
Richard A. Dunn
University of Connecticut

Nathan W. Tefft
Bates College

Abstract: Drinking-and-driving remains a leading cause of preventable mortality and morbidity in the United States. For the past three decades, estimates of the prevalence of drinking-and-driving have come from survey-based instruments, most notably the National Roadside Survey (NRS), which seeks to ascertain the blood alcohol content (BAC) of a random sample of road users. Although subject to potential bias from non-random sample selection, the NRS field design overcomes the well-documented problem of systematic under-reporting of socially undesirable activity. Nonetheless, in 2015 the House of Representatives voted to prohibit the use of federal funds to plan or administer the NRS over concerns that drivers did not believe participation was truly voluntary. As a result, researchers and policy-makers currently lack reliable estimates of drinking-and-driving that can be compared to historic trends. Therefore, in this article, we apply methods introduced by Levitt and Porter (2001) to examine how the prevalence, relative risk, and externality of drinking-and-driving in the United States has evolved over the past three decades. Similar to previous versions of the NRS, we find that drinking-and-driving declined significantly between 1983 and 2007, but has since plateaued. Interestingly, the relative risk of drinking drivers has increased while the external social cost of their behavior has decreased, suggesting that ‘sober-biased technical change’ may have made all driving less dangerous, but had a smaller impact on drivers influenced by alcohol.
I. Introduction

Although deaths from motor vehicle crashes have fallen significantly over the past three decades, drinking and driving remains a leading cause of preventable mortality and morbidity in the United States. In 2016, there were 12,514 deaths in motor vehicle crashes involving at least one drinking driver, approximately one fatality every 50 minutes.¹

Reliable estimates of the prevalence and excess risk of drinking-and-driving are a high priority need for researchers and policy-makers. In this article, we apply methods originally introduced by Levitt and Porter (2001) and refined by Dunn and Tefft (2018) to examine how the prevalence, relative risk, and externality of drinking-and-driving in the United States has evolved over the past three decades using data on fatal motor vehicle crashes from the Fatality Analysis Reporting System (FARS).

Until recently, prevalence estimates were constructed primarily from the National Roadside Survey (NRS), which seeks to ascertain the blood alcohol content (BAC) of a random sample of road users. While the NRS field design overcomes the well-documented problem of systematic under-reporting of socially undesirable activity in other survey instruments (Lund and Wolfe, 1991; Voas, et al., 1998; Mullahy and Sindelar, 2007), there are several potential sources of bias from non-random selection into the NRS sample. Indeed, in their original study, Levitt and Porter (2001) estimate that the NRS may under-estimate prevalence by as much as two-hundred percent. In addition, the cost of planning and administering the NRS means that estimates are made available roughly once each decade at great expense. Thus, a cheaper, more timely approach to estimating prevalence and risk that was immune from sample selection bias and allowed for consistent measurement over time would be an important contribution to the research field.

Since 2015, however, the need for a new approach to estimating prevalence and risk has become even more pressing. In response to concerns that participation in the NRS may not appear voluntary to drivers, Congress prohibited the use of federal funds to plan or administer the NRS. Ironically, one of the principle complaints of civil rights advocates during Congressional testimony was the addition of a passive BAC testing procedure that was intended the help NRS researchers estimate the extent of selection bias. As a result, researchers and policy-makers currently lack reliable contemporary estimates of drinking-and-driving that can be compared to historic trends and have uncertain prospects about their availability in the future.

¹ Further, the age profile of motor vehicle crash fatalities is significantly younger than other leading causes of death. As a result, the CDC estimates that in 2013, 387 years of potential life before age 75 were lost for every 100,000 Americans because of injuries sustained in motor vehicle crashes compared to 952 years for heart disease, 1329 years for malignant neoplasms, and 158 years for cerebrovascular disease. Among males specifically, mortality from motor vehicle crashes accounted for more than eleven times as many years of potential life lost before age 75 than prostate cancer: 552 years versus 47 years per 100000 males under age 75. Among females, mortality from motor vehicle crashes accounted for nearly as many years of potential life lost before age 75 as breast cancer: 219 years versus 250 years per 100000 females under age 75.
Given this gap in public health surveillance, we revive methods first proposed by Levitt and Porter (2001, hereafter L&P) that estimate the prevalence and risk of drinking-and-driving using a statistical approach. Specifically, L&P demonstrated how a census of fatal motor vehicle crashes—data that is readily available in the United States from 1983 onwards through FARS—could be used to recover both the prevalence and relative risk of drinking and driving. By employing a census of crashes, their methods are not subject to the sources of sample selection and misreporting bias faced by survey instruments.

In a preview of our results, we find that the prevalence of drinking and driving has fallen significantly. Though this pattern is consistent with statistics generated from various survey-based approaches, we continue to find that rates of drinking and driving are substantially higher than those recovered from surveys, suggesting that selection and misreporting biases remain significant methodological challenges that researchers who adopt such data sources must address.

Further, at the same time that the prevalence of drinking and driving has decreased, we find that the relative risk of drinking drivers has increased. Given the overall decline in motor vehicle fatalities, this finding indicates that while driving has become much less dangerous over the past three decades, improvements in automobile technology, road design, and traffic enforcement have had proportionally larger effects on reducing the harm caused by non-drinking drivers. Despite the increase in relative risk, however, the externality imposed by drinking drivers on other road users has actually declined.

II. The National Roadside Survey

Surveys that rely on self-reported driving and driving behavior, e.g., the Behavioral Risk Factor Surveillance System (BRFSS), are considered unsuitable for the construction of reliable estimates of prevalence because respondents tend to underreport drinking and driving (Lund and Wolfe, 1991; Voas, et al., 1998; Mullahy and Sindelar, 2007). Furthermore, because the propensity to underreport likely varies across time, these data are also inappropriate for monitoring trends. In addition, survey respondents are typically unable to accurately assess their level of inebriation (Vogel-Sprott, 1975; Greenfield and Rogers, 1999; Johnson, et al., 2008), and thus estimating the prevalence of alcohol-impaired driving above specified thresholds is all but impossible.

The NRS was developed to overcome each of these challenges by periodically constructing a nationally representative random sample of drivers who are asked to provide breathalyzer and blood samples (Lund and Wolfe, 1991; Voas, et al., 1998; Zador, Krawchuk and Voas, 2000; Compton and Berning, 2009; Lacey, et al., 2009b; Voas, et al., 2012; Berning, Compton and Wochinger, 2015). Although the NRS overcomes the tendency of individuals to systematically under-report their alcohol-impaired driving behaviors by directly measuring BAC, drivers cannot be compelled to participate in the NRS, leading to potential sample selection bias.

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2 Because each NRS costs several million dollars, they are conducted infrequently (roughly once every decade: 1973, 1986, 1996, 2007, and 2013)
For example, in the 2007 NRS, 1016 of 9553 drivers that were signaled to enter the testing site at night did not do so (10.6%). And out of the 9553 drivers originally signaled, only 7159 voluntarily submitted to a valid breathalyzer exam (74.9%). If alcohol-impaired drivers are less likely to enter the NRS testing site and less likely to submit a breath sample, then prevalence rates will tend to be under-estimated and, as a result, the relative-risk of alcohol-impaired driving will be over-estimated.

The NRS research team has developed various strategies to impute the BAC level of drivers who refuse to participate, but these come with their own set of assumptions, most notably that drivers who choose not to enter the NRS testing site do not differ in BAC from those that do enter. Further, as strategies to improve participation and address driver selection are adopted and discarded, comparability of NRS estimates across time can become more difficult.

The potential for non-random selection of drivers into NRS has long been recognized, but the NRS potentially suffers from a less well understood source of sample selection. Recent versions of the NRS utilize a stratified-sampling approach based on the 60 primary sampling units (city/county regions) from the National Automotive Sampling System/General Estimates System (NASS/GES). Conducting the NRS survey protocol at a particular primary sampling unit (PSU) requires the cooperation of all law-enforcement agencies with jurisdiction over the area (city, county, state, etc), yet cooperation is not compulsory. For example, during the 2007 NRS, lack of cooperation required 25-30% of PSUs to be substituted with other jurisdictions willing to participate (Lacey, et al., 2009a). To the extent that law enforcement agencies in cities and regions have different procedures that influence the prevalence of alcohol-impaired driving and that these procedures are associated with willingness to participate in the NRS, it is difficult to determine whether the final sample of PSUs are truly representative of the US driving environment.

It is also worth noting that one of the reasons that jurisdictions have refused to participate in the NRS stems from efforts to increase driver participation rates. At survey sites, drivers are directed into the testing area by uniformed police-officers. Although there are always signs indicating that entering the testing site and participating in the survey is voluntary, this aspect of the data collection design has led to protests from the American Civil Liberties Union, as well as several lawsuits claiming violation of 4th Amendment protections against unreasonable search and

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3 The assumption that no systematic differences exist between those who provided a BAC sample and those who refused was examined in the 2007 NRS by offering financial incentives to a sample of initial NRS refusers in an attempt to reverse their decisions. Although they find that drivers who initially refuse participation, but accept the incentive and provide a breath sample, are no more likely to be alcohol-impaired than those who had agreed to participate initially, this does not address the possibility that initial refusers who accept the financial incentive differ systematically from those who continue to refuse or those who decided not to enter the testing site.

The 2013 NRS introduced passive alcohol monitors that provided BAC measures using ambient air prior to drivers providing consent for a more precise breathalyzer method, i.e., before they could refuse participation. Coupled with the possible confusion of testing sites with sobriety check-points, the US House of Representative responded by passing an amendment prohibiting the National Highway Traffic and Safety Administration from using funds to support the NRS.
Based on the response, a number of jurisdictions have decided they will no longer participate in the NRS protocol, including Fort Worth, TX and Reading, PA.

III. The L&P Method

In this section, we briefly present the econometric framework developed by L&P that uses the distribution of driver-types involved in two-vehicle fatal crashes to identify the prevalence and relative risk of drinking drivers. Because the composition of drivers involved in two-vehicle fatal crashes is likely very different from the composition of drivers on the road, the conclusion that the distribution of driver types involved in such crashes is sufficient to identify both prevalence and relative risk may initially seem puzzling. Therefore, before formally recapitulating the theory, we offer some intuition with a highly stylized example.

Suppose two types of drivers exist, A and B. We can classify crashes involving two vehicles according to the types of drivers involved: AA, BB, and AB. If there is only one A driver in the population, then there can be no AA crashes. But, if half the crashes are AB, then that one type A driver must be very dangerous. Hence, the observed distribution of driver types involved in two-vehicle crashes reveals both the prevalence of type A drivers (very small) and their relative risk of causing a crash (very large). Thus, even though drivers involved in two vehicle fatal crashes are not representative of the population of drivers, the distribution of driver types in such crashes provides all the necessary information to identify both prevalence and relative risk.

Generalizing this result and following their notation, classify drivers as sober (denoted S) if they have a BAC=0 and drinking (denoted D) if they have a BAC≥.01 g/dL with $N_D$ and $N_S$ denoting the number of each operating a vehicle within a given geographic area and time period. Assume that the number of interactions a driver has with other vehicles and the composition of the drivers encountered is independent of driver type, i.e., equal-and-independent-mixing (EIM). Then, the probability that an interaction involves a driver of type $i$ and a driver of type $j$ is $Pr(i,j|I=1)=N_iN_j/(N_D+N_S)^2$.

Further assume that a fatal crash occurs when a driver makes a fatal error, the likelihood of which, $\theta_i$, depends upon driver type (allowing for heterogeneity within driver type, $\theta_i$ is the mean fatal error probability for drivers of type $i$). Then, the probability that a fatal crash occurs when a driver of type $i$ interacts with a driver of type $j$ is $Pr(A=1|I=1, i, j)=\theta_i+\theta_j-\theta_i\theta_j$. Ignoring the final term, which is the product of very small fractions, the probability of a fatal crash between drivers of type $i$ and $j$ is:

$$Pr(A=1, i, j|I=1) = Pr(A=1, i, j)Pr(i, j|I=1) = \frac{N_iN_j(\theta_i+\theta_j)}{(N_D+N_S)^2}$$ \[1\]

These probabilities are conditional on an interaction occurring, but FARS is a dataset of crashes, not interactions. Applying Bayes’ Rule, yields:

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4 Regarding one such case, an attorney representing the the independent contractor hired to implement the NRS on behalf of the National Highway Traffic and Safety Administration, replied that the plaintiff, “was in no way compelled to stop, and, indeed, hundreds of other vehicles completely ignored the civilian data collector and continued on their merry way.” This response recalls the concerns about driver selection raised previously.
The collection of these probability expressions offer two linearly independent equations in four unknowns: \( N_D, N_S, \theta_D, \) and \( \theta_S \). Let \( N = N_D/N_S \) denote the ratio of drinking drivers to sober drivers and \( \theta = \theta_D/\theta_S \) denote the relative risk of drinking drivers. Then, the probabilities of observing the three different combinations of driver types in a fatal two-vehicle crash are:

\[
\begin{align*}
P_{DD} &= \frac{\theta N^2}{\theta N^2 + (\theta+1)N + 1}, \\
P_{DS} &= \frac{(\theta+1)N}{\theta N^2 + (\theta+1)N + 1}, \\
P_{SS} &= \frac{1}{\theta N^2 + (\theta+1)N + 1}
\end{align*}
\]

Assuming that the composition of drivers is independent across crashes, the joint distribution of two-vehicle crashes characterized by driver type is multinomial:

\[
Pr(A^{DD}, A^{DS}, A^{SS}) = \frac{(A^{DD} + A^{DS} + A^{SS})!}{A^{DD}! A^{DS}! A^{SS}!} (P_{DD})^{A^{DD}} (P_{DS})^{A^{DS}} (P_{SS})^{A^{SS}}
\]

where \( A^{ij} \) denotes the number of two-vehicle crashes involving one type \( i \) and one type \( j \) driver. Substituting the probabilities from [3] yields the likelihood function maximized over \( \theta \) and \( N \).

**Single-vehicle crashes** Define \( \lambda_i \) as the probability driver of type \( i \) commits an error that causes a fatal one-vehicle crash. If \( C \) is an indicator for a one-vehicle crash occurring, then the probabilities of each driver type’s involvement in a crash (defined as \( Q_i \)) are:

\[
\begin{align*}
Q_D &= Pr(i = D | C = 1) = \frac{\lambda D N_D}{\lambda D N_D + \lambda S N_S}; \\
Q_S &= Pr(i = S | C = 1) = \frac{\lambda S N_S}{\lambda D N_D + \lambda S N_S}
\end{align*}
\]

If the relative risk for drinking and sober drivers is \( \lambda = \lambda_D/\lambda_S \), then \( Q_D/Q_S = \lambda N \) and the distribution of driver types involved in one-vehicle crashes cannot be used to separately identify prevalence and relative risk. Although single-vehicle crashes do not provide additional identification, they are included in the likelihood function to improve the precision of prevalence estimates, increase the rate of model convergence, and separately identify the relative risks of causing a one-vehicle fatal crash.

The EIM assumption requires that the distribution of driver types is constant. Clearly, the prevalence of drinking and driving can differ across both geography and time. L&P operationalize this by defining \( N \) as a fully-interacted function of dummy variables that characterize the spatiotemporal level of aggregation over with EIM is assumed. They recover a nation-wide prevalence estimate by concentrating the maximum-likelihood, i.e., substitute \( \hat{\theta} \) and \( \hat{\lambda} \) from the first estimation when \( N \) is fully interacted into the likelihood function, which is then re-maximized treating \( N \) as a constant.

As an alternative, we substitute for \( N \) in the likelihood function using the relationship for single-vehicle crashes defined in [4]: \( N_r = Q^*_r/\hat{\lambda} Q^*_S \), where \( r \) denotes the spatio-temporal unit at which EIM is assumed. A nationwide prevalence estimate is then constructed as \( \hat{N} = Q^*_D/\hat{\lambda} Q^*_S \), where \( Q^*_i \) is the number of one-vehicle crashes involving drivers of type \( i \) nationally.

**Legally impaired drivers** The method proposed by L&P relies on defining mutually exclusive driver types. Thus, to estimate the relative risk and prevalence of drivers with a BAC above a specified threshold, three driver types are defined: \{BAC=0, 0<BAC<L, BAC\geq L\}, where \( L \) is the
defined threshold. Any crashes involving drivers with $0 < \text{BAC} < L$ are discarded leaving the two-driver type framework just described.

IV. Data and Estimation

A. Defining a drinking driver

Information on motor vehicle crashes come from FARS, a census of all fatal crashes occurring on U.S. public roadways and reported to the police.\(^5\) FARS analysts are stationed in each of the 50 States, the District of Columbia, and Puerto Rico. They collect data in more than 100 categories from several state data sources (including state crash report records, driver records, death certificates, vehicle registration files, and other sources) which they enter into a local computer database. These data are quality controlled and transferred to the national FARS file. Data are entered daily into a file that is finalized at the end of the following year, i.e., the file for crashes in the 2014 calendar year is finalized in December 2015.

From FARS, we use the time, date, and location of the crash to define the level at which \(EIM\) is assumed to hold. Specifically, we assume that distribution of driver types is constant within each state-year-hour-day observation, where day refers to weekend nights (8:00pm to 5:00am, Friday evening to Monday morning) or weekday (8:00pm to 5:00am, Monday evening to Friday morning. As in \(L&P\), the lack of two-vehicle crashes involving alcohol during daytime hours forces us to omit observations between 5:00am and 8:00pm.

FARS contains a separate file with the BAC of all “active road users” involved in a fatal motor vehicle crash. The category \textit{active users} includes all vehicle drivers involved in a fatal crash, but not their passengers. It is the alcohol involvement status of \textit{active users} that define whether a crash was alcohol-related. In the case of two-vehicle crashes, a crash is alcohol-related if at least one driver shows evidence of alcohol involvement.

FARS includes two variables collected from crash documentation that can be used to classify the alcohol involvement status of drivers—the judgement of the responding law enforcement officer and the results of any BAC tests performed. The latter include both breathalyzer and blood samples that may have been collected on-scene; off-site at a medical, police, or detention facility; or during post-mortem analysis.

Our use of these variables to define a drinking-driver follows Dunn and Tefft (2018), who conducted a replication of the original \(L&P\) analysis\(^6\) and evaluated various definitions constructed from these variables. Based on their results, the judgement of the responding officer

\(^5\) A crash is classified as fatal if the death of a participant (driver, passenger, or other road user) is recorded within 30 days of the crash event.

\(^6\) \(L&P\) defined a drinking driver solely based on what they believed to be judgement of the responding officer, arguing that coverage was nearly universal and thus not subject to sample selection concerns. Dunn and Tefft (2018) demonstrate that the FARS variable used by Levitt and Porter was not the recorded judgement of the responding officer (DRINKING), but rather a constructed variable (DR_DRINK) that equals unity if the judgement is affirmative and zero otherwise. The latter variable therefore assigns drivers without affirmative judgement to the non-drinking category. From legal perspective, this is the standard of “innocent until proven guilty,” but from the econometric perspective, this is treating missing with zero.
is treated as primary with BAC test results used when the judgement is not available. Specifically, if the responding officer affirmatively reported that alcohol was involved, then a driver is classified as *drinking*; if the responding officer affirmatively reported that alcohol was not involved, then the driver is classified as *not drinking*. When the officer did not affirmatively report their judgement, i.e., by reporting “do not know” or failing to provide their judgement, then BAC test results are considered. For the drivers without an affirmative judgement, a positive BAC test results in assignment to *drinking*, while a BAC test result of zero is categorized as *not drinking*.

### B. Multiple imputation

As in *L&P*, we do not use BAC test results alone to define alcohol involvement because testing is far from universal. This leads to serious concerns that BAC testing is non-random. For example, if law enforcement officers were less likely to test drivers that they (correctly) believed were not drinking, then prevalence estimates based on the sample of tested drivers would be upward biased.

Unlike *L&P*, however, contemporary users of FARS now have access to imputed BAC values for drivers that did not receive a BAC test. Specifically, researchers at the Department of Transportation have developed a multiple imputation strategy to accommodate missing BAC values in FARS that can be applied to all available incident reports from 1982 onward (Subramanian, 2002).

To do so, they estimate the relationship between BAC and crash characteristics for the sample of drivers with BAC test results. Among the characteristics included in their regression specification are the time of day, the number of vehicles involved, and the number of fatalities. They use the coefficients from this regression to predict the BAC level of drivers that were not tested and add a random chosen residual. By randomly selecting ten residuals for each imputed observation, they effectively create ten hypothetical datasets that each contain the actual measured value when available or a multiply imputed value when it is not.

In each of these ten datasets, an indicator variable for drinking status is set to unity if the imputed BAC value is positive and zero otherwise. We then generate estimated values of \( \theta_i \) and \( \lambda_i \) for each of the \( i = \{1, \ldots, 10\} \) datasets substituting for \( N_i \) in the likelihood function with \( Q^D_i / \lambda Q^D_i \). As these estimates are asymptotically normal, we apply the following general formulae for a multiply imputed regression coefficient:

\[
\hat{p} = \frac{1}{M} \sum_{i=1}^M p_i
\]

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7 Dunn and Tefft (2018) also considered using 1) the judgement of responding officers alone and 2) BAC test results as the primary source and the judgement of responding officers as secondary.

8 The proportion of drivers killed in a fatal motor vehicle crash who are tested to determine BAC has increased from 54% in 1982 to 68% in 1997 to 76% in 2008. For surviving drivers, the proportion has increased from 16% in 1982 to 26% in 1997 to 29% in 2008 (Hedlund, Ulmer, Northrup, 2004; Cassanova, Hedlund and Tilson, 2012)
\[
\tilde{\sigma}_p = \sqrt{\frac{1}{M} \sum_{i=1}^{M} \sigma_i^2 + \left(1 + \frac{1}{M}\right) \left(\frac{1}{M-1}\right) \sum_{i=1}^{M} (p_i - \bar{p})^2}
\]  

[8]

where \( M \) is the number of imputations, \( p_i \) is the coefficient estimate in dataset \( i \), and \( \sigma_i \) is the standard error on the estimate of \( p_i \) (Rubin 1987).

It is worth noting that many of the crash characteristics included in the imputation regression are used to define observations in analysis proposed here, generating a circularity that is generally avoided when using imputed values. Nevertheless, NHTSA has high confidence that these imputations are valid, particularly when researchers use them to categorize drivers by BAC thresholds. Further, Dunn and Tefft (2018) investigated whether estimates of prevalence and risk constructed from the multiply imputed BAC values for the time period examined by L&P were comparable to estimates using alternative definitions. They found that defining a drinking driver based on multiply imputed BAC values yield quantitatively similar parameter estimates as using a definition based on the combination of the judgement of the responding officer and tested BAC as described above while providing smaller standard errors.

C. Prevalence and risk of driving while of alcohol impaired

To overcome the potential non-random selection of drivers into testing when estimating the prevalence of alcohol-impaired driving, which requires knowledge of whether BAC is above a defined threshold, L&P restrict their analysis to state-year pairs in which at least 95% of drivers in fatal motor vehicle crashes are tested for BAC. Although this reduces concern about non-random testing within states, there is the real possibility that states with high testing rates differ systematically in either the prevalence of drinking and driving or the risk associated with drinking and driving. It also leads to rather large standard-errors as many state-year pairs must be omitted. Therefore, we rely exclusively on the multiply imputed BAC values to construct an indicator variable for driving while alcohol impaired using the current per se legal threshold of 0.08 mg/dL.\(^9\)

V. Results

Table 1 summarizes characteristics of fatal motor vehicle crashes in the United States from FARS in five-year intervals. While there has been an obvious decrease in the number of fatal motor vehicle crashes over the past three decades, it has exhibited both notable plateaus and temporary reversals. The share of fatal crashes that involve a drinking driver fell substantially through the 1980s and 1990s, but has also plateaued in more recent periods.

Table 2 reports parameter estimates for the prevalence and relative risk of drinking drivers in five-year intervals using the multiply imputed driver BAC values provided in FARS. In each of

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\(^9\) Dunn and Tefft (2018) compare prevalence and risk estimates from MI and the sample restriction imposed by L&P using a BAC threshold of 0.1mg/dL. The MI estimates of the relative risk of causing a fatal two-vehicle crash are slightly smaller than those for the restricted sample: 12.9 versus 14.4. versus. They offer that this difference could simply reflect a small degree of sample variation. Alternatively, the MI approach may induce a great deal of specification bias that is coincidently offset by a large degree of sample selection bias that arises when relying on only states with high testing rates. They are unable to disentangle these explanations, but conclude that the former is more likely than the latter and suggest MI estimates are valid for the task.
the ten MI FARS datasets, a driver is classified as alcohol-involved if they are assigned a positive BAC value. For each five-year period, ten maximum likelihood estimations are performed and the resulting parameter estimates combined according to equations 7 and 8 and reported here.\textsuperscript{10}

Three patterns are evident. First, the prevalence of drinking-and-driving has fallen substantially over the past three decades from 18 percent in the earliest period to 9 percent in the latest. Yet, the majority of this decline appears to occur during the decade of the 1990s. After large decreases between 1992 and 2002, the prevalence has hardly changed subsequently.

Second, while the prevalence of drinking-and-driving has fallen by half, the relative risk of drinking drivers has actually increased. In the earliest period, drinking drivers were eight times more likely to cause a fatal two-vehicle crash. In every period since 2002, the relative risk of causing a fatal two-vehicle crash has been greater than ten. The relative risk of causing a fatal one-vehicle crash has increased by an even greater amount: from seven times in the earliest period to over eleven between 2008 and 2012.

Third, after monotonic increases in the relative risk of drinking and driving from the first to penultimate 5-year interval, there was a notable decrease in the most recent period, particularly for one-vehicle crashes.

Table 3 reports similar results for the relative risk and prevalence of alcohol-impaired driving defined as a BAC level greater than 0.08mg/dL based on the multiply-imputed BAC values. As with drinking-drivers: 1) prevalence of alcohol-impaired driving has decreased by roughly half, but has been relative flat for the past two decades; 2) the relative risk that an alcohol-impaired driver causes a fatal crash has increased by approximately one-quarter; and 3) the relative risk of causing a fatal one-vehicle crash has fallen noticeably over the most recent periods, though remains substantially larger than in the earliest periods.

\textbf{VI. The externality to drinking and driving}

In order to quantify the externality to drinking and driving through excess mortality risk, we calculate, relative to the counterfactual scenario in which the risk of drinking driving was reduced to that of sober driving, 1) the number of avoidable fatalities and 2) a value of statistical life (VSL) estimate of the per mile external cost. We follow the methods proposed by L&P, illustrating their approach using data for the most recent 5-year interval.

In 2017, there were 37,133 motor vehicle crash fatalities in the United States. We calculate the number of fatalities possibly attributable to drinking-and-driving by summing the number of fatalities in which the deceased was not in the vehicle of a drinking driver.\textsuperscript{11} Avoidable fatalities

\textsuperscript{10} The MI estimates are quantitatively very similar to estimates using a definition of alcohol-involvement based on the judgement of the responding officer supplemented with BAC test results when officers either report that they do not know the alcohol involvement of drivers or fail to report their judgement.

\textsuperscript{11} Excluding passengers in the vehicle of drinking drivers assumes that all passengers internalize their driver’s behavior. To the extent that passengers do not internalize driver behavior—perhaps because they cannot accurately assess driver intoxication or are unable to act on that knowledge—this calculation serves as a lower-bound estimate.
are then calculated by multiplying the proportion of crashes caused by drinking drivers minus the proportion caused by sober drivers according to a crash’s composition of drivers, as implied by the model, or \((N_D \times (\theta - 1))/ (\theta \times N_D + N_S)\).\(^1\)

For the most recent five-year interval, there were 1,006 avoidable fatalities in vehicles driven by sober drivers in crashes that involved a drinking driver and 193 avoidable non-vehicle, e.g. pedestrian or bicycle, fatalities due to drinking drivers in single-vehicle crashes. Thus, there were a total of 1,199 excess deaths attributable to drinking drivers.

Using our estimate for drinking driving prevalence of 8.9 percent for the 2013-2017 period, and restricting attention only to night driving miles (DOT, 2012), we estimate that there were approximately 45.7 billion drinking driving miles over the period. Applying a VSL of $9.6 million to conform with recent Department of Transportation policy (DOT, 2016), the total value of avoidable fatalities was $6.6 billion. This results in an estimate of the external cost of drinking drivers through excess mortality risk of approximately 25 cents per mile over that five-year period.

Figure 8 plots the estimated externality of drinking-and-driving per mile using our estimates for \(\theta\) and \(\lambda\) in 5-year trailing windows. Figure 8 also reports the drunk driving externality (BAC threshold 0.08) for every five-year window. There is a clear downward trend in both external cost estimates, with the drinking driving externality decreasing from 40 to 25 cents per mile between 1987 and 2017, and the drunk driving externality decreasing from 58 to 37 cents per mile, accordingly.

**VII. Conclusion**

Our updated estimates of prevalence and relative-risk are consistent with patterns observed in other data, though, like Levitt and Porter, our estimate of prevalence is nearly three times higher than that reported in the most recent NRS. Our results indicate that the prevalence of drinking and driving has been relatively flat since at least the early 2000’s, while the relative risk of drinking and driving has increased significantly. Hence, the recent plateau in the alcohol-related driving fatality rate after nearly 40 years of steady declines can be explained by two distinct mechanisms: a change in the trajectory of prevalence and a change in the trajectory of risk.

This pattern suggests that the current group of individuals who operate a motor vehicle while impaired by alcohol are more dangerous than the historical average (the most intoxicated when they drive and/or travel the most miles while intoxicated) and may be the least likely to respond to existing policies. Hence, while these policies have been effective at greatly reducing the incidence of drinking and driving in the United States, further reductions among the remaining group of drinking drivers may require innovative policy interventions.

\(^1\) Because we only estimated separate relative risks for drunk drivers in one- and two-vehicle crashes, we assumed that the relative risk for drunk drivers in crashes with more than two vehicles is equal to that for two-vehicle crashes.
Finally, our externality calculations suggest that the external cost of drinking and driving has steadily decreased since the 1980s. Although we cannot identify the absolute risk of causing a fatal crash based on the methods applied here, this result indicates that, on average, drinking drivers are less dangerous today than they once were. This is not unexpected given the steady advances in automobile and roadway safety technology over the past three decades. Given the increase in relative risk of drinking driving, however, these advances appear to be “sober-biased.”

These finding surely present as many questions as they answer. Identifying the relative importance of different technological improvements and policy interventions in reducing the prevalence and social cost of drinking and driving will be a central research question moving forward.
References


**Table 1: Summary statistics for fatal crashes by 5-year interval**

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<td>Sample of crashes between 8:00 PM and 5:00 AM</td>
<td></td>
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</tr>
<tr>
<td>Number of fatal one-car crashes</td>
<td>60,525</td>
<td>56,812</td>
<td>48,911</td>
<td>48,988</td>
<td>51,278</td>
<td>42,848</td>
<td>42,377</td>
</tr>
<tr>
<td>Number of fatal two-car crashes</td>
<td>23,439</td>
<td>21,077</td>
<td>17,349</td>
<td>16,960</td>
<td>17,439</td>
<td>13,353</td>
<td>14,631</td>
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<tr>
<td>Percentage of all drivers in fatal crashes:</td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>Reported to be drinking by police</td>
<td>39.3</td>
<td>38.7</td>
<td>27.9</td>
<td>30.9</td>
<td>31.1</td>
<td>32.9</td>
<td>27.9</td>
</tr>
<tr>
<td>Reported to not be drinking by police</td>
<td>30.7</td>
<td>30.6</td>
<td>41.0</td>
<td>33.4</td>
<td>31.6</td>
<td>34.3</td>
<td>41.0</td>
</tr>
<tr>
<td>Drinking status unreported by police</td>
<td>30.1</td>
<td>30.7</td>
<td>31.1</td>
<td>35.7</td>
<td>37.4</td>
<td>32.9</td>
<td>31.1</td>
</tr>
<tr>
<td>Based on multiply imputed BAC values</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Percentage of fatal one-car crashes with:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One drinking driver</td>
<td>62.4</td>
<td>62.6</td>
<td>57.0</td>
<td>55.1</td>
<td>55.0</td>
<td>55.0</td>
<td>52.1</td>
</tr>
<tr>
<td>One sober driver</td>
<td>37.6</td>
<td>37.4</td>
<td>43.0</td>
<td>44.9</td>
<td>45.0</td>
<td>45.0</td>
<td>47.9</td>
</tr>
<tr>
<td>Percentage of fatal two-car crashes with:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Two drinking drivers</td>
<td>15.1</td>
<td>13.1</td>
<td>9.3</td>
<td>7.4</td>
<td>6.7</td>
<td>7.2</td>
<td>6.2</td>
</tr>
<tr>
<td>One drinking, one sober driver</td>
<td>53.0</td>
<td>52.7</td>
<td>48.7</td>
<td>47.0</td>
<td>45.6</td>
<td>47.0</td>
<td>44.8</td>
</tr>
<tr>
<td>Two sober drivers</td>
<td>32.0</td>
<td>34.2</td>
<td>42.0</td>
<td>45.7</td>
<td>47.7</td>
<td>45.8</td>
<td>49.0</td>
</tr>
<tr>
<td>Period</td>
<td>Relative two-car fatal crash risk for drinking drivers ($\theta$)</td>
<td>Relative one-car fatal crash risk for drinking drivers ($\lambda$)</td>
<td>Prevalence of Drivers with BAC &gt;0</td>
<td></td>
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<tr>
<td>-------------</td>
<td>---------------------------------------------------------------</td>
<td>---------------------------------------------------------------</td>
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</tr>
<tr>
<td>1983-1987</td>
<td>8.06 (0.35)</td>
<td>7.04 (0.23)</td>
<td>0.183 (0.005)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1988-1992</td>
<td>8.29 (0.38)</td>
<td>7.96 (0.28)</td>
<td>0.167 (0.005)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1993-1997</td>
<td>8.98 (0.49)</td>
<td>9.03 (0.38)</td>
<td>0.123 (0.005)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1998-2002</td>
<td>9.81 (0.56)</td>
<td>10.51 (0.50)</td>
<td>0.102 (0.004)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2003-2007</td>
<td>10.16 (0.59)</td>
<td>11.40 (0.52)</td>
<td>0.094 (0.004)</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>2008-2012</td>
<td>10.86 (0.67)</td>
<td>11.24 (0.55)</td>
<td>0.094 (0.004)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2013-2017</td>
<td>10.27 (0.65)</td>
<td>9.19 (0.47)</td>
<td>0.089 (0.004)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Maximum likelihood estimates over one- and two-vehicle fatal crashes assuming equal and independent mixing at the state-year-weekend-hour based on FARS MI values for driver BAC.
Table 3: Relative Risk and Prevalence of Alcohol-impaired Driving by 5 year interval

<table>
<thead>
<tr>
<th>Year Interval</th>
<th>Relative two-car fatal crash risk for drinking drivers ($\theta$)</th>
<th>Relative one-car fatal crash risk for drinking drivers ($\lambda$)</th>
<th>Prevalence of Drivers with BAC &gt;0.08</th>
</tr>
</thead>
<tbody>
<tr>
<td>1983-1987</td>
<td>11.44 (0.54)</td>
<td>10.35 (0.39)</td>
<td>0.112 (0.004)</td>
</tr>
<tr>
<td>1988-1992</td>
<td>11.69 (0.59)</td>
<td>11.65 (0.47)</td>
<td>0.102 (0.004)</td>
</tr>
<tr>
<td>1993-1997</td>
<td>13.54 (0.85)</td>
<td>14.04 (0.75)</td>
<td>0.071 (0.004)</td>
</tr>
<tr>
<td>1998-2002</td>
<td>12.98 (0.94)</td>
<td>14.47 (0.90)</td>
<td>0.064 (0.004)</td>
</tr>
<tr>
<td>2003-2007</td>
<td>13.84 (0.98)</td>
<td>16.37 (1.02)</td>
<td>0.058 (0.003)</td>
</tr>
<tr>
<td>2008-2012</td>
<td>14.42 (1.08)</td>
<td>15.96 (1.03)</td>
<td>0.059 (0.004)</td>
</tr>
<tr>
<td>2013-2017</td>
<td>14.78 (1.15)</td>
<td>13.89 (0.96)</td>
<td>0.051 (0.003)</td>
</tr>
</tbody>
</table>

Notes: Maximum likelihood estimates over one- and two-vehicle fatal crashes assuming equal and independent mixing at the state-year-weekend-hour based on FARS MI values for driver BAC. Crashes involving drivers with 0<BAC<0.08 omitted.
Table 4: External cost per mile driven by year and driver BAC level

<table>
<thead>
<tr>
<th>Year Period</th>
<th>BAC&gt;0</th>
<th>BAC&gt;0.08</th>
</tr>
</thead>
<tbody>
<tr>
<td>1983-1987</td>
<td>$0.40</td>
<td>$0.58</td>
</tr>
<tr>
<td>1988-1992</td>
<td>$0.29</td>
<td>$0.41</td>
</tr>
<tr>
<td>1993-1997</td>
<td>$0.30</td>
<td>$0.44</td>
</tr>
<tr>
<td>1998-2002</td>
<td>$0.30</td>
<td>$0.39</td>
</tr>
<tr>
<td>2003-2007</td>
<td>$0.30</td>
<td>$0.40</td>
</tr>
<tr>
<td>2008-2012</td>
<td>$0.24</td>
<td>$0.32</td>
</tr>
<tr>
<td>2013-2017</td>
<td>$0.25</td>
<td>$0.37</td>
</tr>
</tbody>
</table>

Notes: Assumes $9.6 million VSL for all periods, and using the final year for each period as the population of crashes and drivers.