Drowsy Driving Increases Severity of Safety-Critical Events and Is Decreased by Cell Phone Conversation

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Abstract

A recent study found that drowsy driving prevalence in U.S. national crash databases is substantially higher than previously estimated, especially for fatal crashes. The aims of the current study are to merge this result with a new estimate of the prevalence and odds ratio (OR) of drowsy driving in the 100-Car naturalistic driving study (NDS), and investigate interactions with secondary tasks, particularly cell phone conversation. A 2010 NDS study matched baseline video clips to crash/near-crash video clips for driver demographics, time of day, and GPS location. Using that matched baseline to remove bias from those variables, the current study estimates the drowsy driving OR for crashes to be 63, substantially higher than previous estimates. In addition, observable moderate to severe drowsiness causes an estimated 20% of all crashes, while non-observable microsleeps likely elevate that percentage. A logistic regression analysis on the 100-Car data found no interaction between drowsy driving and secondary tasks as a whole. However, the moderately-difficult task group (which includes cell phone conversation) reduced the drowsy driving crash/near-crash OR, as did cell phone conversation alone. These new NDS analyses provide preliminary evidence that curtailing drowsy driving will reduce more crashes than curtailing secondary tasks while driving.

Introduction[1]

The study is divided into four parts. Part 1 presents and re-analyzes previous data on the prevalence of drowsiness[2] prior to crashes and other safety-related events. Part 2 estimates the relative risk of crashing from drowsiness by comparing the odds of drowsiness during crashes to the odds of drowsiness during baseline driving with no safety-critical event. It provides new analyses of drowsy driving data in naturalistic driving studies (NDS) in cars using standard epidemiological methods (Young 2013). Part 3 studies the interaction of drowsiness and secondary task groups of three difficulty levels with drowsy crashes/near-crashes. Part 4 analyzes the interaction of cell phone conversation with drowsy crashes/near-crashes.

[1] *Abbreviations and symbols:* CI = 95% Confidence Interval; CNC = Crash/Near-Crash; FARS = Fatal Accident Reporting System; GES = General Estimates System; GPS = Global Positioning System; NASS = National Automotive Sampling System; CDS = Crashworthiness Data System; NHTSA = National Highway Traffic and Safety Administration; NDS = Naturalistic Driving Study; OR = Odds Ratio; PAR% = Population Attributable Risk %; PPF% = Population Prevented Fraction %; P_e% = Percentage of Exposed Controls; Talk = cell phone talk/speak (i.e., conversation); VTTI = Virginia Tech Transportation Institute.

[2] *Drowsy* is used here as a general term referring to a driver being reported as drowsy, sleepy, asleep, or fatigued. Although there is a long history of theoretical distinctions among these terms, *drowsy* is used here in the operational sense employed in police reports, national crash databases, or naturalistic driving databases. In the most fundamental sense, *drowsy* is a brain state during which information processing is reduced in efficiency, thereby increasing crash risk. At the extreme of reduced efficiency (falling fully asleep at the wheel), a crash is a near certainty within seconds.

Part 1: Drowsiness Prevalence in Crashes

1.1 European Studies

Several European studies estimated drowsiness prevalence in crashes. Anselm and Hell (2002) did a retrospective analysis of 204 fatal crashes on Bavarian highways in 1991, and found that 24% were caused by the driver falling asleep. Horne and Reyner (1995) conducted a survey of police reports in several locations in England and found that 16% of 3,706 vehicle crashes were "sleep-related," in 23% of the total death and serious injury crashes, and in 15% of the total minor and no injury crashes. Horne and Reyner (1995), in a second study in the same paper, found that 23% of 317 motorway crashes were "sleep-related." However, this percentage may be higher than usual (and possibly more valid) because the police had been briefed by the investigators beforehand about sleep-related crashes, and supplied with a structured driver interview checklist. Evers and Auerbach (2005) found in a 3-month survey in Germany in 2003 that truck driver fatigue caused 19% of 219 truck crashes. (It should be noted, however, that truck drivers travel much longer times than do automobile drivers so these latter results are not necessarily comparable to the current results, which are based on passenger vehicles.)

1.2 U.S. Studies

Knipling and Wang (1994) found a driver drowsiness prevalence of 3.6% of fatal motor vehicle crashes from 1989-1993, using the Fatal Accident Reporting System[3] (FARS) national crash database. Also using FARS, NHTSA (2011) found an average drowsiness prevalence of 2.2% in fatal motor vehicle crashes in 2009. However, the FARS database does not distinguish between fatal crashes in which the driver's level of attention was unknown vs. not drowsy, so many "unknown" fatalities may have involved a drowsy driver.

Masten et al. (2006) developed a regression model to classify a fatally injured driver as drowsy or not drowsy using variables other than the drowsy variable, allowing for prediction of drowsiness even if it had been coded as "unknown." Applying this model to the 2001-2003 FARS database, and based on a conservative criterion of at least 0.7 probability for classifying a driver as drowsy, 9.5% of daytime fatal crashes, and 23.6% of nighttime fatal crashes (or 15.5% of all fatal crashes) involved a drowsy driver. Based on a less conservative criterion of at least 0.5 probability for correctly classifying a fatally injured driver as drowsy, 21.9% of daytime fatal crashes, and 41.9% of nighttime fatal crashes (or 32.5% of all fatal crashes) involved a drowsy driver.

Tefft (2012) analyzed the National Automotive Sampling System Crashworthiness Data System (NASS CDS) database,[4] which, unlike FARS, does distinguish between unknown vs. not drowsy. In the data examined, he found the drowsiness variable was coded as "unknown" for 73% of drivers involved in a fatal crash and 42.4% of drivers involved in a non-fatal crash, suggesting that the drowsiness prevalence estimates for fatal crashes are differentially biased low in the U.S. national

[3] Now named the Fatal Analysis Reporting System.
[4] The NASS CDS is from a representative sample of 47,597 police-reported crashes in the United States from 1999 through 2008 in which a passenger vehicle was towed from the scene.

databases. Tefft (2012) used the method of multiple imputation (Rubin 1987; White et al. 2011) to estimate drowsiness prevalence in crashes when the cause was unknown.

Tefft (2012: Table 2, line 10) found that 16.0% of drivers killed in a crash in the U.S. from 1999-2008 were drowsy.[5] This prevalence estimate is consistent with Masten et al.'s (2006) prevalence estimate of 15.5% of all fatal crashes using their conservative criterion. Furthermore, there was a higher percentage of drowsy drivers in crashes of higher severity (Figure 1),[6] consistent with Horne and Reyner's (1995) European data.

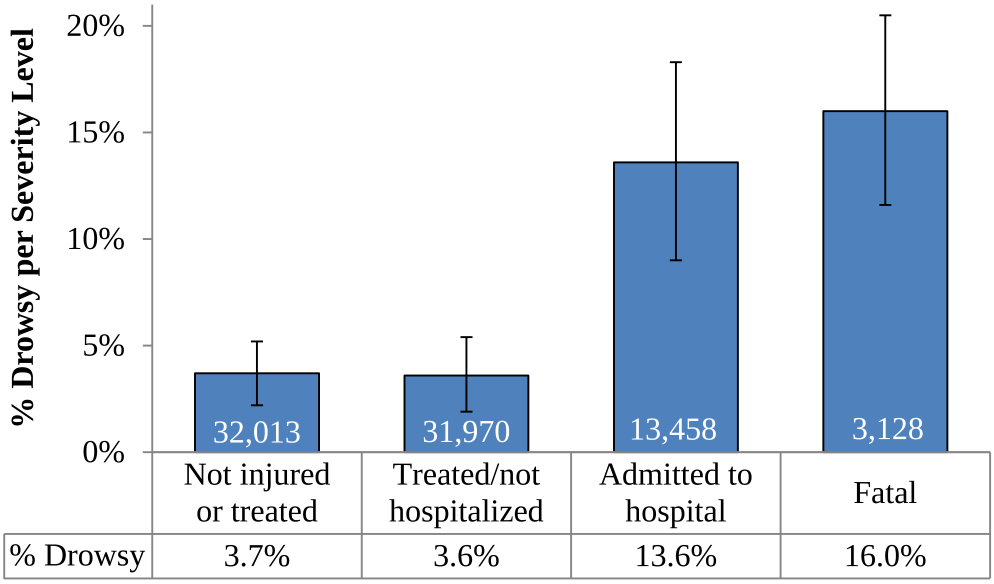

Figure 1 Prevalence estimates of driver drowsiness by number of crashes at four severity levels for the driver. The white number at the bottom of each bar is the count of crashes at that severity level. U.S. representative data from Tefft (2012: Table 2, lines 7-10), driver level data. Error bars are 95% confidence intervals.

1.2.1 100-Car NDS

In the 100-Car study, video analysts assessed the level of drowsiness during a 30-second video clip prior to the trigger[7] for a crash or near-crash event (Klauer et al. 2006: pp.

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[5] This is driver-level drowsiness and driver-level injury severity, where the driver was both drowsy and the one who died, rather than a pedestrian, passenger or occupant of another vehicle. This driver-level estimate (vs. crash-level or vehicle-level where any involved person or vehicle is included in the estimate) was judged in the current paper to be the level most consistent with the level in NDS studies, although this decision can be debated. NDS studies can only estimate whether or not the subject driver was drowsy; they have no data on whether other drivers involved in a safety-critical event were drowsy or not. The crash-level drowsiness prevalence in fatalities (which adds deaths caused to others by a drowsy driver) was 16.5%, only slightly higher.

[6] The total % drowsy drivers (combined across severity strata) is not shown, because analysis of proportions using the "prtesti" command in the statistical package Stata/IC 12.1 found statistically significant increases (heterogeneity) between "admitted to hospital" and "fatal," and between the two lower severity levels and each of the two higher severity levels.

[7] *Trigger* examples are a driver braking at 0.76 g longitudinal deceleration or 0.8 g lateral acceleration (Klauer et al. 2006: p. xvii).

xiv, 165, 176), and during 6-second baseline video clips.[8] Video analysts classified the level of drowsiness using Wierwille and Ellsworth's (1994) definitions:

> A driver who is moderately drowsy will exhibit slack musculature in the facial muscles and limited overall body movement as well as a noticeable reduction in eye scanning behaviors. A severely drowsy driver will exhibit all the above behaviors as well as extended eyelid closures and will have difficulties keeping his/her head in a lifted position.

A driver was classified as drowsy only if moderate or severe drowsiness was observed as per these definitions; all other drivers were classified as non-drowsy. Despite the severe limitation of using such short time spans to assess drowsiness (Anund et al. 2013), the drowsiness estimates from video observations of a driver's face and head prior to a crash are arguably more accurate, even with drowsiness misclassification errors, than the post-crash reconstructions in national crash databases.

Figure 2 shows the percentage of drivers in the "100-Car" NDS who were drowsy as a function of the severity level of their safety-related event.[9] The critical incident data are from Dingus et al. (2006: Table 2.7), and the near-crash and crash data from Guo and Hankey (2009: Table 7).[10]

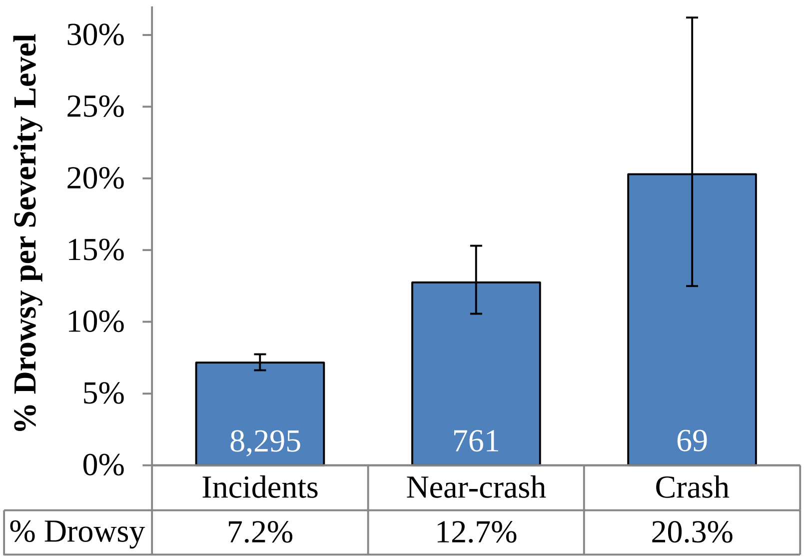

Figure 2 **Prevalence of drowsiness observed in 30-second video clips just before incidents, near-crashes, and crashes. The white number at the bottom of each bar is the total number of valid video clips for that severity level (data from the 100-Car study). Errors bars are 95% confidence intervals.**

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[8] The method of assessing drowsiness in the baseline video clips was not explicitly stated by Klauer et al. (2006), but presumably used the same behavioral criteria. The baseline video clips did not have triggers, and so were randomly selected. The 6-second duration would lead to more drowsiness misclassifications than with 30-second event clips (Anund et al. 2013).

[9] *Safety-related events* were defined by Klauer et al. (2006: p. 2) as: *crash* - any physical contact between the subject vehicle and another vehicle, fixed object, pedestrian, cyclist, animal, etc., as assessed by either the lateral or longitudinal accelerometers; *near-crash* - a conflict situation requiring a rapid, severe, evasive maneuver to avoid a crash; *incident* - a conflict requiring an evasive maneuver, but of lesser magnitude than a near-crash.

[10] The drowsiness prevalence was not combined across severity levels because it is heterogeneous, as found using the analysis of proportions "prtesti" command in Stata/IC 12.1 l.

Figure 2 shows that the 100-Car data has the same higher percentage of drowsy drivers in events of higher severity as do the more serious crashes in the non-NDS studies.[11]

1.3 Drowsiness Increases Crash Severity

Table 1 is a case-control[12] analysis of the driver-level data in three of the studies mentioned above to prove that drowsiness causes increased severity. Table 1 demonstrates that the Drowsy-exposed odds for the more serious events are greater than the Drowsy-exposed odds in the less serious events in all three studies.[13]

Table 1 Drowsiness causes crashes to be more serious. Red means an OR > 1 with $p < 0.05$

A. Horne & Reyner (1995)	Drowsy	Not Drowsy	Total	Prevalence	Odds
Death/Serious Injury	139	477	616	22.6%	0.291
Minor/No Injury	467	2,704	3,171	14.7%	0.173
Total	606	3,182	3,788	16.0%	
OR (95% CI)	**1.69**	(1.35 to 2.10), p = 1.2E-6			
B. Tefft (2012)	**Drowsy**	**Not Drowsy**	**Total**	**Prevalence**	**Odds**
Death/Serious Injury	2,331	14,255	16,586	14.1%	0.164
Minor/No Injury	2,335	61,648	63,983	3.7%	0.038
Total	4,666	75,903	80,569	5.8%	
OR (95% CI)	**4.32**	(2.93 to 6.18), p < 0.001			
C. 100-Car Study	**Drowsy**	**Not Drowsy**	**Total**	**Prevalence**	**Odds**
Crash/Near-Crash	111	719	830	13.3%	0.154
Incidents	597	7,698	8,295	7.2%	0.078
Total	708	8,417	9,125	7.8%	
OR (95% CI)	**1.99**	(1.59 to 2.48), p = 3.1E-10			

For example, the yellow cells in Table 1B shows that the exposure-odds in favor of drowsiness in a minor-injury or no-injury police-reported crash are 0.038, but the exposure-odds in favor of drowsiness in a death or serious-injury crash are 0.164, a four-fold increase in this nationally representative study.[14]

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[11] The 100-Car study had no fatalities, and of the 69 crashes with usable video data in the 100-Car study, only 5 (7%) were airbag and/or injury crashes, 7 (10%) were property damage crashes, 21 (30%) were minor property damage, and the majority 36 (52%) were low *g* or tire strikes (Dingus et al. 2006: Table RO.4, p. xxxvii).

[12] See, for example, Portha (2008: 31) for a definition of a case-control study, and Young (2013) for a description of the case-control method applied to crash risk estimation.

[13] The NHTSA (2011) report provided only crash-level and not driver-level data stratified by severity level and drowsiness prevalence. It is not included in Table 1 because it does not match the level of the driver-level data in Tables 1B and 1C.

[14] The OR confidence band in Table 1B was not calculated with the standard epidemiological method (Young 2013) as in Tables 1A and 1C, because the imputation method of Tefft (2012) used a stratified sample, with clustering and missing values imputed, which requires logistic regression methods on the raw data to estimate confidence bands. Tefft (personal communication) ran such a regression of driver injury severity on his data (dichotomized into two severity levels as per Tables 1A and 1C), and found an OR of 4.4, in agreement with the 4.32 found here. Therefore his confidence bands are those shown in Table 1B for the OR estimate given here.

Table 1C shows the same effect, despite the fact that the drivers represented only one small area of the country (Northern Virginia/Washington, DC metro area), and there were no fatalities and few serious crashes.[11] The Horne and Reyner (1995) European study in Table 1A shows the same drowsiness effect as the other two studies.

Note also that even the lowest severity events in all three studies in Table 1 have a higher drowsiness prevalence than the NHTSA (2011) 2.2% estimate in death/injury crashes, indicating the NHTSA (2011) figure is biased low (which they acknowledge).[15] Even with this bias, the NHTSA study still shows that drowsiness causes increased crash severity, because drowsiness prevalence in property-damage-only crashes was only 1.1% but it was 2.2% in death/injury crashes.

1.4 Prevalence Is Not Cause

The science of epidemiology cautions that cause cannot be determined from prevalence alone; a comparison to an appropriate baseline control is required, from which a relative risk metric can be estimated. For example, consider the 20% drowsiness prevalence in 100-Car study crashes (Figure 2). If the baseline drowsiness prevalence is higher than 20%, then drowsiness has a “protective” effect and prevents crashes. If the baseline prevalence is near 20%, then drowsiness has no causal effect on crashes; that is, drowsiness and crashes are independent. If the baseline prevalence is lower than 20%, then drowsiness causes crashes. In short, prevalence alone is insufficient to assign a causal role to a risk factor; there must be a comparison to an appropriate baseline.

Part 2: Drowsiness in Cases vs. Controls in Naturalistic Driving Studies

Epidemiological methods improve upon the prevalence methods in Part 1 by comparing the prevalence (or odds) of a risk factor during cases (e.g. safety-critical events), to the prevalence (or odds) of that risk factor during controls (baseline driving). Epidemiological methods can therefore infer possible causes of crashes, assuming bias is removed, which prevalence methods cannot (Rothman 2012). Part 2 reviews prior results from three case-control[12] estimates of the relative risk of drowsiness.

2.1 Prior Studies

2.1.1 Klauer et al. (2006)

This study combined crashes and near-crashes into a single case group, and compared the odds of drowsiness in case video clips to the odds of drowsiness in 5,000 randomly sampled baseline video clips[16,17] to estimate a drowsy OR of 4.2. However, Klauer et al. (2006) used different fault conditions between the exposed and unexposed cases, thus inducing an upward bias in their OR estimates (Young 2013). They also used “attentive”[18] rather than “not drowsy” in the unexposed condition, also upwardly

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[15] NHTSA (2011, p. 3): “Under-reporting of the occurrence of drowsy driving is most likely due to lack of firm evidence of such involvement since investigation is done after the crash; drivers unaware of the role that drowsiness played in the crash; drivers reluctant to disclose that they fell asleep or were tired; and fatality of the involved driver.”

[16] Klauer et al. (2006: 34) estimated a 4% prevalence for moderate to severe drowsiness in a sample of 19,827 video clips from randomly selected baseline driving video clips with no safety-relevant event.

[17] The baseline video clips in the Klauer et al. (2006) study were only partially matched to the case video clips by driver and vehicle, and were not matched for any other variable.

[18] *Attentive* as used by Klauer et al. (2006) means that the case or baseline video clip had no observable secondary task or inattentive state (except for driving-related inattention such as glances to mirrors).

biasing prevalence and population attributable risk percent (PAR%) estimates (Young 2013). Finally, their baseline clips were not matched to case clips by driver, GPS location, junction, traffic conditions, time of day, weekday/weekend, etc., which could have unknown biasing effects on drowsiness OR estimates.

2.1.2 Guo and Hankey (2009)

This study selected baseline video samples that were random as did Klauer et al. (2006), but the number of baseline samples selected for each vehicle was proportional to its total hours driven at more than 5 mph. Guo and Hankey (2009) used all cases regardless of fault, along with the standard epidemiological method for case-control studies of comparing drowsy to not-drowsy driving, thus avoiding some of the biases in the Klauer et al. (2006) study. Guo and Hankey (2008: their Table 8) found a drowsy OR of 4.08 for near-crashes and 7.12 for crashes,[10,17] but again used baseline clips that were unmatched to case clips in driver and environmental variables.

2.1.3 Klauer et al. (2010)

This study matched controls to cases more closely than did the two studies above.[19] It estimated a drowsy OR of 38.7 for combined crashes/near-crashes using a regression method in a case-control design.[20] It did not show the data from which this estimate was made, but the data in Table 2 estimated the same OR.[21]

Table 2 100-Car data replicating the Drowsy OR estimate by Klauer et al. (2010). Red means an OR > 1 with *p* < 0.05

	Drowsy	Not Drowsy	Total	Prevalence
Crash/Near-Crash	111	719	830	13.4%
Matched Baseline	27	6,643	6,670	0.40%
OR (95% CI)	**38.0**	(24.8 to 58.2), p = 1.9E-151		
PAR% (95% CI)	**13.0%**	(10.7% to 15.4%)		

The case data (first row) is for all crashes/near-crashes in the 100-Car study regardless of driver fault (Guo and Hankey, 2009: Table 7). The control data (second row) is the matched[19] baseline data from Klauer et al. (2010: Appendix C) for the total of all observed baseline clips summed across task conditions. These data estimate a drowsy OR of 38, an order of magnitude increase from the earlier NDS estimates. The difference could not have arisen from a difference in the crash/near-crash events, because all three studies used the identical event database. The cause of the OR increase must have been the improved matches of the control clips to the case clips in the later study,[19] leading to a decrease in baseline drowsiness odds from at least one of the

[19] Case and control clips were matched for the same driver (hence all demographic and genetic variables), GPS location (within 100 meters or relation to junction), time-of-day (within 2 hours), and weekday/weekend.

[20] This study was not a case-crossover design as it claimed to be, because it did not analyze only the "discordant" pairs; namely, those with drowsiness in a case but not a control, or with drowsiness in a control but not a case, as required by a case-crossover analysis method.

[21] Klauer et al. (2010) did not present the 2x2 matrix data from which their drowsy OR estimate of 38.7 was made, and the current analysis could not reproduce it from the tabulated data in their Appendix C, but the data in Table 1 were found to reasonably approximate their OR estimate.

matching variables,[19] which is in line with Klauer et al. (2010)'s general explanation.[22]

2.2 New Analysis of NDS Data

A new analysis re-calculated the drowsy driving OR and PAR% from NDS data by applying standard epidemiological methods (Young 2013) to that data. The goal was to stratify the results in Table 2 by crash severity level, and at the same time remove possible bias present in previous NDS analysis methods (Young 2013).

2.2.1 Method

The drowsy OR in the 100-Car NDS was re-estimated by comparing the odds of observing drowsiness in "case" video clips to the odds of observing drowsiness in matched[23] "control" video clips. Crashes, near-crashes, and critical incidents were stratified and separately analyzed rather than combining them, because the severity levels had heterogeneous odds and thus should not be merged.[10] The incident[9] data were tabulated from Dingus et al. (2006: Appendix C). The crash and near-crash data were taken from Guo and Hankey (2009: Table 7). All cases were analyzed regardless of driver fault, avoiding possible bias in the assignment of fault (Young 2013). The baseline data used were the tabulated data in Klauer et al. (2010: Appendix C), which were drawn from non-eventful baseline driving, but had been sampled to match the GPS location and traffic conditions of crashes and near-crashes. A standard epidemiological method of case-control analysis was then applied, avoiding errors in prevalence and PAR% estimates otherwise induced by using "no distraction," or "attentive," for the unexposed condition, rather than "not drowsy" (Young 2013).

2.2.2 Results

Table 3 gives the data (left two columns) and drowsy OR estimates (middle three columns) stratified by event severity. The matched 100-Car baseline data is in row 1. Subsequent rows give the counts of drowsy and non-drowsy video clips for incidents, near-crashes, and crashes,[9] regardless of subject driver fault. The last three columns estimate the PAR% for drowsy driving by event severity, also referenced against the row 1 baseline.

[22] Klauer et al. (2010) hypothesized that the reduced baseline drowsiness in the matched controls was specifically because of increased roadway/traffic demands there. To test this hypothesis, the current study re-analyzed the 100-Car data traffic and location variables in the Klauer et al. (2006) unmatched baseline database (VTTI 2010). These additional analyses suggest that the most influential factor in depressing the drowsy OR in the Klauer et al. (2006) study may have been insufficient control for time of day in the control clips vs. the case clips Although there were some reductions in roadway and traffic demands in the unmatched baselines that could have contributed to the increased drowsiness there, these reductions were not large enough to explain the size of the increase in the drowsy driving OR in later vs. earlier naturalistic driving studies.

[23] Klauer et al. (2010) matched the control video clips only to crashes and near-crashes in which they judged the subject driver to be at-fault or partially at-fault.. Klauer et al. (2010) did not match the baselines to the critical incidents. However, "incidents" the same subjects and vehicles as crashes and near-crashes, so there is at least some matching with incidents.

Table 3 **Number of cases and baseline counts for drowsy, OR and PAR% values for incidents, near-crashes and crashes using matched baseline data[17,19] Red means an OR > 1 with $p < 0.05$**

	Drowsy	Not Drowsy	OR	lower CI	upper CI	PAR%	lower CI	upper CI
Baseline	27	6,643	1.0	reference		0.0%	reference	
Incident	594	7,701	**19.0**	12.9	27.9	**6.8%**	6.2%	7.4%
Near-crash	97	664	**35.9**	23.3	55.5	**12.4%**	10.0%	14.8%
Crash	14	55	**62.6**	31.2	125.9	**20.0%**	10.4%	29.5%

Figure 3 plots the drowsy OR and PAR% estimates in Table 3. The graphs show the same upward trend with severity, as do the prevalence estimates in Figures 1 and 2, as expected.

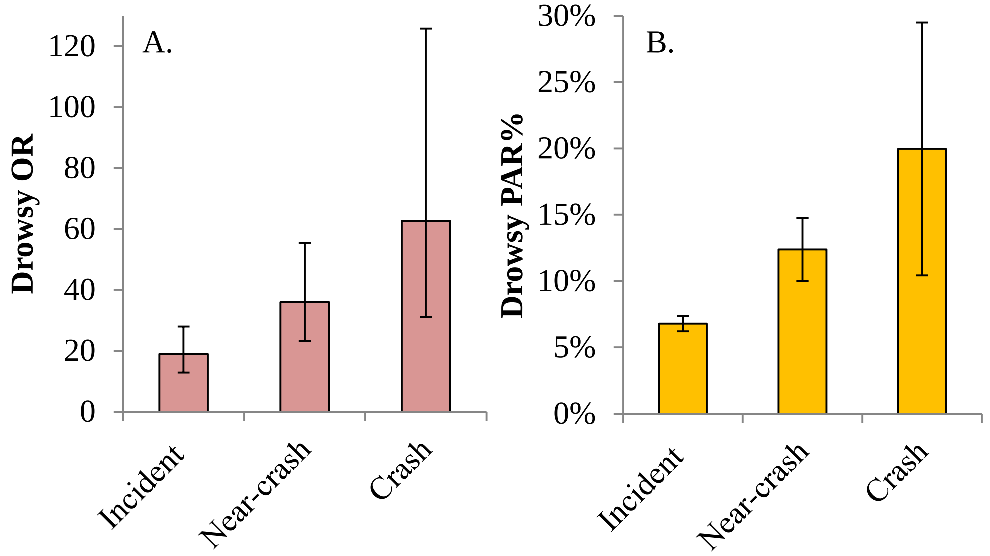

Figure 3 **Drowsy estimates for incidents, near-crashes, and crashes,[9] regardless of fault. Values in Table 3. Error bars are 95% confidence intervals. A. OR estimates. B. PAR% estimates**

2.2.3 Discussion

The crash OR of 62.6 in Table 2 and Figure 3 is substantially higher than any previous drowsy OR estimate in the traffic safety literature. The PAR% value of 20% for crashes means that if drowsiness could be eliminated[24] while driving, then there would be about a 20% reduction in crashes in the general population. The OR and PAR% estimates for crashes and near-crashes are relative to baselines that have been created to match the relationship to junction and other variables associated with crashes and near-crashes, thereby reducing possible bias from confounding by the matched variables.[19]

The reason for the higher crash OR estimate of 62.6 vs. the Klauer et al. (2010) crash/near-crash OR estimate of 38 in Table 1 is because the crash OR is adulterated by

[24] The word *eliminating* and *eliminated* are used in their formal epidemiological sense; e.g. Porta (2008: 10) defines *attributable fraction (population)* as, "With a given outcome, exposure factor, and population, the attributable fraction for the population incidence rate is the proportion by which the incidence rate of the outcome in the entire population would be reduced if exposure was eliminated."

combining it with the 10 times larger number of near-crashes with the lower OR of 35.9 (Table 3). After separating crashes, near-crashes, and incidents into their heterogeneous strata, the drowsiness crash OR increased to 62.6. The crash PAR% of 20% (Table 3 and Figure 3B) was concomitantly increased from the 13% for crashes mixed with near-crashes (Table 2).

The fact that the drowsiness crash PAR% of 20% in Table 3 is almost identical to the drowsiness crash prevalence in Figure 2 of 20.3% provides evidence that virtually every crash with drowsiness in the general population is in fact caused by that drowsiness. That is, drowsiness prevalence in crashes is a good indicator of the absolute magnitude of the attributable risk of drowsiness in the population. That is not the case for other forms of inattention, such as secondary tasks, where the prevalence average of secondary tasks in crashes/near-crashes, after adjustment for bias, is about the same as the prevalence average of secondary tasks in the baseline (Young 2013; also see Part 3 below). Thus, the high drowsiness prevalence in crashes, particularly fatal crashes, is not a random association arising from high drowsiness prevalence in baseline driving; drowsiness is rather a cause of crashes. This new analysis of the 100-Car data has provided epidemiological evidence for a direct causal link between drowsiness and crashes, not just a statistical association (Rothman 2012).

Part 3: Drowsiness and Secondary Task Groups

3.1 Introduction

The first aim in Part 3 is to compare the crash risk of drowsiness to secondary task groups of different difficulty level. The second aim is to determine whether drowsiness and secondary task groups interact. For example, does the performance of secondary tasks reduce drowsiness and therefore decrease crash risk from drowsiness? Alternatively, does crash risk from performing secondary tasks increase if they are performed while drowsy? Part 2 could not answer these questions, because it estimated the drowsy OR independently of whether a concurrent secondary task was being performed or not.

Part 3 also controls for possible confounding from secondary tasks in the drowsy OR estimates in Part 2. For example, the drowsiness crash OR estimate of 62.6 (Table 2 and Figure 3A) could be biased high if drivers performed complex secondary tasks with high crash risk more when drowsy than not drowsy. If so, the apparent high drowsy OR estimate could be biased high by the complex secondary task OR. On the other hand, drowsiness and a concurrent complex task might give rise to a higher crash risk than the sum of the risks, as occurs when drowsiness is combined with alcohol (Iudice et al. 2005; Barrett et al. 2005).

3.2 Method

Part 3 uses the 100-Car tabulated data of Klauer et al. (2010: Appendix C, p. 129), which are reproduced in Appendix Table A1. It gives the counts of the number of crash/near-crash clips observed to contain drowsiness and/or secondary tasks that fall into *simple*, *moderate* or *complex* difficulty level.[25] Crashes and near-crashes are

[25] *Simple*: “none or one button press and/or one glance away from the forward roadway”; *Moderate*: “at most, two glances away from the roadway and/or at most two button presses”; *Complex*: “multiple steps, multiple eyeglances away from the forward roadway, and/or multiple button presses” (Klauer et al. 2006: 25).

combined into one group and not shown separately. The Klauer et al. (2010) data also tabulates baseline driving clip counts for drowsiness and secondary task difficulty groups.[26] These data were used here to examine (10 the relative contribution of drowsy driving and secondary task complexity to relative crash risk, and (2) whether secondary tasks and drowsiness interact, creating confounding effects that need to be controlled for in drowsy OR and PAR% estimates. Logistic regression estimated ORs for secondary task groups and drowsiness, controlling for the influence of each on the other, and for possible interaction effects. The confidence estimates for the 2x2 matrices were all made with exact analysis using the Stata/IC 12.1statistical program.

3.3 Results

3.3.1 Drowsiness has a higher OR and PAR% than secondary task complexity groups

The drowsy OR for crashes and near-crashes, adjusted for the effect of task complexity level, is 54.9 (Table 4). This combined result is lower than the OR for just crashes (62.6, Table 3) because of the dilution of crash risk by near-crash risk (see Section 2.2.3).

Table 4 Results of logistic regression analysis of 100-Car data in Appendix A, controlling for all grouped secondary task risk factors and their interaction with drowsiness. Red means an OR > 1 with *p* < 0.05; grey means an OR near 1 with *p* > 0.05

Task	OR	[95% CI]		P> |z|
Simple	0.95	0.76	1.19	0.6600
Moderate	1.21	0.96	1.54	0.1100
Complex	**2.22**	1.44	3.43	0.0003
Drowsy	**54.9**	32.34	93.08	7.0E-50
Interaction	0.82	0.45	1.50	0.5100
constant	0.07	0.06	0.08	0.0000

Of interest is that the crash/near crash OR for drowsy driving of 54.9 is substantially higher than the adjusted OR for any secondary task group (Table 4). There was also a negligible interaction term between all secondary tasks and drowsiness (Table 4, next to last row). However, individual secondary task groups could still show drowsy interaction effects, even though the average across the task groups did not.

3.3.2 Effect of moderate vs. not moderate task group on drowsy crashes/near-crashes

Table 5 shows that there is an interaction between the Moderate task group and Drowsy in the matched baseline study of Klauer et al. (2010: Appendix C).

- Table 5A shows that the Drowsy OR is 54.7 when not performing a moderate task, near the overall Drowsy OR of 54.9 in Table 4.
- Table 5B shows that the Drowsy OR is 24.4 when performing a moderate task.

This drowsy OR decrease for the Moderate condition is inconclusive because its large confidence range (8.2 to 73.4), which overlaps with the Not Moderate OR estimate. To investigate further, the 2x2 matrix cells in Tables 5A and 5B were

[26] To control for such possible interactions, it would have been preferable to include all cases regardless of fault to avoid possible bias in the assignment of fault (Young 2013), but only at-fault and partially at-fault cases were provided by Klauer (2010: Appendix C).

rearranged to investigate the effect of moderate tasks on drowsiness within the crash/near-crash and baseline databases.

- Table 5C shows that just before a crash/near-crash, the average task in the Moderate task group reduces the odds of a drowsy crash/near-crash by about 1/3 compared to not doing a moderate task (a protective effect).
- Table 5D shows that in baseline driving video clips matched to the crash/near-crash video clips,[17] the average task in the Moderate task group has little effect.

Table 5 **A. Drowsy OR when not doing a moderate task. B. Drowsy OR when doing a moderate task. C. Protective effect of Moderate on drowsiness preceding a crash/near-crash. D. No effect of Moderate on drowsiness during baseline driving. Red means an OR > 1 with *p* < 0.05; grey means an OR near 1 with *p* > 0.05; green means an OR < 1 with *p* < 0.05, a protective effect**

A. Not Moderate	Drowsy	Not Drowsy	Total	Prevalence
Crash/Near-Crash	82	354	436	18.8%
Matched Baseline	22	5,194	5,216	0.4%
Total	104	5,548	5,652	
OR (95% CI)	**54.7**	(33.3 to 88.6), *p* = 1.1E-165		
PAR% (95% CI)	18.5%	(14.8% to 22.1%)		
B. Moderate	Drowsy	Not Drowsy	Total	Prevalence
Crash/Near-Crash	10	119	129	7.8%
Matched Baseline	5	1,449	1,454	0.3%
Total	15	1,568	1,583	
OR (95% CI)	**24.4**	(8.2 to 72.4), *p* = 8.8E-17		
PAR% (95% CI)	5.5%	(2.8% to 8.2%)		
C. Crash/Near-Crash	Moderate	Not Moderate	Total	Prevalence
Drowsy	10	82	92	10.9%
Not Drowsy	119	354	473	25.2%
Total	129	436	565	
OR (95% CI)	***0.36***	*(0.18 to 0.72), p = 0.0028*		
PPF% (95% CI)	***16.0%***	*(5.5% to 26.6%)*		
D. Matched Baseline	Moderate	Not Moderate	Total	Prevalence
Drowsy	5	22	27	18.5%
Not Drowsy	1,449	5,194	6,643	21.8%
Total	1454	5,216	6,670	
OR (95% CI)	0.81	(0.31 to 2.16), *p* = 0.68		
PPF% (95% CI)	4.0%	(-14.7% to 22.8%)		

3.4 Discussion

These results show that Moderate secondary tasks (as a group) reduce the odds of drowsiness causing a crash/near-crash in the 100-Car event database. However, it is possible that some individual tasks in the Moderate task group may be contributing to this interaction with drowsiness and others not; that is, the moderate task group is heterogeneous. That question could not be pursued with the secondary task data in Klauer et al. (2010), because it cross tabulated the data only in groups (simple, moderate, and complex), and not individually, as in the unmatched databases used in the earlier NDS studies (VTTI 2010).

Figure 4 shows that, in particular, hand-held cell phone conversation formed the largest single task prevalence (9.2%) among in the moderate task group's baseline data, suggesting it may have been the strongest contributor to this protective effect. Therefore, the interaction between cell phone conversation and drowsiness is examined using the unmatched databases (VTTI 2010), even though the Drowsy OR of 4.2 (Section 2.1.1) is much smaller than when using a matched baseline (62.6, Table 3).

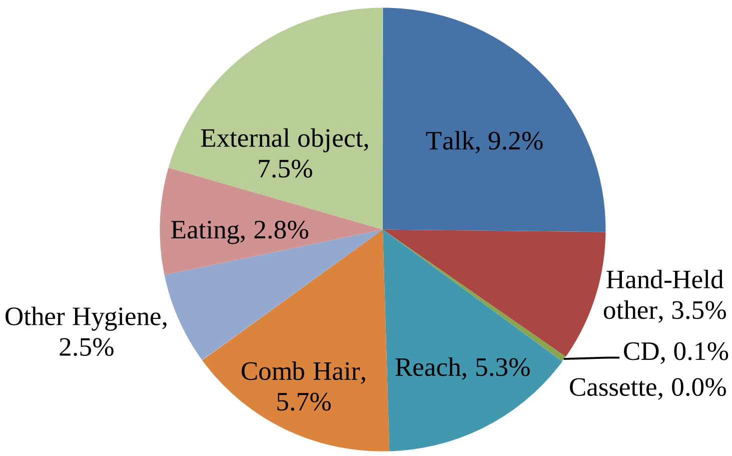

Figure 4 **Prevalence estimates for moderate secondary tasks in the matched baseline 100-Car database (based on Klauer et al. 2010: Figure 15)**

Part 4: Interaction of Cell Phone Conversation with Drowsy Driving

4.1 Introduction

The aim of Part 4 is to analyze an individual secondary task within the moderate group. The auditory-vocal task of hand-held cell phone conversation was chosen for a deeper analysis because the interaction of drowsiness with auditory-vocal tasks has been investigated in five simulator studies. These studies find that the attentional effects of cognitive load from auditory-vocal tasks during drowsy driving reduce drowsiness and improve driving performance:

- Drory (1985) studied 60 professional truck drivers in a driving task from 12 PM to 7 AM with rest breaks every 15 minutes. Their driving performance (measured by brake reaction time, steering reversals, tracking error, and the response time in a choice RT test) was significantly better when a secondary task involving voice communication was added.
- Verwey and Zaidel (1999) found fewer run-off-road incidents and crashes when drivers played voice-interactive games under drowsiness-inducing road and environmental conditions.

- Takayama and Nass (2008) found that auditory-vocal interaction with a language learning system improved the primary driving performance of drowsy drivers, measured with a weighted composite score that included lane excursions, road edge excursions, center line crossings, crashes, and traffic light violations.
- Oron-Gilad et al. (2008) and Gershon et al. (2009) found that an auditory-motor trivia game with verbal questions accessing long-term memory and button presses in a monotonous simulator drive on straight roads with little traffic: (1) improved (i.e. reduced) steering wheel reversal rate compared to “just driving” with no secondary task, (2) stayed in the lane better, (3) improved scores on a sleepiness scale, and (4) improved the ratio of EEG power in the 7-13 Hz alpha band to the 4-7 Hz theta band, indicating improved alertness.
- Atchley and Chan (2011) found that an interactive auditory-vocal task aroused drivers and helped them maintain sustained attention by reducing monotony, resulting in improved driving vigilance and lane keeping.

In real driving in an experimental study on a test track, Jellentrup et al. (2011) validated these simulated driving results by finding that talking on a cell phone helped keep drivers awake during a monotonous drive, and improved alertness as physiologically measured by reduced EEG alpha spindles and shorter blink durations.

In terms of generalizing these data to real driving in a non-experimental setting, Baker et al. (2008) found in a focus group that 6 out of 13 (46%) truck drivers said that they used talking on their Citizens Band (CB) radio as a countermeasure to stay awake when drowsy. This finding may help explain why Olson et al. (2009) found that talking on a CB radio in commercial vehicle drivers gave rise to a significant protective effect (OR = 0.6) for safety-critical roadway events, as did conversation on a hands-free phone (OR = 0.4) (Richard Hanowski, personal communication).

Would individual auditory-vocal secondary tasks also reduce drowsiness in real driving in a non-experimental study with drivers in their own vehicles; that is, in a naturalistic driving study?

4.2 Method

The current study investigated the interaction of cell phone conversation with drowsy driving based on the published 100-Car unmatched databases (VTTI 2010) that were a close match to those used in the Klauer et al. (2006) study. Individual driver-level matched baseline data for individual tasks in Klauer et al. (2010) would be the best to evaluate the interaction of cell phone conversation with drowsiness but this baseline data has not been publicly released, so the VTTI (2010) unmatched baseline data had to be used instead for assessing the interaction of cell phone conversation and drowsiness

4.3 Results

4.3.1 Effect of “Talk” on Drowsy OR and PAR% (unmatched baselines)

Drowsy driving and cell phone conversation (hereafter referred to as “Talk”) interact in specific ways:

- Table 6A shows that drowsy driving when not talking has a crash/near-crash OR of 4.12

- Table 6B shows that Talk reduces the drowsy driving crash/near-crash OR to 2.51, but with a confidence interval that overlaps 1, and overlaps the OR of 4.12 for Not Talk (Table 1A).[27]

This drowsy OR decrease for Talk vs. Not Talk conditions is inconclusive because of overlapping confidence ranges. To investigate further, the 2x2 matrix cells in Tables 6A and 6B were rearranged to investigate the effect of Talk on drowsiness within the crash/near-crash and baseline databases separately.

Table 6 **A. Drowsy OR during Not Talk. B. Drowsy OR during Talk. C. Comparison of drowsy crash/near-crash odds for Not Talk vs. Talk. D. Comparison of drowsy baseline odds for Not Talk vs. Talk. Calculations based on video clip counts in the 100-car databases publicly released by VTTI (2010). Red means an OR > 1 with *p* < 0.05; grey means an OR near 1 with *p* > 0.05; green means an OR < 1 with *p* < 0.05, a protective effect**

A. Not Talk	Drowsy	Not Drowsy	Total	Prevalence
Crash/Near-Crash	115	656	771	14.9%
Unmatched Baseline	746	17,531	18,277	4.1%
Total	861	18,187	19,048	
OR exact (95% CI)	**4.12**	(3.31 to 5.10), *p* = 1.2E-45		
PAR% (95% CI)	11.3%	(8.7% to 13.9%)		
B. Talk	Drowsy	Not Drowsy	Total	Prevalence
Crash/Near-Crash	1	44	45	2.2%
Unmatched Baseline	12	1,327	1,339	0.9%
Total	13	1,371	1,384	
OR exact (95% CI)	2.51	(0.06 to 17.7), *p* = 0.36		
PAR% (95% CI)	1.3%	(-3.0% to 5.7%)		
C. Crash/Near-Crash	Talk	Not Talk	Total	Prevalence
Drowsy	1	115	116	0.9%
Not Drowsy	44	656	700	6.3%
Total	45	771	816	
OR exact (95% CI)	***0.13***	(0.003 to 0.78), *p* = 0.018		
PPF% (95% CI)	*5.5%*	*(2.8% to 8.2%)*		
D. Unmatched Baseline	Talk	Not Talk	Total	Prevalence
Drowsy	12	746	758	1.6%
Not Drowsy	1,327	17,531	18,858	7.0%
Total	1339	18,277	19,616	
OR exact (95% CI)	***0.21***	(0.11 to 0.38), *p* = 5.3E-09		
PPF% (95% CI)	*5.5%*	(4.5% to 6.6%)		

- Table 6C shows that Talk decreases the odds of Drowsy just before a Crash/Near-Crash by about eight times compared to Not Talk. Talk also has a

[27] The confidence interval is large here because drowsy driving during Talk was observed in only 1 crash/near-crash, and cells with low numbers increase the confidence interval.

Population Preventive Fraction % (PPF%) for Drowsy crashes/near-crashes of 5.5%, meaning that if all cell phone conversation were eliminated[24] while driving in automobiles, the number of drowsy crashes/near-crashes would increase by 5.5% in the population as a whole (to the extent that the 100-Car driver sample is representative of the population as a whole)

- Table 6D shows that Talk also decreases the odds of drowsiness in unmatched baseline driving by about 5 times compared to Not Talk.

4.4 Discussion

These data show that cell phone conversation reduces the odds of a crash/near-crash caused by drowsiness. These NDS results provide initial evidence to validate (in real world non-experimental driving) the conclusions of the simulated driving experimental studies cited in Section 4.1. These experimental studies provide driver and driving performance data, as well as EEG data, indicating that auditory-vocal tasks improve the arousal level of drowsy drivers who have low vigilance, leading to driving performance improvements compared to not doing those auditory-vocal tasks.

5. General Discussion

These results provide a new analysis of the 100-car NDS data showing that eliminating[24] drowsy driving will reduce crashes in the population by about 20% (Figure 2). These results are generally consistent with the latest analyses from national crash databases, particularly fatal and major injury crashes requiring hospitalisation.

Evidence is also presented that drowsy driving and secondary tasks as a whole have little interaction when their crash/near-crash odds are compared to baseline driving odds. However, the specific task of cell phone conversation and the task group of moderately difficult tasks reduce drowsy-related crashes/near-crashes. Eliminating these tasks would increase crashes caused by drowsiness. The data also show that curtailing drowsy driving will reduce more crashes/near-crashes than curtailing secondary tasks while driving.

This result might at first appear to conflict with the conclusion suggested by the title of Anderson and Horne's (2013) study, "Driving Drowsy Also Worsens Driver Distraction." The Anderson and Horne study defined *distraction* solely as glances away from the forward roadway, which included glances anywhere outside or inside the vehicle, including driving-related glances to mirrors. Their study of eight subjects in simulated driving found that drowsiness increased glances away from the forward view, and the probability of a lane break (two wheels leaving the roadway). However, the current study that found an improvement in drowsy driving from moderate secondary tasks, including cell phone conversations, defined distraction directly terms of secondary tasks and their relative crash risk.

5.1 Limitations

5.1.1 Sparseness of NDS data

Table 4B shows that there was only 1 crash/near-crash case out of 45 observed in the 100-Car study with Talk by a drowsy driver. Appendix Table A1 (red cells) found 0 complex secondary tasks in the same video clip as drowsiness in the 100-Car study databases, either just before a crash/near-crash, or in the matched baseline video clips.

Therefore, the NDS data currently available are too sparse to conclude with certainty whether talking on a cell phone is a fully effective countermeasure to drowsy driving, or, more likely, only a partially effective countermeasure.

Many complex tasks (and many cell phone conversations) were performed when not drowsy in the 100-Car study. Whether no complex tasks were performed while drowsy because drivers chose not to perform them, or whether drowsy drivers are simply incapable of performing them because they were too drowsy, cannot be determined from the available NDS data in Klauer et al. (2010).

Unlike complex tasks, however, the 100-Car data examined here show that drivers undertake cell phone conversation tasks quite frequently in their baseline driving while drowsy. The fact that drowsiness accompanied only 1 out of 45 cell phone conversations in crash/near-crash cases suggests that cell phone conversations reduce drowsiness, thereby reducing crash risk compared to drowsy driving with no cell phone conversation.

5.1.2 Drowsiness OR underestimates from misclassification errors in NDS studies

Drowsiness misclassification errors were likely in the crash/near-crash event database in Klauer et al. (2006), because of the use of only 30 seconds of observation time in video clips for the drowsiness assessment (Anund et al., 2013). There would almost certainly have been an even higher percentage of misclassification errors in the baseline database, given that there were only 6 seconds of observation time per clip.[9] Assuming the misclassification errors were nondifferential (that is, just as many non-drowsy drivers were classified as drowsy, as drowsy drivers were classified as non-drowsy), they would bias the relative risks “towards the null,” or 1; i.e., lower than the large drowsy OR estimates found here. Therefore, the OR estimates in the current study may be lower than the true population value because of misclassification bias.

5.1.3 Possible overreporting of drowsiness prevalence in NDS studies

Video reduction analysts could have what is termed “observer,” “interviewer” (Young, 2013), or “hindsight bias,” which would tend to cause analysts (knowingly or unknowingly) to classify clips that they knew contained a crash/near-crash as exhibiting drowsiness, and baseline clips that they knew contained no crash/near-crash as not exhibiting drowsiness. This bias would overestimate the drowsy OR and PAR%.

5.1.4 Possible underreporting of drowsiness prevalence in national crash databases

There is a discrepancy between Figures 1 and 2 in the absolute drowsiness prevalences. For example, the 20.3% drowsiness prevalence in the mainly minor crashes in the 100-Car study (Figure 2) was higher than the 13% and 16% drowsiness prevalences in the more serious admitted-to-hospital and fatal crashes (Figure 1). This discrepancy across studies conflicts with the observation that drowsiness increases with severity level, as per Figures 1 and 2. This upward trend predicts that the drowsiness prevalence in fatal crashes (last bar in Figure 1) should be higher than for the less serious crashes and near-crashes in the 100-Car study (last bar in Figure 2). Although these are different studies with different methods and assumptions, and one is local and one is national, the difference is worth examining to see if bias is present in one or both studies. In particular, if the drowsiness prevalences in the 100-Car study in Figure 2 are not biased high (see previous limitation), then the drowsiness prevalence estimates for fatal crashes in Figure 1 are likely biased low, a possibility Tefft (2012: 185) acknowledges.

Tefft (2012) conjectures that one possible reason for a low bias is that his study may particularly underestimate the daytime proportion of crashes that involve a drowsy driver, because daytime drivers may be less aware of their drowsiness than nighttime drivers. Hence, daytime crashes involving drowsiness are more likely than nighttime crashes to be misclassified as involving a cause other than drowsiness. Gastaut and Broughton (1965: 267) found that people had to have been asleep for as long as 2–4 min before half of them acknowledged that they had been asleep. Anund and Akerstedt (2010) and Anund et al. (2013) found weak correspondence of subjective sleepiness and objective measures of drowsiness on an individual level.[28] In addition, drowsiness estimates from trained external observers failed to reliably detect changes in driver sleepiness with less than 5 minutes observation time (Anund et al. 2013). Finally, in the NASS CDS database, if a driver was classified as distracted they could not have also been classified as drowsy because the NASS scale does not permit both classifications for the same crash. Because secondary tasks are several times more prevalent than drowsiness in crashes (as shown by the current study results), then when both occurred together the NASS CDS coding system would underreport drowsiness.

If the matched baseline drowsiness data of Klauer et al (2010) are assumed to be representative of all uneventful driving nationwide[29] and used as a "baseline" in conjunction with the crash data of Tefft (2012), then for fatal crashes, the estimated drowsy OR is calculated as 32, and the PAR% is 11%. This fatal crash drowsy OR estimate is still likely biased low, because it is lower than the non-fatal crash OR of 63 (Table 2 and Figure 3A). This 11% fatal crash PAR% estimate for drowsy driving is also likely biased low, because the NDS data (Table 2, bottom line; Figure 3B) showed that 20% of non-fatal crashes would be eliminated[24] if drowsiness were eliminated, and the drowsiness prevalence is known to increase with severity level (Figures 1 and 2).

5.1.5 Probable underreporting of microsleeps in real-world crash studies

Most crashes occurring during simulator studies do not arise from drowsiness or fatigue in general, but from microsleeps (2-10 seconds). Golz et al. (2012, 2013) found that 98.5% of crashes in a simulator were preceded by a microsleep EEG pattern. Paul et al. (2005) found that during 3-14 sec microsleep episodes, drivers in a simulator showed significantly greater variation in steering and lane position. Boyle et al. (2008) also found significant deterioration in a number of measures of simulator vehicle control during microsleep episodes.

Golz et al. (2012, 2013) classify microsleeps based on EEG (which measures brain waves), and electro-oculograms (which measure eye movements), as well as videos of drivers' faces and heads. One major class of microsleeps, termed *behavioral microsleeps* (Peiris et al. 2006), have clear driver behavioral signs such as those used by Wierwille and Ellsworth (1994) as described earlier, in addition to EEG signs. Another major class of microsleeps, termed *EEG microsleeps* (Peiris et al. 2006), cannot be detected using driver eye, face, or head observation; e.g., drivers may simply exhibit

[28] A subjective perception of drowsiness may increase the prevalence of talking on a cell phone (as well as other secondary tasks such as singing, listening to radio, etc.) specifically to reduce drowsiness. However, drivers who are unaware of their drowsiness would not necessarily take these countermeasures.

[29] This is a strong assumption, because the 100-Car study driver sample included only those who commuted into or out of the Northern Virginia/Washington, DC metropolitan area. Nonetheless, it is still the only estimate of baseline drowsiness prevalence in an NDS study of passenger vehicles.

oculomotor quiescence (i.e., a blank “stare”) (Sommer et al. 2009). This class of microsleeps can however also be readily detected from EEG measures. A driver having an EEG microsleep might not be aware of it (Poudel et al 2009), nor could an external observer reliably detect it from observing the driver’s face, eyes, and head. Also, unlike behavioral microsleeps in which drivers may completely miss events or leave the road just as if they had completely fallen asleep, during an EEG microsleep drivers may continue to drive and respond, although with reduced safety margins compared to their normal driving, particularly on curved roads (Boyle et al. 2008). Such microsleep episodes, and the missed or delayed responses to events or road curvatures that occurs from them, can be mistakenly ascribed to the attentional effects of “cognitive load” (e.g. “inattention blindness”), when in fact they are the result of drowsiness

Note that if a secondary task like carrying on a conversation (either with a passenger or on a cell phone) can prevent the microsleep, it would reduce the causal contribution of microsleeps to crashes.

5.2 Policy Implications

Drowsy driving is an ideal opportunity for new R&D to discover new knowledge and to translate that knowledge into a practical tool or product that will be of benefit to society. Drowsy driving product improvements are needed for: (a) detection; (b) alerts that occur when and only when drivers expect and accept them, to avoid drivers’ rejecting the system because of false alarms (Smith and Källhammer 2010); (c) drowsy driving countermeasures.

OEMs, the insurance industry, the government, driving safety organizations, academic safety researchers, and the public all have the common goal of reducing vehicle crashes, particularly fatal crashes. These results clearly indicate that large improvements in driving safety will occur from curtailing drowsy driving. It is recommended that both private and public funding sources in driving safety should transition resources to drowsy driving, to improve the effectiveness of drowsiness detection, alerts, and countermeasures.

6. Conclusions

These results confirm that drowsy driving is a more serious problem in vehicle safety than most previous studies indicate. Although previous studies hypothesized that their data underestimated drowsiness as a cause of crashes, this new analysis of the 100-Car passenger vehicle naturalistic driving data provides direct evidence to substantiate this hypothesis. Curtailing drowsy driving will reduce more crashes, particularly severe ones, than curtailing secondary tasks while driving.

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Appendix A. Analysis of Klauer et al. (2010: Appendix C) Data

Table A1 Klauer et al. (2010: Appendix C) data with controls matched to cases

Event[a]	Task[b]	Drowsy[c]	Frequency	Key:
1	3	0	26	[a]Event:
1	3	1	0	1 = Crash/Near-Crash
0	3	0	175	0 = Baseline
0	3	1	0	[b]Task group ID *n* :
1	2	0	119	3 = Complex
1	2	1	10	2 = Moderate
0	2	0	1449	1 = Simple
0	2	1	5	0 = No Task
1	1	0	120	[c]Drowsy:
1	1	1	18	1 = Drowsy
0	1	0	1929	0 = Not Drowsy
0	1	1	3	
1	0	0	208	
1	0	1	64	
0	0	0	3090	
0	0	1	19	