

# What Are Drivers Doing When They Aren't on the Cell Phone?

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## ABSTRACT

Cell-phone bans have been motivated by previous research estimating large odds ratios (i.e., 3-4) for using cell-phones while driving. However, large crash reductions have not been realized. One reason may be that drivers may replace cell-phone use with other risky activities and that ORs have often compared cell-phone use to ideal driving rather than a realistic reference. Using SHRP2 data, we developed two cell-phone propensity models, one with age and one without, to develop weights for events without cell phone use. Using these weights, we estimated the probability of engagement in a variety of tasks in place of cell-phone use. We also estimated weighted ORs for cell-phone use (all uses) and cell-phone talking only. Weighted ORs are lower than unweighted ORs and much lower than ORs compared to ideal driving. This is consistent with the idea that in practice, even if cell-phone bans are effective at reducing cell-phone use, they may not greatly reduce risk because drivers may replace cell-phone use with other distracting activities in the same situations in which they normally use cell phones while driving. We also discuss the influence of young drivers on our results. Younger drivers in the dataset are more likely to use cell phones and thus are influential in the propensity model results.

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## INTRODUCTION

Previous research using the Second Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS) reported that the estimated odds ratio (OR) of crashing associated with cell-phone use while driving was 3.6 (CI: 2.9-4.5), when compared to ideal driving, in which drivers were not fatigued, impaired or engaging in any secondary tasks (Dingus et al., 2016). Related work using crash data (e.g., McEvoy et al., 2004) has led to cell-phone bans being pass in various states and countries.

In spite of the evidence for risks associated with cell-phone use, the effect of bans on crashes has not been realized. In the U.S. an analysis of states that banned cell-phone use when driving showed that the bans reduced cell-phone use but not insurance claims (IIHS, 2014). In Europe, the UDrive study found large differences in mobile-phone use in driving by country (Carsten et al., 2017). German drivers used mobile

phones 0.06% of the time as compared to UK (2.87%), French (3.48%), and Polish (9.49%) drivers. All of these countries have mobile-phone bans while driving though very different rates were observed in the data.

One hypothesis for the failure to realize large reductions in crash counts where mobile-phone bans are in place is that drivers who are not using their cell phones may engage in different secondary tasks and be distracted by other means. Since NDS-based OR estimates for cell-phone use are often calculated using ideal driving as a reference activity, it may be that these ORs overestimate the potential benefits that can be realized in actual driving when cell-phone use is reduced. That is, drivers are unlikely to replace cell-phone use with ideal driving, since they are engaged in secondary tasks frequently (more than half the time in SHRP2; Dingus et al., 2016). The question is: What is an appropriate reference activity that better reflects the likely activities with which drivers will replace cell-phone use? In addition, what is the OR for cell-phone use when compared to the likely replacement activity?

In this paper, we approach this problem by developing a new reference in which non-cell-phone events are weighted by the probability that the driver would have used a cell phone in that event, given the context present. Here, context is defined as environmental characteristics (e.g., traffic density, time of day) and driver characteristics (age, gender). This approach is similar to propensity weighting (Freedman & Berk, 2008; Månsson et al., 2007) in that we create a cell-phone-use propensity model that is applied to each event. However, propensity weighting is typically used to correct for overrepresentation of certain cases (based on their covariates) in the treatment group relative to random assignment. Here, we have a random sample of all driving but want it to be a random sample of the driving conditions that are present when drivers are on the cell phone. Thus, we weight events by their cell-phone-use propensity. In this way, cell-phone crash odds are compared to reference driver behaviour and crash risk should better reflect the expected behaviour and crash risk when cell-phone use is discouraged (e.g., by legislative or technological) means.

The two objectives of this study are: 1) identify what drivers are doing when they are not on the cell phone, and 2) estimate the OR for cell-phone use when compared to the set of activities that would be expected to replace cell-phone use in the case of a ban.

## **METHOD**

For this analysis, we used data from the SHRP2 study. SHRP2 is a naturalistic driving study (NDS) that was conducted in 6 locations in the U.S. from 2012-2013. Approximately 3,400 vehicles were monitored with Data Acquisition Systems (DASs), which collected video and kinematic data continuously while the vehicles were driven. This resulted in a total of approximately 5.5 million trips with consented drivers (i.e., study participants, whose data are available for analysis) and approximately 56 million kilometres of driving (Hankey et al., 2016).

As part of the original study, a set of safety-critical and non-safety-critical (baseline) events were extracted from the larger dataset. Safety critical events (SCEs) in the dataset include crashes (as well as near-crashes, which we did not use). In addition, a set of clips, known as “balanced baselines,” were selected at random from all driving over 5 mph. The number of clips selected per driver was proportional to his/her total driving time in the study.

Crashes were defined as:

“Any contact that the subject vehicle has with an object, either moving or fixed, at any speed in which kinetic energy is measurably transferred or dissipated is considered a crash.”

(Hankey et al., 2016)

In addition, crashes were further categorized into Level I, II, III, and IV, in order of decreasing severity, based on video review. Level I is a severe crash, Level II is a moderate crash, Level III is a minor crash, and Level IV is defined as a low-risk tire strike. Detailed definitions and extraction methods can be found in Hankey et al., (2016).

For this analysis, we only used those crashes where the first event was coded as a Level I, II or III crash. Each baseline or crash clip was 20-30 seconds long but was only video-coded for 6 seconds. Video coding was done for the 5 seconds prior and 1 second after the identified precipitating event for crashes and for a random 6 seconds for baselines. This resulted in a dataset with 19,991 balanced-baseline cases and 830 crashes.

We developed our cell-phone propensity model using logistic regression to predict the probability of using the cell phone as a function of available covariates, which included:

- Relation to junction—spatial relationship of vehicle to a junction, if any
- Intersection influence—judgment of whether an intersection influenced driving behaviour such as braking
- Traffic flow—roadway design, including number of lanes and presence of dividers
- Traffic density—traffic density for the specific event, coded from free-flow to flow restrictions (stop-and-go)
- Front seat passengers—codes presence or absence of a front seat passenger
- Lighting—light level coded from forward video (e.g., daylight, dusk/dawn, dark but lighted, dark)
- Weather—weather conditions coded from forward video
- Surface condition—road surface condition coded from forward video (e.g., wet, dry, icy)
- Through travel lanes—number of lanes in driver’s direction of travel (does not include turn lanes)
- Day of week
- Locality—Coded surroundings e.g., residential, business, rural, etc.
- Mean travel speed during full event
- Driver age group—first group includes ages 16-19 (4 years) with 5-year groupings thereafter

All cell-phone interaction types, both with hands-free and hand-held phones, were included in analysis, though talking on a hand-held phone makes up the majority of cases (1656, or 92%).

Only baseline cases were used for the propensity model since if cell-phone use itself increases risk, we would expect crash cases to include cell-phone use with higher probability across all conditions. The model was then used to compute predicted probability of being on the cell phone for all cases in which the driver was *not* engaged in a cell-phone task. The 1803 events (including both crashes and baseline events) where cell phones were in use were given a weight of 1 and the 19018 non-cell-phone cases were weighted according to the predicted propensity of using the cell phone in that case.

To estimate the probability of other tasks (in lieu of cell phone), we used balanced baseline events where cell-phone use was absent. The full list of secondary tasks coded is available on the InSight<sup>1</sup> website, but the most common tasks include talking to passengers, external distractions, talking/singing, etc. The weighted proportion of each alternative task (as well as no secondary tasks) occurring in that sample was used to estimate the probability that each alternative task would replace cell-phone use.

To estimate the OR for cell-phone use compared to the likely set of baseline activities, we also computed the cell-phone OR using the propensity-score weights for the reference group. The ORs were estimated using logistic regression with no covariates in the model. This is equivalent to the 2X2 table in Figure 1 below.

	Cell Phone Used	
	Yes	No
Crash	a	b
Baseline	c	d

\*Shaded cells are weighted in analysis

**Figure 1 Illustration of weighted odds ratio calculation**

The standard OR equation based on the cells in Figure 1 is given in Equation 1. The values *a*, *b*, *c* and *d* are cell counts. This is the calculation used in Dingus et al., 2016 where “no cell phone” (i.e., cells b and d) included only cases of ideal driving with no secondary tasks, fatigue or impairment.

$$OR = \frac{a/c}{b/d} \tag{1}$$

Equation 2 shows how propensity weights are used in the same calculation. Here, we count all events where cell-phone use is absent (but there may be other secondary tasks) in cells b and d, and then we weight them as described in Equation 2.

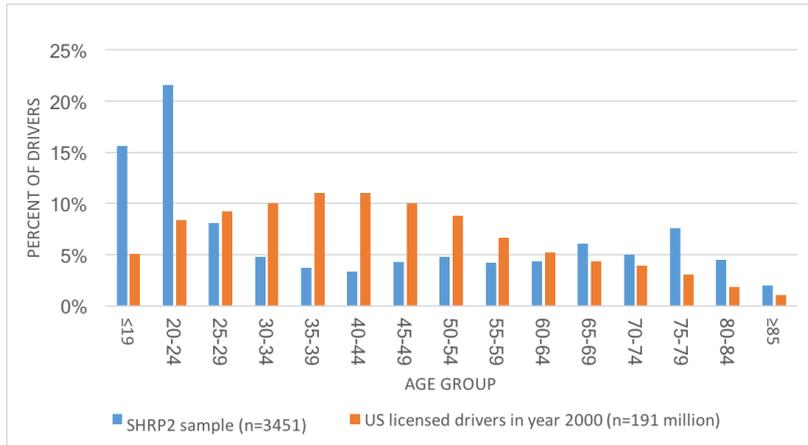
$$OR = \frac{\sum w_a / \sum w_c}{\sum w_b / \sum w_d} = \frac{a/c}{\sum w_b / \sum w_d} \tag{2}$$

where  $w_i$  is the sum of weights for events counted in cell *i*. Note that for cells a and c, the sum of weights is equal to the count of events, as shown on the rightmost side of Equation 2.

## RESULTS

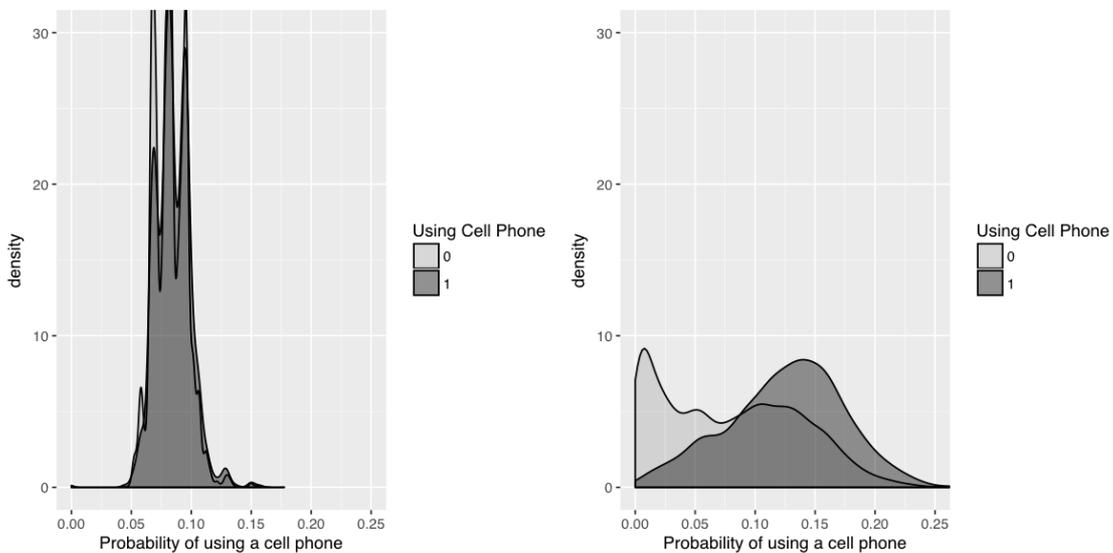
The dataset contained 3,539 unique drivers. The age distribution is shown in Figure 2 compared to the age distribution for licensed drivers in the U.S. Young drivers are substantially overrepresented and older drivers are also overrepresented but not to the same degree. Of the 19,991 baseline events, 1,656 (8%) included some type of cell-phone interaction by the driver. Of the 830 crashes, 147 (18%) included cell-phone interaction.

<sup>1</sup> <https://insight.shrp2nds.us/login/auth#/builder>



**Figure 2** Age distribution of drivers in SHRP2 and U.S. licensed drivers

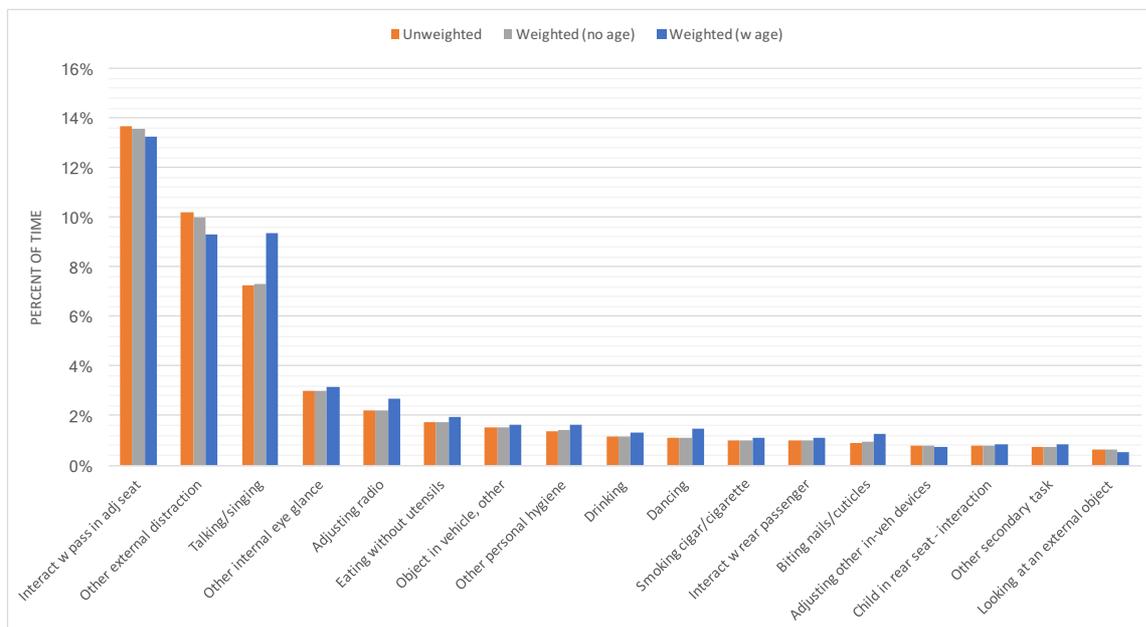
We developed two cell-phone propensity models, one with and one without driver age group. Figure 3 shows the distributions of predicted probability of cell-phone use for baseline events in which the cell-phone was (1) and wasn't (0) used for the two models. For the model without age (left), the mean predicted probability of cell-phone use was 0.0826 for events where the cell phone was not used and 0.0849 for events where the cell phone was used. The corresponding values for the model with age were 0.0796 (no cell) and 0.126 (cell used).



**Figure 3** Propensity distributions by cell-phone use for models without age (left) and with age (right). Note different horizontal scales.

Using the two propensity weights, we first looked at the set of activities that drivers were engaged in when they were not on the cell phone, weighted by propensity. Using the unweighted baseline data, drivers were not engaged in any secondary task (ideal driving) 46.7% of the time. The corresponding propensity-weighted estimates are 47% (no age) and 43.2% (with age). Of the remaining events, Figure 4 shows the

unweighted and propensity-weighted distributions of task involvement for the model without age (gray) and with age (blue).



**Figure 4 Task involvement proportions using unweighted and two propensity-weighted models**

Odds ratios and confidence intervals were computed using logistic regression with no covariates. The results for the unweighted comparison to model driving, the unweighted comparison to task absent, and the two weighted estimates are shown in Table 1. Unweighted and weighted (with age) odds ratio estimates are also included for the cell-phone hand-held talking only task, for comparison.

**Table 1 Simple odds ratio (OR) estimates for crash risk associated with all cell-phone use using different reference groups and cell-phone talk only using unweighted and weighted (with age)**

Reference Group	OR Estimate	95% Confidence Interval
All cell; Unweighted model driving	3.56	2.87-4.40
All cell; Unweighted task absent	2.38	1.97-2.86
All cell; Propensity weighted (no age)	2.45	1.80-3.39
All cell; Propensity weighted (with age)	1.98	1.48-2.70
Cell-phone HH talking only (unweighted)	1.29	0.89-1.81
Cell-phone HH talking only (weighted with age)	1.04	0.68-1.56

## DISCUSSION

A great deal of research has looked at the increase in crash risk associated with cell phone use while driving. This has led to legislation in many states and countries, but large hoped-for reductions in crashes (especially fatal crashes) have not been realized so far. One possible reason for this is that the estimates of crash odds ratios for cell-phone use are based on comparisons to idealized driving that is not achieved even

when drivers are motivated not to use a cell phone while driving. In other words, drivers may replace cell-phone use with other secondary tasks that have similar risk profiles and thus not achieve the expected safety gains.

In this and previous work (e.g., Klauer et al., 2010), ORs using no secondary tasks or other forms of ideal driving are generally higher than those using “task absent” reference groups. We found that in the unweighted analysis, the confidence intervals of the two reference comparisons did not overlap. This is not surprising given that model driving is generally “safe” driving (i.e., attentive, sober).

The propensity-weighted models produced some interesting patterns. In particular, without age, we could not predict the situations under which drivers choose to use the cell phone. This conflicts with other published results, including one by the first author (e.g., Flannagan, Bao & Klinich, 2012), that showed evidence of self-limiting of cell-phone use based on context. If drivers were strongly context-sensitive in their cell-phone use, the context-only propensity model should have done a better job of differentiating events with and without cell-phone use. Instead, the best predictor of cell-phone use was age, suggesting that the biggest contributor is the driver, not the situation.

In keeping with the poor differentiation performance of the no-age-group propensity model, the results of task involvement and ORs using weights from that model look very similar to unweighted results. However, when age is included, some tasks become more likely to occur (in cell-phone-likely situations) including talking/singing, dancing, and adjusting the radio. In addition, the point estimate of crash OR for cell-phone use is lowest using this model. Also, the estimated OR associated with hand-held cell-phone talking only, went down from 1.29 to 1.04 (both not significantly different from 1).

If age is the best predictor of cell-phone use and the largest contributor to cell-phone related risk, it may be necessary to think about the problem differently. Young drivers have long been shown to be riskier than other drivers (Massie, Campbell & Williams, 1995), but cell phones have only been ubiquitous in driving for a decade. Moreover, using SHRP2 data, Guo et al. (2016) show that cell-phone associated crash risk was different for different age groups. Older drivers exhibited the most elevated crash OR for cell-phone use but rarely use the cell phone. Drivers from 16-29 also had higher ORs than middle-aged drivers but use the phone at higher rates. In the SHRP2 study, young drivers are overrepresented in the sample (relative to the population), are overrepresented in crashes (relative to other age groups), and are overrepresented in cell-phone use (relative to other age groups). Even in other studies, such as those using case-crossover designs and crash data, drivers under 29 make up a large portion of the sample ((e.g., 48% in McEvoy, et al., 2005). Thus, some portion of the estimated crash risk may be “borrowed” from risk specific to younger drivers.

It is important to note that although the risks associated with cell-phone use may have been overestimated in many studies (and in the popular press), we do observe a significant estimated crash OR of 1.98 for all cell-phone use in the age-included propensity-weighted model. Given the cell-phone talking-only estimate of 1.04, the all-cell-phone-use risk must be associated with non-talking (or hands-free) cell-phone uses. Although the overrepresentation of young people in SHRP2 may still inflate the OR somewhat, we do not claim that there is no risk or cause for concern. Instead, we have tried to develop a more appropriate estimate of the potential effect of removing cell-phones from the driving population by comparing their use to likely alternative behaviours.

This work could be extended in a number of ways. First, while we did not observe evidence of context-sensitive cell-phone use, it may be that young drivers have not developed this sensitivity while older drivers have. A follow-on study could develop age-group-specific propensity models, which we did not. Another improvement would be to reweight the drivers in SHRP2 to be better representative of the driving population. Finally, repeating this analysis on other NDS datasets such as UDrive would lend further insight into the factors that influence drivers' decision to use the cell phone when driving and improve estimates of crash ORs from cell phone use (and other distractions).

Although the SHRP2 study is large, the number of crashes, especially relatively serious crashes, is still very small. In addition, the study population overrepresents younger and older drivers (relative to the U.S. driver population in general) and relied on self-motivated volunteers. Thus, conclusions from SHRP2 may not fully generalize to the U.S. driver population. Moreover, since the study was conducted in the U.S., results may not fully generalize to the driver population in other countries.

## REFERENCES

- Carsten, O., Hibberd, D., Bärgerman, J., Kovaceva, J., Pereira Cocron, M.S., Dotzauer, M., Utesch, F., Zhang, M., Stemmler, E., Guyonvarch, L., Sagberg, F., Forcolin, F. (2017) UDRIVE deliverable 43.1, Driver Distraction and Inattention, of the EU FP7 Project UDRIVE ([www.udrive.eu](http://www.udrive.eu))
- Dingus, T. A., Guo, F., Lee, S., Antin, J. F., Perez, M., Buchanan-King, M., & Hankey, J. (2016). Driver crash risk factors and prevalence evaluation using naturalistic driving data. *Proceedings of the National Academy of Sciences*, 113(10), 2636-2641.
- Flannagan, C., Bao, S, and Klinich, K. (2012). Driver Distraction from Cell Phone Use and Potential for Self-Limiting Behavior. Report No. UMTRI-2012-34. <http://hdl.handle.net/2027.42/108381>
- Freedman, D. A., & Berk, R. A. (2008). Weighting regressions by propensity scores. *Evaluation Review*, 32(4), 392-409.
- Guo, F., Klauer, S. G., Fang, Y., Hankey, J. M., Antin, J. F., Perez, M. A., ... & Dingus, T. A. (2016). The effects of age on crash risk associated with driver distraction. *International Journal of Epidemiology*, 46(1), 258-265.
- Hankey, J. M., Perez, M. A., & McClafferty, J. A. (2016). Description of the SHRP2 Naturalistic Database and the Crash Near-Crash and Baseline Data Sets: Task Report. Blacksburg.
- Insurance Institute for Highway Safety (2014). Special Issue: Distracted Driving, *Status Report*, October 24, 2014.
- Klauer, S. G., Guo, F., Sudweeks, J., & Dingus, T. A. (2010). An analysis of driver inattention using a case-crossover approach on 100-car data (No. HS-811 334).
- Massie, D. L., Campbell, K. L., & Williams, A. F. (1995). Traffic accident involvement rates by driver age and gender. *Accident Analysis & Prevention*, 27(1), 73-87.
- Månsson, R., Joffe, M. M., Sun, W., & Hennessy, S. (2007). On the estimation and use of propensity scores in case-control and case-cohort studies. *American Journal of Epidemiology*, 166(3), 332-339.
- McEvoy, S. P., Stevenson, M. R., McCartt, A. T., Woodward, M., Haworth, C., Palamara, P., & Cercarelli, R. (2005). Role of mobile phones in motor vehicle crashes resulting in hospital attendance: a case-crossover study. *Bmj*, 331(7514), 428.