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The Effect of Good Samaritan Laws (GSL) on Opioid Overdose Mortality

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Abstract

This paper investigates the effects of Good Samaritan Laws on opioid overdose mortality rates in the United States. Evaluating policy interventions in response to upticks in opioid mortality is crucial to enact federal legislation that protects communities. However, concerns about moral hazard implications could have profound impacts on current efforts to combat the epidemic. This paper will look at various policies proposed and evaluate the effects of such policies on overall mortality rates, elucidating the moral hazard effects of Good Samaritan Laws.

Keywords

Opioid Epidemic, health policy, health economics

Cover Page Footnote

Dr. Christopher Cornwell's guidance was critical for the empirical work in this manuscript.

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I. Introduction

The opioid crisis has claimed over 72,000 American lives due to overdose in 2017 alone, a two-fold increase in a decade (Center for Disease Control). This public health emergency has led to various policy changes at the state level including the incorporation of Good Samaritan Laws (GSL), Standing Order Prescription Laws (SOL), prescription drug monitoring programs (PDMP), and the expansion of Medication Assisted Treatment (MAT) facilities into legislation. While various studies look at the effect of each of these policies, variations in controls, sample sizes, years, and metrics used have led to disagreeing opinions on the effectiveness and impacts of these policies (Doleac and Mukherjee, Rees et al). Discrepancies in Medicaid expansion policies and reimbursements for opioid use disorder (OUD) treatment further compound the error in comparing the effects of these policies between states. Furthermore, many states passed packaged legislation with more than one of these policies at the same time, making it difficult to parse out individual effects from the effects of the aggregate package (Prescription Drug Abuse Policy System). GSL offers legal protection for individuals who provide reasonable medical care to someone who they believe is ill or incapacitated. These types of laws protect an individual from prosecution if they administer naloxone, an opioid antagonist that reverses the effects of an opioid overdose, without mal-intent. SOL allows a layperson to obtain naloxone from a pharmacy without a medical

prescription, while PDMP monitors the number of opioids that a doctor prescribes to a patient. While SOL was implemented specifically to reduce overdose mortality rates, GSL encompasses a wider mandate for any treatment by a layperson, including performing CPR after cardiac arrests or inducing vomiting after alcohol poisoning. However, an unintended consequence of GSL policies could be an increased rate of overdose, since individuals with OUD may abuse an opioid, knowing that a family member or layperson with access to naloxone can deliver life-saving treatment and not face legal challenges (Doleac and Mukherjee). This adverse effect led to questions concerning the moral hazard of GSL and SOL, which other studies seek to evaluate (Doleac and Mukherjee, Rees et al). This paper looks at the impact of GSL on age-adjusted opioid overdose mortality rates from 1999-2017, building upon the current literature, while controlling for population density, census region, national age-adjusted opioid mortality rate, and state unemployment rates.

II. Empirical Question and Relevant Background

This paper seeks to evaluate whether there is statistical validity to the question of moral hazard in the incorporation of only GSL into state legislation. While SOL was used as a control to verify the effects of GSL, this paper primarily focuses on the moral hazard components of GSL. Oftentimes, SOL was packaged with other opioid relief related legislation, while GSL would be passed independently. Understanding the effects of these policies could have drastic effect on standard operating procedure for state legislators to take action to better combat the opioid crisis through risk mitigation strategies. The primary sources of data for this study comes from the Center for Disease Control's (CDC) National Vital Statistics System multiple cause of deaths from the years 1999-2017, accessed in April 2019. Additional sources containing state unemployment rates came from the Bureau of Labor Statistics for 1999-2017, accessed in April 2019. Finally, information

about the status of GLS and SOL laws per state comes from the Prescription Drug Abuse Policy System, accessed in April 2019. If the model indicates that there is a positive association between GLS with age-adjusted opioid mortality rates, then these results could suggest some moral hazard effects in public health policy.

III. Empirical Model and Estimation

Based on the aggregates of these datasets, this paper used longitudinal data, state-based policies, and the national age-adjusted opioid mortality rate to create the following predictive model for the age-adjusted opioid mortality rate per state.

Base Model:

$$ageadj = \beta_0 + \beta_1 SOL + \beta_2 GSL + \beta_3 nageadj + \beta_4 cnum + \beta_5 popden + \beta_6 unemp + \alpha_i + \mu_i$$

This model sets up the age-adjusted rate opioid mortality rate ($ageadj$) as the dependent variable, while examining the treatment of Good Samaritan Laws (GSL). *GSL* and *SOL* were binary variables given a value of 0 if the state did not have the treatment in effect in a particular year and a 1 if the treatment was instituted. The designation of when a treatment was instituted was determined by the year when the legislation was passed and signed into law by the governor for each state. A more robust model might have delayed the effect of the treatment by a year to evaluate the treatment once it was fully implemented. *SOL* was included as a control to determine whether the potential moral hazard impact was due to *GSL* or *SOL.* Since Standing Order Laws were often packaged with other pieces of opioid relief legislation, it would have been difficult to parse out the individual effects of these laws without including controls for PDMP and Medicaid expansion. However, since this paper looks only at the effects of GSL while controlling for SOL, it avoids

over-controlling the model. The national age-adjusted opioid mortality rate (*nageadj)* was used as a control to ensure that changes in mortality rates within the states were due to the treatment effects rather than national trends or the enactment of federal policies i.e. expansions of cannabis dispensaries, roll backs of stringent policing, Medicaid expansion, and the passage of the Patient Protection and the Affordable Care Act (ACA), commonly referred to as Obamacare. Changes in federal policy would impact aggregate state mortality rates, which would influence national rates. That control is critical to ensure that changes in the age-adjusted opioid mortality rate were due to the treatment of GSL rather than federal policies. Variations in census regions such as regional differences in the Midwest versus the South were also controlled for by *cnum.* Literature indicates that regional differences including prominent industries in the area and licensing laws could have effects on opioid overdose mortality rates (Doleac and Muckherjee). A control for census region ensures that states with similar political and economic systems are compared with one another. Population density was also included as a control (*popden)*, since urban areas tend to have higher mortality rates, even though rural areas are more likely to be federally deemed 'high risk' areas (Doleac and Muckherjee). Finally, a control for state unemployment (*unemp)* from 1999-2017 was included, since the 2008 recession, unemployment rates particularly in manufacturing and mining sectors, and the opioid crisis are intertwined in a variety of ways including psychological effects, closures of detoxification centers, and reduction of public health spending (Brown and Wehby). The a_i considers the unobserved effects in the fixed effects model, which will be described later, while the u_i considers all error in the model such as other legislations passed in the package along with GSL.

Furthermore, omitted variable bias played an important role in the model, since state level education levels, law enforcement budgets, and other opioid related policies were not included. However, the controls sought to reduce omitted variable bias, since many of the previously mentioned factors probably effected the national age-adjusted opioid mortality rate or were included in SOL legislation. Specifying the variables included was critical to promote unbiased estimators, while minimizing omitted variable bias. This model also assumes a linear relationship between the dependent and independent variables and no perfect multicollinearity under Gauss Markov assumptions. Both these parameters probably introduce some measurement error into the model. The standard errors are included in the regression table to account for heteroscedasticity.

While the pooled OLS might be the appropriate model when run with panel data, unobserved heterogeneity is most likely present, due to state specific variations, and is most likely correlated with some observed variable. Fixed Effects (FE) exploits within-group variation across longitudinal trends to offer a more consistent and precise estimation. When the FE was used, the dummy variable *i.YearCode* was included in the base model to tease out the effects of specific years on the model.

IV. Data

Since the data were derived from various federal agencies and the legislation enacted from state legislators, it is most likely accurate and close approximations to reality. The inclusion of trends such as heart attack rates or motor vehicle accidents should have been incorporated into the model to ensure that the treatment affected only the dependent variable. If GSL led to significant reductions in either of the aforementioned factors, the model would not be valid. In this paper, opioid overdose mortality rates were determined by any overdose mortality rate due to opium,

heroin, prescription opioids, non-prescription opioids, and synthetic opioids. The only unreliable rates were from North Dakota in 2002, 2003, 2006, and 2007. These four years were removed from the data set, which lead to an unbalanced panel. However, since the rest of the observations are still intact, the model is still reliably robust. The age-adjusted mortality rate was used for both the state and national averages, since it allows for comparisons based on underlying age structures and prevents conclusions based on differing age distributions of the populations between states.

V. Results

It is important to contextualize the policies along a longitudinal time frame, therefore, figure 1 plots the age-adjusted opioid overdose mortality rate over time. This indicates that in all 50 states and the District of Columbia, the mortality rate has increased from 1999-2017. This trend highlights the variance in mortality between states but also identifies the increased national average. The graphs are labeled as Federal Information Processing Standard state codes (FIPS), which can be identified alphabetically i.e. graph 1 is Alabama, while graph 56 represents Wyoming. Gaps in the graphs are due to exclusion of American Samoa, Puerto Rico etc. from the CDC vital statistics report. All government data collection agencies follow the FIPS state codes to normalize inter-agency data comparison. New Mexico was the first state, in 2001, to pass legislation based on combating the opioid crisis (Prescription Drug Abuse Policy System). Since then approximately 48 states have passed either GLS or SOL. Table 1 indicates the pooled summary statistics, showing that there are 964 observations total, with the average age-adjusted mortality rate around 13.62. There is more SOL compared to GSL nationwide, which this paper exploits to parse out the differences between the policies. In Table 2, the means and standard deviations are reported for every variable in the regression model for each year that was accounted

for in the data. These results indicate that every state had some type of Standing Order Law by 2017, while only three-quarters of states had a Good Samaritan Law in place. The greatest increase in SOL was between 2014 and 2015, which might indicate that studies that ended in 2015 (Doleac and Mukherjee, Rees et al), may not account for the effects of the roughly 17 states that passed legislation in 2015. Table 3 are the results of the pooled OLS regression, including the year dummies to tease out the year effects. The first column looks at the model without the inclusion of the Standing Order Law control. *GSL* are statistically significant at the 99% significant level and is positively correlated with mortality rate by a coefficient of 1.88. The adjusted r-squared value of the model is 0.47. However, when *SOL* is re-introduced in the model, seen by column 2, it diminishes the significance of *GSL.* The variable now has a p value of 0.071, which does not make it significant at the 95% significance threshold. However, it still significant at 90% and continues to be positively correlated with mortality rates. While *SOL* could be positively associated with mortality rates, the lack of statistical significance indicates very little effect on the overall rate. The majority of literature, however, indicates that *SOL* should be negatively correlated with mortality rate, so the pooled OLS, since it introduces bias into the model, will be disregarded.

The fixed effects model uses state variations across times in the mortality rate to determine the treatment effects. Table 4 column 1 indicates the FE model without the *SOL* control. This is helpful to determine whether there were indeed variations within each state. The results indicate that *GSL* is still positively correlated with mortality rates at a 98% significance level. The national age-adjusted overdose mortality rate continues to be the best indicator of state mortality rates at a 99% significance level. Neither population density nor State unemployment rates were statistically significant at the qualifying 90% threshold. After the re-introduction of *SOL* back into the model

(Table 4, column 2) *ceterius paribus*, the coefficient for *GSL* actually becomes greater and it becomes significant at the 99% threshold. This model is the most appropriate, since the *SOL* coefficient is negative, albeit not significant, which adheres with most literature. The population density control becomes statistically significant and very slightly positively correlated with mortality rates, which fits the prevailing theories in the field that rural areas tend to have higher overdose mortality rates. Finally, while the state unemployment rate is not significant, the positive coefficient indicates that areas with greater unemployment also have higher overdose mortality rates, which also fits in with the prevailing literature base. The year dummies were included in the regression models in order to capture the effects of aggregate trends. None of the dummies were significant in any of the models, indicating that the aggregate trends did not play an important role in the dependent variable.

VI. Conclusion

The positive association between *GSL* and age-adjusted opioid overdose mortality rates indicate that moral hazard might be an unintended consequence of Good Samaritan Laws. While this does not indicate any causal relationship between *GSL* and mortality rates, it does verify the findings of Doleac's study in certain regards. The presence of moral hazard is very difficult to test, but the positive association might suggest that it requires further investigation with expanded controls with a robust model to develop a more precise estimator of the effect of *GSL* on mortality rates. If further studies reach similar conclusions, then policy makers are faced with an important decision regarding the effectiveness of Good Samaritan legislation. The effects of moral hazard could outweigh any tangential positive benefits of legal protection. Perhaps removing the legal protection but encouraging local prosecutors not to press charges for naloxone administration by a layperson would reduce the incentive for risky behavior from individuals suffering from OUD. The opioid

crisis continues to drastically effect the lives of Americans but understanding the underlying trends in the data allows for scientifically informed policymaking.

Figures and Tables

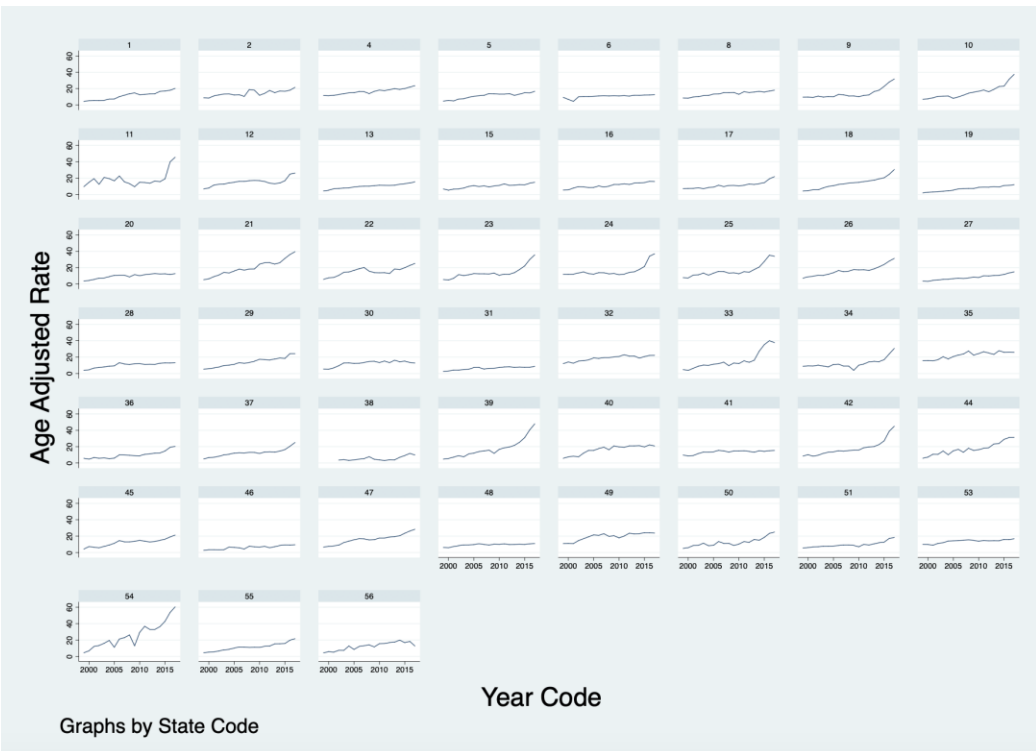

Figure 1: *Each graph represents a different state. The overall trend indicates that age-adjusted opioid overdose mortality death rates have increased from 2000-2017. The mortality rate is per 100,000 individuals in the state. The graphs are labeled as Federal Information Processing Standard state codes (FIPS), which can be identified alphabetically i.e. graph 1 is Alabama, while graph 56 represents Wyoming. Gaps in the graphs are due to exclusion of American Samoa, Puerto Rico etc. from the CDC vital statistics report.*

Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
StateCode	964	28.914	15.712	1	56
Year	964	2008.03	5.475	1999	2017
YearCode	964	2008.03	5.475	1999	2017
Deaths	964	782.835	893.091	20	5495
Population	964	5970000	6670000	492000	3.95e+07
CrudeRate	964	13.498	6.77	2	56.3
AgeAdjuste~e	964	13.625	7.031	2	60.5
StandingOr~w	964	.239	.426	0	1
NationalAg~e	964	12.877	4.12	6.8	22.8
GoodSamari~w	964	.156	.363	0	1
Population~m	964	334.461	1230.231	.939	10154.7
StateUnemp~t	964	5.567	1.969	2.2	13.9
censusnum	964	2.67	1.044	1	4

Table 1: *Identifies descriptive statistics for each variable included in the model.*
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Summary statistics: mean, sd
  by categories of: YearCode (Year Code)
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YearCode	AgeAdj~e	Standi~w	GoodSa~w	Nation~e	census~m	Popula~m	StateU~t
1999	6.576	0	0	6.8	2.68	319.0834	3.926
	2.82146	0	0	0	1.058301	1174.19	.9380418
2000	7.158	0	0	7	2.68	320.7191	3.974
	2.916392	0	0	0	1.058301	1178.008	.888661
2001	8.192	.02	.02	7.6	2.68	323.0183	5.23
	3.049044	.1414214	.1414214	0	1.058301	1183.063	1.044763
2002	9.172549	.0196078	.0196078	9.1	2.666667	317.6926	5.384314
	3.087852	.140028	.140028	0	1.051982	1169.341	1.011607
2003	10.48039	.0392157	.0196078	9.9	2.666667	317.4442	5.335294

	3.899898	.1960392	.140028	0	1.051982	1159.972	1.010114
2004	11.03333	.0392157	.0196078	10.5	2.666667	318.2765	4.976471
	3.74196	.1960392	.140028	0	1.051982	1158.426	.9860199
2005	11.798	.04	.02	11.3	2.68	325.1927	4.644
	3.634331	.1979487	.1414214	0	1.058301	1167.968	1.074597
2006	13.464	.06	.02	12.8	2.68	327.1648	4.26
	3.936732	.2398979	.1414214	0	1.058301	1175.091	.9995918
2007	13.07059	.0588235	.0196078	12.6	2.666667	322.9313	4.439216
	4.278331	.2376354	.140028	0	1.051982	1171.553	1.001415
2008	13.34706	.0784314	.0196078	12.6	2.666667	325.6703	6.807843
	4.326308	.2715244	.140028	0	1.051982	1183.293	1.58251
2009	13.07451	.0784314	.0196078	12.6	2.666667	330.1278	8.943137
	4.052498	.2715244	.140028	0	1.051982	1207.516	2.091244
2010	13.62549	.1176471	.0588235	12.9	2.666667	333.6142	8.486275
	4.749141	.3253957	.2376354	0	1.051982	1226.708	1.972209
2011	14.80392	.1176471	.0784314	13.9	2.666667	339.2619	7.65098
	5.344192	.3253957	.2715244	0	1.051982	1259.576	1.788001
2012	14.7549	.1568627	.0980392	13.8	2.666667	344.3138	7.045098
	5.133043	.36729	.3003266	0	1.051982	1288.574	1.597913
2013	15.63137	.3529412	.1764706	14.6	2.666667	349.2309	6.213725
	5.067168	.4826398	.3850134	0	1.051982	1317.164	1.361766
2014	16.92157	.5686275	.3529412	15.5	2.666667	353.8055	5.27451
	5.72693	.500196	.4826398	0	1.051982	1342.361	1.140499
2015	18.71765	.8235294	.5882353	17.2	2.666667	358.4778	4.713725
	7.05024	.3850134	.4970501	0	1.051982	1369.333	.9996038
2016	22.42157	.9411765	.6666667	20.8	2.666667	361.447	4.42549
	9.730556	.2376354	.4760952	0	1.051982	1387.374	.948861
2017	24.22353	1	.745098	22.8	2.666667	366.1685	3.92549
	11.22737	0	.4401426	0	1.051982	1413.351	.8522542
Total	13.6251	.2385892	.1556017	12.87739	2.670124	334.4611	5.566805
	7.030819	.4264423	.3626654	4.119874	1.043747	1230.231	1.96889

Table 2: *Identifies the mean and standard deviations for each variable included in the regression model for each year in the data. The mean is represented by the top number, while the standard deviation is represented by the bottom number.*

VARIABLES	(1) Pooled OLS	(2) Pooled OLS
StandingOrderLaw		1.061
		(0.728)
GoodSamaritanLaw	1.884***	1.305*
	(0.604)	(0.723)
NationalAgeAdjustedRate	1.013***	0.974***
	(0.0696)	(0.0746)
censusnum	0.382**	0.401**
	(0.161)	(0.161)
PopulationDensitypopsquarem	0.000713***	0.000695***
	(0.000134)	(0.000135)
StateUnemployment	1.045***	1.024***
	(0.132)	(0.133)
2000.YearCode	0.328	0.337
	(1.017)	(1.016)
2001.YearCode	-0.598	-0.548
	(1.013)	(1.013)
2002.YearCode	-1.289	-1.177
	(0.974)	(0.976)
2003.YearCode	-0.740	-0.619
	(0.956)	(0.960)
2004.YearCode	-0.421	-0.284
	(0.938)	(0.942)
2005.YearCode	-0.131	0.0302
	(0.926)	(0.932)
2006.YearCode	0.415	0.605
	(0.910)	(0.918)
2007.YearCode	0.0457	0.233
	(0.907)	(0.915)
2008.YearCode	-2.154**	-1.938*
	(0.984)	(0.995)
2009.YearCode	-4.661***	-4.399***
	(1.126)	(1.140)
2010.YearCode	-4.013***	-3.768***
	(1.086)	(1.099)
2011.YearCode	-3.016***	-2.738***
	(1.025)	(1.042)
2012.YearCode	-2.372**	-2.140**
	(0.987)	(0.999)
2013.YearCode	-1.589*	-1.506
	(0.939)	(0.940)
2014.YearCode	-0.565	-0.593
	(0.898)	(0.898)
2015.YearCode	-0.353	-0.460
	(0.899)	(0.901)
2016.YearCode	-0.146	-0.197
	(0.958)	(0.958)
2017o.YearCode	-	-
Constant	-5.669***	-5.364***
	(1.256)	(1.273)
Observations	964	964
R-squared	0.483	0.484

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: *Shows the pooled OLS results of the regression with and without the Standing Order Law control.*

VARIABLES	(1) Fixed Effects	(2) Fixed Effects
StandingOrderLaw		-0.405
		(0.597)
GoodSamaritanLaw	1.297**	1.489**
	(0.507)	(0.581)
NationalAgeAdjustedRate	1.046***	1.063***
	(0.0504)	(0.0557)
o.censusnum	-	-
PopulationDensitypopsquarem	0.00212	0.00222*
	(0.00132)	(0.00133)
StateUnemployment	0.201	0.207
	(0.148)	(0.148)
2000.YearCode	0.360	0.356
	(0.705)	(0.705)
2001.YearCode	0.483	0.466
	(0.718)	(0.719)
2002.YearCode	0.0362	-0.00529
	(0.697)	(0.700)
2003.YearCode	0.517	0.471
	(0.684)	(0.688)
2004.YearCode	0.513	0.459
	(0.663)	(0.668)
2005.YearCode	0.330	0.265
	(0.648)	(0.655)
2006.YearCode	0.499	0.420
	(0.635)	(0.646)
2007.YearCode	0.450	0.374
	(0.635)	(0.645)
2008.YearCode	0.245	0.162
	(0.759)	(0.769)
2009.YearCode	-0.466	-0.562
	(0.970)	(0.981)
2010.YearCode	-0.195	-0.286
	(0.917)	(0.927)
2011.YearCode	0.0670	-0.0387
	(0.829)	(0.843)
2012.YearCode	0.208	0.119
	(0.771)	(0.783)
2013.YearCode	0.302	0.270
	(0.701)	(0.703)
2014.YearCode	0.601	0.612
	(0.642)	(0.643)
2015.YearCode	0.416	0.460
	(0.632)	(0.636)
2016.YearCode	0.302	0.323
	(0.667)	(0.668)
2017o.YearCode	-	-
Constant	-2.124**	-2.289**
	(1.001)	(1.030)
Observations	964	964
R-squared	0.646	0.646
Number of StateCode	51	51

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: *Shows the Fixed effects model of the regression with and without the Standing Order Law control. None of the year dummies are statistically significant.*

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