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# WITH A LITTLE HELP FROM MY FRIENDS:
# THE EFFECTS OF NALOXONE ACCESS AND GOOD SAMARITAN LAWS ON OPIOID-RELATED DEATHS

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## ABSTRACT

In an effort to address the opioid epidemic, a majority of states have recently passed some version of a Naloxone Access Law (NAL) and/or a Good Samaritan Law (GSL). NALs allow lay persons to administer naloxone, which temporarily counteracts the effects of an opioid overdose; GSLs provide immunity from prosecution for drug possession to anyone who seeks medical assistance in the event of a drug overdose. This study is the first to examine the effect of these laws on opioid-related deaths. Using data from the National Vital Statistics System multiple cause-of-death mortality files for the period 1999-2014, we find that the adoption of a NAL is associated with a 9 to 11 percent reduction in opioid-related deaths. The estimated effect of GLSs on opioid-related deaths is of comparable magnitude, but not statistically significant at conventional levels. Finally, we find that neither NALs nor GSLs increase the recreational use of prescription painkillers.

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# 1. INTRODUCTION

Since the early 2000s, the rate of drug overdose deaths in the United States has more than doubled (Rudd et al. 2016). Overdose deaths are currently at record levels, with more than 60 percent of these deaths due to opioid use, primarily prescription pain relievers and heroin (Rudd et al. 2016). According to the Centers for Disease Control (CDC), the United States is facing "the worst drug overdose epidemic" in its history (Ahmed 2013).

In an effort to reduce the death toll from the use of opioids, New Mexico passed the first Naloxone Access Law (NAL) in 2001. Under this law, trained responders (e.g., police and firefighters) were authorized to administer an "opioid antagonist" (i.e., naloxone) if they believed that someone was experiencing a drug overdose. The law also stated that "a person who administers an opioid antagonist…shall not be subject to civil liability or criminal prosecution as a result of the administration of the drug" (NM Stat § 24-23-1). Since 2001, 44 additional states and the District of Columbia have adopted NALs, which allow lay persons to administer and distribute naloxone without fear of legal repercussions.

New Mexico was also the first state to pass a Good Samaritan Law (GSL). Under this law, anybody "who, in good faith, seeks medical assistance for someone experiencing a drug-related overdose shall not be charged or prosecuted for possession of a controlled substance…" (NM Stat § 30-31-27). Since 2007, 33 additional states and the District of Columbia have followed suit, although some GSLs are stronger than others. For instance, in 23 states the law provides immunity from prosecution for possession of drug paraphernalia in addition to immunity from prosecution for possession of a controlled substance.

GSLs and NALs are viewed as important weapons in the fight against the opioid epidemic. They have received strong bipartisan support (Ollove 2014), and prominent groups such as the

American Medical Association, the U.S. Conference of Mayors, and the American Public Health Association also support the adoption of GSLs and NALs. However, these laws have their critics. For instance, the governor of Maine, Paul LePage, recently vetoed naloxone access and Good Samaritan bills, arguing that they would encourage drug use and hamper law enforcement efforts (Cousins 2013; Sledge 2014; Tesfaye 2016).

This study is the first to examine the effects of GSLs and NALs on opioid-related mortality. Drawing upon data from the National Vital Statistics System (NVSS) multiple cause-of-death mortality files for the period 1999-2014, we estimate standard difference-in-difference models, which exploit within-state variation and control flexibly for common shocks caused by, for instance, the reformulation of OxyContin in 2010.[1]

We find that the adoption of a NAL is associated with a 9 to 11 percent reduction in opioid-related deaths. The relationship between NALs and opioid-related deaths that do not involve heroin appears to be stronger than the relationship between NALs and heroin-related deaths. Moreover, our results suggest that removing criminal liability for possession of naloxone is an important feature of these laws. Removing criminal liability for possession of naloxone is associated with a 13 percent reduction in opioid-related deaths, while Poisson estimates of the effect of NALs without this provision are considerably smaller and statistically indistinguishable from zero. The estimated effects of GSLs on opioid-related deaths are consistently negative, but not statistically significant at conventional levels. We do, however, find stronger evidence that GSLs reduce opioid-related deaths involving alcohol. Finally, contrary to the claims made by

[1] OxyContin was reformulated in 2010 with the goal of making it more difficult to abuse. There is evidence that the reformulation in fact deterred abuse (Havens et al. 2014), but it may have also encouraged the use of heroin and other OxyContin substitutes (Alpert et al. 2017). Figure 1 shows that heroin-related mortality was roughly constant during the period 1999-2010. From 2010 to 2014, the heroin-related mortality rate increased markedly, while mortality involving other opioids peaked in 2011.

some critics of NALs and GSLs, we find little evidence that these laws increase the recreational use of prescription painkillers.

## 2. BACKGROUND

A number of state-level polices have been proposed to combat the opioid epidemic. For instance, lawmakers have argued that prescription drug monitoring programs (PDMPs) should be strengthened (Ronayne 2015; Perrone 2016), and, as noted above, most states have passed some version of a NAL or a GSL.

Naloxone, which is administered by injection or nasal spray, temporarily counteracts the effects of an opioid overdose. Its side effects (e.g., headache, nausea, sweating, and vomiting), can be unpleasant, but are not life threatening (Boyer 2012). Laypersons with little or no training can successfully administer naloxone (Doe-Simkins et al. 2014), giving overdose victims the opportunity to seek assistance from trained medical professionals, although once revived the majority of victims choose not to call 911 (Enteen et al. 2010; Bennett et al. 2011; Doe-Simkins et al. 2014).

NALs are designed to provide bystanders, family members, and first responders with an effective intervention in the event of an overdose. However, NALs could, at least in theory, lead to more drug use by lowering its expected cost, which includes the possibility of overdosing. Critics also worry that increased access to naloxone could discourage overdose victims from calling 911 by giving them an easy, low-cost alternative to utilizing traditional emergency medical services (Seal et al. 2003; Castillo 2015). Indeed, a recent survey of organizations that distribute naloxone kits conducted by the Harm Reduction Coalition (HRC) found that 83 percent of overdose reversals were performed by drug users (Wheeler et al. 2015).[2]

GSLs provide immunity from prosecution for drug possession to anyone who seeks emergency medical assistance in the event of a drug overdose. Some GSLs also provide immunity from prosecution for possession of alcohol (for instance, if the caller is under the minimum legal drinking age) and immunity from prosecution for possession of drug paraphernalia. The intent of these laws is to encourage bystanders and victims to call 911. However, just like NALs, they could lead to more drug use by lowering its expected cost.

### 2.1. Previous studies

Although there is reasonably strong evidence that PDMPs reduce opioid prescribing and drug treatment admissions (Haegerich et al. 2014; Bao et al. 2016), next to nothing is known about the effects of GSLs and NALs (Haegerich et al. 2014, p. 40). What little we do know about these laws comes from a handful of case studies (Mueller et al., 2015).

The first of these case studies, by Albert et al. (2011), examined Project Lazarus, an ambitious community-based overdose prevention program in Wilkes County, North Carolina. As part of Project Lazarus, doctors were trained to identify patients at risk of overdosing on opioids, and naloxone kits were made available free of charge to these patients if they agreed to

[2] This same survey found that drug users represented 82 percent of naloxone kit recipients; twelve percent of recipients were friends of drug users and family members, and 3 percent were service providers (Wheeler et al. 2015). It should be noted that law enforcement organizations, fire departments, and emergency responders were not surveyed by the HRC. Enteen et al. (2010) surveyed drug users who were given naloxone kits and training by a community-based program in San Francisco. They found that only 29 percent of participants who used naloxone to reverse an overdose also called emergency services. Bennett et al. (2011) surveyed drug users before and after receiving naloxone kits and training from a community-based overdose-prevention program operating in Allegheny County, PA. Before receipt of the kits, those surveyed reported calling 911 in 34 percent of overdose situations. After receiving naloxone and training, this figure decreased to 10 percent.

watch a 20-minute educational video. Overdose deaths fell sharply in 2010, the year in which distribution of the naloxone kits began, but, because Project Lazarus involved multiple interventions undertaken concurrently, it is impossible to isolate the effect of any single intervention.

Walley et al. (2013) examined the Overdose Education and Naloxone Distribution (OEND) program in Massachusetts, which began providing naloxone and overdose education to drug users, the friends and families of drug users, and first responders in 2006.[3] These authors found that opioid overdose deaths declined substantially from 2006 to 2009 in communities that participated in the OEND program relative to communities that did not participate. Doe-Simkins et al. (2014), who also analyzed data from the OEND program, were primarily interested in the effect of formal training by OEND staff on outcomes such as whether the overdose victim survived and whether 911 was called. They found no evidence that trained rescuers acted differently than rescuers who obtained naloxone through social networks, nor did they find evidence that trained rescuers had a higher success rate than their untrained counterparts.[4]

Finally, Banta-Green et al. (2013) surveyed police officers and paramedics in Seattle about a Washington law that included both a Good Samaritan immunity provision and allowed naloxone to be carried and administered by laypersons. Banta-Green et al. (2013a) found that, more than a year after the passage of the law, few police officers and paramedics had heard of it. However, awareness increased dramatically after a training video was circulated (Banta-Green

[3] Naloxone and educational materials were delivered through needle exchange and drug treatment programs, at HIV prevention drop-in centers, emergency departments and primary healthcare settings, homeless shelters, and community meetings.

[4] Other, essentially descriptive, studies focused on gauging the effects of local naloxone distribution programs include Enteen et al. (2010), Coffin et al. (2016), and McAuley (2017).

2013b). The authors did not examine drug overdoses or whether drug users, their friends and family members were aware of the change in the Washington law, but concluded that "the impact of Good Samaritan laws on…health outcomes is worth evaluating" (Banta-Green et al. 2013a, p. 1109).

### 2.2. NALs

Information on NALs was obtained from the Policy Surveillance Program, which is funded by the Robert Wood Johnson Foundation.[5] Table 1 shows the effective date of each NAL passed during the period 2001-2014 and provides some basic information about the laws.[6]

During the period under study, 27 states and the District of Columbia adopted NALs. Twenty-three of these laws allowed "standing orders" (also called "non-patient-specific prescriptions"), under which prescribers can authorize the distribution of naloxone to laypersons deemed capable of administering it and to community-based overdose-prevention programs, fire departments, and police departments (Wheeler et al. 2012; Davis et al. 2014; Green et al. 2015); pharmacists can typically dispense naloxone to anyone who meets the standing-order criteria (Davis and Carr 2015).

Eleven NALs adopted during the period under study removed criminal liability for possession of naloxone without a prescription. In theory, removing criminal liability for possession of naloxone should increase access and encourage its use in emergency situations

[5] See http://lawatlas.org/. Additional information on NALs and GSLs was obtained from the Network for Public Health Law (https://www.networkforphl.org/_asset/qz5pvn/network-naloxone-10-4.pdf).

[6] NALs were defined as laws that (i) grant criminal and civil immunity to non-medical professionals who administer naloxone, (ii) grant criminal and civil immunity to medical professionals who prescribe naloxone to patients, or (iii) allow medical professionals to issue third-party naloxone prescriptions. Third-party prescriptions are dispensed to someone other than the patient (e.g., a family member of someone at risk of experiencing an overdose).

(Corey et al. 2013). Naloxone is not considered to be a controlled substance and it cannot be abused or taken recreationally (Jasinski et al. 1967; Seal et al. 2003; Straus et al. 2013). Nevertheless, qualitative studies provide evidence that drug users fear that they may be subject to arrest for possession of naloxone if they call 911 and the police arrive along with the paramedics (Seal et al. 2003; Worthington et al. 2006; Kerr et al. 2008; Gaston et al. 2009).

**2.3. GSLs**

Typically, death from opioid overdose is not sudden (Zador et al. 1996; Boyer 2012), giving bystanders, companions and family members time to seek emergency medical assistance. However, qualitative studies have found that fear of being arrested or harassed by police often discourages drug users from calling 911 (Seal et al. 2003; Tracey et al. 2005; Tobin et al. 2005; Bennett et al. 2011). For instance, Bennett et al. (2011) surveyed drug users who had received naloxone kits and training from a community-based overdose-prevention program.[7] A total of 249 overdoses were reported, but 911 was called only 10 percent of the time. Seventy-one percent of participants cited "fear of police involvement" as the reason for not calling 911 (Bennett et al. 2011, p. 1025).

Table 2 shows the effective date of every GSL passed during the period 1999-2014.[8] During this period, 22 states and the District of Columbia adopted GSLs, which provide immunity from criminal prosecution for possession and/or use of a controlled substance to

[7] A total of 426 participants were recruited by Prevention Point Pittsburgh, which operates in Allegheny County, PA. The study was conducted during the period 2005-2008. See Bennett et al. (2011) for more details.

[8] Information on GSLs was obtained from the Policy Surveillance Program (http://lawatlas.org/) and the Network for Public Health Law (https://www.networkforphl.org/_asset/qz5pvn/network-naloxone-10-4.pdf).

anyone who calls for emergency medical assistance in the event of an overdose. Fifteen of these laws also provide immunity from prosecution for possession of drug paraphernalia; five of these laws provide callers under the age of 21 with immunity from prosecution for possession of alcohol.

## 3. METHODS

### 3.1. The data

Mortality data were obtained from the NVSS multiple cause-of-death mortality files. These data are at the state-year level and cover the period 1999-2014. Our interest is in estimating the effects of NALs and GSLs on opioid-related deaths, defined as those indicated by the following *International Classification of Disease, Tenth Revision* (ICD-10) multiple cause-of-death codes: T40.0 (opium), T40.1 (heroin), T40.2 (other opioids), T40.3 (methadone), T40.4 (other synthetic narcotics), and T40.6 (other/unspecified narcotics).

It should be noted that the ICD-10 defines the term "narcotic" to include both cocaine derivatives and opioids, so that some portion of the deaths identified by the multiple cause-of-death code T40.6 could have been caused by cocaine. However, these deaths represent only a small fraction of total opioid-related deaths. For instance, in 2014 (the last year included in our analysis), there were a total of 29,650 opioid-related deaths in the United States. Of these, only 1,635 (or 5.5 percent) involved "other/unspecified narcotics" and no other type of opioid.

Figure 1 shows opioid-related deaths in the United States per 100,000 population by year. Figure 1 also shows heroin-related deaths (ICD-10 code T40.1) per 100,000 population and non-heroin opioid-related deaths (ICD10 codes T40.0, T40.2, T40.3, T40.4, and T40.6) per

100,000 population.[9] Non-heroin opioid-related mortality increased steadily during the period 1999-2010, peaked in 2011, and then began to decline. This decline is commonly attributed to the introduction of PDMPs and the crackdown on "pill mills" in Florida and elsewhere (Johnson et al. 2014; Griggs et al. 2015), but the adoption of GSLs and NALs could have played a role. Heroin-related mortality was relatively steady through most of the period under study, but exhibited a sharp increase from 2010-2014 as many users of prescription opioids switched to heroin.[10]

### 3.2. Empirical model

Our empirical methodology exploits temporal and geographic variation in the passage of NALs and GSLs to gain a better understanding of their effects. Specifically, we estimate the following baseline Poisson regression:

$$(1) \qquad \ln \lambda_{st} = \alpha_0 + \alpha_1 NAL_{st} + \alpha_2 GSL_{st} + \boldsymbol{X_{st}\beta} + v_s + w_t,$$

where $\lambda_{st}$ represents the expected number of opioid-related deaths in state s and year $t$.[11] The independent variables of interest are $NAL_{st}$ and $GSL_{st}$. $NAL_{st}$ is an indicator, equal to 1 if a NAL

[9] Counts of opioid overdose deaths published by the CDC are restricted to those with ICD-10 underlying cause-of-death codes X40–44 (unintentional), X60–64 (suicide), X85 (homicide), and Y10–Y14 (undetermined intent). See, for instance, Rudd et al. (2016). When we estimated equation (1) using opioid-related deaths with these underlying cause-of-death codes as the dependent variable, the results were very similar to those reported and discussed below.

[10] The evidence that users of prescription opioids switched to heroin as a response to the introduction of PDMPs and the crackdown on pill mills is largely anecdotal. See, for instance, Park and Bloch (2016) and Wilson (2016). There is stronger evidence that the reformulation of OxyContin in 2010, which made it much more difficult to abuse, also fueled the increase in heroin-related deaths (Alpert et al. 2017).

[11] See Cameron and Trivedi (1986) and Grootendorst (2002) for descriptions of the Poisson regression model. As noted by Card and Dahl (2011), an advantage of the Poisson regression model is that

was in effect in state *s* and year *t* (and equal to 0 otherwise). The indicator $GSL_{st}$ is defined analogously.[12] The inclusion of state fixed effects, represented by the term $v_s$, ensures that our estimates of $\alpha_1$ and $\alpha_2$ are identified using within-state variation. The year fixed effects, represented by $w_t$, account for common shocks to the opioid-related deaths caused by, for instance, the reformulation of OxyContin in 2010 or changes in drug enforcement priorities at the federal level.

Only one control, the natural log of population, is used in the baseline regression. In subsequent regressions, we add a PDMP indicator to the vector of controls, $\boldsymbol{X}_{st}$, equal to 1 if there was a PDMP operating in state *s* and year *t*. There is reasonably strong evidence that the implementation of a PDMP reduces opioid prescriptions and drug treatment admissions (Haegerich et al. 2014; Bao et al. 2016), although the evidence with regard to PDMPs and opioid-related deaths is decidedly mixed (Paulozzi et al. 2011; Reifler et al. 2012).

In the fully specified model, the vector of controls, $\boldsymbol{X}_{st}$, also includes the natural log of police officers per capita in state *s* and year *t*, an indicator for whether medical marijuana was legal, the natural log of the beer tax, the natural log of the cigarette tax, and the natural log of the unemployment rate.[13] Previous studies provide some evidence, albeit largely descriptive, of a

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including fixed effects does not lead to an incidental parameters problem. Appendix Table 1 provides descriptive statistics for the variables used in the analysis.

[12] When a naloxone access law was in effect for less than a full year, the indicator $NAL_{st}$ is a fraction. Likewise, when a Good Samaritan law was in effect for less than a full year, the indicator $GSL_{st}$ is a fraction. Tables 1 and 2 provide the exact date in which these laws came into effect.

[13] The fully specified model includes these controls as well as the natural log of beer taxes in state *s* and year *t*, the natural log of cigarette taxes, the natural log of the number of college graduates, the natural log of per capita income, and the natural log of the minimum wage. Information on PDMPs came from the National Alliance for Model State Drug Laws (http://www.namsdl.org/prescription-monitoring-programs.cfm) and Bao et al. (2016). Information on police per capita come from the Bureau of Justice Statistics; MML data come from Sabia et al. (2017) and the Marijuana Policy Project (2016). Beer tax data are obtained from the Beer Institute and cigarette tax data from *Tax Burden on Tobacco.* State-level

negative relationship between policing efforts and drug use (Cooper et al. 2005; Davis et al. 2005; Corsaro et al. 2013). There is also evidence that opioid users are at risk of using other substances, including alcohol and tobacco (Catalano et al. 2011; Fiellin et al. 2013; Bachhuber et al. 2014). Carpenter et al. (forthcoming) documented a substantial increase in substance use disorders involving opioids as a result of the Great Recession.

## 4. RESULTS

### 4.1. Baseline estimates

Table 3 presents Poisson estimates of equation (1) weighted by the population of state *s* in year *t*. Standard errors, reported in parentheses, are corrected for clustering at the state level. The baseline specification suggests that the adoption of a NAL is associated with an almost 11 percent decrease ($e^{-.113} - 1 = -.107$) in opioid-related deaths. The estimated effect of adopting a GSL on opioid-related deaths is of comparable magnitude, but is not statistically significant.

When we include the PDMP indicator as a control, the estimates of $\alpha_1$ and $\alpha_2$ become smaller, but the estimate of $\alpha_1$ remains significant: the adoption of a NAL is associated with a 9 percent decrease in opioid-related deaths. We show the results of including the full set of controls in the third column of Table 1. The estimates of $\alpha_1$ and $\alpha_2$ are not particularly sensitive to controlling for factors such as police officers per capita, the unemployment rate, and beer taxes.

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data on educational attainment are obtained from the Current Population Survey; per capita income data is obtained from the Bureau of Economic Analysis, unemployment data from the Bureau of Labor Statistics, and minimum wage data from the Bureau of Labor Statistics and the Tax Policy Center.

### 4.2. Robustness checks

In an effort to explore the sensitivity of our results, OLS estimates of equation (1) are reported in Table 4. In these regressions, the natural log of population is no longer included as a control, and the natural log of the opioid-related mortality rate in state *s* and year *t* replaces the natural log of $\lambda_{st}$.

The OLS estimates reported in Table 4 are, in general, larger than the Poisson estimates reported in Table 3, but they are less precise. For instance, according to the baseline specification, the adoption of a NAL is associated with a 13 percent decrease ($e^{-.142} - 1 = -.132$) in the opioid-related mortality rate. However, this estimate is not significant at the 10 percent level (p-value = 0.12). When all of the controls are included on the right-hand side, the adoption of a NAL is associated with a 17 percent decrease in the opioid-related mortality rate. Again, the GSL estimates are of comparable magnitude to the estimates of $\alpha_1$, but imprecise: in fact, the estimate of $\alpha_2$ exceeds its standard error only in the fully specified model in column (3).[14]

In Table 5, we present estimates of equation (1) augmented with mutually exclusive leads and lags of the NAL indicator. Consistent with the parallel trends assumption, there is little evidence that opioid-related mortality increased in the years leading up to NAL adoption. Before *Year 0* (the year of NAL adoption), estimates of the relationship between the NAL indicator and opioid-related mortality are small and statistically insignificant. The estimated effect in the year of adoption is larger in absolute magnitude but still insignificant. Significance is not reached until two or more years after adoption. The Poisson estimate suggests that, after two years, NAL adoption is associated with a 21 percent reduction in opioid-related deaths. The corresponding

[14] In Appendix Table 2, we report unweighted OLS and Poisson estimates of equation (1). The results are generally consistent with those discussed thus far: NALs are associated with a 10 percent decrease in opioid-related deaths and a 20 percent decrease in the opioid-related mortality rate. Negative binomial regressions produce quantitatively similar results when models converge.

OLS estimate suggests that, after two years, NAL adoption is associated with a 29 percent reduction in opioid-related deaths.

As a final robustness check, we present the results of a standard event-study analysis in Figure 2. Specifically, we present Poisson estimates obtained by regressing opioid-related deaths on an indicator for NAL adoption, its leads and lags, the natural log of population, 50 state indicators and 15 year indicators. Leading up to the year of adoption (*Year 0*), the Poisson estimates are insignificant relatively small. After one year, the adoption of a NAL is associated with a 6 percent decrease in opioid-related deaths, but this estimate is not significant (p-value = 0.37). After two or more years, adoption of a NAL is associated with a 22 percent decrease in opioid-related deaths.

## 5. EXTENSIONS

### 5.1. Heroin vs other opioids

Heroin overdoses and overdoes involving prescription opioids can both be successfully treated with naloxone (Boyer 2012). Nevertheless, there is evidence that naloxone is used to reverse heroin-related overdoses more often than it is used to reverse overdoses involving prescription opioids such as methadone and oxycodone. For instance, a survey of organizations that distribute naloxone kits conducted in 2014 found that fully 82 percent of overdose reversals involved heroin (Wheeler et al. 2015), perhaps because these organizations have, at least until recently, focused on serving heroin users, or because heroin users are more likely to receive and carry naloxone on their person than the users of prescription opioids.[15]

[15] According to Wheeler et al. (2015, p. 634), "early adopters of naloxone kit provision were mainly syringe exchanges", but these authors went on to note that "organizations providing naloxone kits are increasing rapidly" and that organizations that began operation recently were less likely to have been

In Table 6 we examine the effects of NALs and GSLs on heroin-related deaths and deaths involving opioids other than heroin. Although negative, the Poisson estimate of the effect of NALs on heroin-related deaths is relatively small and statistically insignificant. By contrast, the adoption of a NAL is associated with a 9 percent decrease in opioid-related deaths not involving heroin.[16] The OLS estimates are closer in magnitude, but the estimated effect of adopting a NAL on the heroin-related morality rate is not significant. The adoption of a GSL is associated with a 13 percent decrease in opioid-related deaths not involving heroin, and a 19 percent decrease in the non-heroin opioid-related morality rate. Taken together, the results reported in Table 6 suggest that NALs and GSLs may be more effective weapons in the fight against prescription opioid mortality than previously thought.

### 5.2. Alcohol and opioids

The combination of alcohol and opioids is especially dangerous (Gudin et al. 2013), but naloxone is not harmful to administer to someone suffering from alcohol poisoning, and it may in fact work as an antidote to alcohol poisoning (Badawy and Evans 1981; Wu et al. 2012).

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surveyed. Bennett et al. (2011), who surveyed drug users who had received naloxone kits and training from an overdose prevention program "targeted primarily to heroin users" (p. 1028), found that 92 percent of reversals involved heroin. Gaston et al. (2009) surveyed opioid users in Birmingham and London who had received naloxone kits and training. They found that most participants did not carry naloxone on their persons out of "fear of police engagement, and the awkwardness of carrying something bulky and unwieldy."

[16] However, we cannot reject the hypothesis that the estimated effect of adopting a NAL on heroin-related deaths is equal to the estimated effect of adopting a NAL on opioid-related deaths not involving heroin at conventional levels (p-value = 0.50).

Several GSLs provide immunity from prosecution for drug possession to those seeking medical assistance in the event of alcohol poisoning.[17]

In Table 7 we explore the effects of NALs and GSLs on deaths involving alcohol, deaths involving alcohol but not opioids, and deaths involving a combination of alcohol and opioids.[18] Although consistently negative, the estimated effects of NALs and GSLs on alcohol-related mortality are relatively small and not statistically significant. However, the Poisson regressions provide evidence that these laws lead to fewer deaths involving both alcohol and opioids. The adoption of a NAL is associated with a (statistically insignificant) 8 percent decrease in deaths involving both alcohol and opioids; the adoption of a GSL is associated with a 16 percent decrease in deaths involving both alcohol and opioids. This latter estimate is statistically significant at the 10 percent level. OLS estimates confirm this general pattern of results.

### 5.3. Exploring the effects of specific NAL provisions

As noted in the background section, 23 NALs adopted during the period 1999-2014 allowed standing orders, under which prescribers can authorize the distribution of naloxone to any laypersons deemed capable of administering it and to drug prevention programs (Wheeler et al. 2012; Davis et al. 2014; Green et al. 2015). Eleven NALs adopted during this same period

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[17] For instance, the GSL recently adopted by Arkansas defines a "drug overdose" as "an acute condition resulting from, or that a reasonable person would believe to be resulting from, the consumption or use of alcohol, a controlled substance, or dangerous drug, or a combination of alcohol, controlled substance, or dangerous drug …" GSLs adopted by Alaska, California, Florida, Illinois, Massachusetts, Pennsylvania, and Wisconsin during the period under study pertain specifically to drug/opioid overdoses.

[18] Deaths involving alcohol were defined as those with the following ICD-10 underlying cause-of-death codes: F10 (mental and behavioral disorders due to use of alcohol), G31.2 (degeneration of nervous system due to alcohol), G62.1 (alcoholic polyneuropathy), I42.6 (alcoholic cardiomyopathy), K29.2 (alcoholic gastritis), K70 (alcoholic liver disease), R78.0 (finding of alcohol in blood), X45 (accidental poisoning by and exposure to alcohol), X65 (intentional self-poisoning by and exposure to alcohol), and Y15 (poisoning by and exposure to alcohol, undetermined intent).

removed criminal liability for possession of naloxone without a prescription. In Table 8 we explore the effects of these two provisions by estimating the following Poisson regression:

(2) $\ln \lambda_{st} = \pi_0 + \pi_1 NAL_{st} + \pi_2 NAL_{st} \text{ x } Standing\ Order_{st} + \pi_3 NAL_{st} \text{ x } Possession_{st} + \pi_4 GSL_{st} + \boldsymbol{X_{st}\beta} + v_s + w_t,$

where $\lambda_{st}$ represents the expected number of opioid-related deaths in state s and year $t$. In addition to reporting estimates of equation (1), we report OLS estimates the effects of these provisions on the opioid-related mortality rate.

The Poisson estimates of $\pi_1$ and $\pi_2$ are, without exception, statistically insignificant. By contrast, removing criminal liability for possession of naloxone is associated with a 13 percent decrease in the number of opioid-related deaths. It is also associated with a 13 percent decrease in the number of deaths involving opioids other than heroin.

The OLS estimates of $\pi_1$ are large and negative across the board, and two out of three are statistically significant: NALs that neither provide for standing orders nor remove criminal liability for possession of naloxone are associated with a 17 percent decrease in the opioid-related mortality rate and a 14 percent decrease in the non-heroin opioid-related mortality rate. While the OLS estimates of $\pi_2$ and $\pi_3$ are generally imprecise, removing criminal liability for possession of naloxone is associated with an additional 16 percent decrease in the non-heroin opioid-related morality rate.[19]

[19] In Appendix Table 3 we provide Poisson and OLS estimates of an equation in which we interact the GSL indicator with three separate indicators: the first for whether the GSL includes immunity from prosecution for possession of alcohol, the second for whether it includes immunity for possession of drug paraphernalia, and the third for whether it includes immunity for parole violations. The results are, in general, messy, perhaps due to sufficient independent variation. Several estimated coefficients are large

### 5.4. Non-prescription use of prescription painkillers

Finally, we explore whether there is evidence of moral hazard associated with the adoption of NALs and GSLs. For this task, we turn to state-level data on recreational (i.e., non-prescription) prescription pain reliever use from the National Survey of Drug Use and Health (NSDUH). These data are publicly available and cover the period 2003-2014.[20]

In Table 9, we report OLS estimates of the effects of NALs and GSLs on the recreational use of prescription pain relievers.[21] These estimates provide little evidence that either NALs or GSLs lead to changes in the recreational use of prescription painkillers. NALs are associated with small, statistically insignificant changes in the recreational use of prescription pain relievers.[22] For GSLs, the estimated effects are also insignificant and are negative in two out of three specifications (columns 2 and 3). Together, the results in Table 9 provide little evidence that NALs or GSLs generate moral hazard.

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positive, while others are of equal magnitude, but negative. Given these results, we chose to focus on the NAL provisions.

[20] For more information on the NSDUH data see the Substance Abuse and Mental Health Services Administration. The data are available at: https://www.samhsa.gov/data/population-data-nsduh

[21] Publicly available state-level data on the rate of non-prescription pain reliever use are available for 12-17 year-olds, 18-25 year-olds, and those ages 26 and older for the years 2003-2004, 2005-2006, 2007-2008, 2009-2010, 2011-2012, and 2013-2014. The dependent variable is the natural log of the state-specific rate of non-prescription use of prescription painkillers by age group. Controls include those listed in column (3) of Table 4.

[22] Estimates are precise enough to rule out, with 90 percent confidence, NAL-induced increases in the rate of prescription pain reliever use of greater than 8.2 percent for 12-17 year-olds, 1.0 percent for 18-25 year-olds, and 12.3 percent for those ages 26 and older.

## 6. CONCLUSION

To date, 34 states and the District of Columbia have adopted Good Samaritan Laws (GSLs), which provide immunity from prosecution for possession of a controlled substance to anyone who calls for emergency medical assistance. Forty-five states and the District of Columbia have adopted Naloxone Access Laws (NALs), which allow lay persons to administer and distribute naloxone without fear of legal repercussions. Although they clearly enjoy broad support these laws have received little scrutiny from academic researchers. In fact, next to nothing is known about their impact on outcomes of interest to policymakers, the public, and social scientists.

The current study draws on data from the National Vital Statistics System multiple cause-of-death mortality files for the period 1999-2014 to explore the effects of GSLs and NALs on opioid-related deaths. The estimated effects of GSLs on opioid-related deaths are often large and are consistently negative, but not statistically significant at conventional levels. By contrast, we find evidence that the adoption of a NAL leads to a reduction in opioid-related deaths of 9 to 11 percent. Two or more years after the adoption of a NAL, this effect appears to be stronger: on average, NAL adoption is associated with a 21 percent reduction in opioid-related deaths. Although opponents argue that NALs could encourage recreational opioid use (Sledge 2014; Tesfaye 2016), this effect (if it exists) is clearly outweighed by their intended use as an antidote to opioid overdoses in emergency situations.

We also find evidence that the relationship between NALs and opioid-related deaths that do not involve heroin is stronger than the relationship between NALs and heroin-related deaths. Specifically, we find that, although negative, the Poisson estimate of the effect of NALs on heroin-related deaths is small and statistically insignificant, while the adoption of a NAL is associated with a 9 percent decrease in opioid-related deaths not involving heroin. Finally, our results suggest that removing criminal liability for possession of naloxone is an important feature of these laws. Removing criminal liability for possession of naloxone is associated with a 13 percent reduction in opioid-related deaths, while Poisson estimates of the effect of NALs without this provision are considerably smaller and statistically indistinguishable from zero.

Although only a handful of states have failed to adopt some version of a NAL, there are other barriers to making naloxone available to those who need it. For instance, according to data collected by Truven Health Analytics, the cost of naloxone has risen dramatically in the past decade, from $0.92 per dose to more than $15 per dose (Jacobs 2016). Apparently, the auto-injector version of naloxone now costs more than $2,000 per dose! If these trends continue, it is not clear whether NALs will continue to be as effective at reducing opioid-related deaths as they have been in the past.

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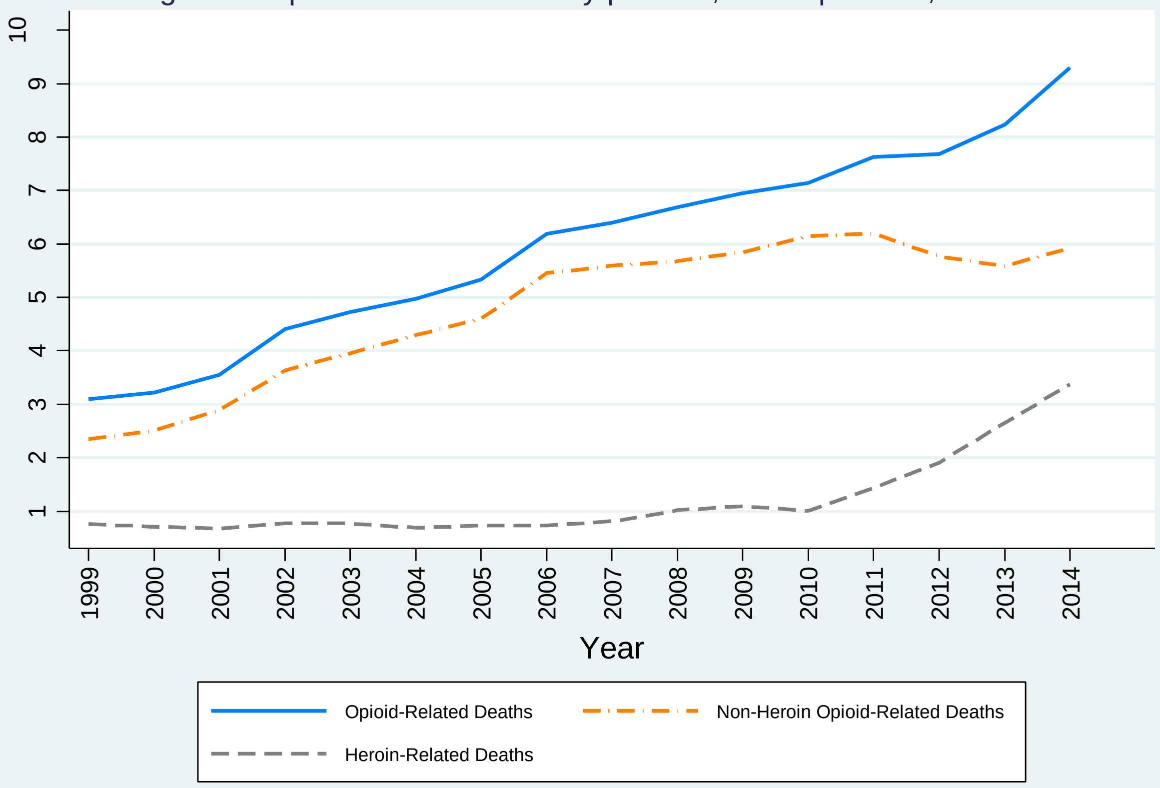
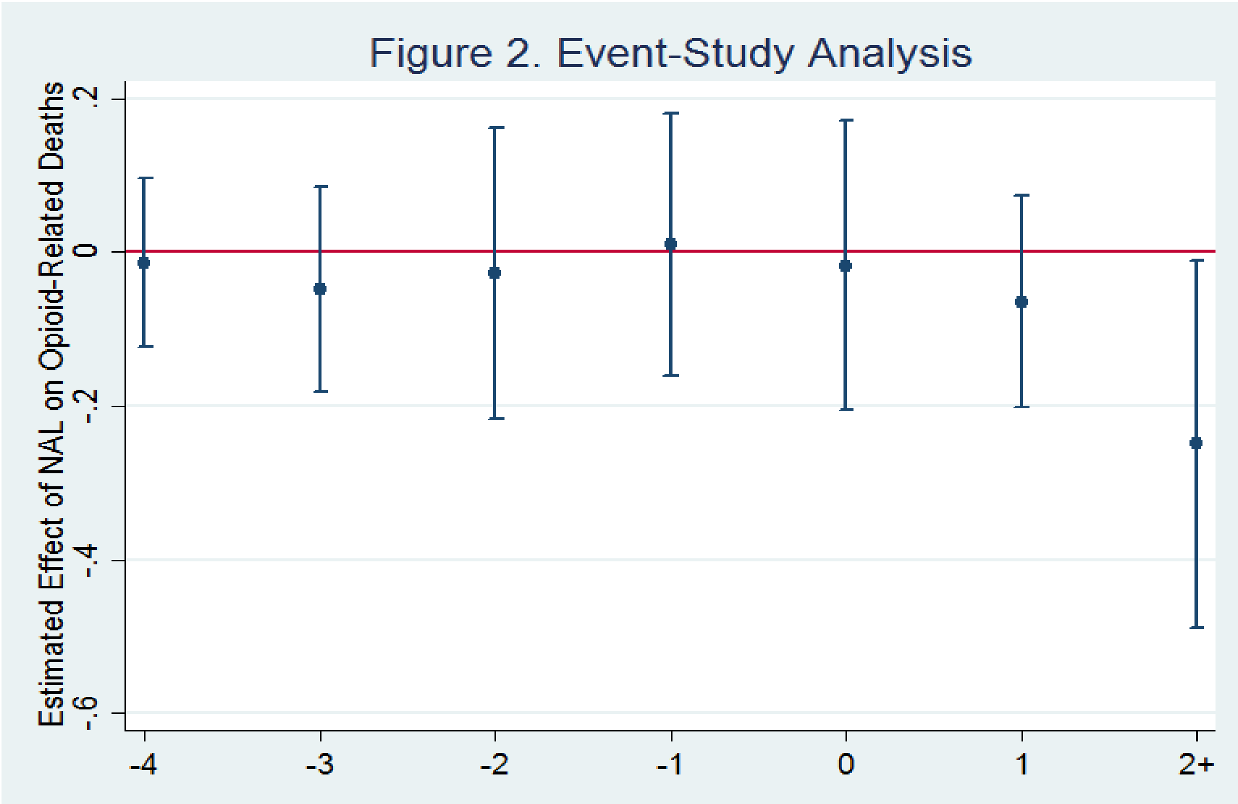
Figure 1. Opioid-Related Mortality per 100,000 Population, 1999-2014






Notes: Population-weighted estimates and 95% confidence intervals from a Poisson regression of opioid-related deaths on the natural log of the population, 15 year indicators, and 50 state indicators are reported. Data are at the state-year level and cover the period 1999-2014.

**Table 1. Effective Dates of NALs, 1999-2014**

| State | NAL date | NAL Provisions: Standing Order | NAL Provisions: Removal of Criminal Liability for Naloxone Possession |
|---|---|---|---|
| | | (Y/N) | (Y/N) |
| California | January 1, 2008 | Y | Y |
| Colorado | May 10, 2013 | Y | N |
| Connecticut | October 1, 2003 | N | N |
| Washington, D.C. | March 19, 2013 | N | Y |
| Delaware | August 4, 2014 | Y | N |
| Georgia | April 24, 2014 | Y | N |
| Illinois | January 1, 2010 | Y | Y |
| Kentucky | June 25, 2013 | Y | Y |
| Maine | April 29, 2014 | Y | N |
| Maryland | October 1, 2013 | Y | N |
| Massachusetts | August 2, 2012 | Y | Y |
| Michigan | October 14, 2014 | N | N |
| Minnesota | May 10, 2014 | Y | Y |
| New Jersey | July 1, 2013 | Y | Y |
| New Mexico | April 3, 2001 | Y | Y |
| New York | June 24, 2014 | Y | Y |
| North Carolina | April 9, 2013 | Y | N |
| Ohio | March 11, 2014 | Y | N |
| Oklahoma | November 1, 2013 | N | N |
| Oregon | June 6, 2013 | Y | N |
| Pennsylvania | November 29, 2014 | Y | N |
| Rhode Island | June 18, 2012 | Y | Y |
| Tennessee | July 1, 2014 | Y | N |
| Utah | May 13, 2014 | Y | N |
| Vermont | July 1, 2013 | Y | Y |
| Virginia | July 1, 2013 | Y | N |
| Washington | June 10, 2010 | Y | Y |
| Wisconsin | April 9, 2014 | Y | Y |

Notes: NALs have been adopted by 18 states since 2014: Alabama, Alaska, Arkansas, Florida, Hawaii, Idaho, Indiana, Iowa, Louisiana, Mississippi, Nebraska, New Hampshire, Nevada, North Dakota, South Carolina, South Dakota, Texas, and West Virginia. The standing order provision in Maryland was implemented in 2015.

**Table 2. Effective Dates of GSLs, 1999-2014**

| State | GSL date | GSL Provisions: Protection Extends to Alcohol | GSL Provisions: Protection Extends to Drug Paraphernalia |
|---|---|---|---|
| | | (Y/N) | (Y/N) |
| Alaska | October 8, 2014 | N | N |
| California | January 1, 2013 | N | Y |
| Colorado | May 29, 2012 | N | Y |
| Connecticut | October 1, 2011 | N | Y |
| Washington, D.C. | March 19, 2013 | Y | Y |
| Delaware | August 31, 2013 | N | Y |
| Florida | October 1, 2012 | N | N |
| Georgia | April 24, 2014 | N | Y |
| Illinois | June 1, 2012 | N | N |
| Louisiana | August 1, 2014 | N | N |
| Maryland | October 1, 2014 | Y | Y |
| Massachusetts | August 2, 2012 | N | N |
| Minnesota | July 1, 2014 | N | Y |
| New Jersey | May 2, 2013 | N | Y |
| New Mexico | June 15, 2007 | N | N |
| New York | September 18, 2011 | Y | Y |
| North Carolina | April 9, 2013 | N | Y |
| Pennsylvania | December 1, 2014 | N | Y |
| Rhode Island | June 18, 2012 | N | Y |
| Utah | March 20, 2014 | N | Y |
| Vermont | June 5, 2013 | Y | N |
| Washington | June 10, 2010 | Y | N |
| Wisconsin | April 9, 2014 | N | Y |

Notes: GSLs have been adopted by 12 states since 2014: Alabama, Arkansas, Hawaii, Kentucky, Mississippi, New Hampshire, Nevada, North Dakota, Oregon, Tennessee, Virginia, and West Virginia.

**Table 3. Poisson Estimates of the Effects of Naloxone Administration Laws (NALs) and Good Samaritan Laws (GSLs) on Opioid-Related Deaths**

| | (1) | (2) | (3) |
|---|---|---|---|
| *NAL* | -0.113** | -0.097* | -0.095** |
| | (0.057) | (0.055) | (0.038) |
| *GSL* | -0.134 | -0.127 | -0.137 |
| | (0.106) | (0.104) | (0.087) |
| *PDMP* | | -0.052 | -0.058 |
| | | (0.068) | (0.040) |
| *Log (Police Per Capita)* | | | 0.516** |
| | | | (0.224) |
| *MML* | | | 0.081 |
| | | | (0.091) |
| *Log (Beer Tax)* | | | 0.156** |
| | | | (0.074) |
| *Log (Cigarette Tax)* | | | 0.058 |
| | | | (0.054) |
| *Log (College Graduates)* | | | -0.318 |
| | | | (0.685) |
| *Log (Per Capita Income)* | | | -0.504 |
| | | | (1.16) |
| *Log (Unemployment Rate)* | | | 0.075 |
| | | | (0.195) |
| *Log (Minimum Wage)* | | | -0.043 |
| | | | (0.249) |
| *Log (Population)* | -2.27*** | -2.21*** | -2.41*** |
| | (0.688) | (0.746) | (0.858) |
| N | 816 | 816 | 816 |

***Statistically significant at the 1% level; **at the 5% level; *at the 10% level

Notes: Population-weighted estimates from Poisson regressions are reported. Data are at the state-year level and cover the period 1999-2014. All regressions include 15 year indicators and 50 state indicators (including an indicator for Washington DC). Standard errors are in parentheses and are corrected for clustering at the state level.

**Table 4. OLS Estimates of the Effects of Naloxone Administration Laws (NALs) and Good Samaritan Laws (GSLs) on ln(Opioid-Related Mortality Rate)**

| | (1) | (2) | (3) |
|---|---|---|---|
| *NAL* | -0.142 | -0.157 | -0.188* |
| | (0.097) | (0.097) | (0.098) |
| *GSL* | -0.134 | -0.137 | -0.157 |
| | (0.135) | (0.143) | (0.133) |
| *PDMP* | | .072 | 0.048 |
| | | (.096) | (0.082) |
| *Log (Police Per Capita)* | | | 0.423 |
| | | | (0.473) |
| *MML* | | | 0.118 |
| | | | (0.128) |
| *Log (Beer Tax)* | | | 0.177** |
| | | | (0.083) |
| *Log (Cigarette Tax)* | | | 0.023 |
| | | | (0.060) |
| *Log (College Graduates)* | | | -0.484 |
| | | | (0.670) |
| *Log (Per Capita Income)* | | | 0.114 |
| | | | (1.05) |
| *Log (Unemployment Rate)* | | | 0.286 |
| | | | (0.189) |
| *Log (Minimum Wage)* | | | -0.417 |
| | | | (0.295) |
| R-squared | 0.80 | 0.80 | 0.81 |
| N | 816 | 816 | 816 |

***Statistically significant at the 1% level; **at the 5% level; *at the 10% level

Notes: Population-weighted OLS estimates are reported. Data are at the state-year level and cover the period 1999-2014. The dependent variable is equal to the natural log of the opioid-related mortality rate. All regressions include 15 year indicators and 50 state indicators (including an indicator for Washington DC). Standard errors are in parentheses and are corrected for clustering at the state level.

**Table 5. Opioid-Related Mortality Before and After NAL Adoption**

| | Poisson | ln(Rate) |
|---|---|---|
| *4 Years before NAL* | 0.027 | -0.002 |
| | (0.048) | (0.087) |
| *3 Years before NAL* | -0.032 | -0.023 |
| | (0.059) | (0.088) |
| *2 Years before NAL* | -0.036 | 0.004 |
| | (0.079) | (0.109) |
| *1 Year before NAL* | -0.037 | -0.001 |
| | (0.073) | (0.116) |
| *Year 0* | -0.059 | -0.073 |
| | (0.090) | (0.143) |
| *1 Year after NAL* | -0.097 | -0.136 |
| | (0.085) | (0.119) |
| *2+ Years after NAL* | -0.240** | -0.351** |
| | (0.111) | (0.206) |
| R-squared | -- | 0.81 |
| N | 816 | 816 |

***Statistically significant at the 1% level; **at the 5% level; *at the 10% level

Notes: Population-weighted estimates from a Poisson regression are reported in the first column, and population-weighted OLS estimates are reported in the second column. Data are at the state-year level and cover the period 1999-2014. Both regressions include 15 year indicators and 50 state indicators (including an indicator for Washington DC). See the third column of Tables 3 and 4 for a full list of controls. Standard errors are in parentheses and are corrected for clustering at the state level.

**Table 6. Estimates of the Effects of NALs on Heroin-Related Mortality vs. Mortality Related to Other Opioids**

| | Heroin | | Other Opioids | |
|---|---|---|---|---|
| | Poisson | ln(Rate) | Poisson | ln(Rate) |
| NAL | -0.047<br>(0.124) | -0.165<br>(0.311) | -0.096**<br>(0.048) | -0.198***<br>(0.055) |
| GSL | 0.043<br>(0.117) | -0.144<br>(0.300) | -0.132*<br>(0.076) | -0.207**<br>(0.078) |
| R-squared | -- | 0.67 | -- | 0.94 |
| N | 816 | 816 | 816 | 816 |

***Statistically significant at the 1% level; **at the 5% level; *at the 10% level

Notes: Population-weighted Poisson and OLS estimates and reported. Data are at the state-year level and cover the period 1999-2014. All regressions include 15 year indicators and 50 state indicators (including an indicator for Washington DC). See the third column of Tables 3 and 4 for a full list of controls. Standard errors are in parentheses and are corrected for clustering at the state level.

**Table 7. Estimates of the Effects of NALs and GSLs on Alcohol-Related Mortality, Mortality Related to Alcohol but not Opioids, and Mortality Related to both Alcohol and Opioids.**

| | Alcohol-Related | | Alcohol, No Opioid | | Alcohol + Opioid | |
|---|---|---|---|---|---|---|
| | Poisson | ln(Rate) | Poisson | ln(Rate) | Poisson | ln(Rate) |
| NAL | -0.036 | -0.040 | -0.032 | -0.042 | -0.083 | -0.213* |
| | (0.023) | (0.025) | (0025) | (0.030) | (0.056) | (0.117) |
| GSL | -0.026 | -0.019 | -0.019 | -0.008 | -0.169* | -0.221* |
| | (0.026) | (0.029) | (0.027) | (0.033) | (0.101) | (0.116) |
| R-squared | -- | 0.99 | -- | 0.99 | -- | 0.88 |
| N | 816 | 816 | 816 | 816 | 816 | 816 |

***Statistically significant at the 1% level; **at the 5% level; *at the 10% level

Notes: Population-weighted Poisson and OLS estimates and reported. Data are at the state-year level and cover the period 1999-2014. All regressions include 15 year indicators and 50 state indicators (including an indicator for Washington DC). See the third column of Tables 3 and 4 for a full list of controls. Standard errors are in parentheses and are corrected for clustering at the state level.

**Table 8. Heterogeneity in Effects of NALs and GSLs on Opioid-Related Mortality**

| | All Opioids | | Heroin | | Non-Heroin | |
|---|---|---|---|---|---|---|
| | Poisson | ln(Rate) | Poisson | ln(Rate) | Poisson | ln(Rate) |
| NAL | -0.043<br>(0.041) | -0.176***<br>(0.080) | 0.006<br>(0.087) | -0.228<br>(0.206) | -0.045<br>(0.037) | -0.146**<br>(0.059) |
| NAL – Standing Order | 0.015<br>(0.071) | 0.169<br>(0.117) | 0.091<br>(0.165) | 0.598<br>(0374) | -0.015<br>(0.067) | 0.073<br>(0.073) |
| NAL – Remove Criminal Liability for Possession | -0.134***<br>(0.051) | -0.128<br>(0.091) | -0.169<br>(0.116) | -0.202<br>(0.271) | -0.134**<br>(0.059) | -0.164***<br>(0.056) |
| GSL | -0.101<br>(0.089) | -0.150<br>(0.144) | 0.070<br>(0.118) | -0.192<br>(0.315) | -0.098<br>(.0.080) | -0.173**<br>(0.085) |
| R-squared | -- | 0.81 | -- | 0.87 | -- | 0.94 |
| N | 816 | 816 | 816 | 816 | 816 | 816 |

***Statistically significant at the 1% level; **at the 5% level; *at the 10% level

Notes: Population-weighted Poisson and OLS estimates and reported. Data are at the state-year level and cover the period 1999-2014. All regressions include 15 year indicators and 50 state indicators (including an indicator for Washington DC). See the third column of Tables 3 and 4 for a full list of controls. Standard errors are in parentheses and are corrected for clustering at the state level.

**Table 9. OLS Estimates of the Effects of NALs and GSLs on Non-Prescription Use of Prescription Painkillers, NSDUH, 2003-2014**

| | *Ages 12-17* | *Ages 18-25* | *Ages 26+* |
|---|---|---|---|
| NAL | 0.026 | -0.001 | 0.016 |
| | (0.032) | (0.007) | (0.061) |
| GSL | 0.010 | -0.002 | -0.033 |
| | (0.030) | (0.004) | (0.052) |
| Mean Dep Var | 0.063 | 0.110 | 0.034 |
| $R^2$ | 0.90 | 0.81 | 0.70 |
| N | 306 | 306 | 306 |

***Significant at 1% level; **at 5% level; *at 10% level

Notes: Population-weighted OLS estimates reported using state-level data from the 2003-2014 National Survey of Drug Use and Health (NSDUH). The dependent variable is equal to the natural log of the state-specific rate of recreational use of prescription painkillers. All regressions include 5 indicators for NSDUH survey years and 50 state indicators (including an indicator for Washington DC). See the third column of Table 4 for a full list of controls. Standard errors are in parentheses and are corrected for clustering at the state level.

# Appendix Tables

**Appendix Table 1. Weighted Means and Standard Deviations of Variables**

| *Variable* | *Mean (StDev)* |
|---|---|
| *Opioid Deaths* | 715.1<br>(556.4) |
| *Heroin Deaths* | 155.5<br>(169.3) |
| *Non-Heroin Opioid Deaths* | 559.5<br>(438.8) |
| *Alcohol Deaths* | 2,020.8<br>(1,989.9) |
| *Alcohol Deaths Without Opioids* | 1,900.5<br>(1,903.3) |
| *Alcohol Deaths With Opioids* | 120.3<br>(101.8) |
| *NAL* | 0.119<br>(0.312) |
| *GSL* | 0.076<br>(0.254) |
| *PDMP* | 0.265<br>(0.434) |
| *Police Per 100,000 Population* | 2.34<br>(0.622) |
| *MML* | 0.232<br>(0.419) |
| *Beer Tax (2014 $)* | 0.293<br>(0.226) |
| *Cigarette Tax (2014 $)* | 1.13<br>(0.842) |
| *College Graduates* | 0.288<br>(0.050) |
| *Per Capita Income (2014 $)* | 43,776.65<br>(6,077.03) |
| *Unemployment Rate* | 6.31<br>(2.14) |
| *Minimum Wage (2014 $)* | 7.46<br>(0.775) |
| N | 816 |

**Appendix Table 2. Unweighted Estimates of the Effects of NALs and GSLs on Opioid-Related Mortality**

| | **All Opioids** | | **Heroin** | | **Non-Heroin** | |
|---|---|---|---|---|---|---|
| | Poisson | ln(Rate) | Poisson | ln(Rate) | Poisson | ln(Rate) |
| NAL | -0.110* | -0.228** | -0.036 | -0.087 | -0.115** | -0.237*** |
| | (0.059) | (0.098) | (0.126) | (0.283) | (0.050) | (0.064) |
| GSL | -0.141* | -0.081 | 0.013 | -0.054 | -0.192*** | -0.185** |
| | (0.076) | (0.100) | (0.131) | (0.278) | (0.065) | (0.068) |
| R-squared | -- | 0.83 | -- | 0.86 | -- | 0.94 |
| N | 816 | 816 | 816 | 816 | 816 | 816 |

***Statistically significant at the 1% level; **at the 5% level; *at the 10% level

Notes: Notes: Population-weighted Poisson and OLS estimates and reported. Data are at the state-year level and cover the period 1999-2014. All regressions include 15 year indicators and 50 state indicators (including an indicator for Washington DC). See the third column of Tables 3 and 4 for a full list of controls. Standard errors are in parentheses and are corrected for clustering at the state level.

**Appendix Table 3. Heterogeneity in Effects of NALs and GSLs on Opioid-Related Mortality**

| | All Opioids | | Heroin | | Non-Heroin | |
|---|---|---|---|---|---|---|
| | Poisson | ln(Rate) | Poisson | ln(Rate) | Poisson | ln(Rate) |
| NAL | -0.034<br>(0.045) | -0.178**<br>(0.079) | -0.053<br>(0.084) | -0.286<br>(0.206) | -0.011<br>(0.036) | -0.131**<br>(0.053) |
| NAL –Standing Order | 0.147<br>(0.138) | 0.147<br>(0.138) | 0.267<br>(0.196) | 0.808**<br>(0378) | -0.102*<br>(0.057) | -0.020<br>(0.079) |
| NAL – Remove Criminal Liability for Possession | -0.116***<br>(0.042) | -0.112<br>(0.100) | -0.195*<br>(0.107) | -0.254<br>(0.219) | -0.121***<br>(0.043) | -0.133**<br>(0.058) |
| GSL | -0.252*<br>(0.109) | -0.271<br>(0.186) | 0.316*<br>(0.189) | -0.145<br>(0.482) | -0.297***<br>(0.054) | -0.316***<br>(0.082) |
| GSL – Drug Paraphernalia | 0.212**<br>(0.083) | 0.159<br>(0.173) | -0.540***<br>(0.177) | -0.451<br>(0.424) | 0.378***<br>(0.051) | 0.314***<br>(0.069) |
| GSL – Parole/Probation Violation | 0.207**<br>(0.092) | 0.241<br>(0.161) | 0.272<br>(0.237) | 0.847*<br>(0.471) | 0.071<br>(0.091) | 0.091<br>(0.128) |
| GSL – Alcohol Protection | 0.030<br>(0.101) | 0.047<br>(0.185) | 0.425***<br>(0.126) | 0.655**<br>(0.299) | -0.115<br>(0.083) | -0.171<br>(0.122) |
| R-squared | -- | 0.81 | -- | 0.88 | -- | 0.94 |
| N | 816 | 816 | 816 | 816 | 816 | 816 |

***Statistically significant at the 1% level; **at the 5% level; *at the 10% level

Notes: Population-weighted Poisson and OLS estimates and reported. Data are at the state-year level and cover the period 1999-2014. All regressions include 15 year indicators and 50 state indicators (including an indicator for Washington DC). See the third column of Tables 3 and 4 for a full list of controls. Standard errors are in parentheses and are corrected for clustering at the state level.