Less is more: The influence of traffic count on drinking and driving behaviour

Non Peer-reviewed author version

VANLAAR, Ward (2008) Less is more: The influence of traffic count on drinking and driving behaviour. In: ACCIDENT ANALYSIS AND PREVENTION, 40(3). p. 1018-1022.

Handle: http://hdl.handle.net/1942/8404

Elsevier Editorial System(tm) for Accident Analysis & Prevention
Manuscript Draft

Manuscript Number: AAP-D-07-00290R1

Title: Less is more: the influence of traffic count on drinking and driving behaviour

Article Type: Full Length Paper

Section/Category:

Keywords: drinking driving; traffic count; multilevel analysis

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Order of Authors: Ward Vanlaar

Manuscript Region of Origin:

Abstract: Drinking and driving road checks are often organized with either a clear prevention or repression objective in mind. The objective of a prevention strategy is to make as many people as possible believe that police officers are enforcing drinking and driving laws and that drinking drivers will most likely be caught. As such, targeting high traffic count road sites with high-visibility road checks is a priority because it serves to increase awareness of the enforcement activity. An alternative to this prevention approach is the "repression" approach that involves targeting times and places where the highest number of drinking drivers are to be expected. Rather than attempting to affect the subjective chance of getting caught, this approach seeks to increase the objective likelihood of getting caught; the aim is to apprehend as many drinking drivers as possible. Regardless of the chosen strategy, there is a need to understand how traffic count influences drinking and driving behaviour as traffic count may play a role in a police officer's choice of sites for a road check. The objective of this paper is to shed some light on this relationship between drinking and driving behaviour and traffic count. In this paper, data from a roadside survey, carried out in British Columbia in 2003, are used. A two-level logistic regression analysis was carried out with data from 2,627 drivers coming from 48 different road sites to replicate a model that was previously obtained with comparable data from a Belgian roadside survey, also carried out in 2003. The present study successfully replicated the findings of the Belgian model, substantiating that the probability for drivers to be drinking and driving significantly decreases with an increasing level of traffic count. This supports the suggestion that drinking drivers avoid high traffic count road sites. The relevance of these findings with respect to organizing preventive or repressive road checks is discussed at the end of this paper.

1. The relevance of traffic count

General deterrence theory predicts that the actual and perceived likelihood (fear) for getting caught are important motivators for people to comply with the law (Ross 1992). Homel (1988) tested this theory using data from random breath testing (RBT) and confirmed that not just the actual chance of getting caught is important but the perception of the likelihood of getting caught plays an equally important role.
These findings led to the practice of using high-visibility road checks when enforcing drinking and driving laws, primarily to increase the subjective chance of getting caught among the public. The objective of such prevention efforts is to make as many people as possible believe that police officers are out on the road, enforcing drinking and driving laws and that drinking drivers will most likely be caught. Such practices have generally acknowledged that high-visibility road checks have little (or less) impact on the actual chances of a drinking driver getting caught but serve to escalate the perceived likelihood of arrest. Further reasoning may lead one to conclude that targeting high traffic count road sites at any time of the day or week with high-visibility road checks should be a priority because it serves to increase awareness of the enforcement activity.

An alternative to this prevention approach is the "repression" approach that involves targeting times and places where the highest number of drinking drivers are to be expected. Rather than attempting to affect the subjective chance of getting caught, this approach seeks to increase the objective likelihood of getting caught -- the aim is to apprehend as many drinking drivers as possible.

Road checks are often organized with either a clear prevention or repression objective in mind. However, it has been suggested that the approaches can be combined (e.g., see Goldenbeld and Hway-Liem 1994). According to such a strategy the prevention approach would largely be applied at high traffic count road sites earlier at night when a lot of people are on the road, while the repression approach would be adopted later at night, close to places where a high number of drinking drivers can be expected, such as areas near to drinking establishments.

This paper attempts to shed some light on the relationship between drinking and driving behaviour and traffic count -- one variable in particular that can play a role when setting priorities regarding when and where to conduct stop checks.

In 2003, the Belgian Road Safety Institute conducted the third national roadside survey (Vanlaar 2005a). An interesting negative relationship emerged between traffic count and drinking and driving -- for every 100 extra cars that drove by a survey site, the odds that a driver would be drinking decreased by 18.1%. Possible confounding factors including intensity of stopping drivers (number of police officers per number of cars driving by), time of day and day of the week, and amount of time spent per road site were controlled for. Considering the exploratory nature of these findings, it was suggested that it may be indicative of drinking drivers anticipating higher chances of getting caught at high traffic count road sites and thus avoiding those places where they expect a lot of traffic (Vanlaar 2005a, p. 396).

Although these findings from the Belgian data were considered inconclusive, they are provocative and warrant further investigation, since they bear on the issue of the likelihood of apprehending drinking drivers using a prevention or repression model and, more practically, on decisions of police officers when deciding where to organize road checks. This paper uses Canadian data from a comparable roadside survey, carried out in British Columbia (B.C.) in 2003, to examine the influence of traffic count on drinking and driving behaviour.

2. Methods

Surveys for this epidemiological study took place in June 2003 at 16 sites in each of three communities in south-western B.C., namely Vancouver, Saanich and Abbotsford. To obtain this total sample of 48 sites, road segments were selected randomly and each selected road segment was then searched for possible survey sites. Traffic cones were used to delineate each selected site and to mark off places where interviews were conducted. Drivers were directed into the survey site by an attending police officer and they were subsequently interviewed by a member of the survey team. Roadside surveys were organized on Wednesday, Thursday, Friday or Saturday evening from 21:00 to 03:00 hours. Each site was surveyed for 90 minutes in one of four shifts – from 21:00 to

22:30, 22:30 to midnight, midnight to 01:30, or 01:30 to 03:00. A total of 2,627 vehicles were selected from the traffic flow and asked to – voluntarily – participate; 2,234 (85%) complied and provided a breath sample (a more detailed description of the methods of the B.C. roadside survey is available in Wilson et al. 2006 and in Beirness et al. 2007).

Incidentally, data from the Belgian study were collected during a mandatory police check. A total of 12,891 drivers were stopped, ten drivers (0.08%) refused to provide a breath sample and 57 (0.44%) were not able to provide a breath sample (a more detailed description of the methods of the Belgian roadside survey is available in Vanlaar 2005a).

The dependent variable in this study is drinking and driving; a binary variable distinguishing between those drivers who were below a preset alcohol limit and those who were not. This variable is based on breath alcohol concentrations (BrAC) obtained by submitting stopped drivers to a breath test. Two corresponding blood alcohol concentration (BAC) cut-off values were used when modeling the data, 0.05% and 0.08%. While the legal BAC limit in Canada is 0.08%, the lower cut-off value was used as well to make the model comparable to the Belgian model – the legal BAC limit in Belgium is 0.05%. Moreover, it is the limit for issuing a roadside suspension in B.C. under the Motor Vehicle Act.

Note that the dependent variable's name is "drinking and driving", but that its category below the cut-off values contains drivers who had not consumed any alcohol at all, as well as drivers who had, but whose BAC was still below the cut-off value. For practical reasons, we refer to those drivers who had a BAC equal to or above a cut-off value as drinking drivers; drivers with a BAC below the cut-off value are referred to as not having been drinking and driving.

The independent variables include: traffic count (a continuous variable indicating the total number of vehicles driving by a survey site during the police check), intensity (a continuous variable calculated by dividing the number of staff per survey site by traffic count for that site), gender, previously stopped (a binary variable distinguishing between drivers who previously have been stopped and tested at a road site at least once in the last six months and drivers who have not been stopped in the last six months), probability of being caught (a categorical variable representing the driver's perception of the likelihood of being caught by the police for drinking and driving; categories include: unlikely, neutral, likely), and age (16-18 years, 19-25 years, 26-35 years, 36-45 years, 46-55 years, older than 55 years).

The data were modeled using a multilevel approach (see Vanlaar 2005b). In multilevel modeling (also referred to as mixed-effects models or random-effects models) account is taken of the hierarchical nature of the data, in this case drivers (level 1), nested in survey sites (level 2), nested in cities (level 3). A three-level and a two-level variance components model were analyzed, although adding the third level did not make any difference with regards to the results for the regression coefficients. The reported results in this paper come from the two-level model.

The two-level model that was fit to the data included 48 road sites at level 2 (m=48) and 2,627 drivers at level 1 (n=2,627). To model the relationship between the binary response (i.e., smaller than one of the cut-off values versus equal to or greater than) and the set of explanatory variables, the logit link function was used, meaning a two-level logistic regression was performed. To interpret the relationship between the binary response and an explanatory variable, logit coefficients were transformed into odds ratios using the exponential transformation. The odds ratios compare the odds for drinking and driving (i.e., a BAC equal to or greater than the cut-off value) of a certain category of an explanatory variable to the reference category of that particular explanatory variable.

Note that there is an important difference between the explanatory variables traffic count and intensity and the remaining explanatory variables. The former two variables are aggregated and do not vary for individuals at the same survey site as opposed to the other explanatory individual variables such as gender and age. These aggregated variables only vary at level two (hence they are called level 2 variables) and their influence on a dependent level 1 variable can be modeled properly with multilevel models.

Probabilities for drinking and driving were also calculated per level of traffic count. The formula to obtain these probabilities is derived from the logit model and takes the following form (Rasbash et al. 2005):

$$\pi = \frac{1}{1 + \exp\left(-\left(\beta_0 + \beta_1 x\right)\right)};$$

where π denotes the probability of drinking and driving (i.e., BAC equal to or greater than the cut-off value), "exp" denotes the exponential function, β_0 refers to the intercept of the model, β_1 to the regression coefficient of the explanatory variable traffic count and x represents the variable traffic count. The probabilities obtained using this formula were then converted into percentages.

Finally, estimation of the models discussed was performed using the restricted iterative generalized least squares method (RIGLS). A first order penalized quasi likelihood estimation (PQL) was used to compensate for potential bias (see Rasbash et al. 2005 for an explanation of these estimation procedures).

3. Results

Table 1 contains a comparison of the results of the Belgian model (Vanlaar 2005a) with the model using the 2003 B.C. data. Both models were controlled for the possible confounding influence of time of day and day of week (the results presented in the tables come from models that did not include time of day and day of week because these variables were not significant; strength and direction of the other variables did not change between models with and models without time of day and day of week).

Coefficients for categorical variables indicate how likely it is for a respondent in a particular category (e.g., aged 26-39 in the Belgian model) to be a drinking driver (i.e., BAC equal to or greater than 0.05%) compared to the reference category of that categorical variable (in this case 18-25 years of age in the Belgian model). Reference categories for the Belgian model are: male for gender; never been caught drinking and driving before for previously stopped; very low probability of being caught; and, age 18-

25. Reference categories for the B.C. model are: male for gender; not stopped and tested for drinking and driving in the last six months; unlikely that you will be caught by police for drinking and driving; and, age 16-18).

As can be seen both models are fairly similar. Of significant interest, corresponding coefficients in both models have the same sign, indicative of the same direction for each relationship between the explanatory variables and the dependent variable. The coefficients are also fairly similar with respect to their magnitude.

While the variables probability of being caught and age were categorized differently in the B.C. model, compared to the Belgian model, a comparable pattern emerges in both. The likelihood of drinking and driving increases as the perceived probability of being caught increases. There is a U-shaped relationship between age and drinking and driving with the lowest probability for drinking and driving assigned to the youngest age category, the highest probability to the middle age categories and, again, a lower probability to the highest age categories. Finally, level 1 variances are constrained to 1, since this is one of the assumptions of the logistic model. Level 2 variance is lower in the B.C. model.

Non-significant parameters were dropped in the next step, resulting in the final model using the B.C. data, displayed in Table 2. Level 2 variance has now become significant (as can be derived from its value of 1.327, which is greater than twice its standard error (S.E.) of 0.248). Using a threshold model approach (See Rasbash et al. 2005 and Snijders and Bosker 1999 for an explanation and formula) it can be calculated that 28.7% of the total variance is level 2 variance due to the variability between survey sites. Such a percent calls for a multilevel approach when analyzing these data.

Exponential coefficients of the final model are presented as well facilitating the interpretation of the explanatory variables' influence on the dependent variable. For example, the odds ratio of 7.941 for the category 19-25 years old means that respondents aged 19-25 are about 7.9 times more likely than the respondents in the reference category (i.e., 16-18) to drink and drive. This effect for respondents aged 19-25 is significant as the value of the corresponding logit coefficient (2.072) is greater than twice its S.E. (0.786). Put another way, being 19-25 years of age corresponds to an increase in odds for drinking and driving of 694.1% (794.1%-100%).

Of particular interest in this paper is the variable traffic count. The odds for drinking and driving are multiplied by a factor of 0.996 for each increase of traffic count with one unit. That is, if traffic count at a survey site increases with one car, the odds of finding a drinking driver at that particular site decrease by a factor of 0.996. The range of traffic count in this B.C. study was 1,392 with a minimum of 14 cars and a maximum of 1,406 cars. The probabilities for drivers to be drinking and driving at various levels of traffic count are shown in Table 3. These probabilities have been calculated using the formula in the Methods section for levels of traffic count ranging from 20 to 1,500 and have been multiplied by 100 to express the results in percentages. Two different calculations have been carried out; one with the parameters of the final B.C. model, excluding the control variables time and day (which yields a β_0-value of -4.026 and a β_1-value of -0.004), and one with the parameters of the final B.C. model, including those two control variables (which yields a β_0-value of -5.456 and a β_1-value of -0.003). The results according to the Belgian model (with a β_0-value of -4.757 and a β_1-value of -0.002) have been inserted for comparison of results between the B.C. data and the Belgian data.

Although the individual probabilities for drinking and driving per level of traffic count differ between the three models, more importantly, the same pattern emerges, regardless of what model is used to calculate those probabilities. Overall, there is a clear decreasing trend in the individual probability of drinking and driving as the level of traffic count increases; at high traffic count survey sites the chances of finding a driver who has been drinking are significantly lower.

Finally, Table 4 displays absolute numbers and row-percentages of BAC by traffic count from the B.C. survey (the grand total in this table does not correspond to the total number of drivers mentioned previously due to missing values in the variables used in Table 4). Four levels of traffic count have been included in this table: survey sites with a count of up to 75; survey sites with a count greater than 75 but smaller than or equal to 250; survey sites with a count greater than 250 but smaller than or equal to 500; and, survey sites with a traffic count greater than 500 but smaller than or equal to 1,500.

These categories correspond to the range of traffic counts in this study. Three categories of BAC are displayed: BAC lower than 0.05%; BAC greater than or equal to 0.05% but smaller than 0.08%; and, BAC equal to or greater than 0.08%.

Not surprisingly, the significant effect that was found for traffic count using the multilevel approach was reproduced in this 4x3 table according to a Chi-square test (df=6; Chi-square=28.35; p=0.015). There were 15 drinking drivers (BAC>=0.05%) at sites with a count of up to 75, compared to 9 at sites with counts of at least 501. Out of a total of 93 drinking drivers (BAC>=0.05%), 63 (i.e., 68%) were detected at the survey sites with a count of up to 250.

4. Discussion

The objective of this article was to provide some insights into the relationship between the variable *traffic count* and drinking and driving behaviour. The relevance of understanding such a relationship becomes clear when examining two important frameworks -- prevention or repression -- that are often used when organizing road checks to enforce drinking and driving legislation. It has been suggested that a prevention approach -- designed to increase the perceived likelihood of arrest -- would best be applied at high traffic count road sites early at night when a lot of people are on the road. The repression approach -- designed to increase the chance of detecting and apprehending drinking drivers -- would best be adopted at night, close to places where a high number of drinking drivers can be expected.

Regardless of the primary objective, there is a need to understand how traffic count influences drinking and driving behaviour as traffic count may play a role in a police officer's choice of sites for a road check.

The present study replicated the findings of the Belgian model substantiating that the probability for drivers to be drinking and driving significantly decreases with an increasing level of traffic count. This supports the suggestion that drinking drivers avoid high traffic count road sites, possibly because they anticipate a higher chance of getting caught at those high traffic count sites.

In addition to probabilities, absolute numbers are important as well, especially if the objective is more related to the apprehension of as many drinking drivers as possible, rather than just raising the perceived likelihood of arrest. It could be argued that it does not matter if the chances for drinking and driving are much higher at low traffic count sites, if the absolute number of drinking drivers at those sites is so low that the costs of organizing a road check, compared to the benefits, would be too high. In this regard, results from Table 4 were enlightening. The majority of drinking drivers were detected at survey sites with lower traffic counts – 250 cars or less per 90 minutes, corresponding to a maximum of less than three cars per minute. To illustrate, 63 out of 93 drinking drivers with a BAC greater than or equal to 0.05% (i.e., 68% of all drinking drivers) were detected at sites with traffic counts equal to or less than 250. Another 21 drinking drivers (i.e., 22%) were detected at sites with traffic counts greater than 250 but smaller than or equal to 500. Only nine drinking drivers (i.e., 10%) were caught at sites with traffic counts of at least 501.

Despite the convergence of evidence resulting from a comparison of the B.C. data with the Belgian data, it may be premature to regard the findings concerning the relationship between traffic count and drinking and driving as conclusive. Possible confounding factors such as time of day and day of week were included both in the Belgian and the B.C. model so they could be kept constant, but the B.C. data are limited in that surveys only took place on Wednesdays through to Saturdays from 21:00 to 03:00, while the Belgian data were representative of the entire week. No data were gathered in either study about the differences between urban and rural survey sites or about characteristics of the roads along which these survey sites were located. Despite the lack of a more detailed classification of sites, there are good reasons to believe that B.C. sites could largely be classified as urban because of the sampling design involving only three major B.C. cities. Aggregated level 2 variables such as urban/rural and variables pertaining to characteristics of roads should be investigated in further research.

In conclusion, the successful replication of the Belgian model using B.C. data suggests that a more thorough investigation of the influence of traffic count on drinking and driving behaviour and possible confounding variables may provide useful insights with respect to the strategic planning of road checks to enforce drinking and driving legislation.

Acknowledgements

The author expresses his gratitude to Laurie Baker from the Insurance Corporation of British Columbia (ICBC), Canada for providing the BC roadside survey data, and to Jean Wilson, also from ICBC, who formulated feedback that was helpful in improving this paper.

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Tables

Table 1: Comparison of the Belgian two-level logistic model with the B.C. two-level logistic model; Logit coefficients and standard errors (S.E.) are displayed for fixed and random parameters

Belgian model		**B.C. model**	
	Logit coefficients (S.E.)		*Logit coefficients (S.E.)*
Fixed parameters			
Intercept	-4.757 (0.285)	Intercept	-4.620 (0.864)
Traffic count	-0.002 (0.000)	Traffic count	-0.002 (0.001)
Intensity	0.896 (0.383)	Intensity	0.787 (2.782)
Female	-1.375 (0.207)	Female	-0.367 (0.279)
Previously stopped	0.409 (0.141)	Previously stopped	0.285 (0.250)
Probability low	0.537 (0.167)	Probability neutral	0.275 (0.391)
Probability medium	0.744 (0.169)	Probability likely	0.661 (0.289)
Probability high	0.312 (0.278)	Age 19-25	1.390 (0.768)
Probability very high	1.432 (0.290)	Age 26-35	1.713 (0.772)
Age 26-39	0.710 (0.242)	Age 36-45	1.669 (0.785)
Age 40-54	1.314 (0.234)	Age 46-55	1.242 (0.841)
Age 55+	0.863 (0.272)	Age 56+	1.044 (0.910)
Random parameters			
Level 2 variance	0.991 (0.197)	Level 2 variance	0.192 (0.173)
Level 1 variance	1.000 (0.000)	Level 1 variance	1.000 (0.000)

Table 2: Final B.C. two-level model containing significant effects only; Logit coefficients and standard errors (S.E.), and exponential coefficients are presented for fixed and random parameters

Parameter	**Logit coefficient (S.E.)**	**Exponential coefficient**
Fixed parameters		
Intercept	-4.026 (0.826)	
Traffic count	-0.004 (0.001)	0.996
Intensity	-5.295 (2.240)	0.005
Age 19-25	2.072 (0.786)	7.941
Age 26-35	2.181 (0.838)	8.855
Age 36-45	2.305 (0.793)	10.024
Age 46-55	2.131 (0.838)	8.423
Age 56+	2.309 (0.869)	10.064
Random parameters		
Level 2 variance	1.327 (0.248)	
Level 1 variance	1.000 (0.000)	

Table 3: Comparison of B.C. and Belgian probabilities (in percent) of drinking and driving by traffic count (parameters for calculation of Belgian probabilities borrowed from Vanlaar 2005a)

Traffic Count	*BC model, excluding control variables time and day*	*BC model, including control variables time and day*	*Belgian model*
	(β_0 =-4.026; β_1 =-0.004)	*(β_0 =-5.456; β_1 =-0.003)*	*(β_0 =-4.757; β_1 =-0.002)*
20	1.621%	0.401%	0.819%
50	1.440%	0.366%	0.771%
100	1.182%	0.315%	0.698%
500	0.241%	0.095%	0.315%
1,000	0.033%	0.021%	0.116%
1,500	0.004%	0.005%	0.043%

Table 4: Traffic count in four categories by BAC in three categories; absolute numbers and row-percentages are presented

Traffic Count	**BAC<0.05%**	**0.05%≤BAC<0.08%**	**BAC>=0.08%**	**Total**
<=75	147	7	8	162
	90.7%	4.3%	4.9%	100.0%
75<.<=250	1,057	19	29	1,105
	95.7%	1.7%	2.6%	100.0%
250<.<=500	607	9	12	628
	96.7%	1.4%	1.9%	100.0%
500<.<=1,500	410	5	4	419
	97.9%	1.2%	0.9%	100.0%
Total	2,221	40	53	2,314