Forecasting the burden of road traffic injuries: a scenario including fully-autonomous vehicles

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Abstract

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Road traffic injuries are one of the largest causes of death for teenagers and adults in the United States. Fully autonomous vehicles (FAV) have the potential to impact not only the transportation industry, but also the population health of the United States by decreasing road traffic fatalities. We forecasted a lower bound of the burden of road traffic fatalities by estimating the decrease in drunk driving fatalities. Comparing scenarios with FAV adoption and baseline scenarios of no FAV adoption, results show that modest adoption of FAVs could prevent around 6,000 drunk driving deaths per year by 2040. This work highlights the current burden of road traffic injuries and how new technology could partly alleviate that burden.

Introduction

Road traffic injuries are one of the largest causes of death for teenagers and adults in the United States. In 2015, motor vehicle injuries accounted for 1 out of every 10 deaths of people aged 15-49 in the United States[1], more deaths than caused by gun violence. Unlike many other cause of death, there is no cure or vaccine for road traffic injuries, and the prevalence of road traffic injuries is seen as a byproduct of a society where driving is ubiquitous. However, road traffic injuries are a serious public health problem, and reducing road traffic fatalities would greatly increase the population health of the US.

Fully Autonomous Vehicles

Fully autonomous vehicles (FAVs) likely will be commercially available by the end of the decade[2,3,4]. This new technology has the potential to transform the transportation industry. Tesla has stated that it wants to have a driverless vehicle drive coast to coast by the end of 2017[5]. Many automakers have released projections for when they will have FAV technology available in their vehicles[2,3,4]. Uber is already testing semi-autonomous vehicles in a few cities in the US. It is important to consider the health impacts of fully autonomous vehicles, which may soon be a part of daily life in the US.

The automotive industry has two general strategies for introducing autonomous technology into the fleet of US cars. The first strategy is a gradual introduction of different autonomous features. We already see many of these features on cars today, things such as automatic breaking, blind spot detection, and cruise control. The National Highway Traffic Safety Administration (NHTSA) classifies these technologies as Level 1 automation, or feature specific automation. In this paper, when we talk about FAV technology, we are referring to Level 4 automation. At this level of automation, there is no need for a driver to monitor the road. Table 1 shows the NHTSA automation classifications.

Levels of Autonomous Vehicles (NHTSA 2013)
***Level 1* – Function-specific Automation:** Automation of specific control functions, such as cruise control, lane guidance and automated parallel parking. Drivers are fully engaged and responsible for overall vehicle control (hands on the steering wheel and foot on the pedal at all times).
***Level 2* - Combined Function Automation:** Automation of multiple and integrated control functions, such as adaptive cruise control with lane centering. Drivers are responsible for monitoring the roadway and are expected to be available for control at all times, but under certain conditions can disengaged from vehicle operation (hands off the steering wheel and foot off pedal simultaneously).
***Level 3* - Limited Self-Driving Automation:** Drivers can cede all safety-critical functions under certain conditions and rely on the vehicle to monitor when conditions require transition back to driver control.
***Level 4* – Self-Driving Under Specified Conditions:** Vehicles can perform all driving functions under specified conditions.
***Level 5* - Full Self-Driving Automation:** Vehicles can System performs all driving functions on all normal road types, speed ranges and environmental conditions.

Table 1. National Highway Traffic Safety Administration classification of autonomous vehicles

It is tempting to assume that FAVs will only decrease the fatality rate due to road traffic injuries, but this may not be the case. It is possible that during early stages of adoption the fatality rate may increase slightly as human drivers act more aggressively around FAVs and try to take advantage of conservative artificially intelligent (AI) drivers[6]. It is also possible that the fatality rate may decrease drastically immediately after adoption, but the truth is that we just do not know yet. Since FAVs have not been widely adopted yet, there is no data on how safe they will be, and therefore this paper makes a few simplifying assumptions. We can safely assume that Level 4 FAVs will not be able to cause drunk driving accidents, and so as adoption of FAVs increases, the number of road traffic fatalities due to drunk driving will decrease. By focusing on reduction of drunk driving as the pathway through which FAVs affect road traffic fatalities, we can create a lower bound of deaths averted by FAVs.

Forecasting

We use the Global Burden of Disease 2015 (GBD) data as the baseline for our forecasts, including the risk assessment framework for the proportion of road traffic fatalities due to drugs and alcohol. The general framework employed in this paper is detailed in Figure 1, which details the entities that are forecasted to arrive at averted deaths. On the left hand side of this figure, in green, are the inputs to our road traffic mortality forecasts. Arrows denote the downstream entities that each input affects. For example, the results of our Lag Distributed Income per capita forecasts are used to forecast road traffic injuries. Then, the results of the road traffic injuries forecasts are combined with our population forecasts to produce aggregated results. Each entity was forecasted for each US state level and by age and sex. Aggregated results were produced for the entire US by taking population weighted sums. The details of each forecasted entity are discussed in the methods section.

To capture the uncertainty of our forecasts, we created three scenarios for each forecasted entity. These scenarios represent a range of possible futures and are propagated through our forecasting framework. The method for creating the scenarios are further discussed in the methods section.

One note about our results is that they are not meant to be exact predictions about the future, as the term “forecasting” may suggest. Rather, we simply aim to show what would happen if past trends were projected into the future.

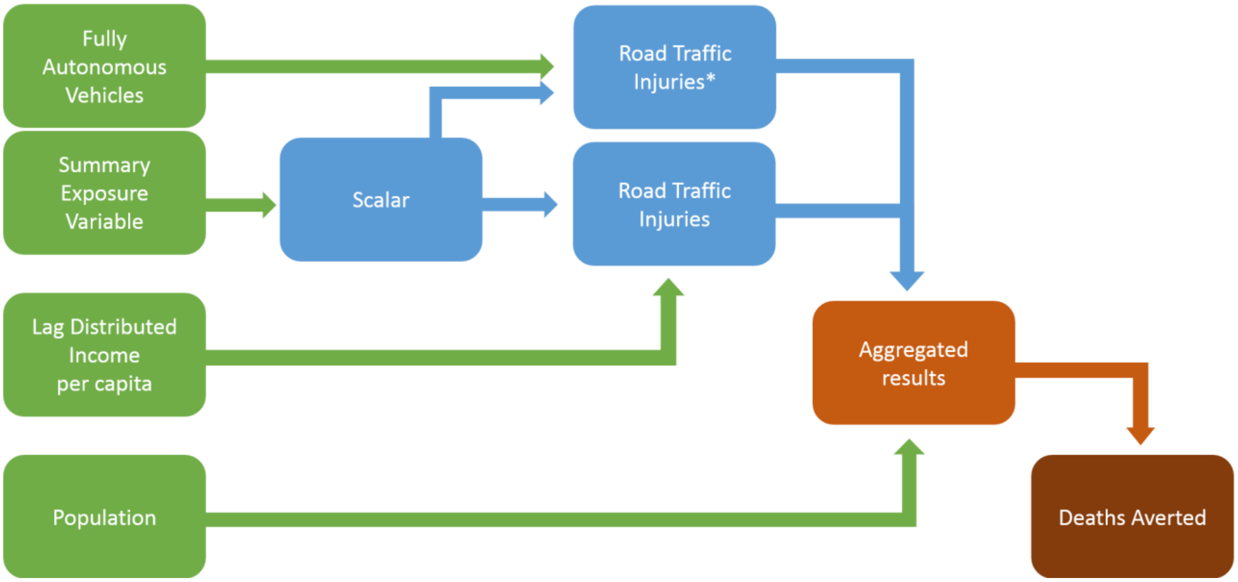

Figure 1. Flow diagram describing the process of our forecasts. The star denotes that this set of Road Traffic Injuries has been adjusted to reflect the FAV scenario.

Methods

Data Sources

Past data by age, sex, and state for the summary exposure variable (SEV) for alcohol use was obtained from the GBD 2015 study[7]. A SEV is a relative risk weighted exposure and measures the exposure of a population to a risk factor. SEVs are measured between 0 and 1, with 1 representing the highest risk weighted exposure[7]. GBD 2015 was also used to obtain past data for lagged distributed income per capita (LDI per capita) and road traffic mortality. LDI per capita is a weighted moving average of GDP over the last 10 years, and is used as a covariate to forecast road traffic injuries. LDI per capita was chosen as a covariate for road traffic injuries because it correlates fairly well with road traffic mortality in the past.

To obtain estimates of future adoption of FAVs, we performed a literature search for existing estimates of adoption. We used a variety of sources, including published academic papers and industry reports[8,9,10,11]. Estimates were only used if they were for level 4 autonomous vehicles and if they had both year and proportion data.

Forecasted estimates for population were obtained from the US census bureau. Two separate time series were used and combined to create a forecasted series of population. The US census bureau has forecasted population estimates by state created in 2005 and based on the 2000 census. The US census bureau also has more recent population forecasts for the United States as a whole, based on the 2010 census. To create our population time series, we combined these two forecasts using a method described below.

Forecasts

We used several different techniques to forecast the different entities we are interested in. Forecasts for LDI per capita were created by calculating a "recent" rate of change and a "total" rate of change. These two rates of change were combined to create a final rate of change that was then projected into the future. The recent rate of change was calculated as the rate of change from 2008 until the end of the past data. This rate of change represents the growth rate since the global recession of 2008. The total rate of change was calculated using the entire time series, 1950 to 2015. These two rates of change were combined by using the recent rate of change in the near future, and gradually shifting to the total rate of change for the distant future.

For the alcohol SEV, we extrapolate past rates of change separate by age and sex. We find the rate of change by calculating the year to year differences of SEV in the past, and then calculating the median difference with a weight towards more recent years. The weight for this model was chosen by calculating the root mean squared error of the forecasts when holding out data from 2006 to 2015. The effect of weighting toward more recent years means that this method is more likely to pick a rate of change that is closer to recent years. Scenarios were created by examining past rates of change. We calculated the 85th and 15th percentile of rates of change by age and sex and projected those rates into the future, and these became the better and worse scenarios. If the reference scenario fell outside the bounds of the better or worse scenarios, the reference replaced the scenario. The forecasted SEVs were transformed into "scalars" by incorporating the relative risks for each SEV. Scalars represent the amount of exposure a location has to risk and how much that exposure affects mortality, and are related to the population attributable fraction. The transformation to a scalar then let's us use risk estimates when forecasting mortality.

Population forecasts were created using the state level forecasts produced by the US census bureau for the 2000 census as well as country level forecasts produced by the US census bureau for the 2010 census. These forecasts were combined by taking the ratio of state level forecasts (from the 2000 census) and applying those ratios to the national level forecasts (from the 2010 census). This method was chosen to both obtain state level population forecasts and make use of the most up to date national level projections. The 2000 census forecasts are projected to 2030, whereas the 2010 census forecasts are projected until 2040. To be consistent with our chosen forecast endpoint of 2040, the ratio of the state to country level forecasted population in 2030 was held constant until 2040 and applied to the national level forecasts from the 2010 census.

To forecast the proportion of FAVs in the US, we used the data obtained in our literature search and ran a linear regression, where the independent variable is the percentage of FAVS and the dependent variable is time, to obtain projections. The data included sources from scientific literature, industry reports, and expert opinion. We also performed a mixed effects regression with fixed effects on data source, however, this method yielded similar results. We made the choice to start the adoption of FAVs in 2020, when industry experts anticipate the first commercial FAVs to be available[2,3]**.** FAV forecasts are the same for each state.

Road traffic mortality for each US state was forecasted using a linear model with random effects and a set of priors favoring smooth outcomes over age and location. We used the Template Model Builder package in R, which allows for the writing of custom likelihood functions. The covariate part of the model is broken into two parts, the risk-attributable and underlying portions. The coefficient on the risk-attributable portion of the model is assumed to be one, meaning that our forecasted scalars are directly additive to the total mortality. The underlying portion of the model is made up of LDI per capita as a covariate and an intercept term. The coefficient on LDI per capita and the intercept term are affected by the space and age priors to ensure that estimates for the states are smooth, and that estimates for adjacent age groups are smooth. Two sets of road traffic mortality were created to represent possible futures with and without FAVs, and from here on will be referenced as the “experimental” and “control” groups, respectively. To create the experimental road traffic mortality, the risk-attributable portion of the model was adjusted using our FAV forecasts.

Experimental group scalar adjustment

To create the experimental group, we combined our scalar forecasts and our FAV forecasts. The scalar was adjusted in the experimental group by multiplying the scalar by 1 minus the FAV proportion in each year. This leads the risk-attributable portion of the road traffic mortality forecast to trend to zero as the proportion of FAVs increases. This method has desirable outcomes such as the elimination of drunk driving accidents if all vehicles are FAVs, and that underlying road traffic mortality still exists even if all vehicles are FAVs. This method also says nothing about what the rate of deaths in FAVs per mile will be, it merely assumes that the risk of drunk driving mortality decreases to 0 as more FAVs are on the road.

Results

In 2015, the Global Burden disease estimated that 29,000 people died from motor vehicle accidents in the United States. We find that in 2040, adoption of FAVs will lead to about 6,000 averted deaths in the reference scenario, or about 20 percent fewer deaths. This is due to both the proportion of FAVs increasing from 0 to around 35 percent in 2040, as well as an increasing risk of death from drunk driving accidents. In the better scenario, we predict that 10,000 deaths will be averted from the reduction in drunk driving fatalities.

Figure 2 shows the percentage of FAVs in use in the United States over time alongside the data compiled from our literature search. We set the adoption of FAVs to start in 2020, consistent with current industry estimates. We constructed scenarios of FAV adoption by assuming 100 percent adoption by 2040 for the optimistic scenario. For the worse scenario, we set the forecast to the lowest estimate seen across different data sources for each time point. Figure 2 also highlights the wide range of estimates that exist for future adoption of FAVs, which is captured by our better and worse scenarios.

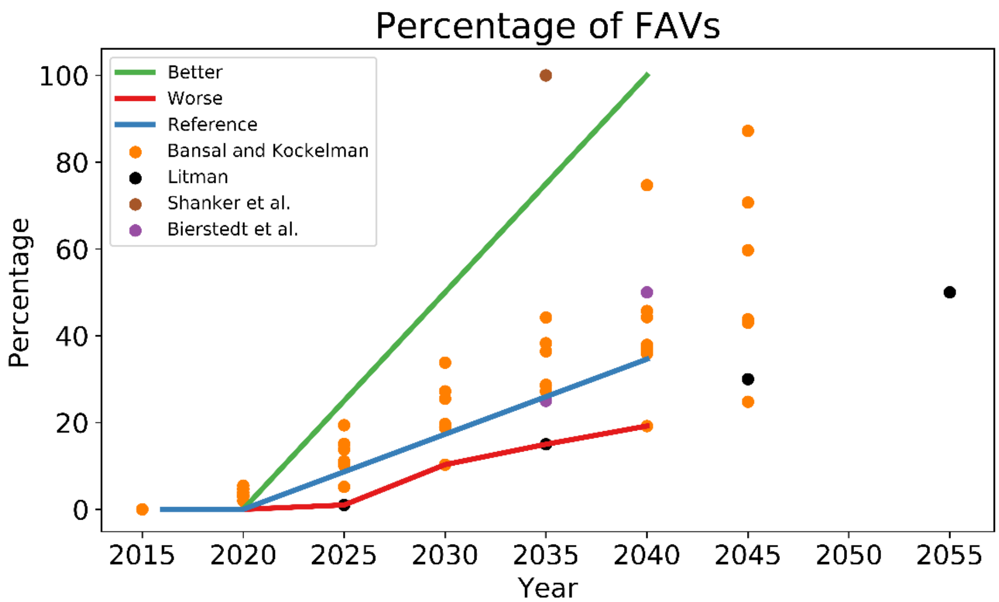

Figure 2. Percentage of FAVs in use in the United States over time. Dots represent estimates from different sources in the literature search, with different colors representing different sources. The estimate used in this paper is the blue line.

Our estimates project that the SEV for alcohol will slightly increase for the length of our forecast, which is consistent with recent trends. Figure 3 shows the age-standardized SEV for the United States as a whole, aggregated up from state level SEV forecasts. The blue line depicting the reference scenario represents a forecast under business as usual terms. The red and green lines denote the better and worse scenarios, respectively, and represent what could plausibly happen in pessimistic and optimistic futures.

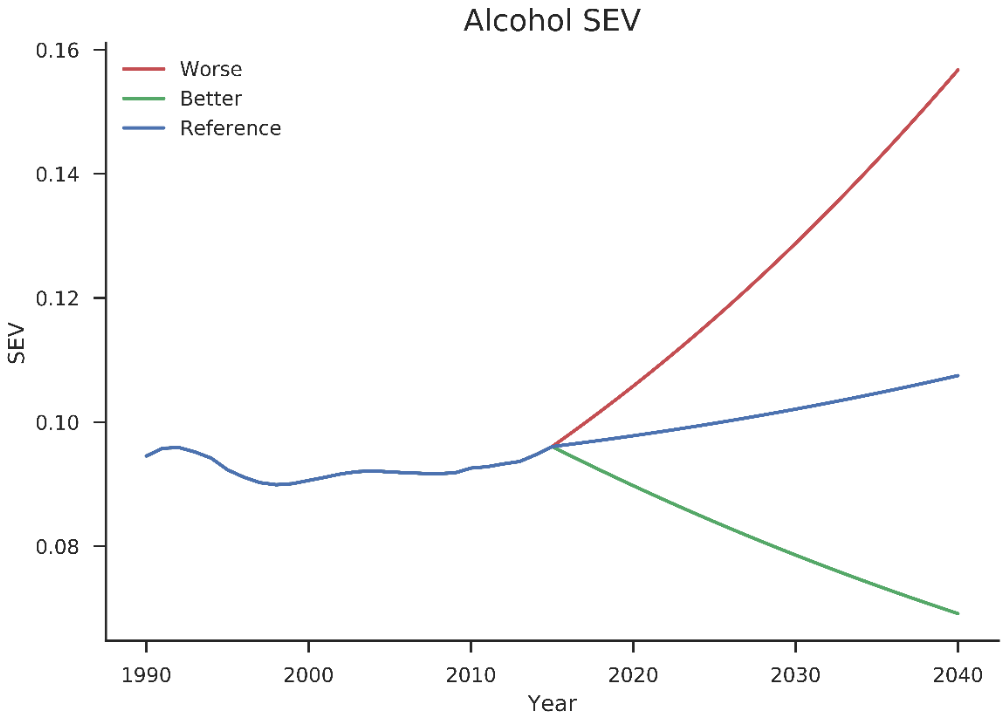

Figure 3. Alcohol SEV forecasts for the United States, age-standardized. We project moderate increases in the reference and worse scenario, while the better scenario shows little change.

Our FAV and alcohol projections are combined to create our control and experimental groups. In the control group, the FAV proportion is set to 0 for the entire forecast period. Figure 4 shows the mortality rate for road traffic fatalities in deaths per 100,000 population, for both the control and experimental groups. The results shown are age-standardized and aggregated to the national US level. In 2020, the forecast for the experimental group (dashed line) starts to decrease sharply, indicating the beginning of FAV adoption and the reduction of drunk driving accidents. The better, worse, and reference scenario from LDI, the alcohol SEV, and the FAV adoption forecasts are matched in the modeling process to create the scenarios for road traffic fatalities. The most marked difference is in the better scenario, due to the rapid increase in FAV adoption. The difference between the control and experimental group in the reference scenario is pronounced enough to lead to continued stagnation in the control and large decreases in the experimental.

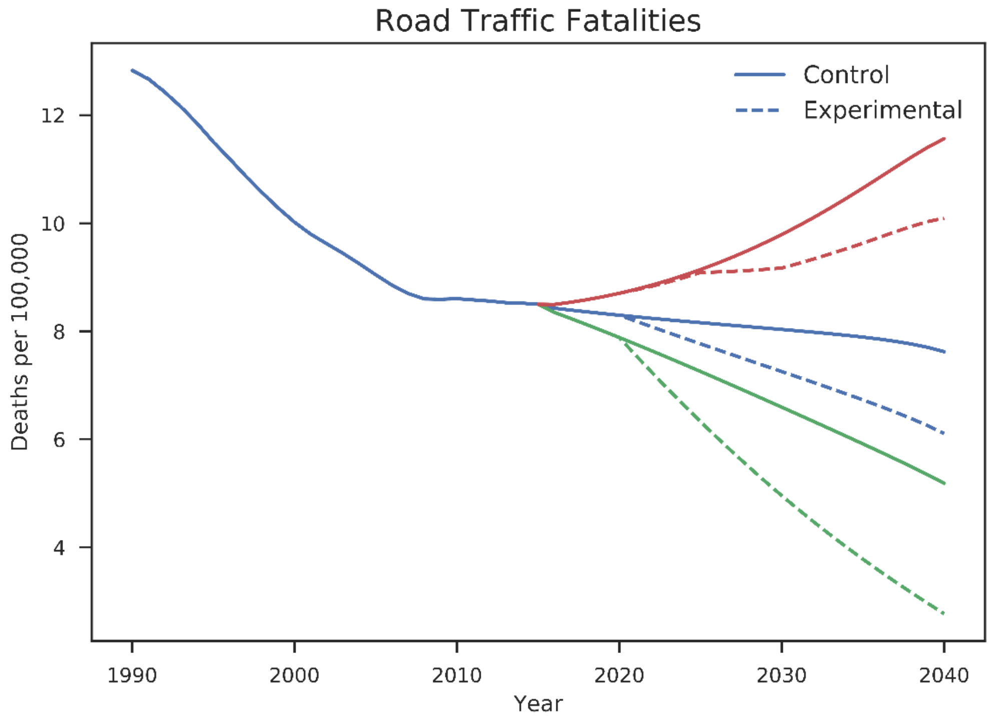

Figure 4. Road traffic mortality for the control (panel A, no FAV) and experimental (panel B, with FAV) groups, age-standardized, US level. Rates are shown in deaths per 100,000 population.

Combining our forecasted mortality rates with our population projections allows us to calculate the number of deaths averted in the experimental group. This time series is shown in Figure 5, and is calculated by multiplying population by the mortality rate of the control and experimental groups, and then subtracting the number of deaths in the experimental group from the number of deaths in the control group. By 2040, around 6,000 deaths are averted by adopting FAVs in the reference scenario. For comparison, the Global Burden of Disease estimates that there were 29,000 deaths in the United States in 2015. These results are for all ages and are aggregated to the national US level.

While we expect FAV technology to reduce drunk driving deaths by around 6,000 deaths per year by 2040 for all age groups, the benefit is even larger for teenagers and young adults. Because road traffic fatalities make up such a large proportion of teenage and young adult death, the relative benefit of FAV technology for these age groups is larger. We project that 1,550 deaths will be averted for teens and young adults aged 15 to 25, representing a 25 percent decrease in road traffic mortality and a 9 percent decrease in all-cause mortality in these age groups.

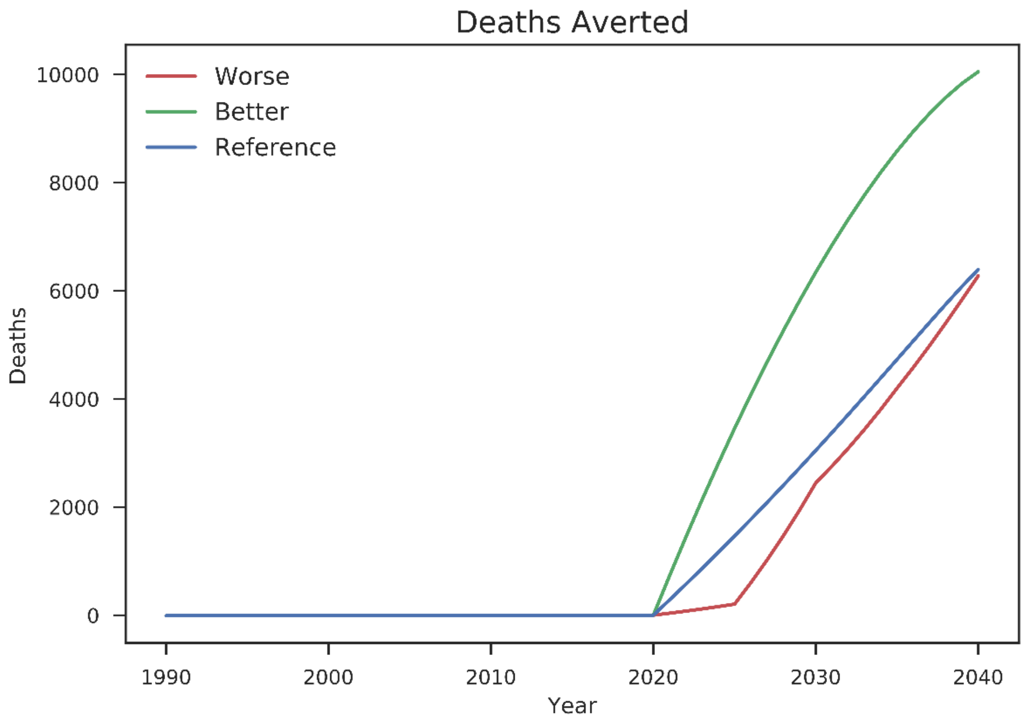

Figure 5. Number of deaths averted in the experimental group, all ages, US level.

Discussion

This paper examined the impact of FAVs on road traffic mortality by looking at how FAVs could reduce drunk driving mortality. However, the impact of FAVs on the overall road traffic mortality may be much larger. To estimate the entire effect of FAVs, we would need some estimate of how safe they would be in the population. Future work with this framework may focus on assuming FAVs will be as least as safe as the safest humans. This would mean that in a given location, a population with 100 percent FAV adoption would have the same rate of mortality as the lowest observed rate in that location. Another method would be to estimate what fraction of all fatal accidents are caused by human error, and assume that those deaths will not occur in a population with 100 percent FAV adoption.

We believe that policy makers should act on FAVs sooner rather than later. Policy makers should realize that FAV technology is coming in the near future, and could be disruptive to several industries. The US should strive to make sure that no undue regulatory burdens are placed on a new industry that has the potential to save many lives, while at the same time making sure that the technology is safe.

There may be more applications for this method, including aversion of distracted driving and texting-while-driving deaths. Additional work would be required to incorporate these risks into the GBD comparative risk assessment framework, however. It will also be interesting to recreate our results once more data on FAV safety becomes available.

This paper is meant to provide estimates on how a near-future technology could impact the population level health of the United States. It also shows how large the burden of road traffic mortality and drunk driving is on the US, especially for young adult age groups. This paper also highlights how different technologies can be incorporated into existing forecasting frameworks to create informative counter-factual scenarios. Overall, we found that a sizable reduction in mortality could be achieved through adoption of FAVs.

Limitations

It is important to consider the assumptions made by our research that led us to this conclusion, especially because there is no existing data on the long term per mile safety of FAVs. The first assumption this paper makes is that level 4 type autonomous vehicles become available in the near future, which would be necessary to reduce drunk driving. Some industry stakeholders think that autonomous vehicles will become available more gradually, with features like self-parking being implemented incrementally. These types of autonomous vehicles would not reduce drunk driving. However, we found several sources which forecasted high proportions of level 4 FAVs in the near future. A second assumption that we make is that the risk of a drunk driving fatality is linearly related to the proportion of FAVs. This assumes that an individual's probability to own an FAV and that individual's probability to drive drunk are independent, which may or may not be true. Another assumption in this paper is that the proportion of FAVs is the same in each state, which probably will not be true, but no data is available to split FAV forecasts by state.

Regardless of our assumptions, our goal is to create a reliable *lower bound* for the number of deaths averted by FAVs. We do not know exactly the rate of fatalities per mile driven in an FAV, but we can reasonably assume that as more people own FAVs, there will be less drunk driving fatalities.

Works Cited

1. Global, regional, and national life expectancy, all-cause mortality, and cause-specific mortality for 249 causes of death, 1980–2015: a systematic analysis for the Global Burden of Disease Study 2015. The Lancet. 20116; 388:1459-1544.

2. Ross, P. E. (2017, January 05). CES 2017: Nvidia and Audi Say They'll Field a Level 4 Autonomous Car in Three Years. Retrieved July 29, 2017, from http://spectrum.ieee.org/cars-that-think/transportation/self-driving/nvidia-ceo-announces

3. Caddy, B. (2016, May 23). Toyota to launch first driverless car in 2020. Retrieved July 29, 2017, from http://www.wired.co.uk/article/toyota-highway-teammate-driverless-car-tokyo

4. Su, J. B. (2016, January 05). CEO Tech Talk: Ford Expects Fully Autonomous Cars In 5 Years. Retrieved July 29, 2017, from https://www.forbes.com/sites/jeanbaptiste/2015/02/05/exclusive-interview-ford-ceo-expects-fully-autonomous-cars-in-5-years/#401a9e1fa0c8

5. Mitchell, R. (2017, March 30). Next step toward driverless cars: Tesla updates Autopilot. Retrieved July 29, 2017, from http://www.latimes.com/business/autos/la-fi-hy-tesla-updates-autopilot-20170330-story.html

6. Tennant, Chris, et al. Think Good Mobility: Autonomous Vehicles Negotiating a Place on the Road. 2016, http://www.thinkgoodmobility.goodyear.eu/the-survey

7. GBD 2015 Risk Factors Collaborators. Global, regional, and national comparative risk assessment of 79 behavioral, environmental and occupational, and metabolic risks or clusters of risks, 1990–2015: a systematic analysis for the Global Burden of Disease Study 2015. *The Lancet.* 2016 Oct 7; 388**:**1659–1724.

8. Bansal, P., & Kockelman, K. M. (2017). Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies. Transportation Research Part A: Policy and Practice,95, 49-63. doi:10.1016/j.tra.2016.10.013

9. Todd Litman (2013), Autonomous Vehicle Implementation Predictions: Implications for Transport Planning, Victoria Transport Policy Institute (www.vtpi.org/documents/evaluation)

10. Shanker, R., Jonas, A., Devitt, S., Huberty, K. et al. (2013). Autonomous Cars: Self-driving the New Auto Industry Paradigm. Morgan Stanley Research.

11. Bierstedt, J., Gooze, A., Gray, C., Peterman, J., Raykin, L., Walters, J., 2014. Effects of next-generation vehicles on travel demand and highway capacity. Technical Report. Fehr & Peers Transportation Consultants.