Do Nudges Induce Safe Driving? Evidence from Dynamic Message Signs*

Kevin D. Duncan† Sher Afghan Asad‡

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Abstract

This paper estimates the causal impact of messages displayed on dynamic message signs adjacent to roads on reported near-to-sign crashes and crash severity. We match accident reports to displayed messages using minute level time and location metrics, along with hourly data on traffic and weather conditions in the state of Vermont from June 2016 through the end of 2018. We evaluate the impact of safe driving messages (behavior messages) differently than those that provide information about current or future road or weather conditions (information messages), and evaluate their impact both on the number and severity of crashes. Using a mixture of difference-in-difference, regression discontinuity, and ordered logit, we show that behavior messages causally decrease the number of accidents by about 45% and the number of vehicles involved in accidents by 30%, while information messages do not, and neither causally impact whether or not an accident induced an injury or fatality. Dynamic Message Signs are popular due to easing the metnal burden of traveling with drivers, and appear to provide modest near-to-sign improvements in driving as measured by number of crashes and crash severity.

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†Federal Housing Finance Agency, kevindduncan@gmail.com. This article was written by Kevin D. Duncan in his private capacity. No official support or endorsement by the Federal Housing Finance Agency is intended or should be inferred.

‡Lahore University of Management Sciences, sherafghan@lums.edu.pk

1 Introduction

In 2019 over 37,000 people died in road accidents in the United States and another 2.35 million individuals were injured or disabled due to road incidents. Since 2010 motor vehicle accidents have ranked 11th overall as a cause of death, and 6th in terms of years of life lost.[1] To address these concerns, many states are adopting intelligent transportation systems to provide real time information to the drivers on the road. As a part of these systems, some state governments in the United States have installed dynamic message signs (DMS)- long term signs fixed over or adjacent to roads that can display varying message content. These signs have become a regular medium through which the government provides information, such as updated time to destination or road conditions, to wear a seat belt, or how many individuals have died on the road this year. The purpose of DMS is to reduce driver anxieties related to commutes and to encourage safer driving, as well as try to reduce unsafe driving practices. These signs generally face broad public approval (Benson (1997); Tay and De Barros (2008)), however despite this popularity, whether or not these signs actively encourage safer driving is more ambiguous. Even small changes to driver behavior can have large effects societal welfare through decreasing road injuries and deaths.

We show that "behavioral" messages displayed on DMSs do impact the number of near-to-sign report crashes, as well as the number of of vehicles involved in accidents. Comparably "information" messages displayed on DMSs do not impact the number of near-to-sign reported crashes, nor the severity of crashes in either number of vehicles involved in an accident. Finally, neither message typeimpact the probability of an accident including injury or death. The distinction between behavioral and information messages has its roots in the psychology literature, where different message types may trigger a different response from drivers. Behavioral messages are supposed to encourage individuals to take precautionary measures and drive safer, however poorly thought out nudges can have opposite effects UM Dholakia (2016). Individuals may feel that they don't like to be told what to do or how to drive and may indulge in over-speeding or more reckless driving. Informational messages are more direct and are aimed at providing information relating to traffic, weather, or excess road risk. This may cause drivers to drive more carefully in light of information, or drive less carefully if the information changes their prior on riskiness in the opposite direction.

[1] https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812203

While these signs and messages might provide auxiliary aid to drivers in reducing overall anxiety on the road or beneficial real time information, they do not improve marginal driver safety in the area immediately after a sign, nor do they provide long-run or overarching benefits to average driver quality.

Our result for behavior messages is unique in that few papers have focused on more tacit reminders of road hazard on near to sign driving behavior. Among recent work, Hall and Madsen (2020) estimates the impacts of Death Toll reminders in Texas on near-to-sign traffic incidents. Using exogenous roll out of Death Toll reminders, they find strong increases in the number of traffic incidents even 10 kilometers after a DMS. Their identification strategy relies on the relative increase in Death Toll reminders as a share of total displayed messages, versus causally identified with times when Death Toll reminders are actually up. However, this only captures distributional changes in the distribution of displayed messages, and cannot precisely parse out differences in total displayed time, and displayed messages at time of a crash. Importantly, we replicate Hall and Madsen (2020) results and show they are consistent with our null result at the actual matched message-accident level. Our paper is among the first to examine otherwise irrelevant messages on impacts of near-to-sign driving while precisely matching accidents to the simultaneously occurring message content.

Comparably, information messages having no impact on near to sign driving behavior is consistent with prior studies that have similar data, such as Norouzi, Haghani, Hamedi, and Ghoseiri (2013) show no treatment effect using both on/off analysis, and comparing downstream traffic incidence to near-to-sign traffic incidents. Fallah Zavareh, Mamdoohi, and Nordfjærn (2017) examine how people respond to DMSs with road risk ratings. Risky behavioral adaptations were not observed under low and medium risk messages during night time. The effects of high risk messages were consistently related to safety adaptations. The effects of messaging on rear-end collisions were significant only in the fast lane at night time.While we rarely get significant results, throughout we get increased road hazards following DMSs when information messages are displayed, potentially agreeing with Song, Wang, Cheung, and Keceli (2016) and Erke, Sagberg, and Hagman (2007) on induced hazard from reading messages. Despite this, the transportation literature is clear that people do respond to information messages, such as taking detours (Ermagun, Kelarestaghi, and Heaslip (2021); Harms, Dijksterhuis, Jelijs, de Waard, and Brookhuis (2019)) and other basic directions that ease road traffic but do not necessarily contribute to improving near-to-sign hazards.

Our contribution is novel in a few ways, first we estimate message content on near-to-sign traffic incidents outside of the initial reason for sign roll out, we match nearby displayed messages at time of accident, and we have information on cause, severity, and driver characteristics. The data set consists of minute level display times of DMS messages matched with reported traffic accidents in Vermont from June 2016 through the end of December 2018. We map each reported crash to the each DMS using ArcGIS® based on driving distance, driving time, and number of turns between signs and the location of the crash. This allows pairing the location and the timing of the crash and the message to evaluate the treatment assignment of each driver before getting into a crash. We combine this with geocoded information on hourly traffic, weather, and temperature data. However, such matching generates its own problems. The point probability of getting into an accident over a very small segment of road at a particular point in time approaches zero as the road segment grows small enough over any fixed period of time. As a result, we pool observations into various levels of heterogeneity, specifically using a one-mile bandwidth difference-in-differences model (J. M. Wooldridge (2021)), as well as a regression discontinuity design (Calonico, Cattaneo, and Titiunik (2014); Kolesár and Rothe (2018)). We use these models to estimate the causal effect of messages on the probability of getting into an accident as well as the number of cars involved in individual crashes. We then estimate an difference-in-differences ordered logit model (Ai and Norton (2003); Athey and Imbens (2006); Karaca-Mandic, Norton, and Dowd (2012)) to show displayed messages do not impact the probability of getting into a more severe accident in the mile after they're displayed.

We test our results against a series of alternative specifications and methodologies checks, including allowing for current messages to be jointly determined with contemporaneous crashes under sequential exogeneity, allowing the effect to change over time to see if there is regional attenuation to the presence of the signs,spillover effects to test if effects are more than local and might be biasing our original estimates, and a Quasi-MLE (QMLE) Poisson model. All these checks confirm our main results that neither behavior nor information messages impact the probability of a crash around a DMS.

This paper contributes to a few distinct literature's. First we contribute to a broader understanding of the impacts of temporary behavioral interventions on individual behavior. Egan (2017) define nudges as “choice architecture that alters people’s behavior in a predictable way without forbidding any options or significantly changing their economic incentives”. These benign behavioral interventions have become increasingly popular with the researchers and the governments all over the world to address various policy problems. There have been hundreds of studies which show that nudges are effective in influencing behavior ranging from donating organs Johnson and Goldstein (2003), reducing energy consumption Allcott and Mullainathan (2010), and saving more money Thaler and Benartzi (2004). However there is a growing body of literature discussing when nudges fail to induce desired agent behavior (Pugatch and Schroeder (2021); Sunstein (2017); Thunström (2019)). In our specific case, we find that in some contexts that while drivers may respond to notices of detours and other information notices (Ermagun et al. (2021); Harms et al. (2019)), these messages do not induce large enough changes in drive behavior to change near to sign accident rates or severity.

Secondly, the broader literature on the effectiveness of DMSs in the transportation literature generally uses a mixture of simulation and stated preference surveys, or observational data comparing before and after using simulated traffic and accident data (see Mounce et al. (2007)). Simulation and stated preference surveys often find quite strong and positive evidence on message boards on driver behavior (Benson (1997); Bonsall (1992); Hassan, Abdel-Aty, Choi, and Algadhi (2012); Peng, Guequierre, and Blakeman (2004); Tarry and Graham (1995); Xu, Zhao, Chen, Bian, and Li (2018)). With observational data, Song et al. (2016) and Erke et al. (2007) show reading messages on DMSs may lead to variations in driving speed making roads more dangerous around the signs. Choudhary, Shunko, Netessine, and Koo (2019) uses an experiment to test driving changes from interventions. They randomly send driving quality feedback messages to a driver’s smartphone and show that personalized nudges improve driving performance compared to the control group. We build on his literature by showing differential responses to message content, where only beneficial actions are taken in response to behavioral messages.

Finally, we contribute to a broader literature on how behavioral and informational responses on roads have been studied in many other contexts. There is a long history of intensive and extensive margin literature relating to seat belts Carpenter and Stehr (2008); Cohen and Einav (2003); Levitt and Porter (2001), and in the context of safe driving or information reminders, we find that people do not alter their driving behavior enough to find responses in near to sign road safety. It is unclear if drivers would be induced to slow down, but such variations in traffic speeds increased aggregate road hazard (Erke et al. (2007); Song et al. (2016)). Or, how overall incentives for risky driving is common through examining how budget shortfalls and resulting decreases in police staffing impact safe driving (Makowsky and Stratmann (2011),DeAngelo and Hansen (2014)), that reduction in accidents following texting bans are short-lived Abouk and Adams (2013), and that scaling DUI punishments associated with how far over the legal limit a driver registers impact recidivism and future driving behavior Hansen (2015). Ultimately, consistent with De Borger and Proost (2013), local department of transportation's believe message boards reduce externalities associated with driving, causing them to over-invest relative to their true value added of mitigating road hazard. We consistently identify that drivers do respond to otherwise irrelevant reminders about safe driving precautions, and that these do decrease near to sign road hazards. Comparably, we precisely identify no such effect for information messages. These results reinforce the use of DMSs as a regular part of overarching road safety paradigms.

The remainder of the paper proceeds as follows. Section 2 provides background information on the DMS system in Vermont and details on data and their sources. Section 3 covers the impact of DMSs on the number of crashes, including empirical design and results Section 4 covers our empirical design and results for crash severity and finally Section 5 concludes.

2 Data

The data on messages is obtained from VTrans from June 2016 to December 2018. Messages were displayed on 57 unique sites during this time period. Table 1 presents the number and duration of various messages during the time period. The installation of DMSs are a part of VTrans' effort under the Intelligent Transportation System to facilitate drivers with updated and timely information on traffic and road conditions.[2] The message boards covered in this study are all portable installations, however the location of individual message signs are fixed in our sample.[3] The signs are

[2]In particular, the DMSs are primarily aimed at providing information on i) road conditions, ii) adverse weather notifications, iii) incident management, iv) in-route emergency evacuation information, iv) national missing and exploited children alert system - amber alerts, v) special events, vi) flight, train, and bus schedules in transportation terminals, vii) congestion management, viii) construction information/detours, ix) road closures, and x) special messages (such as variable speed limits, etc).

[3]The detailed plan of location choice is provided in VHB/Vanasse Hangen Brustlin Inc. (2007), but is determined by identifying areas where it warrants weather notification, advanced notification of substandard roadway conditions,

mounted on trailers or pads and secured in place for longer duration of use, run on solar power or battery, and have a display rate which is set to allow messages to be read at least twice at the posted speed limit. Moreover, signs are placed to be visible from approximately 0.5 miles (or 2,500 feet) under both day and night conditions, mounted in such a way that the bottom of the message sign panel is minimum of seven feet above the roadway, while the message are legible from a minimum distance of an 1/8th of a mile.

The choice of message is determined based on risk factors such as road and weather conditions. For example, if the road conditions are more susceptible to accidents because of icy roads then drivers will be cautioned about the slippery conditions of the road. Behavioral messages encourage safe driving without any concrete information on driving conditions, such as death, seat belt, texting, drinking, and speeding reminders. Information messages provide concrete information on driving conditions to the drivers- covering road condition, weather, traffic, work zone, road closure, crash ahead, other caution, and other messages. Behavioral messages are considered low priority and are only displayed when there is no other important information that needs to be conveyed, and some are part of National Highway and Traffic Safety Administration countrywide campaigns to raise awareness on drunk driving and seat belts use. Figure 1 shows the duration during which the message boards were active. It's clear that there is considerable heterogeneity in the activity and duration of messages across these message boards. As explained in Table 1 and Figure 1 each message is categorized into either behavioral or informational messages.

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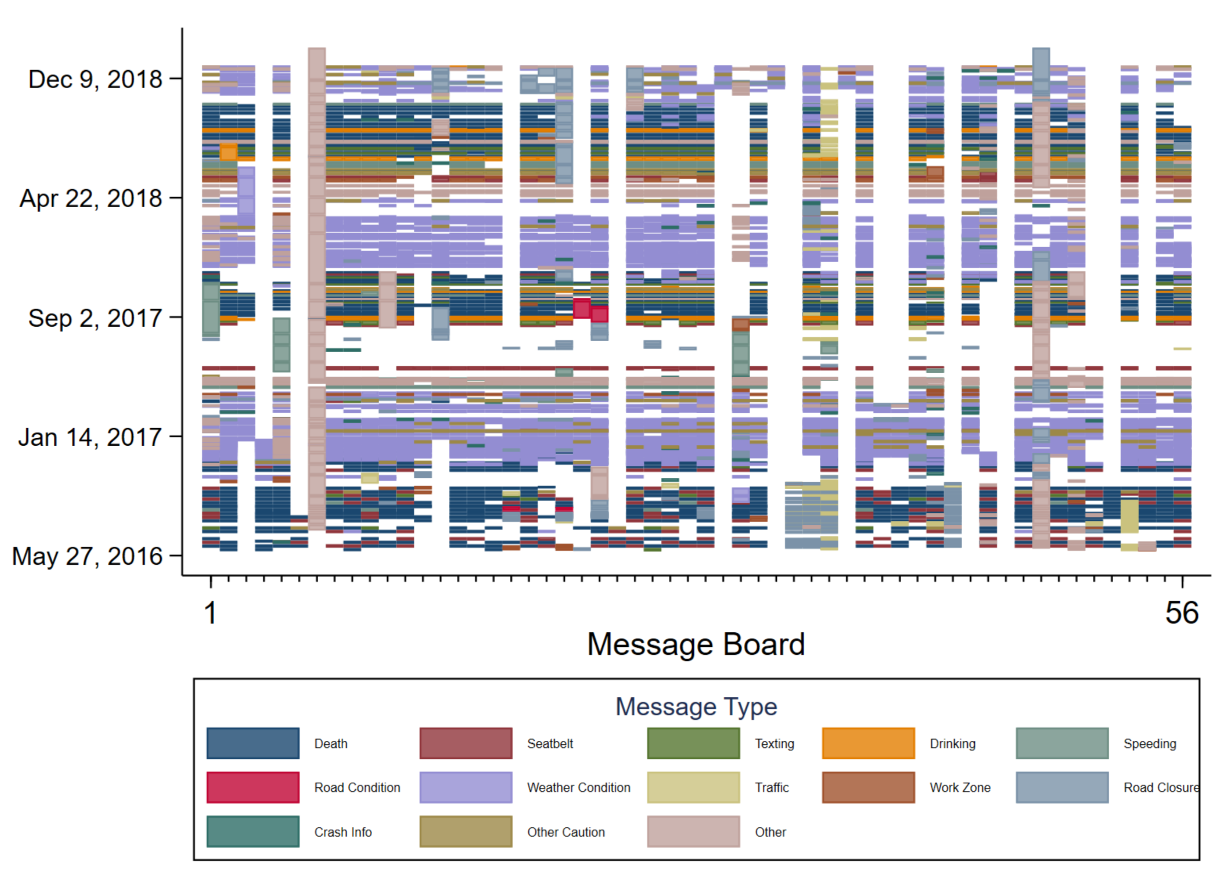
notification of construction and planned events , or notifications can complement counties transportation management plans involving traffic and roadside safety. According to officials at VTrans, "*our goal was just to place them (DMSs) in high traffic areas and close to RWIS (Road Weather Information System). The placement of RWIS was based on high crash areas.... Going forward the goal was decided to place DMS before on/off ramps on interstates and close to major intersections on secondary highways.*" This suggests that these message boards are installed in the areas which are more susceptible to crashes. Once the location of the DMS is determined, the next issue is about the content of messages that needs to be displayed on a particular DMS.

Figure 1: Message Boards Activity



Notes: The figure shows the time periods during which any message was displayed on the message board. Each bar represents a message board, with white areas indicating no message during the time period.

Table 1: Summary of Messages

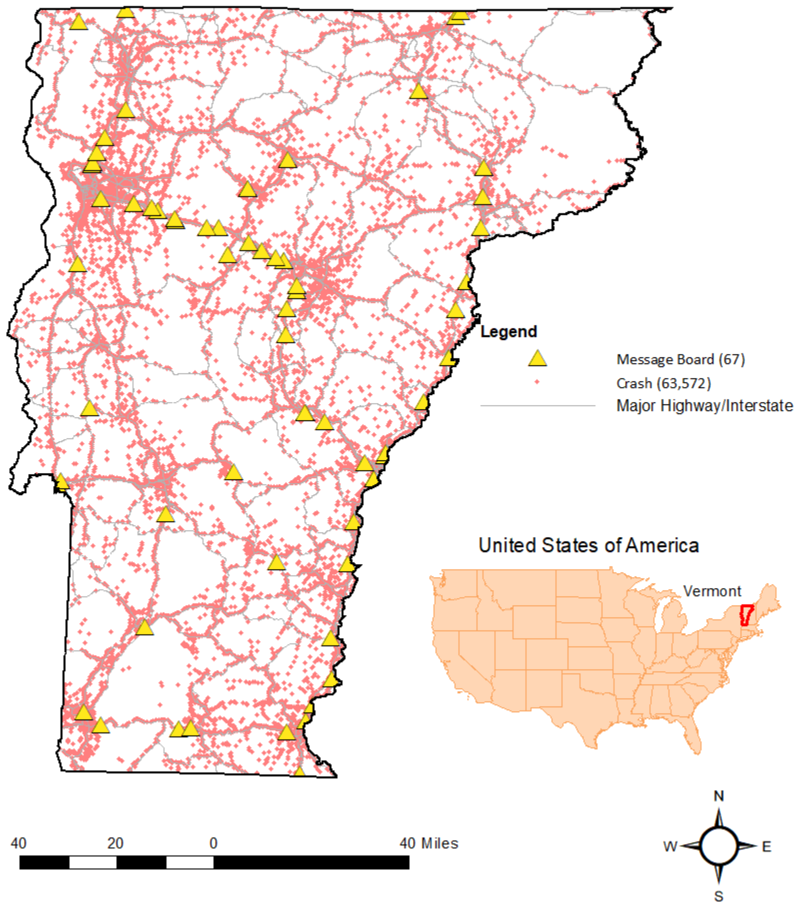
	(1) Proportion of Number of Messages	(2) Proportion of Duration of Messages (in hours)
Death related message	0.19	0.12
Seatbelt related message	0.03	0.07
Phone related message	0.02	0.04
Drinking related message	0.02	0.09
Speed related message	0.16	0.15
Road condition message	0.05	0.04
Weather message	0.49	0.17
Traffic message	0.06	0.08
Work zone message	0.02	0.03
Road closure message	0.05	0.09
Crash message	0.01	0.00
Other caution message	0.03	0.04
Other message	0.09	0.21
Total	10378.00	293092.82

Notes: The table presents the number and duration of various messages during the time period from June 2016 to December 2018 in Vermont.

2.1 Crash Data

Data on crashes is also obtained from VTrans, containing details from the police reports about the crash including location, time and date, road conditions, weather conditions, driver details and condition, vehicle details, number and nature of injuries, and number of passengers involved.The overlapping sample of messages and crashes contains 35,472 crash reports, for information on constructing the geocoded crash report data see Appendix A. The approximately 79% of damages involved just "property damage," while 20% contain injuries, and 1% involved fatalities. . Factors such as fast driving, failure to yield, failure to keep in proper lane, following too closely, and inattention are some of the major drivers of crashes.

Figure 2: Map of Message Boards and Crashes



Notes: This map of Vermont represents crashes and message boards throughout the period between June 2016 and December 2018.

We map crashes to each sign location using ArcGIS® 'Find Closest Facility' tool. This tool maps each crash to every message board based on travel distance (and travel time), and outputs the driving directions between the message board and the crash. Whether or not a crash is "upstream," happened before a sign, or "downstream," happened after, is determined if going from the sign to the crash, or the crash to the sign, is faster, and the number of turns required to take. When finding closest crashes, we specify to find closest crashes within a 10 mile distance to or from a message board and then restrict to crashes which are maximum of two turns away from the message board. We restrict to a maximum of two turns to be reasonably confident of a driver having read the message before getting into the crash. We also adjust for the message read time by adjusting the time of crash by the travel time from the message board to the location of the crash.

2.2 Traffic and Weather Data

Traffic data is obtained from the VTrans which has installed traffic counters along highways. This data covers hourly road volume counts across 86 sites in Vermont over the entire duration of our traffic and message board data. The traffic volume on an average day follows the typical seasonality with traffic peaking during rush hours and returning to low volume during off-peak hours.

We map the traffic information to the message boards by once again using ArcGIS® 'Find Closest Facility' tool. In most instances the closest traffic monitoring station is found on the same road as the message board, and when there is no traffic monitoring station on the road of the message board, we use the nearest traffic monitoring station to map traffic information to the message board. We also account for the direction bound of the road in mapping the stations to the message boards. This gives a local approximation to local traffic trends, and is generally a good approximation as both volume counters and DMSs tend to be placed on busier roads.

Similarly weather data is obtained from National Oceanic and Atmospheric Administration's National Centers for Environmental Information's Local Climatological Data, which provides daily and hourly summaries for approximately 11 Vermont locations, including Automated Surface Observing System and Automated Weather Observing System stations. They provide daily data on snowfall and snow depth, as well as hourly data on dew point temperature, precipitation, wind condition, sky condition , weather condition , and visibility.[4]

[4] `https://www.ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/quality-controlled-local-climatological-data-qclcd`

Table 2: List of Variables

Variable	Source	Description
Dependent Variable (Y_{it}^r)		
Crashes	VTrans	Number of vehicles involved in crashes r miles from site i at time t
Time Varying Covariates (X_{it})		
Traffic	VTrans	Hourly traffic volume from 24 traffic counters in Vermont
Dew Point Temperature	NOAA	Hourly dew point temperature in Fahrenheit.
Precipitation	NOAA	Hourly amount of precipitation in inches to hundredths.
Humidity	NOAA	Hourly relative humidity given to the nearest whole percentage
Visibility	NOAA	Hourly horizontal distance an object can be seen and identified given in whole miles.
Sky Conditions	NOAA	Hourly report of cloud layer with options clear, partly cloudy, and mostly cloudy.
Wind Speed	NOAA	Hourly speed of the wind at the time of observation given in miles per hour (mph).
Snow Depth	NOAA	Daily amount snow depth in inches.
Snowfall	NOAA	Daily amount of snowfall in inches
Message Data (T_{it})		
Behavioral message	VTrans	Dummy variable which takes a value 1 if either of the death, seat belt, texting, drinking, speeding, or other caution was active for at-least some time during the hour t on site i.
Informational message	VTrans	Dummy variable which takes a value 1 if either of the road condition, weather condition, traffic, work zone, road closure, crash info, or other message was active for at-least some time during the hour t on site i.

The exact definition of variables used is provided in Table 2. As a final note, our sample does not include road construction data which might be a relevant piece of information that influences crashes around the DMS.Correspondence with VTrans concluded that obtaining this data would be costly, and empirical design is ideally robust to this missing information due to the overall fixed location of signs during our period of observation, and overall methods described in Section 3.1.

3 Impact of Displayed Messages on the Number of Crashes

3.1 Difference-in-Differences

In this section we estimate the causal impact of displayed messages on DMSs on the number of crashes that happen immediately following a displayed message. A multinomial logit model of message board content and accidents before and after a DMS shows that VTrans does not jointly assigning behavioral messages endogenously to crashes immediately after a DMS (see Appendix B), though the presence of behavioral or information messages appear correlated with excess road hazards around a sign.

We divide the number of crashes in a given hour for a given distance from a DMS by the mean number of accidents in that distance tranche when no signs are active. Under this normalization, our dependent variable becomes $Y_{it}^* = \frac{Y_{it}}{E[Y_t|T_i=0]}$. This has two benefits. First, because the total road surface in each mile bin increases, it normalizes the dependent variable to be more comparable across different distance-to-DMS tranches. Secondly, coefficients from a linear regression directly approximate the incidence rate ratios recovered from traditional Poisson or logit estimation. This linearization provides us easy access to modern diagnostics, and our results remain functionally unchanged as discussed in our robustness check section. This motivates our first estimating equation,

$$\begin{aligned} Y_{itr}^* &= T_{it}'\rho + 1\{r=1\}T_{it}'\tau_{DID,IDxDist} + X_{it}'\beta + \lambda_t + \alpha_{ir} + \varepsilon_{itr} \\ E[\varepsilon_{itr}|\alpha_{ir},\lambda_t,X_i,T_i] &= 0 \end{aligned} \tag{1}$$

Here r indexes relative distance to a DMS. The accidents for both $r=-1$ (the mile before a DMS) and $r=1$ (the mile after a DMS) are combined together, allowing for estimation of level shifts in mean road hazards when messages of a given time are displayed. Y_{itr} is the number of crashes on road segment i, relative distance r, at time t, X_{it} is a vector of traffic and weather conditions, T_{it} is a vector of Behavior and Information Message treatment statuses on road segment i at time t, and λ_t are year-by-month fixed effects to control for seasonal effects that impact road hazard. Equivalently $X_i = [X_{i1}, ..., X_{iT}]$ and $T_i = [T_{i1}, \ldots, T_{iT}]$ are the full sequence of covariates and treatment assignments. Most important to this specification, α_{ir} is a fixed effect that varies by sign location, and before or after sign status. This fixed effect controls for time invariant risks that exist in the mile before or the mile after a DMS, such as a sharp turn or bridge, that influence near to sign road hazard for each tranche relative to a DMS. Moreover road segments with specific features (e.g. rough road, curved road, junctions, merging roads) may feature excess exposure to one message over another.

By allowing relative distance by DMS fixed effects, this model nests estimating a fixed effects regression on the mile before and the mile after a DMS with individual fixed effects separately. Since the mile before a DMS is untreated, if ρ =0 then this is equivalent to just estimating on the post-DMS tranche, comparably if $\tau_{DID} \neq 0$ this captures situations when different messages appear when the total local road hazard around a sign is already abnormally different from the no message mean that are not captured by our weather and traffic controls. Similar to traditional Differences-in-Differences, ρ is the pre-treatment difference relative to the untreated (no sign up norm) when a sign is active in the mile before a sign. This captures level differences in near-to-sign hazards that exist on average when messages of a given type are displayed. Indexing in this fashion implies the causal interpretation that ρ_1 is the impact of a particular message type on the mile wide bin after a sign.[5] Alternatively, assume that rather than each location and bin relative to a DMS has a time invariant fixed effects, assume that the entire road segment has a time varying fixed effect α_{it}, such that equation 1 can now be written as,

$$\begin{aligned} Y^*_{itr} &= T'_{it}\rho + 1\{r=1\}T'_{it}\tau_{DID,IDxTime} + X'_{it}\beta_r + \lambda_d + \alpha_{it} + \varepsilon_{itr} \\ E[\varepsilon_{itr}|\alpha_{it}, \lambda_d, X_i, T_i] &= 0 \end{aligned} \tag{2}$$

Now time varying factors such as occasional unobserved road construction or how weather

[5]This can be thought of as a pseudo Regression Discontinuity Design. Since we do not observe actual traffic data at the DMS, and traffic accidents are very rare, canonical Regression Discontinuity Design estimation strategies are unavailable to us. This approach enables two different ways of trying to proxy for the at-sign hazard rate. Allowing for different hazard rates on either side of the DMS through relative distance level fixed effects controls time invariant factors that might be correlated with the initial sign placement. The variable ρ reflects the mean hazard in the mile immediately before and after a DMS under each of the different signs.

interacts with the road segment are accounted for. The downside is now the whole segment is assumed to have a single fixed effect on both sides of a given DMS over time, such that time invariant road hazards are unaccounted for. However, both Equations 1 and 2 are violated when when $E[\varepsilon_{itr}|\alpha_{ir},\lambda_t,X_i,T_i] \neq 0$ or $E[\varepsilon_{itr}|\alpha_{it},\lambda_d,X_i,T_i] \neq 0$, that is the displayed message sign is correlated with the number of accidents in a current or future time period. This may arise from location choice of message boards. As the message boards are strategically installed on high risk roads, it is likely that the number of crashes are higher on these sites as compared to sites without message boards. However, since all message boards are static throughout our entire sample, this is implicitly controlled for. Alternatively this exogeneity requirement will fail if messages are jointly determined with the crashes.

This is likely to occur given that the messages are not displayed randomly and therefore there is a selection bias from message choice. Informational messages include displayed warnings of crashes ahead, which respond to accidents either contemporaneously or that just happened. The above models are robust to initial placement of DMSs, time varying location specific effects, and unobserved risk factors on the entire road segment around the DMS, they do not account for concerns about endogenous response of messages. Therefore the current value of ε_{is} cannot be correlated with past, present, and future values of T_{it}. Comparably, in the presence of reverse causality this assumption is violated, i.e., if crashes in current time period (Y_{it}) effect choice of message in the next time period (T_{it+1}), then ε_{it} is correlated with T_{it+1}. This violation leads to biased estimates using the fixed effect estimation. We relax the assumption of strict exogeneity presented in Equations 1 and 2 and instead assume the data generating process,

$$E[Y^*_{itr}|\alpha_{ir},X_{i1},...,X_{it},T_{i1},...,T_{it},\lambda_1,...,\lambda_t] = T'_{it}\rho + 1\{r=1\}T'_{it}\tau_{DID,GMM} + \alpha_{ir} + \lambda_t + X'_{it}\beta_r \quad (3)$$

Under this setting future displayed messages can be correlated with past levels of realized crashes. We can now estimate the coefficients using a GMM approach. Letting

$$\begin{aligned} Y^*_{it0} &= T'_{it}\rho + X'_{it}\beta_r + \gamma_{i0} + \varepsilon_{it0} \\ Y^*_{it1} &= T'_{it}\rho + T'_{it}\tau_{DID,GMM} + X'_{it}\beta_r + \gamma_{i1} + \varepsilon_{it1} \end{aligned} \quad (4)$$

Where we now instrument $Behavior\ Message_{it}$ and $Information\ Message_{it}$ with $Behavior\ Message_{i(t-2)}$ and $Information\ Message_{i(t-2)}$. Following the Frisch-Waugh-Lovell theorem, we take the within transformation of all our variables and estimate with GMM.

We present results on the impact of messages displayed on DMSs on just the number of crashes in Table 3. As discussed earlier, this data is very sparse. Despite that, we see that in the mile after a DMS, when behavior messages are displayed crashes tend to decrease by 50 to 70 percent, and these effects are significant at the 5% level.. Comparably, information messages do not cause changes in the number of accidents occuring after a DMS. Importantly, both behavior and information messages are displayed during times when total road hazard has increased around a DMS even after controlling for weather, traffic, year-and-month, and day of week effects. Specific mapping of accidents to concurrently displayed messages therefore is very important, and pooling approaches that cannot specifically control for these responses will find spurious effects far after a DMS is displayed.

Of note about interpretation is that these effects are multiplicative based around prevailing road hazard. In fact, during no-message displayed times, the average number of accidents was 0.005, such that a year of no-message exposure time would imply approximately 45 accidents would occur. With a behavior message displayed, this falls to 20 accidents over that equivalent duration. Across the network it would be reduce the total number of accidents from 2496 to 1149.

3.2 Robustness Checks

In this section we propose some alternative specification, such as by-year effects, spillovers, and pooling on just the quarter mile around a DMS. Finally, we re-approach our main specification under using a Quasi-Poisson Maximum Likelihood structure proposed by J. M. Wooldridge (1999) where we assume that the conditional mean is exponentially distributed. These are meant to test for model misspecification in two ways, first, by allowing drivers to change behavior over time to prolonged sign exposure, if effects are long enough that upstream signs impact downstream exposure to additional messages, and narrowing the effective bandwidth to cover less space. The QMLE Poisson fixed effect estimator confirms that our linear estimates are close enough, which allows us to leverage contemporary techniques for linear difference-in-difference models.

Table 3: Effect of DMS message content on crashes within 1 mile from message board

	ID x Dist	ID x Dist Covar	ID x Time	GMM	GMM Covar
Behavior Message	0.626**	0.626**	0	0.546**	0.546***
	(0.190)	(0.190)	(.)	(0.176)	(0.157)
Information Message	0.702*	0.702*	0	1.066***	0.626*
	(0.273)	(0.273)	(.)	(0.322)	(0.271)
Behavior Message x post	-0.606*	-0.606*	-0.570*	-0.685**	-0.571**
	(0.234)	(0.234)	(0.273)	(0.232)	(0.213)
Information Message x post	0.767	0.767	0.614	0.414	0.406
	(0.453)	(0.453)	(0.356)	(0.431)	(0.366)
Weather Controls	No	No	No	No	No
Traffic Controls	No	No	No	No	No
Seasonal Effects	Yes	Yes	No	No	No

*Notes: The table presents the estimates for the effect of messages on crashes within one mile from the legibility of message board. Column 1 and 2 present results for Equation 1 with and without covariates, Column 3 presents results for Equation 2, and columns 4 through 5 present results for Equation 4 under Sequential Exogeneity (Equation 3) with and without covariates, respectively. The causal effect of interest is Behavior Message x post and Information Message x post, which captures the effects of a given class of message content on driver behavior in the mile tranche directly after a given DMS. Clustered robust standard errors at the MessageBoardID level are reported in parenthesis. * for p < 0.05, ** for p < 0.01, and *** for p< 0.001*

Three major alternative confounders exist. The first two deal with learning behavior. This can appear through two main factors. The first is whether or not drivers on average learn and become less sensitive to messages displayed on signs over time, secondly, if there might be spillovers, such that drivers who view an earlier message are already less sensitive to a nearby, but still subsequently viewed, message. The other major concern is that a mile wide bandwidth of accidents already includes a large number of potential accidents that occurred with no participant in the accident having viewed the sign. In this context, we can estimate three alternative specifications.

In the first specification, we estimate treatment effects for each year in our sample. Under this setting our linear regression becomes

$$Y^*_{itr} = X'_{it}\beta_r + \delta t + T'_{it}\rho + 1\{r=1\}T'_{it}\tau_{DID} + T'_{it}t\rho_2 + 1\{r=1\}T'_{it}t\rho_3 + \alpha_r + \lambda_t + \varepsilon_{itr} \tag{5}$$

Under this structure we have to assume the ID-by-Dist fixed effects structure discussed in Equation 1 . In this regression we fully populate potential time effects, including a time trend (δt), time-dependent hazards ($T_{it}'t\rho_2$), and post-sign time dependent hazards ($1\{r=1\}T_{it}'t\rho_3$). By construction and population of year-month and month-day fixed effects (λ_t), we expect the time trend to be statistically insignificant. The remaining two terms each reflect potential learning over time. The time-dependent hazards reflect whether or not when signs go up changes over time, and the post-sign treatment effect reflects whether or not signs are further decreasing accidents as time goes on ($\rho_3 < 0$) or potentially causing more ($\rho_3 > 0$). One potential issue is drivers entering and leaving Vermont, lead to a constant church of drivers freshly exposed to sign messages. If there is a true effect over time, this turnover will pull both ρ_2 and ρ_3 towards zero, even if drivers are otherwise becoming more or less sensitive to sign effects. However, if there is this learning behavior, the overwhelming mass of individuals are not movers nor vacationers, such that we would still expect to see signs of changing treatment effects over time.

The second approach is to control for the presence of a other DMSs displaying messages upstream from, or prior to, each other subject sign in our sample. To do this we define the joint variables,

$$\begin{aligned}
Spill\ Behavior_{it} &= 1\{\text{Upstream sign within 5 miles of i has an Behavioral Nudge message up}\} \\
Spill\ Information_{it} &= 1\{\text{Upstream sign within 5 miles of i has an Informative Nudge message up}\}
\end{aligned}$$

The aim of this approach is to generate a simple index that controls for whether or not drivers have previously seen a sign prior to a given one. In the context that both messages improve or decrease driver safety, and signs go up at the same time, this would cause our mainline results to overstate the effects of an individual sign to be either better or worse than the impacts of the marginal sign. For ease, define $Spill_{it} = [Spill\ Behavior_{it}\ Spill\ Information_{it}]'$ In this context, we now estimate the models,

$$Y_{itr}^* = X_{it}'\beta_r + T_{it}'\rho + 1\{r=1\}T_{it}'\tau_{DID} + Spill_{it}'\gamma + 1\{r=1\}Spill_{it}'\gamma_1 + \alpha_k + \varepsilon_{itr} \tag{6}$$

where, as before, k indexes these regressions to include either the ID-by-Distance or ID-by-

Time fixed effects structures. The mainline specifications use a modified linear probability to normalize the number of accidents by the mean number of accidents across a given bin when no message is displayed. Alternatively we can estimate our model as a count process following a Poisson distribution. We take this modeling approach for several reasons. First, individual probabilities of accidents on a given road segment at a given time are Bernoulli trials, so the probability of observing a certain number of crashes on a given location follows a Binomial distribution, for which as traffic volume gets large, converges to the Poisson distribution. Secondly, as shown in Chamberlain (1987); Hausman, Hall, and Griliches (1984); J. M. Wooldridge (1999) location specific fixed effects fall out of the Poisson distribution. As above, we estimate the following baseline specification

$$E[Y_{itr}|\alpha_{ir},\lambda_t,X_i,T_i] = \exp(X_{it}\beta_r + T_{it}'\rho + 1\{r=1\}T_{it}'\tau_{QMLE,IDxDist} + \lambda_t + \alpha_{ir}) \tag{7}$$

All the same logic used in Equation 1 holds here. Moreover, the within-transform removes both individual and other time-invariant factors as in the linear additive fixed effects model (J. Wooldridge (2010) Section 18.7.4), such that the remaining variation in accidents comes from variation in displayed message board status, traffic, and weather. Similarly, we estimate a variant of Equation 2,[6]

$$E[Y_{itr}|\alpha_{it},\lambda_r,X_i,T_i] = \exp(X_{it}\beta_r + T_{it}'\rho + 1\{r=1\}T_{it}'\tau_{QMLE,IDxTime} + \lambda_r + \alpha_{it}) \tag{8}$$

As in our main estimates, we report results for both the number of crashes, and the number of vehicles involved in crashes. As in our linear models, we recover a similar estimate for the effect of behavioral messages displayed on the post-mile tranche after a DMS of about 50 to 70 percent that continue to be statistically significant at the 5 percent level. Comparably, we recover estimates that information messages increase the number of accidents by between 30 and 60 percent from our QMLE Poisson estimates. However, the functional form here poses additional structure, where our data is highly skewed towards zero, since accidents are quite uncommon viewed

[6] Compared to earlier we cannot carry out a variant of our mainline estimates using sequential exogeneity. Following the quasi-difference approach of Chamberlain (1992); J. M. Wooldridge (1997, 1999) generated a weak instrument GMM problem such that we felt uncomfortable carrying out further analysis. Discussion of both IV's is in Appendix C.

even just in the mile bandwidth follow a DMS at a given point in time, such that specific targeting of this zero-inflated norm is likely a poor fit for the QMLE Poisson model. Importantly, we see no evidence of long run behavioral changes to the presence of signs through the coefficients on $Behavior\ message\ x\ time$, $Information\ message\ x\ time$, $Behavior\ message\ x\ post\ x\ time$, and $Information\ message\ x\ post\ x\ time$ all statistically insignificant. This model inflates our estimates for both the beneficial impact of Behavior messages, and the negative impact of Information messages, but likely due to issues with overall model fit against such sparse data. Ultimately, as we had hoped through setting up the normalization for the linear model, there is very little difference between the recovered coefficients for the linear model, and the QMLE Poisson fixed effect estimator.

3.3 Regression Discontinuity Design

An alternative approach over the Difference-in-Differences design used above is to use a regression discontinuity design. To do this, we discretize our data set to every 0.01 mile before and after a sign, and map accidents into the corresponding bins based on their relative distance. We then condition on times when either an information or behavioral message are displayed, and calculate mean number of accidents-per-bin by message board ID. We are left with a data set with a very fine, but still discrete, running variable, being distance from a message board, the accidents before hand indexed negatively, and those after a sign indexed positively. From this we run **?** Robust CI Regression Discontinuity Technique. Following Kolesár and Rothe (2018), we account for the discrete nature of our running variable.

One downside of this approach is that because accidents in general are so rare, our approach highly compresses the mean number of accidents per bin towards zero, as well as the variance, since prior to smoothing, there is very little variation within-bin. For this reason, we favor our initial "pooling" approach, that offsets the higher area of approximation by comparing crash rates when signs are on to when they're off, but still believe that the regression discontinuity approach offers additional benefit in making sure that this approximation makes sense. For each we further collapse number of accidents down to the bin-level, and average over Message Board ID's and time dimensions. Moreover, we normalize the number of accidents to control for hazard over the

Table 4: Alternative Specifications for the Effect of DMS Messages on Near to Sign Number of Crashed Vehicles

	ID x Dist	ID x Dist	ID x Time	QMLE Dist	QMLE Dist Covar	QMLE Time
time	-0.000171					
	(0.000215)					
Behavior Message	0.885*	0.611*	0	0.503***	0.432**	
	(0.392)	(0.263)	(.)	(0.151)	(0.141)	
Information Message	0.660	0.787*	0	0.351*	0.817***	
	(0.623)	(0.295)	(.)	(0.167)	(0.180)	
Behavior Message x time	-4.78e-08					
	(0.000000120)					
Information Message x time	0.000000135					
	(0.000000170)					
Behavior Message x post	-1.251*	-0.849*	-0.673	-0.624**	-0.627**	-0.477
	(0.602)	(0.421)	(0.425)	(0.241)	(0.233)	(0.265)
Information Message x post	3.932*	1.316	0.918	0.583*	0.641*	0.384*
	(1.903)	(0.770)	(0.653)	(0.258)	(0.295)	(0.189)
Behavior x post x time	0.000000191					
	(0.000000173)					
Information x post x time	-0.000000816					
	(0.000000449)					
Spill Behavior x post		0.0761	0.0338			
		(0.346)	(0.334)			
Spill Information x post		0.222	0.128			
		(0.321)	(0.281)			

*Notes: The table presents alternative specifications to our mainline results discussed in Section 3.2. Column 1 and 2 presents results for time varying effects of DMSs that change across each year in our sample developed in Equation 5. Columns 3 and 4 present effects of downstream spillovers on upstream driver behavior characterized in Equation 6. Columns 5, 6, and 7 present results of QMLE Poisson estimation. Clustered robust standard errors at the Message Board ID level are reported in parenthesis. * for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$*

no-displayed message mean. This again normalizes hazards relative to when no DMS message is displayed, since while the point probability on any segment of road is zero, by pooling distances, the relative total road space accompanying each slice grows outwards from the origin. Normalizing by the average number of accidents when no sign is up yet again also frames our treatment effect as an incidence rate over regular traffic times. As a result, our dependent variable is,

$$Y_r^* = \frac{Y_r}{E[Y_r|T=0]}.$$

Moreover, for a given tract $r \in [-2, -1.99, -1.98, \ldots, 1.98, 1.99, 2]$ we define

$$Y_r = \frac{1}{NT}\sum_{j=1}^{A} \text{Accident} \, j \text{ happened in [r-.5,r+.5)during period t around sign i}$$

Where N is the number of message boards, T is the number of time periods, and j indexes over all accidents in our sample. For estimating the term $E[Y_r|T=0]$ we rely on local polynomial regression, and estimate models with a 4th degree polynomial estimated over either the before DMS sample or the after DMS sample. We further normalize extreme values to 1, deemed to be estimated local hazard values greater than 10. These require both very small empirical crash rates in the numerator, as well as thinly estimated values in the denominator. We then define our regression discontinuity design as one normally does, we define r to be a running variable of distance from a message board when either a Behavioral or Information Message are displayed, and take

$$\tau_{RDD} = \lim_{r \to^- 0} E[Y|r, T=1] - \lim_{r \to^+ 0} E[Y|r, T=1]$$

We condition on when a message is displayed, and not that the right-most term are individuals who are not yet exposed to the sign even when a message is displayed, since, as discussed in Section 2, we index our data to have zero be the 1/8th of a mile prior to a sign under which VTrans mandates signs be both visible, and messages readable. Results for Information messages are presented in Table 5 and Figure 3, and for Behavior messages in in Table 4 and Figure 4. Our results indicate that there is no treatment effect for Information Messages across any of the polynomial fits. Consistent with our earlier results, we see that average road hazard is higher across the two miles before and after a DMS when Information Messages are displayed as $\frac{E[Y_r|T=1]}{E[Y_r|T=0]} > 1$, in fact, 95 percent confidence intervals generally falls in the half mile leading up to a DMS, and then raises immediately afterwards, consistent with our results in Section 3. However, at the cutoff, while there is evidence that hazard increases, it is not statistically significant from zero. Importantly, we see that hazard remains in excess over the mile before a DMS average, driving our results from the Difference-in-Differences estimators, but that the means across the [-2,-1] and [1,2] tranches seem roughly equivalent. We now repeat this process for when Behavioral Messages are displayed.

Again, at least partially confirming our difference-in-differences estimates, at the cutoff excess road hazard falls significantly, and remains significantly lower for the two miles following a DMS. This is only statistically significant using a 2nd degree polynomial, but across all three polynomial fits we get persistent drops in the estimated ATE. This requires some pause, since in both cases we would imagine that excess road hazard should increase back towards 1 as we get further away from a DMS, or return to a close approximation of the mean across the [-2,-1] tranches mean. Throughout though we have focused on a narrow band of number of crashes, an extensive margin, but there might also be impacts to crash severity, and intensive margin. In the next section we test whether or not message boards increase or lower crash severity, specifically number of vehicles involved in a crash, and whether or not crashes are just property damage, include an injury, or have fatalities. Our near-to-sign approach continues to require throwing out much of the available sample of crashes that occur far from message boards, and we return to having to make strong parametric assumptions.

Table 5: Regression Discontinuity Design Results: Information

	p = 2	p = 3	p = 4
Information Message x post	2.210	2.288	2.684
	(1.41)	(1.53)	(1.57)
N	399	399	399

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 3: Regression Discontinuity Information Messages Number of Crashes

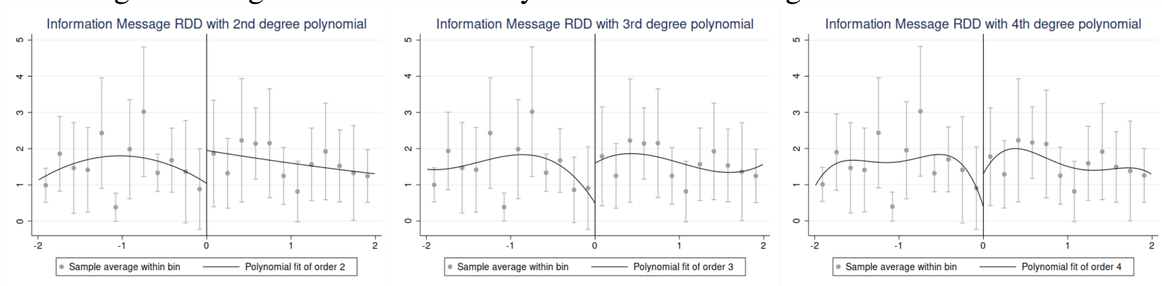


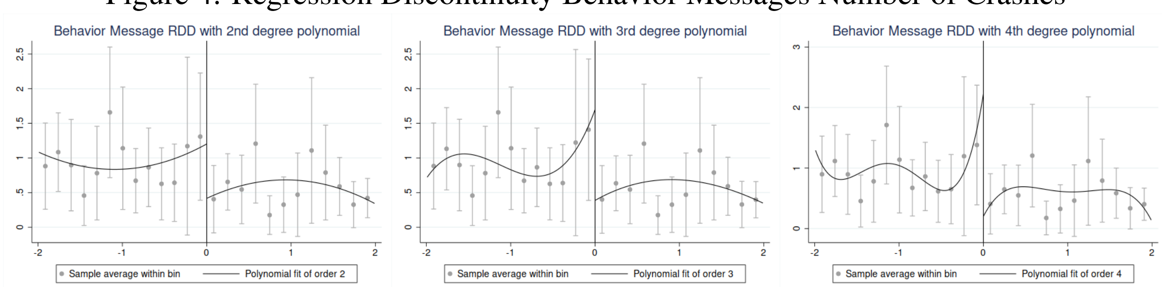
Table 6: Regression Discontinuity Design Results: Behavior

	(1)	(2)	(3)
	p = 2	p = 3	p = 4
Behavior Message x post	-1.629*	-1.752	-1.470
	(-2.06)	(-1.60)	(-1.05)
N	399	399	399

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 4: Regression Discontinuity Behavior Messages Number of Crashes



4 Crash Severity

There are two possible pathways that messages might impact driving safety. The first is in the number of accidents, explored in the previous two sections, and the second is in crash severity, either the number of vehicles involved in a crash in the case of the most reckless driving, or in the probability of an accident doing more than property damage, such as injuries or fatalities. The first approach we use replicates our initial difference in difference approach, but we drop all zero's to condition only on crash severity conditional on crashes occurring. This leads us with a regular

Poisson distribution of number of vehicles involved in a crash conditional on a crash happening, and we directly apply the two way fixed effects difference-in-differences approach above in Table 7.

Table 7: Crash Severity Estimated by Difference-in-Differences

	ID x Dist	ID x Dist Covar	ID x Time
Behavior Message	0.262**	0.222**	0
	(0.0776)	(0.0802)	(.)
Information Message	-0.143**	-0.124*	0
	(0.0504)	(0.0519)	(.)
Behavior Message x post	-0.361**	-0.361**	-0.353*
	(0.121)	(0.126)	(0.135)
Information Message x post	0.234*	0.234*	0.210
	(0.0975)	(0.102)	(0.107)
Weather Controls	No	Yes	No
Traffic Controls	No	Yes	No
Seasonal Effects	No	Yes	No

*Notes: The table presents the estimates for the effect of messages on crashes within one mile from the legibility of message board. Column 1 and 2 present results for Equation 1 with and without covariates, Column 3 presents results for Equation 2, and columns 4 through 5 present results for Equation 4 under Sequential Exogeneity (Equation 3) with and without covariates, respectively. The causal effect of interest is Behavior Message x post and Information Message x post, which captures the effects of a given class of message content on driver behavior in the mile tranche directly after a given DMS. Clustered robust standard errors at the MessageBoardID level are reported in parenthesis. * for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$*

As before we estimate three models, an ID by distance, ID by time, and QMLE Poisson approach. All three methods agree that behavioral messages decrease the number of accidents by about 35-40 percent, while information messages generally increase the number of vehicles involved in a crash by about 20-25 percent, but not all estimation methods show it as statistically significant. As in our section on number of crashes, but information and behavior messages are displayed when road hazard is higher than periods where no message is displayed.

Next, we can replicate the Regression Discontinuity Design, but because we're conditioning only on accidents that occur, we estimate directly on on the set of revealed accidents without further normalization. As before, results for information messages are presented in Table 8 and Figure 5, and for behavior messages in Table 9 and Figure 6. In this case, relative to our difference-in-differences results, we see that neither message type increases near to sign crash severity. Results for our DID estimator can be seen to be mostly driven by the decreasing crash severity that occurs almost 3/4ths of a mile after a DMS, versus immediately near-to-sign, however this might be indicative of some time before sign effects are noticable. Compared to previous results, the far from DMS average hazards are generally similar when driving either a mile before, or after, a given message board. An interesting fact is the seemingly lowering of road hazards in the mile before a message board when information messages are displayed, which might indicate some level of selection or effect of traffic downstream of a message board when certain types of signs are displayed and what they imply for overall near to sign road conditions. We see a somewhat, but less precisely estimated, trend in our results for number of crashes as well. This might support our estimates using sequential exogeneity under our difference-in-differences estimator as an overall preferred estimator.

Table 8: Severity Regression Discontinuity Design Results: Information

	p = 2	p = 3	p = 4
Information Message x post	-0.165	-0.214	-0.166
	(-0.49)	(-0.61)	(-0.42)
N	1	1	1

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 5: Severity Regression Discontinuity Information Messages

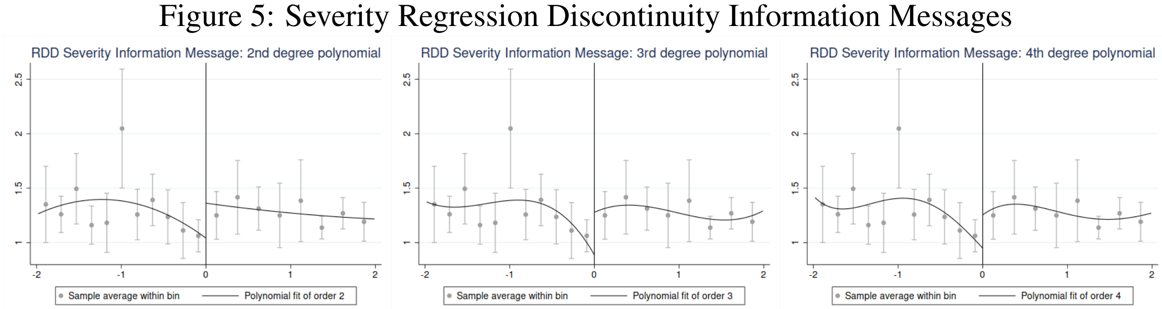


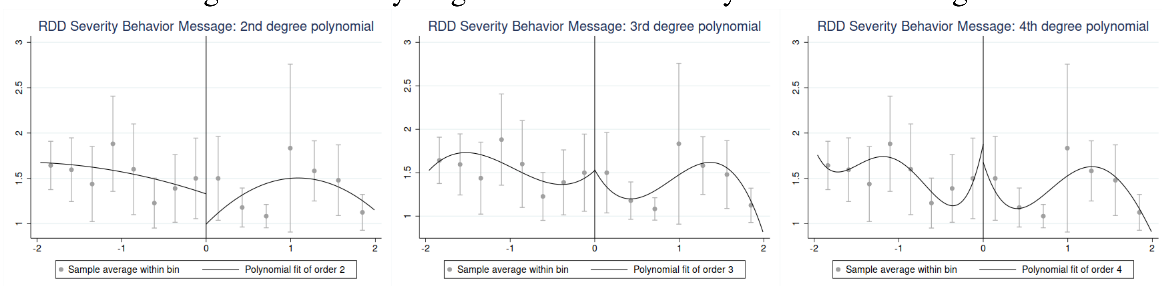
Table 9: Severity Regression Discontinuity Design Results: Behavior

	Behavior p = 2	Behavior p = 3	Behavior p = 4
Behavior Message x post	-0.317	-0.466	-1.406
	(-0.59)	(-0.77)	(-1.70)
N	1	1	1

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 6: Severity Regression Discontinuity Behavior Messages



Finally, we wish to untangle if the probability of being injured, or even killed, might change between when messages are displayed versus not. To do this we construct a non-linear difference-in-differences estimator using an ordered logit with three states, property damage, injury, and fatality. We normalize "property damage" to be our base level, reflecting that just damage to vehicles was done, scaling off of that we have "injury" in which both property damage and someone was injured in the crash, and then finally "fatality" as a more extreme form of injury. Under this characterization, we define our baseline ordered logit model to be,

$$y^*_{itr} = X_i\beta + T_i'\rho + 1\{r=1\}T_i'\tau_{DID} + \lambda_t + \alpha_r + \varepsilon_{itr};\ \varepsilon_{it} \mid X,T,\alpha,\lambda \sim N(0,1)$$

such that

$$\begin{cases} y=0 & y^* \leq \gamma_1 \\ y=1 & \gamma_1 < y^* \leq \gamma_2 \\ y=2 & \gamma_2 < y^* \end{cases}$$

This is our basic difference-in-differences model, but now predicting an ordered set of outcomes where the threshold variables γ_1 and γ_2 are unknown. Output from our ordered logit are presented in Table 10. Following Puhani (2012), for non-linear difference-in-differences models, the treatment effect can be characterized as

$$\tau_{ORDERED\ LOGIT}(T=1,r=1,X) = E[y^1|T=1,r=1,Tr=1,X] - [y^0|T=1,r=1,Tr=0,X] \quad (9)$$

Where $T = 1$ implies that a particular treatment sign is up, and $r = 1$ implies that it is in the mile directly after a DMS, and that it is sufficient to know that the sign of these effects will follow the same of the interaction term within the ordered logit regression. Under this structure we know that within each level of severity, the ATE of having a sign up for the probability of escalation changes, and we present these results in Table 11. Following Athey and Imbens (2006) and Ai and Norton (2003) we present the cross-partial average marginal effects. Generally for either Behavioral Messages or Information Messages we generate 6 marginal probabilities, that is, for each level, the probability of getting into an accident either before or after a message is displayed. These results are presented in Table 11.[7]

While the signs flip between property and higher levels in average marginal effects after a DMS, in all cases there point estimate is statistically indistinguishable from zero, and throughout would have at a very small change in the percentage points difference in accident severity. We therefore conclude there is no impact of displayed messages on post-sign traffic severity.

[7]To estimate these effects, we use the ologit command in Stata, and then estimate cross-partials using margins.

Table 10: Ordered Logit for Crash Severity: Regression Coefficients

Behavior Message	2.065*
	(0.893)
Information Message	1.436
	(0.948)
post	-0.904
	(1.366)
Behavior Message x post	-0.391
	(1.177)
Information Message x post	0.396
	(1.315)
Cut to Injury	2.257
	(1.499)
Cut to Fatality	6.520***
	(1.693)
Observations	425

*Notes: The table presents the estimates for an ordered logit model with increasing levels of property damage only, injury, and finally fatality. The causal effect of interest is Behavior Message x post and Information Message x post, which captures the effects of a given class of message content on driver behavior in the mile tranche directly after a given DMS. * for p < 0.05, ** for p < 0.01, and *** for p< 0.001*

Table 11: Ordered Logit for Crash Severity: Average Marginal Effects

	linear combination	std error	Lower Interval	Higher Interval
Information Message: Property	.0400862	.1258735	-.2066214	.2867937
Information Message: Injury	-.0384339	.1198722	-.2733791	0.1965113
Information Message: Fatality	-.0016522	.0061375	-.0136815	.0103771
Behavior Message: Property	.0660417	.2102204	-.3459827	.4780661
Behavior Message: Injury	-.0620921	.1966441	-.4475074	.3233233
Behavior Message: Fatality	-.0039496	.0138831	-.03116	.0232607

Notes: The table presents the linear combination of marginal effects to calculate treatment effects for an ordered logit model presented in Equation 9. Each result takes the difference between the treated probability and the conditional expectation of the untreated branch conditional on being in the mile after a DMS message and a message of a given type being displayed. Along with point values are p-values and 95% confidence intervals.

5 Conclusion

In this paper we study the impact of behavioral and informational messages on near-to-sign traffic incidents. We generate a large geospatial panel data set using hour level information on weather, traffic, crashes, and the content of messages displayed on dynamic message signs. We estimate a linear probability model that nests a Difference-in-Differences style framework to account for endogenous treatment assignment to increased road hazard when different signs are up along the whole road segment, then further conduct robustness tests shrinking this bandwidth to a quarter mile, treatment effects by year, whether or not spillovers exist, and a Poisson fixed effects specification.

Our results show that without conditioning on near-to-sign excess road hazard that is correlated with variant message signs going up, or the causal relationship between different message types and previous periods or contemporaneous accidents will lead to spuriously positive correlation between believe that informational messages and near-to-sign accidents. After accounting for these relationships, we find that behavior messages decrease both near to sign crashes and number of vehicles involved in crases by about 30 to 60 percent. This implies that drivers do respond to gentle nudges to improve driving behavior, and exhibit near to sign improvements, though the mechanisms by which they improve their driving are unknown. Comparably informational messages have no impact on near-to-sign accidents, nor near to sign crash severity.

The effects that we study in the paper are local to the sign location, and it is unclear if the presence of these signs provide global effects in the form of long run improvements in overall driving behavior. We provide preliminary but incomplete evidence that these messages are not causing long run changes in overall driving behavior, by allowing for drivers to respond either more or less positively to DMS messages as time goes on. Despite this, we cannot completely rule out this effect, and the fact that signs are fixed throughout our sample restricts our ability to use city level variation in new DMSs going up, or others being retired, to estimate these effects. However, a 40 percent reduction in accidents still implies that an extra hour of behavior messages a day across all signs in Vermont would cause about 46 fewer accidents per year, which is a modest improvement.

From the policy perspective, our results indicate that behavioral messages are an effective way to reduce the number of traffic incidents. Behavior messages cause a 40 percent decrease in accidents, and information messages do not impact near-to-sign accidents. These results would imply that an additional hour of behavioral messages a day would cause about 46 fewer traffic accidents, and over a three year period, cause roughly 108 fewer property-only accidents, 26 fewer injuries, and 1.38 fewer deaths an additional hours worth of behavioral messages are displayed every day at a given location. These results are modest but not inconsequential, given that once a DMS is installed they require marginal operating costs outside of electricity, regular maintenance, and choice of messages to be displayed. Overall, showing both behavior and information messages appear to fit well into the existing archetecture by which the VT Department of Transportation aims to improve road safety. More research is needed to further driver responses to disaggregated messages types.

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A Constructing Geospatial Crash Report Data

There were total of 35,554 police reports during the overlapping time period with our message data. For our purposes, the exact location of a crash is crucial to be able to map the crash to a potential message that may have been seen by the driver before getting into the crash. For each crash in our sample we obtain and validate the reported GPS location of the accident. First, VTrans has geocoded the location for most (35,202) of the crash sites during the sample time period.[8] Second, VTrans Public Query tool is considered to have a more accurate geocode than the initial police reports, we find and update update the location of 5,999 police reports that differ between the police reports and the Public Query Tool.[9] Third, 31 crashes locations are converted from the State Plane Coordinate System into GPS coordinates.. Finally, we manually update the GPS coordinates for 140 crash sites where the crash location is provided in the text fields but with missing coordinates.

To check for the validity of the coordinates from the above sources we reverse geocode the GPS coordinates using ArcGIS® and find that coordinates of 94 crash sites are either not street addresses or fall outside the county (within Vermont) in which they are supposed to lie. We then geocode the addresses for these improper locations, and find locations of 42 crash sites. The above measures leave 347 crash sites with missing or incorrect location which are manually looked at using information on various address fields, further identifying 82 crash sites.[10] Overall, longitude and latitude information are attached to 35,472 crashes (99.9 percent of accidents in the raw files). Out of the located crash sites, 8 police reports lack information on the date and time of crash and are dropped from our sample. The geographical location of each crash along with message board location in visually presented in Figure 2. As is typical of the collision data, the crashes are clustered around each other. The value of the nearest neighbor index is 0.11 ($z = -426.66$) which represents high degree of clustering of crashes around each other (Clark & Evans, 1954).

[8] The data set is available at `https://geodata.vermont.gov/datasets/`

[9] This data set can be extracted from `http://apps.vtrans.vermont.gov/CrashPublicQueryTool/`

[10] We use information on street address and distance from intersecting street to manually locate the crash location on the Google Maps. In case of missing information about the street address the nearest intersecting street information is used to approximate the location of the crash. We use Google Map's measurement feature to measure the offset from the intersection based on the information provided, for example, 100 feet south of 1st St. and 1st Ave. We also use the measurement feature to locate addressed based on mile markers, such as, I-89 South, Mile Marker 65.3. We find base mile markers by using a map of Vermont's interstate exits and rest areas which is then located on Google Maps to get a reference mile marker and a measure of specified distance to the target mile marker.

B Evaluating Sign Independence

VTrans displays behavioral messages across the majority of the signs in the system roughly 25% of the time, but information messages are only displayed across the majority of boards 4% of the time. A major concern is whether or not VTrans put up signs of varying message type endogenously to near-to-sign hazards, namely both directly before and after a sign. To make this assessment we estimate a multinomial logit estimator for each of message message types, where no message is taken as the baseline. Two sets of models are estimated in this space, the first accounts for just level differences in the Pre and Post-DMS area for three miles, and then further includes traffic, weather covariates, and sign fixed effects. We then additionally include a spillover effect, whether or not upstream DMSs are also displaying a behavioral or information message.

A concern of this approach is that VTrans may be responding to a mixture of both risk specific to the road segment immediately following a DMS, as well as local near to sign hazards. To capture these effects we create a second model that includes average normalized accidents happening in the three miles before and after a DMS in the contemporaneous time period, as well as the mean hazard for each mile wide bin in the 3 tranches before and after a sign for each year-quarter pair in the sample. In the case where VTrans is responding to hazards specific to the sign, only information closest to it should be a driver of a behavior or information message being displayed. In the case where near to sign hazards are contemporaneously correlated with upstream and downstream behavior, in both directions, these broader measures of near to sign hazards should be a predictive driver of displayed messages.

Table 12: Assessing Sign Independence on Crashes

	(1)		(2)		(3)		(4)	
	MessageCond		MessageCond		MessageCond		MessageCond	
	Behavior_Nudge	Information_Nudge	Behavior_Nudge	Information_Nudge	Behavior_Nudge	Information_Nudge	Behavior_Nudge	Information_Nudge
Post Sign Accidents	-0.0000113	0.000127***	-0.0000271	0.0000951***	0.0000817	0.0000656	0.0000557	0.0000484
	(0.0000539)	(0.0000269)	(0.0000571)	(0.0000289)	(0.0000820)	(0.0000452)	(0.0000866)	(0.0000477)
Second Mile Post Sign Accidents	-0.000000374	0.000254***	0.00000335	0.000237***	0.0000892	0.0000141	0.0000877	0.0000146
	(0.0000554)	(0.0000286)	(0.0000584)	(0.0000303)	(0.0000833)	(0.0000470)	(0.0000880)	(0.0000493)
Pre Sign Accidents	0.0000997*	0.000136***	0.0000916	0.000102***	-0.00000175	-0.0000563	-0.0000192	-0.0000369
	(0.0000526)	(0.0000368)	(0.0000567)	(0.0000390)	(0.000106)	(0.0000815)	(0.000114)	(0.0000850)
Second Mile Pre Sign Accidents	0.000103*	0.000348***	0.000101	0.000275***	-0.0000693	-0.0000398	-0.0000943	-0.0000258
	(0.0000603)	(0.0000378)	(0.0000642)	(0.0000401)	(0.000110)	(0.0000822)	(0.000118)	(0.0000857)
Upstream Behavioral Nudge			2.421***	1.315***			2.431***	1.376***
			(0.00898)	(0.00946)			(0.00902)	(0.00968)
Upstream Information Nudge			0.893***	1.535***			0.898***	1.505***
			(0.00955)	(0.00701)			(0.00968)	(0.00728)
Post 3 Mile Average					-0.000138	0.000151	-0.0000993	0.0000987
					(0.000185)	(0.000107)	(0.000195)	(0.000113)
Pre 3 Mile Average					0.000294	0.000437**	0.000358	0.000320
					(0.000274)	(0.000216)	(0.000296)	(0.000225)
Seasonal Average Post Sign					-0.0342***	-0.00183**	-0.0352***	-0.00130
					(0.00149)	(0.000901)	(0.00162)	(0.000922)
Seasonal Average Pre Sign					0.00643***	0.00854***	-0.000479	-0.000511
					(0.00156)	(0.00115)	(0.00171)	(0.00119)
N	1315200		1315200		1315200		1315200	

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

The number of actual accidents is so low that effectively none of the displayed messages respond to active crashes. When we do not account for a broader set of road specific hazards, we see the apparent fact that both behavioral and information messages have higher probability of being displayed both when the two miles before and after all exhibit excess road hazard. Naturally this does not make much sense, VTrans should not be putting up messages in response to road traffic that is very unlikely to be correlated with observing a given sign. This indicates that there is likely to be differing mean hazards on the roads when certain message types are displayed. In particular, many information messages are weather messages, which are prone to increase total road hazard even far away from the sign.

Comparably, models which include both contemporaneous mean road hazard in the three miles before and after a DMS, and the seasonal variation in road hazards in the three miles before and after a sign, show that this captures much of the variation in what drives individual sign assignment. Moreover, consistent with our claims of joint roll outs, upstream neighbor sign status being the same type is the single strongest predictor of downstream message types, followed closely by any other sign being active at the same time. Secondly, even though shared neighbor message content seem to be highly predictive, so does any active upstream message sign being active. Overall, while not a definitive test of sign independence, this provides good evidence that VTrans does not care about near-to-sign accidents when deciding what behavioral messages to roll out, featured by joint roll out of sign messages.

C Instruments for Regressions under Sequential Exogeneity

Underlying our estimation strategy for Equation 4 is an IV strategy where we utilize the twice-lagged displayed messages as an instrumental variable for current displayed message content. This works by removing the impact of accidents that happen both in period t and $t-1$from impacting current displayed message content. However, this opens up the methodology to issues related to weak instruments. However, as shown in Table 13, current Behavior Messages are highly predicted by the presence of Behavior Messages two hours prior, and Information Messages feature the same criteria.

Table 13: Instrumental Variables: Twice Lagged Displayed Messages on Current Message Content

	wBehaviorNudge Behavior Messages	wInformationNudge Behavior Messages
Behavior Message Lagged Twice	0.945***	-0.00910***
	(0.00258)	(0.00222)
Information Message Lagged Twice	-0.0123***	0.904***
	(0.00299)	(0.0103)
N	1315100	1315100

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D Support for Difference-in-Differences

A major concern here is whether or not the inclusion of a term that provides an estimate of aggregate mean near-to-sign hazard is beneficial. Traffic, time of year, day of week, and weather effects should already absorb much of the meaningful variation, what else could VTrans be selecting on, particular, as discussed in Appendix B we evaluate the seemingly randomness of message assignment. Under this framework, excess near to sign hazard should already be captured by these other factors, and ρ should generally be zero. However, we can show that excluding this term leads to results that intuitively make no sense.