MODELING THE ROLE OF SOCIOECONOMIC FACTORS IN TRAFFIC ACCIDENTS IN KENTUCKY

FINAL REPORT

SOUTHEASTERN TRANSPORTATION CENTER

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16. Abstract:

Many factors factors such as average annual daily traffic (AADT), lane width, shoulder width, and geometry are commonly examined when attempting to understand the level of roadway hazard. Other non-engineering factors may also play a significant role in the traffic safety equation, as various socioeconomic factors have been shown to be correlated with traffic accidents. The socioeconomic variables that were tested were poverty status, gender, educational attainment, marital status, drug-overdose deaths, population density, and ethnicity.

Two models were used. Both predict the number of crashes on a roadway segment as a function of the segment's physical conditions and the socioeconomic factors of the county in which it is located. The first one is broader, focusing on the total number of crashes. The standard Highway Safety Manual (HSM) approach of using a negative binomial model was employed to analyze this data. In the model, the fixed effects of counties and roadway classification were controlled for. Results showed that gender had the largest impact and education the second largest. Moreover, both of these impacts were larger than those for either of the two standard engineering factors: annual average daily traffic (AADT) and length. The only factor that was not statistically significant was marital status.

The second model focused only on fatal and severe injury crashes. For these crashes, the negative binomial proved unworkable and so an unbalanced panel design was chosen. Results for this model pointed to educational status as having the largest impact, followed by the number of overdose deaths. Marital status, population density, poverty, "race", and gender were not shown to be statistically significant.

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EXECUTIVE SUMMARY

In Kentucky, more than 750 people were killed in 2015 and more than 35,000 injured in traffic accidents (KSP, 2016). Many of those accidents occurred on rural two-lane roads. Accordingly, the Kentucky Transportation Cabinet (KYTC) has a goal of reducing the number of accidents that occur on Kentucky's rural two-lane roads, especially those resulting in injury or fatalities. To help reduce the scale of tragedy, this study aims to determine which factors have the greatest impact on traffic safety.

Many factors such as average annual daily traffic (AADT), lane width, shoulder width, and geometry are commonly examined when attempting to predict the how hazardous a roadway is. Other non-engineering factors may also play a significant role in the traffic safety equation, as various socioeconomic factors have been shown to be correlated with traffic accidents. The socioeconomic variables that were tested were poverty status, gender, educational attainment, marital status, drug-overdose deaths, population density, and ethnicity.

Two models were used. Both predict the number of crashes on a roadway segment as a function of the segment's physical conditions and the socioeconomic factors of the county in which it is located. The first one is broader, focusing on the total number of crashes. The standard Highway Safety Manual (HSM) approach of using a negative binomial model was employed to analyze this data. In the model, the fixed effects of counties and roadway classification were controlled for. Results showed that gender had the largest impact and education the second largest. Moreover, both of these impacts were larger than those for either of the two standard engineering factors: annual average daily traffic (AADT) and length. The only factor that was not statistically significant was marital status.

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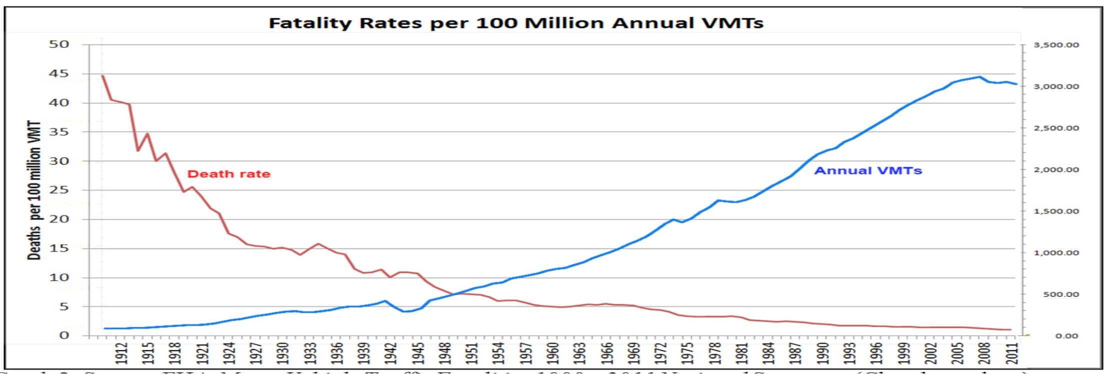
INTRODUCTION

According to the National Highway Transportation Safety Administration, in 2013, the most recent year for which data is available, there were just under 5.8 million traffic accidents in the United States. In these accidents, 32,719 people lost their lives and 2.3 million more people were injured (NHTSA, 2014). Overall though, as Figure 1 shows, the fatality rate has been experiencing a nearly continuous decline for the last one hundred years.

Figure 1:

FHWA Motor Vehicle Traffic Fatalities: 1900-2011



Source: Federal Highway Administration

While the number of traffic deaths per miles driven is decreasing, there are still a large number of fatalities, more than 32,000, each and every year. This fact need not make one fatalistic as, according to researchers at the University of California, Berkeley, "Very substantial additional progress can be achieved by a combination of improving and continuing to apply policies that have contributed to past success and developing and implementing new ones" (Ragland, p. 32). The *Highway Safety Manual* (HSM), which was first published in 2010, has as its objective achieving these further reductions in the absolute and relative number of traffic accidents and fatalities in the United States.

The American Association of State Highway and Transportation Officials (AASHTO) introduced the HSM to establish reliable quantitative methods that transportation agencies and other stakeholders can use to estimate safety improvements for U.S. highways. Highway agencies are expected to take advantage of the HSM's statistical methods and modeling techniques to determine the sites with the greatest safety issues, what factors influence crash rates, and the potential benefits of introducing new countermeasures to bolster road safety. Put simply, its recommended safety-performance based processes and guidelines are intended to sharpen the ability of transportation officials to decide about the relative utility of various planning, design, maintenance, and operational procedures to enhance the safety of roads (AASHTO, 2010).

Included in the HSM are regression models that are used to predict average crash frequency for a site based on data from a number of similar sites. These predictive models, which are identified as safety performance functions (SPFs) in the HSM, have been developed for specific site types and baseline conditions. To properly apply the HSM procedures, researchers can either calibrate an existing SPF using new data or develop a new one using state-specific crash data. The latter approach will be adopted here; state-specific crash data will be used to identify the factors influencing the safety of Kentucky's roadways.

In Kentucky, more than 750 people were killed in 2015 and more than 35,000 injured in traffic accidents (KSP, 2016). Many of those crashes occurred on rural two-lane roads. These roads have long been an area of focus for traffic safety engineers, as they pose many problems for drivers. Their narrow shoulders, numerous hidden entrance/exit points, limited visibility, and non-optimal geometry all are reasons for concern and are reasons for the markedly higher number of crashes on these roads compared to other road types, even after controlling for length and Annual Average Daily Traffic (AADT).

Accordingly, the Kentucky Transportation Cabinet (KYTC) has a goal of reducing the number of accidents that occur on Kentucky's rural two-lane roads, especially those that cause injury or fatalities. To reduce the scale of tragedy, information that will enable the enactment of policies that effectively reduce the number and severity of crashes is much needed. This study aims to help by determining which factors have the greatest impact on traffic safety.

Providing such information is always important, but it is especially salient in the tight budgetary times Kentucky is experiencing today. One need only look at the state's road fund and the marked declines in its collections to understand how important an issue this is. State budget director Jane Driskell recently reported that Kentucky's road fund had "revenue of $110 million in September [2015], compared to $138 million in September 2014" (Brammer, 2015). That is a loss of almost $30 million in just one year. Obviously, in such an environment, money needs to be allocated wisely. Thus, Kentucky's decision-makers need to be given information that enables them to understand why crashes are occurring.

Many factors such as the road's Average Annual Daily Traffic (AADT), lane width, shoulder width, and geometry are commonly examined when trying to predict how hazardous a roadway is. Other non-engineering factors may also be able to play a significant role in the traffic safety equation, as various socioeconomic factors have been shown to be correlated with traffic accidents. For example, being unemployed, divorced, having little education, (Karjalainen, p. 1448) and using a foreign language in the home (Romano, p. 139) have been tied to traffic safety problems. In addition, population density, vehicle size and per capita income have been shown to be predictors of fatal crashes (Males, p. 443). This information may be valuable for two reasons. First, in many localities, comprehensive data concerning the safety features that have been added to roadways does not exist. If a positive correlation can be found between certain salient socioeconomic factors (e.g. income) and roadway improvements, then the socioeconomic factors could well serve as proxies for the roadway data. Secondly, understanding which socioeconomic factors play an important role in predicting crashes may help traffic safety engineers by widening the range of countermeasures that are feasible.

APPROACH AND METHODOLOGY

The socioeconomic variables that were chosen to serve as inputs to the model were poverty status, gender, educational attainment, marital status, drug-overdose deaths, population density, and ethnicity. These variables were chosen not only because of the support provided by previous research but also because these variables theoretically make sense. The socioeconomic data for these variables was all county-level and most was obtained from the American Community Survey's 2014 five-year estimates. However, overdose data was from the 2014 Overdose Fatality Report of the Justice and Public Safety Cabinet of the Commonwealth of Kentucky, and population density numbers were from the 2010 U.S. Census. Being that the socioeconomic data is all county level, the specific relationship between the socioeconomic characteristics of drivers and crash rates is unable to be definitively determined. While that additional level of nuance is ideally sought, such micro-level data is simply not being collected in Kentucky at present. Therefore, this study only hopes to determine what county-level socioeconomic factors are important in predicting the number of crashes on Kentucky's rural two-lane roads.

Poverty is one such factor that is broadly theorized to increase the number of crashes on roadways. One reason for this might be that poverty directly affects driver behavior, as poverty status might imply a lower value of statistical life. This need not be an innate predisposition but rather could be the result of a fatalistic worldview engendered by the daily milieu from which most do not escape. Alternatively, poverty status in a county might only indirectly impact drivers, as poorer counties might have less funds for trash collection. This might lead to an increase in illegal dumping, which could result in more potentially dangerous objects on or next to the roadways.

As to gender, it has certainly been shown to have import for studies of behavioral responses. When it comes to traffic, previous research has shown that, on average, men drive faster and engage more in other types of risky behavior (Zuckerman & Kuhlman, p.1010) and so a county's gender balance is likely to have a direct impact on crash rates on the road segments that lie within. Of course the causal mechanism could be far more complex. For example, a county comprised of only women might have an incredibly high number of crashes with not one caused by a female driver. In this case, it might be that non-local males who pass through the county become overly distracted and crash on the shores of this county's Sirens. The current study would not be able to identify such a relationship. What will be tested is simply whether or not road segments in counties with a higher percentage of women experience more crashes. If that is found to be true, future studies can attempt to identify the exact cause of the phenomenon.

Educational attainment is included, as it may play a role in whether or not people use safety devices such as seat belts. Furthermore, more highly educated people may better grasp the connections between certain road conditions and the most sound driver response. It also could be that counties with lower educational attainment have more jaywalkers or have more pedestrians on the road at night that do not understand the problem created by their wearing dark clothing. Whatever the cause, the hypothesis is that increases in educational attainment will be negatively correlated with crashes.

Marital status is a tricky one. People in stable relationships are often seen as less likely to take risks. Reasons offered for this include the desire to shield the significant other from physical and psychological harm and also the more placid emotional state marriages induce. The quality of a marital relationship, however, is unknowable and so this variable may well prove lacking in its explanatory power due to the extreme tumult that exists in no small share of relationships and also because of the tenuousness of marriage's direct relationship with driving.

The drug overdose variable was chosen because it was believed that these numbers could serve as reasonable proxies for all drug-taking behavior including alcohol consumption, as drinking and various forms of drug consumption are correlated. Counties with higher drug mortality rates might also have higher numbers of other kinds of drug/alcohol problems in the community, such as DUIs. If this behavior exists, it is almost certain to increase the likelihood of traffic accidents.

Population density was included, as it is theorized that in urban and rural zones where people are living closer together the likelihood of crashes is greater simply because there is less open space that will accommodate errors. "Race" is included, as it is commonly seen as a salient feature in America. However, this researcher does not believe that there is a strong causal link between one's skin complexion and crashes that is not better explained by the other variables. All of these ideas will be tested.

To make progress on these fronts, safety engineers at the Kentucky Transportation Center (KTC) first compiled a dataset containing all the rural two-lane roads in each of Kentucky's 120 counties. The Kentucky Transportation Cabinet (KyTC) provided Annual Average Daily Traffic (AADT) values based on the 2012 Highway Performance Monitoring System (HPMS) extract. Then, using the Kentucky State Police's crash database, crash data for a 5-year period, 2009–2013, were plotted onto the roadways and for each road in each county, the HSM statistical modeling procedures described below were applied.

The HSM generally prescribes using negative binomial models because these models assume that unobserved crash variation across roadway segments follows a gamma distribution. Conversely, within-site crash variation follows a Poisson distribution (Washington, 2005). The Poisson, Poisson-Gamma (negative binomial), and other count models form part of the broader class of generalized linear models (GLM). The general HSM form is:

$$\mathbf{E[N]} = \boldsymbol{L * AADT^{a}}\ \mathbf{(1)}$$

where E[N] = predicted number of crashes per year for a roadway segment, *L* = length of a roadway segment, *AADT* = Annual Average Daily Traffic, and *a* = regression coefficient. It can be expanded to include other predictor variables (e.g. shoulder width and lane width). In this case, the formula transforms to:

$$\mathbf{E[N]} = \boldsymbol{L * AADT^{a}} * e^{b0*SW+b1*LW}\ \mathbf{(2)}$$

where *SW* = shoulder width, *LW* = lane width, and *b0* and *b1* are regression coefficients. To test the impact of socioeconomic factors, the model had the following form:

$$\mathbf{E[N]} = \boldsymbol{L * AADT^{a}} * e^{b0*R + b1*G* + b3*Pov + b4*M + b5*Ed + b6*OD + b7*PopD + b8Ky0US1}\ \mathbf{(3)}$$

where *R* = race, *G* = gender, *Pov* = poverty status, *M* = marital status, *Ed* = educational attainment, *PopD* = population density, *Ky0US1* = Roadway classification, and *b0* to *b8* are regression coefficients. The unit of analysis was a roadway segment with its associated crash history. In this study, there were 13,189 segments spread across Kentucky's 120 counties. Using Equation 3, two SPFs were developed, both predicting the number of crashes at a site as a function of the physical conditions of the road segments and the socioeconomic conditions of the counties in which the segments are located.

The first one aimed to predict the total number of crashes. The standard HSM supported negative binomial model was used to analyze this data while controlling for the fixed effects of counties and roadway classification. A fixed effects model was seen as appropriate, as counties, like states, are seen as having certain intangible yet durable differences. As their dissimilarities were theorized as potentially having an impact on crashes, they were controlled for using dummy variables for each county. The other variable that was seen as potentially having a consistent impact where reasons for differences were difficult to articulate was roadway classification. Within the dataset, there were two types of roads: Kentucky roads and U.S. roads. Previous research by this researcher that looked at whether or not safety varied across these two classifications found that, on average, federal roads have a slightly higher number of crashes per year when controlling for other relevant variables. That said, the magnitude of the difference was rather small, amounting to only one extra crash about every sixty years. This result, which is presented in Table 1, reveals a difference that is not easily explained, but which nevertheless seemed to merit attention due to its enduring and statistically significant nature.

TABLE 1:

Kentucky's Federal 2-Lane-Road Crash Comparison relative to State 2-Lane Roads

	Crash-Effect Coefficient	P Value
Federal Routes	0.02	<0.01

Note 1: Statistical significance was determined against an α of 0.05%

The second SPF that was developed focused only on fatal and severe injury crashes, which were identified using the KABCO scale. This scale is used in Kentucky by state and local police to report crash severity. This scale assigns a crash to preset categories with K representing fatal crashes, A for crashes where there is an incapacitating injury, and B for crashes where there are non-incapacitating injuries. C is used to designate crashes in which there was a possible injury, and O encompasses incidents that only resulted in property damage. For reference, the dollar values commonly attached to each of these respective crash levels are presented in Table 2. As these KAB crashes are very damaging economically and physically, much attention is always focused on reducing their occurrence.

TABLE 2:

Crash Severity and Costs

Crash Severity	Economic Cost[1]	Comprehensive Cost[2]
K	$1,410,000	$4,538,000
A	$72,200	$230,000
B	$23,400	$58,700
C	$13,200	$28,000
O	$2,500	$2,500

Source: National Safety Council (2012 data)

Note 1: Economic Costs = costs of motor vehicle collisions (e.g. wage loss, medical expense & administration costs)

Note 2: Comprehensive Costs = economic cost components & a measure of the statistical value of life

Unfortunately, when the KAB negative binomial formula was run through the statistical software, a methodological issue appeared that did not allow this approach to be used. The issue arose from the key requirement of the negative binomial that the variance be greater than the mean value. When all types of crashes were considered, there was no problem: variance was far greater than the mean. However, when only KAB types were considered, variance, as can be seen in Table 3, was at a level below the mean value.

TABLE 3:

Descriptive Statistics for KAB Crash Data

	Observations	Mean	Variance
KAB Crashes	13,189	0.0302	0.0294

This result meant that the negative binomial approach was completely unworkable for the KAB data. Accordingly, the best of the feasible approaches was an unbalanced panel design. This choice came from the fact that there were more than 100 different road-segment observations for each of Kentucky's 120 counties. This large number of observations made this approach a sensible substitute. With this decided, the first idea was to control for the fixed effect of counties, as had been done with the total crash dataset. However, the absolute lack of variation on features like the number of males in a county, which had to be attributed to each and every road segment within the county, and the concomitant collinearity eliminated the fixed-effects option. Therefore, a random-effects model was chosen. This model is theoretically strong, given that the unit of analysis is segments of roads and that it is extremely difficult to see how an inanimate road could have some purposeful and consistent correlation with the socioeconomic factors that were being examined. With the methodological issues resolved, the data was able to be run and processed. The results of this analysis are presented below.

RESULTS AND ANALYSIS

When the descriptive statistics for the variables of interest were calculated across all units, it was found that the average segment length was just under two miles in length, that the average annual daily traffic on each segment was almost 2,000 cars per day, and that the average number of crashes per segment was roughly two per year. KAB crashes were even less, averaging 0.30 per segment per year. This can be seen in Table 4.

TABLE 4:

Summary Statistics

	Mean	Min	Max	Std Dev
Length	1.76	0.001	13.08	1.66
AADT	1941.80	10.000	20401.00	2444.52
Crashes per year	2.01	0.000	55.80	3.22
KAB Crashes per year	0.30	0.000	8.20	0.54

Note 1: Length is measured in miles

Note 2: AADT is measured in thousands of vehicles per day

Length & AADT

When controlling for socioeconomic factors, county and roadway classification, both segment length and AADT were shown to have a statistically significant, positive correlation with both KAB crashes and total crashes. This is quite consistent with the engineering literature and makes great intuitive sense, as one would expect that any road which has higher traffic volume would also experience more crashes. Similarly, the longer the segment, the greater the number of crashes. This data is summarized in Table 5.

TABLE 5:

Effect of 1 % Increase in Length & AADT on Number of Total Crashes per Year

	Crash Impact Coefficient	P-Value
Length	0.0076	<0.01
AADT	0.0080	<0.01

Note 1: Length is measured in miles

Note 2: AADT is measured in thousands of vehicles per day

Note 3: Statistical significance was determined against an α of 0.05%

From these results, the takeaway for length is that a 130% increase in length will result, on average, in one more crash. This is a strong, positive relationship. For the annual average daily traffic (AADT), there would need to be 125% more cars traveling on a road segment daily for the crash rate to double.

For KAB crashes, the correlation between crashes and length/AADT is not nearly as strong. For example, as shown in Table 6, for each four and one half miles that a one-mile segment grows in length, there will be roughly one more crash on that roadway each year.

TABLE 6:

Effect of 1 % Increase in Length & AADT on Number of KAB Crashes per Year

	Crash Impact Coefficient	P-Value
Length	0.0018	<0.01
AADT	0.0015	<0.01

Note 1: Length is measured in miles

Note 2: AADT is measured in thousands of vehicles per day

Note 3: Statistical significance was determined against an α of 0.05%

As for AADT, the results show for a road with an AADT of 1,000, it would take 5,600 more vehicles travelling on the road each day to increase the number of crashes by one unit. This correlation between the two variables clearly is not especially strong.

<u>"Race" & Gender</u>

When looking at how "race" affects the number of crashes, it was found to have a statistically significant effect for the totality of crashes, but no significance was detected for KAB crashes. For all crashes, a three percent increase in the number of "white" people is correlated with one more crash per year. These results are presented in Table 7.

TABLE 7:

Effect of 1 % Increase in Number of "White" People on Total Crashes per Year

	Crash Impact Coefficient	P-Value
% with White Skin	0.37	<0.01

Effect of 1 % Increase in Number of "White" People on KAB Crashes per Year

	Crash Impact Coefficient	P-Value
% with White Skin	0.002	0.22

As mentioned previously, this study posits no theory as to why the color of one's skin should affect crashes, but for all crashes, having a lighter pigmentation is correlated with an increase in crashes.

The results for gender, shown in Table 8, were also mixed. Increases in the number of females are tied with reductions in overall crashes; however, there is no impact on KAB crashes. For all crashes, a two percent increase in the number of females in a county is likely to bring about three less crashes per year.

TABLE 8:

Effect of 1 % Increase in Number of Females on Total Crashes per Year

	Crash Impact Coefficient	P-Value
% Female	-1.464	<0.01

Effect of 1 % Increase in Number of Females on KAB Crashes per Year

	Crash Impact Coefficient	P-Value
% Female	0.001	0.79

While the gender of the drivers involved in crashes and the gender ratio of all drivers in each county is unknowable, this data, if interpreted as a strong proxy for those figures, would align well with previous research that shows that females generally engage in less aggressive driving and are less likely to be involved in crashes.

Education & Poverty

The results for education are very interesting. Compared to people with a high school degree or greater, increases in the numbers of those without such high levels of schooling will actually increase traffic safety: both for all crashes and KAB crashes. These results, presented in Table 9, posit that a four percent increase in the number of people without a high school degree would translate into 1 less crash occurring per year. As to KAB crashes, it would require a 100 percent increase for there to be one less crash per year.

TABLE 9:

Effect of 1 % Increase in Number of People with less than a High School Degree on Total Crashes per Year

	Crash Impact Coefficient	P-Value
% with < HS Education	-0.25	<0.01

Effect of 1 % Increase in Number of People with less than a High School Degree on KAB Crashes per Year

	Crash Impact Coefficient	P-Value
% with < HS Education	-0.01	<0.01

The reason for this result is unclear. Much research has shown that more education leads to increased use of safety devices, like seatbelts. So, it is surprising to see a result which would argue that to decrease the number of crashes, one should not send one's kids for more than eleven years of school. It is possible that this result is simply an example of Type I error.

As to the effect of poverty, the results show that the number in poverty is significant for all crashes but not for KAB crashes. Table 10 provides these results. The results for all crashes mean that a roughly twelve percent increase in poverty would result in one extra crash per year. This result suggests that the relationship between these two is not especially strong.

TABLE 10:

Effect of 1 % Increase in Number of People in Poverty on Total Crashes per Year

	Crash Impact Coefficient	P-Value
% in Poverty	0.082	<0.01

Effect of 1 % Increase in Number of People in Poverty on KAB Crashes per Year

	Crash Impact Coefficient	P-Value
% in Poverty	0.005	0.07

<u>Overdoses & Population Density</u>

When the effect of the number of overdoses per 100,000 people was calculated, it was found to have a significant relationship with both total crashes and KAB crashes. For total crashes, the relationship is negative, indicating that as the number of overdose deaths increase, the number of traffic crashes will fall. It is difficult to theorize exactly why this relationship is found. When KAB crashes are examined, the relationship is positive: the more overdose deaths there are, the more crashes. However, this relationship is very weak. It would require 500 more overdoses per 100,000 people for there to be one more KAB crash. These results are presented in Table 11.

TABLE 11:

Effect of Increase in Number of Overdose Deaths on Total Crashes per Year

	Crash Impact Coefficient	P-Value
Overdose Deaths	-0.042	0.02

Effect of Increase in Number of Overdose Deaths on KAB Crashes per Year

	Crash Impact Coefficient	P-Value
Overdose Deaths	0.002	<0.01

Note 1: Overdose deaths are calculated per 100,000 people

Population density is shown to be a salient factor in predicting the total number of crashes but not one in predicting KAB crashes. Having roughly 67 more people living per square mile would result in one more total crash per year. As such a rapid population influx is highly unlikely, this variable is not extremely salient. Data results for population density are provided in Table 12.

TABLE 12:

Effect of Increase in Population Density on Total Crashes per Year

	Crash Impact Coefficient	P-Value
Population Density	0.0157	<0.01

Effect of Increase in Population Density on KAB Crashes per Year

	Crash Impact Coefficient	P-Value
Population Density	0.0002	0.08

Note 1: Population density is the number of people per square mile

Marriage

When the results for the married variable were examined, marriage, as Table 13 shows, was not found to exhibit a significant relationship with either total crashes or KAB crashes. As previously mentioned, this could simply be because of marriage's ambiguous impact on the individual. It might also be because its impact, no matter how strong, is mostly tangential to the act of driving.

TABLE 13:

Effect of 1 % Increase in Number of Married People on Total Crashes per Year

	Crash Impact Coefficient	P-Value
% Married	-0.0415	0.22

Effect of 1 % Increase in Number of Married People on KAB Crashes per Year

	Crash Impact Coefficient	P-Value
% Married	-0.0007	0.78

Note 1: Population density is the number of people per square mile

DISCUSSION AND CONCLUSIONS

This study attempted to assess whether or not there was value in focusing on socioeconomic factors in addition to the traditional engineering factors of Length and AADT when examining crash rates and developing SPFs. Results are somewhat mixed. Very few socioeconomic factors were found to be very helpful in predicting the most serious KAB crashes. However, there were several socioeconomic factors that had strong and significant relationships with the total number of crashes. That said, the sign of the expected correlation was not always in line with what was expected. Further research is needed to understand exactly how important and how reliable these results are across all types of highways. If answers to those questions can be obtained, it may be possible to pursue a more multi-pronged approach to reducing traffic accidents in Kentucky.

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