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Research Paper

Evidence that social-economic factors play an important role in drug overdose deaths

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ABSTRACT

Background: Drug overdose deaths in the United States increased from approximately 16,000 per year in 2001 to 41,000 per year in 2014. Although every US state witnessed an increase, the increases were much larger in some states than others. There was also variation as a function of race and ethnicity. Non-Hispanic Whites accounted for more than 80% of the deaths, and in some states their rates were about ten times greater per capita than Hispanic and Non-White rates. State and temporal differences provide an opportunity to evaluate explanations of what is driving drug overdose deaths. In this report, we evaluate the degree to which state level variation in opioid prescription rates and social-economic conditions explain state level variation in overdose death rates.
Methods and data: We used publicly available data from the Center for Disease Control (CDC), Bureau of Labor Statistics (BLS), Drug Enforcement Agency (DEA) and the *Opportunity Insights* project.
Results: Legally prescribed opioids, social capital and work force participation accounted for 53–69% of the between-state variation in overdose deaths in Non-Hispanic Whites. Prescriptions and the two social economic measures accounted for about the same amounts of unique variation, but shared variation among the three independent variables was the strongest predictor of overdose deaths. Panel regression results of the year-to-year changes in overdose deaths were similar. However, the pattern of correlations for Hispanics and Non-Whites was quite different. Neither opioid prescriptions nor social capital were significant predictors of overdose deaths in the between-state and between-year Hispanic and Non-White regression analyses.
Conclusions: Common variation in opioid prescriptions rates, social capital, and work force participation proved the strongest predictor of drug overdose deaths in Non-Hispanic Whites. We discuss reasons why the same did not hold for the Hispanic/Non-White population.

Introduction

Accounts of the current drug overdose epidemic have emphasized the roles played by increases in drug availability and declining social-economic conditions. Our goal is to evaluate these perspectives quantitatively. We ask how much of the variation in overdose deaths is correlated with variation in the amounts of legally prescribed opioids and how much can be attributed to differences in social-economic conditions. These questions have practical as well as scientific significance. Most if not all current interventions have focused on reducing drug availability and/or providing overdose antidotes, such as naloxone (e.g., “Narcan”). These efforts are likely to fall well short of their desired effects if the social-economic roots of opioid use are as important as some have claimed (e.g., Dasgupta, Beletsky, & Ciccarone, 2018; Szalawitz, 2017). We begin with a brief outline of key facts about the overdose epidemic.

In the period covered in this report, 2001 to 2014, drug poisoning deaths in the United States increased from approximately 16,000 to approximately 41,000 per year (Centers for Disease Control and Prevention (CDC), https://wonder.cdc.gov/2018). The majority involved opioids (e.g., heroin, Oxycodone, methadone, and fentanyl). In the year 2016, US drug poisoning deaths exceeded the number of American deaths over the entire course of the Vietnam War (58,220). Summarizing these data, the authors of the National Academies of Sciences, Engineering, and Medicine Consensus Report on *Pain Management and the Opioid Epidemic* (2017) wrote: “Not since the HIV/AIDS epidemic has the United States faced as devastating and lethal a health problem as the current crisis of opioid misuse and overdose. . . .” (p. 187). Although drug “epidemics” are not a new phenomenon in the US, the scale of the current one is unprecedented (e.g., see Becker, Sullivan, Tetrault, Desai, & Fiellin, 2008; Jones, Mack, & Paulozzi, 2013; Rossen, Khan, & Warner, 2013; Rudd, Aleshire, Zibbell, &

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Gladden, 2016).

According to one, widely repeated account, the problem lies largely with pharmaceutical companies who have recklessly marketed opioids. Journalists and researchers tell and retell the story of Purdue Pharma's aggressive and highly successful marketing campaign to persuade physicians to prescribe Oxycontin to their chronic pain patients (e.g., Meier, 2018; Quinones, 2017; Zhang, 2017). In support of this explanation, American physicians were prescribing three times more opioids in 2012 than in 2001 (our calculations, see *Results*). However, drug abuse is not simply a matter of access to drugs but varies markedly as a function of social conditions and individual differences (e.g., Robins, 1993; Robins & Regier, 1991; Vaillant, 1995; Warner, Kessler, Hughes, Anthony, & Nelson, 1995). Explanations of the overdose epidemic that do not go beyond increased access to opioids are, at best, incomplete.

According to those who have emphasized the demand side of the epidemic, middle class economic stagnation, demographic changes, and growing anomie have converged to create a sense of helplessness or despair that finds relief in analgesic opioid highs (e.g., Dasgupta et al., 2018). In an article published in *Scientific American*, Szalavitz (2017) described correlations between opioid overdoses, upticks in unemployment, and declines in the quality of civic life. Quinones' widely read account of opioid overdoses in a once vibrant Ohio manufacturing hub tells a similar story (2015). The common thread in these narratives is that civic and economic decline have increased the likelihood that someone prescribed opioids for pain will start using them to solve psychological problems. Many articles, particularly anecdotal accounts in the popular media, point out that Whites have been hit hardest by deteriorating social-economic conditions, and thus they are most vulnerable to iatrogenic drug abuse (e.g., Seelye, 2015; and see Cicero, Ellis, Surratt, & Kurtz, 2014, for a review of the demographic trends in treatment populations).

The two accounts are not incompatible. In the past, changes in drug availability and social factors have played important roles in changes in drug use. The world's first opioid epidemic—which took place in China—was preceded by the switch from "eating" opium to smoking opium and catalyzed by the societal disruptions that followed increased contact with the West (Heyman, 2015). Similarly, increases in drug availability and shifts in attitudes help explain the approximately twenty-fold increase in opium and heroin abuse among American enlistees stationed in Vietnam (Robins, 1993). According to these examples, it is reasonable to suppose that the current overdose epidemic is jointly determined by increases in drug availability and social-economic shocks.

As expected, research supports both etiologies. Paulozzi and his colleagues (Paulozzi, Jones, Mack, & Rudd, 2011) report that states that had higher overdose death rates typically had higher opioid sales rates. Similarly, a study of veteran-hospital pain patients (Bohnert et al., 2014) reported a correlation between prescription rates and overdose deaths. On the other hand economic research revealed correlations between unemployment rates and overdose deaths at both the state and county levels (Hollingsworth, Ruhm, & Simon, 2017).

These studies evaluated either the role of prescriptions or social-economic factors, not both together. We found but two papers that considered drug availability and social-economic factors in the same or parallel analytical approaches. Zoorob and Salemi (2017) tested the hypothesis that social capital protected communities against overdoses, using county level data. The results most relevant to this report were a negative correlation between social capital and overdose deaths, and a positive correlation between Medicare opioid prescriptions and overdose deaths. However, Medicare patients are primarily 65 and older, whereas most overdose deaths involve younger individuals, and it is possible that counties may not provide the best unit of analysis for evaluating quantitative dimensions of overdose deaths, given the high variability in overdose death rates in counties with low populations (e.g., Rossen et al., 2013).

Ruhm (2018) used county level data to test Case and Deaton's (2015) claim that the recent increase in midlife mortality among Non-Hispanic (N-H) Whites was due to long-term economic distress. As drug deaths contributed to the increase in White mortality, Ruhm's goals overlap somewhat with ours. He finds interesting temporal shifts in the demographic characteristics of the overdose deaths, and these trends lead him to reject Case and Deaton's "economic despair" account of the increase in White mortality. However, Ruhm's economic measures omitted ones that we (and Zoorob and Salemi (2017)) found to be among the strongest predictors of overdoses (e.g., social capital), included ones that we found to be weak predictors of overdoses (e.g., household income), and his method for estimating opioid prescriptions rates differed from ours and from Zoorob and Salemi's.

Studies to date then demonstrate that overdose deaths are correlated with prescription rates and also with various social-economic measures. What is not established, and what we test, is whether opioid prescriptions continue to predict overdose deaths when the analyses control for the contribution of social-economic measures that are also strongly correlated with overdoses, and, conversely, whether social-economic factors continue to predict overdose deaths when the analyses control for the contribution of opioid prescriptions to overdoses. We used multiple regression to tease apart the correlations, and the analyses were conducted at the state level. This proved a useful approach. Overdose rates vary widely across states, the differences proved relatively stable, and the regression analyses produced significant and reliable results.

At the start of this research program, we did not know which social economic measures best predicted overdose deaths. Our search was guided by two general considerations. First, previous research established that drug overdose death rates and opioid prescription rates vary as a function of county and state level variation (McDonald, Carlson, & Izrael, 2012; Rossen et al., 2013). Hence, it seemed reasonable to explore social-economic measures that varied geographically. The *Opportunity Insights* project (previously known as the *Equality of Opportunity Project*), directed by Chetty, provided a handy supply of such measures (e.g., Chetty, Hendren, Kline, Saez, & Turner, 2014 and see: https://opportunityinsights.org/). Its goals are to document and find solutions to declining intergenerational upward income mobility in America. Their research showed that the likelihood of an individual born in 1980–1982 faring better economically than his or her parents varied as a function of geography, with geography mattering more during childhood years (Chetty et al., 2014; Chetty, Hendren, & Katz, 2016). In some parts of the country, the probability of earning a higher income than previous generations was as great as in the most economically fluid European democracies (e.g., Denmark), whereas in other parts of the country, the chances for a higher income were lower than in all other Western industrial nations. Accordingly, we explored whether geographic variation in intergenerational income mobility and its correlates predicted geographic variation in overdose deaths. Second, the temporal and geographic pattern of overdose deaths suggested that employment patterns may play an important role in overdose deaths (e.g., Hollingsworth et al., 2017; Quinones, 2015; Szalavitz, 2017). Accordingly, we consulted the United States Department of Labor's Bureau of Labor Statistics yearly state-level measures of employment rates (https://www.bls.gov/lau/ex14tables.htm). This, like Chetty et al.'s *Opportunity Insight* program was a fruitful resource.

Large demographic differences in overdose death rates, described in the *Results* section, indicated that we should not calculate overdoses for the entire population of each state, but should do so separately for N-H Whites and their complement, which we refer to as Hispanics and Non-Whites. This proved useful. The overdose death correlates for the two demographic groups proved quite different, which would not have been apparent if we had not conducted separate analyses.

However, a caution is in order: the distinction between prescription and social-economic conditions may be misleading. For instance, Dasgupta et al. (2018) cite evidence that many people "somaticize social downturns into physical pain." If so then a decline in social-economic conditions will instill and/or strengthen the desire to take opioids and then, given exposure to opioids, will increase the likelihood that they will be used excessively. To test this idea we calculated the variation in overdose deaths that was (1) unique to variation in the amounts of prescribed opioids, (2) unique to variation in social-economic measures, and (3) common to the shared variation in prescription amounts and the social-economic measures. Dasgupta et al.'s essay suggests that the variance in overdoses common to prescriptions and social-economic factors should be substantial.

Our primary goals, then, are to discover which, if any, of the measures provided by the *Opportunity Insight* project and the Bureau of Labor statistics reliably predict drug overdose deaths, and given that we find reliable predictors, quantify their role in overdose deaths relative to that of legally available opioids.

Data and analytic approach

Our analyses used publicly available, de-identified data whose use was exempted from review by the Boston College Institutional Review Board. The study's domain was the 48 continental states, and the years 2001 to 2014. We excluded Alaska and Hawaii because a number of the social-economic measures we were interested in exploring were not available for these two states (e.g., social capital, see the *Opportunity Insights* website).

Data

Drug overdoses

The CDC's WONDER website (e.g., https://wonder.cdc.gov/mcd-icd10.html) provides state by state, year by year information on causes of death. Following common practice, we combined the codes for the underlying cause of death and type drug to identify drug overdose deaths. The underlying cause codes are: X40 - X44, X60 - X64, X85 and Y10 - Y14; the drug codes are T40.0 (opium), T40.1 (heroin), T40.2, T40.3 & T40.4 (opioid analgesics), T40.6 (unspecified narcotics), and T50.9 (unspecified drugs). Notice, that we included overdoses due to "unspecified drugs" as well as those due to opioids. As described in the *Results* section, including "unspecified drug overdoses" yields a more accurate picture of the overdose epidemic.

Opioid prescription sales

The United States Department of Justice Drug Enforcement Administration's ARCOS website provided the data that was used to quantify the amounts of legally available opioids (https://www.deadiversion.usdoj.gov/arcos/retail_drug_summary/). It lists the amounts of sold and dispensed Schedule 1 and II controlled substances, as measured in grams per 100,000 individuals for each state. We translated these amounts into morphine milligram equivalents according to the schedule provided by the CDC (Opioid Overdose. https://www.cdc.gov/drugoverdose/resources/data.html) for the years 2001–2014. For example, a gram of oxycodone counted as 1.5 g of morphine, whereas a gram of codeine counted as 0.15 g of morphine. We completed these computations for the ten most widely prescribed opioids: codeine, oxycodone, hydromorphone, hydrocodone, meperidine, methadone, morphine, oxymorphone, tapentadol, and fentanyl base. This list is similar albeit not identical to ones used in other accounts of geographic differences in prescription rates (e.g., McDonald et al., 2012).

Social-economic measures

Chetty et al.'s *Opportunity Insight* program and the United States Department of Labor, Bureau of Labor Statistics websites were the sources for our social-economic measures. The *Opportunity* website (https://opportunityinsights.org/) lists more than 350 correlates of intergenerational income mobility for counties and "commuting zones" (economic units that could include more than one county). The correlates include parental income, elementary school test scores, income distribution indices, commute times, crime rates, family structure (e.g., divorce), social capital, house prices, household income, tax rates, and so on. These are static measures, based on a particular year. For example, their social capital index is for 1990, whereas elementary school test scores are from the year 2001. Nevertheless, many of these measures were strongly correlated with the 2012 income of individuals who were born between 1980 and 1982. That is, they appear to be slow moving and maintain their predictive power over time. The United States Bureau of Labor Statistics (https://www.bls.gov/lau/ex14tables.htm) provides yearly measures of work force participation and unemployment for Whites and Non-Whites in each state. Work force participation is the number of individuals 16 years or older who are employed or unemployed and have looked for work in the past month relative to the total number of individuals 16 years or older eligible to work. The unemployment rate is the number of unemployed divided by the number in the work force. Work-force participation proved the better predictor of overdose deaths.

The procedure for selecting the *Opportunity Insight* measures was a multi-step process. (1) We began with Chetty et al.'s (2014) list of "representative" correlates of income mobility (see their Figure VIII), various measures of intergenerational income mobility (e.g., likelihood of moving from the lowest to the highest income quintile), and measures of household income. (2) We transformed these measures into state-level measures according to an algorithm that multiplied each measure by the county's share of the state population and then summed the products. (3) The state measures were then sorted into 8 categories: intergenerational economic mobility, income inequality, family social factors, community social factors, community economic factors, early education, and college education. These closely correspond to Chetty et al.'s classification scheme of the same variables. (4) Lastly, we selected the two to four members of each of the 8 social-economic categories that were most highly correlated with overdose deaths. This yielded a list of 24 *Opportunity Insight* measures that were then subjected to further analysis (e.g., see Table A1 in the *Appendix*).

Of all the *Opportunity Insight* measures, social capital proved most important. This is a widely discussed, variously defined concept that describe the values and expectations that encourage individuals to cooperate with one another in activities that promote group ends. For instance, Putnam (1995) defines social capital as "features of social life—networks, norms, and trust—that allow participants to work together more effectively to pursue shared objectives." However, there is no one widely agreed upon definition of social capital, and, most importantly, there is no one widely agreed upon measure of social capital. The version that Chetty et al. (2014) relied on is based on a scale developed by Rupasingha, Goetz, and Freshwater (2006). Their approach has four components: associational densities (for example, membership rates in political organizations and professional organizations), the response rate for the Census Bureau's population and housing survey, percentage of voters who voted in presidential elections, and per-capita non-profit organizations (Penn State College of Agricultural Sciences & Department of Agricultural Economics, Sociology, & Education, 2019: http://aese.psu.edu/nercrd/community/social-capital-resources). The virtue of this approach for our purposes is that it does not include "outcomes," such as drug use or other measures of dysfunction, yet is consistent with Putnam's (1995) widely influential account that social capital involves the "networks, norms, and trust" that abet community goals.

Analytic approach

The goal of the analyses was to evaluate the degree to which state and temporal differences in overdose death rates varied as a function of (1) differences in the availability of legal opioids and (2) differences in social-economic measures. We used commonality regression to evaluate state differences. These were conducted for each year of the period 2001 to 2014. This approach makes explicit the amount of variance in the dependent measure that is correlated uniquely with each predictor and each possible combination of predictors. This is a particularly useful method when the predictors are strongly correlated with each other. Throughout, the primary dependent variable was the number of overdose deaths per 100,000. The predictors were standardized, and the regressions included robust standard errors. The analyses were conducted in Stata (Version 15, 2017) or SPSS (Version 24, 2016). We used panel regression methods to evaluate the correlates of changes in overdose deaths over time from 2001 to 2014.

For both the between-state (commonality) and between-year (panel) analyses, the predictors were the amounts of legally prescribed opioids (per person) and the one or two social economic measures that were most strongly correlated with overdoses. Notice that these regressions include the entire population of states and years; inferential statistics are included but are not paramount because there is no implied generalization beyond the data included in the analyses. Proportions of variance accounted for (referred to as VAF) provide the most *r*elevant results.

Results

The Results are divided into three major sections: (1) Background essentials, in particular differences in the degree to which states identified the drug or drugs that caused an overdose death, (2) nation-wide trends in overdose deaths, focusing on racial/ethnic differences, and (3) statistical analyses of the between-state differences and the between-year differences in overdoses. The *Methods* section lists the data sources; all are publically available.

Background essentials

State differences in specifying opioids as a cause of death

Before describing the relationships between opioid prescription rates, social economic measures and overdose rates for different states, it is critical to understand that states differed in the degree to which they identified the specific drug that caused the overdose death (CDC Wonder Website, https://wonder.cdc.gov). In Massachusetts, only 10% of drug overdose death certificates did not identify the drug or drugs that were involved, whereas in Mississippi, coroners and medical examiners failed to specify the drugs linked to the overdose death in about 70% of cases. In addition for some states there were changes over time. In these states, the percentage of unspecified drug deaths decreased over the years 2001–2014. Figure *A1* in the *Appendix* summarizes these results. The upper panel shows the average percentage of specified overdose deaths for the 48 continental states for the years 2001–2014; the lower panel shows the averages for the three states with the highest specification rates, the three states with the lowest specification rates, and three states in which specifications markedly increased over the years 2001–2014. The significance of these results is that the CDC records are ambiguous; they may reflect differences in the type of drug associated with the overdose death or differences in how overdoses were recorded (see Hanzlick, 2006; Warner, Paulozzi, Nolte, Davis, & Nelson, 2013; Webster & Dasgupta, 2011 for further discussion of these issues). We dealt with this by treating opioid and unspecified deaths as a single category. Medical examiners and coroners are able to identify overdoses although they may not be able to specify the particular toxin. Other researchers have taken this same approach (e.g., Paulozzi et al., 2011, and see Ruhm, 2017).

Although the death certificates are often incomplete, there is evidence that the “unspecified” drugs were usually opioids. The correlation between opioid overdoses and opioid plus unspecified overdoses was 0.87 (pooling across years and states), and the correlation between opioid sales and deaths was higher for opioids plus unspecified deaths (0.69) than for opioid deaths alone (0.63). The simplest explanation for

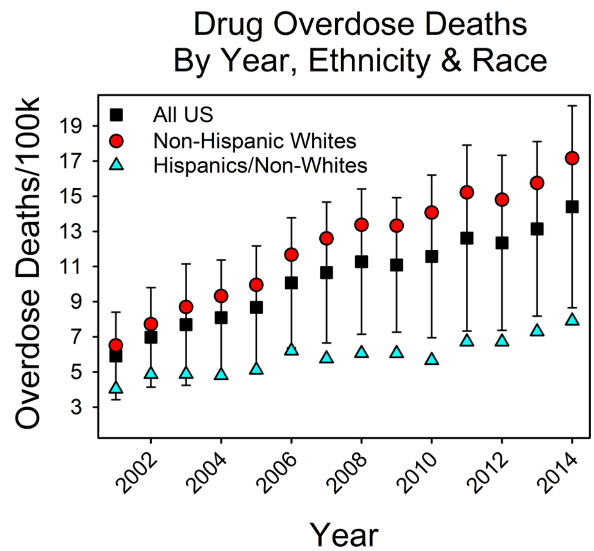

Fig. 1. State average overdose deaths in the US by year and race/ethnicity. On the x-axis is year; on the y-axis are average overdose rates (across states). The error bars index one standard deviation as calculated across the 48 continental states.

this pattern of results is that most unspecified overdose deaths involved opioids. Using different methods, Ruhm (2017) came to the same conclusion. This is a useful result: opioid plus unspecified overdoses taken together are less subject to differences in how local coroners and medical examiners fill out death certificates. Thus, we used the aggregate measure, opioid plus unspecified overdoses as our dependent measure in this report; we refer to it throughout as “drug overdose deaths.”

Nation-wide trends in drug overdose deaths

Racial/ethnic differences increased

Fig. 1 shows overdoses as a function of race, ethnicity and year, averaged across the 48 contiguous states. On the x-axis is year, on the y-axis is overdose deaths for the entire population, for N-H Whites and for their complement, Hispanics and Non-Whites. The error bars indicate plus and minus one standard deviation for the US population.

Each year overdose rates for N-H Whites were greater than for Hispanics and Non-Whites, and these differences increased over the years. From 2001 to 2007, the N-H White overdose rate was about 60 to 95% greater than the Hispanic/Non-White rate; from 2007 to 2014 these differences increased to about 120 to 150%. In contrast, in 1999, the N-H White overdose rate was less than 20% greater than the Non-White rate (data not shown, see *CDC Wonder Online Data Base*, http://wonder.cdc.gov/mcd-icd10.html). Overall N-H Whites accounted for 83% of the overdose deaths between 2001 and 2014 (calculations based on pooled CDC data).

However, if states differ in how they report overdose deaths, it is possible that the racial/ethnic differences reflect differences in reporting deaths rather than differences in the populations. This was not the case. For the years 2001 to 2014 the percentage of specified overdose deaths was about the same for the two populations, with both increasing from about 58% to 71%. In support of these trends, a within-subjects ANOVA revealed a significant year effect ($F(13, 611) = 5.29$, $p < 0.001$), but no suggestion of either a main effect for race/ethnicity or an interaction of year and race/ethnicity, $F < 1.0$ for both effects.

Given that total overdoses and overdose rates for N-H Whites were considerably higher than for Hispanics and Non-Whites, and that these differences were not stable but were increasing, we ran separate analyses for the two groups. We did not divide Hispanic and Non-Whites further because there would have been so many states that had missing data for one group or the other. For instance, the CDC suppressed overdose data for Hispanics in 29 states for most years of this study. Our analyses proceed first for N-H Whites and then for Hispanics and Non-Whites.

Between-state variability and within-state (temporal) variability

For both demographics, between-state variance was greater than between-year variance. For N-H Whites, the between-state variance was 17.99 deaths, whereas the between-year variance was 9.83 deaths. (The measures are per 100,000 individuals.) For the Hispanic and Non-White population, the between-state variance was 10.89 deaths, and the between-year variance was 1.05 deaths. The top and bottom panels of Figure A2 in the *Appendix* show these relations. In addition, they show the overdose death rates for the three states with the highest and lowest overdose rates for Whites and for Non-Whites.

Regression analyses of between-state and between-year variation in overdose deaths

We conducted three regression analyses for each population. First we analyzed the predictors of between-state variation in overdose deaths. These calculations included the correlations between overdoses, the *Opportunity Insight* measures, and employment rates. Then, on the basis of these results, we ran commonality regression with prescriptions and the two strongest social economic correlates as the predictors. Second, we conducted panel regression across all years, using the same predictors. Third, we ran a regression analysis on the entire data set, pooling the overdose deaths for each state in each year. These analyses were conducted first for N-H Whites, and then second for Hispanics and Non-Whites.

White overdose deaths

Zero-order correlations between overdoses, prescriptions, and social economic measures

Table 1 presents bivariate correlations for overdose deaths, legally available opioids, employment, and the eight most highly correlated variables from the *Opportunity Insight* program. Table A1 in the *Appendix* provides additional detail on the 24 *Opportunity Insight* variables. The top three correlates (opioid prescriptions, social capital, and participation in the labor force) had median *r* values of 0.69, - 0.66, and - 0.60, respectively. Other *Opportunity Insight* predictors with moderate to high correlations with overdose deaths were elementary school test scores (r = - 0.55), divorce rates (r = 0.47), and absolute income mobility (r = - 0.44).

Correlations among the predictors

Many of the predictors were as strongly correlated with each other as they were with overdose deaths. For example, the correlation between opioid prescriptions and social capital varied from -0.54 to -0.70. Similarly, the correlations between work force participation and social capital were high with a median value of 0.69. According to “rules of thumb” for multicollinearity, correlations this high are “matters of concern” (e.g., O'Brien, 2007). We dealt with this by including the conventional multicollinearity diagnostics and, most importantly, by using commonality regression analysis to identify the amount of variance in overdoses that was correlated with the shared variance of the regression predictors (see Ray-Mukjerjee et al., 2014 for an overview of commonality regression)

Between-state multiple regression analyses

Figure 2 and Table 2 summarize the regression results. The dependent variable was overdose deaths in each of the 48 continental states; the predictors were amount of legally prescribed opiates per person, social capital, and work force participation percentages. The analyses were carried out for each year of the study (2001–2014).

Table 1
Top 10 correlates of overdoes deaths for N-H Whites. The entries display the median, minimum and maximum correlation coefficients for the years 2001–2014.

Variable	Correlations
Rx (2012)	0.69 (0.62 / 0.72)
Social Capital (1990)	- 0.66 (-0.48/ -0.71)
% in Labor Force (2010)	−0.60 (-0.45/-0.77)
Elem School Test[a]	- 0.55 (-0.45/-0.64)
% Short Commute[b]	- 0.48 (-0.38/-0.53)
Teen Birth Rate	0.47 (0.26/0.64)
% Divorced	0.47 (0.24/0.59)
Gini Coefficient[c]	0.46 (0.39/0.56)
Bottom 5th to top 5th Income Mobility[d]	- 0.44 (-0.31/-0.54)
Prob Earn > Parents	−0.43 (-0.32/-0.49)

a. Elementary school English and math national test scores, George Bush Global Report Card (“No Child Left Behind). This and other measures in this table are from Chetty et al., 2014.
b. Number of workers who commute less than 15 min divided by total number of workers. The 2000 US census provided travel time.
c. The Gini coefficient is an index of the shape of the income distribution. It typically varies from 0 to 1.0, with higher numbers indexing increasingly unequal distributions. Chetty et al. (2014) calculated it on basis of tax records.
d. Probability child had family income in top 5th of income distribution, conditional on parental income in bottom 5th of income distribution, 1980–1985 cohort.

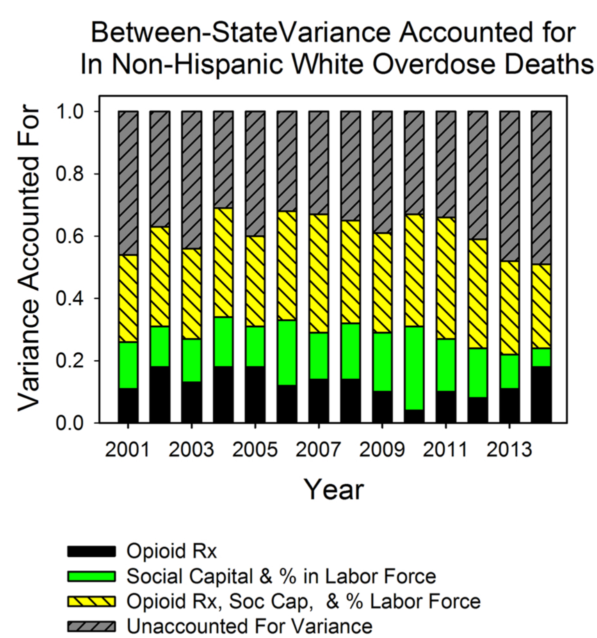

Fig. 2. Multiple regression results for N-H White overdose deaths. The segments are proportional to the variance accounted for scores for the predictors (see Table 2). The strongest predictor of overdoses was the common variance in prescriptions and the two social-economic indices (yellow segment). In 2010 and 2011, work force participation was a stronger predictor than was social capital; for all other years, social capital was a stronger predictor than work force participation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Table 2
Between-state multiple regression results. The entries on the left side of the table list the variance accounted for percentages according to the commonality regression analyses. The entries on the right side of the table list the beta weights for the predictors.

		Variance accounted for (VAF) in overdoses due to opioid prescriptions (column 3), due to the two social-economic measures (column 4), and due to the shared variance in opioid prescription and social-economic factors (column 5).			Betas: Opioid Rxs, Social Capital, % in the Work Force		
Year	VAF	Opioid Rx	Social Capital & % in the Work Force	Rx & SC & % in Work Force	Opioid Rx	Social Capital	% in Work Force
2001	0.53	0.11	0.15	0.28	0.39**	−0.39**	−0.09
2002	0.63	0.18	0.13	0.32	0.49***	−0.37**	−0.07
2003	0.56	0.13	0.14	0.29	0.42***	−0.30*	−0.18
2004	0.69	0.18	0.16	0.35	0.49***	−0.26*	−0.26*
2005	0.62	0.18	0.15	0.29	0.49***	−0.45***	0.03
2006	0.68	0.12	0.21	0.35	0.40***	−0.39***	−0.21
2007	0.67	0.14	0.15	0.38	0.45***	−0.36**	−0.16
2008	0.65	0.14	0.18	0.33	0.44***	−0.33**	−0.22
2009	0.62	0.10	0.19	0.32	0.39***	−0.46***	−0.07
2010	0.67	0.04	0.27	0.36	0.25**	−0.23*	−0.47**
2011	0.66	0.10	0.17	0.39	0.39**	−0.14	−0.41*
2012	0.60	0.08	0.16	0.35	0.36**	−0.22	−0.33
2013	0.52	0.11	0.11	0.30	0.42**	−0.21	−0.23
2014	0.52	0.18	0.06	0.27	0.53***	−0.16	−0.15
Avg (SD)	0.62 (0.06)	0.13 (0.04)	0.16 (0.05)	0.33 (0.04)	0.42 (0.07)	−0.31 (0.10)	−0.20 (0.14)

* < 0.05, ** < 0.01, *** < 0.001.

The three predictors accounted for an average of 62% of the between-state variation in overdose deaths, with a range of 52–69%. The subsections of each bar in Fig. 2 show the amount of variance in overdose deaths that was due uniquely to opioids (black), due uniquely to the two social-economic factors (green), and due uniquely to the common variance of the three predictors (yellow). For every year, the shared variation in opioids, social capital, and work force participation accounted for the most variance in overdoses. The average percentages of explained variance were 13% for legally available opioids, 16% for social capital and work force participation, and 33% for opioid/social-economic shared variation. Columns 6–8 of Table 2 also list the beta weights for each predictor and their significance levels.

Interactions & diagnostic tests

In preliminary analyses, we used product variables to examine whether the three predictor variables interacted. For example, did social capital have more influence in states with higher opioid prescription rates? For only two years did the regressions reveal significant interaction effects, and these were minimal. In 2009 the additional interaction term increased the total amount of explained variance by 0.01 (0.63 to 0.64), and in 2010 the interaction term increased the explained variance by 0.02 (0.67 to 0.69). Due to the minimal contribution to variance accounted for, we do not discuss interaction effects further.

We used Stata's linktest to evaluate whether the 3-predictor, between-state regressions were properly specified. According to the linktest, the model was not poorly specified in any of the 14 years. Diagnostic tests indicated that collinearity was not severe enough to compromise the regression results. The average variance inflation index was 1.74, and the largest was 2.06. In 12 of 14 years, the residuals met the homoscedasticity assumption (Breusch-Pagan/Cook-Weisberg test, Stata Version 15). The two exceptions were 2011 and 2012 (F (1, 46) = 11.19, p = 0.002; F (1, 46) = 6.02, p = 0.01, respectively).

Is there a stronger account? Although the regression analyses were based on the three predictors that had the strongest correlations with overdose deaths, it is possible that some other combination of predictors would have accounted for more variance in overdose deaths. To test this, we used the Stata (Version 15) *tryem* command to identify the three predictors listed in Table 1 that together accounted for the most variance in N-H White overdose deaths. The results were similar to those just described. The average amount of variance accounted for increased only 1%, from 62 to 63% (data not shown), and Stata's *tryem* command three best typically included prescriptions and either social capital, work force participation, or both. Thus, the three measures that were most highly correlated with overdose deaths (opioid prescriptions, social capital and work force participation) provided a robust account of state differences in overdose deaths for each year of the period 2001 through 2014.

Longitudinal (panel) analyses of overdose deaths

We used random and fixed effects panel regressions to evaluate the correlates of year-to-year changes in N-H White overdose deaths. In both analyses, we included year (e.g., 2001–2014) in order to control for time varying variables that were correlated with the predictors and overdose deaths but not measured. Social capital was included in the random effects model but not the fixed effects analysis because it was not time varying. As was the case for the between-state analyses, the time-varying predictors in the panel analyses were highly correlated with each other. The between-year correlation between work force participation and prescriptions was -0.77. There was also an imbalance in the range of variation for the time varying predictors. The year-to-year variation for prescriptions was about ten-fold greater than the year-to-year variation in work force participation, as measured by the coefficients of variation (e.g., 0.352 and 0.036, respectively).

Table 3 summarizes the coefficients and fits for the fixed and random effects accounts of longitudinal changes in overdose deaths. The predictors accounted for about 72% of the between-year variance in overdoses. Thus, the longitudinal regressions were as strong as the strongest between-state regressions. According to a robust Hausman bootstrap test (400 repetitions), the coefficients for the fixed and random effects models were not significantly different (chi sq. (3) = 1.77, p = 0.622). Also, the coefficient for work force participation was not significant in either the fixed effects model (p = 0.327) or the random effects model (p = 0.083).

Table 3
Panel regression results for Non-Hispanic White overdose deaths.2001–2014.

	Fixed Effects Betas	*Random Effects Betas*
Legally Available Opioids	2.128***	2.229***
Work Force Participation	−0.331	−0.510
Year	0.400***	0.368***
Social Capital	——	−1.924***
	Fits	Fits
R^2 Within	0.716	0.715
R^2 Between	0.594	0.681
R^2 Overall	0.577	0.695
Model	F(3, 47) = 114.68***	Wald Chi Square (4) = 469.78***

*** p < 0.001.

All states, all years summary

As a way of summarizing the between-state and between-year regressions, we ran a commonality regression analysis on the entire data set, pooling the results from each state for each year. The predictors were the same as in the between-state and between-year analyses: opioid prescriptions rates, social capital, work force participation rates, and year. They accounted for 70% of the variance in the 672 overdose death rates (14 × 48). Figure A3 and Table A2 of the *Appendix* summarize the results.

Thus, the three different regression analyses yielded similar results. Legally available opioids, social capital and work force participation explained between 50 and 72% of state-level variation in overdose deaths in N-H Whites. However, these labels are somewhat misleading; opioid prescriptions, social capital, and work force participation were highly correlated with each other, and their shared variance was consistently the strongest predictor of overdose deaths.

Hispanic/non-white overdose deaths: general considerations

The analyses for Hispanics and Non-Whites followed the same steps as the analyses for N-H Whites: zero order correlations, between-state multiple regressions, panel regressions, and the pooled state and year regression. However, the predictors were not the same. The search for the strongest *Opportunity Insight* correlates of overdoses yielded a different list, and we used the Bureau of Labor Statistics Non-White employment data. In addition, commonality regression proved uninformative. Prescription rates were weakly correlated with overdoses (see Table 4), and there was little shared variance between prescriptions and social economic factors in the Hispanic/Not White population (see Table A4 in the *Appendix*).

Table 4
Hispanic/Non-White overdose death top correlates. The italics indicate that the sign of the correlation was the opposite of that found in Non-Hispanic Whites. The right-hand column lists the median, minimum and maximum correlations for the years 2001 to 2014. The entries in the first 10 rows are from the *Opportunity Insight* program.

Variable	Correlation with Overdoses
% Black	*-0.38 (-0.53/-0.17)*
% in Manufacturing Jobs	−0.37 (-0.49/-0.19)
Relative Income Mobility[a]	*−0.29 (-0.37/-0.09)*
% Teens in Labor Force	*0.28 (0.19/0.32)*
Absolute Income Mobility[b]	*0.24 (0.14/0.34)*
Bottom 5th to Top 5th Income Mobility	*0.24 (0.11/0.33)*
% in Middle Class	*0.21 (-0.16/0.35)*
Gini99[c]	*−0.21 (-0.30/-0.04)*
% Parents in 2nd lowest income decile	*−0.19 (-0.29/-0.12)*
Teen Age Birth Rate	*−0.18 (-0.34/-0.08)*
Work Force Participation	−0.12 (-0.28/0.18)
Opioid Rx Sales	0.07 (-0.04/0.22)
% Unemployed	*−0.03 (-0.26/0.23)*

a. *Relative intergenerational income mobility*: the correlation between parents rank in the national distribution of incomes in 1996 and their children's rank in 2012.
b. *Absolute intergenerational income mobility*: the expected income rank at approximately age 30 of a child born in 1980–1982 whose parents were in the 25th income rank in 1996.
c. *Gini99*. Gini coefficient minus the top 1% share.

Zero-order correlations (Hispanic/Non-Whites)

Table A3 in the *Appendix* lists the correlations between overdose deaths, prescription rates, the two employment measures, and the 24 *Opportunity Insight* measures for the years 2001–2014 in Hispanics and Non-Whites. Table 4 provides an abbreviated summary of these results. It lists the median, minimum and maximum correlations between Hispanic/Non-White overdose deaths and the (1) ten strongest *Opportunity Insight* predictors (2) amounts of legally available opioids per person, (3) work force participation percentages, and (4) unemployment rates. Overall, the correlations were smaller than those for N-H Whites. No correlation was greater than 0.38, whereas in the analogous analysis for Whites, no correlation was less than 0.43. The correlation between overdose deaths and amounts of prescribed opioids was 0.07, whereas the same relationship in Whites had a correlation coefficient of 0.69.

The direction of the correlations also differed. This is indexed by the italicized predictor labels. With the exception of the amount of prescribed opioids and unemployment, all of the correlations were the opposite of those for N-H Whites. In states that had better economic conditions, more economic mobility, more equality, and more cohesive communities, as measured by social capital, overdose death rates were higher among Hispanics and Non-Whites.

Between-state analyses (Hispanics/Non-Whites)

We conducted two sets of between-state multiple regression analyses. One with prescriptions and the two strongest zero-order correlates of overdose deaths and one with the three predictors that explained the most variance in overdose deaths. Table 5 lists the results.

The average amount of explained variance in the regressions that included prescriptions was 23.3%; the average amount of explained variance for the three "best" predictors was 35.4%. The three best predictors typically included the *Opportunity Insight* estimates of the percentage of Blacks, percentage of manufacturing jobs, and the Bureau of Labor Statistics' percentages of Non-Whites in the work force. The coefficients for all three were negative, meaning that more manufacturing jobs, higher percentages of Blacks in the population, and higher numbers of Hispanics and Non-Whites in the work force were correlated with lower overdose death rates. Notice that opioid prescription rate was never one of the strongest predictors of overdose deaths in the Hispanic/Non-White population. We also ran regressions with the same three predictors used in the analysis of N-H White overdoses (not shown). The average amount of variance accounted for was 17%.

Longitudinal analyses

Table 6 summarizes the panel regressions for overdose deaths in Hispanics and Non-Whites. The fixed effects model did not yield a significant time-varying predictor of yearly changes in overdose deaths other than year. When year was not included in the analysis, the model was not significant (F (2, 47) = 0.73, p = 0.488), and the amount of explained year-to-year variance was practically zero (0.004). In other words, neither of the two time-varying predictors were significant (opioid prescription and work force participation rates). In the random effects model, the percentages of Blacks in each state was a significant predictor. But this was a time-invariant variable that reflects between-state differences not between-year differences.

As in the N-H White analyses we ran a regression on the pooled data from each state for each year as a way of summarizing the between-state and between-year analyses. (See Figure A4 and Table A4 in the *Appendix*.) The variance accounted for percentages were 1% for prescriptions, 6% for years, and 19% for the two social economic measures (work force participation and percent Black residents). In contrast to the results for Whites, the common variance among prescriptions and the two social economic predictors or among years and the other

Table 5
Regression results for Hispanic/Non-White overdoses. Columns 3, 4, 5 list the beta weights for the three variables with the highest zero-order correlations for Non-White & Hispanic overdoses. Columns 7, 8, 9 list the beta weights for the three predictors that accounted for the most variance in overdoses.

	Betas for Rx, % Black, % Manufacturing Jobs					Betas for strongest 3 predictors, see text.		
Year	VAF	Prescribed Opioid Amt/Person	% Black	% manufacturing Jobs	VAF	Largest Beta	Middle Beta	Smallest Beta
2001	0.086	−0.021	−0.103	−0.249	0.252***	% of Parents in 2nd Lowest Income Quintile: −0.439**	% in Middle Class: -0.395*	% Manufacturing Jobs: −0.281
2002	0.234*	0.034	−0.231	−0.370*	0.320***	*Teen Birth Rate: -0.553****	% Manufacturing Jobs: -0.537*	Probability Jump From 5th to 1st Income Quintile: -0.389*
2003	0.281**	0.034	−0.215	−0.424*	0.331**	% Manufacturing Jobs: -0.474**	% Teens in Labor Force: 0.293*	% in Labor Force 03: -0.222
2004	0.225**	0.036	−0.329**	−0.259	0.320**	% Black: -0.376*	% in Labor Force 04: -0.316	% Manufacturing Jobs: −0.284
2005	0.199*	0.017	−0.233*	−0.320	0.246***	% Manufacturing Jobs: -0.397*	% of Parents in 2nd Lowest Income Quintile: -0.312*	% in Labor Force 05: -0.295*
2006	0.214**	0.085	−0.324**	−0.232	0.322**	% Teens in Labor Force: 0.526***	Unemployment Rate: -0.461	% in Labor Force 06: -0.440*
2007	0.255**	−0.084	−0.263**	−0.366*	0.366***	% Manufacturing Jobs: -0.542**	Gini Bottom 99%: -0.396***	% in Labor Force 07: -0.362**
2008	0.247***	−0.015	−0.342***	−0.282	0.422**	*% Black: -0.537****	Labor Force Participation 08: -0.528**	Unemployment 08: -0.385*
2009	0.172*	0.044	−0.304**	−0.205	0.340*	Labor Force Participation 09: -0.560*	% Black: -0.433**	Unemployment 09: -0.356
2010	0.297***	0.034	−0.376***	−0.306	0.490***	% Black: -0.491***	Labor Force Participation 10: -0.458**	% Manufacturing Jobs: -0.337*
2011	0.331***	0.118	−0.489***	−0.197	0.524***	% Black: -0.620***	Labor Force Participation 11: -0.477***	% Manufacturing Jobs: -0.192
2012	0.269***	0.110	−0.357***	−0.293	0.325**	% Black: -0.453***	% Manufacturing Jobs: -0.303*	Labor Force Participation 12: -0.283
2013	0.260**	0.306*	−0.430***	−0.102	0.358***	% Black: -0.870***	Relative Mobility: 0.799**	% Manufacturing Jobs: -0.430*
2014	0.193**	0.220*	−0.338**	−0.159	0.338***	Labor Force Participation 14: -0.680 **	% of Parents in 2nd Lowest Income Quintile: −0.644***	% Manufacturing Jobs: -0.310
Avg (SD)	0.233 (0.060)	0.083 (0.085)	−0.310 (0.097)	−0.269 (0.088)	0.354 (0.078)	0.537**** (0.126)	0.454**** (0.142)	0.326**** (0.073)

* $p < 0.05$, ** $p < 0.01$, *** $p <= 0.001$ **** average of absolute values.

Table 6
Panel regression results for Hispanic & Non-White overdose deaths, 2001- 2014.

	Fixed Effects Betas	*Random Effects Betas*
Legally Available Opioids	0.307	0.325
Work Force Participation	−0.169	−0.261
Year	0.241***	0.241***
% Black		−1.531***
R^2 Within	0.203	0.202
R^2 Between	0.021	0.240
R^2 Overall	0.074	0.228
Model	F(3, 47) = 16.95***	Wald Chi Square (4) = 49.37***

*** $p < 0.001$.

predictors did not explain any of the variance in overdose deaths. Approximately 74% of the variance remained unexplained.

Discussion

Summary of the findings

Overdose death rates varied markedly between states. In Nebraska, North Dakota and South Dakota the overdose rates averaged less than 4 deaths per 100,000 a year, whereas in Nevada, New Mexico, and West Virginia, they averaged more than 21 deaths per 100,000 a year. Year-to-year differences were sizeable as well, although not as large as the between-state differences. There were also large differences as a function of race and ethnicity. N-H Whites accounted for 83% of the overdose deaths, and on average White overdose death rates were about 2.7 times higher than those for Hispanics and Non-Whites.

Prescriptions, social capital and work force participation typically accounted for more than 60% of the between-state variance in overdose deaths in N-H Whites, and the shared (overlapping) variation among these three predictors accounted for the most variance in each of the fourteen years of the study. The unique variance accounted for percentages averaged 13% for opioid prescriptions and 16% for social capital and work force participation. However, prescriptions, social capital and work force participation typically accounted for no more than 17% of the between-state variance in overdose deaths for Hispanics and Non-Whites. Moreover, neither opioid prescription rates nor social capital was ever one of the top three predictors of overdose deaths in Hispanics and Non-Whites.

The panel analyses for the year-to-year changes told a similar story. For N-H Whites, the fixed- and random-effects models accounted for 72% of the year-to-year variance in overdoses, and in the random effects model both opioid prescriptions and social capital were significant predictors. However, work-force participation was not ($p = 0.083$). The panel results for Hispanics and Non-Whites were quite different. The predictors accounted for much less variance (20%), and neither of the two time varying predictors (opioid prescriptions and work force participation) was statistically significant.

There were interesting correlations between overdose death rates and intergenerational income mobility and its correlates in N-H Whites. The strongest predictors of economic immobility were also the strongest predictors of drug overdoses. In a summary table, Chetty et al. (2014) listed 28 representative correlates of absolute income mobility (Table VIII, p. 1604). Twelve had correlation coefficients greater than 0.40. Of these twelve, five were among the ten strongest correlates of overdoses in N-H Whites: social capital (r = -0.66), elementary school test scores (r = -0.55), the Gini coefficient (r = 0.44), divorce rates (r = 0.47), and short commute times (r = - 0.49). However, with the exception of social capital (Quinones, 2015; Szalavitz, 2017; Zoorob & Salemi, 2017), researchers and the media interested in drug overdoses have paid little or no attention to these particular measures. For instance, to our knowledge no one has reported on the relationships between divorce rates and opioid prescriptions although the two are highly correlated with each other.

Similarly, the relative strength of the correlations has received little attention. Divorce was a stronger correlate of overdose deaths than was parents' income, elementary school test scores were a stronger correlate than were college graduation rates, and upward income mobility and income inequality measures were stronger correlates of overdoses than were absolute income measures and poverty rates. These contrasts are consistent with the idea that overdose deaths reflect declining prospects and relative social-economic standing rather than absolute deprivation. They are also consistent with Chetty et al.'s (2014) point that the pathway to adult well-being begins early in life.

Two findings have methodological as well as substantive significance. First, in some states, medical examiners and coroners were highly likely to identify the specific drug or drugs involved in the overdose death, whereas in other states, the drugs involved in overdoses were usually not identified. Researchers who don't resolve this difference can't but help confuse the behavior of medical examiners and coroners with the behavior of drug users. Second, overdose death rates and their correlates differed markedly as a function of race and ethnicity. Consequently, research on overdose deaths in states that have sizeable numbers of both demographics will underestimate the true relations if they fail to conduct separate analyses for each demographic.

The puzzle of racial ethnic differences in the rates and correlates of drug overdose deaths

Greater income inequality, less intergenerational income mobility, and lower levels of wealth predicted more overdose deaths in N-H Whites, but fewer in Hispanics and Non-Whites. The differences reflect methodological problems or etiological differences or both. By definition, the degree to which state level measures apply to any particular demographic group reflects the degree to which the group shares characteristics with the general population. This, in turn, depends on such factors as residential patterns, employment patterns, shared cultural values and the like. Observation suggests that in most if not all states, it is reasonable to assume that N-H Whites are more evenly distributed across geographic, economic, and cultural boundaries. Hence, state level measures should apply best to them, and may apply poorly or not at all to groups who are not so evenly distributed. These problems will be exacerbated in states that have few minority residents. In other words, it is highly likely that the demographic differences in the correlates of overdoses recorded in this report reflect the fact that N-H Whites were better represented by state level measures.

Of course methodological issues do not rule out the possibility of demographic-based differences in etiology. For instance, a study based on not publically available IMS Health data of national prescription sales for the year 2015 reported that N-H Whites were significantly more likely to be prescribed an opioid than were Hispanics and Non-Hispanic Blacks (Guy et al., 2017). This is an important finding: it goes some way in explaining why N-H Whites had higher overdose death rates, and it is consistent with the literature in showing a positive correlations between opioid prescribing rates and overdose death rates. But it seems unlikely that differences in opioid prescription rates are the only non-methodological reason for the White and Non-White differences. For example, the correlations between overdose deaths and work force participation was five times greater in N-H Whites, a difference that is not obviously related to prescriptions and not obviously methodological. In the US, the etiology of overdose deaths may differ as a function of race and ethnicity.

Limitations

Individual differences

There is an immense literature on the individual differences that affect drug abuse (e.g., Edlund, Steffick, Hudson, Harris, & Sullivan, 2007; Heyman, 2013; Kirby, Petry, & Bickel, 1999; Robins, 1993). However, the analyses presented in this paper did not include individual differences. It is possible, of course, that individual variation averages out in state level analyses. On the other hand, there may be correlations between individual differences and geography that remain hidden in the Bureau of Labor Statistics and *Opportunity Insight* measures used in the analyses presented here. For instance, recent reports show state-level differences in IQ (McDaniel, 2006) and in two of the Big-Five personality traits (neuroticism and openness, Rentfrow, 2010).

Illegal drugs

It is beyond the scope of this report to try to estimate state differences in access to illegal drugs, but we can say something about national heroin overdose death rates that has some relevance. According to the CDC (https://wonder.cdc.gov/mcd-icd10.html, 2018), heroin related overdose deaths increased from 0.64 to 3.40 per 100,000 over the years 2001 to 2014, with most of the increases coming in the years 2010 to 2014. Put in terms of percentages of overdose deaths, those that included heroin increased from about 6% in 2001 to 27% in 2014. However, it is unclear how information about heroin availability would alter the analyses presented in this paper. The worst fits for the regression models for N-H Whites were in 2001, 2013, and 2014, which are the years in which there were the least and the most number of heroin deaths. In parallel with these results, Table 2 reveals no discernible trend in how well the regression models fit for the years 2002 to 2012, yet over this period heroin deaths were increasing. For Hispanics and Non-Whites, 2013 and 2014 are the only two years that legally prescribed opioids were significant predictors of overdose deaths, yet these are the two years with the highest levels of heroin deaths. Thus, the relationship between legally prescribed opioids, illegal opioids, and overdose deaths is likely to prove complex.

Since 2014

At the national level, the availability of legally prescribed opioids leveled off in 2009, yet the number of drug overdose deaths (opioid plus unspecified) has continued to climb. For instance, overdose drug deaths almost doubled between the years 2009 and 2017, yet in this same period access to legally prescribed opioids was not increasing. The above mentioned complexities notwithstanding, there is evidence that increases in the availability of illegal heroin and fentanyl played a significant role in post 2009 overdose death increases. Hospital records indicate a nation-wide increase in heroin use for the years 2001 to 2014, with the highest rates of increase taking place between 2010 to 2014 (Unick & Ciccarone, 2017), and DEA records show that seizures of illegal fentanyl increased 1400% from 2013 to 2015 (Ciccarone, 2017). Paralleling the evidence for increases in supply are documented increases in heroin and fentanyl related overdose deaths over this same period (https://wonder.cdc.gov/mcd-icd10.html, 2018). Thus, the supply of heroin and fentanyl increased and heroin and fentanyl related deaths increased.

However, what remains largely unexplored is the degree to which social-economic factors, such as those described in this report, can account for the increases in heroin and fentanyl supplies and heroin and fentanyl overdose deaths. On the one hand, the correlations between overdose deaths and social capital were lowest in 2013 and 2014; on the other hand, the correlations remained "high" by customary standards (e.g., Cohen, 1988): r = -0.59 and -0.54), and according to a recent expert panel, social capital in the US continues to decline, particularly among those not in the upper income echelons, (Joint Economic Committee United States Congress, 2017). Thus, it is possible that the story for overdose deaths, including those that involve heroin and fentanyl, after 2014 may not differ greatly from the analysis presented here for 2001 to 2014.

Conclusions

We conclude with two related points. First, the opioid epidemic has been discussed as a drug problem and a social-economic problem with the emphasis on drug supplies, particularly in the context of interventions. However, the data presented in this report indicate that social-economic factors play a critical role in the drug overdose epidemic and that variation in the supply of legal opioids is highly correlated with variation in social capital and work force participation. Second, the large state differences in overdose rates argue for state level interventions, and the strong correlations with social capital and work force participation argue that such interventions should include a social-economic component. In support of this last point, there are (1) strong inverse correlations between years of heavy drug use and years of school (e.g., Heyman, Dunn, & Mignone, 2014; Warner et al., 1995) and (2) strong positive correlations between years of school and social capital (Putnam, 1995). In other words, there is evidence that interventions that target social-economic factors, particularly extending years of schooling, would prove most successful.

In sum, when we are talking about the overdose epidemic, we are not just talking about changes in the supply of drugs, we are also talking about the decline in social-economic conditions in the United States.

Author contributions

Gene Heyman was involved in all aspects of the research and manuscript preparation.

Nico McVicar played a key role in methodological aspects of the research and data curation.

Hiram Brownell played a key role in the validation of the data, formal analyses, and preparing the manuscript.

Declaration of Competing Interest

None of the authors has a conflict of interest.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.drugpo.2019.07.026.

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