{\sum_{k=1}^{N} Q(t_i + T_i - k\Delta T) w(k)}, \tag{3a}$$

$$\bar{R}_{ia} = \frac{\sum_{k=1}^{N} R(t_i + T_i + k\Delta T) Q(t_i + T_i + k\Delta T) w(k)}{\sum_{k=1}^{N} Q(t_i + T_i + k\Delta T) w(k)}, \tag{3b}$$

where $i = 1$ for CMS accident messages turned on, $i = 2$ for CMS accident messages turned off. The kernel function $w(k)$ is defined as:

Table 4
Linear regression for difference in turning rate (ΔR) versus difference in mainline occupancy ($\Delta\Omega$). Data for the linear regression are generated with the rectangular kernel and a 10-min window size.

		Estimate	S.E.	tStat	pValue
All data	Constant	−0.0016	0.0015	−1.10	0.27
	$\Delta\Omega$	0.17	0.024	6.98	8.1×10^{-12}
CMS accident messages turned on	Constant	−0.0014	0.0022	−0.63	0.53
	$\Delta\Omega$	0.18	0.035	5.16	4.7×10^{-7}
CMS accident messages turned off	Constant	−0.0021	0.0020	−1.06	0.29
	$\Delta\Omega$	0.15	0.033	4.58	7.0×10^{-6}

Goodness of fit: (all data/messages turned on/messages turned off).
Number of observations = 570/294/276, Error degrees of freedom = 568/ 292/ 274.
Root Mean Squared Error = 0.0352/0.0378/0.0323.
R-squared = 0.0791/0.0834/0.0712, Adjusted R-Squared = 0.0774/0.0803/0.0678.
F-statistic vs. constant model = 48.8/26.6/21.0, p-value = 8.08×10^{-12}/4.68×10^{-7}/7.02×10^{-6}.

$$w(k) = \begin{cases} 1, & k \in [1, N], \text{ for rectangular kernels} \\ N - k + 1, & k \in [1, N], \text{ for unilateral triangular kernels} \end{cases} \tag{4}$$

Note that when calculating the average turning rate, the weight accounts for total flow as well as the kernel function. Otherwise, we would be favoring time periods with low flow, and the average turning rate would be biased. For either kernel function, there is a parameter for window size, $N\Delta T$. This parameter is the time period over which to perform local smoothing. We will carry out sensitivity analysis with both the rectangular and unilateral triangular kernels and a range of window sizes to eliminate the artifacts introduced by our choice of parameters.

We will first control for mainline occupancy, which is known to have an effect on diversion. So we also calculate the average occupancy before and after in a similar manner:

$$\bar{\Omega}_{ib} = \frac{\sum_{k=1}^{N} \Omega(t_i + T_i - k\Delta T) w(k)}{\sum_{k=1}^{N} w(k)}, \tag{5a}$$

$$\bar{\Omega}_{ia} = \frac{\sum_{k=1}^{N} \Omega(t_i + T_i + k\Delta T) w(k)}{\sum_{k=1}^{N} w(k)}. \tag{5b}$$

The difference in turning rate and mainline occupancy is defined as:

$$\Delta R = \begin{cases} \bar{R}_{ia} - \bar{R}_{ib}, & \text{if } i = 1 \\ \bar{R}_{ib} - \bar{R}_{ia}, & \text{if } i = 2 \end{cases} \tag{6a}$$

$$\Delta\Omega = \begin{cases} \bar{\Omega}_{ia} - \bar{\Omega}_{ib}, & \text{if } i = 1 \\ \bar{\Omega}_{ib} - \bar{\Omega}_{ia}. & \text{if } i = 2 \end{cases} \tag{6b}$$

5.2.2. Linear regression

We perform a linear regression with $\Delta\Omega$ being the explanatory variable and ΔR being the response variable. The causal effect of CMS accident messages is represented by the constant term, while the coefficient of ΔR captures the average effect of mainline occupancy.

Table 4 shows the result of the linear regression for a rectangular kernel with a 10-min window size. Over all the data points, the estimate of the constant term is small, about −0.0016, and not statistically significant, with a p-value of 0.27. When we distinguish the cases when CMS accident messages are turned on versus turned off, the result is similar: The estimate is small and not statistically significant. The result here indicates that there is no immediate effect when CMS accident messages are turned on or off.[3]

To see if the result is sensitive to the choice of kernel functions and window sizes, we repeat the same analysis for both the rectangular kernel and the unilateral triangular kernel, and a range of window sizes from 1 to 15 min. The estimate of the constant term, which is the causal effect of CMS accident messages, and its 95% confidence interval are shown in Fig. 8. The results are similar and do not seem to be affected too much by our choice of kernel functions and window sizes.

Besides the statistical analysis, we also double-check all the data points with high ΔR values, to see why the turning rate has changed. Very often, high ΔR value happens at night, when mainline and ramp flow is low and granularity produces large

[3] By no immediate effect, we mean when CMS accident messages are turned on or off, there is no significant change to turning rate right away. The causality method would not be able to capture a delayed effect.

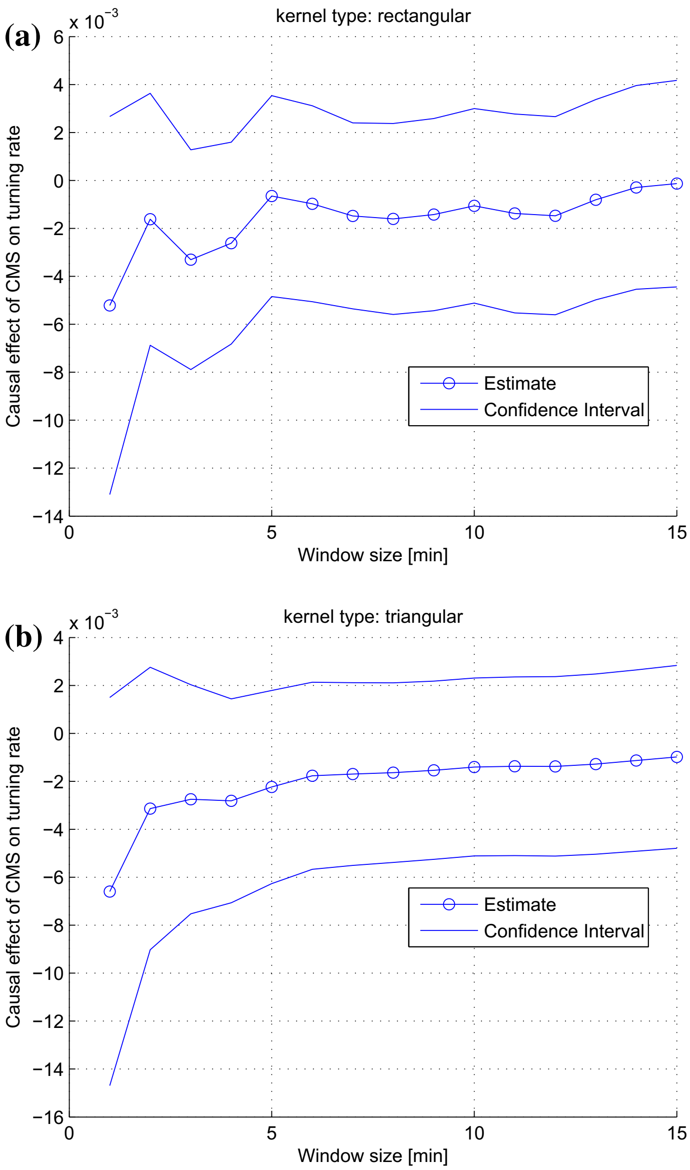

Fig. 8. Estimate of the causal effect of CMS accident messages on turning rate and its 95% confidence interval. (a) Rectangular kernel with varying window size. (b) Unilateral triangular kernel with varying window size.

variation on turning rate. A larger window size would have smoothed out more noise. A check of all the data points does not reveal any obvious pattern in turning rate that can be attributed to CMS accident messages.

5.2.3. Neglecting visible congestion

We also carry out the same analysis, but deliberately neglecting $\Delta\Omega$. This is equivalent to carrying out t-test on ΔR. As shown in Table 5, the result is similar to those in Table 4: The changes in turning rate due to CMS accident messages is not statistically significant.

Table 5
T-test for difference in turning rate (ΔR). Data for the t-test are generated with the rectangular kernel and a 10-min window size.

	Sample mean	Sample std	dF	tStat	pValue
All data	−0.0022	0.0366	569	−1.42	0.16
CMS accident messages turned on	−0.00087	0.0394	293	−0.38	0.70
CMS accident messages turned off	−0.0036	0.0334	275	−1.77	0.078

We also have figures like those in Fig. 8, by neglecting visible congestion. We did not show them here because they are almost the same and the difference is too small to notice.

The reason for the little difference by neglecting visible congestion is likely that the mainline occupancy does not change much when CMS accident messages are turned on or off. This finding seems to support the assumption of the causality method, that factors not captured by this method will not change significantly in a short time window before and after CMS accident messages are turned on or off.

5.3. Findings

Based on our empirical data, we think it is safe to conclude that CMS accident messages do not seem to have any significant immediate effect on driver diversion. The finding is consistent with our observations from the case studies, as well as some previous studies that are carefully carried out (Dudek et al., 1982; Bushman et al., 2004). Visible congestion, on the other hand, seems to be an important factor for driver diversion.

Another important contribution of this paper is the comparison of different methodologies over the same data set. The causality method, which is the correct one to use, shows that CMS accident messages do not seem to have any significant immediate effect on driver diversion. The method is actually robust to whether visible congestion is accounted for or not. The correlation method identifies correlation between the presence of CMS accident messages and driver diversion during congestion. If this method is misused, one may incorrectly conclude that CMS accident messages are effective to driver diversion during congestion. If one further fails to account for the effect of visible congestion, the conclusion would be that CMS accident messages have a small but statistically significant effect on driver diversion.

6. Conclusion and future research

This paper studies the empirical effect of accident messages conveyed through freeway changeable message sign (CMS) on driver diversion. The literature on the empirical effect of CMS is very limited. The few empirical studies we find report mixed results, which we think is caused by the difference in site location as well as the various methodologies adopted by these studies. The main contribution of this paper is twofold. First, we use empirical data to evaluate the effect of CMS accident messages on driver diversion. Second, we compare the various methodologies using the same data set.

With case studies and statistical methods that focus on both correlation and the timing of events, we find that CMS accident messages do not seem to have any significant immediate effect on driver diversion. This conclusion only applies to the three study sites and the duration of data from November 2012 to October 2013, but it is consistent with some previous studies that are carefully carried out (Dudek et al., 1982; Bushman et al., 2004). Visible congestion, on the other hand, seems to be an important factor for driver diversion. We also show that with statistical analysis that only focuses on correlation, one may incorrectly conclude that CMS accident messages are effective to driver diversion during congestion. If one further fails to account for the effect of visible congestion, the conclusion would be that CMS accident messages have a small but statistically significant effect on driver diversion.

There are a few possible directions for future research:

- The study obviously should be expanded to include more study sites, if data are available.
- The CMS accident messages in this study are descriptive (i.e., where and what happened) in nature. There is some evidence, in the literature and through our investigation, that prescriptive messages (i.e., CMS tells drivers to take certain routes) are more effective. Although prescriptive CMS messages are much less frequent, their potential is worth investigating.
- The flow data used in this study only provide insights into aggregated behavior represented by the change of turning rates. GPS data carry much richer information on individual routes, and can help us better understand how drivers change their routes.

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