The Review of Regional Studies

The Official Journal of the Southern Regional Science Association

Explaining Spatial Disparities in Fatal Drug Overdoses, 1970-2016*

Meri Davlasheridze[a], Stephan J. Goetz[b]

[a]*Department of Marine and Coastal Environmental Science, Texas A&M University at Galveston, USA*
[b]*Professor of Agricultural and Regional Economics, Penn State University, USA*
Director, The Northeast Regional Center for Rural Development, USA

Abstract: The opioid crisis has impacted many regions of the United States, transcending socioeconomic, demographic, and political divides and leading to urgent calls for public health and law enforcement interventions. It has hit both micropolitan and rural smaller communities especially hard, with severe increases in prescription drug-induced fatalities over time. This paper explores socioeconomic determinants and spatial disparities of fatalities caused by drug and opioid overdose (both intentional and unintentional), focusing specifically on rural-urban differences and understanding the separate role of net farm income in the drug overdose crisis. Our panel data analysis of all US counties spanning the 1970-2016 period indicates that rurality, as measured by lower population density, is associated with higher deaths rates. Importantly, while our research suggests that the opioid crises went hand in hand with declining net farm income, the effect appears to be small. Specifically, we estimate that each $10,000 reduction in net income per farm is associated with a 0.04 increase in overdose age-adjusted deaths per 100,000 people. This effect is more prominent in counties with persistent poverty, which also is predominantly rural. Given the pronounced variability in farm financial indicators over time, the relative health of the farm sector in rural areas may warrant more attention if the pressing health crisis is to be addressed effectively.

Keywords: drug overdose fatalities, opioid deaths, opioid epidemics, socioeconomic determinants, farm wealth, disparity

JEL Codes: I10, I14, I15, R11

1. INTRODUCTION

The prescription and illicit drug overdoses crisis has reached far into American society, transcending economic, political, and demographic lines and leaving few communities untouched. The Council of Economic Advisors (2017) estimated that fatalities from drug overdoses cost the nation \$432bn in 2015, in terms of the statistical value of lost lives and 2.8% of national GDP. In addition, national Center for Health Statistics (NCHS) data show a dramatic 5.6-fold upward shift in the trend line of age-adjusted mortality rates between 1998 and 1999, from an average increase of 0.13 deaths per year per 100,000 population in 1970-1998 to an increase of 0.73 deaths per year since then. This shift has been attributed to decisions in the 1990s to more aggressively treat pain with opioids (Kolodny et al. (2015); Rosenblum et al. (2008)); importantly, this period also preceded the 2001 recession as well as China's accession to the World Trade Organization on December 11, 2001 (Case and Deaton (2015)).

One common belief is that rising death rates, in particular those related to opioids and synthetic drugs,[1] reflect declining economic opportunities (Monnat (2019)), especially in rural areas (Keyes et al. (2014); Monnat (2019)). A more detailed overview of opioid-induced death distributions across the rural-metro continuum suggests that prescription opioids and synthetic prescription opioid mixtures are overwhelmingly located in sparsely populated rural areas. In contrast, synthetic drugs, heroin, and opioid syndemic counties have been predominantly urban and metro where delivery networks are relatively well-established and people are economically more secure (e.g., see Peters et al. (2020)). Therefore, with agriculture being an important sector in many rural communities, understanding how to farm financial wellbeing potentially buffer negative impacts of economic distress that may lead to drug dependence and induced fatalities is important and may help design policies addressing rural financial hardship and poverty traps. In this paper, we identify factors associated with age-adjusted death rates from a drug overdose, which include prescription drugs, opioids, various sedatives, and illicit drugs, both intentional and unintentional drug overdoses.[2]

We estimate a fixed-effects panel data model using annual data and covering all US counties over the 1970-2016 period, and by splitting the sample, periods of pre-and post-1999 to mark "the wave 1" of the three waves in drug epidemics when the deaths rates started to rise due to prescription opioid overdose.[3] Relating these shifts in death rates[4] to important economic factors also makes the sample split particularly interesting for further study, where individual regressors may have different effects in the different periods. For example, the pre-1999 sample covers the period before potential threats to workers from automation, robots, and artificial intelligence gained more prominence, at least in terms of public awareness (see also Acemoglu and Restrepo (2018)). Moreover, the period roughly coincides with the Reagan era, which started in the 1970s and has also been referred to as

---

[1] A Center for Rural Pennsylvania (2017) in-state opinion survey finds respondents identifying a variety of causes of the crisis, including poor personal decision-making, over-prescription and inadequate law enforcement. Monnat and Rigg (2016) find that prescription opioids abuse rates among youth are highest in rural areas (6.8%) followed by small urban (6.0%), and lowest in large urban areas (5.3%).

[2] Opioid-related deaths make more thank 2/3 of the total drug related deaths rates across all U.S. states Scholl et al. (2019).

[3] Available https://www.cdc.gov/drugoverdose/epidemic/index.html

[4] Throughout the paper death rates refer to drug overdose death rates.

the Me Decade, referencing the general new attitudes of Americans concerning "narcissism, selfishness, personal rather than political awareness" (Schulman (2001); Wolfe (1976)). As for the post-1999, the period covers several recessions. As noted above, China's accession to WTO, major sectoral shifts in employment, including shrinking of farming and factory jobs and the rise in the service-related employment.

In addition to the primary variables of interest (e.g., rurality and net farm income), our model controls various socioeconomic variables, including demographic, sectoral employment, and labor markets variables such as unemployment rates and income. Our results suggest that higher levels of rurality as measured by lower population density are associated with *higher* drug overdose fatality rates. The analysis further reveals that a $10,000 reduction in net income per farm is associated with an increased death rate from opioid overdoses by 0.04 death per 100,000 people. The effect is almost twice as large in the sub-sample of persistent poverty counties. As for other control variables, our results suggest the effect of per capita income is statistically different from zero, and this variable is associated with lower death rates; at the same time, death rates were higher with increased welfare transfer payments (used to proxy for poverty), all else held constant. Regarding sectoral employment shares, we found some variations and differences in effects across regions and the rural-urban continuum, but the differences were primarily in terms of their statistical significance rather than the direction of effects. The agricultural and manufacturing sector employment shares are consistently found to be associated with lower death rates.

Our research draws on and extends earlier work examining socioeconomic and demographic drivers of opioid-induced deaths in the US and various mental health indicators. Overwhelming evidence indicates that a lack of job opportunities, economic downturns and prevalence of deaths rates lead to mental health problems (Arkes (2007); Betz and Jones (2018); Carpenter et al. (2017); Goetz et al. (2015); Hollingsworth et al. (2017); Ruhm (2015)). Importantly, we contribute to the long line of research work that explores rurality and poverty spells of opioid epidemics (Keyes et al. (2014)). Past research has indicated that deaths from prescription opioids have been of particular concern in smaller rural and remote areas (Monnat (2018); Monnat (2019); Monnat et al. (2019); Monnat and Rigg (2016); Peters et al. (2020)) that rely heavily on farming and manufacturing industries, and whose population are predominantly white, poor, and aging (Peters et al. (2020)). These past studies also suggested heterogeneity in the effects of various socioeconomic and employment variables and the subsequent importance of place-specific policies to addressing the crisis. We complement them by focusing on the financial health of farming, which is inherently more cyclical than, for example, earnings from manufacturing, and by further exploring differences in death disparities along the lines of lingering and persistent poverty.

2. DATA AND DESCRIPTIVE STATISTICS

Data for this research were obtained from multiple sources, including the National Center for Health Statistics (NCHS), the US Census Bureau, and the Bureau of Economic Analysis. We extract drug-related mortality statistics from the NCHS Compressed Mortality Files (CMF), which provide county-level mortality and population data to construct the dependent variable. The 1968-1988 data are publicly available, while the CMFs for 1989-2016 are

available on CD-ROMs and are usage restricted. The mortality data files report more than 100 underlying causes of deaths by different age groups using the International Classification of Disease (ICD). The CMF for 1999-2016 uses ICD10 codes to identify underlying causes of deaths, CMF for 1989-1998 uses ICD 9 codes, and all prior years starting in 1968 are based on ICD 8 classification. We used all ICD codes related to illicit drug poisoning deaths (both intentional and unintentional), including opiates, heroin, and prescription drugs.[5]

To calculate age-adjusted mortality rates, and following common practice in the health literature, we first calculate age-specific rates per 100,000 people for each county (a total of 9 age groups is used for the population 15 years and older) and multiply them by the number of people in the specified age group in the standard population. The US year 2000 population was used for the latter. Hence, the final mortality variable is an age-adjusted rate per 100,000 of 15 years and older population.

Independent variables are retrieved from the sources shown in Table 1. Because of data availability for race and unemployment, as well as the significant shift in drug overdose rates marking the start of the first wave in 1999, we carry out separate estimations for the periods 1970-1998 and 1999-2016, in addition to estimating a model covering the entire period. We also lag the regressors by one year, leaving 113,639 observations in the overall panel across 2,966 counties. This also reflects nondisclosure of data in a subset of fewer than 50 small rural counties. Our results should be interpreted with this in mind.

Figure 1 shows a sharp increase in the average annual number of age-adjusted deaths per 100,000 population by US region, rising from less than 1 in 1970 to more than 17 in 2016. The Northeast US especially experienced a sharp increase in recent years, while growth rates have tapered off in the West and South. The maps in Figures 2a and 2b show the same variable for US counties for the two different periods of observations. Both the coasts and non-coastal areas are impacted, but the relatively lower death rates in the agriculturally-dependent center of the country also stand out, as do the high and widespread death rates in the West in the 1970-1998 period. Further, strong regional and state clusters appear in the 1999-2016 period. The Great Plains and New York State show low rates, while the Central Appalachian region and Utah, Arizona, and New Mexico are high.

We measure farm financial status by net farm income per farm proprietor using Bureau of Economic Analysis (BEA) Regional Economic Information System data. We use NCHS population data files to calculate percent black, percent white, and other races and the shares of female and male populations by county. The population with the Hispanic origin is only available starting in 1999; this distinction was not made in prior years. Data on income are from the US Bureau of Economic Analysis. Unemployment rates starting from 1990 were available from the Bureau of Labor Statistics. Because poverty rates from the US Census Bureau are available starting only in 1989, we use welfare receipts per capita as an alternative proxy. Sectoral employment shares and percent self-proprietor employments are calculated using the US BEA employment series. Public sector employment is the excluded category.

---

[5]ICD10 codes used were X40-X44, X60-X64, X85, Y10-Y14. These codes corresponded to 292, 2920-2929, 304, 3040-3049, 3051-3059, 853-858, 9500-9505, 9620, 9800-9805 in ICD9 classifications. ICD 8 codes included various codes within a broader 304 code (drug dependence), 309.1, E853, E854, E 855, E856 and E950 (for more detailed descriptions about ICD 8, 9 and 10 categories of drug overdose deaths see http://www.wolfbane.com/icd/.

Figure 1: Age-Adjusted Opioids-Related Death Rates by U.S. Region, 1968-2016
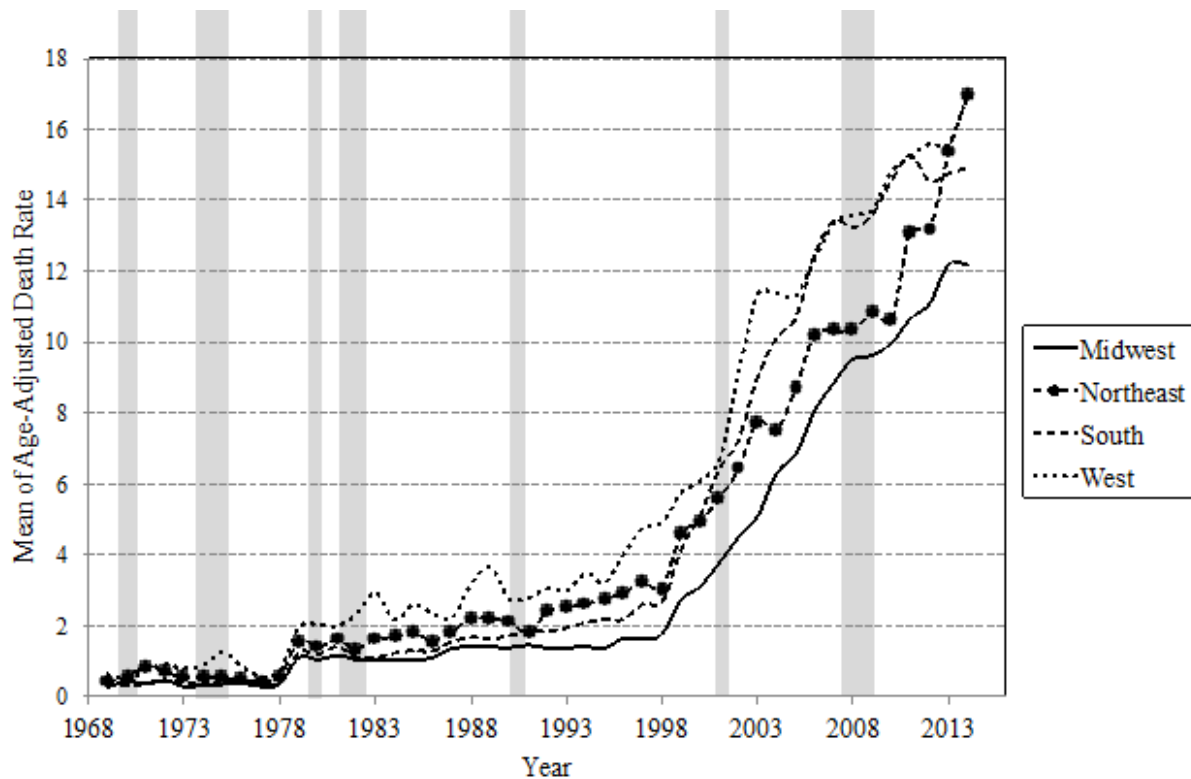
Note: Shared areas denote recession as defined by the National Bureau of Economic Research.

These variables do not allow us to infer that workers in any sector are more or less prone to die from overdoses. We can, however, infer that a higher employment share in a given sector relative to public sector employment is associated with a different overall death rate for the entire county if the parameter estimate is statistically different from zero. As noted, for the main analysis, we consider three separate samples. A full sample corresponding to the years 1970-2016, an early, pre-1999 sample from 1970 to 1998, and the most recent, post-1999 sample for 1999-2016. This provides a structural break in the time series that matches the year in which the death rate dramatically increased. We also explore spatial differences in deaths rates across the rural-urban divide and their regional variations, and for counties in persistent poverty. The US Department of Agriculture's (USDA) Economic Research Service (ERS) defines a persistent poverty county as one in which more than 20% of the population were below the poverty line during the 1980, 1990, 2000 censuses and according to the recent 2007-2011 American Community Survey.[6]

---

[6]For   description   refer   to   https://www.ers.usda.gov/data-products/county-typology-codes/ descriptions-and-maps/.

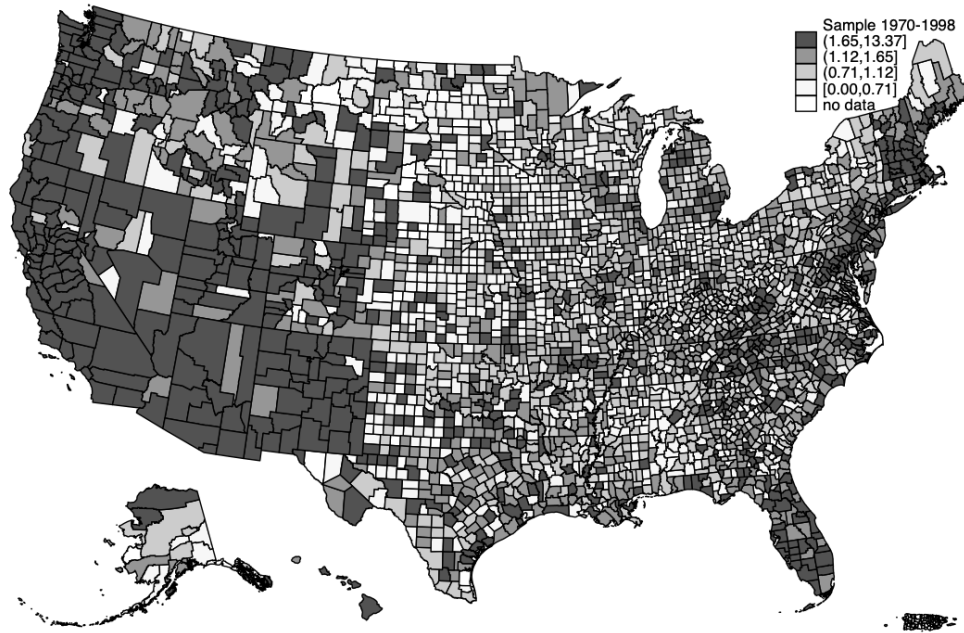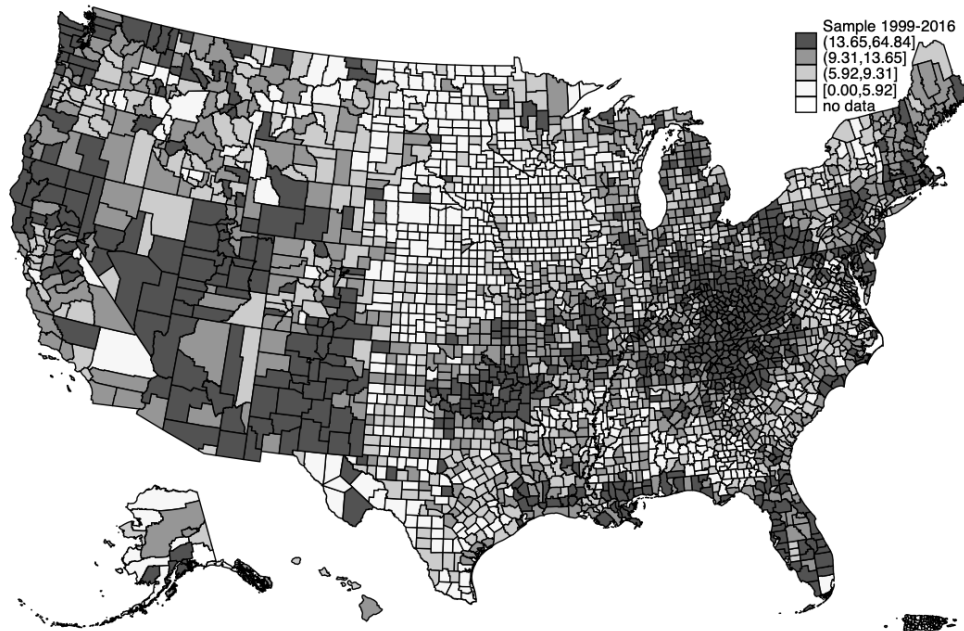**Figure 2a:** Opioids-Related Death Rates by County, 1970-1998

Figure 2b: Opioids-Related Death Rates by County, 1999-2016

Source: Authors. Color version on-line.

Table 1: Variable Definitions, Descriptions, Sources and Summary Statistics

Variable	Description	Source	Mean	Std. Dev.	Min	Max
AgeAdjusted-Death	Age adjusted Deaths per 100,000 people	NCHS (Compressed Mortality Files)	4.10	7.83	0	198.31
Ln_FarmIncome_-FP	Net farm income per farm proprietor, log	BEA	9.74	1.30	-2.61	14.70
Per_Inc_Pc	per capita income, $1000	BEA	26.88	7.99	7.36	180.31
PctBlack	% black/African American	NCHS (Population Files)	9.96	14.47	0	86.9
Male_female	male to female population ratio	NCHS (Population Files)	0.98	0.09	0.74	8.01
Prop_Emp	% proprietor employment	BEA	26.75	11.02	0.20	78.04
Ln_Personal-Transfers_pc	Personal transfer payments per capita, $1000 log	BEA	1.41	0.46	-1.31	2.72
Unemp_rate	% unemployed	BLS	6.16	2.71	0.7	30.60
Emp_ag	% agricultural employment	BEA	2.12	2.95	0	52.41
Emp_constr	% construction employment	BEA	6.83	3.65	0.12	82.58
Emp_manuf	% manufacturing employment	BEA	16.71	11.97	0	75.50
Emp_mine	% mining employment	BEA	2.13	5.12	0	89.30
Emp_retail	% retail employment	BEA	16.67	4.23	0.36	56.39
Emp_wholesale	% wholesale employment	BEA	3.96	2.44	0	43.09
Emp_transp_util	% transportation & utilities employment	BEA	4.27	3.55	0	75.01
Emp_finance	% financial services employment	BEA	6.60	3.09	0	43.86
Emp_service	% Service employment	BEA	19.77	11.23	0.10	85.92
Pop_density	population density	BEA	120.42	366.23	0.16	13,544.8
PctWhiteNon-Hisp*	% white of non-hispanic ethnicity	NCHS (Population Files)	80.27	19.14	2.09	100
PctBlackeNon-Hisp*	% black of non-Hispanic ethnicity	NCHS (Population Files)	9.34	14.67	0	86.73

Notes: The sample contains 113,639 county by year observations, over the 1970-2016 period for the 2,966 counties. * data are only available starting 1999.

3. ESTIMATION METHOD

To examine the effects of socioeconomic and other factors on drug overdoses, we estimate the following fixed effects model employing a panel dataset with c indexing counties and t indexing years (from 1970 to 2016):

$$Death_{ct} = \beta_0 + \beta_1 ln(Net\_Fl_{ct}) + \beta_2 PopDen_{ct-1} + \beta_3 \mathbf{Econ_{ct-1}} + \beta_4 \mathbf{Dem_{ct-1}} + \\ \beta_5 \mathbf{Emp_{ct-1}} + \lambda_t + \lambda_c + \lambda_{st} + \epsilon_{ct} \tag{1}$$

The dependent variable, $Death_{ct}$, as described above represents the age-adjusted drug overdose-related mortality rate per 100,000 people in county c and year t. Net_FI_{ct} is our primary variable of interest that measures net farm income per farm proprietor and is used to proxy the farm wealth. In addressing this farm-level problem, it is also important to consider that in addition to economic hardship perpetuating the drug-dependence crisis in rural areas, the lack of mental health treatment facilities in farming communities can lead to disproportionately higher death rates in rural areas relative to more urban and metro areas. $PopDen_{ct-1}$ measures county population density and captures urban/rural effects on drug overdoses while controlling for metro adjacency status through the fixed effects. As noted, the non-prescription opioid crisis is a growing concern for rural America, and research indicates higher rural rates of deaths from a drug overdose, likely attributable to economic stressors, youth outmigration, greater prescription activity, and hence the availability of opioids in the market and networks that facilitate easy distribution and variety of drugs (Keyes et al. (2014); Monnat (2019); Monnat and Rigg (2016)).[7]

$\mathbf{\textit{Econ}}_{ct-1}$ is a vector of variables measuring a county's socioeconomic conditions, including per capita income, unemployment, and poverty rates (which we proxy using welfare transfers per capita). Higher-income levels are associated, in addition to access to more rewarding forms of employment, with better health services and healthier behaviors, including nutrition, physical activities, and recreation, all of which could lead to lower levels of anxiety and depression (Cross et al. (2001); Lynch et al. (2000); Subramanian et al. (2002); Subramanian and Kawachi (2004)). Welfare-dependency (our proxy for poverty) and unemployment, on the other hand, likely are associated with greater illicit-drug abuse problems (Correa (2021)). However, as documented by the Center for Disease Control and Prevention, in recent years, illicit drug-related problems have surged among all income groups and demographics, including women (Rudd et al. (2016)). $\mathbf{\textit{Dem}}_{ct-1}$ controls for county demographic characteristics including percent black and white population of non-Hispanic origin, and the male/female population share.

$\mathbf{\textit{Emp}}_{ct-1}$ measures county employment shares in agriculture, construction, manufacturing, mining, retail, wholesale, transportation and utility, finance, and the services sector (public sector employment is omitted). We hypothesize that working in certain sectors influences workers' outlook and economic anxiety differently, compared to being employed in the public sector, and that this will be revealed by the coefficient estimates. For example, mining jobs have been in decline; as a result both of labor-saving technical change and environmental regulations. Likewise, manufacturing jobs have been destroyed through outsourcing as

---

[7]More recent estimates across rural-urban lines indicate death rates to be higher in urban areas Hedegaard and Spencer (2021), but this shift happened in 2017, which is not covered in our sample time frame.

well as automation. These shares (percent employed in each sector) are lagged by one year to account for a delayed effect of changing employment opportunities on drug abuse and subsequent mortality. In addition to these major industry employment shares, we control for the share of self-employed. Goetz et al. (2015) found that self-employment significantly reduces the average number of poor mental health days reported, despite well-known stressors associated with working for oneself, such as uncertainty related to income and long working hours. Hence, the effect of self-employment on drug overdose is indeterminate.

Parameter λ_c represents county-specific fixed effects that are time-invariant, including geographic, environmental, and physical conditions, while time-varying factor λ_t affects all counties in the same manner, including national-level policies related to drug epidemics, health insurance policies and the like. λ_{st} correspond to state-specific time trends to capture both the across state differences in death rates as well as state-specific policies and strategies implemented towards addressing the opioid crisis. Last, ε_{ct} is the error term. We cluster errors at the county level to account for potential heteroskedasticity and error correlation over time within a clustering unit.

4.   RESULTS

In Table 2, we report the regression results from the full sample, and the columns (2) and (3) correspond to pre-and post-1999 samples, respectively. Overall, our results indicate farm income to be a significant determinant of drug overdose deaths across US counties. Specifically, the estimated coefficient associated with farm income suggests that for every $10,000 increase in net farm income per farm proprietor, a county's drug-overdose age-adjusted fatality declines by 0.04 per 100,000 people, all else held constant. While this effect may appear to be small, net farm income is a significant determinant of a drug overdose in a county. Importantly, this variable remains highly significant in post-1999 of the opioid epidemics sample and is marginally significant at the 10% significance level in the pre-1990 period; the magnitude also decreases in the later period. In terms of rurality, our results show that more rural counties (lower population density) had higher age-adjusted death rates. However, we note that rurality was not statistically significant in determining age-adjusted death rates during the pre-1999 period.

In terms of other control variables, as seen in Table 2, higher income levels were associated with lower death rates in the entire sample. Specifically, for every $1,000 increase in per capita personal income, we estimated a decline in drug fatality rates by 0.06 per 100,000. Comparing this with the effect of net farm income, we note that a $10,000 increase in income translates into an almost ten times larger effect than that of net farm income; all else held constant. Interestingly, the income effect was not statistically significant when we split the sample into two sub-periods of interest. Higher poverty rates (as proxied by income transfers) were associated with higher death rates over time, except in the 1970-1998 sub-period, where their effect is not statistically significant.

The effects of sectoral employment shares were more consistent across samples. A higher employment share in agriculture is associated with fewer drug overdoses over the entire period and in the pre-1999 period and, while negative, was marginally significant at the 10% significance level in the post-1999 sample. Higher manufacturing employment shares were

estimated to be associated with lower death rates; this is the only variable that consistently remained significant in all periods. Higher employment shares in mining were associated with lower death rates from a drug overdose over the entire period 1970-2016 only, and the higher employment shares in the retail sector were associated with reduced fatality rates over the full period as well as in the post-1999 period, but the effect was not statistically significant in the pre-1999 sample. Higher employment shares in the transportation and utilities sector and finance sector were highly and significantly associated with lower death rates during the full-time and pre-1999 periods. We also note that the share of self-employed was significant statistically in the pre-1999 period only and indicated higher death rates.

A higher share of African-Americans in a county was associated with fewer drug-related deaths over the entire period, but with more deaths in 1970-1998; the effect in the 1999-2016 period was not statistically different from zero. African-Americans may have been relatively more affected by the recessions of the earlier sub-periods than were other ethnic groups, including Whites.[8]

Over the entire period, counties with proportionately fewer males than females had higher age-adjusted death rates. We do note that this does not necessarily imply that death rates are higher among the female population; in fact, the overall average death rate of the male population is higher than that of females across counties. Several factors could explain this observed association. Females tend to experience more chronic illnesses, and they are more susceptible to the risk of addiction from prescription pain medications and notably also use them for longer terms (Office on Women's Health (2017)). Centers Centers for Disease Control and Prevention (2019) suggest that women make up 65% of opioid users. Another factor could be related to the availability of Medicaid among the female population (more than 70% are women rely on Medicaid as their primary insurance), and the opioid prescription rates also tend to be higher among Medicaid patients relative to private insurance holders. A third factor could relate to inappropriate use and abuse of opioids without prescriptions, which have been rising and are particularly of concern among the young population (National Institute on Drug Abuse (2021)). It is possible that access to prescription opioids by the female population also increases drug abuse problems by their male partners and youngsters in a county.

In comparing results across samples, we note that for the period 1970-1998, our regressors generally have less predictive power, with only a few variables exhibiting a statistically significant effect on drug overdose death rates. Another noticeable difference is that while the recent sample (1999-2016) tends to closely mimic the entire sample time frame in terms of signs and magnitudes of the coefficients, the pre-1999 sample overall shows smaller parameter estimates for the few control variables that are statistically significant. One explanation why this latter subsample overall showed less statistical significance is that age-adjusted death after controlling for the county, year, and state-specific time trends exhibit less variation

---

[8]In the appendix Table A.1, we report model results with more refined measure of ethnicity (available only for 1999-2016). These results show that both Whites and African-Americans had significantly higher death rates than Hispanics. In this model, we are also controlling for an unemployment rate also available post-1999 from the Bureau of Labor Statistics. Higher unemployment rates are associated with statistically significant increase in death rates from drug overdose. Death rates decrease with increasing farm income and population density, all else held constant.

Table 2: Determinants of Age-Adjusted Death Rates, different time periods

	(1) 1970-2016	(2) 1970-1998	(3) 1999-2016
L.Per_inc_pc	-0.0576***	0.0014	0.0005
	(0.0066)	(0.0062)	(0.0182)
L.PctBlack	-0.0406***	0.0319***	0.0962
	(0.0109)	(0.0093)	(0.0655)
L.Male_female	-3.4043***	-0.1451	-0.4734
	(0.3869)	(0.3014)	(2.1045)
L.Prop_emp	0.0012	0.0157***	-0.0065
	(0.0060)	(0.0052)	(0.0191)
L.Ln_PersonalTransfers_pc	1.2843***	0.1102	4.2544***
	(0.2249)	(0.1612)	(1.0496)
L.Ln_FarmIncome_FP	-0.1213***	-0.0247*	-0.1222**
	(0.0208)	(0.0146)	(0.0544)
L.Emp_ag	-0.1232***	-0.0616***	-0.0433*
	(0.0127)	(0.0161)	(0.0229)
L.Emp_constr	-0.0032	-0.0078	0.0785**
	(0.0108)	(0.0073)	(0.0400)
L.Emp_manuf	-0.1007***	-0.0092**	-0.0830***
	(0.0055)	(0.0043)	(0.0237)
L.Emp_mine	-0.0785***	-0.0069	-0.0314
	(0.0115)	(0.0077)	(0.0433)
L.Emp_retail	-0.1387***	0.0058	-0.1145***
	(0.0113)	(0.0086)	(0.0401)
L.Emp_wholesale	-0.0034	0.0118	0.0319
	(0.0199)	(0.0141)	(0.0714)
L.Emp_transp_util	-0.0138**	-0.0186***	0.0117
	(0.0061)	(0.0056)	(0.0199)
L.Emp_finance	-0.0504***	-0.0336**	0.0518
	(0.0174)	(0.0132)	(0.0541)
L.Emp_service	-0.0001	0.0015	-0.0027
	(0.0019)	(0.0016)	(0.0052)
L.Pop_density	-0.0027***	-0.0002	-0.0100***
	(0.0004)	(0.0004)	(0.0028)
_cons	-20.6118	-65.4070**	30.1542
	(33.5022)	(31.6007)	(225.1415)
R^2	0.38	0.06	0.14
N	113,639	74,205	39,434

Note: Standard errors in parentheses are clustered by county. Column (1) corresponds to the full sample covering 1970-2016; columns (2) and (3) correspond to pre- and post-1999 samples, respectively. Significant statistically at 1% (***), 5% (**) or 10% (*). Includes county & year fixed effects and state-specific time trends.

compared to the earlier sample period. The lower significance could be the result of fixed effects soaking up much of the variation in the dependent variable compared to the earlier period.[9]

Farm-level income can play a particularly important role in local economic wellbeing and buffer some of the consequences of financial recessions (these periods are shown as shaded areas in Figure 1). In column one of Table 3, we report regression results from the sample restricted to farm recession years (1980, 1983, 1995, 2002, 2006, 2009, and 2014) when farm income declined by at least 20% over the previous year in nominal terms. In this sample, we again estimated the farm income variable to be highly significant statistically and negatively associated with death rates during these recession periods. We also note that the effects of other variables remain relatively consistent with the results reported in Table 2.

In addressing this farm-level problem, it is also important to consider the lack of mental health treatment facilities in farming communities relative to urban areas with higher population densities. For example, Figure 3 shows a dearth of such facilities in a number of farming-dependent counties in 2016. Healthcare disparity is vivid not only across the rural-urban divide but is particularly prominent among the poor and in communities in persistent poverty. Lingering poverty may further exacerbate and create systematic problems with implications for not only poor residents but also for the non-poor. A recent study by USDA showed that approximately 79% of counties with more than 20% of the population in poverty since 2014 were rural – that is, one in every four rural counties were in high poverty (Farrigan et al. (2020)).

Moreover, extremely poor counties, defined as those with high poverty rates over the past 30 years, were all rural in 2018 and geographically concentrated in regions with a high rate of racial minorities (Farrigan et al. (2020)). Rural persistent poverty overlaid by disproportionately large shares of the population that are in poor health condition and aging in rural areas (James et al. (2018)) may make the problem of drug overdose deaths particularly complex to solve. To further explore the effects of farm-level income in persistently poverty counties, we estimate our model including only these counties. As shown in column (2) of Table 3, farm income is also associated with a significant reduction in drug overdose death rates in these persistently poor counties. One important observation from this sample is that the estimated coefficient associated with the farm income variable is twice as large in these areas of persistent poverty. In terms of employment shares, higher shares of agriculture, wholesale, and self-employment are associated with lower death rates, while the financial employment share is associated with higher death rates. Income is statistically significant and associated with fewer death rates. Higher poverty (as proxied by personal transfer payments per capita) is found to be associated with higher death rates in a county; all else held constant. Specifically, every $1,000 dollar increase in welfare transfers per capita, as a measure of poverty and economic distress, is associated with an increase in the number of deaths by 0.6 per 100,000 people in a county.

---

[9]As a sentivity analysis, we also used the year 1996 to mark the appearance of OxyContin in the market to split the sample periods and in addition, considered the year 2002 to mark the period of rapid increase in prescription drug-related deaths. We found no meaningful changes in the estimated coefficients compared to the ones resported in the manuscript. These results are available upon request.

Table 3: Sample of Farm Recession and Persistent Poverty

	(1) Farm recession years only	(2) Persistent poverty counties only
L.Per_inc_pc	-0.0470**	-0.0844**
	(0.0209)	(0.0369)
L.PctBlack	-0.0239	-0.0935***
	(0.0387)	(0.0308)
L.Male_female	-3.1741**	-7.7050***
	(1.4388)	(1.2037)
L.Prop_emp	-0.0385**	-0.0915***
	(0.0193)	(0.0190)
L.Ln_PersonalTransfers_pc	3.0248***	4.2310***
	(0.7965)	(0.7931)
L.Ln_FarmIncome_FP_n	-0.1631**	-0.2137***
	(0.0670)	(0.0681)
L.Emp_ag	-0.1194***	-0.0755**
	(0.0297)	(0.0353)
L.Emp_constr	0.0032	0.0014
	(0.0347)	(0.0379)
L.Emp_manuf	-0.1223***	-0.0452***
	(0.0186)	(0.0166)
L.Emp_mine	-0.0217	-0.0568*
	(0.0349)	(0.0333)
L.Emp_retail	-0.1597***	-0.0736**
	(0.0394)	(0.0361)
L.Emp_wholesale	0.0126	-0.1648**
	(0.0679)	(0.0655)
L.Emp_transp_util	-0.0147	-0.0600
	(0.0196)	(0.0396)
L.Emp_finance	0.0002	0.3971***
	(0.0589)	(0.0733)
L.Emp_service	0.0038	-0.0231**
	(0.0055)	(0.0098)
L.Pop_density	-0.0050***	0.0033
	(0.0015)	(0.0022)
_cons	16.6432	453.0897***
	(133.2585)	(88.3981)
R^2	0.37	0.34
N	17,350	12,507

Note: Standard errors in parentheses are clustered by county. Significant statistically at 1% (***), 5% (**) or 10% (*). Includes county & year fixed effects and state-specific time trends. Column (1) corresponds to a sample that is restricted to farm recession years (1980, 1983, 1995, 2002, 2006, 2009 & 2014); column (2) corresponds to a sample of poverty persistent counties per to USDA typology.

Figure 3: Availability of 2016 Mental Health Treatment Facilities by County
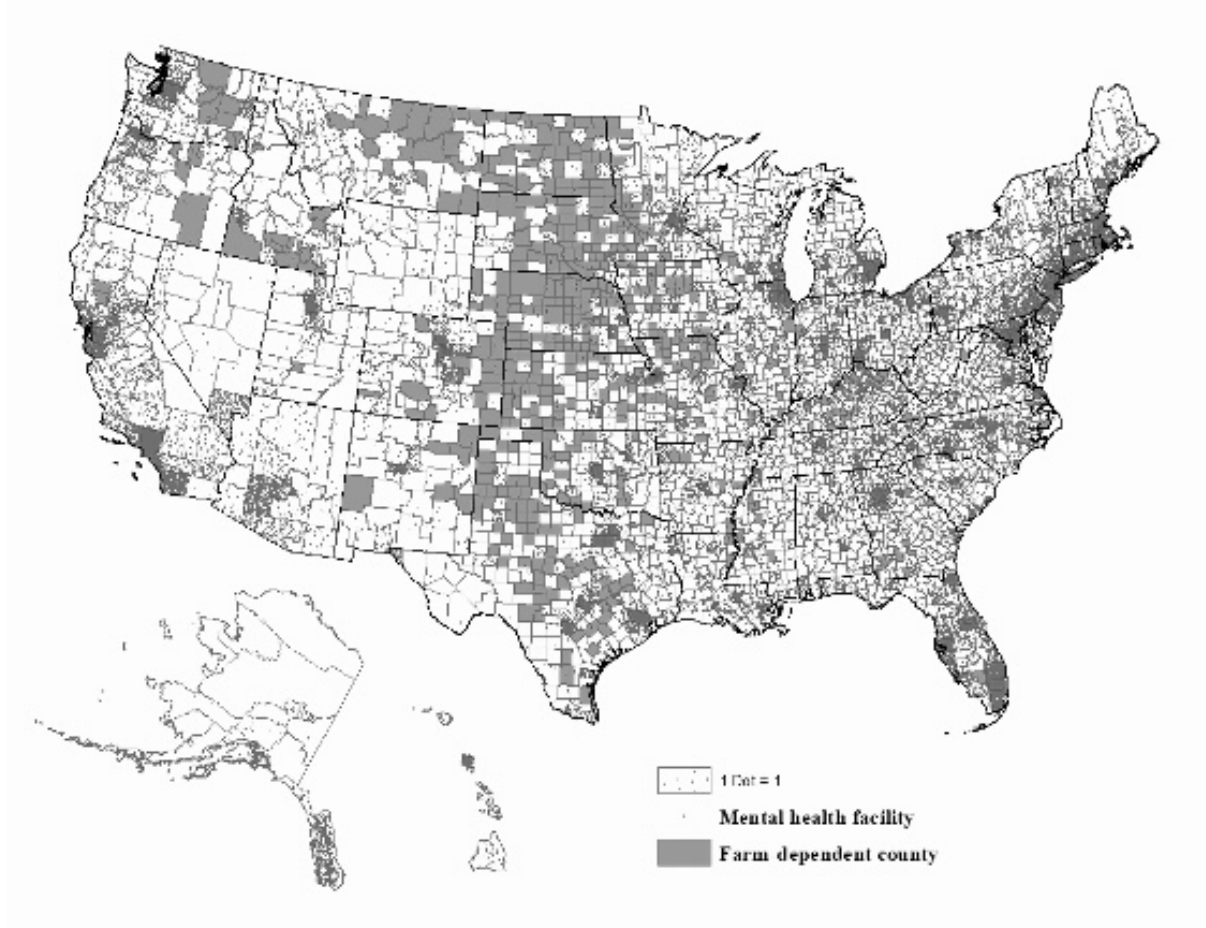
Note: Farming-dependent counties are highlighted

5. SENSITIVITY ANALYSES

Given that opioid addiction rates are unevenly distributed across the nation, we conducted sensitivity analyses across the rural-urban continuum (as defined by the USDA's Economic Research Service) as well as by the Census region. For the former, we specifically compared results of non-metro adjacent and non-adjacent counties separately[10], with the following salient findings based on the full sample including all years (see Appendix Table A.2). Average per capita income retained its statistically significant (and negative) effect in both the metro non-adjacent and the metro adjacent counties. Per capita welfare transfers, as a proxy for poverty, were also consistent across the two samples and were associated with higher drug

---

[10]We employ 2003 Rural-Urban Continuum Codes (RUCC) of USDA (available https://www.ers.usda.gov/data-products/rural-urban-continuum-codes.aspx) to create the two samples. Specifically, counties with RUCC codes 4,6,8 are defined as adjacent to metro, while counties with RUCC codes 5,7, and 9 are referred to as non-adjacent to metro counties. We note that RUCC codes have been updated decennially, and while there have been some changes over time in a county's RUCC codes, the changes have not been much limiting our ability to explore their effect with the FE model.

overdose rates. In terms of farm wealth, the variable was estimated to be highly significant and negative in both samples, but the magnitude was larger in the not-adjacent to metro sample. The population density was associated with higher death rates in metro adjacent counties but was associated with declining rates in the metro non-adjacent counties. One plausible explanation is that increased commuting into the urban core causes more stress and leads to more drug abuse.

In terms of employment shares by sector, larger shares of jobs in the agriculture, manufacturing, and retail sectors were associated with lower death rates in both samples. These findings were consistent with the national sample over the same time period. The importance of manufacturing jobs is noteworthy given that much of this employment occurs outside of core metro areas. Mining sector jobs were associated with lower death rates, as were agricultural and retail sector jobs in both samples. Employment shares in transportation and utilities were also negatively associated with the death rates on both samples, but the effect was only marginally significant in non-adjacent to metro counties. Higher shares of self-proprietors were significant in metro adjacent areas and indicated a negative association with drug overdose death rates; all else held constant, but a positive and marginally significant association in the non-adjacent to metro sample.

Employment shares in the finance and construction sectors were positively and significantly associated with death rates in the metro adjacent counties but had the opposite effect in the non-adjacent counties, although construction sector jobs in the non-adjacent to metro counties were estimated to be only marginally significant at 10% level. The reason for this is not entirely clear except that the finance jobs in metro adjacent counties may be subject to greater competition and, therefore, more stressful. Last but not least, a higher share of the black population was significant statistically and exhibited a negative association with death rates relative to other races/ethnicity in both samples. Higher shares of males to female populations also indicated negative effects on death rates in both samples, which was also consistent with the nation as a whole.

As a next step, we also examined differences in the regression parameters across the four US Census regions, again employing the entire sample (see Appendix Table A.3). Our results suggest that higher per capita income is negatively associated with a drug overdose death in the Northeast and the Midwest and that it has no effect in either the West or the South. Conversely, greater welfare transfers per capita are associated with more deaths in the South and the West, but there is no association in the other regions. In terms of farm income, the effect was estimated to be statistically significant and negative only in the Midwest and the South, marginally significant in the Northeast, and it was not statistically different from zero in the West region. In all regions, rurality, as measured by population density, indicated higher drug overdose death rates; all else held constant.

Agricultural employment shares were estimated to be statistically significant and negative in all Census regions, except for the West; for that region, the effect was marginally significant in the Northeast region. The construction employment share was negatively significant in the Midwest, significant and positive in the Northeast, and had a statistically insignificant association with drug overdose fatalities in the South and the West. Manufacturing employment was estimated statistically significant and negative for all regions; the effect, however, was marginally significant at a 10% level in the Northeast. Employment in

mining was highly significant and negative in the South and marginally significant in the West and was estimated not to matter in the Northeast and Midwest regions.

Employment in the retail sector was also estimated to have negative and significant effects in all regions, but it was only marginally significant in the West. Employment in the wholesale sector was associated with more deaths in the Northeast and lower death rates in the West, and it did not matter in the Midwest or the South. Employment in transportation and public utilities mattered only in the Northeast and the South: in both regions, higher shares were associated with lower death rates. Finance sector employment was estimated to raise death rates in the South and lower them in the West and Midwest. Service sector employment was associated with higher death rates in the Northeast and negative in the West and did not matter for the other two regions. Another interesting difference is observed for the self-employment shares. Specifically, greater shares of self-employment were estimated to be statistically significant and positive in the West region but negative in the South. These significant variations across sectoral employment warrant further investigations. The black population shares mirrored the national pattern in the Midwest and the South, but in the West showed larger death rates relative to other races. Male/female ratios were consistent with the national sample, except for the Northeast, where the effect was indistinguishable from zero.

6. CONCLUSION AND FUTURE RESEARCH

Misuse and abuse of opioid drugs (both prescription and illicit) have contributed to a dramatic increase in drug overdose mortality across the US, with significant implications for overall socioeconomic welfare and wellbeing of individuals, communities, and public health in general. While the drugs have reached almost all parts of the US, disparities in mortality rates across racial, social, and economic lines have been particularly noteworthy. In this paper, we focus on understanding the drug epidemic from the lenses of farm financial status and rurality. Using the sample of all US counties over the period 1970-2016, our results show that farm wealth, as an indicator of financial health, has been an important factor buffering the impacts of drug overdose deaths, and particularly in counties in persistent poverty, which are dominated by rural communities. While significant, the estimated coefficient is economically small, implying that every $10,000 reduction in net farm income per proprietor on average resulted in approximately 0.04 more deaths per 100,000 people in the following year in a county. We also note that death rates in rural areas, as proxied by population density, have been rising, and they are also higher in counties with larger welfare payments per capita, all else held constant.

Another important observation from our analysis is that while we have less complete data for the earlier period, splitting the data into the pre- and post-1999 periods, where 1999 marks Wave 1 of the opioid epidemic, revealed that important structural shifts appear to have occurred in the relationships between these regressors and fatal drug overdose deaths between these two periods. Not only did the trend line turn upward sharply starting in 1999, but the effects of the different variables also changed. Beyond this general finding, our results are consistent with past research suggesting the importance of economic factors, including especially income and unemployment as well as population density (rurality) (Arkes

(2007); Betz and Jones (2018); Carpenter et al. (2017); Hollingsworth et al. (2017); Monnat (2019); Monnat et al. (2019); Ruhm (2015)). We also estimated differences in death rates by race, finding a lower death rate among blacks relative to other races. However, a more refined measure of race and ethnicity in the more recent period shows death rates to be lowest among Hispanics. In terms of sectoral employment, our estimated results indicated important regional and temporal variations, in some cases showing opposite effects. We do, however, note that in most of the models, agricultural and manufacturing employment are consistently associated with lower death rates, implying that communities experiencing job losses in these important sectors in recent decades suffer more from drug abuse problems.

These findings are largely in line with past research on opioid epidemics indicating that the brunt of the opioid health crisis has been borne by socially and economically disadvantaged and "left behind" communities (Monnat (2018); Monnat et al. (2019)). Peters et al. (2020) find that less populated, remote, and rural communities with majority white and aging populations fit perfectly into the narrative of "death of despair" as they have been primarily hit hard by prescription drug-related deaths. These communities have also predominantly relied upon on-farm and factory jobs which have been in decline since the 1990s. The authors also show that the impacted population in urban areas was more ethnically diverse primarily due to heroin and other synthetic mix drugs and well-established network connectivity (Peters et al. (2020)). Past studies have also suggested geographic variations in death rates (Kiang et al. (2019); Ruhm (2015)) and differences in overdose mortality rates across different labor markets (Monnat (2018); Monnat et al. (2019)). Consistent with our findings of manufacturing jobs, Seltzer (2020) also suggested strong evidence of a relationship between rising death rates and changes in the US sectoral labor market, and more specifically, the decline in manufacturing jobs using the two-decade-long data at the state level from 1999-2017.

More broadly, our findings are also consistent with previous research that has focused on understanding the socioeconomic, demographic and labor market effects on all causes of mortality (Cosby et al. (2019); McLaughlin and Stokes (2002); Yang and Jensen (2015); Yang et al. (2011)) and life expectancy (Murray et al. (2006)), in general, as well as on the mortality rates related to specific causes of deaths such as cancer, other chronic conditions, cardiovascular diseases, diabetes (Chan et al. (2015); Turi and Grigsby-Toussanit (2017)) and unintentional injuries (Karb et al. (2016)), among others. An important commonality across different causes of deaths is the increasing disparities in mortality rates between rural and urban, and the most severe outcome in areas where rurality intersects with poverty.

Past research has suggested the importance of health policies tailored for specific geographic needs as opposed to a national level "one size fits all" approach that ignores place-specific heterogeneities. Our research also indicates significant heterogeneity both across geography as well as across social lines such as persistent poverty and rurality. The importance of farm-level income directly speaks to rural policy related to farm financial health indicators, and specifically, in times of farm recessions (e.g., Goetz and Debertin (2001)). The most recent projections for 2021 indicate a staggering 9.1% decline in net farm income relative to 2020 (USDA (2021)). Such a decline may further increase drug-induced fatality rates and will likely also hit rural areas in persistent poverty hard. Meanwhile, while prescription drug overdose rates have fallen, this decline has been more than offset by a

widespread substitution to synthetic illicit drugs (e.g., fentanyl), causing even greater rates of drug overdose fatalities across the US (Park and Powell (2021)). This, in turn, appears to have a greater toll in terms of reduced labor force participation and increased reliance on social security programs such as disability payments (Park and Powell (2021)).

Overall, we acknowledge that these intertwined relationships and the very nature of drug abuse make it challenging to sort out cause and effect. While our study employs a panel data model allowing us to control for time-invariant unobservables across counties through county fixed effects, as well as with the year fixed effects and state-specific trends for potential effects of overall national- and state-specific health disparities, infrastructure, health policies that make this health problem geographically uneven, there remain other time-varying unobservables (e.g., mental and physical health conditions, treatment resources, other county-specific policy interventions, among others), that could potentially confound estimated effects of many of the control variables including labor market outcomes (Krueger (2017); Stephens and Deskins (2018)), income (Davlasheridze et al. (2018)), to name a few. More research is warranted in the future with careful choice of matching methods or suitable instruments to address these reverse causality problems (e.g., Goetz et al. (2018)). For example, Betz and Jones (2018) employ Bartik-style instruments (i.e., national-level industry growth variables) to address the reverse causality between local employment and wage growth and opioid overdose.

While identification will be a challenging task, the effects of mental health treatment facilities and other mental health programs on overdose rates would be a fruitful extension of the present study and will further aid in pinpointing disparities across the rural-urban continuum stemming from public health resources and infrastructure gaps. Because the density of such facilities is largely time-invariant, we were unable to include them in our panel fixed effects model. Relatedly, it is important to examine the efficacy of specific policies designed to reduce overdoses. For example, Erfanian et al. (2019) show that how access is provided to Naloxone and the attendant conditions for immunity matter in important ways, both positive and negative, as do spillover effects across state boundaries. A more recent study by Wettstein (2019), using a quasi-experimental setting, also suggests that the expansion of insurance among young adults under the affordable care act has contributed to a significant decline in opioid mortality among this age population (Wettstein (2019)). Considering that opioid dependence is high among those using Medicaid as primary health insurance (McAdam-Marx et al. (2010); Sullivan et al. (2010)), it would also be a fruitful extension to explore how the increased expenditure on Medicaid contributes to mortality. Furthermore, understanding the effects of other disability payments would be an interesting dimension of future research, although sorting out cause and effect may be especially challenging in this case.

Last but not least, a wide array of other socioeconomic and geographic factors are related to economic decline or resilience (Han and Goetz (2019); Partridge and Tsvetkova (2017)) that were not considered in this study. Some interesting factors include the effects on drug overdose fatalities of unemployment compensation (State vs. non-State) and educational assistance payments and worker displacement due to global trade or technological advancement.

REFERENCES

Acemoglu, Daron and Pascual Restrepo. (2018) "Automation and New Tasks: The Implications of the Task Content of Production for Labor Demand," *Journal of Economic Perspectives*, 33(2), 3–30. http://doi.org/10.1257/jep.33.2.3.

Arkes, Jeremy. (2007) "Does the Economy Affect Teenage Substance Use?," *Health economics*, 16(1), 19–36. http://doi.org/10.1002/hec.1132.

Betz, Michael R and Lauren E Jones. (2018) Wage and Employment Growth in America's Drug Epidemic: Is All Growth Created Equal?

Carpenter, Christopher S, Chandler B McClellan, and Daniel I Rees. (2017) "Economic Conditions, Illicit Drug Use, and Substance Use Disorders in the United States," *Journal of Health Economics*, 52, 63–73. http://doi.org/10.1016/j.jhealeco.2016.12.009.

Case, Anne and Angus Deaton. (2015) "Rising Morbidity and Mortality in Midlife among White Non-Hispanic Americans in the 21st Century," *Proceedings of the National Academy of Sciences*, 112(49), 15078–15083. http://doi.org/10.1073/pnas.1518393112.

Center for Rural Pennsylvania. (2017) Pennsylvania's Heroin/Opioid Crisis: Resident Attitudes and the Role of State Government.

Centers for Disease Control and Prevention. (2019) "Drug Overdose Deaths in the United States," 329.

Chan, Melissa PL, Robert S Weinhold, Reuben Thomas, Julia M Gohlke, and Christopher J Portier. (2015) "Environmental Predictors of US County Mortality Patterns on a National Basis," *PloS one*, 10(12), e0137832. http://doi.org/10.1371/journal.pone.0137832.

Correa, Ginni. (2021) How Does Addiction Impact Low-Income Americans?

Cosby, A. G., M. M. McDoom-Echebiri, W. James, H. Khandekar, W. Brown, and H. L. Hanna. (2019) "Growth and Persistence of Place-Based Mortality in the United States: The Rural Mortality Penalty," *American Journal of Public Health*, 109, 155–162. http://doi.org/10.2105/AJPH.2018.304787.

Cross, J C, B D Johnson, W R Davis, and H J Liberty. (2001) "Supporting the Habit: Income Generation Activities of Frequent Crack Users Compared with Frequent Users of Other Hard Drugs," *Drug Alcohol Depend*, 62(2), 191–201. http://doi.org/10.1016/s0376-8716(01)00121-1.

Davlasheridze, Meri, Stephan J Goetz, and Yicheol Han. (2018) "The Effect of Mental Health on US County Economic Growth," *Review of Regional Studies*, 48(2), 155–171. http://doi.org/doi.org/10.52324/001c.7997.

Erfanian, Elham, Daniel Grossman, and Alan R Collins. (2019) "The Impact of Naloxone Access Laws on Opioid Overdose Deaths in the US," *Review of Regional Studies*, 49(1), 45–72. http://doi.org/10.52324/001c.7932.

Farrigan, Tracey et al.. (2020) "Extreme Poverty Counties Found Solely in Rural Areas in 2018," *Amber Waves: The Economics of Food, Farming, Natural Resources, and Rural America.*

Goetz, Stephan J, Meri Davlasheridze, and Yicheol Han. (2015) "County-level Determinants of Mental Health, 2002–2008," *Social Indicators Research*, 124(2), 657–670. http://doi.org/doi:10.1007/s11205-014-0792-6.

Goetz, Stephan J and David L Debertin. (2001) "Why Farmers Quit: a County-level Analysis," *American Journal of Agricultural Economics*, 83(4), 1010–1023. http://doi.org/10.

1111/0002-9092.00226.

Goetz, Stephan J, Mark D Partridge, and Heather M Stephens. (2018) "The Economic Status of Rural America in the President Trump Era and Beyond," *Applied Economic Perspectives and Policy*, 40(1), 97–118. http://doi.org/10.1093/aepp/ppx061.

Han, Yicheol and Stephan J Goetz. (2019) "Predicting US County Economic Resilience from Industry Input-output Accounts," *Applied Economics*, 51(19), 2019–2028. http://doi.org/10.1080/00036846.2018.1539806.

Hedegaard, Holly and Merianne Rose Spencer. (2021) "Urban-Rural Differences in Drug Overdose Death Rates, 1999-2019," *NCHS Data Brief*, 403, 1–8. http://doi.org/10.15620/cdc:102891.

Hollingsworth, Alex, Christopher J Ruhm, and Kosali Simon. (2017) "Macroeconomic Conditions and Opioid Abuse," *Journal of Health Economics*, 56, 222–233. http://doi.org/10.1016/j.jhealeco.2017.07.009.

James, Wesley, Jeralynn Cossman, and Julia Kay Wolf. (2018) "Persistence of Death in the United States: The Remarkably Different Mortality Patterns between America's Heartland and Dixieland," *Demographic Research*, 39, 897–910. http://doi.org/10.4054/DEMRES.2018.39.33.

Karb, Rebecca A, SV Subramanian, and Eric W Fleegler. (2016) "County Poverty Concentration and Disparities in Unintentional Injury Deaths: a Fourteen-year Analysis of 1.6 million US Fatalities," *PloS One*, 11(5), e0153516. http://doi.org/10.1371/journal.pone.0153516.

Keyes, Katherine M, Magdalena Cerdá, Joanne E Brady, Jennifer R Havens, and Sandro Galea. (2014) "Understanding the Rrural–urban Differences in Nonmedical Prescription Opioid Use and Abuse in the United States," *American Journal of Public Health*, 104(2), e52–e59. http://doi.org/10.2105/AJPH.2013.301709.

Kiang, Mathew V., Sanjay Basu, Jarvis Chen, and Monica J. Alexander. (2019) "Assessment of Changes in the Geographical Distribution of Opioid-Related Mortality Across the United States by Opioid Type, 1999-2016," *JAMA Network Open*, 2(2), e190040–e190040. http://doi.org/10.1001/jamanetworkopen.2019.0040.

Kolodny, Andrew, David T Courtwright, Catherine S Hwang, Peter Kreiner, John L Eadie, Thomas W Clark, and G Caleb Alexander. (2015) "The Prescription Opioid and Heroin Crisis: a Public Health Approach to an Epidemic of Addiction," *Annual Review of Public Health*, 36, 559–574. http://doi.org/10.1146/annurev-publhealth-031914-122957.

Krueger, Alan B. (2017) "Where Have All the Workers Gone? An Inquiry into the Decline of the US Labor Force Participation Rate," *Brookings Papers on Economic Activity*, 2017(2), 1. http://doi.org/10.1353/eca.2017.0012.

Lynch, John W, George Davey Smith, George A Kaplan, and James S House. (2000) "Income Inequality and Mortality: Importance to Health of Individual Income, Psychosocial Environment, or Material Conditions," *Bmj*, 320(7243), 1200–1204. http://doi.org/doi:10.1136/bmj.320.7243.1200.

McAdam-Marx, Carrie, Carl L Roland, Jody Cleveland, and Gary M Oderda. (2010) "Costs of Opioid Abuse and Misuse Determined from a Medicaid Database," *Journal of Pain & Palliative Care Pharmacotherapy*, 24(1), 5–18. http://doi.org/10.3109/15360280903544877.

McLaughlin, Diane K and C Shannon Stokes. (2002) "Income Inequality and Mortality in US Counties: Does Minority Racial Concentration Matter?," *American Journal of Public*

Health, 92(1), 99–104. http://doi.org/10.2105/ajph.92.1.99.

Monnat, Shannon M. (2018) "Factors Associated with County-level Differences in US Drug-related Mortality Rates," *American Journal of Preventive Medicine*, 54(5), 611–619. http://doi.org/10.1016/j.amepre.2018.01.040.

Monnat, Shannon M. (2019) "The Contributions of Socioeconomic and Opioid Supply Factors to US Drug Mortality Rates: Urban-rural and within Rural Differences," *Journal of Rural Studies*, 68, 319–335. http://doi.org/10.1016/j.jrurstud.2018.12.004.

Monnat, Shannon M., David J. Peters, Mark T. Berg, and Andrew Hochstetler. (2019) "Using Census Data to Understand County-Level Differences in Overall Drug Mortality and Opioid-Related Mortality by Opioid Type," *American Journal of Public Health*, 109(8), 1084–1091. http://doi.org/10.2105/AJPH.2019.305136. PMID: 31219718.

Monnat, Shannon M and Khary K Rigg. (2016) "Examining Rural/Urban Differences in Prescription Opioid Misuse Among US Adolescents," *The Journal of Rural Health*, 32(2), 204–218. http://doi.org/10.1111/jrh.12141.

Murray, Christopher J L, Sandeep C Kulkarni, Catherine Michaud, Niels Tomijima, Maria T Bulzacchelli, Terrell J Iandiorio, and Majid Ezzati. (2006) "Eight Americas: Investigating Mortality Disparities Across Races, Counties, and Race-counties in the United States," *PLoS Medicine*, 3(9), e260. http://doi.org/10.1371/journal.pmed.0030260.

National Institute on Drug Abuse. (2021) Opioid Overdose Crisis.

Office on Women's Health. (2017) Opioid Use, Misuse, and Overdose in Women.

Park, Sujeong and David Powell. (2021) "Is the Rise in Illicit Opioids Affecting Labor Supply and Disability Claiming Rates?," *Journal of Health Economics*, 76, 102430.

Partridge, Mark and Alexandra Tsvetkova. (2017) "Road to Despair and the Geography of the America Left Behind," : .

Peters, David J, Shannon M Monnat, Andrew L Hochstetler, and Mark T Berg. (2020) "The Opioid Hydra: Understanding Overdose Mortality Epidemics and Syndemics Across the Rural-Urban Continuum," *Rural Sociology*, 85(3), 589–622. http://doi.org/10.1111/ruso.12307.

Rosenblum, Andrew, Lisa A Marsch, Herman Joseph, and Russell K Portenoy. (2008) "Opioids and the Treatment of Chronic Pain: Controversies, Current Status, and Future Directions.," *Experimental and Clinical Psychopharmacology*, 16(5), 405. http://doi.org/10.1037/a0013628.

Rudd, Rose A, P Seth, and F David. (2016) "Increases in Drug and Opioid-involved Overdose Deaths United States," *MMWR Morb Mortal Wkly Rep*, 67, 1445–1452. http://doi.org/10.15585/mmwr.mm655051e1.

Ruhm, Christopher J. (2015) "Recessions, Healthy No More?," *Journal of Health Economics*, 42, 17–28. http://doi.org/10.1016/j.jhealeco.2015.03.004.

Scholl, Lawrence, Puja Seth, Mbabazi Kariisa, Nana Wilson, and Grant Baldwin. (2019) "Drug and Opioid-involved Overdose Deaths—United States, 2013–2017," *Morbidity and Mortality Weekly Report*, 67(51-52), 1419.

Schulman, Bruce J. (2001) *The Seventies: The Great Shift in American Culture, Society, and Politics.* New York: Free Press.

Seltzer, Nathan. (2020) "The Economic Underpinnings of the Drug Epidemic," *SSM-population health*, 12, 100679. http://doi.org/10.1016/j.ssmph.2020.100679.

Stephens, Heather M and John Deskins. (2018) Economic Distress and Labor Market Par-

ticipation.

Subramanian, S. V., Paolo Belli, and Ichiro Kawachi. (2002) "The Macroeconomic Determinants of Health," *Annual Review of Public Health*, 23(1), 287–302. http://doi.org/10.1146/annurev.publhealth.23.100901.140540. PMID: 11910064.

Subramanian, Subu V and Ichiro Kawachi. (2004) "Income Inequality and Health: What have We Learned So Far?," *Epidemiologic Reviews*, 26(1), 78–91. http://doi.org/10.1093/epirev/mxh003.

Sullivan, Mark D, Mark J Edlund, Ming-Yu Fan, Andrea DeVries, Jennifer Brennan Braden, and Bradley C Martin. (2010) "Risks for Possible and Probable Opioid Misuse Among Recipients of Chronic Opioid Therapy in Commercial and Medicaid Insurance Plans: The TROUP Study," *Pain*, 150(2), 332–339. http://doi.org/10.1016/j.pain.2010.05.020.

The Council of Economic Advisors. (2017) The Underestimaed Costs of the Opioid Crisis, Washington, DC.

Turi, K. N. and D. S. Grigsby-Toussanit. (2017) "Spatial Spillover and the Socio-ecological Determinants of Diabetes-related Mortality Across US Counties," *Applied Geography*, 85, 62–72. http://doi.org/10.1016/j.apgeog.2017.05.005.

USDA. (2021) Highlights from the February 2021 Farm Income Forecast, Farm Sector Profits Forecast to Decrease in 2021.

Wettstein, Gal. (2019) "Health Insurance and Opioid Deaths: Evidence from the Affordable Care Act Young Adult Provision," *Health Economics*, 28(5), 666–677. http://doi.org/10.1002/hec.3872.

Wolfe, Tom. (1976) "The Me Decade and the Third Great Awakening," *New York Magazine*, 23(8), 26–40.

Yang, Tse-Chuan and Leif Jensen. (2015) "Exploring the Inequality-mortality Relationship in the US with Bayesian Spatial Modeling," *Population Research and Policy Review*, 34(3), 437–460. http://doi.org/10.1007/s11113-014-9350-9.

Yang, Tse-Chuan, Leif Jensen, and Murali Haran. (2011) "Social Capital and Human Mortality: Explaining the Rural Paradox with County-level Mortality Data," *Rural Sociology*, 76(3), 347–374. http://doi.org/10.1111/j.1549-0831.2011.00055.x.

APPENDIX

Table A.1: Race Measured Differently And Unemployment

	AgeAdjustedDeath	AgeAdjustedDeath
L.per_inc_pc	-0.0883***	-0.0779***
	(0.0234)	(0.0234)
L.PctWhiteNonHisp	0.2280***	0.2281***
	(0.0537)	(0.0535)
L.PctBlackeNonHisp	0.3230***	0.3379***
	(0.0834)	(0.0820)
L.male_female	-2.2032	-2.2021
	(2.7943)	(2.7827)
L.prop_emp	-0.0154	-0.0196
	(0.0268)	(0.0269)
L.ln_PersonalTransfers_pc	5.4162***	4.7771***
	(1.3848)	(1.3898)
L.ln_FarmIncome_FP_n	-0.1894***	-0.1945***
	(0.0732)	(0.0732)
L.emp_ag	-0.0768**	-0.0785**
	(0.0310)	(0.0309)
L.emp_constr	0.0495	0.0607
	(0.0526)	(0.0529)
L.emp_manuf	-0.1145***	-0.1010***
	(0.0293)	(0.0301)
L.emp_mine	0.0655	0.0709
	(0.0860)	(0.0864)
L.emp_retail	-0.1758***	-0.1687***
	(0.0513)	(0.0509)
L.emp_wholesale	0.0161	0.0138
	(0.0840)	(0.0839)
L.emp_transp_util	0.0466**	0.0457**
	(0.0211)	(0.0208)
L.emp_finance	-0.0411	-0.0413
	(0.0804)	(0.0804)
L.emp_service	0.0033	0.0021
	(0.0048)	(0.0048)
L.pop_density	-0.0088***	-0.0090***
	(0.0023)	(0.0022)
L.unemp_rate		0.1292**
		(0.0556)
_cons	-15.4290**	-15.6005**
	(6.6914)	(6.6699)
R^2	0.11	0.11
N	37,156	37,145

Note: Sample corresponds to 1999-2016. Standard errors in parentheses are clustered by county. Significant statistically at 1% (***), 5% (**) or 10% (*). Includes county & year fixed effects and state-specific time trends.

**Table A.2: Results by Adjacent and Non-adjacent
Metro Counties**

	Adjacent	Non-Adjacent
L.per_inc_pc	-0.0512***	-0.0607***
	(0.0142)	(0.0077)
L.PctBlack	-0.0583**	-0.0437***
	(0.0228)	(0.0128)
L.male_female	-5.5217***	-2.1688***
	(0.6973)	(0.4731)
L.prop_emp	-0.0278***	0.0132*
	(0.0103)	(0.0074)
L.ln_PersonalTransfers_pc	1.5190***	1.3983***
	(0.4139)	(0.2726)
L.ln_FarmIncome_FP_n	-0.0991***	-0.1242***
	(0.0351)	(0.0259)
L.emp_ag	-0.1253***	-0.1157***
	(0.0208)	(0.0161)
L.emp_constr	0.0368**	-0.0230*
	(0.0174)	(0.0137)
L.emp_manuf	-0.0758***	-0.1105***
	(0.0092)	(0.0070)
L.emp_mine	-0.0493**	-0.0898***
	(0.0198)	(0.0142)
L.emp_retail	-0.0886***	-0.1640***
	(0.0199)	(0.0138)
L.emp_wholesale	0.0325	-0.0113
	(0.0346)	(0.0244)
L.emp_transp_util	-0.0521***	-0.0125*
	(0.0184)	(0.0066)
L.emp_finance	0.1001***	-0.0895***
	(0.0327)	(0.0207)
L.emp_service	-0.0065	0.0011
	(0.0040)	(0.0021)
L.pop_density	0.0200***	-0.0028***
	(0.0047)	(0.0004)
_cons	-143.6372	-4.1986
	(116.3347)	(35.3967)
R^2	0.42	0.36
N	39,272	74,367

Note: Sample corresponds to 1970-2016. Standard errors in parentheses are clustered by county. Adjacent to metro counties are defined by RUCC codes 4,6,8, and the non-adjacent to metro counties are defined by RUCC codes 5,7,9. Includes county and year fixed effects and state-specific time trends. Significant statistically at 1% (***), 5% (**) or 10% (*).

Table A.3: Results by Census Regions

	Northeast	Midwest	South	West
L.per_inc_pc	-0.0579***	-0.1081***	-0.0065	-0.0008
	(0.0195)	(0.0098)	(0.0119)	(0.0210)
L.PctBlack	-0.0693	-0.0718*	-0.0440***	0.7436***
	(0.0460)	(0.0399)	(0.0116)	(0.1560)
L.male_female	0.6854	-4.2319***	-3.6975***	-4.6202***
	(1.5262)	(1.0636)	(0.4430)	(1.6922)
L.prop_emp	0.0103	0.0058	-0.0325***	0.0753***
	(0.0210)	(0.0099)	(0.0081)	(0.0242)
L.ln_PersonalTransfers_pc	-1.0396	0.6496	1.2075***	2.8321***
	(0.6520)	(0.4051)	(0.3203)	(0.7668)
L.ln_FarmIncome_FP_n	-0.0814*	-0.0844**	-0.1796***	-0.1168
	(0.0473)	(0.0376)	(0.0292)	(0.0753)
L.emp_ag	-0.1124*	-0.0784***	-0.1554***	0.0100
	(0.0615)	(0.0221)	(0.0172)	(0.0422)
L.emp_constr	0.0980**	-0.1173***	0.0227	0.0080
	(0.0437)	(0.0213)	(0.0139)	(0.0348)
L.emp_manuf	-0.0260*	-0.1078***	-0.1009***	-0.1269***
	(0.0143)	(0.0098)	(0.0073)	(0.0271)
L.emp_mine	0.0075	0.0163	-0.1338***	-0.0520*
	(0.0559)	(0.0222)	(0.0166)	(0.0293)
L.emp_retail	-0.2403***	-0.1897***	-0.1004***	-0.0786*
	(0.0354)	(0.0183)	(0.0160)	(0.0435)
L.emp_wholesale	0.1957***	-0.0164	-0.0054	-0.1964**
	(0.0668)	(0.0298)	(0.0293)	(0.0828)
L.emp_transp_util	-0.0554***	-0.0063	-0.0602***	-0.0509
	(0.0129)	(0.0073)	(0.0155)	(0.0377)
L.emp_finance	-0.0629	-0.0708**	0.0684***	-0.2829***
	(0.0493)	(0.0304)	(0.0244)	(0.0581)
L.emp_service	0.0159***	0.0031	-0.0031	-0.0309***
	(0.0040)	(0.0028)	(0.0028)	(0.0088)
L.pop_density	-0.0042***	-0.0020**	-0.0014**	-0.0062***
	(0.0006)	(0.0010)	(0.0006)	(0.0015)
_cons	-25.0675	-527.2539***	304.5082***	-157.4341***
	(22.3385)	(30.2213)	(32.7094)	(46.7054)
R^2	0.68	0.34	0.42	0.32
N	8,537	41,986	48,845	14,271

Note: Sample corresponds to 1970-2016. Standard errors in parentheses are clustered by county. Significant statistically at 1% (***), 5% (**) or 10% (*). Includes county & year fixed effects and state-specific time trends.