Messaging and Driving: An Empirical Analysis of Dynamic Message Signs in Virginia

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Abstract

Traffic fatalities accounted for 1.3% of all deaths in the United States in 2017 and the average American lost about 100 hours due to congestion in 2019. One tool transportation departments (DOTs) use to address these issues is Dynamic Message Signs (DMS). DMS convey traffic conditions and occasional safety reminders to drivers in order to increase attentiveness and reduce harmful behavior. This study leverages variation in the text and formatting of messages displayed by Virginia's DMS to explain detailed speed and crash data near DMS. This study reports no significant differences in crash risk nor speed when DMS display safety messages compared to default messages. However, this study does uncover large and signficant differences in crash risk and speed when DMS transition, or cycle, between multiple messages, although the effect only lasts for 3-5 kilometers. Results indicate that multi-page messages increased crashes by 1.5% in 2019, and reduced vehicle speed around DMS by 2-4%, relative to single page messages. Although DMS can provide valuable, actionable information to drivers, DOTs should be more selective in the timing and formatting of messages as to not impose additional externalities on drivers.

... thank you to ...

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1 Introduction

Traffic safety and congestion represent large scale, nationwide transportation issues. According to the United States Department of Transportation's (USDOT) Fiscal Year Budget Estimates, government agencies allocated nearly $1 billion to traffic safety measures nationwide in 2021. In 2017, over 37,000 Americans died as a result of traffic crashes, which accounted for just over 1.3% of all deaths in the United States (Murphy et al., 2018). In 2016 the USDOT estimated the statistical value of a life at $9.6 million, implying an approximate total annual cost of fatal crashes of $380 billion. Put into perspective, this represents about 2% of 2017 US GDP. Traffic congestion contributes to a host of negative externalities, including increased travel time and air pollution. For example, Currie and Walker (2011) demonstrated that reductions in congestion, and thus pollution, generated by replacing standard toll booths with electronic toll collection led to increased infant birth weight of about 11% in nearby areas. In addition, the average working American lost about 100 hours due to congestion on their commutes in 2019 (Inrix, 2020).

Unfortunately, many remedies to traffic externalities, such as improving infrastructure (Bock et al., 2021) or investing in law enforcement (DeAngelo and Hansen, 2014), can be prohibitively expensive. In addition, government transportation departments (DOTs), the agencies directly responsible for highways, do not typically have the ability to implement these types of solutions. Rather, DOTs must wait for legislative bodies to recognize and act on these infrastructure problems.[1] In this context, low cost interventions to reduce traffic externalities are especially attractive. Dynamic Message Signs (DMS), also called Variable Message Signs, Changeable Message Signs or Matrix Signs, represent one common action that many DOTs take. DMS quickly update drivers' information sets which can reduce traffic congestion by alerting them to issues on the road ahead.

DMS are large LED signs with the ability to quickly and very inexpensively change

[1] In 2021, the United States Senate passed a $1 trillion infrastructure bill, $110 billion of which was budgeted for roads, bridges and other projects. This bill highlights the government's understanding of the need for quality transportation infrastructure.

the messages displayed based on current traffic conditions. DOTs use these signs to notify drivers of travel time estimates, the presence of congestion, toll prices, and lane impacting events such as crashes, disabled vehicles, or debris in the road. In addition, many DOTs use DMS to display safety slogans with the hope of encouraging drivers to engage in safer behaviors. DMS are popular along highways all over the world and their flexibility provides an important tool for DOTs.

Although DMS are widespread and generally thought to be effective, their impact is not yet well established empirically. Providing updated information to drivers during travel represents an obvious benefit, but there might be unintended consequences from DMS use. Understanding and documenting any externalities is important for DOTs to make better decisions about DMS use. Previous research identified that a specific DMS use in Texas, display of a salient and morbid traffic safety message, increased the risk of crashes near signs (Hall and Madsen, 2021). This study builds on that paper in several ways. First, this study investigates the extent to which this result holds for a broader set of traffic safety messages in a different state. Second, this study offers an alternate explanation for the mechanism generating changes in crash rates. Finally, this study analyzes the effect of DMS messaging on vehicle travel speed, which has never been done in a large scale empirical study.

Data for this study come from Virginia's Department of Transportation (VDOT) and INRIX, a private company specializing in traffic data collection. Like most DOTs in the United States, VDOT uses DMS to communicate with drivers in real time. VDOT maintains detailed minute-by-minute DMS log files that contain information such as location, time of display, and message content. Crash data come from both Virginia's Department of Motor Vehicles and VDOT's 511 system. Traffic speed data come from INRIX.

This study uses two empirical strategies to identify the impacts of DMS messaging on traffic outcomes. First, scheduled safety campaigns provide exogenous variation in the intensity of safety messaging. Second, DMS use is identified by the message occurring at the beginning of the hour. Since DMS are mostly automated, messages are scheduled in advance and are only interrupted if a lane impacting event occurs. The message displayed at the beginning of the hour is therefore intended to persist at least throughout the hour. If an incident occurs that changes the message displayed, this incident can be attributed to the message displayed at the beginning of the hour.

The results provide important information about the impact of DMS messages. First, safety messaging does not appear to impact traffic outcomes differently than other standard DMS messages. This said, standard DMS messaging generates some negative externalities in the form of speed reductions and small increases in the probability of a crash. While this contradicts some results in the traffic safety literature, the second result provides an alternate explanation these findings. DMS messages that transition between multiple messages, or contain multiple pages, have a large, significant effect on both speed and crash risk on highway segments near each DMS. This impact tapers off after 5 kilometers. This result is strengthened by using alternate incidents (debris in the road, disabled vehicles, etc.) as a falsification test resulting in a precisely estimated null result for traffic outcomes.

Put into context, multi-page DMS messaging results in an additional 1,875 crashes per year near DMS, which accounts for about 1.5% of total crashes across the State of Virginia. Furthermore, since .6% of crashes in Virginia result in a fatality, the results suggest an additional 12 fatalities per year in the state. Multi-page DMS messaging also results in a 2-4% reduction in vehicle speed. While small, speed reductions add up over many drivers. For the average commuter in Virginia, a 2-4% slow down in speed would cost \$0.40 per trip, which is about 1/3 of the typical toll charge in Virginia. Over the course of a year, this could amount to \$200 per person, or \$700 million across all Virginia commuters, or about .12% of Virginia's Gross State Product. These results suggest blank DMS messages should be used more often, particularly when communicating relatively less valuable information like a safety slogan or a travel time estimate that indicates no congestion.

The paper proceeds as follows. Section 2 outlines the related literature about traffic outcomes and messaging. Sections 3 and 4 describe the data and the identification strategies used to answer the research questions. Section 5 discusses the empirical results, and Section 6 concludes.

2 Literature Review

A long and substantial literature in economics on highways and traffic outcomes exists. Vickrey (1969) was one of the first to discuss the underprovision, in terms of both quantity and quality, of highway infrastructure and its impact on traffic. Since then, many papers have addressed the externalities associated with traffic. Vehicle crashes and traffic congestion represent two particularly important externalities. The five and half million crashes reported in 2010 generated a total economic cost of $277 billion (Blincoe et al., 2015). Distributed uniformly, this amounts to costs upwards of $900 for each resident in the United States.

The costs of congestion are also well documented in the literature, perhaps even moreso than crashes. Currie and Walker (2011) showed that replacing toll collection plazas with E-ZPass plazas increased infant birthweight, an important health outcome, by 11% immediately near the plazas. Humphreys and Pyun (2018) documented other significant negative outcomes as a result of increased congestion generated by sporting events. Beland and Brent (2018) demonstrated a link between the psychological effects of extreme traffic in Los Angeles and domestic violence.

In addition to important impacts on health and safety, lost time is often cited and easy to understand cost of congestion. Many states and countries have implemented congestion pricing along busy roads. Research on congestion pricing typically focuses on drivers' willingness to pay to avoid it. In theory, this should be proportional to one's wage. Bento et al. (2020) point out that this assumption will severely understate an individual's value of urgency. Specially, people often face discrete costs of being late, for example being fired. In this case, congestion pricing becomes a problem involving the expected future value of wages instead of the current wage.

Reducing the magnitudes of these externalities is of great interest to society. often times, governments implement laws to incentivize safer behavior on the road. Cohen and Einav (2003) and Dee (2009) demonstrated how mandated safety precautions, in the form of seat belt and motorcycle helmet laws, reduced traffic fatalities. Van Benthem (2015) showed that increasing speed limits by 10 miles per hour generated a 9-15% increase in crashes. Alarmingly, this increase in speed limits also resulted in a disproportionate 34-60% increase in fatalities. In a study evaluating bans on texting and driving, Abouk and Adams (2013) reported initial reductions in crashes, but then observed rates returning to previous levels soon after the bans went into effect. The impacts also depended on how strictly the bans were enforced.

These studies show how traffic outcomes depend on the laws in place. However, in the context of the standard "Beckerian" model of crime emphasizes the importance of both sanctions and the probability a sanction occurs. DeAngelo and Hansen (2014) showed how a large cut to the size of a police force in Oregon, which plausibly affected the probability of a levied sanction, led to increases in crashes involving both injuries and fatalities on highways. Importantly, these estimates suggested a single fatality could be prevented by a $309,000 increase in police spending.

The federal and state governments spend billions of dollars on transportation infrastructure each year. In 2021, the United States Senate passed a $1 trillion infrastructure bill, $110 billion of which was budgeted for roads, bridges and other projects. This bill demonstrates a broad understanding of the need for quality transportation infrastructure. Winston and Langer (2006) quantified how much of each dollar spent on highway infrastructure actually reduced congestion. The main finding amounted to about $0.11 of actual impact for each dollar spent. A major implication of this result is the need for a change in congestion alleviation policies. This result suggests a need for dynamic tolling policies rather than other approaches. Another possible way to reduce highway congestion is to offer alternate travel options, such as public transportation. Gu et al. (2021) showed how providing subway lines in China increased rush hour speeds by 4% which reflects less highway congestion.

All of these policies, whether investing more in policing, building more subways, or $1 Trillion legislation, are costly. In addition, these policies may entail unintended consequences. For example, building a new subway is not only costly, but also involves a lot of digging and soil removal, which could negatively impact air quality as much as the congestion did in the first place (Humphreys and Ruseski, 2019). Gallagher and Fisher (2020) reported another example of negative externalities generated by policies designed to reduce traffic congestion. Gallagher and Fisher (2020) studied the effects of red light cameras on traffic outcomes in Texas cities and found that removing red light cameras increased the number of "t-bone" collisions in intersections, but reduced the number of rear end collisions.

In addition to cost, many of policies designed to reduce congestion cannot be implemented by the government agencies charged with building and maintaining highways, DOTs. DMS represent one feasible tool for DOTs to affect congestion. Given the extensive use of DMS around the world, relatively little research documents their effectiveness or considers potential negative externalities. A few early traffic engineering studies showed small speed reductions from DMS weather advisory messages (Cooper and Sawyer, 1993; Hogema et al., 1996; Rämä and Kulmala, 2000; Al-Ghamdi, 2007). More recent research showed a similar effect for DMS congestion messages, but only when the warning was for nearby congestion (Reinolsmann et al., 2018). Finally, in a driver simulation, Jamson and Merat (2007) showed no impact of messages on current driving behavior, but drivers were better able to react to events later in time. he simulation results also showed that drivers became desensitized and these effects declined with too much exposure.

Besides these studies, most of the literature applicable to DMS comes from research on billboards and traffic outcomes. While somewhat similar, DMS and billboards have different functions, and thus may generate different impacts, which makes some billboard research only partially applicable. Oviedo-Trespalacios et al. (2019), in a summary of the literature on billboards, found mixed evidence of a relationship between roadside advertising and traffic safety. One suggestion made by Oviedo-Trespalacios et al. (2019) is that future research focus the impact of on multi-page, transitioning advertisements on traffic outcomes like Belyusar et al. (2016) and Mollu et al. (2018). These two studies showed that message transitions result in more sideways eye glances and less focus on the road ahead of drivers.

Nearly all of these studies are either relatively small in scale or use driver simulations instead of data reflecting actual highway conditions. One recent paper, Hall and Madsen (2021), takes a similar approach to this research. That paper analyzed a specific DMS safety campaign involving a message used in Texas that disclosed to drivers the total number of traffic fatalities in the state to date. This specific DMS safety campaign is implemented in about half of all US states, and might be one that VDOT would endorse based on the findings in Shealy et al. (2020), a VDOT funded report. The results reported by Hall and Madsen (2021) suggest an increase in crashes on highway segments located immediately past DMS in safety campaign weeks compared to the same locations at other times in the same month. The impact on crashes persisted over time and increased with both the reported death count and the complexity of the highway segments. The paper proposed cognitive overload as the mechanism through which DMS messages affect crashes.

Hall and Madsen (2021) rigorously showed some behavioral interventions can be "too salient" and instead backfire, generating impacts opposite of what was intended. This research raises important questions about how should policy makers should use DMS to get drivers to practice safer driving habits. Do safety campaign slogans work and is there some way to structure safety campaign messages to reduce the unintended consequences?

3 Data and Setting

This study draws data from several different sources to create an hour-level panel analysis data set for a large number of Interstate Highway road segments. Data collected for this study include Virginia's linear referencing system (LRS) for road segment and DMS locations, detailed minute-by-minute log files for each DMS, crash counts and vehicle speed estimates from June 2017 until March 2020.

VDOT's LRS is a GIS tool that allows spatial data to be easily referenced to a linearized highway representation via mileposts, which identify the distance from the highway's origin. Although latitude and longitude permit identification of road segment locations in two dimensional space, highways can also usefully be identified in one dimension based on milepost distance from the origin. Most highways feature physical mileposts which allow first responders, construction workers, drivers, and others to communicate their current location or the location of events without GPS coordinates. VDOT's LRS can be thought of as a digital, continuous milepost system. Any point with latitude and longitude identifiers can be spatially matched to an LRS segment and converted to a linear position on a highway. Each of the data sets analyzed in this study are matched to a specific highway segment using the LRS.

VDOT maintains over 1,200 individual DMS; substantial heterogeneity exists in their capabilities and purposes. Many DMS primarily display variable speed limits, travel times to specific destinations, or lane closures, and only display a handful of characters or symbols at any time. These DMS are typically small and often built into standard, static highway signs. Standalone DMS are larger and come in one of two types: stationary or portable. Stationary DMS are typically attached to overhead structures spanning the highway (a gantry) or to a pole beside the road (a cantilever). Portable DMS are attached to frames with wheels so they can be towed to different locations. Portable DMS are usually placed where VDOT plans to put a stationary DMS in the future, where a stationary DMS is currently malfunctioning, or where there is active roadwork. Both types of standalone DMS display information in full phrases instead of a single number or symbol. These are the DMS VDOT uses to inform drivers.

352 standalone VDOT operated DMS located along an Interstate or US Route existed at at least one point in time. This includes 218 (62%) stationary and 134 (38%) portable

DMS. DMS that only serve on/off ramps, arterial or collector roads were not included in the sample because of their different traffic patterns and locational features.[2]

These 352 DMS are located at 391 unique locations. The latter is larger than the former due to some portable DMS being in multiple locations throughout the sample. However, there are also times when two or more DMS resided next to one another. This occurred because of two stationary DMS on the same gantry, a portable DMS placed next to a malfunctioning stationary DMS, or simply two DMS placed a short distance from one another. In addition, it could also be the case that one DMS was swapped out for another DMS. Figure 1 displays road segments included in the sample and the locations of the DMS. Note that the distribution of the driving distance in kilometers between these Virginia DMS locations has a mean, standard deviation and median comparable to the distribution reported by Hall and Madsen (2021) in their analysis of data from Texas; 14.17/36.32/4.2 in this study vs 13.96/29.17/6 in Hall and Madsen (2021).

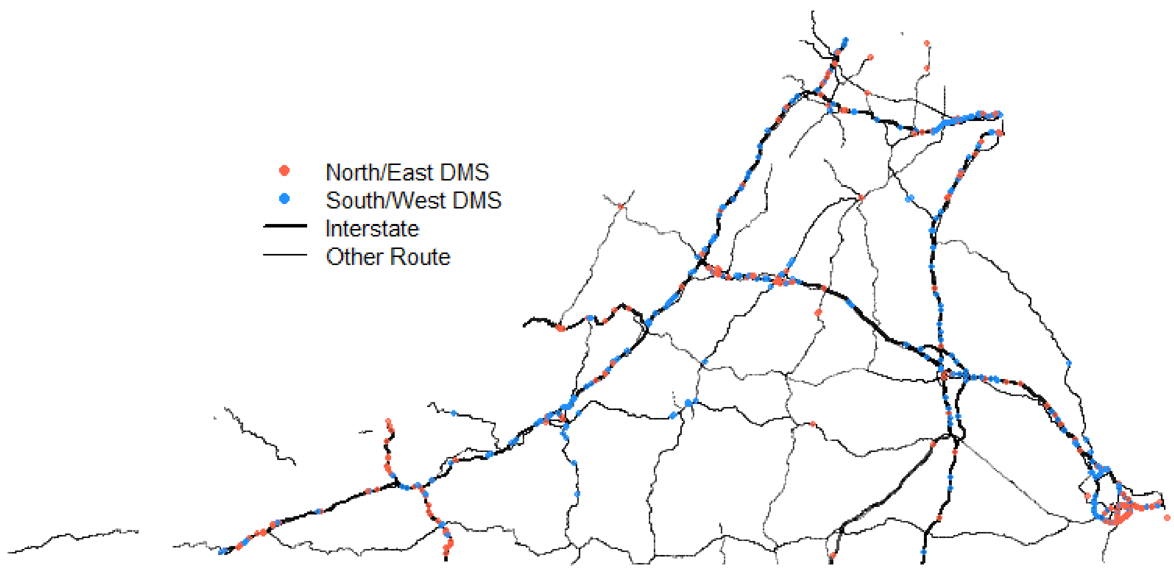
3.1 DMS Messaging

The default display of Virginia DMS is travel time estimates, distances, and toll prices, especially during peak travel hours. This information allows drivers to make more informed decisions. According to VDOT policy, default messages must follow a standard, uniform format. All travel times, distances, and toll prices must update automatically in order to avoid conveying misinformation. In addition to these defaults messages, VDOT also considers blank messages to be valid. Blank messages communicate to drivers the idea that there is no unusual traffic information to be aware of. Blank messages look exactly the same to drivers as DMS that are turned off due to unreliable power sources (e.g. solar) or malfunctioning equipment.

An attractive feature of DMS is their ability to alert drivers to upcoming incidents or congestion and to also offer advice. For instance, in the event of a crash, roadwork, debris

[2]DMS whose primary function is displaying truck stop or HOV information are also removed due to the limited variation in their messaging.

Figure 1: Map of DMS Locations in Virginia



or another lane impacting event, DMS operators switch the displayed message to one that warns drivers of the upcoming delay or obstruction. DMS can also suggest alternate routes in order to avoid the issue. Lane impacting events are reported to Virginia's 511 system and are then confirmed by Virginia's Traffic Operations Center. Since DMS are connected to VDOT's Automated Traffic Monitoring System (ATMS), message updates are triggered almost immediately. Moreover, most messages are auto-generated from a template and only require basic information (location, lane, etc.) that is fed in from the ATMS. Lane impacting items generate messages that take priority over the default message until the lane impacting item is cleared.

Aside from messages about upcoming traffic conditions, DMS occasionally display safety messages. Safety messages are general warnings or slogans intended to nudge drivers to practice safe driving behaviors. "Buckle Up For Safety" and "Click-It or Ticket" represent two of the most popular safety messages displayed. VDOT plans coordinated safety campaigns during which DMS operators are encouraged to display specific safety messages. These campaigns often focus on seat belt usage, distracted driving, speeding, or other dangerous driving habits or activities. During safety campaigns, DMS across Virginia display safety slogans related to the campaign topic instead of their default messages. Although the topic of safety slogans can vary, the themes of the messages often relate to holiday themes or popular culture. The sample contains 24 days of pop culture campaigns (8 total campaigns), 53 days of holiday campaigns (16 total campaigns), along with 93 days of generic safety campaigns (22 total campaigns). Safety messaging is much more likely to occur during safety campaigns, though safety slogans are also displayed outside these campaigns. About 10% of observations where a sign exists during a campaign begin the hour with a safety slogan compared to only about 1% for non-campaign hours. That said, the total hours in the sample where a safety slogan is displayed is much closer (83,000 in campaign hours vs 63,000 in non-campaign hours).

Figure A.1 depicts VDOT's safety message campaign schedule during the sample period.

These campaigns were not planned in reaction to recent traffic conditions, but rather were planned months in advance. This is an important point, as safety campaigns can be treated as exogenous to trends in traffic conditions. There are 46 campaigns over the sample period which take up 170 days in total. These campaigns span between one and seven days with a mode of three days.[3]

3.2 Message Text

Data detailing the actual messages for each DMS is taken from SmarterRoads, a VDOT open data portal. The sample of DMS log files begins at 11:09 am on June 7^{th} 2017 and continues through present day, though the sample used ends 12:00 am on March 1^{st} 2020. The temporal frequency of these log files are by minute and include a timestamp, geolocation, unique identifier and the message's text in MULTI (Mark-Up Language for Transportation Information) format.

The MULTI formatting contains information such as the location of line breaks, font, colors, etc. Most importantly, the format contains information about the number of "pages" each message contains. Like some billboards, DMS have the ability to alternate, or transition, between messages in order to display more information at once. In addition to the number of pages, the length of the message measured by the number of alphanumeric characters. Figure A.2 depicts the relative frequency of the number of characters of the messages displayed at the beginning of each hour across locations and the average number of pages for each number of characters.

The topic of each message is also identified as safety, crash, hazard or other. Hazard messages are made up of messages warning drivers of disabled vehicles or debris ahead. Most other messages contained in the "other" group relate to travel time estimates or toll

[3] The number of days between campaigns is a minimum of 2 days, a maximum of 85 days, and an average of 17. The weekday with the most campaign days is Friday (31) and the least is Sunday (17). The months with the most campaign days over the entire sample are December (25) and August (24) and the months with the least are January, February and May (7).

prices.[4]

Quantifying the use of, and messages displayed on, DMS is an important aspect of this study. Since messages change based on traffic conditions, there is a significant risk of reverse causality that needs to be avoided. For example, if a crash occurs in the middle on an hour, DMS operators will change the message to warn drivers of the upcoming obstruction. To circumvent this, the characteristics of the message displayed at the beginning of the hour are applied to the entire hour. The assumption being made is that, since messages are almost always scheduled in advance, messages that are displayed at the beginning of an hour are intended to span at least that entire hour. Message characteristics will only change in the middle of an hour if there is an event that forces them to do so. For the sake of transparency, there is a slight delay in the updating of DMS messages by about 1 to 2 minutes. Figure A.6 shows the probability of a DMS displaying a safety message, incident message and being turned on for the 0^{th}, 1^{st} and 2^{nd} minute of each hour of the day. It is clear that there is a slight lag in the probabilities of displaying a safety message and being turned on from, say, 10:00 to 10:02. Therefore, what the DMS says two minutes into the hour is used as the definition of the beginning of the hour's beginning. Some examples of messages are displayed in the Appendix.

3.3 Traffic Outcomes

Information about crashes come from two separate data sources. First, Virginia's Department of Motor Vehicles maintains the official repository of crashes in Virginia. When a crash occurs, a police officer goes to the scene and fills out a crash report form, called an FR-300. On this form, the officer records information about the incident, most importantly the time and location. VDOT preforms quality control on a portion of the crash records and matches each one to the LRS. These data are a standard source when analyzing crash outcomes. Unfortunately, given this study's need for temporal accuracy, there is an impor-

[4]Future iterations of this study will include a textual tokenization approach to determine words most associated with crash rates, and latent dirichlet allocation to identify topics.

tant limitation to note when using the DMV data. Figure 2a displays the distribution of the timing of crashes within the hour in which they occur. This distribution has a shape consistent with rounding towards convenient times. For example, the most frequent minutes a crash occurs is the very first minute and 30th minutes. Again, the most likely explanation for this distribution is police officers simply rounding off the times of crashes.

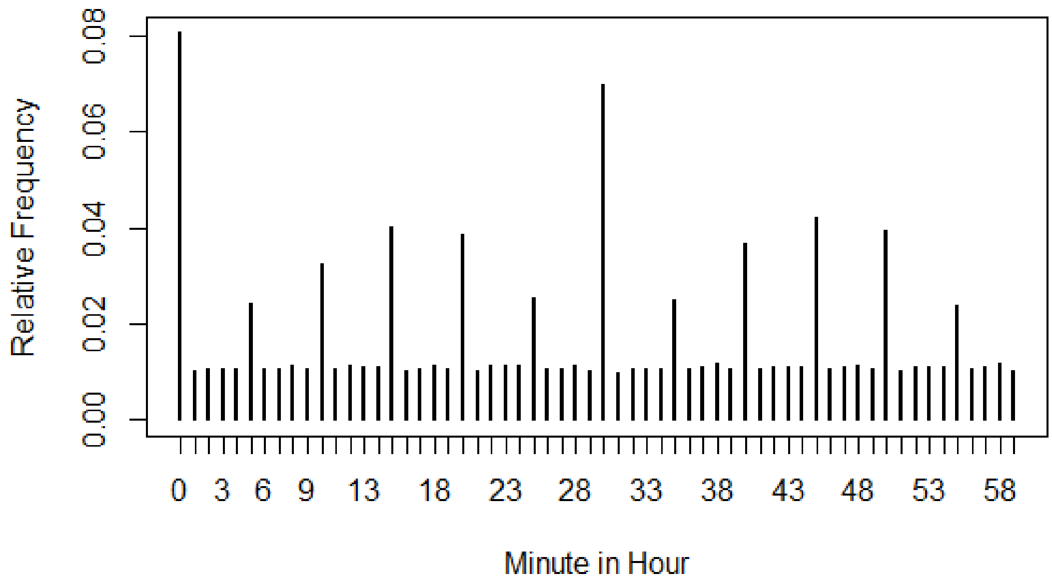
A solution to this issue is to obtain records straight from VDOT's Automated Traffic Monitoring System (ATMS). Like DMS log files, VDOT maintains minute-by-minute 511 log files. VDOT's 511 service feeds directly into VDOT's ATMS, so all relevant incidents are logged by 511. In addition, each time a DMS operator changes a message due to a lane impacting event, this is also pushed to the 511 system. In conversations with VDOT employees, there is no way a sign could be updated before 511, and vice versa. The distribution of crashes across the minutes of an hour are displayed in Figure 2b. This distribution is much more uniform than the distribution in Figure 2a. These data represent a substantial increase in quality due to a higher degree of precision and thus less measurement error.

Besides a more precise measurement of crash times, 511 also has the advantage of recording information on all other lane impacting incidents such as disabled vehicles, fires, debris, and other incidents. These alternate incidents represent a good falsification for crashes, since roadside distractions should have relatively little effect on these other items.

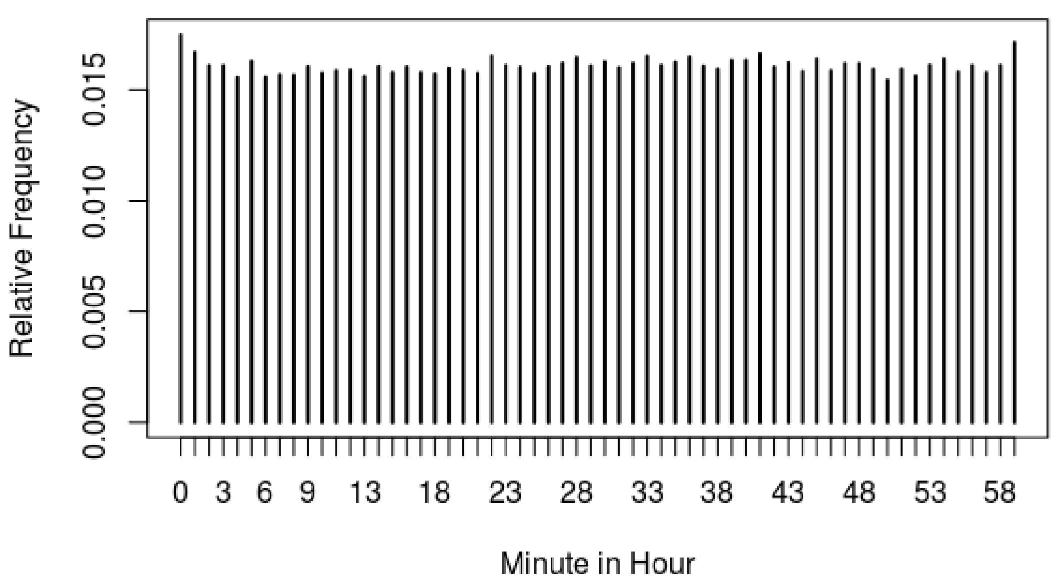
Crash data from the DMV and 511 systems, as well as other 511 incidents, are binned by hour and distance from each DMS. Binning crashes and incidents downstream from DMS allows for testing the impact of DMS over space. If the mechanism of distracted driving is impacting drivers, it would follow that the effect would deteriorate with distance from a DMS. In other words, the effect of a distraction should be largest closest to the distraction, and shrink towards zero as distance increases.

These bins, in relation to each DMS, are -.2 to 1 km, 1 to 3 km, 3 to 5 km, and 5 to 10 km after DMS. The first bin begins at a negative distance to capture people observing the DMS as they approach it, but results are not sensitive to this choice. If drivers travel at

Figure 2: Distribution of Crash Timing According to DMV and 511 Data



(a) Within Hour Distribution of DMV Crash Data



(b) Within Hour Distribution of 511 Crash Data

100 km/h, they will cover these distances in about 45, 72, 72 and 180 seconds, respectively. The number of crashes in bin i is scaled by the average of the segments of the same length and distance from a DMS. This transformation is to ease the interpretation of regression coefficients.

Speed data are obtained from INRIX, a private company specializing in traffic data collection. These speed data are the result of probing GPS devices in smartphones and vehicles instead of by fixed roadway censors. This allows for much more detailed, granular measurements of relevant highway performance metrics for DOTs around the world. While VDOT maintains similar data using traditional roadway censors, these are less comprehensive relative to what INRIX data contains. A measurement from INRIX that is of interest to this study is average vehicle speed on a road segment. Hourly speed aggregates across segments of about 1 kilometer in length are extracted from INRIX's tools and matched to each DMS via road segments. The distribution of speed in kilometers per hour is displayed in Figure A.5.

3.4 Analysis Sample Construction

The analysis sample is an unbalanced panel of 391 road segments with DMS by hour. Summary statistics for key variables in the panel are displayed in Table 1. The average speed is just under 100 kilometers per hour, which translates to about 62 miles per hour. DMS are only turned on, or rather not blank, only about 42% of time throughout the sample. When they are turned on, safety messaging is relatively rare. However, DMS appear to be using multi-page messaging quite frequently – about 50% of the time.

Figure 3 displays the average hourly crash counts per kilometer according to both the DMV and 511, which appear to be similar. In addition, all other non-crash events from 511 are also displayed. The average of about .001 indicates about 1 crash every 1000 hours per kilometer, or 1.4 crashes per kilometer per month. To put this into perspective, Virginia has about 1800 kilometers of Interstate highways, and reported about 25,000 crashes in 2019.

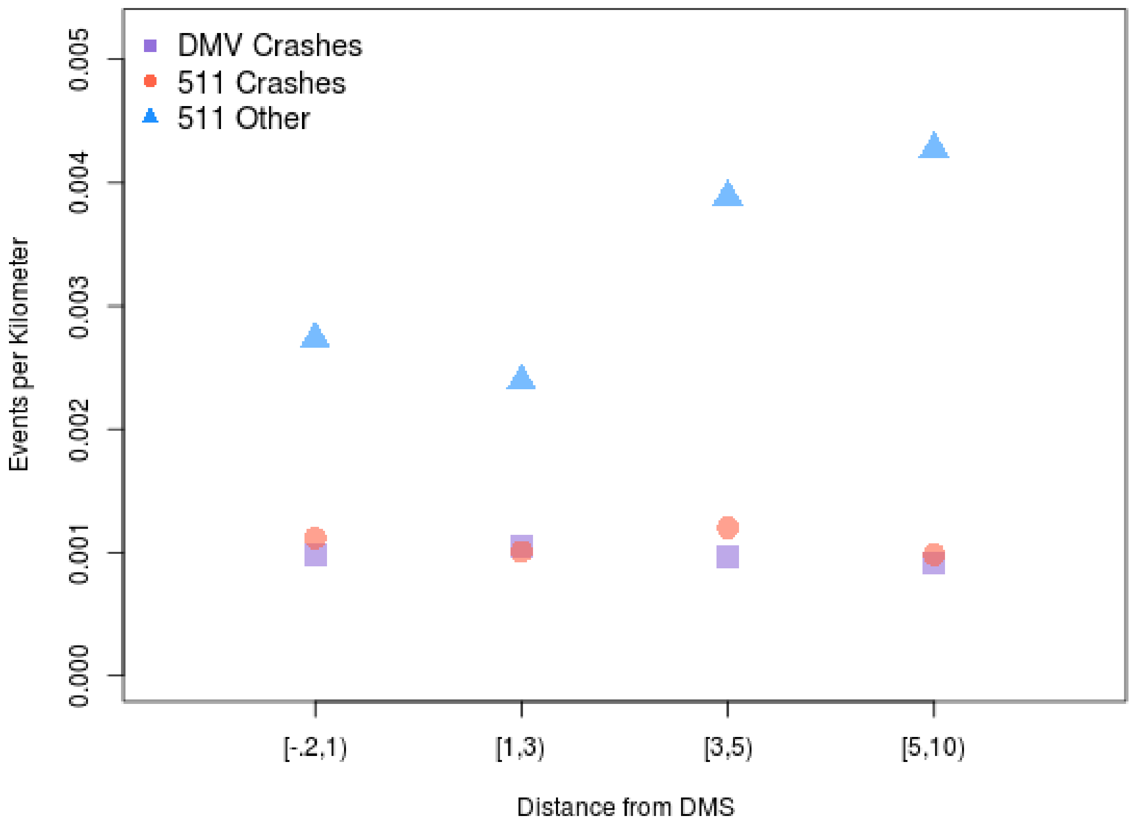
Table 1: Summary Statistics

	Mean	St. Dev.	Min	Max
All Observations (N = 5,583,114)				
Number of DMS	1.019	0.135	1	2
Stationary DMS	0.816	0.421	0	2
Portable DMS	0.203	0.407	0	2
Safety Campaign Day	0.164	0.370	0	1
Speed at Location	99.332	16.202	2	129
Number of DMS On	0.423	0.510	0	2
Saftey Message Displayed	0.026	0.160	0	2
Crash Message Displayed	0.020	0.141	0	2
Pages	0.633	0.825	0	6
Characters	16.796	22.329	0	156
DMS On (N = 2,318,449)				
Saftey Message Displayed	0.063	0.243	0	2
Crash Message Displayed	0.048	0.215	0	2
Pages	1.525	0.529	1	6
Characters	40.447	15.622	1	156

Note: This table contains summary statistics for the analysis sample. Displayed are the averages for all important variables, as well as averages of message characteristics when DMS are turned on.

Simple division yields about 1.16 crashes per kilometer across the entire state. Of course, DMS are not randomly located, and they will likely appear in areas with more traffic. This likely explains the 20% additional crashes compared to the overall state average.

Figure 3: Average Incidents per Kilometer by Distance from DMS



Note: This figure displays the average number of events per kilometer across distances from DMS according to the DMV's crash data, 511's crash data, and all other 511 incidents.

4 Empirical Strategy

This study addresses two research questions about the impact of DMS in Virginia. First, is safety messaging an effective means to improve traffic outcomes and reduce negative externalities? Second, are specific message characteristics related to more crashes? An ideal identification strategy to answer these questions would be random assignment of safety slogans and features of messages to DMS. This sort of experiment, with perfect compliance, would simplify teasing out the effect of messages on traffic outcomes. However, complete randomization is not possible on such a large scale. Instead, it is important to identify comparable instances where DMS use is plausibly exogenous to unobservable factors affecting traffic outcomes.

4.1 Safety Messaging

Like Hall and Madsen (2021), this study uses pre-scheduled, coordinated safety campaigns to generate exogenous variation in DMS messages. Safety campaigns are scheduled months in advance and coincide with events such as motorcycle awareness week or movie releases rather than particularly safe (or dangerous) times for travel. In addition, VDOT mostly deploys safety campaigns during off-peak hours, defined as the hours from 10:00 am up to and including 2:00 pm. This generates a time period where safety messaging would be more concentrated, even within campaign days. This is a slight deviation from the deployment of safety campaigns in Hall and Madsen (2021), where safety messages were displayed relatively uniformly across the entire campaign.

This study exploits within segment-month-weekday-hour variation in DMS usage to isolate the effects of safety messaging. Segment-month-weekday-hour fixed effects control for idiosyncratic factors and general trends in traffic across different segments. These fixed effects partial out differences in crash rates and average speeds due to peak travel times, weekends, seasonality, visibility due to sunlight, and all other constant effects for each segment. Note that each fixed effect cell contains an average of 9 observations. Individual federal holiday fixed effects are also included to account for differences in commuting on those days. This research design compares, for example, all observations for Mondays in June at 2:00 pm for a specific segment to one another. The remaining variation is explained by combinations of campaign days, off-peak hours, and an indicator variable for periods when a DMS is turned on. Equation (1) specifies this identification strategy to explain variation in speed and crash outcomes.

$$
\begin{aligned}
Y_{s+k,t} = {} & \alpha \text{DMS On}_{s,t} + \beta_0 \text{Campaign}_t + \beta_1 (\text{Campaign}_t \text{ x Off-Peak}_t) \\
& + \beta_2 (\text{Campaign}_t \text{ x DMS On}_{s,t}) + \beta_3 (\text{Off-Peak}_t \text{ x DMS On}_{s,t}) \\
& + \delta (\text{Campaign}_t \text{ x Off-Peak}_t \text{ x DMS On}_{s,t}) + \mu_{s,m(t),d(t),h(t)} + \tau_{y(t)} + \eta_{holiday} + \epsilon_{s+k,t}
\end{aligned} \tag{1}
$$

where $Y_{s+k,t}$ is one of the traffic outcomes analyzed k kilometers away from the DMS on highway segment s in hour t. Recall from Section 3, while speed is measured at the location of the DMS, crash and incident outcomes are analyzed in spatial bins downstream from the DMS. If DMS indeed distract drivers, effect sizes should be inversely related to the distance from the DMS. In other words, it would be surprising if an effect existed 5 to 10 kilometers downstream from a DMS, which would be a few minutes of travel time after the person passes the sign. The expectation is to observe a strong effect near the DMS that tapers off with distance. As discussed in Section 3, the bins used are $[-.2, 1)$, $[1, 3)$, $[3, 5)$, and $[5, 10)$ kilometers.

Standard errors of the coefficient estimates are clustered at the segment level to account for possible correlation within segments. Another approach would be to cluster the standard errors by which cell of a geographic grid they exist in. The area of the grid's cells can be made to be k kilometers, where $k \in \{1, 3, 5, 10\}$. This would allow for the errors of two relatively close DMS to be correlated. The rationale behind clustering by grid cell would be that a driver might be exposed to multiple DMS, thus linking a crash to multiple segments. Clustering the standard errors by segment is used in presenting the results since this produced slightly more conservative (i.e. larger) standard errors than clustering by grid cell. Still, the results are qualitatively similar regardless of how the errors are clustered.

In Equation (1), α represents the overall effect of DMS on traffic outcomes. If α is equal to zero, this would imply no difference in traffic outcomes between a DMS being turned on or off. β_0 represents the difference in outcomes during days with planned safety campaigns compared to all other days. There is no direct estimate of different message impacts during off-peak hours due to this being colinear with the fixed effects. However, both previous effects, DMS turned on and campaign days, are allowed to vary during off-peak hours. These are captured by β_2 and β_3. $\mu_{s,m(t),d(t),h(t)}$, $\tau_{y(t)}$, and $\eta_{holiday}$ represent segment-month-weekday-hour, year, and holiday fixed effects.

δ represents the parameter of interest in this model specification. This parameter captures the effect of a DMS being turned on during off-peak hours of safety campaign days. Campaigns are exogenous to traffic outcomes, since they are planned in advance and not scheduled in anticipation of outcomes. If safety messaging causes negative outcomes, the effect should be seen on these days. In addition, since the intensity of safety messaging is concentrated during off-peak hours, any effect that exists should be magnified during these hours. Since the model's fixed effects and other variables remove the influence of time of day, this increase in intensity can be thought of as exogenous as well. Lastly, the DMS must be turned on for any of this to matter. If the observation occurs during an off-peak hour of a campaign day, but the DMS is blank, there should be no impact. δ identifies the effect of all three conditions (campaign day, off-peak hour, turned on DMS) being met at once.

Equation (1) makes assumptions about DMS operators' level of compliance in displaying safety slogans during campaigns. However, this assumption of perfect compliance can lead to downward bias in estimates of the impact of DMS messages. In Virginia, not only are safety messages occasionally not displayed during campaign periods, safety messages are also sometimes displayed outside safety message campaign periods. There are instances when DMS display safety slogans outside the window of scheduled campaigns. Figures A.7 and A.8 demonstrate differences in DMS use across campaign days and non-campaign days.

Rather than making the assumption of perfect compliance, a different identification strategy can be used to tease out the effect of message types. Again, to avoid reverse causality when traffic conditions cause message content displayed, this study assumes that whatever message was displayed at the beginning of the hour was intended to persist throughout that hour. This makes it possible to compare hours beginning with a safety message to hours beginning with other low priority messages. To get this comparison, crash and hazard messages are controlled for with an indicator variable. Equation (2) specifies this identification of message type at the beginning of the hour.

$$Y_{s+k,t} = \alpha \text{DMS On}_{s,t} + \delta(\text{DMS On x Safety Msg})_{s,t} + \beta_1(\text{DMS On x Crash Msg})_{s,t} + \beta_2(\text{DMS On x Hazard Msg})_{s,t} + \mu_{s,m(t),d(t),h(t)} + \tau_{y(t)} + \eta_{holiday} + \epsilon_{s+k,t} \quad (2)$$

Here, α has the same interpretation as in Equation (1). However, δ represents the difference in outcomes for safety messages compared to default messages. Again, this comparison is possible since β_1 and β_2 partial out the effect of higher priority messages.

As a final note about safety messages, a strength of this study is its ability to analyze a representative menu of safety slogans rather than just one in particular. The fatality message studied in Hall and Madsen (2021) is a single, specific type of safety slogan or nudge. However, DOTs are likely to use a variety of safety slogans on DMS. Therefore, it is important to evaluate the effects of a more comprehensive set of safety messages when making policy recommendations.

4.2 Message Characteristics

Previous literature has examined the impact of message content on traffic outcomes. Of course, this is important information for DOTs to know when deciding how to use their DMS. However, the way DMS display messages, or how the messages are constructed, is also an important feature. As an example, consider the particular DMS at mile marker 100 on I-95N. The default for this DMS is to display travel time estimates. The default messages for this sign are of the form

"Exit 126 / 26 Miles / t Min"

and

"US 1 / Exit 126 // 26 Miles / t Min"

where t is the estimated travel time until Exit 126. In these quotes, a single slash represents a new line, and two slashes represents a new page. This is depicted in Figures A.3a and A.3b. For the specific segment where this sign is located, the crash rate for the multi page version of the default is about 20% higher whereas the average difference in t, the estimated travel time, is only about 30 seconds, which suggests little difference in overall traffic conditions. Equation (3) below generalizes this idea by estimating differences in traffic outcomes for single- and multi-page messages relative to when DMS are turned off.

$$\begin{aligned} Y_{s+k,t} = \alpha \text{DMS On}_{s,t} + \delta(\text{DMS On}_{s,t} \text{ x Multi-Page}_{s,t}) + \beta \text{Char}_{s,t} \\ + \mu_{s,m(t),d(t),h(t)} + \tau_{y(t)} + \eta_{holiday} + \epsilon_{s,t} \end{aligned} \quad (3)$$

In this specification, α maintains a similar interpretation – the average difference in outcomes between single-page messages compared to a DMS that is turned off. δ, the parameter of interest, is the change in outcomes for multi-page messages relative to single page.

5 Results

This section reports estimates of the parameters of interest for the three models described above using coefficient plots. Full regression results can be found in the Appendix. Recall the differences in the reported time of crashes in the two sources of crash data, DMV and 511, discussed above. Separate results for models using DMV crashes, 511 crashes, and other 511 incidents as dependent variables are presented first. The results for speed are presented second.

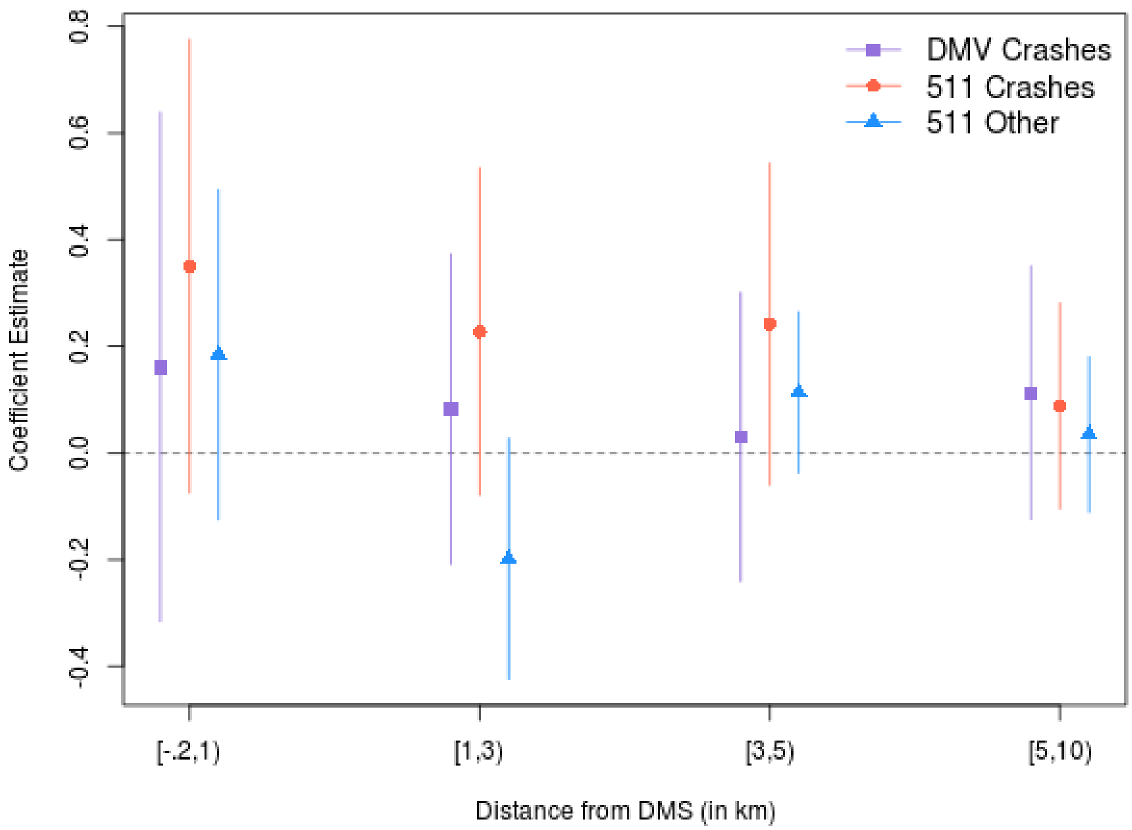
5.1 Safety Messaging and Crashes

Equation (1) identifies times when safety messaging would be, exogenously, more prominent due to scheduled safety campaigns. While these are scheduled months in advance, and usually revolve around events unrelated to traffic, there could still be some fundamental differences in traffic patterns for these days. Luckily for this study, VDOT concentrates their safety campaign efforts during off-peak hours (10:00 am - 2:00 pm), which allows the regression to control for the effect of both campaign days and off-peak hours on traffic outcomes. In addition, this effect can only occur when DMS are turned on – otherwise no message will be displayed. This generates a triple interaction term to identify the effect of safety campaigns on traffic outcomes. This is captured by the parameter δ in Equation (1). 12 estimates of δ for each of the non-speed outcomes and their 95% confidence intervals are displayed below in Figure 4.

Almost every parameter estimate on Figure 4 is positive albeit insignificant at the 5% level. While the significance of these regressions do not correspond with Hall and Madsen (2021), the general relationship between the coefficients and distance from DMS do. The effect of safety campaigns appears to be largest closest to DMS and tapers off as distance increases. The lack of significance for this result could be due to a few different factors. The first is that the safety messages chosen by VDOT are relatively less salient than the ones chosen by Texas's Department of Transportation. If messages are less shocking or powerful, the effect would therefore be smaller. A second reason could be due to the relative lack of statistical power in comparison to Hall and Madsen (2021). The campaigns in Texas make up a larger percentage of the overall sample in addition to the sample itself being larger.

Another important finding of these analyses is that DMS turned on increase the probability of crashes, although the effect is relatively constant across crash sources (see Tables A.1, A.2, and A.3). In addition, this increase in not as large, or as consistently significant for other incidents in the 511 dataset. VDOT considers both travel time estimates and blank (off) messages to be valid defaults. However, these estimates would suggest the effect they

Figure 4: Effect of Safety Campaigns on Traffic Outcomes

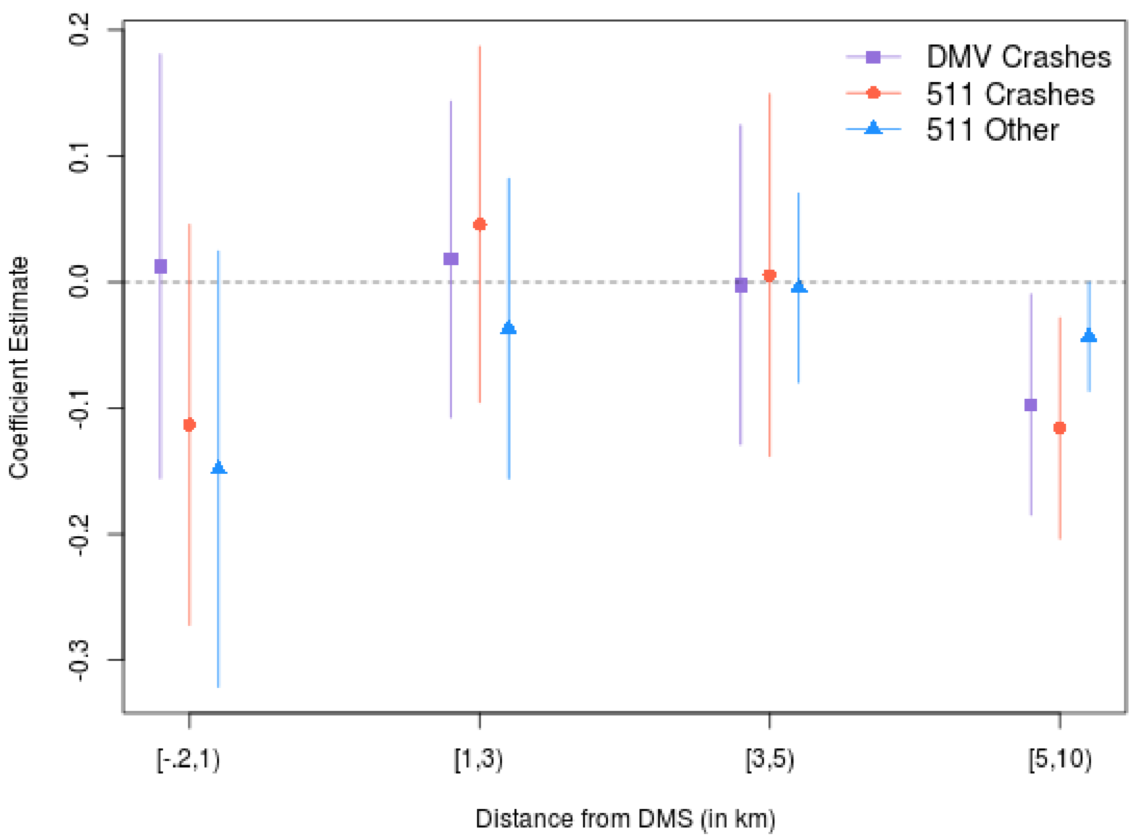


Note: This figure shows the coefficient estimates for δ in Equation (1). Standard errors are clustered at the segment level and 95% confidence intervals are displayed as lines extending from the point estimates.

have on traffic outcomes is not necessarily equivalent, with blanked signs having less risk.

To address the fact that perfect compliance is not guaranteed during safety campaigns, Equation 2 captures the effect of displaying a safety message at the beginning of the hour. The strategy of this equation is to partial out the effects of non-standard messaging, such that hours beginning with safety messages can be compared to hours beginning with standard messages. δ in Equation 2 represents the marginal increase in outcome for displaying a safety message relative to a standard message. Figure 5 displays the coefficients for crashes and incidents by distance from the DMS.

Figure 5: Effect of Safety Messaging on Traffic Outcomes



Note: This figure shows the coefficient estimates for δ in Equation (2). Standard errors are clustered at the segment level and 95% confidence intervals are displayed as lines extending from the point estimates.

Like Figure 4, nearly all parameter estimates are once again insignificant, suggesting little difference between safety messaging and standard messaging. In addition, the previous result that turned on DMS increase crash risk is no longer as pronounced. This suggests that messages alerting drivers are associated with worse outcomes. While this could be due to some form of measurement error in the data from the DMV, the evidence is also strong in the 511 data.[5]

5.2 Safety Message Characteristics and Crashes

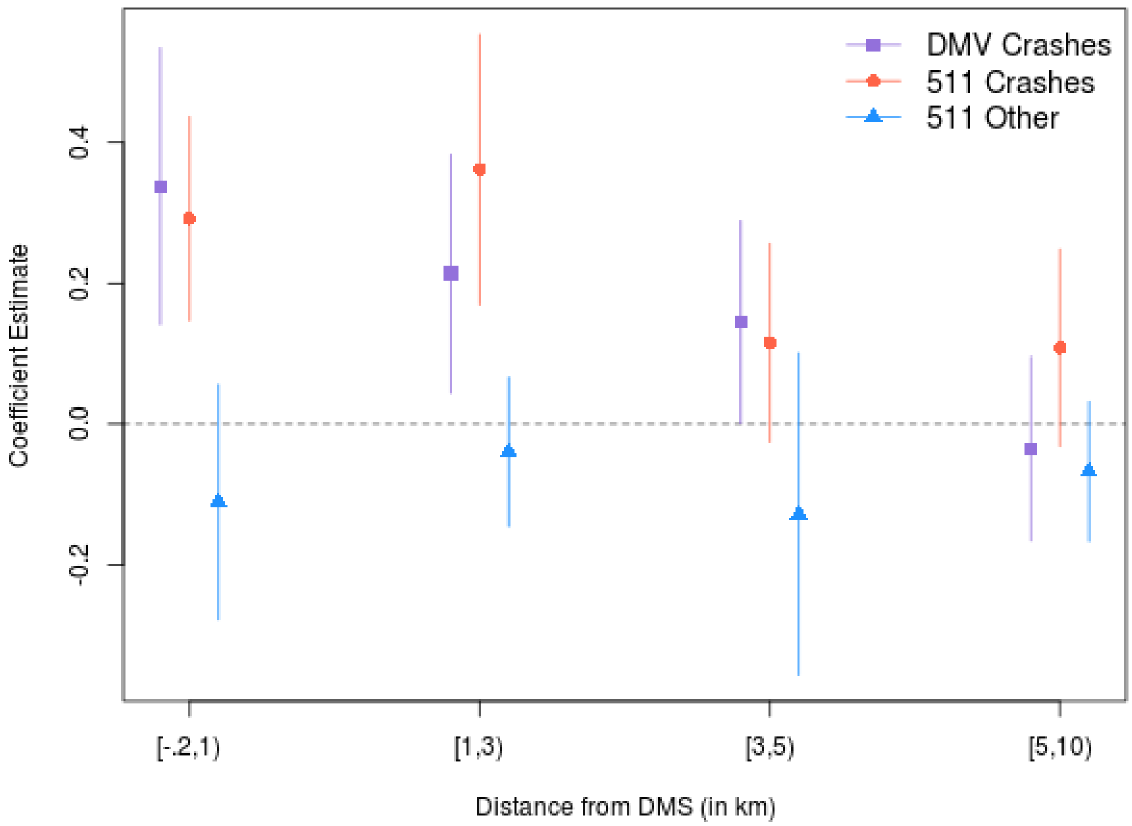
This study offers an alternate explanation for possible changes in crash risk around DMS. Multi-page messaging has been shown in laboratory settings to distract drivers moreso than static, single page messaging. Equation (3) estimates the effects of multi-page messaging, relative to single page, on traffic outcomes. Figure 6 displays the estimates and 95% confidence intervals of δ from Equation (3).

Figure 6 displays large, positive and significant estimated effects for multi-page messaging immediately near the DMS, which become insignificant after about 5 kilometers. This is indicative of multi-page messaging being a large distraction relative to single page messaging. Moreover, an important finding is that multi-page messaging appears to be relatively unrelated with other incidents in the 511 database. This is an important falsification. This suggests that multi-page messaging is not selectively used during poor traffic conditions, but rather is generating additional crashes.

One thing to note is that the shape of the trend in coefficients over space in Figure 6 looks very similar to the shape of the trend in coefficients in Figure 4. In addition, the probability of observing multi-page messages is about 29% for off-peak hours during campaigns, which is higher than all other times (20% in non-off-peak, non-campaign; 23% in non-off-peak, campaign; and 21% in off-peak, non-campaign). Therefore, the consistently positive effect could simply be attributed to multi-page messaging being more common during that time period. More broadly, the result in Hall and Madsen (2021) might be combination of the

[5] The correlation between crashes over 10 kilometers in t and a crash message beginning hour t is 0.03. In comparison, the correlation between crashes over 10 kilometers in $t-1$ and a crash message beginning hour t is 0.25.

Figure 6: Effect of Multi-Page Messaging on Traffic Outcomes



Note: This figure shows the coefficient estimates for δ in Equation (3). Standard errors are clustered at the segment level and 95% confidence intervals are displayed as lines extending from the point estimates.

effects of a salient safety message and these messages being multiple pages.

5.3 Safety Messages and Speed

For each of the above model specifications, this study also analyzing the effects of DMS messages on speed immediately around the DMS, a novel contribution to the literature. Estimates for α and δ from each model are presented in Table 2. Each model demonstrates a relatively constant, marginal reduction in speed when DMS are turned on at the beginning of the hour relative to turned off. The magnitude of this estimate is small, although plausible. Keep in mind, the coefficient estimate represents changes in the average speed of traffic over the entire segment for an hour. A large reduction in speed would be a surprising result, as most people will likely drive past the DMS without hindrance. However, if only a small portion of drivers reduce speed or tap on their brakes, a reduction of this magnitude is not unreasonable.

Table 2: Effect On Speed

	Eq (1)	Eq (2)	Eq (3)
DMS On	-1.075***	-0.665***	-1.121***
	(0.127)	(0.144)	(0.291)
Campaign$_t$ x Off-Peak$_t$ x DMS On$_s$	-0.009		
	(0.140)		
DMS On$_{s,t}$ x Safety Msg$_{s,t}$		0.525***	
		(0.123)	
DMS On$_{s,t}$ x Multi-Page$_{s,t}$			-1.352***
			(0.228)
Num. Obs.	5,583,114	5,583,114	5,583,114
R2	0.791	0.793	0.791

Note: This table presents the estimated coefficients in Equations (1), (2) and (3) with speed as the outcome. Each regression contains segment-month-weekday-hour fixed effects, year-month fixed effects, and holiday fixed effects. The standard errors presented are clustered at the segment level. Standard errors can also be clustered by grid cells of d-by-d kilometers (where $d \in \{1, 3, 5, 10\}$), but this does not make a qualitative difference in the significance of the coefficients. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

δ from Equation (1), or the impact of a DMS being turned on during off-peak hours of a campaign day, is estimated as insignificant. This suggests that there is no additional effect on speed when safety messages are most intended to be shown. δ from Equation (2) represents the effect of displaying a safety messages relative to standard messages. The results suggest a positive effect on travel speed. It is not the case that drivers speed up when a safety message is being displayed, but rather do not slow down as much as standard messaging. This result could be explained by the fact that standard messaging contains some amount of information. If a driver can quickly recognize that the message displayed does not contain useful information, they may spend less time reading it. Finally, δ from Equation (3) is estimated to be negative and significant. This result implies that drivers slow down twice as much when shown messages with multiple pages relative to messages with single pages. This results in a decrease in travel time of about 2%. Running this specification with a log transformation of the speed variable results in coefficients of -0.017 and -0.024, respectively. This suggests an average additional slowdown of about 2.4%, or a total effect of about 4%.

6 Conclusion

Transportation departments across the world rely on Dynamic Message Signs to inform, warn, and even nudge, drivers. Considering the widespread and pervasive use of DMS, little empirical research has investigated the effectiveness and costs of DMS use, or the possibility that they generate externalities. This paper contains three main findings regarding the unintended consequences of updating drivers' information via roadside DMS. First, results indicate the presence of negative externalities when displaying information on DMS. Drivers tend to slow down around DMS and experience a higher risk of a crash when DMS are turned on. Second, this study finds little to no differences in traffic outcomes for DMS displaying generic safety messages relative to default messages, such as estimates for travel times. The current literature contains mixed evidence on the effect of safety messaging on traffic outcomes. This research identifies a solution explain this – multi-page messaging. The third result uncovers large, significant increases in the risk of a crash as well as relatively large reductions in speed due to multi-page messaging.

To put the results in perspective, the average number of crashes per kilometer per month across segments with DMS is about 1.4. DMS are only turned on about 40% of the time and display multi-page messages about 50% of the time they're turned on. Multiplying these percentages by the percent increase in crash risk of multi-page messages, yields a 9% increase in crashes overall. If these multi-page messages were eliminated over the course of a month, this could reduce the average crashes per kilometer per month from 1.4 to 1.3.

Across 391 highway segments and 32 months, this could have prevented about 1,250 crashes over 391 kilometers of highway. However, if the effect extends to 3 to 5 kilometers beyond the DMS, as the results suggest, this would instead translate to about 5,000 unnecessary crashes caused by drivers distracted by multi-page messaging over the sample period. In 2019, there were 128,000 crashes in Virginia. Results indicate 1,875 additional crashes due to multi-page messaging, which is about 1.5% of all crashes over the year. Also in 2019, .6% of crashes resulted in a fatality. Applying this number, 32 fatalities could have been prevented over the same period. In short, multi-page messaging causes roughly one additional fatality per month over the entire state.

According to the US Census Bureau, commuters in Virginia had an average commute of 28.7 minutes per trip. Average hourly income was about $27.28. Therefore, the average time commuting per trip is worth about $13.05. If a 2-4% slowdown applied to the entire trip, this would equate to about $0.40 in costs per trip per person. Assuming 260 work days, and therefore 520 commutes over the course of a year, a 2-4% slow down would cost drivers about $200 each. This figure multiplied by the total 2019 employment in Virginia (3.45 million) would result in $700 million dollars in lost time across all commuters over the course of the year. This is about .12% of Virgina's 2019 GDP. Of note, this calculation makes the assumption of a 2-4% slow down due to multi-page messaging across an entire trip. While this is a rather heroic assumption, Bento et al. (2020) demonstrates how defining willingness to pay for time savings as a fraction of one's wage dramatically understates the value placed on time savings by not accounting for discrete costs of being late.

Policy implications of these results suggest more careful, deliberate use of DMS. Broadly speaking - a blank message should be adopted and more widely in place of uninformative text. Blank signs, at least in Virginia, reflect no worthwhile information for drivers to be aware of. Perhaps the bar for what is considered worthwhile needs to be raised in order to reduce externalities. In addition, while there does not appear to be significantly harmful effects of safety messaging, there is little evidence that it is instead helpful. Of course, there are different levels of complexity across safety messages that might impact outcomes differently.

Directions for future research in this area are plentiful. One step would link the results in Hall and Madsen (2021) to those in Shealy et al. (2020). These two studies support diametrically opposed DMS safety slogan policies, and a DOT that follows the wrong one could experience important changes in traffic outcomes. Future work could also analyze vehicle counts on parallel roads or exits conditional on DMS display messages to determine the extent to which traffic diversion occurs. This would be a direct measure of time savings, crash reductions, and how people adhere to advice. If the benefits of this outweigh the now documented costs, policy recommendations can be clear. It should be noted, however, that spillovers (or lack thereof) onto other routes could also have important implications for highway wear and congestion on these other routes.

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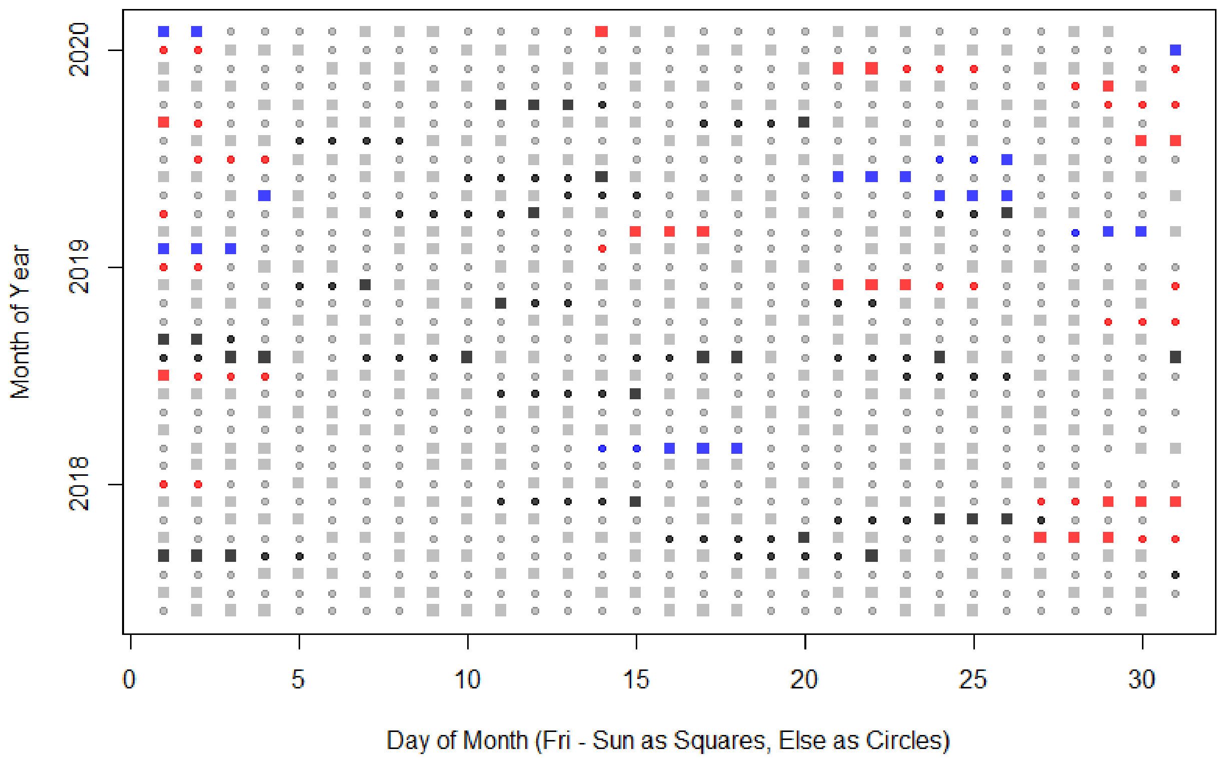
A Appendix

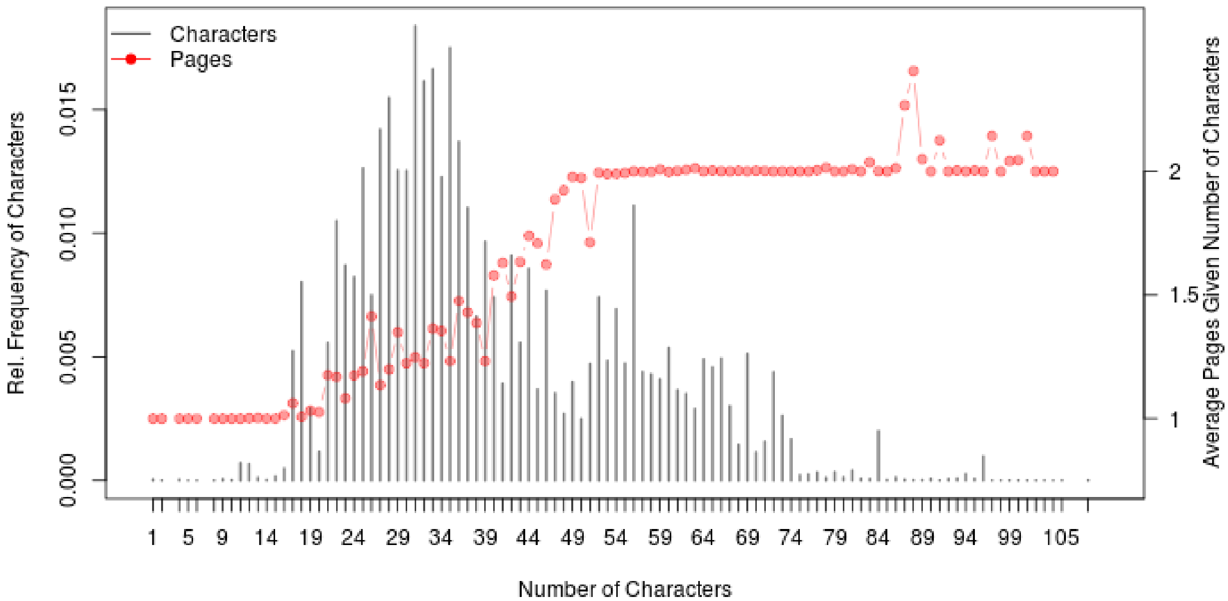
A.1 Additional Figures

Figure A.1: Safety Campaign Schedule



Note: This figure displays a calendar view of VDOT's safety campaigns. Circles represent weekdays (Monday through Thursday) and the squares represent weekends (Friday, Saturday, Sunday). The darker colored dots represent campaign days. The black dots are regular campaigns, red are holiday themed and blue are popular culture themed.

Figure A.2: Number of Characters and Average Pages



Note: This figure displays the distribution of the number of characters across the analysis sample. For each number of characters, the average number of pages is calculated and plotted on top.

Figure A.3: Example of Single Page and Multi-Page Messages

(a) Single Page Message

(b) Two Page Message

Note: These figures represent an example of single- and multi-page messages on a single DMS on I-95N. The DMS would occasionally switch between these two messages as its default. This highlight how DOTs can display the same information but with different formats.

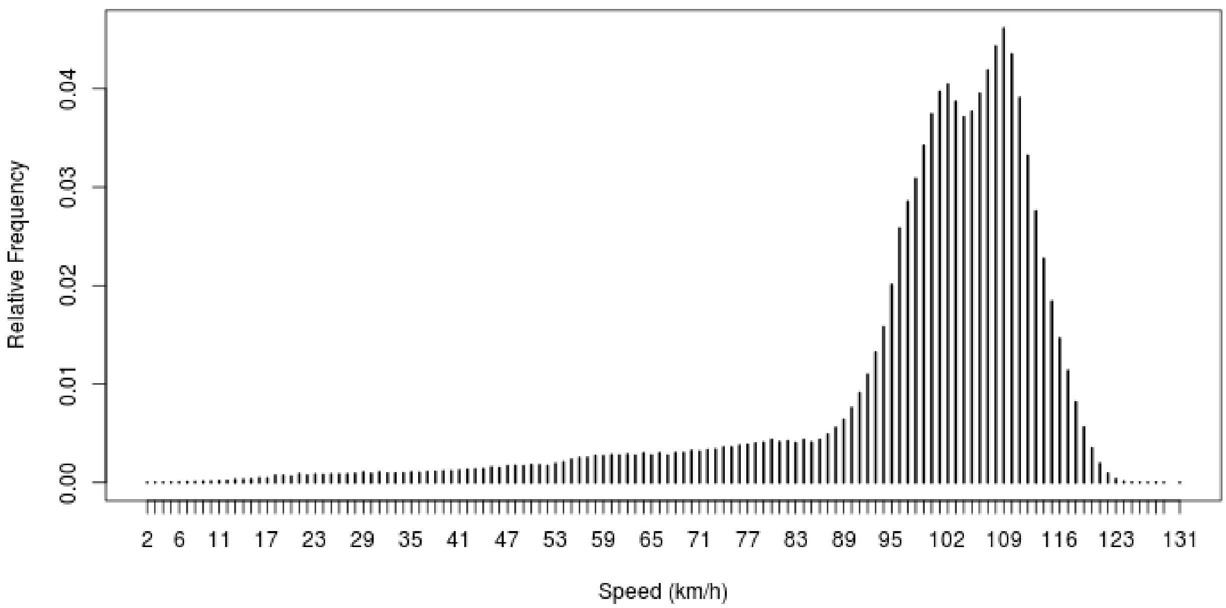
Figure A.4: Examples of Safety Slogans

(a) one pager

(b) two pager

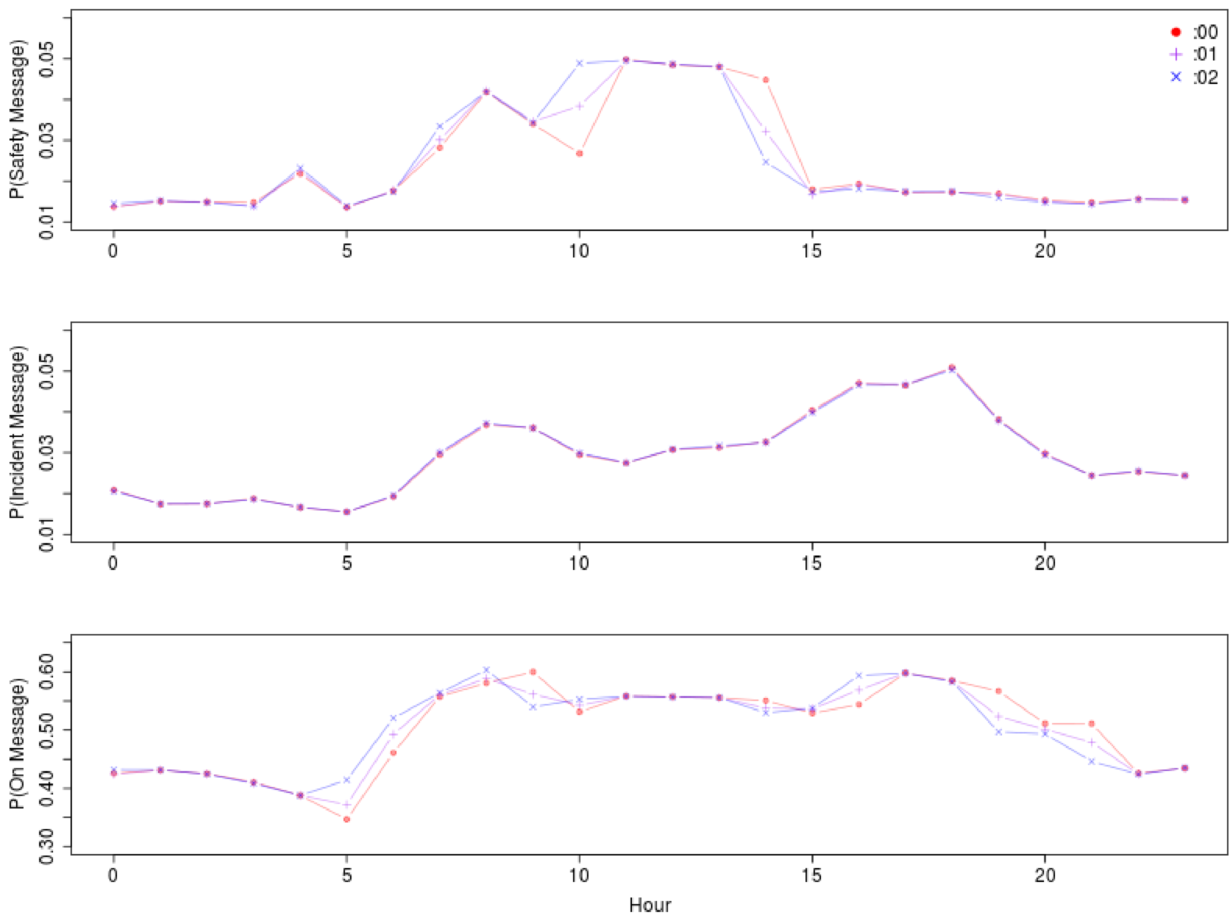
Note: This figure presents two standard safey messages that appear in Virginia during the sample period. There are many unique messages, but these two are fairly representative of the lot.

Figure A.5: Distribution of Speed



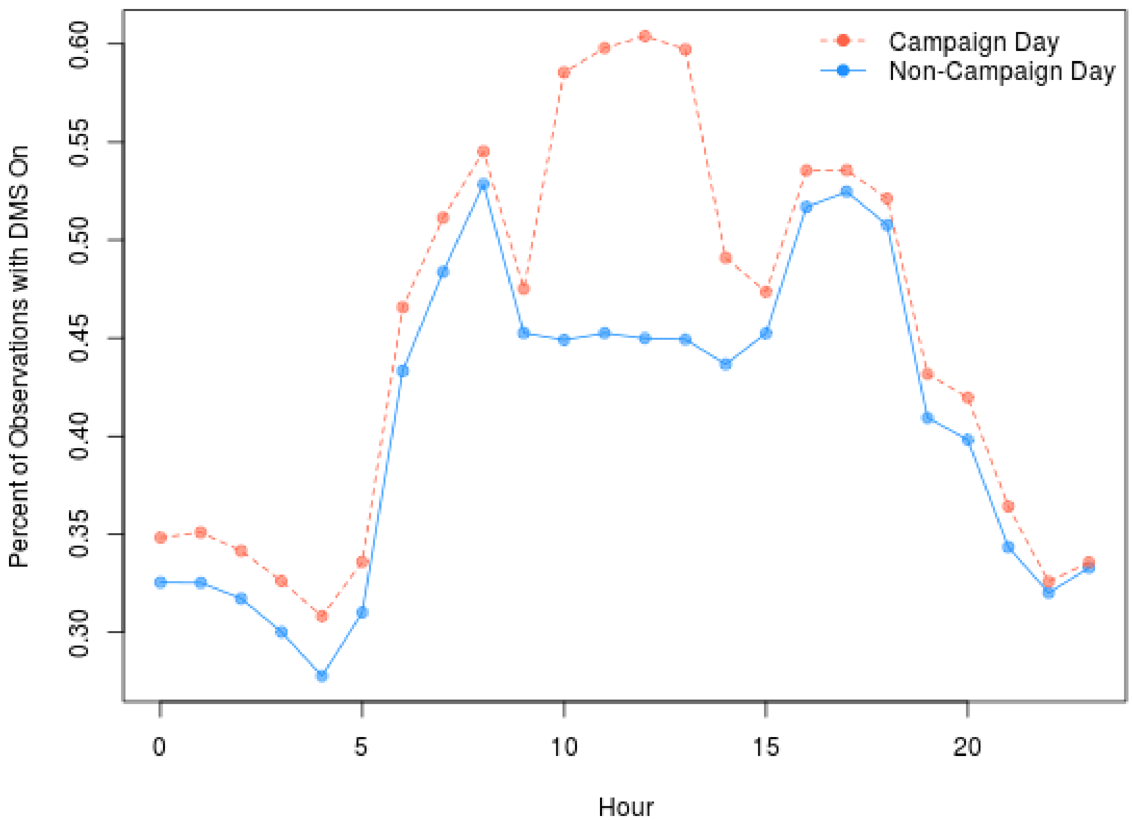
Note: This plot displays the relative frequency of speed across the sample. The bimodal nature of the distribution has to do with differences in speed limits by about 5 kilometers per hour. Inrix computes these averages, but also computes a "reference" speed. This measures the speed at which traffic could move during free flow. The distribution of reference speed subtracted from the actual speed is unimodal with a long left tail.

Figure A.6: Message Timing



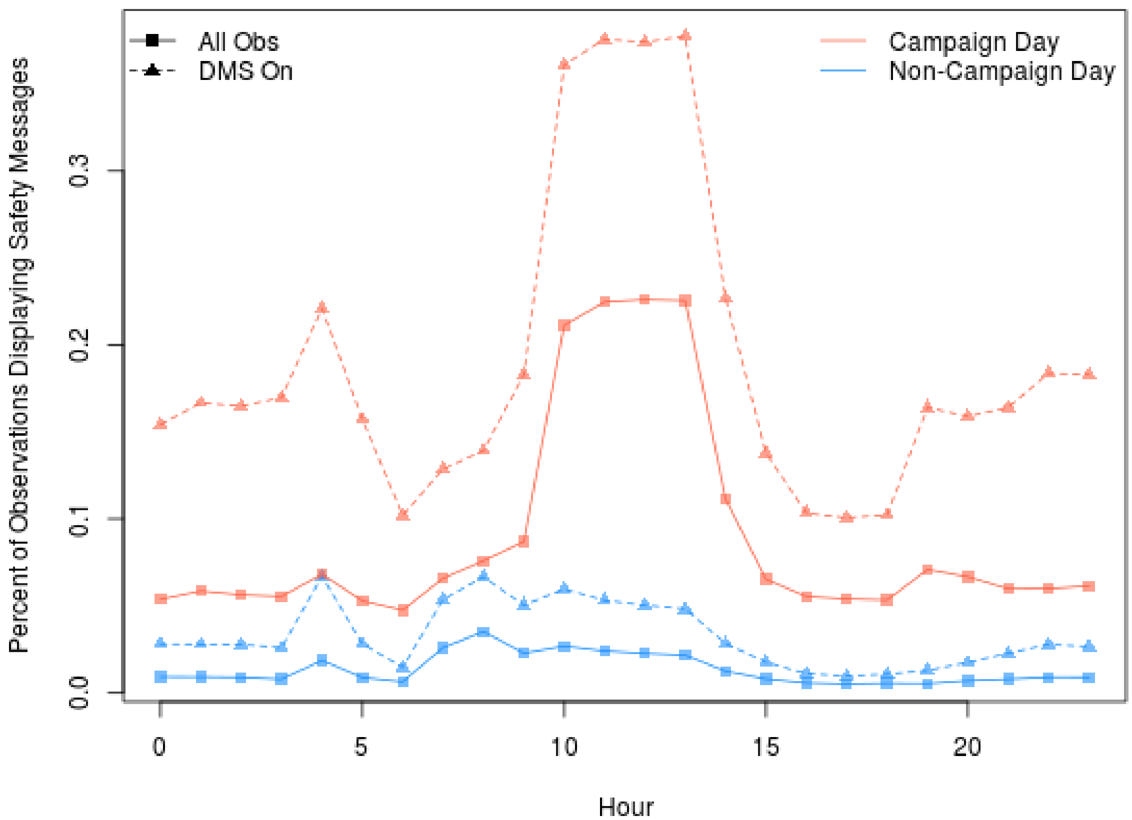
Note: This figure demonstrates the lag in DMS changing messages over the first few minutes of the hour. In the first panel, safety messaging significantly increases from 10:00 am to 10:02 am, and then drops from 3:00 pm to 3:02 pm. This pattern is similar for the probability of observing a DMS turned on (third panel), but not for crash and incident messages (second panel). To account for this, the message displayed at h:02 is used to identify the entire hour.

Figure A.7: Caption



Note: This figure shows the probability of a DMS being turned on over the course of a day. The data are split by whether the day falls into a campaign day. There is a small increase in the likelihood, about 2%, of a DMS being turned on during campaign days compared to non-campaign days. However, this difference substantially increases during the hours 10:00 am to 2:00 pm, when safety campaigns are most intense.

Figure A.8: Caption



Note: Similar to Figure A.7, this figure shows the probability of a DMS displaying a safety message over the course of a day, conditional on the campaign status of the day. The data are displayed for both on and off DMS, and then for only turned on DMS. As one would expect, there is a large increase in the probability of a DMS displaying a safety message during safety campaign days relative to non-campaign days.

A.2 Additional Tables

Table A.1: Effect of Safety Campaigns on Crashes (DMV)

	Crashes_t (-.2 - 1 km)	Crashes_t (1 - 3 km)	Crashes_t (3 - 5 km)	Crashes_t (5 - 10 km)
Campaign	0.041	-0.099***	-0.077*	-0.045*
	(0.054)	(0.038)	(0.044)	(0.026)
DMS On	0.161***	0.138***	0.133***	0.162***
	(0.045)	(0.038)	(0.034)	(0.031)
Campaign x Off-Peak	-0.016	0.013	0.012	-0.074
	(0.165)	(0.099)	(0.114)	(0.089)
Campaign x DMS On	-0.150	-0.017	0.000	-0.053
	(0.092)	(0.069)	(0.073)	(0.039)
Off-Peak x DMS On	-0.132	0.047	0.062	0.018
	(0.107)	(0.077)	(0.096)	(0.063)
Campaign x Off-Peak x DMS On	0.156	0.083	0.030	0.117
	(0.243)	(0.148)	(0.138)	(0.121)
Num.Obs.	5,583,114	5,583,114	5,583,114	5,583,114
R2	0.113	0.115	0.115	0.121

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents the estimated coefficients in 1 with crashes according to the DMV as the outcome. Each column represents a distance farther from the DMS. Each regression contains segment-month-weekday-hour fixed effects, year-month fixed effects, and holiday fixed effects. The standard errors presented are clustered at the segment level. Standard errors can also be clustered by grids of d-by-d kilometers (where $d \in \{1, 3, 5, 10\}$) kilometers, but this does not make a qualitative difference in the significance of the coefficients.

Table A.2: Effect of Safety Campaigns on Crashes (511)

	Crashes_t (-.2 - 1 km)	Crashes_t (1 - 3 km)	Crashes_t (3 - 5 km)	Crashes_t (5 - 10 km)
Campaign	-0.026	-0.057*	-0.084**	-0.025
	(0.049)	(0.033)	(0.033)	(0.025)
DMS On	0.192***	0.175***	0.194***	0.172***
	(0.042)	(0.040)	(0.037)	(0.027)
Campaign x Off-Peak	-0.077	0.062	-0.102	-0.053
	(0.141)	(0.111)	(0.088)	(0.069)
Campaign x DMS On	-0.067	-0.046	0.025	-0.070
	(0.092)	(0.081)	(0.063)	(0.046)
Off-Peak x DMS On	-0.099	-0.014	-0.043	-0.043
	(0.084)	(0.079)	(0.071)	(0.055)
Campaign x Off-Peak x DMS On	0.333	0.230	0.241	0.093
	(0.217)	(0.157)	(0.154)	(0.099)
Num.Obs.	5,583,114	5,583,114	5,583,114	5,583,114
R2	0.114	0.122	0.121	0.127

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents the estimated coefficients in 1 with crashes according to 511 as the outcome. Each column represents a distance farther from the DMS. Each regression contains segment-month-weekday-hour fixed effects, year-month fixed effects, and holiday fixed effects. The standard errors presented are clustered at the segment level. Standard errors can also be clustered by grids of d-by-d kilometers (where $d \in \{1, 3, 5, 10\}$), but this does not make a qualitative difference in the significance of the coefficients.

Table A.3: Effect of Safety Campaigns on Other Incidents (511)

	Incidents_t (-.2 - 1 km)	Incidents_t (1 - 3 km)	Incidents_t (3 - 5 km)	Incidents_t (5 - 10 km)
Campaign	-0.005	-0.012	-0.014	-0.039*
	(0.030)	(0.026)	(0.025)	(0.020)
DMS On	0.027	0.058**	0.067*	0.074***
	(0.030)	(0.025)	(0.040)	(0.020)
Campaign x Off-Peak	-0.090	0.220***	0.024	-0.048
	(0.083)	(0.083)	(0.046)	(0.056)
Campaign x DMS On	0.004	0.010	0.033	0.048*
	(0.064)	(0.046)	(0.033)	(0.029)
Off-Peak x DMS On	-0.093	0.037	0.026	-0.031
	(0.085)	(0.056)	(0.043)	(0.029)
Campaign x Off-Peak x DMS On	0.186	-0.197*	0.113	0.035
	(0.158)	(0.116)	(0.077)	(0.075)
Num.Obs.	5,583,114	5,583,114	5,583,114	5,583,114
R2	0.120	0.133	0.298	0.329

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents the estimated coefficients in 1 with non-crash incidents according to 511 as the outcome. Each column represents a distance farther from the DMS. Each regression contains segment-month-weekday-hour fixed effects, year-month fixed effects, and holiday fixed effects. The standard errors presented are clustered at the segment level. Standard errors can also be clustered by grids of d-by-d kilometers (where $d \in \{1, 3, 5, 10\}$), but this does not make a qualitative difference in the significance of the coefficients.

Table A.4: Effect of Safety Messaging on Crashes (DMV)

	Crashes_t (-.2 - 1 km)	Crashes_t (1 - 3 km)	Crashes_t (3 - 5 km)	Crashes_t (5 - 10 km)
DMS On	0.004	0.015	0.033	0.070**
	(0.045)	(0.037)	(0.032)	(0.030)
DMS On x Safety Message	0.012	0.021	-0.005	-0.096**
	(0.086)	(0.064)	(0.064)	(0.045)
DMS On x Crash Message	1.329***	1.472***	1.401***	1.140***
	(0.238)	(0.213)	(0.159)	(0.147)
DMS On x Hazard Message	0.399*	0.441***	0.133	0.287***
	(0.225)	(0.162)	(0.164)	(0.109)
Num.Obs.	5,583,114	5,583,114	5,583,114	5,583,114
R2	0.113	0.115	0.115	0.122

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents the estimated coefficients in 2 with crashes according to the DMV as the outcome. Each column represents a distance farther from the DMS. Each regression contains segment-month-weekday-hour fixed effects, year-month fixed effects, and holiday fixed effects. The standard errors presented are clustered at the segment level. Standard errors can also be clustered by grids of d-by-d kilometers (where $d \in \{1, 3, 5, 10\}$) kilometers, but this does not make a qualitative difference in the significance of the coefficients.

Table A.5: Effect of Safety Messaging on Crashes (511)

	Crashes_t (-.2 - 1 km)	Crashes_t (1 - 3 km)	Crashes_t (3 - 5 km)	Crashes_t (5 - 10 km)
DMS On	0.070*	0.020	0.084**	0.064**
	(0.037)	(0.038)	(0.035)	(0.025)
DMS On x Safety Message	-0.115	0.050	0.003	-0.115**
	(0.081)	(0.072)	(0.074)	(0.045)
DMS On x Crash Message	1.562***	1.868***	1.383***	1.209***
	(0.230)	(0.187)	(0.165)	(0.147)
DMS On x Hazard Message	-0.047	0.218	0.210	0.297**
	(0.178)	(0.144)	(0.143)	(0.121)
Num.Obs.	5,583,114	5,583,114	5,583,114	5,583,114
R2	0.114	0.122	0.122	0.127

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents the estimated coefficients in 2 with non-crash incidents according to 511 as the outcome. Each column represents a distance farther from the DMS. Each regression contains segment-month-weekday-hour fixed effects, year-month fixed effects, and holiday fixed effects. The standard errors presented are clustered at the segment level. Standard errors can also be clustered by grids of d-by-d kilometers (where $d \in \{1, 3, 5, 10\}$), but this does not make a qualitative difference in the significance of the coefficients.

Table A.6: Effect of Safety Messaging on Other Incidents (511)

	Incidents_t (-.2 - 1 km)	Incidents_t (1 - 3 km)	Incidents_t (3 - 5 km)	Incidents_t (5 - 10 km)
DMS On	0.028	0.051**	0.064*	0.070***
	(0.035)	(0.025)	(0.035)	(0.019)
DMS On x Safety Message	-0.146*	-0.038	-0.004	-0.043*
	(0.088)	(0.061)	(0.038)	(0.022)
DMS On x Crash Message	-0.005	0.001	0.129*	0.066
	(0.098)	(0.066)	(0.078)	(0.053)
DMS On x Hazard Message	0.149	0.459***	0.272***	0.185***
	(0.139)	(0.141)	(0.084)	(0.060)
Num.Obs.	5,583,114	5,583,114	5,583,114	5,583,114
R2	0.120	0.133	0.298	0.329

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents the estimated coefficients in 2 with non-crash incidents according to 511 as the outcome. Each column represents a distance farther from the DMS. Each regression contains segment-month-weekday-hour fixed effects, year-month fixed effects, and holiday fixed effects. The standard errors presented are clustered at the segment level. Standard errors can also be clustered by grids of d-by-d kilometers (where $d \in \{1, 3, 5, 10\}$), but this does not make a qualitative difference in the significance of the coefficients.

Table A.7: Effect of Multi-Page Messaging on Crashes (DMV)

	Crashes_t (-.2 - 1 km)	Crashes_t (1 - 3 km)	Crashes_t (3 - 5 km)	Crashes_t (5 - 10 km)
DMS On	0.283***	0.079	0.140*	0.084
	(0.102)	(0.070)	(0.080)	(0.060)
DMS On x Multi-Page	0.331***	0.212**	0.139*	-0.036
	(0.101)	(0.087)	(0.074)	(0.067)
DMS On x Char	-0.009***	-0.002	-0.002	0.002
	(0.003)	(0.002)	(0.002)	(0.002)
Num.Obs.	5,583,114	5,583,114	5,583,114	5,583,114
R2	0.572	0.113	0.115	0.115

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents the estimated coefficients in 3 with crashes according to the DMV as the outcome. Each column represents a distance farther from the DMS. Each regression contains segment-month-weekday-hour fixed effects, year-month fixed effects, and holiday fixed effects. The standard errors presented are clustered at the segment level. Standard errors can also be clustered by grids of d-by-d kilometers (where $d \in \{1, 3, 5, 10\}$) kilometers, but this does not make a qualitative difference in the significance of the coefficients.

Table A.8: Effect of Multi-Page Messaging on Crashes (511)

	Crashes_t (-.2 - 1 km)	Crashes_t (1 - 3 km)	Crashes_t (3 - 5 km)	Crashes_t (5 - 10 km)
DMS On	0.386***	0.286***	0.217***	0.192***
	(0.101)	(0.080)	(0.070)	(0.059)
DMS On x Multi-Page	0.288***	0.362***	0.116	0.107
	(0.074)	(0.098)	(0.072)	(0.071)
DMS On x Char	-0.009***	-0.008***	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Num.Obs.	5,583,114	5,583,114	5,583,114	5,583,114
R2	0.121	0.114	0.122	0.121

* p < 0.1, ** p < 0.05, *** p < 0.01

Note: This table presents the estimated coefficients in 3 with non-crash incidents according to 511 as the outcome. Each column represents a distance farther from the DMS. Each regression contains segment-month-weekday-hour fixed effects, year-month fixed effects, and holiday fixed effects. The standard errors presented are clustered at the segment level. Standard errors can also be clustered by grids of d-by-d kilometers (where $d \in \{1, 3, 5, 10\}$), but this does not make a qualitative difference in the significance of the coefficients.

Table A.9: Effect of Multi-Page Messaging on Other Incidents (511)

	Incidents_t (-.2 - 1 km)	Incidents_t (1 - 3 km)	Incidents_t (3 - 5 km)	Incidents_t (5 - 10 km)
DMS On	-0.028	-0.028	-0.086	-0.016
	(0.077)	(0.052)	(0.066)	(0.026)
DMS On x Multi-Page	-0.109	-0.039	-0.129	-0.067
	(0.085)	(0.054)	(0.117)	(0.050)
DMS On x Char	0.003	0.003*	0.006	0.003**
	(0.002)	(0.002)	(0.004)	(0.001)
Num.Obs.	5,583,114	5,583,114	5,583,114	5,583,114
R2	0.127	0.120	0.133	0.298

* p < 0.1, ** p < 0.05, *** p < 0.01

Note: This table presents the estimated coefficients in 3 with non-crash incidents according to 511 as the outcome. Each column represents a distance farther from the DMS. Each regression contains segment-month-weekday-hour fixed effects, year-month fixed effects, and holiday fixed effects. The standard errors presented are clustered at the segment level. Standard errors can also be clustered by grids of d-by-d kilometers (where $d \in \{1, 3, 5, 10\}$), but this does not make a qualitative difference in the significance of the coefficients.