Understanding the Decline in Drinking and Driving During
“The Other Great Moderation”

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This paper seeks to explain the large decline in drinking and driving that occurred in the U.S. during the 1980s and 1990s. Using a simple measure of drinking and driving—the fraction of crashes involving drinking drivers—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 seven major drunk driving laws explains only one-fifth of the reduction in drinking and driving over this period, comparable to the effects of alcohol consumption and less than those of demographic shifts and changes in social attitudes. “The Other Great Moderation” is best understood as a two-decade movement of drinking and driving to a new steady state, led by social forces and cemented and extended by law.

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“The most important of all revolutions [is] a revolution in sentiment, manners, and moral opinions.”

Edmund Burke

I. INTRODUCTION

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 what we will call The Other Great Moderation are poorly understood.

This paper seeks to provide such an understanding, describing how drunk driving has evolved over the past forty-five years and revealing the footprint of the social processes shaping this

¹ The estimate of lives saved comes from the calculations underlying Figure 3, below, which imply an annual savings of nearly 15,000 lives from reduced drinking and driving. The estimate of economic value is based on 1994 data on the incidence of fatal injuries, nonfatal injuries (categorized into five levels of severity), and crashes without injury, and the contemporaneous economic values applied to each by the Federal Highway Administration (FHWA; see Blincoe, 1996, and FHWA Memo, “Motor Vehicle Accident Costs,” Oct. 31, 1994). The appropriate computations, available from the author, yield a savings that year of 0.97% of GDP. This value is conservative; after 1994, drinking fell further, while the FHWA’s valuation of fatalities and injuries rose far faster than GDP.
evolution. Ultimately, we decompose the decline in drinking and driving during The Other Great Moderation into components associated with all five major determinants that are recognized in the literature—laws (and their enforcement), demographics, economic factors, alcohol consumption, and social forces—quantifying the magnitude and timing of the effect of each.

That is the primary goal of this paper. Accomplishing it requires solving a problem: seeing the unseen. On a national scale, we do not 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, though the importance of social forces permeates the broader traffic safety literature, public attitudes toward drinking and driving have only rarely been measured in the U.S.

This paper introduces methods that reveal how both intangibles affect traffic safety. These methods are founded on a fundamental fact about drinking drivers: though rare, they are far riskier, on average, than sober drivers are (Grant, 2016). Using this fact, we develop a novel estimation approach that can be applied to disaggregated, driver-level data. This approach accounts for general risk, identifies the effect of social forces, and effectively controls for demographic factors that correlate with drinking. Applying this approach to decades of U.S. data, we break down the nationwide decline in drinking involvement in fatal crashes into the five components listed above.

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.

The policy relevance of this narrative extends into the past as well as the future. It reprises a debate that raged almost half a century ago over the relative efficacy of legislation and social suasion. This debate was won by the former, a triumph of deterrence theory (Reinarman, 1988; Ross, 1992). But this triumph has been unmatched by persistent declines in drinking and driving, which recently completed two decades of stasis. To the extent that this stasis reflects static social attitudes, a technocratic, law-based approach to the problem may not yield further gains.

II. THE OTHER GREAT MODERATION

The Other Great Moderation has been amply documented in numerous reports from the National Highway Traffic Safety Administration (NHTSA). Figure 1 presents three measures used in these reports, all involving fatal crashes, and all beginning in 1982, the first year of suitable data. Each measure shows a steady decline in alcohol involvement from then until the late 1990s 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.

The plausible contributors to this moderation are five-fold: demographics, alcohol consumption, economic factors, laws and their enforcement, and social forces. Many studies show that the first four sets of factors influence traffic fatalities overall. (The studies cited below emphasize the higher-quality panel analyses that account for state and year fixed effects.)

Demographics are relevant because the share of miles driven by females and older drivers
has grown over time. These individuals are not only lighter drinkers, but also safer drivers generally; both should reduce crash incidence.\(^2\) State-level analyses (Benson, Rasmussen, and Mast, 1999; Freeman, 2007; Young and Beilinska-Kwapisz, 2006) affirm the relevance of demographics for overall fatalities, but leave undetermined how much this has to do with alcohol specifically.

Alcohol consumption fell over this period, and there can be no drinking and driving without alcohol. The effects of per-capita consumption, or its proxies, on traffic fatalities are affirmed in several studies (Benson, Rasmussen, and Mast, 1999; Ruhm, 1996; Young and Beilinska-Kwapisz, 2006).

Economic factors such as unemployment can affect the incidence of drinking and driving, while also influencing crash incidence directly. (A stronger economy raises the value of time, which affects speed and risk-taking.) While their relevance for overall traffic fatalities is affirmed by most of the studies cited in this section, the argument for a partial effect on alcohol involvement—beyond any effect on miles driven, general risk, or alcohol consumption—is weaker. We are not aware of prior evidence on this point either way.

The next factor, laws and their enforcement, has received the most attention in the literature by far. In general, these studies find drunk driving legislation to have a salutary effect on traffic fatalities, though the evidence is stronger for some laws than others.

Three laws have been emphasized by academics and policymakers alike: the minimum legal drinking age (MLDA), raised to 21 by many states during the 1980s; zero tolerance (ZT) laws that penalize underage driving with any positive blood alcohol concentration (BAC), enacted by many

\(^2\) An earlier version of this paper, available from the author, contains detailed statistics on drinking involvement in fatal accidents by age, and its evolution over time.
states during the 1990s; and .08 per se BAC limits, lowered from .10 by many states in the early 2000s. Panel analyses find that raising the MLDA lowers fatalities by 5-10% among the ages affected (Dee, 1999; Eisenberg, 2003; Young and Likens, 2000; Young and Beilinska-Kwapisz, 2006; Polnicki et al., 2007; Miron and Tetelbaum, 2009), while lowering the per se standard from .10 to .08 has an effect that is small (Dee, 2001; Eisenberg, 2003) or nil (Young and Beilinska-Kwapisz, 2006; Freeman, 2007). Studies of ZT laws find no effect (Dee, Grabowski, and Morrisey, 2005; Grant, 2010; Anderson, Hansen, and Rees, 2013).

There is some evidence that other laws also have a beneficial effect. These include administrative license revocation (ALR) laws that permit the immediate suspension of the license of a driver who tests above the legal limit or refuses to be tested (Eisenberg, 2003; McArthur and Kraus, 1999; Whetten-Goldstein et al, 2000; Dee, 2001), open container laws that prohibit open containers of alcohol in vehicles (Benson, Rasmussen, and Mast, 1999; Eisenberg, 2003), and dram shop laws that confer liability on hosts or businesses that serve alcohol to inebriated or underage individuals (Benson, Rasmussen, and Mast, 1999; Eisenberg, 2003; Ruhm, 1996; Whetten-Goldstein et al, 2000; Young and Likens, 2000).

These studies generally ignore the role of enforcement. Their estimates are conditional upon prevailing enforcement levels. These are fairly steady over the time period studied. Through 2010, national arrest rates for driving under the influence (DUI) in the Uniform Crime Reports closely track the graphs in Figure 1, both in magnitude and timing. Still, studies indicate that changes in enforcement levels would alter these laws’ effectiveness (Fell et al., 2014; Yao, Johnson, and Tippetts, 2016; Stringer, 2019). We will return to this point toward the end of the paper.

The final factor, social forces, stands apart from these other four. 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). However, in the U.S., social sentiment towards drinking and driving has not been measured with the regularity and geographical detail needed to estimate its effects directly. Our empirical advances allow its effects to be estimated indirectly. Near the end of this paper, we carefully compare these estimates to survey measures of social attitudes during this period.

In summary, the literature adequately supports the relevance of these five factors for overall traffic fatalities, yet leaves several questions unresolved: their effects on drinking and driving or drinking-related fatalities specifically, the timing of those effects, and their overall contribution to reductions in drinking and driving over time. Answers to these questions are needed to explain the decline in drinking and driving during The Other Great Moderation.

III. A SIMPLE MEASURE OF DRINKING AND DRIVING

To answer these questions, we must first develop the measure of drinking and driving that we use in our analysis. Are measures like those reported in Figure 1 adequate, or are more complex measures necessary? How do these measures relate to overall traffic fatalities? In this section, we show that simple measures like those in Figure 1 are both necessary and sufficient for our purposes. Their relation to overall traffic fatalities is equally simple.

A. The Data and its Limitations
Our analysis, like Figure 1, focuses on fatal crashes. Circumstances compel this choice: no other data source is sufficiently comprehensive. On the other hand, NHTSA’s Fatality Analysis Reporting System (FARS) is very comprehensive. Since 1975, it has recorded numerous crash, vehicle, and driver characteristics for all fatal traffic crashes on U.S. public highways. This includes the demographics of each driver involved, the day and location of the crash, the number of vehicles involved, and the total number of fatalities.

In these crashes, most drivers’ blood alcohol concentration (BAC) is reported directly; since 1982, the FARS includes imputations for the remainder, mostly nondrinkers, based on several factors including driver age, passenger BAC, and police reported drinking (Subramanian, 2002). Thus, for various subsets of fatal crashes, such as those involving drivers of a given age range, one can identify those that involved drinking or drunk driving.

The FARS data have been used in numerous studies of drunk driving laws and other traffic safety legislation, including most of those cited above, making it a natural choice for our analysis. Its main weakness, for our purposes, is that a few initially low-reporting states increased BAC reporting in a discrete jump in the early 1980s; this is associated with discrete jumps in measured drinking involvement. In the regressions below, this association biases the estimated effect of the raised MLDA, passed contemporaneously, toward zero. Consequently, in these regressions, we omit

3 Though these data are a census, 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 crashes are infrequent, following a Poisson process around their expected value.
from the sample those years prior to the jump in reporting in those states.\textsuperscript{4}

Our main analysis uses data from 1982 through 2004. This period comfortably spans The Other Great Moderation and roughly aligns with the periods analyzed in the studies cited above.

\textbf{B. The Dominance of the Extensive Margin}

While the FARS data are used by necessity, our main dependent variable resembles Figure 1 by choice. This measure, the fraction of crashes involving at least one BAC-positive driver, is called HBD (for “Had Been Drinking”).\textsuperscript{5} Though simple, it adequately characterizes the dynamics of drinking and driving.

It does so for a simple reason: in the aggregate, changes in drinking and driving take place almost wholly on the extensive margin—whether to drink and drive. The intensive margin, BAC conditional on drinking (BAC > 0), is essentially static.

To show this at the national level, Figure 2 displays the 25\textsuperscript{th}, 50\textsuperscript{th}, and 75\textsuperscript{th} percentiles of BAC for all drinking drivers involved in fatal crashes 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 50\textsuperscript{th} percentile of BAC (conditional on

\footnotesize{\textsuperscript{4} 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.}

\footnotesize{\textsuperscript{5} As first used by Douglass and Millar (1979), this term referred to police-reported drinking. It is being adapted here to reflect drinking as determined by FARS, imputations included.}
drinking) within each state*year cell and regressed these values on a full set of state and year dummy variables. 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. Both nationally and within states, the distribution of BAC, conditional on drinking, has been largely static over time. Therefore, changes in drinking and driving can be adequately tracked on the extensive margin, using HBD.

C. Drinking and Traffic Safety

HBD also has a simple, intuitive relation to traffic fatalities. To show this, define the following variables over any interval of space and time, using upper case for variables that are observable and lower case for those that are not:

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

Drinking and driving 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 2, 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. Thus, almost all collisions between sober and drinking drivers are the drinking driver’s fault; a crash involving drinking drivers is (generally) attributable to one of those drivers (see also Levitt and Porter, 2001).

Using these facts, we can relate crash frequency to HBD. Let \( k \) be the average risk that a drinking driver will cause a fatal crash, relative to a sober driver, and let fatal crashes 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:

\[
\begin{align*}
    f &= (s + kd) \cdot r = (s + d) \cdot r \cdot \left(\frac{s + kd}{s + d}\right) = M \cdot r \cdot \left(\frac{s + kd}{s + d}\right) = M \cdot r \cdot \left[1 + \frac{1}{k} \cdot \frac{h}{1 - h}\right]
\end{align*}
\] (1)

Since \( k > 1 \) (and \( h \approx \frac{1}{2} \)) the bracketed term approaches one, yielding the following close approximation:

\[
\log(f) - \log(M) \approx \log(r) - \log(1 - h)
\] (2)

Expected per mile fatal crashes are directly proportional to general risk and inversely proportional to the expected fraction of crashes that did not involve drinking, which we call “relative sobriety.”

Drinking enters only through \( h \), the latent variable equivalent of HBD.

\[\text{This can be shown numerically, for example using Levitt and Porter’s (2001) framework. The intuition is that many sober drivers are involved in crashes that are caused by drinking drivers. The increase in relative risk is substantial. Details are available from the author.}\]

\[\text{Scaling fatalities by miles, a common normalization in studies of traffic safety, is a serviceable approximation for purposes of this section, and is roughly consistent with estimates of the model introduced below, which does not mandate that fatalities be proportional to miles.}\]
This equation is quite flexible. It applies to fatalities, where \( h \) is the expected fraction of fatalities occurring in crashes involving drinking. It also holds in difference form, and accommodates social or technological changes that alter \( k \), the relative risk of drinking drivers, so long as that relative risk remains large.\(^8\) Nonetheless, \( k \) does in fact appear to be roughly constant over time. This conclusion is supported by the static distribution of BAC among drinking drivers in the FARS 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, that is, in the share of miles driven by drivers who have been drinking.

\[ D. \, The \, Evolution \, of \, General \, Risk \, and \, Relative \, Sobriety \]

Armed with this identity, we can describe how declines in drinking and driving and general risk have affected traffic fatalities over time.

At the national level, there are so many crashes that sampling error is minimal, so that \( f \) 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 3, which depicts the effects of general risk and relative sobriety on total U.S. traffic fatalities from 1982-2015. The upper

\[ \text{To see this, expand the term that is dropped in going from equation (1) to equation (2):} \]

\[ \log(1 + \frac{h}{k}) = \frac{h}{k} = \frac{1}{k} \frac{kd}{s + kd} = \frac{d}{s} \]

This last term does not depend on \( k \). It also varies little over time, with annual changes of a few ten-thousandths (since both \( \Delta d/d \) and \( d/s \) are O(10\(^{-2}\))). Thus equation (2) also holds in difference form.

\[ 11 \]
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 indicates the “shortfall” in fatalities below this projection that is attributed to reductions in drinking and driving (the change in log(1-h)). The bottom shaded area indicates the shortfall that is attributed to reductions in general risk (the change in log(r)).

On this graph, we delineate three phrases in which improvements in traffic safety occurred over this period. 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 the changed driving behaviors that accompanied a large reduction in real gas prices (see Grabowski and Morrisey, 2004, and Burke and Nishitateno, 2015). After 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.

The interplay of general risk, relative sobriety, and fatality rates can also be explored at the state level, by evaluating each term within state*year cells. Here, however, the prevalence of sampling error requires a more complex approach. Appendix A derives the method and presents the results. These indicate that state-level changes in traffic fatalities, beyond those reflecting national
trends, are attributable mostly to general risk, and that state-level innovations to this factor are weakly correlated with analogous innovations to relative sobriety. In summary, during The Other Great Moderation, drinking and driving evolved along the extensive margin, exhibiting a large national component punctuated by state-level innovations that were dwarfed by, and largely independent of, analogous innovations to general risk.

IV. ESTIMATION

This model can be adapted for estimation, presenting an advance over traditional estimation approaches and enabling the micro-level analysis on which our decompositions rely.

A. Three Estimation Approaches

Place all independent variables that can affect traffic safety into three categories: general risk adjusters, G; factors that affect drinking and driving but not general risk, X; and factors that affect both, Z. The model in Section III implies:

\[ F \sim \text{Poisson}(\mu) \]

\[ \log(f) = \mu \log(M) + \log(r(G,Z)) - \log(1-h(X,Z)) \]

where we have relaxed the elasticity between miles and fatalities to be a parameter, \(\mu\), that need not equal one. The marginal effect of X on log fatalities is:
Here, the safety effects of X variables are mediated through \( h \). That is, drunk driving laws reduce fatalities because they reduce drinking and driving. Most empirical analyses lack this property.

Using equation (2), we can compare this novel “restricted estimate” of \( \frac{\partial \log(f)}{\partial X} \) to two alternative estimates of the same relationship: the traditional, widely-used “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:

Unrestricted:  \[
\frac{\partial \log(f)}{\partial X} = \frac{1}{r} \frac{\partial r}{\partial X} + \frac{1}{1-h} \frac{\partial h}{\partial X}
\]

Partially Restricted:  \[
\frac{\partial \log(f)}{\partial X} = \frac{h}{r} \frac{\partial r}{\partial X} + \frac{1}{1-h} \frac{\partial h}{\partial X}
\]

Restricted:  \[
\frac{\partial \log(f)}{\partial X} = \frac{1}{1-h} \frac{\partial h}{\partial X}
\]

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 crashes involving sober drivers.

In theory, these are distinctions without a difference: X variables have no causal effect on \( r \), ceteris paribus, so \( \frac{\partial r}{\partial X} \) 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 (5) would be non-zero, making the unrestricted and partially restricted estimates of \( \frac{\partial \log(f)}{\partial X} \) more variable and possibly biased.
The restricted estimates would eliminate both problems.

B. Specification

Each of these three estimates can be obtained with state panel data, the data typically used in traffic safety analyses. Our unrestricted regression specification extends directly from equation (3):

\[ F_{s,t} \sim \text{Poisson}(\lambda_{s,t}) \]

\[ \log(\lambda_{s,t}) = \beta X_{s,t} + \delta Z_{s,t} + \delta G_{s,t} + \mu M_{s,t} + \sigma_s + \tau_t + \varepsilon_{s,t} \]

where \( s \) indexes states and \( t \) time; \( \beta, \delta, \mu, \) and \( \gamma \) are coefficients; \( \sigma \) and \( \tau \) are state and year fixed effects; and \( \varepsilon \) is an error term. This equation takes the form of a generalized linear mixed model, or GLMM (McCulloch, 2006). This is a robust 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 \( \hat{\beta} \).

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 \( \log(\text{fatalities}) \) resulting from a one unit change in \( X \), is \( \hat{\beta} H_M \), where \( H_M \) is the grand mean of \( H \).

The restricted estimate is also based on a GLMM that extends from our latent variable model.

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9 The GLMM differs from a standard regression by specifying the sampling variation in \( F_{s,t} \) explicitly, in the top line of equation (6), thus treating \( \varepsilon \) 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 is more sound than either ordinary least squares or traditional weighted least squares (both of which are presented below). In addition, in the micro specification introduced shortly, these random effects account for state*year clustering in calculating the standard errors.
Thus, $\Delta h/\Delta X$ is estimated using the following regression:

$$F_{s,t} \cdot H_{s,t} \sim \text{Binomial}(F_{s,t}, h_{s,t})$$

$$h_{s,t} = \lambda X_{s,t} + \phi Z_{s,t} + \sigma_{s,t} + \tau_{s,t} + \epsilon_{s,t}$$

(7)

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 (4), the estimate of $\partial \log(f)/\partial X$ is $\hat{\lambda}/1-H_{M}$.\(^{10}\)

This state-level restricted estimator has an driver-level analog, a binary choice model in which the dependent variable, $\eta$, is one if the crash-involved driver had been drinking and zero otherwise. This model, also a GLMM, is as follows:

$$P(\eta_{i,t} = 1) = \Lambda(\lambda X_{i,t} + \phi Z_{i,t} + \sigma_{i} + \tau_{i} + \epsilon_{i,t})$$

(8)

where $\Lambda$ is the logistic function, $i$ indexes individual drivers, and $\epsilon$ is a state*year random effect. For single vehicle crashes, on which our decompositions rely, $h = E(\eta)$. Thus, 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 crashes can be calculated using equation (4) as before. As we will see, this model has several advantages over state-level estimation.

C. Implementation

\(^{10}\) The term dropped when deriving eq. (2), $h/[k(1-h)]$, is small only when $h$ is not close to one. This rules out any regression that uses log($1-H$) 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.
We follow the literature in choosing the variables represented in G, Z, and X. Our “basic specification” includes those that are nearly universal: 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, indicators for the 21 year-old MLDA, ZT laws, ALR, and .08 and .10 per se limits. Our “extended specification” adds (to X) per-capita alcohol consumption and indicators for open container and dram shop laws. (The .10 law variable 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.) Some driver-level models also include driver demographics (age, gender) and crash-specific factors (dummies for the hour, day, and month of the crash and the number of vehicles involved).

All law variables range in value from zero to one. In the state-level regressions, these values represent the fraction of the relevant population covered by the law (or prohibited from drinking) in that state during that year, with one representing full coverage in that state all year. In the driver-level regressions, instead, we assign an indicator for whether the driver was covered by that law, based on driver age and the crash date and location.\footnote{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 were not grandfathered, and thus subject to the raised drinking age. All laws are coded from the \textit{Digest of State Alcohol-Highway Safety Related Legislation}, supplemented occasionally with Dang (2008) or Grant (2010). Alcohol consumption comes from the National Institute for Alcohol Abuse and Alcoholism, while the unemployment rate is taken from the Bureau of Labor Statistics.}

Raised MLDAs outlawed drinking for drivers aged 18-20, while drinking involvement among drivers over 60 is quite low. Accordingly, state-level estimation is conducted separately for two age ranges: adults aged 21-60, for whom ZT and MLDA variables 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.) In these regressions, HBD is defined as the number of fatal crashes or fatalities involving at least one driver in the specified age range who had been drinking, divided by the number of fatal crashes or fatalities involving drivers in the specified age range. In the driver-level specifications, the law variables are assigned at the driver level, so we do not need—or use—separate regressions for youth and adults (but maintain the same 18-60 age range). Following Dee (1999), Freeman (2007), and others, regressions are conducted on the 48 continental states.

D. State-Level Results

It is impractical to present the full results of every specification we estimate. Accordingly, the first two columns of Table 1 present the full set of restricted and unrestricted estimates for a single, adults-only specification, which, to anticipate slightly, uses the extended set of controls. The coefficients generally take the expected signs and are frequently, though not invariably, significant. Laws have a nil or negative effect on crashes; per capita alcohol consumption has a positive effect, while the effect of unemployment is negative or nil.

Table 2 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 (6). For ease of interpretation, these and all future estimates are multiplied by one hundred, so that they predict the percentage change in fatalities or fatal crashes resulting from that law’s enactment.
Looking vertically within the panel corresponding to any given law, one can compare the results for three alternative fatality measures: the number of fatal crashes involving drivers in the given age range, the total number of fatalities in those crashes, or the number of fatal single-vehicle crashes 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, omit weights, generating inefficiency.)

The restricted estimates in the third column of the table are quite different. They 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. These findings are broadly in line with the literature summarized in Section II. Precision also improves: the standard errors are three-fourths those of the unrestricted estimates. The partially restricted estimates are partway between the two extremes.

12 This result obtains because BAC has no material effect on the number of fatalities per crash. 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 crash. The extensive margin rules here, too.

13 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.
The first two columns of Table 3 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.

E. Driver-Level Results

The last two columns of Table 3 present the results for two driver-level specifications, one for one-and-two-vehicle crashes and the other for single-vehicle crashes. The “plain logit” estimates found at the top of each panel omit state*year random effects and use the basic controls identified above, supplemented only with age dummies and a dummy for two-vehicle crashes when necessary. 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 3 with its state-level equivalent, the restricted specification in the second column.

14 The GLMM model had trouble converging with the full set of crashes, but 94% of the crashes 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.
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.\footnote{These differences, it turns out, come from integrating the youth and adult samples, and not from the switch to driver-level estimation per se. Conducting driver-level estimation on the youth sample alone yields coefficients that resemble those in the second column of Table 3.} Raising the MLDA now cuts the chances of a fatal crash 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 3 analyzes single-vehicle crashes. 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 crashes, 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 insignificant (as in the restricted specification in Table 1).

Progressing down the rows within each panel, the specifications add state*year random effects, the extended set of controls, and, finally, demographic and crash-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 CRASHES
We are now ready to explain the decline in drinking and driving during The Other Great Moderation, breaking down reductions in drinking and driving into components associated with each of the five influences set out above: alcohol consumption, economic factors, demographics, laws and their enforcement, and social forces.

The first four of these are found in the final driver-level specification in Table 3. Our measures of alcohol consumption and economic factors are standard, while we account for demographics more effectively than before. The seven drunk driving laws we include far exceeds the norm in the literature. While no vector of laws can be all-inclusive, the practical case for legislative drunk driving countermeasures rests squarely on these seven laws. No others have received appreciable academic support, significant Congressional impetus, or emphasis from NHTSA. In 2006, NHTSA’s Alcohol and Highway Safety deemed 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.\textsuperscript{16}

The remaining influence, social forces, has not been measured with sufficient regularity to be included directly in these regressions. 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).\textsuperscript{17}

\textsuperscript{16} 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).

\textsuperscript{17} 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
Consequently, we can decompose the decline in HBD during The Other Great Moderation into components associated with each of these five influences.

A. Methods

To execute the decomposition, rewrite equation (8), defining a vector of demographic and crash-specific factors, $D$, to include dummies for driver age and gender and for the hour, day, and month of the crash; a vector of state-level factors, $S$, to include per capita alcohol consumption and the unemployment rate; and a vector of laws, $L$, to include all seven drunk driving laws:

$$P(n_{i,t}=1) = \Lambda(\phi D_{i,t} + \gamma S_{i,t} + \sigma_{i,t} + \tau_{i,t} + \epsilon_{i,t}) \tag{9}$$

where $\phi$, $\gamma$, and $\psi$ are coefficients. 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 three equations:

$$E(H_t | L=L_0, S=S_0) = \Lambda((\phi D_{i,t} + \sigma_{i,t}) + \gamma L_{i,t} + \psi S_{i,t} + \tau_{i,t}) \tag{10}$$

$$E(H_t | L=L_0, S=S_0) = \Lambda((\phi D_{i,t} + \sigma_{i,t}) + \gamma L_{i,t} + \psi S_{i,t} + \tau_{i,t}) \tag{11}$$

$$E(H_t | L=L_0, S=S_0, t=0) = \Lambda((\phi D_{i,t} + \sigma_{i,t}) + \gamma L_{i,t} + \psi S_{i,t} + \tau_{i,t}) \tag{12}$$

The difference between HBD nationwide in any given year, $H_t$, and HBD in the base year, $H_0$, can project regularly surveys attitudes toward drinking and driving.
be broken down into four components, associated with laws and their enforcement (the difference between $H_t$ and equation (10)), state-level factors (the difference between equations (10) and (11)), social forces and other residual factors (the difference between equations (11) and (12)), and demographics and crash-specific factors (the difference between equation (12) and $H_0$). Given estimates of the parameters in equation (9), each component can be calculated for each year of the sample period.\textsuperscript{18}

To implement this approach, we utilize the estimates of the final specification in Table 3 and focus on single-vehicle crashes, for which the mean of driver-level alcohol involvement equates to HBD, and for which laws’ estimated effects are especially favorable. The base year is 2004, and the age range remains 18-60. As it is straightforward to calculate how changes in HBD affect fatalities, our decompositions are conducted directly in terms of HBD.

\textbf{B. Results}

The top line in Figure 4 presents the trend in HBD in this sample. In concert with Figure 1 and relative sobriety in Figure 3, 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. 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.

\textsuperscript{18}Both HBD and the counterfactual predictions in Figure 4 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. In these dropped observations, HBD 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.
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 component corresponding to laws and their enforcement. Our estimates indicate that four laws—the raised MLDA, zero tolerance, .08 limits, and open container laws—substantially affect fatalities. These laws became much more common during our sample period, as shown in Table 1: 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 largest point estimates apply to youth, who are a small fraction of all drivers. In the end, the aggregate effect of these laws, as shown in Figure 4, 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 crash-specific factors. It too develops gradually, as the corps of drivers ages and becomes more female and weekend crashes slightly decline. Its size indicates 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 1). 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 3, 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 crashes 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.

C. Robustness

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

One now-standard check is to add state time trends to the specification (e.g., Dills, 2010;
Adams, Blackburn, and Cotti, 2012). We did this, incorporating their effects into the social forces component. (This is obligatory, as 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 this component and reduce that of laws, which are passed as social attitudes change.\textsuperscript{19} The results of this decomposition, placed in Appendix B, closely resemble those in Figure 4 and fully concord with Section III’s finding that the dynamics of relative sobriety are predominantly national. Laws’ effects are reduced and social forces’ effects increased, as anticipated, 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 directly accommodate this redefinition—indeed, the assumption behind equation (2), \( k \gg 1 \), is strengthened, since mild drinkers are removed from the set of alcohol-involved crashes. This new dependent variable is also better-aligned with .08 per se laws, which seek to reduce drivers’ alcohol consumption, not eliminate it.

When equation (9) 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. The relative magnitudes in the associated decomposition, also found in Appendix B, closely resemble those in Figure 4.\textsuperscript{20} Laws and alcohol consumption are

\textsuperscript{19} 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.

\textsuperscript{20} In absolute terms, the estimated effect of all independent variables falls, since the restricted estimate now considers low-BAC crashes to be unaffected by legislation. The absolute component
slightly more important than before, and demographics and social forces slightly less important, but the latter two components still dominate.

The results are also robust to the period used for estimation. As documented at length in Grant (2011), 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, such as ours. This progression does not hold for the restricted estimates, which 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 using equation (4), and using those implied effects to compute the laws component. A direct comparison is not possible, since fatality regressions cannot control for demographics and crash-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,\textsuperscript{21} which in turn slightly exceed our own unrestricted estimates.

\textit{D. Interpretation of the Social Forces Component}

\textsuperscript{21} One important exception is Dang (2008), the only other study to quantify the aggregate effects of laws on HBD. However, Dang’s regression model omits state and year fixed effects, which strongly biases estimates of drunk driving laws’ effects, as these laws’ incidence trends in the opposite direction from HBD over the sample period. The absence of these fixed effects explains the difference between this paper’s findings and hers, which indicate that laws explain nearly half of the decline in HBD.
American surveys of attitudes towards drinking and driving lack the regularity needed for use in estimation. But they are plentiful enough to establish whether these attitudes changed with the magnitude, timing, and geographic uniformity implied by the social forces component in our decompositions, and to shed light on the behavioral changes that brought drinking and driving down.

We focus first on the 1980s, when the social forces component displayed great change. Drunk driving became one of America’s foremost social issues during this decade. The media coverage devoted to this topic increased substantially (Howland, 1988), while numerous traffic safety officials testified to a concomitant change in social attitudes (Grant, 2015). Also, 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, p. 99).

Surveys detected this attitudinal shift. Greenfield and Room (1997) compared “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 surveys also indicate that attitudinal changes were national in scope. Between 1979 and 1984, Greenfield and Room 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.

Moving past the 1980s, we turn to a different survey, NHTSA’s National Survey of Drinking and Driving Attitudes and Behaviors, conducted periodically from 1991 to 2008. This survey perfectly captures the leveling off in behaviors that occurred during the 1990s, while having less to say about the attitudes behind them.

Throughout the survey period, respondents were asked whether they had ever driven after drinking within the past month or year, the number of times that they had done so, and the number of drinks they had consumed in the process. The results indicate declines in the frequency of drinking and driving through the mid 1990s. The fraction of respondents who admitted to drinking and driving fell by about three percentage points, while the frequency with which they did so fell by roughly 25%. Both measures showed little or no movement after 1997. Based on these findings, the decline in HBD in Figure 4 was achieved by a modest decline in the number of people who drank and drove, coupled with a sizeable decline in the frequency with which they did so. Meanwhile, the average number of drinks consumed by drinking drivers remained steady throughout the survey period, consistent with the dominance of the extensive margin documented in Section III.

The attitudinal questions are more difficult to interpret, because of endogeneity problems. That is, changes in the prevalence in drinking and driving could alter the responses even if attitudes toward the issue remained unchanged. For example, one question asks about perceived danger from others’ drinking and driving. These perceptions could change because of declines in drinking and driving over this period, irrespective of attitudes.

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22 That is, changes in the prevalence in drinking and driving could alter the responses even if attitudes toward the issue remained unchanged. For example, one question asks about perceived danger from others’ drinking and driving. These perceptions could change because of declines in drinking and driving over this period, irrespective of attitudes.
Two questions avoid such problems: one asking about how many drinks one can have before becoming an unsafe driver, and another about permissible BAC levels. Responses to these questions show some beneficial movement during the early-to-mid 1990s and no movement thereafter. This evidence, though less definitive, provides some support for continued attitudinal change during the final years of The Other Great Moderation.

In summary, evidence from various sources indicates that social attitudes towards drinking and driving changed substantially throughout the 1980s. These changes were largely national in scope and continued into the 1990s before tapering off around 1997. In magnitude, scope, and timing, survey evidence supports our interpretation of the social forces component in Figure 4.

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 traffic fatalities (and about 46% of fatal single-vehicle crashes involving drivers aged 18-60).

Traffic fatalities surged during the second half of the 1970s, due in part to recent reductions in the MLDA in twenty-five states (Cook and Tauchen, 1984). This set the stage for The Other Great Moderation, which kicked off around the turn of the decade with changed social attitudes.
towards traffic safety in general and drunk driving in particular (Zimring, 1988, p. 380): 23

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.

This attitudinal shift directly affected drinking and driving, but also had indirect effects, inspiring increased drinking ages and other drunk driving legislation in many states and possibly bringing down alcohol consumption as well. These changes and demographic shifts decreased drinking and driving substantially during the 1980s (Figure 4), accounting for all of the decline in per-mile traffic fatalities through 1988 (Figure 3).

But that was only the beginning. During the late 1980s and the 1990s, social attitudes changed further, while drunk driving legislation continued to diffuse throughout the country. These transitions, abetted significantly by demographic shifts, further reduced drinking and driving through 1997 (Figure 4). The decline in per mile traffic fatalities thereby produced was comparable to that attributable to decreases in general risk (Figure 3).

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 3). The Other Great Moderation had ended. This denouement can be observed in the rate of alcohol involvement in fatal crashes, which has remained constant for twenty years (Figure 1); in the social forces component in our decompositions, which has been static since the early 1990s (Figure 4); and in the rate at which

23 As alcohol imputations are not present in the FARS prior to 1982, one cannot give a precise date when this occurred. In the unimputed FARS data, alcohol involvement rose somewhat in the waning years of the 1970s, then turned down decisively beginning in 1981.
significant new laws are adopted, which has slowed from a 1980s torrent to a post-2004 trickle.

What, then, is the way forward? There are three possible routes: increased legislation, increased enforcement, or further changes in social attitudes towards drinking and driving.

As to legislation, one option is to further lower the per se BAC limit, perhaps to .05, the standard advocated by MADD and used in Utah and in several European countries. Fell and Scherer (2017) argue that this lower standard would significantly reduce alcohol-related crashes in the U.S., while Grant (2016) claims the opposite, arguing that the .08 per se limit places stronger incentives on those drivers who are more impaired (and thus more dangerous). He instead advocates for aggravated drunk driving laws that enhance penalties on drivers with very high BACs. However, there is not yet sufficient U.S.-based empirical evidence to adjudicate these claims, and little new legislation on the horizon that has acquired widespread support.

The role of enforcement has been studied by Benson, Rasmussen, and Mast (1999), Fell et al. (2014), Yao, Johnson, and Tippetts (2016), and Stringer (2019). These authors all show that increased enforcement of existing laws would materially reduce crashes. Instead, the level of enforcement has recently fallen off. From 2010 to 2015, DUI arrest rates in the Uniform Crime Reports fell substantially, though the rate of alcohol involvement in fatal accidents remained unchanged (see Figure 1).

The final alternative, social forces, are not often considered to be a policy option in this context—but they used to be. 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 (until now) never those of social forces. Our decompositions suggest that social suasion is a powerful potential source of gains in traffic safety. Reinarman (1988) deftly shows how advocacy, supplemented by political shifts, laid the groundwork for the change in attitudes in the 1980s (as Okrent, 2010, and Kyvig, 2000, did for the enactment and repeal of Prohibition).

Furthermore, this debate looked at the problem too narrowly. Social attitudes, laws, and enforcement are complements, not substitutes. Changes in social norms provide the basis for laws to be passed, accepted by the public, and enforced. Thus, our narrative treats social attitudes not as an alternative to legislation, but as the foundation for many sources of gains in relative sobriety: laws and their enforcement, alcohol consumption, and the decision to drive conditional on drinking. Were this foundation to shift once again, further gains in alcohol-related traffic safety would be probable, and another Great Moderation would begin.
REFERENCES


Table 1: Full Set of Restricted and Unrestricted Estimates, Extended Crash-Level Specification (effect on the logarithm of the number of fatal crashes, with standard errors in parentheses)

<table>
<thead>
<tr>
<th>SPECIFICATION</th>
<th>POPULATION-WEIGHTED MEAN AND ST. DEVIATION</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Unrestricted, State-Level, Adult Drivers</td>
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<td><strong>Factors Affecting Drinking and Driving (X)</strong></td>
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<td>Zero tolerance law</td>
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<td>Maximum speed limit (mph) (three dummy variables)</td>
<td>jointly significant</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Miles travelled, in logs</td>
<td>0.69</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
</tr>
<tr>
<td>R²</td>
<td>----</td>
</tr>
</tbody>
</table>

NOTES: 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 2: Three Sets of Estimates of the Percentage Effect of Laws on Fatalities or Fatal Traffic Crashes (standard errors in parentheses)

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

NOTES: 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 3: Robustness Checks and Transition to Driver-Level Estimation (implied percentage change in fatal crashes, with standard errors in parentheses).

<table>
<thead>
<tr>
<th>Law</th>
<th>Estimator / Controls</th>
<th>State-Level Estimate</th>
<th>Driver-Level Estimate</th>
<th>Logit, 1 &amp; 2 Vehicle Crashes</th>
<th>Logit, Single Vehicle Crashes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Unrestricted</td>
<td>Restricted</td>
<td></td>
<td></td>
</tr>
<tr>
<td>.10 Per Se Laws</td>
<td>Weighted least squares</td>
<td>3.16</td>
<td>0.53</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.15)</td>
<td>(0.82)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Ordinary least squares / plain logit</td>
<td>0.51</td>
<td>-0.20</td>
<td>0.50</td>
<td>-0.04</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.33)</td>
<td>(1.02)</td>
<td>(0.36)</td>
<td>(0.77)</td>
</tr>
<tr>
<td></td>
<td>GLMM</td>
<td>1.98</td>
<td>0.26</td>
<td>0.44</td>
<td>-0.27</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.17)</td>
<td>(0.87)</td>
<td>(0.55)</td>
<td>(1.07)</td>
</tr>
<tr>
<td></td>
<td>Add extended controls</td>
<td>1.53</td>
<td>0.41</td>
<td>0.59</td>
<td>-0.15</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.13)</td>
<td>(0.86)</td>
<td>(0.56)</td>
<td>(1.06)</td>
</tr>
<tr>
<td></td>
<td>Also add driver and crash controls</td>
<td>----</td>
<td>----</td>
<td>0.29</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>.08 Per Se Laws</td>
<td>Weighted least squares</td>
<td>1.58</td>
<td>-2.93*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.92)</td>
<td>(0.67)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Ordinary least squares / plain logit</td>
<td>0.52</td>
<td>-1.78</td>
<td>-1.99*</td>
<td>-4.07*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.18)</td>
<td>(0.91)</td>
<td>(0.30)</td>
<td>(0.64)</td>
</tr>
<tr>
<td></td>
<td>GLMM</td>
<td>1.00</td>
<td>-2.01*</td>
<td>-1.48*</td>
<td>-3.21*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.05)</td>
<td>(0.78)</td>
<td>(0.48)</td>
<td>(0.92)</td>
</tr>
<tr>
<td></td>
<td>Add extended controls</td>
<td>1.26</td>
<td>-1.79*</td>
<td>-1.42*</td>
<td>-3.04*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.01)</td>
<td>(0.76)</td>
<td>(0.48)</td>
<td>(0.91)</td>
</tr>
<tr>
<td></td>
<td>Also add driver and crash controls</td>
<td>----</td>
<td>----</td>
<td>-0.97*</td>
<td>-1.68*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ALR Laws</td>
<td>Weighted least squares</td>
<td>-1.72</td>
<td>-1.42*</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>(0.87)</td>
<td>(0.63)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Ordinary least squares / plain logit</td>
<td>-4.90*</td>
<td>-0.98</td>
<td>-0.86*</td>
<td>-1.24*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.10)</td>
<td>(0.85)</td>
<td>(0.30)</td>
<td>(0.64)</td>
</tr>
<tr>
<td></td>
<td>GLMM</td>
<td>-3.63*</td>
<td>-0.80</td>
<td>-0.35</td>
<td>-0.32</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.95)</td>
<td>(0.72)</td>
<td>(0.52)</td>
<td>(0.97)</td>
</tr>
<tr>
<td></td>
<td>Add extended controls</td>
<td>-2.42*</td>
<td>-0.33</td>
<td>-0.11</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.93)</td>
<td>(0.71)</td>
<td>(0.53)</td>
<td>(0.97)</td>
</tr>
<tr>
<td></td>
<td>Also add driver and crash controls</td>
<td>----</td>
<td>----</td>
<td>-0.26</td>
<td>-0.17</td>
</tr>
<tr>
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<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>WLS</td>
<td>OLS/Logit</td>
<td>GLMM</td>
<td>Add extended controls</td>
<td>Also add driver and crash controls</td>
</tr>
<tr>
<td>----------------------</td>
<td>--------------</td>
<td>--------------</td>
<td>--------------</td>
<td>-----------------------</td>
<td>-----------------------------------</td>
</tr>
<tr>
<td><strong>MLDA (0 = 18 yrs., 1 = 21 yrs.)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weighted least squares</td>
<td>-1.38 (2.70)</td>
<td>-5.24* (1.71)</td>
<td>-9.67* (0.76)</td>
<td>-6.05* (2.89)</td>
<td>-10.03* (0.78)</td>
</tr>
<tr>
<td>Ordinary least squares / plain logit</td>
<td>-2.98 (3.98)</td>
<td>-4.40 (2.46)</td>
<td>-9.67* (0.76)</td>
<td>-3.73* (1.91)</td>
<td>-10.03* (0.78)</td>
</tr>
<tr>
<td>GLMM</td>
<td>-1.98 (2.91)</td>
<td>-4.39* (1.86)</td>
<td>-9.98* (0.78)</td>
<td>-3.73* (1.91)</td>
<td>-10.03* (0.78)</td>
</tr>
<tr>
<td>Add extended controls</td>
<td>-6.05* (2.89)</td>
<td>-3.73* (1.91)</td>
<td>-10.03* (0.78)</td>
<td>-3.73* (1.91)</td>
<td>-10.03* (0.78)</td>
</tr>
<tr>
<td>Also add driver and crash controls</td>
<td>----</td>
<td>----</td>
<td>----</td>
<td>-7.49* (0.71)</td>
<td>-11.96* (1.47)</td>
</tr>
<tr>
<td><strong>Zero Tolerance Laws</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weighted least squares</td>
<td>-2.50 (2.13)</td>
<td>-2.53 (1.35)</td>
<td>-5.71* (0.47)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ordinary least squares / plain logit</td>
<td>-2.43 (2.90)</td>
<td>-1.41 (1.82)</td>
<td>-5.71* (0.47)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GLMM</td>
<td>-1.61 (2.23)</td>
<td>-2.48 (1.35)</td>
<td>-5.61* (0.47)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Add extended controls</td>
<td>-1.37 (2.17)</td>
<td>-2.60 (1.36)</td>
<td>-5.61* (0.47)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Also add driver and crash controls</td>
<td>----</td>
<td>----</td>
<td>----</td>
<td>-3.96* (0.43)</td>
<td>-5.42* (0.83)</td>
</tr>
</tbody>
</table>

NOTES: 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 2 for the controls in the basic specifications. The extended controls include per capita alcohol consumption and dram shop and open container laws. Driver and crash controls include dummies for driver age and sex, crash hour, day, and month, and the number of vehicles in the crash (when appropriate). MLDA stands for minimum legal drinking age; ALR for administrative license revocation; and GLMM for generalized linear mixed model. In the Weighted Least Squares estimates, weights are the number of crashes 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: Three NHTSA-reported measures of alcohol involvement in fatal accidents, 1982-2015.

NOTES: Data are 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 2: Blood alcohol concentration conditional on drinking, drivers involved in fatal accidents nationwide.
Figure 3: Breakdown of the change in traffic fatalities into contributions associated with drinking, general risk, and miles travelled (author tabulations using the latent variable model described in the text).

NOTE: The components are calculated by applying equation (2) to national totals of fatalities, mileage, and the fraction of fatalities involving drinking.
NOTES: The seven laws include .10 per se laws, .08 per se laws, the minimum drinking age, zero tolerance laws, administrative license revocation, open container laws, and dram shop laws. Each is described in Section II.
APPENDIX A

To apply the latent variable model at the state level, we evaluate F and H within state*year cells and use these values and the method of moments to estimate the statistical properties of the underlying latent variables, f and h, after subtracting state and year fixed effects. Then, employing equation (2), we break down the analogous variation in logged fatalities per mile into components associated with log(r), log(1-h), and their interaction, and estimate the properties of each.

In addition to the variables defined in the text, let \( F^* \) and \( H^* \) be the number of crashes 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 crashes, is also the number of observations within each state*year cell. Then, summing across state*year cells:

\[
\sum (H-H^*)^2 = \sum (H-h)^2 + \sum (h-H^*)^2 = \sum \frac{h(1-h)}{F} + \sum (h-H^*)^2
\]

(13)

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:

\[
\frac{\sum (h-H^*)^2}{C} = \frac{\sum (H-H^*)^2}{C} - \frac{\sum H^*(1-H^*)}{C \cdot F}
\]

(14)

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

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

$$\Sigma \left( \frac{F - F^*}{F^*} \right)^2 = \Sigma \left( \frac{f - f^*}{f^*} \right)^2 + \Sigma \left( \frac{f - f'}{f'} \right)^2 = \Sigma \frac{f}{F^*} + \Sigma \frac{f}{F^*} - 1)^2 = \Sigma \frac{1}{F^*} + \Sigma \log^2 \left( \frac{f}{F^*} \right) = \Sigma \frac{1}{F^*} + \Sigma \left( \log(f) - \log(f^*) \right)^2 = \Sigma \frac{1}{F^*} + \Sigma \left( \log(f/M) - \log(F^*/M) \right)^2$$

The first relationship identifies the variance of $\log(n^N)$, the second the covariance of $\log(r^N) - \log(n^N)$, and the third–along with equation (15)–the variance of $\log(r^N)$.

In implementing these equations, we reduce extraneous variation by analyzing the crash type and age group with the greatest drinking involvement: single vehicle crashes involving drivers aged 21-40. The results are found in Table A1. The third and fourth rows present the standard deviation,
(simplified) spatial correlation, 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.

---

24 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 A1. 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.
Table A1: State-Level Standard Deviations and Correlations of the Fraction of Accidents Involving Drinking (HBD), Logged Fatalities, and General Risk

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

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).
Figure B1: Decomposition of the reduction in the fraction of single-vehicle accidents involving drinking drivers, 1982-2004, state trends added.
Figure B2. Decomposition of the reduction in single-vehicle accidents involving drivers with BAC ≥ .08, 1982-2004.

NOTE: See the note to Figure 4.