The Impact of Michigan’s Text Messaging Restriction on Motor Vehicle Crashes

Johnathon P. Ehsani, Ph.D.\textsuperscript{a,\textdagger}, C. Raymond Bingham, Ph.D.\textsuperscript{b,c}, Edward Ionides, Ph.D.\textsuperscript{d}, and David Childers, M.A.\textsuperscript{e}

\textsuperscript{a}Health Behavior Branch, Division of Intramural Population Health Research, Eunice Kennedy Shriver National Institute of Child Health and Human Development, Bethesda, Maryland
\textsuperscript{b}Young Driver Behavior and Injury Prevention Group, University of Michigan Transportation Research Institute, Ann Arbor, Michigan
\textsuperscript{c}Department of Health Education and Health Behavior, University of Michigan School of Public Health, Ann Arbor, Michigan
\textsuperscript{d}Department of Statistics, College of Literature, Science, and the Arts, University of Michigan, Ann Arbor, Michigan
\textsuperscript{e}Center for Statistical Consultation and Research, University of Michigan, Ann Arbor, Michigan

Article history: Received August 15, 2013; Accepted January 3, 2014

Keywords: Motor vehicle crashes; Texting; Restriction; Law; Distraction; Adolescent driver

ABSTRACT

Purpose: The purpose of this study was to determine the effects of Michigan’s universal text messaging restriction (effective July 2010) across different age groups of drivers and crash severities.

Methods: Changes in monthly crash rates and crash trends per 10,000 licensed drivers aged 16, 17, 18, 19, 20–24, and 25–50 years were estimated using time series analysis for three levels of crash severity: (1) fatal/disabling injury; (2) nondisabling injury; and (3) possible injury/property damage only (PDO) crashes for the period 2005–2012. Analyses were adjusted for crash rates of drivers aged 65–99 years, Michigan’s unemployment rate, and gasoline prices.

Results: After the introduction of the texting restriction, significant increases were observed in crash rates and monthly trends in fatal/disabling injury crashes and nondisabling injury crashes, and significant decreases in possible injury/PDO crashes. The magnitude of the effects where significant changes were observed was small.

Conclusions: The introduction of the texting restriction was not associated with a reduction in crash rates or trends in severe crash types. On the contrary, small increases in the most severe crash types (fatal/disabling and nondisabling injury) and small decreases in the least severe crash types (possible injury/PDO) were observed. These findings extend the literature on the effects of cell phone restrictions by examining the effects of the restriction on newly licensed adolescent drivers and adult drivers separately by crash severity.

Published by Elsevier Inc. on behalf of Society for Adolescent Health and Medicine.

IMPLICATIONS AND CONTRIBUTION

- Few studies have examined the effect of texting restrictions on differing levels of crash severity.
- Small changes in monthly crash rates and trends were observed after the introduction of Michigan’s texting restriction.
- Strategies used to reduce other risky driving behaviors may also prove effective in reducing texting while driving.
10 states have restricted handheld cell phone use for all drivers [11,12]. However, there is little evidence demonstrating the effectiveness of these policies in reducing crashes.

Studies examining the effectiveness of cell phone restrictions show no clear relationship between the presence of restrictions and driver behavior. Survey studies suggest that drivers engage in lower cell phone use in jurisdictions where restrictions are in effect [13,14]. In contrast, observational studies of driver behavior have mixed findings. Three studies found the introduction of cell phone restrictions had no effect on handheld cell phone use while driving [15–17], whereas five studies reported significant declines in handheld use after the introduction of cell phone restrictions [18–22]. Short- and long-term evaluations of a cell phone restriction for 16- and 17-year-old drivers in North Carolina found that the law did not significantly reduce handheld cell phone use while driving [15,16]. Furthermore, although the prevalence of talking on the phone decreased among young drivers after the introduction of the restriction, physical manipulation of cell phones appeared to have increased [16].

To date, few studies have examined cell phone restrictions to determine whether they vary in effectiveness by crash severity, being more effective in reducing crashes of some but not all severities. This question has public health and economic significance. If enforcement costs are high, and social and economic benefits are relatively small (e.g., preventing crashes where minor property damage has occurred), states may consider alternative approaches to reducing cell phone use while driving. If the costs of enforcement are outweighed by the social and economic benefits (e.g., reductions in deaths and disabling injuries), this strengthens the basis for the restriction.

Previous policy evaluation studies on adolescent drivers have recommended the use of methodologically rigorous time series analyses of individual states that include crashes of all severities [23]. Using a natural experiment where a texting restriction was introduced independently of any other driving laws, the purpose of this study was to evaluate the effect of a universal texting restriction on crashes. Specifically, we hypothesized that the introduction of Michigan’s texting restriction for all drivers would be followed by a reduction in crashes of all severities for drivers aged 16–50 years.

Method

Data and measures

The State of Michigan requires all crashes involving an injury (fatal or nonfatal) to any person, or property damage of $1,000 or more, to be reported to police. Monthly frequencies of all vehicles involved in police-reported crashes were extracted for drivers aged 16, 17, 18, 19, 20–24, 25–50, and 65–99 years from Michigan crash records for the period 2005–2012. Each unique vehicle involved in a crash contributed to the frequency, as a single crash could involve drivers in multiple age groups. Crash severities were categorized as fatal/disabling injury, nondisabling injury, and possible injury/property damage only (PDO) according to the KABCO classification of crash severity [24]. Although the KABCO scale is known to overestimate crash severity, in the absence of direct linkage systems between Emergency Medical Services and state crash databases, the KABCO scale correlates well with other more sensitive measures and is a reasonable estimator of variation in injury severity in crashes [25]. The monthly numbers of licensed drivers obtained from the Michigan Driver History Record were used to calculate crash involvement rates per 10,000 licensed drivers by year of age. Crash and licensing data were obtained from the University of Michigan Transportation Research Institute [26]. Due to anomalies in the 2005 licensing data and unavailability of 2012 data, numbers of licensed drivers were extrapolated by age group using cubic regression spline curves and monthly indicators to address seasonality [27].

Covariates

Comparison population. The monthly crash rates for drivers aged 65–99 years were used as a covariate series. This age group was selected as a covariate because it has the lowest prevalence of texting while driving and therefore was least affected by the introduction of the texting restriction [28]. The purpose of the comparison series was to adjust for variability in driver crash rates due to extraneous factors such as weather affecting drivers of all ages. Although time series analyses control for pre-existing secular trends in crash rates, the inclusion of the crash rates of another age group as a historical covariate to control for unmeasured factors that affect all drivers enhances the validity of the findings. Monthly crash rates of 65–99-year-old drivers per 10,000 licensed drivers were calculated using the identical method as for drivers in the study age groups.

Unemployment rate. An inverse relationship exists among economic activity, the amount of driving, and crashes [29,30]. In particular, economic recessions typically reduce recreational driving [31]. Unemployment data for Michigan were obtained from the Bureau of Labor Statistics [32].

Gasoline prices. An inverse relationship has also been identified between gasoline prices and fatal crash rates for drivers of all ages [33]; however, research suggests that adolescent driving behavior may be more sensitive to higher gasoline prices relative to older drivers [34]. Monthly national average gasoline prices, obtained from the U.S. Energy Information Administration [35], were used as a covariate in the analyses to adjust for their effect on the amount of driving exposure and resulting crash risk level.

Texting restriction effective date. Michigan’s texting restriction for all drivers came into effect on July 1, 2010 [36]. The restriction prohibited reading, typing, or sending text messages on wireless two-way communication device and authorized law enforcement officials to cite drivers for engaging in any of these behaviors. Primary enforcement was in effect for the texting restriction, meaning law enforcement officials could stop and cite drivers on the basis of noncompliance alone.

The restriction effective date was used to estimate two covariates. The first was a binary variable indicating if a month period was before (0) or after (1) the implementation of the restriction. This provided an estimate of the change in crash rates at the time the restriction went into effect. The second was the interaction between time and the implementation of the restriction, which estimated the change in monthly crash trends over time after the restriction compared with the trends in crashes prior. All coefficients can be interpreted in units of crashes per 10,000 drivers per month.

Analytical method

Crash rates were analyzed using linear regression with Auto-Regressive Moving-Average (ARMA) errors, an approach that
allows for serial correlation in crashes. Crashes were aggregated in monthly increments. No differencing was conducted, and seasonality was addressed using monthly indicators. Changes in crashes and trends were investigated by fitting the following model [37]:

\[ y_t = \beta_0 + \beta_1 t + \beta_2 Z_t + \beta_3 \Delta Z_t + \gamma X_t + \epsilon_t. \]

where \( t \) indexes the number of months since the law, \( y_t \) is the number of crashes per 10,000 licensed drivers in month \( t \), \( Z_t \) is 1 if \( t \) 0 and 0 if \( t < 0 \), \( X_t \) is a vector of other predictors (comparison population of drivers aged 65–99 years, unemployment rate, gasoline prices), and monthly indicators at month \( t \), and errors \( \epsilon_t \) are ARMA(1,1), that is, \( \epsilon_t = \phi \epsilon_{t-1} + \eta_t + \theta \eta_{t-1} \), where \( \eta_t \) is an independent and identically distributed Gaussian error sequence. The complete model is defined in Appendix 1, which can be found in the online edition of this article. Preliminary analysis suggested that this model structure provided the best or near best Akaike information criterion for all age and severity groups [38]. Therefore, this model was used for all analyses. Model parameters were fit by maximum likelihood using the ARIMA function in R [39].

The coefficient \( \beta_0 \) measures a permanent change in crash rates, and the coefficient \( \beta_2 \) measures the change in crash rate trends. A negative \( \beta_2 \) coefficient would indicate a reduction in crashes after the introduction of the restriction, when averaged across the entire series. A negative \( \beta_3 \) coefficient associated with the monthly trend in crashes would indicate a negative change in the trend after the implementation of the restriction relative to the trend before the restriction was implemented. Thus, \( \beta_3 \) can model a gradual effect of the law.

Analyses were conducted using fatal/disabling injury, nondisabling injury, and possible injury/PDO crash rates as three separate outcome measures. The models were estimated in two stages. First, autoregressive and moving average orders were identified using autocorrelation and partial autocorrelation functions of series residuals. The models were then estimated with inclusion of autoregressive and/or moving average orders identified in the second stage. The data were analyzed in 2013.

**Results**

Across age groups, changes in crash rates and trends were small. Significant increases were observed in crash rates and monthly trends in fatal/disabling injury crashes and nondisabling injury crashes, and significant decreases in possible injury/PDO crashes. Insignificant changes in crash rates and trends largely followed a similar pattern (Table 1, Figure 1). The following findings were observed by age groups:

**16-year-old drivers**

There was no significant change in the number of 16-year-old drivers’ crash rates after the introduction of the texting restriction; however, the monthly trend in nondisabling injury crashes increased by .09 crashes per 10,000 licensed drivers.

**17-year-old drivers**

After the introduction of the restriction, nondisabling crash rates increased by .75 crashes per 10,000 licensed drivers and possible injury/PDO crash rates decreased by 2.79 crashes per 10,000 licensed drivers. Monthly trends in fatal/disabling injury and nondisabling injury crashes increased by .03 and .05 crashes per 10,000 licensed drivers, respectively.

**18-year-old drivers**

After the introduction of the texting restriction, monthly trends of possible injury/PDO crashes decreased by .60 crashes per 10,000 licensed drivers. There was no change in crash rates for this age group.

**19-year-old drivers**

Fatal and disabling injury crash rates increased by .43 crashes per 10,000 drivers. Monthly trends in fatal and disabling injury crashes increased by .02 crashes per 10,000 licensed drivers, whereas the monthly trend in possible injury/PDO crashes decreased by .49 crashes per 10,000 licensed drivers.

**20- to 24-year-old drivers**

Fatal and disabling injury and nondisabling injury crash rates increased by .32 and .33 crashes per 10,000 drivers, respectively. Monthly trends in nondisabling injury crashes increased by .02 crashes per 10,000 licensed drivers after the introduction of the restriction, whereas the monthly trend in possible injury/PDO crashes decreased by .34 crashes per 10,000 licensed drivers.

**25- to 50-year drivers**

Rates of nondisabling injury crashes increased by .30 crashes per 10,000 licensed drivers. Monthly trends of fatal and disabling injury crashes increased by .01 crashes per month per 10,000 licensed drivers after the introduction of the restriction, whereas possible injury/PDO crash trends decreased by .19 crashes per 10,000 licensed drivers.

**Discussion**

The purpose of this study was to evaluate the effect of Michigan’s texting restriction for drivers aged 16–50 years by crash severity. We hypothesized that the introduction of the texting restriction for all drivers would be followed by a reduction in crashes of all severities. Contrary to this hypothesis, statistically significant increases in crash rates and trends in fatal/disabling injury crashes and nondisabling injury crashes and decreases in possible injury/PDO crashes were observed. The significant effects that were identified were small, with the largest change observed in 17-year-old drivers’ possible injury/PDO crash rates, as a decline of approximately three crashes per 10,000 licensed drivers. This suggests that the public health impact of the texting restriction was minor.

The small increase in the most severe crash types (fatal/disabling and nondisabling injury) and the decrease in the least severe crash types (possible injury/PDO) after the introduction of the restriction are challenging to interpret in the absence of data on driver behavior. A study of Australian young drivers found that the majority reported deliberately concealing texting behavior while driving to evade enforcement efforts [40]. If the introduction of the restriction shifted drivers’ texting from an overt to a covert behavior, where cell phones are held below the line of sight of other drivers, this may have resulted in a shift in
the severity of texting-related crashes, where previously minor crashes became more severe, due to longer durations of eye glance behavior away from the forward roadway [41].

Several factors could explain the modest effects of the texting restriction, including confounding factors; however, it is also possible that the small effects are reflective of a lack of change in texting behavior in response to the policy implemented in Michigan. This latter explanation is supported by results of other research examining rates of cell phone use by drivers in the Midwestern region of the United States. Specifically, observational data of handheld cell phone use from the National Occupant Protection Use Survey indicate no significant change in handheld cell phone use by drivers in the Midwestern region of the United States from 2010 to 2011 [42]. These data are collected for 12 states including Michigan and are not reflective of state-specific changes in handheld use; however, the lack of change identified by the National Occupant Protection Use Survey is consistent with the findings of this study and suggests that a likely explanation is that the policy led to a minor change in the texting behavior of Michigan drivers.

Broad public awareness and high-profile enforcement are essential to successful policy implementation. Previous studies have demonstrated both enforcement [17–19] and publicity [20,21] mediate behavior change after the introduction of cell phone restrictions. The current study was limited in its ability to account for rates of enforcement and levels of public awareness of the texting restriction. Future research examining policies related to cell phone use needs to account for these important mediators of behavior change by assessing hours of enforcement.

### Table 1
Parameters of ARMA models estimating the effect of Michigan’s texting restriction on crash rates and trends per licensed driver, 2005–2012

<table>
<thead>
<tr>
<th>Age (years)</th>
<th>Model component</th>
<th>Parameter</th>
<th>Fatal and disabling injury</th>
<th>Nondisabling injury</th>
<th>Possible injury/property damage only</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Crash estimate (SE)</td>
<td>Crash estimate (SE)</td>
<td>Crash estimate (SE)</td>
</tr>
<tr>
<td>16</td>
<td>Change in crash rate</td>
<td>$\beta_2$</td>
<td>.107 (.209)</td>
<td>.089 (.559)</td>
<td>3.155 (2.088)</td>
</tr>
<tr>
<td></td>
<td>Change in crash trend</td>
<td>$\beta_3$</td>
<td>.015 (.015)</td>
<td>.098 (.037)</td>
<td>.162 (.150)</td>
</tr>
<tr>
<td></td>
<td>Control series (65– to 99-year-olds)</td>
<td></td>
<td>-.324 (.461)</td>
<td>.746 (.531)</td>
<td>3.116 (.437)</td>
</tr>
<tr>
<td></td>
<td>Unemployment rate</td>
<td></td>
<td>.075 (.054)</td>
<td>.135 (.127)</td>
<td>.138 (.564)</td>
</tr>
<tr>
<td></td>
<td>Gasoline price</td>
<td></td>
<td>.113 (.166)</td>
<td>.054 (.337)</td>
<td>-.547 (.191)</td>
</tr>
<tr>
<td></td>
<td>Noise (AR 1)</td>
<td></td>
<td>.428 (.717)</td>
<td>.619 (.292)</td>
<td>-.610 (.318)</td>
</tr>
<tr>
<td></td>
<td>Noise (MA 1)</td>
<td></td>
<td>-.314 (.754)</td>
<td>-.341 (.342)</td>
<td>.423 (.364)</td>
</tr>
<tr>
<td>17</td>
<td>Change in crash rate</td>
<td>$\beta_2$</td>
<td>.076 (.181)</td>
<td>.752 (.140)</td>
<td>-.2797 (.1193)</td>
</tr>
<tr>
<td></td>
<td>Change in crash trend</td>
<td>$\beta_3$</td>
<td>.033 (.013)</td>
<td>.047 (.010)</td>
<td>-.184 (.103)</td>
</tr>
<tr>
<td></td>
<td>Control series (65– to 99-year-olds)</td>
<td></td>
<td>.508 (.379)</td>
<td>1.896 (.420)</td>
<td>4.513 (.473)</td>
</tr>
<tr>
<td></td>
<td>Unemployment rate</td>
<td></td>
<td>.062 (.047)</td>
<td>.111 (.039)</td>
<td>-.623 (.436)</td>
</tr>
<tr>
<td></td>
<td>Gasoline price</td>
<td></td>
<td>-.001 (.145)</td>
<td>-.358 (.157)</td>
<td>-.352 (.139)</td>
</tr>
<tr>
<td></td>
<td>Noise (AR 1)</td>
<td></td>
<td>-.859 (.061)</td>
<td>.548 (.089)</td>
<td>.713 (.081)</td>
</tr>
<tr>
<td></td>
<td>Noise (MA 1)</td>
<td></td>
<td>1.000 (.030)</td>
<td>-.100 (.027)</td>
<td>.999 (.026)</td>
</tr>
<tr>
<td>18</td>
<td>Change in crash rate</td>
<td>$\beta_2$</td>
<td>.105 (.231)</td>
<td>.318 (.386)</td>
<td>-.177 (.1310)</td>
</tr>
<tr>
<td></td>
<td>Change in crash trend</td>
<td>$\beta_3$</td>
<td>.008 (.016)</td>
<td>-.026 (.028)</td>
<td>-.597 (.112)</td>
</tr>
<tr>
<td></td>
<td>Control series (65– to 99-year-olds)</td>
<td></td>
<td>.602 (.434)</td>
<td>1.682 (.569)</td>
<td>5.004 (.646)</td>
</tr>
<tr>
<td></td>
<td>Unemployment rate</td>
<td></td>
<td>.010 (.050)</td>
<td>-.141 (.090)</td>
<td>1.029 (.459)</td>
</tr>
<tr>
<td></td>
<td>Gasoline price</td>
<td></td>
<td>.020 (.173)</td>
<td>-.504 (.305)</td>
<td>.096 (.191)</td>
</tr>
<tr>
<td></td>
<td>Noise (AR 1)</td>
<td></td>
<td>.501 (.069)</td>
<td>-.237 (.460)</td>
<td>.756 (.072)</td>
</tr>
<tr>
<td></td>
<td>Noise (MA 1)</td>
<td></td>
<td>-.366 (.647)</td>
<td>.331 (.437)</td>
<td>-.100 (.026)</td>
</tr>
<tr>
<td>19</td>
<td>Change in crash rate</td>
<td>$\beta_2$</td>
<td>.427 (.097)</td>
<td>.383 (.270)</td>
<td>2.677 (.5066)</td>
</tr>
<tr>
<td></td>
<td>Change in crash trend</td>
<td>$\beta_3$</td>
<td>.021 (.008)</td>
<td>.025 (.019)</td>
<td>-.491 (.125)</td>
</tr>
<tr>
<td></td>
<td>Control series (65– to 99-year-olds)</td>
<td></td>
<td>-.135 (.499)</td>
<td>.268 (.466)</td>
<td>5.318 (.442)</td>
</tr>
<tr>
<td></td>
<td>Unemployment rate</td>
<td></td>
<td>.070 (.032)</td>
<td>-.060 (.068)</td>
<td>-.566 (.482)</td>
</tr>
<tr>
<td></td>
<td>Gasoline price</td>
<td></td>
<td>.096 (.128)</td>
<td>-.796 (.211)</td>
<td>1.976 (.1908)</td>
</tr>
<tr>
<td></td>
<td>Noise (AR 1)</td>
<td></td>
<td>.747 (.077)</td>
<td>-.663 (.219)</td>
<td>.834 (.063)</td>
</tr>
<tr>
<td></td>
<td>Noise (MA 1)</td>
<td></td>
<td>-.100 (.027)</td>
<td>.525 (.242)</td>
<td>-.100 (.026)</td>
</tr>
<tr>
<td>20–24</td>
<td>Change in crash rate</td>
<td>$\beta_2$</td>
<td>.317 (.046)</td>
<td>.333 (.156)</td>
<td>.407 (.892)</td>
</tr>
<tr>
<td></td>
<td>Change in crash trend</td>
<td>$\beta_3$</td>
<td>.007 (.004)</td>
<td>.024 (.011)</td>
<td>-.344 (.075)</td>
</tr>
<tr>
<td></td>
<td>Control series (65– to 99-year-olds)</td>
<td></td>
<td>.478 (.200)</td>
<td>1.537 (.192)</td>
<td>4.909 (.343)</td>
</tr>
<tr>
<td></td>
<td>Unemployment rate</td>
<td></td>
<td>.006 (.014)</td>
<td>-.015 (.041)</td>
<td>-.352 (.309)</td>
</tr>
<tr>
<td></td>
<td>Gasoline price</td>
<td></td>
<td>-.069 (.054)</td>
<td>-.277 (.124)</td>
<td>3.491 (.1336)</td>
</tr>
<tr>
<td></td>
<td>Noise (AR 1)</td>
<td></td>
<td>.794 (.067)</td>
<td>-.342 (.208)</td>
<td>.723 (.079)</td>
</tr>
<tr>
<td></td>
<td>Noise (MA 1)</td>
<td></td>
<td>-.100 (.027)</td>
<td>.709 (.159)</td>
<td>1.000 (.027)</td>
</tr>
<tr>
<td>25–50</td>
<td>Change in crash rate</td>
<td>$\beta_2$</td>
<td>.044 (.029)</td>
<td>.304 (.072)</td>
<td>.347 (.1075)</td>
</tr>
<tr>
<td></td>
<td>Change in crash trend</td>
<td>$\beta_3$</td>
<td>.006 (.002)</td>
<td>.002 (.005)</td>
<td>-.186 (.077)</td>
</tr>
<tr>
<td></td>
<td>Control series (65– to 99-year-olds)</td>
<td></td>
<td>.319 (.078)</td>
<td>.604 (.105)</td>
<td>3.075 (.201)</td>
</tr>
<tr>
<td></td>
<td>Unemployment rate</td>
<td></td>
<td>.001 (.007)</td>
<td>-.018 (.019)</td>
<td>-.049 (.286)</td>
</tr>
<tr>
<td></td>
<td>Gasoline price</td>
<td></td>
<td>-.046 (.227)</td>
<td>-.135 (.057)</td>
<td>2.559 (.063)</td>
</tr>
<tr>
<td></td>
<td>Noise (AR 1)</td>
<td></td>
<td>-.748 (.241)</td>
<td>-.124 (.436)</td>
<td>-.076 (.728)</td>
</tr>
<tr>
<td></td>
<td>Noise (MA 1)</td>
<td></td>
<td>.670 (.260)</td>
<td>.276 (.409)</td>
<td>.168 (.711)</td>
</tr>
</tbody>
</table>

Statistically significant changes in crashes are highlighted in bold.

SE = standard error.

- **p < .05.
- ***p < .01.
- ***p < .001.
Figure 1. Crash rates per 10,000 licensed drivers before and after the introduction of the texting restriction by age group and crash severity. PDO: property damage only.
numbers of citations issued, and the deployment of high-
visibility enforcement efforts, as well as data on paid and
earned media coverage of the texting restriction.

This study used the oldest age group of drivers as a control for
factors that might influence the crash rates of all drivers.
Although this is a well-accepted method of adjusting the model,
it could be strengthened in future research with the addition of a
comparison state so that overall trends in crashes could be taken
into account in the interpretation of the results. Finally, as texting
restrictions are introduced across an increasing number of ju-
risdictional evaluation studies could be extended to include
multiple states, and the pooled effect of texting restrictions
across a number of states could be estimated using meta-
analysis.

The findings of this study and previous evaluations [43]
suggest that the relationship between texting restrictions and
crashes is complex. Because of this complexity, effectively
intervening to reduce texting while driving requires a sophisti-
cated response. In addition to legislation, enforcement that is
highly visible and followed by consequences of sufficient cer-
tainty, severity, and celerity has been used to change other risky
driving behaviors, such as safety belt nonuse and drinking and
driving [44,45]. Campaigns to shift attitudes, norms, and social
expectations have reduced other risky driving behaviors [46] and
may also prove effective in reducing texting while driving.

Funding Sources

The University of Michigan Injury Center and the National
Center for Injury Prevention and Control of the Centers for Dis-
ease Control and Prevention provided support for this research.

Supplementary Data

Supplementary data related to this article can be found at
http://dx.doi.org/10.1016/j.jadohealth.2014.01.003.

References

motor vehicle crashes resulting in hospital attendance: A case-crossover
Vol DOT HS 811 555.
Research Center; 2009.
[5] Centers for Disease Control and Prevention. Youth risk behavior surveil-
shows and what states can do. Washington, DC; 2011. Available at: http://
2014.
distracted driving. Washington, DC: U.S. Department of Transportation;
2010.
[13] Brittman KA, McCartt AT. National reported patterns of driver cell phone
[14] Jamson SL. What impact does legislation have on drivers, A\ó in-vehicle use
on teenager driver cell phone use two years after implementation. Accid Anal
[17] McCartt AT, Geary LL. Longer term effects of New York State’s law on
[18] Cosgrove L, Chaudhary N, Roberts S. High visibility enforcement
demonstration programs in Connecticut and New York reduce hand-held
phone use. Washington, DC: National Highway Traffic Safety Administra-
tion; 2010.
[19] McCartt AT, Braver ER, Geary LL. Drivers’ use of handheld cell phones before
[20] McCartt AT, Hellinga LA. Longer-term effects of Washington, DC, law on
[21] McCartt AT, Hellinga LA, Geary LL. Effects of DC Law on
[22] McCartt AT, Hellinga LA, Stouge LM, Farmer CM. Long-term effects of
handheld cell phone laws on drivers handheld cell phone Use. Traffic Inj
crashes involving 16- to 19-Year-Old drivers. JAMA: The J Am Med Assoc
2011;306:1098–103.
Department of State Police; 2010.
crashes. Paper presented at Transportation Research Board 92nd Annual
Meeting; Washington, DC.
[26] University of Michigan Transportation Research Institute. Center for the
Management of Information for Safe and Sustainable Transportation. 2013;
and motor vehicle collisions. New Engl J Med 1997;336:453
[29] Schroeder P, Meyers M, Kostyniuk L. National survey on distracted driving
and motor vehicle collisions. New Engl J Med 1997;336:453
handheld cell phone laws on drivers handheld cell phone Use. Traffic Inj
[31] University of Michigan Transportation Research Institute; 2013.
[33] National Highway Traffic Safety Administration. An analysis of the signifi-
Department of Transportation; 2010.
December, 2013.
[35] Sivak M. Distance driven and economic activity in the individual U.S.
Research Institute; 2013.
[37] Shumway RH, Stoffer DS. Time series analysis and its applications. New
York: Springer; 2000.
version 3.0.1 [computer program]. Vienna, Austria: R Foundation for
[40] Gould CS, Lewis I, White KM. Concealing their communication: Exploring
psychosocial predictors of young drivers’ intentions and engagement in


