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# Patterns of Drug Use in Fatal Crashes

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## Abstract

**Aims—**To characterize drug prevalence among fatally injured drivers, identify significant associations (i.e., day of week, time of day, age, gender), and compare findings with those for alcohol.

**Design—**Descriptive and logistic mixed-model regression analyses of Fatality Analysis Reporting System data.

**Setting—**U.S. states with drug test results for >80% of fatally injured drivers, 1998-2010.

**Participants—**Drivers killed in single-vehicle crashes on public roads who died at the scene of the crash (N=16,942).

**Measurements—**Drug test results, blood alcohol concentration (BAC), gender, age, and day and time of crash.

**Findings—**Overall, 45.1% of fatally injured drivers tested positive for alcohol (39.9% BAC>0.08) and 25.9% for drugs. The most common drugs present were stimulants (7.2%) and cannabinols (7.1%), followed by “other” drugs (4.1%), multiple drugs (4.1%), narcotics (2.1%), and depressants (1.5%). Drug-involved crashes occurred with relative uniformity throughout the day while alcohol-involved crashes were more common at night ($p$<.01). The odds of testing positive for drugs varied depending upon drug class, driver characteristics, time of day, and the presence of alcohol.

**Conclusions—**Fatal single vehicle crashes involving drugs are less common than those involving alcohol and the characteristics of drug-involved crashes differ depending upon drug class and whether alcohol is present. Concerns about drug-impaired driving should not detract from the current law enforcement focus on alcohol-impaired driving.

### Keywords

fatal crashes; alcohol; drugs; DUID; AID

## INTRODUCTION

Since the middle of the 20th century, alcohol consumption has been viewed as the most important behavioral factor for drivers involved in fatal crashes and the primary focus of impaired driving research. In contrast, the contribution of drugs to motor vehicle crashes and related fatalities remains remarkably understudied. Although studies using laboratory and

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simulator data, arrested and crash-involved drivers, and on-road tests of driving skills [1-5] suggest a connection between drug use and impaired driving, we have yet to fully characterize how drugs contribute to crash risk.

One challenge to these efforts has been the inherent complexity of the drug-crash risk association [6-9]. Unlike alcohol, a myriad of drugs can impair driving, each with different pharmacological properties and neurological effects [9], and impairment may depend on the presence of other drugs and/or comorbidities [5, 10-12]. The driving task may also play a role in determining risk [13], and several methodological and technological challenges arise in measuring drug impairment [8, 9].

Though experimental research informs our knowledge of performance impairment, actual crash risk can only be studied through direct road and traffic studies (e.g., [14-17]). Recently, the European Driving under the Influence of Drugs, Alcohol and Medicines (DRUID) project conducted a case-control study of injured drivers from medical facilities and road surveys. The study found an increased risk of injury and death among drivers testing positive for drugs, but the magnitude of the risk increase differed across substances, ranging from “slight” (cannabinols) to “high” (amphetamines, multiple drugs) to “extreme” (alcohol and drugs combined) [18, 19]. Other studies have found that the association between drug use and crashes depends on the traffic infraction (e.g., speeding, red-light running, inattention) [20]. These findings provide more evidence of the complex nature of the drug-crash risk association.

This complexity makes it difficult to enact and enforce sensible and effective regulations governing driving under the influence of drugs (DUID). Driving under the influence of alcohol is governed by a legal framework established several decades ago, which uses blood alcohol concentration (BAC) above a certain level (usually > .08) as legal evidence of impaired driving. Concerns about DUID have motivated the promotion of state laws to reduce drug-related crashes using a similar legal framework [21, 22], and at least 17 states have passed drug *per se* laws, under which testing positive for a specified substance constitutes legal evidence of impaired driving. However, these state laws differ greatly regarding the drugs they cover (e.g., some exclude cannabis and/or its metabolites, others differ in what does constitute a drug (e.g., which metabolites count as drugs), exclude drugs prescribed by a physician, or even the drivers’ age (e.g., North Carolina and South Dakota have per se laws applicable only to drivers under age 21). [23, 24] Whether these laws are appropriately designed to account for the aforementioned complexity of the drug-crash relationship is a subject of debate [25].

More straightforward is the increased burden of enforcing DUID laws in the field. Drug testing generally requires collecting blood or urine, a more complex and expensive undertaking than alcohol breath testing. Accordingly, law enforcement officers largely test for DUID only when a driver with suspected impairment has a BAC<.08. Current U.S. drug *per se* laws have therefore been implemented more as a mechanism to support the prosecution of impaired drivers with BAC<.08 than as an enforcement tool [23]. Finding ways to increase the efficiency of the drug testing process could increase both the efficiency and affordability of well-designed DUID laws.

One possibility for increasing the efficiency of DUID assessment and enforcement is to elucidate further the demographic and temporal characteristics associated with drug use among impaired drivers. These relationships have been elucidated for alcohol and a comprehensive set of policies and programs targeting drivers most at risk of drinking and driving have been developed. No comparable level of understanding exists for drugs. A further understanding of DUID patterns (e.g., by day of the week, hour of the day) could

facilitate better-targeted DUID countermeasures and lead to more efficient testing to identify drug-impaired drivers.

The overall goal of this study is to examine the presence of drugs among fatally injured drivers and its association with day of the week, time of day, age, and gender. Because the factors in alcohol-related crashes have been extensively studied and are relatively well understood, our examination of the patterns of DUID is made relative to that for drinking and driving. Specifically, we sought to identify and compare patterns of alcohol- and drug-related fatal crashes by (a) examining the prevalence of drug- and alcohol-related fatal crashes across drivers' gender, age, day of the week, and time of the day; and (b) investigating associations between these factors and fatal crashes involving drugs.

## METHODS

We analyzed data from the Fatality Analysis Reporting System (FARS), a census of all crashes on U.S. public roads that result in a death within 30 days. FARS contains an estimate of the BAC of every driver involved in a fatal crash, consisting of either an actual BAC measurement or an imputed value based on other factors in the crash [26]. Drug information is more limited, but 20 states have provided drug-testing results for at least 80% of their fatally injured drivers.

### Case selection

We used FARS data from 1998-2010. We limited our sample to fatally injured drivers (surviving drivers are rarely tested for drugs) in single-vehicle crashes (in which the driver was probably responsible for the crash). This strategy relies on a subset of states and drivers with the characteristics of interest (i.e., drug use, crash responsibility) and is typical of many studies using the FARS data [27-29]. To ensure proper identification of crash responsibility, we also excluded drivers who (a) presented a condition signaling them as mentally challenged; (b) were involved in a police chase; (c) were driving buses, snowmobiles, construction or farm equipment; or (d) were parked or in the process of parking a vehicle.

A further screening criterion involved the time that elapsed between the crash and the collection of a biological sample (usually blood). Different drugs metabolize at different rates, making elapsed time relevant to this study. Further, drivers who survive the crash are usually taken to a medical facility, where the medicines they receive may be included on post-mortem drug testing results. To explore the potential effect of survival time on drug-positive test results, we calculated the prevalence of drug-positive results across incremental periods of survival among the drivers in our sample. Table 1 shows that the prevalence of cannabinols and stimulants among drivers who died at the scene of the crash was significantly higher ($p<.01$) than for those who died later, and the prevalence of narcotics ($p<.05$) and depressants ($p<.05$) was lower among those who died at the scene than at any other time. The former may be attributed to metabolism of precrash administered cannabinols and stimulants; the latter may reflect postcrash medical treatment. To represent accurately the drug prevalence at the time of the crash, we also limited our study to drivers who died at the scene of the crash. Figure 1 is a detailed flowchart of the case-selection process.

Table 2 lists the number of records by state ($N=16,942$) that remained in the database for each of the 20 eligible states after applying our selection criteria. Data were provided for each state only for the years in which drug testing results were available for ≥80% of all fatally injured drivers

## Measures

**Age and gender—**We included age and gender into our analyses to capture different age-based patterns of drug prevalence among fatally injured drivers. Ages were categorized as 16-20, 21-34, 35-64, and ≥65 years.

**Time—**We categorized crashes between 6:00 AM and 5:59 PM as "daytime" and crashes at all other hours as "nighttime." We categorized weekdays as 6:00 PM Sunday through 5:59 PM Friday and weekends from 6:00 PM Friday through 5:59 PM Sunday.

**Drugs—**Drug test results are shown as three variables in the FARS database. Each variable is assigned a drug code: 000 (Not Tested for Drugs); 001 (No Drugs Reported/Negative); 100 – 295 (Narcotics); 300 – 395 (Depressants); 400 – 495 (Stimulants); 500 – 595 (Hallucinogens); 600 – 695 (Cannabinols); 700 – 795 (Phencyclidine/PCP); 800 – 895 (Anabolic Steroids); 900 – 995 (Inhalants); 996 (Other Drugs); 997 (Tested for Drugs, Results Unknown); 998 (Tested for Drugs, Drugs Found, Type Unknown/Positive); and 999 (Unknown if Tested/Not Reported). We collapsed codes with small sample sizes (i.e., hallucinogens, phencyclidine/PCP, anabolic steroids, and inhalants) and drugs of an unknown type into the "996-Other Drugs" class. Drivers who tested positive for drugs in more than one class were categorized as "multidrug" users. The resulting drug categories are therefore mutually exclusive.

**Alcohol—**The presence of alcohol was established using (a) the actual BAC as reported in FARS, and (b) for missing values ($n$=78, or 0.5% of our sample), the BAC values imputed by FARS using a multiple imputation technique [26]. We examined three BAC levels: BAC=.00, 0<BAC<.08, and BAC≥.08.

## Analyses

**Drug and alcohol prevalence by demographics and time—**We graphed the hourly prevalence of alcohol and drugs among fatally injured drivers on weekdays and weekends. To test for differences in the curves, we applied regression methods (SAS PROC GLM) to model prevalence by hour and test differences between drug- and alcohol-positive patterns. Quadratic and cubic terms were included to capture the curvilinear nature of the graphs. Linear, quadratic, and cubic time terms (hour) were used to capture the time-changing shape of the prevalence curves. Based on this model, we calculated hourly prevalence and the corresponding 95% confidence intervals (CIs), with nonoverlapping CIs indicative of statistically significant differences across groups.

**Associations between drug-positive driving and demographics, time, and alcohol—**We applied a mixed-effect logistic regression to model the associations between drug-positive drivers and selected exposure variables. To account for state-based variations such as differences in drug testing protocols and/or traffic enforcement, a two-level model was formulated with state at level 2 (random effect) and the drivers' demographics, BACs, and the times of the crashes at level 1 (fixed effects). In all cases, a 0,1 dependent variable was used, with a value of "1" denoting the presence of the drug of interest and "0" denoting a negative test result. We applied the SAS PROC GLIMMIX to represent the two-level model with "state" as a random effect, and PROC MIANALYZE to capture the multiple imputation technique applied to the BAC measure in the FARS database. For each of the six drug classes we ran two regressions: one excluding alcohol as an explanatory variable and one with a variable measuring alcohol at BAC ≥ .08, 0<BAC<.08, and BAC=.00 (the reference level).

# RESULTS

## Drug prevalence

Overall, 25.9% (*N*=4,392) of fatally injured drivers tested positive for drugs and 45.1% (*N*=7,642) for alcohol. Stimulants (7.2%) and cannabinols (7.1%) were the most common drug classes, with significantly higher prevalence than narcotics (2.1%), depressants (1.5%), other drugs (4.1%), and multidrugs (4.1%). Drug classes most commonly found among multidrug users were stimulants (57.3%), cannabinols (53.6%), narcotics (48.2%), and depressants (45.5%). Either a cannabinol or a stimulant was present in about 80% of all multidrug users.

## Hourly distribution of drug- and alcohol-positive fatally injured drivers

Figure 2 shows that alcohol-positive crashes occurred largely at night, on both weekdays or weekends, and that more than 60% of fatal crashes occurring between 10 PM and 3 AM had an alcohol-positive driver (BAC>.00). The percentage of alcohol-positive drivers was particularly high (>80%) on weekends between midnight and 4 AM. In contrast, drug-positive crashes were more evenly distributed throughout the day, with prevalence ranging from 20 to 35%. Although not shown, the confidence intervals for the curves in Figure 2 confirmed that the hourly patterns of alcohol and drugs differ significantly ($p$<.01).

## Prevalence of drugs and alcohol by demographics and time

Table 3 shows the prevalence of drugs and alcohol by demographics and time. A total of 45.1% of drivers had a positive BAC, which can be disaggregated as 5.2% of drivers at .00<BAC<.08 and 39.9% at BAC≥.08. In other words, about 90% of the BAC-positive drivers were at BAC≥.08. About 26% of drivers were drug-positive, which was significantly lower than the prevalence of BAC-positive drivers.

## Gender

Fatally injured male drivers were significantly more likely than females to be alcohol-positive; however, there was no statistically significant gender difference in overall drug prevalence. There were significant gender differences by drug class; specifically, the prevalence of cannabinols was higher among males whereas females were more likely to test positive for depressants, narcotics, and other drugs.

## Age

Drivers aged 21-34 were significantly more likely to be alcohol-positive and to have BAC≥.08 than drivers of other age groups. The highest overall drug prevalence was among those aged 35-64 (27.7%). The highest prevalence of cannabinols, stimulants, and multiple drugs were among drivers aged 16-20 (11.5%), 21-34 (9.2%), and 35-64 (4.7%), respectively. In contrast, the highest prevalence of narcotics/depressants was among drivers 35-64 (3.0%/2.4%) and ≥65 (3.3%/1.9%). “Other drugs” prevalence was highest among drivers aged >65 (7.0%). Thus, the prevalence of drugs in fatally injured drivers showed age-related patterns that varied significantly by drug type.

## Day of week and time of day

Table 3 shows that alcohol prevalence was significantly higher on weekends than on weekdays but there was no difference for drugs or drug class. Similarly, alcohol prevalence was significantly higher at nighttime than at daytime but there was no overall difference for drugs. Differences by time of day, however, were found for individual drug classes; the prevalence of cannabinols and stimulants was significantly higher at nighttime, whereas

depressants, narcotics, and other drugs were significantly higher in daytime crashes. No difference was found for multidrug users.

### Associations between drug-positive driving and demographics, time, and alcohol

Table 4 shows the adjusted odds ratios for fixed effects obtained from the 12 logistic regressions modeling the associations between gender, age, day and time, and alcohol for the six drug classes. Not shown in Table 4 is the solution for the random variable (state), which was statistically significant in each of the models considered ($p<.0001$).

When alcohol was excluded from the models, the age groups with the highest odds of testing positive for drugs were aged 16-20 for cannabinols, aged 21-34 for stimulants, aged 35 and older for depressants, narcotics, and "other drugs," while multidrug use varied across age categories. Female drivers had significantly higher odds of testing positive for depressants, narcotics, and "other drugs," whereas males had higher odds of testing positive for cannabinols and stimulants. No significant gender differences were detected for multidrug use.

Weekday or weekend driving was not significantly associated with any of the drug classes under study. However, fatal crashes involving depressants, narcotics, other drugs, and multiple drugs had significantly higher odds of occurring during the daytime; conversely, crashes involving cannabinols and stimulants were more likely to occur at nighttime. These findings are consistent with those shown in Table 3, which were not adjusted by gender or age. The varying presence of stimulants and depressants by time of day (Table 3) seems to be largely explained by differences in gender and age, with men (particularly young men) being more likely to test positive for stimulants in nighttime crashes and women (particularly aged ≥35) being more likely to test positive for depressants in daytime crashes.

The lower half of Table 4 examines the effect of adding BAC as a covariate. Overall, adding alcohol as a covariate did not alter the odds ratios for gender, age, or day of the week. The sole exception occurs with depressants, for the odds for drivers aged 16-20 no longer differs statistically than that for drivers aged 21-34. The addiction of alcohol however, reveals two interesting peculiarities. First, except for narcotics, adding alcohol to the model made all the remaining daytime versus nighttime comparisons no longer significant. Second, except for cannabinols, alcohol was not significantly associated with any other drug classes. Alcohol, however, was significantly associated with cannabinols regardless of driver BAC level.

## DISCUSSION

This study explored demographic, time-related, and alcohol-related patterns of drug-positive driving among fatally injured U.S. drivers. Overall, we found the prevalence of alcohol was significantly higher than drugs during nighttime hours, regardless of the day of the week. This suggests that concerns about DUID should complement, but not supplant, the current law enforcement focus on alcohol-impaired driving at night. Drug prevalence in our sample was substantially higher than among noncrashed drivers in the 2007 NRS, both at daytime (25.5% vs. 11.2%) and at nighttime (26.5% vs. 14.4%), and for each comparable drug class. [30] This finding and the findings from DRUID [18, 19] and the FARS [20] suggest that drugs may contribute to crash risk, although the cross-sectional nature of our study does not allow us to draw conclusions about causation.

This study also supports the assertion that drug-impaired driving differs from alcohol-impaired driving, as the hourly patterns of crash-related fatalities involving drugs differed significantly from those involving alcohol. Further, drug prevalence differed significantly by drug type: cannabinols and stimulants were higher in nighttime fatal crashes, and narcotics

or depressants were higher in daytime crashes. We also found differences in drug prevalence by gender and age, with cannabinols largely found among fatally injured underage male drivers and stimulants most common among fatally injured drivers aged 21-34 of both genders. These and related findings by Romano and Voas [20] that individual drug classes are associated with different types of traffic violations (e.g., red-light running, speeding, inattention) in fatal crashes suggest that criteria for developing effective laws and enforcement strategies to reduce DUID may need to be significantly different than those currently applied to alcohol.

Except for cannabinols, alcohol was not associated with the presence of other drugs. The association between alcohol and cannabinols may suggest that drivers tend to consume both drugs simultaneously or that alcohol and marijuana have a synergistic impairment effect leading to fatal crashes. Unfortunately, FARS does not allow for testing of these speculations. Thus, the results of this effort suggest a need to pay close attention to drivers' attitudes toward risk and patterns of behaviors and to the contribution of alcohol and cannabinols to crash risk.

Our findings may also provide a foundation for exploring targeted drug testing of impaired drivers. For example, a daytime female driver older than 65 who appears impaired but records a BAC<.08 might be tested for narcotics, which is more likely to yield a positive result than cannabinols. Narrowing down the tests required to identify the drug causing driver impairment could be valuable to law enforcement agencies operating on limited budgets. However, our study only justifies targeted testing as an area for further study as our data were limited to fatally injured drivers who died at the scene of single-vehicle crashes and not the entire driving population. More research on the key components of the DUID problem is needed before targeted drug testing can become a feasible policy. Of primary importance is characterizing the actual contribution of drugs to impairment and crashes, both alone and combined with alcohol.

This study focuses only on fatal crashes that, though of great importance, are not the most common injury observed in motor vehicle crashes. We might find different prevalence and associations in studying nonfatal crashes. Our study is also cross-sectional and thus cannot establish causation; the associations elucidated herein should not be considered measures of crash risk. Another limitation is that the FARS data is incomplete, and our study is limited to the 20 states that provided test results for at least 80% of fatally injured drivers. Lack of standardization for drug screening across states (and even within some states) could have introduced bias into our prevalence estimates. Different states test for different drugs (e.g., some states do not routinely test for marijuana) and rely on different labs with different testing protocols. We attempted to address these differences by including state as a random effect in our mixed models, and the statistical significance of the state variable speaks about the wisdom of our analytical strategy. It also speaks to the need for policy makers to develop standardized, nationwide procedures for measuring drug involvement among drivers.

Finally, our study findings represent only the presence or absence of drugs in a subset of fatally injured drivers and should not be interpreted as evidence of impairment. The wide variety of potentially impairing drugs, their differential pharmacology, and varying levels of individual tolerance make establishing impairment standards for drugs similar to the BAC>0.08 standard for alcohol extremely difficult. For this reason, only three states with drug *per se* laws (Nevada, Ohio, and Virginia) set cutoff levels for certain drugs [23], and the relationship of these cutoff levels to driver impairment is controversial. Unless uniform impairment standards are established for drugs, the presence of drugs remains the best indicator of possible, but not certain, driver impairment.

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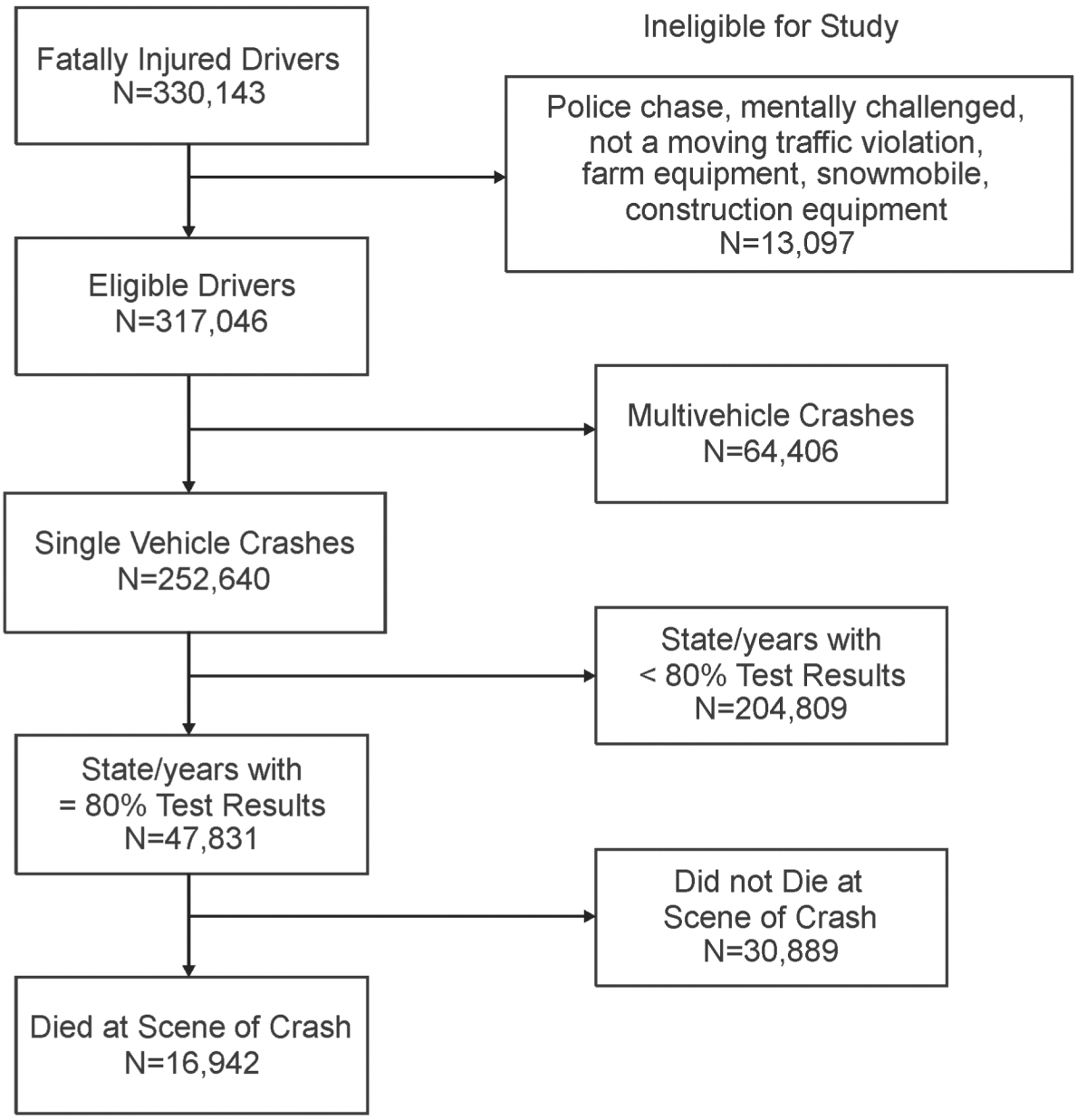


**Figure 1. Case Selection Criteria**

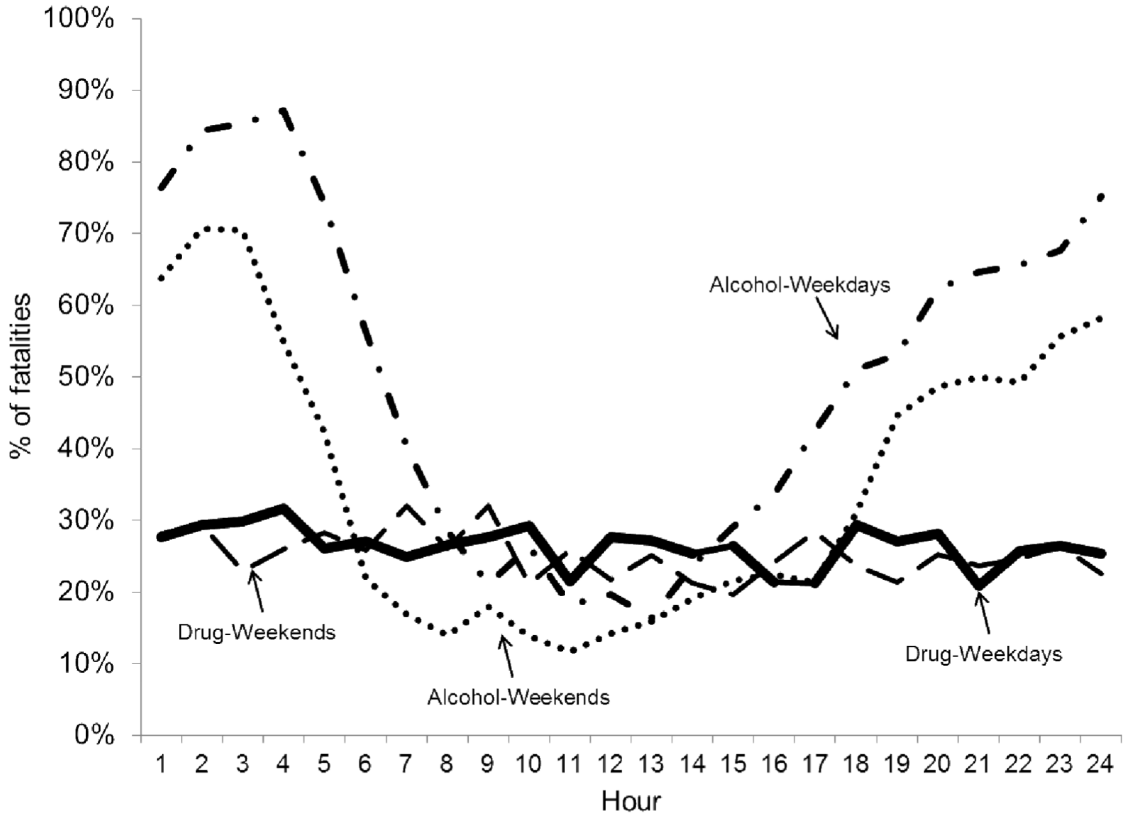


**Figure 2. Prevalence of alcohol- and drug-positives among fatally injured drivers by time of the day and day of the week**

Source: 1998-2010 FARS database, downloaded on August 2012. Drivers fatally injured at the scene of the crash. Single-vehicle crashes in states that had drug-test results for at least 80% of drivers. Weekday crashes include crashes that occurred between Sunday at 6:00 PM and Friday at 5:59 PM. Weekend crashes include those that took place between Friday at 6:00 PM and Sunday at 5:59 PM. The four curves in the graph were estimated separately, yielding R2 of .89, .81, .23, and .23; for alcohol weekdays, alcohol weekends, drug weekdays, and drug weekends, respectively.

**Table 1**

**Drug use prevalence among fatally injured drivers by time elapsed between crash and driver's death**

| Crash-Death: Elapsed Time | N | Percentage of Drivers with a Lab Result | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Positive (by type of drug) | | | | | | Negative |
| | | Cannabinols | Depressants | Narcotics | Stimulants | Other | Multidrug | |
| Death at scene within 1 hr | 16,942 | 7%** | 1%* | 2% | 7%** | 4% | 4% | 74% |
| | 17,199 | 5% | 2% | 3% | 5% | 8% | 4% | 74% |
| 1:01-2:00 hr | 5,975 | 5% | 2% | 2% | 5% | 6% | 4% | 77% |
| 2:01-3:00 hr | 1,989 | 5% | 3% | 2% | 4% | 5% | 3% | 78% |
| 3:01-4:00 hr | 1,153 | 5% | 2% | 3% | 5% | 6% | 4% | 75% |
| 4:01-5:00 hr | 677 | 5% | 2% | 3% | 4% | 5% | 3% | 77% |
| 5:01-6:00 hr | 508 | 5% | 3% | 4% | 2% | 5% | 4% | 77% |
| 6:01-8:00 hr | 663 | 5% | 3% | 3% | 5% | 7% | 3% | 75% |
| 8:01-10:00 hr | 523 | 6% | 4% | 2% | 4% | 4% | 6% | 74% |
| 10:01-20:00 hr | 1,541 | 6% | 3% | 3% | 4% | 4% | 6% | 74% |
| >20 hr | 29 | 3% | 3% | 3% | 3% | 0% | 10% | 76% |

Source: 1998-2010 FARS database, downloaded August 2012. Only includes records for fatally injured drivers in states where at least 80% of the drivers had drug-test results. Crash-Death: Elapsed Time denotes time in hours (hr) between crash and driver's death. Death at scene denotes death at the scene of the crash. Drug classes as defined in FARS. Multidrug denotes drivers positive for drugs in more than one class. * and ** refer to the significance (1% and 5%, respectively) of the comparison between the proportion of deaths at the scene and that of deaths at any other time afterwards (e.g., the % of cannabinols among deaths at the scene was significantly higher ($p$<.01) than the proportion of deaths that occurred afterwards).

**Table 2**

**Number of fatally injured drivers who died at the scene of single-vehicle crashes, by state and year**

| *STATE* | *YEAR* | | | | | | | | | | | | | *Total* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **1998** | **1999** | **2000** | **2001** | **2002** | **2003** | **2004** | **2005** | **2006** | **2007** | **2008** | **2009** | **2010** | |
| California | 659 | 743 | 784 | 888 | 945 | 931 | 964 | 814 | 814 | 787 | 706 | 576 | 620 | 10,231 |
| Colorado | 0 | 0 | 0 | 0 | 0 | 34 | 0 | 15 | 21 | 20 | 22 | 18 | 6 | 136 |
| Connecticut | 47 | 0 | 5 | 7 | 8 | 9 | 0 | 5 | 6 | 3 | 0 | 4 | 0 | 94 |
| DC | 0 | 0 | 324 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 324 |
| Georgia | 7 | 3 | 0 | 0 | 0 | 0 | 1 | 5 | 9 | 3 | 14 | 9 | 4 | 55 |
| Hawaii | 0 | 0 | 0 | 0 | 0 | 0 | 34 | 33 | 34 | 16 | 0 | 0 | 0 | 117 |
| Illinois | 18 | 0 | 0 | 0 | 0 | 0 | 0 | 17 | 43 | 38 | 10 | 12 | 6 | 144 |
| Maryland | 25 | 57 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 82 |
| Massachusetts | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 52 | 59 | 111 |
| Minnesota | 0 | 0 | 0 | 13 | 32 | 33 | 39 | 45 | 47 | 52 | 0 | 26 | 22 | 309 |
| Montana | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 2 | 3 | 5 | 13 |
| Nevada | 27 | 35 | 32 | 0 | 42 | 19 | 26 | 28 | 30 | 0 | 36 | 0 | 36 | 311 |
| New Hampshire | 0 | 16 | 32 | 34 | 36 | 38 | 0 | 33 | 25 | 12 | 10 | 8 | 12 | 256 |
| New Jersey | 0 | 1 | 0 | 0 | 0 | 3 | 1 | 3 | 0 | 3 | 2 | 0 | 1 | 14 |
| New Mexico | 0 | 0 | 0 | 165 | 162 | 169 | 195 | 153 | 167 | 145 | 89 | 45 | 0 | 1,290 |
| North Carolina | 0 | 0 | 0 | 0 | 0 | 15 | 0 | 7 | 0 | 10 | 2 | 0 | 2 | 36 |
| North Dakota | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 74 | 103 | 96 | 79 | 92 | 106 | 550 |
| Ohio | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 81 | 85 | 87 | 79 | 63 | 75 | 470 |
| Pennsylvania | 2 | 3 | 2 | 0 | 5 | 3 | 1 | 1 | 5 | 1 | 0 | 0 | 2 | 25 |
| Rhode Island | 0 | 0 | 0 | 0 | 0 | 10 | 8 | 13 | 14 | 10 | 13 | 18 | 0 | 86 |
| Vermont | 0 | 0 | 0 | 171 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 171 |
| Virginia | 0 | 0 | 0 | 149 | 170 | 159 | 171 | 204 | 184 | 148 | 164 | 152 | 139 | 1,640 |
| Washington | 46 | 59 | 40 | 43 | 56 | 45 | 59 | 39 | 26 | 19 | 16 | 18 | 10 | 476 |
| West Virginia | 659 | 743 | 784 | 888 | 945 | 931 | 964 | 814 | 814 | 787 | 706 | 576 | 619 | 10,230 |
| Total | 831 | 917 | 1,219 | 1,470 | 1,456 | 1,468 | 1,499 | 1,570 | 1,613 | 1,453 | 1,244 | 1,096 | 1,106 | 16,942 |

Source: FARS database, downloaded on August 2012. Includes only states and years in which at least 80% of the fatally injured drivers in single-vehicle crashes had a known drug-test result and died at the scene of the crash. “0” denotes a state/year combination in which the 80% criterion was not reached.

**Table 3**

**Percentage of fatally injured drivers by blood alcohol concentration (BAC) and drug class: gender, age, day of the week, and time of the day**

| | | | *Alcohol* | | | | *Drugs other than alcohol* | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | **Negative** | **BAC>0** | **0<BAC<.08** | **BAC≥.08** | **Negative** | **Positive** | **Cannabinols** | **Depressants** | **Narcotics** | **Stimulants** | **Other** | **Multidrug** |
| Overall | N=16,942 | % | 54.9 | 45.1 | 5.2 | 39.9 | 74.1 | 25.9 | 7.1 | 1.5 | 2.1 | 7.2 | 4.1 | 4.1 |
| | | CI | 54.2 - 55.7 | 44.4 - 45.9 | 4.8 - 5.5 | 39.2 – 40.7 | 73.4 - 74.7 | 25.3 - 26.6 | 6.7 – 7.5 | 1.3 – 1.7 | 1.8 – 2.3 | 6.8 – 7.6 | 3.8 – 4.4 | 3.8 – 4.4 |
| Gender | Male N=13,168 | % | 50.7 | 49.3 | 5.4 | 43.8 | 74.0 | 26.0 | 7.9 | 1.3 | 1.7 | 7.4 | 3.7 | 4.0 |
| | | CI | 49.9 - 51.6 | 48.4 - 50.1 | 5.1 - 5.8 | 43.0 - 44.7 | 73.3 - 74.8 | 25.3 - 26.7 | 7.5 - 8.4 | 1.1 - 1.5 | 1.5 - 2.0 | 6.9 - 7.8 | 3.4 - 4.0 | 3.7 - 4.4 |
| | Female N=3,772 | % | 69.4 | 30.6 | 4.2 | 26.4 | 74.3 | 25.7 | 4.1 | 2.3 | 3.2 | 6.5 | 5.4 | 4.2 |
| | | CI | 67.9 - 70.9 | 29.1 - 32.1 | 3.6 - 4.9 | 25.0 - 27.8 | 72.9 - 75.7 | 24.3 - 27.1 | 3.5 - 4.8 | 1.8 - 2.8 | 2.6 - 3.7 | 5.7 - 7.3 | 4.7 - 6.1 | 3.5 - 4.8 |
| Age | 16-20 N=2,445 | % | 64.2 | 35.8 | 6.4 | 29.4 | 76.5 | 23.5 | 11.5 | 0.5 | 0.7 | 4.2 | 3.6 | 3.0 |
| | | CI | 62.3 - 66.1 | 33.9 - 37.7 | 5.5 - 7.4 | 27.6 - 31.2 | 74.8 - 78.2 | 21.8 - 25.2 | 10.3 - 12.8 | 0.2 - 0.8 | 0.4 - 1.0 | 3.4 - 5.0 | 2.9 - 4.3 | 2.3 - 3.7 |
| | 21-34 N=5,938 | % | 42.5 | 57.5 | 5.4 | 52.1 | 72.5 | 27.5 | 9.1 | 0.8 | 1.2 | 9.2 | 3.0 | 4.3 |
| | | CI | 41.3 - 43.8 | 56.2 - 58.7 | 4.8 - 6.0 | 50.8 - 53.4 | 71.4 - 73.7 | 26.3 - 28.6 | 8.3 - 9.8 | 0.6 - 1.0 | 0.9 - 1.4 | 8.4 - 9.9 | 2.6 - 3.4 | 3.8 - 4.9 |
| | 35-64 N=7,095 | % | 55.5 | 44.5 | 4.9 | 39.6 | 72.3 | 27.7 | 5.3 | 2.4 | 3.0 | 7.9 | 4.5 | 4.7 |
| | | CI | 54.4 - 56.7 | 43.3 - 45.6 | 4.4 - 5.4 | 38.5 - 40.8 | 71.3 - 73.4 | 26.6 -28.7 | 4.7 - 5.8 | 2.0 - 2.7 | 2.6 - 3.4 | 7.3 - 8.5 | 4.0 - 5.0 | 4.2 - 5.2 |
| | 65+ N=1,455 | % | 87.0 | 13.0 | 3.7 | 9.3 | 84.9 | 15.1 | 0.6 | 1.9 | 3.3 | 0.7 | 7.0 | 1.7 |
| | | CI | 85.2 - 88.7 | 11.3 - 14.8 | 2.7 - 4.7 | 7.8 - 10.8 | 83.0 - 86.7 | 13.3 - 17.0 | 0.2 - 0.9 | 1.2 - 2.6 | 2.4 - 4.2 | 0.3 - 1.1 | 5.7 - 8.3 | 1.0 - 2.3 |
| Day of he week | Weekday N=10,125 | % | 62.0 | 38.0 | 4.6 | 33.5 | 73.7 | 26.3 | 6.8 | 1.6 | 2.3 | 7.1 | 4.2 | 4.3 |
| | | CI | 61.0 - 62.9 | 37.1 - 39.0 | 4.2 - 5.0 | 32.6 - 34.4 | 72.9 - 74.6 | 25.4 - 27.1 | 6.3 - 7.2 | 1.4 - 1.9 | 2.0 - 2.6 | 6.6 - 7.6 | 3.8 - 4.6 | 3.9 - 4.7 |
| | Weekend N=6,417 | % | 43.3 | 56.7 | 6.2 | 50.5 | 74.7 | 25.3 | 7.6 | 1.3 | 1.7 | 7.3 | 3.8 | 3.7 |
| | | CI | 42.1 - 44.5 | 55.5 - 57.9 | 5.6 - 6.8 | 49.3 - 51.7 | 73.6 - 75.7 | 24.3 - 26.4 | 7.0 - 8.3 | 1.0 - 1.5 | 1.4 - 2.0 | 6.7 - 8.0 | 3.3 - 4.2 | 3.2 - 4.1 |
| Time of the day | Daytime N=9,197 | % | 73.0 | 27.0 | 4.9 | 22.1 | 74.5 | 25.5 | 5.5 | 1.8 | 2.7 | 6.5 | 4.7 | 4.3 |
| | | CI | 72.1 - 73.9 | 26.1 - 27.9 | 4.5 - 5.3 | 21.2 - 22.9 | 73.6 - 75.4 | 24.6 - 26.4 | 5.1 - 6.0 | 1.5 - 2.1 | 2.3 - 3.0 | 6.0 - 7.0 | 4.2 - 5.1 | 3.9 - 4.7 |
| | Nighttime N=7,745 | % | 33.3 | 66.7 | 5.5 | 61.2 | 73.6 | 26.5 | 9.0 | 1.1 | 1.3 | 8.0 | 3.3 | 3.7 |
| | | CI | 32.3 - 34.4 | 65.6 - 67.7 | 5.0 - 6.0 | 60.1 - 62.3 | 72.6 - 74.5 | 25.5 - 27.4 | 8.3 - 9.6 | 0.9 - 1.4 | 1.1 - 1.6 | 7.4 - 8.6 | 2.9 - 3.7 | 3.3 - 4.2 |

Source: 1998-2010 FARS database, downloaded on August 2012. Includes only states and years in which at least 80% of the fatally injured drivers in single-vehicle crashes had a known drug-test result and died at the scene of the crash. Two rows per category, the top one (%) indicates estimated percentage for that cell, the lower (CI) indicates the 95% confidence interval for that estimate. All percentages are computed based on the corresponding "N" in the row. Except for rounding, individual percentages for Cannabinols, Depressants, Narcotics, Stimulants, Other, and Multidrug add exactly to that for drug Positive. Age "65+" denotes drivers aged 65 years and older. "Weekday" is defined as Sunday at 6:00 PM through Friday at 5:59 PM, and "weekend" is from Friday 6:00 PM through Sunday at 5:59 PM. "Daytime" covers crashes between 6:00 AM and 5:59 PM. "Nighttime" covers crashes at hours other than those considered as "Daytime."

**Table 4**

**Adjusted odds of positive drug test among fatally injured drivers across time and demographic variables**

| | *Cannabinols* | | | *Depressants* | | | *Narcotics* | | | *Stimulants* | | | *Other Drugs* | | | *Multidrug* | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **AOR** | **L95%** | **U95%** | **AOR** | **L95%** | **U95%** | **AOR** | **L95%** | **U95%** | **AOR** | **L95%** | **U95%** | **AOR** | **L95%** | **U95%** | **AOR** | **L95%** | **U95%** |
| **Model 1 (alcohol excluded)** | | | | | | | | | | | | | | | | | | |
| Weekday vs. Weekend | 1.001 | 0.998 | 1.004 | 1.002 | 0.998 | 1.005 | 1.003 | 0.997 | 1.008 | 1.006 | 0.994 | 1.019 | 1.006 | 0.994 | 1.019 | 1.008 | 0.993 | 1.023 |
| Daytime vs. Nighttime | 0.981 | 0.978 | 0.984 | 1.007 | 1.004 | 1.011 | 1.031 | 1.025 | 1.036 | 0.972 | 0.960 | 0.984 | 1.044 | 1.031 | 1.057 | 1.058 | 1.042 | 1.074 |
| 16-20 vs. 21-34 | 1.022 | 1.020 | 1.050 | 0.989 | 0.984 | 0.994 | 0.974 | 0.966 | 0.982 | 0.795 | 0.780 | 0.810 | 1.012 | 0.994 | 1.031 | 0.885 | 0.866 | 0.905 |
| 35-64 vs. 21-34 | 0.962 | 0.959 | 0.965 | 1.040 | 1.036 | 1.044 | 1.065 | 1.059 | 1.072 | 0.953 | 0.940 | 0.967 | 1.083 | 1.068 | 1.098 | 1.010 | 0.993 | 1.027 |
| ≥65 vs. 21-34 | 0.911 | 0.906 | 0.917 | 1.016 | 1.010 | 1.022 | 1.044 | 1.034 | 1.055 | 0.676 | 0.661 | 0.691 | 1.158 | 1.133 | 1.184 | 0.770 | 0.750 | 0.791 |
| Female vs. male | 0.963 | 0.960 | 0.967 | 1.025 | 1.021 | 1.029 | 1.050 | 1.043 | 1.057 | 0.984 | 0.970 | 0.998 | 1.093 | 1.078 | 1.109 | 1.013 | 0.996 | 1.031 |
| **Model 2 (alcohol included)** | | | | | | | | | | | | | | | | | | |
| Weekday vs. Weekend | 1.007 | 0.997 | 1.017 | 1.005 | 0.995 | 1.016 | 1.011 | 0.993 | 1.030 | 1.018 | 0.978 | 1.060 | 1.026 | 0.985 | 1.068 | 1.035 | 0.986 | 1.086 |
| Daytime vs. Nighttime | 1.003 | 0.992 | 1.013 | 1.008 | 0.997 | 1.020 | 1.025 | 1.006 | 1.046 | 0.984 | 0.943 | 1.028 | 1.043 | 0.999 | 1.090 | 1.047 | 0.995 | 1.103 |
| 16-20 vs. 21-34 | 1.035 | 1.020 | 1.050 | 0.991 | 0.976 | 1.007 | 0.969 | 0.943 | 0.996 | 0.811 | 0.763 | 0.861 | 1.004 | 0.945 | 1.067 | 0.864 | 0.804 | 0.929 |
| 35-64 vs. 21-34 | 0.965 | 0.954 | 0.976 | 1.040 | 1.028 | 1.053 | 1.066 | 1.045 | 1.087 | 0.951 | 0.909 | 0.994 | 1.082 | 1.034 | 1.132 | 1.002 | 0.949 | 1.056 |
| ≥65 vs. 21-34 | 0.928 | 0.911 | 0.945 | 1.019 | 1.000 | 1.038 | 1.041 | 1.008 | 1.076 | 0.686 | 0.637 | 0.739 | 1.139 | 1.060 | 1.223 | 0.762 | 0.698 | 0.831 |
| Female vs. male | 0.971 | 0.960 | 0.983 | 1.020 | 1.008 | 1.033 | 1.051 | 1.029 | 1.073 | 0.979 | 0.935 | 1.026 | 1.087 | 1.038 | 1.138 | 1.017 | 0.962 | 1.075 |
| 0<BAC <.08 vs. BAC=.00 | 1.060 | 1.048 | 1.071 | 1.006 | 0.994 | 1.017 | 0.990 | 0.970 | 1.010 | 1.035 | 0.989 | 1.082 | 1.000 | 0.956 | 1.047 | 0.950 | 0.900 | 1.003 |
| BAC≥.08 vs. BAC=.00 | 1.104 | 1.052 | 1.159 | 1.006 | 0.954 | 1.061 | 1.015 | 0.926 | 1.112 | 1.027 | 0.838 | 1.259 | 1.098 | 0.896 | 1.346 | 0.874 | 0.681 | 1.121 |

Source: 1998-2010 FARS database, downloaded on August 2012. Includes only states and years in which at least 80% of the fatally injured drivers in single-vehicle crashes had a known drug-test result and died at the scene of the crash. Odds ratios (ORs) were estimated separately for the different drug classes. Models were run separately for each drug class (i.e., the dependent variable on each model), as well as without including alcohol as an explanatory variable (Model 1, top half) and with alcohol positive (Model 2, lower half). “Weekday” is defined as Sunday at 6:00 PM through Friday at 5:59 PM, and “weekend” is from Friday 6:00 PM through Sunday at 5:59 PM. “Daytime” covers crashes between 6:00 AM and 5:59 PM. “Nighttime” covers crashes at hours other than those considered as “Daytime.” AOR = adjusted odds ratio. L95%=lower bound of 95% confidence interval. U95%=upper bound of 95% confidence interval.