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Traffic environment and demographic factors affecting impaired driving and crashes

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Abstract

Introduction—Data availability has forced researchers to examine separately the role of alcohol among drivers who crashed and drivers who did not crash. Such a separation fails to account fully for the transition from impaired driving to an alcohol-related crash.

Method—In this study, we analyzed recent data to investigate how traffic-related environments, conditions, and drivers' demographics shape the likelihood of a driver being either involved in a crash (alcohol impaired or not) or not involved in a crash (alcohol impaired or not). Our data, from a recent case–control study, included a comprehensive sampling of the drivers in nonfatal crashes and a matched set of comparison drivers in two U.S. locations. Multinomial logistic regression was applied to investigate the likelihood that a driver would crash or would not crash, either with a blood alcohol concentration (BAC)=.00 or with a BAC≥.05.

Conclusions—To our knowledge, this study is the first to examine how different driver characteristics and environmental factors simultaneously contribute to alcohol use by crash-involved and non-crash-involved drivers. This effort calls attention to the need for research on the simultaneous roles played by all the factors that may contribute to motor vehicle crashes.

Keywords

Impaired driving; alcohol-related crashes; traffic environment; demographics; socioeconomic status

1. INTRODUCTION

Public health research identifies three elements in the risk-control process: the environment, the agent, and the host. Each of these factors has received substantial study in efforts to reduce impaired driving in the United States. Although those efforts resulted in a dramatic decrease in alcohol-impaired fatal crashes between 1982 and 1995 (National Highway Traffic Safety Administration [NHTSA], 2009), that beneficial trend has leveled off in recent years (Voas, Romano, Tippetts, & Furr-Holden, 2006).

Researchers looking for new paths to resume progress have been constrained by data availability, with most researchers forced to examine either crash-involved drivers only (e.g., NHTSA, 2009) or non-crashed-involved drivers only (e.g., Lacey et al., 2009). This analytical separation between driving situations and crashes is artificial, however, because it fails to account fully for the transition from impaired driving to an alcohol-related crash. Data to inform about this transition unfortunately are rare. Crash-control studies (Blomberg,

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Peck, Moskowitz, Burns, & Fiorentino, 2005; Borkenstein, Crowther, Shumate, Ziel, & Zylman, 1974) that collect data on motorists passing through crash sites on the same weekday, time, and direction as crash-involved drivers provide a unique opportunity to study simultaneously drivers involved and not involved in crashes, sober or not. Crash-control studies are founded on the basic assumption that both the crash drivers and the control drivers come from the same at-risk population. Based on this assumption, the crash type identified for the crash-involved driver characterizes the risk faced by the population from which the crash driver came. If both crash and noncrash drivers come from the same population, the question arises as to whether the crashed drivers are simply a random (bad luck) sample of the at-risk population or whether there are characteristics that distinguish those that crash from those that do not crash. In this study, we take advantage of data from the Blomberg, Peck, Moskowitz, Burns, and Fiorentino (2009) crash-control study to investigate the factors affecting the likelihood of drivers' involvement in the following traffic situations: (a) being impaired and having a crash, (b) being impaired but not having a crash, (c) not being impaired but having a crash, and (d) not being impaired and not having a crash. Specifically, this study investigates how traffic-related environments, conditions, and drivers' demographics shape the likelihood of a driver either being involved in a crash (alcohol impaired or not) or not being involved in a crash (alcohol impaired or not).

2. METHODS

2.1. Data

As mentioned, we used data from Blomberg et al.'s (2005, 2009) case–control study. Funded by NHTSA as a replication of the classical Borkenstein Grand Rapids Study (Borkenstein et al., 1974), Blomberg et al.'s study was based on a sample of 2,871 property damage and casualty crashes occurring in Long Beach (California) and Fort Lauderdale (Florida) from 4 p.m. to 3 a.m. Two control drivers (N=9,821) were matched to each crash-involved driver (N=4,065) by identifying drivers who one week later were driving on the same day of the week, at the same time, and in the same location and direction of travel as the matching crash-involved driver. The authors interviewed each cooperating driver of the matching crash-control triads and took a blood alcohol measure using an evidentiary quality breath tester (Alco-Sensor IV preliminary breath test [PBT]). More than 90% of the crash and control subjects who were approached at the scene provided valid blood alcohol concentration (BAC) specimens, as well as detailed information on the characteristics of crashes and drivers, including age, gender, education, employment status, ethnicity, marital status, driving exposure, type of vehicle, and alcohol consumption patterns. For a more comprehensive description of this data set, see Blomberg et al. (2005, 2009).

Table 1 shows the number of records in each of the four groups of drivers under study: control and crash driver in two BAC categories. As indicated by its exclusion from Table 1, drivers with low BACs (.01–.04) were not analyzed. Although the potential risk associated with .01-.04 BAC levels should not be dismissed, the decision to discard the .01-.04 BAC drivers was based on previous research findings that showed no statistically significant increase in crash risk until BACs reached or exceeded .05 (Blomberg et al., 2009). Further, by excluding drivers with .00<BACs<.05 from our analyses and comparing only drivers at BAC≥.05 and BAC=0, we are confident that all contrasts between mediating and moderating factors involving these two groups of drivers allow for a clear distinction between impairment and unimpairment as it relates to crash involvement.

2.2. Dependent Variable: Four Groups of Drivers

As shown in Table 1, we divided the driver records into four groups: (a) drivers who had a crash and registered a BAC≥.05; (b) drivers who had a crash and registered a BAC=.00; (c) control drivers who did not crash and registered a BAC≥.05; and (d) control drivers who did not crash and registered a BAC=.00. To make comparisons between these groups, drivers were allocated to these groups regardless of the crash-control triads that were applied to generate the database. As such, we were unable to consider the drivers in each group as representative of all drivers in these groups. Nevertheless, the allocation of drivers to these groups was not systematically biased (i.e., the original case–control design did not favor the collection of data from members of any group), and the information provided by this convenience sample is, therefore, highly informative (albeit not definitive).

Table 1 shows the number of records in each of the four groups under study. Of all the comparisons between the four groups in Table 1 that are logically possible, we identified five comparisons of interest: comparison #1—alcohol-related control drivers versus sober control drivers; comparison #2—sober crash drivers versus sober control drivers; comparison #3—alcohol-related control drivers versus alcohol-related crash drivers; comparison #4—sober crash drivers versus alcohol-related crash drivers; and comparison #5 — alcohol-related crash drivers versus sober control drivers. Comparison #1 addresses differences between impaired and sober noncrash drivers. An examination of the correlates provides information on how noncrash drivers differ when impaired or sober. In comparison #2, the crash and control drivers were sober. Hence, our analysis isolates variables that are associated with crash risk not involving alcohol. In comparison #3, we isolated factors that differentiate crash from noncrash drivers where both were impaired. This comparison addresses the issue of whether these two groups represent a common underlying population of impaired drivers in which crashing versus noncrashing might be a relatively random stochastic occurrence. In comparison #4, we identified how correlates of alcohol-related and sober crashes differ. Finally, by comparing the results of comparison #4 with those from comparison #5, we could determine if the distinctions between noncrash drivers contrasted by alcohol involvement mirror those produced by comparing sober noncrash drivers with impaired crash drivers.

2.3. Independent Variables

Two groups of independent variables were investigated: traffic environment variables and demographic/socioeconomic status (SES) variables. Traffic environment variables include time of the crash (4–7 p.m., 7–9 p.m., 9 p.m.–midnight, and midnight–3 a.m.), trip origin (a bar or restaurant, work, home, and somebody else's home), and weather and road conditions. The last variable was constructed as (0,1) dummy variable in which any condition other than “normal” was signaled out and assigned a value of 1. Although not strictly denoting a traffic environment situation, we included crash severity (property damage vs. casualty) and number of vehicles involved in the crash (single vs. multiple) in this variable pool. To assign crash severity and number of vehicles to control drivers, we used the status corresponding to the origin of the sampled parameters (e.g., the control drivers for a property-damage-only [PDO] crash were also considered PDO). The assignment of crash-related characteristics to control drivers unavoidably adds noise to the statistical evaluation of these characteristics. Nevertheless, we believe that the benefits of adding these crash variables to the analyses (i.e., accounting for some of the observed variation) overcomes its limitations (i.e., the unavoidable noise present in the crash variables).

The demographic/SES variables we considered included gender, age, race/ethnicity, marital status, and employment. Due to sample size restrictions, employment was built as a (1,0) binary variable, with “1” denoting full-time employment and “0” otherwise. Although not strictly a demographic/SES variable, a (0,1) variable denoting the presence of one or more passengers in the vehicle was also modeled for this group.

To account for crash exposure, the self-reported weekly miles driven by each driver were also included. This variable was treated as a continuously scaled metric in which the resultant odds ratios represent changes in odds per each 100-mile increase in weekly mileage.

2.4. Data Analysis

A combination of unconditional multinomial and binary logistic regressions was used to evaluate the five contrasts described in paragraph 2.3. The multinomial analyses required two runs using different referent groups. The first run used sober controls (BAC=0) as the referent, and the second run used unimpaired crash drivers as a referent. For simplicity, the output from these two multinomial regressions was then combined into a single table.

One limitation of the multinomial analysis is that the computer program (STATA- version 9) does not provide an index (e.g., R^2) of the explanatory power of the covariates for the separate binary contrasts. We therefore ran separate binary logistic regressions for each of the five contrasts to produce their corresponding pseudo R^2s. The pseudo R^2 statistic available in STATA is based on McFadden's likelihood ratio index modified for the number of predictors in the full model (Hilbe, 2009). The R^2 produced by this index represents the percentage reduction in the log likelihood attributable to the explanatory covariates, and it is not identical to the coefficient of determination (R^2) in ordinary least squares (OLS) multiple regression. Hence, the adjective “pseudo” is used to distinguish its analogical, rather than algebraic, connection to R^2. It does vary from 0 to 1 and tends to approximate R^2 for data where the binary margins are not extremely skewed (Menard, 2000).

Our use of an unconditional multinomial model, rather than the conditional binary logistic regression model typical of case–control studies used by Blomberg et al. (2009), stemmed from two considerations. First, our analyses involved more than two groups—hence, the estimation of the odds of membership in three or more groups as a function of a set of explanatory variables (covariates). Second, we used an unconditional as opposed to a conditional model because, in creating the different groups of drivers for comparison, we were forced to break the pairing case–control matches created by the original design. Although such a breaking did not allow us to account for within matching triads variance, it allowed for inclusion of more than 1,000 additional crash and control drivers who were rejected by the 1:2 matching design used by Blomberg et al.

To facilitate the understanding of the large number of explanatory variables under consideration, we ran three separate models. First, we ran a model including only traffic-related explanatory variables. In this model, we also included a dummy (0,1) variable to evaluate the possibility that our findings varied across the two sites from which the original data were collected (Long Beach, California, and Fort Lauderdale, Florida). Next, we ran a model including only the demographics/SES variables. Finally, we ran a final model consisting of the variables found statistically significant in the previous steps (a p value of $\leq .01$ was required for statistical significance). Main effects and two-way interactions involving demographic variables were also evaluated in the final model.

Of the 13,886 drivers with valid BAC values in the initial subject pool, some drivers were excluded from the multinomial runs due to missing crash data, missing information on some covariates, or having a $.00<BAC<.05$. As a result, the three separate multinomial regressions we ran included 12,905, 12,761, and 10,729 drivers.

3. RESULTS

We began our analyses by exploring separately the traffic environment and demographic/SES groups of variables.

3.1. Traffic Environment Variables Only

Table 2 shows the outcome of the analysis of the traffic environment variables. Under the $p<.01$ criteria, neither road condition nor bad weather were statistically significant in any of the five comparisons. The time of day yielded statistically significant results, albeit only in case-only and crash-only comparisons involving BAC≥.05 versus BAC=.00 contrasts (comparisons #1, #4 and #5).

Comparison #1 shows that among noncrashed drivers (control), the presence of drivers at BAC≥.05 increased after 9 p.m., with the odds of finding drinking drivers after midnight being about four times larger than between 7 and 9 p.m. Comparisons #4 and #5 reveal the same pattern: the likelihood of finding crash-involved drivers at BAC≥.05 increases as the time of day increases. This finding is not surprising, for it shows once more a substantial association between impaired driving and time of the day, with such association being even stronger for late-night crashes (i.e., the odds of impaired driving—comparison #1—or an alcohol-related crash—comparisons #4 and #5—are much higher between midnight and 3 a.m.). For comparisons involving similar BAC levels for the crash and control groups (i.e., comparisons #2 and #3), the time of day was not significant (comparison #3—BAC≥05 in both crash and control) or showed a decreasing trend after midnight (comparison #2—BAC=.00 in both crash and control).

Injury was marginally significant ($p=.019$) in only one contrast (#2). Alcohol-free crash drivers were less likely to be injured than would be expected based on the percentage of alcohol-free drivers in the noncrash population. This finding, however, is difficult to interpret because the injury status of controls is based on the injury status of their matching crash cases.

Not surprisingly, drivers who initiated their trips at bars were more likely to be involved in impaired driving, either in crashes (comparisons #4 and #5) or not in crashes (comparison #1). Initiating the trip from the workplace was associated with reduced risk of impairment, particularly among noncrashed drivers (comparison #1). For drivers with similar positive BAC conditions (comparison #3), the trip origin variable was not significant. For drivers with similar zero BAC conditions (comparison #2), the trip origin variable was significant for drivers coming from “other's home” and the miscellaneous “other” group. The meaning of this finding is unclear.

Single-vehicle crashes were marginally significant ($p=.032$) in comparisons between alcohol-related and alcohol-free crashes (comparison #4). This finding is not surprising, given that among crashes, nighttime single-vehicle crashes are often used as a proxy for alcoholrelated crashes. The lack of significance of this variable in other alcohol-related versus sober comparisons (comparison #1 and #5) should be taken with caution, for it might be related to the statistical noise generated by the way this variable was created (i.e., by assigning a crash characteristic to control drivers). Weekly mileage was marginally or significantly related to the three comparisons involving impaired driver crashes (comparisons #3 to #5). For comparisons #3 and #4, we found that the odds of being involved in an impaired-driving crash were 9% and 7% higher for each 100-mile increase in mileage. For comparisons involving impaired crash drivers with unimpaired controls, the reverse relationship is evident. Each 100-mile increase in weekly mileage was associated with a 7% decrease in the odds of being in an impaired crash relative to that of alcoholfree control drivers.

Variable site (a variable indicating if the sample was taken in Florida or California) was significant in comparison #2 (between sober drivers), suggesting that some driving and crash differences between the sites may exist, although they seem limited only to driving situations in which alcohol was not involved.

The explanatory power of the independent variables (covariates) is summarized by the pseudo R^2s at the bottom of Table 2. There were substantial variations in predictive power, ranging from 0.007 for comparison #2 to 0.142 for comparison #4. All of the R^2s were low —a finding that was not surprising given the nominal/binary properties of the dependent variable and the stochastic nature of crash involvement (Harano, Peck, & McBride, 1975; Peck & Gebers, 1993; Wahlberg, 2003). Also, the very low magnitudes of the coefficients for comparisons #2 and #3 were not surprising as these contrasts involve groups that do not differ on BAC status for which almost none of the covariates had significant odds ratios. The fact that discrimination was greater in separating alcohol-related crashes from non-alcohol-related crashes (R^2=.142; comparison #4) than it was for separating impaired drivers from unimpaired controls (comparisons #1 and #5) was unexpected. The most likely explanation is that the environmental and crash-type variables are more informative for groups involved in crashes. Recall that for controls, these covariates were based on the characteristics of the crash to which each control was matched rather than on any behaviors of the control drivers (other than driving at the same time and in the same location of a crash driver).

3.2. Demographic/SES Variables Only

Table 3 shows the outcome of comparisons relating demographic variables to crash group and BAC. Comparisons #4 and #5 show that, as expected, males were more likely than females to be involved in alcohol-related crashes, either when compared to unimpaired crash drivers or unimpaired controls. Note that even when the comparisons involved only control drivers (comparison #1), male drivers were more likely than were female drivers to have BACs≥.05. In comparing alcohol-free crash and control drivers (comparison #2), however, male drivers were less likely to be involved in crashes than were their female counterparts. No significant gender differences were found among BAC≥.05 crash and control drivers (comparison #3).

Age was also a significant predictor for most of the contrasted groups with the direction of the relationships depending on the structure of the contrasts. Compared to drivers aged 25 to 54, drivers aged 20 and younger were much less likely to be impaired (comparisons #1, #4, and #5). However, when the contrasts involved relationships to crashes versus controls within BAC=.00 groups (comparison #2), we found the reverse relationship. These results are entirely consistent with an extensive body of literature showing that young drivers are highly overinvolved in crashes in general but are underinvolved in crashes involving impaired driving (e.g., Masten, 2004; Senserrick & Haworth, 2004; Subramanian, 2005; Zador, Krawchuk, & Voas, 2000). This finding may appear to conflict with the recent findings of Peck, Gebers, Voas, and Romano (2008) in which the crash avoidance skill of alcohol-positive minors (younger than 21) was impaired at lower BACs and were impaired more severely than were older drivers. This finding merely indicates, however, that when drivers younger than 21 drink and drive, they are more likely to have crashes than are older drivers who drink and drive. Nevertheless, because young drivers are much less likely to drink and drive, their net involvement in alcohol-related crashes is relatively low.

At the other end of the age spectrum (55+), there is directional evidence of an upswing in crash risk in comparison #2. These results indicate that at some point beyond age 55, drivers are more likely to have crashes where alcohol is not involved compared to the drivers aged 25 to 54.

Compared with White drivers, African-American, Hispanic, and other non-White drivers were less likely to be involved in a BAC≥.05 crash than were noncrashed sober drivers (comparison #5). African-American drivers were less likely than White drivers to be in a BAC≥.05 crash than crash drivers with zero BACs (comparison #4). Hispanics were significantly less likely than Whites to be involved in both non-alcohol-related crashes (comparisons #2) and alcohol-related crashes (comparison #5). Interpretation of the results for drivers categorized as “other” is complex because of the ethnic diversity of the group and the unusual pattern of the results (Asians, Native Americans, Pacific Islanders, and persons designated as “mixed”). This composite group tended to have lower odds of involvement in crashes and incidents involving impairment but was significantly more likely to have crashes unrelated to impairment.

Education also proved to be associated with a number of contrasts. In comparison #5, drivers with fewer than 12 years of education were 1.62 times more likely to be involved in alcohol-related crashes than were drivers with 12 to 14 years of education. They were also significantly more likely to have crashes where neither group was impaired (comparison #2). Compared to the referent group, those with 15+ years of education were significantly less likely (OR=.71) to drive while impaired (comparison #1) or being impaired among those who crashed (comparison #5). None of the other contrasts were significantly associated with higher education.

Unemployed drivers (defined in this study as not having full-time employment) were less likely to be involved in unimpaired crashes (comparison #2). Interpretation of this finding is complicated by the heterogeneous nature of the referent group, which is an aggregate consisting of unemployed, retired, and part-time workers; housewives; and students. Blomberg et al. (2005) suggested that the major source of the effect is the distinction between fully employed and unemployed drivers.

The results for marital status are interesting. Compared to married drivers, single drivers were *significantly* more likely to have negative outcomes in comparisons #1, #4, and #5. This was not unexpected because being single has been associated with increased crash proneness and impaired driving in numerous studies (e.g., Jaffe, Manor, Eisenbach, & Neumark, 2007; Kposowa & Adams, 1998). There was a similar association involving the divorced/separated/widowed group. In particular, separated/divorced/widowed drivers were *1.5 to 1*.9 times more likely than married drivers to drive while impaired or to have crashes involving alcohol *(comparisons #1, #4, and #5)*. Blomberg et al. (2005) also reported similar results in their case–control study of crash correlates.

Carrying passengers was a statistically significant predictor in four of the five comparisons. In comparisons #3 through #5, carrying one or more passengers was associated with a much lower risk of involvement in an unfavorable outcome (i.e., crashes involving impairment). In comparison #1, we see an opposite result involving control drivers. Carrying one or more passengers was associated with impaired driving when neither group was crash involved. This reversal is difficult to explain *and* is almost a mirror-image of comparison #5. It suggests that carrying passengers reduces the risk of crash involvement among impaired drivers but that this effect is not mediated by reductions in impaired driving.

Despite the statistical noise involving the assignment of crash-related variables to controls, single-vehicle crashes were significantly associated with comparisons #2 and #4. The pattern of results indicates that single-vehicle crashes were more likely than multiple-vehicle crashes to involve impairment (comparison #4) but less likely to involve non-alcohol-involved crashes (comparison #4).

The results for miles driven closely mirror those shown in Table 2. Increased mileage increases the odds of being involved in impaired crashes compared to impaired controls and crashes not involving impairment. The opposite relationship is evident for comparison #5. Each-100 mile increase in miles driven decreased the odds of being an impaired crash driver by 11% compared to unimpaired control drivers.

The pseudo R^2s are all low and similar to those obtained for the prior set (Table 2). These differences merely reflect that the importance of any variable set is dependent on the causal and correlational mechanisms that are operative in the contrasted groups. The demographic variables appear to be less discriminating than the traffic and environmental factors in separating impaired drivers from unimpaired drivers.

3.3. Final Model

Table 4 shows the comparisons when all main effects identified as significant in previous steps were jointly included in the model. The main finding of this exercise is that, in most cases, the joint inclusion of the traffic environment and demographic/SES variables did not much alter the results obtained when the analyses were conducted separately. The only variable that notably changed its significance when the two groups of variables were combined was “marital status.” Unlike Table 3, Table 4 shows that the effect of being unmarried is significant at $p<.01$ in only one contrast and at $p<.05$ in three contrasts.

The most likely explanation for this change is covariation between marital status and late-night driving (midnight to 3 a.m.). Recall that late-night driving was strongly associated with alcohol-related crashes (comparisons #4 and #5) in Tables 2 and 4.When marital status and time of crash are entered in the same equation, the higher alcohol crash odds of unmarried drivers (single and separated/ divorced/widowed) are adjusted (partialled) because of the likelihood that these unmarried groups were driving at times when alcohol-related crashes and impaired driving are most likely to occur. Reducing the independent contribution of marital status by this covariation does not mean that single and separated/ divorced/ widowed drivers are not at increased risk of alcohol problems and impaired crashes. The odds ratios and p values in Table 4 still reflect suggestive evidence that unmarried drivers are at increased risk of impaired crash involvement, and they are more likely to drive at hours known to be associated with alcohol consumption and impaired driving.

Only minor changes occurred in relationships involving ethnicity. The pattern of relationships involving other ethnicities is the same as in Table 2, but the findings showing Hispanics to be less involved than Whites in impaired driving (comparisons #1 and #5) is no longer statistically significant.

There were other small changes in the structure of the explanatory variables in Table 4 that were attributable to partialling for covariation when variable pools were combined. A change concerning the variable “one or more passengers” warrants specific mention. Recall that comparison #1 in Table 3 showed that carrying passengers was associated with a 42% increase in being impaired when neither group was crash involved. This finding was difficult to explain given the opposite effects reflected in comparisons of crash-involved drivers in #3 through #5 of Table 3. Table 4 largely removes this paradox by showing that carrying passengers is *still* strongly associated with improved outcome in comparisons #3 through #5 involving drivers in crashes *but* is no longer associated with impairment when neither group is crash involved. Because the latter finding (Table 4) is based on a wider array of covariates, it better adjusts for confounding variables, particularly late-night driving.

As one would expect from the combining of significant variable pools, the pseudo R^2s increased for all five contrasts. The R^2s now range from .021 to .197. By far the smallest R^2 was obtained for comparison #2 (R^2=.021). The value is very close to zero and calls into question the meaningfulness of the contrast in question, namely, isolating correlates of crashes where neither the crash nor control group had any alcohol in their systems. This limitation most likely emanates from the objective of the Blomberg et al. study (BAC-crash relationship) rather than any intrinsic fallacy with evaluating crash causation independent of alcohol. Only three of the contrasts resulted in more than 10% of the deviance being explained by the explanatory variables: comparison #1 (R^2=.120), comparison #4 (R^2=.197), and comparison #5 (R^2=.136).

Table 5 shows the dual interactions added to the final main effects model (Table 4) that were statistically significant. Although they are shown together in Table 5, each dual interaction was evaluated separately to better capture their individual significance. Compared to drivers aged 25 to 54 (the reference group), drivers aged 21 to 24 were more likely to be involved in impaired driving noncrashing events when driving with at least one passenger (comparisons #1 and #3). Interestingly, the lack of statistical significance of this interaction in other comparisons suggests that for this group of young drivers, the presence of a passenger does not affect their chances of crash, either alcohol-impaired or sober. Additionally, young drivers aged 21 to 24 who drive a relatively large number of miles were more likely to be involved in alcohol-related crashes than in alcohol-free crashes than drivers aged 25 to 54. For drivers aged 55 years and older, compared to the 25- to 54-year-old drivers, the more miles they drove, the more likely they were to be involved in a crash, either alcohol-related (comparison # 5) or sober (comparison # 2). When involved in a crash (comparison #4), African American drivers aged 55 and older were more likely to have been drinking than White drivers aged 25 to 54.

Compared to their female counterparts, male drivers who initiated their trip at work were more likely to have been drinking (comparison #1), but less likely to crash when they consumed alcohol (comparison #3). When the trip originated at a bar, male drivers were less likely to be involved in an alcohol-related crash (comparisons #4 and #5) than their female counterparts. Hispanic males were especially likely to be involved in impaired driving situations, either crash-related (comparisons #4 and #5) or not (comparison #1). Being male and African American also increased the odds of involvement in impaired driving, but only in noncrash situations (comparison #1)

4. CONCLUSION

This study provides information about the role that traffic environment and driver demographic/SES factors play (separately and simultaneously) in shaping the likelihood of impaired driving (crash related or not). Unique to this effort is the use of data collected simultaneously through the most tightly controlled data-collection plan comparing crash and noncrash drivers conducted so far in the United States.

This study confirms some well-known relationships; for example, being underage, female, married, and employed (high SES) represent drivers who are less likely to drive while impaired than are middle-aged, male, less-educated, unmarried, and unemployed (low SES) drivers.

An interesting outcome from this study is the identification and evaluation of variables playing a different role in shaping alcohol-related and alcohol-free crashes. Regarding unimpaired driving, the factors that separate sober (BAC=.00) crash-involved drivers from sober (BAC=.00) non-crash-involved drivers were largely demographic and SES.

Although we found evidence confirming that males are more likely to be involved in impaired driving and alcohol-related crashes than females, we also found evidence that they are less likely to be involved in alcohol-free crashes than female drivers.

Age is another demographic variable showing a different effect on impaired driving, alcohol-related crashes, and alcohol-free crashes. Although young drivers are less likely to be involved in alcohol-related crashes than older ones, they are more likely to be involved in “alcohol-free” crashes than older drivers. This finding is not surprising, for it confirms the established U-shape relationship between age and alcohol-free crash involvement, as well as the lower likelihood *of* underage drivers at BAC≥.05 (Voas, Tippetts, Romano, Fisher, & Kelley-Baker, 2007).

Of particular interest are the similarities and differences observed in the significant correlates in comparisons #1 and #5. Environmental factors (e.g., time, trip origin, and destination) yielded similar outcomes in both comparisons.

Another finding of interest involves the role of time on these crashes. Time was a significant explanatory factor in comparisons involving impaired versus unimpaired drivers (comparisons #1, #4, and #5), but not as much in comparisons where all drivers were unimpaired (comparison #2) or impaired (comparison #3). This finding therefore provides support to the use of nighttime crashes as a proxy for impaired driving. Nevertheless, the very low pseudo R^2 for comparison #2 ($R^2 = .021$) is remarkable, even though there were significant differences on a large number of variables. Results from several previous studies, particularly those on California populations, would lead one to expect a greater degree of accuracy in separating non-crash-involved from crash-involved drivers (Peck & Gebers, 1993). However, an important discriminator was not included in the present analysis. Many studies have found prior moving violation frequency to be among the strongest predictors of crash risk, even exceeding the predictive power of prior DUI convictions (Gebers & Peck, 2003; Peck & Gebers, 1993). Unfortunately, traffic conviction data were not collected by Blomberg et al. (2005, 2009) because of the lack of access to driver record files. Another distinction is that most prior studies of driver crash involvement correlates have not excluded drivers with low- or high-BAC values. This would alter the demographic structure of the groups being compared.

The analysis of the dual interactions identifies some groups of drivers at high risk of involvement in impaired driving (e.g., young drivers, Hispanic and African-American males). What is interesting though is that such roles vary depending upon whether the drinking-and-driving event ends in a crash or not (e.g., although males appear to be more likely to drink and drive than females, females are more likely to crash when impaired than males). This finding suggests that the mechanisms by which drinking and driving translates into a crash are complex, for the factors that contribute the most to impaired driving might not be as determinant in causing those drinking drivers to crash. This complexity might be related to elements that were not evaluated in this study (e.g., attitudes toward risk, driving experience, distraction), as well as interactions of higher order we did not analyze in this study. For example, a three-way age by gender by presence of passengers interaction (i.e., three and higher order interactions) were not examined in this effort because of limitations related to data partition and the difficulties associated to their interpretation. In any case, this effort calls attention to the need for additional research, not only on the determinants to drinking and driving, but also on the elements that cause (or prevent) a drinking-and-driving event from becoming an alcohol-related crash.

As noted, this study has some limitations. We cannot consider the drivers in each group as representative of all drivers in these groups. Nevertheless, the information these groups provide are unbiased and, therefore, highly informative. Additionally, this study was based on data obtained from only two locations in two states. Attempts to generalize the results of this study to the entire country should therefore be done cautiously. Some of the variables used in this study are self-reported and, therefore, possibility based on erroneous or biased responses. Also, because crash drivers are much more likely to have highly elevated BACs than controls, some differences between≥.05 control drivers and≥.05 crash drivers could reflect differences in actual impairment.

Although the high-participation rate obtained in this study is a notable strength, ethnicity and other covariate data are missing for several hundred nonparticipants and unrecovered hit-and-run drivers. As expected, none of the logistic regression models accurately predicted the group membership of individual drivers based on the explanatory variables This finding could reflect the indirect nature of some of the explanatory variables for noncrash control drivers.

Despite the shortcomings listed herein, to our knowledge, this study is the first that examines how different driver characteristics and environmental factors simultaneously contribute to alcohol use by crash-involved and non-crash-involved drivers.

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Biographies

Eduardo Romano, Ph.D., is a Research Scientist at PIRE, in Calverton, Maryland, where he contributes to research projects as an Economist and Epidemiologist. Initially, his work involved estimating the incidence and cost of national and state intentional and unintentional injuries, and the evaluation of Mexican policies aimed to deter binge drinking by young American visitors in Tijuana (Mexico). His interest in minority and ethnic issues has been applied to study binge-drinking problems in other border cities: El Paso-Brownsville (Texas)/Ciudad Juárez (Mexico); Laredo (Texas)/Nuevo Laredo (Mexico). He is currently involved in a NIH-funded project looking at the role of acculturation in shaping drinking norms in Southern California; another to study the impact of passengers on impaired driving; as well in a NHTSA-funded project to study the involvement in traffic violations of recent immigrants to Florida and Tennessee. Dr. Romano holds a Ph.D. in Agricultural and Applied Economics from the Virginia Polytechnic Institute and State University.

Raymond C. Peck earned BA and MA degrees in experimental psychology from California State University, Sacramento, and began his professional career with the California DMV in 1962. From 1984 to 2000, Mr. Peck served as Chief of the DMV's Research & Development Branch and was responsible for directing research & evaluation studies in all areas of driver licensing. Upon retirement, Mr. Peck established his own consulting firm, R.C. Peck & Associates. In this capacity, he conducts studies for, or provides technical assistance to, numerous private and governmental institutions. Mr. Peck has also been employed by PIRE as a senior project analyst since 2004. During this time, he was awarded a grant by the NIAAA to better quantify the relationship between BAC and crash risk. He is a member of the American Statistical Association, American Society for Epidemiologic Research, and the International Council on Alcohol, Drugs and Traffic Safety. He serves on the editorial review boards of two accident research journals and is an Emeritus Member of the TRB's Committee on Operator Education and Regulation.

Robert B. Voas, Ph.D., a Senior Research Scientist with PIRE and Director of the Impaired-Driving Center, PIRE, in Calverton, Maryland, has been involved in research on alcohol and highway safety for 35 years, initially as director of the National Highway Traffic Safety Administration's Office of Program Evaluation and more recently as principal investigator for government research programs in drinking-driving and community alcohol problem prevention. Dr. Voas is a Fellow of the American Psychological Association and a Past President of the International Council on Alcohol, Drugs, and Traffic Safety. He is also a member of the Committee on Alcohol and Drugs, the National Safety Council, and the Committee on Alcohol and Other Drugs of the National Transportation Research Board, and has served on the National Board of Mothers Against Drunk Driving.

Table 1

Number of Records in Each of the Four Groups under Study.

	BAC=.00	BAC≥.05	Total
Control	8,716	446	9,162
Crash	3,318	568	3,886
Total	12,034	1,014	13,048

Table 2

Relationship of Traffic-related Conditions to Driving and Crash Involvement (Alcohol Related or Not).

	Comparison # 1		Comparison # 2		Comparison # 3		Comparison # 4		Comparison # 5	
	Control BAC≥.05 versus Control BAC=.00		**Crash BAC=.00 versus Control BAC=.00**		**Crash BAC≥.05 versus Control BAC≥.05**		**Crash BAC≥.05 versus Crash BAC=.00**		**Crash BAC≥.05 versus Control BAC=.00**	
	Odds	**P>z**	**Odds**	**P>z**	**Odds**	**P>z**	**Odds**	**P>z**	**Odds**	**P>z**
Road condition	0.814	0.520	0.948	0.684	1.136	0.756	0.976	0.936	0.925	0.786
Bad weather	1.113	0.717	0.992	0.948	0.900	0.707	0.626	0.023	1.155	0.594
Clear										
Dark	0.713	0.096	1.024	0.694	1.037	0.923	1.164	0.589	0.641	0.028
Daylight										
4 p.m. – 7 p.m.	0.804	0.268	1.089	0.196	0.662	0.121	0.489	0.000	0.532	0.001
9 p.m. – midnight	1.572	0.004	0.892	0.090	0.967	0.869	1.705	0.000	1.521	0.002
Midnight – 3 a.m.	3.555	0.000	0.788	0.024	0.687	0.101	3.100	0.000	2.443	0.392
7 p.m. – 9 p.m.										
Some injury	0.854	0.250	0.882	0.019	1.055	0.762	1.022	0.865	0.901	0.096
PDO										
Trip origin:										
Bar	2.633	0.000	0.928	0.466	1.338	0.184	3.794	0.000	3.522	0.000
Other's home	1.638	0.003	1.428	0.000	1.395	0.122	1.601	0.003	2.286	0.000
Work	0.602	0.004	1.074	0.212	1.277	0.301	0.715	0.050	0.768	0.112
Other	1.101	0.581	1.424	0.000	1.038	0.876	0.803	0.220	1.143	0.443
Own home										
Single-vehicle crash	0.962	0.843	0.891	0.166	1.341	0.229	1.447	0.032	1.289	0.117
Multiple-vehicle crash										
Miles driven	1.01	0.703	.98	0.067	1.09	0.006	1.07	0.020	0.93	0.003
Site	0.037	0.581	0.401	0.000	1.600	0.876	0.149	0.220	0.060	0.443
Pseudo R^2	0.084		0.007		0.020		0.142		0.104	

Comparisons #1 through #5 were obtained by running a single multilogistic model twice, each time applying a different reference group. For comparisons #1, #2, and #5, the reference group was control drivers with a BAC=.00. For comparisons #3 and #5, the reference group included crashed drivers with a BAC≥.05. In comparison #1, no crash is involved; therefore, crash severity (“Some Injury” and “PDO”) is that of the matching crashes.

Table 3

Relationship of Demographic Variables to Driving and Crash Involvement (Alcohol Related or Not).

Self-reports of demographic variables	**Comparison # 1**		**Comparison # 2**		**Comparison # 3**		**Comparison # 4**		**Comparison # 5**	
	Control BAC≥.05 versus Control BAC=.00		**Crash BAC=.00 versus Control BAC=.00**		**Crash BAC≥.05 versus Control BAC≥.05**		**Crash BAC≥.05 versus Crash BAC=.00**		**Crash BAC≥.05 versus Control BAC=.00**	
	Odds	**P>z**	**Odds**	**P>z**	**Odds**	**P>z**	**Odds**	**P>z**	**Odds**	**P>z**
Male	2.622	0.000	0.830	0.000	0.902	0.535	2.849	0.000	2.364	0.000
Female										
Age: <21	0.253	0.000	1.591	0.000	1.784	0.138	0.284	0.000	0.451	0.001
Age: 21–24	0.835	0.290	1.241	0.002	1.018	0.940	0.684	0.027	0.849	0.321
Age: 55+	0.722	0.067	1.198	0.007	1.062	0.800	0.640	0.009	0.767	0.106
Age: 25–54										
African American	0.788	0.073	0.925	0.175	0.784	0.188	0.668	0.004	0.618	0.000
Hispanic	0.743	0.033	0.813	0.001	0.944	0.758	0.862	0.294	0.702	0.008
Other	0.360	0.000	1.221	0.001	1.432	0.166	0.423	0.000	0.516	0.000
White										
<12 years school	1.076	0.626	1.277	0.000	1.501	0.035	1.266	0.084	1.616	0.000
15 + years school	0.708	0.002	0.929	0.124	1.007	0.967	0.767	0.024	0.712	0.002
12–14 years school										
Employed	1.099	0.453	0.798	0.000	0.796	0.165	1.096	0.435	0.875	0.237
Single	1.537	0.000	1.055	0.291	1.110	0.521	1.617	0.000	1.705	0.000
Separated	1.865	0.000	1.152	0.029	0.920	0.679	1.491	0.009	1.717	0.000
Married										
One or more passengers	1.428	0.000	1.020	0.651	0.486	0.000	0.680	0.000	0.694	0.000
Single-vehicle crash	0.847	0.362	0.812	0.007	1.522	0.064	1.589	0.003	1.289	0.085
Multiple-vehicle crash										
Miles driven	1.03	0.190	.99	0.388	1.09	0.008	1.12	0.000	.89	0.000
Pseudo R^2	0.045		0.016		0.042		0.072		0.046	

Comparisons #1 through #5 were obtained by running a single multilogistic model twice, each time applying a different reference group. For comparisons #1 and #2, the reference group was control drivers with a BAC=.00. For comparison #4, the reference group was crash drivers with BAC≥.05. For comparisons #3 and #5, the reference group included crash drivers with a BAC≥.05. In comparison #1, no crash is involved; therefore, crash severity (“Some Injury” and “PDO”) is that of the matching crashes. Pseudo R^2 for this single model is=.0277.

Table 4

Final Model, Main Effects Only. Relationship of Traffic Environment and Demographic/SES Variables to Driving and Crash Involvement (Alcohol Related or Not).

	Comparison # 1		**Comparison # 2**		**Comparison # 3**		**Comparison # 4**		**Comparison # 5**	
	Control BAC≥.05 versus Control BAC=.00		**Crash BAC=.00 versus Control BAC=.00**		**Crash BAC≥.05 versus Control BAC≥.05**		**Crash BAC≥.05 versus Crash BAC=.00**		**Crash BAC≥.05 versus Control BAC=.00**	
	Odds	**P>z**	**Odds**	**P>z**	**Odds**	**P>z**	**Odds**	**P>z**	**Odds**	**P>z**
4 – 7 p.m.	0.729	0.048	1.139	0.017	0.638	0.037	0.408	0.000	0.465	0.000
9 p.m. – midnight	1.731	0.000	0.880	0.042	0.875	0.469	1.720	0.000	1.514	0.001
Midnight – 3 a.m.	4.004	0.000	0.755	0.004	0.571	0.008	3.026	0.000	2.285	0.000
7 p.m. – 9 p.m.										
Trip origin:										
Bar	2.676	0.000	0.904	0.305	1.428	0.085	4.226	0.000	3.822	0.000
Other's home	1.839	0.000	1.320	0.000	1.279	0.212	1.783	0.000	2.353	0.000
Work	0.612	0.003	1.184	0.002	1.102	0.663	0.570	0.001	0.675	0.013
Other	1.283	0.117	1.391	0.000	1.024	0.913	0.945	0.737	1.314	0.093
Own home										
<12 years school	1.220	0.192	1.272	0.000	1.491	0.038	1.430	0.010	1.820	0.000
15+ years school	0.709	0.003	0.919	0.081	1.021	0.894	0.788	0.047	0.724	0.005
12–14 years school										
Employed	1.189	0.176	0.805	0.000	0.796	0.167	1.176	0.181	0.947	0.636
African American	0.842	0.209	0.915	0.129	0.776	0.177	0.714	0.022	0.654	0.003
Hispanic	0.863	0.298	0.805	0.001	0.973	0.885	1.044	0.768	0.840	0.204
Other	0.413	0.000	1.205	0.003	1.441	0.161	0.494	0.000	0.595	0.002
White										
Age: <21	0.214	0.000	1.614	0.000	1.860	0.113	0.246	0.000	0.397	0.000
Age: 21–24	0.726	0.066	1.263	0.001	1.038	0.873	0.597	0.003	0.753	0.093
Age: 55+	0.759	0.128	1.192	0.010	1.057	0.816	0.673	0.023	0.802	0.191
Age: 25–54										
Male	2.210	0.000	0.855	0.000	0.910	0.575	2.353	0.000	2.012	0.000
Female										

	Comparison # 1		Comparison # 2		Comparison # 3		Comparison # 4		Comparison # 5	
	Control BAC≥.05 versus Control BAC=.00		Crash BAC=.00 versus Control BAC=.00		Crash BAC≥.05 versus Control BAC≥.05		Crash BAC≥.05 versus Crash BAC=.00		Crash BAC≥.05 versus Control BAC=.00	
	Odds	**P>z**	**Odds**	**P>z**	**Odds**	**P>z**	**Odds**	**P>z**	**Odds**	**P>z**
One or more passengers	1.088	0.420	1.039	0.396	0.474	0.000	0.497	0.000	0.516	0.000
Single	1.183	0.171	1.088	0.100	1.129	0.460	1.227	0.103	1.336	0.016
Separated	1.584	0.002	1.173	0.015	0.901	0.604	1.217	0.213	1.427	0.018
Married										
Single-vehicle crash	0.791	0.206	0.825	0.014	1.470	0.091	1.410	0.035	1.163	0.320
Multiple-vehicle crash										
Miles driven	.98	0.218	.99	0.472	1.09	0.007	1.11	0.000	.89	0.000
Pseudo R^2	0.120		0.021		0.049		0.197		0.136	

Comparisons #1 through #5 were obtained by running a single multilogistic model twice, each time applying a different reference group. For comparisons #1, #2, and #4, the reference group was control drivers with a BAC=.00. For comparisons #3 and #5, the reference group included crash drivers with a BAC≥.05. In comparison #1, no crash is involved; therefore, crash severity (“Some Injury” and “PDO”) is that of the matching crashes. Pseudo R^2 for this single model is=.1641.

Table 5

Final Model. Statistically Significant Dual Interactions.

	Comparison # 1		**Comparison # 2**		**Comparison # 3**		**Comparison # 4**		**Comparison # 5**	
	Control BAC≥.05 versus Control BAC=.00		**Crash BAC=.00 versus Control BAC=.00**		**Crash BAC≥.05 versus Control BAC≥.05**		**Crash BAC≥.05 versus Crash BAC=.00**		**Crash BAC≥.05 versus Control BAC=.00**	
	OR	**P>z**	**OR**	**P>z**	**OR**	**P>z**	**OR**	**P>z**	**OR**	**P>z**
21–24 * with passenger	2.137	0.036			0.393	0.049				
21–24 * miles driven							1.002	0.020		
55+ * African American							2.876	0.012	2.547	0.019
55+ * miles driven			1.001	0.027					1.002	0.010
Male * Work	2.935	0.030			0.268	0.038				
Male * Bar							0.440	0.036	0.364	0.005
Male * African American	2.451	0.007								
Male * Hispanic	2.215	0.043					3.096	0.004	2.654	0.012
Male * Other							4.453	0.017	3.716	0.035
Male * 4 p.m. – 7 p.m.			0.793	0.035						
Male * 12 a.m. – 3 a.m.							0.433	0.035		
Male * miles driven	1.003	0.013								

Dual interactions were not simultaneously included in the model. Each interaction was evaluated separately, in different models. Main effects and nonsignificant dual interactions were not included to save space. Comparisons #1 through #5 were obtained by running a single multilogistic model twice, each time applying a different reference group. For comparisons #1, #2, and #5, the reference group was control drivers with a BAC=.00. For comparisons #3 and #4, the reference group included control and crash drivers with a BAC≥.05, respectively. In comparison #1, no crash is involved; therefore, crash severity (“Some Injury” and “PDO”) is that of the matching crashes.