A New Look at the Impact of Beer Taxes on Alcohol-Impaired Traffic Fatalities*

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Abstract

Few definitive findings have emerged from the literature studying the impact of beer taxes on traffic fatalities, and as a result, the alcohol tax policy landscape has remained largely unchanged over the last few decades. This paper reexamines the effect of beer excise taxes on alcohol-impaired traffic fatalities in the United States. Using updated data from the National Highway Traffic Safety Administration and a fixed effect Poisson model, we find consistent evidence that beer taxes reduce alcohol-impaired traffic fatalities. Results are consistent across age groups and times of day and are robust to numerous model specifications, including dynamic event study estimators. Overall, our results provide evidence that beer taxes may be a productive tool to reduce alcohol-impaired fatalities.

Keywords: beer excise taxes, alcohol, traffic fatalities, drinking and driving

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1 Introduction

While there has been a downward trend in alcohol-related traffic fatalities over the last few decades, they still have a considerable public health impact in the US. Over thirteen thousand people died in US drunk driving accidents in 2021. To put this number in context, approximately 30% of all US traffic fatalities are alcohol-related, with one person killed by an alcohol-related motor vehicle crash every 39 minutes (National Center for Statistics and Analysis 2024b). Over the last few years, there has been an increase in alcohol-related fatalities and renewed interest in ways to reduce them.[1]

A complex set of policies seeks to mitigate the societal costs of alcohol. Alcohol is regulated in many ways, including zero-tolerance laws, Sunday alcohol sales restrictions, minimum legal drinking age laws, and blood alcohol content (BAC)[2] limits, among others. Generally these policies have been found to be effective in reducing alcohol-related harms (Carpenter 2005; Carpenter and Dobkin 2015; Eisenberg 2003; Lovenheim and Steefel 2011; Stehr 2010; Voas et al. 2003; Zhang and Caine 2011; Zwerling and Jones 1999). Another policy mechanism used to mitigate harm from alcohol is taxation. In theory, alcohol excise taxes should increase the price of alcohol and decrease consumption (Maldonado-Molina and Wagenaar 2010; Xuan et al. 2015), which in turn should reduce impaired driving. However, the alcohol consumption of heavy drinkers has been found to be mostly unresponsive to changes in price, as heavy drinkers tend to substitute to cheaper types of alcohol (Ayyagari et al. 2013; Pryce et al. 2019). Thus, the group of drivers most likely to cause alcohol-related harms may be the least impacted by market mechanisms.

The empirical literature studying the relationship between alcohol taxes and traffic fatalities has produced mixed results (Roodman 2020). Papers by Chaloupka et al. (1993), Cook (1983), and Ruhm (1996) find that beer taxes reduce traffic accidents and fatalities. Alternatively, estimates by Dee (1999), Eisenberg (2003), Mast et al. (1999), McClelland

[1]In 2021 there was a 14% increase in alcohol-related fatalities from 2020 (National Center for Statistics and Analysis 2024b).

[2]BAC is variously defined as blood alcohol content or blood alcohol concentration.

and Iselin (2019), and Wilkinson (1987) do not find a significant impact of alcohol taxes on alcohol-related fatalities, and estimates by Chaloupka et al. (1993) and Young and Bielinska-Kwapisz (2006) find a relatively small negative impact. Dee (1999) argues that prior work is limited by omitted variable bias and that models estimated using state-specific linear time trends produce imprecise results. However, since most of this literature was published, there have been empirical innovations that allow for a more careful evaluation of the impact that alcohol taxes have on alcohol-impaired traffic fatalities. We refer to alcohol-impaired traffic fatalities as fatalities where the driver had a BAC of 0.08 or higher.

In this paper, we reexamine the impact of beer excise taxes on alcohol-impaired traffic fatalities using data from the Fatality Analysis and Reporting System (FARS) provided by the National Highway Traffic Safety Administration (NHTSA). Our preferred specification, a fixed effect Poisson (FEP) model, estimates consistent evidence that beer excise taxes reduce alcohol-impaired traffic fatalities. We also estimate dynamic event study models to address concerns related to staggered treatment timing and heterogeneous treatment effects. These models continue to support the attenuating impact of beer taxes on alcohol-impaired traffic fatalities for beer excise tax increases of $0.10 and more. Results from heterogeneity analyses are largely consistent with our main findings and suggest that beer taxes reduce alcohol-impaired traffic fatalities independent of the time of day or week and across all age distributions. The largest impacts are observed for nighttime alcohol-impaired traffic fatalities and for the 31 to 40 age group.

To understand conflicting findings in the prior literature, we estimate numerous models to replicate previous research methods. Specifically, we estimate a series of two-way fixed effect (TWFE) models with fatality rates/ratios as dependent variables including and excluding state-specific linear time trends. Consistent with prior work, results are somewhat sensitive to the inclusion of state-specific linear time trends (Dee 1999). However, our specifications using the FEP model do not show this sensitivity.

This updated investigation provides strong evidence that beer taxes are associated with a significant reduction of alcohol-impaired traffic fatalities. Our main specification suggests that a $0.10 increase in beer taxes could prevent approximately 1.82% of alcohol-impaired traffic fatalities in the US. A back-of-the-envelope calculation suggests that this tax increase would have prevented 186 alcohol-impaired traffic fatalities nationally in 2019. We also find that count models are best suited for these types of analysis given the nature of the outcome variable. The use of count models is robust to the inclusion of time trends, which is not the case when the outcome variable is transformed to a rate.

Overall, our findings provide insights into the effectiveness of excise taxes as a measure to reduce excessive alcohol consumption and alcohol-attributable traffic fatalities. We present robust evidence that suggests excise taxes are a viable intervention to reduce traffic fatalities. Revenues from such taxes could go to programs to treat alcohol addiction, education campaigns, and driving under the influence (DUI) programs which could further mitigate the negative externalities that arise from drinking and driving.

2 Background

2.1 Alcohol taxes in the US

Alcohol taxes in the US are levied both at the state and federal levels. At the federal level, the beer tax has remained fixed at $18 per thirty-one-gallon barrel (approximately $0.58 per gallon) since 1991, when it was doubled from $9 per barrel. However, as of 2018, certain brewers may qualify for deductions based on their annual beer production volume, resulting in a beer tax range of $0.11 to $0.51 per gallon of beer for eligible brewers. In addition to the federal tax, all 50 states and the District of Columbia (DC) impose state-level alcohol taxes. Excise taxes are usually levied on producers or retailers, but these costs are then passed onto consumers in the form of higher beer prices. Pass through rates for beer have been estimated to be relatively high, with many estimates greater than one (Kenkel 1993; Nelson and Moran 2019; Shrestha and Markowitz 2016). The only taxes the consumer can visibly see on their receipt—depending on the state and whether the alcohol purchase was on- or off-premises—are sales taxes or ad-valorem[3] alcohol taxes (Fritts 2022, August 30). For this paper, we will focus on the effect of state-level beer excise taxes.

Numerous papers have examined the responsiveness of alcohol demand to changes in price. Alcohol is a normal good (Hanson and Sullivan 2016; Meng et al. 2014; Wagenaar et al. 2009). However, alcohol demand is also inelastic, which might limit the feasibility of using taxation to impact consumption (Ayyagari et al. 2013; Gehrsitz et al. 2021; Pryce et al. 2019). The response of consumers to changes in alcohol prices also varies depending on the type of beverage being taxed; that is, increases in beer, wine, or spirits taxes affect alcohol consumption differently (Son and Topyan 2011). A study looking at the 2009 Illinois alcohol excise tax hike finds that it reduced wine and spirits consumption by 3% and 3.5% respectively, but it increased beer consumption by 4% (Gehrsitz et al. 2021). This could mean that when alcohol prices increase, consumers substitute spirits and wine to lower cost alcoholic beverages like beer.

Different types of consumers also have different levels of demand elasticity for alcohol. For example, heavy and binge drinkers tend to have less elastic consumption patterns, especially when it is possible to substitute to lower priced alternatives (Pryce et al. 2019). In contrast, younger adults exhibit greater price sensitivity, likely due to their relatively lower income levels (Shrestha 2015).

2.2 The impact of beer taxes on traffic fatalities

There is a large literature exploring the impact of beer taxes on traffic fatalities. Most studies are dated and exploit variation in beer taxes across space and time using either weighted least squares or linear regression with time and state fixed effects (Chaloupka et al. 1993; Dee 1999; Mast et al. 1999; Ruhm 1996; Son and Topyan 2011; Young and Bielinska-Kwapisz 2006). While numerous papers have found beer taxes associated with reductions in

[3] Ad-valorem taxes are taxes levied as a percentage of a beverage's retail price, and they are usually collected in states where the regular sales tax does not apply to alcoholic beverages (Giertz 1999).

traffic fatalities (Chaloupka et al. 1993; Cook and Durrance 2013; Cook 1983; Ruhm 1996), a number have found no significant impact (Dee 1999; Eisenberg 2003; Mast et al. 1999; McClelland and Iselin 2019).

As most papers studying the effect of changes in state-level beer taxes have generally utilized the same dataset, the mixed results are a bit surprising and likely due to empirical modeling choices (Breznau et al. 2022). One potential cause of differing results is choices regarding dependent variable transformations. A number of papers have created ratios or rates as dependent variables. For instance, papers have used fatality rates per capita (Chaloupka et al. 1993; Dee 1999; Mast et al. 1999; Ruhm 1996; Son and Topyan 2011; Young and Likens 2000) or fatality rates per vehicle mile traveled (VMT) (Ruhm 1996). In addition, some papers have or have not chosen to take the logarithm of the dependent variable (Young and Bielinska-Kwapisz 2006; Young and Likens 2000).

Another important modeling choice is whether or not to include state-specific linear time trends (Dee 1999; Ruhm 1996; Young and Bielinska-Kwapisz 2006; Young and Likens 2000). Dee (1999) argues that models studying the impact of beer taxes on traffic fatalities are not robust to the inclusion of time trends, although findings vary. Most of the studies using time trends identify no significant impact of taxes on fatalities (Dee 1999; Young and Bielinska-Kwapisz 2006; Young and Likens 2000), with the exception of Ruhm (1996). None of these studies use count models.

Another notable modeling choice that may influence results in studies on alcohol and motor vehicle accidents is how to operationalize fatalities. Some papers have used alcohol-related fatalities, which the NHTSA defines as fatalities involving a driver, occupant, or non-occupant with a BAC of 0.01 or higher. Other papers have used alcohol-impaired fatalities, which are fatalities where the driver had a BAC of 0.08 or above (National Center for Statistics and Analysis 2022). Researchers have also made different choices about whether to impute missing data to more accurately estimate models, since alcohol-related traffic fatalities are often underreported (Adams and Cotti 2008; Cummings et al. 2006; Hingson et al. 1989; Villaveces et al. 2003).

All of these different modeling criteria play a role in the estimation process. In this paper, we pay particular attention to models using transformed dependent variables and using non-count models for their estimation. It is possible the discrepancies regarding the effect of alcohol taxes on traffic fatalities come from the use of non-count models for count outcomes. Therefore, using count models might reduce the bias of these estimations and find more consistent treatment effects. In contrast to regression models on the raw scale, log models yield results in terms of geometric means rather than arithmetic means. For a linear dependent variable, the estimate response would be the arithmetic mean. It is very possible that results on a log scale might provide misleading, incomplete, and biased estimation of the covariate's impact on the arithmetic mean (Manning 1998).

Rather than using regular regression models with transformed dependent variables, some modern traffic fatality papers use a FEP estimator (Nesson and Shrestha 2021). The FEP is a quasi-maximum likelihood estimator, and its advantage is that it relies on a weaker assumption that the conditional mean needs to be correctly specified. This means the estimates are consistent even if the count model does not follow a Poisson distribution itself.

Since the literature presents mixed evidence, it is important to revisit the impact state alcohol excise taxes have on alcohol-impaired traffic fatalities. By exploiting the variation across states' beer excise taxes, we analyze their relationship to alcohol-impaired traffic fatalities. Our main contributions to the literature are: (1) addressing the discrepancies regarding the impact of beer excise taxes on alcohol-impaired traffic fatalities, (2) using a two-way fixed effects Poisson estimator to avoid transforming the outcome variable, (3) using newer dynamic event studies estimators that address heterogenous treatment effects and staggered implementation, and (4) revisiting the heterogenous treatment effects for different ages and times of week and day.

3 Data

3.1 Alcohol-related fatal accidents

Traffic fatality data were obtained from FARS for the time period between 1990 and 2019 (we restrict our data to pre-2020 to exclude pandemic years). FARS is provided by the NHTSA and is the most comprehensive available data source on fatal motor vehicle accidents in the US. It offers detailed accident- and person-level information that include alcohol involvement, time and location of the accident, and the driver's BAC. To qualify as a FARS case, an incident must involve a motor vehicle travelling on a road typically accessible to the public, and it must lead to the death of either a driver or a non-driver within 30 days of the collision (National Center for Statistics and Analysis 2024a).

Studies using FARS typically use either alcohol-related or alcohol-impaired traffic fatalities as outcome variables. Our preferred specification uses the count of alcohol-impaired fatalities, as this measure captures the impairment of the driver rather than the overall alcohol involvement in the crash. However, we include models estimated with alcohol-related traffic fatalities in the appendix.

Although the federal government requires the measurement of BAC levels in every fatal crash, it is often underreported. About 50% of FARS accidents do not report a BAC level (Nesson and Shrestha 2021). Relying solely on cases with measured BAC levels can bias our estimates, and we would be severely underestimating the number of crashes that had alcohol involvement. To address this, the NHTSA allows for imputation of BAC levels. Using factors such as age, gender, belt or helmet use, prior traffic convictions, role of the vehicle in the accident, day of the week, time of the accident, and more crash characteristics, the procedure simulates ten different BAC measures for each driver in an accident (Subramanian 2002).[4] The imputed FARS data were provided to us by the NHTSA and has an imputed BAC level

[4]Several papers in the literature use imputed data. See Nesson and Shrestha (2021); Adams and Cotti (2008); Cummings et al. (2006); Hingson et al. (1989); Villaveces et al. (2003)

for drivers whose BAC levels were not originally recorded.[5] We also include models using non-imputed data in the appendix.

3.2 Alcohol-tax variables

Our variable of interest is beer excise tax rates, which were collected from the Urban-Bookings Tax Policy Center (2023). These data have been adjusted for inflation using the Consumer Price Index and are presented in 2019 dollars (US Bureau of Labor Statistics 2024). On average, state excise taxes were $0.37 per gallon of beer. In 2019, Tennessee had the nation's highest beer tax at $1.29 per gallon, and Wyoming had the lowest at $0.20 per gallon. The highest inflation-adjusted beer tax in our historical sample is Alabama's 1990 tax at $2.05 per gallon in 2019 dollars.

3.3 State-level controls and policy variables

Data were collected from different sources for a number of state-level socioeconomic and policy variables. Data on income per capita were collected from the BEA, unemployment rates from the BLS, gasoline tax rates from the Department of Transportation, and population by age distributions from the Census Bureau. Data were also collected for seatbelt laws, BAC laws, graduated driver license laws (GDL), and zero-tolerance (ZT) laws for minors.[6] All of these variables were obtained from Michigan State University's Correlates of State Policy Project (Grossmann et al. 2021).[7] We also include indicator variables for policies that ban texting while driving from the Insurance Institute for Highway Safety (IIHS) (IIHS 2024) , vertical identification laws from Nesson and Shrestha (2021), and medical and recreational marijuana laws from Mathur and Ruhm (2023).[8] Following Adams et al. (2012), we also

[5] The imputed data was requested and given to us via email by: ncsarequests@dot.gov.

[6] Zero tolerance laws set very low BAC limits for drivers under 21 years old. In most states, ZT laws are set at 0.02 BAC for drivers under 21.

[7] The Correlates of State Policy Project did not have data for the 1990–2020 period for the District of Columbia (DC), so we collected data for DC from the Metropolitan Police Department in Washington DC.

[8] Vertical identification laws mandate that underage driver's license and identifications to be oriented vertically rather than horizontally.

include real minimum wage data from the Department of Labor.

4 Methods

To estimate the impact of beer taxes on traffic fatalities, we first use a fixed effects Poisson (FEP) estimator, which can be represented by the following equation:

$$Y_{st} = exp(\beta_0 + \beta_1 BeerTax_{st} + \beta_2 X_{st} + \sigma_s + \lambda_t + \theta_{st}) + \epsilon_{st} \quad (1)$$

In this model, Y_{st} represents the outcome of interest for state s in year t. In our main model, the outcome variable is the count of alcohol-impaired traffic fatalities. Our variable of interest is $BeerTax_{st}$, which represents the excise tax per gallon of beer at state s at time t. State and time fixed effects are represented by σ_s and λ_t. The inclusion of fixed effects allows us to control for state-specific time-invariant characteristics and year-specific state-invariant characteristics. Also, state-specific linear time trends are included in some models and are represented by θ_{st}. X_{st} denotes a vector of socioeconomic and policy variables described in Section 3. ϵ_{st} is a random error term, and standard errors are clustered at the state level. We estimate numerous model specifications, gradually incorporating state-level covariates and state-specific linear time trends. Poisson estimates, with robust standard errors, are more suitable in this context because in log-linear specifications small values may exert disproportionate influence (Wooldridge 2010).

4.1 Heterogeneity analysis

We perform heterogeneity tests to provide a more comprehensive understanding of how beer taxes impact different segments of the population and at various times. Heterogeneity checks are performed by estimating equation 1 for different age distributions, times of day, and days of the week. Seven different age groups are evaluated: individuals aged 17 and younger, 18 to 20, 21 to 25, 26 to 30, 31 to 40, 41 to 64, and 65 and older. Models were also estimated using alcohol-impaired daytime, nighttime, and weekend nighttime traffic fatalities. We define fatalities that occurred from 6 p.m. Friday through 5:59 a.m. Monday as weekend fatalities and traffic fatalities that occurred between 6 p.m. and 5:59 a.m. as nighttime fatalities.

4.2 Robustness checks

Although standard TWFE models have been commonly used to estimate treatment effects, the standard framework relies on relatively strong identification assumptions that might not hold in cases where there is staggered adoption or heterogenous treatment effects (Callaway and Sant'Anna 2021; De Chaisemartin and d'Haultfoeuille 2020; Goodman-Bacon 2021; Sun and Abraham 2021). We address the potential limitations of TWFE models by estimating a dynamic version of the estimator introduced by Callaway and Sant'Anna (2021) using the year before a tax increase as the reference period. Following Callaway et al. (2024), we aggregate treatment into distinct 'doses' of the tax by creating binary treatment bins and the outcome variable is the natural log of alcohol-impaired traffic fatalities. Specifically, we create three treatment groups: states that implemented any tax increase, states that increased taxes by \$0.05 or more, and states that increased taxes by \$0.10 or more.[9] By categorizing the continuous treatment into multiple binary groups, we are able to apply the new difference-in-differences estimators, which are typically designed for binary treatments, to our continuous treatment setting (Callaway et al. 2024).

4.3 Other modeling specifications

As noted, prior work has resulted in mixed results that have led to a largely unchanged alcohol policy landscape. In an effort to replicate prior work, we recreate models used in previous literature which transform the count fatality measure to a rate. Specifically, numerous models are estimated with alcohol-related, alcohol-impaired, and overall traffic

[9]The states of New York, Hawaii, and Washington have both increased and decreased their alcohol excise taxes during the sample period. We exclude these states from the model because they violate the once treated, always treated assumption and can bias our estimates (Callaway and Sant'Anna 2021).

fatalities per 100 million VMT and 100,000 population as outcome variables. For these models, a TWFE specification with state and year fixed effects is used, with and without state-specific time trends.

5 Results

5.1 Main results

Summary statistics for the constructed dataset are presented in Table 1. On average, state excise taxes were \$0.38 per gallon of beer, adjusted to 2019 dollars. Real beer taxes and alcohol-impaired traffic fatalities have both trended downward since 1990, although the decrease in beer excise taxes was small in magnitude. On average, beer excise taxes decreased by about \$0.16 per gallon from 1990 to 2019—about half a cent per year.[10]

Table 2 presents the results of six models estimated using Equation 1. In these models the outcome variable is the count of alcohol-impaired traffic fatalities, and in each model, we progressively add state, year, alcohol controls[11] and control for non-alcohol-related traffic fatalities.[12] Column 6 presents the fully saturated model and is our preferred specification.

In all model specifications a negative and statistically significant impact of beer taxes on alcohol-impaired fatalities is found. Our preferred estimates in column 6 produce a point estimate of -.182, which is significant at the one percent level. Coefficients from this Poisson specification can be interpreted as a \$0.10 increase in beer excise taxes results in a 1.82% decrease of alcohol-impaired traffic fatalities per state per year, all else equal.

[10]The national average beer excise tax per gallon was approximately \$0.47 in 1990 and \$0.31 in 2019.

[11]Alcohol controls include seatbelt laws, texting while driving bans, graduated licensing laws, zero tolerance laws, the presence of BAC 0.08 laws, and the presence of vertical ID laws.

[12]Table A2 in the appendix presents the same estimations for alcohol-related traffic fatalities rather than alcohol-impaired traffic fatalities, with similar results.

5.2 Heterogenous effects

5.2.1 Time of day and week

Table 3 presents the results of models estimated conditioned by time of day and outcome variable. Different models are estimated with the dependent variable restricted to nighttime, daytime, and weekend night alcohol impaired traffic fatalities. The upper panel (panel a) of table 3 presents results estimated without state time trends, and the lower panel (panel b) presents the results after the inclusion of state time trends.

The results from Table 3 show consistent evidence that beer taxes reduce alcohol-impaired fatalities across time periods both with and without state-specific time trends. Estimates are generally consistent with estimates from Table 2. Interestingly, alcohol taxes had a relatively similar effect for both daytime and nighttime fatalities. Recall that Poisson estimates are in percentage terms, so alcohol taxes still had a larger impact on the total number of nighttime fatalities.

5.2.2 Age distribution

Table 4 presents the results of Poisson models estimated conditioned on age. Age is broken into seven different groups: (1) 17 and under, (2) 18 to 20, (3) 21 to 25, (4) 26 to 30, (5) 31 to 40, (6) 41 to 64, (7) 65 and over. The top panel (panel a) of Table 4 presents the estimates without time trends, and the lower panel (panel b) presents the estimates with state-specific linear time trends.

Overall, negative and economically meaningful point estimates are estimated for all age groups. Models that do not include time trends (panel a) produce statistically significant estimates across all age distributions. Models that include time trends find similar results; however, in these models beer taxes are less precise for motorists under 17, motorists between 21 and 25 and motorists over 65. Smaller and imprecise point estimates for younger and older motorists generally make sense. Individuals under 17 are not close to the legal drinking age and often lack driver's licenses.[13] Motorists over 65 exhibit less drinking and driving behavior and perhaps have consumption patterns that are less likely to change (Nelson and McNall 2017). A more unexpected result is the loss of significance of the 21 to 25 age group for the model estimated with state-specific linear time trends. This is a group that was expected to be highly impacted by alcohol taxes, as they are of age to drink, but are younger with likely lower incomes, thus perhaps more responsive to price changes. However, the point estimate is not lower, it is just less precisely estimated. Also, while the point estimate is not significant at traditional levels, the p-value for this estimate is 0.142.

5.3 Dynamic TWFE estimators

Figure 1 presents the dynamic event study estimators from Callaway and Sant'Anna (2021). Recall that to estimate these models, three binary treatment variables were created. The first variable takes a value of one if a state implements any tax increase in a given year. The second takes a value of one if the tax increase is \$0.05 or more, and the third takes a value of one if the tax increase is \$0.10 or more. These distinct treatment variables allow us to explore the dynamic effects of varying levels of tax increases on outcomes over time.

As seen in figure 1, states that increased their beer excise taxes by more than \$0.10 experience a significant decrease in alcohol-impaired traffic fatalities after the tax increase. The effects of any tax increase and increases of more than \$0.05 are not statistically significant. Callaway and Sant'Anna (2021) estimate and average treatment effect on the treated (ATT) of -0.053 for any increase, -0.055 for increases of \$0.05 and more, and a significant ATT of -0.16 for \$0.10 and more. The only significant decrease is the one associated with states who have increased their taxes by \$0.10 and more, significant at the 1% level. This suggests that states that increase their beer tax by \$0.10 or more reduce their alcohol-impaired traffic fatalities by approximately 15% in a given year. This is a large effect size compared to our main estimates which likely arises from the binary treatment variable used in these models.

[13] Dee (1999) also argues that beer taxes have a relatively small and statistically insignificant impact on teen drinking.

For the \$0.10 or more increase, the pre-treatment period shows no significant trends, supporting the parallel trends assumption and strengthening credibility to the interpretation of the post-treatment effects. The pre-trends for the any increase and the \$0.05 or more increase treatments show some minor but mostly insignificant variations.

For the any increase and the \$0.05 or more increase variables, although not statistically significant, the estimates suggest an approximate 5.2% and 5.3% reduction in alcohol-impaired traffic fatalities in a given year. This indicates that our Poisson estimates may be weighted down in the main model by states with minimal tax increases that might not meaningfully affect consumption patterns. In addition, since only nine states in the sample period have implemented a \$0.10 or more increase, the \$0.10 model may also be overestimating the impact of beer taxes on fatalities.[14] Although Callaway and Sant'Anna (2021) estimates support the direction of our findings (i.e. the decrease in fatalities), it is not our preferred methodological approach due to the potential overestimation.[15]

5.4 Other modeling specifications

In our main specification we use a Poisson model, which is commonly used in recent studies using panel-level traffic fatality data, and which we believe fits the data the best. However, one remaining question is why the prior literature finds such inconsistent results for the impact of alcohol taxes. In this section, we re-estimate different types of models that were used in prior work. Notably, quite a few prior studies used TWFE models that transformed the dependent variable to a ratio or rate. Also, numerous outcome variables have been used. To replicate these studies, we estimate models with alcohol-impaired and alcohol-related traffic fatalities per 100,000 population and 100 million VMT as outcome variables, along with overall traffic fatalities per 100,000 population and 100 million VMT. Also, models are estimated with state-specific time trends both included and excluded.

[14]Table A1 in the appendix presents all the states who have increased their beer taxes during our sample period.

[15]We also estimate the model after dropping all states with multiple tax increases or decreases and find consistent results. These estimates are presented in Figure A1 in the appendix.

Figure 2 presents TWFE coefficient estimates for beer taxes using various outcomes and specifications across four panels. Models on the left-hand side use 100,00 population as the denominator for the dependent variable ratio and models on the right-hand side use vehicle miles traveled as the denominator. Models presented in blue represent models estimated for alcohol-related fatalities, models presented in red represent models estimated for alcohol-impaired fatalities and models presented in green represent models estimated for all types of traffic fatalities (both alcohol-related and non-alcohol-related). Also, the models on the top panel are estimated without time trends and the bottom panel are estimated with time trends, all models include state and year fixed effects. The figure displays p-values, and 95% and 90% confidence intervals. The 95% confidence intervals are shown with solid lines, while the 90% confidence intervals are delimited by capped spikes.

All models without state-specific time trends estimate a negative and strongly statistically significant relationship between beer taxes and both alcohol-related and alcohol-impaired fatalities. When state-specific time trends are included, results are no longer significant at conventional levels. This is likely what has driven the mixed narrative surrounding the effectiveness of beer taxes. However, even when using state-specific time trends, models estimated with alcohol-impaired and alcohol-related fatalities have p-values in the range of .110 to .129, which is close to conventional significance levels. Also, in these models point estimates remain economically meaningful. For instance, it is estimated relatively consistently that a $0.10 increase in beer taxes would result in a reduction of approximately 0.1 deaths per hundred thousand population or 0.01 deaths per hundred million vehicle miles traveled. This translates to an estimated reduction of about 328 fatalities nationally in 2019.

Another important thing to note from Figure 2, is that in models estimated with total fatalities (not alcohol-related or alcohol-impaired) statistical significance is diminished even further. When studying the impact of alcohol policies, total fatalities will be a noisier outcome variable, thus it makes sense that significance is weaker using this outcome variable. Historically, it was more common to use total fatalities as an outcome variable before alcohol-related and alcohol-impaired data were more readily available, which could also be a cause for the mixed narrative surrounding the effectiveness of beer taxes.

6 Discussion

In this paper, we find robust evidence that beer taxes are associated with reduced alcohol-impaired traffic fatalities. To contextualize our results, we analyze the effect a \$0.10 increase in per-gallon beer excise taxes would have on alcohol-impaired traffic fatalities. On average, states impose a \$0.37 tax per gallon of beer, which makes \$0.10 a feasible increase. Using our parameter estimates from our empirical model, a \$0.10 increase is associated with a 1.82% reduction of alcohol-impaired fatalities nationally. In 2019, this would have represented a reduction of approximately 186 alcohol-impaired traffic fatalities in the US.

We also perform heterogeneity tests across different times of day and week and different age distributions. We find that an increase in beer taxes reduces all types of alcohol-related traffic fatalities regardless of the time of day or week, with nighttime alcohol-related traffic fatalities seeing the largest impact. We also find that an increase in beer taxes reduces alcohol-impaired traffic fatalities across all age distributions, with some age groups sensitive to the introduction of state-specific time trends. We also estimate dynamic event-study models following the specifications published by Callaway and Sant'Anna (2021), which estimate a negative and statistically significant impact of \$0.10 beer taxes on alcohol-impaired traffic fatalities. This method is more robust to staggered treatment timing and heterogenous treatment effects but is designed for dichotomous treatment variables. To adapt it to our continuous treatment setting, we employ a binning strategy by creating distinct binary treatment groups based on tax increase thresholds (Callaway et al. 2024). Specifically, we classify states into groups that experienced any tax increase, those with an increase of \$0.05 or more, and those with an increase of \$0.10 or more. To our knowledge, we are the first to apply these methods to study the impact of beer taxes on alcohol-impaired traffic fatalities.

In our main Poisson regressions, we consistently estimate that beer taxes significantly reduce alcohol-impaired traffic fatalities. This is somewhat different from the previous beer tax literature, which has produced mixed findings. To better understand the reasons for this difference, we replicate prior studies that have used TWFE models that transform outcome variables to ratios of population and vehicle miles traveled. Parameter estimates in TWFE models with state-specific time trends are insignificant at traditional levels. But parameters are economically meaningful, with p-values slightly above the ten percent significant threshold. It is surprising that these results alone caused such ambiguity in the prior beer tax literature. Also, models estimated with total fatalities as the outcome variable (rather than alcohol-related or alcohol-impaired fatalities) are noisier and less significant, which could also have played a role. Nonetheless, in our updated Poisson estimates, results are largely robust to modeling specification and the inclusion of state specific time trends. Also, results are largely significant for different days, times, and age categories. As traffic fatalities are a count outcome by nature, we believe Poisson models are a better choice than TWFE for empirically estimating the impact of beer taxes on alcohol-impaired fatalities. Overall, it is our recommendation for future research to utilize count models, such as the FEP model, to more accurately capture the dynamics of traffic fatalities.

7 Conclusion

Our study provides strong and robust evidence that an increase in beer excise taxes significantly reduces alcohol-impaired traffic fatalities, potentially saving hundreds of lives in the United States. Estimates suggest that a \$0.10 beer tax increase is associated with a reduction of 1.82% of alcohol-impaired fatalities per state, per year. Overall, alcohol taxes may be associated with other positive and negative effects, but these results provide motivation for a renewed discussion of state-level alcohol tax increases.

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Tables

Table 1: Summary Statistics

Variable	Obs	Mean	SD	Min	Max
Traffic fatalities					
Alcohol-related (AR)	1,530	320.32	354.11	5	2,697
Alcohol-impaired (AI)	1,530	243.03	264.71	3	2,036
Traffic fatalities by time of day and week					
Nighttime AI	1,530	186.40	207.06	2	1,541
Daytime AI	1,530	53.44	56.40	0	457
Weekend nighttime AI	1,530	133.95	129.15	1	964
Daytime non-AI	1,530	301.91	289.23	4	1,696
Weekday non-AI	1,530	315.92	314.72	6	1,762
Traffic fatalities by age distribution					
AI 17 and under	1,524	14.36	19.02	0	154
AI 18 to 20	1,526	21.50	25.30	0	224
AI 21 to 25	1,530	43.50	48.99	0	464
AI 26 to 30	1,530	32.29	36.51	0	333
AI 31 to 40	1,529	51.21	56.04	0	423
AI 41 to 64	1,530	65.78	70.40	0	480
AI 65 and older	1,530	14.27	17.05	0	152
Explanatory variables					
Beer tax	1,530	0.37	0.35	0.02	2.05
Unemployment rate	1,530	5.50	1.87	2.10	13.80
Share of population 15 to 24	1,530	0.14	0.01	0.10	0.20
Share of population 65+	1,530	0.13	0.02	0.04	0.21
Income per capita per 1,000	1,530	34.93	12.18	13.36	84.67
Gasoline tax rate	1,530	29.81	10.03	2.27	95.02
Population per 100,000	1,530	57.19	64.26	4.53	394.38
Vehicle miles traveled (VMT) per 10,000	1,530	5.50	5.75	0.33	34.88
Non-alcohol-related fatalities	1,530	448.20	447	10	2,595
Mandatory seatbelt law	1,530	0.95	0.22	0	1
Texting ban law	1,530	0.30	0.46	0	1
BAC 0.08	1,530	0.69	0.46	0	1
Zero tolerance law	1,530	0.83	0.37	0	1
Graduated Driver's License Law	1,530	0.68	0.47	0	1
Vertical ID law	1,530	0.47	0.50	0	1
Minimum wage	1,530	6.68	2.88	0	14
Medical marijuana legislation	1,530	0.22	0.43	0	1
Recreational marijuana legislation	1,530	0.03	0.17	0	1

Note. Each observation represents a state-year. This dataset contains FARS data from 1990 to 2019 from the 50 states and the District of Columbia. The dataset was combined with data from the National Highway Traffic and Safety Administration, Urban-Bookings Tax Policy Center, the U.S. Bureau of Labor Statistics, Bureau of Economic Analysis, Department of Transportation, Census Bureau, Michigan State University's Correlates of State Policy, Nesson and Shrestha (2021), and Mathur and Ruhm (2023). The beer excise tax, the gasoline tax rate and the minimum wage have been adjusted for inflation and are presented in 2019 dollars.

Table 2: The effect of beer taxes on alcohol-impaired (BAC 0.08+) traffic fatalities

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Beer tax	-0.292***	-0.243***	-0.249***	-0.193***	-0.247***	-0.182***
	(0.107)	(0.0624)	(0.0620)	(0.0487)	(0.0638)	(0.0478)
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State controls	NO	YES	YES	YES	YES	YES
Alcohol controls	NO	NO	YES	YES	YES	YES
Non-AR traffic fatalities	NO	NO	NO	NO	YES	YES
State time trends	NO	NO	NO	YES	NO	YES
N	1530	1530	1530	1530	1530	1530

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note. This dataset contains FARS data from 1990 to 2020. The dataset was combined with data from National Highway Traffic and Safety Administration, Urban-Bookings Tax Policy Center, the U.S. Bureau of Labor Statistics, Bureau of Economic Analysis, Department of Transportation, Census Bureau, Michigan State University's Correlates of State Policy, Nesson and Shrestha (2021), and Mathur and Ruhm (2023). State controls include the unemployment rate, the natural log of population, the natural log of vehicle miles traveled, the share of the population aged 15-24 and 65+, the natural log of income per capita, the real gasoline tax rate, the real minimum wage, and an indicator variable for medical and recreational marijuana legislation. Only columns (5) and (6) control for the natural log of non-alcohol-related traffic fatalities. Alcohol controls include seatbelt laws, texting while driving bans, graduated licensing laws, zero tolerance laws, the presence of BAC 0.08 laws, and the presence of vertical ID laws. The outcome variable is the count of alcohol-impaired traffic fatalities. All specifications include state and year fixed effects. Standard errors are clustered at the state level.

Table 3: The impact of beer taxes on alcohol-impaired and non-alcohol-related traffic fatalities by time of day and week

VARIABLES	Nighttime	Daytime	Weekend nighttime
Panel a: without time trends			
Beer tax	-0.258***	-0.221**	-0.240***
	(0.0707)	(0.0880)	(0.0697)
Panel b: with time trends			
Beer tax	-0.166***	-0.239***	-0.161***
	(0.0543)	(0.0369)	(0.0499)
N	1530	1530	1530

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note. This dataset contains FARS data from 1990 to 2020. The dataset was combined with data from National Highway Traffic and Safety Administration, Urban-Bookings Tax Policy Center, the U.S. Bureau of Labor Statistics, Bureau of Economic Analysis, Department of Transportation, Census Bureau, Michigan State University's Correlates of State Policy, Nesson and Shrestha (2021), and Mathur and Ruhm (2023). State controls include the unemployment rate, the natural log of population, the natural log of vehicle miles traveled, the share of the population aged 15-24 and 65+, the natural log of income per capita, the real gasoline tax rate, the real minimum wage, and an indicator variable for medical and recreational marijuana legislation, and the natural log of (nighttime, daytime, and weekend nighttime) non-alcohol-related traffic fatalities. Alcohol controls include seatbelt laws, texting while driving bans, graduated licensing laws, zero tolerance laws, the presence of BAC 0.08 laws, and the presence of vertical ID laws. Outcome variables are the counts of alcohol-related traffic fatalities for different times of day and week: (1) alcohol-impaired nighttime traffic fatalities, (2) alcohol-impaired daytime traffic fatalities, and (3) alcohol-impaired weekend nighttime traffic fatalities. All specifications (panels a and b) include state socioeconomic controls, alcohol controls, and state and year fixed effects. Specifications in panel b also include state specific linear time trends. Standard errors are clustered at the state level.

Table 4: The effect of beer taxes on alcohol-impaired traffic fatalities by age distribution

VARIABLES	≤ 17	18–20	21–25	26–30	31–40	41–64	65+
Panel a: without time trends							
Beer Tax	-0.220*	-0.213**	-0.202***	-0.256***	-0.252***	-0.154**	-0.198***
	(0.125)	(0.0944)	(0.0689)	(0.0935)	(0.0740)	(0.0690)	(0.0745)
Panel b: with time trends							
Beer Tax	-0.0176	-0.200**	-0.226	-0.261**	-0.179***	-0.120**	-0.129
	(0.119)	(0.0813)	(0.142)	(0.125)	(0.0418)	(0.0582)	(0.100)
N	1524	1523	1530	1530	1529	1530	1530

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note. This dataset contains FARS data from 1990 to 2020. The dataset was combined with data from National Highway Traffic and Safety Administration, Urban-Bookings Tax Policy Center, the U.S. Bureau of Labor Statistics, Bureau of Economic Analysis, Department of Transportation, Census Bureau, Michigan State University's Correlates of State Policy, Nesson and Shrestha (2021), and Mathur and Ruhm (2023). State controls include unemployment rate, natural log of population of the respective age group, natural log of vehicles miles traveled, natural log of income per capita, real gasoline tax rate, natural log of non-alcohol-related traffic fatalities (by respective age groups) and real minimum wage. Alcohol controls include seatbelt laws, texting while driving bans, graduated licensing laws, zero tolerance laws, the presence of BAC 0.08 laws, and the presence of vertical ID laws. The outcome variables are the counts of alcohol-impaired traffic fatalities for different age distributions: (1) 17 and under (2) 18–20 (3) 21–25 (4) 26–30 (5) 31–40 (6) 41–64 (7) 65+. All specifications (panels a and b) include state socioeconomic controls, alcohol controls, and state and year fixed effects. All the specifications in panel b also include state specific linear time trends. Standard errors are clustered at the state level.

Figures

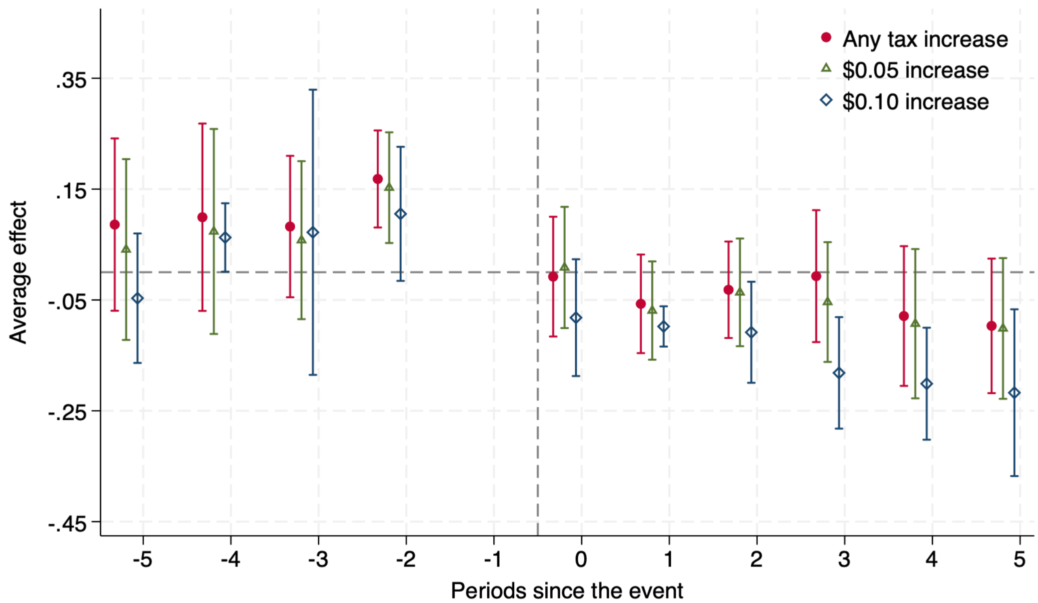

Figure 1: Callaway and Sant'Anna (2021) dynamic event study estimators for alcohol-impaired traffic fatalities

Note. Three distinct binary treatment variables: any tax increase (red dots), a tax increase of \$0.05 or more (green triangles), and a tax increase of \$0.10 or more (blue diamonds). Each point represents an event study coefficient estimate of the impact of these treatments on alcohol-impaired traffic fatalities, with capped lines indicating the 95% confidence intervals.

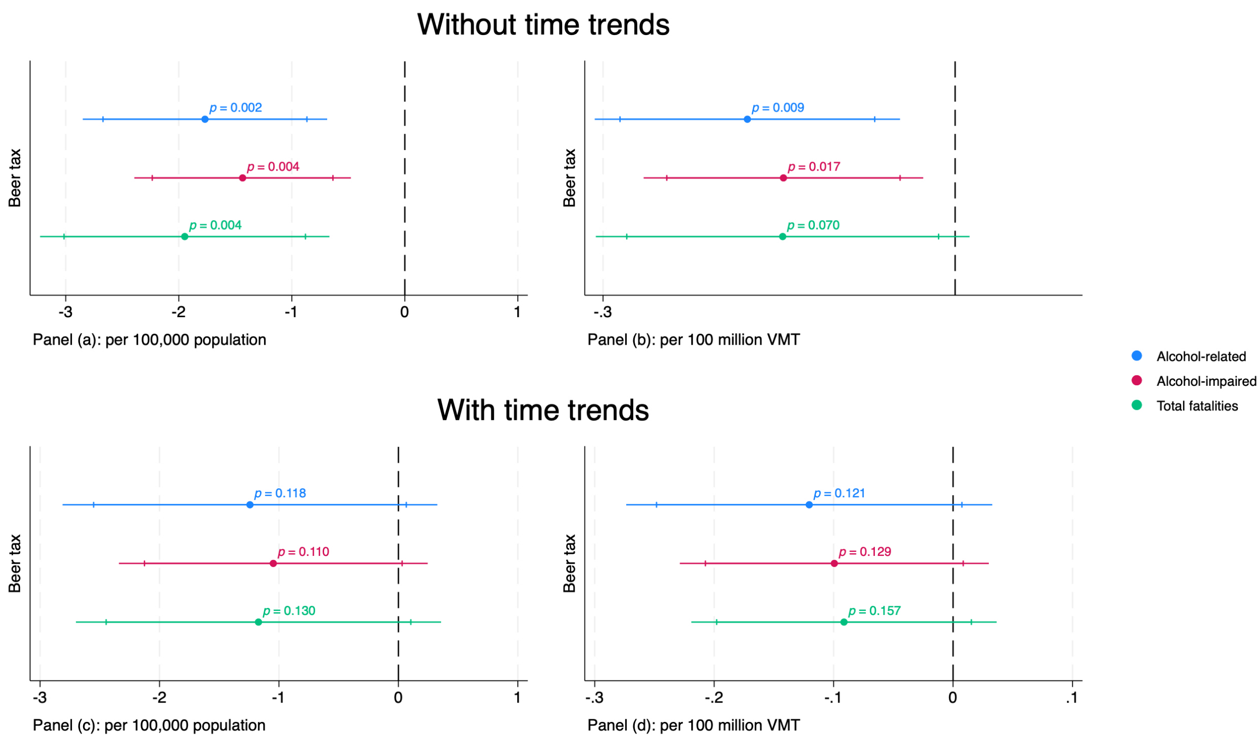

Figure 2: Effect of beer taxes on different fatality rates

TWFE coefficient estimates with and without time trends. Panels a and c use 100,000 population as the denominator for the dependent variable ratio, while panels b and d use vehicle miles traveled. Models in blue represent alcohol-related fatalities, red models represent alcohol-impaired fatalities, and green models represent all types of traffic fatalities (both alcohol-related and non-alcohol-related). Panel a displays models estimated without time trends, while the panel b includes time trends. All models control for state and year fixed effects. The figure also includes p-values and 95% (solid lines) and 90% (capped spikes) confidence intervals.

Appendix A.

Table A1: States that have changed beer excise taxes (1999-2019)

State	FIPS	Year of change	Tax change
Less than $0.05			
Hawaii	15	1997	\$0.01 ↑
Hawaii	15	1998	\$0.01 ↑
Hawaii	15	1999	\$0.01 ↑
New York	36	1999	\$0.025 ↓
New York	36	2002	\$0.01 ↓
New York	36	2004	\$0.01 ↓
New York	36	2010	\$0.03 ↑
Rhode Island	44	2014	\$0.009 ↑
Rhode Island	44	2015	\$0.002 ↑
Tennessee	47	2003	\$0.01 ↑
Washington	53	1993	\$0.03 ↑
Washington	53	1995	\$0.05 ↑
\$0.05-\$0.10			
Connecticut	9	2012	\$0.05 ↑
Delaware	10	1991	\$0.10 ↑
Delaware	10	2019	\$0.10 ↑
Hawaii	15	1995	\$0.08 ↓
Hawaii	15	1996	\$0.09 ↑
Louisiana	22	2017	\$0.08 ↑
Nebraska	31	2004	\$0.08 ↑
Nevada	32	2004	\$0.07 ↑
New Jersey	34	1991	\$0.06 ↑
New Jersey	34	1993	\$0.02 ↑
New Mexico	35	1995	\$0.06 ↑
New York	36	1991	\$0.10 ↑
New York	36	1996	\$0.05 ↓
North Carolina	37	2010	\$0.08 ↑
North Dakota	38	1993	\$0.07 ↑
Utah	49	2004	\$0.05 ↑
Washington	53	1997	\$0.08 ↑
Washington	53	1998	\$0.05 ↓
More than \$0.10			
Alaska	2	2003	\$0.72 ↑
California	6	1992	\$0.16 ↑
Illinois	17	2000	\$0.16 ↑
New Mexico	35	1994	\$0.17 ↑
Tennessee	47	2014	\$1.01 ↑
Tennessee	47	2017	\$0.14 ↑
Washington	53	2011	\$0.50 ↑
Washington	53	2014	\$0.50 ↓

Table A2: The effect of beer taxes on alcohol-related traffic fatalities

VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Beer tax	-0.285***	-0.223***	-0.228***	-0.164***	-0.226***	-0.154***
	(0.101)	(0.0562)	(0.0556)	(0.0366)	(0.0573)	(0.0371)
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State controls	NO	YES	YES	YES	YES	YES
Alcohol controls	NO	NO	YES	YES	YES	YES
Non-AR traffic fatalities	NO	NO	NO	NO	YES	YES
State time trends	NO	NO	NO	YES	NO	YES
N	1530	1530	1530	1530	1530	1530

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note. This dataset contains FARS data from 1990 to 2020. The dataset was combined with data from National Highway Traffic and Safety Administration, Urban-Bookings Tax Policy Center, the U.S. Bureau of Labor Statistics, Bureau of Economic Analysis, Department of Transportation, Census Bureau, Michigan State University's Correlates of State Policy, Nesson and Shrestha (2021), and Mathur and Ruhm (2023). State controls include the unemployment rate, the natural log of population, the natural log of vehicle miles traveled, the share of the population aged 15-24 and 65+, the natural log of income per capita, the real gasoline tax rate, the real minimum wage, and an indicator variable for medical and recreational marijuana legislation. Only columns (5) and (6) control for the natural log of non-alcohol-related traffic fatalities. Alcohol controls include seatbelt laws, texting while driving bans, graduated licensing laws, zero tolerance laws, the presence of BAC 0.08 laws, and the presence of vertical ID laws. The outcome variable is the count of alcohol-impaired traffic fatalities. All specifications include state and year fixed effects. Standard errors are clustered at the state level.

Table A3: The effect of beer taxes on alcohol-impaired (BAC 0.08+) traffic fatalities using a log linear model

VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Beer tax	-0.252***	-0.268***	-0.269***	-0.213***	-0.272***	-0.217**
	(0.0772)	(0.0723)	(0.0723)	(0.0765)	(0.0726)	(0.0845)
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State controls	NO	YES	YES	YES	YES	YES
Alcohol controls	NO	NO	YES	YES	YES	YES
Non-AR traffic fatalities	NO	NO	NO	NO	YES	YES
State time trends	NO	NO	NO	YES	NO	YES
N	1530	1530	1530	1530	1530	1530

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note. This dataset contains FARS data from 1990 to 2020. The dataset was combined with data from National Highway Traffic and Safety Administration, Urban-Bookings Tax Policy Center, the U.S. Bureau of Labor Statistics, Bureau of Economic Analysis, Department of Transportation, Census Bureau, Michigan State University's Correlates of State Policy, Nesson and Shrestha (2021), and Mathur and Ruhm (2023). State controls include the unemployment rate, the natural log of population, the natural log of vehicle miles traveled, the share of the population aged 15-24 and 65+, the natural log of income per capita, the real gasoline tax rate, the real minimum wage, and an indicator variable for medical and recreational marijuana legislation. Only columns (5) and (6) control for the natural log of non-alcohol-related traffic fatalities. Alcohol controls include seatbelt laws, texting while driving bans, graduated licensing laws, zero tolerance laws, the presence of BAC 0.08 laws, and the presence of vertical ID laws. The outcome variable is the natural log of the count of alcohol-impaired traffic fatalities. All specifications include state and year fixed effects. Standard errors are clustered at the state level.

Table A4: Marginal effects of beer taxes on alcohol-impaired (BAC 0.08+) traffic fatalities

VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Beer tax	-70.91***	-59.09***	-60.46***	-46.98***	-60.01***	-44.33***
	(26.11)	(15.18)	(15.06)	(11.82)	(15.50)	(11.61)
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State controls	NO	YES	YES	YES	YES	YES
Alcohol controls	NO	NO	YES	YES	YES	YES
Non-AR traffic fatalities	NO	NO	NO	NO	YES	YES
State time trends	NO	NO	NO	YES	NO	YES
N	1530	1530	1530	1530	1530	1530

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

This dataset contains FARS data from 1990 to 2020. The dataset was combined with data from National Highway Traffic and Safety Administration, Urban-Bookings Tax Policy Center, the U.S. Bureau of Labor Statistics, Bureau of Economic Analysis, Department of Transportation, Census Bureau, Michigan State University's Correlates of State Policy, Nesson and Shrestha (2021), and Mathur and Ruhm (2023). State controls include the unemployment rate, the natural log of population, the natural log of vehicle miles traveled, the share of the population aged 15-24 and 65+, the natural log of income per capita, the real gasoline tax rate, the real minimum wage, and an indicator variable for medical and recreational marijuana legislation. Only columns (5) and (6) control for the natural log of non-alcohol-related traffic fatalities. Alcohol controls include seatbelt laws, texting while driving bans, graduated licensing laws, zero tolerance laws, the presence of BAC 0.08 laws, and the presence of vertical ID laws. The outcome variable is the count of alcohol-impaired traffic fatalities. All specifications include state and year fixed effects. Standard errors are clustered at the state level.

Table A5: The marginal effect of beer taxes on alcohol-related and non-alcohol-related traffic fatalities by time of day and week

VARIABLES	Nighttime	Daytime	Weekend Nighttime
Panel A: Without time trends			
Beer tax	-48.00***	-11.81**	-27.30***
	(13.17)	(4.702)	(7.939)
Panel B: With time trends			
Beer tax	-30.93***	-12.77***	-18.40***
	(10.12)	(1.974)	(5.683)
N	1530	1530	1530

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

This dataset contains FARS data from 1990 to 2020. The dataset was combined with data from National Highway Traffic and Safety Administration, Urban-Bookings Tax Policy Center, the U.S. Bureau of Labor Statistics, Bureau of Economic Analysis, Department of Transportation, Census Bureau, Michigan State University's Correlates of State Policy, Nesson and Shrestha (2021), and Mathur and Ruhm (2023). State controls include the unemployment rate, the natural log of population, the natural log of vehicle miles traveled, the share of the population aged 15-24 and 65+, the natural log of income per capita, the real gasoline tax rate, the real minimum wage, and an indicator variable for medical and recreational marijuana legislation, and the natural log of (nighttime, daytime, and weekend nighttime) non-alcohol-related traffic fatalities. Alcohol controls include seatbelt laws, texting while driving bans, graduated licensing laws, zero tolerance laws, the presence of BAC 0.08 laws, and the presence of vertical ID laws. Outcome variables are the counts of alcohol-related traffic fatalities for different times of day and week: (1) alcohol-impaired nighttime traffic fatalities, (2) alcohol-impaired daytime traffic fatalities, and (3) alcohol-impaired weekend nighttime traffic fatalities. All specifications (panels a and b) include state socioeconomic controls, alcohol controls, and state and year fixed effects. All the specifications in panel b also include state specific linear time trends. Standard errors are clustered at the state level.

Table A6: The marginal effects of beer taxes on alcohol-impaired traffic fatalities by age distribution

VARIABLES	≤ 17	18–20	21–25	26–30	31–40	41–64	65+
Panel A: Without time trends							
Beer Tax	-3.157*	-4.592**	-8.799***	-8.254***	-12.91***	-10.14**	-2.820***
	(1.796)	(2.032)	(2.995)	(3.017)	(3.792)	(4.540)	(1.064)
Panel B: With time trends							
Beer Tax	-0.253	-4.298**	-9.832	-8.413**	-9.170***	-7.915**	-1.840
	(1.703)	(1.750)	(6.161)	(4.037)	(2.140)	(3.828)	(1.431)
N	1524	1523	1530	1530	1529	1530	1530

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

This dataset contains FARS data from 1990 to 2020. The dataset was combined with data from National Highway Traffic and Safety Administration, Urban-Bookings Tax Policy Center, the U.S. Bureau of Labor Statistics, Bureau of Economic Analysis, Department of Transportation, Census Bureau, Michigan State University's Correlates of State Policy, Nesson and Shrestha (2021), and Mathur and Ruhm (2023). State controls include unemployment rate, natural log of population of the respective age group, natural log of vehicles miles traveled, natural log of income per capita, real gasoline tax rate, natural log of non-alcohol-related traffic fatalities (by respective age groups) and real minimum wage. Alcohol controls include seatbelt laws, texting while driving bans, graduated licensing laws, zero tolerance laws, the presence of BAC 0.08 laws, and the presence of vertical ID laws. The outcome variables are the counts of alcohol-impaired traffic fatalities for different age distributions: (1) 17 and under, (2) 18-20, (3) 21-25, (4) 26-30, (5) 31-40, (6) 41-64, (7) 65+. All specifications (panels a and b) include state socioeconomic controls, alcohol controls, and state and year fixed effects. All the specifications in panel b also include state specific linear time trends. Standard errors are clustered at the state level.

Table A7: The effect of beer taxes on alcohol-impaired (BAC 0.08+) traffic fatalities (all covariates)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Beer tax	-0.292***	-0.243***	-0.249***	-0.193***	-0.247***	-0.182***
	(0.107)	(0.0623)	(0.0620)	(0.0487)	(0.0638)	(0.0478)
Unemployment rate		-0.00542	-0.00729	-0.00553	-0.00628	-0.00371
		(0.0102)	(0.0102)	(0.00868)	(0.00964)	(0.00822)
Share of population 15 to 24		6.112***	6.116***	5.875***	5.942***	5.213***
		(1.398)	(1.383)	(1.665)	(1.341)	(1.520)
Share of population 65+		1.215	1.075	-2.541	1.015	-3.253
		(1.722)	(1.890)	(4.979)	(1.972)	(4.926)
LN income per capita		1.016***	1.011***	1.181***	0.948***	1.024***
		(0.179)	(0.186)	(0.220)	(0.224)	(0.223)
Gasoline tax		-0.000790	-0.000845	-0.000433	-0.000877	-0.000481
		(0.000687)	(0.000607)	(0.00100)	(0.000596)	(0.000984)
LN Population		0.651***	0.656***	-0.0707	0.614***	-0.210
		(0.157)	(0.164)	(0.621)	(0.170)	(0.584)
LN VMT		0.209	0.186	0.245	0.146	0.227
		(0.150)	(0.142)	(0.206)	(0.157)	(0.205)
Medical marijuana legislation		-0.0901***	-0.0944***	-0.0660	-0.0904***	-0.0646
		(0.0345)	(0.0351)	(0.0445)	(0.0333)	(0.0403)
Rec. marijuana legislation		0.0276	0.0301	0.125***	0.0289	0.112**
		(0.0545)	(0.0547)	(0.0448)	(0.0545)	(0.0493)
LN non-AR traffic fatalities				0.0850	0.165*	
				(0.0865)	(0.0957)	
Mandatory seatbelt law			0.00241	0.0594	0.00230	0.0671
			(0.0343)	(0.0496)	(0.0337)	(0.0493)
Texting while driving law			-0.0100	-0.00423	-0.00757	-0.00958
			(0.0296)	(0.0223)	(0.0303)	(0.0210)
DUI 0.08			-0.0213	-0.0205	-0.0238	-0.0252
			(0.0183)	(0.0165)	(0.0196)	(0.0167)
ZT laws			-0.0382	-0.0284	-0.0406	-0.0311
			(0.0288)	(0.0242)	(0.0299)	(0.0240)
Graduate driver license law			-0.0201	-0.00755	-0.0169	-0.00125
			(0.0272)	(0.0268)	(0.0263)	(0.0249)
Vertical ID law			-0.0245	-0.0486**	-0.0268	-0.0512**
			(0.0245)	(0.0227)	(0.0246)	(0.0227)
Minimum wage			-0.00291	-0.000992	-0.000714	-0.000919

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
			(0.00886)	(0.00866)	(0.00881)	(0.00794)

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Note. This dataset contains FARS data from 1990 to 2020. The dataset was combined with data from National Highway Traffic and Safety Administration, Urban-Bookings Tax Policy Center, the U.S. Bureau of Labor Statistics, Bureau of Economic Analysis, Department of Transportation, Census Bureau, Michigan State University's Correlates of State Policy, Nesson and Shrestha (2021), and Mathur and Ruhm (2023). Only columns (5) and (6) control for the natural log of non-alcohol-related traffic fatalities. The outcome variable is the count of alcohol-impaired traffic fatalities. All specifications include state and year fixed effects. Standard errors are clustered at the state level.

Table A8: The effect of beer taxes on alcohol-impaired (BAC 0.08+) traffic fatalities using non-imputed data

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Beer tax	-0.223**	-0.174***	-0.166***	0.00002	-0.164***	0.00605
	(0.0998)	(0.0577)	(0.0585)	(0.0537)	(0.0599)	(0.0527)
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
State controls	NO	YES	YES	YES	YES	YES
Alcohol controls	NO	NO	YES	YES	YES	YES
Non-AR traffic fatalities	NO	NO	NO	NO	YES	YES
State time trends	NO	NO	NO	YES	NO	YES
N	1530	1530	1530	1530	1530	1530
Pseudo R-squared	0.941	0.945	0.945	0.950	0.945	0.950

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
This dataset contains FARS data from 1990 to 2020. The dataset was combined with data from National Highway Traffic and Safety Administration, Urban-Bookings Tax Policy Center, the U.S. Bureau of Labor Statistics, Bureau of Economic Analysis, Department of Transportation, Census Bureau, Michigan State University's Correlates of State Policy, Nesson and Shrestha (2021), and Mathur and Ruhm (2023). State controls include the unemployment rate, the natural log of population, the natural log of vehicle miles traveled, the share of the population aged 15–24 and 65+, the natural log of income per capita, the real gasoline tax rate, the real minimum wage, and an indicator variable for medical and recreational marijuana legislation. Only columns (5) and (6) control for the natural log of non-alcohol-related traffic fatalities. Alcohol controls include seatbelt laws, texting while driving bans, graduated licensing laws, zero tolerance laws, the presence of BAC 0.08 laws, and the presence of vertical ID laws. The outcome variable is the count of alcohol-impaired traffic fatalities. All specifications include state and year fixed effects. Standard errors are clustered at the state level.

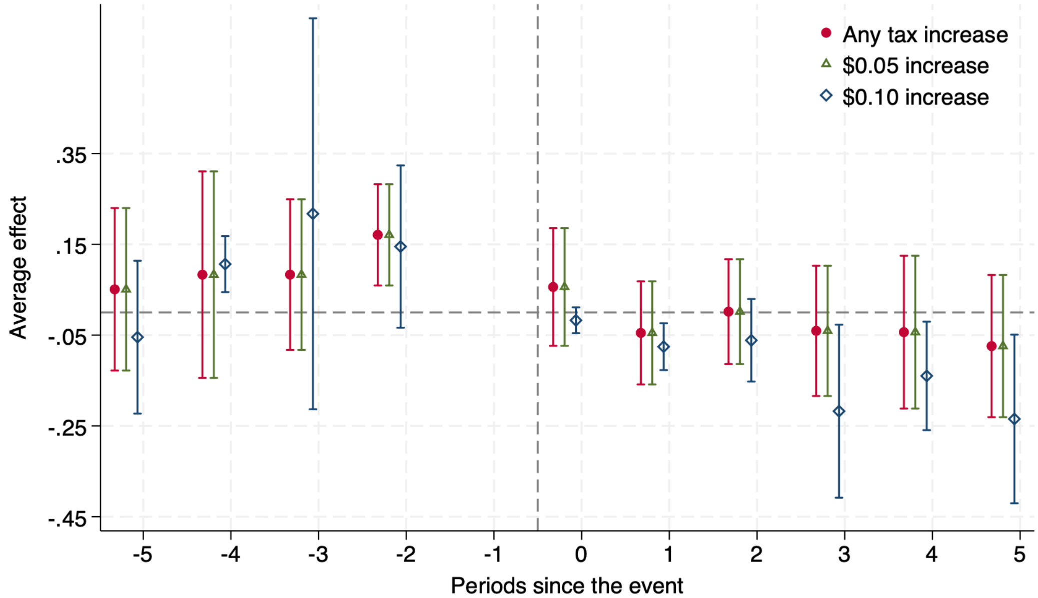

Figure A1: Callaway and Sant'Anna (2021) dynamic event study estimators for alcohol-related traffic fatalities

Note. Three distinct binary treatment variables: any tax increase (red dots), a tax increase of \$0.05 or more (green triangles), and a tax increase of \$0.10 or more (blue diamonds). Each point represents an event study coefficient estimate of the impact of these treatments on alcohol-impaired traffic fatalities, with capped lines indicating the 95% confidence intervals.

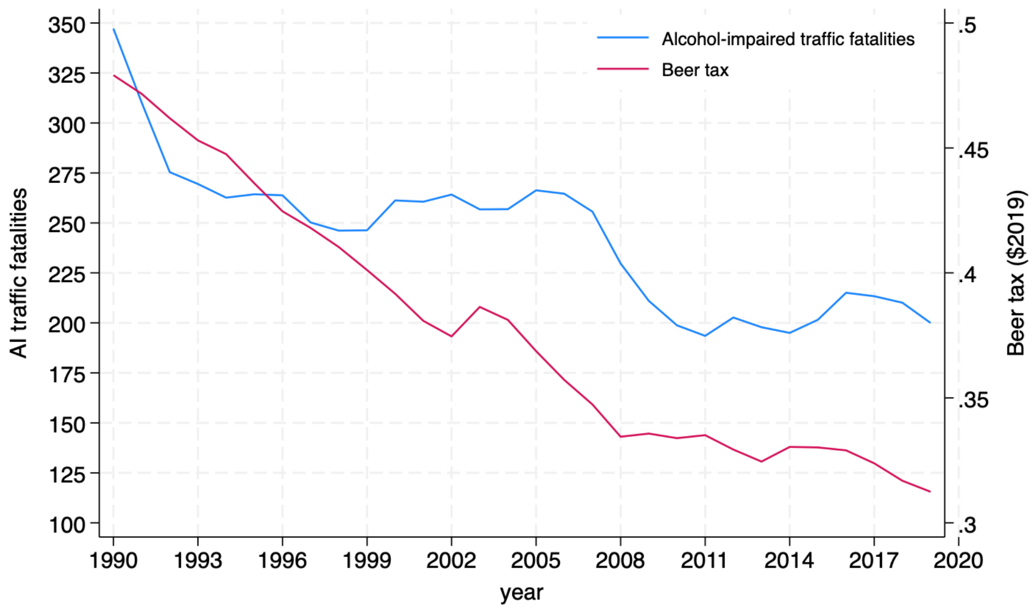

Figure A2: Beer taxes (right) and alcohol-impaired traffic fatalities (left) from 1990 to 2019