UNDERSTANDING THE DECLINE IN DRINKING AND DRIVING DURING "THE OTHER GREAT MODERATION"*

Darren Grant
Department of Economics and International Business
Sam Houston State University
Huntsville, TX 77341-2118
dgrant@shsu.edu

Abstract: We show that the dynamics of drinking and driving can be adequately described using a simple measure: the fraction of accidents involving drinking drivers. Using this measure, we develop a basic traffic safety model that improves estimates of drunk driving laws' effects and breaks down declines in drinking and driving into components associated with each major influence that has been identified in the literature–including unobservable "social forces." In this decomposition, we find that the widespread enactment of key drunk driving laws explains only one-fifth of the reduction in drinking and driving in the 1980s and 1990s, comparable to the effects of demographics and alcohol consumption and less than that of social forces. "The Other Great Moderation" is best understood as a two-decade movement of drinking and driving to a new steady state, which was led by a shift in social attitudes and cemented and extended by law.

JEL Codes: I18, K14, N42

Keywords: drunk driving; traffic safety legislation; panel data analysis

*** This paper has several pages of figures that are best viewed in color. ***

* This research was sponsored by a grant from Choose Responsibility. I am grateful to Raynoo Issarachevawat, Mitchell Graff, and Jadrian Wooten for helpful research assistance, to Don Freeman for sharing data on traffic laws, and to Dhaval Dave, Don Freeman and seminar participants at Sam Houston State University, Texas A&M University, the Federal Reserve Bank of Cleveland, and the ASHE, IAAE, and Southern Economic Association Conferences for helpful comments.

"The most important of all revolutions [is] a revolution in sentiment, manners, and moral opinions."
–Edmund Burke

The extended period of quiescence experienced by the American macroeconomy in the 1980s and 1990s was so remarkable that it has its own name: The Great Moderation. But this was not the only one. A coincident, less-heralded moderation occurred on the nation's roads: a large reduction in the number and fraction of traffic fatalities involving drivers who had been drinking. This latter moderation certainly is more important in human terms, and probably is in economic terms as well. Since its inception, it has prevented half of a million traffic fatalities, tens of millions of injuries, and significant property damage, at an approximate value of 1% of GDP annually.[1]

Nonetheless, our understanding of this other Great Moderation remains piecemeal and incomplete. The smaller questions have been answered, but the big ones have not. A few drunk driving laws have been subjected to intense study, and others to occasional study, but the aggregate effect of such legislation on drinking and driving has not been quantified. Nor has the contribution of other major factors, including the "social forces" that presumably impelled these laws into being. Altogether, the dynamics of The Other Great Moderation are poorly understood.

This paper seeks to provide such an understanding. Employing detailed descriptive statistics, a battery of panel regressions, and decomposition analyses, we describe how drunk driving has evolved over the past forty-five years and reveal the footprint of the social processes shaping this evolution. Ultimately, we decompose the decline in drinking and driving during The Other Great

[1] The savings in lives comes from the calculations underlying Figure 4 below. The incidence of fatal injuries, nonfatal injuries (categorized into five levels of severity), and accidents without injury, and the contemporaneous economic values applied to each by the Federal Highway Administration (FHWA), are available for 1994 (Blincoe, 1996; FHWA Memo, "Motor Vehicle Accident Costs," Oct. 31, 1994). The appropriate computations, available from the author, yield a savings in that year of 0.97% of GDP. This value is somewhat conservative; after 1994, drinking fell further, while the FHWA's valuation of fatalities and injuries rose far faster than GDP.

Moderation into components associated with all five major determinants that are recognized in the literature, quantifying the magnitude and timing of the effect of each.

Accomplishing this task requires solving a problem: seeing the unseen. On a national scale, we don't observe drinking and driving, only its aftermath: fatal crashes. These, in turn, are influenced not just by drinking, but also by a panoply of largely unquantified "general risk" factors that affect everyone, such as the safety features of vehicles, the quality of roads, and the effectiveness of emergency medical care. Furthermore, public attitudes toward drinking and driving are largely unquantified in the U.S., though the importance of such social forces permeates the broader traffic safety literature. Because of the magnitude of these intangibles and their interplay with drinking and driving, accounting for their influence is essential.

The solution to this problem is founded on a basic fact about drinking drivers: though rare, they are far riskier, on average, than sober drivers are. Using this fact, we develop a simple latent variable model that reveals the role of general risk in traffic safety and supports a novel, bias-reducing estimation approach that can be applied to microdata. Altogether, this approach accounts for general risk, identifies the effect of social forces, and controls for demographic factors that correlate with drinking. Applying this approach to data on decades of fatal accidents in the U.S., we break down the nationwide decline in drinking involvement in these accidents into components associated with laws, demographics, economic factors, alcohol consumption, and social forces. With one exception, each contributes to The Other Great Moderation, in varying degrees.

In the narrative supported by our empirical findings, The Other Great Moderation begins around 1980 with a tectonic shift in social attitudes towards drinking and driving. This shift had an immediate direct effect on drinking and driving, but also presaged future changes in the law. This indirect effect, via legislation, was smaller, more gradual, and subject to diminishing returns. As The Other Great Moderation played out, in the late 1990s, a new, long-term steady state emerged in which the rate of drinking and driving remained unchanged.

This narrative clearly has policy relevance, and not only for what it says about drunk driving legislation. It reprises a debate that raged over forty years ago, during the earliest years of our data, over the relative efficacy of legislation and social suasion. This debate was won by the former, a triumph of deterrence theory. But this triumph has been unmatched by persistent declines in drinking and driving, which has now completed two decades of stasis. This stasis did not coincide with the end of legislation, which continued to increase, but could reflect static social attitudes. If so, a technocratic, law-based approach to the problem is unlikely to yield further gains.

The paper systematically develops the methodological advances needed to generate its findings. Accordingly, the first two sections provide descriptive and theoretical support for our simple summary measure of drinking and driving, the fraction of accidents that involve drinking drivers, and integrate it into the latent variable traffic safety model described above. The next two sections adapt this model for estimation, first at the state level, then at the individual level, and compare its estimates of drunk driving laws' effects to those of the fatality analyses that dominate the literature. Using this individual-level model, in turn, the last two sections develop, present, and discuss the decompositions with which we explain the decline in drinking and driving during The Other Great Moderation.

I. A Simple Summary Measure of Drinking and Driving.

Our measure of the extent of drinking and driving is a simple statistic: the fraction of accidents involving drivers who Had Been Drinking, or HBD (Douglass and Millar, 1979). The next section develops theoretical support for this measure. In this section, we support it empirically, by showing that it adequately characterizes the dynamics of drinking and driving.

We do so using data from NHTSA's Fatality Analysis Reporting System (FARS), which records accident, vehicle, and driver characteristics for all fatal traffic accidents on U.S. public highways since 1975. Driver blood alcohol concentration (BAC) is reported in most of these and, since 1982, is imputed for the others, mostly nondrinkers.[2] Our main analysis uses data through 2004. This period comfortably spans The Other Great Moderation and roughly aligns with the periods analyzed in comparison studies discussed below. We use this data throughout the paper.[3]

<u>The Dominance of the Extensive Margin</u>. The most fundamental justification for using HBD has been hiding for years in plain sight. The aggregate dynamics of drinking and driving take place almost wholly on the extensive margin–*whether* to drink and drive. The intensive margin, BAC

---

[2] The data has two major limitations. First, it contains only fatal accidents. These do, however, generate half of all the economic costs of accidents involving alcohol (Blincoe et al., 2002). Second, the imputation of some BACs could affect estimates of state laws' effects, as imputations are not conditioned by state. This should not be a major problem, because few *drinkers'* BACs are imputed and because the strongest predictors of driver BAC are accident-specific factors such as driver age, passenger BAC, and police reported drinking involvement. Estimates presented below, and others available from the author, indicate the basic findings are not corrupted by imputation. Neither limitation has prevented numerous researchers from using this data to analyze the effects of drunk driving laws.

[3] While the FARS data are not a sample, for convenience we use the term "sample period" and call the random variation inherent in any probabilistic process, such as traffic fatalities, "sampling error." The underlying fatality risk in any interval of time and space is imperfectly revealed by the observed fatality rate, because, fortunately, fatal accidents are infrequent, following a Poisson process around their expected value.

conditional on drinking (BAC > 0), is essentially static.

To show this at the national level, Figure 1 documents the 25th, 50th, and 75th percentiles of BAC for all drinking drivers involved in fatal accidents in the U.S. between 1975 and 2004. In all years the BAC distribution is essentially normal with a mean of about 0.16, a standard deviation of about 0.08, and an interquartile range of about 0.05, whether or not the imputed BACs are included.

To show this at the state level, we calculated the 50th percentile of BAC (conditional on drinking) within each state*year cell and regressed these values on a full set of state and year dummy variables. The standard deviation of the state dummies was only .008, indicating geographic stability, while the standard error of the estimate–some of which derives from sampling error–was only .011, indicating that temporal stability extends to the state level. The 25th and 75th percentiles yielded very similar results. Changes in drinking and driving can be adequately tracked on the extensive margin, using HBD.

National Dynamics. Figure 2 presents three NHTSA-reported measures of the presence of alcohol in fatal accidents, analogous to HBD.[4] All three show a steady decline in alcohol involvement from 1982 through 1997 and stasis thereafter. The share of fatalities involving a drinking driver fell from 55% in 1982 to 36% in 1997, a decline of over one-third. This, in a nutshell, is The Other Great Moderation.

This decline was the result of an evolutionary process in which changed attitudes toward

[4] Note that these measures are "HBD-adjacent": they report the fraction of fatalities, not accidents, involving alcohol. The two are nearly synonymous, as drinking has no material effect on the number of fatalities per accident. (Relating this variable to state dummies, year dummies, and the highest BAC among the drivers involved, each .01 increase in BAC generates a minuscule 0.0008 additional fatalities per accident.)

drunk driving, and their political consequences, coursed through society. We can see this most clearly in age profiles of the percentage of drivers in fatal accidents that are BAC-positive. Figure 3 shows how these profiles have changed over time, using five-year time intervals, both including and excluding the imputed data. (Including the imputations increases the magnitude of change but leaves the relative rates of change unaffected.)

During the early and mid-1970s alcohol-related accidents surged, partly due to the lowering of the minimum legal drinking age (MLDA) in many states. This began to reverse around the turn of the decade with the onset of The Other Great Moderation.[5] Its vanguard, apparent in the second panel of Figure 3, was a decline in alcohol involvement among drivers over forty. This probably resulted from increased awareness of the dangers of drunk driving and reduced tolerance for it, both of which foreshadowed the legislation initiated toward the end of this period (see below and Howland, 1988).

This was followed, in the late 1980s and early 1990s, by a substantial decline in drinking and driving among all ages. The greatest progress clearly occurs during this period. By the mid-1990s declines in alcohol involvement among drivers over forty had largely played out, with the remaining decreases concentrated among drivers aged 20-40. While drunk driving legislation certainly played a role in this evolution, it cannot explain these age patterns, which are not connected to the primary legislation enacted during each of these periods (see below). Other factors must be relevant as well.

[5]As alcohol imputations are not present in the FARS prior to 1982, it is hard to give a precise date when this occurred. Anecdotal evidence strongly suggests that alcohol-related accidents increased during most of the 1970s, in part because many states lowered the drinking age to 18. In the unimputed FARS data, alcohol involvement rose somewhat in the waning years of that decade, then turned down decisively beginning in 1981.

II. Drinking and Traffic Safety: A Simple Model.

Our use of HBD can also be supported theoretically. This is demonstrated by the latent variable model we now introduce, which separates drinking and driving from general risk and relates both to fatalities.

A Latent Variable Model of Traffic Safety. Over any interval of space and time define the following variables, using upper case for those that can be observed and lower case for those that cannot:

- s = the miles driven by sober drivers,
- d = the miles driven by drinking drivers,
- r = the general risk environment, due to weather, road quality, automobile technology, general safety laws, general safety attitudes, etc., and
- $M = s + d$ = total miles driven.

The actual outcomes and the latent variables–the expected outcomes–are defined as follows:

- f = the expected number of fatal accidents, given s and d,
- F = the actual number of fatal accidents, with $F \sim$ Poisson(f),
- h = the expected fraction of fatal accidents involving drinking drivers, given s and d,
- H = the actual fraction of such accidents, i.e., HBD, with $F \bullet H \sim$ Binomial(F,h).

The problem with drinking and driving is that it dramatically elevates the risk of a crash. In Blomberg et al.'s (2005, 2009) exhaustive epidemiological study, the risk of crash *involvement* doubles with each standard drink beyond two. At the median BAC in Figure 1, crash risk is about thirty times that of sober drivers. Overall, the average crash risk of drinking drivers is sixteen times that of sober drivers, ceteris paribus; the *fatal* crash risk is higher (Blincoe et al., 2002); the relative risk of *causing* that crash higher still.[6] Thus, almost all collisions between sober and drinking drivers

[6] This is easily shown numerically, for example using Levitt and Porter's (2001) framework. The intuition is that many sober drivers are involved in accidents that are caused by drinking drivers. The increase in relative risk is substantial. Details are available from the author.

are the drinking driver's fault; an accident *involving* drinking drivers is (generally) *attributable* to one of those drivers (see also Levitt and Porter, 2001).

Using these facts, we can derive a simple, intuitive decomposition of accident frequency. Let k be the average risk that a drinking driver will cause a fatal crash, relative to a sober driver, and let fatal accidents be the sum of those involving only sober drivers and those involving at least one drinking driver: $F = F_{\text{SOBER}} + F_{\text{DRINKING}}$. In expectation, the latent variable equivalent is $f = f_{\text{SOBER}} + f_{\text{DRINKING}}$. Without any loss of generality, let $f_{\text{SOBER}} = rs$ and $f_{\text{DRINKING}} = rkd$, so $h = kd/(s+kd)$. Then:

$$f \;=\; (s+kd)*r \;=\; (s+d)*r*\left(\frac{s+kd}{s+d}\right) \;=\; M\cdot r\cdot\left(\frac{s+kd}{s+d}\right) \;=\; M\cdot r\frac{1}{1-h}\cdot\left[1+\frac{1}{k}\cdot\frac{h}{1-h}\right] \tag{1}$$

Since $k >> 1$ (and $h \approx$ ½) the bracketed term approaches one, yielding the following close approximation:

$$\log(f)-\log(M) \;\approx\; \log(r)-\log(1-h) \tag{2}$$

Expected per mile fatal accidents are directly proportional to general risk and inversely proportional to the expected fraction of accidents that did *not* involve drinking, which we call "relative sobriety."[7] The same relation applies to fatalities, where h is the expected fraction of fatalities occurring in accidents involving drinking drivers. Either way, drinking enters only through h, the latent variable equivalent of HBD.

This (approximate) identity requires that k be large, but not that k remain constant over time. It thus accommodates social or technological changes that can alter the relative risk of drinking

[7] Scaling fatalities by miles, a common normalization in studies of traffic safety, is a serviceable approximation for purposes of this section, and is roughly consistent with estimates of the model introduced below, which does not mandate that fatalities be proportional to miles.

drivers, so long as that relative risk remains large. We can see this by expanding the term that was dropped in going from equation **(1)** to equation **(2)**:

$$\log(1+\frac{1}{k}\frac{h}{1-h}) \approx \frac{1}{k}\frac{h}{1-h} = \frac{1}{k}\cdot\frac{kd}{s+kd}\cdot\frac{s+kd}{s} = \frac{d}{s} \qquad \textbf{(3)}$$

This last term does not depend on *k*. It also varies little over time, with annual changes of a few ten-thousandths.[8] An immediate corollary, apropos to panel estimation, is that equation **(2)** holds in difference form as well.

While equation **(2)** doesn't require *k* to be constant over time, this appears to be roughly the case nonetheless. This conclusion is supported by our Section I finding that the distribution of BAC among drinking drivers is static and, more comprehensively, by the evidence discussed at length in Grant (2016); see also Levitt and Porter (2001). Accordingly, one can adopt the "natural" interpretation that changes in the relative sobriety component represent changes in the incidence of drinking and driving.

National Dynamics. How have *f*, *h*, and *r* evolved over time? This is easy to see at the national level, where there are so many accidents that sampling error is minimal, so *f* and *h* in equation **(2)** can be replaced with their empirical counterparts and *r* solved for directly. Doing this annually, treating 1982 as the base year, yields the breakdown in Figure 4, which depicts the effects of general risk and relative sobriety on total U.S. traffic fatalities from 1982-2015. The upper line denotes the projected growth in log fatalities, relative to the base year, that would be required to "keep up" with the increase in miles driven, so that fatalities per mile remained constant. The top shaded area

[8] Because both $\Delta d/d$ and d/s are $O(10^{-2})$.

indicates the "shortfall" in fatalities below this projection that is attributed to reductions in drinking and driving. The bottom shaded area indicates the shortfall attributed to reductions in general risk.

Improvements in traffic safety over this period occurred in three phases, each delineated on the graph. In the first phase, comprising most of the 1980s, all fatality reductions stem from declines in drinking and driving. While improvements in vehicle technology and road quality helped lower general risk during this phase, these were more than offset by a large reduction in real gas prices and the changed driving behaviors that accompanied it (see Grabowski and Morrisey, 2004, and Burke and Nishitateno, 2015). After real gas prices stabilized in the late 1980s, the second phase began, in which steady declines in general risk and continued declines in drinking and driving yielded a reduction in fatalities despite an increase in miles driven. This continued until the late 1990s and the end of The Other Great Moderation. In the third, post-moderation phase, relative sobriety, like HBD, remained unchanged, while reductions in general risk continued apace, accelerating toward the end of the period as gas prices increased and economic activity decreased. According to this breakdown, drinking and driving has changed little in twenty years. The continued decline in the number of alcohol-related traffic fatalities stems from reductions in general risk that improved safety for both sober and drinking drivers.

<u>State Dynamics</u>. The distinction between relative sobriety and general risk emerges even more strongly when analyzing dynamics at the state level.

This can also be done using the latent variable model, by evaluating each term within state*year cells. At this level of analysis, however, sampling error is prevalent, so we cannot apply the model directly. Rather, as the Appendix shows, using F and H we can estimate the statistical properties of the underlying latent variables, f and h, after subtracting state and year fixed effects.

Then, using equation **(2)**, we can break down the analogous variation in logged fatalities per mile into components associated with log(r), log(1-h), and their interaction, and use the method of moments to estimate the properties of each. To reduce extraneous variation, we do this for the accident type and age group with the greatest drinking involvement: single vehicle accidents involving drivers aged 21-40.

The results are found in Table 1. The third and fourth rows of the table present the standard deviation, (simplified) spatial correlation,[9] and serial correlation of h and log(f/M). Both have modest spatial correlations and sizeable serial correlations; for h, this serial correlation drops off sharply after three years. The variation in log fatalities per mile that is not attributable to state fixed effects, year fixed effects, and sampling error is 8.1 percentage points. The last two rows of the table present the contributions of general risk (log(r)) and relative sobriety (log(1-h)) to this variation. The variance of general risk is double that of relative sobriety, and the two are only weakly correlated.

In summary, during The Other Great Moderation, drinking and driving evolved along the extensive margin, non-uniformly by age, and exhibited a large national component punctuated by brief (three year), local (state-specific) innovations that were dwarfed by, and largely independent of, local innovations to general risk.

III. State-Level Estimation.

---

[9] Spatial correlations are calculated across matched pairs of neighboring states, like those used in “case-control” studies of drunk driving laws (e.g., Williams et al., 1983; Arnold, 1985). Vermont is matched with New Hampshire, for example, and New Mexico with Arizona; the full set of pairs is listed in the note to Table 1. The case-control design deems the paired states to be identical but for the law in question; this assumption is contradicted by the low values reported.

Adapting this framework for estimation provides a superior method for gauging the effects of traffic safety legislation and enables the micro-level analysis on which our decompositions rely. Given the novelty of our approach, however, we first apply it to the state-level panel analyses that pervade the literature. Then, in the next section, we proceed to micro-level estimation.

Three Estimation Approaches. Classify all independent variables into three types: general risk adjusters, G; factors that affect drinking and driving but not general risk, X; and factors that affect both, Z. Section II implies:

$$\begin{aligned} F &\sim Poisson(f) \\ \log(f) &= \mu\log(M) + \log(r(G,Z)) - \log(1-h(X,Z)) \end{aligned} \tag{4}$$

where we have relaxed the elasticity between miles and fatalities to be a parameter, μ, that need not equal one. The marginal effect of X on log fatalities is:

$$\frac{\partial\log(f)}{\partial X} = \frac{1}{1-h}\frac{\partial h}{\partial X} \tag{5}$$

In contrast to the standard fatality analysis, this equation requires the safety effects of X variables to be mediated through *h*. That is, drunk driving laws reduce fatalities because they reduce drinking and driving.

Using the identity in equation **(2)**, we can compare this "restricted estimate" of $\partial\log(f)/\partial X$ to two alternative estimates of the same relationship: the more traditional "unrestricted" estimate that is formed by relating $\log(F)$ directly to X, and a "partially restricted" estimate that is formed by relating $\log(F_{\text{DRINKING}})$ to X, then multiplying the result by *h*. Temporarily setting aside the theoretical independence of r from X, these three estimates yield the following:

$$
\begin{aligned}
&\textit{Unrestricted}: && \frac{\partial \log(f)}{\partial X} = \frac{1}{r}\frac{\partial r}{\partial X} + \frac{1}{1-h}\frac{\partial h}{\partial X} \\
&\textit{Partially Restricted}: && \frac{\partial \log(f)}{\partial X} = \frac{h}{r}\frac{\partial r}{\partial X} + \frac{1}{1-h}\frac{\partial h}{\partial X} \\
&\textit{Restricted}: && \frac{\partial \log(f)}{\partial X} = \frac{1}{1-h}\frac{\partial h}{\partial X}
\end{aligned}
\qquad \textbf{(6)}
$$

All three estimates treat the relative sobriety component identically, but not general risk, whose effect is eliminated a priori in the restricted estimate but not in the other two. This is problematic, as general risk is identified only from accidents involving sober drivers.

In theory, these are distinctions without a difference: X variables have no causal effect on r, ceteris paribus, so $\partial r/\partial X$ is zero. In practice, however, the limited G and Z controls available to the analyst may not adequately account for general risk, allowing there to be an incidental partial correlation between X and r. Then the general risk terms in equation **(6)** would be non-zero, making the unrestricted and partially restricted estimates of $\partial \log(f)/\partial X$ more variable and possibly biased. Both problems would be eliminated by the restricted estimates.

Specification. Each of these estimates can be obtained using state panel data. Our unrestricted regression specification extends directly from equation **(4)**:

$$
\begin{aligned}
F_{s,t} &\sim \textit{Poisson}(f_{s,t}) \\
\log(f_{s,t}) &= \beta X_{s,t} + \gamma Z_{s,t} + \delta G_{s,t} + \mu M_{s,t} + \sigma_s + \tau_t + \varepsilon_{s,t}
\end{aligned}
\qquad \textbf{(7)}
$$

where s indexes states and t time; β, δ, μ, and γ are coefficients; and σ and τ are state and year fixed effects. This equation takes the form of a generalized linear mixed model, or GLMM (McCulloch, 2006). This is a simple variant of the standard panel data model that regresses $\log(F_{s,t})$ directly on the independent variables, and the coefficient estimates are interpreted identically: thus $\partial\log(f)/\partial X$ is estimated by $\hat{\beta}$. This model effectively handles econometric concerns, such as weighting, as well.[10]

For the partially restricted estimate, we utilize the same specification, replacing all fatalities with fatalities involving drinking drivers. Then the estimate of $\partial\log(f)/\partial X$, the *population* change in log(fatalities) resulting from a one unit change in X, is $\hat{\beta} H_M$, where H_M is the grand mean of H.

For the sake of consistency, the restricted estimate is also based on a GLMM that extends from our latent variable model. Accordingly, the regression used to estimate $\Delta h/\Delta X$ is as follows:

$$\begin{aligned} F_{s,t} \cdot H_{s,t} &\sim Binomial(F_{s,t}, h_{s,t}) \\ h_{s,t} &= \lambda X_{s,t} + \varphi Z_{s,t} + \sigma_s + \tau_t + \varepsilon_{s,t} \end{aligned} \qquad \textbf{(8)}$$

As with the preceding model, this specification resembles a traditional panel regression that relates $H_{s,t}$ directly to the independent variables, and its coefficient estimates can be interpreted accordingly. The estimate of $\Delta h/\Delta X$ is $\hat{\lambda}$, so, following equation **(5)**, the estimate of $\partial\log(f)/\partial X$ is $\hat{\lambda}/1\text{-}H_M$.[11]

---

[10] The GLMM differs from a standard regression by explicitly specifying the sampling variation in $F_{s,t}$, in the top line of equation **(7)**, thus treating ε as a random effect. By formally accounting for sampling variation as well as specification error, via the random effect, the weighting implicit in the GLMM should be more sound than either OLS or traditional WLS (both of which will be presented below). In addition, in the micro specification introduced in Section IV, these random effects account for state*year clustering in the calculation of the standard errors.

[11] The term that is dropped when deriving eq. **(2)**, $h/[k(1\text{-}h)]$, is small only when h is not close to one. This rules out any regression that uses $\log(1\text{-}H)$ directly as a dependent variable when there are few fatal crashes within state*year cells (as for young drivers). Then H deviates substantially from h, due to sampling error, and can be very close to one; the resulting bias is severe.

Implementation. Our initial estimations focus on three drunk driving laws: the MLDA, zero tolerance (ZT) laws lowering the per se illegal BAC for youth to .01 or .02, and laws lowering the per se illegal BAC for adults to .08. The signature legislation passed during each of the three phases in Figure 4, respectively, these three laws are now universal within the U.S., partly due to federal legislation withdrawing highway funds from "non-adopters." Thirty-five states and the District of Columbia adopted all three during our sample period, 1982-2004; the others adopted two of the three. And each has a mature, reasonably convergent literature, amounting to a total of over one hundred published studies. All law variables range in value from zero (nonexistent) to one (full coverage in that state all year).[12] Following Dee (1999), Freeman (2007), and others, regressions are conducted on the 48 continental states.[13]

To facilitate a comparison of estimation approaches, we adopt those controls that are reasonably standard in the literature. Based on the review of Grant (2011), these are as follows. General risk controls, G, include seat belt laws and speed limits. Factors affecting drinking and driving, X, include drunk driving laws and alcohol prices or consumption. Factors affecting both drunk driving and general risk, Z, include economic factors and demographics (added in the

---

[12] In intermediate cases the value equals the fraction of the relevant population covered by the law in that state during that year. For MLDA laws, then, the fraction of 18-20 year olds covered by the law is multiplied by the fraction of the year the law was in effect. All laws are coded from the *Digest of State Alcohol-Highway Safety Related Legislation,* supplemented occasionally with Dang (2008) or Grant (2010).

[13] Some initially low-reporting states dramatically increased BAC reporting in a discrete jump in the early 1980s; this is associated with discrete jumps in measured drinking involvement. This sharply biases the estimated effect of the raised MLDA, passed contemporaneously, toward zero. Thus, the regressions omit from the sample those years prior to the jump in reporting in those states. The affected states and last year of omitted data are as follows: AL, 1982; AR, 1989; FL, 1985; ID, 1984; IN, 1985; IA, 1982; KS, 1987; MS, 1991; MD, 1985; NC, 1982; ND, 1984; TX, 1985.

individual-level regressions found in the next section).[14] The X and Z vectors are included in fatality and HBD regressions, while G is included in the fatality regressions only. All variables are measured at the state*year level.

To reflect the variety of specifications in the literature, we use two sets of controls. Our "basic" set includes those that are most common: for G, dummies for primary and secondary seat belt laws and for the maximum speed permitted in that state that year; for Z, the unemployment rate; and for X, the three laws above, along with dummies for .10 per se laws and administrative license revocation (ALR) laws that allow the state to suspend or revoke an individual's license immediately upon testing positive for drunk driving or refusing to be tested. (The .10 law dummy equals one whenever the per se limit is at or below .10, so the .08 law coefficient estimates the effect of lowering the per se limit from .10 to .08.) An "extended" set of controls adds (to X) per-capita alcohol consumption and dummies for open container and dram shop laws, the only other drunk driving laws that receive consistent support in the comprehensive panel studies in the literature (Benson and Rasmussen, 1999; Eisenberg, 2003; Ruhm, 1996; Whetten-Goldstein et al, 2000).

Drivers under 18 were not directly affected by the raised MLDA, while drinking involvement among drivers over 60 is quite low (see Figure 3). Thus, we conduct estimation separately for two age ranges: adults aged 21-60, for whom ZT and MLDA laws are excluded, and youth aged 18-20, for whom they are included. (The youth regressions retain the ALR, .08, and .10 law controls, but these coefficients are not reported below.) HBD is defined as the number of fatal accidents or fatalities involving at least one driver in the specified age range who had been drinking, divided by

[14] Measures of religious affiliation, included in several studies, are omitted here, because they are measured in just two years, 1980 and 1990, and extrapolated to the rest (see, for example, footnote 21 of Benson, Rasmussen, and Mast, 1999).

the number of fatal accidents or fatalities involving drivers in the specified age range.

Results. We estimate a large number of specifications, and it would be impractical to present the complete results for each one. Accordingly, the first two columns of Table 2 present the full set of restricted and unrestricted estimates for a single, adults-only, accident-level specification, which, to anticipate slightly, uses the expanded set of controls. It is immediately clear that the coefficients generally take the expected signs and are frequently, though not invariably, significant. Laws have a nil or negative effect on accidents; per capita alcohol consumption has a positive effect, while the effect of unemployment is negative or nil.

Table 3 compares the three estimators laid out above. To facilitate this comparison, only the law estimates are provided, and the table is organized by law, not regression. Estimates from the same regression are placed in the same location *within* each panel of the table. For example, the upper-left cells of the .10 law, .08 law, and ALR panels all come from the same regression–equation **(7)**. For ease of interpretation, henceforth all estimates are multiplied by one hundred, so that they predict the percentage change in the number of fatalities or fatal accidents resulting from the enactment of that law.

Looking vertically within the panel corresponding to any given law, one can compare the results for three alternative fatality measures: the number of fatal accidents involving drivers in the given age range, the total number of fatalities in those accidents, or the number of fatal single-vehicle accidents involving said drivers. The estimates are not sensitive to the measure used.

Looking horizontally, across columns, compares the unrestricted, partially restricted, and restricted estimates. The unrestricted estimates are unusual, implying that .10 and .08 laws raise fatalities and that the drinking age is ineffectual; only ALR is consistently significant. These inauspicious findings reflect the sample period, which is on the long side for these literatures (see Freeman, 2007 and Grant, 2011), and the fact that the GLMM does not weight all states equally. (Higher-profile studies of .08 laws, such as Dee, 2001, do not use weights.)

Moving to the partially restricted and then fully restricted estimates, the results change substantially. The restricted estimates, especially, are more credible: .08 laws now lower fatalities by 2%, while raised MLDA's reduce them by 4-6%; ALR, ZT, and .10 laws have generally negative (though insignificant) effects. Precision also improves, as expected: the standard errors of the restricted estimates are three-fourths those of the unrestricted estimates. The partially restricted estimates are partway between the two extremes.

The first two columns of Table 4 examine the robustness of these findings to estimator and specification. This table is also organized by law, not regression, and so should be read vertically within panels. The unrestricted estimates in the first column of each panel are relatively sensitive, responding to the weighting applied to the observations and to the inclusion of additional controls. In contrast, the restricted estimates in the second column are remarkably stable, rarely varying by more than one percentage point across specifications. Overall, the findings in these two tables are consistent with the presence of unmeasured general risk factors that substantially impact unrestricted fatality regressions, but not restricted estimates based on HBD.

Altogether, our restricted estimates are not out of line with the results of extant panel fatality analyses. Early panel studies of .08 laws, particularly Dee (2001) and Eisenberg (2003), find that the .08 law's net effect is about 3%, while later panel studies by Young and Beilinska-Kwapisz (2006) and Freeman (2007) find effects that are smaller or nil. Similarly, while the early MLDA literature finds double-digit effects, six later panel estimates (Dee, 1999; Eisenberg, 2003; Young and Likens, 2000; Young and Beilinska-Kwapisz, 2006; Polnicki et al., 2007; and Miron and Tetelbaum, 2009) average six or seven percent. A similar trend is also found for ZT laws; recent fatality analyses by Dee, Grabowski, and Morrisey (2005), Grant (2010), and Anderson, Hansen, and Rees (2013) find no material effect. (Grant, 2011, extensively reviews all three literatures.) Our nil findings for .10 laws and ALR are somewhat milder than is typical in the literature (Eisenberg, 2003; McArthur and Kraus, 1999).[15]

IV. Micro-level Estimation.

We now extend the restricted estimator to an individual-level specification that can be applied to the microdata available in FARS.

Estimation on Microdata. The individual-level analog of the restricted estimator adapts equation **(8)** into a binary choice model in which the dependent variable, η, is one if the accident-involved driver had been drinking and zero otherwise. The GLMM version of this model is as follows:

$$P(\eta_{i,s,t}=1) = \Lambda(\lambda X_{i,s,t}+\psi Z_{i,s,t}+\sigma_s+\tau_t+\varepsilon_{s,t}) \tag{9}$$

where Λ is the logistic function, i indexes individual drivers, and ε is a normally distributed

[15] Findings are much stronger in another set of analyses that do not control for state and year fixed effects, including several studies that analyze a simple transformation of HBD: the ratio of F_{DRINKING} to F_{SOBER} (Hingson, Heeren, and Winter, 1996; Robertson, 1989; Voas, Tippetts, and Fell, 2000, 2003; Fell et al., 2008). In these studies, cross-sectional variation favorably influences coefficient estimates, accounting for the difference in findings.

state*year random effect. The average marginal effect of a one-unit change in any variable x estimates $\Delta h/\Delta x$; from this the implied percentage reduction in fatal accidents can be calculated using equation **(5)** as before.[16]

This driver-level regression specification, possible only with our estimation approach, has three advantageous features. It allows accident-specific factors, such as the time of day, to be controlled for. It accounts for demographics more effectively than state-level analyses using population averages, such as the fraction of drivers in a given age range. Increases in miles driven by females and older drivers, who drink less and crash less even when sober, make demographics potentially important, despite their scarce attention in the literature (Dang, 2008). And it lets the state-level MLDA and zero tolerance law variables be replaced with driver-specific indicators that are based on driver age and the accident date. In consequence, we no longer need–or use–separate regressions for youth and adults.[17]

---

[16] This is obvious for single-vehicle accidents, for which accident-level alcohol involvement equates to driver-level alcohol involvement. But it holds for multiple-vehicle accidents too.

In Section II, the fact that the relative accident risk of drinking drivers, k, was much larger than one served two purposes. First, it was used to simplify equation **(1)** in the latent variable model. Second, it was used to assign accident *responsibility*: an accident-involving a drinking driver was attributed to that driver. In consequence h was interpreted as the fraction of *accidents* involving drinking drivers, and the state-level empirics were conducted accordingly. This interpretation carries over directly to individual-level estimation on single-vehicle accidents.

However, the latent variable model could be reformulated in terms of accident *involvement*, remaining agnostic as to the accident's cause. That is, the fact that $k >> 1$ could be used for the first purpose, but not the second. Then f becomes the number of accident-involved drivers and h the fraction of those *drivers* who had been drinking. This reformulation directly supports individual-level estimation on multiple-vehicle accidents.

[17] When raising the MLDA, some states grandfathered in 18-20 year olds who had been allowed to drink. For these individuals, the MLDA variable is the probability that they weren't grandfathered, and thus subject to the raised drinking age.

Results. The last two columns of Table 4 present the results for one-and-two-vehicle accidents and just single-vehicle accidents. The "plain logit" estimates found at the top of each panel omit the state*year random effects and use the basic set of controls identified above, supplemented only with age dummies and a dummy for two-vehicle accidents when necessary.[18] We then progressively add variables until we arrive at the final, all-inclusive specification used in our decompositions.

We first compare the estimates from the one-and-two-vehicle specification in the third column of Table 4 with the restricted state-level specification in the second column. For ALR, .10, and .08 laws, the two sets of estimates are similar, indicating that the transition to micro-level estimation does not create unanticipated issues. Larger differences occur with the youth-oriented laws, the drinking age and zero tolerance, whose effects increase noticeably.[19] Raising the MLDA now cuts the chances of a fatal accident by about 10%, almost in line with Dobkin and Carpenter's (2009) regression discontinuity estimate. The zero tolerance estimates, which are now somewhat above the consensus in the literature, make up for any shortfall.

The fourth column of Table 4 analyzes single-vehicle accidents. These estimates are modestly larger in magnitude, as expected, since more of these drivers had been drinking. Though not reported in the table, for both sets of accidents, the estimated effect of open container laws is a significant 2% reduction in fatalities, while the estimated effect of dram shop laws is very small and

[18] The GLMM model had trouble converging with the full set of accidents, but 94% of the accidents in the data had at most two vehicles. The age dummies affect the estimates little except for the MLDA coefficient. This changes substantially because, early in the sample period, many states set the MLDA at nineteen or twenty; thus the incidence of the MLDA is correlated with age, which itself correlates with drinking. Age dummies must be included to remove this bias.

[19] These differences, it turns out, come from integrating the youth and adult samples, and not from the switch to individual-level estimation per se. Conducting individual-level estimation on the youth sample alone yields coefficients that resemble those in the second column of Table 4.

insignificant (as in the restricted specification in Table 2).

Progressing down the rows within each panel, the specifications add state*year random effects, the extended set of controls, and, finally, demographic and accident-specific factors. Only this last set of factors is consequential, moderating the law estimates notably. This finding suggests a mild favorable bias in state-level analyses, which usually omit these controls (and cannot include them at the micro level). Altogether, the estimates indicate that little is lost, and something is gained, by moving to micro-level estimation.

V. Explaining the Decline in Alcohol Involvement in Fatal Accidents.

We are now ready to explain the decline in drinking and driving during The Other Great Moderation.

To do so we must account for all major influences that have been recognized in the literature: alcohol consumption, economic factors, demographics, laws, and social forces. The first four of these are included directly in the final individual-level specification in Table 4. Our measures of alcohol consumption and economic factors are standard for the literature, while we account for demographics more effectively than before, as previously discussed.

Including the controls, this regression specification also accounts for seven drunk driving laws, more than is typical. Certainly, no vector of laws can be all-inclusive. Nonetheless, the *practical* case for legislative drunk-driving countermeasures rests squarely on these seven laws. No others have received appreciable support in the academic literature, strong financial incentives from Congress, or emphasis from NHTSA. For example, NHTSA's *Alcohol and Highway Safety* (2006) deems these laws five of the six "most important pieces of alcohol safety legislation in the last quarter century"–that is, during The Other Great Moderation.[20]

The beginning-of-period and end-of-period means in Table 2 show that each of these laws became much more common, more strict, or both over the sample period. Between 1982 and 2004, per se limits went from rare to .10 to .08, while the MLDA increased substantially and the remaining laws went from almost-absent to almost-universal. Equally large movements are demonstrated by alcohol consumption and unemployment; demographics also changed substantially, as we will see.

The remaining influence, social forces, is not measured with sufficient regularity to be included directly in the analysis. However, to the extent these forces are a product of national culture, as discussed at length below, their effect is national in scope and is thus captured by the year dummies in our regressions (along with the nationwide effect of any residual factors).[21] Consequently, we can decompose the decline in HBD during The Other Great Moderation into components associated with each of these major influences.

To execute the decomposition, return to the final specification in Table 4, and let the vector of demographic and accident-specific factors, D, include dummies for driver age and gender and for the hour, day, and month of the accident; the vector of state-level factors, S, include per capita

[20] The remaining piece of legislation, increased sanctions for repeat drunk driving offenders, has been studied little and is often implemented at the local level, rather than the state level. It is thus omitted from L. See Lapham et al. (2006), Jones and Lacey (2000), and NHTSA (1996).

[21] This approach is analogous to the standard decomposition used to infer the wage effects of labor market discrimination. A large literature infers these effects to be the group-wise difference in productivity-adjusted wages; here, the effect of social forces is inferred to be the temporal difference in alcohol involvement, adjusted for the effects of demographics, alcohol consumption, economic factors, and laws. A more direct approach could be used in Europe, where the SARTRE project regularly surveys attitudes toward drinking and driving.

alcohol consumption and the unemployment rate; and the vector of laws, L, include all seven drunk driving laws analyzed above. Now equation **(9)** becomes the following:

$$P(\eta_{i,s,t}=1) \;=\; \Lambda(\varphi D_{i,s,t}+\gamma L_{i,s,t}+\varphi S_{s,t}+\sigma_s+\tau_t+\varepsilon_{s,t}) \qquad \textbf{(10)}$$

where φ, γ, and ψ are coefficient vectors. Note that alcohol consumption and economic factors are combined into a single vector, S, for reasons that will soon be clear.

Next, subsume the state fixed effects into the category of demographics and define t=0 as a base year. Now (excusing some abuse of notation) consider the following four equations:

$$H_t \;=\; \bar{\eta}_t \;=\; \bar{\hat{\eta}}_t \;=\; \overline{\Lambda([\varphi D_{i,s,t}+\sigma_s]+\gamma L_{i,s,t}+\psi S_{s,t}+\tau_t)} \qquad \textbf{(11)}$$

$$E(H_t|L=L_0) \;=\; \overline{\Lambda([\varphi D_{i,s,t}+\sigma_s]+\gamma L_{i,s,0}+\psi S_{s,t}+\tau_t)} \qquad \textbf{(12)}$$

$$E(H_t|L=L_0,S=S_0) \;=\; \overline{\Lambda([\varphi D_{i,s,t}+\sigma_s]+\gamma L_{i,s,0}+\psi S_{s,0}+\tau_t)} \qquad \textbf{(13)}$$

$$E(H_t|L=L_0,S=S_0,t=0) \;=\; \overline{\Lambda([\varphi D_{i,s,t}+\sigma_s]+\gamma L_{i,s,0}+\psi S_{s,0}+\tau_0)} \qquad \textbf{(14)}$$

The difference between HBD nationwide in any given year, H_t, and HBD in the base year, H_0, can be broken down into four components, associated with laws (the difference between the first two equations), state-level factors (the difference between the next two equations), social forces and other residual factors (the difference between the two equations after that), and demographics and accident-specific factors (the difference between equation **(14)** and H_0). Given parameter estimates from equation **(10)**, each of these components can be calculated for each year of the sample period.[22]

[22] Both HBD and the counterfactual predictions in Figures 5-7 are obtained using all continental states in all years, though the estimation sample dropped a few early years of data for a few states because of BAC-reporting issues (see footnote 11). In these dropped observations, HBD

Though social forces are not explicitly measured in the U.S., their relevance is widely recognized in the literature on alcohol control (e.g., Okrent, 2010; Kyvig, 2000), in the broader literature on traffic safety (e.g., Borkenstein, 1985; Vereeck and Vrolix, 2007), and by policymakers (Grant, 2015). Their presence during, at least, the "first phase" of our study period, the 1980s, is well-documented.

Greenfield and Room (1997) compare "situational norms" regarding drinking and driving in three comparable national surveys taken in 1979, 1984, and 1990. These surveys indicate large declines in the social acceptance of drinking before driving and drinking "enough to feel the effects" away from home, while the acceptance of drinking at home or having "one or two drinks" away from home was undiminished (their Tables 3 and 4). Similar results are found for high school seniors in the Monitoring the Future surveys (Linkenbach and Young, 2012). Throughout the 1980s–but not after–there was a dramatic increase in the fraction of seniors nationwide who disapproved of, or perceived "great risk" in, having five drinks or more (their Figure 6). These attitudes were closely related to drinking behavior.

These intangible forces also found tangible expression. The 1980s saw large increases in the media coverage devoted to drunk driving and the number of organizations dedicated to combatting it (Howland, 1988). Numerous traffic safety officials have testified to a concomitant change in social attitudes (Grant, 2015). And the social advocacy group Mothers Against Drunk Driving (MADD) grew explosively. In 1985, five years after being founded, it had "over 600,000 members and donors, 360 chapters in all fifty states, and a budget approaching $10 million" (Reinarman, 1988,

---

was slightly under-reported; correcting for this would raise the demographic component in these decompositions by a few tenths of a percentage point, leaving the others unchanged.

p. 99).

These facts suggest that these social forces were national in scope. The limited evidence available on this point supports this conclusion as well. Between 1979 and 1984, Greenfield and Room (1997) find some diminution of regional differences in the acceptance of drinking, but these differences are far smaller for drunkenness, and disappear after 1984. Overall (p. 45) they conclude that "there is little evidence of a secular change in the pattern of demographic contributors [to the acceptance of drinking]"; this is consistent with a broad, general shift in attitudes. In any event, to the extent that social forces are *not* national in scope, their effects will be *understated* in our decompositions, and some of their explanatory power redirected to the other components.[23] Evidence on this point will be provided below.

Results. To implement this approach, we use the final specification in Table 4 and focus on single-vehicle accidents, for which the mean of driver-level alcohol involvement equates to HBD, and for which laws' estimated effects in Table 4 are especially favorable. The base year is 2004, and the age range remains 18-60. (The results are similar using a base year of 1982.) As it is easy to calculate how changes in HBD affect fatalities, our decompositions are conducted directly in terms of HBD.

The top line in Figure 5 presents the trend in HBD in this sample. In concert with Figure 1 and relative sobriety in Figure 4, it falls dramatically in the early years of this period, ultimately dropping 13.5 percentage points. But it is essentially constant after The Other Great Moderation ends in 1997.

[23] As for DeCicca et al. (2008), who document a similar effect of anti-smoking sentiment on smoking, which seems to favorably bias the estimated "deterrent" effect of cigarette taxes.

The shaded areas below this line present the decomposition. Each area narrows over time, as new laws, reductions in drinking, population aging, etc., “remove” some of the drinking-related fatalities that were previously there. Thus, the height of each component in 1982 measures the aggregate contribution of that factor to the reduction in HBD over the sample period.

First consider the laws component. Recall that this component aggregates the effects of all legislation with any appreciable academic support for a subset of accidents with especially favorable point estimates. Our estimates find that four of these laws–the raised MLDA, zero tolerance, .08 limits, and open container laws–substantially affect fatalities, while the others do not. Furthermore, these four laws became much more common our sample period, as shown in Table 2: the fraction of 18-20 year-olds who could drink legally went from about half to zero, while the other three laws went from mostly or wholly absent to universal, or nearly so.

However, the two largest point estimates apply to youth, who are only a fraction of all drivers. In the end, the aggregate effect of these laws, as shown in Figure 5, is modest: a 2.4 percentage point reduction in HBD, 18% of the total. This component builds gradually across the sample period, as increasing amounts of drunk driving legislation took effect, first raised MLDAs and .10 per se limits, then ALR and ZT laws, and finally .08 per se limits, with dram shop and open container laws interspersed throughout. Formal instruments–legal sanctions–diffuse slowly, a product of cumbersome political processes.

A larger component, which accounts for a 4.2 percentage point reduction in HBD, is associated with demographic and accident-specific factors. It too develops gradually, as the corps of drivers ages and becomes more female and weekend accidents slightly decline. Its size suggests that inattention to these factors can be consequential and reinforces the value of our microdata estimation approach that captures them best.

The remaining two components fall precipitously in the first decade of the sample period and little thereafter. The smaller of these represents the two state-level factors, unemployment and per capita alcohol-consumption, and explains 1.7 percentage points of the reduction in HBD. It mostly reflects changes in alcohol consumption; controlling for this, the unemployment coefficient disappears (as in the restricted specification in Table 2). Its downward trend cannot be explained by alcohol prices, which slightly trailed inflation throughout the period, or by the demographic and law variables in our regressions, which are weakly related to consumption. (Thus, in Table 4, the law estimates change little when per capita consumption is controlled for.)

The final component is associated with social forces and other residual factors. It is the largest of the set, accounting for a 5.2 percentage point reduction in HBD, 39% of the total. Its decline, concentrated in the early years of the sample, coincides with the period of greatest social ferment vis-a-vis drunk driving. It also coincides with the above-mentioned decrease in alcohol consumption. This coincidence, the documented presence of relevant social pressures during this period (Room, Greenfield, and Weisner, 1992), and the absence of an alternative explanation for this drinking decline intimate that social forces played a role here as well, as argued by Greenfield, Midanik, and Rogers (2000) and Linkenbach and Young (2012). If so, social forces reduced accidents indirectly, by reducing drinking, and directly, by reducing driving conditional on drinking. These two channels are represented in these last two components.

Altogether, then, while many factors contributed to the decline in drinking and driving during The Other Great Moderation, the largest and most immediate are associated with social forces.

Robustness. A sequence of robustness checks affirms our conclusions and sheds interpretive light.

One standard check (e.g., Dills, 2010; Adams, Blackburn, and Cotti, 2012) is to add state time trends to the specification. We did so and then replicated the decomposition above, incorporating the effects of these trends into the component associated with social forces and other residual factors. (This is obligatory: these trends and the year dummies are collinear.) To the extent these trends capture inter-state variation in the rate of change in social attitudes, their inclusion should increase the size of the social forces component and reduce that of laws, which are passed as social attitudes change. Were this to happen to any significant degree, it would demonstrate sensitivity to specification, conflict with the notion that these cultural attitudes are predominantly national, and undermine our interpretation of this component as reflecting social forces.

This decomposition is presented in Figure 6. It fully concords with our interpretation and with Section II's finding that the dynamics of relative sobriety are predominantly national. The components closely resemble those in Figure 5. As anticipated, laws' effects are reduced and social forces' effects increased, but the differences are small.

Another variant would be to define HBD in terms of *drunk driving*, instead of *drinking and driving*, and redo the analysis using a different dependent variable: a dummy that equalled one if the driver had a BAC of at least .08, the dominant per se drunk driving standard for the last twenty years. Our techniques easily accommodate this redefinition. Indeed, it strengthens the approximation used in deriving the latent variable model in Section II, $k >> 1$, since the mildest drinkers are removed from the set of alcohol-involved accidents. (The value of k almost doubles.) This new dependent variable is also better-aligned with .08 per se laws, which seek to reduce the amount of alcohol consumed by drivers, not eliminate it.

When equation **(10)** is re-estimated using this new dependent variable, the coefficient estimates resemble those obtained previously, with a “sharper and stronger” .08 per se law coefficient, as one would expect. In absolute terms, the estimated effect of drunk driving laws falls, since the restricted estimate now considers low-BAC accidents to be unaffected by legislation. The magnitudes in the associated decomposition, in Figure 7, are similarly reduced. In relative terms, however, this decomposition closely resembles its compatriot in Figure 5. Laws and alcohol consumption are slightly more important than before, and demographics and social forces slightly less important, but the latter two components still dominate.

Our findings are also robust to the inclusion of a different set of trends, motivated by Figure 3, which showed that declines in drinking occurred at different times for different ages. To account for this, we broadened the original specification to include a full set of decade*year dummies, where decade is determined by driver age (teens, 20s, 30s, etc.) The components, not reported here, hardly differ from those in Figure 5.

The results are also robust to the period used for estimation. As noted in Section III, early studies of the raised MLDA, zero tolerance laws, and .08 laws all find relatively large effects that dissipate to varying degrees in later studies with longer sample periods. As our sample period is on the long side for these literatures, it is reasonable to wonder this holds for the restricted estimates as well. It does not. While our unrestricted estimates reproduce this same progression, the restricted estimates remain remarkably stable if the sample period is cut by one quarter or even by one half.

Finally, we can ask what would happen if we “reverse engineered” the process by taking estimates of laws’ effects from fatality regressions, calculating the implied effects of these laws on HBD, and using those to compute the laws component. A direct comparison is not possible, since fatality regressions cannot control for demographics and accident-specific factors as we do, but the evidence suggests that little would change. As noted above, the prevailing estimates in the literature roughly concord with our restricted estimates, which in turn slightly exceed our own unrestricted estimates.

There is, however, one set of estimates that differs greatly from ours: those of Dang (2008), the only other study to try to quantify the aggregate effects of laws on HBD. Once again, however, these differences are more illusory than real. Dang's data and methods resemble those used here, except that she uses a pooled regression model that omits state and year fixed effects. As in other similar studies, this model strongly biases estimates of drunk driving laws' effects, as the incidence of these laws trends in the opposite direction from HBD over the sample period. The absence of these fixed effects explains the difference between our findings and hers, which indicate that laws explain nearly half of the decline in HBD.

VI. Discussion and Conclusion.

To synthesize the findings in this paper, we must harness that most un-dynamic of dynamic concepts: the steady state. The Other Great Moderation is best understood as a long, multifaceted social convergence to a new steady state of drinking and driving, in which alcohol is present in about 36% of all accident fatalities (and about 44% of fatal single-vehicle accidents).

Things kicked off in the late 1970s and early 1980s with changed social attitudes towards traffic safety in general and drunk driving in particular:

> The most substantial change in the status of drunk driving in the United States and throughout the Western world is not a matter of either law or technology, but one of

> social psychology. Driving while intoxicated, always a crime in the statute books, has come to be regarded in society as more of a "real crime" worthy of condemnation by the general public and punishment by the criminal justice system. (Zimring, 1988, p. 380)

This attitudinal shift directly affected drinking and driving, first among older drivers (Figure 3). It also had indirect effects, inspiring the passage of raised drinking ages and drunk driving laws in many states and possibly bringing down alcohol consumption as well. These changes and demographic shifts decreased drinking and driving substantially during the 1980s (Figures 5-7), accounting for all of the decline in per-mile traffic fatalities through 1988 (Figure 4).

But that was only the beginning. During the late 1980s and 1990s, alcohol involvement in fatal accidents continued to fall across a sequence of birth cohorts (Figure 3), while drunk driving legislation continued to diffuse throughout the country. These transitions, abetted significantly by demographic shifts, further reduced drinking and driving through 1997 (Figures 5-7). The decline in per mile traffic fatalities thereby produced was comparable to that produced by decreases in general risk (Figure 4).

Absent further shifts in public sentiment, however, it would be unrealistic to expect declines in drinking and driving to continue unabated. Indeed, they did not. After 1997, per-mile traffic fatalities fell solely because of decreases in general risk (Figure 4). The Other Great Moderation had ended. This denouement can be observed in the rate of alcohol involvement in fatal accidents, which remained constant for twenty years (Figure 2); in the social forces component in our decompositions, which has been static since the early 1990s (Figures 5-7); and in the rate at which significant new laws are adopted, which has slowed from a 1980s torrent to a post-2004 trickle.

What, then, is the way forward? More drunk driving legislation is one possibility, but it is not the only option. Before the onset of The Other Great Moderation, in the mid-1970s, laws and social suasion were viewed as alternative ways to expend political and social capital in order to reduce drunk driving, and a debate raged over the efficacy of these two approaches (Whitehead, 1975; Ross, 1992). This tradeoff has since been obscured by the dominance of deterrence in U.S. policy (Ross, 1992; Grant, 2015) and by the academic literature, which has repeatedly quantified the effects of laws but never those of social forces. Our decompositions suggest that social suasion is, indeed, a potential source of gains in traffic safety, now that the deterrence approach has long since encountered diminishing returns.

Furthermore, this debate looked at the problem too narrowly. Laws can't create norms, but they can codify and extend them. Thus, our narrative treats social attitudes not as an alternative to legislation, but as the foundation upon which are grounded many sources of gains in relative sobriety: laws, alcohol consumption, and the decision to drink and drive conditional on these two. Were this foundation to shift once again, further gains in alcohol-related traffic safety would be probable, and another Great Moderation would begin.

APPENDIX

In addition to the variables defined in the text, let F^* and H^* be the number of accidents and HBD predicted from state and year fixed effects. Also, let C be the total number of state*year cells. Note that F, the number of fatal accidents, is also the number of observations within each state*year cell.

Then, summing across state*year cells:

$$\begin{aligned}\Sigma(H-H^*)^2 = \Sigma(H-h)^2 + \Sigma(h-H^*)^2 \;&=\; \Sigma\frac{h\cdot(1-h)}{F} + \Sigma(h-H^*)^2 \\ &\approx\; \Sigma\frac{H^*\cdot(1-H^*)}{F} + \Sigma(h-H^*)^2\end{aligned} \qquad \textbf{(15)}$$

Numerical experiments confirm that the approximation of sampling error, achieved by replacing h with H^*, is very close. The sample analog of var(h - H^*) is then:

$$\Sigma\frac{(h-H^*)^2}{C} \;\approx\; \Sigma\frac{(H-H^*)^2}{C} - \Sigma\frac{H^*\cdot(1-H^*)}{C\cdot F} \qquad \textbf{(16)}$$

The adjusted serial and spatial correlations of h - H^* are calculated by scaling the unadjusted correlations by the estimate of var(H - H^*)/var(h - H^*).

Similarly, the properties of log(f/M) - log(F^*/M) can be inferred by extracting sampling error as follows:

$$\begin{aligned}&\Sigma\Big(\frac{F-F^*}{F^*}\Big)^2 = \Sigma\Big(\frac{F-f}{F^*}\Big)^2 + \Sigma\Big(\frac{f-F^*}{F^*}\Big)^2 \;=\; \Sigma\frac{f}{F^{*2}} + \Sigma\Big(\frac{f}{F^*}-1\Big)^2 \;\approx \\ &\Sigma\frac{1}{F^*} + \Sigma\log^2\Big(\frac{f}{F^*}\Big) \;=\; \Sigma\frac{1}{F^*} + \Sigma(\log(f)-\log(F^*))^2 \;\equiv\; \Sigma\frac{1}{F^*} + \Sigma(\log(f/M)-\log(F^*/M))^2\end{aligned} \qquad \textbf{(17)}$$

The adjusted correlation between HBD and log fatalities per mile, that is, between h - $H*$ and $\log(f/M)$ - $\log(F*/M)$, can also be calculated by scaling their unadjusted correlation.

Finally, to identify the variance of the general risk factor, r, and its correlation with h, define n = 1 - h, and N and $N*$ accordingly. Also define $n' = n/N*$, and f' and r' accordingly. Then:

$$\Sigma\left(\frac{N-N^*}{N^*}\right)^2 = \Sigma\left(\frac{N-n}{N^*}\right)^2 + \Sigma\left(\frac{n-N^*}{N^*}\right)^2 \;=\; \Sigma\frac{n\cdot(1-n)}{F\cdot N^{*2}} + \Sigma\left(\frac{n}{N^*}-1\right)^2$$
$$\approx\; \Sigma\frac{1-N^*}{F\cdot N^*} + \Sigma(\log(n)-\log(N^*))^2$$

$$cov(\log(F)-\log(F^*),\log(N)-\log(N^*)) \;=\; cov(\log(f'),\log(n')) \;=$$
$$cov(\log(r')-\log(n'),\log(n')) \;=\; cov(\log(r'),\log(n'))-var(\log(n'))$$

$$\Sigma(\log(f/M)-\log(F^*/M))^2 \;=\; \Sigma\left(\log\frac{r/n}{r^*/N^*}\right)^2 \;=\; \Sigma([\log(r)-\log(r^*)]-[\log(n)-\log(N^*)])^2$$
$$\rightarrow\; C\cdot[var(\log(r')+var(\log(n')-2cov(\log(r'),\log(n')]$$

The first relationship identifies the variance of $\log(n')$, the second the covariance of $\log(r')$ and $\log(n')$, and the third–along with equation **(17)**–the variance of $\log(r')$.

REFERENCES

Adams, S., Blackburn, M., and Cotti, C. Minimum wages and alcohol-related traffic fatalities among teens. *Review of Economics and Statistics* 94:828-840, 2012.

Anderson, D.M., Hansen, B., and Rees, D. Medical marijuana laws, traffic fatalities, and alcohol consumption. *Journal of Law and Economics* 56: 333-369, 2013.

Arnold, R.D. Effect of Raising the Legal Drinking Age on Driver Involvement in Fatal Crashes: The Experience of Thirteen States. NHTSA Technical Report HS 806 902, National Highway Traffic Safety Administration, 1985.

Benson, B., Rasmussen, D., and Mast, B. Deterring drunk driving fatalities: an economics of crime perspective. *International Review of Law and Economics* 19: 205-225, 1999.

Blincoe, L., Seay, A., Zaloshnja, E., Miller, T., Romano, E., Luchter, S., and Spicer, R. The Economic Impact of Motor Vehicle Crashes, 2000. NHTSA Technical Report DOT HS 809 446, National Highway Traffic Safety Administration, 2002.

Blincoe, L. The economic cost of motor vehicle crashes, 1994. NHTSA Technical Report DOT HS 808425, National Highway Traffic Safety Administration, 1996.

Blomberg, R., Peck, R., Moskowitz, H., Burns, M., and Fiorentino, D. The Long Beach/Fort Lauderdale relative risk study. *Journal of Safety Research* 40:285-292, 2009.

-----. Crash risk of alcohol impaired driving: A case-control study. Manuscript, Dunlap and Associates, 2005.

Borkenstein, R.F. Historical perspective: North American traditional and experimental response. *Journal of Studies on Alcohol* 10 (Supplement):3-12, 1985.

Burke, P., and Nishitateno, S. Gasoline prices and road fatalities: international evidence. *Economic Inquiry* 53:1437-1450, 2015.

Dang, J.N. Statistical analysis of alcohol-related driving trends, 1982-2005. NHTSA Technical Report HS 810 942, National Highway Traffic Safety Administration, 2008.

DeCicca, P., Kenkel, D., Mathios, A., Shin, Y-J., and Lim, J-Y. Youth smoking, cigarette prices, and anti-smoking sentiment. *Health Economics* 17:733-749, 2008.

Dee, T.S. State alcohol policies, teen drinking and traffic fatalities. *Journal of Public Economics* 72: 289-315, 1999.

----. Does setting limits save lives? The case of 0.08 BAC laws. *Journal of Policy Analysis and Management*, 20: 111-128, 2001.

Dee, T.S., Grabowski, D.C., and Morrisey, M.A. Graduated driver licensing and teen traffic fatalities. *Journal of Health Economics* 24: 571-589, 2005.

Dills, A. Social host liability for minors and underage drunk-driving accidents. *Journal of Health Economics* 29:241-249, 2010.

Dobkin, C. and Carpenter, C. The effect of alcohol consumption on mortality: regression discontinuity evidence from the minimum drinking age. *American Economic Journal: Applied Economics* 1: 164-182, 2009.

Douglass, R.L. and Millar, C.W. Alcohol availability and alcohol-related casualties in Michigan 1968-1976. In Galanter, M. (Ed.), *Currents in Alcoholism, Vol 6: Treatment and Rehabilitation and Epidemiology*. New York: Grune & Stratton, 1979.

Eisenberg, D. Evaluating the effectiveness of policies related to drunk driving. *Journal of Policy Analysis and Management* 22: 249-274. 2003.

Fell, J.C., Fisher, D.A., Voas, R.B., Blackman, K., and Tippetts, A.S. The relationship of underage drinking laws to reductions in drinking drivers in fatal crashes in the United States. *Accident Analysis and Prevention* 40: 1430-1440, 2000.

Freeman, D. Drunk driving legislation and traffic fatalities: New evidence on BAC 08 laws. *Contemporary Economic Policy* 25:293-308, 2007.

Grabowski, D., and Morrisey, M. Gasoline prices and motor vehicle fatalities. *Journal of Policy Analysis and Management* 23,3:575-593 (2004).

Grant, D. Dead on arrival: zero tolerance laws don't work. *Economic Inquiry* 48: 756-770, 2010.

----. Policy analysis and policy adoption: a study of three national drunk driving initiatives. Manuscript, Sam Houston State University, 2011.

----. Politics, policy analysis, and the passage of the National Minimum Drinking Age Act of 1984. Manuscript, Sam Houston State University, 2015.

----. A structural analysis of U.S. drunk driving policy. *International Review of Law and Economics* 45:14-22, 2016.

Greenfield, T., Midanik, L., and Rogers, J. A 10-year national trend study of alcohol consumption, 1984-1995: is the period of declining drinking over? *American Journal of Public Health* 90:47-52, 2000.

Greenfield, T., and Room, R.. Situational norms for drinking and drunkenness: trends in the U.S. adult population, 1979-1990. *Addiction* 92:33-47, 1997.

Hingson, R., Heeren, T., and Winter, M. Lowering state blood alcohol limits to 0.08 percent: the effect on fatal motor vehicle crashes. *American Journal of Public Health* 86,9:1297-1299, 1996.

Howland, J. Social norms and drunk driving countermeasures, in John Graham, Ed., *Preventing Automobile Injury: New Findings from Evaluation Research*. Dover, Mass.: Auburn House, 1988.

Jones, R., and Lacey, J. State of knowledge of alcohol-impaired driving: research on repeat DWI offenders. NHTSA Technical Report, National Highway Traffic Safety Administration, 2000.

Kyvig, D. *Repealing National Prohibition*. Kent, OH: Kent State University Press, 2000.

Lapham, S., Kapitula, L., deBaca, J., and McMillan, G. Impaired-driving recidivism among repeat offenders following an intensive court-based intervention. *Accident Analysis and Prevention* 38,1:162-169 (2006).

Levitt, S., and Porter, J. How dangerous are drinking drivers? *Journal of Political Economy* 109:1198-1237, 2001.

Linkenback, J., and Young, D. Accounting for changes in alcohol use and abuse in the United States. *Sage Open* July-September:1-8, 2012.

McArthur, D.L., and Kraus, J.F.. The specific deterrence of administrative per se laws in reducing drunk driving recidivism. *American Journal of Preventive Medicine* 16:68-75, 1999.

McCulloch, C. Generalized linear mixed models. In A. El-Shaarawi and W. Piegorsch, eds., *Encyclopedia of Environmetrics*. New York: Wiley, 2006.

Miron, J., and Tetelbaum, E. Does the minimum legal drinking age save lives? *Economic Inquiry* 47: 317-336, 2009.

National Highway Traffic Safety Administration. *Traffic Safety Facts*, March 2009.

----. Evaluation of alternative programs for repeat DWI offenders. Technical report HS 808 493 (1996).

Okrent, D. *Last Call: The Rise and Fall of Prohibition*. New York: Scribner, 2000.

Reinarman, C. The social construction of an alcohol problem: the case of Mothers Against Drunk Drivers and social control in the 1980s. *Theory and Society* 17:91-120, 1988.

Robertson, L.S. Blood alcohol in fatally injured drivers and the minimum legal drinking age. *Journal of Health Politics, Policy, and Law* 14: 814-825, 1989.

Ross, H.L. *Confronting Drunk Driving: Social Policy for Saving Lives*. New Haven: Yale University Press, 1992.

Ruhm, C.J. Alcohol policies and highway vehicle fatalities. *Journal of Health Economics* 15: 435-454, 1996.

Solon, G., Haider, S., and Wooldridge, J. What are we weighting for? NBER Working Paper 18859 (2013).

Vereeck, L., and Vrolix, K. The social willingness to comply with the law: the effect of social attitudes on traffic fatalities. *International Review of Law and Economics* 27:385-408, 2007.

Voas, R.B., Tippetts, A.S., Fell, J. The relationship of alcohol safety laws to drinking drivers in fatal crashes. *Accident Analysis & Prevention* 32: 483-492, 2000.

----. Assessing the effectiveness of minimum legal drinking age and zero tolerance laws in the United States. *Accident Analysis and Prevention* 35:579-587, 2003.

Whetten-Goldstein, K., Sloan, F., Stout, E., and Liang, L. Civil liability, criminal law, and other policies and alcohol-related motor vehicle fatalities in the United States: 1984-1995. *Accident Analysis and Prevention* 32:723-733, 2000.

Whitehead, P.C. Effects of liberalizing alcohol control measures. *Addictive Behaviors* 1: 197-203, 1975.

Williams, A.F., Zador, P.L., Harris, S.S., and Karpf, R.S. The effect of raising the legal minimum drinking age on involvement in fatal crashes. *Journal of Legal Studies* 4:169-179, 1983.

Young, D.J. and Beilinska-Kwapisz, A.. Alcohol prices, consumption, and traffic fatalities. *Southern Economic Journal* 72:690-703, 2006.

Zimring, F. Law, society, and the drinking driver: Some concluding reflections. In M.D. Laurence, J.R. Snortum, and F.E. Zimring, eds., *Social Control of the Drinking Driver*. Chicago: University of Chicago Press, 1988.

Table 1. Standard Deviations and Various Correlations of HBD, Log Fatalities, and More.

	Standard Deviation	Spatial Correlation	Serial Correlation	Cross Correlation
Raw (Unadjusted)				
HBD (perc. points)	5.7	0.07	0.15	0.08
Log Fatalities (times one hundred)	13.2	0.18	0.32	0.08
Adjusted for Sampling Error				
HBD	2.3	0.41	0.81	0.32
Log Fatalities	8.1	0.46	0.84	0.32
Latent Variables				
Implied General Risk Factor (percent)	7.5	----	----	0.19
Implied Drinking Factor (percent)	4.9	----	----	0.19

Note: All observed and latent variables are measured (or presumed measured) at the state*year level, in deviations from state and year fixed effects (and, for fatalities, scaled by the log of vehicle miles traveled). Spatial correlations are calculated across matched state pairs. Using postal codes, the pairs are as follows: ME/MA, VT/NH, CT/RI, NY/NJ, TX/OK, KS/NE, ND/SD, WA/OR, CA/NV, UT/CO, ID/MT, MN/WI, AZ/NM, MI/OH, IL/IN, IA/MO, AR/LA, AL/MS, TN/KY, GA/FL, NC/SC, VA/WV, MD/PA, DC/DE, AK/HI. "Adjusted" means that the effects of sampling variance have been removed. Cross correlations are the correlation of HBD and log fatalities, and the general risk factor with the implied drinking factor. There are 1173 observations (51 states * 23 years).

Table 2. Estimates of Two Models, Extended GLMM Accident-Level Specification (effect on the logarithm of the number of fatal accidents, with standard errors in parentheses).

	SPECIFICATION†		POPULATION-WEIGHTED MEAN AND ST. DEVIATION	
	Unrestricted, State-Level, Adult Drivers	Restricted, State-Level, Adult Drivers	All Drivers, 1982	All Drivers, 2004
Factors Affecting Drinking and Driving (X)				
.10 per se Law	0.0153 (0.0113)	0.0041 (0.0086)	0.36 (0.40)	1
.08 per se Law	0.0126 (0.0101)	-0.0179 (0.0076)	0	0.97 (0.15)
Administrative License Revocation	-0.0242 (0.0093)	-0.0033 (0.0071)	0.03 (0.17)	0.78 (0.41)
Dram Shop Law	-0.0124 (0.0124)	0.0110 (0.0094)	0	0.91 (0.28)
Open Container Law	-0.0044 (0.0095)	-0.0224 (0.0072)	0	0.90 (0.31)
Minimum Legal Drinking Age (years of age)	----	----	19.60 (1.15)	21
Zero Tolerance Law	----	----	0	1
Per Capita Alcohol Consumption (gal./yr.)	0.1725 (0.0244)	0.0587 (0.0158)	2.71 (0.47)	2.22 (0.32)
Factors Affecting Both (Z) Unemployment Rate (percent)	-0.0208 (0.0027)	0.0017 (0.0020)	9.73 (2.19)	5.39 (0.86)
General Risk Factors (G) Primary Seat Belt Law	-0.0458 (0.0127)	----	0	0.58 (0.49)
Secondary Seat Belt Law	0.0036 (0.0098)	----	0	0.41 (0.49)
Maximum Speed Limit (mph) (three dummy variables)	jointly significant	----	55	68.49 (3.23)
Miles Travelled, in logs	0.69 (0.04)	----	10.79 (0.80)	11.44 (0.82)
R^2			----	----

† All models include a full set of state and year fixed effects. For regressions, N = 1058, 48 states (not AK, DC, HI) for 23 years, excluding years prior to discrete jumps in BAC reporting in twelve states (see the text); adults include drivers aged 21-60. Means are for all 48 continental states.

Table 3. Three Sets of GLMM Estimates of the Percentage Effect of Laws on Fatalities or Fatal Traffic Accidents (standard errors in parentheses).

Law / Sampling Unit	***Unrestricted*** (*Estimate*)	***Partially Restricted*** (*Estimate*)	***Restricted*** (*Estimate*)	Grand Mean of HBD
0.10 Per Se Laws				
Fatalities	1.34 (1.20)	0.90 (0.80)	0.47 (0.91)	0.424
Accidents	1.98 (1.17)	0.98 (0.77)	0.26 (0.87)	0.422
Single Vehicle Accidents	2.08 (1.42)	0.89 (1.07)	-0.92 (1.31)	0.523
0.08 Per Se Laws				
Fatalities	0.74 (1.08)	-0.68 (0.73)	-2.13* (0.82)	0.424
Accidents	1.00 (1.05)	-0.57 (0.71)	-2.01* (0.78)	0.422
Single Vehicle Accidents	0.97 (1.27)	-1.02 (0.98)	-3.73* (1.17)	0.523
ALR Laws				
Fatalities	-3.82* (0.98)	-1.61* (0.65)	-0.84 (0.75)	0.424
Accidents	-3.63* (0.95)	-1.52* (0.64)	-0.80 (0.72)	0.422
Single Vehicle Accidents	-3.19* (1.16)	-1.85* (0.88)	-1.04 (1.07)	0.523
MLDA (0 = 18 yrs., 1 = 21 yrs.)				
Fatalities	-2.23 (3.16)	-2.80 (1.64)	-4.75* (2.00)	0.347
Accidents	-1.98 (2.91)	-2.59 (1.49)	-4.39* (1.86)	0.339
Single Vehicle Accidents	2.19 (3.67)	-1.45 (2.39)	-6.86* (3.08)	0.475
Zero Tolerance Laws				
Fatalities	-1.77 (2.39)	-1.91 (1.37)	-1.92 (1.46)	0.347
Accidents	-1.61 (2.23)	-2.29 (1.29)	-2.48 (1.35)	0.339
Single Vehicle Accidents	-1.07 (2.88)	-2.54 (2.06)	-3.39 (2.45)	0.475

Note: N = 1058, 48 states (not AK, DC, HI) for 23 years, excluding years prior to discrete jumps in BAC reporting in twelve states. Separate regressions are conducted for adults aged 21-60 (the first three laws) and youth aged 18-20 (the last two laws). The restricted estimates include controls for the unemployment rate and (for youth) .08 and .10 per se laws and ALR. The other estimates also include controls for seat belt laws and speed limits, as described in the text. * indicates $p < 0.05$.

Table 4. Robustness Checks and Transition to Individual-Level Estimation (implied percentage change in fatal accidents, with standard errors in parentheses).

	Estimate		Specification (Restricted Estimate)	
Law Estimator / Controls	***Unrestricted***	***Restricted***	***Logit, 1 & 2 Vehicle Accidents***	***Logit, Single Vehicle Accidents***
.10 Per Se Laws Weighted Least Squares	3.16 (1.15)	0.53 (0.82)	----	----
Unweighted Least Squares / Plain Logit	0.51 (1.33)	-0.20 (1.02)	0.50 (0.36)	-0.04 (0.77)
GLMM	1.98 (1.17)	0.26 (0.87)	0.44 (0.55)	-0.27 (1.07)
Add Extended Controls	1.53 (1.13)	0.41 (0.86)	0.59 (0.56)	-0.15 (1.06)
Also Add Driver and Accident Controls	----	----	0.29 (0.49)	0.13 (0.95)
.08 Per Se Laws Weighted Least Squares	1.58 (0.92)	-2.93* (0.67)	----	----
Unweighted Least Squares / Plain Logit	0.52 (1.18)	-1.78 (0.91)	-1.99* (0.30)	-4.07* (0.64)
GLMM	1.00 (1.05)	-2.01* (0.78)	-1.48* (0.48)	-3.21* (0.92)
Add Extended Controls	1.26 (1.01)	-1.79* (0.76)	-1.42* (0.48)	-3.04* (0.91)
Also Add Driver and Accident Controls	----	----	-0.97* (0.43)	-1.68* (0.81)
ALR Laws Weighted Least Squares	-1.72 (0.87)	-1.42* (0.63)	----	----
Unweighted Least Squares / Plain Logit	-4.90* (1.10)	-0.98 (0.85)	-0.86* (0.30)	-1.24* (0.64)
GLMM	-3.63* (0.95)	-0.80 (0.72)	-0.35 (0.52)	-0.32 (0.97)
Add Extended Controls	-2.42* (0.93)	-0.33 (0.71)	-0.11 (0.53)	0.18 (0.97)
Also Add Driver and Accident Controls	----	----	-0.26 (0.46)	-0.17 (0.86)

MLDA (0 = 18 yrs., 1 = 21 yrs.) Weighted Least Squares	-1.38 (2.70)	-5.24* (1.71)	----	----
Unweighted Least Squares / Plain Logit	-2.98 (3.98)	-4.40 (2.46)	-9.67* (0.76)	-15.36* (1.62)
GLMM	-1.98 (2.91)	-4.39* (1.86)	-9.98* (0.78)	-16.12* (1.65)
Add Extended Controls	-6.05* (2.89)	-3.73* (1.91)	-10.03* (0.78)	-16.34* (1.65)
Also Add Driver and Accident Controls	----	----	-7.49* (0.71)	-11.96* (1.47)
Zero Tolerance Laws Weighted Least Squares	-2.50 (2.13)	-2.53 (1.35)	----	----
Unweighted Least Squares / Plain Logit	-2.43 (2.90)	-1.41 (1.82)	-5.71* (0.47)	-8.89* (0.93)
GLMM	-1.61 (2.23)	-2.48 (1.35)	-5.61* (0.47)	-8.77* (0.94)
Add Extended Controls	-1.37 (2.17)	-2.60 (1.36)	-5.61* (0.47)	-8.76* (0.94)
Also Add Driver and Accident Controls	----	----	-3.96* (0.43)	-5.42* (0.83)

Note: In the leftmost two columns, N = 1058 state*year cells. In rightmost two columns, N = 858,094 and 386,695 driver-level observations. See Table 3 for the controls in the basic specifications. The extended controls include per capita alcohol consumption and dram shop and open container laws. Driver and accident controls include dummies for driver age and sex, accident hour, day, and month, and the number of vehicles in the accident (when appropriate). In the WLS estimates, weights are the number of accidents in each state*year cell. In the first two columns, separate state-level regressions are conducted for youth and adults (but not in the last two columns). * = $p < .05$.

Figure 1. BAC Conditional on Driving after Drinking, Drivers Involved in Fatal Accidents, Nationwide: with Imputed Data (on left) and without.

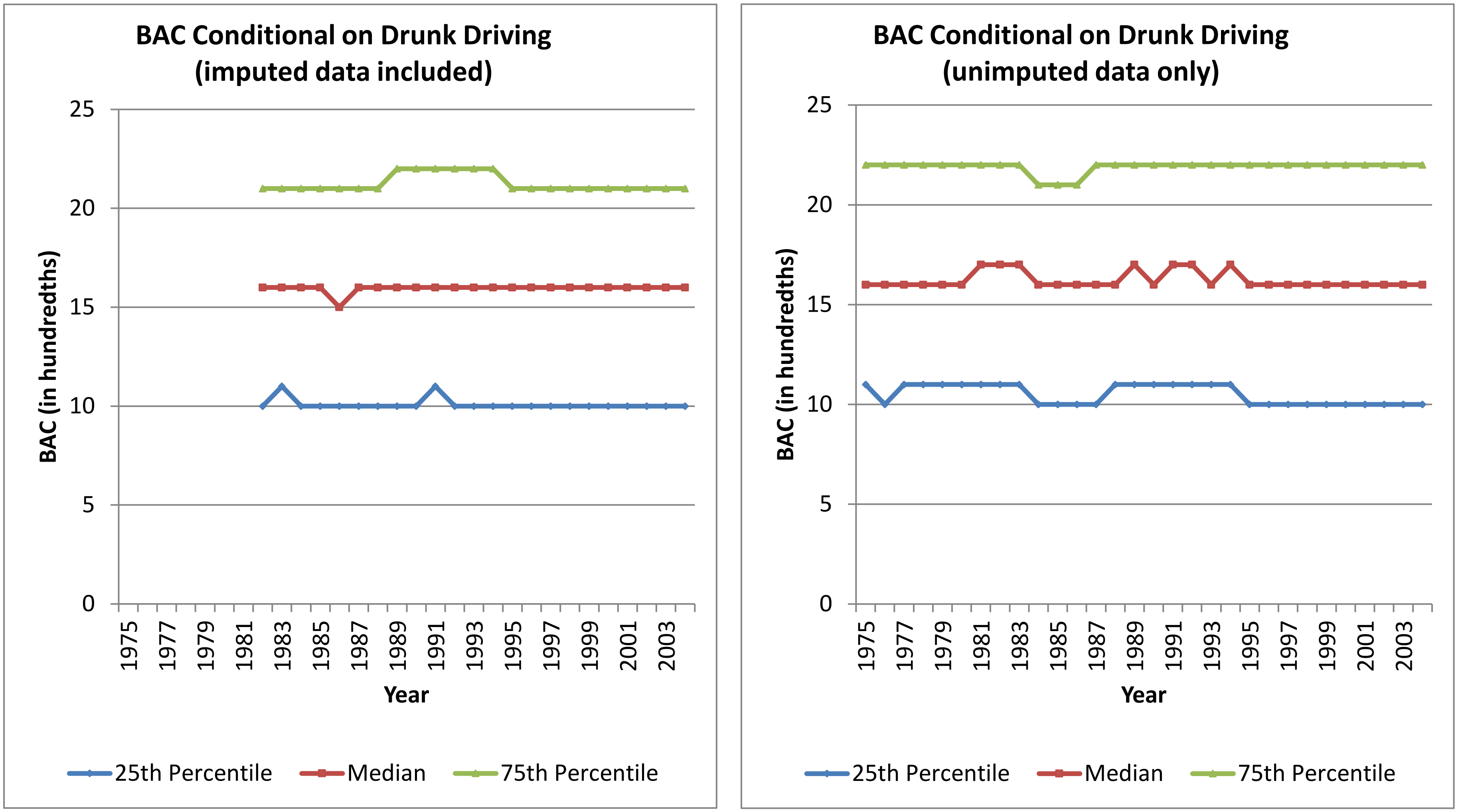
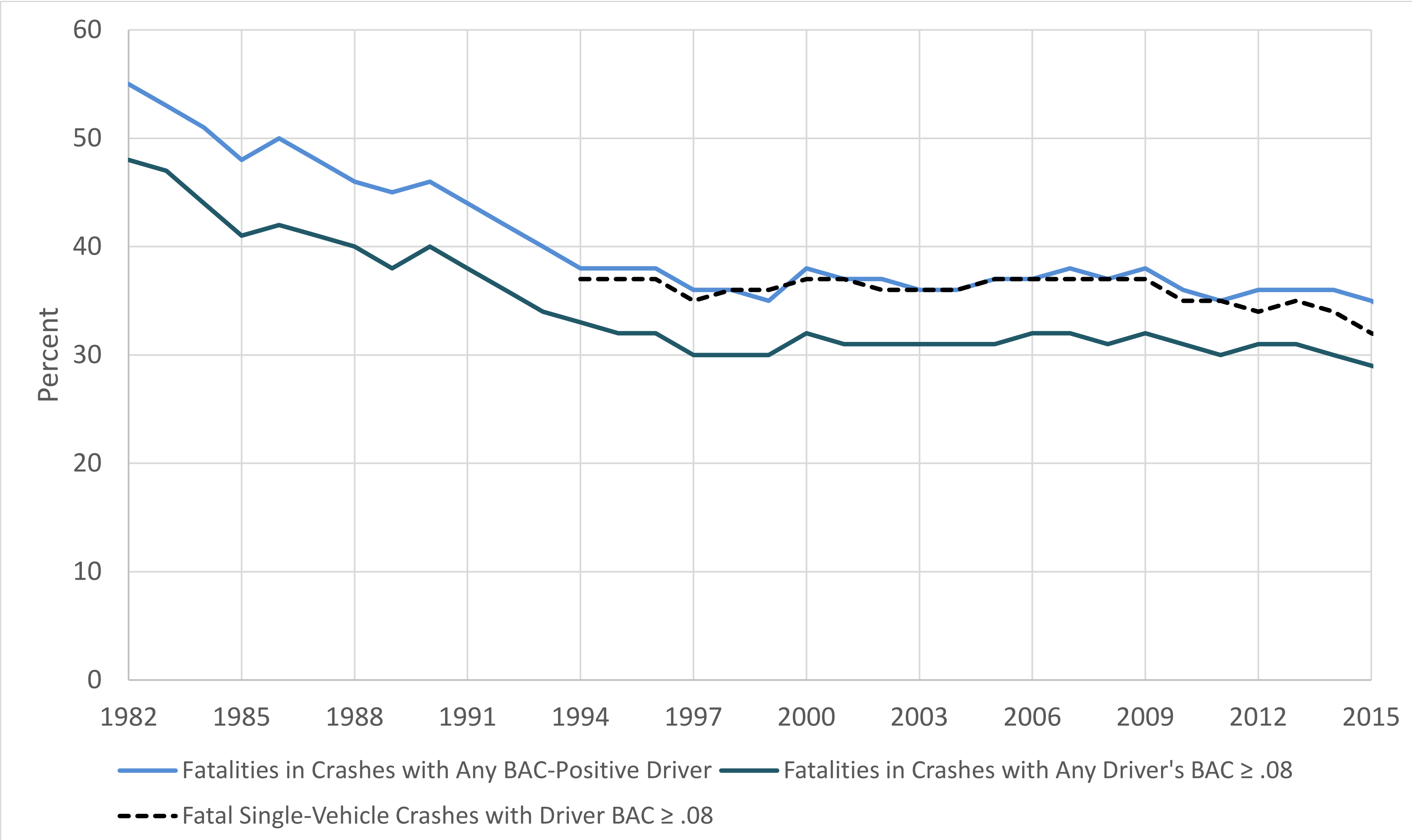


Figure 2. Three NHTSA-Reported Measures of Alcohol Involvement in Fatal Accidents, 1982-2015.



Note: Data from Table 13 of the Traffic Safety Reports Tables and in the FARS Data Tables, under Crashes–Alcohol, both of which are located within FARS, at www-fars.nhtsa.dot.gov.

Figure 3. Evolution of HBD in the U.S.: Profiles by Age, with Imputed Data (on left) and without.

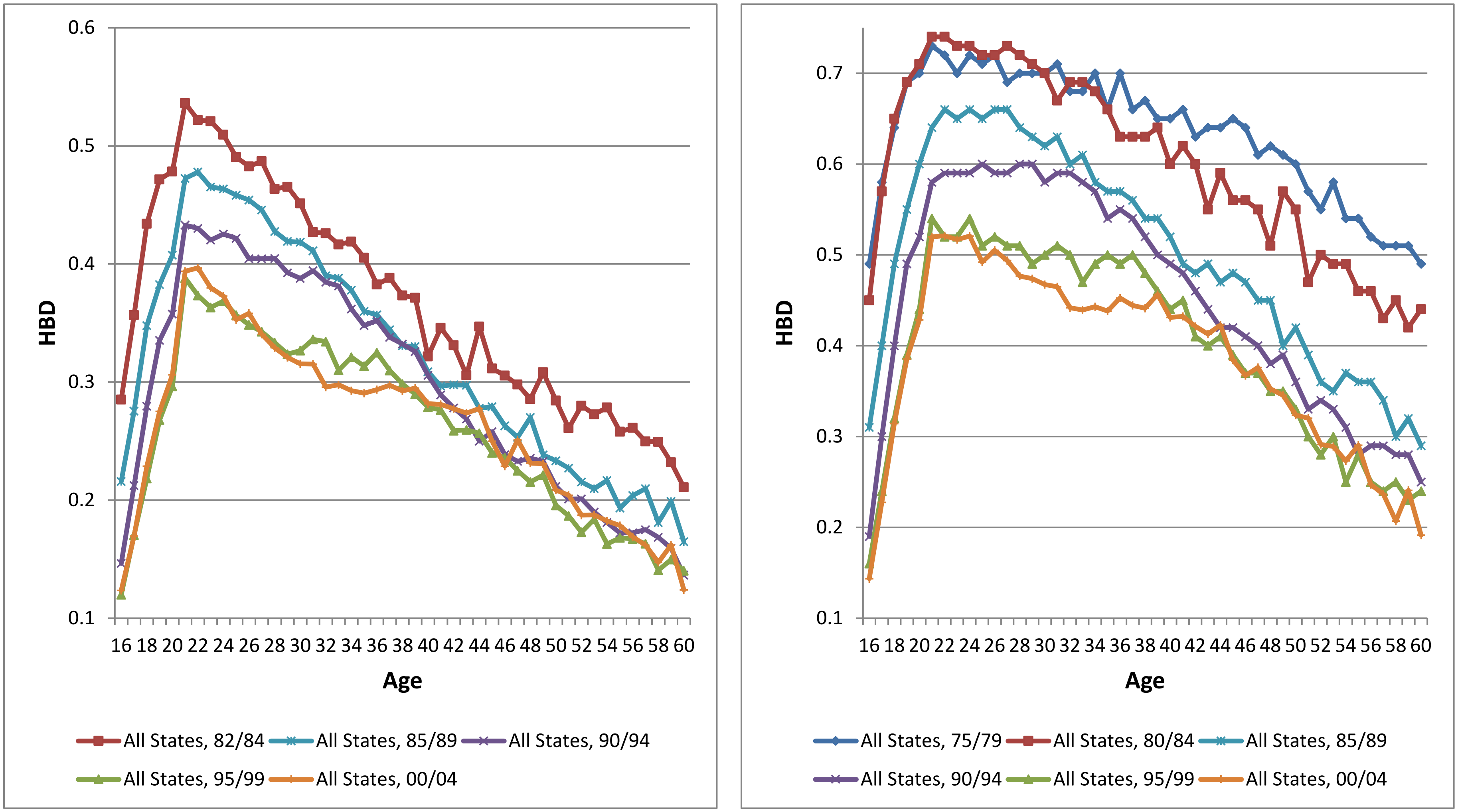


Figure 4. Breakdown of the Change in Traffic Fatalities into Contributions Associated with Drinking, General Risk, and Miles Travelled.

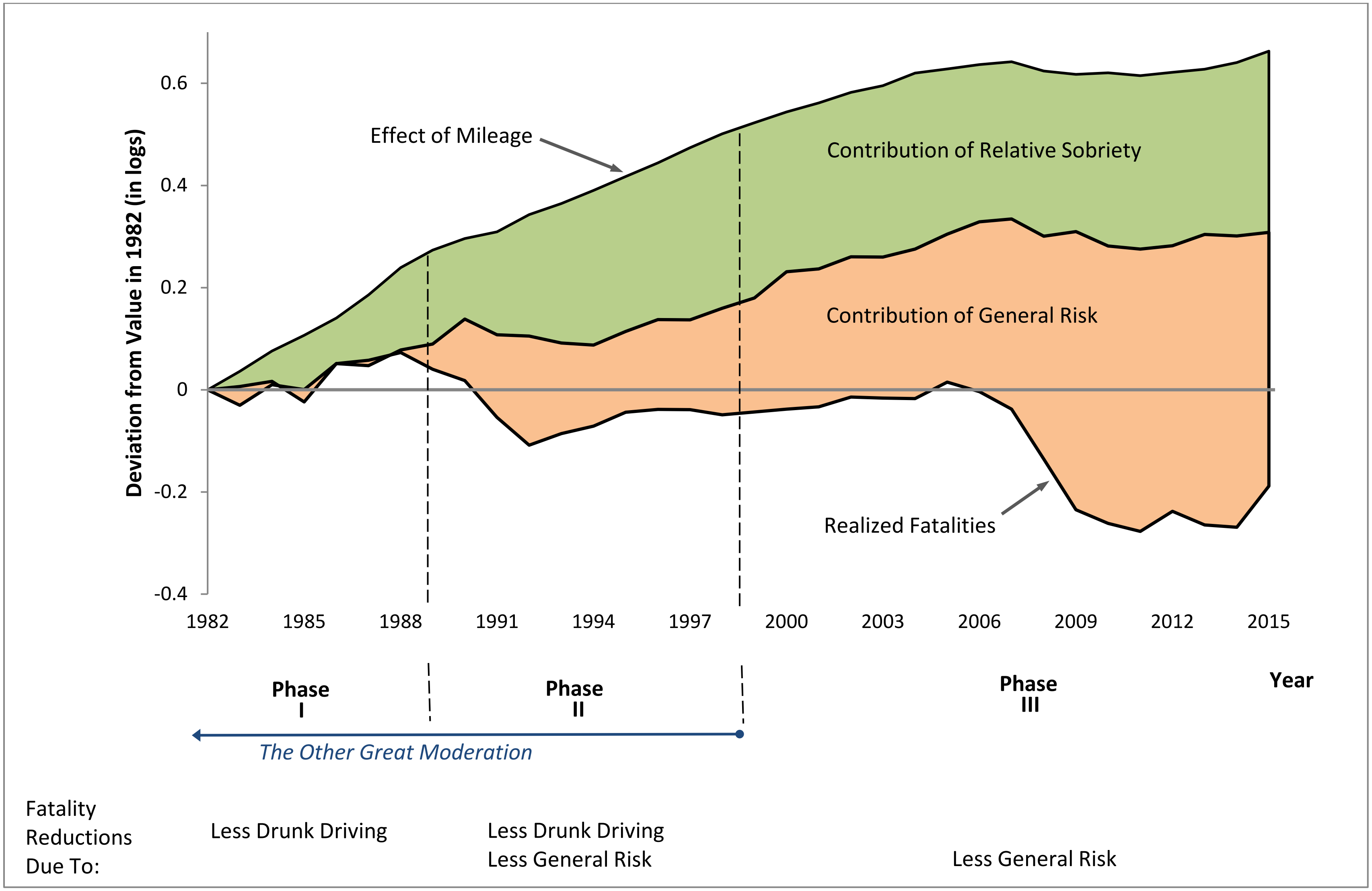


Figure 5. Decomposition of the Reduction in HBD in Single-Vehicle Accidents, 1982-2004.

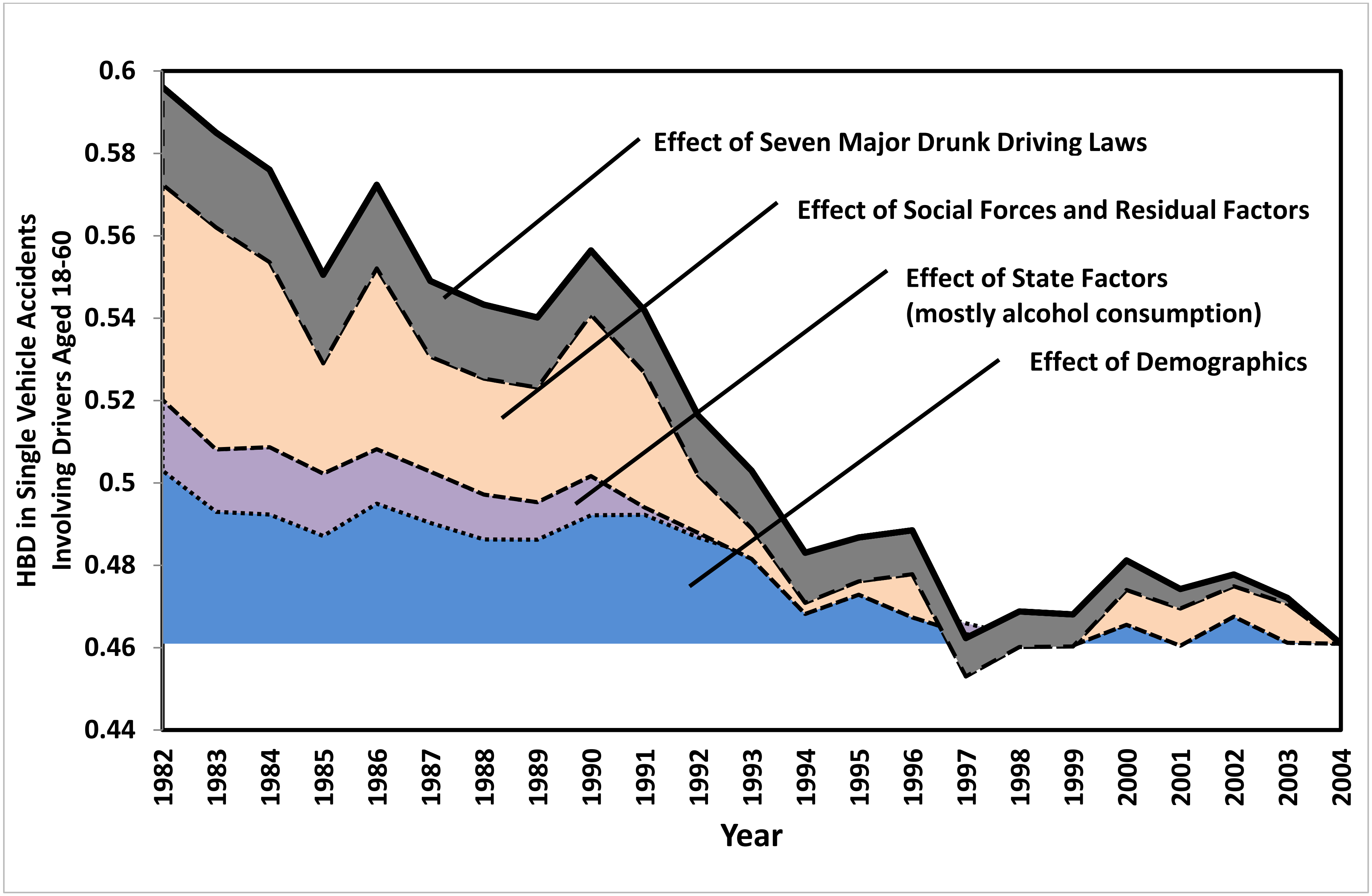


Figure 6. Decomposition of the Reduction in HBD in Single-Vehicle Accidents, 1982-2004, State Trends Added.

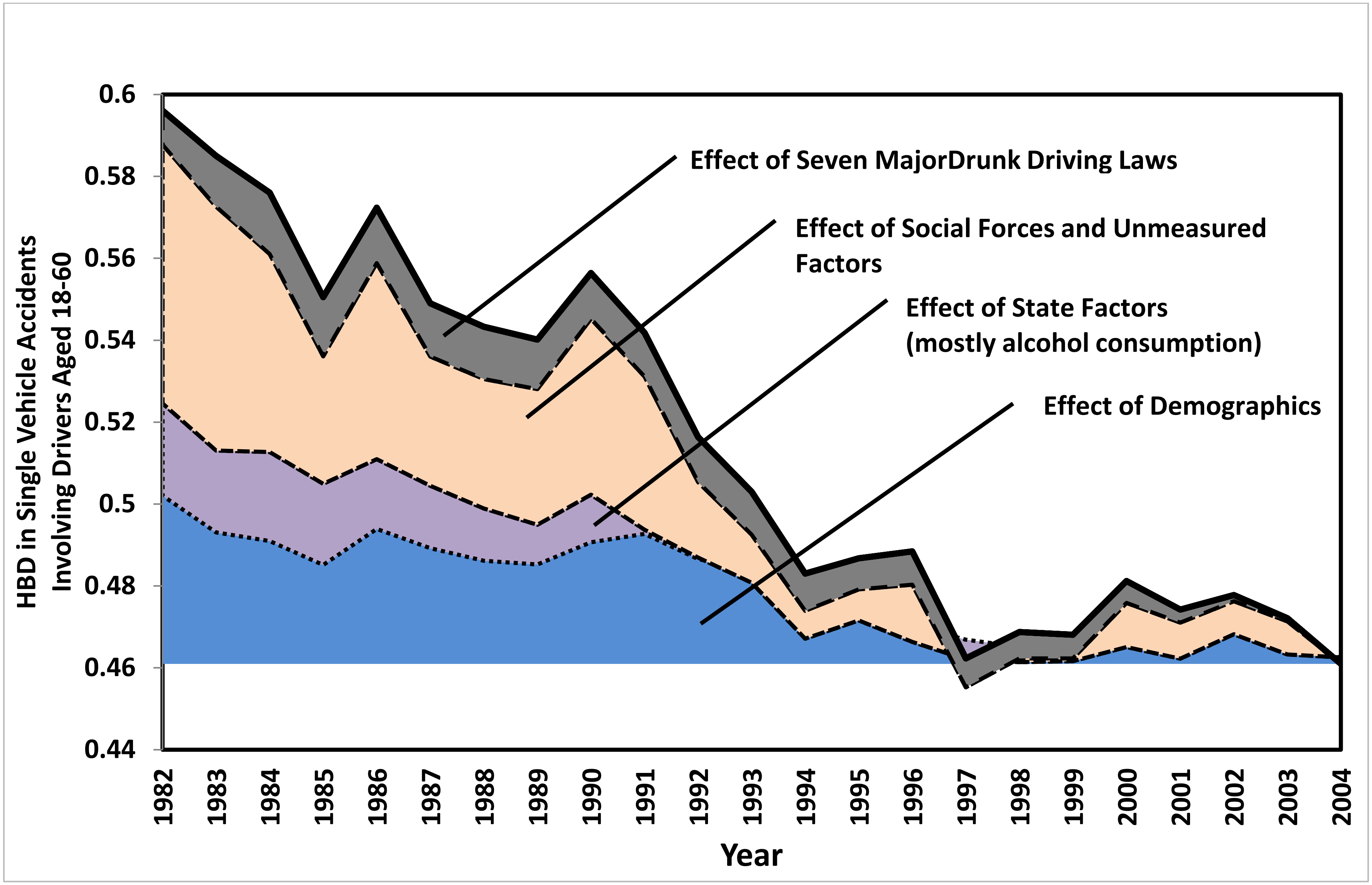


Figure 7. Decomposition of the Reduction in Single-Vehicle Accidents Involving Drivers with BAC ≥ .08, 1982-2004.