Health insurance mandates and traffic fatalities: The effects of substance use disorder parity laws

Ioana Popovici[a]; Johanna Catherine Maclean[b,*]; Michael T. French[c]

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Abstract: We investigate whether state-specific health insurance parity laws for substance use disorder (SUD) treatment reduce traffic fatalities. Parity laws compel private insurers to cover SUD treatment more generously. We employ 26 years of administrative data from the Fatality Analysis Reporting System coupled with a differences-in-differences design to study this question. Our findings indicate that passage of a parity law is associated with a 7.6 to 8.2% reduction in traffic fatality rates. These findings suggest that government regulations requiring insurers to cover SUD treatment can significantly improve traffic safety, possibly by reducing the number of impaired drivers on roadways.

Keywords: traffic fatalities; substance use disorder treatment; traffic safety; health insurance; parity laws.
JEL classification: I1; I13; I18

[a] Department of Sociobehavioral and Administrative Pharmacy, College of Pharmacy, Nova Southeastern University, 3200 South University Drive, Fort Lauderdale, FL, USA, 33328-2018; Telephone: 954-262-1393; Fax: 954-262-2278; ip153@nova.edu.
[b] Department of Economics, Temple University, NBER, and IZA, Ritter Hall Annex 869, 1301 Cecil B. Moore Avenue, Philadelphia, PA 19122; Telephone: 215-204-0560; catherine.maclean@temple.edu.
[c] Department of Health Management and Policy, Department of Sociology, Department of Public Health Sciences, and Department of Economics, University of Miami, 5202 University Drive, Merrick Building, Room 121F, P.O. Box 248162, Coral Gables, FL, USA, 33124-2030; Telephone: 305-284-6039; Fax: 305-284-5310; mfrench@miami.edu.

* Corresponding author.

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I. Introduction

Substance-impaired driving is a serious public safety concern as individuals who choose to drive while impaired increase the risk of traffic crashes for themselves, their passengers, and other drivers with whom they share roadways. In 2016, motor vehicle traffic crashes were the second leading cause of injury-related death in the United States with 38,748 fatalities (Centers for Disease Control and Prevention 2016). Annually, approximately 10,000 individuals are killed in alcohol-impaired traffic crashes in the U.S., representing nearly one third of all traffic-related deaths, while psychoactive drugs are involved in 20% of all fatal traffic crashes (National Center for Statistics and Analysis 2016). The annual societal costs of alcohol-involved fatal crashes is estimated to be over $78 billion (Zaloshnja, Miller, and Blincoe 2013).[1] In response to these high costs, governments at all levels have taken steps to reduce impaired driving. For example, governments have imposed maximum allowable blood alcohol concentration (BAC) thresholds for drivers, prohibited driving while under the influence of psychoactive drugs, instituted roadside sobriety check points, set minimum prison sentences and/or financial penalties for those found guilty of driving under the influence, and financed public media campaigns that outline the dangers and costs of impaired driving.

The above-noted government actions attempt to directly regulate or address substance use among drivers, but fail to acknowledge that substance use disorders (SUDs) are chronic, addictive diseases that should be treated through medical interventions rather than punitive public policies (Popovici, French, and McKay 2008). For individuals who suffer from these chronic conditions, a potentially better policy approach is to address their SUDs through the promotion of effective and affordable treatment (Stewart, Gossop, and Marsden 2002, Reuter

[1] This estimate is adjusted from 2010 dollars (as reported in the cited manuscript) to 2018 dollars using the Consumer Price Index—Urban Consumers—by the authors.

and Pollack 2006). Treating individuals with SUDs should decrease the number of impaired drivers on roadways, and hence substance-use-attributable traffic crashes.

The effectiveness of numerous SUD treatment approaches is well-established (Rajkumar and French 1997, Lu and McGuire 2002, Stewart, Gossop, and Marsden 2002, Kunz, French, and Bazargan-Hejazi 2004, Reuter and Pollack 2006, Popovici and French 2013b), offering a potential pathway through which expanded access to SUD treatment can reduce traffic fatalities. Indeed, a study by Freeborn and McManus (2010) finds that one additional specialty SUD treatment facility per U.S. county decreases the number of county-level alcohol-related traffic fatalities by 15% per year.[2]

Despite the established effectiveness of SUD treatment, many individuals who could benefit from various treatment approaches do not receive it. While approximately 20.1 million people aged 12 or older had an SUD in 2016,[3] only 10.8% of these individuals received any treatment (Substance Abuse and Mental Health Services Administration 2017). Among individuals seeking treatment, commonly cited barriers to receiving care are inability to pay and lack of insurance coverage (Substance Abuse and Mental Health Services Administration 2016). These barriers could be diminished by ensuring equitable and affordable coverage of SUD treatment in insurance plans.

Within the U.S., private insurance plans have historically covered SUD treatment less generously than medical/surgical treatment (Starr 2002).[4] For example, patient cost-sharing

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[2] We note that the Freeborn and McManus study emphasizes changes in the number of facilities in a local area while we focus on mandated state-level insurance coverage for SUD treatment in private markets. However, both studies consider how changes in prices (either non-financial costs as measured by facilities in operation or financial costs as measured by insurance coverage) may lead to changes in traffic fatalities associated with substance use.
[3] Specialty SUD treatment is offered in a hospital, a residential facility, an outpatient treatment facility, or other location with a licensed SUD treatment program that offers the following services: outpatient, inpatient, or residential/rehabilitation treatment; detoxification; opioid substitution treatment; and/or halfway-house services.
[4] We note that public insurance plans (e.g. Medicaid), which offer coverage for the poor, have also historically offered less generous coverage for SUD treatment relative to medical/surgical treatment.

(e.g., copayments, deductibles) has historically been higher for SUD treatment and insurers have tended to restrict such treatment utilization through a variety of provisions (e.g., setting annual or lifetime maximums on treatment episodes, use of prior authorization, or stepped therapy) to a greater extent than other medical/surgical procedures. These barriers likely dissuade many individuals from seeking care, or obtaining adequate care,[5] for their SUDs.

In the present study, we examine whether state-specific equal-coverage laws for SUD treatment (often referred to as 'parity laws') affect one of the costliest negative consequences associated with substance misuse—fatal traffic crashes. State parity laws regulate private insurance markets and expand affordable coverage for alcohol and psychoactive drug treatment. In particular, the laws we study require insurers to provide SUD treatment services at 'parity' with medical/surgical services in terms of cost sharing, non-pecuniary barriers to treatment, and service restrictions.[6] As state parity laws increase coverage for SUD treatment, and therefore lower out-of-pocket financial exposure and increase access to care for covered individuals, standard economic theory predicts that these regulations will increase the probability that individuals with SUDs seek treatment (Grossman 1972). Previous research reports that these laws increase SUD treatment use (Dave and Mukerjee 2011, Wen et al. 2013, Maclean, Popovici, and Stern 2018, Wen, Hockenberry, and Cummings 2017).

To explore this question, we analyze 26 years (1988 to 2013) of administrative data from the Fatality Analysis Reporting System (FARS). During this period, 12 states passed a law that required parity in terms of cost-sharing, service use, and other features for both alcohol and

[5] Care that is of reasonable duration and is matched to patient need (National Institute on Drug Abuse 2012).
[6] We note that some states have passed laws that increase coverage for SUD treatment services in private contracts, but do not require equal coverage. These laws often require insurers to offer SUD treatment to beneficiaries or to cover a specified set of services, but permit higher cost-sharing and/or service limitations for SUD treatment vis-à-vis medical/surgical services. We focus our analysis on full parity laws for alcohol and psychoactive drugs for two reasons. First, the literature suggests that full parity laws are more effective than partial laws. Second, current policy decisions at both the state and federal level within the U.S., the context of our study, relate to full parity.

psychoactive drug treatment vis-à-vis medical/surgical services in private insurance contracts, facilitating a novel quasi experiment. We apply differences-in-differences methods and control for a wide range of time-varying state-specific characteristics. Increased SUD treatment receipt and, in turn, reduced substance use and abuse are the channels through which we expect parity laws to impact traffic crashes. To study these pathways, we also examine the effect of state parity laws on fatal alcohol poisonings and psychoactive drug overdose deaths, a common proxy for substance misuse and abuse (Swensen 2015).

The paper proceeds as follows. Section 2 provides background and provides a simple conceptual framework linking parity laws to traffic fatalities, and reviews the economic literature on state SUD parity laws. Data, variables, and methods are presented in Section 3. The main results are reported in Section 4, and extensions and robustness checks are listed in Section 5. Finally, section 6 provides a discussion and potential policy implications.

2. Background, a conceptual framework, and related literature

2.1 The demand for healthcare services and state parity laws

In standard economic models, healthcare demand is derived from consumers' demand for health (Grossman 1972). Stated differently, consumers do not demand healthcare in isolation, but rather desire the associated health improvements. Individuals maximize a utility function conditional on prices of healthcare and other goods/services, preferences, health stock, and other factors that determine health (e.g., ability), subject to budget and time constraints. Price changes have standard effects on the quantity demanded of healthcare (i.e., an inverse relationship).

Insurance coverage for healthcare reduces the out-of-pocket price faced by consumers. The Grossman model predicts that any policy that reduces price should increase the quantity demanded (*ceteris paribus*). Following passage of a state parity law for SUD treatment, the price of SUD treatment should fall for privately insured patients whose insurance contracts are affected by the passage of such laws; including beneficiaries who gain SUD treatment coverage for the first time and those whose existing coverage for these services becomes more generous. As a result, in the aggregate (because not all people require or seek SUD treatment), we expect the quantity of SUD treatment consumed to increase.[7]

Several factors may mute or at least diminish this price effect. Many individuals with SUDs do not wish to stop using substances. Insurance-induced price changes are unlikely to alter the quantity of care they demand. Insurance may lead to *ex-ante* moral hazard or income effects, and/or increase access to addictive medication (e.g., prescription opioids), all of which may increase SUDs and need for treatment. On the other hand, increased awareness of treatment coverage and/or benefits may follow an insurance expansion and, in turn, increase demand. Similarly, if public discourse that occurs with passage of an SUD treatment parity law reduces stigma associated with this condition, treatment use may further increase.

2.2 Conceptual framework linking parity law passage to fatal traffic crashes

Given that we study a second-order outcome, it is important to consider the causal pathway from changes in state parity laws to changes in traffic fatalities. We next develop a simple conceptual framework that offers intuition on these pathways. We supplement this framework with a discussion of theory and empirical evidence on the sequence of 'paths' that lead us from the policy change to changes in certain outcomes.

First, consider a fatal traffic crash production function of the following form:

$$C = f(SUD, X)$$

[7] Increasing coverage breadth may increase health insurance premiums, which may lead some individuals to drop private coverage. We return to this issue formally later in the manuscript.

Where C is fatal traffic crashes, which are determined by SUD and other factors (X). We can further model SUD as a function of treatment (T) and other factors (H): $SUD = g(T, H)$. Individuals elect to receive SUD treatment when the expected benefits outweigh the expected costs. We predict that, through price effects or through increased awareness of treatment, passage of a parity law (P) leads to changes in treatment receipt. Thus, we characterize this phenomenon as $T = h(P, J)$.

We can combine these three equations to arrive at a reduced-form relationship between parity law passage and fatal traffic accidents. For simplicity, we assume that $X = H = J$.

$$C = k(SUD(T(P)), X)$$

Thus, taking the derivative of this reduced-form fatal traffic crash production function with respect to state parity laws (P) gives us:

$$\frac{\partial C}{\partial P} = \frac{\partial C}{\partial SUD} * \frac{\partial SUD}{\partial T} * \frac{\partial T}{\partial P}$$

The traffic safety literature suggests that $\frac{\partial C}{\partial SUD} > 0$. In a recent meta-analysis, Elvik (2013) finds that substance use just prior to or during driving increases the odds of an accident by up to 8.7 times. Government reports suggest that risk levels are even higher (Governors Highway Safety Association 2017). Numerous clinical trials document the effectiveness of SUD treatment (McLellan et al. 2000, Prendergast et al. 2002). These studies suggest that $\frac{\partial SUD}{\partial T} < 0$. Freeborn and McManus (2010) show that an additional specialty SUD treatment facility in a county decreases the annual number of county-level alcohol-related traffic fatalities by 15%. Finally, as discussed in the review of the related literature, a series of economic studies document an increase in treatment utilization following passage of a state parity law, indicating that $\frac{\partial T}{\partial P} > 0$. As an example, Maclean, Popovici, and Stern (2018) find that admissions to specialty treatment increase by 9.2%, although the overall increase in care is potentially larger as the authors focus on only one, costly, modality of care. This hypothesis (increases in treatment that extend beyond the specialty sector) is supported by studies of public insurance expansions. Following a major expansion of public insurance, Medicaid-financed medications used to treat SUDs and prescribed in outpatient settings, arguably a setting more acceptable to patients (Center for Substance Abuse Treatment 2004), increased by up to 70% (Wen et al. 2017, Maclean and Saloner 2018a, Meinhofer and Witman 2018).

Overall, our framework suggests that (i) $\frac{\partial C}{\partial P} < 0$ and (ii) the magnitude of $\frac{\partial C}{\partial P}$ is potentially large given estimates of the effect size for each derivative in our reduced-form traffic crash production function. We will test the overall effect in our empirical models.

2.3 Related literature

Several recent economic studies estimate the effect of state parity law passage on specialty SUD treatment outcomes. Dave and Mukerjee (2011) use the Treatment Episode Dataset (TEDS) and show that parity laws for behavioral health (i.e., both mental health and SUD treatment) increase the number of SUD treatment admissions by 12.8%. Using data drawn from the National Survey on Substance Abuse Treatment Services (N-SSATS), Wen et al. (2013) find that state parity laws increase treatment admissions by 9% with larger effects among providers that accept private insurance. Maclean, Popovici, and Stern (2018) also analyze N-SSATS data and show that, following passage of a state parity law, admissions to specialty treatment increase by 9.2%. Similarly, Wen, Hockenberry, and Cummings (2017) document, again using N-SSATS, that parity laws increase SUD treatment rates.[8] Finally, Hamersma and

[8] The main focus of the Wen et al (2017) study is Medicaid Health Insurance Accountability waivers on crime; with parity laws serving as a control variable.

Maclean (2018) find no change in specialty SUD treatment admissions among children ages 12 to 17, but their estimates are noisy and thus the authors cannot rule out non-trivial increases.

Two studies use changes in insurance coverage generated by a large-scale healthcare reform initiative in Massachusetts in 2006, which expanded both public and private coverage. Private plans were required to cover a set of SUD treatment services; although Massachusetts did not require full parity. Meara et al. (2014) find a post-reform decline of 28% in SUD-related emergency department episodes and inpatient hospitalizations among young adults. These results suggest that insurance coverage lead to increased SUD treatment in settings such as outpatient and other modalities of specialty care. Care received in these alternative settings may be more acceptable to patients than inpatient hospital-based treatment (Center for Substance Abuse Treatment 2004). Further, an emergency department episode or hospitalization may reflect unnecessary care that could have been avoided if the patient had received adequate disease management treatment. In line with this hypothesis, Maclean and Saloner (2018b), analyzing the N-SSATS, find that the reform increased admissions to specialty SUD treatment.[9]

Overall, several recent economic studies provide evidence that state laws expanding coverage for SUD treatment services, particularly laws that require equality between SUD treatment and medical/surgical treatment, increases treatment use. We extend this literature by examining the effects of parity laws on fatal traffic accidents.

3. Data and methods

3.1 Fatality Analysis Reporting System (FARS)

[9] Results are somewhat sensitive to specification. While differences-in-differences, using geographically similar states as a comparison group, generate a precisely estimated increase in admissions, synthetic control methods generate imprecise findings. More details available on request.

Data on fatal crashes occurring on public roads in the U.S. is obtained from the FARS of the National Highway Traffic Safety Administration (NHTSA). These data are widely employed by economists to study the effects of public policies on traffic fatalities (Abouk and Adams 2013, Adams, Cotti, and Tefft 2015, French and Gumus 2015), and by governments of all levels to monitor trends in traffic safety and to develop strategies to reduce fatal crashes (Koehler and Brown 2009). FARS data represent the census of police-reported fatal traffic crashes occurring on U.S. public roadways (more specifically, crashes resulting in the death of an involved person within 30 days) within the 50 states and DC. Thus, these data are the best available to study the effects of state parity laws on fatal traffic accidents.

To construct FARS, administrators collect and combine several state-specific data sources including police reports, driver records, vehicle registration files, state highway department data, medical examiners' reports, toxicology reports, and death certificates. These data are compiled into more than 100 individually-coded data elements that characterize the crash, the vehicles, and the persons involved. We pool FARS data for the period 1988 to 2013. Concerns related to the reliability of data during the initial years of FARS data collection convinced us to avoid information collected in the 1970s and early 1980s.[10] Other recent economics studies define the analysis period in similar ways (French and Gumus 2014). At the upper end of the panel we truncate the analysis sample in 2013 as we wish to focus on a period before the core provisions of the ACA were implemented (Sommers et al. 2013).

3.2 State parity laws

Our source of variation is within and between changes in state parity laws that compel private insurers to provide equal coverage for medical/surgical services and both alcohol and

[10] Based on personal communications between the authors and FARS administrators. More details are available on request from the corresponding author.

psychoactive drug treatment.[11] We rely on three sources to construct our parity variables: Robinson et al. (2006), Barry and Sindelar (2007), and Wen et al. (2013). During our study period from 1988 to 2013, 12 states passed a parity law. Maryland was the first state in the U.S. to do so in 1994. In Table 1, we list the states that passed a parity law through 2013 (the last year of our study period) along with the effective date.

Table 1 also reports whether states transitioned from no regulation of SUD treatment to parity or from a weaker law (e.g., mandated benefits or mandated offer) to parity. Broadly, mandated benefit laws compel insurers to cover a specified set of services while mandated offer laws require that insurers offer coverage of SUD treatment services to beneficiaries. The 'bite' of a parity law will likely vary across states based on the regulation in place prior to passage of the parity law. In other words, transitioning from no law to parity is likely to have larger effects than transitioning from a generous mandated benefit law to parity.

We aggregate the FARS data to the annual level. For each law, in the passage year, the indicator is set equal to the fraction of the year for which the law was in effect. Years before passage of the parity law are coded as zero and years after passage are coded as one (e.g., if a law became effective July 1st, 2002, we code the law as 0.5 in 2002). We are unable to identify the exact implementation day for some states (i.e., Connecticut, Delaware, Maine, Maryland, Rhode Island, Vermont, and West Virginia). For these states, we use July 1st of the implementation year. As a robustness check reported later in the manuscript, instead of July 1st, we use the date of January 1st and the results are very similar. We then lag this variable by one year to allow for a time delay between the implementation of a parity law and its effects on

[11] In previous versions of this manuscript we relied on effective dates provided by the National Council of State Legislatures. However, we detected some errors in the effective dates and hence opted to update our coding to the scheme outlined in the manuscript. More details are available on request from the corresponding author.

traffic fatalities as these laws are hypothesized to affect fatality rates indirectly through treatment access. Hence, in the first year after parity law passage, the indicator is set equal to the fraction of the year for which the law was in effect in the implementation year.

3.3 Outcome variables

We construct several measures of traffic fatality rates per 100,000 population. The first and most comprehensive outcome measure is the rate per 100,000 population of the overall number of persons killed in traffic crashes within a particular state and year (i.e., total fatality rate). Second, alcohol involvement is documented by BAC test results collected from police or coroner reports. Despite federal mandates, approximately 60% of fatal crashes in the FARS are missing BAC reports. As these data contain measurement error and several states do not uniformly collect BAC information (Eisenberg 2003, Anderson, Hansen, and Rees 2013), when BAC information is missing, BAC level is statistically imputed by FARS administrators based on characteristics of the crash and driver using the Multiple Imputation procedure (National Highway Traffic Safety Administration 2002). We follow the economic literature and use the pharmacological and imputed information to construct measures for the number of traffic fatalities with alcohol involvement (Adams, Blackburn, and Cotti 2012, French and Gumus 2014, Abouk and Adams 2013). We then employ two thresholds for alcohol-involved crash rates: (i) fatalities per 100,000 population in crashes where at least one of the drivers had a BAC level over the legal limit of 0.08 g/dL; and (ii) fatalities per 100,000 population in crashes where at least one of the drivers had a BAC level above 0.15 g/dL.

Ideally, we would like to analyze the number of fatalities in crashes where at least one of the drivers was under the influence of alcohol and/or psychoactive drugs. Unfortunately data on psychoactive drug (i.e., substances other than alcohol) involvement is not uniformly collected by states and is subject to several other important limitations. FARS administrators began collecting data pertaining to psychoactive drug tests in 1991 and coding procedures for test results changed substantially in 1993. We are unable to determine psychoactive drug-involved fatalities prior to this year. Although the majority of drivers are not tested for psychoactive drugs, the testing rate for fatally injured drivers is higher than the testing rate for surviving drivers than non-surviving drivers (National Highway Traffic Safety Administration 2010, Slater et al. 2016). Finally, FARS reports the presence of any psychoactive drug regardless of its legal status, including over-the-counter and prescription medications. Given these issues related to psychoactive drug involvement information in FARS, we restrict our analysis to alcohol-involved fatalities.[12] We acknowledge our inability to study psychoactive drug-involved fatalities as a limitation of the study.

For the reasons noted above, we contend that examining the effects of parity law passage on total fatalities, including those from crashes where all drivers had BAC levels under the legal alcohol limit of 0.08, is a sensible approach for several reasons.[13] First, while information on whether these drivers are under the influence of psychoactive drugs is not available, drug involvement in these crashes is still possible. There is substantial scope for parity laws to reduce both alcohol use disorders and psychoactive drug use disorders. For instance, in 2013 (the last year of our study), the share of patients receiving care in a SUD treatment center for alcohol use, psychoactive drug use, and both substances was as follows: 23%, 28%, and 49% (authors' calculations based on the 2013 N-SSATS, details available on request). Second, the total fatalities measure could capture other types of impaired driving that are attributable to SUDs

[12] Measurement error in the outcome variable can lead to bias in multivariate regression models. See Bound, Brown, and Mathiowetz (2001) for an excellent discussion.
[13] These reasons prevent us from using fatal traffic accidents as a within-state comparison group in a triple difference estimator as these fatalities are potentially treated.

(e.g., sleep deprivation, hangovers, and general cognition problems) among those drivers with SUDs. For instance, individuals with SUDs are at elevated risk for sleep problems (Popovici and French 2013a) and numerous studies document that sleep deprivation is a major cause of traffic crashes (Eoh, Chung, and Kim 2005, Hack et al. 2001, Terán-Santos, Jimenez-Gomez, and Cordero-Guevara 1999). Hangover effects from substance use are plausibly more common among those with SUDs than other individuals, and hangovers could impede the ability to drive even when BAC levels are below the legal limit. Similarly, SUDs impede general cognition.

3.4 Control variables

Because traffic fatalities are influenced by numerous factors apart from state parity laws, we control for a broad set of explanatory variables in our regression models. In particular, to mitigate potential omitted variable bias in the estimated coefficients, we include controls that can influence both substance-attributable traffic crashes and the propensity of a state to pass an SUD parity law. To this end, we link data from several other administrative and survey sources to the FARS dataset based on state and year.

We include four policy variables that proxy for state attitudes toward SUDs generally and impaired driving specifically. These variables are likely to affect the number of traffic fatalities and might also be correlated with parity laws for SUD treatment (French and Gumus 2014). (i) State-specific blood alcohol concentration (BAC) limit is the maximum legal BAC level for the operator of a motor vehicle. We include an indicator for a state BAC limit of 0.08 g/dL or higher (NHTSA Alcohol-Highway Safety Digest Topics and Alcohol Policy Information System). (ii) An indicator variable for a state-specific administrative license revocation (ALR) law (Anderson, Hansen, and Rees 2013). This policy allows law enforcement officials to suspend or revoke the license of a driver who refuses to submit to alcohol testing or fails an alcohol test after a traffic stop or crash. (iii) An indicator variable for a prescription drug monitoring program (PDMP) in the state (Ali et al. 2017). (iv) An indicator variable for a state law that permits marijuana use for medical purposes (Sabia and Nguyen 2016).

We control for state-by-year average demographic variables (gender, age, race, ethnicity, marital status, education, and family income) from the Annual Social and Economic Supplement to the Current Population Survey (Flood et al. 2015). These variables proxy for state-specific characteristics and attitudes that could predict our outcomes and are not captured by other included controls (Maclean et al. 2018).

3.5 Empirical model

We model the relationships between state parity laws and traffic fatalities using a differences-in-differences (DD) framework, as outlined in Equation (1):

(1) $$Y_{st} = \alpha_0 + \alpha_{PL}PL_{st-1} + X_{st}\alpha_X + \theta_S + \tau_t + \mu_{st}$$

Y_{st} is a traffic fatality rate outcome in state *s* and year *t*; PL_{st-1} is a lagged parity law indicator in state *s* and year *t*. We lag the parity law by one year to allow for a time delay between passage of a law and our outcomes. Given that we expect parity laws to increase treatment which will in turn reduce SUDs and related traffic fatalities (see Section 2.2), this causal pathway implies that fatality effects should occur after some time has passed. X_{st} is a vector of state demographics and policies outlined in Section 3.4.; and θ_s and τ_t are vectors of state and year fixed effects. State fixed effects control for time-invariant state-level factors that affect traffic fatalities and/or passage of parity laws. Year fixed effects account for time-changing factors impacting the U.S. as a whole (e.g., nationwide trends in traffic fatalities influenced by national safe-driving campaigns). α_{PL} and α_X are parameters to estimate. All regressions are estimated with OLS weighted by the state population from the U.S. Census Bureau. We report 95% confidence intervals that account for clustering within states.

4. Results

4.1 Summary statistics

Table 2 reports summary statistics for the full sample in the first column and by whether a state has a parity law in the last two columns (states with a parity law during the analysis period vs. states without a parity law by 2013). We report traffic fatalities per 100,000 state residents. The mean fatality rate across all states and years is 16.11. The mean fatality rate where at least one driver had a BAC greater than 0.08 is 5.43, while the mean fatality rate where at least one driver had a BAC greater than 0.15 is 3.73. Approximately 7.6% of state-year observations in our analysis sample have a parity law in place during a particular year.

4.2 Internal validity of the research design

A necessary assumption for DD models to recover causal estimates is that the treatment (i.e., states that passed a parity law) and comparison (i.e., states that did not pass parity law) groups would have followed the same trends had the treatment group not been treated. In other words, the comparison group can provide a suitable counterfactual trend for the treatment group post-parity law adoption ('parallel trends'). This assumption is not testable as the treatment group is not observed in the counterfactual untreated condition after parity law adoption.

We attempt to provide suggestive evidence on the ability of our FARS data to satisfy the parallel trends assumption. We conduct an event study following Autor (2003). Equation (2) outlines the specification of our event study analysis.

(2) $$Y_{st} = \beta_0 + \sum_{j=1}^{8} \delta_j \, Rel\_time_{sj} + X_{st}\beta_X + S_S + \tau_t + \epsilon_{st}.$$

We first center the data around the event (i.e., parity law passage) for states that pass a parity law by 2013. That is, for states that pass a parity law, we define the year of the event (e) as the first full year in which the parity law is in place. We then calculate the variable Rel_time_{sj} which is the difference between the crash year (t) and the effective year (e) for adopting states. Next, following Kline (2011), we construct an event window that includes the period seven years prior to law passage and seven years after law passage for the twelve states that passed a law. We use all years of data for comparison states. Imposing such endpoint restrictions implicitly assumes that no anticipatory effects are present more than seven years in advance of the parity law passage and the effects dissipate after seven years. Under this definition, 102 state-year observations are excluded from the event study analysis. We then create bins equal to seven years pre-law, five to six years pre-law, three to four years pre-law, one to two years pre-law, year of law passage, one to two years post-law, three to four years post-law, five to six years post law, and seven years post-law. The omitted period is seven years prior to law passage; thus j=1 is five to six years pre-law, j=2 is three to four years, pre-law, and so forth through j=8 (seven years post-law). We follow Lovenheim (2009) and code states that do not pass a parity law by 2013 as zero for all bins. The estimates for the leads are our primary focus as they can reveal pre-implementation effects (i.e., policy endogeneity). All covariates are the same as those defined for Equation (1). We graphically report results from the event study in Figures 1 (total fatalities), 2 (BAC greater than 0.08), and 3 (BAC greater than 0.15). Table 3 contains corresponding coefficient estimates and 95% confidence intervals.

The event study results show no evidence of pre-implementation trends as all estimated coefficients for the leads are non-significant at conventional levels. Moreover, χ^2 tests indicate that the estimates for the lead variables are jointly non-significant (full results not reported, but available on request from the corresponding author). We interpret our results as offering suggestive evidence that the FARS data satisfy the parallel trends assumption. We report results generated in DD models for the remainder of the study to provide a concise summary of treatment effects and to maximize statistical power.

4.3 Differences-in-differences regression results

Table 4 reports selected results from our DD analysis of the effects of parity laws on total and alcohol-involved traffic fatalities. All coefficient estimates are negative, indicating that parity laws reduce traffic fatality rates. A full set of coefficient estimates are reported in Appendix Table 1. Although the sign is negative, the estimate for the total fatality rate is not statistically significant at conventional levels. When examining results by BAC level, we find that parity laws have a stronger effect on fatalities involving more severely impaired drivers (i.e., BAC levels exceeding 0.15). Parity laws lead to a 0.41 (7.6% of the sample mean) decrease in the fatality rate where at least one driver had a BAC greater than 0.08 (p<0.10) and a 0.31 (8.2% of the sample mean) reduction in the fatality rate where at least one driver had a BAC above 0.15 (p<0.05). However, we note that 95% confidence intervals overlap, so heterogeneity by BAC level should not be overstated.

5. Extensions and robustness checks

5.1 SUD outcomes

Although we are primarily focused on whether private health insurance expansions decrease traffic fatalities through increases in access to and affordability of SUD treatment, it is also prudent to examine whether these expansions decrease SUDs within the general population. Namely, if parity laws do not reduce SUDs, then the causal mechanisms for the effects we identify in FARS are more obscure.

To address this question, we examine the public use National Vital Statistics Mortality Files (NVSM) between 1999 and 2013. Ideally, we would examine NVSM data for our full study period (1988 to 2013). However, an important break in the NVSM data occurred between 1998 and 1999 as data administrators transitioned from International Statistical Classification of Diseases and Related Health Problems (ICD) 9 to the ICD 10 coding scheme. To the best of our knowledge, no established method exists to crosswalk across these two systems. Hence, we follow the related literature and employ data from 1999 onward for our analyses of parity laws and fatal alcohol poisonings and psychoactive drug overdoses (Popovici et al. 2018).

NVSM tracks all-cause mortality in the U.S. and thus provides us with the universe of deaths classified as fatal alcohol poisonings and psychoactive drug-related overdoses. Operationally, we construct a measure of the total number of deaths in these two categories combined for the population 21 to 64 years of age. We calculate the rate per 100,000 state residents and use the same procedure outlined above for FARS to link effective dates for state parity laws to the NVSM data.[14] NVSM results are reported in Table 5.

We find evidence that passage of a parity law significantly reduces the alcohol and psychoactive drug-related overdose death rate. Quantitatively, passage of a parity law is associated with a 1.81 unit decrease in the death rate, which represents a 10.2% decline relative to the sample mean.

5.2 Changes in the composition of the insured population

[14] Specifically, we use the public use Underlying Cause of Death files from the Centers for Disease Control and Prevention to determine deaths attributable to alcohol and psychoactive drugs. We aggregate the NVSM to the state-year level. Monthly data contain a substantial amount of left censoring, which is imposed by the National Center for Health Statistics due to privacy concerns. We elected to use the annual data to avoid such censoring and to estimate a model comparable to the model we estimate in FARS.

If implemented as intended, parity laws should increase coverage for SUD treatment services among the privately insured. However, it is possible that, following passage of a parity law and the ensuing increase in coverage for SUD treatment services in private insurance contracts, uninsured and publicly insured individuals with SUDs may opt to enroll in private coverage to take advantage of the newly covered services (i.e., a form of adverse selection). If such adverse selection occurs post-parity law, then the composition of the privately insured market may change, which opens the door to conditional-on-positive bias (Angrist and Pischke 2009). In particular, it may be the case that post-parity law, any changes in SUD treatment service use and attributable changes in substance-impaired traffic crashes are due to differences in the population of privately insured individuals rather than changes in treatment use and reductions in SUDs among the original group of privately-insured individuals that can be attributable to parity laws *per se*. Presumably, those individuals who take up private insurance to access SUD benefits have, on average, more severe SUDs than the original group of privately insured (i.e., adverse selection). Similarly, some individuals in the original group of insured may opt to drop coverage due to increased premiums following a parity law (Bailey and Blascak 2016, Bailey 2014). Such phenomena, if present, can bias regression coefficient estimates.

We investigate changes in the composition of the insured by regressing the proportion of the state with any insurance, private insurance, and public insurance from the Annual Social and Economic Supplement to the Current Population Survey (ASEC) over the period 1989 to 2013 on the parity indicator and state demographics. ASEC insurance variables pertain to the past calendar year. Thus, these data capture insurance coverage over the period 1988 to 2012.[15] This analysis considers only the extensive margin of insurance (i.e., it does not account for those who

[15] Due to a break in the ASEC insurance questions that occurred in 2014, we cannot incorporate later data to better match our FARS study period. See Pascale, Boudreaux, and King (2016) for a discussion.

switch from one private plan to another private plan). The regression results indicate that passage of a parity law does not induce changes in overall, private, or public insurance coverage (see Table 6). We interpret these null findings as suggestive evidence that conditional-on-positive (i.e., changes in the composition of the privately insured) does not lead to bias in our coefficient estimates.

5.3 Changes in the number of specialty SUD treatment providers

Another form of composition-on-positive bias could occur if parity laws induce some providers to enter or exit the market (Angrist and Pischke 2009). To explore whether this form of bias is present, we regress the number of treatment providers per 100,000 population from the County Business Patterns from the U.S. Census Bureau on the parity law indicator and state demographics. We use the six-digit North American Industry Classification System (NAICS) to classify specialty SUD treatment facilities (Swensen 2015). Prior to 1998, the CBP industry codes did not offer sufficient detail to identify SUD treatment facilities (information available on request from the corresponding author). Using data for the period 1998 to 2013, we find no statistically significant evidence that state parity laws alter the composition of providers (see Table 7). Thus, the null findings suggest that parity law passage does not lead to substantial changes in the population of SUD treatment providers.

5.4 Other robustness checks

We conduct several additional checks and the results are broadly robust. For brevity, we summarize these robustness checks and only discuss substantial departures from our main results. First, we use a contemporaneous parity law variable (see Appendix Table 2). Second, in our DD specification, we reduce the size of the sample to that from the event study by excluding observations outside the event study window that includes the period seven years prior to law passage and seven years after law passage (see Appendix Table 3). In contrast to our core findings, when the sample is restricted in this way, we find a statistically significant effect of a parity law on the total fatality rate. Third, recall that we are unable to identify the exact parity implementation day for some states (i.e., Connecticut, Delaware, Maine, Maryland, Rhode Island, Vermont, and West Virginia). In revised analyses, we specify the date of January 1st instead of July 1st as used in the core analyses and the results are very similar. These alternative estimation results are presented in Appendix Table 4. Fourth, we construct 9 division indicators and re-estimate our main DD regressions by replacing the state and year fixed effects with geographical division by year fixed effects (Appendix Table 5).

Finally, we evaluate the validity of our estimates by performing a placebo analysis following Abadie and Gardeazabal (2003). In particular, we conduct a randomization exercise in which we randomly reshuffle parity law indicators across states, and re-estimate Equation (1) with these placebo indicators. New indicators are randomly assigned and used to estimate Equation (1) in 100 separate simulation trials. We expect that estimates generated using the randomly reshuffled parity laws to be small in magnitude, in particular smaller than the estimate based on actual parity laws in place in U.S. states, and imprecise. Thus, we expect our estimate based on actual parity law assignments to be an outlier. Such a finding suggests that our estimates are not capturing some other unknown policy or social factor that changes contemporaneously with our parity law indicator. Each of these 100 placebo coefficient estimates are plotted along with the estimate of our primary DD analysis. We present these graphs in Figures 4 (total fatalities), 5 (BAC greater than 0.08), and 6 (BAC greater than 0.15). As expected, the estimate based on actual parity laws (indicated by a black diamond marker) is an outlier in each graph and provides further support for our design and that we are not falsely attributing reductions in traffic fatalities to parity laws rather than some other factor.

6. Discussion

The primary objective of this study is to determine whether state parity laws—those that compel private insurers to provide equal coverage for substance use disorder (SUD) treatment vis-à-vis medical/surgical treatment—have positive spillover effects on fatal traffic crashes, one of the largest negative externalities associated with substance misuse. We conjecture that an increase in the number of substance users seeking SUD treatment because of parity legislation will reduce the number of impaired drivers on roadways and, consequently, decrease the number of traffic fatalities.

Our main finding supports this conjecture as state-specific traffic fatalities decline after passage of a parity law. We identify some evidence of heterogeneity in the estimated effects, however, pertaining to BAC levels of the drivers. In line with the premise that alcohol involvement in crashes decreases when parity laws are in place, we find a dose-response relationship between parity laws and traffic fatalities—the effect size increases with the BAC level of the drivers involved in fatal crashes.

We can use our findings to estimate related benefits and costs to society as they relate to traffic safety. Implementation of a parity law reduces the fatality rate where at least one driver had a BAC greater than 0.08 by 7.6%. In other words, adopting parity laws in the rest of the states in the U.S. would avoid approximately 533 lives across the U.S. in a given year.[16] Using a customary estimated value of $9.4 million for a statistical life (United States Environmental Protection Agency 2018), adopting parity laws would avert $5 billion to society in terms of

[16] Calculations are based on the 2013 number of fatalities where at least one driver had a BAC greater than 0.08 in states that did not pass a parity law in the analysis period.

saved lives. The average cost of SUD treatment per episode is $8,317 (authors' calculations using estimates in Table 2 in French, Popovici, and Tapsell (2008)). If we assume that one treatment episode averted one impaired driver-associated fatal accident, then the costs of preventing our estimated 533 deaths is $4.4M.[17] We also find evidence that parity laws reduce the number of fatal alcohol poisonings and psychoactive drug-related overdoses within the adult population (the population most likely to be affected by state parity laws). The reductions in fatal alcohol poisonings and psychoactive drug-related overdoses – in addition to benefits not considered in this study – suggest that the benefits to society attributable to expanding SUD parity laws to all states could be non-trivial.

Given that our study estimates the effects of parity laws on traffic fatalities rather than a 'first stage' effect on SUDs, it is important to determine whether the magnitudes of the estimates are reasonable. One way to examine plausibility is to consider the extent to which private insurance is used to pay for SUD treatment services. While private insurance has historically played a more modest role in the financing of SUD treatment compared to medical/surgical services, this differential does not imply that private insurance is an unimportant source of financing within the SUD treatment system. Indeed, data from the National Survey of Drug Use and Health (NSDUH) reveals that in 2013, the last year in our analysis period, 41.7% of patients receiving SUD treatment used private health insurance as a source of payment for their last treatment episode (Substance Abuse and Mental Health Services Administration 2014). This percentage may actually understate the true penetration of private insurance in the financing of SUD treatment as it only captures the use of private insurance for the last service episode. For

[17] We note that more than one episode of treatment may be required to avert an impaired-driving related fatality given the chronic nature of SUDs. A more conservative estimate of three treatment episodes per averted impaired-driving related fatality suggests that the cost is $13.2M, which is well below the savings in terms of averted deaths.

example, individuals who receive SUD treatment multiple times within a year, and use private insurance to pay for more distal treatment episodes would not be included in this percentage. Finally, given that numerous studies in the clinical and health services research literatures report on the effectiveness of different SUD treatment approaches (McLellan et al. 2000), we expect that many of the additional patients who are receiving SUD treatment due to parity are less likely to use substances and drive while impaired.

Another approach to gauge whether our estimated effect sizes are reasonable is to consider the share of the population that is impacted by state parity laws. According to Jensen and Morrisey (1999), in the 1990s, 33 to 43% of the U.S. population was impacted by a private health insurance expansion. Wen et al. (2013) report that passage of a state parity law leads to a 9% increase in admissions to specialty SUD treatment facilities, and Maclean, Popovici, and Stern (2018) document a similar increase in admissions. While none of these estimates are definitive, they collectively suggest that parity legislation can have an important effect on private insurance markets and the use of private insurance to pay for SUD treatment, thereby supporting the validity of our DD estimates for traffic fatalities.

An additional argument to defend the reasonableness of the effect sizes is that state parity laws could affect both the extensive and intensive margins of SUD treatment. We have considered mechanisms that influence the extensive margin of treatment, but the relationships between parity laws and traffic fatalities could also work through the intensive margin. Namely, while some individuals will *gain* insurance coverage for SUD treatment through parity legislation, others may experience an increase in the *generosity* of their current plan. For example, during the pre-parity period, an insured individual may have had coverage for a basic set of heavily restricted services (e.g., pre-authorization, stepped therapy, high cost-sharing, limited number of allowable annual/lifetime episodes of care). After passage of a parity policy, these restrictions may be loosened or eliminated. This hypothesis is supported by McGinty et al. (2015) who show that MHPAEA increased use of out-of-network services and by Thalmayer et al. (2016) who show that post MHPAEA nearly all plans dropped quantitative treatment limits, which may reflect expanded access to/more generous coverage of SUD treatment providers for beneficiaries. Although individuals acting in this way would have been designated as having coverage for SUD treatment pre-parity, the coverage may not have adequately met his/her treatment needs in terms of either service availability, intensity, or cost. Thus, increased insurance generosity because of parity legislation may now allow some individuals to obtain more comprehensive SUD treatment (e.g., treatment that addresses overall patient health, relies on the use of both counseling and medications, and is of sufficient duration with appropriate follow up care) and/or treatment that is better matched to patient needs. While we cannot observe or measure such coverage gains in our data, it is conceivable that these gains, if present, would facilitate more comprehensive and effective SUD treatment, and thereby reduce both SUD prevalence and fatal traffic crashes.

Our study has several limitations. (i) We are unable to obtain data on non-fatal traffic crashes, those that are not reported to the police, or crashes that occur on private roadways. Clearly, non-fatal traffic injuries are more common and potentially result in greater healthcare expenditures compared to fatal traffic crashes. (ii) While we have information on alcohol-involved and alcohol-impaired traffic fatalities, we lack data on traffic fatalities involving other drugs due to reporting issues in FARS. (iii) Although parity laws might impact the number of substance users seeking treatment and hence the rates of untreated SUDs in the population, our data on fatal alcohol poisonings and psychoactive drug-related overdoses are second-best proxies for direct clinical measures of adult SUDs. Future work, using different data sets, could explore these additional and important aspects of the parity law – SUD-related traffic safety question.

Despite these limitations, our findings are timely, original, and policy relevant for several reasons. First, they document the public health value of mandating that private insurers offer an equitable and affordable level of healthcare coverage, thus contributing to the broader public policy debate on this topic. Second, the ACA requires that most private health insurance plans on state and federal exchanges, as well as many public plans, offer SUD treatment at parity with medical/surgical benefits. Our findings suggest that this Act may reduce the number of impaired drivers, thereby improving overall traffic safety. Recent uncertainty surrounding the political fate of the ACA—the Trump Administration and Republican Congress have a long-standing objective of repealing this Act (Levintova 2018, Patashnik and Oberlander 2018)—particularly the essential health benefit package (which includes SUD treatment), the state Medicaid expansions, and the guaranteed coverage issue, magnifies the significance of these research findings as they can inform policymakers on the benefits of expanding SUD treatment availability. Third, these findings contribute to the growing literature on the clinical and economic benefits of SUD treatment, and reveal that such services can lead to significant social welfare gains that extend beyond the affected individual.

In conclusion, traffic safety is a major public health issue and fatal traffic crashes are a leading cause of death in the U.S. Many current policies adopt a punitive approach to reducing substance-related traffic crashes (e.g., legal penalties associated with DUI such as monetary fines and even incarceration) or simply provide basic information about the dangers of driving under the influence of substances (e.g., media campaigns). Despite the implementation of these and other traffic safety initiatives, rates of substance-involved traffic fatalities remain alarmingly high—adults reported driving after drinking 112 million times in 2010 (Centers for Disease Control and Prevention 2015). Our research suggests that policy makers should consider the indirect benefits of ancillary policies such as health insurance parity laws as a viable and effective approach to enhance traffic safety.

Table 1. States that passed a parity law during the study period: 1988-2013

State	Effective date	Parity law transition
Arkansas	October 2009	Mandated offer to parity
Connecticut	2000 (no month)	None to parity
Delaware	2001 (no month)	None to parity
Kansas	July 2009	Mandated benefits to parity
Louisiana	January 2009	Mandated benefits to parity
Maine	2003 (no month)	Mandated benefits to parity
Maryland	1994 (no month)	None to parity
Oregon	July 2007	Mandated benefits to parity
Rhode Island	2002 (no month)	Mandated benefits to parity
Texas	April, 2005	Mandated benefits to parity
Vermont	1998 (no month)	None to parity
West Virginia	2004 (no month)	None to parity

Notes: See text for details on parity law sources. Mandated offer means private insurers are compelled to offer coverage for SUD treatment to beneficiaries; this coverage may be at parity with medical/surgery services benefits or not. Mandated benefits means private insurers are compelled to cover a set of SUD treatment services; the covered services, limits on service use, and cost-sharing arrangements may be less generous than those offered for medical/surgical services.

Table 2. Descriptive statistics for the full sample and by type of parity law, FARS 1988-2013

Variables:	All states	States with parity*	States without parity*
Traffic fatality rates per 100,000 population			
Total fatalities	16.11	15.52	16.30
BAC >= 0.08 fatalities[1]	5.428	5.280	5.473
BAC >= 0.15 fatalities[2]	3.731	3.564	3.782
Parity law			
Parity	0.076	0.322	0
Demographics and other state characteristics			
Age	46.45	46.90	46.31
Female	0.528	0.532	0.527
Male	0.472	0.468	0.473
White	0.832	0.860	0.824
African American	0.104	0.103	0.104
Other race	0.064	0.037	0.072
Hispanic	0.171	0.166	0.173
Married	0.627	0.627	0.627
Divorced, separated, or widowed	0.194	0.200	0.192
Never married	0.179	0.173	0.181
Less than high-school education	0.197	0.206	0.194
High-school diploma or equivalent	0.293	0.301	0.291
Some college but no degree	0.276	0.257	0.282
College degree	0.234	0.236	0.233
Annual family income	56,923	56,573	57,031
BAC limit <=0.08	0.535	0.561	0.527
Administrative license revocation policy	0.742	0.853	0.708
Prescription drug monitoring program	0.396	0.346	0.411
Medical marijuana law	0.127	0.162	0.116
Observations	**1,326**	**312**	**1,014**

[1] At least one driver involved in the crash had a BAC of 0.08 or more.
[2] At least one driver involved in the crash had a BAC of 0.15 or more.
*States with parity include states that pass a parity law, before and after the law passage. States without parity include all states that do not pass a parity law by 2013 in all years.
Notes: The unit of observation is a state/year. Data are weighted by the state population.

Table 3. Effects of state parity laws for SUD treatment on traffic fatality rates using an event study model, FARS 1988-2013

Outcome:	Total fatality rate	BAC >= 0.08 fatality rate [1]	BAC >= 0.15 fatality rate [2]
Sample mean	16.11	5.43	3.73
5-6 years pre-implementation	0.214 [-0.296,0.723]	-0.130 [-0.414,0.154]	0.076 [-0.160,0.312]
3-4 years pre-implementation	0.263 [-0.554,1.081]	-0.215 [-0.705,0.274]	-0.050 [-0.363,0.262]
1-2 years pre-implementation	0.357 [-0.795,1.509]	-0.189 [-0.739,0.361]	0.029 [-0.328,0.387]
Implementation year	-0.149 [-1.730,1.433]	-0.445 [-1.154,0.264]	-0.115 [-0.707,0.477]
1-2 years post-implementation	-0.595 [-1.883,0.693]	-0.559** [-1.065,-0.054]	-0.314* [-0.679,0.051]
3-4 years post-implementation	-0.275 [-1.203,0.654]	-0.522** [-0.989,-0.055]	-0.195 [-0.519,0.130]
5-6 years post-implementation	-0.888 [-2.123,0.347]	-0.675** [-1.228,-0.122]	-0.315 [-0.697,0.066]
7 years post-implementation	0.154 [-1.157,1.464]	-0.320 [-0.975,0.335]	-0.175 [-0.622,0.273]
Observations	**1,224**	**1,224**	**1,224**

[1] At least one driver involved in the crash had a BAC of 0.08 or more.
[2] At least one driver involved in the crash had a BAC of 0.15 or more.

Notes: The dependent variable in each specification is the state-specific annual rate per 100,000 population of the respective fatality type. Unit of observation is a state/year. Omitted category is 7 years prior to the law passage. The event window is -7 to +7 years for states that pass a parity law. Observations outside the event window are excluded. States that do not pass a parity law by 2013 are coded as 0 for all bins. All models are estimated with OLS and control for state average demographics (age, gender, race/ethnicity, marital status, education, and family income scaled by 1,000), administrative license revocation policy, BAC limit <=0.08, prescription drug monitoring program, medical marijuana law, and state and year fixed effects. 95% confidence intervals account for clustering within states and are reported in square brackets. Observations are weighted by the state/year population.
***; **; * = statistically different from zero at the1%; 5%; 10% levels.

Table 4. Effects of lagged parity laws for SUD treatment on traffic fatality rates, FARS 1988-2013

Outcome:	**Total fatality rate**	**BAC >= 0.08 fatality rate [1]**	**BAC >= 0.15 fatality rate [2]**
Sample mean for dependent variable	16.11	5.43	3.73
Parity law (lagged)	-0.416 [-0.953,0.122]	-0.414** [-0.758,-0.070]	-0.305** [-0.545,-0.065]
Observations	**1,326**	**1,326**	**1,326**

[1] At least one driver involved in the crash had a BAC of 0.08 or more.

[2] At least one driver involved in the crash had a BAC of 0.15 or more.

Notes: The dependent variable in each specification is the state-specific annual rate per 100,000 population of the respective fatality type. Unit of observation is a state/year. All models are estimated with OLS and controls include state average demographics (age, gender, race/ethnicity, marital status, education, and family income scaled by 1,000), administrative license revocation policy, BAC limit <=0.08, prescription drug monitoring program, medical marijuana law, and state and year fixed effects. 95% confidence intervals account for clustering within states and are reported in square brackets. Observations are weighted by the state/year population.

***; **; * = statistically different from zero at the1%; 5%; 10% levels.

Table 5. Effects of state parity laws for SUD treatment on alcohol poisoning and drug overdose death rate, NVSM 1999-2013

Outcome:	**Fatal alcohol poisoning and drug overdose death rate**
Sample mean	17.76
Parity law (lagged)	-1.807**
	[-3.379,-0.236]
Observations	**764**

Notes: The dependent variable is the state-specific annual rate per 100,000 population. Unit of observation is a state/year. Model is estimated with OLS and controls for state average demographics (age, gender, race/ethnicity, marital status, education, and family income), prescription drug monitoring program, medical marijuana law, and state and year fixed effects. 95% confidence intervals account for clustering within states and are reported in square brackets. Observations are weighted by the state/year population.
***; **; * = statistically different from zero at the1%; 5%; 10% levels.

Table 6. Effects of state parity laws for SUD treatment on insurance status, Annual Social and Economic Supplement to the Current Population Survey, 1988-2012

Outcome:	**Any insurance**	**Private insurance**	**Public insurance**
Sample mean	0.838	0.750	0.127
Parity law (lagged)	-0.001	-0.003	0.003
	[-0.007,0.006]	[-0.011,0.005]	[-0.007,0.013]
Observations	**1,275**	**1,275**	**1,275**

Notes: All models are estimated with OLS and controls include state average demographics (age, gender, race/ethnicity, marital status, education, and family income scaled by 1,000), administrative license revocation policy, BAC limit <=0.08, prescription drug monitoring program, medical marijuana law, and state and year fixed effects. 95% confidence intervals account for clustering within states and are reported in square brackets. Observations are weighted by the state/year population. Annual Social and Economic Supplement to the Current Population Survey insurance variables reflect the previous calendar year. These data are drawn from the 1989 to 2013 surveys.

***; **; * = statistically different from zero at the1%; 5%; 10% levels.

Table 7. Effects of state parity laws for specialty SUD treatment on SUD facility rate, County Business Patterns, 1988-2013

Outcome:	**SUD facility rate**
Sample mean	6.19
Parity law (lagged)	-0.230
	[-0.932,0.472]
Observations	**816**

Notes: The dependent variable is the rate per 100,000 population of the number of specialty SUD facilities in the state. Model is estimated with OLS and controls include state average demographics (age, gender, race/ethnicity, marital status, education, and family income scaled by 1,000), administrative license revocation policy, BAC limit <=0.08, prescription drug monitoring program, medical marijuana law, and state and year fixed effects. 95% confidence intervals account for clustering within states and are reported in square brackets. Observations are weighted by the state/year population.
***; **; * = statistically different from zero at the1%; 5%; 10% levels.

Appendix Table 1. Effects of lagged parity laws for SUD treatment on traffic fatality rates, FARS 1988-2013

Outcome:	**Total fatality rate**	**BAC >= 0.08 fatality rate** [1]	**BAC >= 0.15 fatality rate** [2]
Sample mean for dependent variable	16.11	5.43	3.73
Parity law (lagged)	-0.416	-0.414**	-0.305**
	[-0.953,0.122]	[-0.758,-0.070]	[-0.545,-0.065]
Medical marijuana law	-1.116**	-0.501**	-0.333**
	[-2.087,-0.145]	[-0.886,-0.116]	[-0.604,-0.062]
Prescription drug monitoring program	-0.556*	-0.288	-0.225*
	[-1.166,0.054]	[-0.649,0.072]	[-0.477,0.027]
Administrative license revocation	-0.067	-0.144	-0.058
	[-0.904,0.769]	[-0.584,0.297]	[-0.380,0.264]
BAC limit <=0.08	0.192	-0.138	-0.127
	[-0.184,0.568]	[-0.362,0.085]	[-0.290,0.036]
Age	0.017	0.013	0.001
	[-0.258,0.291]	[-0.144,0.170]	[-0.113,0.115]
Female	-13.862	-4.536	-2.977
	[-31.019,3.295]	[-13.202,4.130]	[-8.983,3.029]
African American	-0.316	5.478*	3.882
	[-9.410,8.778]	[-0.228,11.185]	[-0.814,8.578]
Other race	1.965	2.841	2.296
	[-11.107,15.038]	[-4.044,9.726]	[-2.801,7.393]
Hispanic	0.038	0.031	0.027*
	[-0.039,0.115]	[-0.011,0.073]	[-0.005,0.059]
Divorced, separated, or widowed	11.114**	4.762	4.008
	[0.233,21.994]	[-2.972,12.495]	[-1.606,9.622]
Never married	3.428	0.735	0.249
	[-8.575,15.431]	[-6.002,7.473]	[-4.615,5.113]
High-school diploma or equivalent	9.294**	1.949	1.241
	[1.676,16.911]	[-1.731,5.628]	[-1.231,3.712]
Some college but no degree	9.289**	0.143	-0.323
	[2.038,16.541]	[-3.501,3.787]	[-3.061,2.414]
College degree	-0.969	4.313	2.682
	[-13.805,11.867]	[-2.141,10.767]	[-1.915,7.278]
Family income scaled by 1,000	0.137***	0.057***	0.041***
	[0.087,0.187]	[0.028,0.086]	[0.020,0.061]
Observations	**1,326**	**1,326**	**1,326**

[1] At least one driver involved in the crash had a BAC of 0.08 or more.
[2] At least one driver involved in the crash had a BAC of 0.15 or more.
Notes: The dependent variable in each specification is the state-specific annual rate per 100,000 population of the respective fatality type. Unit of observation is a state/year. All models are estimated with OLS and control for state and year fixed effects. Omitted categories are male, white race, married or living as married, and less than high school education. 95% confidence intervals account for clustering within states and are reported in square brackets. Observations are weighted by the state/year population.
***; **; * = statistically different from zero at the1%; 5%; 10% levels.

Appendix Table 2. Effects of state parity laws for SUD treatment on traffic fatality rates using the contemporaneous parity law, FARS 1988-2013

Outcome:	**Total fatality rate**	**BAC >= 0.08 fatality rate [1]**	**BAC >= 0.15 fatality rate [2]**
Sample mean for dependent variable	16.11	5.43	3.73
Parity law (contemporaneous)	-0.406 [-0.978,0.167]	-0.424** [-0.803,-0.044]	-0.308** [-0.578,-0.038]
Observations	**1,326**	**1,326**	**1,326**

[1] At least one driver involved in the crash had a BAC of 0.08 or more.

[2] At least one driver involved in the crash had a BAC of 0.15 or more.

Notes: The dependent variable in each specification is the state-specific annual rate per 100,000 population of the respective fatality type. Unit of observation is a state/year. All models are estimated with OLS and controls include state average demographics (age, gender, race/ethnicity, marital status, education, and family income scaled by 1,000), administrative license revocation policy, BAC limit <=0.08, prescription drug monitoring program, medical marijuana law, and state and year fixed effects. 95% confidence intervals account for clustering within states and are reported in square brackets. Observations are weighted by the state/year population.

***; **; * = statistically different from zero at the1%; 5%; 10% levels.

Appendix Table 3. Effects of lagged parity laws for SUD treatment on traffic fatality rates using event study sample, FARS 1988-2013

Outcome:	**Total fatality rate**	**BAC >= 0.08 fatality rate** [1]	**BAC >= 0.15 fatality rate** [2]
Sample mean for dependent variable	16.11	5.43	3.73
Parity law (lagged)	-0.668***	-0.374***	-0.275***
	[-1.168,-0.167]	[-0.652,-0.096]	[-0.464,-0.086]
Observations	**1,224**	**1,224**	**1,224**

[1] At least one driver involved in the crash had a BAC of 0.08 or more.

[2] At least one driver involved in the crash had a BAC of 0.15 or more.

Notes: Sample excludes observations outside the -7 to +7 years event study window for adopting states, observations outside this window are excluded from the sample. The dependent variable in each specification is the state-specific annual rate per 100,000 population of the respective fatality type. Unit of observation is a state/year. All models are estimated with OLS and controls include state average demographics (age, gender, race/ethnicity, marital status, education, and family income scaled by 1,000), administrative license revocation policy, BAC limit <=0.08, prescription drug monitoring program, medical marijuana law, and state and year fixed effects. 95% confidence intervals account for clustering within states and are reported in square brackets. Observations are weighted by the state/year population.

***; **; * = statistically different from zero at the1%; 5%; 10% levels.

Appendix Table 4. Effects of lagged parity laws for SUD treatment on traffic fatality rates assigning the date of January 1st of the implementation year for states with unavailable implementation dates, FARS 1988-2013

Outcome:	**Total fatality rate**	**BAC >= 0.08 fatality rate [1]**	**BAC >= 0.15 fatality rate [2]**
Sample mean for dependent variable	16.11	5.43	3.73
Parity law (lagged)	-0.276	-0.371*	-0.278**
	[-0.922,0.371]	[-0.762,0.020]	[-0.548,-0.008]
Observations	**1,326**	**1,326**	**1,326**

[1] At least one driver involved in the crash had a BAC of 0.08 or more.
[2] At least one driver involved in the crash had a BAC of 0.15 or more.
Notes: The dependent variable in each specification is the state-specific annual rate per 100,000 population of the respective fatality type. Unit of observation is a state/year. All models are estimated with OLS and controls include state average demographics (age, gender, race/ethnicity, marital status, education, and family income scaled by 1,000), administrative license revocation policy, BAC limit <=0.08, prescription drug monitoring program, medical marijuana law, and state and year fixed effects. 95% confidence intervals account for clustering within states and are reported in square brackets. Observations are weighted by the state/year population.
***; **; * = statistically different from zero at the1%; 5%; 10% levels.

Appendix Table 5. Effects of lagged parity laws for SUD treatment on traffic fatality rates using division by year fixed effects, FARS 1988-2013

Outcome:	**Total fatality rate**	**BAC >= 0.08 fatality rate [1]**	**BAC >= 0.15 fatality rate [2]**
Sample mean for dependent variable	16.11	5.43	3.73
Parity law (lagged)	-1.786*** [-2.848,-0.724]	-0.538** [-1.076,-0.000]	-0.459** [-0.881,-0.036]
Observations	**1,326**	**1,326**	**1,326**

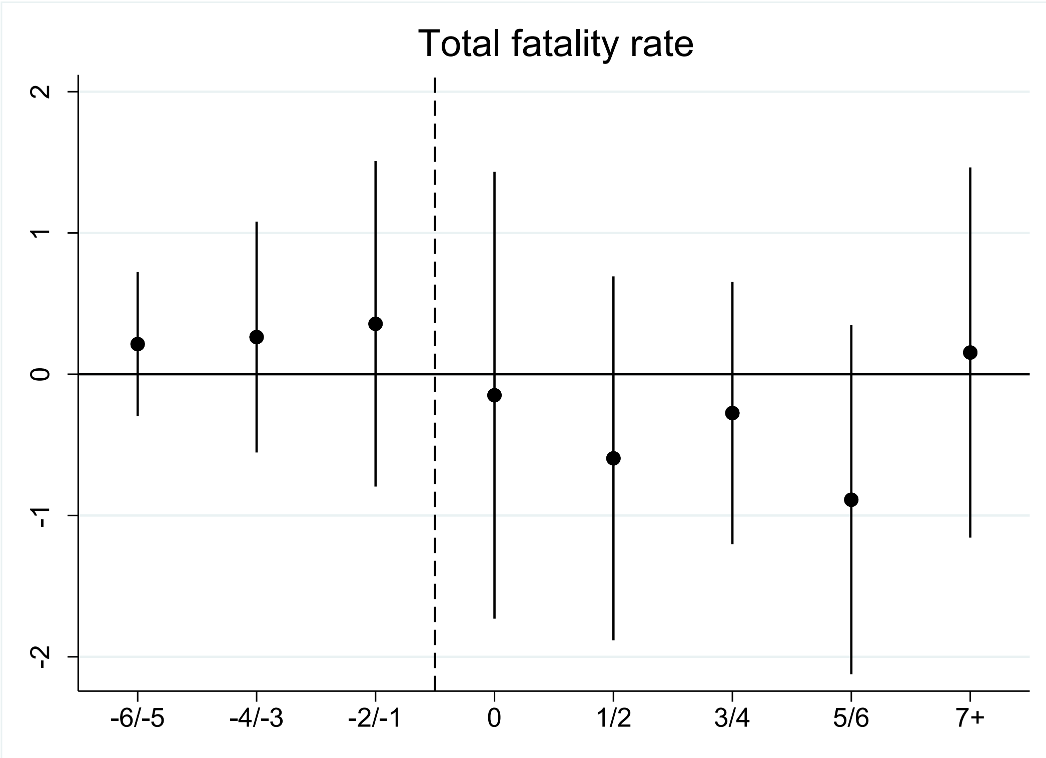
[1] At least one driver involved in the crash had a BAC of 0.08 or more.

[2] At least one driver involved in the crash had a BAC of 0.15 or more.

Notes: The dependent variable in each specification is the state-specific annual rate per 100,000 population of the respective fatality type. Unit of observation is a state/year. All models are estimated with OLS and controls include state average demographics (age, gender, race/ethnicity, marital status, education, and family income scaled by 1,000), administrative license revocation policy, BAC limit <=0.08, prescription drug monitoring program, medical marijuana law, and division by year fixed effects. 95% confidence intervals account for clustering within states and are reported in square brackets. Observations are weighted by the state/year population.

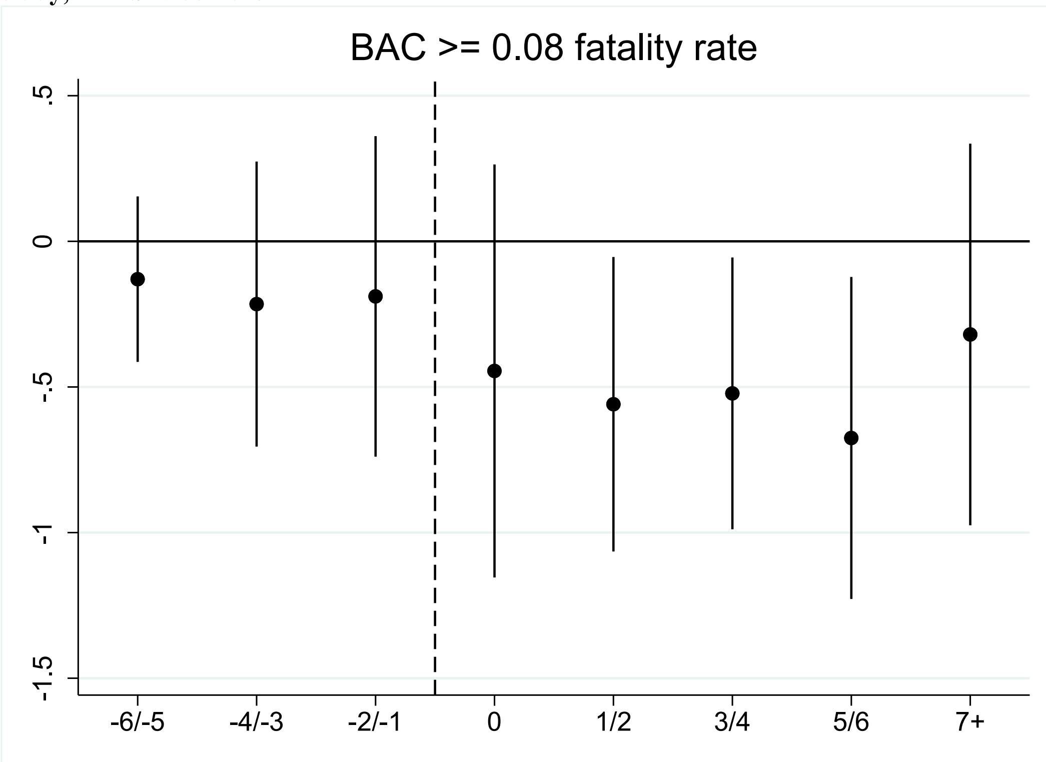
***; **; * = statistically different from zero at the1%; 5%; 10% levels.

Figure 1. Effect of state parity laws for SUD treatment on total traffic fatality rates using an event study, FARS 1988-2013



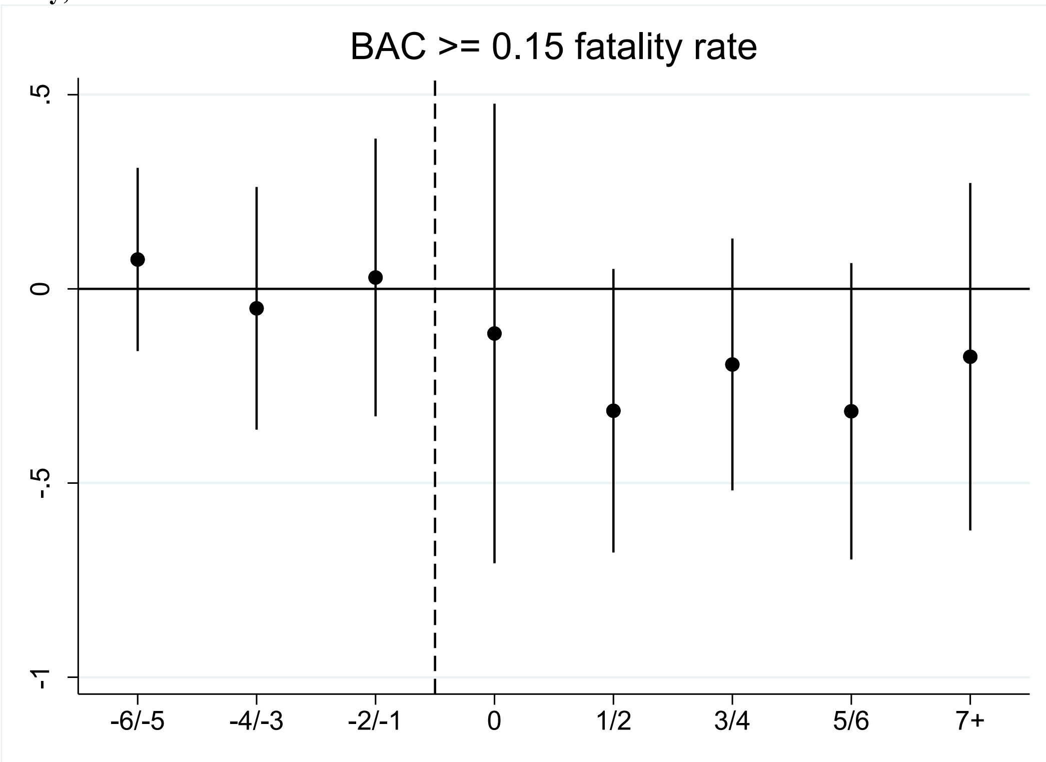
Notes: Unit of observation is a state/year. Event study includes three leads (binary indicators for 5 to 6 years, 3 to 4 years, and 1 to 2 years prior to implementation), four lags (binary indicators for 1 to 2 years, 3 to 4 years, 5 to 6 years and 7 years post-implementation), and an indicator for the policy implementation year. Omitted category is 7 years prior to the law passage. The event window is -7 to +7 years. Observations outside the event window are excluded. States that do not pass a parity law by 2013 are coded as 0 for all bins. All models are estimated with OLS and control for state average demographics (age, gender, race/ethnicity, marital status, education, and family income scaled by 1,000), administrative license revocation policy, BAC limit <=0.08, prescription drug monitoring program, medical marijuana law, and state and year fixed effects. 95% confidence intervals account for state-level clustering and are reported in vertical bars. Observations are weighted by the state/year population. See Table 3 for coefficient estimates.

Figure 2. Effect of state parity laws for SUD treatment on BAC >= 0.08 traffic fatality rates using an event study, FARS 1988-2013



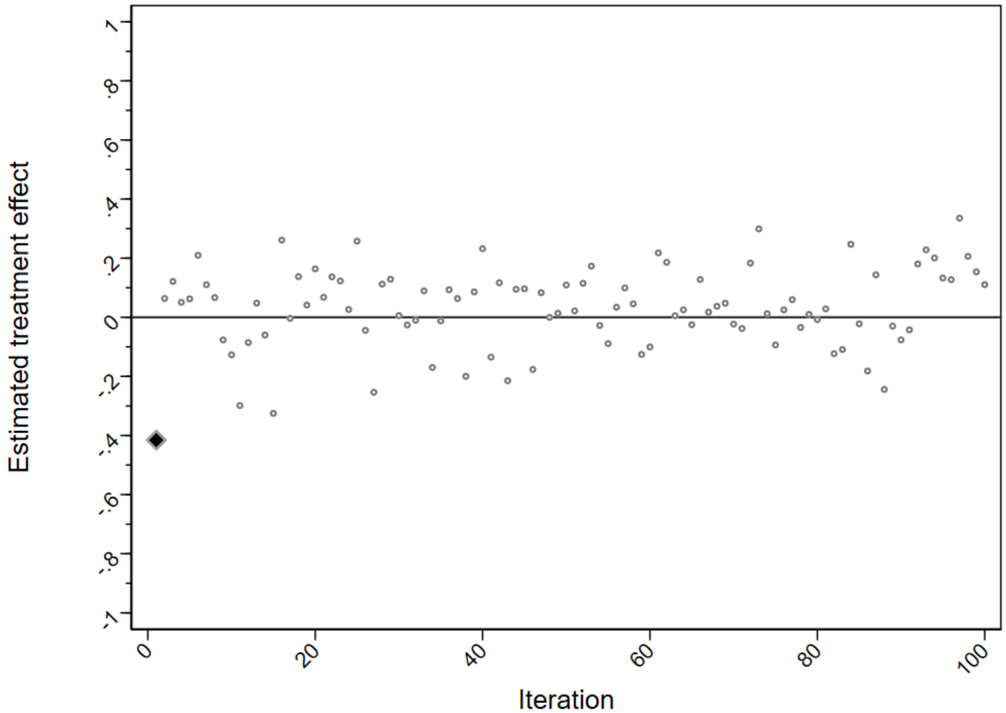
Notes: Unit of observation is a state/year. Event study includes three leads (binary indicators for 5 to 6 years, 3 to 4 years, and 1 to 2 years prior to implementation), four lags (binary indicators for 1 to 2 years, 3 to 4 years, 5 to 6 years and 7 years post-implementation), and an indicator for the policy implementation year. Omitted category is 7 years prior to the law passage. The event window is -7 to +7 years. Observations outside the event window are excluded. States that do not pass a parity law by 2013 are coded as 0 for all bins. All models are estimated with OLS and control for state average demographics (age, gender, race/ethnicity, marital status, education, and family income scaled by 1,000), administrative license revocation policy, BAC limit <=0.08, prescription drug monitoring program, medical marijuana law, and state and year fixed effects. 95% confidence intervals account for state-level clustering and are reported in vertical bars. Observations are weighted by the state/year population. See Table 3 for coefficient estimates.

Figure 3. Effect of state parity laws for SUD treatment on BAC >= 0.15 traffic fatality rates using an event study, FARS 1988-2013



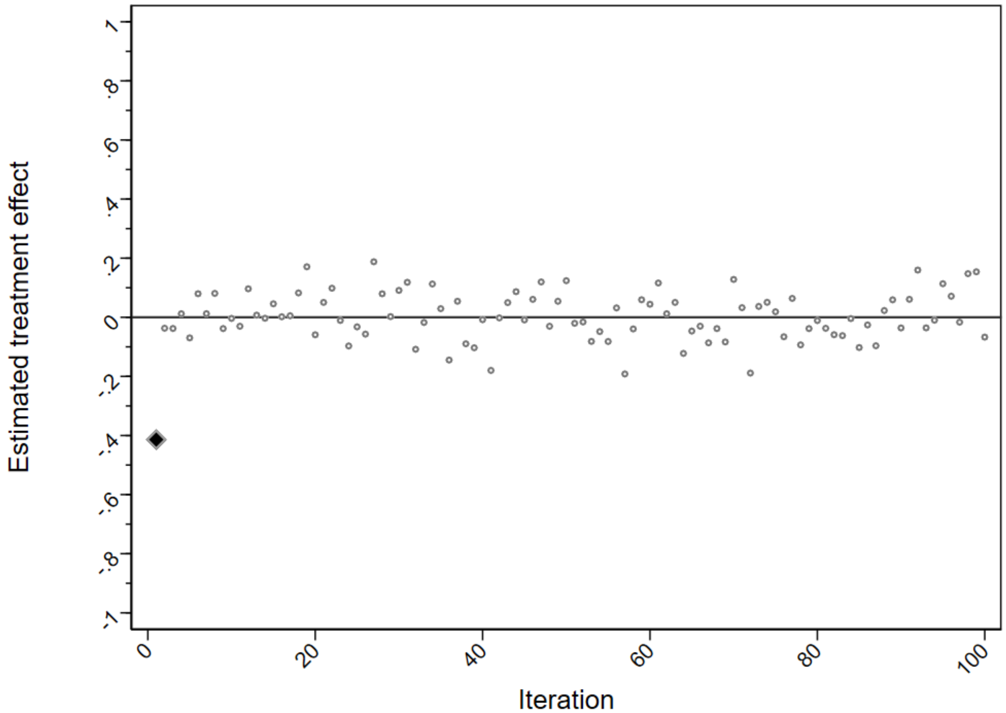
Notes: Unit of observation is a state/year. Event study includes three leads (binary indicators for 5 to 6 years, 3 to 4 years, and 1 to 2 years prior to implementation), four lags (binary indicators for 1 to 2 years, 3 to 4 years, 5 to 6 years and 7 years post-implementation), and an indicator for the policy implementation year. Omitted category is 7 years prior to the law passage. The event window is -7 to +7 years. Observations outside the event window are excluded. States that do not pass a parity law by 2013 are coded as 0 for all bins. All models are estimated with OLS and control for state average demographics (age, gender, race/ethnicity, marital status, education, and family income scaled by 1,000), administrative license revocation policy, BAC limit <=0.08, prescription drug monitoring program, medical marijuana law, and state and year fixed effects. 95% confidence intervals account for state-level clustering and are reported in vertical bars. Observations are weighted by the state/year population. See Table 3 for coefficient estimates.

Figure 4. Effect of state parity laws for SUD treatment on total traffic fatality rates using a placebo simulation exercise, FARS 1988-2013



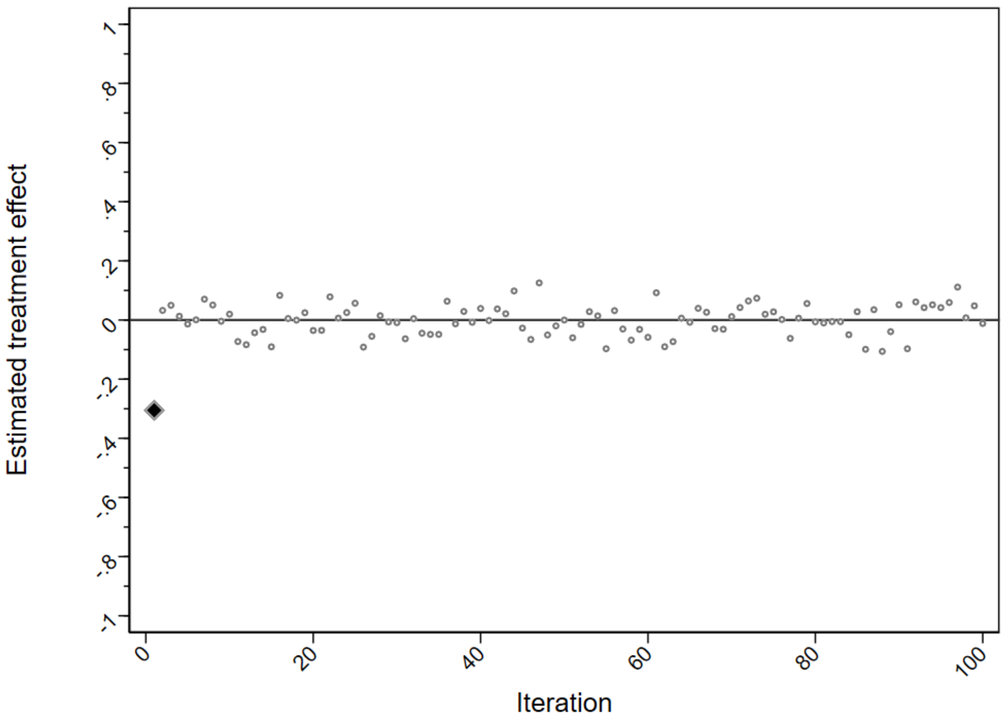
Notes: Unit of observation is a state/year. The Y-axis captures the estimated treatment effect. The X-axis captures the specific iteration. The dark diamond reflects our coefficient estimate generated in Equation (1), see Table 4. The grey circles reflect estimates generated in Equation (1) with the treatment variable (i.e., full parity law) randomly reshuffled across states following Abadie and Gardeazabal (2003). All models are estimated with OLS and controls include state average demographics (age, gender, race/ethnicity, marital status, education, and family income scaled by 1,000), administrative license revocation policy, BAC limit <=0.08, prescription drug monitoring program, medical marijuana law, and state and year fixed effects. 95% confidence intervals account for clustering within states and are reported in square brackets. Observations are weighted by the state/year population.

Figure 5. Effect of state parity laws for SUD treatment on BAC >= 0.08 traffic fatality rates using a placebo simulation exercise, FARS 1988-2013



Notes: Unit of observation is a state/year. The Y-axis captures the estimated treatment effect. The X-axis captures the specific iteration. The dark diamond reflects our coefficient estimate generated in Equation (1), see Table 4. The grey circles reflect estimates generated in Equation (1) with the treatment variable (i.e., full parity law) randomly reshuffled across states following Abadie and Gardeazabal (2003). All models are estimated with OLS and controls include state average demographics (age, gender, race/ethnicity, marital status, education, and family income scaled by 1,000), administrative license revocation policy, BAC limit <=0.08, prescription drug monitoring program, medical marijuana law, and state and year fixed effects. 95% confidence intervals account for clustering within states and are reported in square brackets. Observations are weighted by the state/year population.

Figure 6. Effect of state parity laws for SUD treatment on BAC >= 0.15 traffic fatality rates using a placebo simulation exercise, FARS 1988-2013



Notes: Unit of observation is a state/year. The Y-axis captures the estimated treatment effect. The X-axis captures the specific iteration. The dark diamond reflects our coefficient estimate generated in Equation (1), see Table 4. The grey circles reflect estimates generated in Equation (1) with the treatment variable (i.e., full parity law) randomly reshuffled across states following Abadie and Gardeazabal (2003). All models are estimated with OLS and controls include state average demographics (age, gender, race/ethnicity, marital status, education, and family income scaled by 1,000), administrative license revocation policy, BAC limit <=0.08, prescription drug monitoring program, medical marijuana law, and state and year fixed effects. 95% confidence intervals account for clustering within states and are reported in square brackets. Observations are weighted by the state/year population.

References:

Abadie, Alberto, and Javier Gardeazabal. 2003. "The economic costs of conflict: A case study of the Basque Country." *American Economic Review* 93 (1):113-132.

Abouk, Rahi, and Scott Adams. 2013. "Texting bans and fatal accidents on roadways: Do they work? Or do drivers just react to announcements of bans?" *American Economic Journal: Applied Economics* 5 (2):179-199.

Adams, Scott, McKinley L Blackburn, and Chad D Cotti. 2012. "Minimum wages and alcohol-related traffic fatalities among teens." *Review of Economics and Statistics* 94 (3):828-840.

Adams, Scott, Chad Cotti, and Nathan Tefft. 2015. "Seatbelt use among drunk drivers in different legislative settings." *Economic Inquiry* 53 (1):758-772.

Ali, Mir M, William N Dowd, Timothy Classen, Ryan Mutter, and Scott P Novak. 2017. "Prescription drug monitoring programs, nonmedical use of prescription drugs, and heroin use: Evidence from the National Survey of Drug Use and Health." *Addictive Behaviors* 69:65-77.

Anderson, Mark D, Benjamin Hansen, and Daniel I Rees. 2013. "Medical marijuana laws, traffic fatalities, and alcohol consumption." *Journal of Law and Economics* 56 (2):333-369.

Angrist, Joshua D., and J Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press. Book. Original edition, Princeton University Press.

Autor, David H. 2003. "Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing." *Journal of Labor Economics* 21 (1):1-42.

Bailey, James. 2014. "The effect of health insurance benefit mandates on premiums." *Eastern Economic Journal* 40 (1):119-127.

Bailey, James, and Nathan Blascak. 2016. "The effect of state health insurance benefit mandates on premiums and employee contributions." *Applied Economics Letters* 23 (14):1042-1046.

Barry, Colleen L, and Jody L Sindelar. 2007. "Equity in private insurance coverage for substance abuse: A perspective on parity." *Health Affairs* 26 (6):w706-w716.

Bound, John, Charles Brown, and Nancy Mathiowetz. 2001. "Measurement error in survey data." *Handbook of Econometrics* 5:3705-3843.

Center for Substance Abuse Treatment. 2004. Clinical Guidelines for the Use of Buprenorphine in the Treatment of Opioid Addiction. Treatment Improvement Protocol (TIP) Series 40. In *Series 40. DHHS Publication No. (SMA) 04-3939.* , edited by Substance Abuse and Mental Health Services Administration. Rockville, MD: Substance Abuse and Mental Health Services Administration

Centers for Disease Control and Prevention. 2015. "http://www.cdc.gov/vitalsigns/drinkinganddriving/." accessed May 27.

Centers for Disease Control and Prevention. 2016. "10 Leading Causes of Injury Deaths by Age Group Highlighting Unintentional Injury Deaths, United States – 2016." accessed October 9. https://www.cdc.gov/injury/images/lc-charts/leading_causes_of_injury_deaths_unintentional_injury_2015_1050w760h.gif.

Dave, Dhaval, and Swati Mukerjee. 2011. "Mental health parity legislation, cost-sharing and substance-abuse treatment admissions." *Health Economics* 20 (2):161-183.

Eisenberg, Daniel. 2003. "Evaluating the effectiveness of policies related to drunk driving." *Journal of Policy Analysis and Management* 22 (2):249-274.

Elvik, Rune. 2013. "Risk of road accident associated with the use of drugs: a systematic review and meta-analysis of evidence from epidemiological studies." *Accident Analysis & Prevention* 60:254-267.
Eoh, Hong J., Min K. Chung, and Seong-Han Kim. 2005. "Electroencephalographic study of drowsiness in simulated driving with sleep deprivation." *International Journal of Industrial Ergonomics* 35 (4):307-320.
Flood, Sarah, Miriam King, Steven Ruggles, and J Robert Warren. 2015. "Integrated public use microdata series, Current Population Survey: Version 4.0.[Machine-readable database]." *Minneapolis: University of Minnesota*.
Freeborn, Beth A, and Brian McManus. 2010. "Substance abuse treatment and motor vehicle fatalities." *Southern Economic Journal* 76 (4):1032-1048.
French, Michael T, and Gulcin Gumus. 2014. "Macroeconomic fluctuations and motorcycle fatalities in the US." *Social Science & Medicine* 104:187-193.
French, Michael T, and Gulcin Gumus. 2015. "Fast times during spring breaks: Are traffic fatalities another consequence?" *Economic Inquiry* 53:745–757.
French, Michael T, Ioana Popovici, and Lauren Tapsell. 2008. "The economic costs of substance abuse treatment: Updated estimates and cost bands for program assessment and reimbursement." *Journal of Substance Abuse Treatment* 35 (4):462-469.
Governors Highway Safety Association. 2017. Drug-imparired Driving.
Grossman, Michael. 1972. "On the concept of health capital and the demand for health." *Journal of Political Economy* 80 (2):223-255.
Hack, M. A., S. J. Choi, P. Vijayapalan, R. J. O. Davies, and J. R. Stradling. 2001. "Comparison of the effects of sleep deprivation, alcohol and obstructive sleep apnoea (OSA) on simulated steering performance." *Respiratory Medicine* 95 (7):594-601.
Hamersma, Sarah, and Johanna Catherine Maclean. 2018. "Title." National Bureau of Economic Research Working Paper Series, Cambridge, MA.
Jensen, Gail A, and Michael A Morrisey. 1999. "Employer-sponsored health insurance and mandated benefit laws." *Milbank Quarterly* 77 (4):425-459.
Kline, Patrick. 2011. "The impact of juvenile curfew laws on arrests of youth and adults." *American Law and Economics Review* 14 (1):44-67.
Koehler, Steven A, and Peggy A Brown. 2009. *Forensic Epidemiology*: CRC Press.
Kunz, F Michael, Michael T French, and Shahrzad Bazargan-Hejazi. 2004. "Cost-effectiveness analysis of a brief intervention delivered to problem drinkers presenting at an inner-city hospital emergency department." *Journal of Studies on Alcohol* 65 (3):363-370.
Levintova, Hannah. 2018. "Paul Ryan says Republicans will take another run at Obamacare after the midterms." *Mother Jones*. https://www.motherjones.com/politics/2018/09/paul-ryan-obamacare-reform-2018-midterm-elections/.
Lovenheim, Michael F. 2009. "The effect of teachers' unions on education production: Evidence from union election certifications in three midwestern states." *Journal of Labor Economics* 27 (4):525-587.
Lu, Mingshan, and Thomas G McGuire. 2002. "The productivity of outpatient treatment for substance abuse." *Journal of Human Resources* 37 (2):309-335.
Maclean, Johanna Catherine, M. Oney, J. Marti, and Jody L Sindelar. 2018. "What factors predict the passage of state-level e-cigarette regulations?" *Health Economics*.

Maclean, Johanna Catherine, Ioana Popovici, and Elisheva Stern. 2018. "Health insurance expansions and provider behavior: Evidence from substance use disorder providers." *Journal of Law & Economics*.

Maclean, Johanna Catherine, and Brendan Saloner. 2018a. "The effect of public insurance expansions on substance use disorder treatment: Evidence from the Affordable Care Act." *Journal of Policy Analysis and Management*.

Maclean, Johanna Catherine, and Brendan Saloner. 2018b. "Substance use treatment provider behavior and healthcare reform: Evidence from Massachusetts." *Health Economics* 27 (1):76-101.

McGinty, Emma E, Susan H Busch, Elizabeth A Stuart, Haiden A Huskamp, Teresa B Gibson, Howard H Goldman, and Colleen L Barry. 2015. "Federal parity law associated with increased probability of using out-of-network substance use disorder treatment services." *Health Affairs* 34 (8):1331-1339.

McLellan, A Thomas, David C Lewis, Charles P O'brien, and Herbert D Kleber. 2000. "Drug dependence, a chronic medical illness: Implications for treatment, insurance, and outcomes evaluation." *JAMA* 284 (13):1689-1695.

Meara, Ellen, Ezra Golberstein, Rebecca Zaha, Shelly F Greenfield, William R Beardslee, and Susan H Busch. 2014. "Use of hospital-based services among young adults with behavioral health diagnoses before and after health insurance expansions." *JAMA Psychiatry* 71 (4):404-411.

Meinhofer, Angélica, and Allison E Witman. 2018. "The role of health insurance on treatment for opioid use disorders: Evidence from the Affordable Care Act Medicaid expansion." *Journal of Health Economics* 60:177-197.

National Center for Statistics and Analysis. 2016. State alcohol-impaired-driving estimates: 2014 data. edited by National Highway Traffic Safety Administration. Washington, DC.

National Highway Traffic Safety Administration. 2002. Transitioning to multiple imputation-A new method to estimate missing blood alcohol concentration (BAC) values in FARS. edited by Department of Transportation. Washington, DC.

National Highway Traffic Safety Administration. 2010. Drug involvement of fatally injured drivers. In *US Department of Transportation Report No. DOT HS*: National Highway Traffic Safety Administration.

National Institute on Drug Abuse. 2012. "Principles of drug addiction treatment: A research-based guide.", accessed December 21. https://d14rmgtrwzf5a.cloudfront.net/sites/default/files/podat_1.pdf.

Pascale, Joanne, Michel Boudreaux, and Ryan King. 2016. "Understanding the new Current Population Survey health insurance questions." *Health Services Research* 51 (1):240-261.

Patashnik, Eric, and Jonathan Oberlander. 2018 "Republicans are still trying to repeal Obamacare. Here's why they are not likely to succeed." *The Washington Post.*

Popovici, Ioana, and Michael T French. 2013a. "Binge drinking and sleep problems among young adults." *Drug and Alcohol Dependence* 132 (1-2):207-15.

Popovici, Ioana, and Michael T French. 2013b. "Economic evaluation of substance abuse interventions: Overview of recent research findings and policy implications." In *Addictions: A comprehensive guidebook*, edited by Barbara S McCrady and Elizabeth E Epstein. Oxford University Press.

Popovici, Ioana, Michael T French, and J. R. McKay. 2008. "Economic evaluation of continuing care interventions in the treatment of substance abuse: recommendations for future research." *Evaluation Review* 32 (6):547-68.
Popovici, Ioana, Johanna Catherine Maclean, Bushra Hijazi, and Sharmini Radakrishnan. 2018. "The effect of state laws designed to prevent nonmedical prescription opioid use on overdose deaths and treatment." *Health Economics* 27 (2):294-305. doi: 10.1002/hec.3548.
Prendergast, Michael L, Deborah Podus, Eunice Chang, and Darren Urada. 2002. "The effectiveness of drug abuse treatment: A meta-analysis of comparison group studies." *Drug and Alcohol Dependence* 67 (1):53-72.
Rajkumar, Andrew S, and Michael T French. 1997. "Drug abuse, crime costs, and the economic benefits of treatment." *Journal of Quantitative Criminology* 13 (3):291-323.
Reuter, Peter, and Harold Pollack. 2006. "How much can treatment reduce national drug problems?" *Addiction* 101 (3):341-347.
Robinson, Gail K, Jerome B Connolly, Melanie Whitter, and Candy A Magana. 2006. State Mandates for Treatment for Mental Illness and Substance Abuse Disorders. Substance Abuse and Mental Health Services Administration.
Sabia, Joseph J, and Thanh Tam Nguyen. 2016. The Effect of Medical Marijuana Laws on Labor Market Outcomes. In *Discussion Paper No. 9831* Bonn, Germany: IZA.
Slater, Megan E, I-Jen P Castle, Barry K Logan, and Ralph W Hingson. 2016. "Differences in state drug testing and reporting by driver type in US fatal traffic crashes." *Accident Analysis & Prevention* 92:122-129.
Sommers, B. D., E. Arntson, G. M. Kenney, and A. M. Epstein. 2013. "Lessons from early Medicaid expansions under health reform: interviews with Medicaid officials." *Medicare Medicaid Research Review* 3 (4). doi: 10.5600/mmrr.003.04.a02.
Starr, Sonja B. 2002. "Simple fairness: ending discrimination in health insurance coverage of addiction treatment." *The Yale Law Journal* 111 (8):2321-2365.
Stewart, Duncan, Michael Gossop, and John Marsden. 2002. "Reductions in non-fatal overdose after drug misuse treatment: Results from the National Treatment Outcome Research Study (NTORS)." *Journal of Substance Abuse Treatment* 22 (1):1-9.
Substance Abuse and Mental Health Services Administration. 2014. Results from the 2013 National Survey on Drug Use and Health: Summary of National Findings. In *NSDUH Series H-48*, edited by Substance Abuse and Mental Health Services Administration. Rockville, MD.
Substance Abuse and Mental Health Services Administration. 2016. Receipt of Services for Substance Use and Mental Health Issues among Adults: Results from the 2015 National Survey on Drug Use and Health.: Substance Abuse and Mental Health Services Administration.
Substance Abuse and Mental Health Services Administration. 2017. Key substance use and mental health indicators in the United States: Results from the 2016 National Survey on Drug Use and Health. Rockville, MD: Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration.
Swensen, Isaac D. 2015. "Substance-abuse treatment and mortality." *Journal of Public Economics* 122:13-30.

Terán-Santos, J., A. Jimenez-Gomez, and J. Cordero-Guevara. 1999. "The association between sleep apnea and the risk of traffic accidents." *New England Journal of Medicine* 340 (11):847-851.

Thalmayer, Amber Gayle, Sarah A Friedman, Francisca Azocar, Jessica M Harwood, and Susan L Ettner. 2016. "The Mental Health Parity and Addiction Equity Act (MHPAEA) evaluation study: Impact on quantitative treatment limits." *Psychiatric Services* 68 (5):435-442.

United States Environmental Protection Agency. 2018. "Mortality Risk Valuation." https://www.epa.gov/environmental-economics/mortality-risk-valuation.

Wen, Hefei, J. R. Cummings, J. M. Hockenberry, L. M. Gaydos, and B. G. Druss. 2013. "State parity laws and access to treatment for substance use disorder in the United States: Implications for federal parity legislation." *JAMA Psychiatry* 70 (12):1355-62.

Wen, Hefei, Jason M Hockenberry, and Janet R Cummings. 2017. "The effect of Medicaid expansion on crime reduction: Evidence from HIFA-waiver expansions." *Journal of Public Economics* 154:67-94.

Zaloshnja, Eduard, Ted R Miller, and Lawrence J Blincoe. 2013. "Costs of alcohol-involved crashes, United States, 2010." *Annals of Advances in Automotive Medicine* 57:3-12.