Do Nudges Induce Safe Driving?
Evidence from Dynamic Message Signs

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Abstract

Behavioral economics has transformed the way we think about policy problems of our age. Governments all over the world are using nudges, one of the tools from behavioral economics, to direct people's behavior towards socially desirable outcomes. However, the literature has also shown that the distributive effects of nudges are not uniform, meaning that there are people who gain from a particular nudge, while others are made worse off. In this research, we are looking at the impact of traffic-related messages such as "drive sober," "x deaths on roads this year," and "click it or ticket," on reported near-to-sign traffic accidents. While these signs aim to make drivers think of the dangers of unsafe driving and hence potentially lead to safe driver and a lower number of crashes and fatalities, it also causes welfare-reducing emotional/moral discomfort to the drivers. We develop a model of unsafe driving that highlights the potential channel by which nudges can affect driving outcomes along with imposing a disutility to the drivers. To estimate the causal effect of these nudges, we build a new panel dataset using the information on the time and location of messages, traffic incidents, overall traffic levels, and weather in the state of Vermont. We estimate several models that induce independence between signs by taking signs that are either 10 or 5 miles apart. We then build two Poisson fixed effects models with spillover effects that enable the estimation of near to sign treatment effects when upstream signs have non-zero impacts on driver behavior on downstream signs. The first allows for a sign to have its nearest upstream neighbor within 10 or 5 miles, as long as that neighbor has no upstream neighbor within 10 or 5 miles. The second tests whether or not any upstream sign within 10 or 5 miles had a nudging message during a given hour. These enable us to increase our sample and get more robust estimates for our treatment effects.

JEL Codes: O18 R41 R42

1 Introduction

Considerable attention has gone into understanding and estimating the impact of how government policies cause behavioral nudges, with the aim to induce socially desribale behavior. Recent advances have tried to go from small scale nudges in experimental settings to larger roll outs at the state or national level Benartzi et al. (2017)Bird et al. (2019). In 2019 over 37,000 people died in accidients, and another 2.35 million individuals are injured or disabled after accidents. 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 help encourage safe driving Dynamic Message Signs (DMSs) have seen large growth throughout the United States over the past thirty years and have become a regular mechanism that state Departments of Transportation use for both informational purposes, such as updated time to destination or road conditions, as well as behavioral nudges such as reminders to buckle up or how many individuals have died on the road this year. The aim of DMS systems is to reduce driver anxieties related to commutes, and to encourage safer driving. These signs generally face broad public approval (Benson (1997) Tay and De Barros (2008)), where despite this popularity, whether or not DMSs actively encourage safer driving is is quite divided.

This paper quantifies the causal impact of DMSs on near-to-sign reported traffic incidents. This answers the question of whether or not non-informative messages provide a credible nudge in drivers behavior. Non-informative messages aim to remind driver safers to check their driving behavior immediately following reading the message, inducing them to drive more cautiously. We further develop models with signs with no upstream or downstream neighbor within a certain driving distance, then develop two spatial models that incorporate upstream sign information to allow a rich set of plausible spillover effects. Finally, we estimate the impacts of DMS messages on the the composition of driver characteristics getting involved in accidents.

This papers first contribution is to provide estimates for the relative impacts of both non-informative and informative messages on the near-to-sign traffic incidents. Our estimates show that DMSs with non-informative messages, nudges, do not improve near-to-sign reported accident rates. This extends previous studies on driver behavior local to DMSs. A broad overview of previous technical methods to evaluate DMS messages is available through Mounce et al. (2007), suggesting a mixture of simulation and stated preference surveys, or observational work comparing before-after using prevailing traffic and accident data. 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); W. Xu, Zhao, Chen, Bian, and Li (2018)Tarry and Graham, 1995). More related to our study are observational studies, which have often shown no response of drivers to DMSs, or negative consequences that appear from active drivers under certain driving conditions. Erke, Sagberg, and Hagman (2007) show while there is high compliance with the DMSs,undesirable slow downs often occur due to inattentive driving. 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. Song, Wang, Cheung, and Keceli (2016) show reading DMSs may lead to a slowing down and speeding up effect among drivers, potentially making roads more dangerous around the messages. Fallah Zavareh, Mamdoohi, and Nordfjærn (2017) examine how people respond to

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

DMSs with road risk ratings. Risky behavioural adaptations were observed under low and medium risk messages during night time. The effects of high risk messages, however, were consistently related to safe adaptations. The effects of messaging on rear-end conflicts were significant only in the fast lane at night time. Choudhary, Shunko, Netessine, and Koo (2019) conduct a field experiment using random driving quality meessages, showing that high-performing drivers who are not frequent feedback seekers benefit the most from personal best nudges, while low-performing drivers who are also frequent feedback seekers benefit the most from the personal average nudges.

To accomplish our estimation strategy we develop a new panel data set from January 2016 to December 2018 for the state of Vermont that includes geocoded sign location with minute-by-minute tracking of DMS messages, the population of reported accidents in the state, hourly traffic data, and daily weather and temperature data. This builds upon unique geocoded and network nature of driving to incorporate driving distance, driving time, and number of turns between signs and local accidents, allowing us to include far more information relating to near-to-sign traffic accidents in a causal framework with spillover effects. Similar work has been carried out by economists, such as M. Xu and Xu (2020), who evaluate how the introduction of new fracking wells is associated with near-to-well fatal car accidents. General studies of changing 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). Understanding and improving driver responsiveness to DMSs may lead to moderate reductions in traffic accidents, injuries, and fatalities. Alternatively, towns may be overstating belief in DMS value to drivers. De Borger and Proost (2013) show that the city government over-invest in externality-reducing infrastructure whenever this infrastructure increases the generalized cost of through traffic. We can therefore expect an excessive number of speed bumps and traffic lights, but the right investment in noise barriers. In turn, we would expect higher rates of DMSs to exist along roads than socially optimal, and understanding these effects might help governments and public policy groups set more socially optimal levels of message signage.

We estimate the causal impacts of message content on near to sign accidents using a Poisson fixed effects model that incorporates network effect of downstream DMSs. This is accomplished by allowing upstream sign messages to have non zero impacts, when upstream sign messagesare grouped by whether or not they provided behavioral or informative nudges. We further provide robustness checks by restricting the sample of DMSs to only sites with message boards more than 10 or 5 miles apart under an assumption of only local effects existing shorter than their separation, and a class of models that allows for a single neighbor within a 10 or 5 mile distance, and directly estimate compound spillover effects. Identification of DMS content comes from exogeneity of message content to local changes in accident rates. Many messages trying to create a behavioral nudge for saver driving are part of National Highway and Traffic Safety Administration that aim to elicit a behavioral response appear to be rolled out simultaneously across the DMS network. As a result, messages containing behavioral nudges are exogenous to prevailing local accident rates, weather, and traffic conditions. Instead preference seems to be given based around broad cross-road segment trends in traffic volume, nearby construction, long-term weather trends such as total snowpack, and near-to-sign hazards like bridges or sharp corners. In this later case fixed effects estimators directly control for time invariant factors that might drive higher accident rates correlated with these hazards. We see this in how messages are rolled out uniformly across the DMS network, rather than road specific sign heterogeneity.

Our results show that signs trying to induce a behavioral nudge in drivers risk preference tend to have either no, or detritus effects on near-to-sign driving behavior, causing an increase in accidents. Across a variety of specifications both multiple and joint hypothesis tests show that individual and joint messsage content of non-informative messages do not meaningfully alter reported accident rates immediately after the sign. We show that informative messages are associated with higher accident rates, but this is likely due to unaccounted for categorization of construction zones, or other time-varying parameters that might otherwise make segments of the road more dangerous. Joint tests show that the positive effect associated with caution messages is is significantly different from zero from the mile for accidents in the mile before and a mile after a DMS. These results are consistent with previous literature that ancipates excess variation in driving speeds around signs that may causally drive higher accidents in near-to-sign areas.

These results are consistent with previous results that indicate that unexpected variation in driving speeds, such as slowdowns to read the signs, might cause additional collisions. We further show that messages trying to pass along informative nudges, caution of road or weather conditions, or expected travel times, also cause no effect on near-to-sign accidents. These results appear robust across subsets of accident types, such as collisions or property damages. These results indicate that message board signs do not induce even local changes in driver risk-preferences. Particularly in areas where there is a large number of routine driving, habit setting behavior leads to rational ignorance of both behavioral and informational nudges provided by dynamic message signs. From a utility perspective, dynamic message signs appear to increase driver utility by providing better information about time to destination and other upcoming road conditions but do not seem to fit into a larger, safer driving policy paradigm.

The remainder of the paper proceeds as follows.. Section 2 provides background information on the DMS system in Vermont and detailed analysis and background information on our primary data and their sources. Section 3describes the empirical strategy and series of models to be estimated. Section 4 provides the estimation results of our models, and Section 6 concludes.

2 Data

This section provides detailed information on how Dynamic Message Signs (DMSs) location and message content is decided upon by The Vermont Agency of Transportation (VTrans). This is accumulated from a series of primary documents and direct communication with the department. We further describe our accident, traffic, and weather data, and how these data are combined. Finally, we provide basic descriptions of the final variables that we use in our estimation procedures.

2.1 Sign Message Location

The installation of DMSs are a part of VTrans' effort under the Intelligent Transportation System (ITS) to facilitate drivers with updated and timely information on traffic and road conditions.[2] VTrans initially deployed these boards with portable installations with the aim to eventually phase in permanent installations. The message boards covered in this study are all portable installations - called portable variable message signs (PVMS).The signs are typically mounted on trailers orpads, often with the wheels removed and secured in place for longer duration of use. Typically, PVMS run on solar power or battery. The PVMS have the ability for an adjustable display rate, which is typically set to allow for the message to be read at least twice at the posted speed limit.

The location of the message board is determined based on multiple factors including frequency of crashes and weather related incidents on a road segment. The detailed plan of location choice is provided in Vanasse Hangen Brustlin (2007). Broadly, the general location is determined by identifying areas where it warrants weather notification to the drivers of hazardous conditions, advanced notification of substandard roadway conditions and upcoming "chain up" areas can be provided to the truck drivers, notification of construction and planned events can be provided to avoid congestion on relevant roads, 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 (DMS boards) 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.

Most importantly the specific location of the message board is determined considering horizontal and vertical alignment of the message board. Typically, PVMS is visible from approximately 0.5 miles (or 2,500 feet) under both day and night conditions. The message is legible from a minimum distance of an 1/8th of a mil (or 650 feet). When possible, the PVMS signs are placed behind guardrail sections or outside the clear zone for errant vehicles. PVMS are mounted in such a way that the bottom of the message sign panel is minimum of seven feet above the roadway. 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.

2.2 Message Data

Based on the conversations with officials at VTrans, 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. Nudge messages (such as nudging drivers to drive sober or notifying traffic death counts) are considered low priority messages and are only displayed when there is no other important information that needs to be conveyed to the drivers. Some of the nudge messages such as "Click

[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).

It and Ticket", "Drive Sober or Get Pulled Over", etc are based on national campaigns run by National Highway and Traffic Safety Administration (NHTSA). NHTSA run regular campaigns countrywide to raise awareness on drunk driving, seat belts etc. Just like other nudge messages, the campaign messages are displayed if the message boards are not being used for more important messages such as construction, crashes, winter weather, etc. The death messages in particular are aimed at frightening people into buckling up—or putting down the cellphone, or backing away from the car while drunk, or traveling closer to the speed limit. Death messages in the state of Vermont are specifically influenced by consistently updated traffic fatality signs in states such as Tennessee, Colorado, Illinois, Ohio, Texas, and Utah.

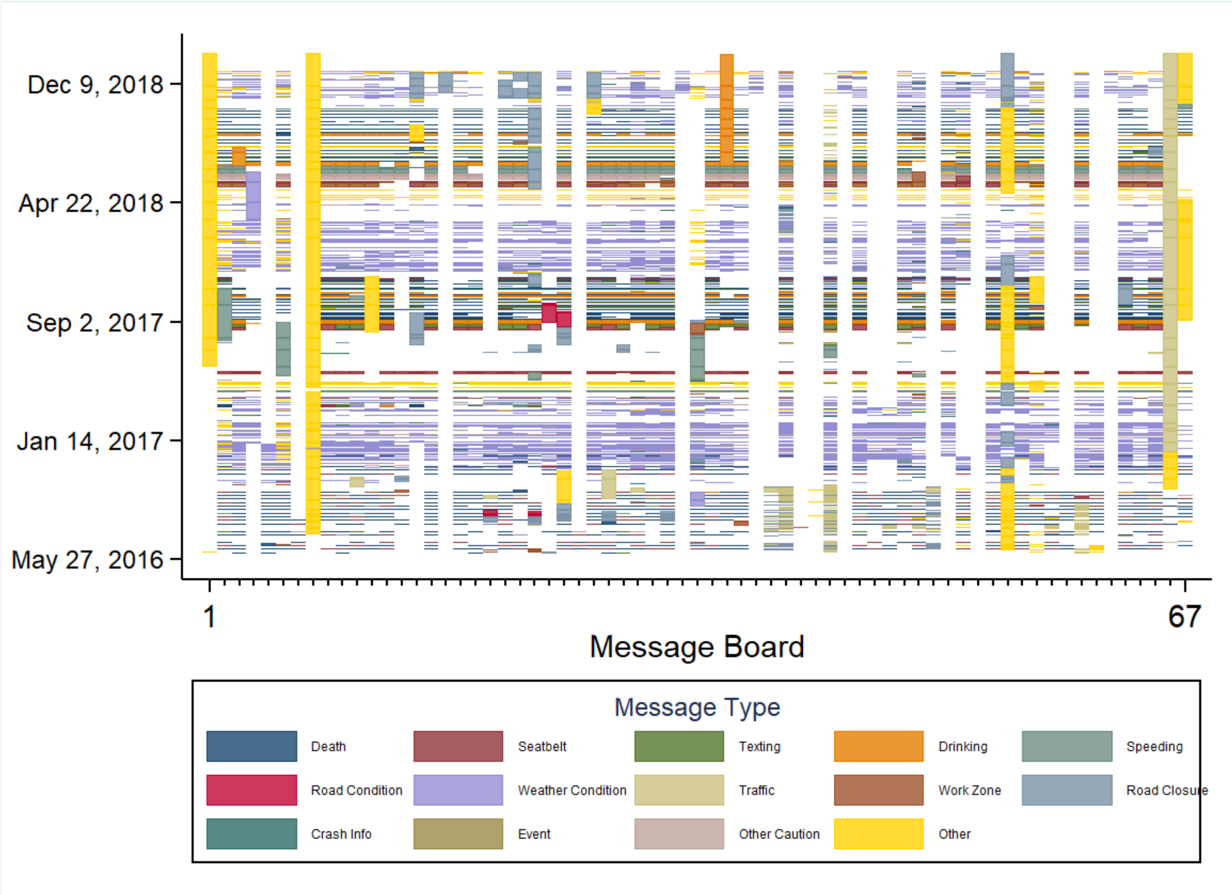
The data on messages is obtained from VTrans from June 2016 to December 2018. Messages were displayed on 67 unique sites. Table 1 presents the number and duration of various messages during the time period. During this period, there were total of 10,409 messages. The most displayed message type is the "Other message" (48 percent) which includes messages aimed at giving information to the drivers about the roadblocks, diversions, road works, distance to an exit/road, weather forecasts or any other traffic updates. The remaining 52 percent of the messages were aimed at nudging drivers to drive safely. "Death related message" inform drivers about the number of people who have died that year from traffic accidents. "Seat belt related messages" remind drivers about the seat belt. "Phone related messages" discourage the use of mobile phones and texting while driving. "Drinking related messages" nudge drivers to drive sober. "Speed related message" are aimed at nudging drivers to stay within a speed limit. "Other caution message" is any other message which does not fall into the above category such as "Caution: Rough Road Ahead..." or "Caution: Winter Driving...". Some messages can have overlapping content between these types, for example, "40 Lives Lost in 2017 Buckle Up" is categorized in both "Death related message" and "Seat belt related message". The average duration of message is approximately 30 hours with the shortest duration for any displayed message being 2-minutes and the longest being 98 days Figure 1 shows the durations at which the message boards were active during the study time period. It's clear that there is considerable heterogeneity in the activity and duration of messages across these message boards. We exploit this variation to identify the effect of nudges.

The most improtant aspect of message data comes from how message content is rolled out uniformly across the DMS network. As shown in Figure 1 VTrans rolls out message content across the network simultaneously and for equal duration. A few signs feature specific messages, often semi-permanent road hazard informative messages. But, this still provides meaningful exogeneity of DMS message content to road segment specific accident rates.

While the VTrans data has minute level data on when DMS messages where active, along with exact message content, we instead reduce these two the seven message types (Death, Seatbelt, Texting, Drinking, Speeding, Caution, Other), and reduce the treatment variable of interest to the share of the current hour during which a given message type was active. This generates the variables

$$MessageTypeShare = \text{Percent of the hour where MessageType was visible on the DMS}$$

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.

2.3 Crash Data

Data on crashes between the periods January 2016 and December 2018 is also obtained from VTrans. This dataset reports wide set of 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, number of passengers involved etc. There were total of 35,554 police reports, that involved 64,027 vehicles, of crashes during this time period in the state of Vermont.

Since the data on crashes come from police reports in a busy field setting of a crash site, the spatial location of each crash may not always be accurate. 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. Here we describe the measures that we have taken to validate the spatial location of each crash. The VTrans has taken steps to geocode precise crash location for the recent data in their efforts to improve the quality of data for traffic safety and analysis purposes.[3] We use this data to get precise spatial location of 35,202 crash sites during the said time period.

[3]The dataset is available at https://geodata.vermont.gov/datasets/

Table 1: Summary of Messages

	(1) Proportion of Number of Messages	(2) Proportion of Duration of Messages (in hours)
Death related message	0.19	0.11
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	0.14
Road condition message	0.05	0.03
Weather message	0.48	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
Event message	0.00	0.00
Other caution message	0.03	0.04
Other message	0.09	0.24
Total	10409.00	308799.85

Notes: The table presents the number and duration of various messages during the time period from June 2016 to December 2018 in Vermont. "Death related message" inform drivers about the number of people who have died that year from traffic accidents. "Seat belt related messages" remind drivers about wearing seat belt. "Phone related messages" discourage the use of mobile phones and texting while driving. "Drinking related messages" nudge drivers to drive sober. "Speed related message" are aimed at nudging drivers to stay within a speed limit. "Other caution message" is any other message which does not fall into the above category such as "Caution: Rough Road Ahead..." or "Caution: Winter Driving...". "Other message" includes messages aimed at giving information to the drivers about the roadblocks, diversions, road works, distance to an exit/road, upcoming weather forecasts or any other traffic updates.

Additionally, we are able to update geographic location of 5,999 police reports using spatial location of overlapping subset of crash data provided on VTrans Public Query Tool.[4] Few of the police officers report geographic coordinates using SPC coordinate system (rather than GPS coordinate system), we convert those to GPS coordinates and are able to update spatial location of 31 crash sites (58 vehicles).

Next, there are cases for which address information is provided in the text fields however the coordinates are missing, we use ArcGIS to geocode these addresses and are able to update spatial location of 140 crash sites. 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 (as determined on the basis of county of crash site). We then, once again, geo-code the addresses for which either GPS coordinate is missing, not a street address, or found to lie outside the respective county and are able to find locations of 42 crash sites.

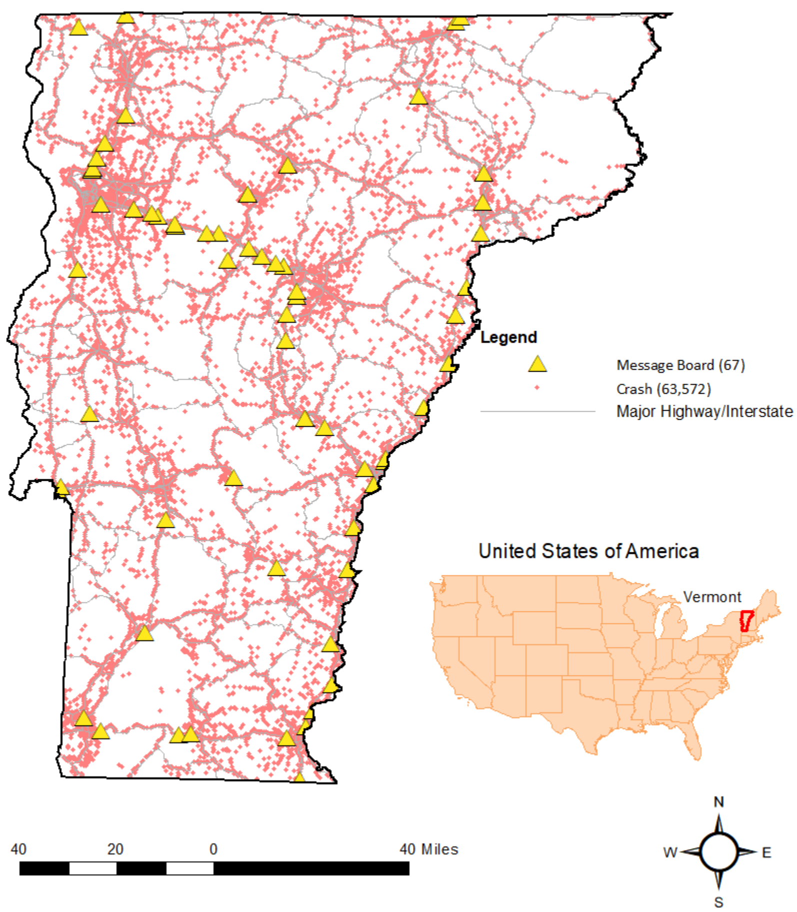
This leaves us with missing or incorrect location for 347 crash sites which are manually looked at using information on various address fields. We use information on street address and distance from intersecting street to manually locate the crash location on the Google Maps. In case of missing information about the street address the nearest intersecting street information is used to approximate the location of the crash. We use Google Maps' 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

[4]This dataset can be extracted from http://apps.vtrans.vermont.gov/CrashPublicQueryTool/

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. Given the information, we remain unable to locate 82 crash sites i.e. overall, we are able to locate 35,472 crashes with reasonable degree of accuracy.

Out of the located crash sites, 8 police reports lack information on the date and time of crash and therefore we drop them. Our final dataset of crashes has 35,472 crash reports majority of which (approxomately79%) involved "property damage" only while the rest of them constitute injuries (approxomately 20%) and fatalities (approxomately 1%). 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). The contributing circumstances for the crashes as recorded by the VTrans are presented in Table 2. Factors such as fast driving, failure to yield, failure to keep in proper lane, following too closely, and inattention are some of the major factors contributing to the 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.

Table 2: Contributing Circumstances to the Crash

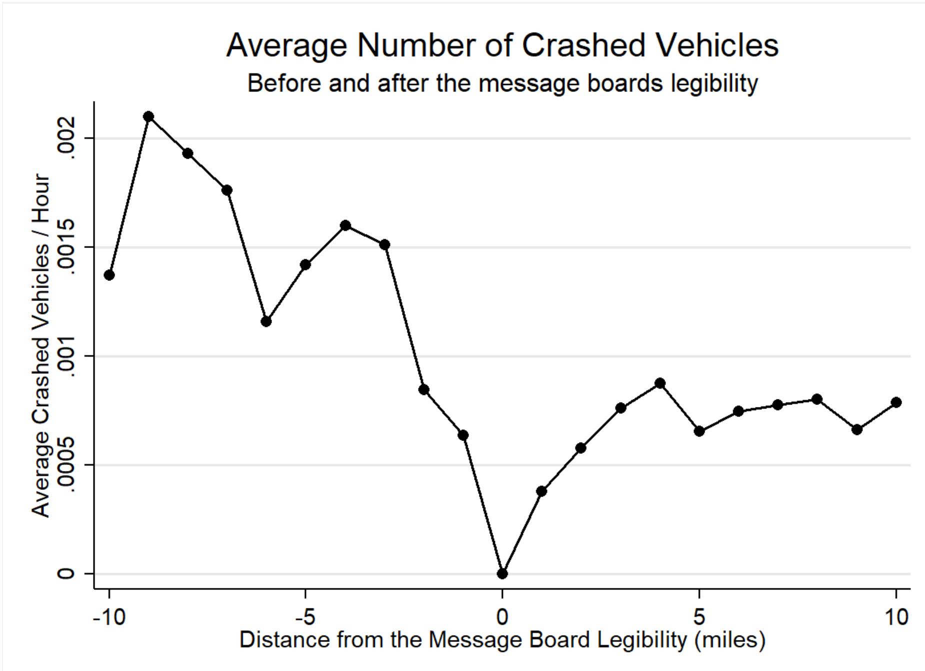
	(1) Proportion
No improper driving	35.62
Inattention	12.47
Other improper action	11.06
Driving too fast for conditions	9.42
Failed to yield right of way	8.23
Failure to keep in proper lane	7.77
Other	5.97
Followed too closely	5.74
Under the influence of medication/drugs/alcohol	1.86
Visibility obstructed	1.52
Other Activity- Electronic Device	0.33
Distracted	0.02
Total	100.00

Notes: This table presents the share of each contributing factor in a crash as recorded by the Vermont Agency of Transportation.

The purpose of this study is to assess the impact of a particular message on the probability of a crash. To analyze that, we restrict our analysis to the regions where a message board is installed for at-least some duration during the study time period. This implies that we use 67 locations/message-boards around which we focus our analysis. We map crashes to these 67 locations using ArcGIS' 'Find Closest Facility' tool. This tool finds one or more crashes that are closest from a message board based on travel distance (and travel time), and outputs the driving directions between the message board and the crash. 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. We also assign the status of "pre" or "post" to each crash to determine whether the crashed occurred before the mapped message board or after. We use driving directions along with direction of travel of a vehicle to determine the pre/post status. There are 19,452 crashes that are eventually mapped to any message board.

The average number of crashed vehicles at different distances from the legibility point of message board is shown in Figure 3. There are fewer crashed vehicles just before and after the message board, representing the fact that the the specific location of message board is such that the conditions are safe for driving in its vicinity. However, beyond the immediate vicinity of message board, the average number of crashed vehicles is increasing in both directions. It seems that the rate of increase in the average number of crashed vehicles after the message board legibility is less than the rate of increase before. Though this variation is interesting, we cannot directly compare roads before the message board with roads after it because of difference in road conditions etc.. Also, since message boards are generally installed in locations which are leading to sensitive roads, one might expect that crashes after the message board location should be higher than before, however, this is not what is observed here. This might hint that the message boards have a large causal effect in a way that not only the number of crashed vehicles is not rising after the message board, but it is in-fact decreasing.

Figure 3: Average Number of Crashed Vehicles - Before and After the Message Boards Legibility



Notes: This figure presents the average number of crashed vehicles within 10 miles before and after the legibility of message board. It includes data on all the message boards. The negative distance represents the distance before the message board legibility point and positive distance represents distance after the location of message board legibility point.

The average number of crashed vehicles by different message types is presented in Figure 4. It seems like the most effective message type is the "text message related" messages along with seat belt and drinking related messages. All the other message types seem to be indifferent in average number of accidents as compared to the time when there is no message on the message board. Interesting, there are more crashes when the "other caution" message is displayed.

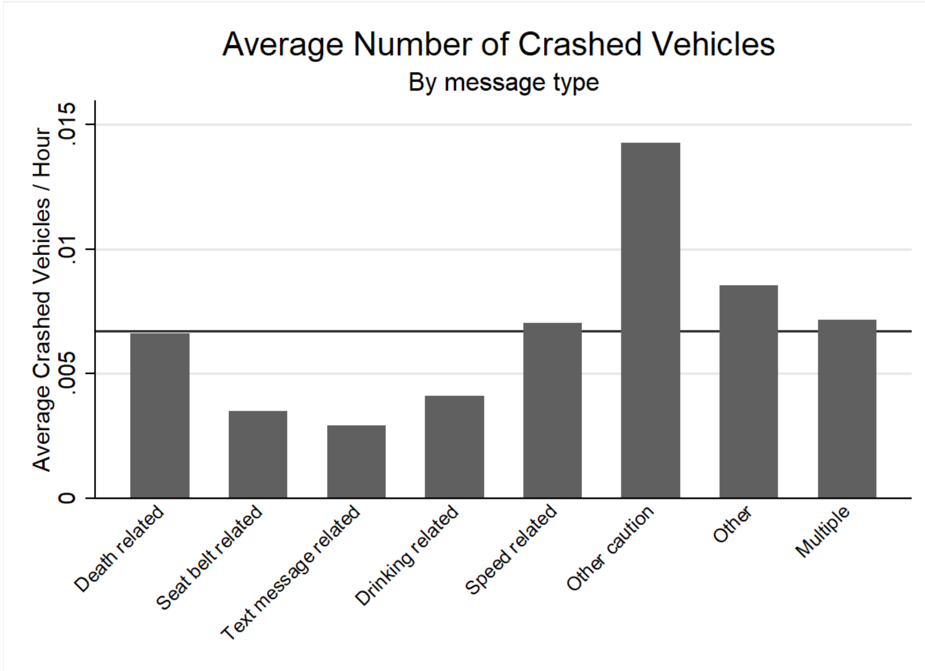
The aim of this paper is to estimate the impacts of DMS message type on near-to-sign accidents. Accordingly we bin accident data into mile longrelative distance tranches. In general, we count the number of accidents that happened in mile increments indexed at -1/8th of a mile (-.125 miles) before a sign. This starts as the initial treatment point due to statements of preferred distance for drivers to visually see each sign as discussed aboved. This generates the two series

$$Posti = \text{\# of accidents within } (i-1)-0.125 \text{ to } (i-1)+0.725 \text{ driving miles}$$

$$Prei = \text{\# of accidents within } -(i-1)-1.125 \text{ to } -(i-1)-0.125\text{driving miles}$$

This benchmarking sets up uniform mile-wide blocks indexed at "0" based around the minimum-visibility distance

Figure 4: Average Number of Crashed Vehicles by Message Type



Notes: This figure presents the average number of crashed vehicles by message type within 10 miles post the message sign. "Death related message" inform drivers about the number of people who have died that year from traffic accidents. "Seat belt related messages" remind drivers about wearing seat belt. "Phone related messages" discourage the use of mobile phones and texting while driving. "Drinking related messages" nudge drivers to drive sober. "Speed related message" are aimed at nudging drivers to stay within a speed limit. "Other caution message" is any other message which does not fall into the above category such as "Caution: Rough Road Ahead..." or "Caution: Winter Driving...". "Other message" includes messages aimed at giving information to the drivers about the roadblocks, diversions, road works, distance to an exit/road, upcoming weather forecasts or any other traffic updates. "Multiple message" nudges driver on more than one of the other nudges. "No message" means there was no message displayed at the time the driver may have passed the location of the message board.

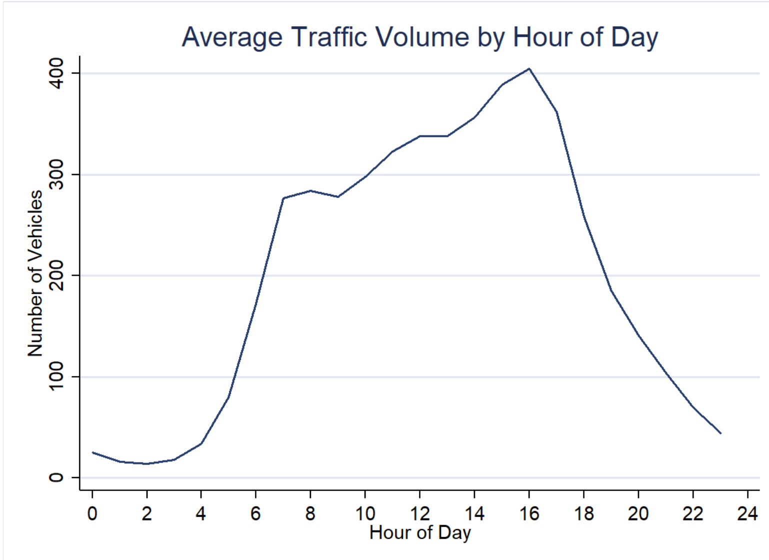
VTrans uses to place signs, and fanning out in each direction. One problem with this approach is the available road-area naturally grows in each bin further away from the central node.

2.4 Traffic and Weather Data

Traffic on a particular road is considered to be one of the crucial factors that can effect the probability of a crash. The traffic data is obtained from the VTrans which has installed traffic counters on various highways in the state of Vermont. This data covers hourly road volume counts across 24 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. The traffic volume throughout an average day is presented in Figure 5.

We next 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, however in other cases, 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

Figure 5: Average Traffic Volume by Hour of a Day



Notes: The figure presents the average traffic volume by an hour of a day across 82 traffic counters in the state of Vermont.

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.

We further obtain hourly weather data from National Oceanic and Atmospheric Administration's National Centers for Environmental Information's Local Climatological Data (LCD). LCD provides daily and hourly summaries for approximately 1600 U.S. locations, including Automated Surface Observing System (ASOS) and Automated Weather Observing System (AWOS) stations. We use daily data on snowfall and snowdepth and hourly data on dew point temperature, precipiation, wind condition, sky condition (cloudy, overcast, etc), weather condition (snowing, raining, drizzle, hail etc) and visibility. [5] Consistent with previous methodlogies, we map weather recorded at the 11 different stations in Vermont to the nearest DMS. This provides the nearest weather conditions, such as visibility, percipitation/snow, snow accumulation, and wind, to nearby signs.

From this data we generate the variables,

$$Traffic = \text{Volume of traffic at nearest volume counter}$$

$$DailySnowDepth = \text{Daily depth of snowpac in inches}$$

$$DailySnowFall = \text{Daily estimated new snowfall}$$

$$HourlyPercipitation = \text{Hourly percipitation/percipitation equivalent}$$

$$HourlyVisibility = \text{0 to 10 system indexing ability to see}$$

$$HourlyWindspeed = \text{Windspeed in knots}$$

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

$SkyCondition$ = Description of visibility (clear, mostly clear, partially cloudy, showering, etc)

$WeatherCondition$ = Any other prevailing hazards (snowing, mist, fog, or smoke, drizzle, ash, dust, sand or haze)

A full set of summary statistics is provided in 2.1. Broadly, there are more accidents after a sign than before, of the message types "Others" on average lasts the longest, but much of that is driven by a few signs that almost alway have an Other Message available as shown in Figure 1. Drastically different averages are associated between behavioral nudges, where texting and drinking message reminders only rarely happen (> 1% of the time), Death and Seatbelt reminders happen about 1.5% of the time, and Speeding reminders slightly above 2.5%. Daily snowfall and daily snow depth are very close, with some serial correlation in snow depth given it's slightly higher average implying snowpack buildup. Visibility is usually considered good (9+), and sky condition either clear or light clouds. Using hour long blocks from January 2016 to December 2018 across the 67 signs gives us just over 1.6 million observations.

Table 3: Summary Statistics

	mean	sd	max
Accidents Mile Before Sign	.0014205	.0551084	6
Accidents Mile After Sign	.0003784	.0241784	5
Accidents7	.0005799	.0301506	5
DeathMessageShare	.0183763	.1330609	1
DrinkingMessageShare	.0080791	.0893288	1
SeatBeltMessageShare	.012486	.1107959	1
TextMessageShare	.007519	.0861576	1
SpeedMessageShare	.0261897	.1588251	1
CautionMessageShare	.0290601	.1663029	1
OtherMessageShare	.0777841	.2669981	1
Traffic	321.5502	395.2822	4033
DailySnowDepth	.2789336	1.165289	20
DailySnowfall	.206982	1.014059	17.8
HourlyPrecipitation	.0045278	.0206271	1
HourlyVisibility	9.00895	2.350092	10
HourlyWindSpeed	5.613897	4.861047	46
SkyCondition==1	.3460027	.4756942	1
SkyCondition==2	.5252518	.4993621	1
SkyCondition==3	.0160474	.1256579	1
SkyCondition==4	.1126982	.3162236	1
WeatherCondition==1	.1072601	.3094438	1
WeatherCondition==2	.0703696	.255769	1
WeatherCondition==3	.0006628	.025737	1
WeatherCondition==4	.4780591	.4995185	1
WeatherCondition==5	.1872894	.3901438	1
WeatherCondition==6	.147399	.3545034	1
WeatherCondition==7	.0089599	.0942315	1
Observations	1657152		

As a final note, our sample does not include construction data in the state of Vermont. This data does exist, however the costs associated with curating the data for our use imposed strong financial burdens on the authors. Secondly, while traffic accident reports provide a large pool of information on driver characteristics, there are selection issues associated with these data. Driver characteristics may be highly correlated with driver characteristics, particularly among the chance of causing an accident. Secondly, since accidents are rare, they provide little information on the distribution of driver characteristics when we observe no accidents in a given hour. Since we observe only roughly 35,000 accidents over a period of roughly 26,280 hours, there was only about 1.3 accidents per hour across the entire state of Vermont in the sample. This puts limitations on our ability to understand the distribution of driver characteristics on various road segments over time, such as the share of commuting drivers who might regularly see a sign, compared to individuals who only irregularly drive on those roads and see the sign. In practice we assume that drivers are naive and continually check signs for message content, and are subject to plausible behavioral or informational nudges. We formalize this in the next section.

2.5 Assessing Sign Independence

A major concern is whether or not VTrans put up signs of varying message type endogenously to near-to-sign traffic, namely both directly before and after a sign. To make this assessment we estimate a multinomial logit estimator for each of our seven message types, where no message is taken as the baseline. The model employed includes post1, pre1 through pre5, traffic, weather covariates, and sign fixed effects.[6] These results are presented in Table 4. This captures location specific factors that might be correlated with different types of signs. However, it leaves out time series fixed effects structurethat might capture long-term trends in Vermont accident rates, as well as filters out daily trends associated with high and low accident time periods throughout the week. A variant with year-month and day of week- hour fixed effects was also ran, and is provided in Table 5, however the process did not converge. Intrinsic to our assumptions is that none of the accident variables should matter in determining when messages containing behavioral nudges are active.

[6] This is run with the command 'mlogit' in Stata.

Table 4: Multinomial Logit for Sign Message Type no Time FE

	Other	Caution	Death	Message Text	Speed	Drinking	Seatbelt
Post1	0.309**	0.435**	-0.286	-32.91	0.214	-0.139	0.231
	(0.154)	(0.174)	(0.405)	(21905699.4)	(0.230)	(0.596)	(0.461)
Pre1	0.0279	0.513***	0.200	-0.854	0.468***	0.673***	-0.866
	(0.132)	(0.123)	(0.219)	(1.146)	(0.138)	(0.224)	(0.614)
Pre2	0.0481	0.395***	-0.183	0.292	0.0237	0.555**	0.145
	(0.0920)	(0.107)	(0.227)	(0.335)	(0.120)	(0.218)	(0.261)
Pre3	-0.00132	0.201*	-0.174	0.409	-0.0426	0.449***	0.298*
	(0.0991)	(0.104)	(0.216)	(0.280)	(0.143)	(0.156)	(0.170)
Pre4	0.0162	0.120	0.138	0.510***	-0.114	0.340*	-0.165
	(0.0784)	(0.102)	(0.134)	(0.197)	(0.113)	(0.178)	(0.269)
Pre5	-0.0552	0.0355	-0.133	0.172	0.0286	0.0124	-0.0126
	(0.0853)	(0.0965)	(0.145)	(0.230)	(0.0956)	(0.197)	(0.172)
NeighDeathMessage	1.070***	1.462***	5.779***	-0.185	1.075***	0.867***	-0.234***
	(0.0354)	(0.0566)	(0.0271)	(0.121)	(0.0463)	(0.209)	(0.0666)
NeighSeatBeltMessage	1.395***	0.624***	0.756***	3.779***	4.343***	1.331***	6.898***
	(0.0483)	(0.117)	(0.0611)	(0.111)	(0.0343)	(0.308)	(0.0382)
NeighTextMessage	1.008***	1.390***	-0.762***	8.150***	2.144***	4.130***	1.722***
	(0.0627)	(0.102)	(0.113)	(0.0634)	(0.0733)	(0.155)	(0.220)
NeighDrinkingMessage	1.760***	2.652***	-44.28	-34.12	2.503***	11.06***	-38.27
	(0.0560)	(0.0707)	(1.27049e+09)	(24869439.8)	(0.0668)	(0.132)	(98859652.2)
NeighSpeedMessage	1.482***	3.165***	1.434***	2.563***	5.395***	3.331***	4.307***
	(0.0310)	(0.0297)	(0.0643)	(0.105)	(0.0220)	(0.0821)	(0.0409)
NeighCautionMessage	1.662***	5.093***	1.134***	0.759***	3.090***	-31.21	0.607***
	(0.0289)	(0.0207)	(0.0849)	(0.275)	(0.0290)	(2028053.0)	(0.176)
NeighOtherMessage	3.486***	1.650***	1.210***	1.800***	1.339***	1.800***	0.711***
	(0.0140)	(0.0257)	(0.0374)	(0.0705)	(0.0270)	(0.0591)	(0.0567)
N	1311360						
traffic	yes						
weather	yes						
year-month FE	no						
dow-hour FE	no						

Standard errors in parentheses

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

Consistent with our logic, VTrans does not seem to put value on accidents on the road segments around behavioral messages. Comparably both Other Messages and Caution Messages can be partially predicted by near-to-sign accidents, even after conditioningindividual fixed effects, weather, and traffic. However, even here, coefficients for the pre and post accident regions appears to be very similar to each other, and plausibly reflect unaccounted for time varying covariates. Morever, 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. This is highly indicative of fixed rollouts times by VTrans with preprogrammed messages, rather than fast reaction to on the ground road conditions. 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 mess

3 Empirical Model

To quantify the impacts of message sign content on near to sign accidents we estimate a Poisson fixed effects model. We can view individual choices over driving speed and probability of crash leads to a binomial representation for individuals risk of a crash. As traffic volume increases, the probability of a crash on a particular road segment converges to a Poisson distribution. As discussed in Section 2, messages containing behavioral nudges are exogenous due to either joint roll out across the entire DMS network, or active participation in National Highway Traffic Safety Administration campaigns. Caution messages and other informative messages are correlated with location specific hazards, and a fixed effects approach removes those impacts.

As discussed earlier, signs that are too too close together might create spillover effects if $\rho^r \neq 0$ for large enough r. Finding ways to model this dependence to recover average treatment effects is important. Considerable attention has been generated on estimation of spatial Poisson models (see for example LeSage, Fischer, and Scherngell (2007); Li et al. (2015); Quddus (2008); Wen, Zhang, Zeng, Lee, and Yuan (2019); Yao, Tang, Wei, Zheng, and Li (2019)). Broadly these approaches build on imbedding a spatial auto-regressive model within a count data model, however accident counts coded at the road and direction level no longer generate symmetric adjacency matrices, coupled with general arguments against spatial autoregressive models Gibbons and Overman (2012). In our context we simply condition on upstream neighbor sign status withing x miles of each subject sign. To do so, define variables

$$NeighBehavioral_{it}(x) = 1\{\text{Upstream sign withing x miles of i has an Behavioral Nudge message up}\}$$

$$NeighInformative_{it}(x) = 1\{\text{Upstream sign withing x miles of i has an Informative Nudge message up}\}$$

In the case where there is no spatial dependence, the coefficients on these terms converges to zero and this becomes a regular Poisson fixed effects model, while if they're non-zero incorporates downstream sign information. Finally, with recent discussion on biases induced by the two-way fixed effects estimators, implicit in our model is a belief that ρ^r is time invariant. This implies no learning behavior from drivers induced by signs that would could long-term changes in driver behavior.

One concern is that there may be differences in prevailing norms in accident norms associated with different message board signs. This might be caused by unobserved heterogeneity in when different message types go up. Namely, any road segment that has a message of type j may differ from locations that never present a particular type of sign, such as shown in Figure 1 there are a few signs that almost always staticly display the same message,Let a sign be positioned at location i, define Y_{itr} to be the number of crashes r= -1,1,2 miles fromsign i at time t, and let $T_{it} \in [0,1]$ represent the share of time t during which the nudge message was displayed on road segment i. In practice this is vector valued, but for simplicity assume it is a single covariate. This leads to the following fixed effects baseline specification:

$$\begin{aligned} E[Y_{itr}|\alpha, \lambda_t, X_{it}, T_{it}] = \exp(&\alpha_{ir} + \lambda_t + X_{it}\beta + \rho T_{it} + \rho^{-2} T_{it} 1\{r=-2\} + \rho^1 T_{it} 1\{r=1\} + \rho^2 T_{it} 1\{r=2\} \\ &+ \phi_1 NeighBehavioral_{it} + \phi_2 NeighInformative_{it} + \varepsilon_{it}) \end{aligned} \tag{1}$$

where α_{ir} are road segment by distance fixed effects that encompass time-invariant unobserved characteristics, λ_t are time year-month and day of week-hour fixed effects, and X_{it} is the vector of observed time-varying covariates such as traffic and weather conditions. Recall that the dependent variable is a count variable, and Poisson regression models the log of the expected count as a function of the predictor variables. We can interpret the Poisson regression coefficient as follows: for a one unit change in the predictor variable, the difference in the logs of expected counts is expected to change by the respective regression coefficient, given the other predictor variables in the model are held constant. The key parameters of interest are ρ, ρ^1, ρ^2. Similar to traditional Differences-in-Differences, ρ is the pre-treatment effect when a sign is active in the mile before a sign, ρ^1 is the impact for the mile wide bin after a sign, and ρ^2 is the mile bin after that. Under the parameterization of equation **??** the Averate Treatment Effect for message type j at distance r becomes ρ^r.

Due to recent discussion on biases imposed by the two way fixed effect model (cfe ...), implicit to our assumption is that ρ^r is time-invariant. Under this assumption the biases implied by the two-way fixed effect model is zero, and the Poisson regression recovers the correct average treatment effect. The same logic causing bias of the two-way fixed effect with differential does not appear even if we estimate sign-by-time and distance fixed effects, as under this settup all treatment effects happen for $r \geq 1$ and are 0 otherwise, leading to no variation in "treatment timing." We still estimate these models to provide

$$\begin{aligned} E[Y_{itr}|\alpha, \lambda_t, X_{it}, T_{it}] = \exp(&\alpha_{it} + \lambda_r + \rho T_{it} + \rho^{-1} T_{it} 1\{r=-1\} + \rho^1 T_{it} 1\{r=1\} + \rho^2 T_{it} 1\{r=2\} \\ &+ \phi_1^r NeighBehavioral_{it} + \phi_2^r NeighInformative_{it} + \varepsilon_{it}) \end{aligned} \tag{2}$$

Under this transformation $X_{it}\beta$ drops out since it is invariant across the near-to-sign road segments. This allows for very local-to-sign fixed effects to vary by hour, without imposing a specific interactive fixed effects structure. In turn, the time dimension is rendered quite small. All models are estimated with robust standard errors.

4 Main Results

Event-study style tables for each of our seven message contents for Message Board ID by Distance FE are presented in Figure 6, and ID by Time FE are presented in 7. Regression results are presented in Table **??**. Column (1) corresponds to ID-by-Time fixed effects, such that the four mile segment of road has a specific fixed effect at each point in time, and then there is a relative-to-sign distance shifter. Column (2) corresponds to ID-by-Distance fixed effects, such that each mile tranch before and after a message board has it's own fixed effect, and then there is a time fixed effect that shifts levels relative to the mean.In each case these results coinspond to Equations 1 and 2, incorporating binary variables if any upstream sign within a 5 mile bandwidth is passing along an informative or behavioral nudge.

Consistent with claims made in Section 2, these parameter values change very little across successive models, indicating that they are largely exogenous to trends at the individual road-segment level.[7] Across behavioral nudges there is no discernable impact on near-to-sign accidents outside of texting messages. For both ID-by-Distance and ID-by-Time FE, the two mile tranch prior to a sign has statistically significantly lower accidents. However, this artifact is likely coming from variation in the road type, volume, and speed present on the areas that feed into DMS placement. Similarly, both caution message share and other message share have strong impacts on near-to-sign accidents, particularly estimates for CautionMessageShare are nearly identical across all three identified regions, though Other-MessageShare is considerably lower in the post-DMS region for the ID-by-Distance Fixed Effects model, indicating that some of the accidents coming from the ID-by-Time FE model might be coming from post-sign related hazards. Noteably, death message share, drinking message share, text message share, and seat belt message share seem to have no impact. Primarily, it may be that speeding reminders have heterogeneous impacts on near to sign driving, where signs actually get individuals to slow down, but induced variation in driving speed marginally increase accident rates.

Consistent with earlier claims, there exists meaningful differences in the impacts of message signs on accidents four to five miles before a sign. Across most models, the first and second mile before a sign appear to be largely indestinguishable from zero, besides for Speed Message Share. Overall, these results indicate that behavioral nudges do not improve near-to-sign accidents in a manner consistent with the simple model developed in Section **??**. Instead, as with previous observational work on impacts of DMSs on near-to-sign accidents, these messages are correlated with higher accidents. The causal mechanism being changes in near-to-sign driving speeds. Naturally in this context, speed message reminders, caution, or other road reminders may have the highest chance of induced these speed change shifts, while texting, seat belt, drinking, and even death reminders do not change drivers risk preferences locally.

[7] This is further confirmed with multinomial logit estimators that incorporate all seven message classifications. Our full set of covariates have marginal predictive power on all message content outside of Caution Message's, which care correlated with seasonal trends. Results are omitted, but available upon request.

5 Robustness Checks

In this section we provide two sets of robustness checks over our mainline specification in Section 4. The first robustness check induces indepence between sign locations. This is done by only conditioning on signs with minimum distance to the next upstream sign (signs that come before it) greater than 5 miles. The second approach is to subsample signs with either minimum distance to the next upstream sign being 5 miles, or with a single neighbor in that range, but the next upstream sign from the neighbor is greater than 5 miles. In both cases this limits the probability of spillovers existing between signs, either between induced better or worse driving. The first identifies our effects in the purest sense while removing almost half of the data, while the second allows us to examine heterogeneity in upstream sign content on downstream driving impacts- a form of plausible compounding explored in our mainline specification. These two alternative specification remove plausible spillovers between signs without the dimension reduction techniques used in our mainline results.

5.1 Robustness Checks: 5 Miles of Seperation

A major concern with our mainline results is our method of capturing spillover effects is not correctly identified. Reducing dimentionality of the underlying spatial spillover structure might mitigate impacts of upstream signs on the downstream network, whether through safer driving effects, or induced variation in driving speeds, higher accidents, slow downs, etc. To remedy this problem we induce independence between signs to be signs with at least 5 miles of difference between them and any upstream or downstrream neighbor.

As before Table **??** provides estimates for ID-by-Distance by Time, and ID-by-Time by Distance Fixed Effects models. Figures 8 and 9 plot these effects into event study style graphs. Overall these results are very close to our mainline specification. The primary deviation is that TextMessageShare has a very strong and statistically significant decrease in accident rates across both specifications. Economicly these values are functionally equivalent, both imply a greater than 100% decrease in the number of accidents. Given these values are large outliars, part might be driven by a very few number of accidents occuring in the period immediately after a text message reminder, which by itself is further a super rare event within the subsample.

Overall, and as before Speed Message Share has no effect, and neither does Other Message Share with ID-by-Distance fixed effects. Caution Message Share is still positive and significantly correlated with higher accidents across both specifications. The Caution Message Share coefficient is significantly higher among this subsample of signs using ID-by-Time fixed effects, and equivalent with ID-by-Distance FE's. In practice, these results largely confirm with our earlier ones,there is a persistent effect in Caution Message Share that grows as vehicles get closer to the message board, and tapers off afterwards, and a lack of results elsewhere.

5.2 Robustness Checks: 5 Miles of Seperation, Single Downstream Sign

In the next set of robustness checks we want to allow for spillover effects in signs. Compared to our mainline results, we again trim the sample to include either signs with no neighbor within 5 miles, or with an upstream neighbor within

5 miles, but the second closest neighbor is more than 5 miles away. This structure again aims to . We then pair the treatment status of the downstream sign, to create a series of plausible treatment spillover effects. This allows for explicit tests for whether or not upstream message content has homogeneous or heterogeneous impacts on downstream accident rates. As before, Table **??** provides results for each of the seven message type share treatment effects, Figures 10 and 11 plot these results in Event Study style graphs.[8]

Consistent with our earlier results, Caution Message Share continues to differ significantly from zero in the mile immediately after a message board. This effect continues to range between an increase in accident rates by 100-200%. Outside of this effect, a number of message type shares have significant deviations from zero in the two miles before a sign, but as discussed earlier we attribute this to differences in the average road quality being meaningful in the -2 and +2 relative distance bins. Across the remainder of the sample, different message signs do not impact driver behaviors. On neighbor effects there is no clear story. At face value 8 of 35 coefficients are significant, which is almost 20% of these effects. One problem with how we calculate these effects is they are not weighted by the distance to the sign. This might bias effects. Despite this, most of the significant effects are positive besides for Seat Belt Reminders, which is again consistent with reading signs inducing variation in driving speed as a causal mechanism for increasing accidents. Noteably however, speed message reminders appear to have reasonable decreases on downstream regions.

6 Conclusion

In this paper we study the impacts of seven different message types used in Dynamic Message Systems (DMSs) to provide either behavioral or informational nudges to drivers on near-to-sign accidents. We generate a large geospatial panel data set using hour level information on weather, traffic, accidents, and message board locations plus message content. Using exogeneity of behavioral messages to local road conditions we estimate a Poisson fixed effects model that incorporates information about upstream messages, allowing there to exist medium duration effects of DMS messages on driver behavior. Parameter estimates for both messageboard ID by relative distance and message board ID by time as cross sectional variation both show consistently there is an increase in near-to-sign deaths from Caution and Other messages, and little sign of causal impacts of other DMS messages on near-to-sign accidents.

The results indicate that messages aiming to provide a behavioral nudge for safer driving do not induce safer driving, likely due to rational ignorance of drivers to these type of messages. Comparably informational messages such as road hazard cautions or time to destintion reminders appear to causally increase the number of accidents around DMSs. Consistent with previous work using observational data to access the impacts of DMSs on driver behavior, a leading cause is due to changes in driver speed. We test this hypothesis by looking at changes in the composition of driver characteristics when different message types are visible, as well as changes in the composition of accident causes. Thus, even if drivers do aim to alter their driving to be safer, the induced variation in driving speed to read the sign causes a greater share of accidents than the safer driving saves.

Our results show that signs trying to induce a behavioral nudge in drivers risk preference tend to have either no,

[8] Plan on adding in the same table for neighbor treatment shares

or detritus effects on near-to-sign driving behavior, causing an increase in accidents. This is consistent with previous results that indicate that unexpected variation in driving speeds, such as slowdowns to read the signs, might cause additional collisions. We further show that messages trying to pass along informative nudges, caution of road or weather conditions, or expected travel times, also cause no effect on near-to-sign accidents. These results appear robust across subsets of accident types, such as collisions or property damages. These results indicate that message board signs do not induce even local changes in driver risk-preferences. Particularly in areas where there is a large number of routine driving, habit setting behavior leads to rational ignorance of both behavioral and informational nudges provided by dynamic message signs. From a utility perspective, dynamic message signs appear to increase driver utility by providing better information about time to destination and other upcoming road conditions but do not seem to fit into a larger, safer driving policy paradigm.

References

Abouk, R., & Adams, S. (2013). Texting bans and fatal accidents on roadways: Do they work? Or do drivers just react to announcements of bans? *American Economic Journal: Applied Economics*, *5*(2), 179–199. doi: 10.1257/app.5.2.179

Benartzi, S., Beshears, J., Milkman, K. L., Sunstein, C. R., Thaler, R. H., Shankar, M., ... Galing, S. (2017). Should Governments Invest More in Nudging? *Psychological Science*, *28*(8), 1041–1055. doi: 10.1177/0956797617702501

Benson, B. G. (1997, jan). Motorist attitudes about content of variable-message signs. *Transportation Research Record*, *1550*(1550), 48–57. Retrieved from `http://journals.sagepub.com/doi/10.1177/0361198196155000107` doi: 10.1177/0361198196155000107

Bird, K. A., Castleman, B. L., Denning, J. T., Goodman, J., Lamberton, C., & Rosinger, K. O. (2019). Nudging at Scale: Experimental Evidence from FAFSA Completion Campaigns. *NBER Working Paper Series*, 58. Retrieved from `http://www.nber.org/papers/w26158`

Bonsall, P. (1992, feb). The influence of route guidance advice on route choice in urban networks. *Transportation*, *19*(1), 1–23. doi: 10.1007/BF01130771

Choudhary, V., Shunko, M., Netessine, S., & Koo, S. (2019). *Nudging Drivers to Safety: Evidence from a Field Experiment.* Retrieved from `https://www.ssrn.com/abstract=3491302` doi: 10.2139/ssrn.3491302

Clark, P. J., & Evans, F. C. (1954). Distance to Nearest Neighbor as a Measure of Spatial Relationships in Populations. *Ecology*, *35*(4), 445–453. doi: 10.2307/1931034

De Borger, B., & Proost, S. (2013, jul). Traffic externalities in cities: The economics of speed bumps, low emission zones and city bypasses. *Journal of Urban Economics*, *76*(1), 53–70. doi: 10.1016/j.jue.2013.02.004

DeAngelo, G., & Hansen, B. (2014). Life and death in the fast lane: Police enforcement and roadway safety. *American Economic Journal: Economic Policy*, *6*(2), 231–257.

Erke, A., Sagberg, F., & Hagman, R. (2007, nov). Effects of route guidance variable message signs (VMS) on driver behaviour. *Transportation Research Part F: Traffic Psychology and Behaviour*, *10*(6), 447–457. doi: 10.1016/j.trf.2007.03.003

Fallah Zavareh, M., Mamdoohi, A. R., & Nordfjærn, T. (2017, apr). The effects of indicating rear-end collision risk via variable message signs on traffic behaviour. *Transportation Research Part F: Traffic Psychology and Behaviour*, *46*, 524–536. doi: 10.1016/j.trf.2016.09.019

Gibbons, S., & Overman, H. G. (2012, may). Mostly pointless spatial econometrics? *Journal of Regional Science*, *52*(2), 172–191. Retrieved from `http://doi.wiley.com/10.1111/j.1467-9787.2012.00760.x` doi: 10.1111/j.1467-9787.2012.00760.x

Hansen, B. (2015). Punishment and deterrence: Evidence from drunk driving. *American Economic Review*, *105*(4), 1581–1617. doi: 10.1257/aer.20130189

Hassan, H. M., Abdel-Aty, M. A., Choi, K., & Algadhi, S. A. (2012). Driver behavior and preferences for changeable message signs and variable speed limits in reduced visibility conditions. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, *16*(3), 132–146. doi: 10.1080/15472450.2012.691842

LeSage, J. P., Fischer, M. M., & Scherngell, T. (2007, aug). Knowledge spillovers across Europe: Evidence from a Poisson spatial interaction model with spatial effects. *Papers in Regional Science*, *86*(3), 393–421. Retrieved from `http://doi.wiley.com/10.1111/j.1435-5957.2007.00125.x` doi: 10.1111/j.1435-5957.2007.00125.x

Li, L., Su, X., Wang, Y., Lin, Y., Li, Z., & Li, Y. (2015, sep). Robust causal dependence mining in big data network and its application to traffic flow predictions. *Transportation Research Part C: Emerging Technologies*, *58*, 292–307. doi: 10.1016/j.trc.2015.03.003

Makowsky, M. D., & Stratmann, T. (2011, nov). More tickets, fewer accidents: How cash-strapped towns make for safer roads. *Journal of Law and Economics*, *54*(4), 863–888. doi: 10.1086/659260

Mounce, J. M., Ullman, G. L., Pesti, G., Pezoldt, V., Institute, T. T., of Transportation, T. D., & Administration, F. H. (2007). Guidelines for the Evaluation of Dynamic Message Sign Performance. , *7*(2), 252p. Retrieved from `http://tti.tamu.edu/documents/0-4772-1.pdf{%}0Ahttps://trid.trb.org/view/806971`

Norouzi, A., Haghani, A., Hamedi, M., & Ghoseiri, K. (2013). *Impact of Dynamic Message Signs on occurrence of road accidents.*

Peng, Z. R., Guequierre, N., & Blakeman, J. C. (2004, jan). Motorist response to arterial variable message signs. *Transportation Research Record*, *1899*(1899), 55–63. Retrieved from `http://journals.sagepub.com/doi/10.3141/1899-07` doi: 10.3141/1899-07

Quddus, M. A. (2008, jul). Modelling area-wide count outcomes with spatial correlation and heterogeneity: An analysis of London crash data. *Accident Analysis and Prevention*, *40*(4), 1486–1497. doi: 10.1016/j.aap.2008.03.009

Song, M., Wang, J.-H., Cheung, S., & Keceli, M. (2016). Assessing and Mitigating the Impacts of Dynamic Message Signs on Highway Traffic. *International Journal for Traffic and Transport Engineering*, *6*(1), 1–12. doi: 10.7708/ijtte.2016.6(1).01

Tay, R., & De Barros, A. G. (2008, jan). Public perceptions of the use of dynamic message signs. *Journal of Advanced Transportation*, *42*(1), 95–110. Retrieved from `http://doi.wiley.com/10.1002/atr.5670420107` doi: 10.1002/atr.5670420107

Vanasse Hangen Brustlin, I. (2007). *Dynamic Message Sign Study* (Tech. Rep.). Vermont Agency of Transportation.

Wen, H., Zhang, X., Zeng, Q., Lee, J., & Yuan, Q. (2019, jan). Investigating spatial autocorrelation and spillover effects in freeway crash-frequency data. *International Journal of Environmental Research and Public Health*, *16*(2), 219. Retrieved from `http://www.mdpi.com/1660-4601/16/2/219` doi: 10.3390/ijerph16020219

Xu, M., & Xu, Y. (2020, may). Fraccidents: The impact of fracking on road traffic deaths. *Journal of Environmental Economics and Management*, *101*, 102303. doi: 10.1016/j.jeem.2020.102303

Xu, W., Zhao, X., Chen, Y., Bian, Y., & Li, H. (2018). Research on the Relationship between Dynamic Message Sign Control Strategies and Driving Safety in Freeway Work Zones. *Journal of Advanced Transportation*, *2018*, 1–19. doi: 10.1155/2018/9593084

Yao, H., Tang, X., Wei, H., Zheng, G., & Li, Z. (2019, jul). Revisiting Spatial-Temporal Similarity: A Deep Learning Framework for Traffic Prediction. *Proceedings of the AAAI Conference on Artificial Intelligence*, *33*(01), 5668–5675. doi: 10.1609/aaai.v33i01.33015668

A Tables

Table 5: Multinomial Logit for Sign Message Type

	Other	Caution	Death	Message Text	Speed	Drinking	Seatbelt
Post1	0.380**	0.502***	-0.280	-41.40	0.384*	0.104	0.127
	(0.153)	(0.175)	(0.419)	(1.26029e+09)	(0.232)	(0.616)	(0.490)
Pre1	0.00981	0.530***	0.168	-1.728	0.521***	0.628**	-0.845
	(0.136)	(0.132)	(0.270)	(1.749)	(0.145)	(0.267)	(0.719)
Pre2	0.0697	0.374***	-0.155	0.426	-0.0474	0.640**	0.140
	(0.100)	(0.116)	(0.241)	(0.366)	(0.126)	(0.259)	(0.281)
Pre3	0.0604	0.239**	-0.251	0.461	-0.0569	0.263	0.148
	(0.103)	(0.110)	(0.239)	(0.307)	(0.149)	(0.177)	(0.202)
Pre4	0.0858	0.109	0.171	0.578***	-0.0879	0.213	-0.0112
	(0.0803)	(0.105)	(0.156)	(0.220)	(0.117)	(0.192)	(0.292)
Pre5	-0.0306	0.0904	-0.251	0.144	0.0300	0.147	0.0448
	(0.0878)	(0.0970)	(0.159)	(0.241)	(0.102)	(0.226)	(0.183)
NeighDeathMessage	0.443***	1.559***	3.444***	4.082***	0.387***	-0.102	2.569***
	(0.0400)	(0.0641)	(0.0302)	(0.113)	(0.0541)	(0.253)	(0.0700)
NeighSeatBeltMessage	1.180***	0.247**	2.456***	3.877***	3.465***	1.484***	5.142***
	(0.0559)	(0.121)	(0.0630)	(0.132)	(0.0406)	(0.389)	(0.0437)
NeighTextMessage	0.00570	2.046***	1.060***	6.950***	1.600***	3.208***	2.166***
	(0.0703)	(0.114)	(0.121)	(0.0825)	(0.0795)	(0.171)	(0.224)
NeighDrinkingMessage	0.836***	3.151***	-41.30	-39.53	2.010***	9.068***	-46.67
	(0.0597)	(0.0797)	(330735496.9)	(285779113.5)	(0.0709)	(0.135)	(.)
NeighSpeedMessage	1.034***	1.988***	0.640***	2.056***	4.083***	3.294***	3.642***
	(0.0347)	(0.0319)	(0.0820)	(0.126)	(0.0246)	(0.110)	(0.0488)
NeighCautionMessage	1.471***	3.765***	1.015***	2.227***	2.106***	-37.54	0.855***
	(0.0314)	(0.0221)	(0.0946)	(0.289)	(0.0332)	(151841403.5)	(0.181)
NeighOtherMessage	2.792***	1.336***	0.755***	0.791***	0.854***	0.688***	-0.0611
	(0.0149)	(0.0286)	(0.0435)	(0.0858)	(0.0335)	(0.0901)	(0.0741)
N	1311360						
traffic	yes						
weather	yes						
year-month FE	yes						
dow-hour FE	yes						

Standard errors in parentheses

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

Table 6: Near-to-Sign Estimates by 5 Mile Tranches and Sign Spillovers

	(1)	(2)
	ID-by-Time FE	ID-by-Distance FE
CautionMessageShare -2	-0.302 (-1.40)	-0.0333 (-0.15)
CautionMessageShare -1		0.585*** (3.96)
CautionMessageShare 1	0.685*** (2.90)	0.614* (1.82)
CautionMessageShare 2	0.543** (2.24)	0.442 (1.07)
OtherMessageShare -2	0.0377 (0.20)	0.133 (0.58)
OtherMessageShare -1		0.0884 (0.43)
OtherMessageShare 1	0.979*** (4.63)	0.533* (1.69)
OtherMessageShare 2	1.207*** (6.68)	0.0533 (0.18)
DeathMessageShare -2	-0.191 (-0.60)	0.0761 (0.23)
DeathMessageShare -1		0.391 (1.45)
DeathMessageShare 1	0.0158 (0.04)	0.0874 (0.22)
DeathMessageShare 2	0.114 (0.27)	0.108 (0.25)
DrinkingMessageShare -2	-0.302 (-0.57)	0.239 (0.56)
DrinkingMessageShare -1		0.0561 (0.23)
DrinkingMessageShare 1	-0.390 (-0.54)	-0.116 (-0.21)
DrinkingMessageShare 2	-0.209 (-0.30)	0.0663 (0.09)
TextMessageShare -2	-0.592 (-1.06)	-0.0572 (-0.09)
TextMessageShare -1		0.323 (0.79)
TextMessageShare 1	-1.276 (-1.59)	-0.967 (-1.23)
TextMessageShare 2	-1.638** (-2.09)	-1.314* (-1.70)
SpeedMessageShare -2	-0.626** (-2.29)	-0.613* (-1.92)
SpeedMessageShare -1		0.592*** (3.63)
SpeedMessageShare 1	0.00968 (0.03)	0.0728 (0.20)
SpeedMessageShare 2	0.0367 (0.12)	0.0661 (0.17)
SeatBeltMessageShare -2	-0.645* (-1.69)	-0.331 (-0.91)
SeatBeltMessageShare -1		0.285 (1.47)
SeatBeltMessageShare 1	-0.764 (-1.12)	-0.458 (-0.83)
SeatBeltMessageShare 2	-0.608 (-0.96)	-0.300 (-0.49)
SpillNudge -2	0.691* (1.90)	0.367 (1.56)
SpillNudge -1		-0.0937 (-0.44)
SpillNudge 1	1.275*** (2.63)	0.307 (1.19)
SpillNudge 2	0.862** (2.10)	0.231 (0.73)
SpillInformative -2	-0.234 (-1.01)	-0.401 (-1.42)
SpillInformative -1		0.396 (1.61)
SpillInformative 1	0.963*** (4.18)	-0.0267 (-0.07)
SpillInformative 2	0.824*** (3.62)	-0.114 (-0.34)
N	15720	6128832

t statistics in parentheses

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

Table 7: Near-to-Sign Estimates by 5 Mile Tranches and Sign Independence

	(1) ID-by-Time FE	(2) ID-by-Distance FE
CautionMessageShare -2	-0.521* (-1.66)	-0.0784 (-0.25)
CautionMessageShare -1		0.728*** (4.18)
CautionMessageShare 1	1.107*** (3.67)	0.686** (2.13)
CautionMessageShare 2	0.643** (2.05)	0.325 (1.15)
OtherMessageShare -2	0.0215 (0.09)	0.216 (1.26)
OtherMessageShare -1		-0.00494 (-0.04)
OtherMessageShare 1	1.071*** (3.65)	0.276 (0.53)
OtherMessageShare 2	1.751*** (7.79)	0.0156 (0.06)
DeathMessageShare -2	-0.373 (-0.80)	0.0921 (0.18)
DeathMessageShare -1		0.582 (1.37)
DeathMessageShare 1	0.328 (0.60)	0.0341 (0.06)
DeathMessageShare 2	0.547 (1.10)	0.288 (0.47)
DrinkingMessageShare -2	0.156 (0.22)	0.939* (1.73)
DrinkingMessageShare -1		-0.136 (-0.33)
DrinkingMessageShare 1	-0.190 (-0.17)	-0.553 (-0.66)
DrinkingMessageShare 2	0.477 (0.52)	0.330 (0.30)
TextMessageShare -2	-1.060 (-0.87)	-0.567 (-0.46)
TextMessageShare -1		-0.629 (-1.63)
TextMessageShare 1	0.232 (0.23)	0.377 (0.50)
TextMessageShare 2	-14.55*** (-18.69)	-290.1*** (-5.41)
SpeedMessageShare -2	-0.984*** (-2.71)	-0.699** (-2.34)
SpeedMessageShare -1		0.783*** (3.60)
SpeedMessageShare 1	0.0346 (0.07)	-0.321 (-0.72)
SpeedMessageShare 2	0.0863 (0.21)	-0.0966 (-0.21)
SeatBeltMessageShare -2	-1.460** (-2.02)	-0.982* (-1.75)
SeatBeltMessageShare -1		0.306 (1.52)
SeatBeltMessageShare 1	-1.229 (-1.19)	-1.504 (-1.53)
SeatBeltMessageShare 2	-1.758* (-1.69)	-1.849* (-1.93)
N	9516	3708864

t statistics in parentheses

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

Table 8: Near-to-Sign Estimates with Sign Neighbor Effects

	(1) ID-by-Time FE	(2) ID-by-Distance FE
CautionMessageShare -2	0.0971 (0.32)	0.148 (0.59)
CautionMessageShare -1		0.361* (1.66)
CautionMessageShare 1	0.597* (1.79)	1.054*** (2.70)
CautionMessageShare 2	0.588 (1.51)	1.039 (1.46)
OtherMessageShare -2	0.00490 (0.02)	-0.0616 (-0.16)
OtherMessageShare -1		0.257 (0.72)
OtherMessageShare 1	0.110 (0.27)	0.471 (1.01)
OtherMessageShare 2	-0.245 (-0.67)	0.109 (0.22)
DeathMessageShare -2	-0.104 (-0.20)	-0.0234 (-0.06)
DeathMessageShare -1		0.485** (1.97)
DeathMessageShare 1	-1.219 (-1.64)	-0.487 (-1.16)
DeathMessageShare 2	-0.839 (-1.50)	-0.563 (-1.28)
DrinkingMessageShare -2	-0.142 (-0.19)	-0.0496 (-0.09)
DrinkingMessageShare -1		0.339 (1.38)
DrinkingMessageShare 1	0.0864 (0.10)	0.554 (0.78)
DrinkingMessageShare 2	-28.07*** (-10.89)	-0.431 (-0.66)
TextMessageShare -2	-0.193 (-0.30)	-0.0213 (-0.04)
TextMessageShare -1		0.910*** (3.06)
TextMessageShare 1	-16.10*** (-19.38)	-431.0*** (-6.99)
TextMessageShare 2	-0.876 (-1.15)	-0.413 (-0.67)
SpeedMessageShare -2	-0.198 (-0.49)	-0.527 (-0.98)
SpeedMessageShare -1		0.439** (2.03)
SpeedMessageShare 1	-0.00216 (-0.00)	0.743 (1.40)
SpeedMessageShare 2	0.0819 (0.20)	0.366 (0.59)
SeatBeltMessageShare -2	-0.0807 (-0.15)	-0.0820 (-0.17)
SeatBeltMessageShare -1		0.262 (0.95)
SeatBeltMessageShare 1	-0.112 (-0.13)	0.351 (0.57)
SeatBeltMessageShare 2	0.144 (0.21)	0.483 (0.71)
N	6376	2525184

t statistics in parentheses

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

Table 9: Near-to-Sign Neighbor Estimates with Sign Neighbor Effects

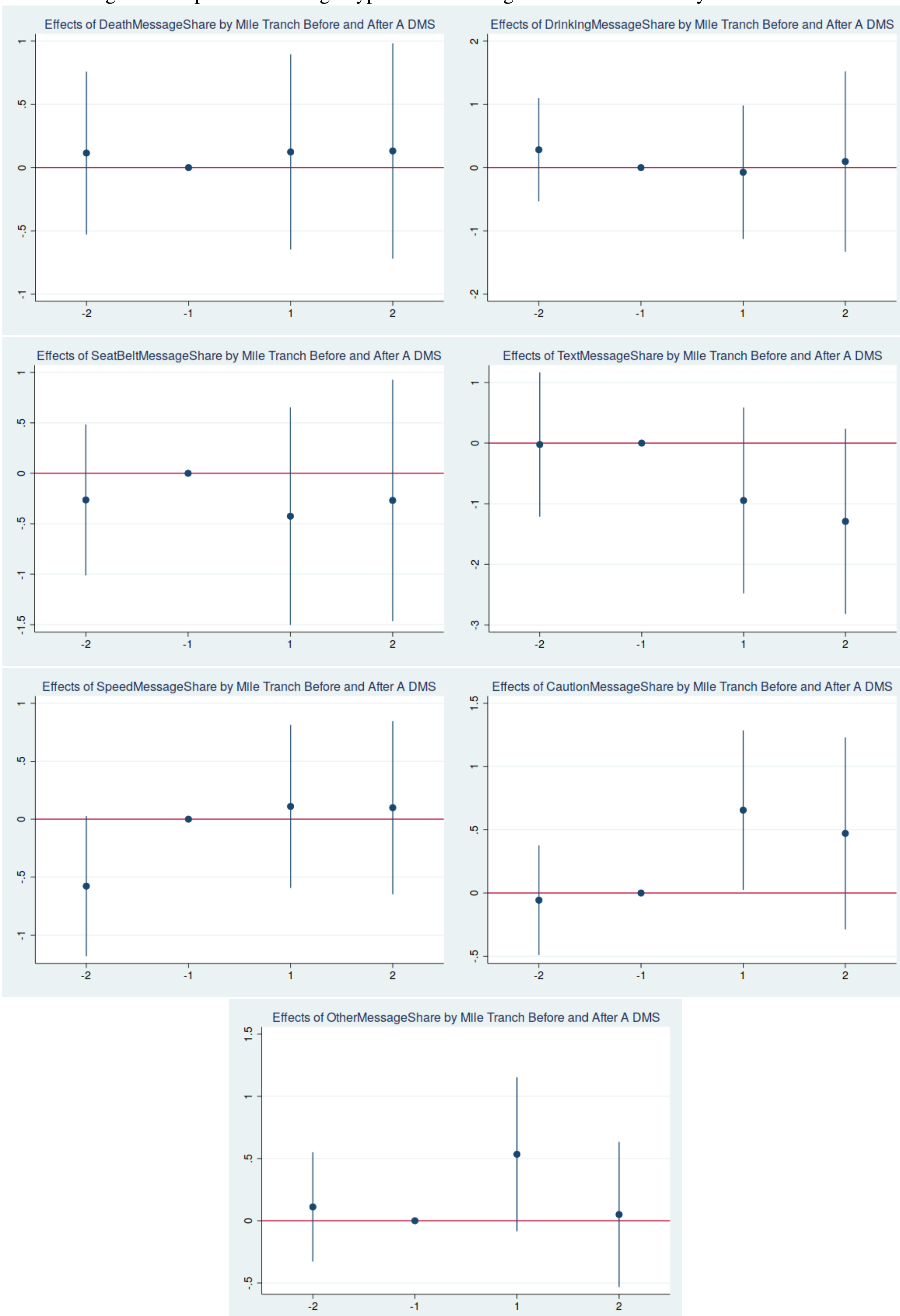
	(1) ID-by-Distance FE	(2) ID-by-Time FE
NeighCautionMessageShare -2	-2.122*** (-3.36)	-2.371*** (-2.70)
NeighCautionMessageShare -1	0.439 (1.19)	
NeighCautionMessageShare 1	0.535 (0.98)	1.443*** (3.49)
NeighCautionMessageShare 2	-0.485 (-0.72)	0.731 (1.54)
NeighOtherMessageShare -2	0.123 (0.39)	0.0904 (0.32)
NeighOtherMessageShare -1	0.0863 (0.31)	
NeighOtherMessageShare 1	-0.198 (-0.42)	0.625* (1.81)
NeighOtherMessageShare 2	0.156 (0.40)	1.351*** (4.99)
NeighDeathMessageShare -2	-0.838* (-1.96)	-0.873 (-1.19)
NeighDeathMessageShare -1	0.644** (2.25)	
NeighDeathMessageShare 1	0.304 (0.89)	1.048 (1.48)
NeighDeathMessageShare 2	-0.220 (-0.46)	0.406 (0.57)
NeighDrinkingMessageShare -2	-287.1*** (-4.19)	-16.88*** (-13.54)
NeighDrinkingMessageShare -1	-0.950* (-1.83)	
NeighDrinkingMessageShare 1	-419.1*** (-4.32)	-15.80*** (-11.89)
NeighDrinkingMessageShare 2	1.141 (1.27)	29.22*** (9.95)
NeighTextMessageShare -2	1.422* (1.85)	1.066 (1.12)
NeighTextMessageShare -1	-1.507*** (-3.29)	
NeighTextMessageShare 1	2.292*** (3.86)	1.999 (1.56)
NeighTextMessageShare 2	-355.4*** (-7.45)	-14.77*** (-16.91)
NeighSpeedMessageShare -2	0.0433 (0.11)	-0.217 (-0.48)
NeighSpeedMessageShare -1	0.575** (2.35)	
NeighSpeedMessageShare 1	-1.594** (-2.01)	-1.234 (-1.30)
NeighSpeedMessageShare 2	-0.0826 (-0.20)	0.216 (0.48)
NeighSeatBeltMessageShare -2	1.680 (1.48)	1.446 (1.08)
NeighSeatBeltMessageShare -1	-1.547** (-2.03)	
NeighSeatBeltMessageShare 1	1.848* (1.82)	2.165 (1.64)
NeighSeatBeltMessageShare 2	1.152 (1.25)	1.573 (1.14)
N	2525184	6376

t statistics in parentheses

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

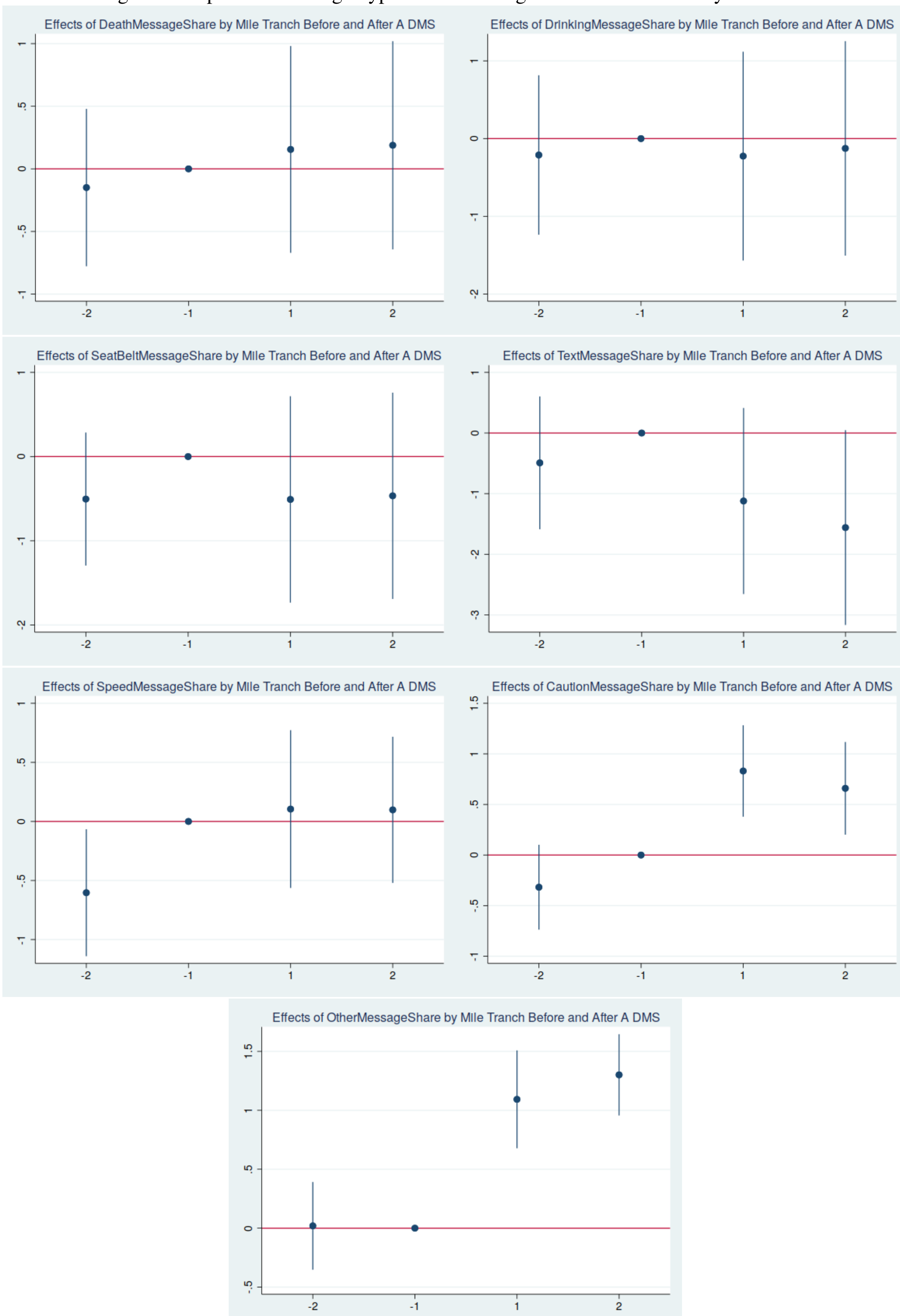
B Figures

Figure 6: Impacts of Message Type on Near to Sign Accidentswith ID-by-Distance FE



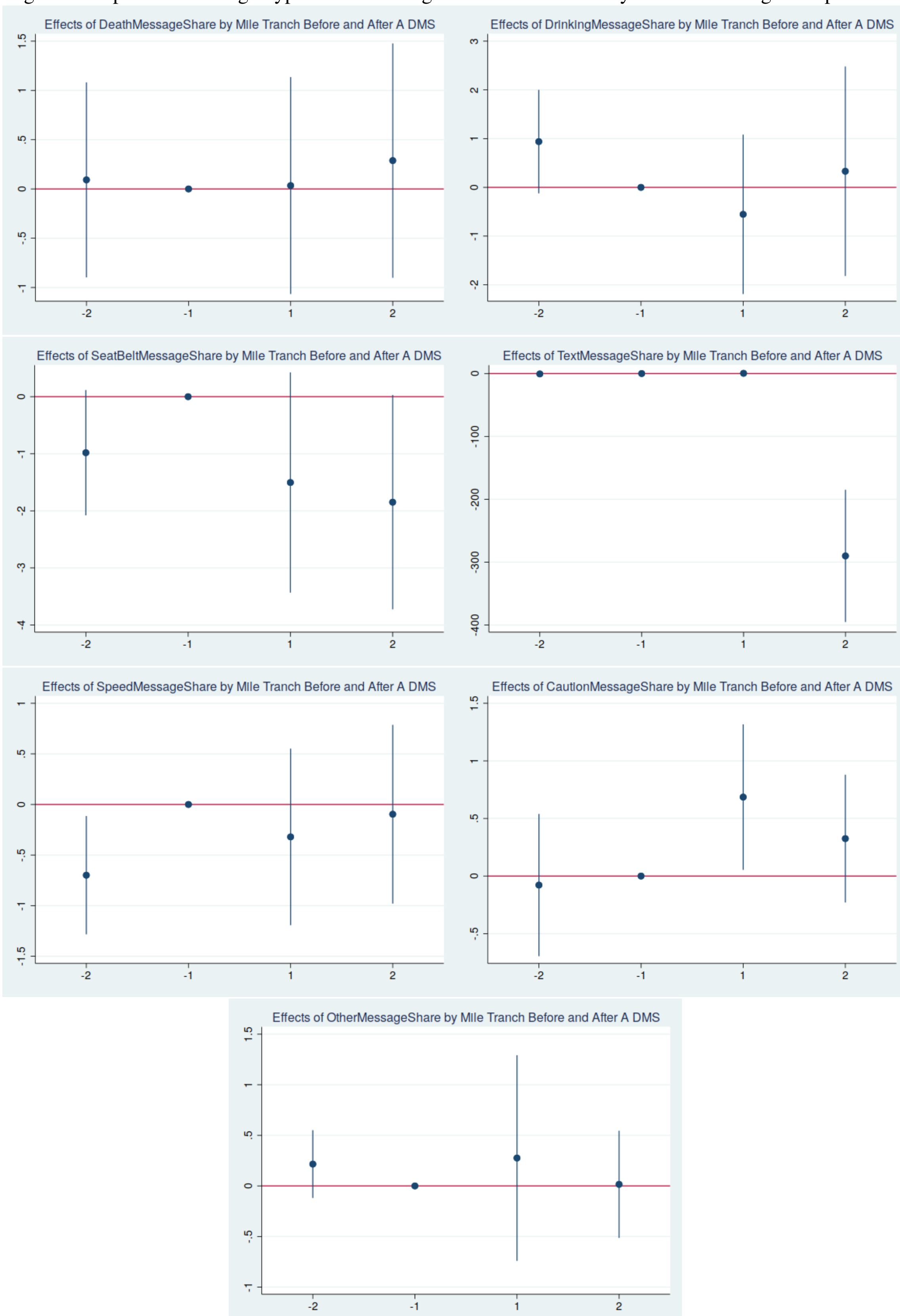
Notes: These figures plot the causal impacts of an hour long message on near to sign accidents for each of our seven message types. Coefficients cannot be characterized as a change in the number of accidents, but are evaluated in terms of statistically significant from zero. Coefficients can be interpreted as percentage increase if taking the transformation $\exp(\beta_j) - 1$. We do not assign causal interpretation for β_{-2}, β_2, but include them as a psuedo pre and post-trend.

Figure 7: Impacts of Message Type on Near to Sign Accidents with ID-by-Time FE



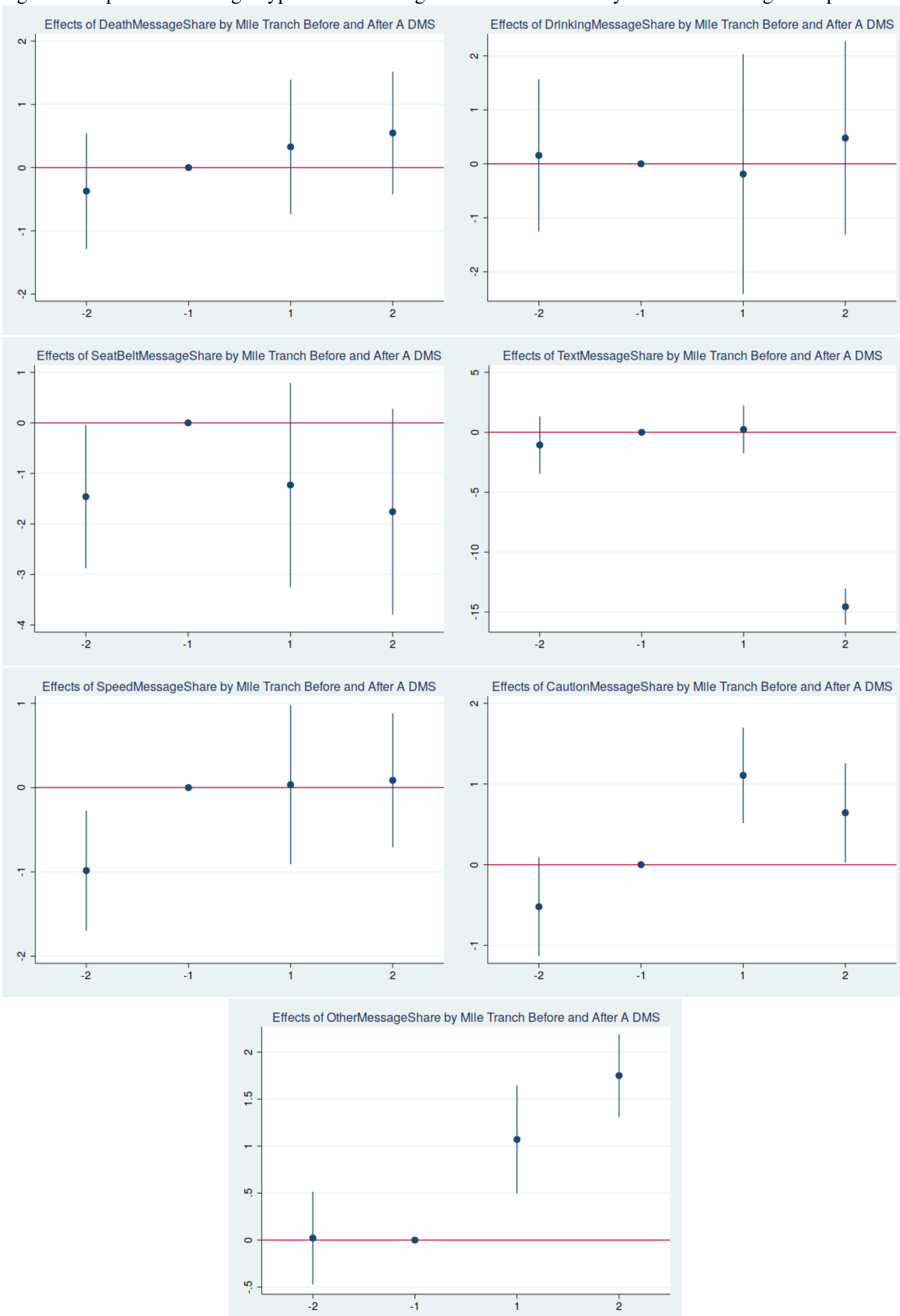
Notes: These figures plot the causal impacts of an hour long message on near to sign accidents for each of our seven message types. Coefficients cannot be characterized as a change in the number of accidents, but are evaluated in terms of statistically significant from zero. Coefficients can be interpreted as percentage increase if taking the transformation $\exp(\beta_j) - 1$. We do not assign causal interpretation for β_{-2}, β_2, but include them as a psuedo pre and post-trend.

Figure 8: Impacts of Message Type on Near to Sign Accidents with ID-by-Dist FE and Sign Independence



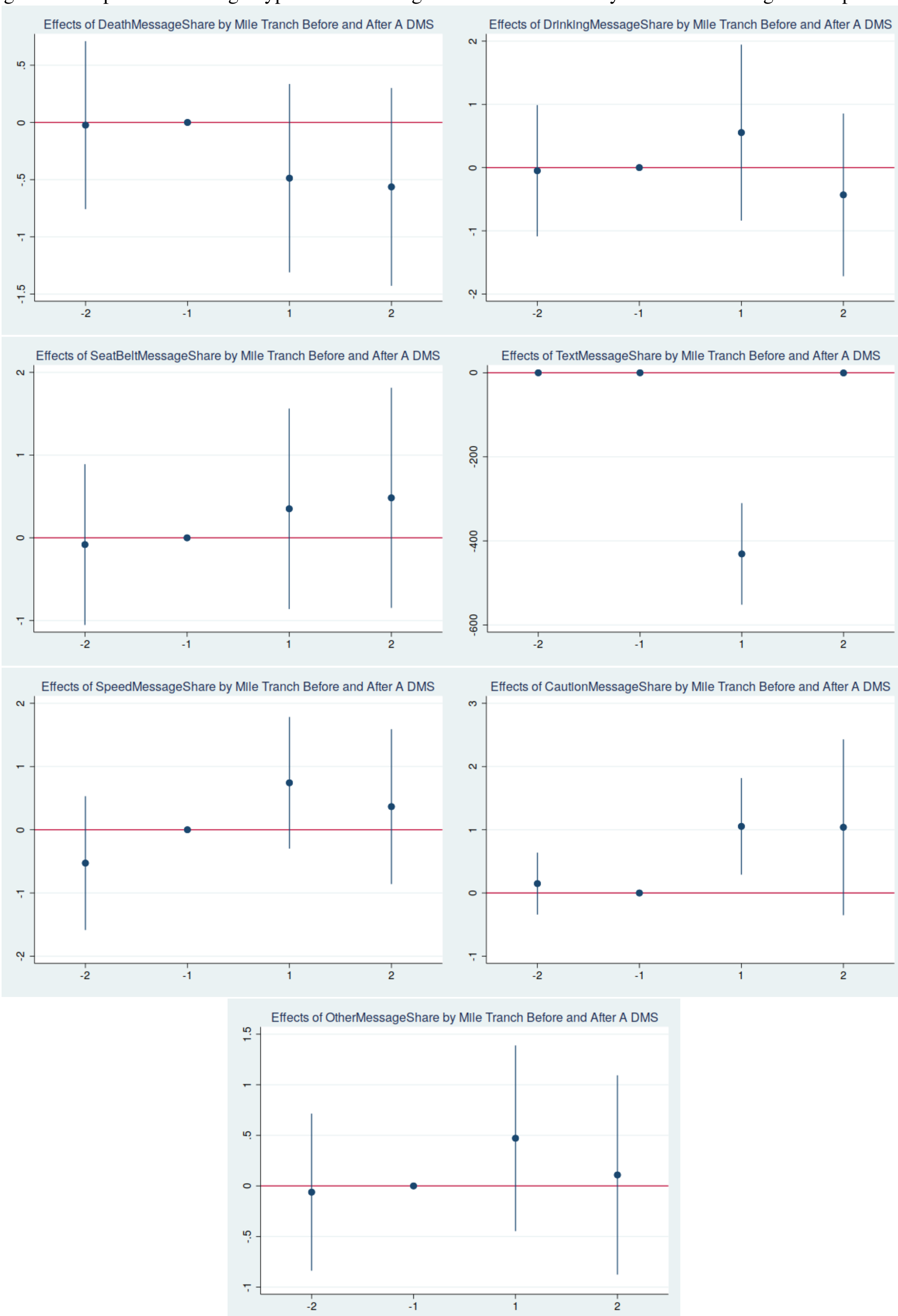
Notes: These figures plot the causal impacts of an hour long message on near to sign accidents for each of our seven message types. Coefficients cannot be characterized as a change in the number of accidents, but are evaluated in terms of statistically significant from zero. Coefficients can be interpreted as percentage increase if taking the transformation $\exp(\beta_j) - 1$. We do not assign causal interpretation for β_{-2}, β_2, but include them as a psuedo pre and post-trend.

Figure 9: Impacts of Message Type on Near to Sign Accidents with ID-by-Time FE and Sign Independence



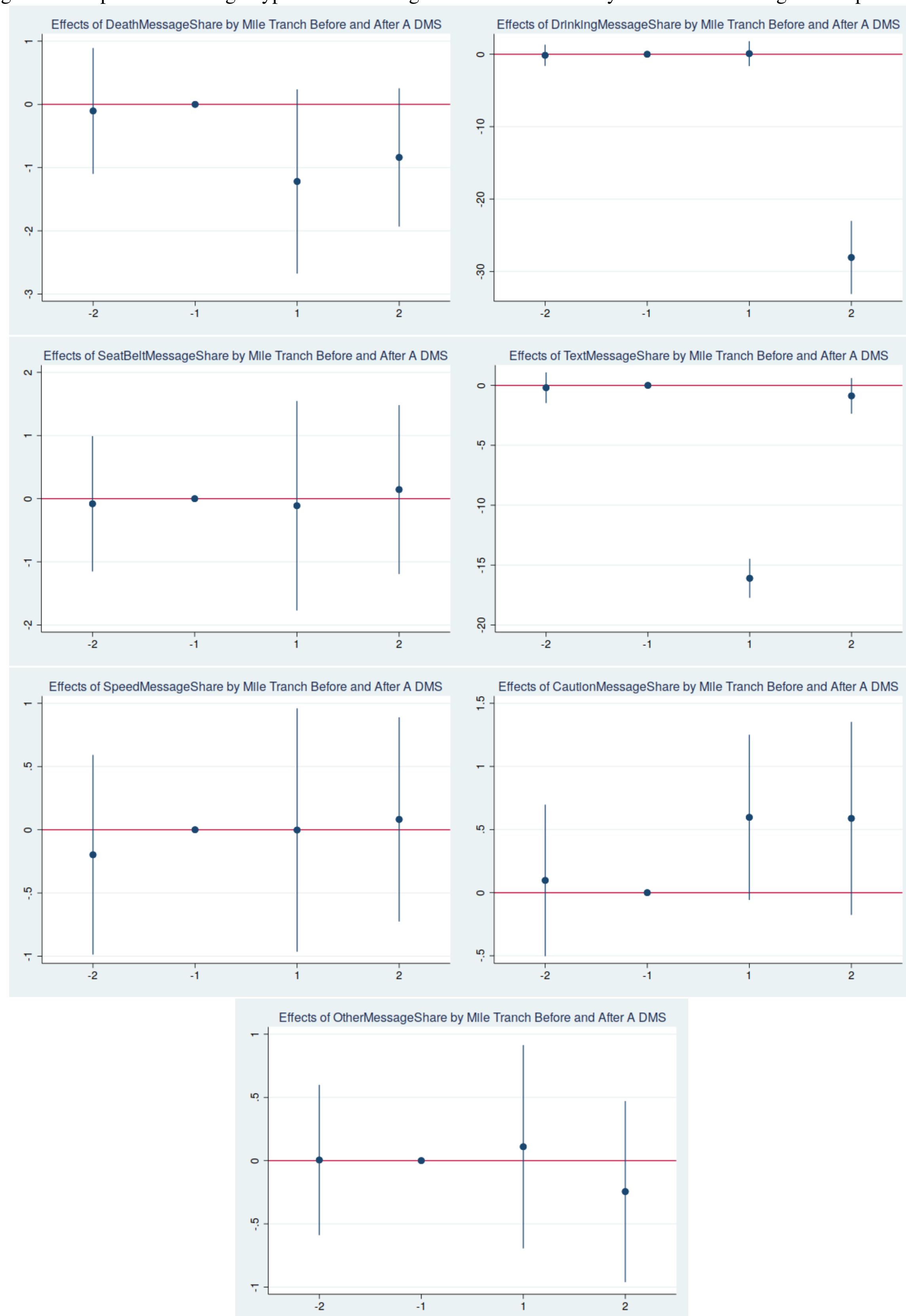
Notes: These figures plot the causal impacts of an hour long message on near to sign accidents for each of our seven message types. Coefficients cannot be characterized as a change in the number of accidents, but are evaluated in terms of statistically significant from zero. Coefficients can be interpreted as percentage increase if taking the transformation $\exp(\beta_j) - 1$. We do not assign causal interpretation for β_{-2}, β_2, but include them as a psuedo pre and post-trend.

Figure 10: Impacts of Message Type on Near to Sign Accidents with ID-by-Dist FE and Neighbor Dependence



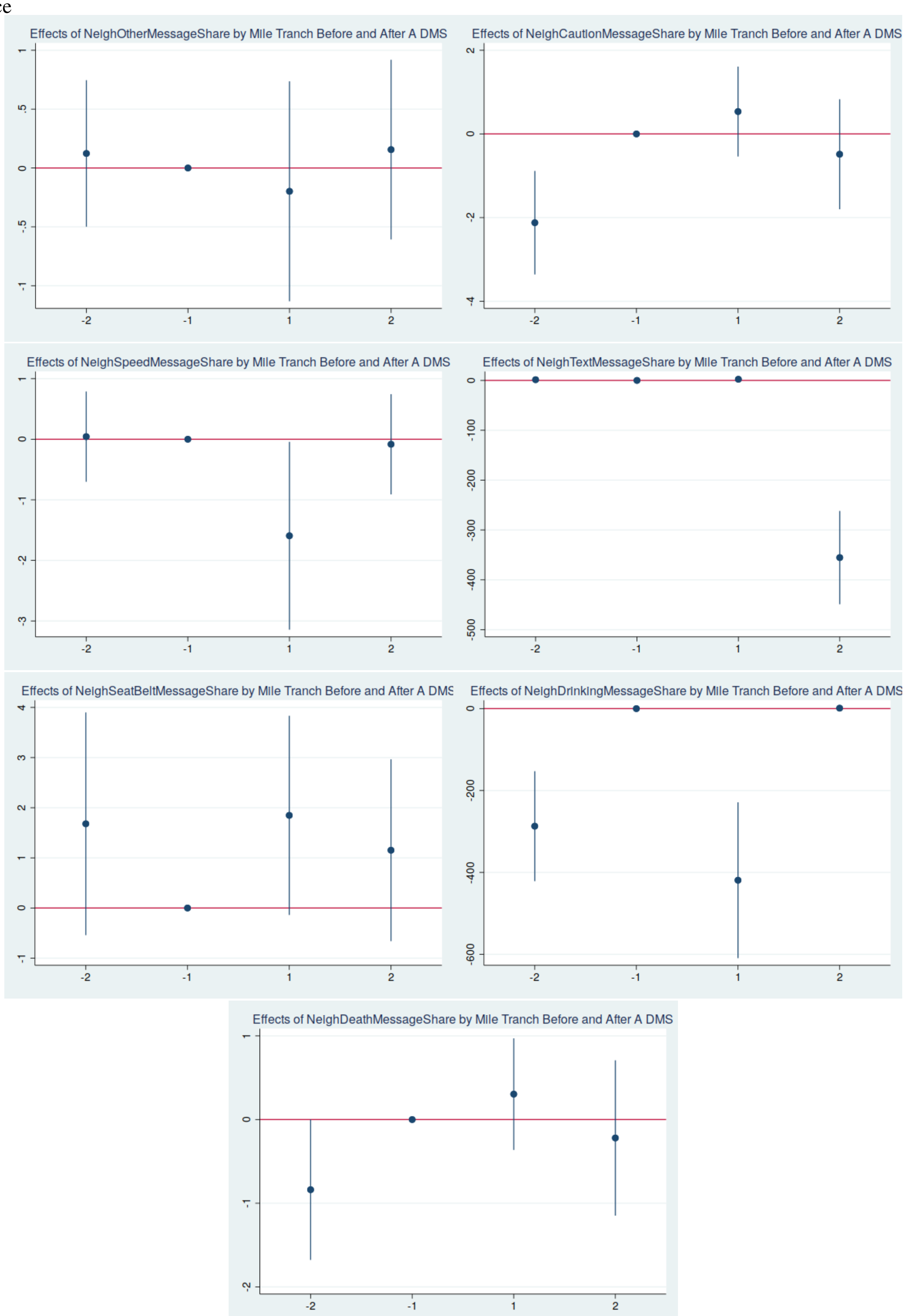
Notes: These figures plot the causal impacts of an hour long message on near to sign accidents for each of our seven message types. Coefficients cannot be characterized as a change in the number of accidents, but are evaluated in terms of statistically significant from zero. Coefficients can be interpreted as percentage increase if taking the transformation $\exp(\beta_j) - 1$. We do not assign causal interpretation for β_{-2}, β_2, but include them as a psuedo pre and post-trend.

Figure 11: Impacts of Message Type on Near to Sign Accidents with ID-by-Time FE with Neighbor Dependence



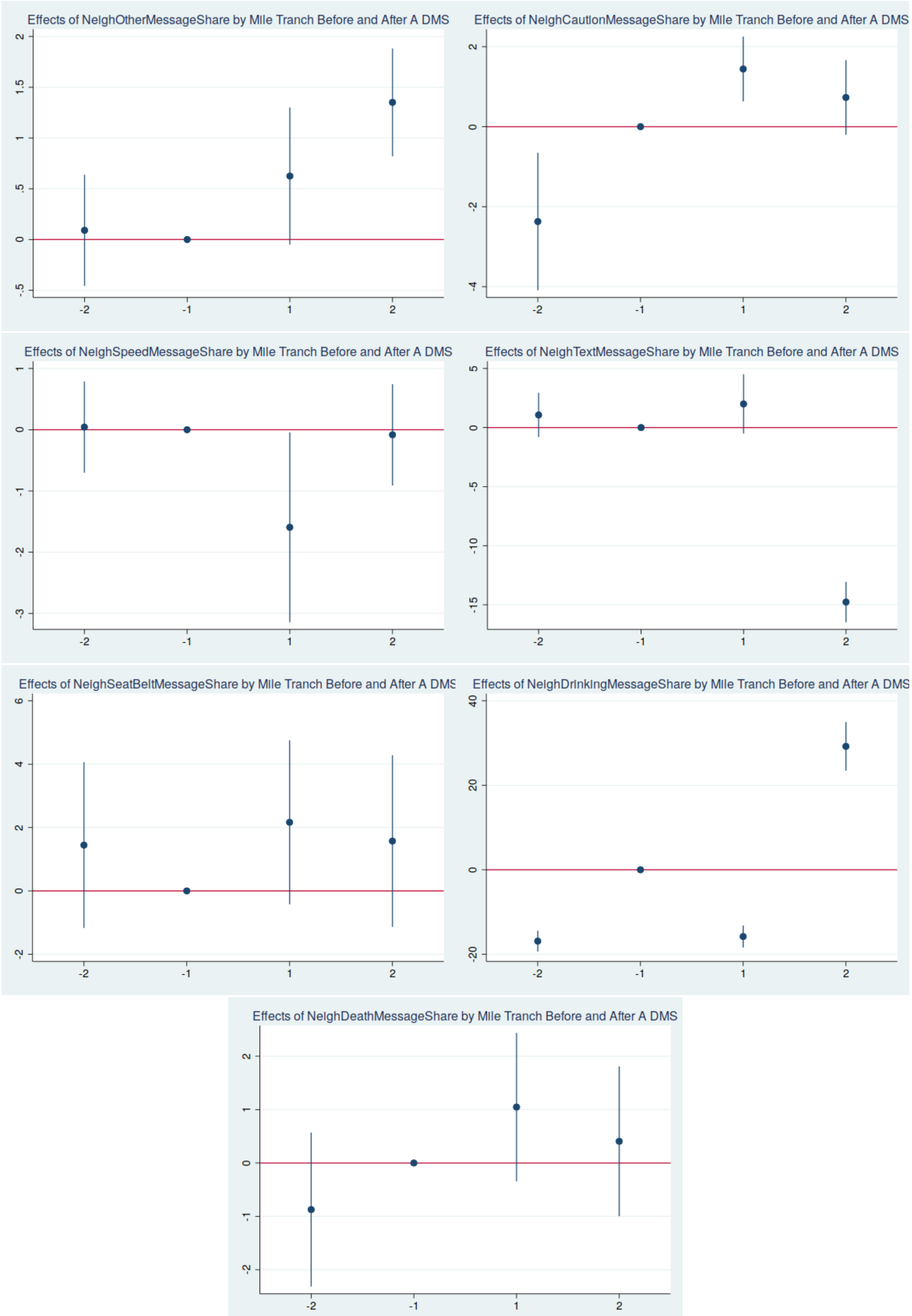
Notes: These figures plot the causal impacts of an hour long message on near to sign accidents for each of our seven message types. Coefficients cannot be characterized as a change in the number of accidents, but are evaluated in terms of statistically significant from zero. Coefficients can be interpreted as percentage increase if taking the transformation $\exp(\beta_j) - 1$. We do not assign causal interpretation for β_{-2}, β_2, but include them as a psuedo pre and post-trend.

Figure 12: Impacts of Neighbor Message Type on Near to Sign Accidents with ID-by-Dist FE and Neighbor Dependence



Notes: These figures plot the causal impacts of an hour long message on near to sign accidents for each of our seven message types. Coefficients cannot be characterized as a change in the number of accidents, but are evaluated in terms of statistically significant from zero. Coefficients can be interpreted as percentage increase if taking the transformation $\exp(\beta_j) - 1$. We do not assign causal interpretation for β_{-2}, β_2, but include them as a psuedo pre and post-trend.

Figure 13: Impacts of Neighbor Message Type on Near to Sign Accidents with ID-by-Dist FE and Neighbor Dependence



Notes: These figures plot the causal impacts of an hour long message on near to sign accidents for each of our seven message types. Coefficients cannot be characterized as a change in the number of accidents, but are evaluated in terms of statistically significant from zero. Coefficients can be interpreted as percentage increase if taking the transformation $\exp(\beta_j) - 1$. We do not assign causal interpretation for β_{-2}, β_2, but include them as a psuedo pre and post-trend.