

Exploring the Transferability of Safety Performance Functions

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ABSTRACT

Safety performance functions (SPFs) by predicting the number of crashes on roadway facilities have been a vital tool in the highway safety area. The SPFs are typically applied for identifying hot spots in network screening and evaluating the effectiveness of road safety countermeasures. The Highway Safety Manual (HSM) provides a series of SPFs for several crash types by various roadway facilities. The SPFs provided in the HSM were developed using data from multiple states. In regions without local jurisdiction based SPFs it is common practice to adopt national SPFs for crash prediction. There has been little research to examine the viability of such national level models for local jurisdictions. Towards understanding the influence of SPF transferability, we examine the rural divided multilane highway models from Florida, Ohio, and California. Traffic, roadway geometry and crash data from the three states are employed to estimate single state SPFs, two state SPFs and three state SPFs. The SPFs are estimated using the negative binomial model formulation for severity and crash types. To evaluate transferability of models, we estimate a transfer index that allows us to understand which models transfer adequately to other regions. The results indicate that models from Florida and California seem to be more transferable compared to models from Ohio. More importantly, we observe that the transfer index increases when we used pooled data (from two or three states). Finally, to assist in model transferability, we propose a Modified Empirical Bayes (MEB) measure that provides segment specific calibration factors for transferring SPFs to local jurisdictions. The proposed measure is shown to outperform the HSM calibration factor for transferring SPFs.

Keywords: Transferability of Safety Performance Functions, Rural Divided Multilane Highway Segments, Negative Binomial Models, Highway Safety Manual, Calibration Factor, Empirical Bayes Method

1 INTRODUCTION

According to the Local and Rural Road Safety Program of the Federal Highway Administration, 54% of traffic fatalities in the US occurred on rural roads in 2012. Hence, it is not surprising that safety on rural roads is identified as an area of critical importance in enhancing traffic safety. Safety Performance Functions (SPF) form a crucial part of improving traffic safety by allowing us to predict crash frequency and identify hot spots. SPFs are employed to predict the number crashes of any type (vehicular, pedestrian or bicyclist) or severity level (fatal (K), incapacitating injury (A), non-incapacitating injury (B), possible injury (C) and property damage only (O)). The SPFs are developed by regressing crash frequency data, with traffic volume and geometric characteristics of segments or intersections. Ordinary linear regression models are inappropriate since crash frequencies are non-negative (Miaou and Lum, 1993; Miaou, 1994; Kim et al., 2005; Garber and Wu, 2001). Generalized linear regression models have been used in recent studies (Sawalha and Sayed, 2006; Taylor et al., 2002; Harnen et al., 2004; Donnell and Mason, 2006). Furthermore, the mathematically appropriate frameworks for SPFs are count modeling approaches such as Poisson and Negative Binomial (NB) models. However, due to the assumption of equal mean and variance, Poisson models are quite restrictive for crash frequency modeling. That is, the variance of the observed crash frequency per site is usually greater than the mean (what is referred to as over-dispersion). The NB framework, by allowing for over-dispersion, is more flexible and has been used as the pillar for SPF development in the safety literature (Miaou and Lum, 1993; Miaou, 1994; Donnell and Mason, 2006; Lord et al., 2005).

The Highway Safety Manual (HSM), of the American Association of State Highway and Transportation Officials (2010), includes several NB based SPFs for different types of roadway segments. The HSM's default NB SPFs for divided rural multilane highway segments are developed based on pooled data from California and Texas (Lord et al., 2008). The rationale behind providing the HSM's default SPFs is to employ these SPFs for a particular jurisdiction if the jurisdiction specific SPFs are not available. To elaborate, if a region does not have localized SPFs, the default SPFs from the HSM would be considered as the SPFs and used for crash frequency prediction. Some jurisdictions might not have the expertise or resources to process the data and estimate SPFs. Hence, if the transferred SPFs are shown to be efficient in predicting crashes, the jurisdiction could simply apply the SPFs instead of developing local ones thereby cutting costs and time. To customize the SPF for the study region, the SPF is calibrated by using an aggregate correction measure based on the ratio of total observed crashes and total predicted crashes. The correction factor can be viewed as correcting the intercept in the SPF to correspond to the study region. In past studies, the HSM's default SPFs were applied to rural divided multilane highway segments in specific states in the US and abroad. The observed and predicted crash frequencies were compared to assess the HSM's SPF prediction accuracy. Furthermore, jurisdiction specific SPF's are compared with those of the HSM in terms of goodness of fit measures.

The current study contributes to growing literature on SPF transferability by considering a detailed and rigorous assessment of SPF transferability across multiple regions. Specifically, we consider transferability of jurisdiction specific SPFs of Florida (FL), Ohio (OH) and California (CA) and compare their predictive performance across the three states. The study effort has two main objectives. First, we explore the influence of pooling data from multiple states for SPF

development and compare the transferability of the SPFs developed from the pooled data with those developed from single state data. We consider two states and three states for pooling the data for SPF development and comparison. The comparison is undertaken based on a Transfer Index measure. Second, we propose a more disaggregate calibration measure that customizes SPFs from elsewhere for the study region without local SPFs. The predictive performance of the calibrated SPF from the new calibration parameter is compared to the predictive performance of the calibrated SPF using the HSM calibration approach. Even though Florida, Ohio and California are distant states that represent different regions of the nation, they are chosen for this study because pooling data from states having different features enriches the data. That is, the pooled data will better represent regions surrounding the three chosen states and hence the SPFs developed from the pooled data may be applicable to the surrounding regions. It should be noted that transferability research is not limited to microscopic SPFs. For instance, Hadayeghi et al. (2006) assessed the temporal transferability of macroscopic SPFs in Toronto. The concept of transferability is also applicable to travel demand modeling. In one recent study by Sikder et al (2014), transferability of choice models, which are based on tours rather than trips, among San Francisco Bay Area's counties is evaluated.

2 LITERATURE REVIEW

In traffic safety literature, examining transferability of SPFs is a relatively new research topic. The analysis approach involves applying the default HSM's SPFs to a specific jurisdiction with the HSM calibration factor (ratio of the sum of the observed number of crashes to that of crash frequencies predicted by the HSM's SPF). In some cases, the jurisdiction specific SPFs are also developed using the local data and compared with the HSM's SPFs multiplied by the calibration factor. The approach has been employed for studies of rural divided multilane highway segments, among other types of segments and intersections, in the states of Missouri, North Carolina, Oregon, and Alabama and internationally for Messina-Catania, Italy and Riyadh, Saudi Arabia (Sun et al., 2014; Salifu, 2004; Srinivasan and Carter, 2011; Xie et al., 2011; Cafiso et al., 2012; Al Kaaf and Abdel-Aty, 2015; Mehta and Lou, 2013). The same approach was chosen for roadway facilities other than rural divided multilane highway segments in Louisiana, Ohio and Regina, Saskatchewan, Canada (Sun et al., 2006; El-Dabaja and McAvoy, 2015; Young and Park, 2012).

Sun et al. (2014) employing KABCO crash data from 2009 to 2011, compiled from the Transportation Management System (TMS) of the Missouri Department of Transportation (DOT), employed the HSM's SPF. The HSM's negative binomial model that takes the following form is used to predict the number of crashes per segment.

$$N_{SPF} = \exp [A + B \ln (AADT) + \ln (L)] \quad (1)$$

In the model, L , represents the segment length, an offset variable, and $AADT$ is the average annual daily traffic, both of which are exposure measures. The regression coefficients are represented by A and B . The model is applicable to segments conforming to the defined base conditions of the HSM only. Therefore, crash modification factors (CMFs) of the HSM are applied to account for deviations from the base conditions. The model, while simplistic with only exposure measures is quite useful for identifying the hot spots (Salifu, 2004). For the case of Missouri, the calibration

factor was calculated to be 0.98 indicating that the HSM's SPF marginally over-predicts the frequency of total crashes in rural divided multilane highway segments in Missouri. Srinivasan and Carter (2011) undertook a similar exercise for rural divided multilane highway segments in North Carolina using data between 2004 and 2008 from the accident analysis system of the North Carolina DOT. The analysis is also conducted for total crashes. The HSM's SPF marginally over-predicted total crashes to yield a calibration factor of 0.97. Likewise, Xie et al. (2011) estimated KABCO crash frequency in Oregon using data from 2004 to 2006. The CMFs are also taken into consideration. The prediction analyses arrived at a calibration factor of 0.78 for rural divided multilane highways indicating that the national model over-predicts crashes in Oregon by 22%.

In Alabama, Mehta and Lou (2013), expanded on earlier work by estimating the calibration factor as well as developing a local SPF. The authors employed records of KABCO crashes from the years 2006 to 2009. With the calibration factor, the HSM model was adapted to Alabama to yield a calibrated HSM version. Subsequently, the authors developed local SPFs with different functional forms. The predictions from the calibrated HSM were compared with predictions from the local SPF model using a validation dataset of 2000 segments. The comparison exercise included measures such as the mean absolute deviation (MAD), mean predicted bias (MPB), mean squared predicted error (MSPE), and Akaike's information criterion (AIC). The local SPF developed with additional parameters such as a dummy variable representing the year, the lane width, coefficient for segment length (restricted to 1 in the HSM SPF) and the posted speed limit outperformed the calibrated HSM SPF.

The calibration of the HSM's SPFs has been undertaken internationally as well. Cafiso et al. (2012) conducted a study in the Messina-Catania region in Italy using KAB crash data from 2005 to 2008. The authors computed calibration factors for every year independently while taking into account the CMFs. The calibration factors range from 1.14 to 1.43. The average calibration factor is 1.26 indicating that the calibrated model under predicts crashes. The research team also developed a local SPF with the AADT, segment length, horizontal curvature and grades as variables. The predictions of the local model are compared by those of the calibrated HSM SPF in terms of the root mean square error. The model predictions are not to a large extent different as per the results. In another international study, using data from Riyadh, Saudi Arabia, Al Kaaf and Abdel-Aty (2014) calibrated HSM models of urban divided multilane roads for fatal and injury (FI) crash records using data from 2004 to 2009. The calibration factor was calculated to be 0.31 using the HSM's SPFs and CMFs indicating substantial over-prediction of crashes. The authors also developed local SPFs with different variables. The local SPF with the log transformation of the AADT, segment length with a regression coefficient, driveway density and posted speed limit outperformed all other local models.

Overall, there is a growing interest in exploring the issue of calibrating HSM SPFs for local conditions. However, the work undertaken so far is still preliminary. Most studies employ the default HSM SPFs with calibration. Not in all of the studies, discussed, the authors compared the calibrated HSM model to the local jurisdiction model. Moreover, there has been limited systematic analysis exploring the value of pooling data from multiple states to estimate SPFs. Only the HSM's SPFs are developed from pooled data mainly to satisfy a sufficient sample size. Also, the studies

employ a simplistic calibration factor to customize the HSM's SPFs to the study region. The current study addresses these limitations as follows. First, we examine the value of pooling data from multiple states (Florida, Ohio and California) in developing SPFs. Specifically, the specification of the SPF developed is augmented with state specific dummy variables in the count and over-dispersion components. Second, we develop a transfer index that evaluates the performance of the SPF developed for various jurisdictions. Finally, we propose and examine the advantage of a disaggregate level (segment) calibration factor on prediction.

3 DATA PREPARATION

Crash data are collected for divided rural multilane highway segments in Florida, Ohio and California. In Florida, the data are collected from the Florida DOT. Specifically, there are 1,320 segments comprising 835.86 mi of which data are collected from the Roadway Characteristics Inventory. Data of crashes that occurred between 2009 and 2011 are collected from the Crash Analysis Reporting System. The data of Ohio is composed of crash records from 1,261 segments comprising 665.11 mi for the period 2009 to 2011. The California crash data are obtained from 1,349 segments comprising 709.83 mi from 2009 to 2010. The Ohio and California data are collected from the national Highway Safety Information System (HSIS). In all three states, the minimum segment length from which crash data are collected is 0.1 mi in accordance with the HSM. The crash types and severities, classified for data processing, are KABCO, KABC, KAB, KA, single vehicle (SV) and multi-vehicle (MV) crashes. The descriptive statistics of the crash data of the three states are shown in Table 1. Also, each state's crashes are normalized per hundred million vehicle miles travelled (VMT) per year to obtain the crash rates.

Table 1 States' Data Descriptive Statistics

	Number of Crashes			Mean			Standard Deviation			Crash Rates (per Hundred Million VMT per Yr)		
	Florida	Ohio	California	Florida	Ohio	California	Florida	Ohio	California	Florida	Ohio	California
Segment Length (mi)	-	-	-	0.633	0.527	0.526	0.993	0.582	0.568	-	-	-
AADT (vpd)	-	-	-	25,710.482	9,896.954	19,018.744	12,001.344	5,600.405	14,370.401	-	-	-
Lane Width (ft)	-	-	-	11.845	11.733	10.088	0.489	0.484	4.426	-	-	-
Shoulder Width (ft)	-	-	-	4.225	6.452	7.681	2.277	2.504	2.377	-	-	-
Median Width (ft)	-	-	-	28.258	43.41	36.787	18.114	21.616	31.262	-	-	-
KABCO	10,028	2,541	5,120	7.597	2.015	3.795	15.001	4.028	6.805	47.70	32.75	53.93
KABC	4,815	799	1,997	3.648	0.634	1.48	6.486	1.507	2.734	22.91	10.3	21.03
KAB	2,399	580	1,014	1.817	0.46	0.752	3.094	1.069	1.392	11.41	7.48	10.68
KA	753	145	283	0.57	0.115	0.21	1.146	0.382	0.54	3.58	1.87	2.98
SV	1,929	1,362	2,170	1.461	1.08	1.609	2.364	2.094	3.273	9.18	17.55	22.86
MV	8,099	1,179	2,950	6.136	0.935	2.187	14.055	2.605	4.532	38.53	15.2	31.07

Note: Number of segments in Florida, Ohio and California are 1,320, 1,261 and 1,349 respectively

As shown in Table 1, the standard deviations of the shoulders in all three states are similar. Therefore, the variability in shoulder widths in each state is comparable. The state of Florida has the narrowest average shoulder width, followed by Ohio's followed by California's. That is a factor which may inhibit SPF transferability among states. Also, the standard deviation of the median widths in each state is large, especially that of California, an indication that median widths vary considerably within states. The differences in median widths may also impede transferability of SPFs. When it comes to crash rates, Ohio experiences the least KABCO, KABC, KAB, KA and MV crashes per hundred million VMT per year. On the other hand, those of Florida and California are considerably higher. It should be noted that the crash rates of Florida and California are similar. That is specifically for KABCO, KABC, KAB and KA crashes. However, Florida experiences the least SV crashes per hundred million VMT per year followed by Ohio and California.

The data prepared reflect the average conditions of the divided segments. That is, the segments do not necessarily satisfy any specified conditions. The HSM's defined base conditions rural divided multilane highway segments are:

- Lane width = 12 ft
- Shoulder width = 8 ft
- Median width = 30 ft
- Paved shoulders
- No street lighting
- No automated speed enforcement

The data are subset to reflect the base conditions such that the analysis is conducted for both average and base conditions. However, due to lack of samples, the base conditions are relaxed to include lanes 12 ft in width or wider, shoulders 8 ft in width or wider and medians of which widths are 30 ft or wider. These conditions are termed modified base conditions.

4 RESEARCH METHODOLOGY

The model development exercise includes developing SPFs for each state for KABCO, KABC, KAB, KA, SV and MV crashes. The model structure employed is the same as the model structure of the HSM's SPFs. The model structure for crash frequencies per year is considered as follows:

$$N_{SPF} = \exp [A + B \ln (AADT) + \ln (L \times y)] \quad (2)$$

The over-dispersion parameter is parameterized as follows:

$$k = \frac{1}{\exp [C + D \ln (L \times y)]} \quad (3)$$

where $AADT$ is the Average Annual Daily Traffic, L , is the length of the segment and y is the number of years used as an offset variable. The number of years' variable reflects the fact that the SPF yields the predicted crash counts per year. Based on the model specification, a set of 4 parameters (A , B , C , and D) are estimated. It should be noted that the parameter D is set to unity in the over-dispersion formula for the HSM's SPFs of rural divided multilane highway segments.

Subsequently, data from each pair of two states are pooled to estimate state pairwise SPFs. The system for two states takes the following form:

$$N_{SPF} = \exp [A + B \ln (AADT) + E(state - 2) + F(state - 2 \times \ln (AADT)) + \ln (L \times y)] \quad (4)$$

$$k = \frac{1}{\exp [C + G \times (state - 2) + (D + H \times (state - 2)) \ln (L \times y)]} \quad (5)$$

The system estimates four additional parameters E , F , G and H which represent differences between the two states. It is critical to note that the number of years, y , plays a crucial role since it accounts for differences in crash years among states especially when data of multiple states are pooled. As previously mentioned, the Florida and Ohio available data are from the years 2009 to 2011 while the availability of those of California are from 2009 to 2010. Three two-state model systems are estimated. Finally, a three-state pooled model is estimated. The model takes the following form.

$$N_{SPF} = \exp \left[\begin{array}{l} A + B \ln (AADT) + E(state - 2) + I(state - 3) + F(state - 2 \times \ln (AADT)) \\ + J(state - 3 \times \ln (AADT)) + \ln (L \times y) \end{array} \right] \quad (6)$$

In the three-state model, a total of 12 parameters are estimated. Any state can be selected as the reference state and the other two state identifier variables can be employed in the equations described. The over-dispersion parameter for the three-state model takes the following form.

$$k = \frac{1}{\exp [C + G \times (state - 2) + K \times (state - 3) + (D + H \times (state - 2) + M \times (state - 3)) \ln (L \times y)]} \quad (7)$$

In addition to the model parameters, MADs and MSPEs are calculated to assess the Goodness of Fit (GOF). The MAD and MSPE are dependent on the difference between the predicted and observed number of crashes, N_{obs} , per segment i . They are defined as follows.

$$MAD = \frac{\sum_{i=1}^n |N_{SPF_i} - N_{obs_i}|}{n} \quad (8)$$

$$MSPE = \frac{\sum_{i=1}^n (N_{SPF_i} - N_{obs_i})^2}{n} \quad (9)$$

The one-state, two-state and three state SPFs are developed for average conditions. For the modified base conditions, only one-state and two-state SPFs are developed. That is because Florida's modified base conditions' sample size is low relative to that of the other states. Therefore, Florida's modified base conditions data cannot be pooled with those of the other two states since the results would be biased.

4.1 Transferability Assessment

The transferability of the SPFs is assessed by applying the jurisdiction specific models, two-state models and three-state models to each state's data for validation. Then a further step in the transferability assessment is the calculation of the transfer index, TI , which was used in previously discussed studies of Sikder et al. (2014) and Hadayeghi et al. (2006). The TI measure provides an indication of the performance of the transferred model for the jurisdiction of interest.

The measure is calculated as follows.

$$TI_j(\beta_i) = \frac{LL_j(\beta_i) - LL_j(\beta_{reference_j})}{LL_j(\beta_j) - LL_j(\beta_{reference_j})} \quad (10)$$

The term $LL_j(\beta_i)$ represents the log-likelihood of the SPF, developed from data, i , that is being applied to data of a specific state, j . The term $LL_j(\beta_j)$ is the log-likelihood of state j 's SPF and the term $LL_j(\beta_{reference_j})$ is log-likelihood of state j 's intercept only SPF. The TI measure compares the performance of the model of interest with respect to the performance of an intercept only model. The higher the TI value the better is the performance relative to the intercept model. The closer TI is to unity, the SPF, developed from data i , is more transferable to state j . A negative TI indicates that state j 's intercept only model performs better than the SPF of state i applied to state j .

4.2 Empirical Bayes Measure

A Modified Empirical Bayes (MEB) measure is proposed as an alternative to the current calibration factor method of the HSM. That is to adjust crash frequencies that are being predicted for a future year. The current HSM calibration factor method has one major limitation. The calibration factor is a single value that applies to the entire study region over-simplifying the calibration procedure.

To develop a more disaggregate approach, we propose a modified version of the Empirical Bayes method, provided in the HSM, to calibrate the SPF for improving transferability. The original Empirical Bayes (EB) Method is used for estimating counts of crashes that would have happened at sites marked for treatment if the treatment is not implemented in before / after studies. Its advantage is that it takes into account the regression to the mean bias. However, in this study, the method is different. Our approach is similar to that applied by Elvik (2008). Yet, instead of adjusting crash frequencies predicted by the SPF for a future year in the same jurisdiction, the MEB method is applied to facilitate transferability of SPFs among different jurisdictions. The approach employs a weighted average of observed crashes in the region (N_{obs}) and predicted crashes from the SPF to arrive at the expected crash frequency, N_{exp} , as shown.

$$N_{exp_i} = (1 - w_i)N_{obs_i} + w_i \times N_{SPF_i} \quad (11)$$

The subscripts i represent the segment number. Also the weight, w_i , is defined as follows.

$$w_i = \frac{1}{1 + k_i \times N_{SPF}} \quad (12)$$

The over-dispersion parameter, k , is that of the SPF being applied to segment i of the application data. While the approach is elegant, a big question to answer is how we will obtain segment level observed crash data (N_{obs}). In fact, if such data were available, the analysts could estimate a localized SPF and use it for prediction. Hence in cases where N_{obs} is unavailable, we believe using past observed data for the study region will be very useful. That is, the proposed measure allows for the past observed crash counts to affect the predicted counts. At the same time, we don't want the measure to be purely based on past history. Hence, we proposed a weighted measure of past observed counts for the region and predicted counts from a transferred model. The weight parameter is affected by the over-dispersion parameter. Thus, if the transferred SPF has a lower dispersion value, the weight for the transferred model is higher. Hence, as the confidence in the transferred model increases, the weight from past observed crashes is reduced. The MEB method proposed here would enhance the transferability of the model by allowing for segment specific calibration.

5 EMPIRICAL ANALYSIS

5.1 Model Estimation Results

In this section, we present the results of the pooled models. Specifically, the average conditions results presented are: (1) Florida and Ohio joint SPFs, (2) Florida and California joint SPFs, (3) Ohio and California joint SPFs and (4) Florida, Ohio and California joint SPFs. The modified base conditions results of the Ohio and California joint SPFs are presented as well. The five sets of SPFs are developed for KABCO, KABC, KAB, KA, SV and MV cases. The model estimation process involved a total of 66 models including the single state models. The estimation process was guided by earlier research, intuitive parameter interpretation and statistical significance (at the 95% level). While the discussion of the results of all 66 models in detail is beyond the scope of the paper, we focus on the most important findings.

5.1.1 Average Conditions Florida and Ohio Joint Safety Performance Functions

The results for the Florida and Ohio joint SPFs are presented in Table 2. The dummy indicator for Ohio region has a statistically significant and negative coefficient indicating that all else equal, Ohio region has a lower crash rate (as indicated in the descriptive analysis) for all crash classifications. The influence of Ohio specific AADT has a statistically significant impact only on SV crashes. That is, for all other crash types, AADT does not have any difference in the observable influences in Florida and Ohio. The over-dispersion parameters specific to Ohio are significant indicating differences in the two states.

Table 2 Average Conditions Florida and Ohio Joint Safety Performance Functions

Crash Type or Severity	KABCO	KABC	KAB	KA	SV	MV
Parameters	Parameter Estimates and P-Values					
Intercept	-8.773 ($<.0001$)	-9.21 ($<.0001$)	-8.4354 ($<.0001$)	-6.931 ($<.0001$)	-3.323 ($<.0001$)	-12.4247 ($<.0001$)
Ln(AADT)	1.0366 ($<.0001$)	0.9964 ($<.0001$)	0.8458 ($<.0001$)	0.5761 ($<.0001$)	0.3142 ($<.0001$)	1.3741 ($<.0001$)
OH	-0.6091 ($<.0001$)	-0.9475 ($<.0001$)	-0.6256 ($<.0001$)	-1.000 ($<.0001$)	-3.9077 ($<.0001$)	-0.9284 ($<.0001$)
OH× Ln(AADT)	-	-	-	-	0.4271 ($<.0001$)	-
C	0.6793 ($<.0001$)	0.7171 ($<.0001$)	0.9804 ($<.0001$)	0.8405 (0.0151)	0.4376 (0.0002)	0.3652 ($<.0001$)
G	-0.381 (0.0018)	-0.5039 (0.0434)	-0.917 (0.0043)	-0.9145 (0.3546)	-0.1285 (0.519)	-0.7125 ($<.0001$)
D	-0.1958 (0.0004)	-0.04821 (0.4897)	-0.03411 (0.7566)	0.2049 (0.3483)	0.4729 ($<.0001$)	-0.2278 ($<.0001$)
H	0.7809 ($<.0001$)	0.3019 (0.1324)	0.392 (0.1298)	1.6752 (0.0961)	0.2936 (0.1487)	0.7553 ($<.0001$)
Goodness of Fit Measures						
-2LL	11,345.0	7,946.5	6,162.3	3,127.5	6,949.4	9,562.7
MAD	3.894	1.692	0.952	0.383	1.004	3.386
MSPE	102.963	15.316	3.224	0.460	2.455	96.157
	- : statistically insignificant variables at alpha = 0.05 removed from the SPF					

5.1.2 Average Conditions Florida and California Joint Safety Performance Functions

The results of the Florida and California joint SPFs are presented in Table 3. The California state indicator is significant and negative in all models except that of KABCO. The AADT interaction variable is significant only for the SV crashes (as was the case in the Florida-Ohio model). The state indicators in the over-dispersion are significant in all crash classifications.

Table 3 Average Conditions Florida and California Joint Safety Performance Functions

Crash Type or Severity	KABCO	KABC	KAB	KA	SV	MV
Parameters	Parameter Estimates and P-Values					
Intercept	-9.0931 ($<.0001$)	-9.3789 ($<.0001$)	-8.392 ($<.0001$)	-7.1268 ($<.0001$)	-3.323 ($<.0001$)	-11.8394 ($<.0001$)
Ln(AADT)	1.0658 ($<.0001$)	1.013 ($<.0001$)	0.8415 ($<.0001$)	0.5955 ($<.0001$)	0.3142 ($<.0001$)	1.3166 ($<.0001$)
CA	-	-0.1951 ($<.0001$)	-0.1673 (0.0019)	-0.257 (0.0017)	-4.9467 ($<.0001$)	-0.3041 ($<.0001$)
CA×Ln(AADT)	-	-	-	-	0.5758 ($<.0001$)	-
C	0.6783 ($<.0001$)	0.7183 ($<.0001$)	0.9801 ($<.0001$)	0.8451 (0.0149)	0.4376 (0.0002)	0.3641 ($<.0001$)
G	-0.4231 ($<.0001$)	-0.5048 ($<.0001$)	-0.6706 (0.0012)	-0.5999 (0.2326)	-0.04098 (0.7776)	-0.7927 ($<.0001$)
D	-0.1727 (0.0011)	-0.04601 (0.5091)	-0.03469 (0.7526)	0.2015 (0.3564)	0.4729 ($<.0001$)	-0.2372 ($<.0001$)
H	0.6434 ($<.0001$)	0.751 ($<.0001$)	0.9613 ($<.0001$)	0.2812 (0.6184)	-0.04686 (0.7586)	0.7256 ($<.0001$)
Goodness of Fit Measures						
-2LL	13,118.0	9,502.0	6,959.3	3,681.6	7,838.0	11,455.0
MAD	4.472	1.951	1.03	0.439	1.178	3.94
MSPE	109.273	16.678	3.385	0.517	4.756	98.706
	- : statistically insignificant variables at alpha = 0.05 removed from the SPF					

5.1.3 Average Conditions Ohio and California Joint Safety Performance Functions

The results of the Ohio and California joint SPFs are presented in Table 4. In this model, the dummy variable for Ohio is significant in all crash types. At the same time, the AADT interaction with the Ohio variable is statistically insignificant across all crash severities and types. In these models, also, the interaction variables in the over-dispersion component are significant and account for unobserved differences across the two states.

Table 4 Average Conditions Ohio and California Joint Safety Performance Functions

Crash Type or Severity	KABCO	KABC	KAB	KA	SV	MV
Parameters	Parameter Estimates and P-Values					
Intercept	-9.2195 (<.0001)	-9.3468 (<.0001)	-8.5024 (<.0001)	-8.091 (<.0001)	-7.8223 (<.0001)	-12.3026 (<.0001)
Ln(AADT)	1.0751 (<.0001)	0.9898 (<.0001)	0.8357 (<.0001)	0.6675 (<.0001)	0.8444 (<.0001)	1.3329 (<.0001)
OH	-0.5197 (<.0001)	-0.7498 (<.0001)	-0.465 (<.0001)	-0.6908 (<.0001)	-0.3637 (<.0001)	-0.6663 (<.0001)
OH×Ln(AADT)	-	-	-	-	-	-
C	0.2666 (<.0001)	0.2133 (0.0168)	0.31 (0.0331)	0.2422 (0.5054)	0.3913 (<.0001)	-0.4281 (<.0001)
G	0.03701 (0.7682)	-0.00157 (0.9951)	-0.2491 (0.4354)	-0.2813 (0.7821)	-0.08927 (0.6277)	0.072 (0.6279)
D	0.502 (<.0001)	0.7086 (<.0001)	0.9285 (<.0001)	0.4713 (0.3582)	0.437 (<.0001)	0.4904 (<.0001)
H	0.07615 (0.5854)	-0.4535 (0.0363)	-0.5685 (0.0513)	1.4232 (0.206)	0.3158 (0.1136)	0.04359 (0.7909)
Goodness of Fit Measures						
-2LL	9,672.5	6,122.9	4,677.3	2,154.6	6,893.2	7,276.9
MAD	2.128	0.958	0.625	0.24	1.062	1.549
MSPE	17.978	3.155	1.011	0.188	4.346	11.228
	- : statistically insignificant variables at alpha = 0.05 removed from the SPF					

5.1.4 Average Conditions Florida, Ohio and California Joint Safety Performance Functions

The results of the Florida, Ohio and California joint SPFs are presented in Table 5. The number of parameters estimated in the three state model increases because of two state indicator variables being interacted with the intercept, the transformed AADT variable in crash propensity and over-dispersion components. The model results indicate that a majority of the intercept indicator state dummies are significant (as seen in the two state models). In terms of the AADT and state interaction, only SV crash types have significant differences (as observed in two state models). The interaction variables in the over-dispersion component are all statistically significant highlighting the variation in unobserved factors across the three states.

Table 5 Average Conditions Florida, Ohio and California Joint Safety Performance Functions

Crash Type or Severity	KABCO	KABC	KAB	KA	SV	MV
Parameters	Parameter Estimates and P-Values					
Intercept	-9.0923 ($<.0001$)	-9.2633 ($<.0001$)	-8.3885 ($<.0001$)	-7.2242 ($<.0001$)	-3.323 ($<.0001$)	-12.0694 ($<.0001$)
Ln(AADT)	1.0657 ($<.0001$)	1.0016 ($<.0001$)	0.8412 ($<.0001$)	0.6052 ($<.0001$)	0.3142 ($<.0001$)	1.3392 ($<.0001$)
OH	-0.5599 ($<.0001$)	-0.943 ($<.0001$)	-0.6295 ($<.0001$)	-0.9777 ($<.0001$)	-3.9077 ($<.0001$)	-0.9586 ($<.0001$)
CA	-	-0.1991 ($<.0001$)	-0.1674 (0.0018)	-0.2546 (0.0018)	-4.9467 ($<.0001$)	-0.2954 ($<.0001$)
OH×Ln(AADT)	-	-	-	-	0.4271 ($<.0001$)	-
CA×Ln(AADT)	-	-	-	-	0.5758 ($<.0001$)	-
C	0.6783 ($<.0001$)	0.7175 ($<.0001$)	0.9801 ($<.0001$)	0.8474 (0.0148)	0.4376 (0.0002)	-0.3547 (0.0072)
G	-0.3758 (0.0021)	-0.5032 (0.0438)	-0.9179 (0.0042)	-0.9091 (0.3615)	-0.1285 (0.519)	0.7194 ($<.0001$)
K	-0.4231 ($<.0001$)	-0.504 ($<.0001$)	-0.6706 (0.0012)	-0.6019 (0.2315)	-0.04098 (0.7776)	-0.07328 (0.6216)
D	-0.1727 (0.0011)	-0.04751 (0.4953)	-0.03473 (0.7522)	0.1996 (0.361)	0.4729 ($<.0001$)	0.533 (0.0002)
H	0.7527 ($<.0001$)	0.3001 (0.1342)	0.3936 (0.1279)	1.6858 (0.0962)	0.2936 (0.1487)	-0.7666 ($<.0001$)
M	0.6434 ($<.0001$)	0.7543 ($<.0001$)	0.9614 ($<.0001$)	0.2822 (0.6168)	-0.04686 (0.7585)	-0.04186 (0.7988)
Goodness of Fit Measures						
-2LL	17,069.0	11,786.0	8,899.4	4,482.3	10,839.0	14,148.0
MAD	3.492	1.536	0.87	0.355	1.082	2.966
MSPE	76.401	11.735	2.544	3.846	3.969	57.264
	- : statistically insignificant variables at alpha = 0.05 removed from the SPF					

5.1.5 Modified Base Conditions Ohio and California Joint Safety Performance Functions

The Ohio and California joint SPF results are shown in Table 6. The interaction term between the state dummy indicator and the transformed AADT variable is statistically insignificant in the SPFs of all crash classifications. Therefore, the impact of the AADT on crash frequencies is the same in both states' rural divided segments, a result consistent with the Ohio and California average conditions SPFs. Also, the state dummy variable representing California is significant and positive

for all crash types and severity levels. That is, California experiences more crashes than Ohio for the same AADT. That is also a consistent result with the average conditions SPFs estimated from the pooled Ohio and California data.

Table 6: Modified Base Conditions Ohio and California Joint Safety Performance Functions

Crash Type or Severity	KABCO	KABC	KAB	KA	SV	MV
Parameters	Parameter Estimates and P-Values					
Constant	-10.4375 ($<.0001$)	-11.0919 ($<.0001$)	-10.6220 ($<.0001$)	-9.8039 ($<.0001$)	-8.3530 ($<.0001$)	-14.5149 ($<.0001$)
Ln(AADT)	1.1371 ($<.0001$)	1.0723 ($<.0001$)	0.9904 ($<.0001$)	0.7557 ($<.0001$)	0.8613 ($<.0001$)	1.4704 ($<.0001$)
CA	0.3096 ($<.0001$)	0.6451 ($<.0001$)	0.3416 (0.0046)	0.6377 (0.0011)	0.1922 (0.0151)	0.4072 (0.0002)
CA×Ln(AADT)	-	-	-	-	-	-
C	0.5442 (0.0073)	0.1215 (0.7788)	0.05130 (0.9225)	9.7495 (0.9715)	0.2823 (0.2693)	-0.1336 (0.5964)
G	-0.05102 (0.8236)	0.2822 (0.5422)	0.4394 (0.4653)	-9.7658 (0.9715)	0.8175 (0.0135)	-0.2578 (0.3501)
D	0.6473 (0.0027)	0.5680 (0.1079)	0.4024 (0.3237)	1.0930 (0.9937)	0.8964 (0.0008)	0.7255 (0.0094)
H	-0.06195 (0.8018)	0.09297 (0.8177)	0.6697 (0.1977)	0.5744 (0.9967)	-0.4491 (0.2051)	-0.07034 (0.8177)
Goodness of Fit Measures						
-2LL	3672.7	2248.8	1732.3	815.7	2743.1	2619.9
MAD	1.901	0.868	0.588	0.235	1.031	1.347
MSPE	13.149	2.161	0.816	0.177	2.581	9.794
	- : statistically insignificant variables at alpha = 0.05 removed from the SPF					

5.1.6 Remarks on the Joint Safety Performance Functions

The estimation of the joint SPFs (two states and three states) clearly highlights the differences in observed and unobserved factors across the three states. It appears that once we account for differences in the over-dispersion component, the differences in crash frequencies across states can be accommodated through simple state indicator variables across all crashes except for SV crashes which also require an AADT and state interaction term. The results highlight how critical it is to consider the interaction variables in the over-dispersion, a commonly ignored aspect in SPF development. The over-dispersion parameters account for state specific characteristics such as shoulder width, lane width, driving behavior and other missing variables that are likely to affect the crash frequency in the state.

5.2 Transferability Evaluation

We can employ the developed SPFs to evaluate their transferabilities to different states. The approach employed to compute the transfer index in our study is as follows. We choose a state to which we want to transfer the models. For this state, we employ several SPFs from all the models (single state, two state and three state) estimated and compute the transfer indices. The process is repeated for all three states and for all crash classifications.

5.2.1 Average Conditions Transfer Index Comparisons

The transfer indices computed for all states and crash types/severities for average conditions are presented in Table 7. The reader would note that transferring the Florida model to Florida region will yield the best TI value of 1. The same holds for any state. From the single state model transferability, we observe that in general the transferability is poor (except for Florida to California). The transfer indices improve substantially when at least two states are considered. In our empirical case, when two state models are considered only the Florida and California SPF for Ohio has a negative value. The result has significant implications. From our transfer index calculations, we can see that Florida and Ohio regions are substantially different and have very poor model transferability. However, when we augment Ohio data with California's, the joint SPFs have an improved transferability. Hence, in cases where local jurisdiction data are unavailable, we recommend using data from at least two jurisdictions for model analysis to avoid considering completely unrepresentative SPFs for model prediction.

When a three-state SPF is considered, the transferability, as can be expected, is very close to 1. With increase in the number of states, the variability available in the data increases and hence, the models are likely to be more transferable. Across crash type and severity types, we observe similar trends. That is, as the number of states increase, transferability improves. Of course, it would have been beneficial to conduct an extensive assessment of the performance of the three-state model when applied to data of a fourth unused state. An in-depth assessment is not performed for brevity. However, the joint Florida, Ohio and California total crash SPF for average conditions is applied to crash data from Washington State. The resulting transfer index for the application is 0.344 indicating that the joint SPF is to a certain degree transferable to Washington. This emphasizes the improvement in transferability of SPFs when pooling data from more than one or even two states. In addition, log-likelihood ratio tests are conducted to check the validity of the transfer indices. The test statistic is computed as twice the difference between the transferred SPF's prediction log-likelihood and that of the jurisdiction specific constants only SPF. The level of significance is that of the 95th percentile while the degrees of freedom are the number of additional parameters in the transferred SPF. In all average conditions SPFs, the transfer indices are statistically significant indicating that they are valid.

Table 7 Average Conditions Transfer Indices

Crash Type or Severity	SPF	Application Data		
		Florida	Ohio	California
KABCO	Florida	1	-0.273	0.716
	Ohio	-0.367	1	0.429
	California	0.453	0.172	1
	Florida and Ohio	1	0.999	0.72
	Florida and California	0.996	-0.033	0.998
	Ohio and California	0.454	1	1
	Florida, Ohio and California	0.995	1	0.998
KABC	Florida	1	-3.2	0.738
	Ohio	-2.718	1	-0.47
	California	0.518	-1.85	1
	Florida and Ohio	0.999	0.996	0.732
	Florida and California	1	-3.24	1
	Ohio and California	0.508	0.997	1
	Florida, Ohio and California	1	0.995	1
KAB	Florida	1	-1.573	0.728
	Ohio	-0.982	1	0.328
	California	0.453	-0.642	1
	Florida and Ohio	1	1	0.728
	Florida and California	1	-1.62	1
	Ohio and California	0.453	1	1
	Florida, Ohio and California	1	1	1
KA	Florida	1	-9.671	0.581
	Ohio	-7.464	1	-1
	California	0.352	-3.418	1
	Florida and Ohio	0.998	0.978	0.603
	Florida and California	0.994	-8.913	0.99
	Ohio and California	0.356	1.001	1
	Florida, Ohio and California	0.991	0.989	0.993
SV	Florida	1	0.634	-0.864
	Ohio	-6.371	1	0.512
	California	-20.822	0.187	1
	Florida and Ohio	1	1	-0.865
	Florida and California	1	0.634	1
	Ohio and California	-19.985	0.981	0.997
	Florida, Ohio and California	1	1	1
MV	Florida	1	-0.83	0.208
	Ohio	-0.818	1	0.361
	California	0.25	0.186	1
	Florida and Ohio	0.999	0.998	0.212
	Florida and California	0.999	-0.937	0.999
	Ohio and California	0.265	0.995	0.998
	Florida, Ohio and California	1	0.996	0.998

5.2.2 *Modified Base Conditions Transfer Index Comparisons*

The transfer indices are also calculated for modified base conditions. The log-likelihood ratio tests are conducted as well. Their results are presented in Table 8. From what may be interpreted from the table, the transfer indices of Florida and California's KABC SPFs are mutually transferable. The transfer indices are greater than their counterparts in the average conditions case. That is because the segments in both states satisfy the modified base conditions. However, according to the results of the log-likelihood ratio test, the index resulting from California's KAB SPF applied to Florida, 0.587, has a chi-squared value of 2.345, 1 degree of freedom and a p-value of 0.125. Therefore, California's KAB SPF is not superior to the constants only KAB SPF of Florida with 95% confidence. Also, Florida and Ohio's SPFs are not mutually transferable as is the case of the average conditions. In addition, it should be noted that for single-vehicle crashes, the intercept SPF of Florida did not converge thereby deterring transfer indices of the single vehicle crashes' SPFs of the other states to be calculated. Furthermore, the Ohio and California joint SPFs may not apply to the state of Florida. These results contradict those of the average conditions perhaps due to the smaller sample of Florida's modified base conditions segments.

Table 8: Modified Base Conditions Transfer Indices

Crash Type or Severity	SPF	Application Data		
		Florida	Ohio	California
KABCO	Florida	1	-1.478	-0.076
	Ohio	-0.948	1	0.838
	California	-1.229	0.505	1
	Ohio and California	-0.485	0.990	0.999
KABC	Florida	1	-5.705	0.726
	Ohio	-1.009	1	0.339
	California	0.649	-1.418	1
	Ohio and California	-2.405	0.968	0.999
KAB	Florida	1	-3.803	0.654
	Ohio	-0.359	1	0.683
	California	0.587	-0.112	1
	Ohio and California	-1.825	0.928	0.996
KA	Florida	1	-20.978	-1.803
	Ohio	-38.673	1	-0.676
	California	-11.185	-2.426	1
	Ohio and California	-59.267	0.914	0.994
SV	Florida	NA	-1.290	-1.544
	Ohio	NA	1	0.710
	California	NA	0.451	1
	Ohio and California	NA	0.978	0.998
MV	Florida	1	-2.481	-0.094
	Ohio	-0.441	1	0.779
	California	-0.843	0.508	1
	Ohio and California	-0.436	0.990	0.999
	NA : constants only model of jurisdiction specific data failed to converge			

5.2.3 Sample Results of the Modified Empirical Bayes Measure

The second measure proposed in our study is the modified Empirical Bayes correction to improve the model transferability. The MEB correction allows for segment specific calibration factors and is based on segment specific attributes. The applicability of the proposed approach is considered in comparison to the HSM calibration method. The comparison is illustrated by transferring average conditions single state models of total crashes to other states. So, every single-state model is transferred to the other two states providing 6 model prediction comparisons. The results of MAD and MSPE computed for three models are computed: (1) transferred model (no correction), (2) transferred model with HSM calibration factor and (3) transferred model with modified EB correction. It should be noted that in the majority of the cases where the modified EB correction is made, the expected crash counts are not overly dependent on the observed crash frequencies but rather on both the predicted and observed crash frequencies. The results are presented in Table 9. The following observations can be made based on the results. First, the HSM calibration factor

does not always improve model prediction (for example see Ohio to Florida). Second, the modified EB correction measure improves the transferred model's prediction substantially. Hence, the proposed measure is a useful contribution to consider when adopting SPFs from other jurisdictions for locations with no SPFs.

Table 9 Average Conditions Comparison of Predicted, Calibrated and Expected KABCO Crash Frequencies

Goodness of Fit Measures	Based on Predicted Crash Frequency	Based on Predicted Crash Frequency Multiplied by the HSM's Calibration Factor	Based on Predicted Crash Frequency with EB Correction
Application of Florida's KABCO SPF to Ohio			
MAD	2.329	1.423	0.676
MSPE	15.194	6.883	0.663
Application of Florida's KABCO SPF to California			
MAD	2.906	2.679	0.890
MSPE	29.550	26.949	2.187
Application of Ohio's KABCO SPF to Florida			
MAD	4.609	5.149	1.075
MSPE	161.521	163.573	4.184
Application of Ohio's KABCO SPF to California			
MAD	2.471	2.676	0.848
MSPE	28.418	27.076	2.233
Application of California's KABCO SPF to Florida			
MAD	5.977	5.142	0.820
MSPE	186.324	163.869	1.669
Application of California's KABCO SPF to Ohio			
MAD	2.088	1.423	0.629
MSPE	12.386	6.816	0.649

6 CONCLUSIONS

Safety Performance Functions (SPF) form a crucial part of improving traffic safety by allowing us to predict crash frequencies and identify hot spots when used in conjunction with the HSM's Empirical Bayes Method. SPFs are employed to predict the number of crashes of any type (vehicular, pedestrian or bicyclist) or severity level (fatal (K), incapacitating injury (A), non-incapacitating injury (B), possible injury (C) and property damage only (O)). The Highway Safety Manual employs several NB based SPFs for different types of roadway segments. These default SPFs are employed for local jurisdictions in the absence of local SPFs. To customize the SPF for the study region, the SPF is calibrated by using an aggregate correction measure based on the ratio of total observed crashes to total predicted crashes. The approach has been employed recently in traffic safety literature. However, there has been little research exploring the validity of such model transferability approach.

The current study contributes to growing literature on SPF transferability by considering a detailed and rigorous assessment of SPF transferability across multiple regions. Specifically, we consider transferability of jurisdiction specific SPFs of Florida (FL), Ohio (OH) and California (CA) and compare their predictive performances across the three states. Towards this end, we estimate HSM based NB models (for KABCO, KABC, KAB, KA, SV and MV crashes) separately for three states, by pooling data from all pairs of states and by pooling the data of all three states. The study effort has two main objectives. First, we explore the influence of pooling data from multiple states for SPF development on the transferability of the pooled SPFs relative to single state data based SPFs. The comparison exercise is undertaken using the Transfer Index measure that has been employed before in transportation. The comparison clearly highlighted the improvement in Transfer Indices for two-state and three-state models. Among the states, Florida and California's SPFs are mutually more transferable relative to the Ohio SPFs. It is also critical to note that the transferability of SPFs did not improve for every state under the modified base conditions, relative to the average conditions, possibly due to lack of samples especially in Florida. Further, we propose a more disaggregate calibration measure that customizes SPFs from elsewhere for the study region without local SPFs. The proposed measure is a modified version of the Empirical Bayes method and is tested in comparison with the HSM suggested calibration factor. The results clearly illustrate the applicability of the proposed measure and also confirm that the disaggregate measure performs better than the aggregate HSM calibration factor method.

As interpreted by the transferability assessment results, Ohio's crash patterns are different from both Florida's and California's. Even though Florida represents the southeast while California represents the west with different weather trends and topography, crash patterns might be similar. That is possibly because of similarities in demographics, e.g., tourism is common in both states. Also, California's roads located in mountainous (usually two lane roads) areas are not included in the data. Thus, Florida and California's data do not include information on segments that experience snow. On the other hand, Ohio experiences snow during Winter. Also, tourism is not as active in Ohio as in Florida and California. In addition, in Summer and Fall, the rainfall intensity in Florida surges. Furthermore, it should be noted that the crash reporting thresholds, measured by property damage cost, vary among the three states. The thresholds mainly affect the count of property damage only crashes reported. Florida, Ohio and California's reporting thresholds are \$500 according to the traffic regulations section of the Florida Statutes, \$400 according to the Ohio Bureau of Motor Vehicles and \$750 (Xie et al., 2011), respectively. However, Ohio the reporting threshold of Ohio changed to \$1,000 of property damage in 2011 according to the HSIS description of the Ohio crash records.

The study is not without limitations. The NB model based SPFs employed in our research are quite simplistic and do not consider variables such as lane width, shoulder width, grades, presence of horizontal curves and speed limits. Although, it was difficult in our study to add such factors as they were not consistently available for all the states used in this study, adding such information will enhance the SPFs developed and more critically possibly enhance transferability. There is also growing evidence that recommends considering socio-demographic information in SPF development (Lee et al., 2014). In addition, it might be useful to examine the variability in the transfer index with different samples. Of course, this would necessitate an increased number of

data samples for each state. Furthermore, it would be useful to extend the work undertaken for rural divided multilane highways to other types of roadways.

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REFERENCES

- Al Kaaf, K., Abdel-Aty, M., 2015. Transferability and Calibration of Highway Safety Manual Performance Functions and Development of New Models for Urban Four-Lane Divided Roads in Riyadh. Presented at: 94th Annual Meeting of the Transportation Research Board, Washington, D.C.
- American Association of State Highway and Transportation Officials, 2010. Highway Safety Manual. Washington, D.C.
- Cafiso, S., Di Silvestro, G., Di Guardo, G., 2012. Application of Highway Safety Manual to Italian Divided Multilane Highways. *Procedia-Social and Behavioral Sciences* 53, 910-919.
- Donnell, E., Mason, J., 2006. Predicting the Frequency of Median Barrier Crashes on Pennsylvania Interstate Highways. *Accident Analysis & Prevention* 38 (3), 590-599.
- El-Dabaja, S., McAvoy, D., 2015. Application of the Highway Safety Manual Predictive Method: A Before/After Case Study of Ohio State Route 682 in the Plains, Ohio. Presented at: 94th Annual Meeting of the Transportation Research Board, Washington, D.C.
- Elvik, R. 2008. The Predictive Validity of Empirical Bayes Estimates of Road Safety. *Accident Analysis and Prevention* 40 (6), 1964-1969.
- Elvik, R., Vaa, T., Erke, A., Sorensen, M., 2009. *The Handbook of Road Safety Measures*. Emerald Group Publishing, Bradford, U.K.
- Florida Statutes. Title XXIII – Motor Vehicle. The Florida Legislature, Tallahassee, Florida. http://www.leg.state.fl.us/Statutes/index.cfm?App_mode=Display_Statute&Search_String=&URL=0300-0399/0316/Sections/0316.065.html. Accessed Oct. 28, 2015.

- Garber, N., Wu, L., 2001. Stochastic Models Relating Crash Probabilities with Geometric and Corresponding Traffic Characteristics Data. Presented to: National Intelligent Transportation Systems Implementation Research Center. U.S. Department of Transportation.
- Hadayeghi, A., Shalaby, A., Persaud, B., Cheung, C., 2006. Temporal Transferability and Updating of Zonal Level Accident Prediction Models. *Accident Analysis & Prevention* 38 (3), 579-589.
- Harnen, S., Umar, R., Wong, S., Hashim, W., 2004. Development of Prediction Models for Motorcycle Crashes at Signalized Intersections on Urban Roads in Malaysia. *Journal of Transportation and Statistics* 7 (2), 27-39.
- Highway Safety Information System. Guidebook for the Ohio State Data Files. Highway Safety Research Center, University of North Carolina, Chapel Hill, North Carolina. <http://www.hsisinfo.org/guidebooks/ohio.cfm>. Accessed Nov. 11, 2015.
- Highway Safety Information System. State Data. Highway Safety Research Center, University of North Carolina, Chapel Hill, North Carolina. <http://www.hsisinfo.org/>. Accessed Sept. 28, 2015.
- Kim, S., Chung, S., Song, K., Chon, K., 2005. Development of an Accident Prediction Model using GLIM (Generalized Log-linear Model) and EB method: A case of Seoul. *Journal of the Eastern Asia Society for Transportation Studies* 6, 3669-3682.
- Kloeden, C., Ponte, G., McLean, A., 2001. Travelling Speed and the Risk of Crash Involvement on Rural Roads. Submitted to: Road Accident Research Unit of Adelaide University, Adelaide, U.K.
- Lee, J., Abdel-Aty, M., Choi, K., 2014. Analysis of Residence Characteristics of at-Fault Drivers in Traffic Crashes. *Safety Science* 68, 6-13.
- Local and Rural Road Safety Program. 2012 Traffic Safety Facts "Rural and Urban Comparison" DOT-HS-812-050. Federal Highway Administration, United States Department of Transportation, Washington D.C. http://safety.fhwa.dot.gov/local_rural/#programs. Accessed July 7, 2015.
- Lord, D., Geedipally, S., Persaud, B., Washington, S., Van Schalkwyk, I., Ivan, J., Lyon, C., Jonsson, T., 2008. NCHRP 126 Report: Methodology for Estimating the Safety Performance of Rural Multilane Highways. National Cooperative Highway Research Program, Transportation Research Board, Washington, D.C.

- Lord, D., Washington, S., Ivan, J., 2005. Poisson, Poisson-gamma and Zero-Inflated Regression Models of Motor Vehicle Crashes: Balancing Statistical Fit and Theory. *Accident Analysis & Prevention* 37 (1), 35-46.
- Mehta, G., Lou, Y., 2013. Calibration and Development of Safety Performance Functions For Alabama: Two-Lane, Two-Way Rural Roads and Four-Lane Divided Highways. *Transportation Research Record* (2398), 75-82.
- Miaou, S.-P., 1994. The Relationship between Truck Accidents and Geometric Design of Road Sections: Poisson versus Negative Binomial Regressions. *Accident Analysis & Prevention* 26 (4), 471-482.
- Miaou, S.-P., Hu, P., Wright, T., Davis, S., Rathi, A., 1993. Development of the Relationship between Truck Accidents and Geometric Design: Phase I. Publication FHWA-RD-91-124. Federal Highway Administration. U.S. Department of Transportation.
- Miaou, S.-P., Lum, H., 1993. Modeling Vehicle Accidents and Highway Geometric Design Relationships. *Accident Analysis & Prevention* 25 (6), 689-709.
- Ohio Bureau of Motor Vehicles. When Involved in an Automobile Crash. Ohio Department of Public Safety, Columbus, Ohio. http://www.bmv.ohio.gov/fr_laws.stm. Accessed Oct. 28, 2015.
- Quimby, A., Maycock, G., Palmer, C., Buttress, S., 1999. The Factors That Influence A Driver's Choice of Speed: A Questionnaire Study. Publication TRL325. Transport Research Laboratory, Wokingham, Berkshire, U.K.
- Salifu, M., 2004. Accident Prediction Models for Unsignalised Urban Junctions in Ghana. *IATSS Research* 28 (1), 68-81.
- Sawalha, Z., Sayed, T., 2006. Traffic Accident Modeling: Some Statistical Issues. *Canadian Journal of Civil Engineering* 33 (9), 1115-1124.
- Sikder, S., Augustin, B., Pinjari, A., Eluru, N., 2014. Spatial Transferability of Tour-Based Time-of-Day Choice Models: An Empirical Assessment. *Transportation Research Record* (2429), 99-109.
- Srinivasan, R., Carter, D., 2011. Development of Safety Performance Functions for North Carolina. Publication FHWA/NC/2010-09. Research and Analysis Group, North Carolina Department of Transportation.
- Sun, C., Brown, H., Edara, P., Claros, B., Nam, K., 2014. Calibration of the HSM's SPFs for Missouri. Publication CMR14-007. Missouri Department of Transportation.

- Sun, X., Li, Y., Magri, D., Shirazi, H., 2006. Application of “Highway Safety Manual” Draft Chapter: Louisiana Experience. *Transportation Research Record (1950)*, 55-64.
- Taylor, M., Baruya, A., Kennedy, J., 2002. The Relationship between Speed and Accidents on Rural Single-Carriageway Roads. Publication TRL511. Transport Research Laboratory, Wokingham, Berkshire, U.K.
- Xie, F., Gladhill, K., Dixon, K., Monsere, C., 2011. Calibration of Highway Safety Manual Predictive Models for Oregon State Highways. *Transportation Research Record (2241)*, 19-28.
- Young, J., Park, P., 2012. Comparing the Highway Safety Manual’s Safety Performance Functions with Jurisdiction Specific Functions for Intersections in Regina. Presented at: 2012 Annual Meeting of the Transportation Association of Canada Federation, New Brunswick.