Do Mandatory Ignition Interlock Device Laws Reduce Drunk Driving Fatalities?

Lamar Hunt III

October 28, 2016

Introduction

On October 1st, 2014, in response to concerns about having some of the highest rates of drunk driving fatalities in the United States, the South Carolina General Assembly enacted Emma's law, which requires anyone convicted of a first-time DUI offense with a blood-alcohol content (BAC) greater than 0.15 to install an ignition interlock device (IID) on their vehicle for 6 months.[1] The device prevents drivers from starting their vehicle unless they pass a breathalyzer test, and periodically requires them to perform a breathalyzer test while driving in order to continue normal operation of the vehicle.

Assuming that other factors relevant to drunk driving fatality rates in South Carolina did not suddenly change with the passing of Emma's law, we may view this event as constituting the application of an intervention in a "quasi-experiment" from which we might be able to draw causal inferences about the effect of the policy on drunk driving fatality rates in South Carolina. (See Gribbons et al. for a discussion of quasi-experiments,) One method of analyzing quasi-experimental data is to perform an interrupted time series analysis, whereby a shift in a time series model is specified following the enactment of the policy. Assuming that data before and after the policy change come from populations that are comparable in terms of the factors relevant for the outcome, the estimate of the shift in the model can be interpreted as a causal effect. (See Wagner et al. for a discussion of interrupted time series.)

In order to examine whether there was a change in the proportion of drivers involved in a traffic fatality who were driving under the influence due to the enactment of Emma's law we apply the interrupted time series method to monthly traffic fatality data from South Carolina for years 2008 to 2015, assuming a shift in the model occuring on October 1st, 2014. Further, we compare the results of this analysis to the same analysis applied to data from Texas, which had similar rates of drunk driving fatalities over the past 8 years and which does not mandate intallation of IIDs after a first offense.[2] The findings will be informative for future legislators seeking to reduce the public health burden of drinking and driving.

Methods

Data Acquisition

We used Fatality Analysis Reporting System (FARS)[3] data provided by the National Highway Traffic Safety Administration (NHTSA), which we downloaded from ftp://ftp.nhtsa.dot.gov/fars. They provide data on every car fatality in the US from 1975 to 2015. The data we needed for the analysis can be found in the "person" file associated with each year. This file contains information regarding each person (drivers, passengers, pedestrians, bikers) involved in each fatality incident, such as their age, sex, BAC, and whether a police officer categorized them as drunk.

[1] http://scstatehouse.gov/sess120_2013-2014/bills/137.htm (Emma's law)

[2] See section 521.246 (c) of the Texas Transportation code. Note that IIDs are not strictly required in all cases. http://www.statutes.legis.state.tx.us/Docs/TN/htm/TN.521.htm

[3] http://www.nhtsa.gov/Data/Fatality-Analysis-Reporting-System-(FARS)

Key Variable Definitions

Main Outcome

The outcome is the log-proportion of drivers involved in a traffic fatality who were reported to have been drunk by police, or who had BAC measured above 0.08. We chose 0.08 as the threshold because this is the legal limit in the state of South Carolina. We computed this proportion for each month from January of 2008 through Decemeber of 2015, and performed a log transformation in order to make the data normally distributed and to linearize the relationship between the predictors and the outcome, as it is a proportion (see supplementary document). We chose to look at data going back to 2008 because that is when the number of drunk driviers involved in fatalities in the U.S. overall seemed to begin to decrease most recently (see Figure 1).

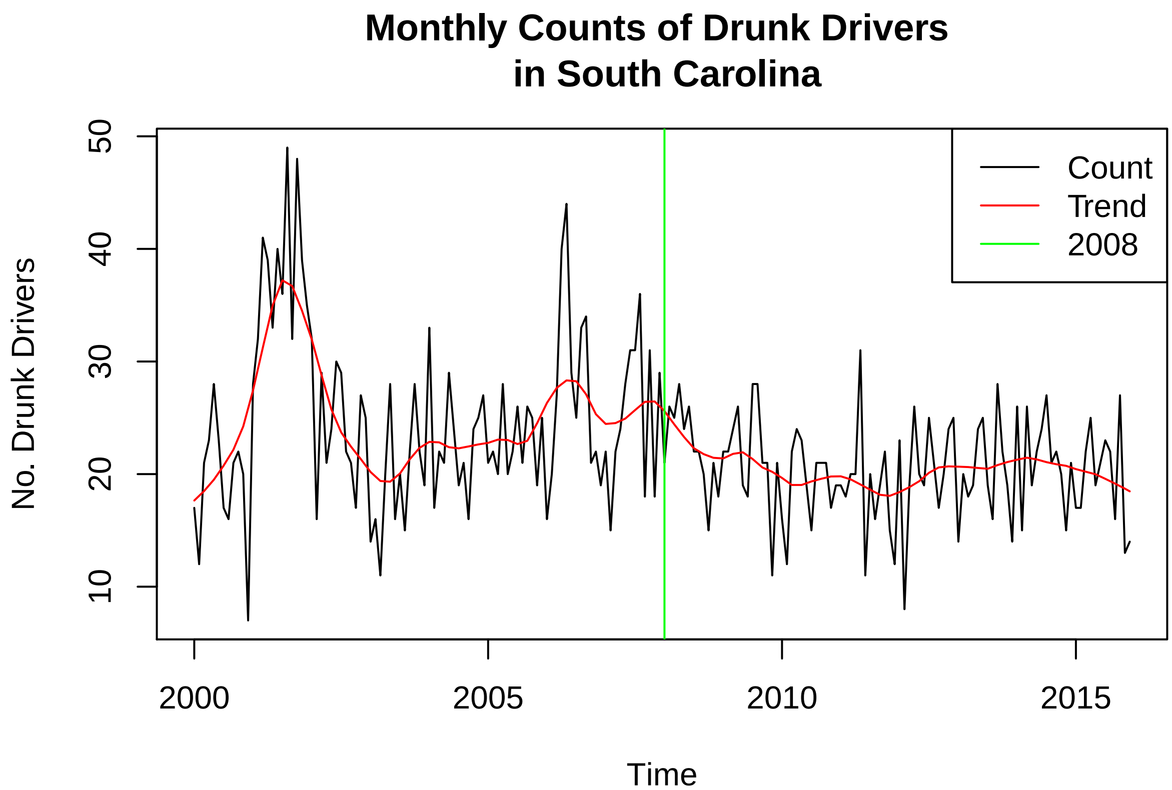

Figure 1: Number of drunk drivers involved in a crash fatality each month in South Carolina from January 2000 to December 2015. Note the trend stabalizing after 2008 (marked in green) indicated by the loess smoother in red.

Calendar Time

FARS data records the date (down to the day) of each traffic fatality, but we chose to take proprtions on a monthly basis. Therefore, we defined the date (down to the day) of each proportion for each month using an average of the days within that month on which a drunk driving fatality occured, in order to capture the most representative date of the accidents for that month. This is in contrast to arbitrarily setting the date to be the first of the month. Thus, if by chance most drunk driving accidents occured very early or late in the month this would be captured by our choice of day for that monthly proportion on the time series.

Intervention

Finally, we defined a categorical variable indicating whether the date was prior to or after the onset of Emma's law (October 1st, 2014). Although participants are not being randomized to pre- or post-policy intervention, because we assume that other factors relevant to drunk driving (e.g., age, race, sex, socioeconomic status) do not suddenly change in South Carolina after Emma's law came into effect, we treat the date of policy change as an intervention is a quasi-experiment.

Statistical Analysis

Let Y_m be the log proportion of for month m, D_m be the date associated with that proportion, c be October 1st, 2014, and $X = I(D > c)$ be an indicator variable. We performed an interrupted time series analysis with an interruption at October 1st, 2014, using the following linear model, which we fit using least squares:

$$Y_m = \beta_0 + \beta_1(D_m - c) + \beta_2 X + \beta_3(X * (D_m - c)) + \epsilon_m$$

where we have used the value $D_m - c$ for ease of interpreting the intercept coefficients. In this model, β_0 is the average log-proportion of drunk drivers just prior to the enactment of Emma's law, β_1 is the slope of the time series prior to the Emma's law, β_2 is the intercept shift occuring after Emma's law, and β_3 is the slope shift of the time series after Emma's law. We assume $\epsilon_m \overset{\text{i.i.d.}}{\sim} N(0, \sigma)$.[4] We perform Wald t-tests for each coefficient, testing whether each one is different from 0. We perform the same analysis on data from Texas and South Carolina and compare the results.

Results

In Table 1, we report the coefficient estimates and standerd errors for both models. In Figure 2, we plot the time series of log proportion of drivers who were drunk, along with the regression lines from fitting each model.

Prior to October 1st, 2014, both Texas and South Carolina seem to be trending similarly, with the monthly log-proportion of drunk drivers estimated to be increasing by 4.301e−05 ($SE = 3.021\text{e}{-05}, p = 0.158, df = 92$) and 8.132e−05 ($SE = 1.584\text{e}{-05}, p = 1.59\text{e}{-06}, df = 92$) per month for South Carolina and Texas, respectively. However, after the policy change in South Carolina we see a significant change in slope of −2.253e−03 ($SE = 3.822\text{e}{-04}, p = 6.13\text{e}{-08}$) compared to the smaller shift of −5.434e−04 ($SE = 2.004\text{e}{-04}, p = 0.00799$) seen in Texas after that time.

We also see that the intercept change, interpreted as the shift in average log-proportion at the time Emma's law is enacted, is much larger for South Carolina (−2.994e−01, $SE = 1.089\text{e}{-01}$, $p = 0.00718$) than for Texas (1.317e−02, $SE = 5.708\text{e}{-02}$, $p = 0.81804$).

Discussion

Both the intercept shift and slope shift are larger for South Carolina compared to Texas, despite both states having a similar trend prior to the intervention. We interpret this to be consistent with the claim that there was a greater decrease in the proportion of drivers involved in fatalities who were drunk in South Carolina after the enactment of Emma's law compared to Texas.

Texas does have IID requirements for DUI offenders, however the law does not require offenders to install them in every case. Thus, the foregoing results suggest that the harsher penalties enacted for first time offenders in South Carolina with Emma's law are associated with a drop in the proportion of drivers involved

[4] This assumption is probably false, making our estimates of the standard errors overly optimistic.

Table 1: Linear Model Results. Parentheses contain standard errors.

	South Carolina	Texas
Avg. at 10/1/14	−0.890***	−0.875***
	(0.043)	(0.023)
Slope before 10/1/14	0.00004	0.0001***
	(0.00003)	(0.00002)
Intercept Shift	−0.299***	0.013
	(0.109)	(0.057)
Slope shift	−0.002***	−0.001***
	(0.0004)	(0.0002)
Observations	96	96
R^2	0.710	0.257
Adjusted R^2	0.701	0.232
Residual Std. Error (df = 92)	0.194	0.101
F Statistic (df = 3; 92)	75.084***	10.592***
Note:	*p<0.1; **p<0.05; ***p<0.01	

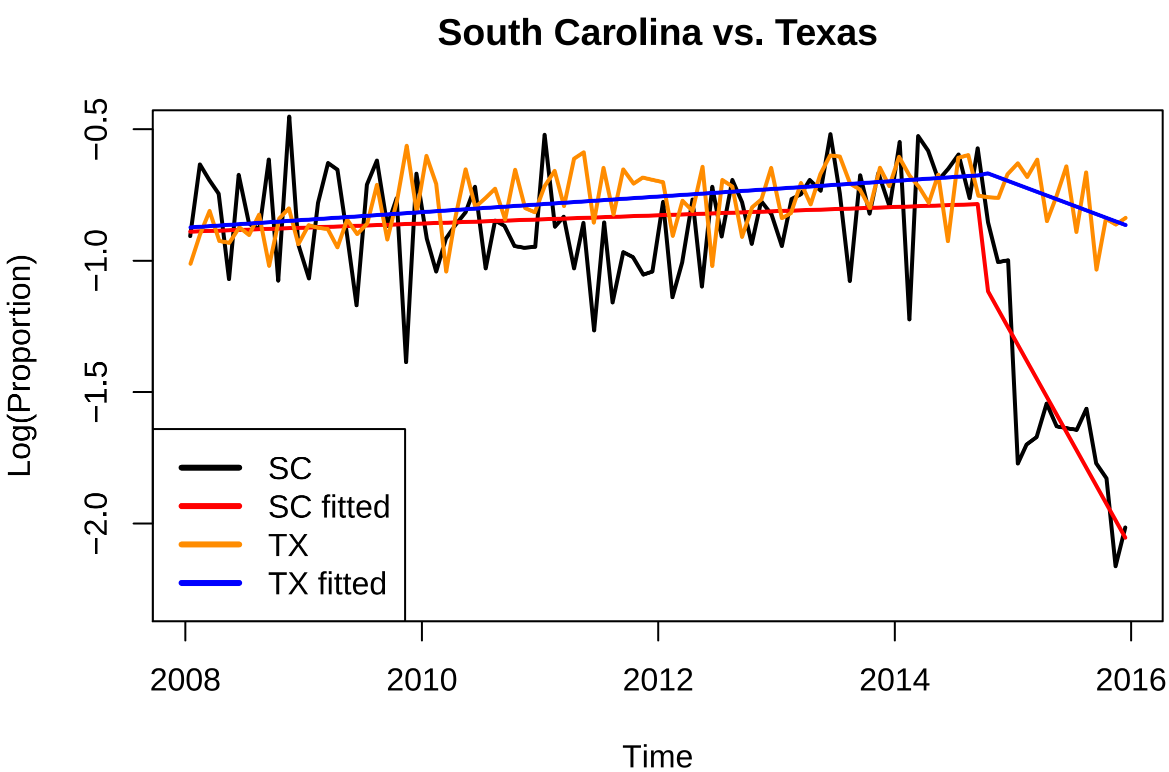

Figure 2: We plot log-proportion of drivers involved in traffic fatalities in Texas and South Carolina who were drunk plotted against calender time from January 2008 through December 2015. Overlayed in red and blue are the interrupted time series model fits for SC and TX, respectively. Note the interruption at October 1st, 2014 when Emma's law came into effect. Prior to Emma's law SC and TX trend similarly; however, after enactment of the law we see a more drastic shift in the intercept and slope in SC compared to TX.

in traffic fatalities who were drunk. Assuming that other factors relevant to drunk driving rates do not significantly change in South Carolina or Texas after the date of the policy change in South Carolina, we may interpret these results to indicate that the policy causes the slope and intercept change seen in South Carolina. This is informative for legislators interested in reducing the public health burden of drunk driving.

Limitations

As Emma's law only recently came into effect, we do not have much data available to address this question. Moreover, we have only shown an association between the enactment of the law and a reduction in drunk driving fatalities. Since we did not control for state level variables that may be relevant for the rates of drunk driving within a state (age, sex, race, socioeconomic status), it is difficult to draw a causal conclusion. It is possible that mainly demographic differences between South Carolina and Texas account for the difference in both the slope and intercept shift seen here. Indeed, rates of drunk driving throughout the U.S. in general seem to be dropping over time (see Figure 1), and the effect we see in South Carolina may simply be related to this general trend. Finally, because of obvious seasonal changes in the data, our assumption that the error terms are independant and identically distributed is likely false. This casts doubt on the standard errors in the model, and therefore the results of the significance tests.

Further study

The obvious next step would be to account for the seasonal trends in the data in the linear model, in order to obtain more accurate standard errors. Secondly, it would be good to gather demographic data relavant to drunk driving from all states in the U.S. and use that to standardize state populations for a better comparison (e.g., using propensity scores). Thirdly, methods such as Difference and Differences could be used to account for the fact that drunk driving rates seem to generally be decreasing as a function of time. Finally, it would be interesting to examine the drunk driving penalties in all states to gather more information about the effect of laws similar to Emma's law.

References

1. Wagner et al.
2. Gribbons et al.