Invited paper presented at the 2018 Annual Meeting of the Allied Social Sciences Association (ASSA), January 5-7, 2018 in Philadelphia, PA

Explaining Spatial Disparities in Drug Overdoses, 1970-2014

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Invited paper presented at the Allied Social Sciences Association Annual Meeting,
Session on The Geography of American Despair and Declining Economic Opportunity,
Philadelphia, PA, January 6, 2018.

Partial support from USDA/NIFA and The Pennsylvania State University, Agricultural Experiment Station is gratefully acknowledged. Opinions expressed are strictly those of the authors, who also are responsible for any errors or omissions.

Abstract

We estimate a fixed effects county level panel data model to relate socioeconomic variables to opioid-related drug overdoses, which cost the nation in excess of $430bn in 2015. In addition to demographic and labor market variables we include lagged employment shares by major industry and self-employment shares, as well as cumulative counts of presidentially declared disasters. We find that rurality, as measured by lower population density, is associated with higher overdose rates. Also, for each $10,000 reduction in net income per farm, opioids overdoses rose by 10% from a national average of 10.2 deaths per 100,000 people.

Introduction

The opioids-related drug crisis has reached deep into American society, transcending economic, political and demographic lines, and leaving few communities untouched. The Council of Economic Advisors (2017) estimates that opioids-related drug overdoses cost the nation $432bn in 2015, in terms of the statistical value of lost lives. This number is orders of magnitude larger than the costs associated with all weather-related disasters in 2017 (NOAA, 2017). 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 (Rosenblum et al. 2008), and 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 reflect declining economic opportunities, especially in rural areas.[1] In this paper we identify factors associated with age-adjusted death rates from drug poisonings, which include prescription drugs, opioids and both intentional and unintentional drug overdoses. This is a more narrow set of causes than the "deaths of despair" considered in the accompanying paper presented in this session (Betz and Jones, 2018).

We estimate a fixed effects panel data model to relate the effects of various socioeconomic variables to opioid-related drug overdoses in U.S. counties. In addition to

[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

demographic and labor market variables such as unemployment rates and income, we include the lagged employment shares by major industry from the previous year to assess the effect of the local economic sector job mix on overdoses. We consider self-employment and presidentially declared disasters (Green and Solomon, 1995) among the regressors. Our results suggest that while most variables have the expected effects, including per capita income levels and cumulative exposure to natural disasters, others are counter to expectations. As expected, higher levels of rurality as measured by lower population density are associated with higher overdose rates. A sensitivity analysis further reveals that for each $10,000 reduction in net income per farm the death rate from opioids overdoses rises by 1 death per 100,000, increasing the national average death rate from 10.2 to 11.2 per 100,000 people.

Data and Descriptive Statistics

We use data from NCHS computer files for the period 1968 to 2014 as the dependent variable. Independent variables regressors are retrieved from the sources shown in Table 1 along with descriptive summary statistics. Because of data availability for race and unemployment, as well as the significant structural break in the trend line occurring between 1998 and 1999, we carry out separate estimations for 1970-1998 and 1999-2014, in addition to estimating a model covering the entire period. We also lag the regressors by one year, leaving 128,421 observations in the overall panel across 3,043 counties. This also reflects nondisclosure of data in less than 50 small rural counties. Our results should be interpreted with this in mind.

More specifically, we extract drug-related mortality statistics from the NCHS Compressed Mortality Files (CMF), which provide county-level mortality and population data. The 1968-1988 data are publicly available, while the CMFs for 1989-2014 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). ICD versions 8, 9 and 10 were used to identify causes of deaths related to opioid, heroin, and prescription medication overdose. 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 are 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 population 15 years and older. To identify causes of deaths for ICD 9 and 10 versions, we use ICD codes related to drug poisoning (both intentional and unintentional). These included the following ICD10 and corresponding ICD9 categories for underlying cause of deaths: X40-X44, X60-X64, X85, Y10-Y14. The CMF for 1999-2014 use 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.

Figure 1 shows a sharp increase in the average annual number of age-adjusted deaths per 100,000 population, by U.S. region, rising from less than 1 in 1968 to more than 13 in 2014. The Northeast U.S. 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 widely spread death rates in the West in the 1970-1998 period. Further, strong regional and state clusters appear in the 1999-2014 period, with the Great Plains and New York State showing low rates, while the Central Appalachian region and Utah, Arizona and New Mexico showing high rates.

We use NCHS population data files to calculate percent black, percent white and other races as well as the shares of female and male populations by county. The population with Hispanic origin is only available starting in 1999; this distinction is not made in prior years. Data on income are from the U.S. Bureau of Economic Analysis. Unemployment rates starting from 1990 were available from the Bureau of Labor Statistics. Because poverty rates from the U.S. Census Bureau are available starting only in 1989, we use welfare receipts per capita as an alterative proxy. Sectoral employment shares and percent self-proprietor employments are calculated using the U.S. Bureau of Economic Analysis employment series. Public sector employment is the excluded category. Use of these variables does not allow us to infer that workers in any one 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. Last, we used presidentially declared disasters (PDD) to create a cumulative count of disasters by county available through the Federal Emergency

Management Agency (FEMA). The data starts in year 1959 and report all types of PDDs by county. As noted, for the analysis we consider two separate samples. A full sample corresponding to the years 1968-2014, which excludes poverty and unemployment rates, and the most recent sample for the period 1999-2014, which includes all model variables specified in equation (1) above.

Estimation Method

To examine the effects of socioeconomic and other factors on drug overdose, we estimate the following fixed effects model employing panel dataset with c indexing counties and t indexing years:

$$Death_{ct} = \beta_0 + \beta_1 \boldsymbol{Econ_{ct-1}} + \beta_2 \boldsymbol{Dem_{ct-1}} + \beta_3 \boldsymbol{Emp_{ct-1}} +$$

$$\beta_4 Disaster_{ct-1} + \beta_5 PopDen_{ct-1} + \lambda_t + \lambda_c + \varepsilon_{ct} \qquad (1)$$

The dependent variable, $Death_{ct}$, represents the age adjusted drug overdose-related mortality rate per 100,000 people in county c and year t. $\boldsymbol{Econ_{ct-1}}$ 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 are associated with lower levels of anxiety and depression (Cross et al., 2001; Lynch et al., 2000; Subramanian, Belli, and Kawachi 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. However, as documented by the Center for Disease Control and Prevention, recent years have seen a surge of illicit drug-related problems among all income groups and demographics including women (Rudd et al., 2016). $\boldsymbol{Dem}_{ct-1}$ controls for county demographic characteristics including percent black and white population of non-Hispanic origin, and the male/female population share.

$\boldsymbol{Emp}_{ct-1}$ 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 different 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 under the Obama administration. Likewise, manufacturing jobs have been destroyed through outsourcing as 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 worker share self-employed. Goetz, Davlasheridze, and Han (2015) found that self-employment significantly reduces the average number of poor mental health days, despite well-known stressors such as uncertainty related to income and long working. Hence, the effect of self-employment on drug overdose is ambiguous.

$Disaster_{ct-1}$ measures the cumulative number of Presidentially declared disasters since 1956, to account for the long-term effects of experiencing a natural calamity. We also identify this variable based on past literature, which suggests increased prevalence of mental health problems among survivors of disasters (Osofsky et al. 2009; Calvo et al. 2014; Goetz, Davlasheridze, and Han 2015; Green and Solomon, 1995). $PopDen_{ct-1}$ 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 drug overdose, likely attributed to economic stressors, youth outmigration, greater prescription and hence availability of opioids in the market and networks that facilitate easy distribution and diversification of drugs (Keyes et al., 2014; Monnat and Riggs, 2016).

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. Last, ε_{ct} is the error term. We cluster errors at the county level to account for potential heteroscedasticity and error correlation over time within a clustering unit.

Results

We are interested, in addition to the effects of individual regressors, in whether and how effects of regressors vary between the two periods 1970-1998 and 1999-2014 in particular, and what difference alternative controls make (e.g., unemployment rates). In broad terms, higher income levels and lower poverty rates (as proxied by income transfers) are each associated with lower death rates over time, except in the 1970-1998 sub-period where their effect is not statistically significant; also, the effect of welfare transfers was no longer statistically different from zero when the more refined measure of race is used (percent black or white non-Hispanics). Given that educational attainment rates are not reported annually at the county level and likely change only slowly over time, we were unable to include this important measure; however, this variable tends to be highly correlated with per capita income. Higher unemployment rates were also associated with a higher rate of overdoses in the following year, in the latter period examined.

A higher employment share in agriculture is associated with fewer drug overdoses over the entire period but not in the sub-periods. Higher manufacturing employment shares are associated with lower death rates; this is the only variable that has the same effect in all periods. Higher employment shares in mining, retail, transportation and public utilities, and finance are all associated with lower death rates from opioids over the period 1970-2014, but the effects vary in each of the two sub-periods. For example, mining had no effects in the earlier sub-period (1970-1998) but it turned positive in the period 1990-2014, possibly reflecting the advent of automation and increasingly stringent environmental regulations. On the other hand, higher employment shares in retailing, as in manufacturing, were associated with lower death rates. Higher shares of services employment as well as of self-employment (our proxy for entrepreneurship) were associated with a higher death rate in the 1970-1998 period, but a lower rate in 1999-2014. For the self-employed the benefits of working for oneself apparently increased over the two periods relative to the anxiety and other stresses of working for an employer.

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 1999-2014 period was not different from zero. African-Americans may have been affected more by the recessions of the earlier sub-periods than were other ethnic groups, including Whites. The more refined measure of ethnicity (available only for 1999-2014) shows that both Whites and African-Americans had significantly higher death rates than Hispanics. Including these latter variables (as well as the unemployment rate) also changes the effect of welfare transfers and service sector employment shares to zero statistically. It is worth underscoring that counties with higher shares of Hispanic populations had statistically fewer deaths from opioid overdoses over the time frame analyzed here.

Over the entire period, counties with proportionately fewer males than females, more cumulative disasters, and those that were more rural (lower population density) had higher age-adjusted death rates. The finding for the gender variable is counter to expectations, as male death rates are higher than those for females; this likely reflects the effect of including the other regressors. Also noteworthy is the fact that death rates were higher in more rural, less densely settled areas, although in the 1970-1998 period the effect was not statistically significant (in this period we also are not controlling for the unemployment rate). In supplemental regressions available from the authors upon request we also included a vector of Rural Urban Continuum codes, with results generally confining higher death rates in more remote, smaller places.

More generally, the period 1970-1998 appears to have been markedly different from the subsequent sub-period. Here, neither income nor welfare transfers mattered, perhaps in part because this period contained five separate recessions, shown as shaded areas in Figure 1. Also, the effects of mining and retail employment shares were not significant while services employment had a positive effect, as did self-employment. The latter turned negative in the later sub-period, suggesting a shift in how these workers operated or fared. Likewise the effect of cumulative disasters, unexpectedly, was negative in this period, suggesting fewer deaths from opioids (a sensitivity analysis using a nonlinear effect does not change this). Along with the greater occurrence of recessions, this was also the period before China acceded to the WTO, and before the potential threats to workers of automation, robots and artificial intelligence gained more prominence, at least in terms of public awareness. The period roughly coincides with the Reagan era, which started in the 1970s and has also been referred to as the Me Decade.[2]

By using an age-adjusted death rate we lose potential insights into differences by age category. In figure 3, deaths by age cohort weighted by county population in the

[2] According to Wikipedia, "The term describes a general new attitude of Americans towards atomized individualism and away from communitarianism, in clear contrast with the 1960s." See: https://en.wikipedia.org/wiki/The_%22Me%22_Decade_and_the_Third_Great_Awakening

same age group and adjusted by U.S. standard population, are depicted. As indicated by the line trends, while overall death rates are higher for prime working age groups, age group 35-44 years had the highest death rates on average, followed by age groups 45-65 and 25-34. Importantly, deaths rates for the 19-24 age group show a declining trend in the last decade.

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 Census region. For the former, we compared results of non-metro adjacent and non-adjacent counties separately, with the following salient findings which we consider only for the 1999-2014 period. Average per capita income retained its statistically significant (and negative) effect in the metro non-adjacent counties, but it was not significant in the metro adjacent counties. The opposite was true for per capita welfare transfers, which mattered for the metro adjacent counties only. The unemployment rate, on the other hand, still mattered in both county types.

In terms of employment shares by sector, greater shares of jobs in agriculture were associated with lower death rates in metro adjacent areas, while the opposite was true for mining jobs, as in the nation overall. In metro non-adjacent counties, on the other hand, greater employment in retailing as well as in finance was associated with lower death rates, possibly providing some kind of buffer ever during the financial crisis. Unlike for the nation as a whole, the effect of manufacturing employment shares was not significant; this is noteworthy given that much of this employment occurs outside core metro areas. Likewise, self-employment shares were not associated with any differences in death rates from opioids.

As a next step we also examined differences in the regression parameters across the four U.S. Census regions, again focusing on the 1999-2014 period. One remarkable finding is that a higher per capita income is positively associated with opioid overdoses in the Northeast, and that it has no effect in either the Midwest or West (in the South, the effect remains negative and statistically significant). Conversely, greater welfare transfers per capita are associated with fewer deaths in the Northeast, and there is no association in the other regions. The unemployment rate mattered in the Northeast and Midwest, but not in the other two regions. These differences are worth further examination in future research.

The construction employment share (which like agriculture did not matter in the national model), was statistically significant in Midwest and West, with negative and positive coefficients respectively; for the West, this was in fact the only sector that mattered statistically. This may reflect the fact that the Great Recession was felt more on the two U.S. coasts, and to a lesser degree in the nation's middle. Manufacturing employment shares mattered in the South and Midwest. Employment in mining (positive) and retailing as well as self-employment shares (in both cases negative) mattered only in the South, while wholesale employment (positive) mattered only in the Northeast. 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.

The non-Hispanic population shares mirrored the national pattern in the Northeast and South, but in the Midwest only the percent White non-Hispanic mattered and neither made a difference in the West. Male/female ratios made no difference in the Midwest and West and, perhaps reflecting intensity of prior exposure, past cumulative disasters mattered only in the South and the Midwest. Population density – our measure of rural status of a county – mattered everywhere except in the Midwest.

In light of the higher death tolls in rural areas we also investigated whether farm financial stress independently affected the number of drug overdoses in the United States. We measure farm financial status by net farm income per farm proprietor using Bureau of Economic Analysis Regional Economic Information System data. The coefficient estimate associated with farm income confirmed higher death rates resulting from a marginal decline in farm revenues, all else held constant. In particular, every $10,000 reduction in net farm income per proprietor resulted in approximately one additional death per 100,000 nationwide. Importantly, this estimated effect is twice as large during farm recession years.[3] Including this farm income variable does not materially change the other coefficient estimates. In addressing this farm-level problem, it is also important to consider a relative lack of mental health treatment facilities in farming communities relative to urban areas with higher population densities. For example, Figure 4 shows a

[3]In 1980, 1983, 1995, 2002, 2006, 2009 and 2014 farm income declined by at least 20% over the previous year in nominal terms; we use these to define farm recession years.

dearth of such facilities in a number of farming-dependent counties in 2014. This should be investigated in future research.

Conclusion and Future Research

One overall conclusion of our analysis is that, while we have less complete data for the earlier period, important structural shifts appear to have occurred in the relationships between these regressors and opioids deaths over these two periods. Thus, not only did the trend line turn upward sharply in 2000, but the effects of the different variables also changed. Beyond this general finding our results confirm that economic factors, including especially income and unemployment as well as population density (rurality) are important. As we are controlling for economic factors, population density appears to play an independent role in accounting for the disparate death rates. Other stress factors, such as the cumulative impact of natural disasters also matter, suggesting yet another margin at which disaster effects are felt, as does employment in specific economic sectors relative to public sector employment (which appears to be associated with higher death rates compared to other sectors in the 1970-2014 model). Race also matters, with the lower death rate among Hispanics being especially prominent.

In future research it would be important to examine a wider array of socio-economic and geographic factors related to economic decline or resilience, as in Partridge and Tsvetkova (2018). It also would be worth examining whether reduced access to mental health treatment facilities accounts for the higher rural overdose rate. Because the density of such facilities is largely time invariant, we were unable to include these in the model. More generally, careful research needs to be undertaken in the future using matching methods or by developing suitable instruments (e.g., Goetz, Partridge and Stephens, 2018). The very nature of drug abuse makes it challenging to sort out cause and effect. For example, Krueger (2017) examines the "intertwined" relationship between opioid addiction and labor force participation rates; Stephens and Deskins (2018) similarly consider the relationship between labor force participation and economic distress. In addition, these complex factors are likely to interact with poor mental health more generally (Davlasheridze, Goetz and Han, 2018). Finally, specific policies designed to reduce overdoses could be examined in greater detail. For example, Erfanian, Collins and D. Grossman (2017) 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.

The effects of other policy variables, and public spending in particular, should be investigated more carefully, keeping in mind possible reverse causation. For example, spending data on veterans per capita are available from the Bureau of Economic Analysis' Regional Economic Information System, and this could be included along with the number of veterans per capita. In addition, Medicaid and Medicare expenditures as well as disability payments could be included along with county-level measures on the physical health status of the population. Likewise, both unemployment compensation (State vs. non-State) and educational assistance payments could be included along with actual unemployment rates as well as measures of worker displacement due to global trade or technological advance.

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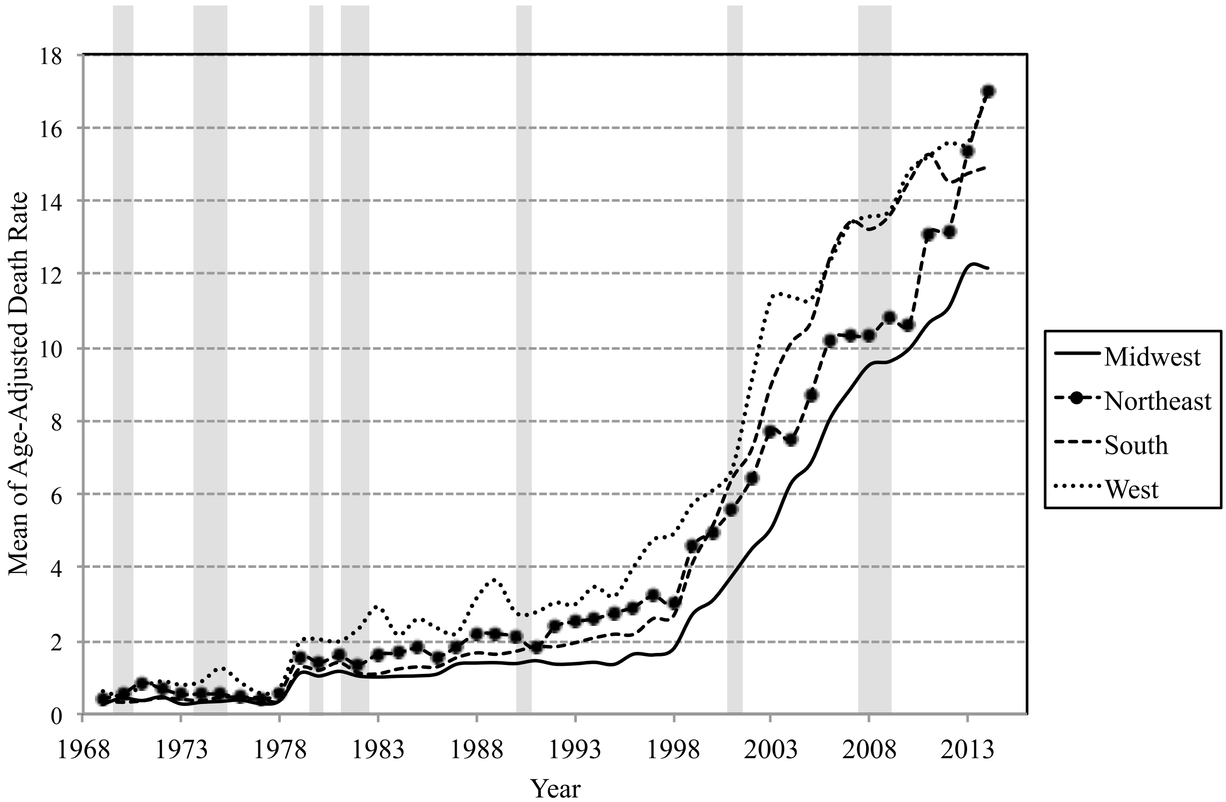
Figure 1: Age-Adjusted Opioids-Related Death Rates by U.S. Region, 1969-2014



Note: Shared areas denote recession as defined by the National Bureau of Economic Research.

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

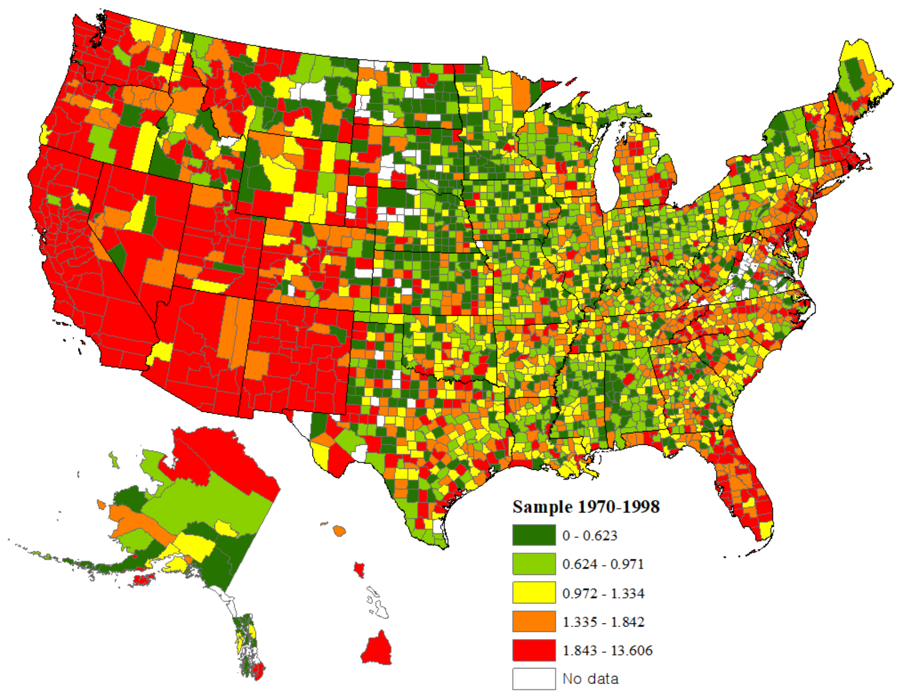
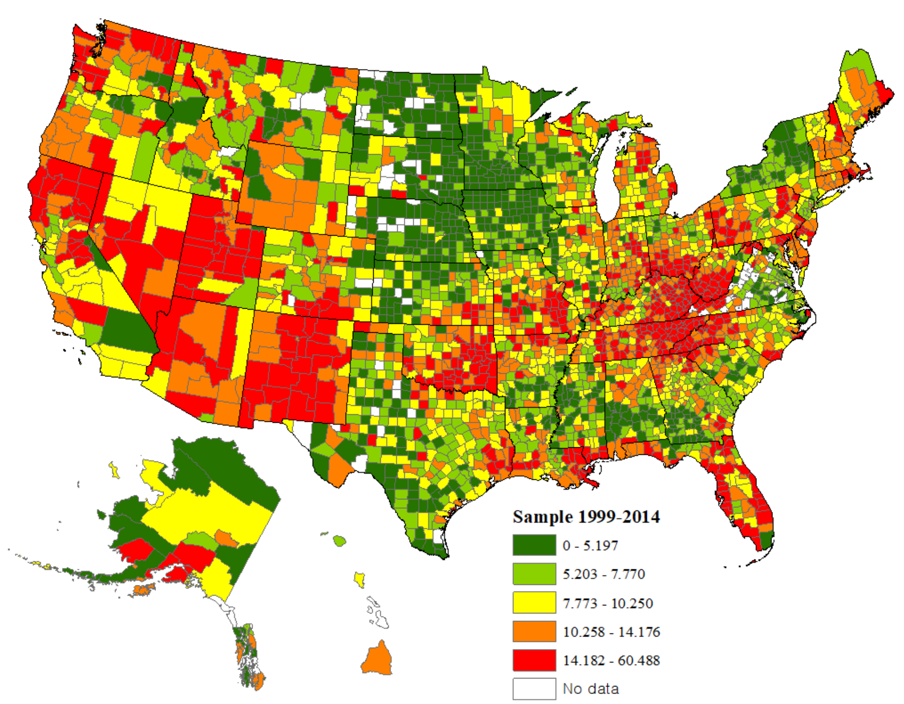
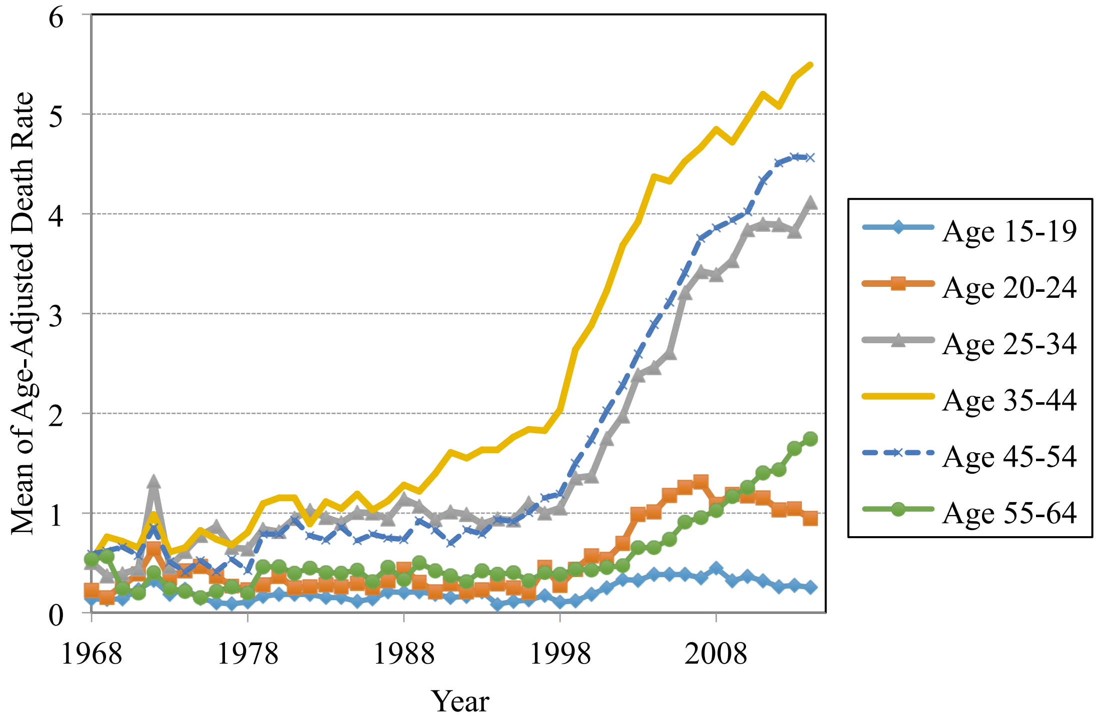


Figure 2b: Opioids-Related Death Rates by County, 1999-2014



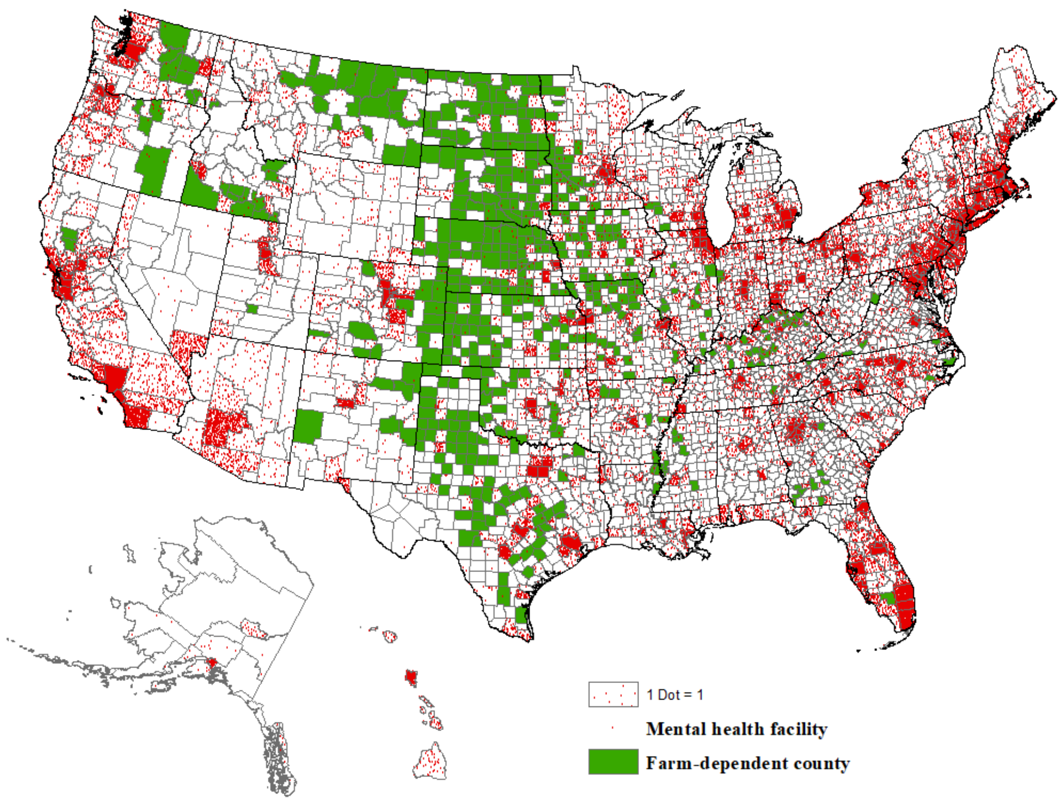
Source: Authors. Color version on-line.

Figure 3: Adjusted Opioids-related death rates by age group, 1969-2014



Note: Excludes age cohorts of 65-74, 75-84 and 85+ years, each of which has <0.5 deaths per 100,000 and does not vary materially over time.

Figure 4: Availability of 2014 Mental Health Treatment Facilities by County



Note: Farming-dependent counties are highlighted.

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

Variable	Description	Source	Mean	Std. Dev.	Min	Max
AgeAdjustedDeath	Age adjusted Deaths per 100,000 people	National Center for Health Statistics (Compressed Mortality Files)	10.21	11.29	0	201.4
per_inc_pc	per capita income	Bureau of Economic Analysis	32.64	7.856	12.80	121.0
PctBlack	% black / AfricanAmerican	National Center for Health Statistics (Population Files)	9.280	14.46	0	86.9
male_female	male to female population ratio	National Center for Health Statistics (Population Files)	0.996	0.096	0.740	2.571
prop_emp	% proprietor employment	Bureau of Economic Analysis	27.64	10.75	2.205	78.04
ln_PersonalTransfers_pc	Personal transfer payments per capita, $1000 log	Bureau of Economic Analysis	1.845	0.271	0.148	2.704
unemp_rate	% unemployed	Bureau of Labor Statistics	6.241	2.771	0.7	30.60
cum_dis	cumulative number of declared disasters since 1959	FEMA	8.760	5.579	0	38
emp_ag	% agricultural employment	Bureau of Economic Analysis	1.545	2.232	0	44.66
emp_constr	% construction employment	Bureau of Economic Analysis	6.436	2.652	0.348	55.85
emp_manuf	% manufacturing employment	Bureau of Economic Analysis	10.40	7.943	0	62.64
emp_mine	% mining employment	Bureau of Economic Analysis	1.578	3.868	0	104.1
emp_retail	% retail employment	Bureau of Economic Analysis	11.48	3.262	0.962	40.36
emp_wholesale	% wholesale employment	Bureau of Economic Analysis	2.909	1.633	0	25.61
emp_transp_util	% transportation & utilities employment	Bureau of Economic Analysis	2.307	2.593	0.014	85.41
emp_finance	% financial services employment	Bureau of Economic Analysis	6.217	2.554	0	40.37
emp_service	% Service employment	Bureau of Economic Analysis	15.73	17.25	0.132	291.0
pop_density	population density	Bureau of Economic Analysis	198.4	1,217	0.037	48,125
PctWhiteNonHisp	% white of non-hispanic ethnicity	National Center for Health Statistics (Population Files)	80.68	19.17	2.088	100
PctBlackeNonHisp	% black of non-hispanic ethnicity	National Center for Health Statistics (Population Files)	9.046	14.32	0	86.73

Notes: The sample contains 43,890 county by year observations, over 1999-2014 period.

Table 2: Determinants of Age-Adjusted Death Rates, Various Periods 1970-2014

	1970-2014	1970-1998	1999-2014	
L.per_inc_pc	-0.1046***	-0.0014	-0.109***	-0.0735**
	(0.0129)	(0.0084)	(0.0296)	(0.0319)
L.ln_PlTsfers_pc	1.8015***	-0.1331	2.5224*	0.3395
	(0.3870)	(0.1833)	(1.4188)	(1.5229)
L.unemp_rate				0.2092***
				(0.0559)
L.emp_ag	-0.1801***	-0.0327	-0.0639	-0.0672
	(0.0313)	(0.0226)	(0.0439)	(0.0454)
L.emp_constr	0.0029	-0.0031	0.0707	0.0942
	(0.0196)	(0.0076)	(0.0679)	(0.0731)
L.emp_manuf	-0.1200***	-0.0087*	-0.132***	-0.0890***
	(0.0108)	(0.0048)	(0.0299)	(0.0334)
L.emp_mine	-0.2132***	0.0023	0.1489*	0.1791**
	(0.0398)	(0.0096)	(0.0868)	(0.0900)
L.emp_retail	-0.1129***	0.0009	-0.162***	-0.1406***
	(0.0213)	(0.0107)	(0.0461)	(0.0504)
L.emp_wholeale	-0.0094	-0.0069	0.0194	0.0046
	(0.0325)	(0.0161)	(0.0828)	(0.0890)
L.emp_trnsp_util	-0.0485***	-0.0160**	-0.0203	-0.0063
	(0.0167)	(0.0068)	(0.0234)	(0.0307)
L.emp_finance	-0.1149***	-0.0334*	-0.1039	-0.0846
	(0.0357)	(0.0177)	(0.0739)	(0.0754)
L.emp_service	-0.0002	0.0027*	-0.0082*	-0.003
	(0.0039)	(0.0016)	(0.0045)	(0.0046)
L.prop_emp	0.0134	0.0380***	-0.0656**	-0.0791**
	(0.0133)	(0.0065)	(0.0299)	(0.0323)
L.PctBlack	-0.0817***	0.0389***	-0.0453	
	(0.0188)	(0.0110)	(0.0614)	
L.PctWNonHisp				0.3854***
				(0.0560)
L.PctBlNonHisp				0.3743***
				(0.0819)
L.male_female	-3.9618***	0.2573	-5.3024*	-5.5550*
	(0.9047)	(0.5566)	(2.9271)	(3.0624)
L.cum_dis	0.1684***	-0.0227*	0.3026***	0.2664***
	(0.0261)	(0.0129)	(0.0409)	(0.0411)
L.pop_density	-0.0022***	-0.0009	-0.007***	-0.0047***
	(0.0005)	(0.0006)	(0.0015)	(0.0010)
_cons	10.85***	-0.5939	14.58***	-20.01***
	(1.3358)	(0.7723)	(4.8590)	(6.9424)
R^2	0.34	0.05	0.13	0.11
N	128,421	84,545	43,876	40,937

Note: Data availability varies across the periods shown. Standard errors in parentheses. Significant statistically at 1% (***), 5% (**) or 10% (*).