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Drug-overdose death rates: the economic misery explanation and its alternatives

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ABSTRACT

'Deaths of despair' is the most commonly cited explanation for the 151% increase in drug-overdose deaths that occurred in the USA between 2010 and 2018. We use panel data describing 84 Virginia cities and counties to assess the validity of the deaths of despair hypothesis and alternate explanations that focus on disability rates, travel time to work, urban vs. rural location, educational attainment, racial and ethnic characteristics, the influence of other health conditions such as obesity, and supply-side factors that include pill availability and pharmacy market shares. We find deaths of despair to be only a partial explanation for the upsurge in drug-overdose deaths and conclude that a much broader view of the causes of drug-overdose deaths is merited.

KEYWORDS

Opioids, deaths of despair, drug overdoses, government efficiency

JEL CLASSIFICATION

H51, H41, H23, H53

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I. Introduction

Deaths attributed to drug overdoses surged by 151% in the United States between 2010 and 2018.[1] The Centres for Disease Control and Prevention (CDC 2020a) estimated that approximately 70% of these deaths were due to opioid abuse, with methamphetamines and cocaine accounting for most of the remainder of the drug-overdose deaths.[2] The CDC (2019) also estimated that an average of 41 individuals died each day in 2018 in the United States from overdoses involving prescription opioids (CDC 2020b).

What are the factors that have contributed to the appearance of this wave of increased drug abuse and mortality? With few exceptions, major media outlets have suggested that economic misery is the major culprit. *The New York Times* (2019), for example, headlined that 'Opioid deaths rise when auto plants close …' and wrote as if adverse economic conditions were the obvious and most important causal factor. This is not an unreasonable inference because rates of opioid use and deaths due to opioid overdoses often are more elevated in regions that have higher rates of unemployment and declining economic prospects. Nevertheless, more science-based formal inquiries into the factors influencing drug abuse and overdose are necessary if we are to formulate the most efficient public policy responses to these challenges.

II. Background and study objectives

In response to the growing drug-overdose problem, a substantial scholarly literature has appeared. This literature reflects a diverse variety of methodologies, data, and perspectives (Case and Deaton 2015, 2017; Hansen and Netherland 2016; Dwyer-Lindgren et al. 2016, 2017, 2018; Childhuri and Li, 2017; Jones, Baldwin, and Compton 2017; Dasgupta, Beletsky and Ciccarone, 2018; Jalal et al. 2018; Ruhm 2018; Aliprantis, Fee, and Schweitzer 2019; Currie, Lin, and Schnell 2019; Metcalf and Wong, 2019; Shiels et al. 2019).

Case and Deaton (2015, 2017) provided a significant and very credible professional voice to the view espoused by the major media when they spoke of 'deaths of despair' – referring to those individuals whom they believe died of overdoses because they perceived their economic prospects to be so bleak. Similarly, the work of Dasgupta, Beletsky and Ciccarone (2018) is representative of those who argue that economic conditions predominate as the principal cause of drug abuse. Even so, evidence on the specific linkage between drug use and abuse and economic conditions is not entirely clear (Chilhuri and Li 2017; Ruhm 2018; Aliprantis, Fee, and Schweitzer 2019; Currie, Lin, and Schnell 2019; Metcalf and Wang 2019). Ruhm (2018), for example, estimated that changes in economic conditions could account for less than one-tenth of the rise in drug and opioid mortality rates.

Excepting Currie, Li, and Schnell (2019), *economic* studies of drug abuse death rates typically have not relied upon the city- and county-level data even though it is in city and county jurisdictions that the proverbial rubber meets the road in terms of the effects and costs of drug overdoses. Reliance on county-level data has been much more common in studies published in medical journals (for Dwyer-Lindgren et al. 2016, 2017, 2018; Monnat 2018; Monnat et al. 2019; Shiels et al. 2019).

Among the most compelling recent contributions in the arena of studies of drug abuse and overdose is the work of Nosrati et al. (2019), who utilized an annual county-level panel data-set to estimate how county mortality rates were influenced by crime and imprisonment, ethnicity, household income, and the opioid prescription rate. Our study effectively builds upon this general context but investigates a half-dozen additional significant hypotheses concerning the determinants of drug-overdose death rates. The overall objective of our work to identify the key economic, demographic, and other factors that influence the drug-overdose death rate.

Following Nosrati et al. (2019), our focus on drug-overdose death rates that occur in local governmental jurisdictions. City and county governmental units and health providers are among the most prominent first responders and bear heavy costs when drug overdoses occur and there is need accurate information about the nature of the challenges they face. We utilize annual panel data describing 84 Virginia independent cities[3] and counties between 2008 and 2017 to identify key factors (including those that can reasonably be connected to the deaths of despair hypothesis) that influence the drug-overdose death rate.

The empirical analysis we present suggests that while the deaths of despair hypothesis exhibits some empirical validity, supply-side factors and often overlooked demand-side influences such as mean travel time to work and the risky nature of certain modes of employment also warrant attention. Further, we consider two hypotheses that have governmental origins. The first is the contention of the President's Council of Economic Advisors (2019) that the government has in effect unwittingly financed and enabled the drug-overdose crisis by supporting overly generous disability payments, supplementing the incomes of drug abusers, making drugs less expensive, and failing to prevent fraud (Loftsgordon 2020). The second hypothesis is the opinion expressed by the CDC (2020d) that the United States entered a new, more destructive era with respect to drug abuse around the year 2013, when synthetic opioids such as fentanyl began to flood the country.[4]

Two policy implications flow from our work. First, improved economic conditions are not likely to put as large a dent in drug-overdose death rates as many contend. Second, consistent with Chilhuri and Li ((2017), focusing attention on the supply side of the market, and especially on the practices of those who write prescriptions, would be productive as a strategy to reduce the severity of the drug abuse problem. Our empirical results suggest that ease of access is an important factor contributing to drug-overdose death rates.

III. Factors influencing drug-overdose deaths: an eclectic framework

Whereas some factors that lead to drug overdoses and death may be unobservable (for example, an individual's personal mental condition), many other economic and social indicators are observable, especially when the focus is upon groups of individuals.

The dependent variable in this analysis is the logarithm of the age-adjusted[5] drug-overdose death rate (*DEATHRATE*) in each year of our 2008–2017 study period for each of 84 Virginia cities and counties.[6] Age-adjusted death rates recognize that varying age distributions of populations in jurisdiction could drive differences in behaviour. Small population size is the reason that a specific city or county was not included in the sample; drug-overdose data are not published for the smallest cities and counties.

Presumably, the demographic and economic characteristics of a community affect deadly drug overdoses. Among possible relevant factors are income, the unemployment rate, rural vs. urban location, racial background, the level of educational attainment, the prevalence of accident-prone employment, and the ease with which one can obtain drugs, legally or illegally.

Our explanatory variables naturally fall into several categories. Data sources for all variables are provided in the text below. Our *a priori* expectations for the signs on the coefficients of the explanatory variables in the estimating equation are provided below.

Supply-side considerations

As suggested in Childuri and Li (2017), Jones, Baldwin, and Compton (2017), Nosrati et al. (2019), and Monnat et al. (2019), the greater the supply/availability of drugs, the greater their usage and potential abusive usage. We hypothesize that the higher the opioid prescription rate in any given community, the greater the expected drug-overdose death rate, *ceteris paribus*. This expectation is predicated on the idea that the greater the availability of drugs in a community, the greater the rate of potential drug overdoses and subsequent deaths. To reflect this, we use the *Average Opioid Prescribing Rate* (*PRESCRIBE*), the opioid prescribing rate per 100 individuals (CDC 2020b).

In addition, we hypothesize that the greater the concentration of legal sellers of opioids in a community, the easier it is for them to keep track of those who might abuse prescriptions. Hence, we expect the drug-overdose death rate in a community to be a decreasing function of the market concentration of pharmacies in that community (other influences held constant). To reflect this perspective, we use the *Market Share of the Five Largest Pharmacy Suppliers* (*MRKTCONC*), as measured by the share of pills supplied by the five largest pharmacy suppliers in each jurisdiction (Washington Post 2020).

Demand – side considerations

Economic despair

Following the analyses of Case and Deaton (2015, 2017) and Nosrati et al. (2019), we seek to measure the potential impacts of economic despair on the drug-overdose death rate. We adopt two explanatory variables that address economic distress: the median household income and the unemployment rate in each jurisdiction. Nosrati et al. (2019) argued that one of the effects of lower household income acts is to create feelings of hopelessness and fear. Similarly, greater unemployment breeds similar emotional stress and despair and thereby also elevates the demand for drugs. Once drugs such as opioids are in use, there is an increased risk of addiction (and ultimately overdoses) that drive higher drug-overdose death rates. Accordingly, we utilize two specific variables: *Median Annual Household Income, MEDHHINC*, which is the median annual value of household income in a jurisdiction (FRED, 2020a); and *Average Annual Percentage Unemployment Rate, UNEMPL* (FRED (Federal Reserve Bank of St. Louis) 2020a) in a city or county. We hypothesize that the drug-overdose death rate is a decreasing function of *MEDHHIN*, but an increasing function of *UNEMPL* (*ceteris paribus*).

Workplace risk

Active employment has multiple dimensions, one of which is workplace risk. Consider that employment in a riskier workplace usually leads to elevated risk, more injuries and increased use of drugs. We reflect one important component of workplace risk by means of the percentage of employment involved in mining in a jurisdiction: *Mining Employment Risk* (*MINING)*. We hypothesize that the greater the percentage of a jurisdiction's employment found in a risky environment such as mining, the greater will be its drug-overdose death rate, other things held the same. Moreover, because coal mining also is an industry in decline, our MINING variable may also assume the role of an indicator of economic despair.

Disability transfer payments and health insurance

Disability status is often accompanied by reported discomfort, pain and sometimes debilitating side-effects. Disability-related issues usually stimulate an increased demand for drug prescriptions, which in turn can lead to subsequent drug abuse (American Public Health Association 2018; Lauer, Henly, and Brucker 2019). We measure the extent of disability in our city and county sample by means of *Percent Disability* (*DISABILITY*) – the percent of the population aged 18–64 that have qualified for some level of disability benefits under Social Security (NORC 2020c).[7] We hypothesize that, *ceteris paribus*, the greater the percentage of the population that is receiving disability payments, the greater will be the drug-overdose death rate (*DEATHRATE)*.

Related to disability is the matter of health insurance. To the extent that individuals are covered by health insurance, they can better afford to purchase prescriptions. Ergo, even though health insurance serves many laudable purposes, it may have the potential to underwrite an increase in the demand for drugs (Council of Economic Advisers, 2019). To test this possibility, we use the *Percent of the Population under Age 65 with Heath Insurance* (U.S. Census 2020), or *PCTHLTHINS*. The hypothesis we proffer is that the *DEATHRATE* is an increasing function of *PCTHLTHINS, ceteris paribus*.

Demographic considerations

Because rural locations often exhibit higher rates of drug abuse (Oppel 2019), we utilize a population density metric to see if the degree of 'rural-ness' remains an important determinant of drug-overdose death rates when it is considered within the context of a multivariate model. Our measure of population density is *Population Per Square Mile* (*POPDENSITY*) – the number of residents per square mile in each jurisdiction (FRED 2020b; U.S. Census 2020). Consistent with Oppel (2019) and Misra (2019), we hypothesize that the variable *DEATHRATE* is a decreasing function of population density.

The relationship of completed formal education (as opposed to targeted drug education) to drug-overdose death rates is not clear. However, Monnat et al. (2019, p. 1090) found that higher opioid mortality counties '… have larger concentrations of professional workers and are less economically disadvantaged'. This leads us cautiously to expect that the drug-overdose death rate will be an increasing function of the educational attainment level, *ceteris paribus*. We measure educational attainment by *Percent HS or More* (*HSCOMPLPLUS*) – the percent of the persons in each jurisdiction in our study age 25 years and older that has earned at least a high school diploma.

Longer commutes from residence to place of principal employment may impose greater financial, temporal, and emotional costs on individuals that discourage labour force participation and reduce the rate of employment. We hypothesize that longer commutes increase drug-overdose death rates. Our measure of commuting time to work is *Mean Travel Time Expressed in* *minutes to Work* (*TRAVELTIME*) within each Virginia independent city and county (U.S. Census 2020).

Another potentially salient demographic consideration involves incarceration. Nosrati et al. (2019, 1087) observed that ‘Extensive evidence has linked incarceration to various factors that are associated with drug overdose deaths, including stigma, family disruption, and neighborhood decline.’ Our measure of incarceration is the *Jailing Rate* (*JAIL*), the percent of residents aged 15–64 in prison or in jail per 100,000 in each jurisdiction (VERA 2020). Not only do those who have been incarcerated exhibit higher levels of drug abuse, but so also do their friends and family (Nosrati et al. 2019). Hence, because of the disruptive impact that incarceration has on families and communities, we expect the drug-overdose death rate to be an increasing function of *JAIL*, other things held constant.

Finally, both scholarly studies (Hansen and Netherland 2016) and popular media (NPR, 2017) have suggested that drug overdoses leading to death are predominantly a non-Hispanic White problem. Muennig et al. (2018, 29) state that ‘It is hardly a mystery that … Whites are disproportionately affected by the opioid crisis. Whites have better access to … prescription pain medications – than do Hispanics or Blacks [and] are much more likely to be treated for pain with opioids than are Blacks or Hispanics.’ Further, like cocaine a century previous, drugs such as opioids may be a more common recreational drug for Whites than for other groups. To capture these possibilities, we use the *Percent White age 15 years and above (WHITE)*, the percentage of the population in each area that is Caucasian. *Ceteris paribus*, we expect the drug-overdose death rate (*DEATHRATE*) to be an increasing function of WHITE.

IV. Empirical evidence

Summary descriptive statistics frequently help one capture the overall nature of a situation. In Table 1 we supply means, standard deviations, minima, and maxima for each of the variables we utilize in our analysis. These data reflect the tremendous variations in circumstances that exist in our 84 cities and counties. Drug-overdose death rates, for example, vary from a low of 5.30 per 1,000 individuals to a high of 250.47. Opioid prescription rates vary from a low of 3.80 prescriptions annually to a high of 583.80. These diverse circumstances match those of the United States overall.

Table 1. Descriptive statistics. (Table view)

Variable	Mean	Standard Deviation	Maximum	Minimum
$DEATHRATE_{it}$	24.07	21.76	250.47	5.30
$Log(DEATHRATE_{it})$	2.978	0.599	5.42	1.668
$PCTHLTHIN_{it-1}$	85.51	5.97	98.19	15.0
$MEDHHINC_{it-1}$	51,029	19,346	136,191	23,267
$UNEMPL_{it-1}$	5.506	2.369	19.29	1.358
$DISABILITY_{it-1}$	12.107	5.112	30.50	3.10
$PRESCRIBE_{it-1}$	106.17	85.37	583.80	3.80
$MRKCONC_{it-1}$	76.33	24.48	100.0	15.90
$HSCOMPLPLUS_{it-1}$	84.36	6.26	98.20	66.90

Variable	Mean	Standard Deviation	Maximum	Minimum
$MINING_{it-1}$	5.024	3.531	20.80	0.00
$TRAVELTIME_{it-1}$	27.172	6.404	41.40	14.50
$JAIL_{it-1}$	5.24	4.087	33.79	0.59
$WHITE_{it-1}$	73.55	17.95	99.01	14.40
$POPDENSITY_{it-1}$	922.32	1,603.18	10,693.50	17.76

Predicated upon the hypotheses developed above, we rely upon this estimating model: DEATHRATE= fPRESCRIBE, MRKTCONC,\breakMEDHHINC, UNEMPL, MINING, DISABILITY,\breakPCTHLTHIN, POPDENSITY, HSCOMPLPLUS,\breakTRAVELTIME, JAIL, WHITE.

(1)

The dependent variable (*DEATHRATE*) is the log of the age-adjusted drug-overdose death rate per 100,000 in each jurisdiction.
fPRESCRIBE> 0,fMRKTCONC< 0,fMEDHHINC< 0,fUNEMPL> 0,fMINING> 0,fDISABILITY> 0,fPCTHLTHIN> 0,fPOPDENSITY< 0,fHSCOMPLPLUS> 0,fTRAVELTIME> 0,fJAIL> 0,fWHITE> 0.

(2)

Within this context, we hypothesize that:

The empirical evidence is derived from a semi-log period, fixed effects estimating equation involving 84 jurisdictions in the state of Virginia between 2008 and 2017.[8] We estimate two versions of the model. In the first, all explanatory variables are lagged by 1 year; this is done to minimize potential endogeneity problems. In the second, the explanatory variables are unlagged. The initial lagged regression estimation estimate is provided in Table 2, whereas the second estimation, the unlagged version, is provided in Table 5.

Table 2. Determinants of drug-overdose death rates in 84 virginia cities and counties, 2008–2017. (Table view)

	Variable	Coefficient	Standard Error t-Statistic	Probability
Constant	0.825001	0.208973	3.95	0.0001***
$PCTHLTHIN_{it-1}$	0.019012	0.00619	3.11	.0000***
$MEDHHINC_{it-1}$	−.0000140	.00000152	−9.17	.0000***
$UNEMPL_{it-1}$	.032349	.009319	3.47	.0006***
$DISABILITY_{it-1}$	.009948	.007745	1.28	.1996
$PRESCRIBEi_{t-1}$	.002059	.0000812	25.35	.0000***
$MRKTCONC_{it-1}$	−.006087	.000981	−6.20	.0000***
$HSCOMPLPLUS_{it-1}$	−.001510	.005375	−0.28	.7789
$MINING_{it-1}$	.018085	.002653	6.82	.0000***
$TRAVELTIME_{it-1}$	.043966	.004603	9.55	.0000***
$JAIL_{it-1}$	.014324	.003088	4.64	.0000***

	Variable	Coefficient	Standard Error t-Statistic	Probability
$WHITE_{it-1}$	.001322	.000822	1.61	.1082
$POPDENSITY_{it-1}$	−.0000228	.00000991	−2.30	.0218**

Notes: Dependent variable is the drug-overdose death rate per 100,000 population (DEATHRATE) in the jurisdictions. The White (1980) cross section heteroscedasticity correction has been applied. Total observations (n) = 533 from 84 cities and counties. R^2 adj. = .443; F = 22.17 (.0000). ***, **, and * indicate statistical significance at the .01, .05, and .10 levels, respectively, in two-tailed tests.

Table 3. How drug-overdose death rates respond to changes in selected environments of 84 virginia cities and counties, 2008–2017. (Table view)

Variable	Magnitude of Change from Median Value	Percent Change in Drug Overdose Death Rate
$MEDHHINC_{it-1}$	$10,000 increase annually in median household income	1.40% decrease
$UNEMPL_{t-1}$	2.0% absolute increase in median unemployment rate	6.47% increase
$PRESCRIBE_{it-1}$	5 additional prescriptions annually above the median	1.03% increase
$MRKTCONC_{it-1}$	5 percent absolute increase in median market concentration	3.05% decrease
$PCTHLTHIN_{it-1}$	5% increase population with health insurance	9.5% increase
$MINING_{it-1}$	5% absolute increase in median workers in mining	9.05% increase
$TRAVELTIME_{it1}$	5 minute increase in median travel time	21.95% increase
$JAIL_{it-1}$	5% absolute increase in the jail population	7.11% increase
$POPDENSITY_{it-1}$	5% absolute increase in population density	0.66% decrease

Table 4. Variance inflation factors. (Table view)

Variable	VIF
$PCTHLTHIN_{it-1}$	3.91
$MEDHHINC^{it-1}$	3.97
$UNEMPL_{it-1}$	2.84
$DISABILITY_{it-1}$	3.33
$PRESCRIBE_{it-1}$	1.75
$MRKCONC_{it-1}$	1.97
$HSCOMPLPLUS_{it-1}$	4.69
$MINING_{it-1}$	1.40
$TRAVELTIME_{it-1}$	1.84
$JAIL_{it-1}$	1.33
$WHITE_{it-1}$	1.91
$POPDENSITY_{it-1}$	1.56

Table 5. Determinants of drug-overdose death rates in 84 Virginia cities and counties, 2008–2017 (Unlagged Model). (Table view)

Variable	Coefficient	Standard Error	t-	StatisticProbability
Constant	0.881427	0.220702	3.70	0.0002***

Variable	Coefficient	Standard Error	t-	StatisticProbability
$PCTHLTHIN_{it}$	0.012644	0.007484	1.67	.0960*
$MEDHHINC_{it}$	−.0000133	.00000185	−7.15	.0000***
$UNEMPL_{it}$	.034143	.007963	4.29	.0000***
$DISABILITY_{it}$	.014504	.008240	1.76	.0789*
$PRESCRIBE_{it}$	.001937	.000117	16.53	.0000***
$MRKTCONC_{it}$	−.005614	.000915	−6.14	.0000***
$HSCOMPLPLUS_{it}$	.002514	.006103	0.41	.6806
$MINING_{it}$	.017496	.002319	7.55	.0000***
$TRAVELTIME_{it}$	.042458	.005262	8.07	.0000***
$JAIL_{it}$	.010947	.002196	4.99	.0000***
$WHITE_{it}$	.002638	.000896	2.94	.0034**
$POPDENSITY_{it}$	−.000011	.0000093	−1.20	.2324

Notes: Dependent variable is the drug-overdose death rate per 100,000 population (DEATHRATE) in the jurisdictions. The White (1980) cross section heteroscedasticity correction has been applied. Total observations (n) = 612 from 83 cities and counties. R^2 adj. = .463; F = 26.06 (.0000). ***, **, and * indicate statistical significance at the .01, .05, and .10 levels, respectively, in two-tailed tests.

Focusing first on the results shown in Table 1, nine of the 12 explanatory variables are statistically significant at the 5% level or beyond and have the expected signs. The *DISABILITY, HSCOMPLPLUS*, and *WHITE* variables are not statistically significant at the 10% level. Thus, based on this first estimation, the drug-overdose death rate is an increasing function of the variables *PRESCRIBE, MINING, PCTHLTHIN, PCTHLTHIN, JAIL*, and UNEMPL, but a decreasing function of *MRKTCONC, MEDHHIN*, and *POPDENSITY*.

Supply-side results

The estimated coefficient of our supply-side factor, the average opioid prescription rate in a city or county (*PRESCRIBE*), is positive and statistically significant at the 1% level. Table 3 reveals that a five-unit increase in a jurisdiction's prescription rate is associated with a 1.03% increase in that jurisdiction's age-related premature death rate. Believing that 'too easy' prescription practices have become problematic, states such as Texas have adopted 'triplicate' prescription-drug-monitoring-programmes, that require physicians to use a specially devised pads to prescribe controlled substances. They must supply a copy of their prescription order to a state agency that monitors their activities. Some physicians bridle at these requirements, but they have been effective in diminishing opioid abuse (Khazan 2020). The national opioid prescription rate per 100 individuals peaked at 81.3 in 2012 but by 2018 had fallen to 51.4 (CDC 2020b).

Another supply factor relates to the degree of seller concentration among pharmacies in the jurisdictions. Highly concentrated markets in which a few sellers account for a very high proportion of sales often are frowned on by economists because they frequently lead to consumers paying high prices (Mankiw 2019). In the case of drug abuse, however, it is possible that higher seller concentration enables pharmacies to keep better track of potential drug abusers and/or individuals who are illicitly using multiple prescriptions to obtain drug supplies. The evidence presented in Table 1 encourages this view. The estimated coefficient on the *MRKTCONC* variable (the share of opioid pills supplied by the five pharmacies supplying the most pills) is negative and statistically significant at the 1% level. A five-unit (five percentage point) increase in median seller concentration is associated with a 3.05% decline in a jurisdiction's drug-overdose death rate (see Table 3).

Deaths of despair?

The evidence in Table 1 relating to prevailing economic conditions provides support for the deaths of despair hypothesis. The estimated coefficient of the *MEDHHINC* variable is negative as expected and statistically significant at the 1% level. Table 3 reports that a 10,000 USD higher median household income is associated with a 14.0% decline in the drug-overdose death rate. One should not gainsay this finding, but it is not as strong a relationship as some have assumed (Chen 2015). Consider that Buchanan County Virginia, traditionally heavily involved in coal mining, had a median household income of 32,993 USD in 2017 (FRED 2020b). An unprecedented 100% increase in median household incomes in Buchanan would drive only a 46.19% decline in that county's drug-overdose death rate. Incomes do make a difference but as we will see, other factors are equally or more important determinants of drug-overdose death rates.

Another window on the deaths of despair hypothesis focuses on unemployment rates. The estimated coefficient of each jurisdiction's unemployment rate is positive as expected and statistically significant at the 1% level. Table 3 reveals that a 2.0% absolute increase in a jurisdiction's median unemployment rate is associated with a 6.47% increase in its drug-overdose death rate. Once again, this is important, but it is clearly not the only major influence upon drug-overdose death rates.

The greater the extent of employment in mining, the greater the degree of risk of injury on the job and possibly also the greater the degree of economic despair about economic prospects. This is another possible indicator of economic misery – but one in which is the employment of a jurisdiction is tied to a declining industry. We find that the percent of employment in mining (*MINING*) in a jurisdiction is a statistically significant predictor (at the 1% level) of city and county drug-overdose death rates. A 5.0% absolute increase in the percentage of workers employed in mining leads to a 9.05% increase in a jurisdiction's drug-overdose death rate [consistent with the previous work of Monnat (2018)].

Yet, the mining picture is more complicated than it might first appear. In Buchanan County, for example, the proportion of workers engaged in coal mining declined by more than one-fifth between 2008–2012 and 2013–2017 (NORC, 2020a). At the same time, coal mining was declining, however, the county's unemployment rate also was falling – from a peak of 11.0% in 2013 to 7.0% in 2017 (FRED (Federal Reserve Bank of St. Louis) 2020a). Thus, it was possible for many workers leaving coal mining to find alternate employment in their home county. Nevertheless, Buchanan experienced net outmigration in every year in our sample

(FRED 2020b). However, net migration is a mixed indicator of economic misery. Relatively wealthy jurisdictions such as Fairfax County, Virginia have consistently recorded net outmigration rates in recent years.

In sum, there is some empirical reality to the deaths of despair hypothesis but economic despair is far from being the primary or sole determinant of drug-overdose death rates. Other factors come into play, perhaps even dominate.

Travel time to work

Table 2 reports that the estimated coefficient of the variable *TRAVELTIME* is positive and statistically significant at the 1% level and the quantitative impact is quite large. A 5.0 minute increase in the median commuting time of workers in a jurisdiction (this is roughly a 25% relative increase) is associated with a 21.95% increase in the drug-overdose death rate. Many individuals appear to attach considerable disutility to longer commutes and this leads to increased drug abuse. One could interpret this commuting-time relationship to be an added dimension of deaths of despair. One cannot find an acceptable job nearby and this results in elevated drug usage. Perhaps, but we note that most of the longest commuting times in Virginia exist in Northern Virginia (suburban Washington, D.C.), where unemployment rates have been very low and incomes were very high for many decades. Thus, the mean travel time to work variable is not a reliable indicator of economic distress.

Governmental hypotheses

The President's Council of Economic Advisors (2019) has broadly asserted that governments bear considerable responsibility for the opioid crisis because they have provided overly generous transfer payment income and promoted health insurance coverage to potential abusers. We test two aspects of this hypothesis: (1) assessing the impact of disability status upon the drug-overdose death rate and (2) assessing the impact of the percent of the population under age 65 with health insurance.

With respect to disability status, in 2013, roughly midway in our study period, the percent of adults aged 16 to 64 receiving disability income from the US Government ranged from only 4.1% in Washington suburban Arlington County to 26.8% in Lee County in coal country (NORC, 2020b) Do differentials such as these influence drug overdose death rates? Table 1 reveals that the estimated coefficient on our disability rate variable is positive but fails to attain statistical significance at the 10% level. This provides at best tepid support for the views of the Council of Economic Advisors and others such as Lauer, Henly, and Brucker (2019) on this issue.

On the other hand, the estimated coefficient on the health insurance coverage variable is positive, statistically significant at the 1% level, and Table 3 reports that a 5 percentage point increase in the under age 65 population elevates the drug-overdose death rate by 9.5%. Thus, more generous health insurance policies have effectively contributed to the drug-overdose crisis in a powerful fashion.

The urban-rural question

Opioid abuse often has been considered to be a rural phenomenon (Dwyer-Lindgren et al. 2017; Monnat 2018; Shields et al., 2019; Oppel 2019). Our empirical results support this view of the world. The variable adopted in this study to measure of urban-ness is population per square mile (*POPDENSITY*) and, *ceteris paribus*, the estimated coefficient on this variable is negative and statistically significant at the 2.5% level. Arguably, this may reflect the comparative dearth of economic opportunities that exist in many rural areas.

Incarceration

We hypothesized that the drug-overdose death rate (*DEATHRATE*) is an increasing function of *JAIL*, other things held constant and find that the drug-overdose death rate is an increasing function of the percent of the population that is incarcerated. The estimated coefficient is statistically significant at the 1% level. This is consistent with Nosrati et al. (2019, 1087), who concluded that 'Extensive evidence [linking] incarceration to various factors that are associated with drug overdose deaths.' Table 3 informs us that a five percent absolute increase in jail population elevates the drug-overdose death rate by 7.11%.

V. Further observations on the model

In this section of the study, we address three statistical issues. First, we provide a test of the degree of multi-collinearity among the explanatory variables via Table 4, which provides VIFs (Variance Inflation Factors). All the VIF values are less than 5, implying that the absence of significant multi-collinearity among the explanatory variables in the estimated equation (Woolridge, 2009). This increases our confidence in our results.

The second statistical issue acknowledges that the estimating equation we presented in Table 2 utilized lagged explanatory variables, primarily to avoid econometric endogeneity. In Table 5, we now re-estimate our basic model *without* the one-year lags. There are no differences of consequence between the two estimations, though from an econometric standpoint, the lagged version (Table 2) is preferable.[9] This increases our confidence in our Table 2 (lagged) results.

The third issue is both statistical and medical in nature. The CDC (2020d) believes that fentanyl, which began to flood into the United States circa 2012, fundamentally changed the drug-overdose world. This is a reasonable supposition because fentanyl is 80 to 100 times more powerful than morphine (DEA 2020).

To test this hypothesis, we divided our study period is divided into two sub-periods – 2008-2012 and 2013-2017 – and estimated separate equations for both time periods, once again relying upon the basic model described in Equation (2). These new sub-period regressions are reported in Tables A1 and A2 in the Appendix. We use a Chow Test to ascertain whether a structural change occurred in the data set in 2013. The estimated coefficients in the 2009–2012 regression so nor differ significantly those in the 2013–2017 regression? The Chow Test F-statistic was 1.51 and this fell short of the critical 1.74 value required for statistical significance at the 10%

level. Thus, although fentanyl is an extremely deadly drug, the basic determinants of drug-overdose death rates did not change between the two periods.

VI. Final considerations

Mortality rates are complicated, evolving phenomena. The causes and effects are multiple as well as complex. Whatever the causes, however, it is city and county governments that stand on the front lines and bear the brunt of the costs generated by drug overdoses and related deaths.

It is within the capabilities of state and local governments to recognize and capitalize upon our policy findings, though we some of the initiatives implied by our results might not be greeted with acclaim. For example, it is easier politically to propose expending additional funds on improving economic conditions to combat drug abuse than it is to suggest reductions in, or increased monitoring of, health insurance coverage.

The tools local governments can bring to bear on the challenges presented by drug abuse are limited, but three stand out. First, they can influence the supply of opioids via monitoring of the individuals (primarily physicians) who prescribe opioids. Prescribing physicians and nurses bear all the responsibility for the spike in the drug-overdose death rate, but they do merit some blame. Hence, finding effective ways to convince or require them to utilize more discerning standards in deciding to issue or renew prescriptions would make a major difference.

Second, cities and counties have some ability to influence the safety of the workers in their jurisdictions and how disability claims are treated. They should not 'leave it up to the feds' where workplace safety and disability claims are concerned. When a worker is injured and takes disability, nearly always this results in an economic loss for the jurisdiction.

Third, incarcerating large numbers of individuals (including drug abusers) appears to be a losing societal strategy. We find that this approach does not reduce drug-overdose deaths and besides is associated with significantly shorter post-incarceration life spans (Nosrati et al.)

At the end of the day, however, drug abuse is difficult terrain for cities and counties to navigate because even though they bear most of the costs associated with drug overdoses, they do not control many of the things in their environment that generates drug overdoses. The secular decline of the coal and textile industries in Virginia, for example, is not something that an individual Virginia city or county can reverse. Nor can local jurisdictions control the national economy. It is appropriate, therefore, to include cities and counties among the victims of the opioid crisis that has swept the United States.

Notes

1. Specifically, the age-adjusted death rate per 100,000 individuals rose from 6.8 in 2010 to 17.1 in 2018. These death rates are age-adjusted and therefore adjust raw death rate data for the gradually changing age distribution of the populace. Centres for Disease Control and Prevention, 'Drug Overdose Deaths,' www.cdc.gov/drugoverdose/data/statedeaths.html. Accessed 15 April 2020.

2. The CDC reports that opioid abuse accounted for 69.5% of drug overdose deaths in 2018. CEC (2020a).

3. Independent cities in Virginia function as counties even when they are surrounded by a county. Thus, Charlottesville, Virginia is an independent city located inside Albemarle County, but is not part of Albemarle County. In some instances, cities and counties share the provision of some services such as law enforcement.

4. Interestingly, in 1996, the U.S. Food and Drug Administration had approved OxyContin as a "minimally additive pain reliever (Hansen and Netherland 2016).

5. Age-adjusted death rates recognize that varying age distributions of populations in jurisdiction could drive differences in behaviour. For example, we would not expect to find high levels of drug abuse among pre-teens or among the very mature.

6. These data come from the National Opinion Research Center (2020a). NORC data in turn come from the CDC but are more accessible on a city and county basis than CDC data. The NORC data are averaged over five-year periods, 2009–2013 and 2014–2018.

7. Our data source is NORC, the National Opinion Research Centre at the University of Chicago. NORC provides U.S. Census data in very accessible formats.

8. The panel is unbalanced; the fixed-effects specification (based on the Hausman 1978) test involves period fixed-effects (dummy variables).

9. Our findings for the variables *WHITE* and *POPDENSITY* did differ between the two estimates, with the coefficient for *WHITE* being statistically significant at the 1% level in the unlagged estimation. We did consider alternative variations of the model with regression specifications that identified the percent of each jurisdiction's population that identified as Black or African-American, Hispanic/Latino, Asian, and White only. Among these categories of race, only the 'whiteness' (*WHITE*) estimated coefficient ever emerged as statistically significant.

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Appendix A

Table A1. Determinants of drug-overdose death rates in 83 Virginia cities and counties, 2009–2012. (Table view)

Variable	Coefficient	Standard Error	t-Statistic	Probability
Constant	.937877	.092386	10.58	.0000***
MEDHHINC$_{it-1}$	−.0000103	.00000102	−11.22	.0001***
UNEMPL$_{it-1}$	.038801	.010867	3.54	.0005***
DISABILITY$_{it-1}$	.014361	.007700	1.87	.0631*
PRESCRIBE$_{it-1}$	.001476	.000149	9.91	.0000***
MRKTCONC$_{it-1}$	−.005762	.001465	−3.93	.0001***
HSCOMPLPLUS$_{it-1}$	.015017	.002589	5.80	.0000***
MINING$_{it-1}$	.025670	.003545	7.24	.0000***
TRAVELTIME$_{it-1}$	.037702	.005447	6.92	.0000***
JAIL$_{it-1}$	.009903	.004649	2.13	.0340**
WHITE$_{it-1}$	.005240	.000852	6.16	.0000***
POPDENSITIY$_{it-1}$	.00000917	.0004109	.84	.4012

Notes: Dependent variable is the drug-overdose death rate per 100,000 in jurisdictions. The White (1980) cross-section heteroscedasticity correction was applied. Total observations = 319 from 83 cities and counties. R^2 adj. =.488. F = 19.97 (.0000). ***, **, and * indicate statistical significance at the .01,. 05, and.10 levels, respectively, in two-tailed tests.

Table A2. Determinants of drug-overdose death rates in 83 Virginia cities and counties, 2013–2017. (Table view)

Variable	Coefficient	Standard Er.000000754ror	t-Statistic	Probability
Constant	1.8477	.4404	4.20	.0000***
MEDHHINC$_{it-1}$	−.0000173	.00000250	−6.93	.0000***
UNEMPL$_{iy-1}$	.030892	.010269	3.01	.0003***
DISABILITY$_{it-1}$	−.010408	.004991	−2.09	.0393**
PRESCRIBE$_{it-1}$	.002196	.0000821	26.40	.0000***
MRKTCONC$_{it-1}$	−.006996	.000278	−25.12	.0000***
HSCOMPLPLUS$_{it-1}$	.009655	.005798	1.67	.0975*
MINING$_{it-1}$	.010068	.006080	1.66	.0993*
TRAVELTIME$_{it-1}$	.054082	.005597	9.66	.0000***
JAIL$_{it-1}$	.017313	.003813	4.54	.0049***
WHITE$_{it-1}$	.001173	.000917	1.28	.2021
POPDENSITY$_{it-1}$	−.0000427	.00000566	−7.53	.0000***

Notes: Dependent variable is the drug-overdose death rate per 100,000. (−1) signifies that the variable has been lagged one year. White diagonal standard errors and covariance corrections applied. Total annual observations = 211 from 83 cities and counties. R^2 adj. =.461. F = 13.00 (.0000). ***, **, and * indicate statistical significance at the.01,.05, and.10 levels, respectively, in two-tailed tests.