Did Medicaid Expansion Change the Trajectory of Drug Overdose Deaths in Appalachia?

Neil Kejian Chin (nkc2124) & Nicole Yahui Wu (yw3551)

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1 Introduction

Deaths due to drug overdose are a pressing problem facing United States policymakers and society at large, with reportedly more than 932,000 people dying due to overdose since 1999 (CDC, 2022). Rates of overdose deaths increased in nearly every US state from 2013-2017, with particularly severe incidence in the Appalachian region (CDC, 2020; CDC, 2021). The increase in deaths is driven primarily by the ongoing US opioid crisis, with the vast majority (>80%) of overdose deaths associated with opioid use (CDC, 2022).

In this context, we hope to assess whether expansion of the social safety net through government policy can be causally linked to reductions in drug overdose death rates. Specifically, we propose to use a panel dataset of Appalachian counties to estimate the effects of the expansion of the US Medicaid program, which increased income-based eligibility for healthcare (including drug addiction treatment) in some Appalachian states, on drug overdose deaths. We hope that the findings from this study can assist policymakers in determining whether expanding access to healthcare in low-income areas is a viable policy mechanism for addressing the ongoing drug overdose crisis.

1.1 Why Appalachia?

In addition to the pressing need for causal analysis due to the escalating drug overdose crisis, we focus our study on the Appalachian region for a few methodological reasons. First, in the pre-expansion period, Medicaid was already a widely-embraced program in Appalachia relative to the rest of the country and expansion was projected to increase enrollment by tens of millions of people, indicating that our policy "treatment" of interest (i.e., Medicaid expansion) had considerable uptake (ARC, 2012). That is to say, intent-to-treat (ITT) effects measured by our study should be more reflective of average treatment-on-treated (ATT) effects than they would be in other geographies where Medicaid participation is not as high. Second, the Appalachian region is defined at the county-level, which enables us to avoid potential selection bias and small sample size issues that would confound state-level analysis. Finally, we believe that Appalachian counties are largely similar in terms on non-measurable, unobserved characteristics across state lines, meaning that they can be fairly reliably construed as pseudo "control" and "treatment" groups.

2 Policy Background & Research Hypothesis

The Affordable Care Act (ACA) was passed by the United States Congress and signed into law by President Barack Obama in 2010, drastically changing the policy landscape for health care in the United States. Among the major provisions in the ACA was expanded eligibility for Medicaid (i.e., "Medicaid Expansion"), which allowed states to raise the income-eligibility threshold to 138% of the federal poverty level (KFF, 2022).

Of the 13 states whose boundaries overlap with the broad geographical definition of Appalachia, five states (Kentucky, Maryland, New York, Ohio, and West Virginia) passed legislation mandating the expansion of Medicaid as of January 1st, 2014 (KFF, 2022). Two additional states, Pennsylvania and Virginia, would later expand Medicaid, with the former in 2015 and the latter in 2019. Six states (Alabama, Georgia, Mississippi, North Carolina, South Carolina, and Tennessee) have not expanded Medicaid to-date.

In our study, we identify this policy adoption discrepancy as a "treatment" (i.e., "differential exposure between entities over time") affecting drug overdose incidence in Appalachian communities. Our *hypothesized* causal mechanism is that expanded Medicaid eligibility allowed for greater access to low-cost health care among Appalachian counties in expansion states, therefore enabling people struggling with drug addiction to receive substance use disorder (SUD) treatment when they otherwise would not have been able to receive care, reducing overall deaths from drug overdose in these areas. In general, health insurance via Medicaid covers SUD treatment, with slight differences in extent of coverage across states (American Addiction Centers, 2022).

Existing literature has also examined the counter-hypothesis that Medicaid expansion may have actually *increased* drug overdose death rates by increasing access to prescription opioids. Swartz and Beltran (2019) find that, while Medicaid expansion did increase prescription opioid availability, there was no accompanying increase in overdose mortality. Venkataramani and Chatterjee (2018) examine early 2000s Medicaid expansion in Arizona, Maine, and New York, and find that expansion did in fact *decrease* overdose death rates relative to neighboring non-expansion states. More recently, Averett, Smith, and Yang (2019) find that, at a state level, Medicaid expansion is not related to opioid deaths.

3 Data Description

Our data is a county-year panel dataset, which we use to examine drug overdose deaths in Appalachian counties over the period 2010-2019. For analysis, however, we restrict the panel to only the four years prior to Medicaid expansion and the five years after, resulting in a final dataset of 3807 observations, due to Pennsylvania's one-year delayed adoption of Medicaid.

The subset of US counties defined as "Appalachian" is based on the jurisdiction of the Appalachian Regional Council (ARC, 2021). Accordingly, our units of observation for this study are counties, with the representative population being people living in the Appalachian region.

Identification of state-level Medicaid expansion is based on tracking done by the Kaiser Family Foundation (KFF, 2022). Note that, due to the fact that Pennsylvania implemented Medicaid expansion a year after other expansion states, the timing of "treatment" for Appalachian counties in Pennsylvania is delayed by one year relative to other counties in expansion states. Additionally, Virginia did eventually enact Medicaid expansion in 2019, but these observations are not included in our analytical sample (2019 observations are only analyzed for Pennsylvania), and thus Appalachian counties in Virginia are considered to be "non-expansion" counties.

Data on drug overdose death rates (i.e., deaths per 100,000 residents) comes from estimates modeled by the National Center for Health Statistics (NCHS), which are available at the county-level for the period 2003-2020. Unfortunately, county-level statistics on overdose deaths based on final counts of cause of death reporting only became available starting in 2020, outside of the study time frame.

County-level demographic covariates are taken from the US Census Bureau American Community Survey (ACS). Using these covariates, we hope to control for omitted variable bias (OVB) stemming from county-level factors such as poverty rates, median age, and sex and race compositions. In particular, we expect that poverty rates would relate positively to overdose deaths, as poverty levels and overdose deaths have been previously linked (Pear et al, 2019). We include controls for median age as drug overdose death incidence tends to vary by age group (KFF, 2022). Drug overdose deaths are also more common among individuals identified as male than female (CDC, 2022). Furthermore, access to drug treatment has been shown to differ according to race (NIDA, 2019), potentially leading to differentials in drug overdose deaths depending on racial composition of counties. We acknowledge that some of these factors may actually be mostly time-invariant, but include them anyways to minimize OVB.

Given that both the NCHS data on overdose death rates and ACS control variables are estimated at the county-level, we expand our study period to the four years prior to Medicaid expansion and the five years after (i.e., 2010-2019), in order to smooth over any potential estimation errors. We also hope that this larger time frame will capture any lags in treatment effects, given that reductions in drug overdose deaths due to expanded access to health care may not be reflected in the data until more than a year after Medicaid expansion.

From the sources, data is largely already available at the county-level, thus we are not required to perform any aggregation or dis-aggregation steps to make the data suitable for use. Furthermore, variables of interest are entirely quantitative, thus cleaning needs are minimal. All source data include county FIPS codes as merging indices. The only intermediate data transformation we perform is the calculation of county-level racial composition shares and poverty rates, based on Census Bureau population data.

3.1 "High" and "Low Risk" Counties

To further distinguish between our hypothesis, that Medicaid expansion has reduced drug overdose deaths in Appalachia, and the counter hypothesis, that oppositely suggests Medicaid expansion increased drug overdose deaths, within our county-year panel dataset we separately analyze "high" and "low risk" county subsets. Operationally, we define "high risk" counties as Appalachian counties that were already experiencing substantial increases in drug overdose death rates prior to the expansion of Medicaid. "Low risk" counties are counties where overdose death rates were either stagnant or declining pre-expansion.

Specifically, we expect that our hypothesized mechanism (i.e., Medicaid expansion increasing access to substance abuse treatment) would have a particularly strong causal effect in "high risk" counties where drug overdose rates were already accelerating prior to expansion. Essentially, we think that Medicaid-eligible individuals would face a strong individual and communal impetus to seek out substance use disorder (SUD) treatment through the Medicaid program if deaths from drug overdose are already an acute problem in their community. Conversely, we think there would be less scope for causal effect in "low risk" counties, as drug overdose deaths are perceived as less of a crisis or already improving.

For the counter-hypothesis mechanism, we would expect opposite results with regards to relative strength of causal effect. In "high risk" counties circulation of prescription opioids is likely already ubiquitous pre-expansion, and thus while Medicaid expansion could exacerbate the issue, the overall trajectory of opioid deaths will not change by a high degree. In "low risk" counties, however, it is possible that stagnant or receding overdose death rates pre-expansion could be due to a dwindling supply of prescription opioids, and a post-expansion supply shock leads to a rapid increase in drug overdose deaths.

See Appendix II for our methodology in defining "high" and "low risk" counties, as well as a detailed breakdown of the characteristics of each group.

4 Descriptive Statistics

4.1 Variation in Policy "Treatment"

In total, 210 Appalachian counties are located in expansion states and 213 Appalachian counties are located in non-expansion states.

We map Appalachian counties by Medicaid expansion status in Figure 1:

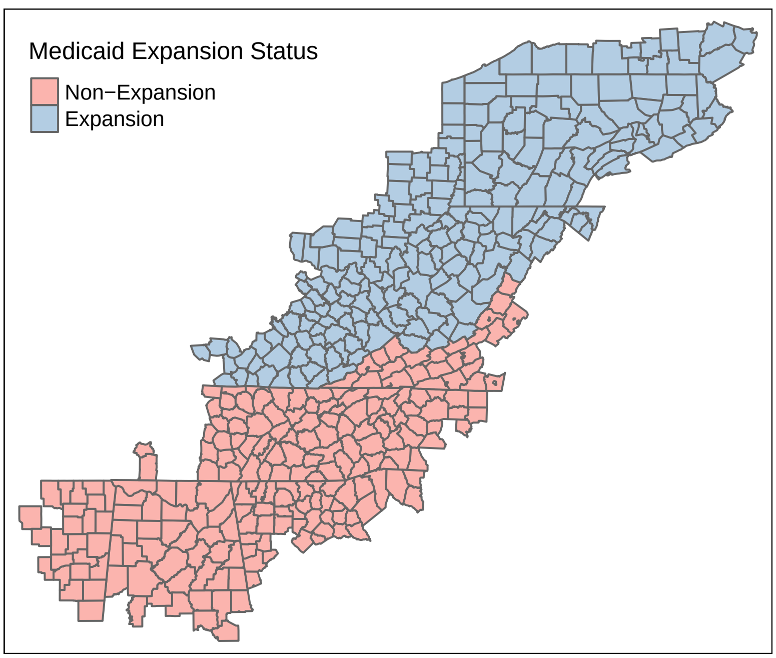

Figure 1: Map of Medicaid Expansion Status Across Appalachian Counties

Clearly, at the state level there is a degree of "North-South" bias in terms of which states elected to expand Medicaid. However, our empirical strategy (as discussed in section 5) aims to minimize any associated omitted variable bias with county-level fixed effects.

4.2 Variation in Drug Overdose Death Rate

In Figure 2, we plot the weighted-average of county-level drug overdose death rate over time (i.e., "Years since Medicaid Expansion"), separating counties in expansion states from counties in non-expansion states.

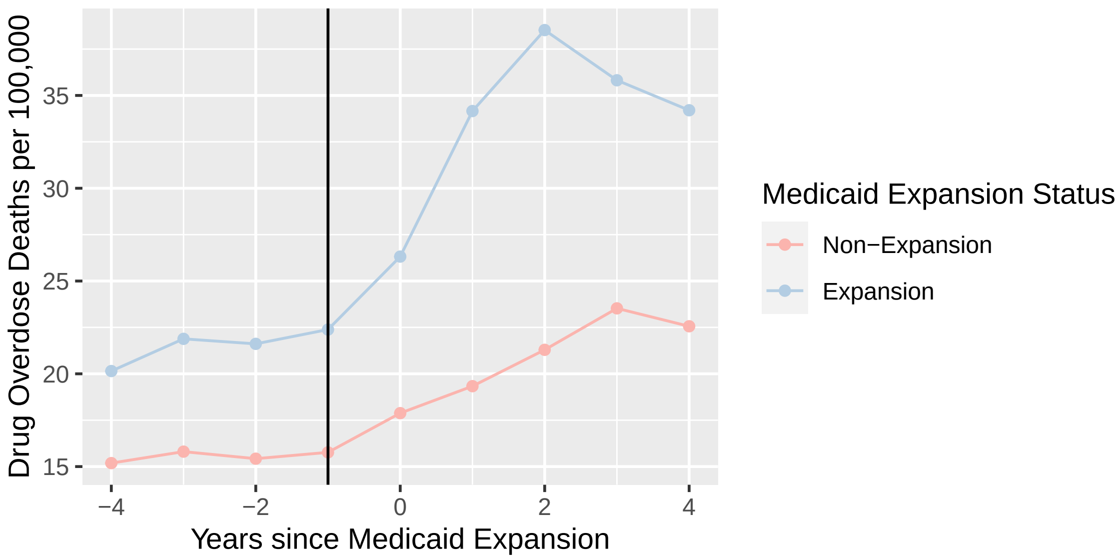

Figure 2: Yearly County-Level Drug Overdose Death Rates by Medicaid Expansion Status

While drug overdose death rates are persistently higher in expansion counties than in non-expansion counties, it appears that expansion counties and non-expansion counties experience near-parallel trends prior to Medicaid expansion. In the first few years following expansion, however, we observe an *steepening trend* of overdose death rates in *expansion counties* relative to *non-expansion counties*, indicating that Medicaid expansion had a *positive* effect on overdose death rates, contradicting the direction of our hypothesized causal effect.

Yet, we also observe that this steepening trend of overdose death rates in expansion counties *declines* following the first two years after Medicaid expansion. Between years three and four after Medicaid expansion, this trend reverses. Overall, this suggests that, to the extent Medicaid expansion has increased overdose death rates in expansion counties, this effect may be inconsistent over time. We explore this possibility in our empirical strategy by employing an "event study" approach, which also allows us to more rigorously assess the assumption of parallel trends.

4.3 Variation in Key Continuous Variables

We also explore the balance across key continuous variables between counties in expansion states and counties in non-expansion states, a year prior to the time when Medicaid expansion occurs.

Table 1: Difference-in-means between Expansion and Non-Expansion Counties, One Year Prior to Medicaid Expansion

	Non-Expansion (N=213)		Expansion (N=210)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	p
Poverty Rate	19.17	4.42	18.47	6.06	-0.70	0.17
Median Age	41.21	4.09	41.77	3.19	0.55	0.12
Male Share	49.14	1.32	49.93	2.18	0.79	<0.001
Black Share	10.58	14.49	2.45	2.91	-8.13	<0.001
Hispanic Share	4.00	4.10	1.55	1.60	-2.45	<0.001
White Share	82.94	14.72	94.06	4.60	11.12	<0.001
Asian Share	0.69	1.09	0.53	0.91	-0.16	0.10

Note: Observations are weighted by the population in each county.

Table 1 shows difference-in-means between "treatment" (i.e., Medicaid expansion) counties and "control" counties in the year of Medicaid expansion. We observe statistically significant differences between "treatment" and "control" groups for male share of population and racial composition (i.e., Black, White, and Hispanic share of population). This suggests that these factors are unbalanced between the two groups of Appalachian counties, which would lead to omitted variable bias if they are not controlled for in our estimation specification.

5 Empirical Strategy

The primary variation that we seek to exploit through our analysis is the differential in state-level adoption of Medicaid expansion across the Appalachian region, with policy variation at the state-level thus filtering down to the county-level. We do this in two ways:

To establish a single average causal treatment effect estimate over the five years after Medicaid was expanded, we first take a difference-in-differences approach. This approach allows us to simply establish evidence of a causal linkage between Medicaid expansion and drug overdose deaths in Appalachia. We then go a step further by exploring an event study approach, examining year-by-year treatment effects relative to the year prior to Medicaid expansion. This second approach allows us to demonstrate the robustness of our measured treatment effect over time, and also provides a more granular lens to critically assess the validity of the differences-in-differences result.

Finally, we look for heterogeneous treatment effects among "high" and "low risk" counties in both approaches.

5.1 Difference-in-Differences

To evaluate the effect of Medicaid expansion on drug overdose deaths in Appalachian counties, we estimate the following "differences-in-differences" specification:

$$ODR_{it} = \beta Expansion_{it} + \mathbf{X}_{it}\gamma + \nu_i + \tau_t + \varepsilon_{it}$$

where ODR_{it} is deaths attributed to drug overdose per 100,000 county residents for county i at time t, $Expansion_{it}$ is a binary variable that indicates "treatment" status (i.e., enactment of Medicaid expansion) for a county-year, $\mathbf{X}_{it}$ is a vector of time varying controls (e.g., poverty rates, median age, male population share, racial composition) for potential county-level determinants of overdose death rates outside of our policy variation of interest.

Additionally, we include an array of county fixed effects, ν_i, that control for unobserved time-invariant factors that are specific to individual counties. An example of one such factor would be if, throughout the entire 2010-2019 period, a specific county had its own drug treatment program that reduced drug overdose deaths compared to other counties, all else equal. We further include τ_t, year fixed effects, to control for unobserved county-invariant factors that might have changed between each year included in our panel. Such factors would include events such as periodic economic shocks that affect the entire Appalachian region in certain years, which potentially could be deterministic of the rate of overdose deaths. Finally, ε_{it} is the idiosyncratic error term.

5.2 Event Study

In this approach, we apply a modified specification that isolates treatments effects by year, before and after Medicaid expansion, which corresponds to the following population regression function:

$$ODR_{it} = 1\{\text{Expansion}_i\} \left[\sum_{y=-4}^{-2} \beta_y^{pre} 1\{t - t_i^* = y\} + \sum_{y=0}^{4} \beta_y^{post} 1\{t - t_i^* = y\} \right] + \mathbf{X}_{it}\gamma + \nu_i + \tau_t + \varepsilon_{it}$$

where $1\{\text{Expansion}_i\}$ is a binary variable identifying high-eligibility states, and t_i^* is the year Medicaid was expanded in county i. The $1\{t - t_i^* = y\}$ terms are dummy variables corresponding to an *event year*, i.e., the year relative to the expansion of Medicaid at time t_i^*. The coefficients of interest are β_y^{pre} and β_y^{post}, which measure the relationship between drug overdose death rates and expansion status in each of the four years leading up to Medicaid expansion and five years after. We omit the dummy for the year before Medicaid expansion ($y = -1$), so that the estimates of β_y^{pre} and β_y^{post} capture effects relative to just before Medicaid expansion.

In particular, we measure β_y^{pre} parameters to capture the relationship between expansion status and overdose death rates before Medicaid was expanded, allowing us to establish the assumption of parallel trends; statistically significant estimates during the pre-treatment period would be inconsistent with the parallel trends assumption, as this would indicate that expansion counties already experienced a different trajectory of overdose death rates prior to the expansion of Medicaid. The β_y^{post} parameters represent the causal effect of Medicaid expansion for each event year (y) after medicaid has been expanded.

Finally, we include the same vector of time-varying controls ($\mathbf{X}_{it}$), county fixed-effects (ν_i), and year fixed-effects (τ_t), as specified in the differences-in-differences approach.

6 Findings

6.1 Difference-in-Difference Results

We estimate difference-in-differences effects for all counties, "high risk," and "low risk" counties.

Table 2: Effect of Medicaid Expansion on Drug Overdose Death Rates

	All Counties	High Risk	Low Risk
Medicaid Expansion	5.6176***	5.1436***	4.5752***
	(0.7056)	(0.7142)	(1.2315)
Poverty Rate (0-100)	0.9121***	0.4263*	0.7200**
	(0.2106)	(0.2466)	(0.3263)
Median Age	0.3399	−0.1889	0.4579
	(0.2900)	(0.4612)	(0.4656)
Male Population Share (0-100)	0.0001**	0.0000	0.0003**
	(0.0000)	(0.0001)	(0.0001)
Black Population Share	−0.0001***	−0.0001	−0.0008***
	(0.0000)	(0.0001)	(0.0003)
Hispanic Population Share	0.0000	0.0004**	−0.0008
	(0.0001)	(0.0002)	(0.0007)
Asian Population Share	0.0003	0.0005	0.0036**
	(0.0003)	(0.0005)	(0.0016)
N	3807	1899	981
R-squared	0.760	0.801	0.866
Adj. R-squared	0.737	0.778	0.849
County FEs	X	X	X
Year FEs	X	X	X

Robust standard errors clustered by county are shown in parentheses. Observations are weighted by the population in each county.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2 displays difference-in-difference estimation results. We find evidence that Medicaid expansion *increased* the drug overdose death rate by roughly 5.62 deaths per 100,000 across all Appalachian counties in the post-expansion period, holding constant demographic factors and county and time fixed effects. This effect is slightly larger in "high risk" counties than it is in "low risk" counties, although the difference is not substantial, and smaller in both subgroups than it is across the entire sample. In all cases, this estimate of causal effect is quite significant ($\alpha < .01$).

6.2 Event Study Results

For our event study approach, we plot β_y^{pre} and β_y^{post} estimates for all counties, "high risk," and "low risk" counties in Figures 3-5. A complete table of event study approach estimates, across all Appalachian counties, "high risk," and "low risk" counties, can be found in Appendix III, Table 5.

Figure 3 displays the yearly estimated effect of Medicaid expansion on drug overdose death rates across all counties Appalachia, before and after expansion occurs. With regards to the pre-expansion β_y^{pre} estimates, it appears that the assumption of parallel trends mostly holds true, as the parameters are centered around zero and are non statistically significant with the exception of $y = -4$. The β_y^{post} estimates show a *positive* effect of Medicaid expansion on drug overdose deaths that increases in the period one-to-two years after Medicaid expansion, then stabilizes afterwards. Together, β_y^{pre} and β_y^{post} estimates in the event study approach largely conform to the results of the difference-in-differences approach when analyzing all counties in Appalachia.

Figure 4 displays the yearly estimated effect of Medicaid expansion on drug overdose death rates across "high risk" counties in Appalachia, before and after expansion occurs. For the pre-expansion β_y^{pre} estimates, it appears that the assumption of parallel trends does not hold true. In the period four to one year prior to Medicaid expansion, it appears that the time-trend in drug overdose death rates is already diverging between expansion and non-expansion counties, as the β_y^{pre} estimates

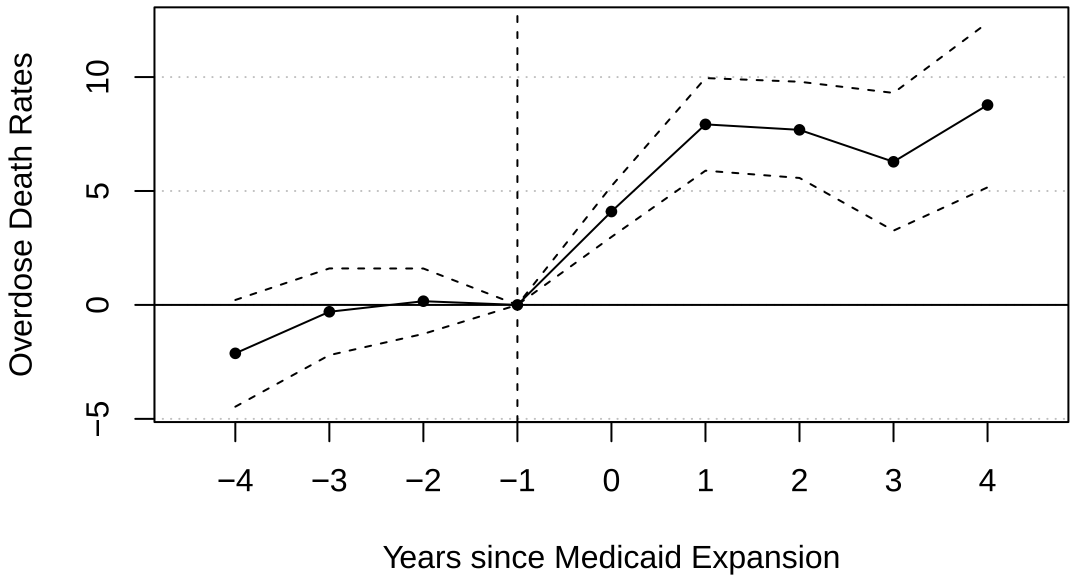

Figure 3: Medicaid Expansion's Effect on Drug Overdose Death Rates in All Appalachian Counties

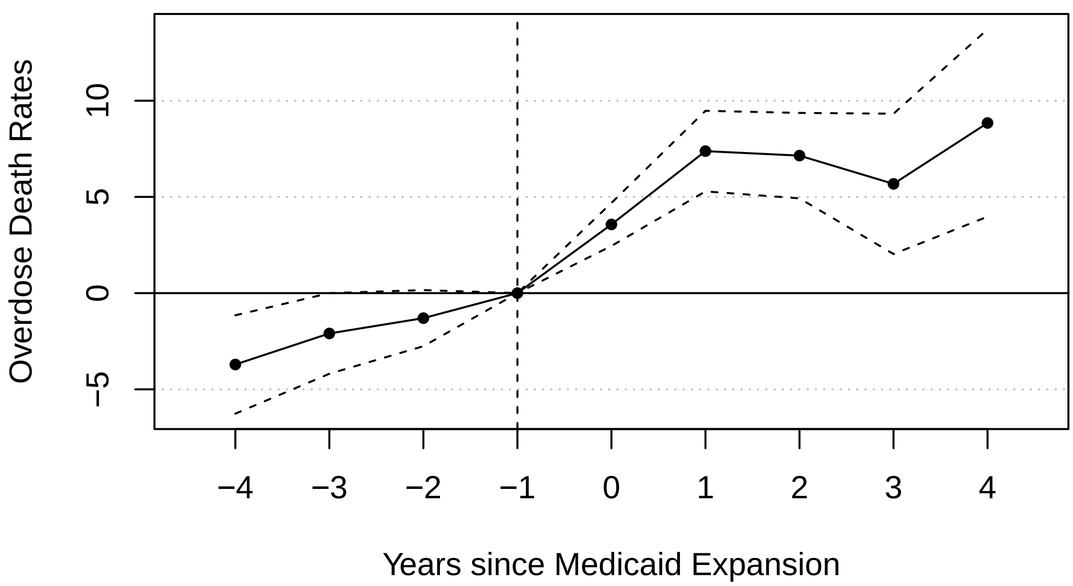

Figure 4: Medicaid Expansion's Effect on Drug Overdose Death Rates in High Risk Counties

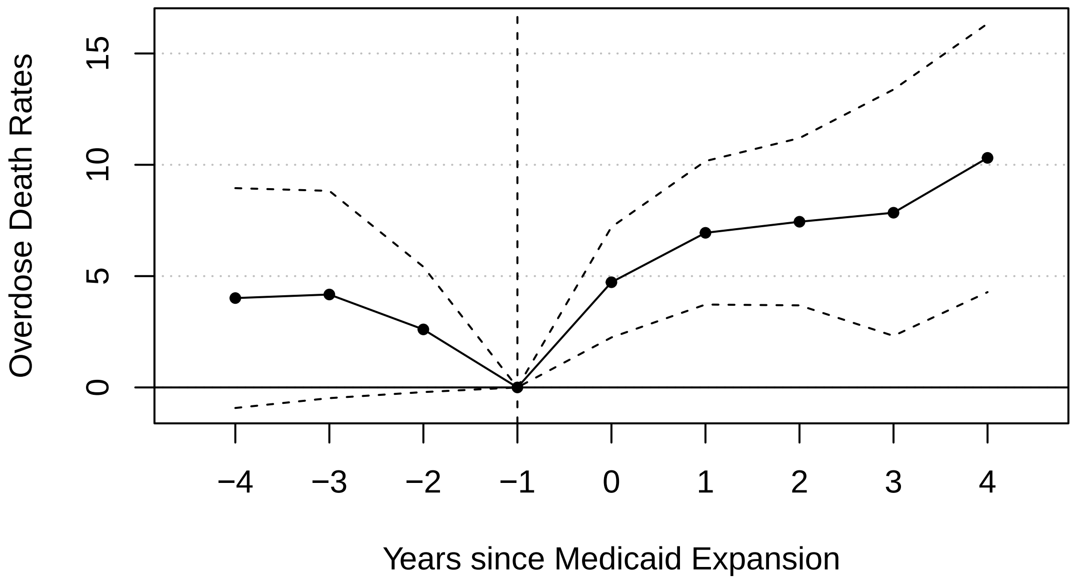

Figure 5: Medicaid Expansion's Effect on Drug Overdose Death Rates in Low Risk Counties

are statistically significant and are moving in an upwards direction over time. The β_y^{post} estimates show a *positive* effect of Medicaid expansion on drug overdose deaths that increases in the period one-to-two years after Medicaid expansion, afterwards causal effects estimates stabilize but are increasingly noisy (i.e., widening 95% confidence intervals). Overall, the event study findings for "high risk" counties cast doubt on the validity of difference-in-difference results, as the assumption of parallel trends is shown to be dubious.

Figure 5 displays the yearly estimated effect of Medicaid expansion on drug overdose death rates across "low risk" counties in Appalachia, before and after expansion occurs. Based on the pre-expansion β_y^{pre} estimates, the assumption of parallel trends also appears to be fairly weak, as some of the β_y^{pre} estimates are relatively statistically significant. Unlike the "high risk" county estimates, although the 95% confidence interval is quite large, the β_y^{pre} estimates actually suggest that the difference in overdose death rates between expansion and non-expansion counties is shrinking in "low risk" counties over the period up until one year before expansion. Once again, β_y^{post} estimates show a *positive* effect of Medicaid expansion on drug overdose deaths that increases in the period one-to-two years after Medicaid expansion, only to stabilize afterwards. For "low risk counties," in particular, causal effect estimates are increasingly noisy after expansion (i.e., the 95% confidence interval is very large and widening). The event study findings for "low risk" counties cast some doubt on the validity of difference-in-difference results because the assumption of parallel trends is again not very strong, but the causal effects estimates are fairly consistent with the possible exception of the final year ($y = 4$).

7 Conclusion

7.1 Consistency and Validity of Findings

Overall, we find that strong evidence *against* our hypothesis that Medicaid expansion would *reduce* drug overdose death rates in Appalachia. Causal effects estimates, both in the difference-in-differences and event study approach, point in the *positive* direction when measured among all Appalachian counties, "high risk" counties, and "low risk" counties.

Instead, these results provide limited evidence to support the counter-hypothesis that Medicaid expansion *increased* drug overdose death rates in Appalachia. When examining all counties in Appalachia, the results of both difference-in-differences and event study approaches suggest that a positive causal effect is likely. However, the results from separate analysis of "high risk" and "low risk" counties casts some doubt on this conclusion as well. First, the assumption of parallel trends weakens when estimating causal effects for these subsets, and also causal effects estimates for "high risk" counties are noisy. Second, the pattern of results for "high" and "low risk" counties does not conform with the mechanism proposed by the counter hypothesis (i.e., Medicaid expansion increasing access to prescription opioids), as this would have likely lead to a stronger effect in "low risk" counties, but in fact our estimates are broadly similar between the two groups.

If anything, the event study results do show evidence to support a claim of lagged effects, as causal estimates are largest two-to-five years after Medicaid expansion across all groups. This trajectory of effects is theorized but not tested by Swartz and Beltran (2019), who find that expansion increased the supply of prescription opioids but did not affect overdose deaths.

We also cannot rule out the potential alternative hypothesis that Medicaid expansion simply increased the ability of expansion counties to collect data and attribute deaths to drug overdoses. This last explanation would seem most consistent with the fact that the size of our causal effects do not vary much by group, as we imagine this effect would be rather agnostic to pre-expansion growth in overdose death rates. To summarize, we find evidence against the original hypothesis (i.e., Medicaid expansion reduced drug overdose deaths), but we also cannot conclusively differentiate the evidence supporting the counter-hypothesis from this possible alternative explanation.

Furthermore, there are a few key limitations that potentially challenge the validity of this study. First, we are unable to control for potential OVB due to county-year variation in number of substance use disorder (SUD) treatment facilities, as this data was unavailable at the county-level. However, it is unclear what the direction of this bias would be. On one hand, SUD treatment facilities could be negatively correlated with deaths from drug overdose due to the services that they provide; on the other, it could also be the case that there are simply more SUD treatment facilities in areas with high rates of drug overdose deaths.

Lack of SUD treatment center data also impedes our ability to test the mechanism behind our original hypothesis, as it is possible that the effect of enhanced access to healthcare through Medicaid expansion on drug overdose death rates would have been mediated by the presence of SUD treatment centers. Second, we similarly lack data on the supply of prescription opioids in Appalachian counties over this period, making it difficult to assess the mechanism in the counter-hypothesis as well. Finally, we believe that the focus of our sample on Appalachian counties limits external validity, which potentially could explain the difference between our results and prior research.

7.2 Policy Implications

With regards to policy, our results show that simply increasing access the healthcare by itself is not a solution to the ongoing crisis of drug overdose deaths in the United States, and possibly could be an exacerbating factor. Our findings suggest, although weakly, that there is a positive linkage between the healthcare system in Appalachia and deaths from drug overdose. If this is indeed the case, then policymakers ought to consider steps that decouple medical care (i.e., access to doctors and prescription medication) from drug addiction. Interventions suggested by experts include stronger limitations on amounts of opioids prescribed, increasing access to rehabilitation treatment, and liability placed on prescription drug companies (University of Pennslyvania, 2019).

As for the Medicaid program in particular, it should be emphasized that, even to the extent that these detrimental linkages exist, communities in Appalachia are heavily reliant on the program to meet broader healthcare needs and any potential reforms should be careful not to restrict access to these critical services. Above all, it should be noted that the evidence found in our study is quite ambiguous, and taken alone, does not necessarily warrant decisive policy response.

8 Appendices

8.1 Appendix I: Data Sources

We compile publicly-available data from the Appalachian Regional Council (ARC), Kaiser Family Foundation (KFF), National Center for Health Statistics (NCHS), and the US Census Bureau into a single county-year panel data set.

8.1.1 Appalachian Counties

The Appalachian Regional Commission defines 423 counties in 13 states (West Virginia, Alabama, Georgia, Kentucky, Maryland, Mississippi, New York, North Carolina, Ohio, Pennsylvania, South Carolina, Tennessee, and Virginia) as demarcating the Appalachian region. We adopt this geographical definition in our research approach. More information available at: https://www.arc.gov/appalachian-counties-served-by-arc/.

8.1.2 Medicaid Expansion

According to the Kaiser Family Foundation, five states within Appalachia (Kentucky, Maryland, New York, Ohio, and West Virginia) passed legislation mandating the expansion of Medicaid as of January 1st, 2014. Two additional states, Pennsylvania and Virginia, would later expand Medicaid, with the former in 2015 and the latter in 2019. Six states (Alabama, Georgia, Mississippi, North Carolina, South Carolina, and Tennessee) have not expanded Medicaid to-date. Information on state-level Medicaid expansion available at: https://www.kff.org/medicaid/issue-brief/status-of-state-medicaid-expansion-decisions-interactive-map/.

8.1.3 Overdose Deaths

Our data on drug overdose deaths comes from estimates modeled by the National Center for Health Statistics (NCHS), which are available at the county-level for the period 2003-2020. Estimates are based on the National Vital Statistics System multiple cause-of-death mortality files. Populations used for computing death rates for 2011–2018 are postcensal estimates based on the 2010 U.S. census. Rates for census years are based on populations enumerated in the corresponding censuses. Rates for noncensus years before 2010 are revised using updated intercensal population estimates and may differ from rates previously published.

Death rates for some states/counties and years may be low due to a high number of unresolved pending cases or misclassification of ICD–10 (cause of death) codes for unintentional poisoning as R99, "Other ill-defined and unspecified causes of mortality." For example, this issue is known to affect New Jersey in 2009 and West Virginia in 2005 and 2009 but also may affect other years and other states or counties. Drug overdose death rates may be underestimated in those instances. Source link: https://www.cdc.gov/nchs/data-visualization/drug-poisoning-mortality/.

8.1.4 County-Level Demographics

To control for time-variant, county-variant factors, we pull county-level demographic data from the US Census Bureau's American Community Survey (ACS), for years 2010-2019. Unfortunately, due to lack of data for small-population counties, we are only able to use data from the five-year edition of the ACS, likely obscuring time-variation among the demographic measures. Specifically, we include factors such as poverty rates, median age, male population share, and racial composition.Data is downloaded from the US Census Bureau API using the R package tidycensus.

8.1.5 Geographic Boundaries

In addition to county-level demographics, we pull county shapefiles from the Census Bureau for mapping visuals: https://www.census.gov/geographies/mapping-files/time-series/geo/cartographic-boundary.html

8.2 Appendix II: Defining "High" and "Low Risk" Counties

To define "high" and "low risk" counties, we examine the trajectory of drug overdose death rates in Appalachian counties prior to Medicaid expansion. In particular, we calculate the annual growth rates of overdose death rates in Appalachian counties in the pre-expansion period (i.e., between one and four years prior to expansion).

$$Avg.\ Pre\ Expansion\ Growth\ Rate_i = 100 * \frac{1}{3} \sum_{t=-4}^{-2} \frac{ODR_{t+1} - ODR_t}{ODR_t}$$

Shown in Figure 6, growth of overdose death rates varies considerably across Appalachian counties during this period, with some counties experiencing a drastic reduction in overdose death rates, while others see massive increases.

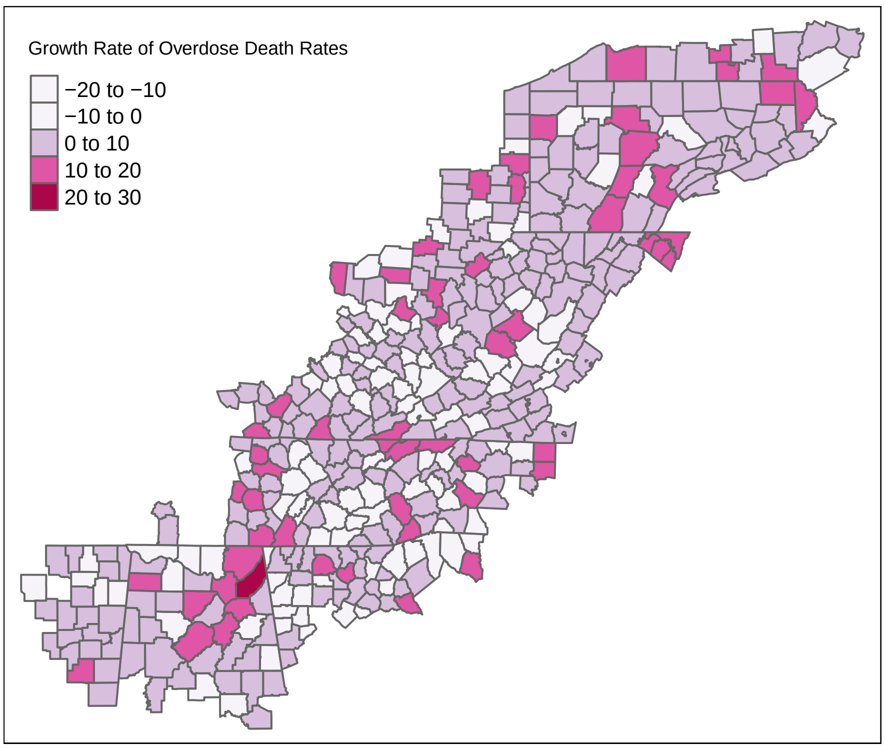

Figure 6: Map of Pre-Expansion CAGR of Overdose Death Rates Across Appalachian Counties

Over this period, annual average growth of overdose death rates ranged from -16.31% to 20.28%, with a median of 3.68%. We define "high risk" counties as counties with average pre-expansion growth of drug overdose death rates above the median, and define "low risk" counties as counties with a pre-expansion growth of drug overdose death at or below zero. Qualitatively, "high risk" counties can be thought of as Appalachian counties that were already experiencing substantial increases in drug overdose death rates prior to the expansion of Medicaid. Conversely, "low risk" counties are counties where overdose death rates were either stagnant or declining. Counties in between are simply defined as "moderate risk."

From Table 3, it is evident that "high risk" counties are relatively more concentrated among expansion counties, while "low risk" counties are more concentrated among non-expansion counties.

Table 3: Two-Way Table of County Expansion and Risk Status

	High	Low	Moderate
Non-Expansion	93	63	57
Expansion	118	46	46

This lack of balance likely impacts our estimates of causal effects among these subsets. In our event study findings (see Appendix III), estimates for "high" and "low" risk counties are noisier than for all counties, so this discrepancy could be a detriment to internal validity.

We also explore demographic differences between "high" and "low risk" counties, one year prior to Medicaid expansion.

Table 4: Difference-in-means between High and Low Risk Counties, One Year Prior to Medicaid Expansion

	High (N=211)		Low (N=109)			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff. in Means	p
Poverty Rate	18.22	5.20	19.82	5.33	1.60	0.01
Median Age	41.61	3.61	40.84	3.38	-0.77	0.06
Male Share	49.38	1.32	49.56	2.37	0.18	0.47
Black Share	6.35	11.43	6.33	8.67	-0.02	0.98
Hispanic Share	2.65	3.23	3.11	3.29	0.46	0.23
White Share	88.76	12.00	88.08	11.40	-0.68	0.62
Asian Share	0.65	1.09	0.66	1.14	0.007	0.96

Note: Observations are weighted by the population in each county.

From Table 4, we make the somewhat odd observation that "high risk" counties are poorer and older than "low risk" counties. This would seem to run contrary to the established findings that poverty and youth are factors that tend to *increase* incidence of drug overdose deaths. However, it could just be the case that these factors only affect the *level* of drug overdose death rates in a particular county, but do not play a role in *rates of growth*. In terms of male population share and racial composition, however, there are no statistically significant differences.

8.3 Appendix III: Event Study Estimates

Table 5: Effect of Medicaid Expansion on Drug Overdose Death Rates

	All Counties	High Risk	Low Risk
(Year -4) * Expansion	−2.1247*	−3.7093***	4.0139
	(1.1949)	(1.3042)	(2.5190)
(Year -3) * Expansion	−0.3008	−2.0959*	4.1743*
	(0.9706)	(1.0688)	(2.3752)
(Year -2) * Expansion	0.1632	−1.3009*	2.6056*
	(0.7323)	(0.7442)	(1.4357)
(Year 0) * Expansion	4.0977***	3.5690***	4.7244***
	(0.5692)	(0.5707)	(1.2648)
(Year 1) * Expansion	7.9242***	7.3800***	6.9449***
	(1.0366)	(1.0682)	(1.6436)
(Year 2) * Expansion	7.6838***	7.1457***	7.4423***
	(1.0774)	(1.1325)	(1.9165)
(Year 3) * Expansion	6.2820***	5.6779***	7.8475***
	(1.5417)	(1.8601)	(2.8231)
(Year 4) * Expansion	8.7733***	8.8411***	10.3101***
	(1.8434)	(2.4835)	(3.0762)
N	3807	1899	981
R-squared	0.771	0.817	0.872
Adj. R-squared	0.749	0.795	0.854
County FEs	X	X	X
Year FEs	X	X	X

Control covariates include county-level poverty rate, median age, male pop. share, Black pop. share, White pop. share, Hispanic pop. share, and Asian pop. share.
Robust standard errors clustered by county are shown in parentheses.
Observations are weighted by the population in each county.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$