Differences in the risk profiles of drunk and drug drivers: Evidence from a mandatory roadside survey

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Background: The study assesses the prevalence rates of alcohol- and drug-involved driving in Catalonia (Spain). **Method:** Drivers were randomly selected for roadside testing using a stratified random sampling procedure representative of all vehicles circulating on non-urban roads. Mandatory alcohol and drug tests were performed during autumn 2017. A sample of 6,860 drivers were tested for alcohol use, of these 671 were also tested for drugs. Standard procedures were employed by traffic officers to detect alcohol and drug use. Alcohol breath tests were performed with breathalyser devices and on-site drug screening systems were used to test for drugs. **Results**: The prevalence of alcohol use above the legal limit and drug use were 1.2% (95% CI: 0.9-1.5%) and 8.3% (95% CI: 5.8-11.2%), respectively. The most frequent drugs detected were THC (5.6%, 95% CI: 3.7-8.0%), cocaine (3.5%, 95% CI: 2.0-5.5%) and amphetamines (1.6%, 95% CI: 0.6-3.4%). Alcohol use was detected more frequently on conventional roads, at weekends and during night-time hours. Drug use was detected more frequently in young males during daytime hours. **Conclusions:** Driver risk profiles associated with alcohol use and drug use differ. Positive alcohol use is not a predictor of drug use when controlling for all other factors.

1. Introduction

The use of alcohol and other drugs (AOD) by drivers is estimated to be responsible for just over 18% of road traffic deaths worldwide (WHO, 2016). Indeed, drinking alcohol and driving is a well-studied risk factor for road traffic accidents. But while drunk-driving interventions around the world have been effective in cutting alcohol prevalence rates (Sweedler et al., 2009; Perkins et al., 2010), there is growing concern about non-alcohol drug use and road safety. In fact, driving under the influence (DUI) of non-alcohol drugs presents an upward trend in many counties (Christophersen et al., 2020; Brady and Li, 2014).

To determine the extent of this emerging problem, the Catalan Traffic Authority (Catalonia, Spain) has promoted a project addressed at periodically measuring the prevalence of driving under the influence of alcohol and other psychoactive drugs and medicines (2014–2020 Strategic Road Safety Plan). A first roadside survey representative of the Catalan driving population was carried out in 2014. Drug prevalence rates obtained during that survey were analysed in Alcañiz et al. (2018), but alcohol prevalence rates were excluded from that analysis.

To continue monitoring the situation, a new roadside survey was conducted in 2017. In this article, the main results of this second Catalan roadside survey are analysed. Alcohol is included in our analysis to shed new light on the prevalence of alcohol and drug use by Catalan drivers. Our objectives in this cross-sectional study are threefold: (i) to estimate the prevalence rates of alcohol and drug use by drivers; (ii) to compare the risk factors of DUI of drugs with the results obtained in the 2014 edition, (iii) to identify differences in the risk driving profiles of alcohol use and drug use.

A key focal point in road safety and motor crash prevention is the identification of risky drivers, defined as those with an increased likelihood of driving under the influence of alcohol or drugs. Identifying risk driving profiles of alcohol use and drug use should help the authorities to design better educational policies and preventive campaigns, and to provide a baseline for evaluating whether significant reductions follow the implementation of enforcement interventions. This study sheds new light on road safety, by analysing the evolution of prevalence rates of drug use by drivers on Catalan roads and it also implements a methodology that tests for drugs only in a subsample of drivers tested for alcohol, which is more costly. It also serves as a reference for comparisons of what characterizes DUI of alcohol versus DUI of drugs.

The terminology used in this article follows the definitions provided by the WHO (2016). The term *drug* is used as an equivalent of a psychoactive drug, that is, a substance that has the ability to affect mental processes such as an individual's consciousness, mood or thinking. The term does not include alcohol. *Illicit drugs* refer to drugs whose use is globally prohibited (e.g. cocaine, heroin, methamphetamines and cannabis) and *prescription drugs* refer to those that can be bought legally or on prescription from a doctor (e.g. antidepressants, benzodiazepines and opioid analgesics). Finally, when we refer to drivers that tested positive for alcohol we refer to those with alcohol concentrations above the legal limit established in the corresponding jurisdiction.

The National Roadside Survey of Alcohol and Drug Use by Drivers (NRS) in the United States and the Driving Under the Influence of Drugs, Alcohol and Medicines (DRUID) project in the European Union constitute two major research projects that employ roadside surveys of AOD use by drivers. The NRS survey is conducted roughly every 10 years and driver participation is voluntary (Lacey et al., 2011; GAO, 2018). The most recent survey was conducted in 2013–2014 and found no significant differences in the prevalence of drug use between weekend night-time hours (19.8%) and weekday daytime hours (19.0%). In the case of alcohol, the rates were 1.5 and 0.4%, respectively (Berning et al., 2015).

In the DRUID project, AOD prevalence in the driving population was assessed in thirteen European countries between 2007 and 2009, with driver participation being voluntary in most countries (Schulze et al., 2012). The DRUID project reported that 3.5% of drivers tested positive for alcohol, 1.9% for illicit drugs and 1.4% for prescription drugs. In Spain these figures were 6.6, 10.9 and 2%, respectively (Gómez-Talegón et al., 2012). Two additional roadside surveys were conducted in Spain in 2013 and 2015 with 4.1 and 9.7% of Spanish drivers testing positive for alcohol and drugs, respectively, in the first year (Fierro et al., 2015) and 2.6 and 9.7%, respectively, in the second (Domingo-Salvany et al., 2017).

2. Alcohol and drug survey

2.1 AOD-impaired driving in Spain

The cross-sectional study reported here covers the geographical area of Catalonia (Spain), a Mediterranean region with a population of over 7.6 million inhabitants in 2019. Spanish legislation on drink and drug driving (Government Decree 1428/2003) establishes a standard legal breath alcohol content (BAC) limit of 0.25 milligrams of alcohol per litre of breath and 0.15 mg/l for professionals and novice drivers. Alcohol tests were conducted following normal police procedures with a preliminary alcohol test being carried out using a portable breathalyser. If the BAC level is above the legal limit, the test is repeated using an evidential breath testing device. If the BAC outcome is again above the limit, a confirmatory test is carried out after half an hour. The lower of the two BAC measures is retained as evidence, which is the level we consider in this study.

In the case of drugs, driving following the consumption of narcotic and psychotropic drugs, as well as other stimulants or similar substances, including medicines that affect the physical or mental skills needed to drive safely, is considered a serious infringement of the Spanish criminal code. Here, mandatory on-site oral fluid drug tests were carried out by traffic officers. If the saliva sample revealed a positive result for any substance, the driver was requested to provide a larger oral fluid sample, which was then taken to a laboratory for confirmation. The drugs test was conducted using the mobile drug screening system AlereTM DDS®2 Test Kit, which allows a relatively wide range of illegal and prescription substances to be tested. The drug cut-off concentrations are 25 ng/ml for tetrahydrocannabinol (THC), 50 ng/ml for methamphetamines and amphetamines, 30 ng/mg for cocaine, 40 ng/mg for opiates, and 20 ng/ml for benzodiazepines. As the results of subsequent laboratory analyses were not available for our observations, we used the outcomes of the initial saliva tests performed at the roadside. The performance of the Alere DDS Test Kit in terms of sensitivity, specificity and overall accuracy is similar to that of other drug screening systems, including the Dräger® Drug Test 5000 device (Logan and Mohr, 2015; Lema-Atán et al., 2019).

2.2 Sample design

The sample design was defined in two distinct stages. The first stage aimed at selecting the road sections at which checkpoints could be set up and which would constitute our primary sampling units (PSUs). The Catalan interurban road network is divided by the traffic authority in 2,265 road sections, 89% of which are conventional sections and 11% of which are motorway sections. Road sections with an average daily traffic volume below 4,000 vehicles per day were excluded to ensure that checkpoints were not empty at low flow time-frames. Eventually, 844 road sections were included: 70% conventional and 30% motorway sections. PSUs were selected using five stratification variables: geographical area (divided into six areas), road type (conventional or motorway), flow direction (according to the road kilometre counter), day of week, and time-slots (divided into six four-hour intervals beginning at 22:00). This first stage in our sample design constitutes a stratified non-proportional sample and as such weights are required to ensure the correct representation of the global network. The weighting methodology is described in Alcañiz et al. (2014).

The secondary sampling units (SSUs) are the drivers selected to be AOD tested. These drivers were chosen using a simple random sampling method. Thus, any driver circulating on the selected road section had the same probability of being chosen, regardless of their gender, age, type of vehicle, or driving behaviour. Once the checkpoint had been installed by the traffic officers, the first driver to approach it was tested both for alcohol and drugs. Subsequent drivers arriving at the unoccupied checkpoint were tested only for alcohol. This restriction was introduced because of the high cost of the drugs tests, but it meant we had larger samples for alcohol than for drugs. As only the first driver approaching the police checkpoint was tested for both alcohol and drugs, the sample of drivers is not affected by selection bias.

3. Data

3.1 Sample size

A list of the 690 checkpoint locations was provided to police officers. Each designated location was provided with a substitute location to be used if the original checkpoint could not be set up due to unexpected factors, such as road works. This alternative location was identical to the original one in terms of its stratification variables. The target was to guarantee 720 hours of operating AOD controls across Catalonia, with 630 checkpoints operating for one hour and 60 for an hour and a half. The extension of the fieldwork was determined by the availability of resources. The sample was gathered between October 2 and November 26, as spring and, specifically, autumn are associated in Catalonia with intermediate rates of alcohol-impaired driving (Chuliá et al., 2016). Days with atypical traffic flows (such as holidays) were intentionally excluded.

A total of 6,860 drivers were tested for alcohol, of which 671 were also tested for drugs. The estimation error associated with this sample size is ±0.3% as regards drivers testing positive for alcohol P, assuming P=0.02 and a confidence level of 95%. In the case of drugs, the estimation error is ±2.3% for a maximum percentage of positive drug results of tested drivers and a 95% confidence level. After eliminating records due to incomplete information, the sample comprised 6,460 valid observations of alcohol tested drivers and 650 valid observations of drug tested drivers.

3.2 Descriptive statistics

The information used in the analysis undertaken here was recorded by police officers for each driver and their vehicle when conducting the AOD test. The classification variables included are gender, age, number of years in possession of a driving licence, nationality, vehicle type, number of occupants, road type, day of the week, and time of day. The number of years in possession of a driving licence correlated closely with age (Pearson correlation coefficient equal to 0.88) and so was not used in the analysis. The definition of the variables used in the study are provided in Table 1.

Table 1. Definition of variables

Variable	Description
Gender	1 if the driver is female, 0 if male
Age	Age of the driver in years
Nationality	1 if the driver is non-Spaniard, 0 if Spaniard
Road type	1 if motorway, 0 if conventional road
Vehicle type	
Car	1 if the vehicle is a passenger car, 0 otherwise
Van	1 if the vehicle is a van, 0 otherwise
Lorry	1 if the vehicle is a lorry or coach, 0 otherwise
Motorbike	1 if the vehicle is motorbike, moped or bicycle, 0 otherwise
Occupants	Number of occupants in the vehicle
Day of the week	
Monday	1 if the AOD test was performed on Monday, 0 otherwise
Tuesday-Thursday	1 if the AOD test was performed between Tuesday-Thursday, 0 otherwise
Friday	1 if the AOD test was performed on Friday, 0 otherwise
Saturday	1 if the AOD test was performed on Saturday, 0 otherwise
Sunday	1 if the AOD test was performed on Sunday, 0 otherwise
Time	
2:00–6:00.	1 if the AOD test was performed in the time interval 2:00–6:00, 0 otherwise
6:00–10:00	1 if the AOD test was performed in the time interval 6:00–10:00, 0 otherwise
10:00–14:00	1 if the AOD test was performed in the time interval 10:00–14:00, 0 otherwise
14:00–18:00	1 if the AOD test was performed in the time interval 14:00–18:00, 0 otherwise
18:00–22:00	1 if the AOD test was performed in the time interval 18:00–22:00, 0 otherwise
22:00–2:00	1 if the AOD test was performed in the time interval 22:00–2:00, 0 otherwise
Alcohol	1 if the alcohol test was positive, 0 otherwise
Drug test	1 if the drug test was carried out, 0 otherwise
Drug output	1 if the drug test was positive, 0 otherwise

So as to avoid biased outcomes, all results were calculated taking the complex sample design into consideration (Lohr, 2009). The analysis of the survey sample was conducted using R-package survey (Lumley, 2019). Descriptive statistics are shown in Table 2. Confidence intervals of proportions were computed based on the Rao-Scott method (Rao and Scott, 1984). In general, samples of drivers tested for alcohol and for drugs present a similar composition as regards the features of the driver, the vehicle and the road type, and the day and time-slot in which the test was performed. Welch's two sample t-test of equal means was computed and the test was statistically significant at the 5% significance level in the case of age, gender, number of occupants, passenger cars and vans. The null hypothesis of equal means was not rejected for the other classification variables.

Table 2. Descriptive statistics

Variable	Min	Max	ALCOHOL TESTED DRIVERS {N=6,460} Mean	95% CI	DRUG TESTED DRIVERS {N=650} Mean	95% CI
Gender	0	1	0.188	(0.175-0.201)	0.116	(0.087-0.154)
Age	17	93	42.680	(42.238-43.122)	39.721	(38.495-40.947)
Nationality	0	1	0.127	(0.116-0.139)	0.142	(0.110-0.179)
Road type	0	1	0.441	(0.424-0.459)	0.416	(0.364-0.469)
Vehicle type						
Car	0	1	0.814	(0.800-0.828)	0.770	(0.723-0.813)
Van	0	1	0.113	(0.102-0.124)	0.145	(0.109-0.186)
Lorry	0	1	0. 048	(0.040-0.056)	0. 060	(0.037-0.089)
Motorbike	0	1	0.025	(0.020-0.031)	0.025	(0.012-0.045)
Occupants	0	5	1.584	(1.555-1.613)	1.501	(1.422-1.579)
Day of the week						
Monday	0	1	0.183	(0.171-0.196)	0.180	(0.144-0.221)
Tuesday-Thursday	0	1	0.350	(0.333-0.368)	0.336	(0.286-0.389)
Friday	0	1	0.147	(0.136-0.158)	0.154	(0.122-0.191)
Saturday	0	1	0.161	(0.150-0.172)	0.161	(0.128-0.198)
Sunday	0	1	0.159	(0.147-0.171)	0.168	(0.134-0.207)
Time						
2:00–6:00	0	1	0.088	(0.079-0.098)	0.100	(0.075-0.129)
6:00–10:00	0	1	0.171	(0.158-0.184)	0.187	(0.148-0.230)
10:00–14:00	0	1	0.223	(0.209-0.237)	0.207	(0.166-0.252)
14:00–18:00	0	1	0.179	(0.167-0.192)	0.171	(0.135-0.211)
18:00–22:00	0	1	0.223	(0.208-0.237)	0.220	(0.178-0.265)
22:00–2:00	0	1	0.117	(0.106-0.127)	0.117	(0.088-0.150)
Alcohol	0	1	0.012	(0.009-0.015)	0.015	(0.007-0.030)
Drug test	0	1	0.114	(0.103-0.125)	-	-
Drug output	0	1	-	-	0.083	(0.058-0.112)

The prevalence of alcohol use by drivers was 1.2% (95% CI: 0.9-1.5%). This figure is similar to those reported in the previous surveys in Catalonia (Alcañiz et al., 2014; 2018). Among the alcohol tested drivers 11.4% were also tested for drugs. The alcohol prevalence rate of the subsample of drug tested drivers was not statistically different to that of the whole sample (Welch’s t=-0.75, df=751, p-value=0.45).

3.3 Alcohol and drug combinations

Among the drivers that tested positive for drugs – 79% of whom tested positive for single drug use and 21% for multiple drug use – only 5% were positive for alcohol too.

The prevalence of drug use among all tested drivers was 8.3% (95% CI: {5.8, 11.2}, i.e. 54 (weighted) positive cases over 650 tests. The most frequent drugs were THC (5.6%, 95% CI: {3.8, 8.0}), cocaine (3.5%, 95% CI: {2.0, 5.5}) and amphetamines (1.6%, 95% CI: {0.6, 3.4}). The frequency of occurrence of the other drugs tested for was much lower: thus, the prevalence of methamphetamines, opiates and benzodiazepines was lower than 0.3% in all cases. These percentages are notably lower than those observed in 2014, except in the case of cocaine whose frequency was higher (Alcañiz et al., 2018).

4. Factors affecting AOD prevalence rates

4.1 Univariate analysis

The χ^2 test (see Table 3) was employed to analyse the association between the classification variables and the presence of AOD. In the case of the categorical variables, the AOD prevalence rates for each category are reported. Male drivers had significantly higher prevalence rates of alcohol and drug use than female drivers. In the case of alcohol, the prevalence rates were 1.3% of males (95% CI: 0.9-1.7%) vs. 0.6% of females (95% CI: 0.3-1.2%). The gender difference was markedly higher in the case of drugs: 9.3% of males (95% CI: 6.6-12.6%) vs. 0.4% of females (95% CI: 0.0-2.0%). The χ2 test was statistically significant at the 10% significance level for alcohol and at the 1% level for drugs (χ^2=3.24, df=1, p-value=0.07; χ^2=13.32 df=1, p-value<0.01, respectively). No differences in the AOD prevalence rates were found between Spaniards and other nationalities.

The age of the driver vehicle was significant in explaining differences in drug use prevalence rates (χ2=15.41, df=1, p-value<0.01). As the driver age is a continuous variable, to understand the effect of the age on drug use, a simple logit regression with age as covariate was fitted to estimate the probability of drug use. The odds-ratio (OR) was 94.51% (95% CI: 91,78- 97.32%), indicating that the probability of drug use decreases when the age increases one year. In the case of alcohol use, differences in prevalence rates of alcohol use with one year age increase were not detected ($\chi2$=1.14, df=1, p-value=0.29 and OR: 98.62%; 95% CI: 96.16%- 101.15%).

Table 3. Prevalence and 95% confidence intervals (CI) for alcohol and other drugs

	Alcohol			Drugs		
Characteristic	Prevalence for alcohol %	95% CI	χ^2 test {p,value}	Prevalence for drugs %	95% CI	χ^2 test (p-value)
TOTAL	1.2	(0.9- 1.5)		8.2	(5.8-11.0)	
Gender						
Male	1.3	(0.9- 1.7)		9.3	(6.6- 12.6)	
Female	0.6	(0.3- 1.2)	3.242 (0.072)	0.4	(0.0- 2.0)	13.324 (<0.001)
Age	-	-	1.137 (0.286)	-	-	15.407 (<0.001)
Nationality						
Spanish	1.2	(0.9-1.6)		7.3	(4.9- 10.2)	
Other	0.9	(0.3- 2.0)	0.428 (0.513)	14.2	(6.3- 25.8)	2.586 (0.108)
Road type						
Conventional	1.5	(1.1- 2.1)		7.4	(4.9- 10.6)	
Motorway	0.7	(0.3- 1.2)	5.082 (0.024)	9.4	(5.2- 15.3)	0.508 (0.476)
Vehicle type						
Car	1.1	(0.8- 1.5)		8.3	(5.7- 11.6)	
Van	0.6	(0.2- 1.3)		10.5	(3.6- 22.2)	
Lorry	2.5	(0.1- 6.5)		1.2	(0.2- 3.9)	
Motorbike	2.7	(0.1- 7.4)	5.571 (0.134)	8.8	(0.9- 29.0)	9.517 (0.023)
Occupants	-	-	3.418 (0.064)	-	-	0.222 (0.638)
Day of the week						
Monday	0.1	(0.0- 1.7)		12.3	(6.0- 21.3)	
Tuesday-Thursday	0.5	(0.0- 1.1)		6.0	(2.5- 11.6)	
Friday	0.4	(0.0- 1.0)		8.3	(3.1- 16.9)	
Saturday	2.0	(1.2- 3.1)		9.0	(4.2- 16.2)	
Sunday	2.7	(1.6- 4.1)	20.308 (<0.001)	7.6	(3.2- 14.6)	2.277 (0.685)
Time						
2:00–6:00	1.6	(0.8- 2.8)		3.1	(0.9- 7.2)	
6:00–10:00	1.8	(1.0- 3.1)		15.5	(8.2- 25.5)	
10:00–14:00	0.6	(0.2- 1.2)		10.3	(5.0- 17.9)	
14:00–18:00	0.8	(0.3- 1.6)		11.0	(4.8- 20.6)	
18:00–22:00	0.9	(0.4- 1.8)		3.6	(1.0- 8.6)	
22:00–2:00	2.0	(1.0- 3.5)	9.882 (0.079)	2.2	(0.7- 5.0)	20.985 (0.001)
Alcohol						
Negative	-	-		8.0	(5.5- 10.9)	
Positive	-	-	-	27.0	(4.3- 65.0)	2.961 (0.085)

As for the characteristics of the road and vehicle, the type of road on which the checkpoint was located and number of occupants in the vehicle were significant in accounting for the prevalence of alcohol use by drivers at the 1 and 10% significance levels, respectively. The alcohol prevalence rates were 1.5% on conventional roads (95% CI: 1.1-2.1%) vs. 0.7% on motorways (95% CI: 0.3-1.2%). Unlike alcohol, no differences were detected in the drug prevalence rates with road type and number of occupants. However, vehicle type was significant in explaining differences in drug use by drivers, but not alcohol consumption. Drivers of heavy vehicles presented lower prevalence rates of drug use than those of passenger cars, vans or two-wheel vehicles.

The day of the week and time-slot during which the AOD test was conducted were both significant in accounting for the prevalence of alcohol use by drivers. The prevalence of alcohol detection was higher during the weekend, and at night-time and during the hours of the early morning (from 22:00 to 10.00). Unlike alcohol, the prevalence of drug detection did not statistically differ between the weekend and the rest of the week (χ^2=2.68, df=4, p-value=0.68). The time-slots during which the positive drug outcomes were recorded showed significant differences: the highest prevalence rates were found during the daytime from 6:00 to 18:00. Finally, the difference in the drug prevalence rate in relation to the result of the alcohol test was statistically significant (χ^2=2.96, df=1, p-value=0.09). Thus, alcohol use was associated with a higher frequency of drug use, the drug prevalence rate being 27% for alcohol-impaired drivers (95% CI: 4.3-65%) and 8% for drivers testing negative for alcohol (95% CI: 5.5-10.9%).

4.2 Multivariate analysis

A univariate analysis cannot consider the interactions between classification variables, whereas a multivariate analysis, by employing a Probit regression model, can take into account these interactions and provide a measure of the impact of each variable on the likelihood of AOD use. Three Probit regressions were fitted to our data to model the likelihood of a driver being found (a) positive for alcohol; (b) positive for drugs and, (c) positive for drugs when including the alcohol test output as a classification variable. The corresponding coefficient estimates are shown in Table 4. In the three models, the measures of sensitivity and specificity and the misclassification errors indicated a reasonable goodness of fit of the Probit regressions.

A number of findings in the multivariate analysis of the alcohol prevalence rate vary from those found in the univariate analysis reported above. Gender differences in the alcohol prevalence rates are no longer significant when the interactions are included in the analysis, whereas the likelihood of a driver testing positive for alcohol use is higher if driving a heavy vehicle than a passenger car (Coeff.=0.814). The rest of the variables that account for differences in the alcohol prevalence rate were detected previously in the univariate analysis. If the checkpoint is located on a motorway, the alcohol test is less likely to be positive (Coeff.= -0.422). The probability of a driver being alcohol impaired is positively associated with the number of occupants in the vehicle (Coeff.= 0.097)., Similarly, the likelihood of being alcohol impaired is higher on Saturday (Coeff.= 0.591) and Sunday (Coeff.= 0.773) than on Tuesday to Thursday. Likewise, when fixing the time slot from 10:00 to 14:00 as our reference category, the likelihood of detecting a drink driver is higher from 22:00 to 2:00 (Coeff.= 0.494), 2:00 to 6:00 (Coeff.= 0.393) and 6:00 to 10:00 (Coeff.= 0.376).

The multivariate analysis of the drug prevalence rate provides additional information to the univariate study. If we examine the results from the extended regression model (c) in which the alcohol test outcome is included as a regressor, the coefficient associated with alcohol use was not significant at the 10% level in accounting for the likelihood of a driver using drugs. The use of drugs is more likely to be detected in non-Spanish drivers than it is in their Spaniards counterparts (Coeff.= 0.502). The likelihood of drug use is higher on Mondays (Coeff.= 0.463) than it is on the days in the middle of the week (Tuesdays to Thursdays). The rest of the significant variables were previously detected also in the univariate case. Female drivers are less likely to use drugs than male drivers (Coeff.= -1.353) and the use of drugs decreases with age (Coeff.= -0.027). Drivers of heavy vehicles are less likely to provide a positive result for drugs than are drivers of passenger cars (Coeff.= -0.905). Compared to the 10:00 to 14:00 time-slot, the likelihood of detecting a drug-impaired driver is lower if the test was carried out from 18:00 to 22:00 (Coeff.= -0.543), 22:00 to 2:00 (Coeff.= -0.877) and 2:00 to 6:00 (Coeff.= -0.592).

Table 4. Probit regression for alcohol or drug driving

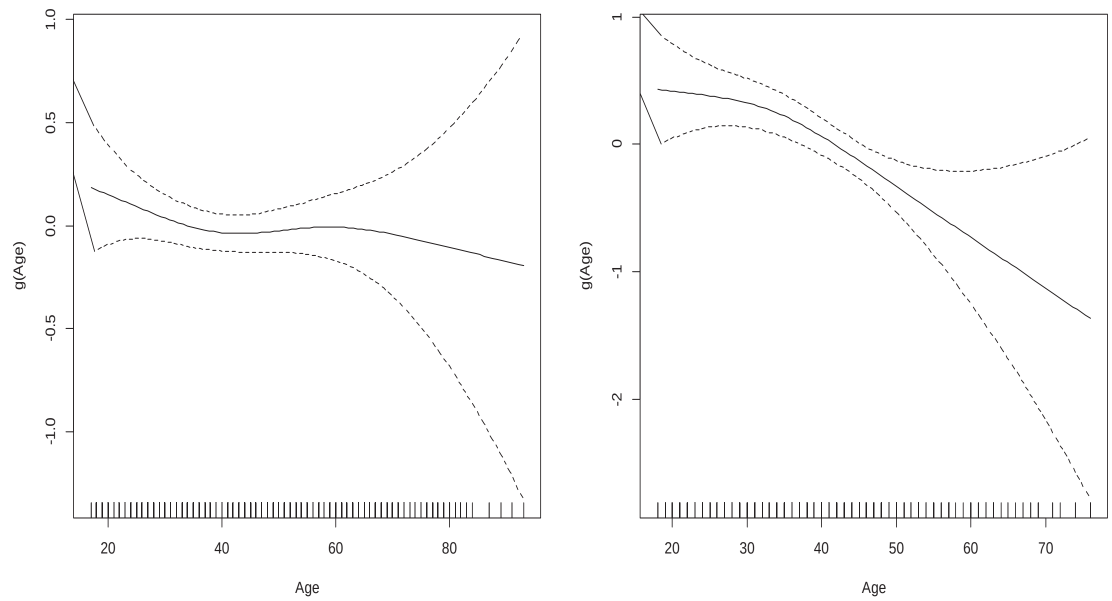
	POSITIVE ALCOHOL (a)		POSITIVE DRUGS (b)		POSITIVE DRUGS-EXTENDED (c)	
Variable	Coeff.	St.Error	Coeff.	St.Error	Coeff.	St.Error
Intercept	-2.790	0.359***	-0.448	0.471	-0.487	0.478
Gender	-0.253	0.178	-1.345	0.416***	-1.353	0.424***
Age	-0.003	0.005	-0.027	0.008***	-0.027	0.008***
Nationality	-0.267	0.188	0.496	0.264*	0.502	0.264*
Road type	-0.423	0.127***	0.126	0.208	0.151	0.209
Vehicle type						
Car (ref)	-	-	-	-	-	-
Van	-0.093	0.181	-0.218	0.309	-0.203	0308
Lorry	0.815	0.276***	-0.937	0.384**	-0.906	0.381**
Motorbike	0.484	0.300	-0.148	0.491	-0.102	0.490
Occupants	0.097	0.058*	0.016	0.129	0.026	0.127
Day of the week						
Monday	0.336	0.208	0.478	0.279*	0.464	0.279*
Tuesday-Thursday (ref)	-	-	-	-	-	-
Friday	0.004	0.269	0.209	0.305	0.209	0.303
Saturday	0.592	0.192***	0.225	0.282	0.203	0.278
Sunday	0.774	0.178***	0.115	0.296	0.052	0.320
Time						
2:00–6:00	0.393	0.222*	-0.583	0.292**	-0.592	0.296**
6:00–10:00	0.376	0.211*	0.265	0.281	0.232	0.289
10:00–14:00 (ref)	-	-	-	-	-	-
14:00–18:00	0.109	0.238	-0.063	0.304	-0.049	0.304
18:00–22:00	0.182	0.236	-0.561	0.304*	-0.543	0.304*
22:00–2:00	0.494	0.223**	-0.881	0.311***	-0.878	0313***
Alcohol output	-	-	-	-	0.568	0.568
Model diagnosis						
Optimal cut-off (%)	1.15		10.40		9.20	
Sensitivity (%)	70.48		73.85		69.40	
Specificity (%)	77.29		78.35		82.54	
Misclassification error (%)	29.44		25.78		29.52	

*** significance at 1%; ** significance at 5%; * significance at 10%.

4.3 Driver's age and likelihood of AOD use

We next carried out an in-depth analysis of the effect of the driver's age on the likelihood of AOD use. The traditional Probit regression considers a linear association between the (transformed) dependent variable and driver's age. However, the continuous nature of the age variable may conceal an alternative relationship, i.e. one that is more appropriate than a linear association. Thus, a semiparametric Probit regression model was fitted to the data in which the age of the driver was included as a non-parametric effect. The rest of the classification variables were left unchanged from the way they were introduced in the traditional Probit regression model framework. Figure 1 shows the estimated effect of driver's age in the semiparametric Probit regression when modelling the likelihood of a driver testing positive for alcohol (Fig.1a) and for drugs (Fig.1b).

Figure 1. Effect of driver's age on the linear predictor when modelling the likelihood of testing positive for alcohol (a) and drugs (b) (95%CI)



(a) (b)

Confidence interval estimates are noticeably wider in the tails of the driver's age variable, particularly in the case of more advanced ages. In both instances, a linear association between age and the (transformed) dependent variable seems appropriate. A Chi-squared test was computed in which the null hypothesis was that the estimated effect of the driver's age was zero for any age, H0: $g(Age)=0$. The null hypothesis could not be rejected in the case of alcohol use (χ^2=2.401, df=3.03, p-value=0.61) but was rejected for drug use (χ^2=1.71, df=2.16, p-value<0.01).

4. Discussion

This roadside study makes a series of interesting findings: (i) the use of drugs by drivers is frequent in Spain, involving 1 in every 13 drivers; (ii) the prevalence of drug use among drivers is much greater than that of alcohol, which involves 1 in every 84 drivers; (iii) THC was the most frequently detected substance, followed by cocaine and amphetamines; (iv) almost 80% of drug-impaired drivers were found positive for one substance only; (v) positive tests for alcohol use were more frequently recorded on conventional roads, at weekends and during night-time hours; (vi) positive tests for drugs occurred more frequently in young males during daytime hours.

The present study represents a continuation of the AOD survey carried out in Catalonia during autumn 2014 by the Catalan Traffic Authority (Alcañiz et al., 2018). The alcohol prevalence of 1.3% detected in the previous edition remained largely unchanged at 1.2% in the 2017 edition. In contrast, a significant fall in positive outcomes for drugs was observed (16.4% in 2014 vs. 8.2% in 2017). Most of this reduction was attributable to the fall in THC (12.4% in 2014 vs. 5.6% in 2017) and methamphetamine use (3.4% in 2014 vs. 0.2% in 2017). However, the prevalence of cocaine use by drivers rose in the same period (1.8% in 2014 to 3.5% in 2017).

Differences between the prevalence rate in our study and previous roadside surveys carried out in Spain may be partially explained by the road type included in the analysis. Our study only includes interurban roads, but other studies also include urban roads. In addition, roadside survey studies carried out in Spain over the last fifteen years show a remarkable declining trend in the alcohol prevalence rates and a less sharped fall on the drug prevalence rates (Gómez-Talegón et al., 2012; Fierro et al., 2015; Domingo-Salvany et al., 2017). Gómez-Talegón et al. (2012) in a prior 2008-2009 roadside survey conducted in Spain reported that 6.6% and 11% of drivers tested positive for alcohol and illicit drugs, respectively. Domingo-Salvany et al. (2017) reported in a survey of 2,744 drivers conducted across all the regions of Spain in 2015 a prevalence of 2.6% for alcohol and 9.7% for other drugs (THC: 7.5% and cocaine: 4.7%), which is relatively close to our results. Relative to other roadside surveys, the prevalence rates for alcohol and drug use by drivers in our study are smaller (1.2% and 8.2% tested positive for alcohol and drugs, respectively). Domingo-Salvany et al. (2017) disaggregated the analysis between urban and interurban roads. The percentage of positives in interurban roads was 1.6% for alcohol, 6.4% for THC and 4.0% for cocaine, which are closer figures to the results reported in our study. Gómez-Talegón et al. (2012) differentiated between urban vs. rural roads, and, similarly, found that alcohol and drug-impaired drivers were more frequently detected on urban than on rural roads.

In line with our findings here, Domingo-Salvany et al. (2017) found that the most frequently used drug was THC, followed by cocaine and amphetamines-methamphetamines. The same order of the three most prevalent drugs was reported by Lema-Atán et al. (2019) in oral fluid samples collected from Spanish drivers testing positive between 2013 and 2015, while Gómez-Talegón et al. (2012) found benzodiazepines to be the third most frequent drug after THC and cocaine. Studies carried out in other countries have shown cannabis to be the most common substance detected in drivers (Berning et al., 2015; Gjerde et al., 2008; Institoris et al., 2013). Other studies have shown varying outcomes. For instance, cocaine was more frequently detected than cannabis in Italy (Strano-Rossi et al., 2012) and methamphetamine was more prevalent than cannabis in Australian drivers (Davey et al., 2014).

A major finding herein is that the risk group profile of drug driving differs in relation to non-alcohol and alcohol drug analyses. Male drivers were found more likely to test positive for non-alcohol drugs than females (Walsh and Mann, 1999; Beirness and Beasley, 2010; Alcañiz et al., 2018). However, the evidence was more equivocal in analyses of alcohol. Thus, gender differences in relation to drunk driving were evident when this characteristic was isolated and analysed individually, but we failed to find evidence of such differences when this characteristic was included in the multivariate analysis and interactions between classification variables were captured. Previous studies have shown that the gender gap for DUI arrests attributable to alcohol use is narrowing (Robertson et al., 2011; Vaca et al., 2014), but the majority of studies find that the alcohol prevalence rate remains higher among males (Alcañiz et al., 2014, Institoris et al., 2013; Bergen et al., 2011; Kelley-Baker et al., 2013; Kim et al., 2013).

Mixing results for the gender effect depending on the univariate or multivariate analysis have been also found in previous road survey studies in Spain (Gómez-Talegón et al., 2012; Domingo-Salvany et al., 2017). In line with our results, higher prevalence rates of alcohol and drugs for male drivers were found in the univariate analysis. However, Gómez-Talegón et al. (2012) did not find gender differences in the prevalence of only alcohol in the multivariate analysis. On the contrary, Domingo-Salvany et al. (2017) found gender differences in the alcohol use but not in the use of THC and cocaine in the multivariate analysis. Thus, when gender differences are analyzed in multivariate road survey studies, special attention should be paid to interactions with other characteristics.

A driver's age has been closely associated with drug use, with young drivers being more likely to use drugs (Lema-Atán, 2019; Arroyo et al., 2008; Valen et al., 2017). Our random sample study found in both the univariate and the multivariate analysis that the driver age was negatively associated with driving and non-alcohol drug use. However, differences in the prevalence of alcohol use based on driver′s age were not detected in both analyses. Similarly, Domingo-Salvany et al. (2017) did not find any evidence of differences in the prevalence of alcohol use based on driver′s age. Gomez-Talegón, (2012) analysed the relationship of age and alcohol alone and with other drugs. They found that only-alcohol positive cases increased with age, while "alcohol combined with other drugs" positive cases decreased with age. Yet, other studies – also based on random samples of drivers – found that the prevalence of alcohol use is higher among middle- and advanced-aged drivers (Alcañiz et al., 2014; Schulze et al., 2012). In contrast, studies based on non-random samples of suspected impaired drivers often conclude that young drivers are more likely to test positive for alcohol (Bergen et al., 2010; Kelley-Baker et al., 2013).

Here, evidence of a mild association between driving with passengers and alcohol use was suggested (statistical tests were only significant at 10% in both analysis). However, unlike the 2014 roadside survey edition (Alcañiz et al., 2018), differences in drug use among drivers according to the number of occupants were not significant in the individual analysis and neither in the multivariate analysis. Beirness and Beasley (2010) found that driver alcohol and drug use was related to the number and configuration of occupants in a vehicle. Here, both analyses found that vehicle type was also informative of the prevalence of alcohol and drug use, with drivers of lorries and heavy vehicles being more likely to be tested positive for alcohol and negative for drugs than drivers of passenger cars. Kweon and Kockelman (2013) found that drivers of pick-ups and heavy trucks are less likely to use alcohol, while other studies have identified a high prevalence of alcohol and illicit drug use among commercial drivers (Couper et al., 2002; Girotto et al., 2014), where the prevalence of alcohol use among truck drivers is higher than that of other drugs (Yonamine et al., 2014).

Earlier studies suggest that drugged driving, in contrast to drunk driving, is less concentrated in terms of day of the week and time of day (Berning et al., 2015; Schulze et al., 2012). Consistent with other roadside surveys, here the uni- and multivariate analyses appointed out that the distribution of alcohol use was particularly concentrated at weekends and night-time (Schulze et al., 2012; Vanlaar, 2005; Alcañiz et al., 2014) while the distribution of drivers' drug use was more stable across the week (Beirness and Beasley, 2010; Domingo-Salvany et al., 2017; Lema-Atán et al., 2019). Here, the highest prevalence of drug use was detected during the daytime (6:00–18:00); however, in the 2014 roadside survey edition no significant differences in the prevalence of drug use during the day time were found (Alcañiz et al., 2018).

Different patterns of alcohol use among drivers emerge according to the type of road on which the checkpoint was set up. Thus, the uni- and multivariate analyses suggested that alcohol-impaired drivers used conventional roads more frequently than they did highways. In 2012, Alcañiz et al. (2014) found that the prevalence of alcohol among drivers on highways was slightly higher than that on conventional roads. However, as in the 2014 roadside survey edition, no differences in the prevalence rates of drug use based on road type were found (Alcañiz et al., 2018).

Particular attention should be paid to the effect of the alcohol test outcome on the likelihood of drug use by drivers. The unitary cost of a drug test is relatively expensive compared to that of an alcohol test. Due to financial restrictions, drivers suspected of DUI are often sequentially tested for alcohol and drugs at checkpoints. An alcohol test is first carried out and, in some instances, the driver is then also tested for drugs. The explanatory capacity of the outcome of the alcohol test for the probability of drug use should prove useful to police officers who need to maximize the likelihood of drug detection success. Previous studies in Spain have found that more than 70% of drivers testing positive for alcohol tested negative for drugs (Domingo-Salvany, 2017; Gómez-Talegón et al., 2012, Fierro et al., 2015). In the present study, we found in the univariate analysis that the drug prevalence rate of drivers testing negative for alcohol was more than three times lower than the corresponding rate among those testing positive (the statistical test was significant at 10%). However, when controlling for the other classification variables in the multivariate analysis, we found no evidence that the outcome of the alcohol test was informative of the likelihood of drug use.

5.1 Study limitations

This study of AOD driving is based on a stratified probabilistic sample specifically designed to be representative of all vehicles circulating in the Catalan road network. However, studies based on roadside surveys of this type normally present a series of limitations. Here, data were collected in the autumn, in line with the alcohol-use seasonality pattern presented by Catalan drivers (Chuliá et al., 2016); yet, drug-use seasonality may differ and, hence, our results might only reflect drug prevalence in that season.

In the case of the sampling design employed here, the drug test survey represents a subsample of the sample of alcohol-tested drivers. Thus, while all drivers tested for drugs were also tested for alcohol, most of the drivers, almost 90%, were only alcohol tested. Reservations might be expressed as to whether the analysis of alcohol prevalence should be limited to the subsample of drivers who were also tested for drugs. However, the small number of drivers in that subsample testing above the legal BAC limit and the impact this would have had on our results explain why we opted to undertake the analysis of alcohol prevalence with the sample of all alcohol-tested drivers. Note that, after weighting, the sample size of the total number of drivers that tested above the legal BAC limit is slightly higher than one hundred. Given the small number of alcohol-impaired drivers, the use of a small sample advises against undertaking a disaggregated analysis of the factors that influence the likelihood of alcohol use by drivers. Aggregate results are more reliable when a relatively low number of 'successes' is observed in a small sample-size survey, and caution should be exercised when a high degree of disaggregation (joint analysis of multiple characteristics) is undertaken.

Conclusions drawn in this study are based on the assumption that the sample of alcohol-tested drivers is a random sample of drivers circulating on Catalan roads and the sample of drug-tested drivers is a random subsample of the alcohol-tested drivers. The first driver after the checkpoint was installed was tested for alcohol and drugs and subsequent drivers arriving at the unoccupied checkpoint were tested for alcohol. Police officers were strongly advised about the importance of following random testing instructions and avoiding the selection of tested drivers based on non-random criteria. So, it is reasonable to assume (as we do) that the alcohol-tested and drug-tested surveys are both random samples and, therefore, results can be compared. However, the difference in sample size between the sample of alcohol tested drivers and the smaller (sub)sample of those who were drug tested is a limitation.

The same size argument holds to explain why we opted not to study the different drug types individually. Although the prevalence rates of each drug (THC, cocaine, amphetamines, methamphetamines, opiates and benzodiazepines) are reported, the analysis of factors influencing the use of drugs by drivers is not disaggregated by drug type. In this study THC and cocaine, and to a lesser extent amphetamines, were by far the most frequent drugs detected in tests. Additionally, the combined use of drugs was less frequent than their separate use. A multivariate analysis of the factors that influence drug use would therefore be biased to the more predominant drugs, but we have no motives to believe that these factors affect the prevalence rates of all drug types in the same fashion. Risk factors of drug use and driving unveiled in this study particularly affect the use of THC and cocaine. Additional specific studies should be carried out to investigate the risk driving profiles associated with the use of less frequent drugs such as methamphetamines, opiates and benzodiazepines.

One final limitation that we should recall is that the presence of drugs was tested using oral fluid samples, given that blood sample results from laboratory analyses were unavailable. Since the confirmatory tests were not available, a number of positive drivers could have been undetected and a number of negative drivers could have incorrectly been classified as positive. The performance in terms of sensitivity, specificity and overall accuracy of the drug screening system used in this roadside survey is high as indicated in the literature. So, conclusions related to risk factors affecting the likelihood of being drug tested positive are not expected to be significantly altered after confirmation in laboratory results.

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Declaration of interests

None.

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