Motorcycling and Impaired Motorcycling in Hawaii: Rider Characteristics, Environmental Factors, and Spatial Patterns

International Motorcycle Safety Conference "The Human Element" Orlando, Florida March 1-4, 2001

Karl Kim, Ph.D., Professor and Chair Joseph Boski, Research Assistant Department of Urban and Regional Planning University of Hawaii at Manoa 2424 Maile Way o #107 Honolulu, Hawaii 96822

Tel: 808 956-7381; FAX 808 956-6870

Email: karlk@hawaii.edu

Abstract

In this paper, we report the results of our research investigating motorcycling and alcohol-impaired motorcycling in Hawaii. Our investigation expands the scope of rider characteristics analysis by examining the combined effects of rider behavior (helmet use, speeding, actions taken before crash, etc.), and environmental factors (urban v. rural locations, roadway alignment, etc.) and spatial patterns on motorcycle crashes.

We begin with the development of a typology of motorcycle crashes. This crash typology was then used to derive logistic regression models for explaining alcoholinvolved crashes, single vehicle crashes, and injury outcomes (including fatalities) associated with motorcycle crashes. The logistic models enable us to compare the relative importance of various rider characteristics, temporal and environmental correlates associated with motorcycle crashes and the associated crash types and injury outcomes.

Finally, the results of a spatial cluster analysis are presented, using both GIS (geographic information systems) and spatial analytical tools. The analysis suggests that overall behavioral, and temporal factors are more significant predictors of alcoholinvolved crash patterns than environmental or roadway features. We qualify our findings both in terms of the usefulness of the methods to motorcycle safety researchers as well as in terms of the relevance to motorcycle safety initiatives within our state.

INTRODUCTION

Motorcycle safety is a topic of continuing concern, not just in Hawaii, where we have based our research, but throughout the world. Annually, in the United States, there are more than 50,000 riders injured in crashes and approximately 2,000 rider fatalities (U.S. DOT, 1999). While the numbers are much smaller in Hawaii (approximately 450 injured riders and 15 fatalities per year), they exceed the state's expected share based on a simple ratio of population. Moreover, Hawaii provides an ideal environment for closely studying motorcycle safety. With a year round favorable climate, with relatively short

travel distances associated with island living, and high costs of fuel and transportation in comparison to mainland cities, motorcycling is a popular travel mode. There are several other reasons why Hawaii provides an excellent location to conduct motorcycle safety research. With only four county governments, with only four police departments in the entire state, the quality of police crash reporting is better than in other places. Approximately 70% of the state's population resides within the largest county, the City and County of Honolulu. We limit our analysis to this one county, which is the single island of Oahu, so it can be analyzed spatially. Specially trained accident investigators are dispatched to the scene of injury-producing crashes. In addition, the University of Hawaii has developed a special expertise in accident analysis and statistical modeling. In 1992, it received a CODES (Crash Outcome Data Evaluation System) grant from the U.S. Department of Transportation, National Highway Traffic Safety Administration. This project involved the acquisition of crash data, EMS data, hospital, insurance, and other information related to traffic safety. In addition to producing a linked database and performing various statistical analyses, the project also led to the development of a comprehensive traffic safety GIS for mapping and analyzing all police reported crashes in Hawaii. Additionally, we have conducted various motorcycle safety research projects over the years (See for example Kim and Wiley, 1992; Kim, Kim, and Yamashita, in press, and Kim and Boski, in press).

The purpose of this research is threefold. First, using data from Hawaii, we seek to develop a typology of motorcycle crashes which we can then extend to develop a deeper understanding of the most important dimensions or factors influencing the likelihood of a motorcycle crash. Second, using this typology and logistic regression techniques, we want to build a statistical model that enables us to examine the interrelationships between rider, temporal and environmental factors, and the likelihood of crashes and the associated injury outcomes. Finally, using GIS tools, we will characterize the spatial pattern of motorcycle crashes in order to determine if there are key locations for introducing interventions for increasing motorcycle safety. While we focus on Hawaii, the intent of the research is to explore both methodologies as well as the implications of our findings for enhancing motorcycle safety. By rider characteristics we are focusing on rider behavior during or immediately preceding the crash. As the variety of data in our study is already quite extensive, and since rider demographics have been discussed well and at length elsewhere for both Hawaii and other regions. For example see Kim and Wiley, 1992; Baker and Fisher, 1977; and U.S. DOT 1999.

DATA AND METHODS

There are an estimated 35,000 persons with motorcycle licenses in Hawaii. There are approximately 18,000 registered motorcycles in the state. Insurance data indicates that there are approximately 11,000 current policies covering motorcyclists in the state. Crash data, police citation data, and anecdotal sources indicate that are significant numbers of unregistered motorcycles, unlicensed riders, and uninsured motorcyclists in Hawaii. Over the 10 year period we examined (1986 to 1995), there were approximately 525 police reported motorcycle crashes per year. According to police crash data, around 20 crashes per year involved alcohol. We suspect a large amount of underreported alcohol involvement in crashes. Using linked police crash and hospital records, the CODES Project (see Kim, 2000) found that among hospitalized victims of motor vehicle

crashes, police reported alcohol involvement in 8% of the cases. Yet hospital records for the same individuals show alcohol involvement in 25% of the cases, more than three times the number reported by the police.

In this paper, we built a database of all police reported motorcycle crashes over the period 1986 to 1995. We analyzed the data using the Sun workstation and PC version of SAS, a statistical analysis package. After running basic frequency distributions and inferential statistical tests, we set out to characterize the nature of motorcycle crashes in terms of key environmental, temporal and behavioral factors. We examine alcoholimpaired crashes as well as single-vehicle crashes. We construct some multipliers (Kim, in press), calculate expected values that are then compared to the actual values for various combinations of rider factors, temporal and environmental conditions, and crash outcomes. These results are summarized in a series of tables which provide a revealing look at the principal factors associated with motorcycle accidents. Next using inputs from the preceding analysis, we construct a series of logistic regression models and calculate the odds ratios for various events such as alcohol-impaired crashes, singlevehicle motorcycle crashes, injury-producing crashes, and fatality producing crashes as a function of various rider, temporal, and environmental correlates. We use logistic regression because it provides a powerful tool for estimating the odds of a particular event occurring subject to various conditions. It enables us to examine categorical data such as whether or not an alcohol-impaired crash occurred or whether or not an injury producing accident resulted, while controlling for various environmental, temporal, or behavioral factors. To illustrate, we might specify the dependent variable, E, as the odds of a particular event occurring (such as an alcohol-impaired crash), as a function of various behavioral, B, roadway, R, and temporal factors, T,:

$$Log_{e}\{(Pr(E)/[1 - Pr(E)]\} = f(B, R, T).$$

The dependent variable, the logged odds of an event occurring over the odds of it not occurring $Log_{\epsilon}\{(Pr(E)/[1-Pr(E)]\}$, is contingent upon the *behavioral characteristics of the riders, B*, as well as roadway, R, and temporal, T, factors. The modeling processing involves fitting various terms and factors associated with the events occurring and assessing model fit by using various goodness of fit measures and by examining the concordance between the fitted and observed pairs. This approach builds on our previous research on loglinear modeling (Kim, et. al. 1995), an application of methods and analytical techniques that have been described in detail elsewhere (Feinberg, 1980, Agresti, 1990).

After building the logistic regression models, we used ArcView to map and spatially analyze the locations of various types of motorcycle crashes. Using a spatial clustering procedure, we mapped the spatial location of various types of crashes in order to determine if there where key locations for launching motorcycle safety initiatives.

FINDINGS: CRASH TYPE ANALYSIS

We begin by examining the nature and extent of alcohol-related motorcycle crashes. As shown in Table 1, Characteristics of Alcohol-related Crashes, there were a total of 3,960 police reported motorcycle crashes over the period 1986 to 1995. Of these,

115 were alcohol-impaired. The multiplier approach, developed in an earlier paper (see Kim, in press), gives us a convenient, yet robust tool for examining relative frequencies. The overall multiplier for alcohol related motorcycle crashes (115/3,960) is 0.0290. In other words, for each crash there are approximately 0.029 alcohol-involved crashes. The table also enables us to compare the multipliers of other types of alcohol-involved crashes. For example, the multiplier for rural, alcohol-involved crashes (12/265) is 0.0453, which is higher than the overall multiplier for alcohol-involved crashes. We can gauge the extent to which the rural factor contributes more to alcohol crashes by comparing the expected value (265 x .0290) to the actual number of rural alcoholinvolved crashes. We see that actual number exceeds the expected value by 4 crashes. This suggests that rural locations are somewhat prone to alcohol-involved motorcycle crashes. By applying the same method to other factors, we see that time of day (night), speeding, careless risky and reckless behaviors (CRR) which includes disregarding of traffic controls, failure to yield, speeding, and other rider actions are also strongly associated with alcohol-related crashes. It is important to note that in addition to the CRR variable, we also coded speeding by itself in order to isolate the associations between speeding and alcohol-impaired crashes. The actual number of speeding-related alcohol-impaired crashes (57) was 150% greater than the expected value (23). In addition the actual number of night time alcohol-crashes (106) was more than double the expected value (50). Crashes involving risky and reckless actions on the part of riders also accounted for a larger number of alcohol-impaired crashes (76) than expected (40). This finding, along with the association between unhelmeted rider crashes and impaired rider crashes, also supports the notion that personal, behavioral, and temporal factors are strongly associated with alcohol-impaired crashes. The table also shows that alcoholimpairment also is more likely in single-vehicle crashes than in other crashes. The expected value is 46, yet there were 83 alcohol-impaired single vehicle crashes over the period we examined.

In order to have a better understanding of the nature of single vehicle motorcycle crashes, we produced Table 2, Characteristics of Single Vehicle Crashes, using the same methods as in Table 1. Of the 3,960 crashes, 1,599 were single-vehicle motorcycle crashes. As Table 2 reveals, the actual number of both speeding and alcohol-impaired crashes exceeds the expected values by 69.7% and 79.7%, respectively. Table 2 also contains data on environmental factors such as the effects of curved roads, roadway defects, rural location, or if the roadway surface was wet or oily. Each of these factors produced higher than expected frequencies for single vehicle crashes. There were 301 more crashes on curved roads than expected. There were 80 more crashes on surfaces with defects, 78 more than expected on wet or oily surfaces, and 47 more crashes in rural locations than expected. These findings suggest that roadway conditions are relevant for single vehicle crashes.

Table 3, Characteristics of Crashes with Serious Injuries was prepared to investigate the relationships between various types of crashes and injury outcomes. In this table, we have isolated the various types of crashes and examined the injuries that they have produced. Again, we have employed the multiplier technique that was used in the first two tables. We have defined injuries to include all fatal and incapacitating injuries. This corresponds with the K (killed) and A (incapacitating) injury levels on the police KABC0 scoring system (where B is non-incapacitating injury, C is possible injury,

and 0 is no injury). Using the injury multiplier for all motorcycle crashes and applying it to the frequency of certain types of crashes (e.g. curved road, rural, night, etc.), we can derive an expected injury frequency and then compare it to the actual frequencies to measure the extent to which certain conditions produce a higher than expected level of injury. Table 3, thus reveals that curved roads produce 55.6% more serious injury crashes than expected, while rural locations are associated with 53.3% more injury crashes than expected. Night is responsible for 17.5% more injury crashes than expected, while speeding and alcohol-involved crashes greatly increase the likelihood of fatal and non-incapacitating crashes. The actual number of alcohol-impaired crashes with serious injuries is 39, compared to the expected value of 20. The actual frequency of speeding related crashes is 254, compared to the expected value of 121. Single vehicle crashes produce 23.9% more fatalities and incapacitating injuries than expected.

LOGISITIC REGRESSION RESULTS: EXPLAINING CRASHES AND OUTCOMES

In order to further explain the relationships between various demographic, temporal, and environmental factors and motorcycle crashes and injury outcomes, a series of multiple regression models were constructed. Many different models were specified and fitted, only the best performing, summary results are provided in the paper. Four basic models have been derived: 1) Alcohol-impaired Crashes; 2) Single-vehicle Crashes; 3) Serious Injury (KA level) Model; and 4) Fatal Crash (K) Model. For each of the models, various combinations of rider, roadway, and environmental terms were fitted. The advantage of logistic regression is that it enables us to consider the simultaneous effects of many different types of factors. In addition to allowing for the handling of categorical data, it also enables us to measure the relative effects of individual variables and combinations of factors. In addition to presenting the parameters, the odds ratios (O.R.) are also contained in the tables. The larger the odds ratio, the larger the effect. Odds ratios of 1 or close to 1 suggest a neutral or weak effect, while an odds ratio of less than one suggests a negative relationship.

Alcohol-impaired Crashes

Table 4, Alcohol-impaired Crashes shows the effects of four different variables, helmet use, cumulative risky behaviors (speeding, failure to yield, etc.), night, and single vehicle crashes on the likelihood of alcohol-impaired motorcycle crashes. The model demonstrates that helmeted riders are only 0.46 times as likely as unhelmeted riders to be involved in impaired crashes. This means that unhelmeted riders are more than 2 times more likely to be involved in alcohol-impaired crashes than helmeted riders. Those engaged in risky or reckless actions (speeding, failure to yield, etc.) are 3.75 times more likely to also be involved in impaired rider crashes than those not exhibiting these actions at the time of crash. The table also reveals that alcohol-impaired crashes are 5.45 times more likely to occur at night than during the day time. Finally, impaired crashes are 2.68 times more likely to involve single-vehicle crashes than crashes between motorcycles and other vehicles.

Single-vehicle Crashes

Tables 5, Single Vehicle Crashes, contains the results of the regression models explaining the occurrence of single vehicle motorcycle crashes. The most significant factors explaining single vehicle crashes including speeding (O.R. = 3.23), night (O.R. = 3.23)

1.51), curved roads (O.R. = 5.66), rural locations (O.R. = 1.54), oily or wet surfaces (O.R. = 3.33), roadway defects (O.R. = 5.46), and vertical alignment (O.R. = 1.37). Rain was associated with a lower incidence of single vehicle crashes (O.R. = 0.46). It is interesting to note that when rider characteristics or factors such as speeding, alcohol, night and weekend are run in the model without the environmental factors, they are all significant explanatory variables in terms of single vehicle crashes. Yet, when run together with the independent variables listed in Table 5, all of the terms, except for speeding and night are not statistically significant at the .05 level, and hence were dropped from the final models. This suggests the importance of examining environmental factors in explaining the prevalence and occurrence of single vehicle motorcycle crashes.

Serious Injury and Fatal Crash Models

Tables 6 and 7 contain the results of the regression models explaining injury outcomes. Table 6 (Serious Injury Model) includes both A level (incapacitating injuries) and K (fatalities). Table 7 (Fatal Crash Model) uses only fatalities as the dependent variable. Both of the models produce similar results. The most serious injuries (including fatalities) are produced by speeding (O.R. = 2.77), alcohol (O.R. = 1.83), curved roads (O.R. = 1.52), and rural locations (O.R. = 1.56). In comparing Table 6 and Table 7, it is evident that alcohol has a stronger effect on fatalities – with an odds ratio of 4.73 in the fatality model compared to only 1.83 in the combined injury and fatality model.

Summary of Regression Model Results.

Examining all of the models (Table 4 to Table 7) produces a fairly consistent picture when it comes to motorcycle crashes. Clearly, personal and behavioral factors are strongly associated with alcohol-impaired crashes. Yet impaired rider *behavior is* clearly not the only factors associated with motorcycle crashes. Indeed, roadway and environmental factors are also quite significant in explaining single vehicle motorcycle crashes. It is evident, however, that there are interactions between behavior and temporal factors as these covariates often turned up as significant factors in alcohol-related crashes, single-vehicle crashes, and the associated injury outcomes. Perhaps it should come as no surprise, but it is evidence supporting a full range of different factors associated with motorcycle crashes and injury outcomes. Policy makers, safety advocates, motorcycle educators, and riders themselves need to be made aware of the full range of factors including not just the human element, but also the roadway and environmental factors that influence the propensity to crash and the likelihood of injury and fatality. It remains to be investigated whether or not roadway and environmental factors are more significant in motorcycle crashes than in automobile crashes.

SPATIAL ANALYSIS: SINGLE VEHICLE CRASHES

To further analyze the nature and extent of motorcycle crashes, we prepared a series of spatial analyses such as the one contained in Figure 1., Single Vehicle Crash Clusters. After geocoding (assigning coordinates) the location of every motor vehicle crash involving a motorcycle, the data were entered into ArcView for mapping and display. We also used a version of a point analysis program, known as CrimeStat (Levine, 1999) for performing various spatial statistics on the point locations of

motorcycle crashes in Hawaii. In addition to calculating the mean center and various measures of dispersion, we used a clustering routine to identify the major concentrations or groupings of motorcycle crashes. We mapped various types of crashes as well as rider characteristics (alcohol-impaired, helmeted, etc.). Our analysis has revealed a couple of central patterns useful to the development and eventual deployment of motorcycle safety strategies.

Not surprising, motorcycle crashes tend to cluster in areas where people live and work. These are locations where there are, typically, various activity generators. This makes sense, since most riders are traveling to work, school, or various types of activities. When mapping the location of alcohol-impaired crashes, they roughly correspond to the locations of single vehicle crashes. Indeed, it makes sense to treat alcohol-impaired crashes as a subset of the overall problem of single-vehicle crashes. Single-vehicle crashes exhibit a distinctly different pattern than vehicle-to-motorcycle crashes, which appear to be related to congestion and traffic volumes. To us, that represents a different type of problem than the single-vehicle motorcycle crash where not only are the effects of alcohol, speeding, and risky or reckless actions more significant, but also, where the influences of environmental and roadway factors are more clearly evident. Engineering, enforcement, and educational strategies when applied directly to single vehicle crash locations seem all the more potent than trying to address the problems and locations where multiple-vehicle crashes seem to predominate. Using GIS and spatial analysis tools, we have an opportunity to identify, isolate, and fix roadway defects or to educate or at least warn riders of potentially hazardous locations.

Figure 1 reveals several different spatial patterns which could be further refined and accentuated in the design of motorcycle safety programs. First, it demonstrates the presence of crash clusters and concentration points for further analysis and investigation. Second, by using a standard deviational ellipse to characterize the dispersion of crashes, it helps to identify not just the range and distance around the mean location, but also the directionality of crashes. This may be helpful in the design of both community based programs as well as in terms of isolating specific locations, intersections, roadways, and areas for treatment. Finally, the shape and area of the ellipses may also be useful in prioritizing where it make the most sense to implement various safety strategies. Because of limited resources and the need to prioritize locations, it may be necessary to identify strategic locations for the deployment of engineering, enforcement or educational resources. Having targeted areas not only helps in the design of more concentrated countermeasures, but it also helps in program evaluation.

Clearly, we could have gone further in terms of the analysis and interpretation of spatial features of motorcycle crashes. Our future research will do just that. But for now, we thought it useful to include this discussion as part of a larger picture of motorcycle safety in Hawaii. GIS, like regression analysis, provides a powerful tool for measuring and prioritizing various aspects of motorcycle safety.

SUMMARY AND CONCLUSIONS

In this paper, we set out to investigate the nature of motorcycle accidents in Hawaii. After examining comprehensive, multi-year police crash data, we constructed a

series of tables to characterize the predominant features of motorcycle crashes, impaired rider crashes, and the associated injury outcomes. We identified the major behavioral, roadway, temporal, and environmental factors associated with crashes. Using a multiplier technique, we estimated the likelihood of motorcycle crashes as a function of various conditions and then compared these estimated frequencies to the actual occurrence. Seeing when and where the actual occurrence exceeded the expected values enabled us to identify particularly problematic types of crashes or conditions which were associated with a higher than expected level of crashes. We used these results on crash expectancies in formulating our logistic regression models, which in turn have helped us to better understand the relative importance and interrelationships between rider characteristics, roadway and environmental conditions, crashes and injury outcomes.

Motorcycle crashes are complex. That should come as no surprise, since motorcycling itself is a complex activity, requiring both a high level of skill as well as coordination and mental ability. The fact that alcohol impairment should figure so centrally in not just single vehicle crashes, but also in terms of injuries and fatalities, should therefore come as no surprise. Indeed, given our results, we find support for continued efforts to address the impaired rider problem.

At the same time, given the interactions and connections between alcoholimpairment, risky riding behaviors (speeding, failure to yield, and other dangerous actions), it is clear that alcohol-impaired riding must be seen as part and parcel of a larger problem. Simply focusing on impairment without looking at the larger issues regarding speeding and other risky and reckless behaviors associated with riding will only solve part of the problem. There is no doubt, with many of these variables, somewhat of a chicken and egg problem – while there is evidence that alcohol may impair judgement leading to speeding and other risk taking behaviors, there is also reason to believe that those engaging in speeding and other risky behaviors are also more prone to consuming alcohol. This is reinforced by our finding that there is a statistically significant negative relationship between helmet use and impaired rider crashes.

Our study has also demonstrated that certain environmental factors – such as curved roads, roadway defects, oil or wet surfaces, and other roadway conditions are associated with an elevated risk of motorcycle crashes, injury and fatality. No doubt these conditions, when combined also with behavioral and temporal factors (riding at night) can also exacerbate the problem of motorcycle safety. This suggests an increased role for motorcycle safety advocates in terms of not just examining and documenting roadway hazards, but also working to ensure funding of projects to fix these dangerous locations. Combined with GIS and perhaps with rider information systems, there is much that can be done to enhance rider safety.

The fact that we found a negative relationship between rain and single vehicle motorcycle crashes suggests that riders themselves may take appropriate actions to limit their exposure to the hazards of wet roads or riding in the rain. Perhaps most simply and effectively by avoiding riding in the rain. This suggests that more information about roadway hazards could be communicated to riders to reduce the risks of crash involvement and injury as riders are willing and able to modify their behavior, either while riding or by choosing not to ride.

In this paper we have presented a number of tools (loglinear modeling and GIS) that have found their way into other traffic safety applications. It is evident that these methods have a role in enhancing motorcycle safety. Tools such as these not only provide a means of connecting the human element with the roadway and environment, but also, ultimately, provide opportunities for increasing the safety of riders.

REFERENCES

Agresti, A. (1990) Categorical Data Analysis. John Wiley and Sons. New York.

Baker, S. P. and R. S. Fisher (1977). Alcohol and Motorcycle Fatalities. American Journal of Public Health. V67 n3.

Feinberg, S. (1980) The Analysis of Cross Classified Categorical Data. The MIT Press. Cambridge.

Kim, K. and M. Willey (1992). Improving Motorcycle Safety in Hawaii: Recommendations Based on a Survey of Motorcycle Owners and Operators. Transportation Research Record. 1325. Pp. 62-68.

Kim, K., S. Kim, and E. Yamashita (in press). An Analysis of Alcohol-Impaired Motorcycle Crashes in Hawaii, 1986-1995. Transportation Research Record.

Kim, K. and J. Boski (submitted). Finding Fault in Motorcycle Crashes in Hawaii: Environmental, Temporal, Spatial, and Human Factors. Transportation Research Record.

Kim, Karl (1999) "The Lie Factor in Traffic Safety." Transportation Research Record. 1665. Pp. 141-146.

Kim, Karl (in press) "Crash and Injury Outcome Multipliers." Transportation Research Record.

Kim, K., L. Nitz, J. Richardson, and L. Li. (1995) "Personal and Behavioral Predictors of Automobile Crash and Injury Severity." Accident Analysis and Prevention Vol. 27, No. 4. pp. 469-481.

Levine, N. (1999) CrimeStat: Users Manual. Bethesda, Maryland.

U.S. Department of Transportation, National Highway Traffic Safety Administration (1999), Motorcycle Traffic Safety Facts. Washington, D.C.

Table 1 Characteristics of Alcohol Related Crashes

		Alcohol		Expected	Exceeds Expected by		
	Crashes	(Actual)	Multiplier	Value	#	%	
All Oahu Crashes	3960	115	0.0290	n/a	n/a	n/a	
Environmental Factors							
Rural	265	12	0.0453	8	4	55.9%	
Temporal Factors							
Night	1727	106	0.0614	50	56	111.4%	
Rider Characteristics and B	ehavior						
CRR	1370	76	0.0555	40	36	87.8%	
Speeding	785	57	0.0726	23	34	150.0%	
No helmet	2122	82	0.0386	65	17	26.9%	
Other Factors							
Single Vehicle	1599	83	0.0519	46	37	78.7%	

Table 2 Characteristics of Single Vehicle Crashes

		S	Single		Exceeds	Expected by:
	Crashes	(Actual)	Multiplier	Value	#	%
All Oahu Crashes	3960	1599	0.4038	n/a	n/a	n/a
Environmental Fa	ctors					
Curved	788	618	0.7843	317	301	95.0%
Road Defect	207	163	0.7844	83	80	96.4%
Rural	265	154	0.5811	107	47	43.9%
Road was Wet,	537	294	0.5475	216	78	36.1%
Oily, etc.						
Rider Characteristic	cs and Be	havior				
Speeding	785	538	0.6853053	317	221	69.7%
Alcohol	115	83	0.7217391	46	37	79.7%

Table 3 Characteristics of Crashes with Serious Injuries

		Inju	Injuries		Exceeds Expected b				
	Crashes	(Actual)	Multiplier	Value	#	%			
All Oahu Crashes	3749	664	0.1771	n/a	n/a	n/a			
Environmental Factors									
Curved Rd.	759	210	0.2767	135	75	55.6%			
Rural	254	69	0.2717	45	24	53.3%			
Temporal Factors									
Night	1616	336	0.2079	286	50	17.5%			
Rider Characteristics of	and Behav	rior							
Speeding	750	254	0.3387	133	121	91.0%			
Alcohol	112	39	0.3482	20	19	95.0%			
Other Factors	Other Factors								
Single	1197	337	0.2197	272	65	23.9%			

Table 4 Alcohol-Impaired Crashes

Variable	Parameter	s.e.	Chi-Square	ii-Square p-value Odds Ratio		95%	6 CL
			1	1	_	Low	High
Intercept	-6.2606	0.4324	209.6369	< 0.0001			
Helmet	-0.7766	0.2822	7.5702	0.0059	0.46	0.27	0.80
Risky	1.3220	0.2966	19.8678	< 0.0001	3.75	2.10	6.71
Night	2.4357	0.3773	41.6655	< 0.0001	11.42	5.45	23.94
Single	0.9841	0.2618	14.1322	< 0.0002	2.68	1.60	4.47

Likelihood Ratio Chi-sq=160.1273 (4 degrees of freedom), p-value <0.0001, Concordant = 83.1%, Discordant = 11.0%, Ties = 5.9%, 1255 missing values, cases with alcohol=84, without=2621.

Table 5 Single Vehicle Crashes

Variable	Parameter	s.e.	Chi-Square	p-value	Odds Ratio	95% CL	
					_	Low	High
Intercept	-1.5556	0.0646	580.1640	< 0.0001	•		
Speeding	1.1718	0.0968	146.6466	< 0.0001	3.23	2.67	3.90
Night	0.5629	0.0770	53.4358	< 0.0001	1.76	1.51	2.04
Raining	-0.7700	0.1977	15.1771	< 0.0001	0.46	0.31	0.68
Curved	1.7337	0.1064	265.4740	< 0.0001	5.66	4.60	6.97
Rd.							
Rural	0.4341	0.4559	7.7498	0.0054	1.54	1.14	20.95
Surface	1.2039	0.1727	48.5653	< 0.0001	3.33	2.38	4.68
Rd.	1.6977	0.1896	80.1573	< 0.0001	5.46	3.77	7.92
Defect							
Vert. Al.	0.3142	0.0885	12.5911	1.0004	1.37	1.15	1.63

Likelihood Ratio Chi-sq=990.6459 (8 degrees of freedom), p-value <0.0001, Concordant = 72.6%, Discordant = 19.3%, Ties = 8.1%, 130 missing values, cases single=1518, multiple=2312.

Table 6 Serious Injury Model

Variable	Parameter	s.e.	Chi-Square	p-value	Odds Ratio	95% CL	
					_	Low	High
Intercept	-1.9611	0.0585	1122.2218	< 0.0001			
Speeding	1.0203	0.0994	105.3614	< 0.0001	2.77	2.28	3.37
Alcohol	0.6060	0.2135	8.0554	0.0045	1.83	1.21	2.79
Curved Rd.	0.4215	0.1038	16.4963	< 0.0001	1.52	1.24	1.87
Rural	0.4426	0.1568	7.9676	0.0048	1.56	1.15	2.12

Likelihood Ratio Chi-sq=183.5666 (4 degrees of freedom), p-value <0.0001, Concordant = 48.2%, Discordant = 19.2%, Ties = 32.6%, 252 missing values, cases serious injury =659, other=3049.

Table 7 Fatality Model

Variable	Parameter	s.e.	Chi-Square	p-value	Odds Ratio	95% CL	
						Low	High
Intercept	-4.3799	0.1645	708.7105	< 0.0001			
Alcohol	1.5541	0.3131	24.6410	< 0.0001	4.73	2.56	8.74
Speeding	1.2126	0.2286	28.1307	< 0.0001	3.36	2.15	5.26
Curved Rd	. 0.6209	0.2300	7.2881	0.0069	1.86	1.19	2.92

Likelihood Ratio Chi-sq=75.0537 (3 degrees of freedom), p-value <0.0001, Concordant = 58.3, Discordant = 15.4%, Ties = 26.3%, 252 missing values, cases with alcohol=93, without=3615.

Figure 1.

Oahu Motorcycle Crashes: Single Vehicle Crash Clusters

