The Economic and Public Health Costs of the Opioid Crisis: A State-Level Panel Analysis

Emily Nam

May, 2025

Proposal

The opioid crisis in the United States has evolved over multiple decades, and is marked by three interlinked waves. These waves are the rising prescription opioid use in the 200s, a surge in heroin-related deaths in the 2010s, as well as a massive increase in deaths from synthetic opioids, such as fentanyl, beginning in 2013. Studies have shown that by 2017, opioid overdoses have been responsible for over seventy thousand deaths annually; this number is higher than that of HIV at its peak, and even from the entirety of the Vietnam War. Research has suggested that increased prescribing practices, fueled by aggressive pharmaceutical marketing and a lack of regulations, has contributed significantly to the early rise in cursing opioids. Economic shifts, such as the decline in manufacturing and stable employment, have also made these vulnerabilities worse, especially when it comes to lower-income and rural communities. This project focuses on two core questions: 1. What are the key economic and structural factors contributing to opioid overdose deaths in the United States? Specifically, how do labor force participation rates, manufacturing employment, and prescription rates affect death rates? 2. How do opioid-related deaths affect public healthcare costs, particularly in terms of Medi-care and Medi-caid expenditures? A key component to this involves counterfactual modeling; if labor force participation rates have remained at the same levels as 2000, how many opioid deaths could have been avoided? Further, we ask how much each state, as well as the country as a whole, could have saved in public healthcare expenditures by preventing those deaths. For the econometric model, we will use two panel-data regression models. The first model will examine how state-level economic conditions (ie. labor and manufacturing employment) and healthcare-related variables (ie. prescription rates) influence opioid overdose death rates. The second model will investigate how these opioid deaths then affect state level Medi-care and Medi-caid expenditures. These models will help us estimate both the direct and indirect effects of labor and healthcare variables when it comes to overdose mortality and public cost. We will do this using fixed-effects estimation across states and years.

This research will utilize a panel dataset from 2000 to 2020 at the state level. Some key variables will include opioid overdose deaths, Medi-care and Medi-caid expenditures, population, prescription rates, and labor force indicators like the labor force participation rate and manufacturing employment share. Additional controls include GDP per capita, education levels, as well as insurance coverage. All the financial values used are adjusted to 2020 dollars using the CPI. Derived variables, such as per capita GDP and log-overdose rates, are constructed in both Excel and Stata.

It is anticipated that lower labor force participation rate and declining manufacturing rates are both associated with higher opioid death rates, such supports our "deaths of despair" hypothesis. Higher prescription rates will likely be a strong predictor for overdose deaths, particularly being applicable in the earlier years. We also can expect that states with higher opioid mortalities will show significantly higher spending in both Medi-care and Medi-caid sectors. We will simulate a scenario where the labor force participation rate remains constant since 2000, and we can expect this to reveal thousands of preventable deaths, as well as billions in avoidable public healthcare spending. These findings could highlight the importance of addressing root economic causes and prescribing patterns in mitigating this opioid crisis.

Abstract

The opioid crisis in the United States is responsible for causing immense social, economic, and public health concerns; it has led to a dramatic increase in overdose deaths, particularly affecting over seventy thousand individuals annually by 2017. This paper investigates the relationships between opioid-related deaths and economic factors, such as labor force participation, manufacturing employment, and prescription rates. Additionally, the analysis explores the impact of these deaths on public healthcare costs, particularly Medi-care and Medi-caid expenditures. Utilizing a state-level panel dataset from 2000 to 2020, the study applies two different econometric models, these being pooled OLS and fixed-effects panel regressions, to assess the effects of said factors on opioid mortality rates. A counterfactual simulation is conducted to estimate the potential number of deaths prevented and healthcare savings if labor force participation remained at 2000 levels. The results show the significant role of economic and structural factors in shaping the opioid epidemic, and highlight the importance of policy interventions focused on economic revitalization and prescription regulation to mitigate public health and economic burdens.

I. Introduction

1. Background

The opioid crisis in the United States has quickly become one of the deadliest public health emergencies in the 21st century, being responsible for tens of thousands of deaths a year. This crisis is characterized by three distinct interlinked waves: the rise in prescription opioid usage in the 2000s, a surge in heroin-related deaths in the 2010s, and the most recent being a dramatic increase in deaths caused by synthetic opioids such as fentanyl. The Centers for Disease Control and Prevention (CDC) reports that in 2017, opioid overdose deaths claimed the lives of over 70,000 individuals, this being more than the total number of U.S. soldiers killed during the entirety of the Vietnam War. While the epidemic began with the over-prescription of painkillers, it evolved and exacerbated the crisis as heroin and fentanyl became more accessible.

Initial research has shown that aggressive pharmaceutical marketing and a lack of regulatory oversight have played pivotal roles in driving the early years of this crisis.

Additionally, these socioeconomic shifts have exacerbated vulnerabilities, especially in rural and lower-income communities. The most notable has been the decline of manufacturing jobs, as well as stable employment in general becoming more scarce. These structural factors, alongside healthcare policies, have contributed significantly to how the crisis is persisting, affecting both healthcare systems and the broader economy. The burden of this epidemic is not just public health-related, but also extends to state and federal expenditures, especially Medi-care and Medi-caid programs, which take the majority of healthcare costs associated with opioid overdose treatments and long-term addiction care.

2. Research Questions

This paper will aim to explore three critical questions:

- 1. What are the key economic and structural factors contributing to opioid overdose deaths in the United States? Specifically, how do labor force participation rates, manufacturing employment, as well as prescription rates influence death rates?
- 2. How do these opioid-related deaths affect public healthcare costs, particularly in terms of Medi-care and Medi-caid expenditures?
- 3. What category of states are the most affected and troubled by opioid deaths in the last couple of decades?

To answer these questions, this paper will utilize a state-level panel dataset from the years 2000 to 2020. The study focuses on two econometric models; one examines the impact of economic and healthcare variables on opioid overdose deaths, and the second investigates the subsequent effects of opioid-related deaths on public healthcare spending. Both of the models use fixed-effects estimations to account for unobserved heterogeneity across states and years; this allows us to isolate the effects of the key variables on opioid mortality and public health expenditures.

3. Discussion of Opioid Market Dynamics

The dynamics of the opioid epidemic can be understood through a demand-supply framework; the prescription opioid availability represents the supply side, and the rising demand side for opioids is driven by socioeconomic factors, such as unemployment, poverty, low education levels, as well as the public release of oxycodone. The role of prescription opioids is more pronounced in the early stages of the crisis from aggressive marketing and a lack of regulations. Pharmaceutical companies played a significant role in fueling the crisis through

aggressive marketing tactics that downplayed the addictive potential of prescription opioids. This led to increased over-prescriptions, leading to a higher number of overdose deaths. However, the later waves of the crisis, marked by more heroin and synthetic opioids, show how changes in the drug supply can also influence this death count. In addition, the role of labor force participation and manufacturing employment is also crucial, since economic decline and declining stable jobs in marginalized communities have contributed to the rise of "deaths of despair" for vulnerable populations. These structural economic issues, combined with the availability of cheap opioids, have created a perfect environment for the opioid epidemic, particularly in rural and working-class communities.

States with lower labor force participation rates and higher levels of manufacturing job loss have experienced higher opioid mortality rates, suggesting that economic factors are integral to understanding opioid misuse and overdose deaths. Additionally, research indicates that opioid overdose deaths are closely linked to the level of legal prescription opioid use, with higher prescription rates correlating to higher death rates in the early stages.

4. Data and Methodology

As mentioned before, this study utilizes a panel dataset spanning from the years 2000 to 2020 at the state level. Key variables will include opioid overdose deaths, prescription rates, labor force participation, manufacturing employment, as well as Medi-care and Medi-caid expenditures. These variables are used to assess how economic and healthcare factors influence opioid overdose mortality and the subsequent impact on state healthcare costs.

This analysis will use two primary econometric regression models:

- Pooled OLS Regression: This model estimates the relationship between opioid overdose deaths and economic and healthcare variables across all states and years, using pooled cross-sectional data.
- 2. Fixed-Effects Panel Regression: This model controls for state-specific, time-invariant unobserved heterogeneity, allowing for a more precise estimate of how opioid deaths affect public healthcare expenditures. This data will be analyzed using STATA, and the results will be robust to standard errors clustered at the state level to account for within-state correlation.

We also performed a counterfactual simulation assuming that the labor force participation remained constant at 2000 levels to estimate how the opioid epidemic could have been mitigated. The simulation calculates the number of deaths that could have been avoided, as well as the potential savings in healthcare costs.

II. Background & Previous Research

Previous research on the opioid crisis has primarily focused on the role of prescription drugs and their contribution to overdose deaths. Dasgupta et al. (2018) emphasize that the opioid epidemic is driven by both demand-side factors and supply-side factors; they argue that the opioid epidemic is a consequence of both social and economic determinants, with increased prescribing driven by aggressive marketing by pharmaceutical companies and economic instability exacerbating demand for opioids. Florence et al. (2016) also provide a more comprehensive analysis of the economic burden of opioid abuse, as well as giving an estimate that prescription opioid overdose, abuse, and dependence have cost the U.S. economy over \$78 billion annually in healthcare, loss of productivity, and criminal justice costs alone. Scavette (2019) focuses on the economic effects of opioid misuse, particularly in areas that have experienced declines in manufacturing employment. These economic disruptions are linked to higher opioid addiction rates and deaths, particularly in rural and working-class communities. This paper builds on these findings by incorporating economic variables, such as labor force participation and manufacturing employment, into the analysis and examining their impact on opioid mortality and public health expenditures.

With these findings in mind, this paper hypothesizes that states with lower labor force participation rates and higher manufacturing employment declines are more likely to have a higher number of opioid overdose deaths. Additionally, prescription rates are expected to significantly influence the overdose mortality rate, especially in the earlier years of the crisis. We also hypothesize that states with higher opioid mortality rates will experience higher public healthcare costs, specifically through Medi-care and Medi-caid expenditures.

III. Data Description

The dataset used for this analysis spans from the years of 2000 to 2020, and encompasses key economic and public health variables across 51 U.S. states. These variables are collected from national sources such as the Bureau of Labor Statistics (BLS) for labor force participation and manufacturing employment, Kiser Family Foundation (KFF) for overdose deaths, and the Centers for Medi-care & Medi-caid Services (CMS) for healthcare expenditures, and more.

The dataset includes the following key variables:

TABLE I Variable Descriptions

Variable Name	Description	Source	Unit of Measurement	Mean	Standard Deviation
state	state name	-	-	-	-
t	time variable (2000 to 2020)	-	-	-	-
stateid	state identifier	-	-	-	-
year	year (2000 to 2020)	-	-	-	-
medicarml	Medi-care spending, current dollars	Centers for Medi-care & Medi-caid Services	million dollars	9405.18	11727.76
Medi-caid	Medi-caid spending, current dollars	Centers for Medi-care & Medi-caid Services	million dollars	7318.15	10420.07
oddeaths	opioid overdose deaths in a state	Kiser Family Foundation	number of deaths	519.51	675.99
population	population of state	U.S. Census Bureau	number of residents	6039.75	6783.97
medhhinc	median household	U.S. Census	dollars	52444.30	11638.42

	income, current dollar	Bureau			
gdp	gross domestic product, current dollar	Bureau of Economic Analysis	dollars	304040.49	389747.96
lfpr	labor force participation rate (%)	Bureau of Labor Statistics	percentage	65.46	4.26
unemprate	unemployment rate (%)	Bureau of Labor Statistics	percentage	5.58	2.03
pchinsured	percentage of population insured	U.S. Census Bureau	percentage	88.25	4.28
percenthsgra d	percentage of high school graduates	U.S. Census Bureau	percentage	87.23	3.66
prescriptionr ate	number of prescriptions dispensed per 100 people	Centers for Disease Control	prescriptions per 100 people	47.76	12.83
cpi	consumer price index	Bureau of Labor Statistics	index	214.30	26.60
temearemeai dml	total Medi-care and Medi-caid spending	-	million dollars	16723.33	19218.44
temearemeai dmladj	adjusted Medi-care and Medi-caid spending (2020 dollars)	-	million dollars	19729.53	21564.67
medhhincadj	adjusted mean household income (2020 dollars)	-	dollars	62966.89	10228.04
gdpadj	adjusted gdp (2020 dollars)	-	dollars	361604.43	447066.40

pegdpmanu	percentage of gdp contributed by manufacutring sector	Bureau of Economic Analysis	percentage	11.98	5.58
pcempmanu	percentage of employment in manufacturing sector	Bureau of Economic Analysis	percentage	4.33	1.93
logtcmcarem caidmladj	log-transofmred adjusted Medi-care and Medi-caid spending	-	log of million dollars	9.45	0.96
oddeathsrate	opioid overdose death rate per 100,000 population	Kiser Family Foundation	deaths per 100,000 residents	0.09	0.10
logoddeathsr ate	log transformed opioid overdose death rate	-	log of deaths per 100,000	-	-
gdpadjpc	gdp per capita adjusted for 2020 dollars	-	dollars	60.30	22.67
lfpr1	labor force participation rate, 2000 level maintained	Bureau of Labor Statistics	percentage	-	-

IV. Econometric Models

1. Pooled OLS Regression Model

The first model estimates the relationship between opioid overdose deaths and various economic and healthcare variables using pooled OLS regression:

$$log(oddeaths100k) = \beta0 + \beta1pcempmanu + \beta2log(medhhincadj) + \beta3log(gdpadj)$$

+ $\beta4pchinsured + \beta5percenthsgrad + \beta6lfpr + \epsilon$

This model captures the direct effects of various economic and social factors on opioid mortality, but does not account for any unobserved heterogeneity across states that may influence the outcome.

2. Fixed-Effects Panel Regression Model

The second model controls for unobserved heterogeneity by incorporating state-level fixed effects:

```
log(oddeaths100k) = \alpha i + \beta 1 pcempmanu + \beta 2 log(medhhincadj) + \beta 3 log(gdpadj)
+ \beta 4 pchinsured + \beta 5 percenthsgrad + \beta 6 lfpr + ut + \epsilon it
```

This model provides more accurate estimates of the relationships between opioid deaths and economic factors by controlling for state-specific and time-varying factors, ensuring that the results are not confounded by unmeasured heterogeneity.

3. Analysis

Both the pooled OLS and fixed-effects panel regression models provide consistent evidence that increasing labor force participation could serve as an important lever in reducing opioid overdose deaths. Specifically, in the pooled OLS regression, a 1% increase in labor force participation is associated with a 0.5% reduction in opioid death rates; this suggests that economic engagement, especially employment, plays a vital role in reducing opioid mortality.

Labor force participation could offer both social and economic benefits, such as increased stability, access to healthcare, and social connection, which help mitigate substance misuse and overdose deaths. We will further explore these findings through simulations, estimating how much opioid mortality could be reduced if labor force participation had remained at 2000 levels.

V. Estimation Results

The results from both the pooled OLS and fixed-effects panel regression models show strong relationships between economic, healthcare variables, and opioid mortality rates.

Specifically, labor force participation and manufacturing employment are significant predictors of opioid overdose deaths, while prescription rates show a strong positive correlation with these deaths.

1. Labor Force Participation and Opioid Death

Chart I
Labor Force Participation Rate (LFPR) Trend
(United States, Kentucky, New Mexico)

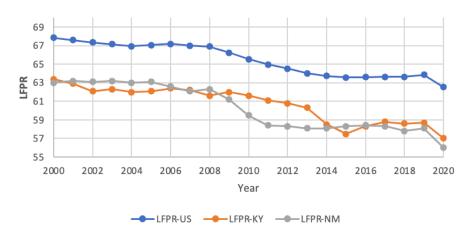


Chart II
Overdose Deaths Per 100k Residents
(United States, Kentucky, New Mexico)

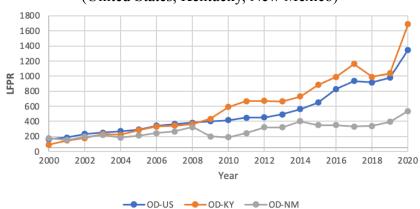
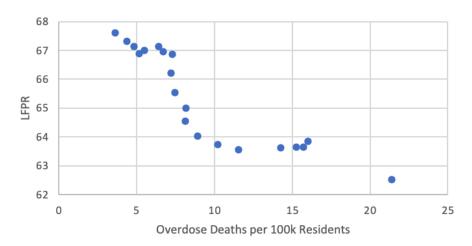


Chart II shows a clear upward trend in overdose deaths, with Kentucky experiencing a sharper increase than the national average. The results from the regression analysis show that the labor force participation rate is a crucial variable in predicting opioid overdose deaths across all states. States with higher LFPR, which is indicative of a healthier economy, tend to have lower opioid mortality rates, as shown through an inverse relationship in Charts I and II.

Chart III
Opioid Overdose Death Rate vs. Labor Force Participation (LFPR)
(All Three States Combined)



For example, North Dakota, with an LFPR of 71.76%, ranks first for having the lowest opioid death rate in the country, with an overdose death rate of 2.49 per 100,000 in 2000. Their average cost per death is calculated at 6.1 million dollars, resulting in a total annual cost saving of \$12.3 million by avoiding opioid deaths. In contrast, states with lower labor force participation rates tend to have higher opioid mortality rates. For instance, West Virginia, with an LFPR of 54.648%, had one of the highest overdose death rates at 24.336 per 100,000 in 2020.

2. Manufacturing Employment and Opioid Mortality

States with higher levels of manufacturing employment experience lower opioid overdose deaths, suggesting that economic stability and manufacturing jobs play a key role in reducing the opioid epidemic.

For instance, Michigan, with a manufacturing employment share of 63.081%, ranks in the middle in terms of overdose deaths, but still sees a reduction in opioid deaths relative to states with a higher dependence on non-manufacturing sectors. California, with a 64.2% manufacturing employment rate, had opioid deaths reduced by 0.3% per year as compared to states with lower employment in manufacturing. On the other hand, states with lower manufacturing employment share tend to have higher opioid death rates. For example, Alabama ranks in the top 10 for opioid deaths, and Mississippi, with lower manufacturing employment, experiences high overdose mortality rates; with only 58.452% manufacturing employment, Mississippi ranked 50/51 for opioid deaths. This shows how the manufacturing sector has contributed to higher opioid death rates in many states.

3. Prescription Rates and Opioid Deaths

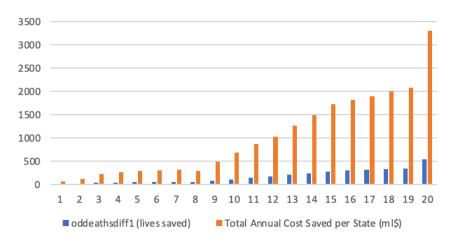
Prescription opioid rates have been a major driver of the opioid crisis, particularly in the earlier stages. States with higher prescription rates, or the number of prescriptions per capita, often correlate with higher overdose death rates.

Delaware had one of the highest prescription rates in the U.S. and an average overdose death rate of 13.543 per 100,000 in 2020; this high rate of prescription medications contributed to a higher mortality rate. They experienced an annual total cost saving of \$136.76 million due to the reduction in opioid deaths by maintaining the labor force participation at 2000 levels.

VI. Simulation Results

A key aspect of this study was the counterfactual simulation, which assumed that labor force participation rates remained constant at 2000 levels. By running this simulation, we estimated the potential number of opioid deaths that could have been avoided and the corresponding savings in public healthcare costs if the labor force participation rates had remained at these levels.

Chart IV
Estimated Lives Saved & Total Annual Cost Saved Per State (millions)



1. Estimated Lives Saved

The simulation results suggest that if labor force participation had not decreased from its 2000 level, approximately 342,000 opioid overdose deaths could have been avoided across the United States over the period from 2001 to 2020.

For example, in 2020 alone, West Virginia saw 542.722 opioid overdose deaths per 100,000, but with an increased LFPR at 2000 levels, this number could have been reduced by 310 deaths, preventing a total of \$33.1 million in Medi-care and Medi-caid expenditures for the state.

2. Healthcare Cost Savings

The potential savings in public healthcare costs are also substantial; based on the estimated number of lives saved per state and the average cost per opioid death of approximately \$6.1 million, the total savings across the country is approximately \$168 million annually from the model.

For states such as Mississippi and West Virginia, where opioid overdose death rates are among the highest, the potential savings from maintaining 2000 labor force participation levels could amount to over \$147 million in healthcare savings annually.

VII. Policy Implications and Limitations

1. Policy Implications

The findings of this paper show the importance of addressing economic factors, such as labor force participation and manufacturing employment, to mitigate the opioid crisis. States with stronger labor markets and higher levels of employment in stable industries, such as manufacturing, show lower opioid death rates. Policymakers should focus on economic revitalization in areas with high opioid death rates, doing this by investing in manufacturing and other high-employment industries. They should also put more attention on prescription regulation to reduce the over-prescription of opioids, particularly in states where prescription rates correlate strongly with opioid deaths. Policies that promote higher education and workforce participation are essential, particularly for states like West Virginia and Mississippi, where labor force participation and manufacturing jobs have declined significantly.

2. Limitations

While the study demonstrates a significant relationship between labor force participation and opioid overdose deaths, it does not establish a definite causal link. There could be further research done to incorporate additional variables, such as healthcare access, law enforcement policies, and mental health services, to provide a more comprehensive analysis. In addition to this, regional variations in healthcare access and drug law enforcement could have influenced the generalizability of these findings.

VIII. Conclusion

This paper provides a comprehensive analysis of the significant role that economic factors, such as labor force participation and manufacturing employment, play in influencing opioid overdose deaths across states. The analysis shows that states with higher labor force participation and more manufacturing jobs tend to experience lower opioid mortality rates, while areas with high economic distress, such as declining job opportunities, are more vulnerable to the opioid crisis. The counterfactual simulation further suggests that maintaining labor force participation at 2000 levels could have prevented hundreds of thousands of deaths, as well as saved billions of dollars in public healthcare costs. These findings emphasize the importance of addressing economic disparities as part of a more comprehensive strategy to combat the rising opioid epidemic.

The results also show the critical need for policy interventions that combine economic revitalization with stricter prescription regulations. States should prioritize reviving manufacturing sectors, expanding job training programs, and strengthening prescription monitoring to reduce opioid misuse. Future research should also be conducted to focus on refining these models, such as by incorporating additional variables like healthcare access and law enforcement policies, as well as exploring mechanisms to inform more effective policy responses in the future.

References

- Brill, A., & Ganz, S. (2018). *The geographic variation in the cost of the opioid crisis*. American Enterprise Institute.
- Chattopadhyay, S. (2025). Does Declining Labor Force Participation in the United States Have a Role in Opioid Deaths? A State Level Analysis of The Economic Cost.
- Council of Economic Advisers. (2019). *The role of opioid prices in the evolving opioid crisis*.

 Executive Office of the President of the United States.
- Dasgupta, N., Beletsky, L., & Ciccarone, D. (2018). Opioid crisis: No easy fix to its social and economic determinants. *American Journal of Public Health*, 108(2), 182–186.
- Florence, C., Luo, F., Xu, L., & Zhou, C. (2016). The economic burden of prescription opioid overdose, abuse, and dependence in the United States, 2013. *Medical Care*, *54*(10), 901–906.
- Parramore, L. (2019, February 20). *Opioid crisis shows how economic inequality kills*. Institute for New Economic Thinking.
- Scavette, A. (2019). Exploring the economic effects of the opioid epidemic. Federal Reserve Bank of Philadelphia.

Appendix

```
. xtset stateid t
```

panel variable: stateid (strongly balanced)

time variable: t, 0 to 20 delta: 1 unit

. gen oddeaths100k= oddeaths*100000/ population

. gen logoddeaths=log(oddeaths)
(12 missing values generated)

. gen logoddeaths100k=log(oddeaths100k)
(12 missing values generated)

. gen logmedhhincadj =log(medhhincadj)

. gen loggdpadj =log(gdpadj)

. gen logtcmcaremcaidmladj=log(tcmcaremcaidmladj)

. reg logoddeaths100k pcempmanu logmedhhincadj loggdpadj pchinsured percenthsgr > ad lfpr

	Source	SS	df	MS	Number of obs		1,059
•					F(6, 1052)	=	122.27
	Model	249.050071	6	41.5083452	Prob > F	=	0.0000
	Residual	357.138985	1,052	.339485727	R-squared	=	0.4108
-					Adj R-squared	=	0.4075
	Total	606.189056	1.058	.57295752	Root MSE	=	.58265

logodde~100k	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
pcempmanu	075633	.0115109	-6.57	0.000	0982199	053046
logmedhhin~j	1.230141	.1917859	6.41	0.000	.8538148	1.606468
loggdpadj	.0248219	.0211857	1.17	0.242	0167491	.0663929
pchinsured	.0145523	.0059549	2.44	0.015	.0028676	.0262371
percenthsg~d	.0644997	.0072568	8.89	0.000	.0502602	.0787391
lfpr	1061213	.0065505	-16.20	0.000	1189749	0932678
_cons	-4.67466	1.49118	-3.13	0.002	-7.600686	-1.748634

. reg logoddeaths100k pcempmanu logmedhhincadj loggdpadj pchinsured percenthsgr > ad lfpr, vce(cluster oddeaths100k)

 Linear regression
 Number of obs
 =
 1,059

 F(6, 1058)
 =
 84.00

 Prob > F
 =
 0.0000

 R-squared
 =
 0.4108

 Root MSE
 =
 .58265

(Std. Err. adjusted for 1,059 clusters in oddeaths100k)

logodde~100k	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
pcempmanu	075633	.0126047	-6.00	0.000	1003661	0508999
logmedhhin~j	1.230141	.2159366	5.70	0.000	.8064287	1.653854
loggdpadj	.0248219	.0220967	1.12	0.262	0185365	.0681803
pchinsured	.0145523	.0060097	2.42	0.016	.00276	.0263447
percenthsg~d	.0644997	.007512	8.59	0.000	.0497596	.0792398
lfpr	1061213	.0070794	-14.99	0.000	1200126	09223
_cons	-4.67466	1.693815	-2.76	0.006	-7.998278	-1.351042

. xtreg logoddeaths100k pcempmanu logmedhhincadj loggdpadj pchinsured percenths > grad lfpr,fe robust

Fixed-effects (within) regression	Number of obs =	1,059
Group variable: stateid	Number of groups =	51
R-sq:	Obs per group:	
within = 0.6693	min =	15
between = 0.0704	avg =	20.8
overal1 = 0.2404	max =	21
	F(6,50) =	50.63
corr(u_i, Xb) = -0.6592	Prob > F =	0.0000

logodde~100k	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
pcempmanu	2956021	.0504064	-5.86	0.000	3968463	1943579
logmedhhin~j	.8602529	.3424273	2.51	0.015	.1724674	1.548038
loggdpadj	.5103568	.2919032	1.75	0.087	075948	1.096662
pchinsured	0047023	.0111879	-0.42	0.676	0271739	.0177692
percenthsg~d	.0997978	.0175345	5.69	0.000	.0645787	.135017
lfpr	0654553	.0184853	-3.54	0.001	1025841	0283265
_cons	-9.638175	3.318088	-2.90	0.005	-16.30275	-2.973598
sigma u	.75488915					
sigma e	.34992481					
rho	.82313088	(fraction	of varia	nce due	to u_i)	

. xtreg logoddeaths100k pcempmanu logmedhhincadj loggdpadj pchinsured percenths > grad lfpr,re robust

Random-effects GLS regression	Number of obs	=	1,059
Group variable: stateid	Number of groups	=	51
R-sq:	Obs per group:		
within = 0.6645	min	=	15
between = 0.1055	avg	=	20.8
overall = 0.3293	max	=	21
	Wald chi2(6)	=	307.00
corr(u_i, X) = 0 (assumed)	Prob > chi2	=	0.0000

logodde~100k	Coef.	Robust Std. Err.	z	P> z	[95% Conf.	Interval]
pcempmanu	2351398	.0326409	-7.20	0.000	2991148	1711648
logmedhhin~j	.8122064	.31836	2.55	0.011	.1882322	1.436181
loggdpadj	.205033	.0953624	2.15	0.032	.0181262	.3919398
pchinsured	0050099	.0102229	-0.49	0.624	0250464	.0150267
percenthsg~d	.1095009	.013489	8.12	0.000	.0830629	.135939
lfpr	0874811	.0141423	-6.19	0.000	1151995	0597628
-cous	-5.003216	2.820298	-1.77	0.076	-10.5309	.5244658
sigma u	. 43221505					
sigma_e	.34992481					
rho	.60405978	(fraction	of varia	nce due t	to u_i)	

. xtreg logtcmcaremcaidmladj logoddeaths logmedhhincadj loggdpadj pchinsured pe > rcenthsgrad unemprate, fe robust

Fixed-effects (within) regression	Number of obs	=	1,059
Group variable: stateid	Number of groups	=	51
R-sq:	Obs per group:		
within = 0.1460	min	=	15
between = 0.8438	avg	=	20.8
overall = 0.6802	max	=	21
	F(6,50)	=	39.59
$corr(u_i, Xb) = -0.3752$	Prob > F	=	0.0000

		Robust				
logtcmcare~j	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
logoddeaths	.1685417	.0330604	5.10	0.000	.102138	.2349454
logmedhhin~j	4617617	.2750853	-1.68	0.099	-1.014287	.0907633
loggdpadj	.6924182	.2977538	2.33	0.024	.094362	1.290474
pchinsured	.033189	.0071881	4.62	0.000	.0187512	.0476268
percenthsg~d	031941	.0143928	-2.22	0.031	0608497	0030323
unemprate	.0191919	.0088973	2.16	0.036	.0013211	.0370627
_cons	4.857024	5.271986	0.92	0.361	-5.732071	15.44612
sigma u	.36616423					
sigma_e	.44508098					
rho	. 40363339	(fraction	of varia	nce due t	to u_i)	

. xtreg logtcmcaremcaidmladj logoddeaths logmedhhincadj loggdpadj pchinsured pe > rcenthsgrad unemprate,re robust

Random-effects GLS regression	Number of obs	=	1,059
Group variable: stateid	Number of groups	=	51
R-sq:	Obs per group:		
within = 0.1448	min	=	15
between = 0.8490	avg	=	20.8
overall = 0.6847	max	=	21
	Wald chi2(6)	=	272.21
corr(u_i, X) = 0 (assumed)	Prob > chi2	=	0.0000

logtcmcare~j	Coef.	Robust Std. Err.	z	P> z	[95% Conf.	Interval]
logoddeaths	.1708944	.0271058	6.30	0.000	.117768	.2240208
logmedhhin~j	6116224	.2492728	-2.45	0.014	-1.100188	1230567
loggdpadj	.5758631	.0653481	8.81	0.000	.4477831	.703943
pchinsured	.0309916	.0074851	4.14	0.000	.016321	.0456623
percenthsg~d	0215125	.0124174	-1.73	0.083	0458502	.0028251
unemprate	.0129744	.0085137	1.52	0.128	0037121	.0296609
_cons	7.253955	2.606998	2.78	0.005	2.144333	12.36358
sigma u	.31057447					
sigma e	. 44508098					
rho	.32746674	(fraction	of varia	nce due t	o u_i)	

```
. gen lfprtemporary=lfpr
. gen lfpr2000=lfpr
. replace lfpr2000=lfpr2000[ n-1] if year>2000
(997 real changes made)
. xtreg logoddeaths100% pcempmanu logmedhhincadj loggdpadj pchinsured percenths
> grad lfpr,fe robust
                                            Number of obs = 1,059
Number of groups = 51
Fixed-effects (within) regression
Group variable: stateid
                                             Obs per group:
R-sq:
                                                                      15
    within = 0.6693
                                                           min =
                                                           avg =
max =
    between = 0.0704
                                                                     20.8
    overall = 0.2404
                                                                       21
                                              F(6,50) = 50.63

Prob > F = 0.0000
corr(u_i, Xb) = -0.6592
                             (Std. Err. adjusted for 51 clusters in stateid)
```

logodde~100k	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
pcempmanu	2956021	.0504064	-5.86	0.000	3968463	1943579
logmedhhin~j	.8602529	.3424273	2.51	0.015	.1724674	1.548038
loggdpadj	.5103568	.2919032	1.75	0.087	075948	1.096662
pchinsured	0047023	.0111879	-0.42	0.676	0271739	.0177692
percenthsg~d	.0997978	.0175345	5.69	0.000	.0645787	.135017

```
lfpr -.0654553 .0184853 -3.54 0.001 -.1025841 -.0283265
_cons -9.638175 3.318088 -2.90 0.005 -16.30275 -2.973598

sigma_u .75488915
sigma_e .34992481
rho .82313088 (fraction of variance due to u_i)
```

```
. predict logodd100khat1
(option xb assumed; fitted values)
. replace lfpr=lfpr2000
(997 real changes made)
.
. predict logodd100khat2
(option xb assumed; fitted values)
. replace lfpr=lfprtemporary
(997 real changes made)
. gen exp1=exp(logodd100khat1)
.
. gen exp2=exp(logodd100khat2)
.
. gen exp1minus2= exp1- exp2
.
. gen oddeathsdiff= exp1minus2/100000* population
```

. sum oddeathsdiff

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeathsdiff	1,071	149.543	433.7825	-219.3848	5693.357

. sum oddeathsdiff if oddeathsdiff>0 & year>2000

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeathsdiff	862	188.0262	475.5143	.0715648	5693.357

. gen oddeathsdiff1= oddeathsdiff

. replace oddeathsdiff1=. if year==2000 | oddeathsdiff<=0 (209 real changes made, 209 to missing)

. sum oddeaths100k lfpr oddeathsdiff1

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	1,071	9109.694	7586.809	0	63014.54
lfpr	1,071	65.46032	4.264343	53.3	75.4
oddeathsdi~1	862	188.0262	475.5143	.0715648	5693.357

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	3119.982	2291.77	0	9883.594
lfpr	51	67.84706	3.718514	55.8	75.1
oddeathsdi~1	0				

. sum oddeaths100k lfpr oddeathsdiff1 if year==2001

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	3639.941	2364.566	0	9098.199
lfpr	51	67.59804	3.818769	55.7	75.4
oddeathsdi~1	29	10.89553	20.93892	.3178935	106.7897

. sum oddeaths100k lfpr oddeathsdiff1 if year==2002

Variable	0bs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	4358.402	2563.198	0	10564.27
lfpr	51	67.32549	3.844052	55.6	75.1
oddeathsdi~1	33	20.18558	35.20004	.2769856	148.1071

Max	Min	Std. Dev.	Mean	Obs	Variable
11610.75	0	3107.464	4819.789	51	oddeaths100k
74.9	55	3.884229	67.12745	51	lfpr
352.7977	.3561758	78.16303	37.14806	37	oddeathsdi~1

. sum oddeaths100k lfpr oddeathsdiff1 if year==2004

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	5160.336	2838.269	899.9623	13818.24
lfpr	51	66.89412	3.85328	54.8	74.4
oddeathsdi~1	42	43.41882	94.37593	. 4111777	506.4861

. sum oddeaths100k lfpr oddeathsdiff1 if year==2005

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	5504.941	2952.817	0	13280.49
lfpr	51	67.00588	3.742802	55.1	73.4
oddeathsdi~1	35	48.10101	90.88174	.9769437	497.3667

Variable	0bs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	6415.11	3379.363	0	15591.58
lfpr	51	67.13333	3.797456	55.5	73.3
oddeathsdi~1	32	49.70497	108.7029	1.640941	585.2175

[.] sum oddeaths100k lfpr oddeathsdiff1 if year==2007

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	6715.247	3492.158	2186.785	18102.01
lfpr	51	66.95882	3.917917	55.3	73.9
oddeathsdi~1	36	52.87494	99.71065	.0715648	495.0943

.

. sum oddeaths100k lfpr oddeathsdiff1 if year==2008

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	7283.266	3610.157	1614.358	20159.65
lfpr	51	66.85882	3.989646	55.2	74.2
oddeathsdi~1	36	48.72229	93.07636	.2096331	419.2523

.

. sum oddeaths100k lfpr oddeathsdiff1 if year==2009

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	7222.011	3312.322	628.1694	16352.1
lfpr	51	66.21176	4.088748	55.3	73.1
oddeathsdi~1	41	79.13301	141.5979	.5161111	713.0413

.

	Variable	Obs	Mean	Std. Dev	. Min	Max
od	ldeaths100k	51	7471.042	3849.328	2667.647	24322.24
	lfpr	51	65.53922	4.004102	54.7	73
od	ldeathsdi~1	45	112.3714	208.9785	1.134203	1221.81

. sum oddeaths100k lfpr oddeathsdiff1 if year==2011

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	8153.355	4563.263	1458.734	29623.88
lfpr oddeathsdi~1	51	65.00392	3.983866	54.3	72.9
oddeathsdi~1	49	143.7027	268.1421	.3699442	1605.351

.

. sum oddeaths100k lfpr oddeathsdiff1 if year==2012

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	8118.551	4336.05	0	25195.83
lfpr	51	64.55098	3.969906	54.4	72.8
oddeathsdi~1	49	169.0646	317.9527	1.282725	1882.381

. sum oddeaths100k lfpr oddeathsdiff1 if year==2013

Variable	Obs	Mean	Std. Dev.	Min	Маж
oddeaths100k	51	8907.896	4541.338	1521.125	26418.37
lfpr	51	64.02745	4.086812	53.9	71.9
oddeathsdi~1	49	206.8426	375.3466	2.205889	2192.781

.

[.] sum oddeaths100k lfpr oddeathsdiff1 if year==2014

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	10200.07	5403.961	2978.787	29936.72
lfpr	51	63.73725	4.18736	53.7	71.8
oddeathsdi~1	49	243.4175	434.5159	2.957884	2508.882

.

. sum oddeaths100k lfpr oddeathsdiff1 if year==2015

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	11560.76	6689.483	2906.885	34123.03
lfpr	51	63.55686	4.088044	53.5	70.7
oddeathsdi~1	50	282.3588	524.1963	.2686878	2872.94

•

. sum oddeaths100k lfpr oddeathsdiff1 if year==2016

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	14258.62	8670.477	2307.918	40001.31
lfpr	51	63.62549	4.050671	53.3	70.7
oddeathsdi~1	50	299.0932	567.5647	.2816156	3084.396

.

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	15701.2	9922.08	3077.726	45802.45
lfpr	51	63.64902	4.026828	53.5	70.6
oddeathsdi~1	50	311.5952	603.4023	.5779236	3269.214

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	15250.02	9470.285	3184.04	38871.51
lfpr	51	63.64314	3.979159	54.4	70.5
oddeathsdi~1	50	328.6264	640.4972	2.540756	3423.727

. sum oddeaths100k lfpr oddeathsdiff1 if year==2019

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	16032.79	9595.233	3518.631	39624.52
lfpr	51	63.84118	3.977747	54.7	71.1
oddeathsdi~1	50	341.1504	694.9375	2.619838	3863.551

. sum oddeaths100k lfpr oddeathsdiff1 if year==2020

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	51	21410.24	12347.57	5099.053	63014.54
lfpr	51	62.53137	4.020522	53.9	69.8
oddeathsdi~1	50	542.7217	1083.513	5.810489	5693.357

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==1

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	4420.897	2973.043	965.8212	12139.66
lfpr	21	59.59048	2.296716	56.7	63.6
oddeathsdi~1	20	56.97676	45.36501	3.472301	141.2557

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==2

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	7955.388	4834.13	0	15279.32
lfpr	21	69.03333	2.939105	63.5	73.3
oddeathsdi~1	20	23.13401	18.46167	2.184877	62.12768

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==3

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	9678.401	5013.704	4553.743	26213.49
lfpr	21	62.7619	2.158582	59.9	66.1
oddeathsdi~1	17	223.8463	153.7762	9.888554	401.4411

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	5346.73	1990.051	746.6614	9420.975
lfpr	21	60.34286	2.002392	57.4	63.1
oddeathsdi~1	15	20.45605	16.55032	.3561758	49.97456

.

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==5

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	5186.853	2368.536	1598.053	13936.56
lfpr	21	64.2	1.921197	60.9	67.1
oddeathsdi~1	19	1856.811	1539.044	91.75381	5693.357

•

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==6

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	7852.895	2958.347	4021.336	16899.57
lfpr	21	70.12381	2.186757	66.8	72.8
oddeathsdi~1	14	210.6074	146.8186	4.400076	474.4522

.

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	12446.19	10111.33	4340.429	34916.98
lfpr	21	66.95238	1.174572	64.6	68.8
oddeathsdi~1	15	39.05549	27.8479	3.997923	103.6605

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	13543.16	12013.71	3431.344	41031.2
lfpr	21	64.30952	2.885464	60.9	69.6
oddeathsdi~1	19	22.41932	16.071	2.154262	53.07466

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==9

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	14355.11	12934.21	2195.1	50229.76
lfpr	21	68.82857	1.287689	66.6	71.1
oddeathsdi~1	4	2.390457	1.486958	.492828	3.88011

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==10

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	9445.128	5166.073	3464.71	25333.41
lfpr	21	61.25714	1.836184	57.5	63.9
oddeathsdi~1	16	1426.657	1173.296	148.1071	4319.041

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	5548.711	2843.444	1397.785	12158.89
lfpr	21	65.21429	2.678112	61.1	68.9
oddeathsdi~1	20	269.2667	245.2108	12.66344	846.7703

.

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==12

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	4365.14	876.3743	2389.742	5928.493
lfpr	21	63.55238	2.346619	59.1	67.3
oddeathsdi~1	20	74.09788	61.31247	1.681886	226.5994

.

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==13

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	4874.24	1574.854	2154.791	8651.36
lfpr	21	66.28571	2.311122	63.5	70
oddeathsdi~1	19	21.36581	16.75031	.3558231	57.46506

.

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	9182.7	5532.646	3663.584	23032.89
lfpr	21	66.18095	1.58859	62.6	69.4
oddeathsdi~1	20	352.4289	266.3526	34.47221	1117.429

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	7358.56	7125.859	673.0281	27641.56
lfpr	21	65.43333	1.833667	63	67.9
oddeathsdi~1	18	40.5576	28.12669	.6170846	103.1669

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==16

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	4063.523	1953.217	648.67	7019.435
lfpr	21	70.66191	1.464744	66.8	72.6
oddeathsdi~1	13	12.51844	11.24727	.3595008	43.95364

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==17

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	4492.875	1722.475	816.7266	8917.115
lfpr	21	69.15238	1.524013	66.9	71.2
oddeathsdi~1	12	18.56787	12.31172	1.879599	39.32456

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	13776.68	8984.81	2272.155	37441.89
lfpr	21	60.69048	1.930519	57.1	63.3
lfpr oddeathsdi~1	20	32.24907	33.21811	1.700863	124.3107

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	5435.775	4410.246	1162.819	20312.54
lfpr	21	60.41905	1.440701	57.3	63.2
oddeathsdi~1	16	47.59662	44.49543	1.341046	161.1243

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==20

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	12131.45	8150.507	3210.474	30778.93
lfpr	21	64.97143	2.008019	59.6	68.2
oddeathsdi~1	20	17.61325	17.43733	1.222942	73.70982

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==21

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	16400.59	10810.44	8761.588	40531.31
lfpr	21	68.37619	1.092201	66.6	70.2
oddeathsdi~1	20	171.4528	132.8395	4.081563	486.1141

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	14759.96	8847.2	4936.253	29522.77
lfpr	21	66.54762	1.107076	64.9	68.7
oddeathsdi~1	17	118.8074	86.13951	10.4936	305.1967

Variable	Obs	Mean	Std. Dev.	Min	Маж
oddeaths100k	21	9222.798	6604.305	1808.6	21741.94
lfpr	21	63.08095	2.662821	60.1	68.6
oddeathsdi~1	20	321.3594	182.2984	14.72017	664.2007

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==24

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	4840.352	2532.282	1155.322	11872.37
lfpr	21	71.89048	2.046193	69.6	75.4
oddeathsdi~1	18	92.81315	57.17272	2.554471	187.5807

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==25

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	3799.213	3066.746	421.2965	13689.18
lfpr	21	58.45238	2.565467	54.8	62.4
oddeathsdi~1	20	24.18783	20.26382	2.203935	66.55698

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	9731.87	5533.889	2336.244	22373
lfpr	21	66.15238	2.25136	62.7	70
oddeathsdi~1	20	126.8739	97.15745	2.783206	339.0051

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	5175.051	1901.077	1217.12	9044.881
lfpr	21	65.21905	1.710737	62.9	68.5
oddeathsdi~1	20	22.08313	15.49289	3.705848	49.27103

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==28

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	2506.912	1014.925	805.2271	5144.164
lfpr	21	71.85714	1.55228	69.4	74.1
oddeathsdi~1	15	11.01556	8.097798	.8904843	24.7921

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==29

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	13555.65	2557.495	8673.275	17934.08
lfpr	21	65.99524	2.94219	61.3	70.4
oddeathsdi~1	19	89.4466	66.16544	10.61849	231.7262

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	14763.25	10101.75	2338.936	32522.38
lfpr	21	69.88095	1.43165	66.8	72.3
oddeathsdi~1	20	10.74923	8.562291	. 6569962	34.22534

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	9775.196	8991.024	628.1694	29049.46
lfpr	21	65.36667	1.357325	62.9	67
oddeathsdi~1	15	267.9767	256.7262	23.66743	792.227

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==32

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	13949.9	4192.67	8243.753	25252.4
lfpr	21	60.21905	2.439799	55.9	63.3
oddeathsdi~1	17	50.46508	36.96933	2.145858	135.7487

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==33

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	8146.165	5480.087	2498.491	21054.29
lfpr	21	61.87143	1.170958	59.1	63.2
oddeathsdi~1	14	825.6361	749.7108	53.70948	2754.496

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	10248.65	5472.578	3538.899	25206.58
lfpr	21	63.79524	2.590265	59	67.5
oddeathsdi~1	19	236.9507	234.5537	5.378391	894.9479

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	2848.686	2591.916	0	9107.667
lfpr	21	71.75714	1.401989	69	74.2
oddeathsdi~1	6	2.016552	2.152551	.2686878	5.810489

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==36

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	14097.52	11868.24	2200.019	37164.45
lfpr	21	64.94762	2.089885	61.6	67.6
oddeathsdi~1	14	231.3224	149.0595	11.34986	535.9906

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==37

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	9947.773	3414.698	3676.502	15278.8
lfpr	21	62.64762	1.385503	60.7	64.5
oddeathsdi~1	16	47.67898	32.42581	1.167698	99.04891

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	7938.353	2039.987	3090.64	11758.39
lfpr	21	64.39048	2.375901	61.3	68.6
oddeathsdi~1	20	98.68598	80.54241	5.0012	271.53

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	9227.98	8256.144	2048.952	30062.77
lfpr	21	63.71429	.9128448	62.3	65.1
oddeathsdi~1	13	201.0513	118.9046	9.829557	452.8982

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==40

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	15220.15	7728.995	5427.176	30186.13
lfpr	21	66.19048	1.432448	63.7	68.3
oddeathsdi~1	13	4.716457	4.559405	.2769856	15.43671

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==41

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	7888.698	6578.971	1971.859	27453.85
lfpr	21	61.17143	2.448906	57.9	65
oddeathsdi~1	20	74.48391	71.92925	2.237101	228.1024

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	3063.081	1535.31	0	5180.483
lfpr	21	71.22381	1.544637	69	73.3
oddeathsdi~1	14	3.438154	2.326424	.2872919	7.862599

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	11559.08	7863.505	1753.242	34815.75
lfpr	21	62.48571	1.859109	59.7	65.3
oddeathsdi~1	20	74.47096	67.56613	.5468202	204.8701

..

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==44

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	4285.357	1064.995	1809.544	7264.128
lfpr	21	65.75238	1.649127	63	68.4
oddeathsdi~1	20	779.9165	756.3671	27.95015	2665.288

.

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==45

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	12718.38	2528.632	6874.749	15484.99
lfpr	21	69.7381	1.932997	66.7	72.6
oddeathsdi~1	18	42.99782	32.70984	.9769437	99.91278

.

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	10593.5	5671.571	3608.817	24417.67
lfpr	21	69.11905	2.099195	63.4	71.3
oddeathsdi~1	12	3.81554	3.781909	.0715648	13.623

C11100	addastha100k	1 E2220	oddeathsdiff1	- F	a+a+aid47
o um	Oddeathsioos	TIDE	oddeathadilli		Buaueru

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	8363.944	4760.965	3518.243	21962.07
lfpr	21	67.08571	1.578381	64.2	69.6
oddeathsdi~1	12	260.8482	180.2618	24.07195	653.3395

•

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==48

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	9568.593	1979.759	5412.882	15464.83
lfpr	21	65.97143	1.976903	63.1	68.6
oddeathsdi~1	20	232.8797	211.8427	17.08229	659.5086

•

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==49

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	24335.86	15188.94	2766.987	63014.54
lfpr	21	54.64762	.7839761	53.3	55.8
oddeathsdi~1	20	11.93023	9.710507	.3178935	27.58891

.

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==50

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	8829.485	5209.114	2084.109	21212.81
lfpr	21	69.67619	2.094016	66.1	73.1
oddeathsdi~1	19	40.66513	30.43995	2.174382	113.5592

•

. sum oddeaths100k lfpr oddeathsdiff1 if stateid==51

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths100k	21	5771.963	3188.985	0	10386.35
lfpr	21	69.29048	2.44702	65.3	71.9
oddeathsdi~1	14	11.27776	8.387799	.3345646	23.41114

. gen acoddeaths= 0.1104962* tcmcaremcaidmladj/oddeaths (12 missing values generated)

. sum acoddeaths

Variable	Obs	Mean	Std. Dev.	. Min	Max
acoddeaths	1,059	9.834574	30.63766	.7407368	623.3339

	sum	oddeaths	if	year==2000	æ	stateid==18
--	-----	----------	----	------------	---	-------------

Variable	edO	Mean	Std.	Dev.	Min	Max
oddeaths	1	92			92	92
. sum oddeaths	s if year==2001	& stateid	==18			
Variable	Obs	Mean	Std.	Dev.	Min	Max
oddeaths	1	144			144	144
. sum oddeaths	s if year==2002	& stateid	==18			
Variable	edO	Mean	Std.	Dev.	Min	Max
oddeaths	1	177			177	177
. sum oddeaths	s if year==2003	& stateid	==18			
Variable	Obs	Mean	Std.	Dev.	Min	Max
oddeaths	1	234			234	234
. sum oddeaths	s if year==2004	& stateid	==18			
Variable	Obs	Mean	Std.	Dev.	Min	Max
oddeaths	1	221			221	221

:	sum oddeaths	if year==2005	&	stateid=	==18			
	Variable	Obs		Mean	Std.	Dev.	Min	Max
_	oddeaths	1		285			285	285
	gym oddostha	if war-2006	c	atatai d	10			
•		if year==2006	œ					
_	Variable	Obs		Mean	Std.	Dev.	Min	Max
	oddeaths	1		331		•	331	331
:	sum oddeaths	if year==2007	£	stateid:	==18			
	Variable	Obs		Mean	Std.	Dev.	Min	Max
_	oddeaths	1		343			343	343
	sum oddeaths	if year==2008	£	stateid=	==18			
	Variable	Obs		Mean	Std.	Dev.	Min	Max
_	oddeaths	1		365			365	365
:	sum oddeaths	if year==2009	£	stateid:	==18			
	Variable	Obs		Mean	Std.	Dev.	Min	Max
	oddeaths	1		434			434	434
:	sum oddeaths	if year==2010	&	stateid=	18			
	Variable	Obs		Mean	Std.	Dev.	Min	Max
	oddeaths	1		591			591	591
:	sum oddeaths	if year==2011	&	stateid=	18			
	Variable	Obs		Mean	Std.	Dev.	Min	Max
	oddeaths	1		669			669	669
:	sum oddeaths	if year==2012	Æ	stateid=	18			
_	Variable	Obs		Mean	Std.	Dev.	Min	Max
_	oddeaths	1		673			673	673

[.] sum oddeaths if year==2013 & stateid==18

Variable	Obs	Mean	Std.	Dev.	Min	Max
oddeaths	1	665			665	665
. sum oddeaths	s if year==2014	& stateid	==18			
Variable	Obs	Mean	Std.	Dev.	Min	Max
oddeaths	1	729			729	729
. sum oddeaths	s if year==2015	& stateid	==18			
Variable	Obs	Mean	Std.	Dev.	Min	Max
oddeaths	1	885			885	885
. sum oddeaths	s if year==2016	& stateid	==18			
Variable	Obs	Mean	Std.	Dev.	Min	Max
oddeaths	1	989			989	989
. sum oddeaths	s if year==2017	& stateid	==18			
Variable	Obs	Mean	Std.	Dev.	Min	Max
oddeaths	1	1160			1160	1160
'	l					
. sum oddeaths	s if year==2018	& stateid	==18			
Variable	Obs	Mean	Std.	Dev.	Min	Max
oddeaths	1	989			989	989
. sum oddeaths	s if year==2019	& stateid	==18			
Variable	Obs	Mean	Std.	Dev.	Min	Max
oddeaths	1	1036			1036	1036
. sum oddeaths	s if year==2020	& stateid	==18			
Variable	Obs	Mean	Std.	Dev.	Min	Max
oddeaths	1	1688			1688	1688

. sum oddeaths if year==2000 & stateid==32

Variable	Obs	Mean	Std.	Dev.	Min	Max	
oddeaths	1	180			180	180	
. sum oddeaths	s if year==2001	& stateid	==32				
Variable	Obs	Mean	Std.	Dev.	Min	Max	
oddeaths	1	151			151	151	
. sum oddeaths	s if year==2002	& stateid	==32				
Variable	Obs	Mean	Std.	Dev.	Min	Max	
oddeaths	1	196			196	196	
. sum oddeaths	if year==2003	& stateid	==32				
Variable	Obs	Mean	Std.	Dev.	Min	Max	
oddeaths	1	218			218	218	
. sum oddeaths	s if year==2004	& stateid	==32				
TT			20-1	D	W:-		
Variable	Obs	Mean	Sta.	Dev.	Min	Max	
oddeaths	1	185			185	185	
. sum oddeaths	s if year==2005	& stateid	==32				
Variable	Obs	Mean	Std.	Dev.	Min	Max	
oddeaths	1	211			211	211	
. sum oddeaths if year==2006 & stateid==32							
Variable	Obs	Mean	Std.	Dev.	Min	Max	
oddeaths	1	243			243	243	
. sum oddeaths	. sum oddeaths if year==2007 & stateid==32						
Variable	Obs	Mean	Std.	Dev.	Min	Max	
oddeaths	1	266			266	266	

[.] sum oddeaths if year==2008 & stateid==32

	Variable	Obs	Mean	Std.	Dev.	Min	Max
	oddeaths	1	324			324	324
	sum oddaatha	if year==2009	C stated	30			
•	sum oddeaths	il year—2009	a staterd	32			
_	Variable	Obs	Mean	Std.	Dev.	Min	Max
	oddeaths	1	200			200	200
•	sum oddeaths	if year==2010	& stateid	==32			
	Variable	Obs	Mean	Std.	Dev.	Min	Max
	oddeaths	1	191			191	191
	sum oddeaths	if year==2011	& stateid	==32			
	Variable	Obs	Mean	Std.	Dev.	Min	Max
-	oddeaths	1	243			243	243
	sum oddeaths	if year==2012	& stateid	==32			
	*******	01	V	20-1	D	Wi-	V
-	Variable	Obs	Mean	Sta.	Dev.	Min	Max
	oddeaths	1	319		•	319	319
•	sum oddeaths	s if year==2013	& state1d	==32			
_	Variable	Obs	Mean	Std.	Dev.	Min	Max
	oddeaths	1	322			322	322
	sum oddeaths	if year==2014	& stateid	==32			
	Variable	Obs	Mean	Std.	Dev.	Min	Max
-	oddeaths	1	402			402	402
	sum oddeaths	if year==2015	& stateid	==32			
	Variable	Obs	Mean	Std.	Dev.	Min	Max
-	oddeaths	1	351			351	351
	arm oddostha	if warm-0016	Catatoid				

[.] sum oddeaths if year==2016 & stateid==32

Variable	Obs	Mean	Std. De	v. Min	Max
oddeaths	1	349		. 349	349
. sum oddeaths	s if year==2017	& stateid	==32		
Variable	Obs	Mean	Std. De	v. Min	Max
oddeaths	1	332		. 332	332
. sum oddeaths	s if year==2018	& stateid	==32		
Variable	Obs	Mean	Std. De	v. Min	Max
oddeaths	1	338		. 338	338
. sum oddeaths	if year==2019	& stateid	==32		
Variable	Obs	Mean	Std. De	v. Min	Max
oddeaths	1	394		. 394	394
:					
. sum oddeaths	s if year==2020	& stateid	l==32		
Variable	Obs	Mean	Std. De	v. Min	Max
oddeaths	1	535		. 535	535
-					
. sum oddeaths	s if year==2000				
Variable	Obs	Mean	Std. De	v. Min	Max
oddeaths	51	164.6667	194.427	1 0	1012
. sum oddeaths	s if year==2001				
Variable	Obs	Mean	Std. De	v. Min	Max
oddeaths	51	185.7647	191.889	5 0	846
. sum oddeaths	s if year==2002				
Variable	Obs	Mean	Std. De	v. Min	Max
oddeaths	51	233.5882	271.137	2 0	1453
ouded on 5	31	200.0002	2,1,137	_ 0	1400

[.] sum oddeaths if year==2003

Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths	51	253.2745	273.4384	0	1398
. sum oddeaths	s if year==2004				
Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths	51	269.7255	282.0492	10	1413
. sum oddeaths	s if year==2005				
Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths	51	292.3529	284.4426	0	1372
. sum oddeaths	s if year==2006				
Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths	51	343.9412	333.2574	0	1511
. sum oddeaths	s if year==2007				
Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths	51	363.0588	352.8229	15	1657
. sum oddeaths	s if year==2008				
Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths	51	383.9608	371.0422	29	1801
. sum oddeaths	s if year==2009				
Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths	51	400.4314	403.8558	13	1987
. sum oddeaths	s if year==2010				
Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths	51	413.5098	409.584	18	1929
. sum oddeaths	s if year==2011				
Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths	51	446.7451	425.8471	10	1938
. sum oddeaths	s if year==2012				
Variable	Obs	Mean	Std. Dev.	Min	Max
oddeaths	51	454.0588	418.6083	0	1719

[.] sum oddeaths if year==2013

Variable	Obs	Mean	Std. Dev.	Min	Max		
oddeaths	51	491.2157	452.8093	11	1948		
. sum oddeaths if year==2014							
Variable	Obs	Mean	Std. Dev.	Min	Max		
oddeaths	51	561.7059	507.8842	31	2106		
. sum oddeaths	s if year==201	.5					
Variable	Obs	Mean	Std. Dev.	Min	Max		
oddeaths	51	648.8431	617.3873	27	2698		
. sum oddeaths	s if year==201	.6					
Variable	Obs	Mean	Std. Dev.	Min	Max		
oddeaths	51	828.4118	846.7209	42	3613		
. sum oddeaths	s if year==201	.7					
Variable	Obs	Mean	Std. Dev.	Min	Max		
oddeaths	51	933.3333	971.7007	35	4293		
. sum oddeaths if year==2018							
Variable	Obs	Mean	Std. Dev.	Min	Max		
oddeaths	51	917.6863	933.4335	28	3237		
. sum oddeaths if year==2019							
Variable	Obs	Mean	Std. Dev.	Min	Max		
oddeaths	51	977.6471	1005.369	39	3771		
. sum oddeaths if year—2020							
Variable	Obs	Mean	Std. Dev.	Min	Max		
oddeaths	51	1345.686	1399.674	46	5508		

