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ABSTRACT

The Effects of Health Insurance Parity Laws for Substance Use Disorder Treatment on Traffic Fatalities: Evidence of Unintended Benefits*

Each year, 10,000 individuals die in alcohol-impaired traffic accidents in the United States, while psychoactive drugs are involved in 20% of all fatal traffic accidents. We investigate whether state parity laws for substance use disorder (SUD) treatment have the unintended benefit of reducing fatal traffic accidents. Parity laws compel insurers to cover SUD treatment in private insurance markets, thereby reducing the financial costs of and increasing access to treatment for beneficiaries. We employ over 20 years of administrative data from the national Fatal Accident Reporting System coupled with a differences-in-differences research design to investigate the potential spillover effects of parity laws to traffic safety. Our findings indicate that passage of a state parity law reduces fatal traffic accident rates by 4.1 to 5.4%. 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.

JEL Classification: I1, I13, I18

Keywords: traffic fatalities, substance use disorder (SUD) treatment, traffic safety, health insurance parity laws

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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 accidents for themselves, their passengers, and other drivers with whom they share roadways. In 2014, motor vehicle traffic accidents were the second leading cause of injury-related death in the United States with 33,736 deaths (Centers for Disease Control and Prevention, 2014). Annually, approximately 10,000 individuals are killed in alcohol-impaired traffic accidents in the U.S., representing nearly one third of all traffic-related deaths, while psychoactive drugs are involved in 20% of all fatal traffic accidents (National Center for Statistics and Analysis, 2016). Moreover, the annual societal costs of alcohol-involved fatal crashes is estimated to be over $75 billion (Zaloshnja, Miller, & Blincoe, 2013).[1] In response to these high costs, governments at all levels have taken steps to reduce impaired driving, including imposing maximum allowable blood alcohol concentration (BAC) thresholds for drivers, prohibiting driving while under the influence of psychoactive drugs, instituting roadside sobriety check points, setting minimum prison sentences and/or financial penalties for those found guilty of driving under the influence of alcohol or psychoactive drugs, and financing public media campaigns that outline the dangers and costs of impaired driving.

The above-noted policies attempt to directly regulate or address substance use among drivers, but fail to acknowledge that substance abuse and dependence is a chronic, addictive disease that should be treated through medical interventions rather than punitive public policies (Popovici, French, & McKay, 2008). For individuals who suffer from these diseases, a potentially more effective policy approach is to address their substance use disorders (SUD) through the promotion of effective and affordable treatment. Treating individuals with SUDs

[1] This estimate is adjusted from 2010 dollars (as reported in the cited manuscript) to 2017 dollars using the Consumer Price Index – Urban Consumers by the authors.

should decrease the number of impaired drivers on roadways, and hence substance-use-attributable traffic accidents. The effectiveness of SUD treatment is well-established (Bondurant, Lindo, & Swensen, 2016; Kunz, French, & Bazargan-Hejazi, 2004; Lu & McGuire, 2002; Popovici & French, 2013b; Rajkumar & French, 1997; Reuter & Pollack, 2006; Stewart, Gossop, & Marsden, 2002; Swensen, 2015).[2] Indeed, a study by Freeborn and McManus (2010) finds that one additional specialty SUD treatment facility per U.S. county can decrease the number of county-level alcohol-related traffic fatalities by 15%.

Despite established effectiveness of various SUD treatment modalities, many individuals who could benefit from such treatment do not receive it. While approximately 22 million people aged 12 or older displayed patterns of substance use that would have benefited from specialty SUD treatment in 2015,[3] only 10.8% of these individuals received such treatment (Center for Behavioral Health Statistics and Quality, 2016). The majority of untreated individuals with a SUD do not feel they need treatment. However, among individuals seeking treatment, commonly cited barriers are cost 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., public as well as private health insurance plans have historically covered SUD treatment less generously than medical/surgical treatment (Starr, 2002). For example, patient cost-sharing (e.g., copayments, deductibles) has historically been higher for SUD treatment and insurers have tended to restrict such treatment utilization (e.g., setting annual or

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[2] Although treatment approaches for SUD comprise many forms ranging for screening and brief intervention to long-term residential, not all modalities are effective or cost effective for the majority of patients (French & Drummond, 2005; Homer, Drummond, & French, 2008; McCollister & French, 2003).

[3] Specialty SUD treatment is offered in a hospital, a residential facility, an outpatient treatment facility, or other facility with an SUD treatment program that offers the following services: (i) outpatient, inpatient, or residential/rehabilitation treatment; (ii) detoxification; (iii) opioid treatment; and (iv) halfway-house services.

lifetime maximums on treatment episodes, use of prior authorization, or stepped therapy) to a greater extent than other medical/surgical procedures. These differentials likely prevent many individuals from seeking care, or obtaining adequate care, for their SUDs.

In this study, we examine whether state-specific equal coverage laws for SUD treatment (often referred to collectively as 'parity laws') impact an unintended or secondary outcome—fatal traffic accidents. State parity laws regulate private insurance markets and expand affordable coverage for alcohol and psychoactive drug treatment by requiring insurers to offer SUD treatment coverage to beneficiaries, cover some minimum set of SUD benefits, or to provide SUD treatment services at 'parity' with medical/surgical services in terms of cost sharing, non-quantitative barriers to treatment, and service restrictions. As state parity laws increase coverage for SUD treatment and therefore lower out-of-pocket costs to individuals, basic demand theory predicts that these regulations will increase the probability that individuals with SUDs will seek treatment.[4] Indeed, previous research documents these laws and other insurance expansions increase SUD treatment utilization (Dave & Mukerjee, 2011; McConnell, Ridgely, & McCarty, 2012; Wen, Cummings, Hockenberry, Gaydos, & Druss, 2013; Wen, Hockenberry, Borders, & Druss, 2017). To explore this question, we analyze 23 years (1988-2010) of administrative data from the Fatal Accident Reporting System (FARS). During this period, 27 states passed parity laws, offering a novel quasi experiment. We apply differences-in-differences methods and control for a wide range of time-varying state-specific characteristics. We also investigate heterogeneity across states in how they choose to regulate private insurance markets. Because reduced substance use and abuse is the key channel through which we expect

[4] While parity laws only affect private insurance plans, 41.7% of persons receiving SUD treatment in 2013 used private health insurance as a source of payment (Substance Abuse and Mental Health Services Administration, 2016). Moreover, this is likely an underestimate of the true share of patients using private insurance to pay for treatment as the survey applies only to the last treatment episode.

parity laws to impact traffic accidents, we also examine the impact of state parity laws on alcohol misuse within the general population in an extension to the main analyses.

2. Conceptual framework and related literature

We briefly review the related economic theory and corresponding literature that guides our empirical analysis.

2.1 Conceptual framework

In standard models in the health economics literature, the demand for healthcare services is derived from consumers' demand for health (Grossman, 1972). Within this framework, consumers do not demand healthcare services *per se*, rather they demand the health improvements attributable to utilization of such services. Rational consumers maximize a utility function given the price of healthcare services and other goods, preferences, a health endowment, a health production function, other factors that determine health such as education, and a budget constraint. Consumers are assumed to respond to price changes for healthcare in a manner broadly comparable to other goods and services.[5]

Insurance coverage for any healthcare service should reduce the out-of-pocket price faced by consumers who are deciding whether to utilize a particular service. The Grossman model predicts that, in line with basic demand theory, any policy that reduces price should increase the quantity demanded (*ceteris paribus*). Following passage of a state parity law for SUD treatment, it is likely that the price of SUD treatment for privately insured patients will fall for those whose insurance contracts are affected by the passage of such laws. In turn, the quantity of SUD treatment demanded among such individuals should increase.

[5] As is standard in modern economic analyses of risky behaviors, including substance misuse, we rely on the intuition offered by the Grossman model rather than a strict adherence to the model's theoretical predictions (Cawley & Ruhm, 2012).

The discussion thus far assumes that insurance expansions, and the ensuing reductions in out-of-pocket prices faced by consumers, will simply and directly translate into increases in the quantity of SUD treatment demanded. However, several factors unique to both the individuals seeking SUD treatment and the providers delivering care may dilute the effects of parity laws on treatment utilization and hence their impact on traffic fatalities.

On the demand side, according to the 2015 National Survey on Drug Use and Health (NSDUH), the majority of individuals suffering from SUDs do not feel they need treatment (Substance Abuse and Mental Health Services Administration, 2016). Lower out-of-pocket prices likely have little impact on the quantity of SUD treatment demanded by such individuals. Even among those individuals who may consider treatment when they face a lower out-of-pocket price, other barriers such as the stigma associated with SUDs could deter treatment-seeking.

On the other hand, due to *ex ante* moral hazard, health insurance mandates may lead to increased substance use by lowering the cost of treatment and hence the full cost of substance use. Such a pathway would offset the above-noted reductions in substance misuse (Klick & Stratmann, 2006). In addition, if insurance coverage acts as an in-kind income transfer to those individuals who gain coverage, and substances are normal goods, then passage of a parity law could lead to increases in substance use and, in turn, traffic fatalities.

On the supply side, SUD treatment providers face substantial financial constraints and often operate at or near full capacity, which limits their ability to respond to increases in demand due to health insurance expansions such as parity laws (Andrews et al., 2015). Moreover, providers may lack the administrative resources (e.g., electronic billing encounter systems) to bill insurers for services rendered (Buck, 2011). Finally, under the Employee Retirement Income Security Act (ERISA) of 1974, large self-insured firms are exempt from state health insurance legislation (e.g., parity laws), which reduces to approximately 33-45% of the population being affected by these laws (Jensen & Morrisey, 1999).

2.2 Related literature

Several studies have examined the effect of private insurance expansions that occur through implementation of state parity laws on SUD treatment utilization.[6] Meara et al. (2014) examine changes in inpatient hospital care among young adults after the 2006 healthcare reform in Massachusetts (this initiative increased both private and public insurance coverage for SUD treatment). The authors find substantial declines in SUD-related emergency department episodes and inpatient hospitalizations, which suggests expanded use of outpatient SUD treatment services among young adults. Maclean and Saloner (2017) document that this reform translated into increases in admissions to specialty SUD treatment, although the finding is not precisely estimated across all specifications.

In 2001, a Presidential Directive in the Federal Employees Health Benefits (FEHB) Program required parity between behavioral and medical/surgical healthcare services in terms of cost-sharing, deductibles, lifetime and annual expenditures, and service limitations. Several studies find that parity for SUD treatment generated by the FEHB program led to modest increases in treatment utilization (Azzone, Frank, Normand, & Burnam, 2011; Goldman et al., 2006; Sasso & Lyons, 2004).[7]

Golberstein et al. (2015) document that the Affordable Care Act (ACA) dependent coverage provision—implemented in 2010 and that requires private insurers to offer coverage to

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[6] A much larger literature examines the impact of insurance broadly defined on SUD treatment. However, we focus on studies that examine expansions to the private market and quasi-experimental methods as they are most relevant to our work.

[7] The population affected by this program (federal employees) is heavily screened for SUDs pre-employment, so demand for treatment within this population is likely limited. Nevertheless, a substantial share of the FEHB enrollees consists of spouses and dependents who are not screened for SUDs.

dependent children of beneficiaries through the child's 26th birthday (if the insurance contract covers dependents)—is associated with increases in the number of psychiatric hospital admissions, with substance abuse admissions accounting for the largest share. However, using the NSDUH, Saloner and Cook (2014) find no effect of the provision on SUD treatment utilization among survey respondents who display need for SUD treatment. The authors caution that their study may be underpowered to detect significant effects due to small sample sizes. Using a national database of specialty SUD treatment admissions to predominantly publicly-supported facilities, Saloner, Antwi, Maclean, and Cook (2017) find that the ACA dependent coverage provision *decreases* admissions. The authors hypothesize that the provision may actually allow patients to receive care in other, perhaps more desirable, settings (e.g., private doctors' offices). Moreover, Saloner et al. (2017) show that, among patients receiving treatment, a greater proportion use private insurance as a source of payment following the provision.

Two recent studies examine the effect of the 2008 Mental Health Parity and Addiction Equity Act (MHPAEA) (Busch et al., 2014; McGinty et al., 2015). MHPAEA is a federal legislation that prohibits differences in treatment limits and cost-sharing and extends coverage requirements to SUD treatment services in most private and public health insurance plans in the U.S. offering coverage for behavioral health. Findings from these studies suggest a modest impact of MHPAEA on SUD treatment utilization overall, but larger increases in out-of-network service utilization.

Finally, and perhaps most relevant to the present study, several recent projects examine the effects of state parity laws on treatment outcomes. Broadly, these studies find that state parity laws translate into increases in SUD treatment utilization. Using data from the Treatment Episode Data Set (TEDS), Dave and Mukerjee (2011) show that parity laws increase the number of admissions to SUD treatment as well as the fraction of clients using private insurance as a source of payment. Wen et al. (2013) also find that state parity laws increase treatment admissions using data from the National Survey of Substance Abuse Treatment Services (N-SSATS). Using the same data set, Maclean, Popovici, and Stern (2017) find that, following passage of a state parity law that requires equal coverage between substance use and medical/surgical services, providers increase the quantity of SUD treatment admissions overall as well as the number of patients in specialty treatment.[8] Finally, Wen, Hockenberry, and Cummings (2014) use state parity laws as instrumental variables while examining the effect of SUD treatment rates on crime. In first-stage regressions, parity laws increase treatment rates. Collectively, these studies imply that state parity laws increase utilization of SUD treatment. In combination with the above-noted established effectiveness of numerous modalities of SUD treatment, these studies open the door to the possibility of spillover effects from parity laws to traffic fatalities. We test this relationship in the FARS data.

3. Data and methods

3.1. Fatal Accident Reporting System (FARS)

Data on fatal accidents occurring on public roads in the U.S. is obtained from the Fatality Analysis Reporting System (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 & Adams, 2013; Adams, Cotti, & Tefft, 2015; French & Gumus, 2015) and by governments of all levels to monitor trends in traffic safety and to develop

[8]These studies capture more intensive forms of treatment: treatment that is received in a facility that has a specialized SUD treatment program. Moreover, these studies do not capture care that is received in private doctors' offices or in office-based therapy sessions. If those individuals who gain insurance coverage for SUD treatment through the state-level expansions are more likely to use non-specialty care, then these studies might underestimate the effect of parity laws for such individuals.

strategies to reduce fatal accidents (Koehler & 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 the District of Columbia.

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 accident, the vehicles, and the persons involved. We pool FARS data for the period 1988 to 2010. Concerns related to the reliability of data during the initial years of FARS data collection convinced us to avoid using data collected in the 1970s and early 1980s.[9] We truncate the analysis sample in 2010 as we wish to focus on a period before implementation of the ACA. Six states (California, Connecticut, DC, New Jersey, Minnesota, and Washington) expanded their Medicaid programs in advance of January 1st, 2014, the date at which the core provisions of the ACA went into effect (Sommers, Arntson, Kenney, & Epstein, 2013). In addition, several other early provisions of the ACA (e.g., the dependent coverage provision) were implemented in 2010. By focusing on an earlier period, we are able to avoid confounding from the ACA.

3.2. State parity laws

Our source of policy variation is changes in state parity laws between 1988 and 2010. We use information on state parity laws maintained by the National Council of State Legislatures (NCSL) and our own reading of the original state statutes. The NCSL is a common source of state-level regulations within the economics literature (Bachhuber, Saloner, Cunningham, &

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

Barry, 2014; Bradford & Bradford, 2016; Dave & Mukerjee, 2011; Maclean et al., 2017; Meer & West, 2011). Although substantial heterogeneity in states' regulatory efforts exists, state parity laws can be classified into three categories (National Council of State Legislatures, 2015). First, 'full parity' laws mandate that private insurers provide equal coverage for SUD treatment and medical/surgical services in terms of visit limits, cost-sharing (deductibles, co-payments, etc.), use of pre-authorization, and lifetime and annual service limits. Second, 'mandated benefit' laws require some minimum coverage level for SUD treatment. In other words, 'mandated benefit' laws permit differences between the benefit levels provided for SUD treatment and physical health services. Third, 'mandated offer' laws either: (i) require that an option of SUD treatment be provided to the insured (this option can be accepted or rejected by the insured individual and, if accepted, the insurance contract typically requires a higher premium for SUD treatment) or (ii) require that, if SUD treatment benefits are offered, they must be equal to physical health benefits. Broadly, full parity laws require the most generous coverage for SUD treatment services vis-à-vis general medical/surgical services while mandated offer results in the least generous coverage, with mandated benefit laws falling between these two extremes.

Several states implemented what we refer to as 'weak' parity laws during our study period. Such laws extend full parity to specific beneficiary groups (e.g., state employees, Veterans, those currently receiving mental health services). We assign these states to the mandated offer category because, although they offer full parity to the targeted group, they are unlikely to impact a large share of the state population.

During our study period, 27 states implemented a state parity law. Specifically, ten states (Connecticut, Delaware, Hawaii, Illinois, Maryland, Minnesota, Oklahoma, Rhode Island, Virginia, and West Virginia) implemented full parity, nine states (Alaska, Indiana, Kansas, Missouri, Oregon, Pennsylvania, Tennessee, Texas, and Wisconsin) implemented a mandated benefit law, and eight states (Colorado, Florida, Georgia, Indiana, Louisiana, New Mexico, North Carolina, and Utah) implemented a mandated offer law. These law changes provide the variation we use for identification.

States that adopted parity laws before and after our analysis period (1988-2010) do not offer policy variation in our empirical models (difference-in-differences, described later in the manuscript). Adopting states and effective years (regardless of whether they occurred during our study period) are presented in Table 1. Asterisks are used to indicate law changes that occurred during our study period.

We construct three variables based on the parity law classifications described earlier: (i) an indicator for full parity, (ii) an indicator for strong parity (full parity or mandated benefit), and (iii) an indicator for any parity law (full parity, mandated benefit, or mandated offer). These laws may affect specific groups of insurance contracts (e.g., group only)[10] or the full population of the privately insured.

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. For example, if a law became effective July 1st, 2002, we code the law as 0.5 in 2002.[11]

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[10] Over our study period, the majority of private insurance is group coverage based on our analysis of Current Population Survey data (results available on request from the corresponding author). Thus, we suspect that laws targeting group insurance will impact a substantial share, if not the majority, of the private market.

[11] We are unable to identify the exact implementation day for some states (i.e., Florida, Georgia, Minnesota, Oregon, Pennsylvania, Rhode Island, and West Virginia). In these cases, we used January 1st of the implementation year as the majority of states in our sample have implemented the laws at or around this date. Instead of January 1st, we used the date of July 1st and the results were very similar. These alternative estimates are available upon request from the corresponding author.

3.3. Outcome variables

We construct several measures of traffic fatality counts. First, total fatalities is the total number of persons killed in traffic accidents within a particular state and year. Second, Dee (1998) documents that a large proportion of fatal weekend and nighttime crashes involve alcohol or psychoactive drugs. Thus, we follow Dee's insight and decompose the number of fatalities by time of the day and day of the week. We hypothesize that traffic accidents occurring on the weekend and at nighttime are more likely to be substance-related accidents, and are therefore more responsive to parity laws than traffic accidents occurring at other times and days. Weekend fatalities represent the number of persons killed in crashes occurring between 6 p.m. on Friday and 6 a.m. on Monday. Weekday fatalities denote the number of persons killed in accidents occurring between 6 a.m. on Monday and 6 p.m. on Friday. Daytime (nighttime) fatalities represent the number of persons killed in crashes occurring between 6 a.m. and 6 p.m. (6 p.m. and 6 a.m.).

These four time-of-day outcomes can provide additional perspective on the role of alcohol and psychoactive drugs in fatal traffic crashes. One potential limitation of this type of stratification, however, is potential endogeneity as parity laws may affect the composition of drivers by time of the day or day of the week (i.e., conditional-on-positive bias). Consequently, the stratified results should be interpreted with this potential bias in mind.

3.4. Control variables

Traffic fatalities are undoubtedly influenced by numerous factors apart from state parity laws for SUD treatment. We control for a broad set of explanatory variables in our regression models to proxy for such factors. To this end, we link data from several other administrative and survey sources to the FARS dataset.

First, we adjust for the fact that our outcome variables are measured as counts, which are heavily influenced by the size of states. To control for exposure, we follow Dee and Evans (2001) and include the natural logarithm of the state population age 21 and older. We use state population data from National Vital Statistics Mortality Files 1988-2010.

Second, we include four state policy variables that potentially proxy for state attitudes toward SUDs generally and impaired driving specifically. These variables are likely to affect the number of traffic fatalities and might be correlated with state parity laws for SUD treatment (French & Gumus, 2014). (i) The state BAC limit is the maximum legal blood alcohol concentration level for the operator of a motor vehicle. We include an indicator for a state BAC limit of 0.08 g/dL or lower (NHTSA Alcohol-Highway Safety Digest Topics and Alcohol Policy Information System). (ii) Our models include an indicator for a state administrative license revocation (ALR) law (Anderson, Hansen, & Rees, 2013). This policy allows law enforcement officials to suspend or revoke the license of a driver who refuses to submit to chemical alcohol testing or fails an alcohol test after a traffic stop or accident. (iii) We include an indicator for a prescription drug monitoring program (PDMP) in the state (National Alliance of Model State Drug Laws, 2016).[12] Aimed to deter prescription drug abuse and diversion, PDMPs are electronic databases used to record and track the prescribing and dispensing of controlled prescription drugs. (iv) We add an indicator variable for a state law that permits marijuana use for medical purposes (Pacula, Powell, Heaton, & Sevigny, 2015).[13]

Third, to condition for other policy effects, we include the state-specific real excise tax per gallon of beer (in dollars) from the Brewers' Almanac (The Beer Institute, 2012). We

[12] These data were kindly shared with us by Jonathan Woodruff, J.D. Details are available on request.
[13] We thank Rosalie Pacula for sharing an updated version of the medical marijuana variable coding from the RAND Drug Policy data set.

include this variable to proxy for state-specific sentiment toward alcohol and psychoactive drug use. Although the beer tax is an imperfect proxy, other measures (e.g., state-level substance use prevalence rates) are themselves potential outcomes of state parity laws and including such variables in regression models can lead to over-controlling bias. Fourth, we include other state-level variables that are likely correlated with the number of traffic accidents: the natural logarithm of the number of motor vehicle miles traveled on rural and urban roads per 10,000 population (Federal Highway Administration (FHWA), U.S. Department of Transportation 2011), average daily temperature (degrees Fahrenheit) over the course of a year, and the annual precipitation (inches) in the state (French & Gumus, 2014; Houston & Richardson, 2008).

Finally, 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, King, Ruggles, & Warren, 2015). These variables proxy for other state-specific attitudes that could predict our outcomes.

3.5 Empirical model

We model the relationships between state parity laws and traffic fatalities using the empirical specification outlined in Equation (1):

(1) $$Y_{st} = \alpha_0 + \alpha_{PL} PL_{st} + \alpha_X' X_{st} + S_S + \tau_t + \Omega_{st} + \varepsilon_{st},$$

Where Y_{st} is a traffic fatality outcome in state *s* and year *t*; PL_{st} is one of the three parity law indicators (either full parity, strong parity, or any parity law) in state *s* and year *t* (*i.e.*, each parity law indicator is included in a separate regression equation); X_{st} is a vector of state demographics and policies outlined in Section 3.4; and S_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 passage of parity laws. Year fixed effects account for factors impacting the U.S. as a whole (*e.g.*, nationwide trends in traffic fatalities influenced by national safe-driving campaigns, improvements in vehicle safety). Ω_{st} is a vector of state-specific linear time trends (i.e., we interact each state fixed effect with a separate linear time trend that takes on a value of 1 for 1988, 2 for 1989, and so forth) that accounts for state-level time-varying factors (albeit, in a linear manner); α_{PL} and α_X' are parameters to estimate, and ε_{st} is the error term.

We cluster standard errors around the state.[14] All regressions are unweighted. We estimate Poisson models as our dependent variables are counts (Silva & Tenreyro, 2006). Despite this estimation choice for the core models, results are robust to alternative specifications (*e.g.*, OLS using a log transformation, negative binomial regression). We discuss findings generated in these models in the robustness checks and extensions section below**.**

When estimating Equation (1), a critical assumption to generate causal effects is that the outcome variables in the 'treated' and 'comparison' groups would have trended similarly in the absence of the parity laws, commonly referred to as 'parallel trends' (Angrist & Pischke, 2009). To test the validity of the research design, we estimate regression models using the pre-law period data only as outlined in Equation (2):

(2) $$Y_{st} = \gamma_0 + \gamma_1(Treat_s * Time_t) + \gamma_2' X_{st} + \theta_s + \tau_t + e_{st}.$$

$Treat_s$ is an indicator variable for the treatment group (states that pass any parity law) and $Time_t$ is a linear time trend. In these analyses, we center the data around the law passage year. Thus, the linear time trend variable takes on a value of 0 in the year of passage, 1 in the first year post-law, -1 in the year prior to the law passage, and so forth. We randomly assign false effective dates to states in the comparison group and center the data around this false

[14] The FARS includes all states (including DC) in all years. Thus, we have 51 clusters in our data, which is a sufficient number to consistently estimate standard errors based on recent work on clustered data (Cameron & Miller, 2015).

effective date. We do not include the state-specific linear time trends in Equation (2) as including such variables in a regression model that allows for dynamics (i.e., the interaction between the treatment indicator and the linear time trend) can muddle interpretation of the estimated coefficients (Wolfers, 2006). Not being able to reject the null hypothesis that γ_1 is zero provides further support that our FARS data satisfy the parallel trends assumption.

4. Results

4.1. Summary statistics

Our analysis sample consists of 1,173 state-year observations. Table 2 reports summary statistics for the full sample in the first column and by state parity law category in the last three columns. We report the annual numbers of traffic fatalities. The mean number of fatalities across all states and years is 812 deaths (adjusted for population, the fatality rate per 100,000 residents is 23.52). Decomposing the annual number of fatalities by day of the week, we find that the mean number of weekend fatalities is 350, while the mean number of weekday fatalities is 462. Considering time of day, the mean number of daytime (nighttime) fatalities is 376 (430).

While 14% of state-year observations in our analysis sample have a full parity law, 40% have a strong parity law (mandated benefit or full parity), and 49% have any parity law in place (mandated benefit, full parity, or mandated offer). 45% of the state-year observations have a BAC limit of 0.08 g/dL or below, 69% have ALR laws, 21% have a prescription drug monitoring program, and 10% have a medical marijuana law. State-specific demographics are comparable to the U.S. population.

Examining state-specific characteristics based on whether the state implemented a parity law by the end of our study period, we find that states with a mandated offer parity law have higher fatality rates per 100,000 (27.76 versus 18.88 in states with full parity and 22.71 in states with mandated benefit), a BAC limit of 0.08 g/dL or below, and an administrative license revocation (ALR) law. States with a full parity law are more likely to have a PDMP. We conduct non-parametric Kruskal and Wallis (1952) rank-sum tests and find that the majority of control variables have statistically significant differences in median values across state groups classified by parity law. While there are some differences across these groups of states, we control for all factors in our regression model.

4.2. Validity of the research design: Parallel trends

As noted earlier in the manuscript, a critical assumption for differences-in-differences models to recover causal estimates is that, in the absence of parity legislation, the treatment and comparison groups would have trended similarly in terms of the outcome variables in the post treatment-period. This assumption is not directly testable, but we can offer suggestive evidence that the trends would have been similar.

Results from regression-based testing of the parallel trend assumption are reported in Appendix Table 1. We estimate the parallel trend models using OLS due to the challenges associated with interpreting an interaction term in a non-linear model. In these analyses, we cannot reject the null hypotheses of parallel trends between the treatment and comparison groups in the pre-treatment period (i.e., we cannot reject γ_1=0) in all regressions. These findings further support the hypothesis that the FARS data is able to satisfy the parallel trends assumption.

4.3. Regression results

Table 3 reports selected results from our differences-in-differences analysis of the effects of state parity laws on total and disaggregated (by day of the week and time of the day) traffic fatalities.

We report the estimated incidence rate ratios (IRRs) for our key regressors. IRRs represent the exponentiated coefficients and denote the effect of a unit change in the explanatory variable on the rate of fatalities while holding everything else constant. An IRR greater than one indicates a positive relationship between the fatality measure and the explanatory variable (e.g., parity law), and an IRR less than 1 represents a negative relationship. Each cell in Table 3 pertains to a separate regression model.

All IRR estimates for the parity variables are less than 1, indicating that parity laws have a negative effect on the number of traffic fatalities. Not all IRRs are significantly different from one, however. For example, parity laws are associated with a 4.1% to 5.4% decrease in the annual total traffic fatality rates, but only the IRR for any parity is statistically significant at conventional levels. While we would expect that the full parity law would have the most 'bite', our study period offers substantially more variation in the any parity law than the other law variables (see Table 1). Thus, we suspect that we have more power to detect effects in the regression models in which we include the any parity law measure.

Next, we report results based on fatality measures decomposed by day of the week and time of the day. As noted earlier in the manuscript, we argue that stratifying the sample in this manner can allow us to isolate substance-involved accidents (Dee, 1998), however, we do note that results generated in these samples may be vulnerable to conditional-on-positive bias.

In line with the premise that weekend crashes are more likely to involve alcohol and/or psychoactive drugs, our results confirm that parity laws are much more likely to be associated with reductions in weekend than weekday fatalities. Quantitatively, full parity is associated with an 8.7% decrease in weekend fatalities, while a strong (any) parity law is associated with an 8.0% (6.8%) decrease in weekend fatalities. Moreover, all estimated IRRs for weekend fatalities are statistically significant at the 5% level or better, but estimates for weekday fatalities are closer to one (still below) and none reach statistical significance.

Surprisingly, when disaggregating fatalities by time of the day, results indicate that any parity law is significantly associated with both daytime and nighttime fatalities. *A priori*, we hypothesized that nighttime fatalities are more responsive to passage of state parity laws as substance use is more common among drivers in nighttime traffic accidents (Dee, 1998). A possible explanation of our finding is that, while less serious forms of substance misuse (*e.g.*, binge drinking) may display substantial variation across days of the week and times of the day, individuals with SUDs (that are more likely to seek treatment following parity law passage) are less adherent to drinking norms.[15]

5. Robustness checks and extensions

5.1. Policy endogeneity

A concern with our analysis thus far is that the policies we study may be passed by states in part to address problems related to impaired driving among their residents rather than the parity laws leading to changes in traffic fatalities (Besley & Case, 2000). If true, the coefficients estimated in Equation (1) may be subject to bias from policy endogeneity (i.e., reverse causality at the state level).

To explore this possibility, we conduct an event study as described in Autor (2003) and specified in Equation (3) below:

$$(3) \qquad Y_{st} = \beta_0 + \sum_{j=-2}^{2} \delta_j PL_{st} + \beta_X' X_{st} + S_S + \tau_t + \mu_{st}.$$

[15] For example, a common symptom of a substance abuse includes spending a lot of time using substances (http://www.mayoclinic.org/diseases-conditions/alcohol-use-disorder/basics/symptoms/con-20020866; accessed October 7th, 2016). This common symptom suggests that many individuals who suffer from SUDs are likely to consume substances frequently and thus not simply during 'standard' consumption periods.

The event study introduces two leads (binary indicators for 3 to 4 years prior to implementation and 1 to 2 years pre-implementation), two lags (binary indicators for 1 to 2 years post-implementation and 3+ years post-implementation), and an indicator for the policy implementation year. The omitted category is 5 or more years pre-implementation. The estimates for the leads can reveal pre-implementation effects (i.e., policy endogeneity), while the estimates for the lags offer insight on whether the effects of parity laws persist beyond the implementation period. We do not include state-specific linear time trends in the event study model as including such trends may muddle interpretation of the coefficient estimates in models that allow for dynamics (Wolfers, 2006). All other covariates are the same as those defined for Equation (1).

If we uncover evidence of policy endogeneity (i.e., estimates on the policy leads that are statistically different from zero), controlling for pre-policy leads in the regression model should allow us to isolate the direct effect of parity laws on traffic fatalities. Put differently, once we control for the policy leads, we can minimize concerns regarding bias due to reverse causality in our policy lags. For brevity, we report results from the event study using any parity law (see Appendix Table 2 and Figure 1), but results using alternative parity law variables are comparable and available on request from the corresponding author.

The event study results are broadly robust to the inclusion of lead and lag indicator variables. Namely, we find no evidence of pre-implementation trends as all estimated IRRs for the leads are non-significant at conventional levels. Moreover, χ^2 tests indicate that the estimated IRRs for the lead variables are not jointly significant (results not reported, but available on request from the corresponding author). However, compared to the results from Equation (1), while the year-of-implementation and post-implementation parity estimates from

Equation (3) are largely in the same direction (negative), they are statistically significant only for weekend fatalities. This change in precision is perhaps not surprising as we estimate heavily saturated regression models and event studies are known to be data hungry. In general, these findings are comparable to our main results in that parity laws are negatively related to traffic fatalities and are more likely to be associated with declines in weekend than weekday fatalities.

5.2. Substance misuse

Although we are mainly focused on whether private health insurance expansions decrease traffic fatalities through increases in access to SUD treatment, it is also prudent to examine whether these expansions decrease substance misuse within the general population. To address this issue, we estimate the effects of state-level parity laws on two measures of alcohol misuse: binge and heavy drinking.[16] To this end, we analyze individual-level data from the 1991 to 2010[17] cross-sections of the Behavioral Risk Factor Surveillance System (BRFSS).

The BRFSS is a large, annual, state-administered, cross-sectional telephone survey designed to measure behavioral risk factors in the U.S. non-institutionalized adult population. These data are commonly used by economists to study the effects of public policies on health outcomes (Adams et al., 2015; Courtemanche & Zapata, 2014; Horn, Maclean, & Strain, 2017; Sabia, Swigert, & Young, 2017). The Centers for Disease Control and Prevention (CDC) act in

[16] Ideally, we would like to estimate the effects of parity laws on conventional substance abuse and dependence measures. However, to the best of our knowledge, such information is not available over our study period. For example, the NSDUH provides information on clinical measures of substance abuse and/or dependence. However, the NSDUH is only available from 2002 to the present, thus substantially reducing the number of policy changes we can leverage to study the effect of parity laws (see Table 1). Alternatively, we could explore the effect of parity laws on measures of overdose deaths (e.g., the CDC Compressed Mortality Files). However, these data are only available from 1999 to the present due to substantial changes in the ICD death classification system. The break in the ICD classification scheme (ICD-9 to ICD-10) does not allow direct comparison of substance-attributable deaths and we are unaware of any validated crosswalks. Collectively, these factors prevent us from considering more germane measures of substance abuse and dependence.

[17] We chose this analysis period as data from several states was not collected in early years and coverage improved after 1990. For example, data from only 33 states were collected in 1987 while the number of states grew to 48 in 1991.

collaboration with state agencies to collect and maintain the BRFSS. We aggregate BRFSS data to the state-year level using sample weights. Our three state-year dependent variables are the share of the state population ages 18 and older that reports (i) past month heavy drinking, (ii) past month binge drinking, and (iii) both heavy and binge drinking. Heavy drinking is defined by the CDC as an adult man (woman) who has more than two (one) drinks per day. Binge drinking is defined by the CDC as an adult who consumes five or more drinks on one occasion (same criterion for men and women). Unfortunately, the BRFSS does not collect information on a clinical diagnosis of alcohol abuse or dependence. In addition, data on psychoactive drug use is absent in the BRFSS so we limit our analysis to measures of alcohol misuse. Results for the individual-level analysis of BRFSS data are reported in Appendix Table 3.

We find evidence that passage of a state parity law reduces both heavy and binge drinking. Although most coefficient estimates are negative and statistically significant, they are relatively small in magnitude. For example, any parity law is associated with a 0.4 percentage point decrease (or 9.76% decrease relative to the baseline proportion of 0.041) in the prevalence of past month heavy drinking.

5.3 Alcohol-involved fatalities

Ideally, we would like to analyze the number of fatalities in accidents where at least one of the drivers was under the influence of alcohol and/or psychoactive drugs. Unfortunately, data on psychoactive drugs (i.e., substances other than alcohol) involvement is not uniformly collected by states and it is subject to several other limitations. FARS administrators began collecting data pertaining to drug tests in 1991, so we are unable to determine drug-involved fatalities prior to this year. Moreover, coding procedures for drug test results changed in 1993, further constraining the analysis period. Although the majority of drivers are not tested for drugs, the testing rate for fatally injured drivers is likely to be higher than the testing rate for surviving drivers (National Highway Traffic Safety Administration, 2010). In 2009, 63% of drivers who were fatally injured in crashes were tested for drugs. Further complicating the analysis, testing rates vary widely across states. For example, while Maine did not report any drug testing in 2009, California has a drug testing rate of over 80%. Discrepancies also exist across states in drug testing procedures. Even when drug testing data are collected, quantity or concentration information is rarely recorded—testing positive for drugs does not necessarily imply impairment. Finally, FARS reports the presence of any drug regardless of its legal status, including over-the-counter and prescription drugs.

Given these issues related to drug involvement information in FARS, we restrict our analysis to alcohol-involved fatalities. We note our inability to study psychoactive drug-involved fatalities as a limitation of the study. Although alcohol involvement is documented by BAC test results collected from police or coroner reports, it contains measurement error as well as some states do not uniformly collect BAC information (Anderson et al., 2013; Eisenberg, 2003). When BAC information is missing, BAC level is statistically imputed based on characteristics of the crash and driver (Subramanian, 2002). We use both the pharmacological and imputed information to construct measures for the number of traffic fatalities with alcohol involvement.

Appendix Table 4 reports results for the effect of parity laws on alcohol-involved traffic fatalities. No-alcohol-involved fatalities include individuals killed in accidents in which all drivers had a BAC of 0.00 g/dL. We use the current BAC legal limit of 0.08 g/dL to decompose alcohol-involved crashes into two groups: (i) fatalities in crashes in which at least one of the drivers had a positive BAC, but under the legal limit of 0.08; and (ii) fatalities in crashes in which at least one of the drivers had a BAC level over the legal limit of 0.08. Finally, to assess whether the parity effects are stronger at more elevated drinking (i.e., more likely to be associated with SUDs), we consider the number of fatalities in crashes in which at least one of the drivers had a BAC level above 0.15 g/dL.

Reviewing the results in Appendix Table 4, most IRRs are less than 1, suggesting a negative association between parity laws and alcohol-involved traffic fatalities. Unexpectedly, we find that any parity law is associated with a 4.9% decline in no-alcohol-involved fatalities. This result may reflect the fact that parity laws reduce the number of impaired drivers using psychoactive drugs (or at least no alcohol use that is captured by the FARS). Moreover, this variable could also capture a reduction in other types of impaired driving (e.g., sleep deprivation) among those drivers with SUDs (Popovici & French, 2013a). Several studies find that sleep deprivation is a major cause of traffic accidents (Eoh, Chung, & Kim, 2005; Hack, Choi, Vijayapalan, Davies, & Stradling, 2001; Terán-Santos , Jimenez-Gomez , Cordero-Guevara , & Burgos–Santander, 1999). When comparing 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). While parity laws are associated with a 4.3% to 8.6% decrease in fatalities where at least one driver had a BAC greater than 0.08 ($p<0.10$), they are associated with a 5.8% to 10.5 % reduction in fatalities where at least one driver had a BAC above 0.15. When considering the highest BAC level (0.15 or higher), effect sizes are greater for the strongest parity laws. While any parity law (strong parity law) is associated with a 5.8% (7.8%) decrease in fatalities where at least one driver has a BAC>0.15, a full parity law is associated with a 10.5% decrease.

5.4 Other robustness checks

We conduct several robustness checks to explore the stability of our findings. For brevity, we simply summarize findings from these analyses in the text, but a full set of results is available on request from the corresponding author. First, we estimate OLS regressions using a log transformation of our fatality measures. These results are comparable to those from the Poisson models. Next, we estimate all models using negative binomial as an alternative approach to modeling count data. Again, the results are very similar to those from our core specifications. Finally, our results thus far are unweighted. However, there is some controversy within the economic literature on whether weighting is appropriate in studies that seek to estimate causal effects (Angrist & Pischke, 2009). Given this controversy, we have re-estimated Equation (1) using population weights: specifically, we weight the regressions with the state population age 21 and older. The results are comparable with our core results but the estimated effects are slightly larger in magnitude.

6. Discussion

In this study, we investigate whether state parity laws for substance use disorder (SUD) treatment have spillover effects on fatal traffic accidents. We hypothesize that an increase in the number of substance users seeking SUD treatment because of state parity legislation will reduce the number of impaired drivers on roadways and, thus, decrease the number of traffic fatalities.

Our main finding indicates that state-specific traffic fatalities decline after passage of a state parity law. However, we identify heterogeneity in terms of law effects by type of parity legislation, time of the day/week of the crash, and BAC levels of the drivers. In line with the premise that weekend crashes are more likely to involve substance-impaired drivers, we find that parity laws are associated with greater reductions in weekend compared to weekday fatalities.

Predictably, the magnitude of the effect of a parity law on traffic fatalities increases with the strength of the law. Moreover, parity laws have the greatest impact on fatalities involving alcohol-impaired drivers. Finally, we find evidence that parity laws reduce the level of substance misuse within the adult population.

Given that our analysis estimates the effect of parity laws on traffic fatalities rather than a 'first stage' effect on SUDs, it is important to determine whether the magnitude of the estimates is 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 less substantial 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, 41.7% of patients receiving SUD treatment used private health insurance as a source of payment for their last treatment episode. This estimate may understate the true penetration of private insurance in the financing of SUD treatment as the estimate only captures the use of private insurance for the last service episode. For 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.

Another approach to assess the magnitude of our estimated effect sizes is to consider the share of the population that is impacted by state parity laws. According to Jensen and Morrisey (1999), 33% to 43% of the U.S. population is impacted by a private health insurance expansion. According to more recent evidence from the Medical Expenditure Panel Survey, 46% to 57% of insurance beneficiaries from the private-sector worked for a self-insured firm between 1997 and 2010, suggesting that 43% to 54% of such employees were potentially impacted by the policies we study here.[18] 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 et al. (2017) document a comparable increase in admissions. While none of these estimates are conclusive, 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 estimates.

Finally, an additional argument suggesting that our effect magnitudes are reasonable is that state parity laws could affect both the extensive and intensive margins of SUD treatment. We have focused our discussion on 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, in 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 numbers of allowable annual/lifetime episodes of care). This hypothesis is supported by McGinty et al. (2015) who show that MHPAEA increased use of out-of-network services, which may reflect expanded access to SUD treatment providers for beneficiaries. Although such an individual would have been designated as having coverage for SUD treatment, the coverage may not have adequately met his/her treatment needs in terms of either service availability or intensity. Thus, increased insurance generosity because of parity legislation may now allow some individuals to obtain more comprehensive SUD treatment (e.g., treatment that addresses

[18] Data accessed on April 10th, 2017 from the following table: https://meps.ahrq.gov/mepsweb/data_stats/quick_tables_results.jsp?component=2&prfricon=yes&searchText=insured&subcomponent=2&tableSeries=2&year=-1.

overall patient health, relies on the use of both counseling and medications, and is of sufficient duration with appropriate follow up care rather than detoxification services that simply allow the body to expel substances) and/or treatment that is better matched to patient needs. While we cannot measure such coverage gains, it is plausible that these gains would facilitate more effective SUD treatment, and thereby reduce both SUD prevalence and fatal traffic accidents.

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 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. (iii) Although parity laws might impact the number of substance users seeking treatment and hence the rates of untreated SUDs in the population, our alcohol misuse measures from the BRFSS are proxies for clinical measures of adult SUDs.

Despite these limitations, our findings are timely and policy relevant for several reasons. (i) They document the 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. (ii) The ACA in conjunction with MHPAEA requires that most 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 suggests that these two Acts generate a positive and unintended benefit by reducing the number of impaired drivers, thereby improving overall traffic safety. Recent uncertainty surrounding the political fate (the Trump Administration and Republican Congress have a long-standing objective of repealing this Act) of the essential health benefit package (which includes SUD treatment), the state Medicaid expansions, and the guaranteed coverage issue only increases the significance of these research findings as they can inform policymakers on the benefits of expanding SUD treatment availability. (iii) These findings contribute to the growing literature on the benefits of SUD treatment, and reveal that such services 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 consequences as associated with DUIs that involve financial payment, community service, and/or 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 policies, 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 ancillary policies such as health insurance parity laws as a viable and effective approach to enhance traffic safety.

Table 1. Effective dates for state parity laws

Type of law and states	Effective year
Full parity	
Arkansas	1987
Connecticut	2000*
Delaware	1999*
Hawaii	1988*
Illinois	2010*
Maryland	1997*
Minnesota	1999*
New Jersey	1985
Oklahoma	2000*
Rhode Island	1994*
Vermont	2011
Virginia	2000*
West Virginia	2002*
Mandated benefit	
Alaska	2004*
Indiana	2003*
Iowa	2011
Kansas	2009*
Maine	1984
Massachusetts	1973
Michigan	1982
Mississippi	1975
Missouri	1991*
Montana	1987
Nebraska	1980
Nevada	1979
New Hampshire	1975
North Dakota	1985
Ohio	1979
Oregon	2007*
Pennsylvania	1990*
Tennessee	2000*
Texas	2005*
Wisconsin	2010*
Mandated offer/weak parity	
Colorado	2003*
Florida	1993*
Georgia	1998*
Indiana	1997*
Louisiana	2009*
New Mexico	1999*
New York	2011
North Carolina	1997*
South Carolina	1976
Tennessee	1982
Utah	2010*

Notes: Source is the National Conference of State Legislatures Mental Health Benefits Database (accessed May 5th, 2015) and the authors' reading of the original statutes.
*Law change occurred during our study period (1988-2010). We do not consider law changes in 1988, the first year of the panel, as changes at the start of the panel do not offer variation in our difference-in-differences models.

Table 2. Descriptive statistics for the full sample and by type of parity law, FARS 1988-2010

Sample:	**All states**	**Full parity states**	**Mandated benefit parity states**	**Mandated offer parity states**
Traffic fatalities				
Total fatalities***	812.15	465.75	692.14	1,379.92
Weekend fatalities***	349.73	194.28	292.02	591.00
Weekday fatalities***	462.22	271.35	400.02	788.82
Daytime fatalities***	375.58	217.53	318.94	622.64
Nighttime fatalities***	430.11	245.93	368.74	748.81
Type of parity law				
Full parity (%)	14.13	100	0	0
Strong parity (full parity or mandated benefit) (%)	40.24	100	100	0
Any parity (full parity, mandated benefit, or mandated offer) (%)	49.47	100	100	100
Demographics and other policies				
Log of state population age 21+***	14.66	14.52	14.58	15.28
	(1.03)	(0.78)	(1.02)	(0.64)
Age***	46.28	46.93	46.62	46.73
	(1.38)	(1.05)	(1.05)	(1.40)
Female (%)***	52.85	53.08	52.69	53.56
Male (%)***	47.14	46.92	47.31	46.44
White (%)***	83.76	73.75	87.45	77.54
African American (%)***	10.19	11.19	8.10	18.32
Other race (%)***	6.05	15.06	4.45	4.14
Hispanic (%)***	8.79	7.61	5.21	13.54
Married (%)***	63.11	62.58	63.38	62.11
Divorced, separated, or widowed (%)***	19.37	19.01	19.43	20.64
Never married (%)***	17.52	18.41	17.19	17.24
Less than high-school education (%)***	20.78	16.56	18.09	20.26
High-school diploma or equivalent (%)**	29.20	31.54	31.26	30.83
Some college, but no degree (%)***	27.50	25.65	27.95	26.16
College degree (%)***	22.52	26.25	22.70	22.75
Annual family income***	54,584	66,385	55,648	55,155
	(14,877)	(16,465)	(14,636)	(11,759)
Ln(urban vehicle miles traveled per 10,000 people)***	4.25	4.39	4.16	4.41
	(0.30)	(0.25)	(0.34)	(0.23)
Ln(rural vehicle miles traveled per 10,000 people)***	4.08	3.75	4.15	4.17
	(0.57)	(0.75)	(0.58)	(0.41)
BAC limit <=0.08 (%)***	44.76	43.63	49.17	66.66
Administrative license revocation (%)***	68.96	56.97	66.01	79.04
PDMP (%)	20.95	27.27	20.18	23.97
Medical marijuana law (%)	9.83	9.77	12.70	10.95
Real beer excise tax ($ per gallon)***,†	0.24	0.19	0.19	0.49
	(0.19)	(0.08)	(0.11)	(0.24)
Average annual temperature (degrees F)***	55.23	55.57	51.64	62.69
	(7.48)	(4.92)	(6.38)	(6.07)
Average annual precipitation (inches)***	35.66	42.58	34.70	41.02
	(15.72)	(9.19)	(14.93)	(18.46)
Observations	**1,173**	**165**	**303**	**105**

Notes: Traffic fatalities are defined as follows: Weekend fatalities refer to persons killed in traffic accidents occurring between 6 p.m. on Friday and 6 a.m. on Monday. Weekday fatalities are those occurring between 6 a.m. on Monday and 6 p.m. on Friday. Daytime (between 6 a.m. and 6 p.m.) versus nighttime (between 6 p.m. and 6

a.m.) fatalities are classified depending on the time of the accident. The unit of observation is a state/year.
†In 2010 dollars.
***Statistically significant difference in variable medians across the parity type categories, $p<0.01$, Kruskal-Wallis (1952) equality of populations rank test.
**Statistically significant difference in variable medians across the parity type categories, $p<0.05$, Kruskal-Wallis (1952) equality of populations rank test.
*Statistically significant difference in variable medians across the parity type categories, $p<0.10$, Kruskal-Wallis (1952) equality of populations rank test.

Table 3. Effect of state SUD treatment parity laws on traffic fatalities, FARS 1988-2010

Variable:	**Total fatalities**	**Weekend fatalities**	**Weekday fatalities**	**Daytime fatalities**	**Nighttime fatalities**
Sample mean	812.15	349.73	462.22	375.58	430.11
Full parity	0.946	0.913**	0.971	0.936	0.949*
	(0.040)	(0.035)	(0.046)	(0.061)	(0.030)
Strong parity (full parity or mandated benefit)	0.949 (0.032)	0.920** (0.036)	0.971 (0.030)	0.939* (0.036)	0.951 (0.033)
Any parity (full parity, mandated benefit, or mandated offer)	0.959* (0.022)	0.932*** (0.025)	0.979 (0.021)	0.952* (0.027)	0.962 (0.024)
Observations	**1,173**	**1,173**	**1,173**	**1,173**	**1,173**

Notes: The dependent variable in each specification is the state-specific annual count of the respective fatality type. Unit of observation is a state/year. All models are estimated with a Poisson model and control for logarithm of state population age 21+, state demographics for population ages 21+ (age, gender, race/ethnicity, marital status, education, and family income), average temperature and precipitation, administrative license revocation law, BAC limit <=0.08, PDMP, medical marijuana law, real beer excise tax, natural logarithm of per capita vehicle miles traveled on rural and urban roads, state and year fixed effects, and state-specific time trends. Incidence rate ratios are reported. Standard errors are clustered at state level and are reported in parentheses.
***; **; * = statistically different from one at the1%; 5%; 10% levels.

Appendix Table 1. Parallel trends test in pre-treatment period for state SUD treatment parity laws on traffic fatalities, FARS 1988-2010

Variable:	**Total fatalities**	**Weekend fatalities**	**Weekday fatalities**	**Daytime fatalities**	**Nighttime fatalities**
Sample mean	812.15	349.73	462.22	375.58	430.11
Full parity	1.991	1.737	0.254	-0.168	2.286
	(4.970)	(2.559)	(2.623)	(1.908)	(3.360)
Observations	**606**	**606**	**606**	**606**	**606**
Strong parity (full parity or	6.784	4.484	2.341	2.834	4.007
mandated benefit)	(5.907)	(2.948)	(3.162)	(3.111)	(3.662)
Observations	**481**	**481**	**481**	**481**	**481**
Any parity (full parity,	7.901	3.919	4.071	4.236	4.172
mandated benefit, or	(8.224)	(4.109)	(4.293)	(4.466)	(4.823)
mandated offer)					
Observations	**479**	**479**	**479**	**479**	**479**

Notes: The dependent variable in each specification is the annual state-specific count of the respective fatality type. Unit of observation is a state/year. All models are estimated with OLS and control for logarithm of state population age 21+, state demographics for population ages 21+ (age, gender, race/ethnicity, marital status, education, and family income), average temperature and precipitation, administrative license revocation law, BAC limit <=0.08, PDMP, medical marijuana law, real beer excise taxes, natural logarithm of per capita vehicle miles traveled on rural and urban roads, state and year fixed effects. Standard errors are clustered at state level and are reported in parentheses.
***; **; * = statistically different from zero at the1%; 5%; 10% levels.

Appendix Table 2. Effects of any state SUD treatment parity law on traffic fatalities using an event study model, FARS 1988-2010

Variable:	**Total fatalities**	**Weekend fatalities**	**Weekday fatalities**	**Daytime fatalities**	**Nighttime fatalities**
Sample mean	812.15	349.73	462.22	375.58	430.11
3-4 years pre-implementation	1.008	1.006	1.011	1.032	0.987
	(0.017)	(0.018)	(0.018)	(0.020)	(0.016)
1-2 years pre-implementation	1.000	0.990	1.007	1.012	0.988
	(0.022)	(0.022)	(0.023)	(0.021)	(0.025)
Implementation year	0.977	0.954*	0.994	0.995	0.960
	(0.021)	(0.023)	(0.022)	(0.023)	(0.024)
1-2 years post-implementation	0.980	0.949**	1.004	0.989	0.971
	(0.021)	(0.022)	(0.022)	(0.021)	(0.025)
3+ years post-implementation	0.992	0.972	1.007	1.015	0.976
	(0.025)	(0.025)	(0.027)	(0.026)	(0.028)
Observations	**1,173**	**1,173**	**1,173**	**1,173**	**1,173**

Notes: The dependent variable in each specification is the annual state-specific count of the respective fatality type. Unit of observation is a state/year. All models are estimated with a Poisson model and control for natural logarithm of state population age 21+, state demographics for population ages 21+ (age, gender, race/ethnicity, marital status, education, and family income), average temperature and precipitation, administrative license revocation law, BAC limit <=0.08, PDMP, medical marijuana law, real beer excise taxes, natural logarithm of per capita vehicle miles traveled on rural and urban roads, state and year fixed effects. Incidence rate ratios are reported. Standard errors are clustered at state level and are reported in parentheses.
***; **; * = statistically different from one at the1%; 5%; 10% levels.

Appendix Table 3. Effects of state SUD treatment parity laws on alcohol misuse, BRFSS 1991-2010

Variable:	**Heavy alcohol use**[1]	**Binge drinking**[2]	**Both heavy use and binge drinking**
Sample mean	0.041	0.125	0.030
Full parity	0.001	0.009	0.001
	(0.002)	(0.009)	(0.002)
Strong parity (full parity or mandated benefits)	-0.006**	-0.006	-0.004*
	(0.003)	(0.008)	(0.002)
Any parity (full parity, mandated benefits, or mandated offer)	-0.004*	-0.003	-0.003*
	(0.002)	(0.007)	(0.002)
Observations	**858**	**862**	**858**

[1] Heavy alcohol use is defined as adult men (women) having more than two (one) drinks per day.

[2] Binge drinking is defined as adults having five or more drinks on one occasion.

Notes: Unit of observation is a state/year. All models estimated with OLS and control for state demographics for population ages 21+ (age, gender, race/ethnicity, marital status, education, and family income), administrative license revocation law, BAC limit <=0.08, PDMP, medical marijuana law, real beer excise tax, state and year fixed effects. Observations are weighted by the state population. Standard errors are clustered at state level and are reported in parentheses. Sample sizes vary due to missing alcohol misuse data.

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

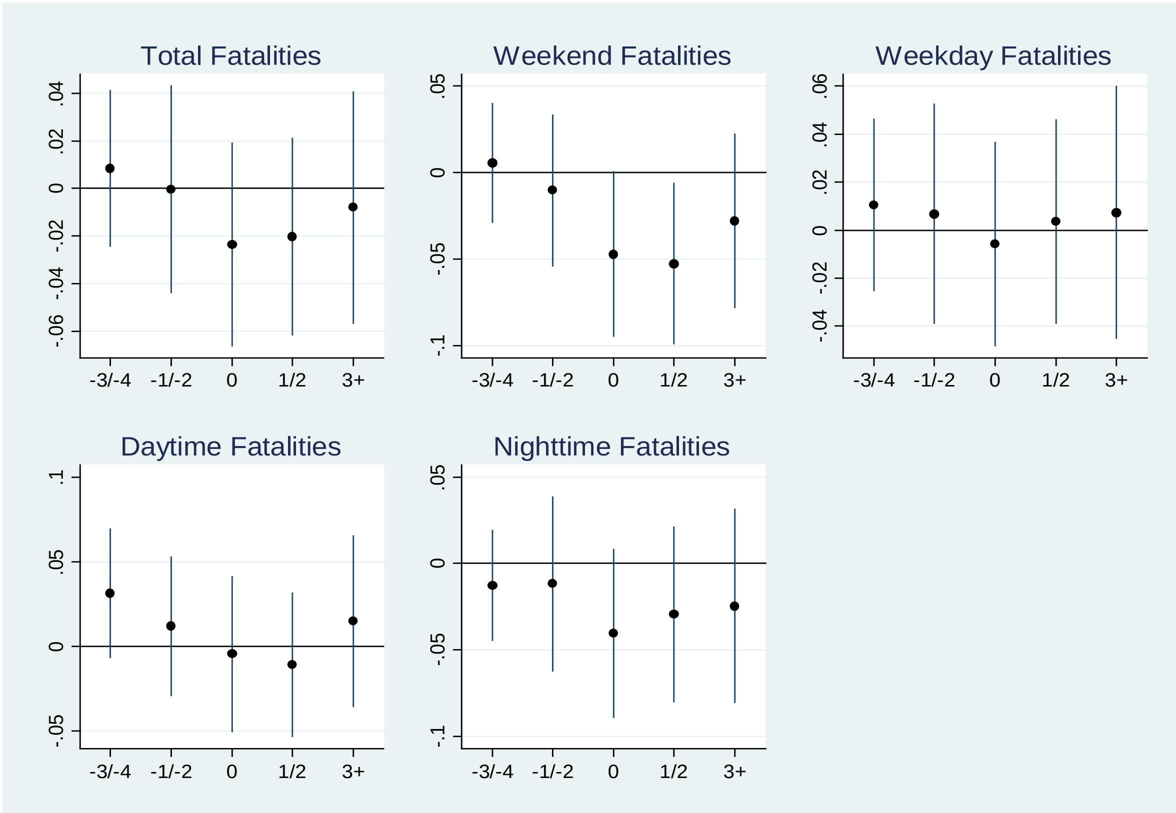
Appendix Table 4. Effects of state SUD treatment parity laws on traffic fatalities, by type of alcohol involvement, FARS 1988-2010

Variable	**BAC = 0 fatalities**[1]	**0 < BAC > 0.08 fatalities**[2]	**BAC ≥ 0.08 fatalities**[3]	**BAC ≥ 0.15 fatalities**[4]
Sample mean	494.69	46.72	268.22	181.80
Full parity	0.950	1.066	0.914*	0.895**
	(0.044)	(0.094)	(0.049)	(0.047)
Strong parity (full parity or	0.936	0.978	0.954	0.922**
mandated benefit)	(0.038)	(0.035)	(0.038)	(0.036)
Any parity (full parity,	0.951*	0.984	0.954*	0.942**
mandated benefit, or mandated offer)	(0.028)	(0.026)	(0.025)	(0.026)
Observations	**1,173**	**1,173**	**1,173**	**1,173**

[1] BAC level of all drivers involved in the crash is 0.
[2] At least one driver involved in the crash had a positive BAC below 0.08.
[3] At least one driver involved in the crash had a BAC of 0.08 or more.
[4] 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 annual state-specific count of the respective fatality type. Unit of observation is a state/year. All models estimated with a Poisson model and control for natural logarithm of state population age 21+, state demographics for population ages 21+ (age, gender, race/ethnicity, marital status, education, and family income), average temperature and precipitation, administrative license revocation law, BAC limit <=0.08, PDMP, medical marijuana law, real beer excise taxes, natural logarithm of vehicle miles traveled on rural and urban roads per capita, state and year fixed effects, and state-specific time trends. Incidence rate ratios are reported. Standard errors are clustered at state level and are reported in parentheses.
***; **; * = statistically different from one at the1%; 5%; 10% levels.

Figure 1. Effect of any state SUD treatment parity law on traffic fatalities using an event study, FARS 1988-2009



Notes: Unit of observation is a state/year. Event study includes two leads (binary indicators for 3 to 4 years prior to implementation and 1 to 2 years pre-implementation), two lags (binary indicators for 1 to 2 years post-implementation and 3+ years post-implementation), and an indicator for the policy implementation year. The omitted category is 5 or more years pre-implementation. All models are estimated with a Poisson model and control for natural logarithm of state population age 21+, state demographics for population ages 21+ (age, gender, race/ethnicity, marital status, education, and family income), average temperature and precipitation, administrative license revocation law, BAC limit <=0.08, PDMP, medical marijuana law, real beer excise taxes, natural logarithm of per capita vehicle miles traveled on rural and urban roads, state and year fixed effects. 95% confidence intervals account for state-level clustering and are reported in vertical bars. See Appendix Table 2 for coefficient estimates.

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