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MACROECONOMIC CONDITIONS AND OPIOID ABUSE

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ABSTRACT

We examine how deaths and emergency department (ED) visits related to use of opioid analgesics (opioids) and other drugs vary with macroeconomic conditions. As the county unemployment rate increases by one percentage point, the opioid death rate per 100,000 rises by 0.19 (3.6%) and the opioid overdose ED visit rate per 100,000 increases by 0.95 (7.0%). Macroeconomic shocks also increase the overall drug death rate, but this increase is driven by rising opioid deaths. Our findings hold when performing a state-level analysis, rather than county-level; are primarily driven by adverse events among whites; and are stable across time periods.

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I. Introduction

Covering a variety of countries and time periods, voluminous research conducted over the last two decades indicates that physical health improves when economic conditions temporarily deteriorate.[1] In the case of mental health, however, research shows apparent declines during periods of economic weakness (Ruhm, 2000; Ruhm, 2003; Charles & DeCicca, 2008; and Modrek et al., 2015). Some evidence suggests, moreover, that the procyclicality of physical health has declined considerably in recent years (Stevens et al., 2015; McInerney and Mellor, 2012; Lam and Piérard, 2015; Ruhm, 2015) just as drug poisoning deaths, often involving opioid analgesics (henceforth opioids) such as hydrocodone and oxycodone, have trended sharply upwards (Rudd et al., 2016).[2]

Understanding the relationship between local economic conditions and drug-related adverse outcomes is important because the United States is "experiencing an epidemic of drug overdose (poisoning) deaths" (Rudd et al., 2016, p. 1378), with fatal drug poisonings increasing by 146% from 1999 to 2014 (Figure 1). Poisoning deaths, around 90% of which are now caused by drugs (Warner et al., 2011), were the most important source of growth in the all-cause mortality rates of 45-54 year old non-Hispanic whites between 1999 and 2013 (Case and Deaton, 2015). The involvement of opioids and, more recently, heroin in these deaths has received particular attention (Volkow et al., 2014; Jones et al. 2015; and Rudd et al., 2016), including a White House Summit in August 2014 (Hardesty, 2014). Drug poisoning deaths are higher for males than females, but have been rising rapidly over time for both sexes, as well as for almost all age groups, but

[1] This literature often dates from Ruhm (2000)'s study of the US for the 1972-1991 period. However, there are indications that mortality was procyclical in research from as early as the 1920s (Ogburn & Thomas, 1922).

[2] Heroin is classified as a separate category of narcotics. Heroin deaths have risen extremely rapidly since 2010 but were relatively stable before that (Ruhm, 2017). This increase is too recent to be adequately captured in our study's timeframe.

particularly rapidly for 25-64 year olds (Ruhm, 2017). One notable feature is that non-Hispanic white (hereafter simply "white") and non-Hispanic black (hereafter "black") drug fatality rates closely tracked each other during the 1980s and 1990s, but since 1999 (the period examined here), white mortality rates have grown much faster. Figure 2 illustrates this divergence. From 1999 to 2014 the U.S. white drug death rate per 100,000 grew by 203%, while the black and Hispanic drug death rates increased by 49% and 31%, respectively. Rising deaths are not the only indication of serious health consequences related to the growing use of opioids. Emergency department (ED) visits involving narcotic pain relievers increased 117% between 2005 and 2011 (Crane, 2015) and opioid-related ED visits grew by 39.5% from 2006 to 2014 (see Figure 3). While this rise has mostly occurred among prime-aged adults, all age groups have seen an increase in the risk of opioid poisoning ED visits (Tadros et al., 2016).

This analysis examines how serious adverse health outcomes related to opioid and other drugs vary with short-term fluctuations in macroeconomic conditions. Specifically, we study how deaths and ED visits due to opioids and other drugs are related to local unemployment rates. Our main findings are that opioid deaths and ED visits are predicted to rise when county unemployment rates temporarily increase. The same is true for all sources of drug poisoning mortality, and consistent results are obtained when performing the analysis at the state-level rather than the county-level, proxying for macroeconomic conditions with employment-to-population ratios rather than unemployment rates, and conducting a variety of other robustness and sensitivity checks. Importantly, our findings are relatively stable regardless of the time period considered, indicating that they represent a general connection between economic conditions and severe adverse consequences of substance abuse that is not restricted to periods of recession. Moreover, our results are predominantly driven by changes among whites (rather than blacks or Hispanics) in most specifications.

II. Prior Research and Contribution of this Investigation

The vast literature examining the connection between economic fluctuations and health has considered effects on mortality and morbidity, health-related behaviors, health insurance and health care use.[3] Mortality has been found to be procyclical in investigations covering a wide variety of countries and time periods (e.g. Ruhm, 2000; Neumayer, 2004; Tapia Granados, 2005; Gerdtham & Ruhm, 2006; Buchmueller et al., 2007; Lin, 2009; Gonzalez & Quast, 2011; and Ariizumi & Schirle, 2012). Similarly, many (though not all) studies suggest that lifestyle factors such as exercise, obesity, smoking and heavy drinking improve in bad economic times (e.g. see Freeman, 1999; Ruhm & Black, 2002; Ruhm, 2005; Gruber & Frakes, 2006; and Xu, 2013).[4] However, some current research suggests that these patterns have weakened or reversed in recent years for both mortality (McInerney & Mellor, 2012; Stevens et al., 2015; Lam & Piérard, 2015; and Ruhm, 2015) and health behaviors (Dávalos et al., 2012; Colman & Dave, 2013; and Tekin et al., 2013).

Particularly relevant to the current analysis is suggestive evidence, provided by Ruhm (2015), that one of the main reasons deaths shifted from being sharply procyclical to acyclical or countercyclical in recent years is because poisoning fatalities have been rapidly increasing and now exhibit a strong countercyclical pattern. However, the precision of these estimates is low and the analysis did not separately examine *drug* (rather than more general poisoning) fatalities or the involvement of specific drugs, such as opioids.[5]

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[3] See Ruhm (2012) for a review of much of this research.
[4] However, there are exceptions (e.g. Dee, 2001; and Johansson et al., 2006).
[5] More recently, Pierce & Schott (2016) provide evidence that accidental poisoning deaths rise when local economic conditions deteriorate.

There has been substantial investigation of the relationship between macroeconomic conditions and a variety of health behaviors – including drinking, smoking and exercise, as discussed above – but corresponding effects on drug use have received less attention, largely because of data limitations. Arkes (2007) provides evidence that teenage use of both marijuana and harder (illicit) drugs rises in economic downturns. Using data from 2002-2013 and a broader age range, Carpenter et al. (2016) find that such downturns are associated with increases in self-reported use of hallucinogens (particularly ecstasy) but with insignificant effects for most other drugs, and with self-reported substance-use disorders related to analgesics (including opioid and non-opioid forms) as well as hallucinogens. Whether these estimated effects are large enough to result in higher rates of ED visits or deaths is unclear. Similarly, using survey data, Martin Bassols and Vall Castelló (2016) find that in Spain, the Great Recession caused increases in the reported use of both marijuana and cocaine. Frijters et al. (2013) show that internet searches for terms related to alcohol abuse and treatment increase when economic conditions deteriorate. However, Maclean, Cantor, and Pacula's (2015) analysis of 1992-2010 data suggests that alcohol and illicit drug admissions to (non-ED) substance abuse programs *decrease* in such periods. The exact mechanisms driving this reduction are unclear, as the utilization of substance abuse programs depends on both underlying health status and changes in the availability of treatment.[6] If temporary economic downturns simultaneously increase the demand for but lower access to treatment, the net result might be a rise in both deaths and ED visits.

Our analysis extends beyond prior research by focusing on drug poisonings, which have grown rapidly in the past fifteen years and are likely to be related to economic conditions in

[6] For example, Cawley et al. (2015) show that increases in state unemployment rates during the 2004-2010 period were associated with sharp decreases in health insurance coverage, especially for 50-64-year-old men and college-educated individuals.

different ways than other types of poisoning. Furthermore, we study the severe outcomes of ED visits and deaths. While examining all types of drug overdoses, we pay particular attention to those involving opioids. We do so because opioids comprise the majority of drug overdose deaths and are quite possibly the most sensitive to macroeconomic conditions. For example, opioids were estimated to be involved in 53% of fatal drug overdoses in 2014 and to play a role in 64% of the increase in drug deaths occurring between 1999 and 2014 (Ruhm, 2017). Next most important was heroin, which was estimated to be involved in 30% of 2014 drug fatalities. We do not focus on heroin, however, because rates of deaths and ED visits were relatively low for most of our study period (until 2010) after which they rose extremely rapidly.[7]

We separately examine the connection between economic conditions and severe adverse drug outcomes for whites, blacks, and Hispanics. Differences across racial groups may be important given recent evidence by Case and Deaton (2015) that mortality rates increased for 45-54-year-old whites, even while rapidly decreasing for blacks and Hispanics. Although poisonings are an important source of the observed changes in mortality rates, it is not obvious that the effects of macroeconomic conditions on deaths or emergency department visits involving opioids necessarily follow the same pattern. For instance, to the extent that minorities are more affected by economic downturns, we might anticipate stronger patterns for nonwhites than whites. On the other hand, drug deaths have increased more slowly for nonwhites than for whites since 1999 (Ruhm, 2017), which might predict a weaker relationship.

III. Data and Descriptive Statistics

[7] These statistics refer to any involvement of these drugs rather than the exclusive involvement of a particular drug. The distinction is important because many drug poisoning deaths involve combinations of drug classes (e.g. 49% in 2014 according to Ruhm, 2017).

Mortality data come from the Centers for Disease Control and Prevention *Multiple Cause of Death* (MCOD) files for 1999-2014, which provide information from the universe of death certificates (Centers for Disease Control and Prevention, 2016). Mortality data are one of the few health measures collected over a long time period and in a relatively comparable manner across areas of the country. The MCOD provide information on a single underlying cause of death (UCD), up to twenty additional causes, and basic demographics. Cause of death is categorized using a four-digit International Classification of Diseases, Tenth Revision (ICD-10) code. Details are also provided on place of residence, age, race/ethnicity, gender, year, and weekday of death. We obtained a restricted-use version of the data with information on state and county of residence for this study.

Drug poisoning deaths were defined using ICD-10 UCD codes, where the underlying cause is the "disease or injury that initiated the chain of morbid events that led directly and inevitably to death" (Centers for Disease Control and Prevention, 2014). Drug poisonings occur when the underlying cause of death is X40-X44, X60-X64, X85, Y10-Y14, or Y35.2 (World Health Organization, 2014). In cases of drug poisoning, the death certificate lists one or more drugs involved as immediate or contributory causes of death. These are identified as ICD-10 cause of death "T codes," with opioids defined to be involved for T-codes 40.2-40.4 and heroin for T-code 40.1.[8]

Death certificate information tends to understate the involvement of opioids (and other drug categories) because the type or types of drugs involved are left unspecified (ICD-10 code, T50.9) in 20%-25% of fatal overdoses (Ruhm, 2017). To correct for this undercount, we follow Ruhm (2017) and impute opioid involvement in cases where the death certificate indicated only

[8] See http://www.icd10data.com/ICD10CM/Codes/S00-T88 for additional details.

unspecified drugs. To do so, we estimated year-specific probit models on the sample of fatal overdoses where at least one drug was specified. The dichotomous dependent variable was set to one if opioids were mentioned and to zero if they were not. The explanatory variables included dichotomous indicators for: sex, race (white, black, other nonwhite), Hispanic origin, currently married, education (high school dropout, high school graduate, some college, college graduate), age category (≤20, 21-30, 31-40, 41-50, 51-60, 61-70, 71-80, >80), day of the week of death (seven dummy variables) and a vector of state fixed-effects. Next, we used the probit results to calculate year-specific predicted probabilities of opioid-involvement for cases where no drug was specified on the death certificate. We then calculated adjusted mortality rates using reported involvement for deaths where at least one specific drug was mentioned and the imputed probabilities where no drug was specified.[9]

There is no comprehensive national source of ED data comparable to the Mortality files. ED data are only made available to researchers for specific states, who decide terms of access individually. We have assembled what, to our knowledge, is the most comprehensive currently available data on ED visits related to opioid and other drug use, covering 16 states in total. Our main dataset consists of counts of ED visits occurring in a given county and year, aggregated from microdata available for 5 states over some or all of the 2002-2014 period. We supplement this with a collection of aggregated state-level data for 15 states available for all or a portion of the 2000-2013 period.

Our microdata come from the State Emergency Department Databases (SEDD) for five states, assembled by the Agency for Healthcare Research and Quality (AHRQ) Healthcare Cost

[9] Over the full time period (1999-2014), the overall drug mortality rate was 10.77 per 100,000. The opioid-involved death rate *without imputations* was 4.04 per 100,000. The adjustments increased this by around one third, to 5.35 per 100,000. The same procedure was used to adjust estimates of heroin involvement.

and Utilization Project (HCUP).[10] These were derived from uniform medical billings at the ED visit level, but only for visits that did not result in an inpatient stay. By comparing this information to available state-level aggregate data on both inpatient and outpatient ED visits, we determined that our microdata contains one-half to two-thirds of all ED visits for opioid overdoses, depending on the state and year.[11] The ED visit microdata include information on patient characteristics, diagnoses, procedures, and charges. Since the SEDD are not available for every year, and some state files are prohibitively expensive, our micro data cover the following states and years: Arizona (2005-2014), Kentucky (2008-2012), Florida (2005-2014), Maryland (2002-2012), and New Jersey (2004, 2006-2103). To increase the geographical representation of our data, we also obtained state-level aggregated ED visit records from the HCUPnet system (which provides a click-through public-access system for these counts) for 15 states in select years. Specifically, these include counts of ED visits (regardless of whether or not they subsequently resulted in an inpatient admission) for the following states and years: Arizona (2005-2013), Florida (2005-2013), Hawaii (2003-2010, 2013), Iowa (2004-2013), Illinois (2009-2013), Kentucky (2008-2013), Maryland (2005-2013), Minnesota (2001-2013), North Carolina (2007-2013), Nebraska (2001-2013), New Hampshire (2003-2009), South Carolina (2005-2013, Tennessee (2005-2013), Utah (2000-2011, 2013), and Vermont (2002-2013). The level of data available for each state and year combination is displayed in Table 1.

Unlike the mortality data, which use ICD-10 codes to classify reason for death, the ED data use ICD-9-CM codes. To ensure that our ED results are comparable to our mortality data, we used a CDC crosswalk that links ICD-10 cause of death and ICD-9-CM diagnosis codes for various

[10] Further information on the HCUP online aggregated data access system is available at: http://hcupnet.ahrq.gov.
[11] Obtaining information on ED visits resulting in an inpatient stay would have required the purchase of the inpatient discharge records from HCUP for each state and year.

categories of drug poisoning (CDC 2013). In the ED data, drug poisonings corresponded to ICD-9 codes 960.00 through 979.99;opioid overdoses to ICD-9 codes 965.00, 965.02, 965.09, E850.1, and E850.2; and heroin overdoses to codes 965.01and E850.0.

Our county-level mortality data covered 3,138 counties over 16 years, with almost every county reporting each year, yielding a maximum of 50,148 observations. When we examined deaths among specific racial or ethnic groups, our sample size decreased as some counties had no black or Hispanic residents.[12] The county-level ED information (obtained from the microdata) included 1,873 county-year observations from the 5 states in the SEDD sample. From 2005 to 2008, Arizona did not report patient race, so we omit Arizona from the ED analyses examining race. In addition, we discovered inconsistency in the reporting of Hispanic ethnicity across states and years, so were unable to separately estimate specifications for Hispanics using the ED data.[13] Our state-level ED data contain 140 state-year cells for the 15 states providing aggregated ED visit data.

We compiled additional data on county characteristics that we use either as right-hand side control variables or to explore heterogeneity in the estimated effects. We obtained county population data from the National Cancer Institute's Surveillance, Epidemiology, and End Results Program (SEER) to turn counts of deaths or ED visits into rates per 100,000.[14] In addition to the full sample rates, we separately computed mortality and ED rates for whites and blacks, as well as death (but not ED) rates for Hispanics. Information on county and state unemployment rates, our main proxy for macroeconomic conditions, came from the Bureau of Labor Statistics' Local Area Unemployment Statistics (www.bls.gov/lau/lauov.htm). County level median incomes were

[12] The number of counties with either no black or no Hispanic residents decreased over our sample, from 265 in 1999 to 2 in 2014.
[13] We verified this issue through personal communications with AHRQ researchers.
[14] Further information is available at http://www.seer.cancer.gov/data.

obtained from the U.S. Census Bureau's Small Area Income and Poverty Estimates (www.census.gov/did/www/saipe/). Table 2 contains summary statistics for our county-level data.

Figure 1 illustrates the relationship between the unemployment rate, our primary proxy for macroeconomic conditions, and death rates (per 100,000) from all drugs and from opioids. Over the 1999-2014 period, 49.7% of drug deaths involved opioids, 17.1% involved heroin, and 38.7% involved only drugs other than heroin or opioids.[15] All three rates have risen over time.[16] At this national level of aggregation, Figure 1 does not reveal an obvious relationship between the economic climate and drug poisoning death rates. Although the average unemployment rate was on the rise during this time period, drug-related mortality increased even when the national unemployment rate decreased between recessions and especially during the steep decline in unemployment after 2011. However, the strong upwards trend in drug mortality may conceal any macroeconomic effects.

Figure 2 separates opioid mortality rates (the largest component of all drug deaths) by race, and demonstrates that white opioid death rates have risen considerably (closely tracking the all-drug death rate) while the rates for blacks, and especially for Hispanics have been low and relatively flat over this time period.

Figure 3 shows nationwide trends in ED visits (per 100,000) for opioid overdoses and all drug poisonings from 2006 to 2014. Both series display a similar, increasing trend. From 2006 to 2014, the rate of opioid-related ED visits grew by 6.82 per 100,000 (39.50%) and the rate of all drug-related ED visits rose by 13.70 per 100,000 (8.0%). These data come from the National Emergency Department Sample (NEDS), a 20% sample of records from all participating states

[15] These numbers sum to more than 100% because 2.6% of drug deaths involved the use of *both* opioids and heroin.
[16] In 2014, the drug death rate per 100,000 was 14.76, of which 7.34 were opioid related, 4.05 involved heroin, and 4.25 involved only drugs other than opioids or heroin.

(but not containing state identifiers) disseminated through HCUP. The NEDS estimates are based upon the entire set of SID and SEDD data and are weighted to be nationally representative. For expositional clarity, we plot the national estimates based upon the NEDS here, rather than state-level estimates based upon the SEDD data for the five states used in our analysis.[17]

Figure 3 also highlights a key distinction between the mortality and ED data. Opioid deaths are responsible for roughly half of all drug deaths in any given year, but opioids ED visits account for fewer than 14% of all drug-related ED visits. Breaking down drug-related ED visits further, we find that eight drug categories constitute approximately 60% of the drug poisoning ED visits in any given year: opioids, benzodiazepines, heroin, anti-depressants, aromatic analgesics (e.g. acetaminophen), insulin, anti-psychotics, and cocaine. Figure 4 displays the nationwide ED visit rate for each drug category from 2006 to 2014. While both opioid and heroin overdose ED rates have risen since 2006, the rate of overdose visits to the ED for all other majority drug categories remained constant or declined.[18]

The NEDS further allow us to determine the percentage of in-hospital deaths that occur after an ED overdose visit for each drug type.[19] Cocaine, heroin, and opioids are by far the deadliest of the eight major drug categories, resulting in around two to three times more deaths per visit than the other four top drug categories. For every one-hundred ED visits for cocaine poisoning there are approximately 1.5 in-hospital deaths. Similarly, 1.4% of heroin and 1.2% of opioid overdose ED visits result in an in-hospital death. The death rate associated with an ED visit for a

[17] When a similar figure is created for each state, a clear relationship between the ED visit rate for opioids and for all drugs is still present. However, some states in our sample do not exhibit strictly increasing trends over this time period. As we only have data for 5 states for county-level ED visits, we verified that the mortality trends were similar for these states as for the U.S. average. When we limit the mortality data from Fig 1 to these same 5 states: there is a 117 % increase in drug-related death rates and a larger (339%) rise in opioid deaths.
[18] Similar figures created for each state using the micro-data display consistent results.
[19] This includes all deaths that occur in the ED as well as all deaths that occur during any related inpatient stay following an admission from the ED.

benzodiazepine overdose is roughly one-third as large or 0.4%. The weighted average death rate of an ED visit for the remaining four categories (anti-depressants, aromatic analgesics, anti-psychotics, and insulin) is <0.4%. One implication of these results is that the relationship between overall drug-related ED visit and death rates may be quite weak, since many of the most important sources of visits rarely result in death, whereas the relationship between opioid-related ED visits and deaths may be considerably stronger.

IV. Empirical Approach

We perform both a county and state-level analysis of the relationship between macroeconomic conditions and adverse drug outcomes. We first describe the county-level analysis and subsequently discuss the modifications required when using state data.

Our main regression specifications take the form:

$$\boldsymbol{Y_{jt} = \beta U_{jt} + \eta_j + \delta_t + \mu_{st} + \epsilon_{jt}}\ , \qquad \textbf{(1)}$$

where the dependent variable, Y_{jt} is the mortality or ED visit rate, per 100,000, in county j and year t; U_{jt}, the county annual unemployment rate, is the main proxy for macroeconomic conditions. We include county and year fixed-effects (η_j and δ_t) in all models, to control for potential confounding factors that vary across counties but are fixed over time, as well as determinants of mortality or ED visits that differ nationally across time, and we report results from these specifications in our full sample analysis.

One concern is that local policies influencing drug mortality or ED visits could have changed over time in ways that are spuriously correlated with unemployment rates. The most important of these – such as prescription drug monitoring programs, recreational or medical marijuana legalization, and Medicaid policies – occur at the state rather than county level (Rees et al., 2017; Dowell et al., 2016; and Buchmueller and Carey, 2017). Therefore, our preferred specifications also include state-by-year fixed effects (μ_{st}). In alternative specifications, we instead include a vector of county-specific linear time trends.

Macroeconomic conditions may have worsened (or improved) in areas that for other reasons were on different trajectories in terms of drug mortality. If so, a model with county, year and state-by-year fixed effects could still incorrectly attribute a continuing pre-existing trend in mortality to changes in unemployment rates. Theoretically, we could address this by simultaneously controlling for both county-specific time trends and state-by-year fixed-effects. However, doing so for every county in the United States would leave our model with virtually no useful variation.[20] We address this issue in section VII, when describing our robustness checks.

Several points about our preferred regression specification deserve mention. First, given comprehensive controls for location and time-specific determinants, we generally do not include additional supplementary covariates. Second, we use levels, rather than natural logs, as the dependent variable. We do so because some counties (particularly smaller ones) will have zero values for the dependent variables in at least some years.[21] Third, we weight observations by population, to obtain nationally representative treatment effects. Unweighted estimates would overstate the influence of treatment effects in small counties. Fourth, the tables display robust standard errors clustered at the county level, which is the level of variation for our key regressor, the unemployment rate.

There are pros and cons to using counties, rather than larger geographic aggregates such as states, as the unit of observation. On the one hand, there is likely to be more error in the

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[20] A regression of county unemployment rates over this time on a set of county FE, year FE, state by year FE and county-specific linear time trends has an R^2 of 0.96.

[21] Prior related research (e.g. Ruhm, 2000) shows that comparable predicted effects are obtained using linear versus log-linear specifications. An alternative would be to estimate zero-inflated negative binomial models, although the interpretation of the coefficients in such specifications would be less transparent.

measurement of both mortality and unemployment rates for smaller geographic units.[22] On the other hand, counties within the same state could face different economic climates, and what happens far away may not affect lives as much as what occurs nearby (e.g. in funding of public health). However, a further question involves the level of geographic aggregation at which the macroeconomic effects actually take place. In this regard, Lindo's (2015) conclusion that more disaggregated analyses often understate the extent to which downturns affect health is particularly instructive. For our application, an additional advantage to using a broader level of geography is that we only have ED visit data at the county level for 5 states, while we have state level data for 15. For these reasons, we provide a full replication of analysis at the state level. When doing so, we are naturally no longer able to include state-by-year fixed effects and so we instead estimate specifications with and without state-specific linear time trends, and include state and year fixed effects in all specifications.

As mentioned, we also performed a series of robustness and sensitivity checks. These are summarized in Section VII and detailed in the supplementary appendix.

V. County-Level Results

Table 3 shows three county-level specifications for our dependent variables of primary interest: opioid-involved drug-related death rates, all drug-related mortality rates, opioid overdose ED visit rates, and all drug overdose ED visit rates. The first column shows the specification with only county and year fixed effects. The second column adds county specific time trends, while the third instead includes state-by-year fixed-effects, and corresponds to Equation 1. We view the

[22] The greater measurement error in county as opposed to state unemployment rates is well known (see for example Ganong and Liebman, 2013). Errors in classifying county of residence at death have been less studied, but Pierce and Denison (2006) provide evidence of substantial misrecording of counties using mortality data from Texas.

models in columns (2) and (3) as superior to column (1) because they better control for possible confounding factors. However, we generally prefer models that include state-by-year fixed effects since, as mentioned, many potential policy determinants are likely to vary across both time and states, but less so across counties within states.

Turning to the primary findings in column (3) of the first panel for opioid-involved drug-related deaths, the coefficient of 0.19 implies that a one percentage point rise in the county unemployment rate is predicted to increase opioid fatalities by a statistically significant 0.19 per 100,000. This represents a 3.55 percent growth from the sample average of 5.35 per 100,000. A one standard deviation change in the unemployment rate corresponds to 2.59 percentage points, suggesting effect sizes of around a 0.49 per 100,000, or an 9.2 percent, increase in fatal opioid overdoses. This also implies an unemployment rate elasticity of around 0.23.[23]

The estimated unemployment rate effect for all drug fatalities is also highly significant but somewhat sensitive to the inclusion of state-year fixed-effects versus county-specific time trends. In the preferred model (column 3), a one-point rise in unemployment predicts a 0.36 per 100,000 increase in drug mortality rates, corresponding to a 3.3 percent increase from the sample average of 10.77 per 100,000, and an unemployment rate elasticity of around 0.21 Results from this specification suggest that around half of the macroeconomic effect on drug mortality operates through opioid-related deaths. We confirmed this by estimating our preferred specification where the dependent variable was non-opioid related drug deaths. The unemployment coefficient is (a statistically significant) 0.17, accounting for the remainder of the total effect. (Details are provided in the supplementary appendix.) Conversely, in the model with county time trends, rather than state-by-year fixed effects, the one-point rise in unemployment predicts a much smaller, 0.18 per

[23] A one percentage point rise in unemployment represents a 15.65 percent increase from the sample mean rate of 6.39 percent, yielding an elasticity of 0.23 (3.55%/15.65%).

100,000, increase in the all drug death rate, which is then dominated by changes in fatalities involving opioids.

The two lower panels of Table 3 show results for drug-related ED visits, rather than deaths. Being restricted to selected county-year observations from five states, the samples are smaller, leading us to anticipate less precise estimates. Nevertheless, we find that, as with mortality rates, there is a strong and significant positive relationship between opioid-related overdose ED visits and unemployment rates that is relatively robust across specifications. In the model with state-year fixed-effects (column 3), a one percentage point rise in unemployment predicts a 0.95 per 100,000, or 7.0 percent, increase in opioid overdose ED visits, corresponding to an elasticity of around 0.56.

The results for all drug-related ED visits are more sensitive to choice of specification, but still suggestive of a countercyclical macroeconomic effect. In our preferred model, a one-point rise in unemployment predicts a statistically insignificant 1.19 per 100,000, or 1.2 percent, increase in drug-related ED visits. This imprecision of results is not unexpected since, as discussed above, a large set of drugs cause individuals to seek ED care; however, many of these drugs relatively infrequently result in death. One consequence is that opioid overdose ED visits reflect a small share (13.9%) of all drug overdose ED visits, and it is unlikely that our analysis will have sufficient statistical power to detect any plausible minimum effect size. Put differently, opioid overdose ED visits would need to be implausibly sensitive to the unemployment rate for there to be statistically significant effects of the unemployment rate in the large category of ‘all drug’ ED visits.[24]

[24] To show this more formally, we conducted a simulated power analysis, where we estimated the minimum detectable effect size across all power levels and for a range of type-I error thresholds. Following conventional standards, for 80% power and a 0.05 type-I error threshold, the minimum detectable effect size in the county-level all-drug overdose ED visit specification was just below 3.5 visits per 100,000 caused by a one percentage point increase in the unemployment rate. The minimum detectable effect size for all power levels and for a variety of type-I error thresholds (0.1, 0.05, 0.01, and 0.001) is reported in the supplementary appendix. To put this in context, in our preferred model, a one percentage point increase in the unemployment rate predicts a 0.95 per 100,000 (or 7.0%) increase in the mean opioid overdose ED visit rate, from the baseline average of 13.54. Such an increase in the opioid ED rate, ceteris paribus, would imply a 0.97% increase in the mean “all drug” overdose ED rate (from 97.52 to 98.47. This expected

Substance use disorders are a public health threat and are thought to have an uneven toll across different segments of the population (Wu et al. 2011). Therefore, we next examine whether the effects of macroeconomic decline on opioid adverse events differ across race/ethnicity groups. Table 4 provides results from our preferred specification for each race/ethnic group.[25] The first column repeats the full sample results (from column 3 of Table 3). The remaining columns separately present the findings for whites, blacks, and Hispanics. As mentioned, we do not present ED visit results for Hispanics because this category is not classified consistently in the ED data.

The countercyclical variation in opioid-involved deaths is primarily driven by effects on whites, where a one-point rise in unemployment predicts a highly significant 0.23 per 100,000 (or 3.6 percent) mortality increase. The predicted effects are negative for blacks (-0.14 per 100,000) and positive but smaller for Hispanics (0.04 per 100,000). This finding is consistent with the common trends in white and total opioid death rates as depicted in Figure 2.[26] It is worth pointing out that the smaller estimates for nonwhites often represent lower levels for mortality risk, rather than smaller percentage effects. For instance, the 0.04 unemployment coefficient for Hispanics in the model corresponds to a 2.5 percent growth from the relatively low average rate of 1.60 per 100,000, which is similar to the corresponding relative change for whites.

The predicted macroeconomic effects on all drug deaths are also dominated by whites with a 0.48 per 100,000 (4.5 percent) increase anticipated to result from a one-point rise in the unemployment rate. Corresponding estimates are -0.13 per 100,000 for blacks and 0.11 per 100,000 for Hispanics. For opioid-related ED visits the patterns are somewhat different, with

effect size of 0.95 is well below the minimum detectable effect size of 3.5. (Our power simulations show that for a minimum detectable effect size of 1 and a type-I error threshold of 0.05, the power is below 6%) Indeed, the point estimate we recover, 1.19, is quite near the expected effect size, but it is imprecisely estimated due to a lack of power.

[25] Tables in the supplementary appendix report results across a variety of specifications by race, mirroring Table 3.

[26] There are similar observable common trends between the total and white opioid ED visit rates.

strong countercyclical predicted effects for both whites and blacks: a one-point increase in unemployment is expected to raise white ED visits by 0.91 per 100,000, or 4.8% percent, and black visits by 1.25 per 100,000, or 17.4% percent. However, the results for nonwhites should be interpreted with caution as they are often reasonably sensitive to choice of specifications. For instance, when examining all-drug or opioid-related mortality rates, small and statistically insignificant unemployment coefficients are obtained for blacks in models that include county and year fixed effects and county-specific time trends, but not when state-by-year fixed effects replace the county-specific trends.

VI. State-Level Results

Table 5 replicates the previous analysis at the state rather than county-level. Aggregated information on ED visits is used here for 15 states (rather than for the 5 states for which we have micro-data). Observations are weighted by relevant state (rather than county) population and standard errors are clustered at the state-level. Our preferred specification includes state and year fixed-effects, as well as state-specific time trends. See the supplementary appendix for a table reporting the relevant sample means for the outcomes and explanatory variables.

The first two columns of Table 5 present full-sample estimates. Separate findings for whites, blacks and Hispanics are shown in columns (3) through (8). The full sample results largely correspond to those observed using county-level data. Specifically, drug and opioid-related drug deaths, as well as opioid-related ED visits, are all strongly countercyclical. For example, a one-point increase in the unemployment rate is predicted to raise the opioid-related mortality rate by 0.33 per 100,000, a growth of 6.2 percent and an elasticity of around 0.39. Similarly, a one-point increase in the unemployment rate increases the predicted opioid ED visit rate by 3.12 per 100,000

(6.2%) and an implied elasticity of 0.22, with small positive (but statistically insignificant) predicted effects on drug ED visits. Although this pattern of results is similar to our county-level findings, the magnitude is larger for each coefficient. This is consistent with Lindo's (2015) evidence that macroeconomic effects are often understated when using county-level data.[27] These estimates further suggest that almost all of the predicted increase in drug deaths is due to opioid-related mortality, as evidenced by the similar (0.35 vs. 0.33) unemployment coefficients for the two dependent variables.

The third through eighth columns of Table 5 again indicate that the mortality effects are primarily due to changes among whites and, more generally, that the countercyclical variation in opioid-related deaths and ED visits is very strong for this group. Interestingly, while the unemployment coefficients on drug and opioid mortality were negative for blacks in some specifications when using county-level data, they reverse sign (but are often insignificant) with state-level analysis. This provides further evidence of the sensitivity of the estimates for blacks to changes in samples or specifications, suggesting that we should be cautious about making conclusive statements about macroeconomic effects for them. Conversely, evidence of countercyclical variation in Hispanic drug deaths is obtained using both county and state level data.[28]

[27] Another important driver of the difference in coefficient size for opioid ED visit rates between our preferred county-level specification (0.95) and our preferred state-level specification (3.12) is a difference in data. The county-level ED data count the number of *individuals* with an opioid overdose diagnosis, whereas the state-level ED data count the number of opioid overdose *ED visits* (of which there could be more than one per individual). However, a one percentage point increase in the unemployment rate has similar percentage effects on county-level opioid ED visits (7.0%) and state-level ED visits (6.2%).

[28] We also estimated models for heroin-related ED visits. These showed no clear pattern, ranging from strongly and significantly positive to strongly and significantly negative, and were highly sensitive to the choice of specifications. These results are displayed in the supplementary appendix. The majority of the coefficients were not statistically different from zero. Thus we cannot make statements about the relationship between heroin abuse and local macroeconomic conditions.

VII. Robustness Checks

Our results to this point indicate that drug mortality is strongly counter-cyclical, with the most important role being played by deaths involving opioids in most specifications. Opioid-related ED visits are also counter-cyclical and both of these effects are strongly driven by changes among whites. Conversely, the results for Hispanics and, particularly, blacks are more sensitive to model choices. We conducted a variety of further tests of the robustness of our main results to various changes in samples or specifications. We summarize these results here, with full discussion and details of the estimates provided in the supplementary appendix.

All of our county-level specifications include county and year fixed-effects, and most contain either state-by-year fixed effects (in our preferred specification) or county-specific linear time trends. Unfortunately, it is not possible to simultaneously control for both together, because doing so leaves our model with no useful variation.[29] As an alternative, we examined the robustness of our results to incorporating alternative, but more limited, sets of time trends. These included separate trends for counties by population quintiles (5 trends) or percentiles (100 trends). Alternatively, we allowed the top 1% of counties (by population size) to have their own individual trends, with separate trends by percentile for the other 99% of counties. We estimated models with individual trends for the top 5% of counties, and with separate trends by population vigintile (5% bins) for the other 95% of counties. Finally, we ran models that incorporated consumer zone rather than county time trends. Countercyclical variations in opioid death and ED visit rates were obtained in all of these specifications. The estimates were almost always statistically significant, although sometimes smaller than in the main specifications. For instance, the unemployment

[29] A regression of county unemployment rates on a full set of county, year, state-by-year fixed-effect, and county linear time trends, has an adjusted R^2 of 0.96.

coefficient on opioid death rates was 0.19 in the preferred model and ranged from 0.12 to 0.19 in the alternative specifications just described.[30]

We allowed for heterogeneous relationships between the economic climate and adverse drug outcomes – across factors such as time, county population density, education level, and industrial structure – by estimating models that excluded categories of counties. The first of these examined whether the relationship between macroeconomic shocks and opioid abuse differed by time period. This was done by systematically removing sets of three years at a time from the analysis sample.[31] For drug deaths, the unemployment coefficients and 95% confidence intervals were always well above zero, although they did fluctuate a bit. Importantly, the estimate that excluded 2008-2010 was typical of those obtained when removing other periods, indicating that the results were not driven by unusual effects occurring during the Great Recession. For opioid-related deaths and ED visits, we obtained a similar story of fairly consistent and strong (although not always statistically significant) effects when removing sub-periods. We did not find significant results for any drug ED visit specifications.[32]

We next investigated sensitivity of the results to the proxy used for macroeconomic conditions by running a model where the key explanatory variables is employment-to-population (EP) ratios.[33] Since there is no readily available series of county level EP ratios, specifications that

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[30] Similarly, the ED findings were robust to a majority of alternative time trends, but given the smaller number of counties in our sample, the results were insignificant when using commuter-zone-specific trends.

[31] Three year bins (as opposed to other numbers of years) were chosen to ensure that the full great recession period was removed in one specification, to insure that our results are not driven by that recession or other short-run macroeconomic events.

[32] It is possible that adverse events may respond asymmetrically to short term increases, rather than decreases, in the unemployment rate. To test for asymmetry, we perform our analysis on two subsamples of the data, one where the county-level unemployment rate has decreased relative to the previous year and the other where it has increased. For the mortality specifications, we find some evidence that economic downturns are driving the magnitude of our findings, but not the significance. For our ED specifications, we find no statistical difference between the results of the two sub-samples. The results from this check are reported in the supplementary appendix.

[33] Results for EP ratios could differ from those using unemployment rates because, for instance, declines in labor force participation rates were particularly pronounced during the "Great Recession" that began in 2007, when compared to other economic downturns (Shierholz, 2012).

included them were run at the state level. As expected, they provided coefficient estimates that were of the opposite sign and slightly smaller in magnitude than those obtained when controlling for unemployment rates.[34] We also decompose our sample into areas differentially impacted by changes in manufacturing employment and import exposure (Autor et al. 2013), we followed a strategy analogous to that used for different time periods, by examining how the results changed when successively omitting sample county quintiles for each variable. We obtained consistent coefficients across these for both proxies, indicating that our findings were not being driven by areas with the greatest loss of manufacturing jobs or largest increase in imports.

We explored potential heterogeneity in the effects across urban and rural areas by successively excluding quintiles of counties based on 2010 population density.[35] The mortality findings were not driven by population density, except that the estimated effects for opioid deaths were slightly weaker (and statistically significant at the 10% but not the 5% level) when excluding the densest areas. The results for all-drug ED visits were noisier and centered around zero, while those for opioid-related ED visits were statistically significant and consistent in magnitude across all quintiles. Next, we performed the same exercise but systematically dropped counties by quintile of 2010 high school graduation status and percent nonwhite. Our main results were robust to these exclusions.

As the reported number of opioid deaths is an undercount of the true number, we use an imputation procedure to more accurately capture the correct number. In the Appendix we show that the uncertainty from the imputation process is of minimal concern to the statistical significance

[34] Slightly smaller magnitudes were expected since a one-percentage point rise in the unemployment rate usually translates into a more than one point reduction in EP ratios (since some discouraged jobless individuals drop out of the labor force in bad times).

[35] County characteristics, including percent of persons aged 25 and over who had graduated high school and land area (to calculate population density) were extracted from the 2010 U.S. decennial census. (www.census.gov/2010census/data/).

of our main findings. As expected, accounting for this additional source of uncertainty increases our standard errors, but only by a miniscule amount.

We attempted to decompose the effect of the unemployment rate on opioid-related ED visits by age and payer type group. The opioid ED visits results were consistent across all age groups and payer types, except for the elderly, for whom both an age group analysis and the Medicare payer type estimates were positive but not statistically different from zero.[36]

Finally, we performed a series of placebo tests, examining the unemployment coefficients on ED visit rates for causes not anticipated to be related to macroeconomic conditions. These included: vomiting during pregnancy, open head wounds, broken legs or arms and broken noses. With the exception of broken noses, none of these outcomes were statistically related to macroeconomic conditions.

VIII. Discussion

Overall, we obtain strong evidence that opioid-related deaths and ED visits increase during times of economic weakness, although the results vary somewhat with the unit of observation (county vs. state) and the exact specifications estimated. In the main county-level models, our preferred specification indicates that a one percentage point increase in the unemployment rate raises predicted opioid-involved mortality rates by 0.19 per 100,000, corresponding to a 3.6 percent growth and an unemployment elasticity of mortality of around 0.23. These effects are largely driven by changes in the death rates of whites in most estimates, with much smaller (but still mostly positive) increases predicted for Hispanics. Opioid-related ED visits are also anticipated to rise in economic downturns, with strong effects here observed for blacks as well as whites. There are weaker, and less consistent, results for other mortality and ED outcomes (e.g.

[36] This null finding makes sense, since job losses and economic declines during recessions should affect the working age population and children more than the elderly.

heroin-involved or other drug deaths), although often these results are in the same direction as for opioids.

We find negative economic shocks to have larger adverse effects on drug related mortality and ED visits when we conduct our analysis at the state (rather than county) level. A one-point rise in unemployment is predicted to increase overall opioid-related mortality by 0.33 per 100,000, over one and a half times the size of the county-level estimates, corresponding to growth of 6.2 percent and an unemployment elasticity of around 0.39. These larger estimates could occur because counties are too narrow a unit of observation to observe the full macroeconomic effects (Lindo, 2015) or because the county-level models are more fully able to control for potential confounding factors.

Our results should be interpreted in light of several limitations. First, while we have data for all deaths to US residents, the information on ED visits is more restricted, especially in our county level analysis. Second, although we use the two proxies of macroeconomic conditions most often used in the related literature (unemployment rates and employment to population ratios), and provide a limited investigation using changes over time in manufacturing employment or import penetration, a variety of other macroeconomic variables could be considered. These include measures like home foreclosures at the zip-code level (Currie and Tekin, 2015) and stock market losses at the national level (Schwartz et al., 2012) that capture different dimensions of economic decline. Third, there could be errors in the recording of the specific drugs involved in fatal overdoses and in the reasons for ED visits. We use imputation procedures to minimize effects of the former, but cannot be sure that our methods are completely successful. Finally, it is unclear which model specification or unit of analysis is the "best". We have attempted to address this issue by providing estimates for a wide variety of models and samples. Most results are robust to these alternatives, but some are not. In particular, unemployment rates are negatively correlated with black drug mortality rates in the county-level models but not in the state-based specifications and most, but not all, specifications suggest that the countercyclical variation in drug mortality rates is predominantly due to changes in opioid-related related deaths, as opposed to other types of drug fatalities.

There are numerous potential causal pathways linking macroeconomic developments to health behaviors and their consequences but we know little about the mechanisms for the effects observed here. For instance, lower incomes might lead to reduced purchases and use of legal or illicit drugs during periods of economic weakness (Riddell and Riddell, 2006; Dobkin and Puller, 2007) and explanations emphasizing reductions in time costs (e.g. having more time to engage in time-intensive health-improving behaviors like exercise or recovery treatment programs) would lead to better outcomes in economic downturns. Neither of these appear to be a dominant factor for opioids or other drugs that lead to ED visits or deaths, since both are predicted to increase as a result of negative macroeconomic shocks.[37] On the other hand, our results could be consistent with a role for supply-side factors, such as the loss of health insurance or of public health funding for treatment or prevention during periods of economic weakness.

Notwithstanding the possible pathways just described, we suspect that the dominant factor linking macroeconomic conditions to adverse drug outcomes is that fatal and near fatal abuse of opioids often (and increasingly over time) reflects a physical manifestation of mental health problems that have long been known to rise during periods of economic decline.[38] In this regard, we note that although opioids are prescribed to treat pain, there are strong linkages between pain,

[37] However, worsening economic conditions could lead to reductions in some types of drug use, while increasing adverse events through changes in composition towards more lethal types of drugs.
[38] This dates back to Durkheim's (1897) work on suicides and includes a great deal of later research including that by Hamermesh and Soss (1974), and in the more closely related literature, to Ruhm (2000) and others.

mental health problems and the use of analgesics.[39] With the increased availability of prescription opioids (and reductions in heroin prices), it seems likely that consumption of these drugs rise when economic conditions worsen and that some of this increased use leads to adverse outcomes including emergency department visits or death. Developing a better understanding of the causal pathways for the results we observe is an important direction for future research.

[39] Depression and other forms of mental illnesses increase the experience of pain; pain is associated with more depressive symptoms and the two share many of the same biological pathways (Bair et al. 2003). Persons with depression, dysthymia and generalized anxiety or panic disorders use narcotics at relatively high rates (Sullivan et al., 2006; Braden et al., 2009) and opioids have been shown to have a palliative effect on mental health problems such as depression and obsessive-compulsive disorder (Koran et al. 2005; Bodkin, Zornberg, and Lukas, 1995).

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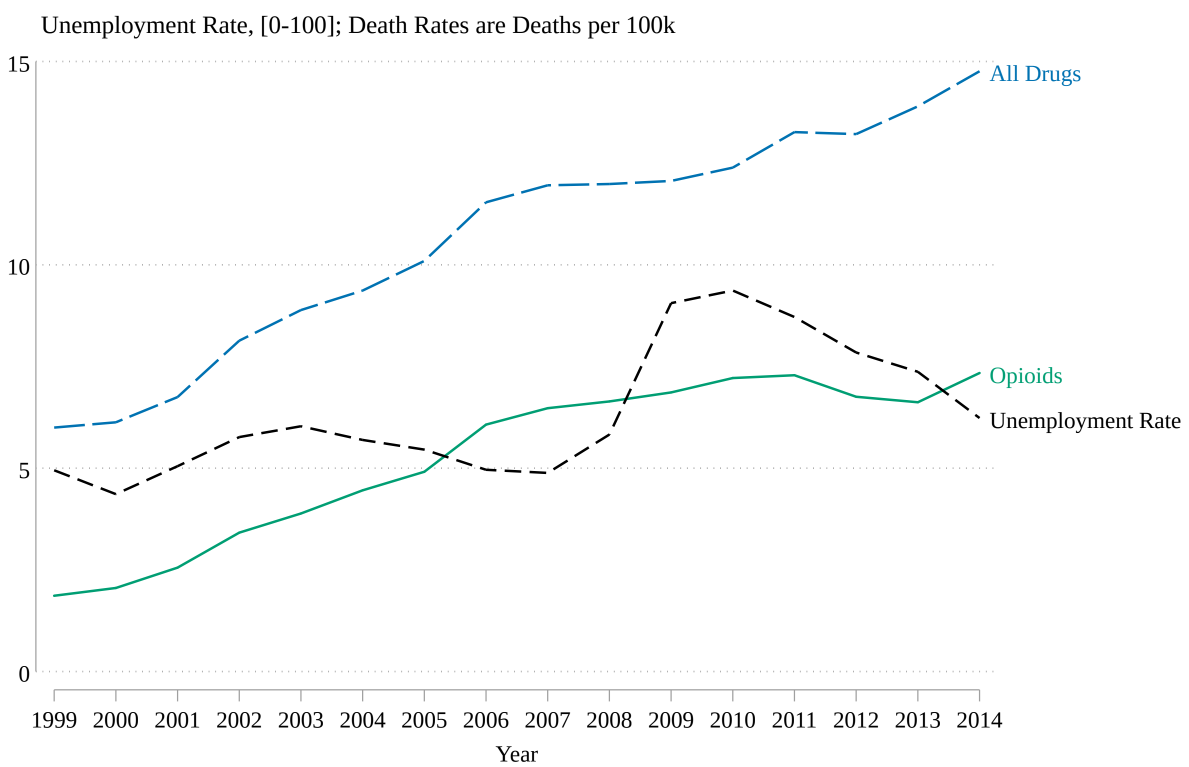
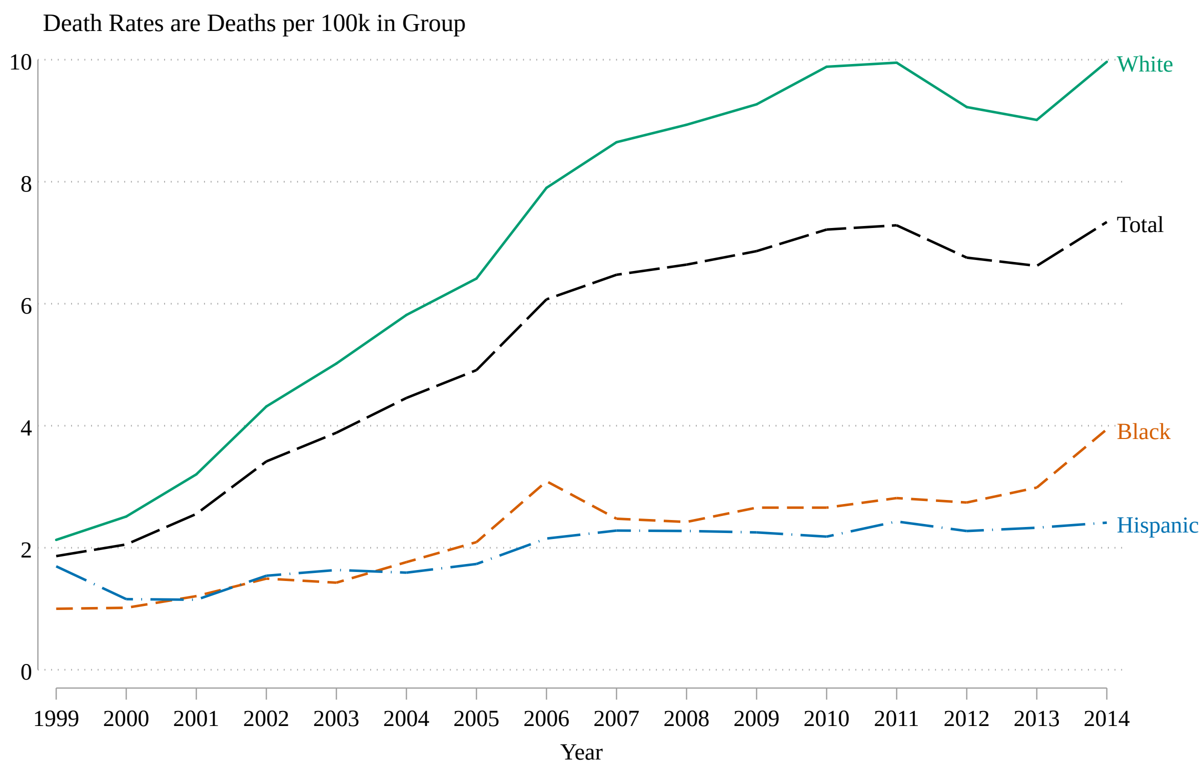
Figure 1: U.S. Unemployment Rate and Drug Death Rates by Type, 1999-2014



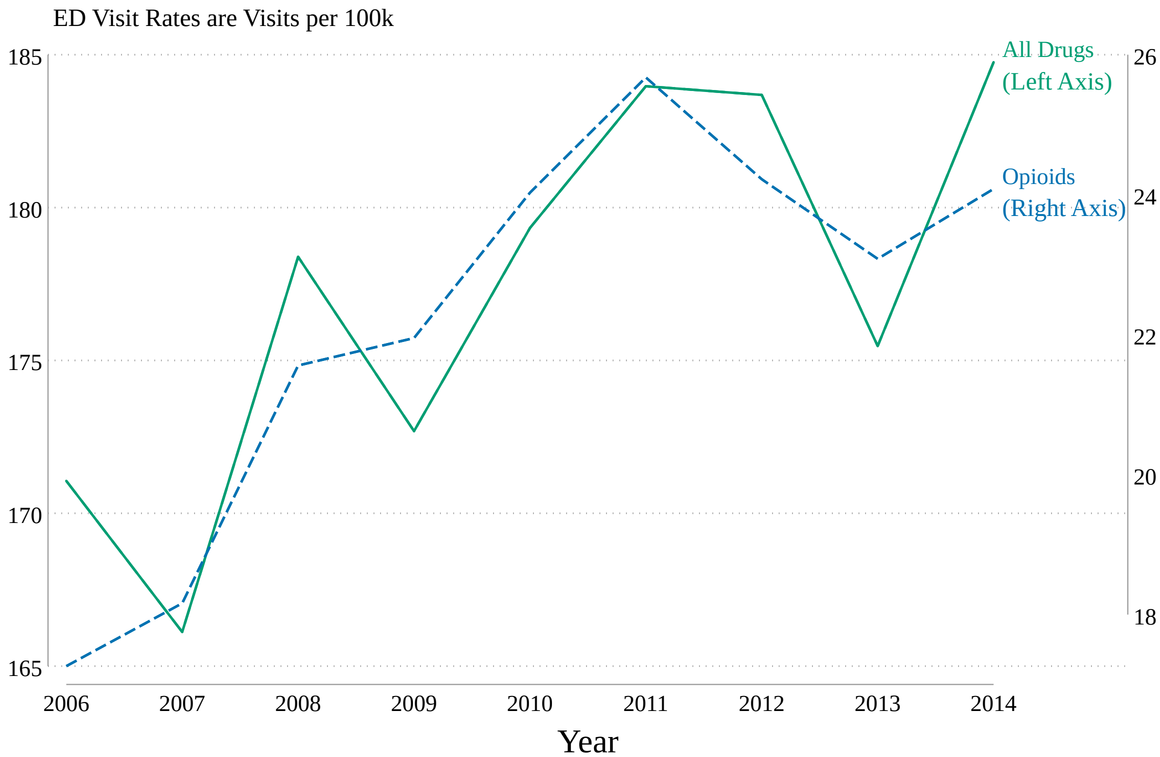
Source: Author calculations using National Vital Statistics System of the Centers for Disease Control and Prevention Multiple Cause of Death (MCOD) files for 1999-2014, together with unemployment rates from the Bureau of Labor Statistics.

Figure 2: Total Opioid Death Rate by Race, 1999-2014



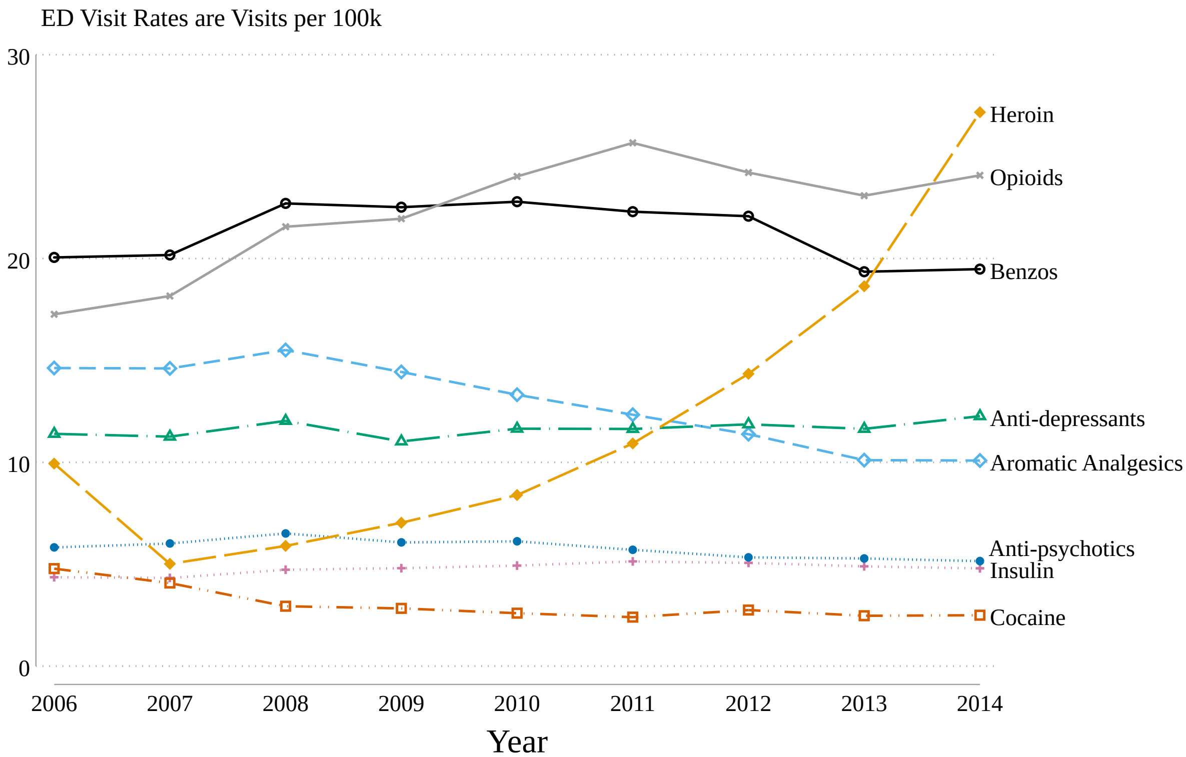
Source: Author calculations using National Vital Statistics System of the Centers for Disease Control and Prevention Multiple Cause of Death (MCOD) files for 1999-2014.

Figure 3: Opioid and All Drug Overdose ED Visit Rate, 2006-2014



Source: Author calculations using the Healthcare Cost and Utilization Project's Nationwide Emergency Department Sample for 2006-2014.

Figure 4: Drug Overdose ED Visit Rate by Major Drug Type, 2006-2014



Source: Author calculations using the Healthcare Cost and Utilization Project's Nationwide Emergency Department Sample for 2006-2014.

Table 1: Emergency Department Data: Geographic Detail and Years Used in Analysis

State	County-Level Data	Years	State-Level Data	Years
Arizona	Yes	2005-2014	Yes	2005-2013
Florida	Yes	2005-2014	Yes	2005-2013
Hawaii	No		Yes	2003-2010, 2013
Iowa	No		Yes	2004-2013
Illinois	No		Yes	2009-2013
Kentucky	Yes	2008-2012	Yes	2008-2013
Maryland	Yes	2002-2012	Yes	2005-2013
Minnesota	No		Yes	2001-2013
North Carolina	No		Yes	2007-2013
Nebraska	No		Yes	2001-2011, 2013
New Hampshire	No		Yes	2003-2009
New Jersey	Yes	2004, 2006-2013	No	
South Carolina	No		Yes	2005-2013
Tennessee	No		Yes	2005-2013
Utah	No		Yes	2000-2013
Vermont	No		Yes	2002-2013

Note: County-level data are constructed from the micro-data (visit-level) provided by the Healthcare Cost and Utilization Project's (HCUP) State Emergency Department Databases (SEDD). The state-level data is taken directly from the "State Statistics on All ED Visits" portion of HCUPNet, available at https://hcupnet-archive.ahrq.gov.

Table 2: County-Level Summary Statistics for Drug Related Deaths and ED Visits

	Mean	S.D.	Min.	Max.	N
Mortality Data					
Unemployment Rate, [0-100]	6.39	2.59	0.70	30.30	50148
Year	2006.50	4.61	1999.00	2014.00	50162
All					
Population, in 100k	0.95	3.07	0.00	101.17	50162
Opioid Death Rate per 100k	5.35	4.84	0.00	127.80	50162
Drug Death Rate per 100k	10.77	6.92	0.00	194.46	50162
White					
Population, in 100k	0.63	1.48	0.00	31.22	50162
Opioid Death Rate per 100k	7.03	6.14	0.00	161.64	50162
Drug Death Rate per 100k	13.07	8.61	0.00	234.19	50162
Black					
Population, in 100k	0.12	0.54	0.00	14.08	50162
Opioid Death Rate per 100k	2.28	4.65	0.00	4166.67	49661
Drug Death Rate per 100k	8.50	9.67	0.00	8333.33	49661
Hispanic					
Population, in 100k	0.14	1.10	0.00	48.98	50162
Opioid Death Rate per 100k	2.00	3.87	0.00	1492.54	50120
Drug Death Rate per 100k	5.25	6.53	0.00	3571.43	50120
Emergency Department Data					
Unemployment Rate, [0-100]	7.95	3.25	2.20	25.50	1873
Year	2009.50	2.86	2002.00	2014.00	1873
All					
Population, in 100k	2.21	4.24	0.02	40.87	1873
Opioid Overdose ED Visit Rate per 100k	13.54	8.41	0.00	145.84	1873
Drug Overdose ED Visit Rate per 100k	97.52	36.91	0.00	460.87	1873
White					
Population, in 100k	1.34	2.29	0.02	23.73	1873
Opioid Overdose ED Visit Rate per 100k	17.18	10.31	0.00	152.56	1828
Drug Overdose ED Visit Rate per 100k	109.05	42.06	0.00	464.01	1828
Black					
Population, in 100k	0.34	0.82	0.00	5.69	1873
Opioid Overdose ED Visit Rate per 100k	9.46	7.93	0.00	246.31	1828
Drug Overdose ED Visit Rate per 100k	90.60	38.24	0.00	4347.83	1828

Source: Mortality data are at the county-year and come from the Centers for Disease Control and Prevention's Multiple Cause of Death files from 1999-2014 and are adjusted as in text. ED data at the county-year level and are provided via the Healthcare Cost and Utilization Project's State Emergency Department Databases (SEDD). SEDD data come from Arizona (2005-2014), Kentucky (2008, 2010-2012), Florida (2005-2014), Maryland (2002-2012), and New Jersey (2004, 2006-2103). See text for ICD-9 definitions of outcomes. County level unemployment data come from Bureau for Labor Statistics. Unemployment rate, death rates, and ED visit rates are all weighted by total county population of group. Hispanic ED visits are omitted as the ED data do not contain a reliable indicator of Hispanic ethnicity.

Table 3: The estimated effect of county-level unemployment on the rate of opioid/drug mortality and emergency department visits across multiple specifications.

	(1)	(2)	(3)
Opioid Death Rate per 100k			
Unemployment Rate, [0-100]	0.22***	0.19***	0.19***
	(0.05)	(0.04)	(0.05)
Mean of Dependent Variable	5.35	5.35	5.35
Observations	50148	50148	50148
Drug Death Rate per 100k			
Unemployment Rate, [0-100]	0.29***	0.18***	0.36***
	(0.08)	(0.05)	(0.07)
Mean of Dependent Variable	10.77	10.77	10.77
Observations	50148	50148	50148
Opioid Overdose ED Visit Rate per 100k			
Unemployment Rate, [0-100]	0.57**	1.10***	0.95***
	(0.26)	(0.30)	(0.28)
Mean of Dependent Variable	13.54	13.54	13.54
Observations	1873	1873	1873
Drug Overdose ED Visit Rate per 100k			
Unemployment Rate, [0-100]	0.71	1.54	1.19
	(0.88)	(1.04)	(1.20)
Mean of Dependent Variable	97.52	97.52	97.52
Observations	1873	1873	1873
County Fixed-Effects	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes
County Specific Time Trends	No	Yes	No
State-by-Year Fixed-Effects	No	No	Yes

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the county level in parentheses. Each regression is weighted by total county population.

Table 4: The estimated effect of county-level unemployment on the rate of opioid/drug mortality and emergency department visits for our preferred specification across race/ethnicity.

	(1) All	(2) White	(3) Black	(4) Hispanic
Opioid Death Rate per 100k				
Unemployment Rate, [0-100]	0.19***	0.23***	–0.14**	0.04
	(0.05)	(0.05)	(0.07)	(0.03)
Mean of Dependent Variable	5.46	6.33	2.19	1.60
Observations	50132	50132	49630	50090
Drug Death Rate per 100k				
Unemployment Rate, [0-100]	0.36***	0.48***	–0.13	0.11*
	(0.07)	(0.08)	(0.10)	(0.06)
Mean of Dependent Variable	9.46	10.71	6.16	3.45
Observations	50132	50132	49630	50090
Opioid Overdose ED Visit Rate per 100k				
Unemployment Rate, [0-100]	0.95***	0.91**	1.25***	
	(0.28)	(0.37)	(0.45)	
Mean of Dependent Variable	16.91	18.92	7.18	
Observations	1873	1828	1828	
Drug Overdose ED Visit Rate per 100k				
Unemployment Rate, [0-100]	1.19	1.01	–1.07	
	(1.20)	(1.29)	(1.97)	
Mean of Dependent Variable	117.43	123.45	99.26	
Observations	1873	1828	1828	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the county level in parentheses. All specifications include county fixed-effects, year fixed-effects, and state-by-year fixed effects. Each regression is weighted by county population of group. Hispanic ED visits are omitted as the ED data do not contain a reliable indicator of Hispanic ethnicity.

Table 5: The estimated effect of state-level unemployment on the rate of opioid/drug mortality and emergency department visits across multiple specifications and race/ethnicity.

	All		White		Black		Hispanic	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opioid Death Rate per 100k								
Unemployment Rate, [0-100]	0.24***	0.33***	0.45***	0.41***	0.08	0.13	0.05	0.14***
	(0.08)	(0.08)	(0.10)	(0.11)	(0.06)	(0.09)	(0.05)	(0.05)
Mean of Dependent Variable	5.35	5.35	7.03	7.03	2.28	2.28	2.00	2.00
Observations	816	816	816	816	816	816	816	816
Drug Death Rate per 100k								
Unemployment Rate, [0-100]	0.24**	0.35***	0.54***	0.40***	0.18	0.33**	0.05	0.18**
	(0.10)	(0.11)	(0.11)	(0.14)	(0.12)	(0.14)	(0.07)	(0.09)
Mean of Dependent Variable	10.75	10.75	13.06	13.06	8.50	8.50	5.25	5.25
Observations	816	816	816	816	816	816	816	816
Opioid ED Visit Rate per 100k								
Unemployment Rate, [0-100]	3.24***	3.12***	5.45***	4.52***	0.73	1.05		
	(0.58)	(0.82)	(1.14)	(1.58)	(0.69)	(0.81)		
Mean of Dependent Variable	50.50	50.50	65.98	65.98	29.05	29.05		
Observations	138	138	101	101	73	73		
Drug ED Visit Rate per 100k								
Unemployment Rate, [0-100]	2.46	5.03	5.19	4.10	8.23	3.60		
	(2.65)	(3.25)	(6.48)	(6.72)	(5.22)	(5.17)		
Mean of Dependent Variable	318.67	318.67	352.22	352.22	264.87	264.87		
Observations	139	139	106	106	100	100		
State Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Specific Time Trends	No	Yes	No	Yes	No	Yes	No	Yes

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the state level in parentheses. Each regression is weighted by total state population of group. Hispanic ED visits are omitted as the ED data do not contain a reliable indicator of Hispanic ethnicity.

Supplementary Appendix

Our main analysis results indicate that drug mortality is strongly counter-cyclical, with deaths involving opioids playing the most important role. Opioid-related ED visits are also counter-cyclical and both the mortality and ED effects are strongly driven by the changes among whites. The results for Hispanics and, especially, blacks are more sensitive to the choice of model specification, suggesting difficulties in making conclusive statements for these demographic groups. We conducted a variety of tests of the robustness of our results to changes in samples or specifications.

Given that our main specifications do not simultaneously include both a full set of county linear time trends and state-by-year fixed effects, we replicated our full sample analysis using controls for state and year fixed-effects, state-by-year fixed effects and a variety of time trend specifications. The results from this exercise, presented in Appendix Table A1, show that the findings are robust. As in Table 3, each specification contains county, year, and state-by-year fixed-effects, with standard errors clustered at the county level. The number of time trends included increases as we move down the table and, when doing so, the coefficients of interest gradually attenuate towards zero. However, our mortality findings are robust to every alternative linear time trend specification, except in the last row which includes a separate trend for each county. As discussed, the inclusion of this large number of time trends removes all remaining useful variation. Similarly, our ED findings are robust to a majority of alternative time trends, but given the smaller number of counties in our sample, the results are also statistically insignificant when using commuter zone specific time trends.

We next examined whether the relationship between macroeconomic shocks and opioid abuse differed by time period. This is investigated in Figure A1 which shows, for our preferred county-level specification, the effect on the coefficients of systematically removing sets of three years at a time. Three year bins are chosen to ensure that the full great recession period is removed in one specification, to insure that our results are not driven by the recession or other short run macroeconomic events. The left side column has all deaths and the right side column shows corresponding effects for the ED visits.

For drug deaths, the coefficients and 95% confidence intervals are always well above 0, although they do fluctuate a bit. The estimate that excludes the Great Recession is marked by “08-10” is typical of the estimates obtained when removing other sub-periods. For opioid deaths we obtain a similar story of fairly consistent and strong effects. Opioid-related ED visits show a similar, consistent and significant estimates when removing sub-periods but we do not find significant results for any drug ED visit specifications.

Table A2 in the Appendix summarizes the data used in the remaining robustness checks. County characteristics, including percent of persons aged 25 and over who have graduated high school and land area (to calculate population density) are extracted from the 2010 U.S. decennial census. (www.census.gov/2010census/data/). Information on county level median income comes from the Census’ Small Area Income & Poverty Estimates. County characteristics intending to capture alternative measures of local economic conditions are obtained from Autor et al. (2013) and include the percent change in manufacturing and percent change in import exposure (from 1990-2007).

The next robustness check we performed is to include median income as an additional control variable in our specification of interest. This check is reported in Appendix Table A3 and follows Table 4 except with the addition of median income. We include this check as median income represents a potential mechanism for some of the effect of changing macroeconomic conditions. The income coefficient is negative and statistically significant when the dependent variable is mortality. A comparison of the unemployment coefficients in from Table 4 and Table A3 indicates that its inclusion generally does not material affect the estimated macroeconomic effect of unemployment, consistent with the results often obtained in previous related research (e.g. Ruhm, 2000).

We next tested whether the results were robust to using employment-to-population (EP) ratios rather than unemployment rates as the proxy for macroeconomics conditions. These results, summarized in Appendix Table A4, are conducted at the state level since there is no readily available series of county EP ratios. These results are a virtual mirror (although slightly smaller in absolute value) of the findings in Table 5, showing that the estimates are not sensitive to this choice.

We also explored whether the effects differ across urban and rural areas by successively excluding quintiles of counties based upon 2010 population density. For these results, shown in Figure A2 the right column again refers to ED visits and the left column to deaths. The mortality findings are not driven by population density, with the slight exception that the coefficient on opioid deaths falls slightly (and remains significant at the 10% but not the 5% level) when excluding the densest areas. The results for ED visits for all drugs are again noisier and centered around zero, while those for opioid-related ED visits are statistically significant and consistent in magnitude across all quintiles. Next, we performed the same exercise except systematically dropping counties by quintile of 2010 high school graduation status (Figure A3) and percent non-white (Figure A4). Our main results are robust to these exclusions.

Figures A5 and A6 examine the robustness of our results to dropping counties that experienced different levels in the percent change in manufacturing employment and the percent change in import exposure, (changes are calculated from 1990 to 2007). These variables, which were obtained from Autor et. al (2013), were only available as a cross-section and so could not be used as an independent variable in our main analysis. Instead, we followed the previously described strategy of examining whether areas most or least impacted by changes in manufacturing employment or foreign imports were driving our main findings. Once again, we obtained consistent coefficients across the omitted quintiles for each variable, indicating that those areas with the greatest loss of manufacturing jobs or the largest increase in imports did not drive our findings.

Figure A7 performs a series of placebo tests, examining the unemployment coefficients on ED visit rates for causes not anticipated to be related to macroeconomic conditions. These included: vomiting during pregnancy, open head wounds, broken legs or arms and broken noses. With the exception of broken noses, none of these were related to unemployment rates. Finally, Figure A8 decomposes the effect of the unemployment rate by age and payer type group for ED opioid overdose admission rates. The results show that opioid-related ED visits are driven by increases across all age groups and payer types, except for the elderly. While the point estimates for the elderly (and for Medicare as an expected payer type) are positive, they are not statistically different from zero. This null finding makes sense, since job losses and economic declines during recessions should affect the working age population and children more than the elderly.

In addition to the robustness checks just described, we conducted a number of other descriptive and econometric analyses. Figure A9 shows that all drug deaths follow similar patterns (although with higher rates) than fatal overdoses involving opioids – with faster growth and higher rates for whites than for blacks and Hispanics. Figure A10 provides details of our simulated power analysis, summarized briefly in footnote 25 of the main text.

Tables A5 and A6 summarize county-level analyses for other drug outcomes including mortality or ED visit rates related to heroin, drugs other than opioids and drug other than either heroin or opioids. These results confirm a countercyclical variation in most types of drug death rates, although with somewhat less consistent patterns for ED visits.

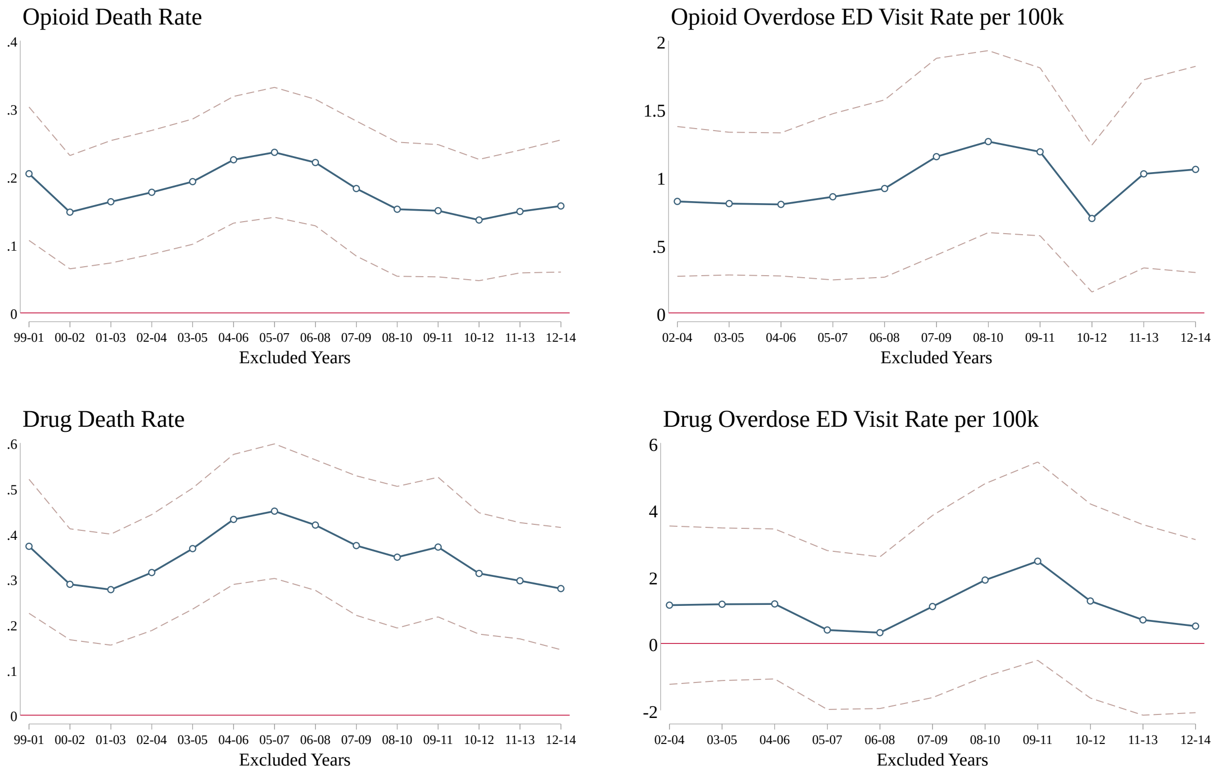
Tables A7 through A9 provide detailed results for race/ethnicity-specific adverse drug outcomes. A countercyclical variation is observed for whites for virtually all outcomes and specification (although it is not always statistically significant for all drug ED visits). For blacks, the mortality rates are more sensitive to the choice of specifications and, while opioid-related ED visits are always strongly countercyclical, overall drug death rates or ED visits are generally statistically insignificant. The point estimates always suggest a countercyclical pattern of Hispanic drug or opioid mortality but the coefficients are not always statistically significant.

Table A10 provides separate estimates for periods of decreasing versus increasing unemployment. The general result of a countercyclical variation in adverse drug outcomes holds across both periods, with no clear pattern of differences.

As mentioned in the paper, data using death certificates will understate the involvement of opioids (or any other drug category) because in 20%-25% of fatal overdoses the type(s) of drug(s) responsible for the overdose is(are) left unspecified (Ruhm, 2017). As previously outlined, to correct for the undercount in opioid deaths, we use an imputation procedure. Table A11 examines the sensitivity of our findings to accounting for the uncertainty introduced in the imputation stage. The first panel in Table A11 reports our estimates from Table 4. The second panel displays the results from a multiple imputation analysis with standard errors that account for fact that some of the opioid deaths are estimated. This process follows a standard multiple imputation framework (Rubin, 1987). Following White et al. (2011), we first generate 100 different datasets each of which is imputed (only for those individuals who died of a drug overdose and whose death certificate is missing information on the specific drug(s) responsible) via a draw from a probit model estimated conditional on the observed data. We then re-estimate our specification of interest using each of these 100 simulated datasets, storing the coefficient and standard error from each iteration. Each final coefficient and standard error is calculated by combining the vector of results using Rubin's (1987) rules. The final, corrected standard error accounts for both within specification variation and between specification variation. The between specification variation is driven by the difference in estimated coefficients across the 100 datasets and is identical to the square of the bootstrapped standard error (the standard deviation of the coefficient). The results presented in A11 demonstrate that the uncertainty from the imputation process is of minimal concern to the statistical significance of our main findings. As expected, accounting for this additional source of uncertainty increases the standard errors, but only minimally. Most differences are only salient once the number decimal places reported is extended to four.

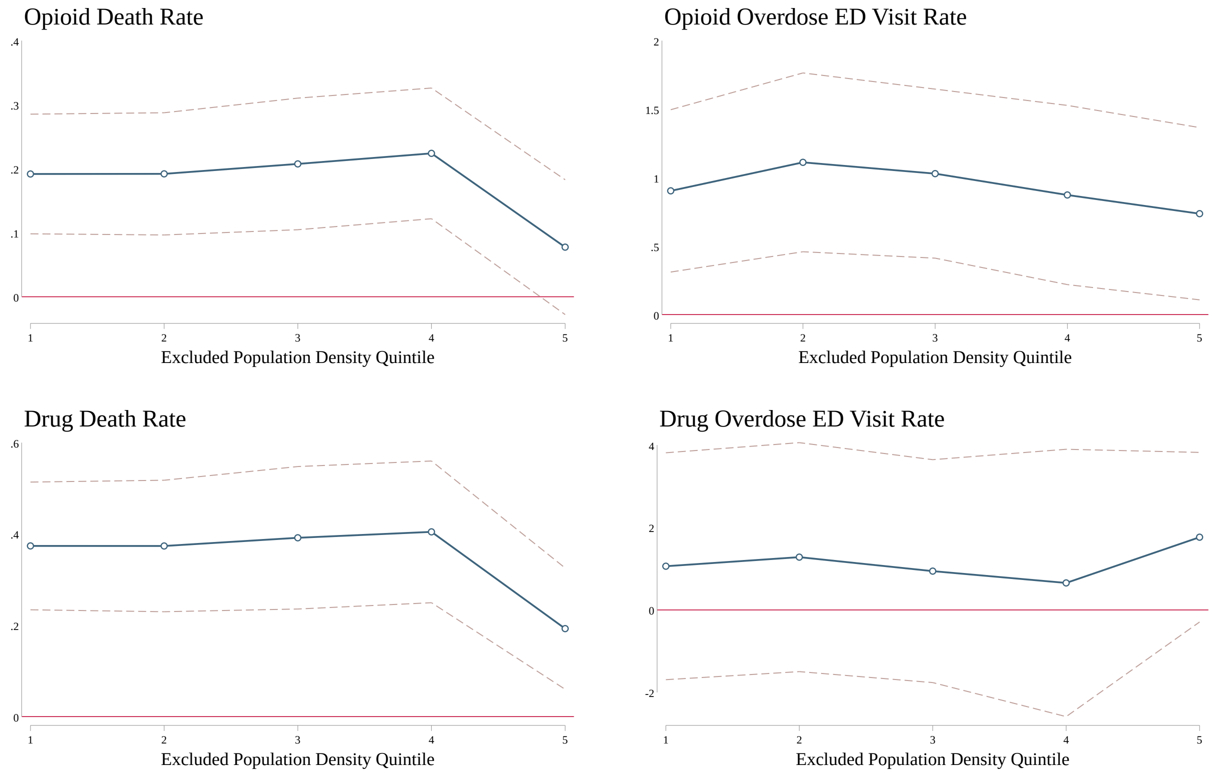
Finally, Table A12 shows county-level estimates for ED visits due to drugs other than opioids or heroin. The unemployment coefficients vary in sign and are usually statistically insignificant, except for benzodiazepine-related visits, which vary countercyclically. This finding is unsurprising as benzodiazepines are often taken with opioids. A CDC report found that in 2011, benzodiazepines were present in 31% of the opioid deaths (Chen et al. 2014).

Figure A1: The estimated effect of county-level unemployment on the rate of opioid/drug mortality and emergency department visits excluding various three-year bins.



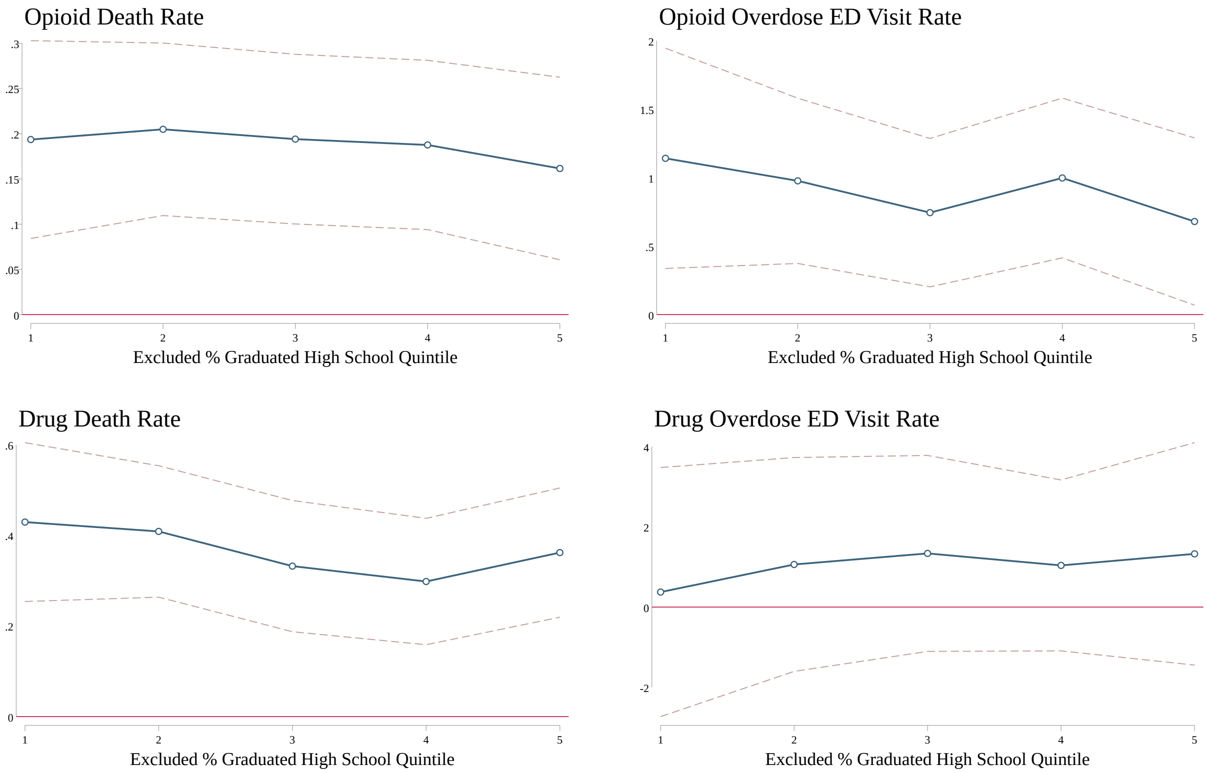
Note: Each point is from a separate regression that corresponds to our preferred specification in the text. Each regression has county fixed-effects, year fixed-effects, and state-by-year fixed effects. Each regression excludes the years noted. 95% confidence intervals are displayed by dashed lines and are calculated using robust standard errors clustered at the county level. Each regression is weighted by total county population.

Figure A2: The estimated effect of county-level unemployment on the rate of opioid/drug mortality and emergency department visits excluding population density quintiles.



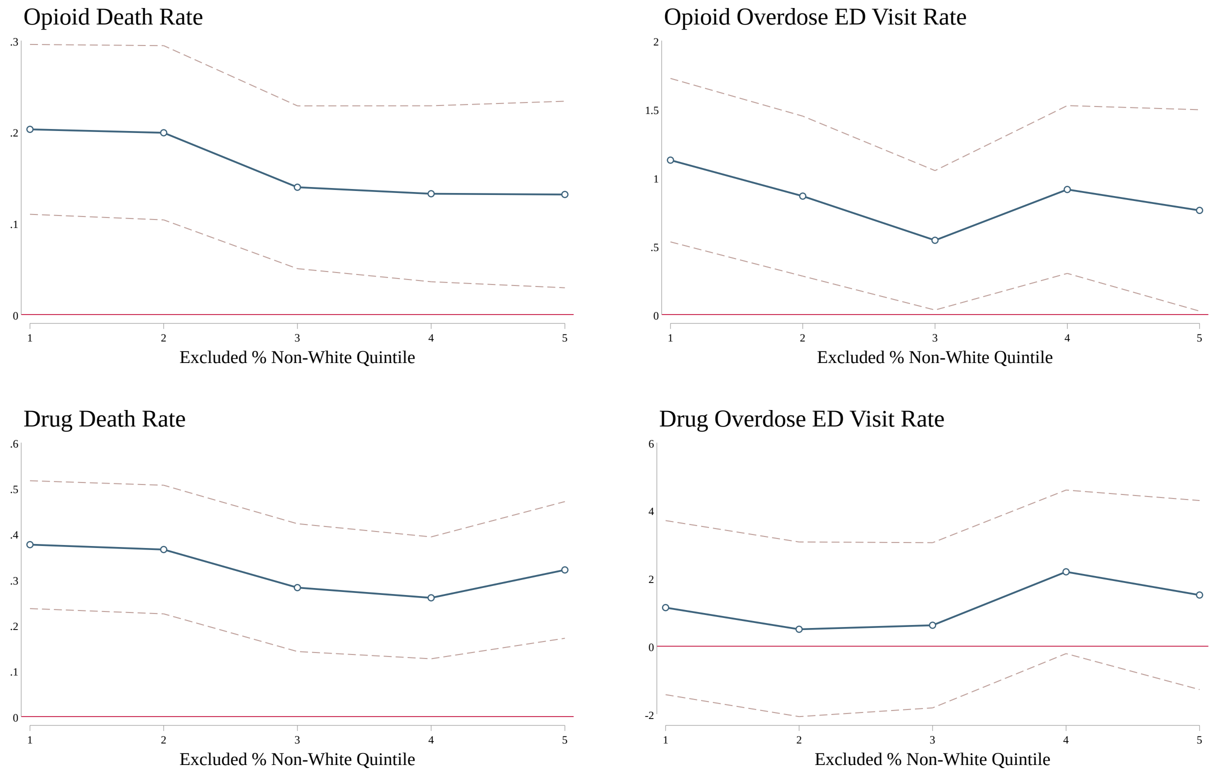
Note: Each point is from a separate regression that corresponds to our preferred specification in the text. Each regression has county fixed-effects, year fixed-effects, and state-by-year fixed effects. Each regression excludes the quintile noted. 95% confidence intervals are displayed by dashed lines and are calculated using robust standard errors clustered at the county level. Each regression is weighted by total county population.

Figure A3: The estimated effect of county-level unemployment on the rate of opioid/drug mortality and emergency department visits excluding % graduated high school quintiles



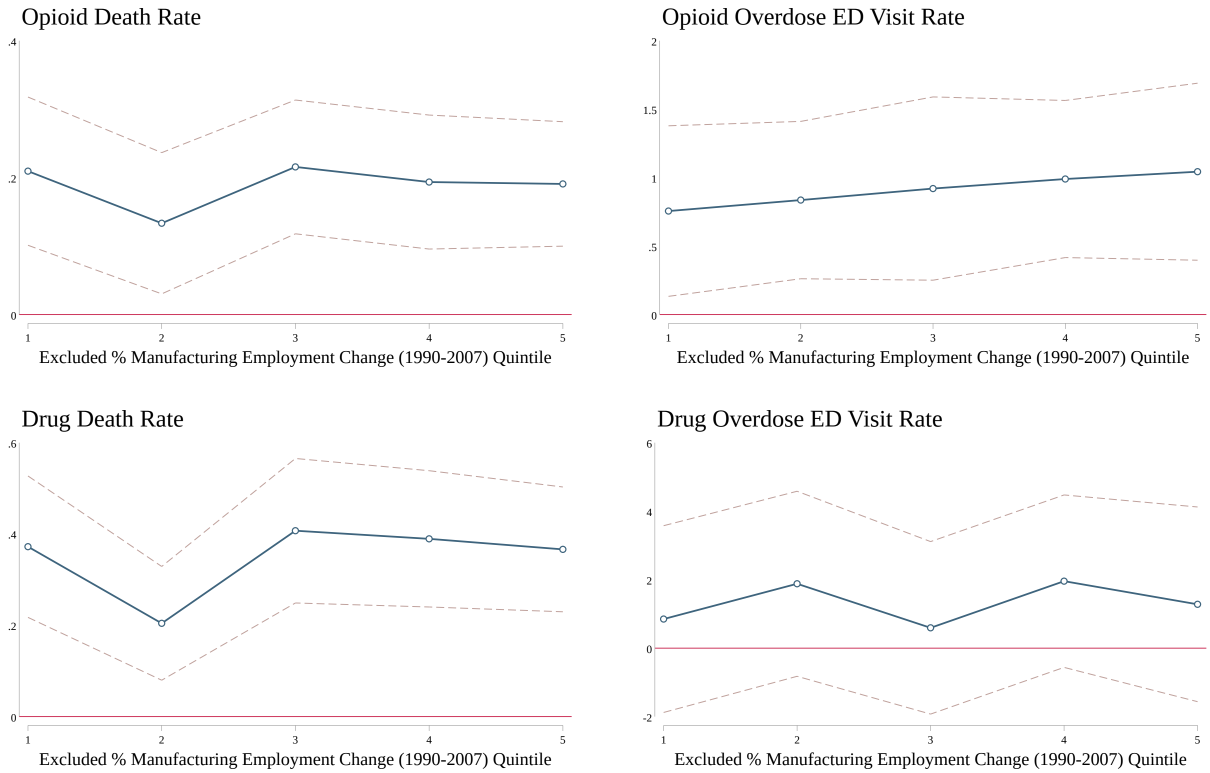
Note: Each point is from a separate regression that corresponds to our preferred specification in the text. Each regression has county fixed-effects, year fixed-effects, and state-by-year fixed effects. Each regression excludes the quintile noted. 95% confidence intervals are displayed by dashed lines and are calculated using robust standard errors clustered at the county level. Each regression is weighted by total county population.

Figure A4: The estimated effect of county-level unemployment on the rate of opioid/drug mortality and emergency department visits excluding % non-white quintiles



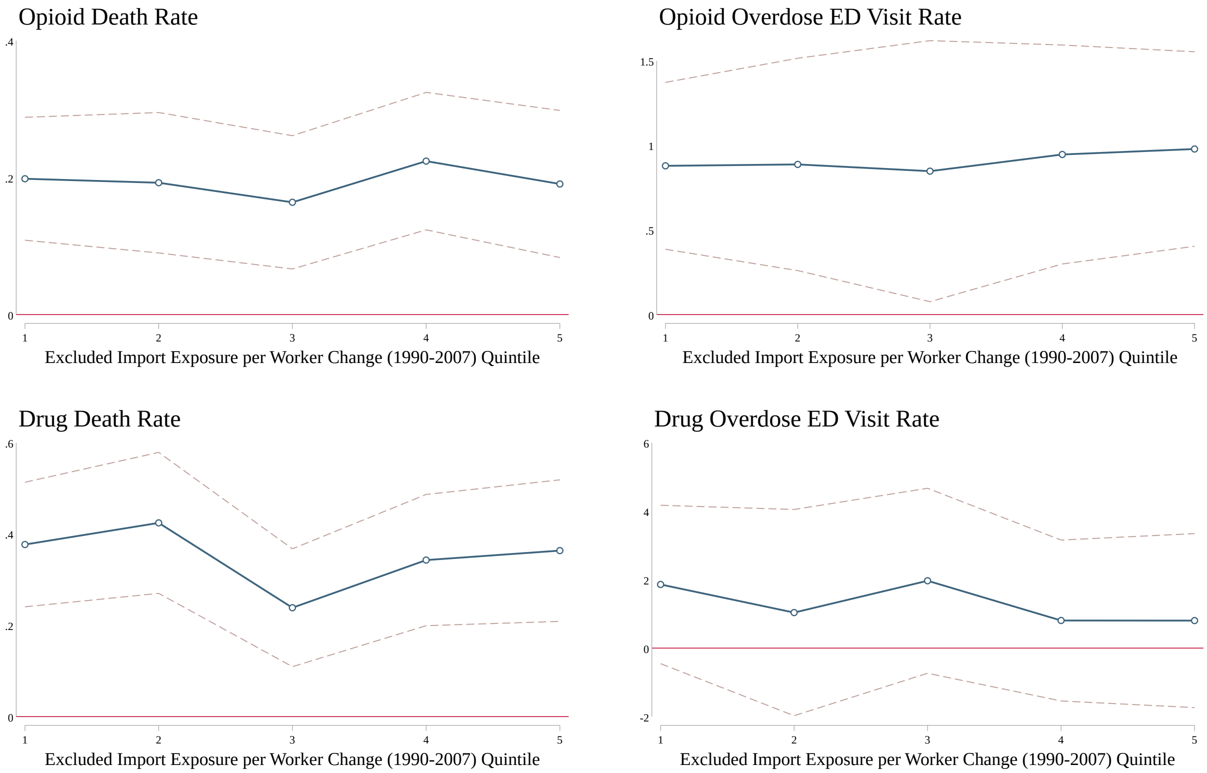
Note: Each point is from a separate regression that corresponds to our preferred specification in the text. Each regression has county fixed-effects, year fixed-effects, and state-by-year fixed effects. Each regression excludes the quintile noted. 95% confidence intervals are displayed by dashed lines and are calculated using robust standard errors clustered at the county level. Each regression is weighted by total county population.

Figure A5: The estimated effect of county-level unemployment on the rate of opioid/drug mortality and emergency department visits excluding change in % manufacturing employment (1990-2007) quintiles



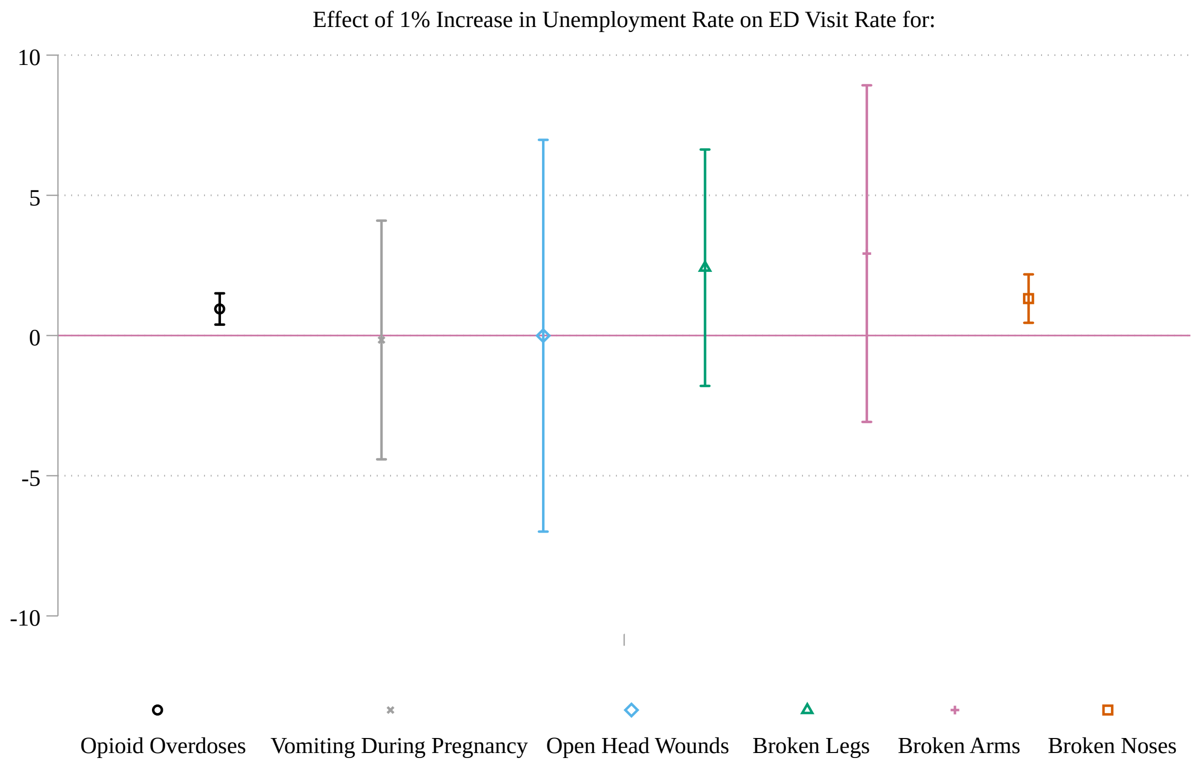
Note: Each point is from a separate regression that corresponds to our preferred specification in the text. Each regression has county fixed-effects, year fixed-effects, and state-by-year fixed effects. Each regression excludes the quintile noted. 95% confidence intervals are displayed by dashed lines and are calculated using robust standard errors clustered at the county level. Each regression is weighted by total county population. Data on change in manufacturing employment come from Autor et al. (2013). The lower the quintile, the larger the decrease in the share of manufacturing employment.

Figure A6: The estimated effect of county-level unemployment on the rate of opioid/drug mortality and emergency department visits excluding change in import exposure (1990-2007) quintiles



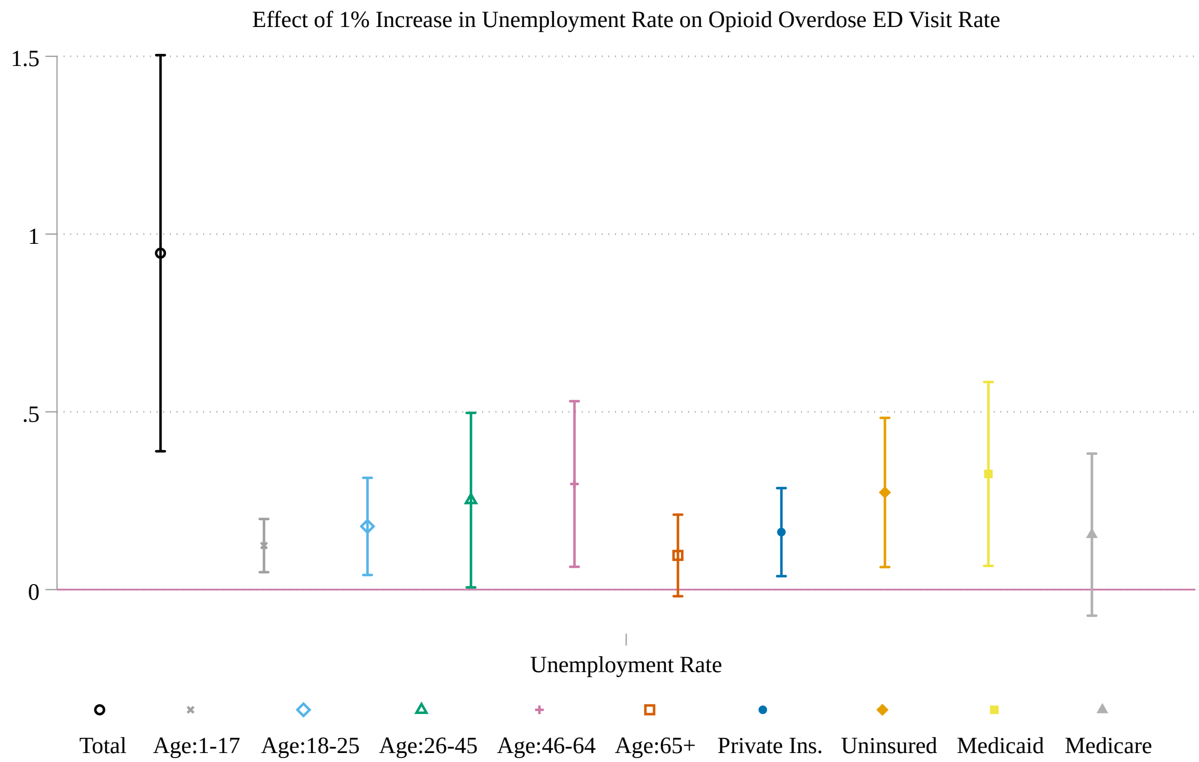
Note: Each point is from a separate regression that corresponds to our preferred specification in the text. Each regression has county fixed-effects, year fixed-effects, and state-by-year fixed effects. Each regression excludes the quintile noted. 95% confidence intervals are displayed by dashed lines and are calculated using robust standard errors clustered at the county level. Each regression is weighted by total county population. Data on change in manufacturing employment come from Autor et al. (2013). The lower the quintile, the smaller the change in import exposure.

Figure A7: The effect of county-level unemployment on the rate of opioid ED visits and the rate of ED visits for various placebos.



Note: Each point is from a separate regression that corresponds to our preferred specification in the text. Each regression has county fixed-effects, year fixed-effects, and state-by-year fixed effects. 95% confidence intervals are displayed by bracketed lines and are calculated using robust standard errors clustered at the county level. Each regression is weighted by total county population.

Figure A8: The effect of county-level unemployment on the opioid ED visit rate across various age groups and expected payer.



Note: Each point is from a separate regression that corresponds to our preferred specification in the text. Each regression has county fixed-effects, year fixed-effects, and state-by-year fixed effects. 95% confidence intervals are displayed by bracketed lines and are calculated using robust standard errors clustered at the county level. Each regression is weighted by total county population.

Figure A9: All Drug Death Rate by Race, 1999-2014

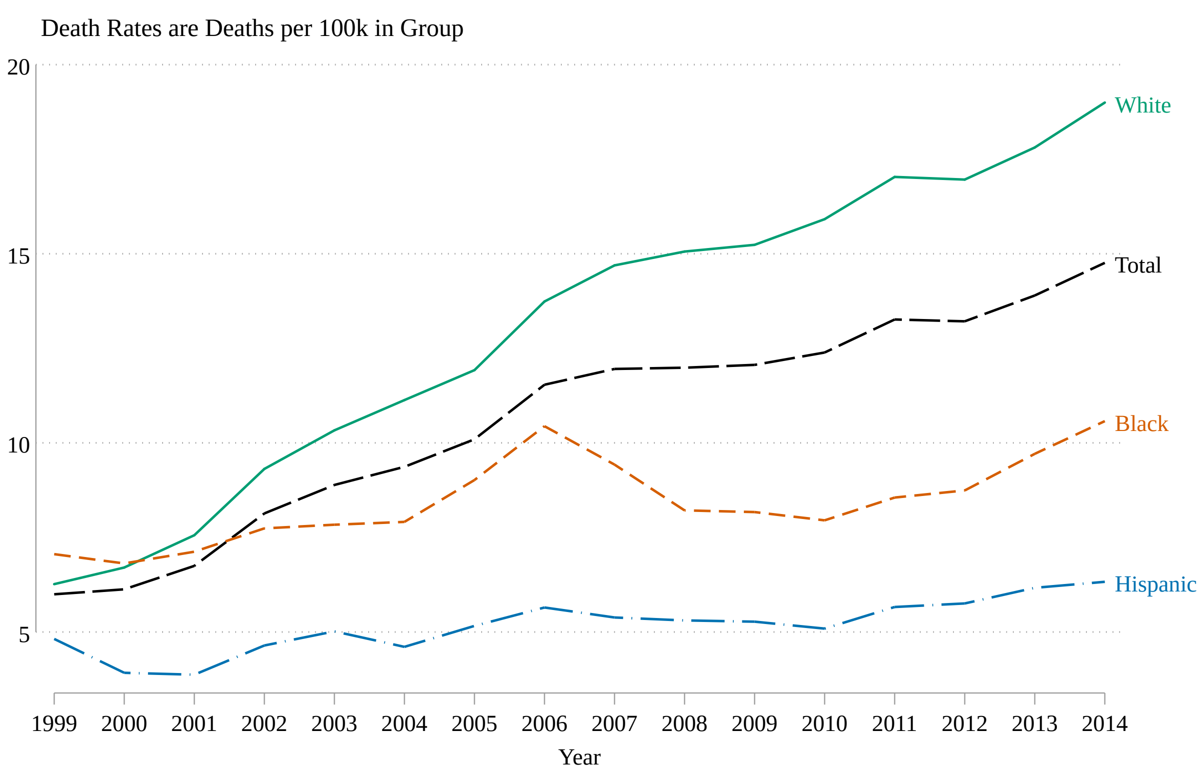
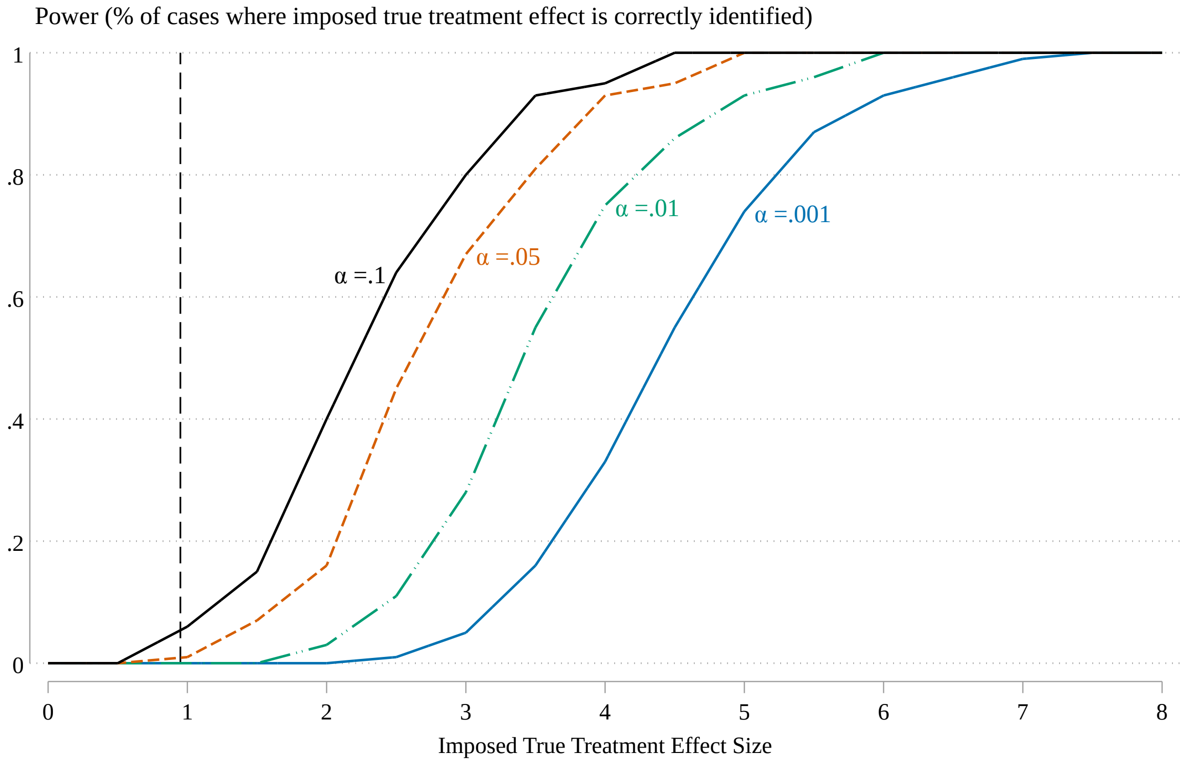


Figure A10: Simulated Power Analysis For All Drug Overdose ED Visit Rate



Note: The dashed vertical line is the estimated effect size of 1 percentage point increase in the unemployment rate on the opioid overdose ED visit rate. α is the probability of a type I error.

Table A1: The estimated effect of county-level unemployment on the rate of opioid/drug mortality and emergency department visits across various types of time trends.

	Opioid Death Rate (1)	All Drug Death Rate (2)	Opioid ED Visit Rate (3)	Drug ED Visit Rate (4)
All Races/Ethnicities				
No Time Trends	0.19***	0.36***	0.95***	1.19
	(0.05)	(0.07)	(0.28)	(1.20)
5 County Time Trends by Pop. Quintile	0.19***	0.36***	0.92***	1.28
	(0.05)	(0.07)	(0.28)	(1.29)
100 County Time Trends by Pop. Percentile	0.18***	0.33***	0.66**	–0.32
	(0.04)	(0.06)	(0.29)	(0.97)
Top 1% of Counties Have a Specific Trend, 99 Other Trends by Pop. Percentile	0.16***	0.26***	0.68**	–0.78
	(0.04)	(0.06)	(0.30)	(0.95)
Top 5% of Counties Have a Specific Trend, 19 Other Trends by Pop. Vigintile	0.12***	0.18***	0.82***	0.44
	(0.04)	(0.05)	(0.27)	(1.06)
Commuter Zone Specific Time Trends	0.12***	0.18***	0.38	–1.86
	(0.04)	(0.06)	(0.31)	(1.17)
County Specific Time Trends	0.03	0.01	0.49	–1.49
	(0.04)	(0.05)	(0.38)	(1.33)
Observations	50148	50148	1873	1873
County Fixed-Effects	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes
State-by-Year Fixed-Effects	Yes	Yes	Yes	Yes

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the county level in parentheses. Each regression is weighted by total county population.

Table A2: Summary Statistics for Appendix

	Mean	S.D.	Min.	Max.	N
State-Level Mortality Data					
Unemployment Rate, [0-100]	6.31	2.14	2.30	13.70	815
Median Income, $1000s	48.06	7.66	29.30	76.17	815
Employment to Population Ratio	70.20	4.23	46.67	83.48	815
Year	2006.51	4.61	1999.00	2014.00	815
All					
Population, in 100k	58.73	65.69	4.92	388.02	815
Opioid Death Rate per 100k	5.35	3.11	0.00	28.70	815
Heroin Death Rate per 100k	1.53	1.59	0.00	11.76	815
Drug Death Death Rate per 100k	10.77	4.18	1.82	34.23	815
Drug Death Rate per 100k, Exluding Opioids	5.41	2.00	0.34	15.60	815
Drug Death Rate per 100k, Exluding Opioids and Her	4.17	1.43	0.34	15.14	815
White					
Population, in 100k	39.05	34.80	1.62	163.90	815
Opioid Death Rate per 100k	7.03	4.13	0.00	29.70	815
Heroin Death Rate per 100k	1.75	1.87	0.00	13.06	815
Drug Death Rate per 100k	13.07	5.58	0.97	35.37	815
Black					
Population, in 100k	7.46	8.71	0.03	32.49	815
Opioid Death Rate per 100k	2.28	1.81	0.00	25.79	815
Heroin Death Rate per 100k	1.26	1.58	0.00	19.73	815
Drug Death Rate per 100k	8.50	4.59	0.00	39.58	815
Hispanic					
Population, in 100k	8.86	21.85	0.05	149.89	815
Opioid Death Rate per 100k	2.00	1.86	0.00	21.57	815
Heroin Death Rate per 100k	1.22	1.13	0.00	11.55	815
Drug Death Rate per 100k	5.25	3.33	0.00	28.37	815
State-Level Emergency Department Data					
Unemployment Rate, [0-100]	6.99	2.57	2.60	11.20	140
Median Income, $1000s	49.07	7.39	38.59	71.84	140
Employment to Population Ratio	70.82	5.25	61.70	82.41	140
Year	2008.11	3.30	2000.00	2013.00	140
All					
Population, in 100k	51.01	45.58	6.15	196.00	140
Opioid ED Visit Rate per 100k	50.50	18.85	9.07	87.22	139
Heroin ED Visit Rate per 100k	9.79	10.57	0.54	52.10	131
Drug ED Visit Rate per 100k	318.67	58.18	139.17	493.38	140
White					
Population, in 100k	35.10	27.28	2.72	111.87	140
Opioid ED Visit Rate per 100k	65.98	28.06	3.94	115.12	103
Heroin ED Visit Rate per 100k	11.25	12.38	0.63	64.21	99
Drug ED Visit Rate per 100k	352.23	98.26	2.52	557.93	108
Black					
Population, in 100k	6.99	8.95	0.05	31.37	140
Opioid ED Visit Rate per 100k	29.05	12.54	10.03	82.50	74
Heroin ED Visit Rate per 100k	12.37	17.58	0.48	60.70	46
Drug ED Visit Rate per 100k	264.87	62.22	87.78	522.99	101
Hispanic					
Population, in 100k	6.43	10.65	0.07	46.48	140
Opioid ED Visit Rate per 100k	18.85	11.20	4.19	73.56	70
Heroin ED Visit Rate per 100k	6.95	7.20	1.32	70.13	37
Drug ED Visit Rate per 100k	161.30	67.82	18.45	610.70	93
County-Level Variables for Mortality Data					
% High School Graduates, 2010	77.36	8.84	0.00	97.00	3135
Population per sq. Mile, 2010	215.51	1224.37	0.04	47038.61	3134
% Non-White, 2010	0.21	0.20	0.00	0.97	3135
Median Income, $1000s	43.14	10.75	20.58	119.08	3135
County-Level Variables for Emergency Department Data					
% High School Graduates, 2010	73.18	10.17	49.20	93.10	247
Population per sq. Mile, 2010	364.23	1006.97	4.51	10192.12	247
% Non-White, 2010	0.20	0.18	0.01	0.85	247
Median Income, $1000s	45.75	15.06	19.83	108.23	1873
Heroin Overdose ED Visits per 100k	4.72	12.72	0.00	180.18	1873
White Heroin Overdose ED Visits per 100k	4.04	11.84	0.00	180.18	1828
Black Heroin Overdose ED Visits per 100k	0.38	1.95	0.00	31.07	1828
Hispanic Heroin Overdose ED Visits per 100k	0.25	1.13	0.00	24.78	1828
Drug ED Visit Rate per 100k, Exluding Opioids	100.52	46.63	0.00	441.26	1873
Drug ED Visit Rate per 100k, Exluding Opioids and Heroin	95.92	48.76	–67.95	441.26	1873
Vomiting During Pregnancy ED Visits per 100k	95.30	44.62	0.00	332.43	1873
Open Head Wound ED Visits per 100k	851.25	162.30	246.09	1954.58	1873
Broken Leg ED Visits per 100k	284.51	75.39	105.89	882.06	1873
Broken Arm ED Visits per 100k	583.51	126.05	209.62	1462.88	1873
Broken Nose ED Visits per 100k	63.51	16.62	6.92	242.00	1873

Table A3: The estimated effect of county-level unemployment on the rate of opioid/drug mortality and emergency department visits for our preferred specification with median income across race/ethnicity.

	(1) All	(2) White	(3) Black	(4) Hispanic
Opioid Death Rate per 100k				
Unemployment Rate, [0-100]	0.16***	0.19***	–0.15**	0.03
	(0.05)	(0.05)	(0.07)	(0.03)
Median Income, $1000s	–0.04**	–0.08***	–0.02	–0.01
	(0.02)	(0.02)	(0.04)	(0.01)
Mean of Dependent Variable	5.46	6.33	2.19	1.60
Observations	50132	50132	49630	50090
Drug Death Rate per 100k				
Unemployment Rate, [0-100]	0.34***	0.42***	–0.09	0.11*
	(0.07)	(0.08)	(0.09)	(0.06)
Median Income, $1000s	–0.04	–0.11***	0.08	–0.01
	(0.04)	(0.04)	(0.06)	(0.02)
Mean of Dependent Variable	9.46	10.71	6.16	3.45
Observations	50132	50132	49630	50090
Opioid Overdose ED Visit Rate per 100k				
Unemployment Rate, [0-100]	0.92***	0.90**	1.10***	
	(0.28)	(0.36)	(0.41)	
Median Income, $1000s	–0.09	–0.05	–0.32***	
	(0.10)	(0.12)	(0.12)	
Mean of Dependent Variable	16.91	18.92	7.18	
Observations	1873	1828	1828	
Drug Overdose ED Visit Rate per 100k				
Unemployment Rate, [0-100]	1.25	0.98	–0.50	
	(1.19)	(1.27)	(1.88)	
Median Income, $1000s	0.20	–0.07	1.17*	
	(0.37)	(0.38)	(0.70)	
Mean of Dependent Variable	117.43	123.45	99.26	
Observations	1873	1828	1828	
County Fixed-Effects	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes
County Specific Time Trends	No	No	No	No
State-by-Year Fixed-Effects	Yes	Yes	Yes	Yes

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the county level in parentheses. All specifications include county fixed-effects, year fixed-effects, and state-by-year fixed effects. Each regression is weighted by county population of group. Hispanic ED visits are omitted as the ED data do not contain a reliable indicator of Hispanic ethnicity.

Table A4: The estimated effect of state-level employment-to-population ratio on the rate of opioid/drug mortality and emergency department.

	All		White		Black		Hispanic	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opioid Death Rate per 100k								
Employment to Population Ratio	–0.09***	–0.12***	–0.21***	–0.18***	0.01	–0.02	0.02	–0.02
	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)
Mean of Dependent Variable	5.35	5.35	7.03	7.03	2.28	2.28	2.00	2.00
Observations	816	816	816	816	816	816	816	816
Drug Death Rate per 100k								
Employment to Population Ratio	–0.12***	–0.14***	–0.27***	–0.21***	–0.02	0.01	–0.02	–0.04
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.03)	(0.04)	(0.05)
Mean of Dependent Variable	10.75	10.75	13.06	13.06	8.50	8.50	5.25	5.25
Observations	816	816	816	816	816	816	816	816
Opioid ED Visit Rate per 100k								
Employment to Population Ratio	–1.15***	–0.32	–1.64*	–1.58	–0.04	–1.11*		
	(0.38)	(0.58)	(0.88)	(1.20)	(0.58)	(0.59)		
Mean of Dependent Variable	50.50	50.50	65.98	65.98	29.05	29.05		
Observations	138	138	101	101	73	73		
Drug ED Visit Rate per 100k								
Employment to Population Ratio	–0.06	1.38	–2.51	1.44	–6.40*	–1.05		
	(1.38)	(1.55)	(3.41)	(4.68)	(3.80)	(3.64)		
Mean of Dependent Variable	318.67	318.67	352.22	352.22	264.87	264.87		
Observations	139	139	106	106	100	100		
State Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Specific Time Trends	No	Yes	No	Yes	No	Yes	No	Yes

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the state level in parentheses. Each regression is weighted by total state population of group. Hispanic ED visits are omitted as the ED data do not contain a reliable indicator of Hispanic ethnicity.

Table A5: The estimated effect of county-level unemployment on the rate of non-opioid and non-heroin drug mortality and emergency department visits.

	(1) All Drugs	(2) Only Opioids	(3) Only Heroin	(4) All Excluding Opioids	(5) All Excluding Both
Deaths per 100k					
Unemployment Rate, [0-100]	0.36***	0.19***	0.07***	0.17***	0.10***
	(0.07)	(0.05)	(0.02)	(0.04)	(0.03)
Mean of Dependent Variable	10.77	5.35	1.53	5.41	4.17
Observations	50148	50148	50148	50148	50148
ED Visits per 100k					
Unemployment Rate, [0-100]	1.19	0.95***	–0.68**	0.25	0.94
	(1.20)	(0.28)	(0.31)	(1.12)	(1.19)
Mean of Dependent Variable	97.52	13.54	5.81	83.98	78.28
Observations	1873	1873	1873	1873	1873
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes
County Specific Time Trends	No	No	No	No	No
State-by-Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the county level in parentheses. Each regression is weighted by county population of group.

Table A6: The estimated effect of county-level unemployment on the rate of heroin mortality and emergency department visits across multiple specifications.

	(1)	(2)	(3)
Heroin Death Rate per 100k			
Unemployment Rate, [0-100]	0.01	–0.01	0.07***
	(0.03)	(0.02)	(0.02)
Mean of Dependent Variable	1.53	1.53	1.53
Observations	50148	50148	50148
Heroin Overdose ED Visit Rate per 100k			
Unemployment Rate, [0-100]	0.37	1.08**	–0.68**
	(0.38)	(0.47)	(0.31)
Mean of Dependent Variable	5.81	5.81	5.81
Observations	1873	1873	1873
County Fixed-Effects	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes
County Specific Time Trends	No	Yes	No
State-by-Year Fixed-Effects	No	No	Yes

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the county level in parentheses. Each regression is weighted by total county population.

Table A7: The estimated effect of county-level unemployment on the white rate of opioid/drug mortality and emergency department visits across multiple specificationsn.

	(1)	(2)	(3)
White Opioid Death Rate per 100k			
Unemployment Rate, [0-100]	0.37***	0.23***	0.23***
	(0.05)	(0.05)	(0.05)
Mean of Dependent Variable	7.03	7.03	7.03
Observations	50148	50148	50148
White Drug Death Rate per 100k			
Unemployment Rate, [0-100]	0.51***	0.22***	0.48***
	(0.07)	(0.06)	(0.08)
Mean of Dependent Variable	13.07	13.07	13.07
Observations	50148	50148	50148
White Opioid Overdose ED Visit Rate per 100k			
Unemployment Rate, [0-100]	0.69**	1.43***	0.91**
	(0.31)	(0.36)	(0.37)
Mean of Dependent Variable	17.18	17.18	17.18
Observations	1828	1828	1828
White Drug Overdose ED Visit Rate per 100k			
Unemployment Rate, [0-100]	1.20	2.30*	1.01
	(0.98)	(1.18)	(1.29)
Mean of Dependent Variable	109.05	109.05	109.05
Observations	1828	1828	1828
County Fixed-Effects	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes
County Specific Time Trends	No	Yes	No
State-by-Year Fixed-Effects	No	No	Yes

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the county level in parentheses. Each regression is weighted by total white county population.

Table A8: The estimated effect of county-level unemployment on the black rate of opioid/drug mortality and emergency department visits across multiple specifications.

	(1)	(2)	(3)
Black Opioid Death Rate per 100k			
Unemployment Rate, [0-100]	–0.01	0.01	–0.14**
	(0.04)	(0.05)	(0.07)
Mean of Dependent Variable	2.28	2.28	2.28
Observations	49646	49646	49647
Black Drug Death Rate per 100k			
Unemployment Rate, [0-100]	0.08	0.05	–0.13
	(0.10)	(0.08)	(0.10)
Mean of Dependent Variable	8.50	8.50	8.50
Observations	49646	49646	49647
Black Opioid Overdose ED Visit Rate per 100k			
Unemployment Rate, [0-100]	0.33*	0.76**	1.25***
	(0.18)	(0.31)	(0.45)
Mean of Dependent Variable	9.46	9.46	9.46
Observations	1828	1828	1828
Black Drug Overdose ED Visit Rate per 100k			
Unemployment Rate, [0-100]	–1.12	0.20	–1.07
	(1.49)	(1.31)	(1.97)
Mean of Dependent Variable	90.60	90.60	90.60
Observations	1828	1828	1828
County Fixed-Effects	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes
County Specific Time Trends	No	Yes	No
State-by-Year Fixed-Effects	No	No	Yes

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the county level in parentheses. Each regression is weighted by total black county population.

Table A9: The estimated effect of county-level unemployment on the Hispanic rate of opioid/drug mortality across multiple specifications.

	(1)	(2)	(3)
Hispanic Opioid Death Rate per 100k			
Unemployment Rate, [0-100]	0.03	0.08**	0.04
	(0.04)	(0.03)	(0.03)
Mean of Dependent Variable	2.00	2.00	2.00
Observations	50106	50106	50106
Hispanic Drug Death Rate per 100k			
Unemployment Rate, [0-100]	0.03	0.08	0.11*
	(0.07)	(0.06)	(0.06)
Mean of Dependent Variable	5.25	5.25	5.25
Observations	50106	50106	50106
County Fixed-Effects	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes
County Specific Time Trends	No	Yes	No
State-by-Year Fixed-Effects	No	No	Yes

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the county level in parentheses. Each regression is weighted by total Hispanic county population. Hispanic ED visits are omitted as the ED data do not contain a reliable indicator of Hispanic ethnicity.

Table A10: The estimated effect of county-level unemployment on the rate of opioid/drug mortality and emergency department across decreasing/increasing unemployment rate relative to prior year.

	(1) Full Sample	(2) Decreasing Unemployment	(3) Increasing Unemployment
Opioid Death Rate per 100k			
Unemployment Rate, [0-100]	0.19***	0.10	0.25***
	(0.05)	(0.07)	(0.05)
Observations	50132	24287	23709
Drug Death Rate per 100k			
Unemployment Rate, [0-100]	0.36***	0.22**	0.43***
	(0.07)	(0.10)	(0.08)
Observations	50132	24287	23709
Opioid Overdose ED Visit Rate per 100k			
Unemployment Rate, [1-100]	0.95***	1.21***	0.97**
	(0.28)	(0.32)	(0.38)
Observations	1873	874	929
Drug Overdose ED Visit Rate per 100k			
Unemployment Rate, [1-100]	1.19	2.04*	0.88
	(1.20)	(1.23)	(1.51)
Observations	1873	874	929
County Fixed-Effects	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes
County Specific Time Trends	No	No	No
State-by-Year Fixed-Effects	Yes	Yes	Yes

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the county level in parentheses. Each regression is weighted by total county population.

Table A11: The estimated effect of county-level unemployment on moratality rate from opioids, baseline and accounting for variance in imputation procedure.

	(1) All	(2) White	(3) Black	(4) Hispanic
Baseline:				
	0.1889***	0.2350***	–0.1411**	0.0399
	(0.0453)	(0.0516)	(0.0718)	(0.0289)
Accounting for uncertainty in imputation:				
	0.1901***	0.2363***	–0.1397**	0.0414
	(0.0460)	(0.0528)	(0.0735)	(0.0304)
Observations	50132	50132	49630	50090
County Fixed-Effects	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes
County Specific Time Trends	No	No	No	No
State-by-Year Fixed-Effects	Yes	Yes	Yes	Yes

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the county level in parentheses. Each regression is weighted by county population of group. The specification that accounts for imputation uncertainty is an average of 100 different specifications, each identical except using a different dataset. Each datasets is drawn from the imputed variables to capture the uncertainty in the measurement. Coefficients and standards errors are calculated using Rubin's (1987) rules as outlined in White et al. (2011). Coefficients and standard errors are reported to four decimal points so differences are salient.

Table A12: The estimated effect of county-level unemployment on the rate of emergency department visits for each of the top ED categories.

	(1)	(2)	(3)
Pharmaceutical Overdose ED Visit Rate per 100k			
Unemployment Rate, [0-100]	0.34	0.78	0.48
	(0.72)	(0.87)	(0.85)
Mean of Dependent Variable	66.29	66.29	66.29
Observations	1873	1873	1873
Benzo Overdose ED Visit Rate per 100k			
Unemployment Rate, [0-100]	0.52	0.85**	0.95**
	(0.32)	(0.39)	(0.37)
Mean of Dependent Variable	18.84	18.84	18.84
Observations	1873	1873	1873
Aro. Analgesic Overdose ED Visit Rate per 100k			
Unemployment Rate, [0-100]	–0.20*	–0.31**	0.02
	(0.11)	(0.14)	(0.17)
Mean of Dependent Variable	9.87	9.87	9.87
Observations	1873	1873	1873
Anti-depressant Overdose ED Visit Rate per 100k			
Unemployment Rate, [0-100]	0.17	–0.01	–0.03
	(0.19)	(0.10)	(0.23)
Mean of Dependent Variable	3.83	3.83	3.83
Observations	1873	1873	1873
Insulin Overdose ED Visit Rate per 100k			
Unemployment Rate, [0-100]	–0.04	–0.02	–0.02
	(0.06)	(0.06)	(0.08)
Mean of Dependent Variable	3.54	3.54	3.54
Observations	1873	1873	1873
Cocaine Overdose ED Visit Rate per 100k			
Unemployment Rate, [0-100]	–0.10	–0.11	–0.04
	(0.14)	(0.11)	(0.17)
Mean of Dependent Variable	2.41	2.41	2.41
Observations	1873	1873	1873
Anti-Psychotic Overdose ED Visit Rate per 100k			
Unemployment Rate, [0-100]	–0.08	–0.06	–0.01
	(0.06)	(0.08)	(0.09)
Mean of Dependent Variable	4.05	4.05	4.05
Observations	1873	1873	1873
County Fixed-Effects	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes
County Specific Time Trends	No	Yes	No
State-by-Year Fixed-Effects	No	No	Yes

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the county level in parentheses. Each regression is weighted by county population of group.