Using Crash Prediction Models with Economic Factors for State Highway Safety Planning

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ABSTRACT

We describe two models of fatality counts that were developed as part of the National Cooperative Highway Research Program (NCHRP) 17-67 project (*8*). The two models were developed using a state-level dataset of annual fatality counts, as well as state-level economic, demographic, spending and countermeasure predictors for the years 2001-2012. One model predicted annual fatality counts at the state level, and the other modeled the *change* in fatality counts over the previous year at the state level, each using generally the same predictors.

The two models were then used to set state-level projections for fatality counts, one model in Michigan and one in Texas. This paper describes the models, the way in which they were used for SHSP target-setting, and advantages and disadvantages of this type of approach.

Both models predicted state-level fatality counts well for the years 2013-2016. Projected input parameters were developed in-house or taken from reliable public sources. The count model predicted a steady rise in fatalities in Texas, largely driven by an assumed increase in vehicle-miles traveled (VMT) over the next 5 years. Michigan projections rose more gently, but were driven by a more conservative estimate of VMT growth for that state.

We conclude that this approach has potential value for states to set more realistic targets for SHSP purposes. However, the projections are only as good as the projected input. We discuss ways to improve the models for more widespread practical use.

INTRODUCTION

The sharp reduction in traffic fatalities during the period from 2008-2011 led to a number of studies to try to understand what safety countermeasures and other factors led to the decline (e.g., (*1*), (*2*), (*3*)). Although some studies did show an effect of safety countermeasures, such as increased belt use and improved Federal Motor Vehicle Safety Standards (*4, 5*), many found that economic factors were the best predictors of short-term fluctuations in fatalities.

The U.S. decline in motor vehicles fatalities over this period was paralleled in many other countries that were affected by the global recession. A comprehensive report by IRTAD (International Traffic Safety Data and Analysis Group) of the International Transport Forum showed that traffic fatalities in many countries declined significantly over the period. One analysis considered 18 European countries. In this analysis, each of the countries experienced a substantial decline, ranging from 14% in France to 60% in Lithuania (*6*). In comparison, the reduction in the U.S. over the same period was about 21.3%, which fit within the range observed for the IRTAD countries.

Elvik (*7)* studied the remarkable drop in traffic fatalities in the countries of the Organization for Economic Cooperation and Development (OECD). Traffic fatalities in the countries studied dropped by a combined 12.6% from 2008 through 2010. He attributed 65% of the reduction to the recession. Decreases in vehicle-miles traveled (VMT) accounted for relatively little of the decline, implying that a decline in fatal crash *risk* as such was the primary factor. Although data were not available to test this hypothesis directly, he suggested factors could have included a disproportionate reduction in travel by high-risk groups (e.g., young people) or more cautious driving including reduced leisure travel.

Although fluctuations in fatality counts occur year-to-year, the magnitude of the drop in fatalities during the Great Recession and the subsequent dramatic rise in fatalities as the economy has improved bring the challenges that states have in predicting fatalities for future years into sharp focus. Strategic Highway Safety Plans (SHSPs) require states to project the expected fatality counts five years into the future and then set targeted reductions based on those projections. In most states, economic factors are not taken into account. Often, changes in VMT are not taken into account, even though this is the basic measure of exposure and greater VMT should lead to more crashes under equally safe conditions.

In this paper, we describe two models of fatality counts that were developed as part of the National Cooperative Highway Research Program (NCHRP) 17-67 project (*8*). The two models were developed using the same dataset, which included economic, demographic, and countermeasure predictors. The two models were then used to set state-level projections for fatality counts, one model in Michigan and one in Texas. By including economic factors, existing crash trends, and safety countermeasures, these models (or similar approaches) may provide a more accurate basis for planning targets for SHSPs. This paper describes the models, the way in which they were used for SHSP target-setting, and advantages and disadvantages of this type of approach.

DATA DESCRIPTION

Data for Modeling

Data series for developing the models were assembled from a variety of sources. The dataset consisted of series aggregated annually at the state level for the period from 2001 through 2012. However, data were not available at the state level on vehicle fleets. Accordingly, data on vehicle characteristics at the national level were used in the models. Unless otherwise indicated, all data series are by year and state and included 50 states. The District of Columbia was excluded because it introduced excessive variance and only accounted for 0.1% of traffic fatalities in the period.

The original series assembled covered a wide variety of vehicle, driver, economic, and environmental factors identified as related to traffic safety. However, the final models included only a subset of the original predictors. This section provides a list and discussion of the data and sources used in the models. A more detailed description of all predictors considered can be found in the NCHRP 17-67 final report (*8*).

Fatality data

The National Highway Traffic Safety Administration's (NHTSA) Fatality Analysis Reporting System (FARS) is the standard source for data on fatal traffic crashes in the U.S. FARS provides a census file of all motor vehicle crashes in the U.S. that occurred on a traffic way customarily open to the public, and in which one or more persons died of crash injuries within 30 days of the crash (*9*). FARS was the data source for all fatality counts in this paper.

Predictors

The predictors used in the two models are listed below. All predictors were the same except that wine consumption was used only in the change model. The models will be explained in more detail in the methods section.

- Total VMT
- Rural VMT as proportion of total VMT
- Capital spending (in $1000 per mile)
- Safety spending (in $1000 per mile)
- GDP per capita (in $10,000)
- Unemployment for age 16 to 24 (%)
- Pump price ($ per gallon)
- Beer per capita (gallons)
- Wine per capita (gallons)
- DUI rating
- Belt rating
- Motorcycle Helmet rating
- Median Income (in $10,000)

- Post1991 (% of vehicles manufactured after 1991 in the fleet)

Table 1 lists the sources of predictors used in the models. The first two rows (unshaded) represent travel exposure measures. The next three rows (shaded) represent economic indicators. Rows 6-7 cover fuel costs. Rows 8-10 (shaded) cover contents of state laws, which were assigned ratings based on the presence or absence of law features considered to affect safety *(10)*. Row 11 covers alcohol consumption; rows 12-13 address vehicle safety (features and use rates); and rows 14-16 cover safety expenditures by states.

1 **Table 1 Data and Data Sources for Model Development**

Row	Data	Source
1	Road miles by roadway function class and year, by state	*Highway Statistics,* Federal Highway Administration (FHWA), Table hm10 for each year, 2001-2012.
2	VMT by roadway function class, vehicle type, urban/rural, by state	*Highway Statistics*, FHWA, Table VM-1 for each year, 2001-2012.
3	Unemployment rate, by state, month, & year	Bureau of Labor Statistics, Current Population Survey
4	State GDP by year	US Department of Commerce, Bureau of Economic Analysis, Regional Economic Accounts: Download
5	State median household income by year	US Census Bureau, Current Population Survey, Annual Social and Economic Supplements.
6	Fuel tax by state by year	*Highway Statistics*, FHWA. Table MF-205.
7	Fuel costs	US Energy Information, State Energy Data System, prices for regular gasoline, data are converted from prices per million BTUs.
8	Seat belt laws, primary vs secondary, by state and year	Compiled from Insurance Institute for Highway Safety, digest of state laws, available at http://www.iihs.org/iihs/topics/laws/safetybeltuse
9	BAC limit, per se, other alcohol related laws and penalties, by state by year	http://www.lexisnexis.com.proxy.lib.umich.edu/hottopics/lnacademic/

Row	Data	Source
10	Motorcycle helmet by state by year	Digest of motorcycle helmet laws from IIHS website, accessed at http://www.iihs.org/iihs/topics/laws/helmetuse/helmethistory?topicName=Motorcycles#tableData
11	Alcohol consumption	Compiled from National Institute of Alcohol Abuse and Alcoholism (*11*).
12	Belt use rates	Compiled from NHTSA's NOPUS program, reported in (*12, 13*).
13	Post1991 model year	Estimated from National Automotive Sampling System General Estimates System, using a quasi-induced exposure technique. https://www.nhtsa.gov/national-automotive-sampling-system-nass/nass-general-estimates-system
14	Capital expenditures	Compiled from *Highway Statistics,* FHWA, Table SF-2, includes construction, relocation, resurfacing, restoration, rehabilitation and reconstruction, widening, capacity improvements, restoration of failed components, additions and betterments of roads and bridges. See (*14*)
15	Law enforcement and safety	Compiled from *Highway Statistics,* FHWA, Table SF-2, including all relevant Federal Safety programs, sections 402, 403, 405,406, 407, 408, 410, and 411 of Title 23 of the United State Code, as well as MCSAP. Also includes capital expenditures designated by states as safety-related.
16	Highway Safety Improvement Program	Compiled from FHWA funding tables under SAFETEA-LU and MAP-21, available from https://www.fhwa.dot.gov/safetealu/fundtables.htm and https://www.fhwa.dot.gov/map21/funding.cfm

VMT is the most direct measure of exposure used. We also used the proportion of state VMT that is rural VMT, since rural VMT are generally higher risk than urban VMT. The FHWA Highway Statistics publication provides annual VMT estimates by roadway function class (including urban and rural) and vehicle type. Road miles by FHWA functional classes were used to normalize state highway expenditures, in order to control for differences in the sizes of states.

Data series on unemployment are available by year and month for each state; annual state-level estimates were obtained by summing across the employment and labor force counts and taking the average. Unemployed persons were defined as all persons 16 or older who had not employment, were available for work, and had made specific efforts to obtain employment. We used unemployment for those aged 16-24 because this group was identified in initial analyses as responsible for a larger-than-expected proportion of the fatality decrease in 2008-2011. In addition, we hypothesize that this group's driving behavior may be most influenced by economic change. Elvik (*7)* proposed a similar hypothesis.

Gross domestic product (GDP) measures the gross productive output of a state, so it is used as a gross estimate of economic activity. The estimates were divided by population estimates (available from the Census Bureau) to produce GDP per capita estimates. Median household income estimates available were for two- to three-year periods, not for individual years. Estimates for individual years were obtained by averaging over spans of years. For example, to obtain an estimate for 2010, estimates for 2009-2010 and 2010-2011 were averaged. Household income combines all incomes within a household, while GDP/capita is on a per person basis. All monetary estimates were converted to constant 2013 dollars using the CPI (Consumer Price Index) calculator at the Bureau of Labor Statistics (*15*).

Prices for regular-grade gasoline were selected for fuel prices, since they represent the most common grade of fuel used. The prices were converted from prices per million BTUs to gallons, and then converted to constant 2013 dollars. Fuel tax values were converted to constant 2013 dollars and summed with the fuel cost to produce an estimate of the price at the pump.

The Insurance Institute for Highway Safety (IIHS) maintains a valuable set of digests of state laws respecting critical aspects of traffic safety. These data were used to develop the indexes on the strength of state belt laws and motorcycle helmet requirements. Per capita consumption of beer, wine, and alcoholic spirits are available by state and year. Finally, the penetration of post-1991 model year vehicles into the fleet was estimated using quasi-induced exposure methods (*16*). The rate of penetration was used as a surrogate for the spread of more crashworthy vehicles, in response to NHTSA's New Car Assessment Program and the strengthening of the Federal Motor Vehicle Safety Standards.

Highway spending was used in the statistical models to capture the effect of infrastructure and state highway programs on safety. Clearly, highway spending is an imperfect surrogate because the cost-benefit ratio of projects differs. However, it is believed that this surrogate is the best currently available. A safety-related spending variable was constructed that aggregates all spending states themselves identified as safety-related: law enforcement, state educational safety programs, and the portion of capital spending that the states declared to be safety-related.

Data for Prediction

To implement the models for prediction of future crash counts, it was necessary to project model predictors into future years. Table 2 summarizes the sources of such projections for the Michigan and Texas implementations. Details of the assumptions are given in the next paragraphs. It is important to note that Texas used the count model for their projections, whereas Michigan used the change model. However, irrespective of the model used, the projections will approximately be the same.

Table 2 Data sources for predictors for future-year model implementation

Predictor	Source for Change Model (Michigan)	Source for Count Model (Texas)
Total VMT	Assumed	Developed in-house
Rural VMT as proportion of total VMT	Assumed	Developed in-house
Capital spending (in $1000 per mile)	Assumed	Developed in-house
Safety spending (in $1000 per mile)	Assumed	Developed in-house
GDP per capita (in $10,000)	International Monetary Fund projections (*17*)	Developed in-house
Unemployment for age 16 to 24 (%)	Trading Economics projections (*18*)	Developed in-house
Pump price ($ per gallon)	Energy Information Administration (*19*)	Assumed
Beer per capita (gallons)	Assumed	Assumed
Wine per capita (gallons)	Assumed	Assumed
DUI rating	Based on known plans	Based on known plans
Belt rating	Based on known plans	Based on known plans
Motorcycle Helmet rating	Based on known plans	Based on known plans
Median Income (in $10,000)	Brown University projections (*20*)	Developed in-house
Post1991 (% of vehicles manufactured after 1991 in the fleet)	Effectively all of fleet by 2017	Effectively all of fleet by 2017

Texas Implementation

Researchers in the Texas A&M Transportation Institute's (TTI) Infrastructure Investment Analysis Program developed estimates for each of the variables. Estimates of population growth were developed by the Texas Demographic Center, under the direction of the Texas State Demographer. The population scenario used in this estimation assumes population change due to migration at a rate equal to the 2000-2010 migration rate with other changes due to natural increase (births and deaths) and is typically used for short range projections (*21*).

TTI used its own TRENDS model to predict VMT from predicted fuel sales, which are in turn calculated based on per capita fuel consumption trends and population estimates (*22-24*). Capital and safety funding was predicted based on recent trends and forecasts of Texas Department of Transportation spending. Predicting fuel prices is challenging, but an assumption was made that prices would increase 3.5% each year.

Youth unemployment was based on the historical relationship to total unemployment, which was in turn based on predictions from the Texas Workforce Commissions' Labor Market & Career Information Department (LMCI) (*25*). Beer and wine consumption per capita were calculated using statistics from the Texas Comptroller's Office and an annual growth rate in beer sales of 0.33% and wine sales of 6.10% (*26*).

The percent of the fleet consisting of post 1991 vehicles is expected to peak at nearly 100% in 2015 and not increase after that point. In essence, the influence of post 1991 vehicles reaches a constant level after that year. Finally, no changes in seat belt, motorcycle helmet or DUI laws are expected in Texas during the short term, so these were assumed to stay the same as previous years.

Michigan Implementation

The Michigan implementation relied on assumptions (often of no change) for some variables and existing published projections for others. VMT was modeled using an assumed 0.5% increase year over year and no change to the relative proportion of rural VMT. Trends in rural VMT proportion over earlier Michigan data show a steady decrease from 2001-2014. However, in 2015, the proportion went up slightly, suggesting that the downward trend might be flattening or turning around. Similarly, capital and safety spending, as well as beer and wine consumption were assumed to remain at 2015 levels for the fatality predictions. Finally, law ratings for DUI, seatbelt and alcohol were all projected to remain unchanged since there was no related legislation known to be in the pipeline.

Projections for economic indicators and fuel prices were found from reliable publicly available sources. Since Michigan used the change model, it was only necessary to identify projected changes in GDP per capita, youth unemployment, median income, and fuel prices for the U.S.. We assumed that the rate of change for Michigan would be the same as for the country as a whole, though the actual numbers might not be the same as the average U.S. values. As with the Texas implementation, post-1991 model year proportion was assumed to have reached its maximum in 2015.

METHODS

The modeling approaches were patterned after Elvik (*27)*, who reviewed a number of statistical methods for looking at predictors of fatalities over time in a group of countries. Two of these methods he recommended were used to develop the prediction models in the current study: a Poisson-gamma count model (equivalent to a negative binomial model) and the log-change regression model of year-over-year change.

Both models were fitted using the same set of parameters, which are listed in Table 1. The one exception was wine consumption, which was used only for the change model. Predictors were selected based on extensive analysis of a large set of candidates, as described in (*8*). Predictors were not included or excluded based on significance tests.

Count Model

The negative binomial model uses raw fatality counts and incorporates VMT as exposure. This means that coefficients of predictors can be interpreted as influencing fatalities per VMT, or a fatality rate in each state and year. Thus, though different factors can influence risk or exposure, in this model they are interpretable primarily as influencing risk rather than exposure. The model also uses a state fixed effect to remove the stable differences among states and focus on changes over time.

The functional form used for the count model is shown in Equation 1.

$$\mu = \mathrm{VMT} \times e^{(\beta_0+\gamma_s)+\sum_i \beta_i X_i} \qquad \text{Eq. 1}$$

Where,

μ = the estimated number of fatalities per year (for each state);

VMT = the number of vehicle-mile traveled in millions (for each state);

X_i = variable i;

β_0, β_i= estimated coefficients, and,

γ_s = state-specific parameter for states.

Change Model

The change model translates the data into percent change from year to year within each state. Thus, the data begin with 2002, for which each independent and dependent variable is represented by its percent change compared to the previous year (Eq. 2).

$$z_t = \frac{x_t}{x_{t-1}} \qquad \text{Eq. 2}$$

Where,

x = any original variable in the model;

z = transformed change variable;

x_t = value of x in a given year; and,

x_{t-1} = value in the prior year.

Taking the log to convert to a linear model, which is mathematically more straightforward to deal with (Eq. 3).

$$ln(y_t) - ln(y_{t-1}) = \beta_0 + \sum_{j=1}^{k} \beta_j\, z_t = \beta_0 + \sum_{j=1}^{k} \beta_j \left(ln(x_t) - ln(x_{t-1})\right) \qquad \text{Eq. 3}$$

Where,

y_t = number of traffic fatalities in year t;

y_{t-1} = number of traffic fatalities in year t-1;

z_t = transformed change variable; and,

β_0, β_i = estimated coefficients.

When exponentiated, the coefficients (βs) in this model can be interpreted as multipliers on how the rate of change in a predictor influences the rate of change in fatalities (Eq. 4).

$$\frac{y_t}{y_{t-1}} = e^{\beta_0} \prod_{j=1}^{k} e^{\beta_i} \frac{x_t}{x_{t-1}} \qquad \text{Eq. 4}$$

A key quality of the change model is that it removes overall differences between states on all variables. Large states may have larger numbers of fatalities, larger expenditures, and larger numbers of miles driven, but change in those states is proportional. Small states do, however, produce more volatile change values because of the smaller samples.

MODELING RESULTS

Count Model

The parameter estimates and goodness-of-fit statistics for the count model are shown in Table 3. Parameters that were significantly different from 0 are shown in bold and include proportion rural VMT, GDP per capita, age 16-24 unemployment, beer consumption per capita, DUI law rating, motorcycle helmet law rating, median income, and the proportion of vehicles in the fleet newer than model-year 1991. Note that state-specific intercepts are not included in Table 3, but they are listed in the original report (8).

Table 3 Parameter Estimates for the Count Model

Variable	Estimate	Standard Error	P-value	Exponentiated parameter
Intercept	10.6995	0.302	<.0001	
Rural VMT proportion	**-0.1916**	**0.0972**	**0.0486**	**0.826**
Capital spending (in $1000 per mile)	-0.0002	0.0002	0.2255	1.000
Safety spending (in $1000 per mile)	-0.0006	0.001	0.5176	0.999
GDP per capita (in $10,000)	**0.046**	**0.0117**	**<.0001**	**1.047**
Unemployment for age 16 to 24 (%)	**-0.0118**	**0.0015**	**<.0001**	**0.988**
Pump price ($ per gallon)	0.0065	0.0125	0.6034	1.007
Beer per capita (gallons)	**0.4022**	**0.0747**	**<.0001**	**1.495**
DUI rating	**-0.0074**	**0.003**	**0.0119**	**0.993**
Belt rating	-0.0058	0.0073	0.4274	0.994
Motorcycle Helmet rating	**-0.0347**	**0.0156**	**0.0261**	**0.966**
Median Income (in $10,000)	**0.0375**	**0.0188**	**0.0459**	**1.038**
Post1991 (% of vehicles manufactured after 1991 in the fleet)	**-0.0177**	**0.0026**	**<.0001**	**0.982**
Dispersion Parameter	0.0025	0.0003	--	--
AIC*	5643			
MAD*	35.80			
MSPE*	3165.32			

* Smaller values are preferred.
Bold font denotes p-values <=0.1.
Note: State fixed effect parameters are not presented here.

Figure 1 compares observed and predicted counts for Texas based on the count model. Note that although the model does contain a state-specific intercept parameter for Texas, the effects of predictors were determined by all states in the dataset. Moreover, the model was developed on crash years 2001-2012 but fits almost as well for 2013-2016. The largest residual of 267 (8% overestimate relative to the observed value for that year) occurred in 2015.

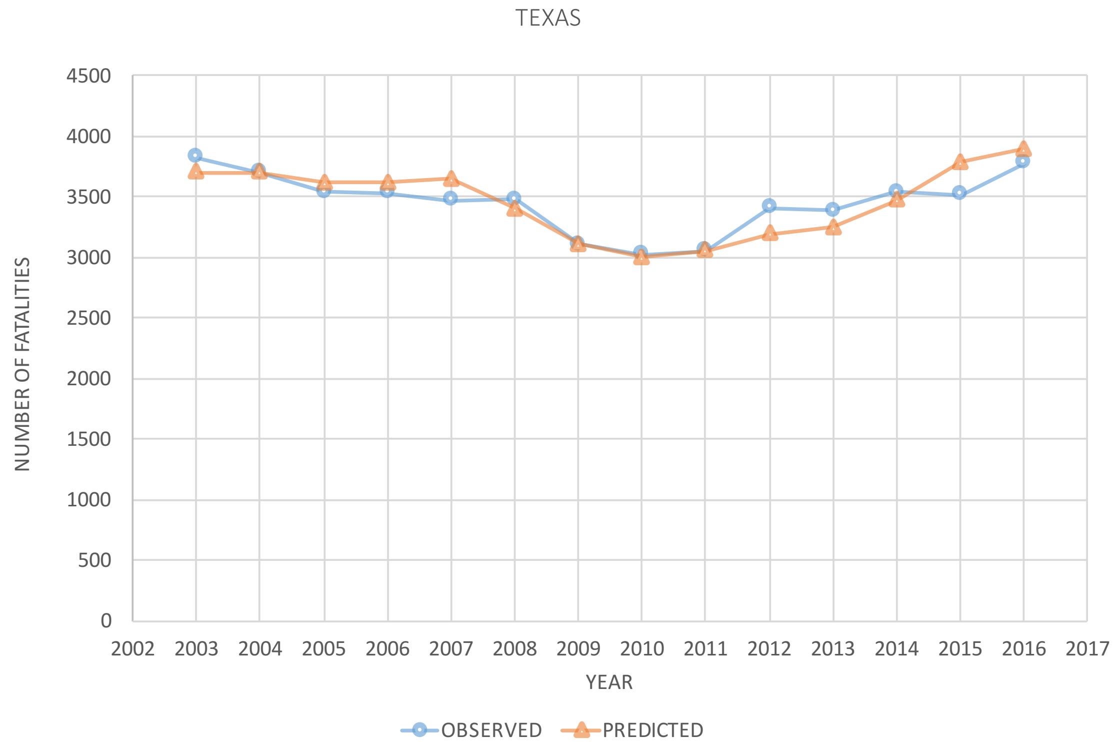

Figure 1 Observed versus count model predicted fatalities in Texas 2003–2016.

Change Model

The parameter estimates and goodness-of-fit statistics for the change model are shown in Table 4, along with standard errors of the estimates and *p*-values. Parameters that were significantly different from 0 are shown in bold and include: total VMT, GDP per capita, median income, age 16-24 unemployment, and DUI law ratings.

Model diagnostics indicated that the assumptions of linear regression were generally met. However, overall R-square was relatively low with only 16.8% of the total variance accounted for. This indicates that additional processes beyond those included influenced the specific change observed. However, these processes are not likely to have been captured in any measures available to us.

Table 4 Parameter Estimates for Change Model

Variable	Estimate	Standard Error	P-value	Exponentiated parameter
Intercept	-0.011	0.008	0.1719	
Total VMT change	**0.540**	**0.188**	**0.0042**	**1.716**
Prop Rural VMT change	0.022	0.061	0.7171	1.022
Pump price change	-0.024	0.040	0.5597	0.976
GDP per cap change	**0.128**	**0.067**	**0.0552**	**1.137**
Median Income change	**0.505**	**0.155**	**0.0012**	**1.657**
16-24 Unemployment change	**-0.138**	**0.026**	**<.0001**	**0.871**
Cap spend/mile (lag) change	-0.008	0.022	0.7084	0.992
safety spend/mile (lag) change	0.011	0.014	0.4071	1.011
Belt use rate change	-0.051	0.122	0.6748	0.950
DUI law rating change	**-0.181**	**0.093**	**0.0521**	**0.834**
Motorcycle helmet law rating change	-0.013	0.100	0.8986	0.987
Beer consumption change	0.170	0.141	0.2304	1.185
Wine consumption change	-0.029	0.087	0.7385	0.971
MY>1991 change	0.057	0.550	0.9179	1.059
R-square	0.168			
Adj. R-square	0.144			

Bold font denotes p-values >=0.1.

Figure 2 shows observed vs. predicted fatality counts for Michigan for 2003-2016. As with Texas, the correspondence is quite good. For Michigan, the largest residual value was 105 (12% overestimate relative to the observed value) in 2014. Note that for these predicted values, the change for each year was predicted based on that year's observed values of predictors and then the percent change was applied to the previous year's observed fatality count.

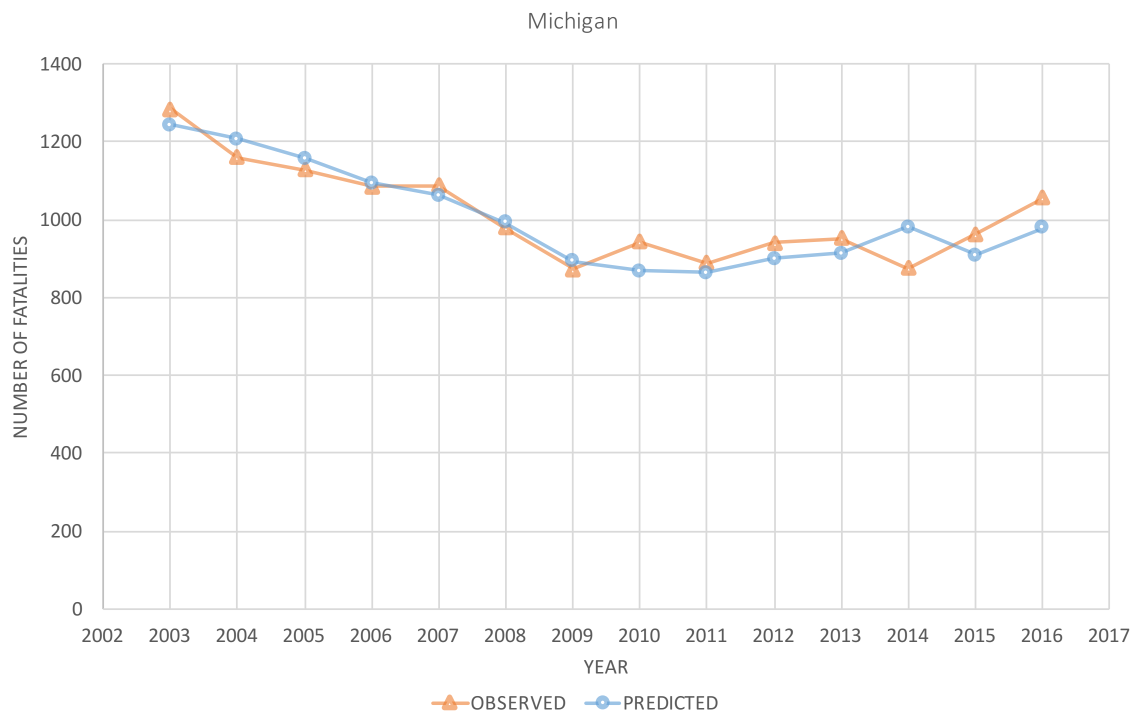

Figure 2 Observed versus change-model predicted fatalities in Michigan 2003 – 2016.

Prediction of Future Fatality Counts

The count model was used in Texas as part of the target-setting process for the state's Strategic Highway Safety Plan (SHSP). The results of the initial model run, based on the projections described in the data section, are shown in Figure 3. The model predicts a nearly linear rise in fatalities to a level of nearly 4300 in the year 2022. The rise is driven by the increases in VMT. The Texas economy and population are predicted to grow steadily during the near term and no disruptions to this steady growth are like to occur and affect traffic safety risk. The model predicts risk to remain at current levels and therefore exposure becomes the dominant factor in fatality variation.

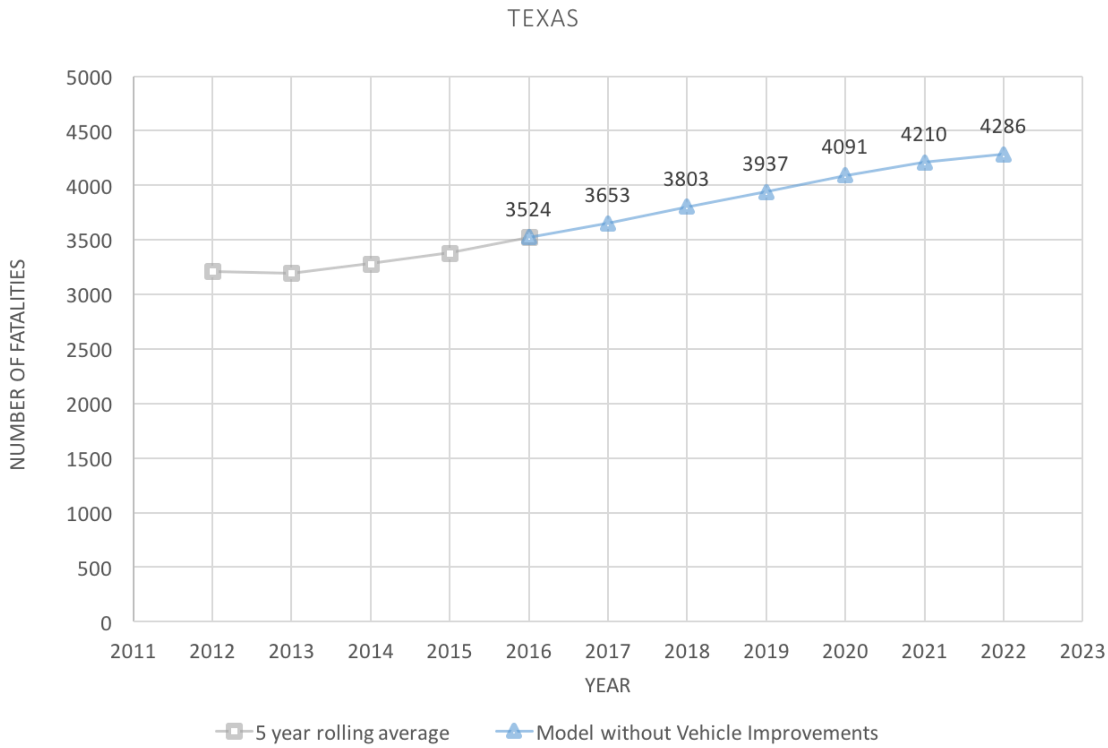

Figure 3 Initial implementation of count model for Texas fatality projections

Automobile crashworthiness and safety improvements have provided steady downward pressure on fatality risk for decades, and the count model captured this effect by modeling the percentage of post 1991 vehicle in the fleet. However, this penetration of post 1991 vehicles is complete by 2015, and therefore the model, as currently configured, cannot capture any additional risk reductions.

To investigate this further, we adjusted the model to incorporate the same level of risk-reduction seen from the post-1991 model-year effect going into the future. This simulates the effect of a new-vehicle-model predictor that has the same (assumed) influence as the post-1991 predictor had. The effect of vehicle safety improvements on predicted fatalities is shown in Figure 4. With this effect included, fatalities flatten out substantially (offsetting the effect of increasing VMT) and result in 496 fewer predicted fatalities in 2022.

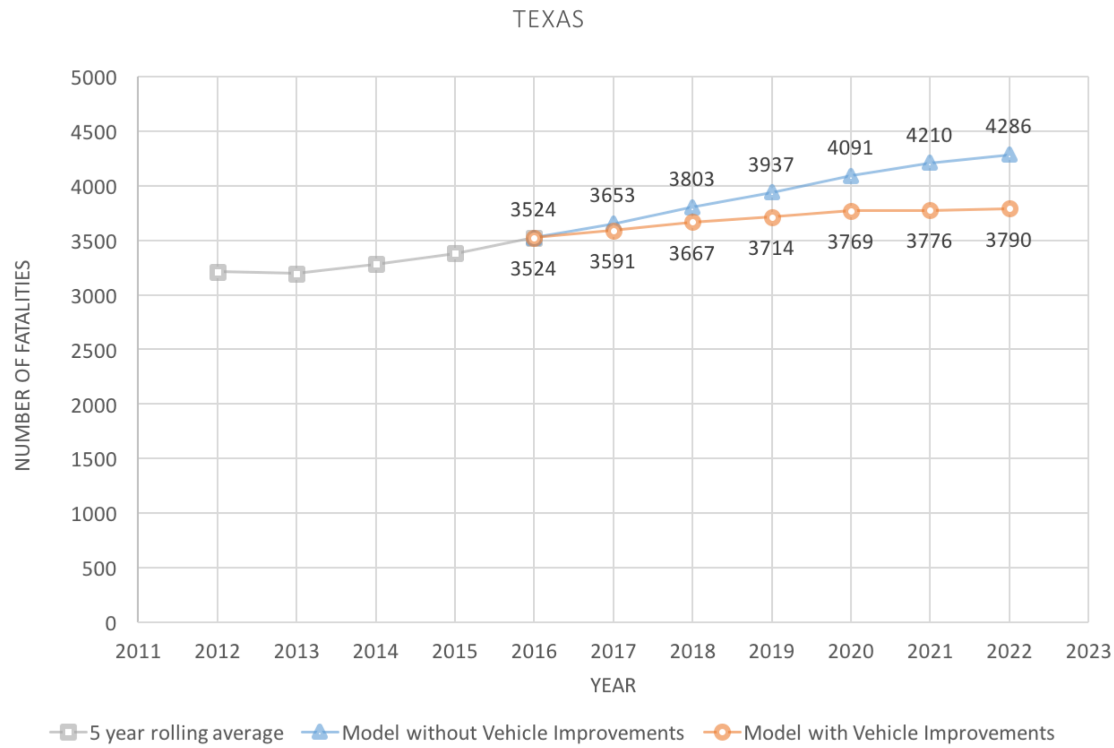

Figure 4 Count model predictions vs results if vehicle safety improvements continue to reduce risk

For Michigan, the change model requires a previous-year fatality count to multiply by the predicted rate of change. Thus, projections for each year were multiplied by the previous-year projection. The starting point for these projects must be selected, but in Michigan, 2016 fatalities were higher than in 2015 by 92, or 10%. Thus, projections based on 2016 were much higher than those based on a 2015 starting point. This is shown in Figure 5. In both cases, fatalities are projected to rise very slowly over the 5 years, primarily driven by relatively flat VMT projections. Among economic factors, 16-24 unemployment and GDP per capita have the strongest effect and these were projected to improve (unemployment down, GDP up). Unemployment for that age group was projected to improve at about 5-6% per year (relative to previous year's unemployment) and GDP was projected to go up by about 2% per year. More aggressive economic growth and VMT growth would produce fatality targets that increase more steeply.

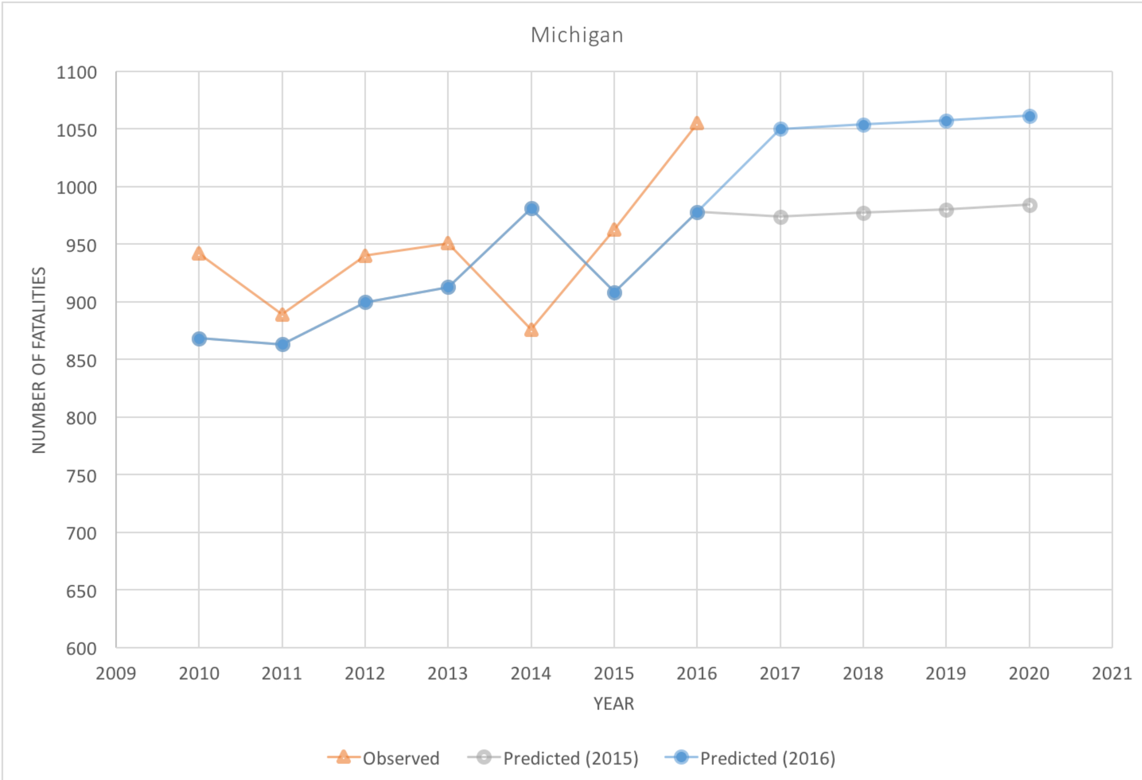

Figure 5 Projected fatality counts for Michigan based on the change model applied to either 2015 or 2016 observed counts as a starting value.

DISCUSSION

We developed count- and change-based general linear models of fatality counts using a variety of predictors. The predictor set included safety, spending, exposure (VMT) and economic factors, and the models were developed using a database of annual state-level predictors and fatality counts for each year from 2001-2012. However, when applied to specific states, the count model fit Texas data for 2013-2016 and the change model fit Michigan data for the same period quite well.

Based on the promising performance for predicted state-specific fatality counts, the models were used to develop predictions for Strategic Highway Safety Plan (SHSP) targets for 2017-2022. A critical component of using such models is obtaining projections for the predictors. In the case of economic predictors, there are often projection models developed and publicly available. Similarly, demographic changes that might lead to VMT changes can be tracked and studied. Finally, fuel costs are predicted by the Department of Energy and can be used both for gas price as a predictor and in models of VMT change over time.

In principle, good projections of these variables should account for information that improves the accuracy of the projected targets. Often, the alternative is a rolling average or a linear trend based on previous years. This simply assumes that the general pattern over the last five years will continue. However, the fatality projections are only as good as the projected inputs.

The two models have different strengths and weaknesses. The change model was suggested by Elvik *(7)* because of its statistical properties. However, to implement this model, change over time must be multiplied by a base year that itself might be anomalous. It is possible to guard against a this problem by using the moving average of a few prior years. One advantage is that the predictors are expressed as proportion of change rather than absolute numbers. Thus, national estimates of change in economic measures can be applied to a state's prediction without needing to address the base level (high or low) of that state in the first place.

The count model directly estimates fatality count for each year, and its state-specific intercept comes from the original model. Thus, this intercept could drift over time and might need to be re-estimated. That said, the model directly predicts fatality counts for future years based on state-specific predictions of VMT, economic indicators, changes in laws, and alcohol consumption. It does so for each year independently and is not influenced by anomalous values from recent years.

One issue with the original models is that they represent automobile crashworthiness and safety improvements by modeling the percentage of post-1991 vehicle in the fleet. For a dataset with years 2001-2012, this gave reasonable values in the middle and upper range of vehicle proportions. However, this penetration of post-1991 vehicles was complete by 2015, and therefore the model, as currently configured, cannot capture any additional risk reductions.

Exercising the Texas model with and without additional vehicle-safety effects showed a substantial difference in the predicted fatality counts for the future. This prompts the question of whether it is realistic to predict that more reductions are immediately forthcoming from vehicle improvements. A great deal of attention is focused on a revolutionary reduction in risk from self-driving vehicles, but in the interim, it is unclear whether vehicle safety features provide a consistent reduction in fatality risk. Some safety features, such as automatic braking, do hold promise in reducing risk, but the penetration into the vehicle fleet is small, and not likely to make a significant impact in the next 5 or so years.

For the purpose of setting SHSP targets, the state must make a number of assumptions or educated guesses about the future of vehicle-based safety systems, changes in laws, and changes in VMT. Economic factors and VMT can be estimated more "objectively" using existing prediction methods, but it is worth conducting sensitivity analyses to understand the range of potential predicted targets and how the underlying assumptions about changes over time will influence those targets.

Future improvements should be made to these models for SHSP target-setting use. First, the models should be re-run with updated data. Second, the effect of vehicle safety systems needs to be more flexibly implemented. A year-based predictor that is essentially an assumed constant trend in vehicle-safety countermeasures may be the best way to implement such an effect. Since the vehicle fleet turns over slowly (5% annually), even dramatic improvements will have a slow, steady effect on fatalities. Different sources of projected predictor values (e.g., future economic conditions) should be evaluated for their performance and the expectation of producing meaningful economic projections that add value to these models. Finally, the models should be exercised to better measure and present uncertainty bounds on the predicted values. Sensitivity analysis is one approach, but model variance should also be included.

Given the strong relationship between economic factors and fatalities, more complex models that include economic and other factors can be useful in developing state-specific SHSP targets. While these models will not predict the year-to-year variation that occurs with any small sample, they can provide an idea of the expected trends to come, against which safety countermeasures must perform. This approach can set more realistic targets than moving averages (which lag behind actual changes over time) or linear trends (which fail particularly during changing economic times).

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