J Primary Prevent
DOI 10.1007/s10935-017-0478-3

ORIGINAL PAPER

Marijuana and the Risk of Fatal Car Crashes: What Can We Learn from FARS and NRS Data?

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Abstract Lab studies have shown that marijuana can severely impair driving skills. Epidemiological studies, however, have been inconclusive regarding the contribution of marijuana use to crash risk. In the United States, case–control studies based on the merging of comparable crash Fatality Analysis Reporting System (FARS) and non-crash National Roadside Survey (NRS) data have been applied to assess the contribution of drugs to crash risk, but these studies have yielded confusing, even contradictory results. We hypothesize that such a divergence of results emanates from limitations in the databases used in these studies, in particular that of the FARS. The goal of this effort is to examine this hypothesis, and in doing so, illuminate the pros and cons of using these databases for drugged-driving research efforts. We took advantage of two relatively recent cannabis crash risk studies that, despite using similar databases (the FARS and the NRS) and following similar overall approaches, yielded opposite results (Li, Brady, & Chen, 2013; Romano, Torres-Saavedra, Voas, & Lacey, 2014). By identifying methodological similarities and differences between these efforts, we assessed how the limitations of the FARS and NRS databases contributed to contradictory and biased results. Because of its

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Published online: 12 May 2017

limitations, we suggest that the FARS database should neither be used to examine trends in drug use nor to obtain precise risk estimates. However, under certain conditions (e.g., based on data from jurisdictions that routinely test for drugs, with as little variation in testing procedures as possible), the FARS database could be used to assess the contribution of drugs to fatal crash risk relative to other sources of risk such as alcohol.

Keywords Cannabis · Alcohol · Crash risk · FARS · NRS

Introduction

Societal acceptance, or at least tolerance, of marijuana consumption has been increasing in the United States (Rubens, 2014). This acceptance has induced a number of states to decriminalize the use of marijuana; eight states (Alaska, California, Colorado, Maine, Massachusetts, Nevada, Oregon, and Washington) have legalized the possession and recreational consumption of cannabis for adults; and another jurisdiction (the District of Columbia) has legalized the use, possession, and small-scale growing (but not sales) of marijuana. Despite this trend, lab studies have shown that marijuana use can severely impair driving skills (Moskowitz, 1985), causing "impairment in every performance area that can reasonably be connected with safe driving of a vehicle, such as tracking, motor coordination, visual functions, and particularly complex tasks that require divided attention" (Sewell, Poling, & Sofuoglu, 2009, p. 187). Epidemiological studies, however, have been much less conclusive. As also pointed out by Sewell et al., "surprisingly, given the alarming results of cognitive studies, most marijuana-intoxicated drivers show only modest impairments on actual road tests" (2009, p. 187). After conducting a meta-analysis of a mixture of nine case–control and culpability studies based on self-reported and/or biological samples, Asbridge, Hayden, and Cartwright (2012) found that acute marijuana use contributed significantly to the risk of suffering serious injuries in motor vehicle crashes (odds ratio [*OR*] = 2.10), although the contribution was non-significant among non-serious injuries (*OR* = 1.74; Asbridge et al., 2012). A similar significant contribution of marijuana to crash risk (*OR* = 2.66) was reported by the meta-analysis of nine studies conducted by Li et al. (2012). On the other hand, in 2013, Elvik conducted a meta-analysis of 66 studies in which he attempted to control for the quality of the reviewed studies and reported a very modest contribution of marijuana to crash risk (*OR* = 1.48), which was further reduced after correcting for publication bias (*OR* = 1.36; Elvik, 2013). After a new revision and update, a similarly modest contribution was recently reported by Røgeberg and Elvik (2016). Further, the authors revised earlier meta-analyses and reported the contribution of marijuana to crash risk to be lower than that reported by Asbridge et al. (2012) and Li et al. (2012) once the estimates were adjusted by relevant confounders.

For a drug that has shown it can severely impair driving skills, the current uncertainties surrounding how the deleterious effects observed in lab studies translate into actual crash risk disturb researchers and policymakers. To a large

extent, these uncertainties stem from the complexities surrounding the pharmacokinetics and psychomotor effects of tetrahydrocannabinol (THC; Huestis, 2016) and the myriad of cannabis preparations, each of which is associated with different use patterns and effects (Kleinman, 2016), and which are consumed under a vastly heterogeneous and rapidly evolving array of policies and laws (Pacula & Sevigny, 2014). Differences in the frequency and comprehensiveness of state tests for drugs among crashed drivers (Berning & Smither, 2014), the biological matrices used to measure drug use (e.g., blood, urine, oral fluid), the cutoff levels applied, and the interval between crash and the time in which the biological matrices are sampled further add to the continuing uncertainty in the contribution of marijuana to crash risk (Berning & Smither, 2014; Gjerde & Mørland, 2016; Hartman & Huestis, 2013; Hartman, Richman, Hayes, & Huestis, 2016).

To reduce this uncertainty, two case–control drug risk studies based on the matching of roadside data from the 2007 National Roadside Survey (NRS) with comparable fatal crash data from the Fatality Analysis Reporting System (FARS) were conducted in the United States (Li et al., 2013; Romano et al., 2014). Case–control studies based on the merging of comparable FARS and NRS databases have been previously applied to assess the contribution of alcohol to crash risk and have consistently shown that alcohol increases this risk (Blomberg, Peck, Moskowitz, Burns, & Fiorentino, 2005; Voas, Torres, Romano, & Lacey, 2012). Unlike those for alcohol, the FARS-NRS drug studies yielded diametrically different results. Li et al. reported a statistically significant contribution of marijuana to fatal crash risk (*OR* of 1.83; 95% confidence interval [CI] 1.39, 2.39) that occurred regardless of the presence of alcohol or other drugs. Romano et al., on other hand, reported a non-significant contribution of marijuana to crash risk when the model also accounted for the presence of other drugs ($OR = 0.92$, 95% CI 0.60, 1.40 for drivers at BAC $= 0.00$; and $OR = 0.86$, 95% CI 0.61, 1.23 for drivers at BAC ≥ 0.00). The reasons for this discrepancy are unclear. We hypothesize that the discrepancy originates from the studies' failure to account for limitations in the databases, in particular that of the FARS, whose information on drivers' drug use has been reported to be questionable (Berning & Smither, 2014). The goal of this effort is to examine this hypothesis, and in doing so, illuminate the pros and cons of using the FARS and NRS databases for drugged-driving research efforts. To achieve this goal, we will compare the contribution of drugs in general and cannabis in particular to crash risk, as estimated by Li et al. (2013) and Romano et al. (2014), after considering different inclusion and exclusion criteria.

Methods

We began our examination by summarizing the FARS-NRS crash risk approach, including a summary description of the FARS and NRS databases. Next we identified specific methodological similarities and differences between Li et al. (2013) and Romano et al. (2014). To facilitate comparisons between both studies, we first compared the way they manipulated the databases, and then modified Romano et al.'s approach to make it as similar as possible to that of Li et al. We

subsequently assessed whether the outcome of the studies converged and whether limitations in the databases may have affected such a convergence.

The Databases

Maintained by the National Highway Traffic Safety Administration (NHTSA), the FARS is a record-keeping system for all police-reported motor vehicle crashes on public roadways in the United States that result in the death of at least one road user within 30 days of the event. FARS provides detailed information about the fatally injured drivers' gender, age, level of alcohol consumption, and maneuvering skills. Previously used to study alcohol-related crashes (e.g., Voas et al., 2012; Zador, Krawchuk, & Voas, 2000), the FARS was recommended for use in drug-related analyses by Hingson, Winter, and Heeren (2010), who suggested that FARS data gathering and reporting have progressed to the point that the FARS now contains information large and accurate enough for meaningful drugged-driving studies. Twelve states test at least 80% of deceased drivers for drug usage (Hingson et al., 2010), the threshold for sufficiently complete data that has been previously applied to study alcohol-related crashes (Fell, 1983).

The use of the FARS for drug analyses, however, presents limitations. Berning and Smither (2014) listed several shortcomings: for example, the database informs only about drug presence but not concentration, and there are sharp variations in how states test for drugs, including variations in the type of road users tested, the biological specimen they use (e.g., blood, urine, oral fluid), the drugs for which they test, the type of test, and the cut-off levels they use. Pollini, Romano, Johnson, and Lacey (2015) also suggested that lab procedures within a jurisdiction may change from year to year.

Exposure data for the compared studies came from the 2007 National Roadside Survey, or NRS. A detailed description of the survey appears in Lacey et al. (2009). The overall objective of the NRS was to collect a stratified random sample of U.S. drivers to estimate the incidence of alcohol and drugs on our nation's roadways. To acquire this information, the 2007 NRS requested the voluntary provision of oral fluid samples from participating drivers. More than 9000 drivers were interviewed to determine the prevalence of drivers with various BACs, as well as the prevalence of those having various over-the-counter, prescription, and illegal drugs in their systems. Unlike the varying drug information available in the FARS, drug information in the 2007 NRS was more homogeneous. Drug information in the 2007 NRS was collected following uniform sampling and analytical protocols that include the voluntary collection of oral fluid samples from participating drivers, which were analyzed by a single lab following non-changing protocols.

The main limitation of the 2007 NRS relates to the voluntary participation of the drivers. Although overall more than 70% of the drivers provided an oral sample, sampling bias in the NRS would exist if a greater proportion of drug-positive than drug-negative drivers were to decline participation in the survey. If the 2007 NRS underestimated the prevalence of drugs, then the crash risk estimates obtained by Li et al. and Romano et al. would have had an upward bias. Unfortunately, we were not able to examine this potential source of bias. Some reassurance seems to come from

Lacey et al. (2009), who provided evidence that many of those who declined participation made that decision based on concerns about the time needed to complete the survey rather than on worrying about testing positive for drugs. Nevertheless, sampling selection in the NRS remains a possibility that should always be acknowledged by users of this database.

Case–Control Studies Based on the FARS and NRS

Estimating the relative risk of crash involvement requires the merging of the FARS and NRS databases. To this merged FARS-NRS database, both Li et al. and Romano et al. applied logistic regression to estimate the odds of crashing under the presence of marijuana, alcohol, or other drugs. The main similarities and differences between these approaches are summarized in Table 1.

As shown in this table, "cases" in both studies included drivers in the FARS for whom a lab test result was available and who died in a crash that occurred during the same days and hours in which the 2007 NRS was conducted. "Controls" in both studies included drivers in the 2007 NRS who provided an oral fluid sample. A significant difference between both studies occurred in the merging of the FARS-NRS, with Li et al. using data from all U.S. states visited by the 2007 NRS, whereas Romano et al. used only crashes from nine states that were visited by the 2007 NRS and tested at least 80% of their fatally injured drivers. The studies also differed in the selection of data from the FARS. Li et al. used data from all fatally injured drivers in the United States in 2007 for whom known lab test results were available, while Romano et al. used crash data from 2006, 2007, and 2008, which the authors claimed were needed to compensate for the reduced sample they used. Other data restrictions include Li et al.'s decision to restrict the crash sample to the months in which the 2007 NRS was conducted (no such restriction was applied by Romano et al.); and Romano et al. restricted crashes to only those that occurred on the types of roads and jurisdictions sampled in the 2007 NRS (no such restriction was applied by Li et al.). Further, Li et al. estimated crude *OR*s stratified by drug category, driver demographics, geographic region, and time of the day. Romano et al., on the other hand, were able to use individual drivers as the unit of analysis to also fit logistic regressions to obtain *OR*s for the presence of marijuana adjusted by drivers' demographics, testing variations across states, and the presence of alcohol or other drugs.

Models and Statistical Analyses

We assessed the contribution of cannabis and other drugs to fatal crash risk through the estimation and comparison of *OR*s obtained for a series of models under study. Data for all the analyses were based on the merging of fatal crash (FARS) and exposure (NRS) data. We then compared the following analytical models (95% confidence interval was used to compare the different *OR*s):

Table 1 Summary of main analytical and database similarities and differences between Li et al. (2013) and Romano et al. (2014) studies

	Li et al. (2013)	Romano et al. (2014)
Crashes		
Data source	FARS	FARS
Years covered	2007	2006–2008
Drivers included	Those tested and with a known lab result	Those tested and with a known lab result
States	Drivers from all continental U.S. states	Only states that participated in the NRS, and have 80% or more of the FARS drivers tested for drugs and with a known lab result: California, Colorado, Illinois, Maryland, New Jersey, New Mexico, North Carolina, Ohio, Pennsylvania
Months	July 20 to December 1	No restriction
Hours	Drivers who crashed at the same times of day that the NRS was conducted	Drivers who crashed at the same times of day that the NRS was conducted
	Fridays: 9:30 a.m. to 11:30 a.m.; 1:30 p.m. to 3:30 p.m.	Fridays: 9:00 a.m. to 4:00 a.m.
	Saturdays and Sundays: 10:00 p.m. to midnight; 1:00 a.m. to 3:00 a.m.	Saturdays and Sundays: 10:00 p.m. to 3:00 a.m.
Crash location	No restriction	Outside of Indian Country, on paved roads not classified as interstate or an urban freeway or expressway; in counties with a population $\geq$20,000
N	737 (varied by stratification level)	1766
Control		
Data source	NRS	NRS
Years covered	2007	2007
States	All states that participated in the NRS	Only states that participated in the NRS, and have 80% or more of the FARS drivers tested for drugs and with a known lab result: California, Colorado, Illinois, Maryland, New Jersey, New Mexico, North Carolina, Ohio, Pennsylvania
Drivers included	Those who provided an oral fluid sample	Those who provided an oral fluid sample
N	7719 (varied by stratification level)	3424

Table 1 continued

	Li et al. (2013)	Romano et al. (2014)	
Analytical strategy			
Approach	Merged FARS-NRS files	Merged FARS-NRS files	
Model	Crude *OR*s stratified by drug categories, driver demographics, geographic region, and time of day	Crude *OR*s	Logistic regression (separated by BAC = 00, and all drivers) Dependent variable: being a case or a control

FARS Fatality Analysis Reporting System; *NRS* National Roadside Survey; *BAC* Blood Alcohol Content

(*i*) *Li et al.'s model—all states* As reported by Li et al. (2013), this model was based on the merging of FARS-NRS data from all U.S. states visited by the 2007 NRS, with crude *OR*s estimated for strata defined by driver demographics, geographic region, and time of day. Missing drug testing data were imputed using sequential regression multiple imputation (SRMI). The authors reported no difference in results based either on actual drug data or the combination of actual and imputed drug data.
(*ii*) *Romano et al.'s model—nine states* As reported by Romano et al. (2014), this model was based on the merging of FARS-NRS data only from the states (California, Colorado, Illinois, Maryland, New Jersey, New Mexico, North Carolina, Ohio, and Pennsylvania) that were visited by the 2007 NRS and that tested at least 80% of their fatally injured drivers. Only actual drug results were used. To compensate for the reduced number of NRS drivers, crashed drivers from the 2006–2008 FARS were included. Crude as well as adjusted *OR*s were estimated. Adjusted ORs were estimated by applying logistic regression to model the likelihood of fatal crash involvement as a function of the drivers testing positive for drugs (cannabis) as well as for their BAC, age, gender, and race/ethnicity.
(*iii*) *Romano et al.'s model—all states* This model is essentially similar to Romano et al.'s (2014) 9-state model described above but uses data from all U.S. states visited by the 2007 NRS (as in the Li et al. model).
(*iv*) *Romano et al.'s model—seven states* This model is also essentially similar to Romano et al.'s (2014) 9-state model but excludes the two states that do not test for marijuana—North Carolina and New Mexico.

By examining the crude and adjusted *OR*s estimated from these models, we examined sources of bias in FARS-NRS drug risk analyses originated by (a) the inclusion of data from jurisdictions that do not regularly test for drugs, (b) the inclusion of data from states that do not test for the drug of interest, and (c) the failure to properly account for relevant risk factors.

Results

Table 2 shows the testing rates and the prevalence of drug-positive drivers among states that do not routinely test their fatally injured drivers for drugs (as it was applied by Li et al.) and among the nine states in which at least 80% of their fatally injured drivers had a known drug test result (as it was applied by Romano et al.). This table shows that while more than 80% of the drivers in the 2007 NRS were tested for drugs, that was not the case for drivers in the FARS database, where the >80% testing rate was achieved only in the nine selected states (as intended), and the remaining states showed only a 46.8% lab test rate.

As noted in this table, the prevalence of drug- and marijuana-positive drivers in the FARS file was significantly higher among the states that routinely do not test for drugs (35.3% for any drug, 13.8% for marijuana-positive) than those that test at least 80% of the drivers in the FARS file (19.9 and 9.3%, respectively). This disparity provides support to the Hingson et al. (2010) hypothesis that in low-testing states drug-based prevalence and risk estimates are biased upwards.

Table 3 offers a more detailed comparison of the *OR* estimates, both crude and adjusted by drivers' age, gender, and race/ethnicity. The crude *OR* estimates for drug-positive drivers reported by Li et al. (2.98) are significantly higher than the crude and adjusted *OR*s reported by Romano et al. (1.66 and 1.80, respectively). When the crude and adjusted *OR*s for drug-positive drivers reported by Romano et al. are re-estimated based on data from all the FARS-NRS available states, the

Table 2 Drug results for states depending on the drug testing rates (<80%, +80%)

	FARS (Cases)		2007 NRS (Controls)	
	States with less than 80% of drug-test results in 2006–2008 FARS	States with at least 80% of drug-test results in 2006–2008 FARS[a]	States with less than 80% of drug-test results in 2006–2008 FARS	States with at least 80% of drug-test results in 2006–2008 FARS[a]
Negative	64.7	80.1	85.1	87.1
Positive[b]	35.3	19.9	14.9	12.9
Marijuana[c]	13.8	9.3	7.5	6.4
Testing rate[d]	46.8	84.1	85.8	83.8
Sample size (n)[e]	4838	2171	4875	4088

[a] Nine states in Romano et al.'s paper (California, Colorado, Illinois, Maryland, New Jersey, New Mexico, North Carolina, Ohio, Pennsylvania)

[b] Differences in drug positive rates for cases and controls are statistically significant (Chi squared $p < 0.0001$ and $p = 0.0105$, respectively)

[c] Differences in marijuana prevalence for both cases and controls are statistically significant (Chi squared $p < 0.0001$ and $p = 0.0368$, respectively)

[d] Differences in drug testing rates for both cases and controls are statistically significant (Chi squared $p < 0.0001$ and $p = 0.0014$, respectively)

[e] Sample size is the number of drivers

Table 3 Crude and adjusted odds ratio estimates for the contribution of drugs other than alcohol to crash risk, based on estimates reported by Li et al. (2013) and Romano et al. (2014)

	OR (95% CI)			
	Based on data from all available states, as reported by Li et al. (2013) in Tables 1 and 3[a]	Based on data from nine selected states, as reported by Romano et al. (2014) in Tables 3 and 4[b]	Based on Romano et al.'s approach but using data from all available states[c]	Based on Romano et al.'s approach but using data from only seven states[d]
Any drug				
Crude	2.98 (2.51, 3.53)	1.66 (1.42, 1.94)	2.44 (2.22, 2.68)	2.12 (1.80, 2.49)
Adjusted[e]		1.80 (1.36, 2.39)	2.79 (2.13, 3.66)	2.36 (1.75, 3.18)
Marijuana				
Crude	1.83 (1.39, 2.39)	1.55 (1.25, 1.92)	2.03 (1.78, 2.31)	2.02 (1.61, 2.52)
Adjusted[e]		0.86 (0.61, 1.23)	1.22 (0.91, 1.63)	1.27 (0.88, 1.83)

[a] All states in 2007 FARS, following the sampling design criteria of 2007 NRS

[b] States that test for drugs 80% or more of the fatally injured drivers—nine states—and are sampled in the 2007 NRS

[c] All the states in 2006–2008 FARS and 2007 NRS databases, regardless the drug testing rates

[d] States that test for drugs 80% or more of the fatally injured drivers and are sampled in the 2007 NRS, excluding the two states that do not test for marijuana, North Carolina and New Mexico, seven states

[e] Following Romano et al. (2014), the model estimated separately the contribution of drivers positive for marijuana, and those positive for drugs other than marijuana, after adjusting for gender, age, and race/ethnicity

estimates are much higher (2.44 and 2.79, respectively), and are no longer statistically different from the crude *OR*s reported by Li et al. (2013). The rightmost column in Table 3 shows the crude *OR*s obtained applying Romano et al.'s approach but excluding data from North Carolina and New Mexico—two states that have lab results for 80% or more of the deceased drivers but did not include marijuana among the panel of drugs tested. As expected, after eliminating the data from North Carolina and New Mexico, the resulting crude and adjusted *OR*s (2.12 and 2.36, respectively) are also higher than those reported by Romano et al. (1.66 and 1.80, respectively). Table 3 therefore provides evidence that the inclusion of data from states that do not test routinely for drugs tends to bias upward the drug-related risk estimates (a bias present in Li et al., 2013), whereas the inclusion of data from states that, despite testing 80% or more of their fatally injured drivers, do not test for marijuana tends to bias the risk estimates downward (a bias present in Romano et al., 2014).

Regarding cannabis, the crude *OR* estimate reported by Li et al. (1.83) suggests a significant contribution of marijuana to crash risk. A significant contribution of marijuana to crash risk was also suggested by the crude *OR* estimates obtained by Romano et al. (1.55), as well as by the crude *OR* estimates obtained by using data from all the FARS-NRS available states (2.03) or after the elimination of data from North Carolina and New Mexico (2.02). However, once adjusted by drivers' age, gender, and race/ethnicity, the contribution of marijuana to crash was no longer

significant, either as reported by Romano et al. (0.86) using data from all the FARS-NRS available states (1.22), or after discarding data from North Carolina and New Mexico (1.27). Table 3 therefore also provides evidence of the need to account for as many factors as possible when assessing crash risk. In this example, failure to account for drivers' demographics has biased upward crude crash estimates.

Discussion

We explored the impact of limitations in the FARS and NRS databases when used to assess drug crash risk by examining the divergent findings reported by Li et al. (2013) and Romano et al. (2014). We found strong evidence indicating that the risk estimates for the contribution of marijuana and other drugs to fatal crash risk reported by both Li et al. and Romano et al. are biased. The limitations that have biased upward the risk estimates include the inclusion of data from states that do not test routinely for drugs (those that test drivers only when suspected of impairment); the failure to adjust the drug risk estimates by demographics (those that are caused by age or gender); and self-selection bias among participants in the NRS. On the other hand, the inclusion of data from states that do not test their drivers for marijuana biased the risk estimates downward. This source of bias was particularly relevant to Romano et al.'s effort, for the larger number of states included in Li et al.'s analyses diluted to some extent the impact of this source of bias (at least relative to those obtained by Romano et al. based on only nine states).

Although they work in opposite directions, the relative effects of these sources of bias on crash estimates do not necessarily cancel each other out. Depending on the type of drug considered and the analytical approach applied, some sources of bias would likely be more damaging than others. For instance, the bias generated by estimating drug risk without controlling for drivers' demographics would be more severe when drug use varies sharply with age (e.g., marijuana or some medications). Further, because the youth and the elderly are among the groups of drivers more prone to crash risk regardless of drug use, a failure to account for drivers' age would bias such drug risk estimates upward.

Another limitation relates to the source of drug information available in the FARS and NRS databases. The 2007 NRS reported drug prevalence from oral fluid (saliva) samples (Lacey et al., 2009), while the FARS obtained the information largely from blood samples and/or urine collected from their deceased drivers. Despite recent studies showing that oral fluid and blood samples yield lab results close enough for some meaningful analyses (Kelley-Baker, Moore, Lacey, & Yao, 2014), the reliance on crash and control data on drug use obtained by two different methodologies raises concern about the accuracy of Li et al.'s and Romano et al.'s findings.

Another limitation of the FARS database is the lack of drug concentration data. As such, the contribution to crash risk by drivers who consumed cannabis at levels that in lab-based studies showed impairment in their driving skills will not be properly captured in FARS-based studies such as those by Li et al. (2013) or Romano et al. (2014). Berning and Smither (2014) pointed out that differences in

how states test for drugs, including variation in the type of road users tested, the biological matrix they sample, the type of test, and the cut-off levels they use add concern about the use of FARS for analyses. It would be relevant to point out that even if the FARS were to begin to report on drivers' THC concentrations, the availability of this measure would not be free of limitations. The availability of THC concentrations in the FARS would likely come from blood samples, a matrix that for regular marijuana users could contain measurable THC quantities even days after cessation, subsequently causing some non-impaired individuals to be misclassified as THC-positive (Gjerde & Mørland, 2016).

Although the discussion so far has focused on potential bias caused by limitations in the FARS and NRS databases, it is worth considering the source of bias associated with how these databases are analyzed. Although necessary for achieving a desirable statistical power, data aggregation may be a source of bias (i.e., ecological fallacy). Bias caused by data aggregation can be caused by conducting the estimation of drug crash risk not for individual drugs but instead for aggregated drugs classes. Crash risk estimates obtained for a class of substances may ignore the varying and differing impacts of individual drugs on driving behaviors, in particular if only some of them are considered active metabolites. By examining crash risk for drug classes rather than for individual drugs, risk estimates such as those by Li et al. (2013) and Romano et al. (2014) are likely to be biased.

The occurrence of annual changes in drug testing protocols at the state level only adds confusion to the already blurred picture. Pollini, Romano, Johnson, and Lacey (2015) found anecdotal evidence suggesting that lab procedures within a jurisdiction tend to change from year to year. Unfortunately, lack of documentation on how such tests are conducted has impeded a confirmation of this evidence. Lack of transparency on how drug tests are conducted as well as on the modifications that take place over time not only renders any trend examination meaningless, but also raises concern about the validity of the drug information in the FARS database as it applies to crash risk studies. It also cautions against any attempt to impute into the FARS database the drug use of drivers for whom lab information is absent.

Another example of ecological bias originates in the assumption that the contribution of drugs to crash risk does not vary by crash type. Romano and Voas (2011) noticed that the contribution of marijuana and other drugs to crash risk varied with the type of crash under study. Their observation underscored that the psychotropic effects of a drug like marijuana may induce those who consume it to be more prone to some specific types of crashes (e.g., inattention-related) than to others (e.g., those associated with aggressive driving). Studies based on the aggregate effect of marijuana on overall crashes (such as the DRUID project and Li et al.'s and Romano et al.'s studies) may yield "average" risk estimates, lower than the actual contribution to risk the drug may have in specific crash types.

In summary, crash risk estimates are highly dependent on the quality of the data on which they are based. Because they were based on imperfect FARS and NRS data characterized by unknown imperfections, to which imperfect analytical models have been applied, the resulting estimates must be taken with caution. Also, not surprisingly, many of these estimates were highly contradictory. In this regard, we suggest that:

1. There is an urgent need to improve the drug information available in the FARS. A normalization and standardization of the sample collection protocols and analytical procedures is crucial to a better understanding of the drug-crash problem. Information on the presence of active metabolites and their concentration levels is necessary.
2. Future drug crash risk research should depart from the use of aggregate data as much as possible, focusing instead on the estimation of crash risk for specific driving situations and for drivers at different levels of drug consumption.
3. Future research efforts should depart from studying drug crash risk as we do alcohol crash risk. To some extent, policymakers and researchers have been focused on estimating drug-crash relative risk curves (i.e., risk at different drug concentrations relative to that which occurs in the absence of the drug) that would follow the format of the well-known BAC relative risk curve. Such an approach may not be optimal, or even feasible, to follow. Not only might the way that different drugs and their metabolites contribute to crash risk be too complex for obtaining such a straightforward relative risk curve, but they may even be impossible to obtain. For instance, cannabis follows a counterclockwise hysteresis—that is, for the same individual at a same measured THC level, marijuana may show a very different impact depending on how long ago the drug was consumed (Schwope, Bosker, Ranaekers, Gorelick, & Huestis, 2012). By showing more than one level of crash risk per concentration level, a BAC-like relative risk curve for THC may not be feasible.

Despite all the severe limitations in drug information it presents, should the FARS database still be used in drug-related studies? To answer this question, first consider the types of studies for which the use of the database is inadvisable. As mentioned, the FARS database should not be used to examine trends in drug use. Unexplained and undocumented changes in testing and lab procedures preclude such analyses. Because of this limitation, it would be impossible to assess if increases in the prevalence of marijuana among fatally injured drivers over time corresponds to an increase in consumption or simply to improvements in detecting efforts. Neither should the FARS database be used to obtain precise risk estimates. This study shows how volatile the crash risk estimates for cannabis based on the FARS are, with such volatility depending heavily on the type of data and analyses applied. Statements indicating that the presence of marijuana doubles the likelihood of fatal crash risk are as plausible as statements indicating no significant contribution at all.

Although inadequate for obtaining precise results, the FARS database, in some cases and under certain conditions, could be used to assess the contribution of drugs to fatal crash risk relative to other sources of risk. Despite their divergent results, both Li et al. and Romano et al. reported that the contribution of marijuana to fatal crash risk is lower than that of alcohol. This is a finding that has been consistently reported in the literature both in previous studies using the FARS (Romano & Pollini, 2013; Romano & Voas, 2011), and in studies not based on the FARS or NRS, using different biological matrices and a variety of analytical approaches (e.g., Gadegbeku, Amoros, & the SAM Group, 2010; Kuypers, Legrand, Ramaekers, &

Verstraete, 2012; Schulze et al., 2012). Although they may be appropriate for broad, relative comparisons, studies based on the FARS should nevertheless minimize the possibility of bias as much as possible. Restricting a study to include crashes from jurisdictions that routinely test for drugs and have minimal lab variation should be required.

In conclusion, we believe the data and methodological limitations we have described and discussed in this manuscript should not be a cause of discouragement, but a motivation for researchers and policymakers to improve our understanding of this important subject.

Compliance With Ethical Standards

Conflict of Interest All the authors declare that they have no conflict of interest.

Human and Animal Rights Statements This article performs secondary analyses on data containing no personal identifiers. This article does not include any studies with human participants or animals conducted by any of the authors.

References

Asbridge, M., Hayden, J. A., & Cartwright, J. L. (2012). Acute cannabis consumption and motor vehicle collision risk: Systematic review of observational studies and meta-analysis. *British Medical Journal, 344,* e536. doi:10.1136/bmj.e536.bmj.e536.

Berning, A., & Smither, D. D. (2014). *Understanding the limitations of drug test information, reporting, and testing practices in fatal crashes*. Washington, DC: Department of Transportation, National Highway Traffic Safety Administration.

Blomberg, R. D., Peck, R. C., Moskowitz, H., Burns, M., & Fiorentino, D. (2005). *Crash risk of alcohol involved driving: A case-control study*. Stamford, CT: Dunlap & Associates, Inc. Retrieved from: http://www.dunlapandassociatesinc.com/crashriskofalcoholinvolveddriving.pdf.

Elvik, R. (2013). Risk of road accident associated with the use of drugs: A systematic review and meta-analysis of evidence from epidemiological studies. *Accident Analysis and Prevention, 60,* 254–267.

Fell, J. C. (1983). Tracking the alcohol improvement problem in U.S. highway crashes. In *27th Annual proceedings of the american association for automotive medicine*, San Antonio, TX.

Gadegbeku, B., Amoros, E., & the SAM Group. (2010). *Responsibility study: Main illicit psychoactive substances among car drivers involved in fatal road crashes in FranceDRUID* (*Driving Under the Influence of Drugs, Alcohol and Medicines*) *Deliverable 2.3.2*. Bergisch-Gladbach: Federal Highway Research Institute. Retrieved from http://www.druid-project.eu/cln_031/nn_107548/Druid/EN/deliverales-list/downloads/Deliverable__2__3__2,templateId=raw,property=publicationFile.pdf/Deliverable_2_3_2.pdf.

Gjerde, H., & Mørland, J. (2016). Risk for involvement in road traffic crash during acute cannabis intoxication. *Addiction, 111*(8), 1492–1495. doi:10.1111/add.13435.

Hartman, R., & Huestis, M. (2013). Cannabis effects on driving skills. *Clinical Chemistry, 59*(3), 478–492.

Hartman, R. L., Richman, J. E., Hayes, C. E., & Huestis, M. A. (2016). Drug recognition expert (DRE) examination characteristics of cannabis impairment. *Accident Analysis and Prevention, 92,* 219–229. doi:10.1016/j.aap.2016.04.012.

Hingson, R., Winter, M., & Heeren, T. (2010). Alcohol and drug use in fatally injured drivers in states that test over 80% for both alcohol and drugs. In *The tri-annual meeting of the international conference on alcohol, drugs and traffic safety, August 22, 2010*, Oslo, Norway.

Huestis, M. (2016). Effects of cannabis on human psychomotor performance. Speaker at the Marijuana and Cannabinoids: A Neuroscience Research Summit. Psychomotor Performance and Detection session. NIH Campus, Bethesda, MD. Retrieved from: https://www.youtube.com/watch?v=PnUce0c90x0&index=11&list=PLE4ZNGaomJBnFoW82EjtVAtRimC84B3Bm.

Kelley-Baker, T., Moore, C., Lacey, J. H., & Yao, J. (2014). Comparing drug detection in oral fluid and blood: Data from a national sample of nighttime drivers. *Traffic Injury Prevention, 15*(2), 111–118. doi:10.1080/15389588.2013.796042.

Kleinman, M. (2016). A cannabis research agenda for policy design: What do we need to know? Speaker at the Marijuana and Cannabinoids: A Neuroscience Research Summit. Policy Research: Challenges and Future Directions session. NIH Campus, Bethesda, MD. Retrieved from: https://www.youtube.com/watch?v=PnUce0c90x0&index=11&list=PLE4ZNGaomJBnFoW82EjtVAtRimC84B3Bm.

Kuypers, K. P., Legrand, S. A., Ramaekers, J. G., & Verstraete, A. G. (2012). A case-control study estimating accident risk for alcohol, medicines and illegal drugs. *PLoS ONE, 7*(8), e43496. doi:10.1371/journal.pone.0043496.

Lacey, J. H., Kelley-Baker, T., Furr-Holden, C. D. M., Voas, R. B., Romano, E., Ramirez, A.,⋯ Berning, A. (2009). *2007 national roadside survey of alcohol and drug use by drivers: Drug results*. (DOT HS 811 249). Washington, DC: U.S. Department of Transportation, National Highway Traffic Safety Administration. Retrieved from http://www.nhtsa.gov/Driving+Safety/Research+&+Evaluation/2007+National+Roadside+Survey+of+Alcohol+and+Drug+Use+by+Drivers.

Li, G., Brady, J., & Chen, Q. (2013). Drug use and fatal motor vehicle crashes: A case-control study. *Accident Analysis and Prevention, 60,* 205–210.

Li, M. C., Brady, J. E., DiMaggio, C. J., Lusardi, A. R., Tzong, K. Y., & Li, G. (2012). Marijauana use and motor vehicle crashes. *Epidemiologic Reviews, 34,* 65–72.

Moskowitz, H. (1985). Marihuana and driving. *Accident Analysis and Prevention, 17,* 323–345.

Pacula, R. L., & Sevigny, E. L. (2014). Marijuana liberalization policies: Why we can't learn much from policy still in motion. *Journal of Policy Analysis and Management, 33*(1), 212–221.

Pollini, R. A., Romano, E., Johnson, M. B., & Lacey, J. H. (2015). The impact of marijuana decriminalization on California drivers. *Drug and Alcohol Dependence, 150,* 135–140.

Rogeberg, O., & Elvik, R. (2016). The effects of cannabis intoxication on motor vehicle collision revisited and revised. *Addiction, 111*(8), 1348–1359.

Romano, E., & Pollini, R. A. (2013). Patterns of drug use in fatal crashes. *Addiction, 108*(8), 1428–1438. doi:10.1111/add.12180.

Romano, E., Torres-Saavedra, P., Voas, R. B., & Lacey, J. H. (2014). Drugs and alcohol: Their relative crash risk. *Journal of Studies on Alcohol and Drugs, 75*(1), 56–64.

Romano, E., & Voas, R. B. (2011). Drug and alcohol involvement in four types of fatal crashes. *Journal of Studies on Alcohol and Drugs, 72*(4), 567–576.

Rubens, M. (2014). Political and medical views on medical marijuana and its future. *Social Work in Public Health, 29*(2), 121–131.

Schulze, H., Schumacher, M., Urmeew, R., Alvarez, J., Bernhoft, I. M., de Gier, H. d. G.,⋯ Pilgerstorfer, M. (2012). *Driving under the influence of drugs, alcohol and medicines in Europe—Findings from the DRUID project*. Lisbon: European Monitoring Centre for Drugs and Drug Addiction.

Schwope, D. M., Bosker, W. M., Ranaekers, J. G., Gorelick, D. A., & Huestis, M. A. (2012). Psychomotor performance, subjective and physiological effects and whole blood Δ9-tetrahydrocannabinol concentrations in heavy, chronic cannabis smokers following acute smoked cannabis. *Journal of Analytic Toxicology, 36*(6), 405–412.

Sewell, R. A., Poling, J., & Sofuoglu, M. (2009). The effect of cannabis compared with alcohol on driving. *American Journal on Addictions, 18*(3), 185–193. doi:10.1080/10550490902786934.

Voas, R. B., Torres, P., Romano, E., & Lacey, J. H. (2012). Alcohol-related risk of driver fatalities: An update using 2007 data. *Journal of Studies on Alcohol and Drugs, 73*(3), 341–350.

Zador, P. L., Krawchuk, S. A., & Voas, R. B. (2000). Alcohol-related relative risk of driver fatalities and driver involvement in fatal crashes in relation to driver age and gender: An update using 1996 data. *Journal of Studies on Alcohol and Drugs, 61*(3), 387–395.