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Opioid Crisis in America

Section 0: Abstract

In this paper we will be analyzing how factors such as manufacturing states, the 2008 recession, and labor force participation rate impact overdoses and the total cost of Medicare and Medicaid. Manufacturing states are disproportionately impacted and have higher average costs than other states. The growth rate of overdoses also is higher in manufacturing states since 2011. It is for those reasons these states need additional support in the opioid crisis.

Section 1: introduction

For the past twenty years America has been struggling with a quiet and lingering battle with opiate addiction. Prescription opiates like Vicodin, Oxycontin, and morphine are some of the main opioids that many people have been constantly abusing. These drugs are highly addictive and easily accessible. By the end of the 1990s 86 percent of the people who were

prescribed opiates were using them for non-cancer pain¹. Typically, these medications are supposed to be used for cancer patients to manage pain, but this fell out of the norm by the 2000s.

Accessibility however is not the only issue that is factoring into the reason of why America is dealing with a national wide substance abuse problem, there are economic factors that contribute to opioid related addiction and death. It was agreed by researchers that factors such as economic opportunity, poor working conditions, and eroded social capital Dasgupta et al, are just a few factors that drive people to abuse opioids. These two factors lead to an alarming rate of abuse, so alarming that the CDC noted in 2017 that there were 1,000 emergency room visits a day for patients who needed medical attention in relation to opioid prescription abuse (CDC2017a). These thousand visits a day may have a tremendous social cost and effect government spending. In 2007 it was reported that opioid abuse had a societal cost of \$55.7 billion dollars². This study however is over ten years old and a lot of data can change in ten years. This paper's more present state of data can provide more insight on how Prescription Drug Monitoring Programs are helping reduce the financial and productivity costs in the United States. We can examine this through a simulation after running our data analysis.

This paper looks to specifically examine how certain economic variables effect the number of overdoses in a given state in a given time. To do this we will be using panel data on all fifty states and the District of Columbia from 2000 to 2018 to figure out how specific factors

¹ Scavette, "Adam Exploring the Economic Effects of the Opioid Epidemic" Federal Reserve Bank of Philadelphia Research Department, 2019 Q2.

² Brill, Alex. Gnaz, Scott "The Geographic Variation in the Cost of the Opioid Crisis"
AEI 2018 and referencing Birnbaum et al. 2011

in a given state relate to overdose death rates. Once this information is found and evaluated next the paper would like to address how these deaths effect Medicare and Medicaid spending and what the cost to society is in monetary and productivity terms. The variables that will be specifically assessed are labor force participation rate, states who are heavily dependent on manufacturing in their job markets, and lastly states after the recession of 2008. This hopefully can give insight on how economic variables and factors can affect overdosing on opioids and what that cost to the country is. Ideally this paper will be able to give the public an idea on how to reduce both overdoses as well as Medicare and Medicaid costs.

The economic variable labor force participation rate typically is an indicator of the health of an economy. The next variable are states that have manufacturing jobs that make up a large percentage of their job market. This variable is included because economic success is beneficial for these states, but economic troubles hit these states harder than other states. Also, opioid abuse is used more within these states therefore we would like to quantify how much harder they are hit than other states to see if these states may need special attention in aid and or policy. Both variables above have been reported to impact opioid abuse and overdose death and with the use of panel data we will be able to quantify this impact as accurately as we can which has yet been done in this topic. The last variable of the recession from 2008 we want to see how life after the recession, a major economic event that effected every state and millions of people, is impacting opioid overdoses. There will be more socioeconomic variables that will be included in the regression equation but will be described more in section 4 and will primarily be used as controls in the equations.

Section 2: Previous Research

Curtis Florence, PhD, discusses in “The Economic Burden of Prescription Opioid Overdose, Abuse and Dependence in the United States, 2013” how the opioid crisis in the US is affecting the country. In this study Florence uses data from various sources such as the National Vital Statistical System and the National Survey of Drug Use and Health, along with data on fatal and non-fatal opioid cases on the US population. Florence used a logistic regression model to account for all patients and the regression included many variables such as age, sex, residence of patient, health care plan, race and others over a 12-month observation period. The results found were over 2 million people met the qualification of abuse and dependence on opioids and there were over 16,000 deaths. Medicare costs of dependence and abuse were more than \$17,000 and Medicaid above \$13,700. Lastly Florence found that abuse of opiates ended up costing over \$28 billion, while overdose, abuse, and dependence had cost the country more than \$78.5 billion. Florence’s work had shown the country how detrimental the opiate crisis in the country is and in addition shows how immense the burden on all levels of government (local, state, and federal) has in accounting for the cost of opioid related abuse, dependence, and overdose. Florence also notes that about 25 percent of the economic burden is funded by public resources. The study puts the issue of the crisis in a monetary value which helps emphasize how big the issue of the opioid abuse is in the US.

Alex Brill and Scott Ganz take a look at the opioid abuse and how it effects each state in “The Geographic Variation in the Cost of the Opioid Crisis”. They view the total opioid cost per capita in terms of health care, criminal justice, and productivity costs in 2015, and on the chart it is seen that areas in the north eastern part of the country are hit the hardest with some states having their per capita cost being within the range of \$1827 to \$2530 which is the second highest range of cost in this chart. There are three to four states in the north eastern part of the nation that

are being hit the hardest where the per capita costs in these states ranges between \$2530 to \$4378. Again a similar chart is produced but this time at the county level and this is where we see a national issue because across the nation a majority of the states have counties that are in the second and first highest range of costs per capita when excluding mortality. When including mortality, the results slightly change geographically and is more concentrated in the Midwest, parts of the south and north east but nonetheless a majority of the states are experiencing high levels of per capita costs. This study shows how a lot of the states that rely on manufacturing as their primary job market are hit the hardest. States like Kentucky, Alabama, Ohio, West Virginia, and Connecticut are just some of the states that have very high per capita costs at both state and county levels and rely on manufacturing jobs in the states job market.

Lastly a highlight comes from Adam Scavettte where he is discussing the idea of economic effects on the opioid epidemic, and in this paper he mentions another paper by Alan Krueger where Kreuger finds how labor force participation in the 2000s is at a lower level in states where opioid medication is prescribed per capita. Krueger however fails to distinguish this patter from state level to county level. This is notable because labor force participation is one of the variables we will be examining in this paper and we would like to see in this variable's behavior follows suit with Kreuger's study.

Section 3: Data Resources

A majority of the data found on the variables in this paper heavily relies on data from the US census for variables for each state from 2000 to 2018. Variables' whose data relied on information from the census are population, median household income, percent of state population insured, and percentage of state population that is a high school graduate. For Medicaid and Medicare spending the information was found through Kaiser's medical records as

well the number of overdose deaths. Deciding whether or not a state is a manufacturing state was through constructconnect where they rank each state by industrial subsector jobs by manufacturing. Unemployment rate data is found through the Bureau of Labor Statistics' website. Lastly this paper got its data through the RI Department of Labor and Training Labor Market information. Since the paper is including the Recession of 2008, we had created a dummy variable to mark the years in which the recession occurred and the years after.

The socioeconomic variables of state GDP, population, median household income, percent of state population insured, percentage of state population that graduated from high school, Medicare spending, Medicaid spending, and unemployment are served to be controls in the regression equation. The main variables we will be assessing are labor force participation, manufacturing states³, and the Recession of 2008.

Section 4: Economic Model

One thing to mention before we break down the models we will be using in this paper, it is worth mentioning that when discussing an addictive good—in this case opioids—their demand curves are very inelastic and steep. This is because once someone is addicted to opioids it isn't something that can stop being consumed instantly, it takes time to quit. This model is to illustrate factors that impact the number of overdoses per state at a given time and how much these overdose deaths cost. We will go into more depths about how the addictive nature of opioids can impact our results later in this paper.

³ States that are labeled as “manufacturing states” in this paper are states that have more than 50 manufacturing jobs per million residents. There are twelve states that meet this criteria and they are Wisconsin (83.4 per million), Indiana (79.8 per million), Iowa (71.5), Michigan (62.1), Ohio (59.7), Minnesota (57.7), Kansas (56.7), Kentucky (56), Alabama (55), Arkansas (52.9), Nebraska (52.7), and New Hampshire (52.6).

The model we will be using to determine the impact of the variables of manufacturing, recession and labor force participation rate is:

$$\text{Overdose} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots \dots \dots u \quad (1)$$

β_n = slope parameters of overdose function that will be estimated from the data.

x_1 = recession dummy variable⁴

x_2 = recession dummy * manufacturing dummy variable⁵

x_3 = labor force participation rate

As for the rest of the variables in our panel data set, the socioeconomic variables, these will be $x_4 \dots x_n$ and will primarily serve as controls in the equation. Lastly u represents the error term for things we can't quite account for. In this equation we will also include 19 dummy variables for each year (from 2000-2018) to account for unobserved year specific effects. This model will be ran under a standard OLS regression.

The next model we will analyze is the Total Cost function which is:

$$\text{Total Cost} = \gamma_0 + \gamma_1 \text{overdose} + \gamma_2 z_2 + \cdots \dots \dots u \quad (2)$$

γ_n = slope parameters of overdose function that will be estimated from the data.

overdose = the number of overdose deaths in a given year in a given state

z_2 = recession dummy * manufacturing dummy variable

⁴ In stata we will be marking a 0 for the years 2000-2007 and a 1 for the years 2008-2018 to signify the pre and post-recession periods for each state in the 19 year period we are observing.

⁵ Recession times manufacturing variable is to address how manufacturing states are impacted by the recession and how both these variables together interact with overdoses instead of both variables independent effects on overdoses.

z_3 = labor force participation rate

Total cost will be equal to the aggregate of Medicare and Medicaid in a given year. The same socioeconomic variables will be used as controls again but this time from $z_4 \dots z_n$. The error term remains the same as well. In this model however we, created 51 dummy variables, one for each state and the District of Columbia, to account for the unobserved specific effect of each state. This model will also be ran through a standard OLS regression but it will also be ran through a Fixed Effects regression which will drop all the variables that do not change over time like manufacturing.

Section 5: Empirical Analysis

5.1 Overdose Model (overdose model) Analysis

The first regression we ran was a standard OLS regression of logoverdoses on the recession variable dummy, $recmanu^6$, labor force participation rate, all our socioeconomic variables, and year dummy variables. The output shows that the recession results in 36%⁷ rise/fall on overdoses. The recession manufacturing variable shows something quite interesting; it shows that manufacturing states have an additional 45% rise of overdoses along with the recession percentage (36% + 45%) which illustrates how much harder manufacturing states are impacted by the opioid crisis. Our last key variable shows if there is a 1 percentage point increase in labor force participation overdoses decrease by 11%.

5.2 Endogeneity Test for Total Cost Model

⁶ Variable that accounts for manufacturing states in a recession as well.

⁷ Due to the unexplained output of the recession variable in my own regression, we will be borrowing Dr. Chattopadhyay's recession output in his model which is very similar to my own in terms of data and values used in the data.

As our next step in our analysis we take logoverdoses and put it into the Total Cost equation. Doing this we risk the chance of the model suffering from endogeneity. To make sure our output is reliable and there are no endogeneity in the variable logoverdoses we ran the Wu-Hausman test on the residuals of the equation. If the residuals are ran through an OLS regression with the rest of the variables in the equation and if the residuals are statistically significant at a 5% level then there is endogeneity in the equation variables. Our residuals had a p-value of 0.832 which confirms that there is no endogeneity in this model, and we can proceed with our analysis.

5.3 Total Cost Model Analysis

Again, in the cost model we will be focusing on our key variables, manufacturing states, the recession, and in addition overdoses and how they interact with total cost. Manufacturing states surprisingly have 78% lower costs on average, compared to other states—in terms of total Medicare plus total Medicaid. When discussing the recession variable, we found total costs increased by 24% after the recession (2008-2018) compared to before (200-2007). For everyone overdose death total cost goes up by about 13%. An interesting observation in this model is how percentage of population insured and percentage of population who graduated high school had hardly an effect on total costs, they're impact was 1.3% and 2.6%, respectively, increase in total costs if they both increased by one percent.

In the analysis above we analyzed an OLS regression with 50 state dummy variables (omitted state1) which is essentially the same as a fixed effect regression. The only major difference that running a fixed effect regression does is it would drop our manufacturing variable but all the other variables in the regression would have the same values.

Section 6: Simulation Analysis

With the results we got from our Stata output we were able to apply these findings to some simulations.

Section 6.1 Growth Rate of overdoses, Manufacturing states versus other states

The first simulation we ran is how manufacturing states growth rate of opioid overdoses compared to the other states, this is assuming that other states growth rates are fixed. We first ran a regression in the overdose model of manufacturing and tmanufacturing on overdoses to see what the rate of growth was for manufacturing, hence tmanufacturing variable. Next, we used this growth rate and multiplied it to the growth rate of other states plus the difference of manufacturing states and then multiplied this by each year. What we find, as you can see in Figure 1, is in 2000 manufacturing states growth rate in overdoses is lower than the growth rate in non-manufacturing states but by 2011 the growth rate of manufacturing states begins to exceed the growth rate of non-manufacturing states. By 2018 manufacturing states growth rates were higher than non-manufacturing states by .87. This simulation illustrates the disproportional rate at which manufacturing states are subject to in this opioid crisis.

Section 6.2: Trend in Total and Trend in Average Costs in Manufacturing States Versus Other States

Again, in our second simulation we are still comparing the disproportional effects manufacturing states face in this opioid crisis. This second simulation we summed the total cost of each opioid overdose death and summed each opioid overdose for each year for both manufacturing states and non-manufacturing states. The monetary impact of the total cost from 2000 to 2018 came to be \$37,648,373 in manufacturing states and \$49,173,254 in non-manufacturing states. Although non-manufacturing has a higher total cost for this can be

attributed to there being 39 states to gather data on versus the 12 manufacturing states. The average cost is a more telling statistic of the data. To get the average cost we took overdose deaths for each year and divided it by each year's total costs. The average of the average costs in manufacturing states is \$7,232,364 for a given year versus non-manufacturing states having an average average cost of \$6,004,255. This gives us a more accurate representation of how manufacturing states are being hit by this crisis more than other states.

Section 6.3: Average Annual Cost Per Opioid Death in 2018 Dollar

Next, we look at a simulation where we observe how a 1 percent increase on labor force participation would affect overdoses. As you may recall our stata output when running the overdose model gave our variable labor force participation rate a value of 0.113999 we then multiply this value on the number of overdoses each year and this gives us how many lives would not be lost if labor force participation rate was 1 percent higher. In Figure 2 we can see in 2000 we see a 1 percent increase would have saved about 18 lives but as time goes on and the opioid crisis got worse, we can see that the 1 percent increase in labor force participation would save more people. In 2018 the amount of lives a 1 percent increase would have saved is 104 people. The labor force participation rate also impacts the total cost model and we also observe cost avoided by an increase of labor force participation rate by 1 percent. On average the 1 percent increase would reduce total cost by \$278,766,662.7. To help the government be more cost efficient it is shown that finding ways to keep the labor force participation at a high level can be extremely beneficial in helping the government reduce spending.

Section 6.4: State Ranking With Respect To Average Cost and Total Cost of Overdose Deaths

Finally, we look at each state's total overdoses, total cost, average cost, from years 2000-2018. Next, we ranked each state to see who had the highest total and average cost. Again to get a more accurate representation of our data and the costs of this crisis we will look at the average costs for each state. The top five states who had the highest averages costs were: Mississippi (\$14,727,369), Nebraska (\$14,378,609), North Dakota (\$10,784,010), Louisiana (\$10,628,353), and South Dakota (\$10,191,171). Of these five, Nebraska is a manufacturing state, the other manufacturing states Alabama, Iowa, and Minnesota were ranked in the top 10. Their rankings and average cost can be seen in Table1.

Section 7: Discussion and Policy

Through the use of our overdose model and our total cost model we are able to create these simulations to analyze overdose deaths and their costs on states in numerous ways. Through each simulation one thing remained frequent which was the 12 manufacturing states being hit harder in this opioid crisis harder than the other 38 states (and District of Columbia). This has caused manufacturing states to be strong contributors to the Medicare and Medicaid spending because on average the cost is over a million dollars higher than that of a non-manufacturing state.

Now that we know the severity of the issue, we must provide some sort of ideas on how to address this issue. Many people seek opioids to treat chronic pain and working in the industrial job, a worker is likely to be subjected to chronic pain than others. A potential way to help with chronic pain may be to implement a policy that could be preventative of chronic pain is to offer workers paid leave for a period of time to meet with physical therapists to address the pain in a health way and to give their bodies a break, maybe three times a year. This could help

workers gain knowledge on how to deal with pain, so it doesn't compound overtime and become chronic pain.

Perhaps another solution could be for industrial workers to get a yearly or biyearly mandatory physicals to evaluate the health of workers and monitor their pain if they have any. The government could help companies subsidize this mandatory assessment through company insurance policies. This with the programs that oversee the prescription of opioid prescriptions could not only reduce overdose deaths but the monetary burden it puts on Medicare and Medicaid.

Because opioids are an addictive good the demand is not very elastic because it is not easy to quit. So with any policy implemented we would have to wait for a couple years to start seeing the changes and effectiveness of policies.

Section 8: Conclusion

By using our overdose and total cost models we were able to monetize the effect manufacturing state are subject to during this crisis and what events, such as labor force participation rate, impact overdoses and the cost of those overdoses. As a country were facing a crisis with opioids that has been extremely costly but for those states that are being hit harder than other, they need help and special attention.

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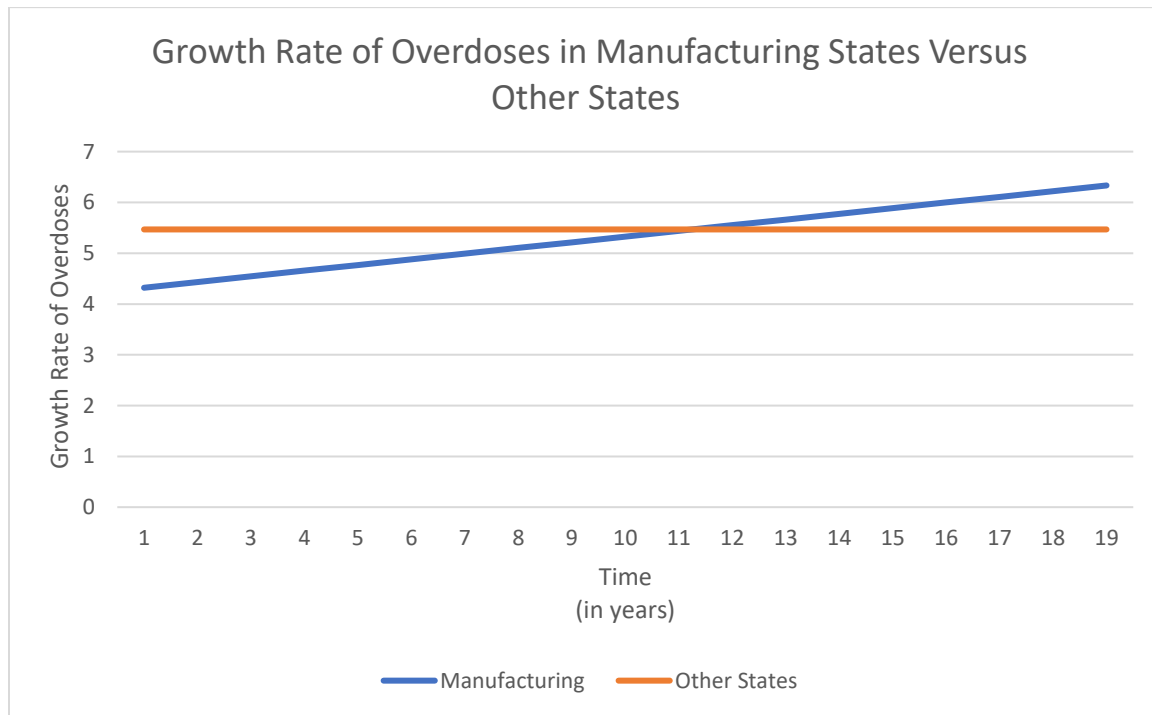
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Section 10: Graphs and Tables

Graph 1 (sheet 1)



Graph 2 (sheet 3)

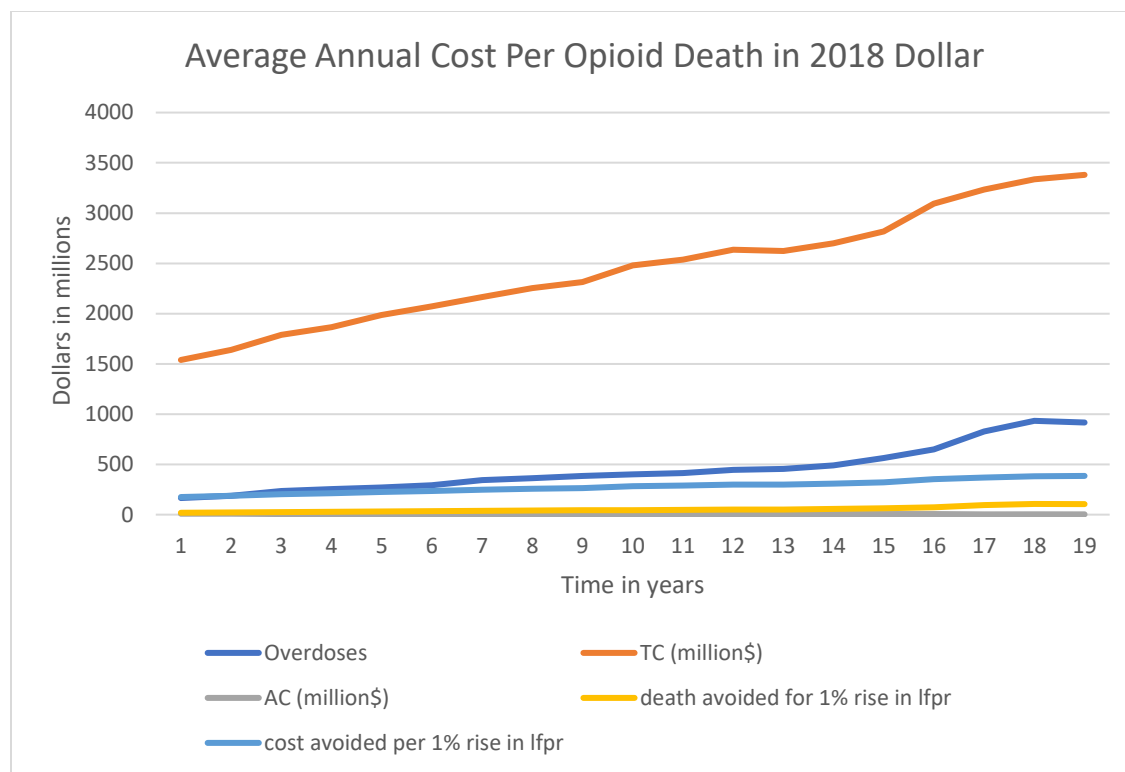


Table 1

State	# of Overdoses	TC	AC	Ranking (TC)	Ranking (AC)	Manufacturing
Alabama	181.8421	1820.18	10.0096	24	6	y
Alaska	53.60526	253.068	4.72096	49	29	n
Arizona	536.9474	2338.25	4.35471	16	34	n
Arkansas	147.1053	1217.05	8.27335	31	11	y
California	1702.737	14605.3	8.57756	1	10	n
Colorado	367.2105	1417.42	3.85996	27	40	n
Connecticut	366.4737	1723.16	4.70202	26	31	n
Delaware	98.36842	484.388	4.92423	41	26	n
Dist of Columbia	73.52632	312.917	4.25585	46	35	n
Florida	1567.053	7992.36	5.10025	4	25	n
Georgia	495.6842	2930.71	5.91245	12	19	n

Hawaii	58.63158	437.982 9	7.47008 5	44	14	n
Idaho	70.68421	452.152 4	6.39679 5	43	18	n
Illinois	1022.526	4665.59 7	4.56281 5	7	33	n
Indiana	373.3684	2397.25 1	6.42060 5	15	17	y
Iowa	118.2105	1086.63 7	9.19239	32	7	y
Kansas	118.2632	937.920 4	7.93078 8	33	13	y
Kentucky	525.0526	1892.36 7	3.60414 7	23	44	y
Louisiana	197.2632	2096.58 3	10.6283 5	21	4	n
Maine	139.6316	656.553 1	4.70203 8	37	30	n
Maryland	825.1579	2282.15 8	2.76572 3	18	47	n
Massachusetts	883.9474	3473.97 1	3.93006 5	11	39	n
Michigan	807.1053	4182.23 4	5.18177	8	23	y
Minnesota	231.7368	2124.11 7	9.16607 5	20	8	y
Mississippi	90.31579	1330.11 4	14.7273 7	30	1	n
Missouri	517.5263	2507.40 2	4.84497 5	14	27	n
Montana	48.94737	318.289 5	6.50268 8	45	16	n
Nebraska	42.42105	609.955 7	14.3786 1	38	2	y
Nevada	353	763.468 3	2.1628	36	50	n
New Hampshire	180.6316	474.454 3	2.62664 1	42	48	y
New Jersey	693.5263	3777.01 9	5.44610 8	9	21	n
New Mexico	264.2632	826.189 4	3.12638 8	35	46	n
New York	1382.105	12374.3 4	8.95325 6	2	9	n
North Carolina	870.3684	3585.33 5	4.11933	10	37	n

North Dakota	21.15789	228.166 9	10.7840 1	50	3	n
Ohio	1399.579	4994.35 5	3.56847	6	45	y
Oklahoma	382.0526	1396.49 3	3.65523 8	29	42	n
Oregon	296.1053	1399.88 1	4.72764 6	28	28	n
Pennsylvania	936.4211	6160.70 9	6.57899 4	5	15	n
Rhode Island	148.5789	547.669 3	3.68605	40	41	n
South Carolina	303.5789	1772.17 2	5.83759 9	25	20	n
South Dakota	25.86842	263.629 5	10.1911 7	48	5	n
Tennessee	626.6316	2624.94 9	4.18898 3	13	36	n
Texas	1026.158	8445.79 2	8.23049 9	3	12	n
Utah	347.7368	582.360 2	1.67471 5	39	51	n
Vermont	59	307.220 9	5.20713 4	47	22	n
Virginia	588.6842	2320.88 5	3.94249 6	17	38	n
Washington	616	2226.95 1	3.61518	19	43	n
West Virginia	396.4211	888.106 8	2.24031 2	34	49	n
Wisconsin	444.5789	2041.39 3	4.59174 5	22	32	y
Wyoming	31.97368	164.801 5	5.15428 6	51	24	n

Appendix: Stata outputs

```
reg logoverdoses manufacturing tmanufacturing
```

Source	SS	df	MS	Number of obs	=	969
-----+-----				F(2, 966)	=	28.98
Model	89.1114717	2	44.5557359	Prob > F	=	0.0000
Residual	1485.40097	966	1.53768217	R-squared	=	0.0566
-----+-----				Adj R-squared	=	0.0546
Total	1574.51244	968	1.62656244	Root MSE	=	1.24

logoverdoses	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
manufactur~g	-1.148639	.1644043	-6.99	0.000	-1.471269	-.8260079
tmanufactu~g	.1118731	.0149936	7.46	0.000	.0824494	.1412969
_cons	5.46791	.0455538	120.03	0.000	5.378514	5.557306

```
. reg logoverdoses recession recmanu medianhouseholdincomein2018dolla statagedpi
> n2018dollars percentinsured percentofhighschoolgraduate unemploymentrate labo
> rforceparticipationrate d1 d2 d3 d4 d5 d6 d7 d8 d9 d10 d11 d12 d13 d14 d15 d1
> 6 d17 d18, robust
note: d18 omitted because of collinearity
```

```
Linear regression                                Number of obs    =          969
                                                F(25, 943)        =          43.95
                                                Prob > F          =          0.0000
                                                R-squared         =          0.6086
                                                Root MSE         =          .8084
```

		Robust				
logoverdoses		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+-----						
recession		1.08437	.1930946	5.62	0.000	.7054249 1.463315
recmanu		.4578976	.0757328	6.05	0.000	.3092733 .606522
medianhous~a		.0000351	4.46e-06	7.87	0.000	.0000264 .0000439
statagedpin~s		1.45e-06	1.03e-07	14.13	0.000	1.25e-06 1.65e-06
percentins~d		-.0121643	.0098091	-1.24	0.215	-.0314144 .0070858
percentofh~e		.008148	.0129301	0.63	0.529	-.0172271 .0335232
unemployme~e		.1488418	.0270495	5.50	0.000	.0957576 .2019259
laborforce~e		-.113999	.0110026	-10.36	0.000	-.1355914 -.0924067
d1		.1592047	.1581759	1.01	0.314	-.1512127 .4696221
d2		.1855796	.1591656	1.17	0.244	-.1267801 .4979394
d3		.2175676	.1690793	1.29	0.198	-.1142476 .5493829
d4		.3296542	.1674566	1.97	0.049	.0010234 .6582849
d5		.4709435	.1675931	2.81	0.005	.1420448 .7998422

```

d6 | .6913191 .1641959 4.21 0.000 .3690874 1.013551
d7 | .7233171 .1656814 4.37 0.000 .3981703 1.048464
d8 | -.430444 .1877656 -2.29 0.022 -.7989307 -.0619573
d9 | -.8695772 .2470724 -3.52 0.000 -1.354453 -.3847019
d10 | -.9959247 .2288538 -4.35 0.000 -1.445046 -.5468031
d11 | -.8543239 .2190385 -3.90 0.000 -1.284183 -.4244646
d12 | -.7844752 .2098578 -3.74 0.000 -1.196318 -.3726328
d13 | -.6509623 .1977026 -3.29 0.001 -1.03895 -.2629744
d14 | -.4294533 .1850145 -2.32 0.020 -.7925412 -.0663655
d15 | -.2890282 .1788725 -1.62 0.106 -.6400625 .062006
d16 | -.0827196 .1847143 -0.45 0.654 -.4452183 .2797791
d17 | .0129847 .1901914 0.07 0.946 -.3602627 .3862321
d18 | 0 (omitted)
_cons | 9.27487 .9313651 9.96 0.000 7.447082 11.10266

```

```

. predict uhat, resid
variable uhat already defined
r(110);

. reg logtmcaremcaidreal recession manufacturing logoverdoses medianhouseholdin
> comein2018dolla stategdpin2018dollars percentinsured percentofhighschoolgradu
> ate unemploymentrate uhat

```

```

Source |      SS      df      MS      Number of obs   =      969
-----+-----
Model | 1028.87307      9    114.31923      Prob > F       =      0.0000
Residual | 138.800705     959    .144734833      R-squared       =      0.8811
-----+-----
Total | 1167.67378     968    1.20627457      Adj R-squared   =      0.8800
Root MSE      =      .38044

```

```

-----+-----
logtmcarem~l |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
recession | -.0667315   .0365419    -1.83   0.068    -0.1384429    .0049798
manufactur~g | .3018936   .0307225     9.83   0.000     .2416025    .3621848
logoverdoses | .555052    .0258287    21.49   0.000     .5043646    .6057393
medianhous~a | -.0000114   1.82e-06    -6.28   0.000    -0.000015    -7.84e-06

```

```

stategdpin~s |    9.51e-07    5.22e-08    18.20    0.000    8.48e-07    1.05e-06
percentins~d |    .027083    .0038874    6.97    0.000    .0194541    .0347118
percentofh~e |   -.0265567    .0051266   -5.18    0.000   -.0366174   -.0164959
unemployme~e |    .0311781    .0079132    3.94    0.000    .015649    .0467073
      uhat |    -.00639    .0300267   -0.21    0.832   -.0653156    .0525356
      _cons |    6.320635    .4900097    12.90    0.000    5.35902    7.28225
-----

```

```

. reg logtmcaremcaidreal recession manufacturing logoverdoses medianhouseholdin
> comein2018dolla stategdpin2018dollars percentinsured percentofhighschoolgradu
> ate unemploymentrate state2 state3 state4 state5 state6 state7 state8 state9
> state10 state11 state12 state13 state14 state15 state16 state17 state18 state
> 19 state20 state21 state22 state23 state24 state25 state26 state27 state28 st
> ate29 state30 state31 state32 state33 state34 state35 state36 state37 state38
> state40 state41 state42 state43 state44 state45 state46 state47 state48 stat
> e49 state50 state51, robust

```

```

Linear regression                                Number of obs    =          969
                                                F(57, 911)          =       2320.36
                                                Prob > F             =         0.0000
                                                R-squared            =         0.9911
                                                Root MSE            =         .10689

```

```

-----
|               Robust
logtmcarem~l |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----
      recession |   .2435599   .0123389    19.74   0.000    .219344    .2677758
manufactur~g |  -.7826068   .0372054   -21.03   0.000   -.8556251  -.7095885
logoverdoses |   .1287909   .0112128    11.49   0.000    .1067851    .1507968
medianhous~a |   8.37e-07   1.34e-06     0.63   0.532   -1.79e-06    3.47e-06
stategdpin~s |   4.80e-08   2.09e-08     2.30   0.022    7.02e-09    8.91e-08
percentins~d |   .0139577   .0019992     6.98   0.000    .0100342    .0178812
percentofh~e |   .0265149   .0035737     7.42   0.000    .0195014    .0335285
unemployme~e |   .0002787   .0029664     0.09   0.925   -.005543    .0061005
      state2 |  -2.825309   .0644826   -43.82   0.000   -2.951861  -2.698757
      state3 |  -.7665695   .0504782   -15.19   0.000   -.8656365  -.6675025
      state4 |  -.3739846   .0265724   -14.07   0.000   -.4261349  -.3218343

```

state5		.9117126	.058	15.72	0.000	.7978834	1.025542
state6		-1.391744	.0435258	-31.98	0.000	-1.477166	-1.306321
state7		-1.192051	.0351191	-33.94	0.000	-1.260975	-1.123127
state8		-2.232694	.0436314	-51.17	0.000	-2.318324	-2.147065
state9		-2.587985	.0443242	-58.39	0.000	-2.674975	-2.500996
state10		.3277618	.035011	9.36	0.000	.2590503	.3964734
state11		-.4770514	.0299412	-15.93	0.000	-.5358132	-.4182896
state12		-2.398516	.0508786	-47.14	0.000	-2.498369	-2.298663
state13		-2.237946	.0484283	-46.21	0.000	-2.33299	-2.142902
state14		-.2583379	.0288397	-8.96	0.000	-.3149379	-.201738
state15		.0333382	.0289374	1.15	0.250	-.0234536	.0901299
state16		-.7540608	.0419554	-17.97	0.000	-.8364013	-.6717204
state17		-.8493557	.0378102	-22.46	0.000	-.923561	-.7751505
state18		-.110762	.0288147	-3.84	0.000	-.1673129	-.0542111
state19		-.5904184	.0388109	-15.21	0.000	-.6665876	-.5142491
state20		-2.015574	.0434042	-46.44	0.000	-2.100757	-1.93039
state21		-.9929577	.040657	-24.42	0.000	-1.07275	-.9131654
state22		-.647575	.0308965	-20.96	0.000	-.7082115	-.5869384
state23		.4048334	.0338866	11.95	0.000	.3383284	.4713383
state24		-.2662213	.047584	-5.59	0.000	-.3596083	-.1728342
state25		-.9224203	.0417676	-22.08	0.000	-1.004392	-.8404484
state26		-.773149	.0282705	-27.35	0.000	-.828632	-.7176661
state27		-2.600258	.0579922	-44.84	0.000	-2.714072	-2.486444
state28		-1.176219	.0495203	-23.75	0.000	-1.273406	-1.079032
state29		-1.834108	.062679	-29.26	0.000	-1.95712	-1.711096
state30		-1.656751	.0503348	-32.91	0.000	-1.755537	-1.557966
state31		-.4006764	.0372787	-10.75	0.000	-.4738385	-.3275144
state32		-1.606911	.0421774	-38.10	0.000	-1.689687	-1.524135
state33		.7198904	.0385842	18.66	0.000	.6441661	.7956147
state34		-.3579907	.0298765	-11.98	0.000	-.4166254	-.2993559
state35		-2.8468	.0626796	-45.42	0.000	-2.969813	-2.723787
state36		.5361457	.0375293	14.29	0.000	.4624918	.6097996
state37		-1.220829	.0341622	-35.74	0.000	-1.287875	-1.153783
state38		-1.338995	.0415055	-32.26	0.000	-1.420453	-1.257537
state40		-2.068315	.0388311	-53.26	0.000	-2.144524	-1.992107
state41		-.8997637	.0329333	-27.32	0.000	-.9643977	-.8351297
state42		-2.708768	.0557956	-48.55	0.000	-2.818271	-2.599265
state43		-.6041162	.0349611	-17.28	0.000	-.6727299	-.5355025

```

state44 | .6052238 .0520884 11.62 0.000 .5029966 .7074511
state45 | -2.296716 .0472777 -48.58 0.000 -2.389502 -2.20393
state46 | -2.743572 .0497807 -55.11 0.000 -2.84127 -2.645873
state47 | -.9020049 .038792 -23.25 0.000 -.9781369 -.8258729
state48 | -1.035543 .035742 -28.97 0.000 -1.105689 -.9653965
state49 | -1.606462 .0386321 -41.58 0.000 -1.68228 -1.530644
state50 | -.293573 .0349588 -8.40 0.000 -.3621821 -.224964
state51 | -3.213432 .0598029 -53.73 0.000 -3.3308 -3.096065
_cons | 6.088324 .2874616 21.18 0.000 5.52416 6.652488

```

```
. sum overdoses_n tcopioid if year==2000
```

```

Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      51   165.1765   194.0031      10    1012
tcopioid |      51  1538.903   1888.161   97.44191  9161.64

```

```
.
```

```
. sum overdoses_n tcopioid if year==2001
```

```

Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      51   186.5392   191.1489      12     846
tcopioid |      51  1640.231   1967.461  103.8055  9292.986

```

```
.
```

```
. sum overdoses_n tcopioid if year==2002
```

```

Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      51   233.8333   270.9274      12    1453
tcopioid |      51  1788.755   2151.394  110.6668 10242.66

```

```
.
```

```
. sum overdoses_n tcopioid if year==2003
```

```

Variable |      Obs      Mean   Std. Dev.      Min      Max

```



```

-----+-----
overdoses_n |          51    254.1176    272.662         11    1398
  tcopioid |          51    1864.271    2273.319   125.8859   10816.3

```

```

.
. sum overdoses_n tcopioid if year==2004

```

```

  Variable |          Obs          Mean    Std. Dev.         Min         Max
-----+-----
overdoses_n |          51    269.7255    282.0492         10    1413
  tcopioid |          51    1985.302    2362.622   135.5093   11104.57

```

```

.
. sum overdoses_n tcopioid if year==2005

```

```

  Variable |          Obs          Mean    Std. Dev.         Min         Max
-----+-----
overdoses_n |          51    292.6078    284.1811         10    1372
  tcopioid |          51    2070.888    2469.442   143.1711   11462.08

```

```

.
. sum overdoses_n tcopioid if year==2006

```

```

  Variable |          Obs          Mean    Std. Dev.         Min         Max
-----+-----
overdoses_n |          51    344.2353    332.9543         14    1511
  tcopioid |          51    2165.205    2572.463   151.5522   11974.79

```

```

.
. sum overdoses_n tcopioid if year==2007

```

```

  Variable |          Obs          Mean    Std. Dev.         Min         Max
-----+-----
overdoses_n |          51    363.0588    352.8229         15    1657
  tcopioid |          51    2254.162    2652.949   154.2764   12356.47

```

```

.
. sum overdoses_n tcopioid if year==2008

```

```

      Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      51   383.9608   371.0422      29     1801
  tcopioid |      51  2314.731   2745.144   162.0823  13082.39

```

```

.
. sum overdoses_n tcopioid if year==2009

```

```

      Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      51   400.4314   403.8558      13     1987
  tcopioid |      51  2480.839   2913.807   174.3642  13941.36

```

```

.
. sum overdoses_n tcopioid if year==2010

```

```

      Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      51   413.5098   409.584      18     1929
  tcopioid |      51  2535.517   2979.008   178.7896  14029.81

```

```

.
. sum overdoses_n tcopioid if year==2011

```

```

      Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      51   446.7451   425.8471      10     1938
  tcopioid |      51  2635.97   3191.437   181.5464  16114

```

```

.
. sum overdoses_n tcopioid if year==2012

```

```

      Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      51   454.2647   418.3831     10.5     1719
  tcopioid |      51  2624.262   3106.267   181.6137  15405.56

```

.

. sum overdoses_n tcopioid if year==2013

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	51	491.2157	452.8093	11	1948
tcopioid	51	2700.141	3273.804	186.3338	17196.81

.

. sum overdoses_n tcopioid if year==2014

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	51	561.7059	507.8842	31	2106
tcopioid	51	2817.313	3359.228	188.4277	17556.73

.

. sum overdoses_n tcopioid if year==2015

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	51	648.8431	617.3873	27	2698
tcopioid	51	3094.238	3826.579	200.1386	21170.88

.

. sum overdoses_n tcopioid if year==2016

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	51	828.4118	846.7209	42	3613
tcopioid	51	3234.983	3947.716	208.9497	21307.14

.

. sum overdoses_n tcopioid if year==2017

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	51	933.3333	971.7007	35	4293

```

    tcopioid |          51    3335.592    4081.717    216.3191    21408.8

```

```

.

```

```

. sum overdoses_n tcopioid if year==2018

```

```

    Variable |          Obs          Mean    Std. Dev.          Min          Max
-----+-----
overdoses_n |          51    917.6863    933.4335          28        3237
    tcopioid |          51    3380.215    4075.669    230.3544    21582.6

```

```

. *find overdoses and tc of overdoses for each state

```

```

.

```

```

. sum overdoses_n tcopioid if state1==1

```

```

    Variable |          Obs          Mean    Std. Dev.          Min          Max
-----+-----
overdoses_n |          19    181.8421    113.2526          43        422
    tcopioid |          19    1820.181    345.8654    1212.096    2403.814

```

```

.

```

```

. sum overdoses_n tcopioid if state2==2

```

```

    Variable |          Obs          Mean    Std. Dev.          Min          Max
-----+-----
overdoses_n |           0
    tcopioid |           0

```

```

.

```

```

. sum overdoses_n tcopioid if state1==2

```

```

    Variable |          Obs          Mean    Std. Dev.          Min          Max
-----+-----
overdoses_n |           0
    tcopioid |           0

```

```

.

```

```

. sum overdoses_n tcopioid if state2==1

```

```

      Variable |           Obs       Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |           19    53.60526    33.7452         10     102
   tcopioid |           19   253.0687    71.70903   132.0224   388.4505

```

.

```
. sum overdoses_n tcopioid if state3==1
```

```

      Variable |           Obs       Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |           19   536.9474   222.7112       235     1106
   tcopioid |           19   2338.25   744.6204   1033.895   3523.677

```

.

```
. sum overdoses_n tcopioid if state4==1
```

```

      Variable |           Obs       Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |           19   147.1053    55.54167       20     208
   tcopioid |           19   1217.054   307.8423   699.2443   1728.359

```

.

```
. sum overdoses_n tcopioid if state5==1
```

```

      Variable |           Obs       Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |           19   1702.737   440.5302       551     2410
   tcopioid |           19   14605.34  4386.018   8532.129   21582.6

```

.

```
. sum overdoses_n tcopioid if state6==1
```

```

      Variable |           Obs       Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |           19    367.2105   131.8006       174     578
   tcopioid |           19   1417.421   471.8072   797.4127   2206.438

```

```
.
. sum overdoses_n tcopioid if state7==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	366.4737	282.9767	149	955
tcopioid	19	1723.167	354.8949	1204.086	2308.462

```
.
. sum overdoses_n tcopioid if state8==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	98.36842	83.79287	29	355
tcopioid	19	484.3887	140.1784	274.0463	713.7862

```
.
. sum overdoses_n tcopioid if state9==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	73.52632	65.82584	13	244
tcopioid	19	312.917	73.77396	206.4306	436.8117

```
.
. sum overdoses_n tcopioid if state10==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	1567.053	741.7311	556	3245
tcopioid	19	7992.363	1924.387	4791.785	11284.39

```
.
. sum overdoses_n tcopioid if state11==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	495.6842	268.6038	115	1014

```
tcopioid |          19      2930.71    625.6842   1750.677   3999.058
```

```
.
```

```
. sum overdoses_n tcopioid if state12==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	58.63158	13.50807	29	78
tcopioid	19	437.9829	126.4428	260.7411	649.0218

```
.
```

```
. sum overdoses_n tcopioid if state13==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	70.68421	24.50862	28	120
tcopioid	19	452.1524	128.5271	248.3475	679.9894

```
.
```

```
. sum overdoses_n tcopioid if state14==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	1022.526	546.4333	460	2202
tcopioid	19	4665.597	893.548	3153.754	6089.03

```
.
```

```
. sum overdoses_n tcopioid if state15==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	373.3684	326.7818	41	1176
tcopioid	19	2397.251	608.4162	1458.019	3434.562

```
.
```

```
. sum overdoses_n tcopioid if state16==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
----------	-----	------	-----------	-----	-----

```
-----+-----
overdoses_n |          19    118.2105    60.29242          19        206
  tcopioid |          19    1086.637    232.992    701.2697    1462.85
```

.

```
. sum overdoses_n tcopioid if state17==1
```

```
Variable |          Obs          Mean    Std. Dev.          Min          Max
-----+-----
overdoses_n |          19    118.2632    41.26048          22        173
  tcopioid |          19    937.9204    172.6409    635.3589    1226.711
```

.

```
. sum overdoses_n tcopioid if state18==1
```

```
Variable |          Obs          Mean    Std. Dev.          Min          Max
-----+-----
overdoses_n |          19    525.0526    321.8627          92        1160
  tcopioid |          19    1892.367    489.9302    1170.13    2688.128
```

.

```
. sum overdoses_n tcopioid if state19==1
```

```
Variable |          Obs          Mean    Std. Dev.          Min          Max
-----+-----
overdoses_n |          19    197.2632    111.7263          52        444
  tcopioid |          19    2096.583    390.3423    1429.174    2899.766
```

.

```
. sum overdoses_n tcopioid if state20==1
```

```
Variable |          Obs          Mean    Std. Dev.          Min          Max
-----+-----
overdoses_n |          19    139.6316    89.01761          41        360
  tcopioid |          19    656.5531    123.4209    419.5587    862.7437
```

.

```
. sum overdoses_n tcopioid if state21==1
```



```

      Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      19   825.1579   532.2057      481     2087
  tcopioid |      19  2282.158   584.2351  1366.036  3243.249

```

.

```
. sum overdoses_n tcopioid if state22==1
```

```

      Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      19   883.9474   551.9417      314     1991
  tcopioid |      19  3473.971   655.4356  2457.13  4535.967

```

.

```
. sum overdoses_n tcopioid if state23==1
```

```

      Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      19   807.1053   583.034      180     2033
  tcopioid |      19  4182.234   896.8324  2812.664  5672.475

```

.

```
. sum overdoses_n tcopioid if state24==1
```

```

      Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      19   231.7368   109.6179      57      422
  tcopioid |      19  2124.117   553.6981  1203.997  3032.418

```

.

```
. sum overdoses_n tcopioid if state25==1
```

```

      Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      19    90.31579    54.92121      12      185
  tcopioid |      19  1330.114   266.7105   811.5468  1765.327

```

.

. sum overdoses_n tcopioid if state26==1

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	517.5263	280.1488	131	1132
tcopioid	19	2507.402	490.8242	1599.003	3321.217

.

. sum overdoses_n tcopioid if state27==1

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	48.94737	18.85168	11	89
tcopioid	19	318.2895	85.07315	194.5238	496.1627

.

. sum overdoses_n tcopioid if state28==1

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	42.42105	15.84409	14	66
tcopioid	19	609.9557	101.2055	421.1222	786.5786

.

. sum overdoses_n tcopioid if state29==1

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	353	90.62193	178	461
tcopioid	19	763.4683	296.7754	355.0133	1293.594

.

. sum overdoses_n tcopioid if state30==1

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	180.6316	134.9338	29	437

```
tcopioid |          19    474.4543    110.4732    300.9563    678.3592
```

```
.
```

```
. sum overdoses_n tcopioid if state31==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	693.5263	632.3952	55	2583
tcopioid	19	3777.019	689.8457	2672.477	4956.574

```
.
```

```
. sum overdoses_n tcopioid if state32==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	264.2632	74.4803	151	402
tcopioid	19	826.1894	244.2601	416.612	1216.812

```
.
```

```
. sum overdoses_n tcopioid if state33==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	1382.105	888.8509	479	3224
tcopioid	19	12374.34	1908.027	9161.64	16552.62

```
.
```

```
. sum overdoses_n tcopioid if state34==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	870.3684	452.7712	286	1953
tcopioid	19	3585.335	829.2392	2116.523	5011.044

```
.
```

```
. sum overdoses_n tcopioid if state35==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
----------	-----	------	-----------	-----	-----

```

-----+-----
overdoses_n |          19    21.15789    12.10837          10          54
  tcopioid |          19    228.1669    56.59607    159.204    336.6124

```

```

.
```

```

. sum overdoses_n tcopioid if state36==1

```

```

  Variable |          Obs          Mean    Std. Dev.          Min          Max
-----+-----
overdoses_n |          19    1399.579    1222.476          250          4293
  tcopioid |          19    4994.355    1118.074    3134.126    6809.439

```

```

.
```

```

. sum overdoses_n tcopioid if state37==1

```

```

  Variable |          Obs          Mean    Std. Dev.          Min          Max
-----+-----
overdoses_n |          19    382.0526    136.9118          127          568
  tcopioid |          19    1396.493    310.1864    832.4014    1901.192

```

```

.
```

```

. sum overdoses_n tcopioid if state38==1

```

```

  Variable |          Obs          Mean    Std. Dev.          Min          Max
-----+-----
overdoses_n |          19    296.1053    81.58356          106          392
  tcopioid |          19    1399.881    457.0003    817.1143    2171.331

```

```

.
```

```

. sum overdoses_n tcopioid if state39==1

```

```

  Variable |          Obs          Mean    Std. Dev.          Min          Max
-----+-----
overdoses_n |          19    936.4211    775.7339          252          2866
  tcopioid |          19    6160.709    1150.644    4346.745    8012.902

```

```

.
```

```

. sum overdoses_n tcopioid if state40==1

```

```

      Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      19   148.5789   74.16821       57     279
    tcopioid |      19   547.6693   91.58472   393.9012   694.9562

```

```

.
. sum overdoses_n tcopioid if state41==1

```

```

      Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      19   303.5789   233.4534       81     835
    tcopioid |      19  1772.172   420.7593  1080.663  2539.346

```

```

.
. sum overdoses_n tcopioid if state42==1

```

```

      Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      19   25.86842    9.005927       12       42
    tcopioid |      19   263.6295   53.6615   169.9445  357.5425

```

```

.
. sum overdoses_n tcopioid if state43==1

```

```

      Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      19   626.6316   369.1113      100    1307
    tcopioid |      19  2624.949   475.7935  1755.417  3424.607

```

```

.
. sum overdoses_n tcopioid if state44==1

```

```

      Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      19   1026.158   283.1329      379    1458
    tcopioid |      19  8445.792   2454.027  4608.526 12582.13

```

.

. sum overdoses_n tcopioid if state45==1

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	347.7368	99.89708	156	466
tcopioid	19	582.3602	163.3041	320.6758	866.9642

.

. sum overdoses_n tcopioid if state46==1

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	59	28.4312	22	127
tcopioid	19	307.2209	79.78067	176.5642	437.7292

.

. sum overdoses_n tcopioid if state47==1

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	588.6842	303.9695	250	1241
tcopioid	19	2320.885	630.4747	1332.933	3399.3

.

. sum overdoses_n tcopioid if state48==1

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	616	125.1958	324	742
tcopioid	19	2226.951	564.4163	1408.384	3267.221

.

. sum overdoses_n tcopioid if state49==1

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	396.4211	228.7338	50	833

```
tcopioid |          19    888.1068    194.7923    571.1217    1204.757
```

```
.
```

```
. sum overdoses_n tcopioid if state50==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	444.5789	247.6845	112	926
tcopioid	19	2041.393	442.3723	1277.992	2781.464

```
.
```

```
. sum overdoses_n tcopioid if state51==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	19	31.97368	16.26215	10	54
tcopioid	19	164.8015	38.25605	97.44191	230.3544

```
.
```

```
. *measuring overdoses and TC in manu states for the 19 year period.
```

```
.
```

```
. sum overdoses_n tcopioid if year==2000 & manufacturing==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	12	73.41667	74.06933	16	250
tcopioid	12	1252.248	885.0125	300.9563	3134.126

```
.
```

```
. sum overdoses_n tcopioid if year==2001 & manufacturing==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	12	101.75	90.69642	27	336
tcopioid	12	1354.928	947.6288	324.3369	3377.416

```
.
```

```
. sum overdoses_n tcopioid if year==2002 & manufacturing==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	12	128.25	110.1983	25	421
tcopioid	12	1467.121	1004.308	358.3384	3678.558

```
.
```

```
. sum overdoses_n tcopioid if year==2003 & manufacturing==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	12	136.8333	104.7619	14	365
tcopioid	12	1510.122	1052.436	350.1527	3821.666

```
.
```

```
. sum overdoses_n tcopioid if year==2004 & manufacturing==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	12	173.6667	138.3101	26	515
tcopioid	12	1619.354	1137.468	402.6953	4191.906

```
.
```

```
. sum overdoses_n tcopioid if year==2005 & manufacturing==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	12	202.75	166.9709	43	560
tcopioid	12	1676.964	1166.345	423.3624	4272.289

```
.
```

```
. sum overdoses_n tcopioid if year==2006 & manufacturing==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	12	236.8333	197.4302	34	634
tcopioid	12	1768.815	1217.245	419.6436	4515.975

.

. sum overdoses_n tcopioid if year==2007 & manufacturing==1

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	12	255.5833	193.478	39	705
tcopioid	12	1844.681	1282.334	440.674	4706.271

.

. sum overdoses_n tcopioid if year==2008 & manufacturing==1

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	12	288.0833	234.6822	29	814
tcopioid	12	1878.115	1280.767	457.7231	4619.296

.

. sum overdoses_n tcopioid if year==2009 & manufacturing==1

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	12	309.1667	213.6581	66	736
tcopioid	12	2014.148	1391.987	483.6989	5051.019

.

. sum overdoses_n tcopioid if year==2010 & manufacturing==1

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	12	345.8333	314.9862	58	1124
tcopioid	12	2046.157	1427.083	482.5885	5180.724

.

. sum overdoses_n tcopioid if year==2011 & manufacturing==1

Variable	Obs	Mean	Std. Dev.	Min	Max
----------	-----	------	-----------	-----	-----

```

overdoses_n |          12    384.3333    352.2172         53        1272
tcopioid |          12    2113.251    1464.112    502.3125    5303.749

```

```

.
```

```

. sum overdoses_n tcopioid if year==2012 & manufacturing==1

```

```

      Variable |          Obs          Mean    Std. Dev.         Min         Max
-----+-----
overdoses_n |          12    393.5833    368.2964         53        1355
tcopioid |          12    2131.565    1478.452    476.5857    5334.021

```

```

.
```

```

. sum overdoses_n tcopioid if year==2013 & manufacturing==1

```

```

      Variable |          Obs          Mean    Std. Dev.         Min         Max
-----+-----
overdoses_n |          12    444.25    454.8397         41        1630
tcopioid |          12    2160.865    1498.189    487.8043    5436.525

```

```

.
```

```

. sum overdoses_n tcopioid if year==2014 & manufacturing==1

```

```

      Variable |          Obs          Mean    Std. Dev.         Min         Max
-----+-----
overdoses_n |          12    535.0833    571.6304         56        2106
tcopioid |          12    2299.96    1601.618    515.1413    5848.629

```

```

.
```

```

. sum overdoses_n tcopioid if year==2015 & manufacturing==1

```

```

      Variable |          Obs          Mean    Std. Dev.         Min         Max
-----+-----
overdoses_n |          12    635.5833    740.7138         55        2698
tcopioid |          12    2503.308    1750.557    596.1829    6345.401

```

```

.
```

```

. sum overdoses_n tcopioid if year==2016 & manufacturing==1

```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	12	811.8333	1007.191	44	3613
tcopioid	12	2608.845	1803.854	650.4076	6493.765

.

```
. sum overdoses_n tcopioid if year==2017 & manufacturing==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	12	954.4167	1200.606	59	4293
tcopioid	12	2678.92	1870.094	678.3592	6771.971

.

```
. sum overdoses_n tcopioid if year==2018 & manufacturing==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	12	824.4167	944.0513	63	3237
tcopioid	12	2719.006	1881.14	663.6678	6809.439

.

```
. *measuring overdoses and TC in non manu states for the 19 year period
```

.

```
. sum overdoses_n tcopioid if year==2000 & manufacturing==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	39	193.4103	210.8494	10	1012
tcopioid	39	1627.105	2104.834	97.44191	9161.64

.

```
. sum overdoses_n tcopioid if year==2001 & manufacturing==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	39	212.6282	206.7032	12	846

```
tcopioid |          39    1728.017    2190.829    103.8055    9292.986
```

```
.
```

```
. sum overdoses_n tcopioid if year==2002 & manufacturing==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	39	266.3205	297.4261	12	1453
tcopioid	39	1887.72	2399.049	110.6668	10242.66

```
.
```

```
. sum overdoses_n tcopioid if year==2003 & manufacturing==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	39	290.2051	298.2689	11	1398
tcopioid	39	1973.241	2535.261	125.8859	10816.3

```
.
```

```
. sum overdoses_n tcopioid if year==2004 & manufacturing==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	39	299.2821	308.7481	10	1413
tcopioid	39	2097.901	2629.616	135.5093	11104.57

```
.
```

```
. sum overdoses_n tcopioid if year==2005 & manufacturing==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	39	320.2564	307.9886	10	1372
tcopioid	39	2192.095	2750.637	143.1711	11462.08

```
.
```

```
. sum overdoses_n tcopioid if year==2006 & manufacturing==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
----------	-----	------	-----------	-----	-----

```

-----+-----
overdoses_n |          39    377.2821    360.305         14    1511
  tcopioid |          39    2287.171    2865.926    151.5522    11974.79

```

```

.
. sum overdoses_n tcopioid if year==2007 & manufacturing==0

```

```

  Variable |          Obs          Mean    Std. Dev.          Min          Max
-----+-----
overdoses_n |          39    396.1282    384.9528         15    1657
  tcopioid |          39    2380.156    2952.196    154.2764    12356.47

```

```

.
. sum overdoses_n tcopioid if year==2008 & manufacturing==0

```

```

  Variable |          Obs          Mean    Std. Dev.          Min          Max
-----+-----
overdoses_n |          39    413.4615    401.7571         31    1801
  tcopioid |          39    2449.074    3059.735    162.0823    13082.39

```

```

.
. sum overdoses_n tcopioid if year==2009 & manufacturing==0

```

```

  Variable |          Obs          Mean    Std. Dev.          Min          Max
-----+-----
overdoses_n |          39    428.5128    444.9164         13    1987
  tcopioid |          39    2624.436    3243.543    174.3642    13941.36

```

```

.
. sum overdoses_n tcopioid if year==2010 & manufacturing==0

```

```

  Variable |          Obs          Mean    Std. Dev.          Min          Max
-----+-----
overdoses_n |          39    434.3333    436.0318         18    1929
  tcopioid |          39    2686.089    3314.896    178.7896    14029.81

```

```

.
. sum overdoses_n tcopioid if year==2011 & manufacturing==0

```

```

Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      39   465.9487   448.4341       10    1938
tcopioid |      39  2796.806   3559.258   181.5464   16114

```

```

.
. sum overdoses_n tcopioid if year==2012 & manufacturing==0

```

```

Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      39   472.9359   435.3574     10.5    1719
tcopioid |      39  2775.861   3458.748   181.6137  15405.56

```

```

.
. sum overdoses_n tcopioid if year==2013 & manufacturing==0

```

```

Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      39   505.6667   457.1517       11    1948
tcopioid |      39  2866.072   3651.372   186.3338  17196.81

```

```

.
. sum overdoses_n tcopioid if year==2014 & manufacturing==0

```

```

Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      39   569.8974   494.4913       31    2024
tcopioid |      39  2976.498   3740.967   188.4277  17556.73

```

```

.
. sum overdoses_n tcopioid if year==2015 & manufacturing==0

```

```

Variable |      Obs      Mean   Std. Dev.      Min      Max
-----+-----
overdoses_n |      39   652.9231   585.3556       27    2166
tcopioid |      39  3276.062   4270.297   200.1386  21170.88

```

```
.
. sum overdoses_n tcopioid if year==2016 & manufacturing==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	39	833.5128	805.9601	42	3009
tcopioid	39	3427.641	4404.776	208.9497	21307.14

```
.
. sum overdoses_n tcopioid if year==2017 & manufacturing==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	39	926.8462	908.2537	35	3245
tcopioid	39	3537.645	4553.149	216.3191	21408.8

```
.
. sum overdoses_n tcopioid if year==2018 & manufacturing==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
overdoses_n	39	946.3846	940.6721	28	3189
tcopioid	39	3583.664	4544.423	230.3544	21582.6

